Overview

Understanding different types of ML algorithms and use cases

Working with numerical and categorical data

Standardization of numerical data input into an ML model

Working with text, representing text data in numerical form

Representing pixel intensities and extracting features from images

Prerequisites and Course Outline

Beginner course on building ML models using scikit-learn

Comfortable with Python programming

Software and Skills

Be very comfortable programming in Python (Python 3)

Be comfortable working with Jupyter notebooks

Understand some basics of machine learning

Course Outline

Processing data

- Data preparation, representing text as numbers, representing images as matrices

Building specialized regression models

- Lasso and Ridge regression, Support Vector Regression

Building SVM and gradient boosting models

- Support Vector Machines for text and image classification, Gradient Boosting for regression

Clustering and dimensionality reduction

- Mean-shift clustering, Principal Components Analysis

Understanding Machine Learning

A machine learning algorithm is an algorithm that is able to learn from data

Machine Learning

Work with a huge maze of data

Find patterns

Make intelligent decisions

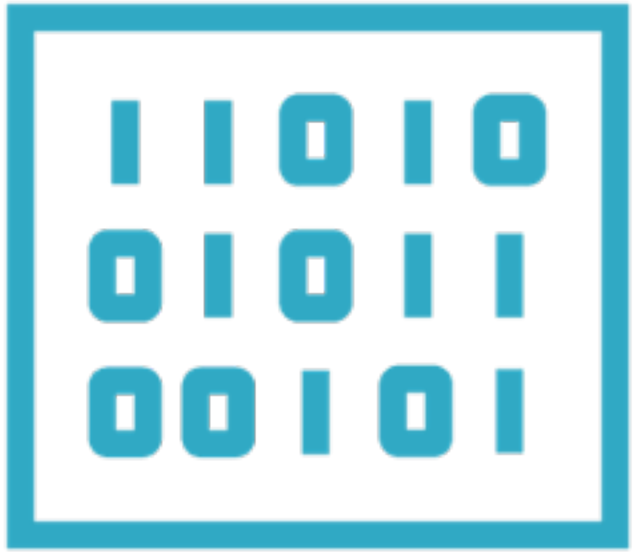
Machine Learning

Emails on a server

Spam or Ham?

Trash or Inbox

Machine Learning



Images represented as pixels

Identify edges, colors, shapes

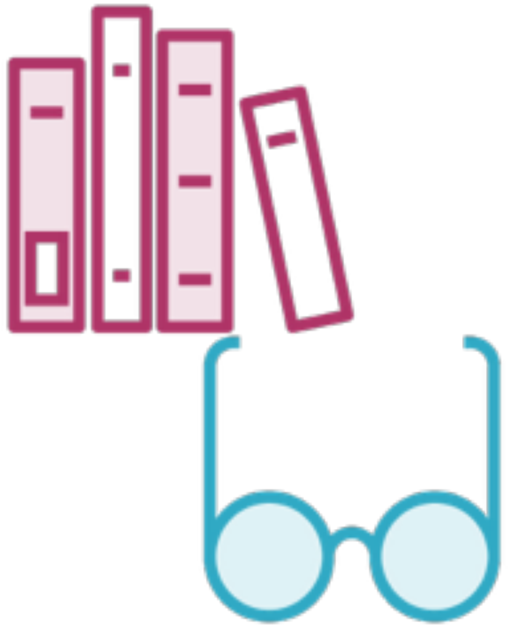
A photo of a little girl

Types of Machine Learning Problems

Classification

Regression

Clustering



Rule-extraction

Types of Machine Learning Problems

Classification

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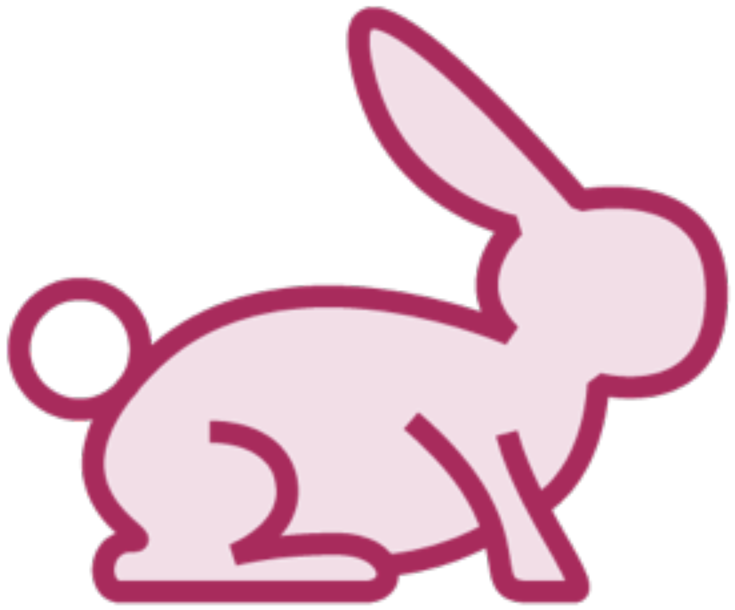
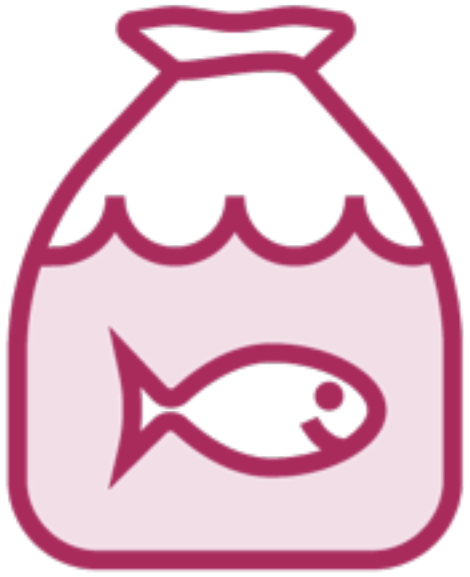
Rule-extraction

Whales: Fish or Mammals?



Mammals

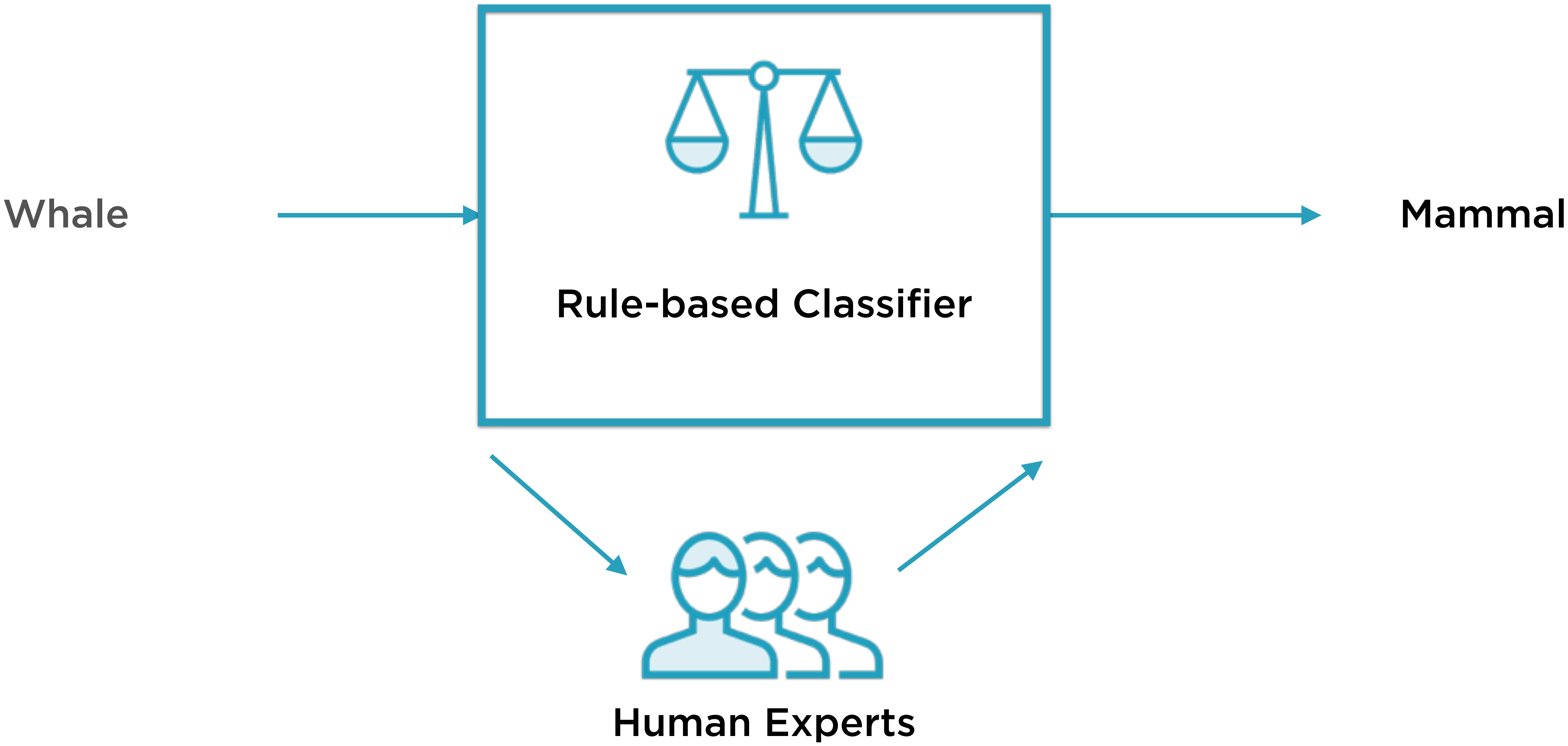
Members of the infraorder *Cetacea*



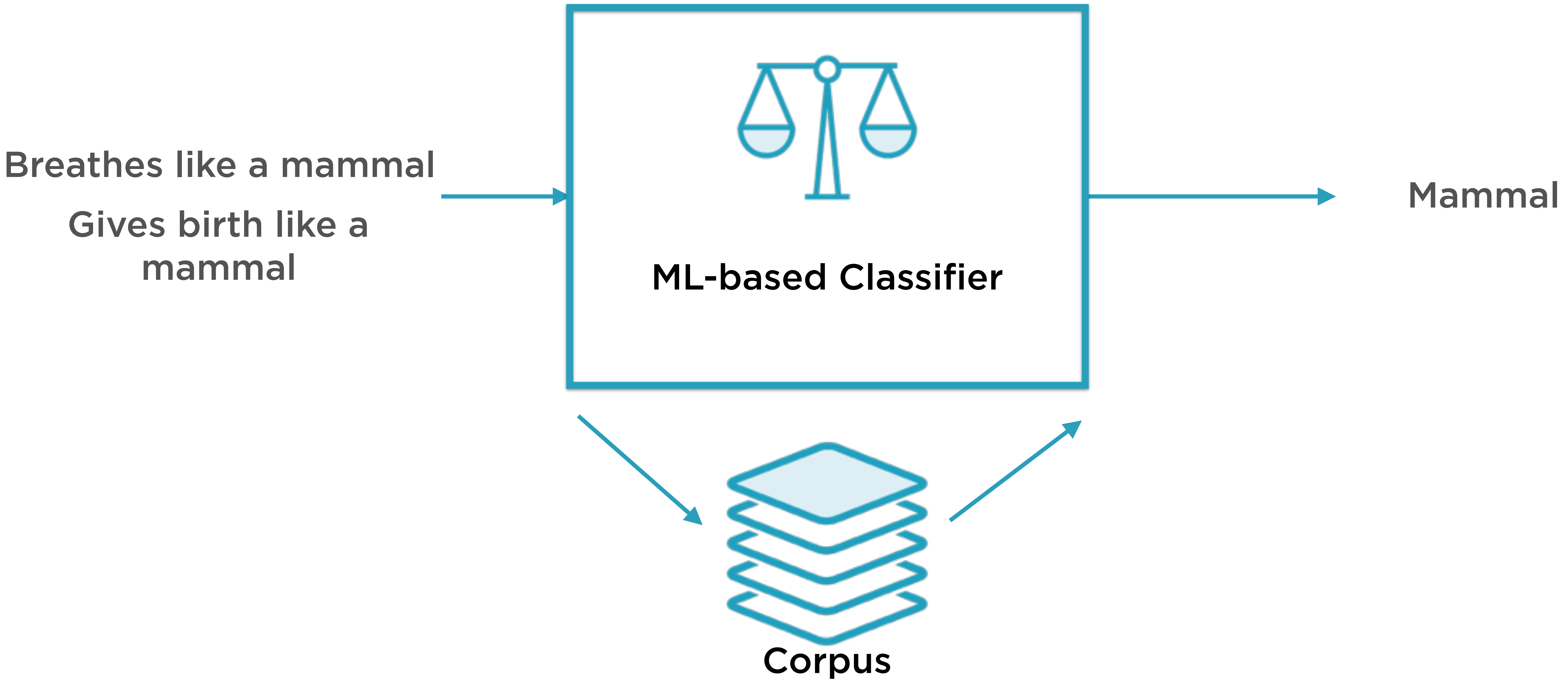
Fish

Look like fish, swim like fish, move with fish

Rule-based Binary Classifier



ML-based Binary Classifier



ML-based Binary Classifier

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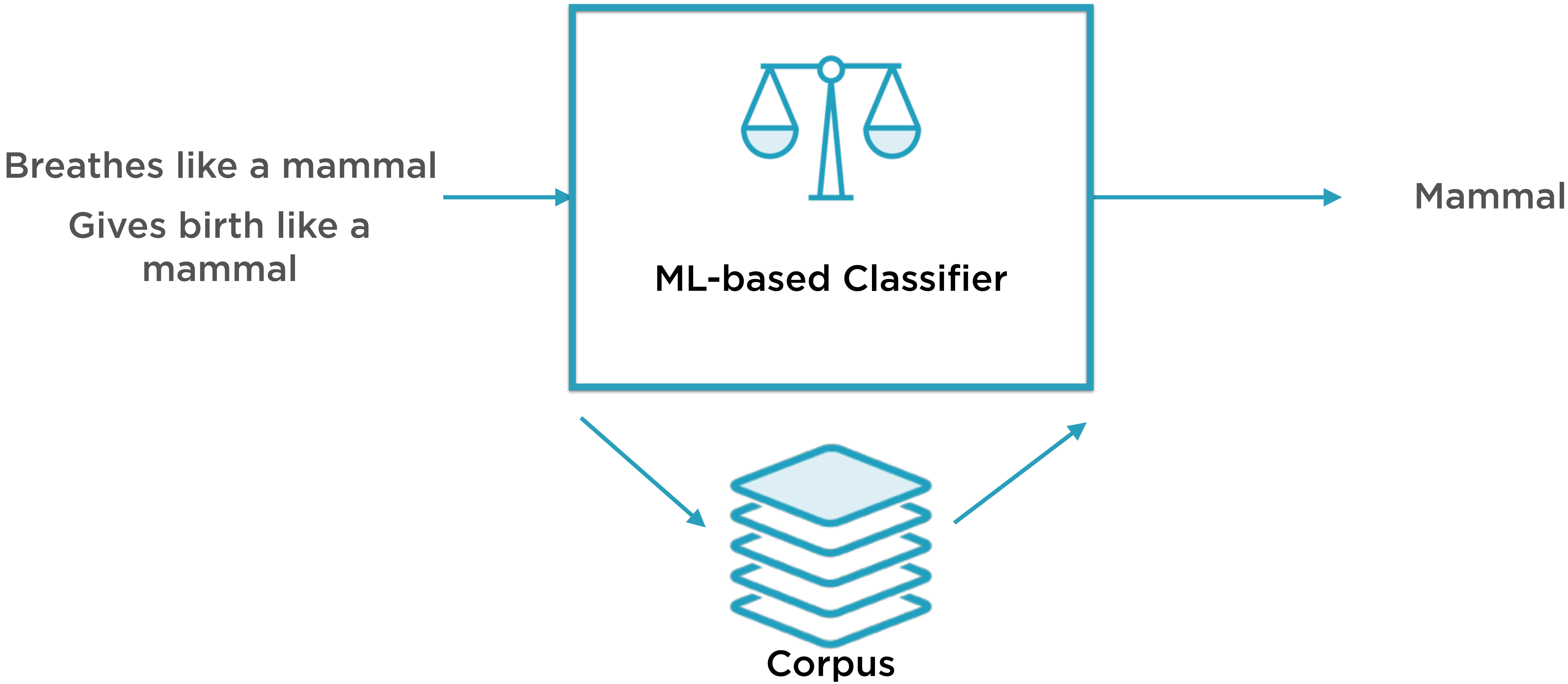
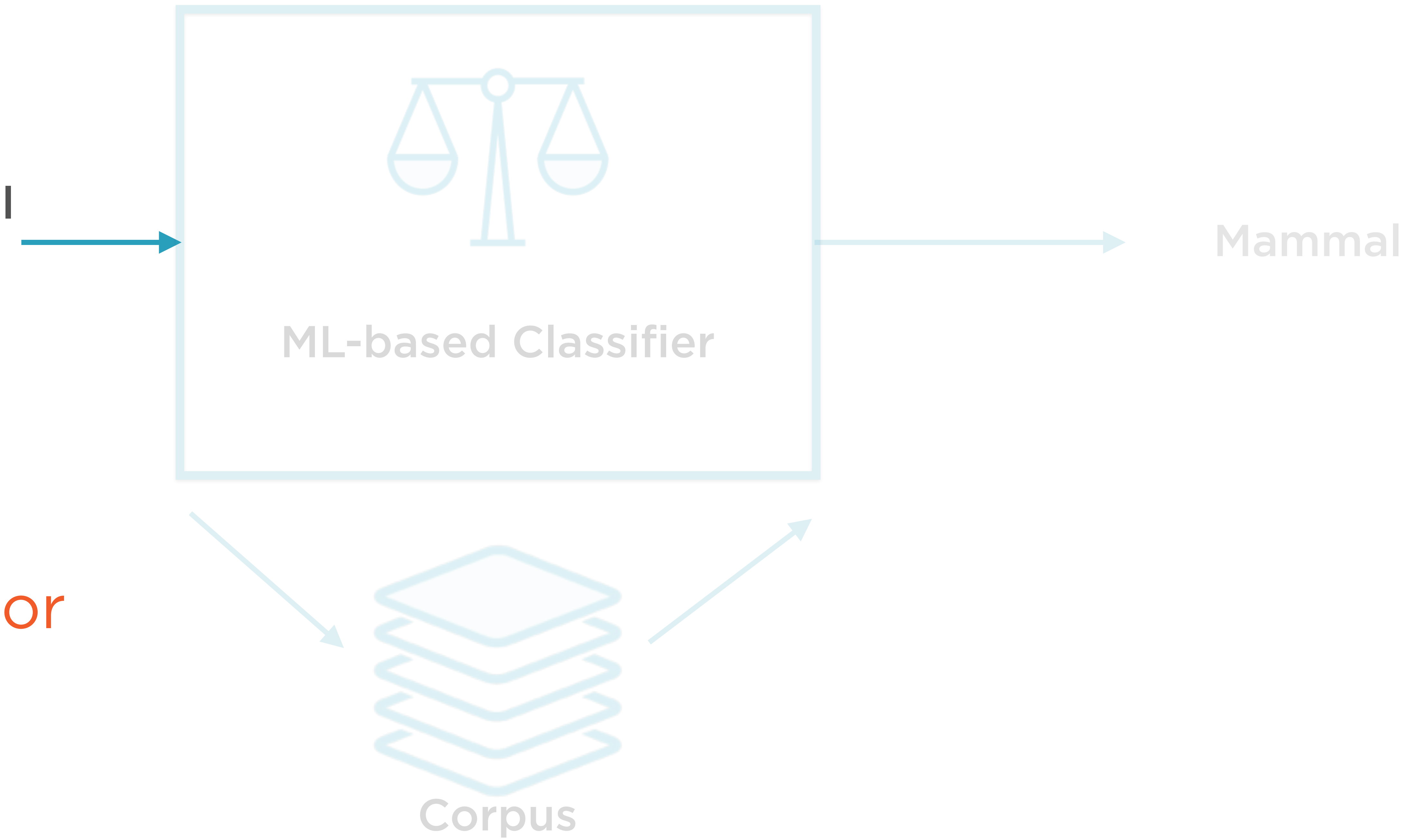


ML-based Binary Classifier

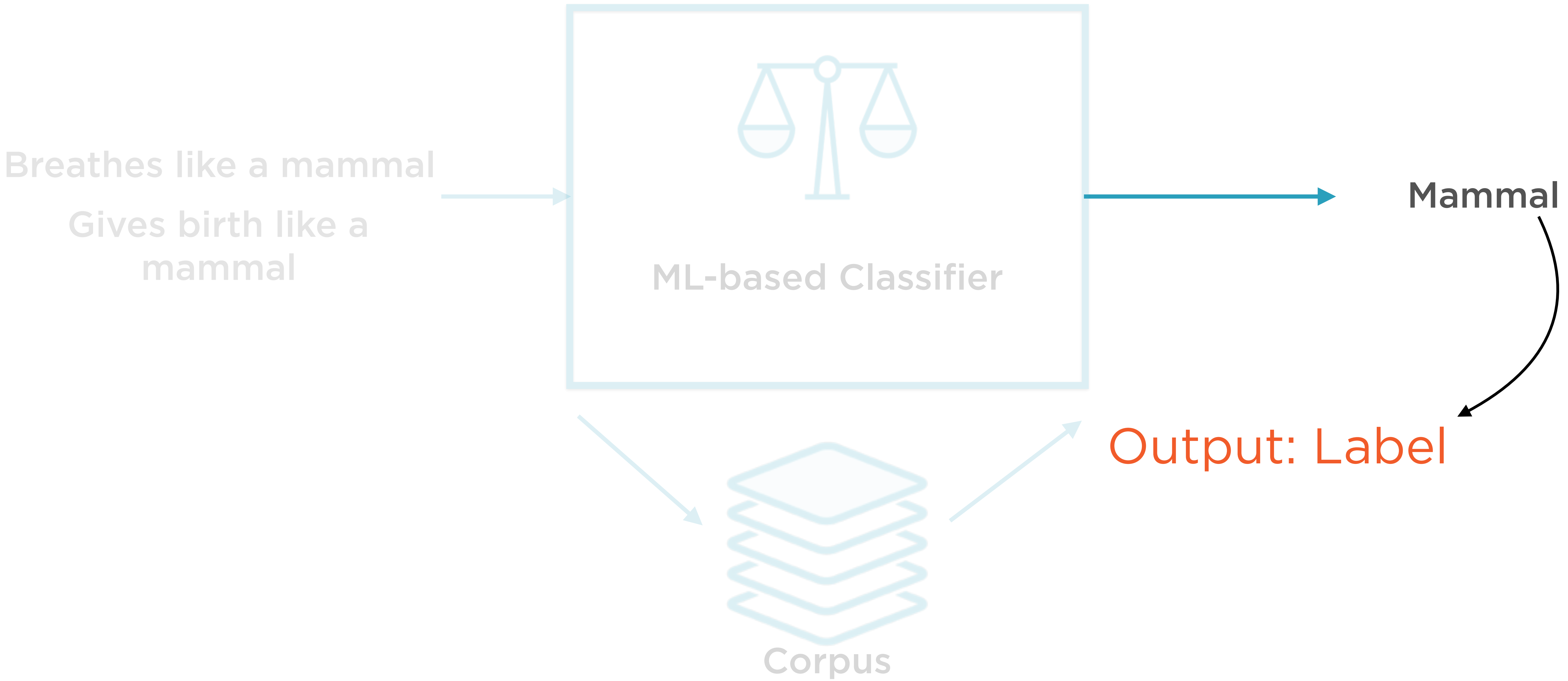
Breathes like a mammal

Gives birth like a mammal



Input: Feature Vector

ML-based Binary Classifier



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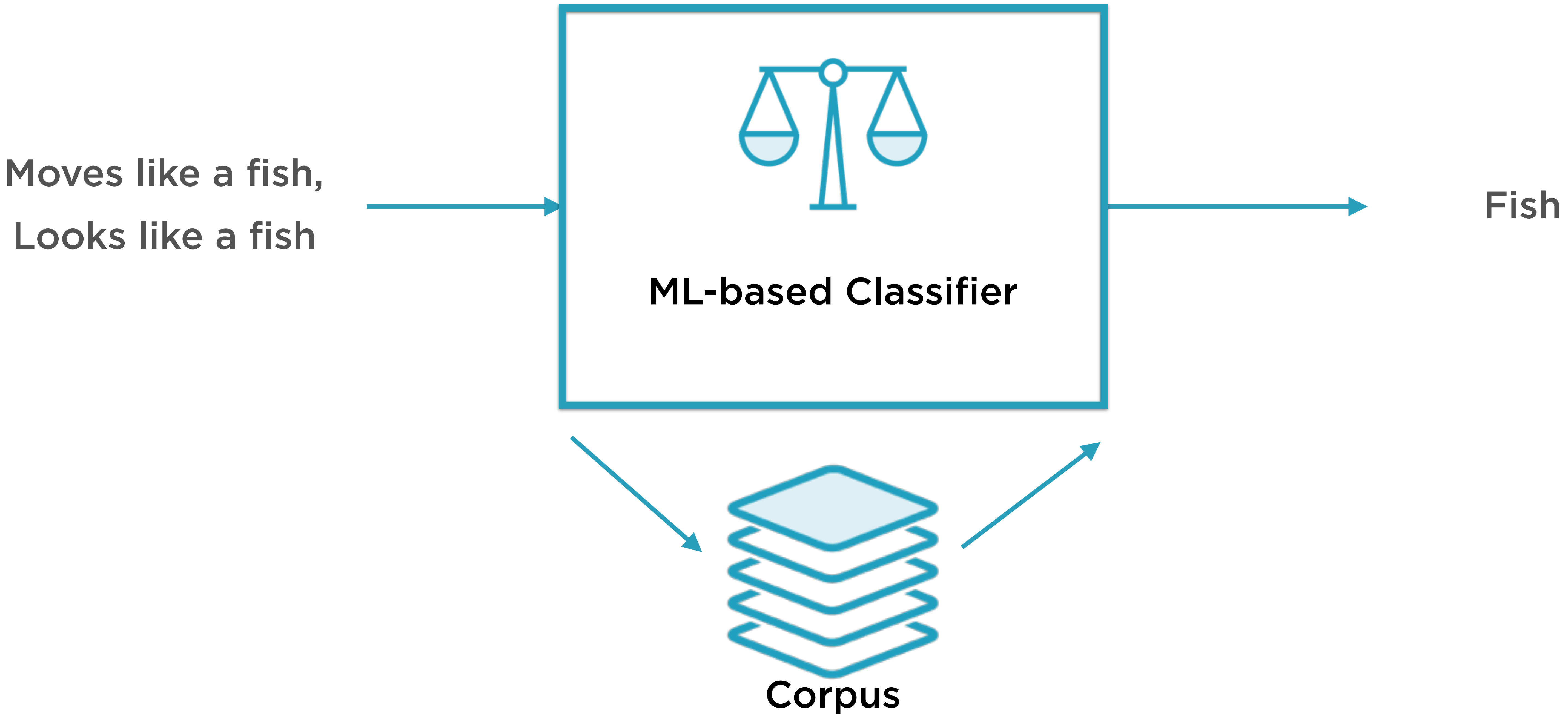

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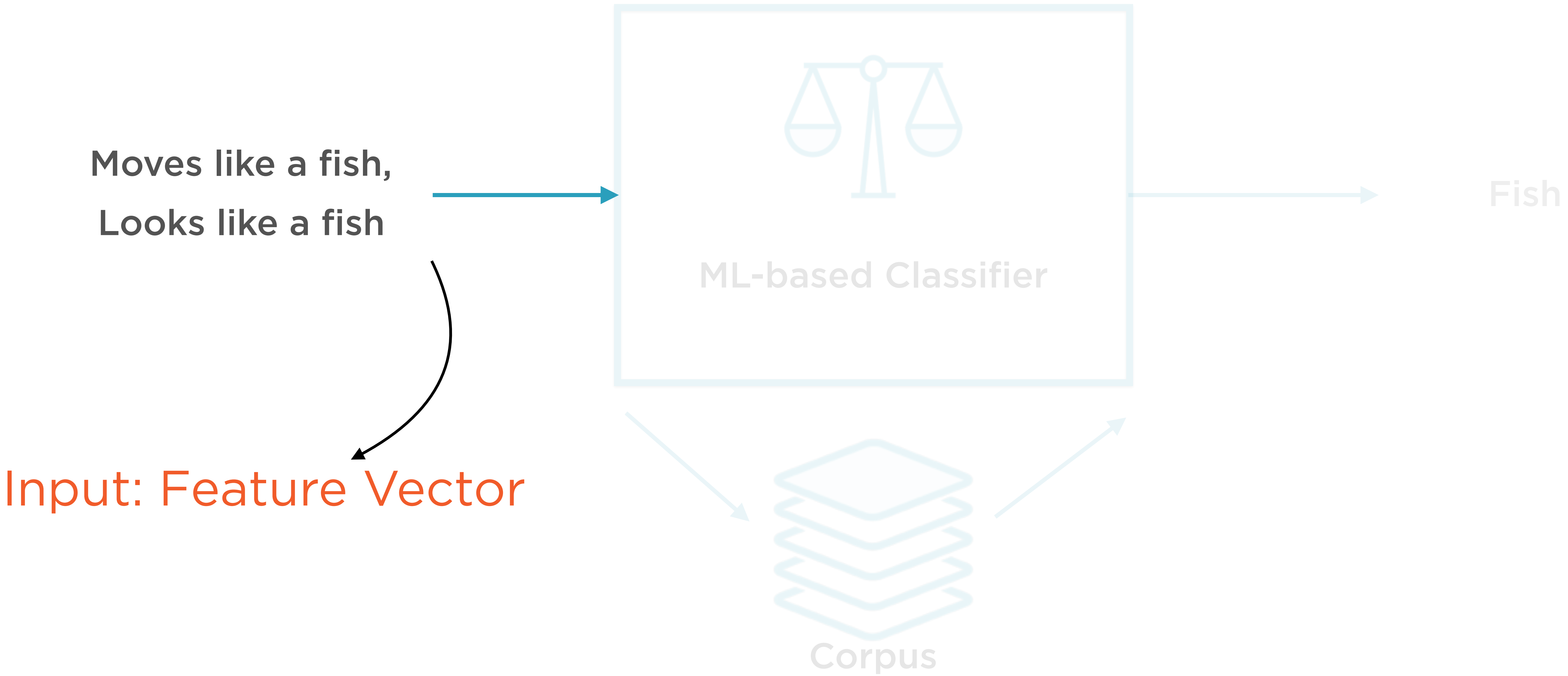

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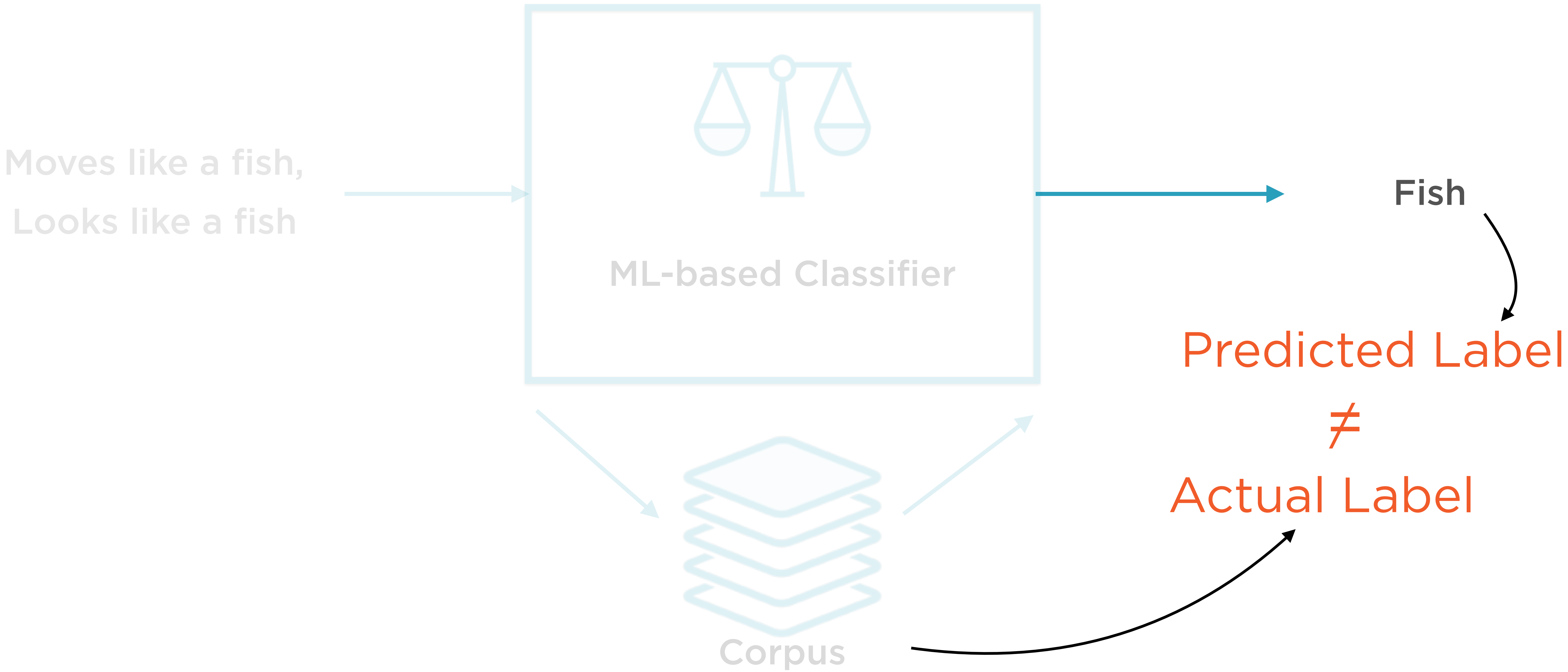


“Traditional” ML-based systems still rely on experts to decide what features to pay attention to

Traditional ML Models

Regression models: Linear, Lasso, Ridge, SVR

Classification models: Naive Bayes, SVMs, Decision trees

“Representation” ML-based systems figure out by themselves what features to pay attention to

Representation ML Models

Deep learning models such as neural networks

scikit-learn - a popular, open source, Python library

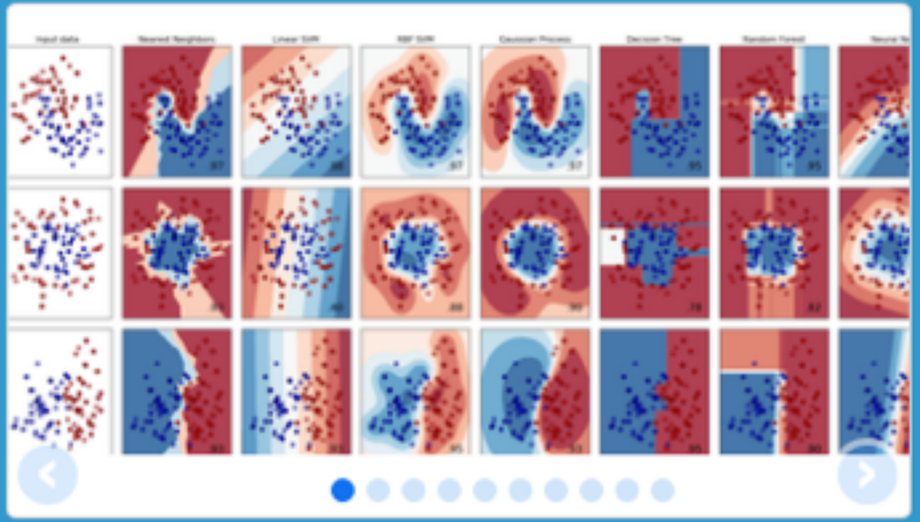
Classification, regression, clustering, dimensionality reduction algorithms scikit-learn: machine learning

scikit-learn.org/stable/

scikit learn

Home Installation Documentation Examples

Google Custom Search Search



scikit-learn

Machine Learning in Python

- Simple and efficient tools for data mining and data analysis
- Accessible to everybody, and reusable in various contexts
- Built on NumPy, SciPy, and matplotlib
- Open source, commercially usable - BSD license

Classification

Identifying to which category an object belongs to.

Applications: Spam detection, Image recognition.
Algorithms: SVM, nearest neighbors, random forest, ... — Examples

Regression

Predicting a continuous-valued attribute associated with an object.

Applications: Drug response, Stock prices.
Algorithms: SVR, ridge regression, Lasso, ... — Examples

Clustering

Automatic grouping of similar objects into sets.

Applications: Customer segmentation, Grouping experiment outcomes
Algorithms: k-Means, spectral clustering, mean-shift, ... — Examples

Dimensionality reduction

Reducing the number of random variables to consider.

Applications: Visualization, Increased efficiency
Algorithms: PCA, feature selection, non-negative matrix factorization. — Examples

Model selection

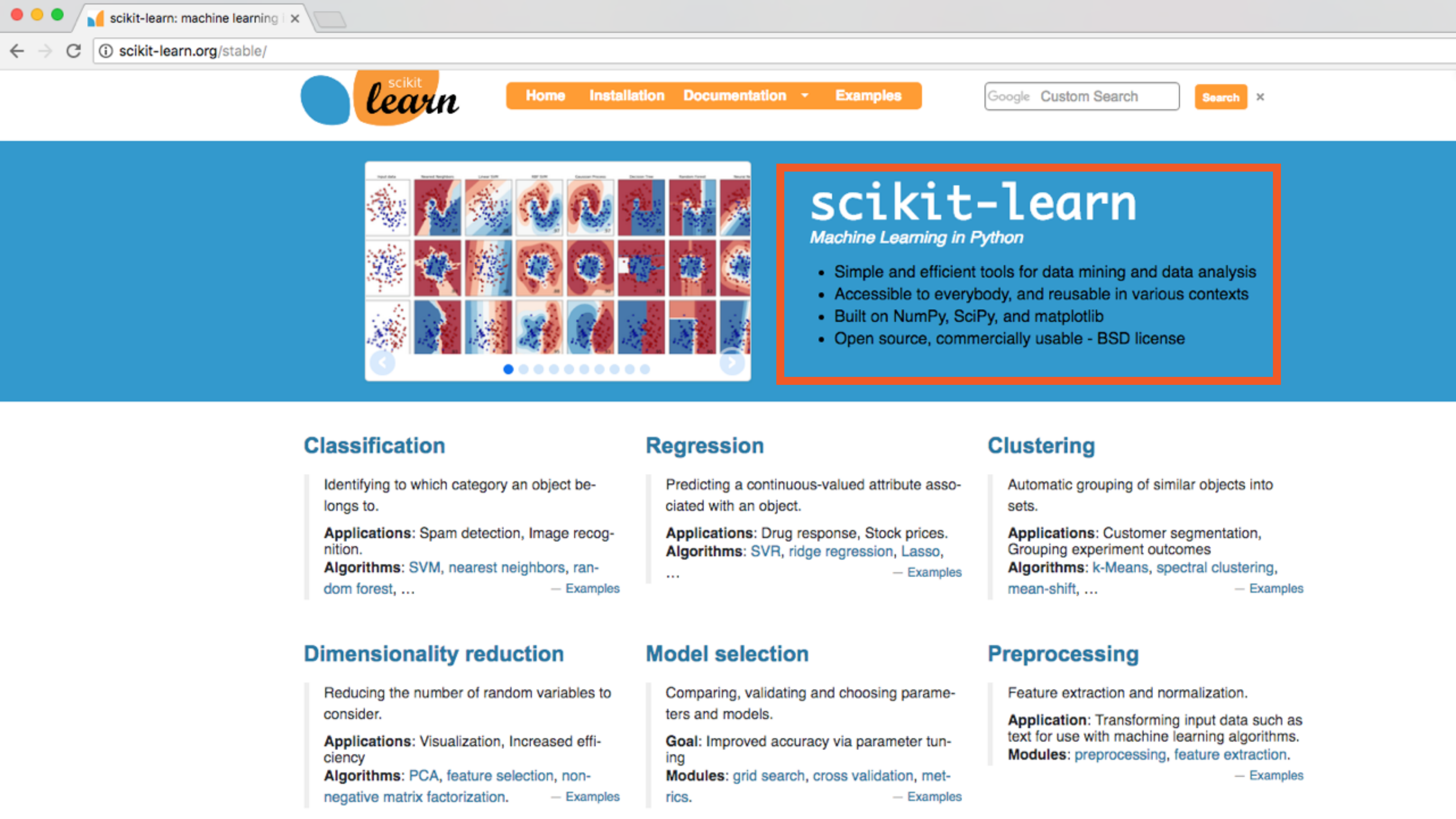
Comparing, validating and choosing parameters and models.

Goal: Improved accuracy via parameter tuning
Modules: grid search, cross validation, metrics. — Examples

Preprocessing

Feature extraction and normalization.

Application: Transforming input data such as text for use with machine learning algorithms.
Modules: preprocessing, feature extraction. — Examples


scikit-learn: machine learning
scikit-learn.org/stable/
scikit learn
Home
Installation
Documentation
Examples
Google Custom Search
Search
scikit-learn
Machine Learning in Python
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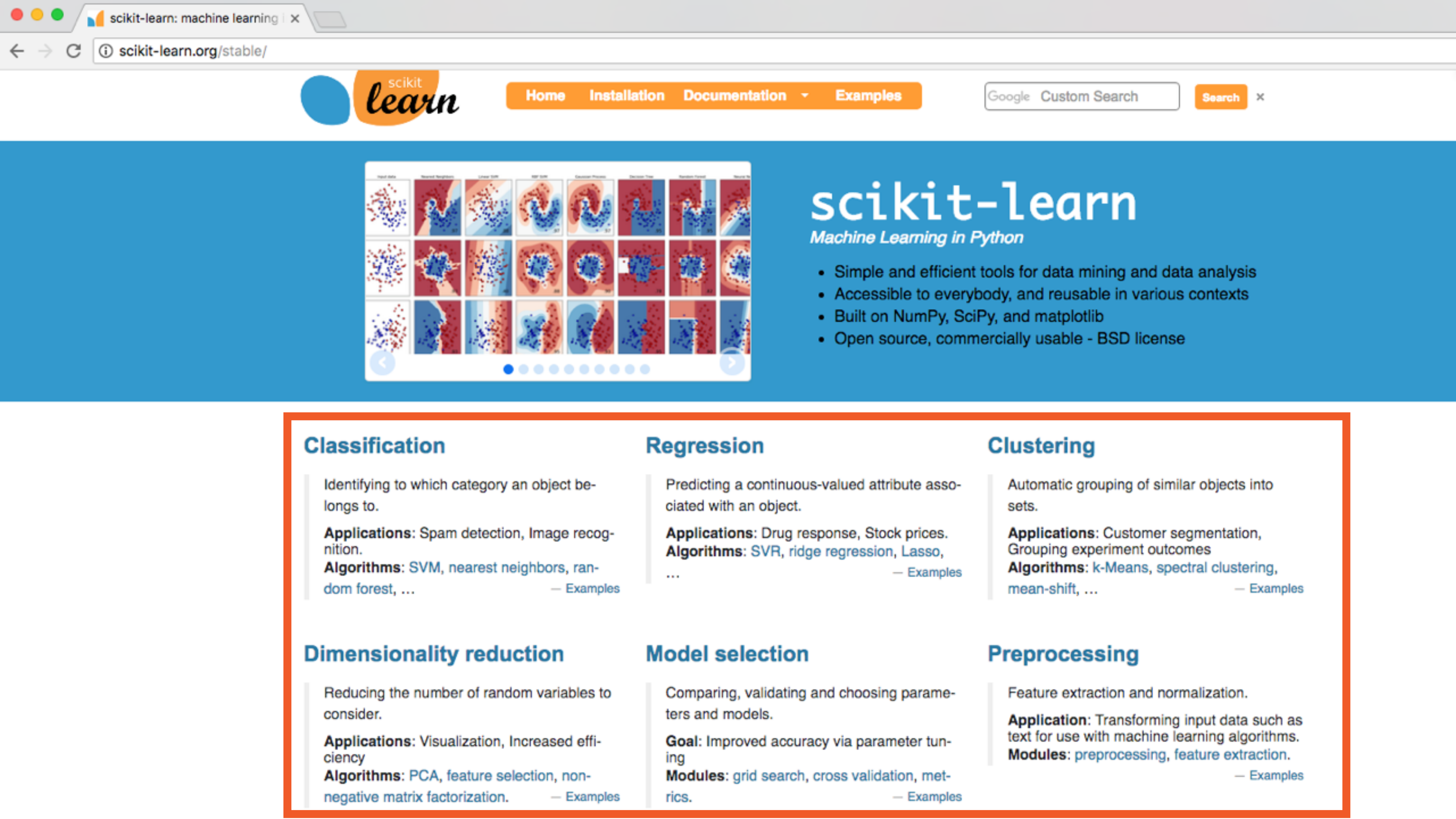
scikit-learn: machine learning
scikit-learn.org/stable/
scikit learn
Home Installation Documentation Examples
Google Custom Search
Search
scikit-learn
Machine Learning in Python
Simple and efficient tools for data mining and data analysis
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Supervised and Unsupervised Learning

Types of ML Algorithms

Supervised

Labels associated with the training data is used to correct the algorithm

Unsupervised

The model has to be set up right to learn structure in the data

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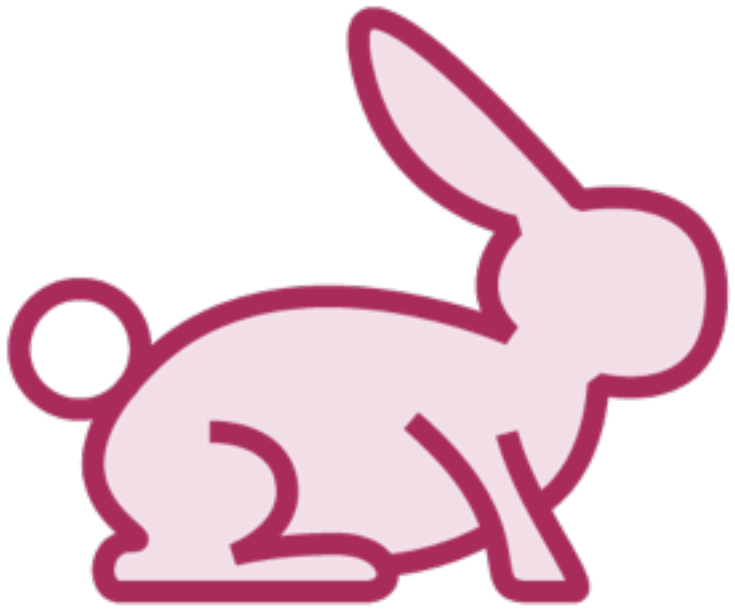

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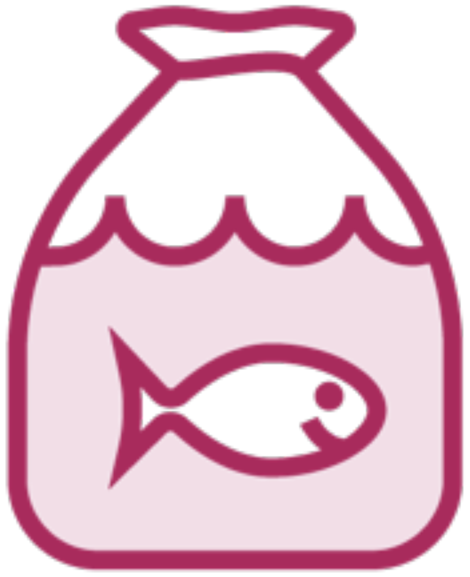


Fish

Look like fish, swim like fish, move with fish

Whales: Fish or Mammals?

ML-based Classifier

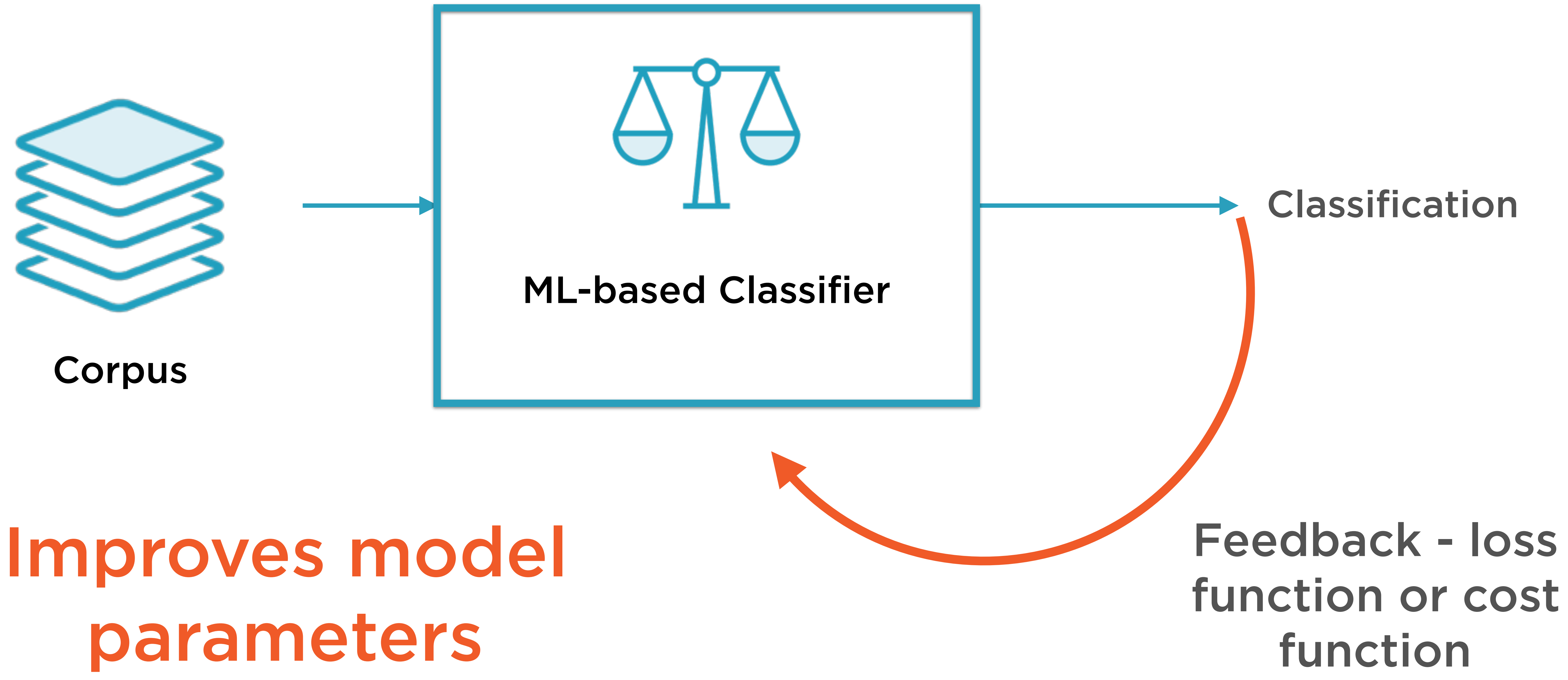
Training

Feed in a large corpus of data classified correctly

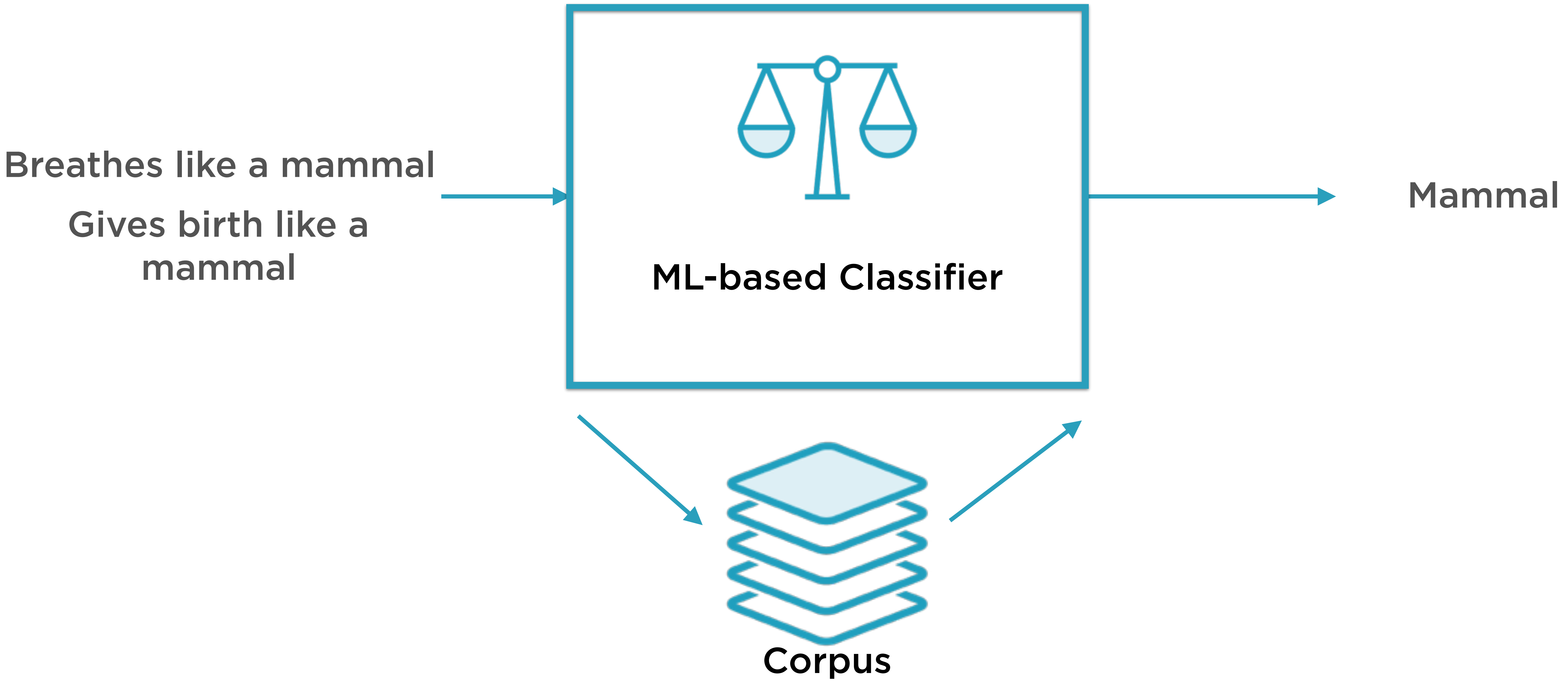
Prediction

Use it to classify new instances which it has not seen before

Training the ML-based Classifier



ML-based Binary Classifier



x Variables

The attributes that the ML algorithm focuses on are called features

Each data point is a list - or vector - of such features

Thus, the input into an ML algorithm is a feature vector

Feature vectors are usually called the x variables

y Variables

The attributes that the ML algorithm tries to predict are called labels

Types of labels

- categorical (classification)
- continuous (regression)

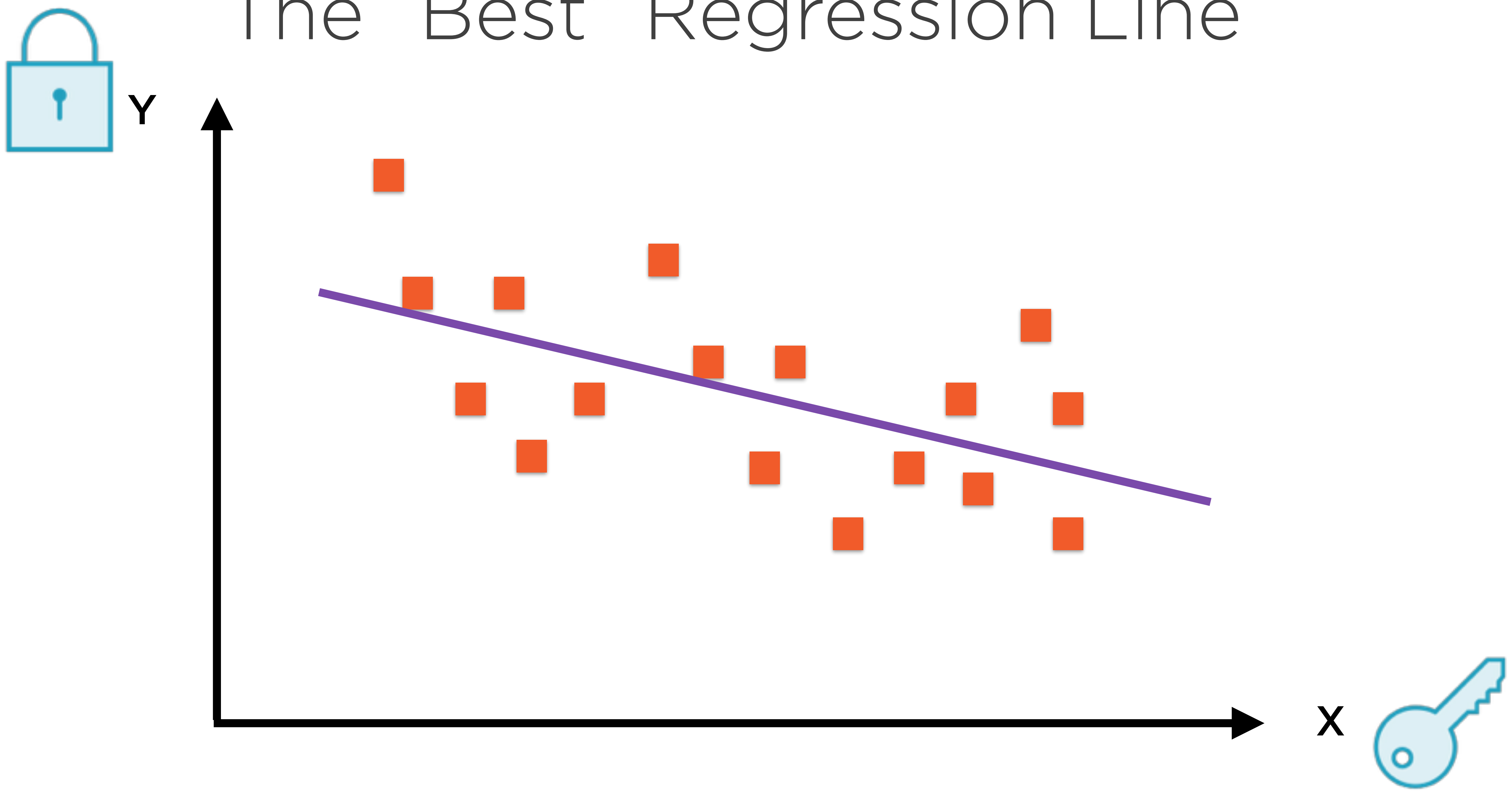
Labels are usually called the y variables

$$y = f(x)$$

Supervised Machine Learning

Most machine learning algorithms seek to “learn” the function f that links the features and the labels

The “Best” Regression Line



Linear Regression involves finding the “best fit” line via a training process

```
y = Wx + b
```

$$f(x) = Wx + b$$

Linear regression specifies, up-front, that the function f is linear

```
def doSomethingReallyComplicated(x1,x2…):
  …
  …
  …
  return complicatedResult
```

f(x) = doSomethingReallyComplicated(x)

ML algorithms such as neural network can “learn” (reverse-engineer) pretty much anything given the right training data

Types of ML Algorithms

Supervised

Labels associated with the training data is used to correct the algorithm

Unsupervised

The model has to be set up right to learn structure in the data

Unsupervised Learning does not have:

- y variables
- a labeled corpus

Supervised Learning

Input variable x and output variable y

Learn the mapping function `y = f(x)`

Approximate the mapping function so for new values of x we can predict y

Use existing dataset to correct our mapping function approximation

Unsupervised Learning

Only have input data x – no output data

Model the underlying structure to learn more about data

Algorithms self discover the patterns and structure in the data

Unsupervised ML Algorithms

Clustering

Identify patterns in data items e.g. K-means clustering

Dimensionality reduction

Identify significant factors that drive data e.g. PCA

Continuous and Categorical Data

Continuous and Categorical Variables

Continuous

Can take an infinite set of values (height, weight, income...)

Categorical

Can take a finite set of values (Male/ Female, Day of week...)

Categorical variables that can take just two values are called binary variables

Continuous and Categorical Variables

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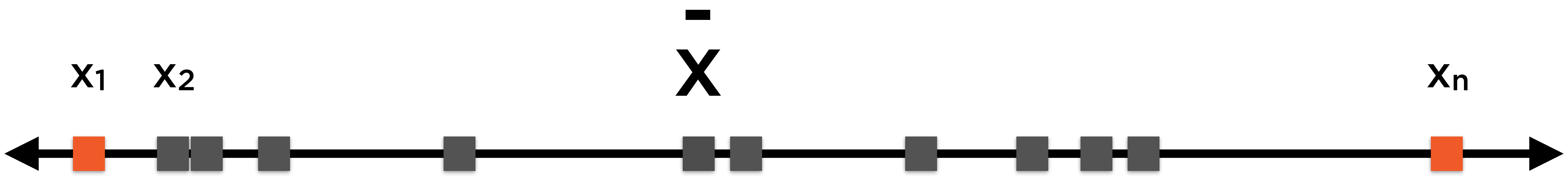
Standardizing Data: Mean and Variance

Mean as Headline

The mean, or average, is the one number that best represents all of these data points

$$\bar{x} = \frac{x_1 + x_2 + \dots + x_n}{n}$$

Variation Is Important Too

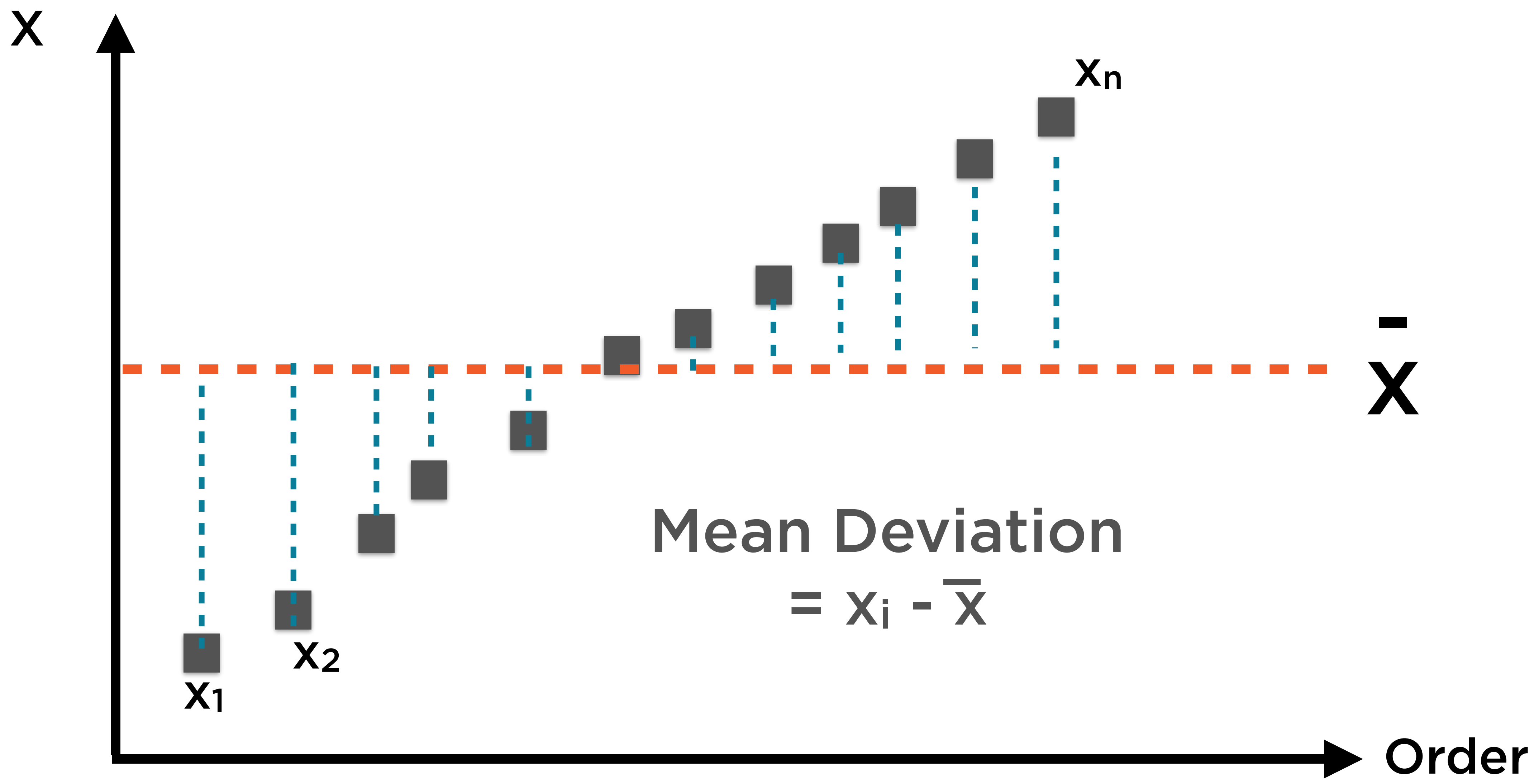


"Do the numbers jump around?"

$$\text{Range} = X_{max} - X_{min}$$

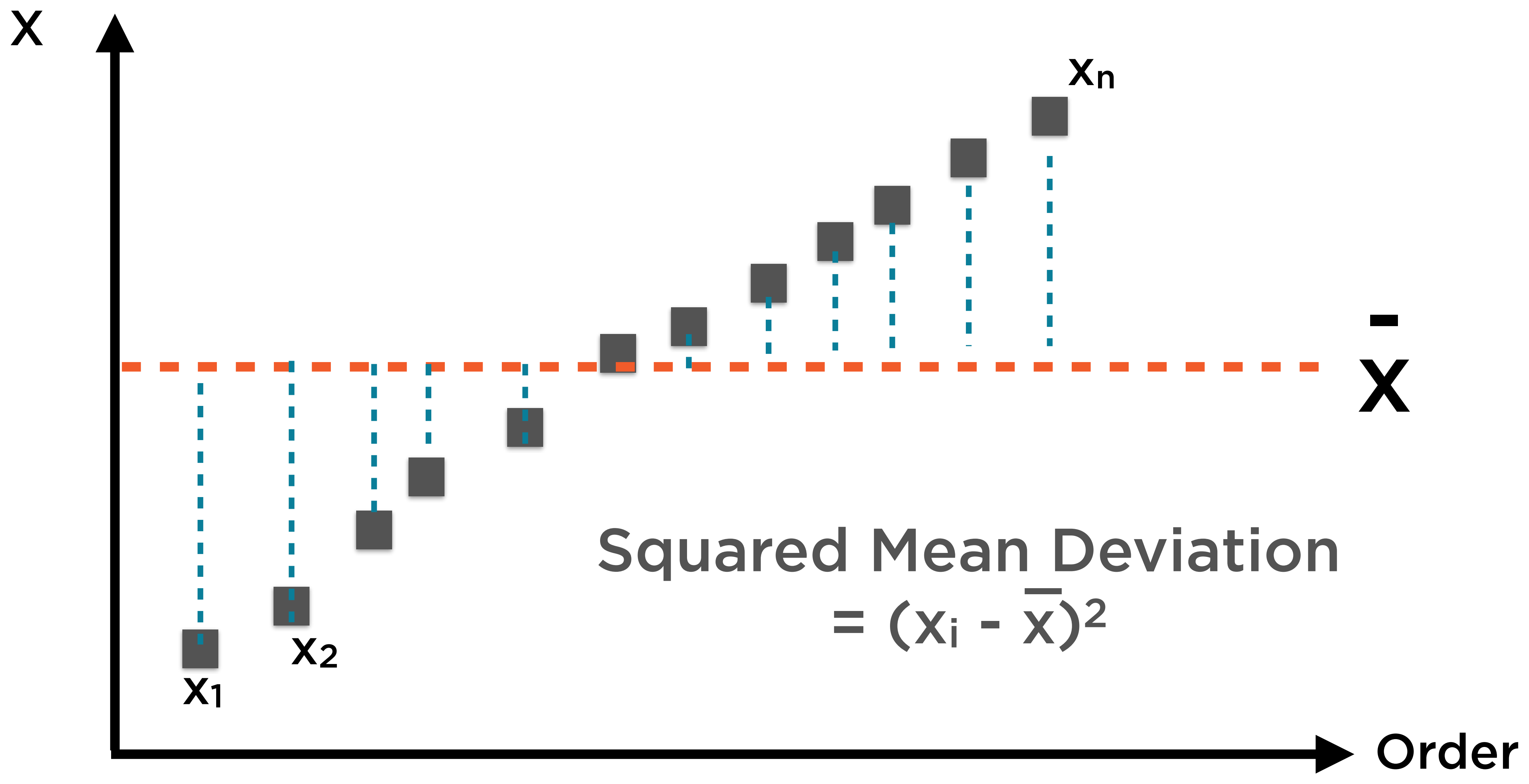
The range ignores the mean, and is swayed by outliers - that's where variance comes in

Variance as Asterisk



Variance is the second-most important number to summarize this set of data points

Variance as Asterisk



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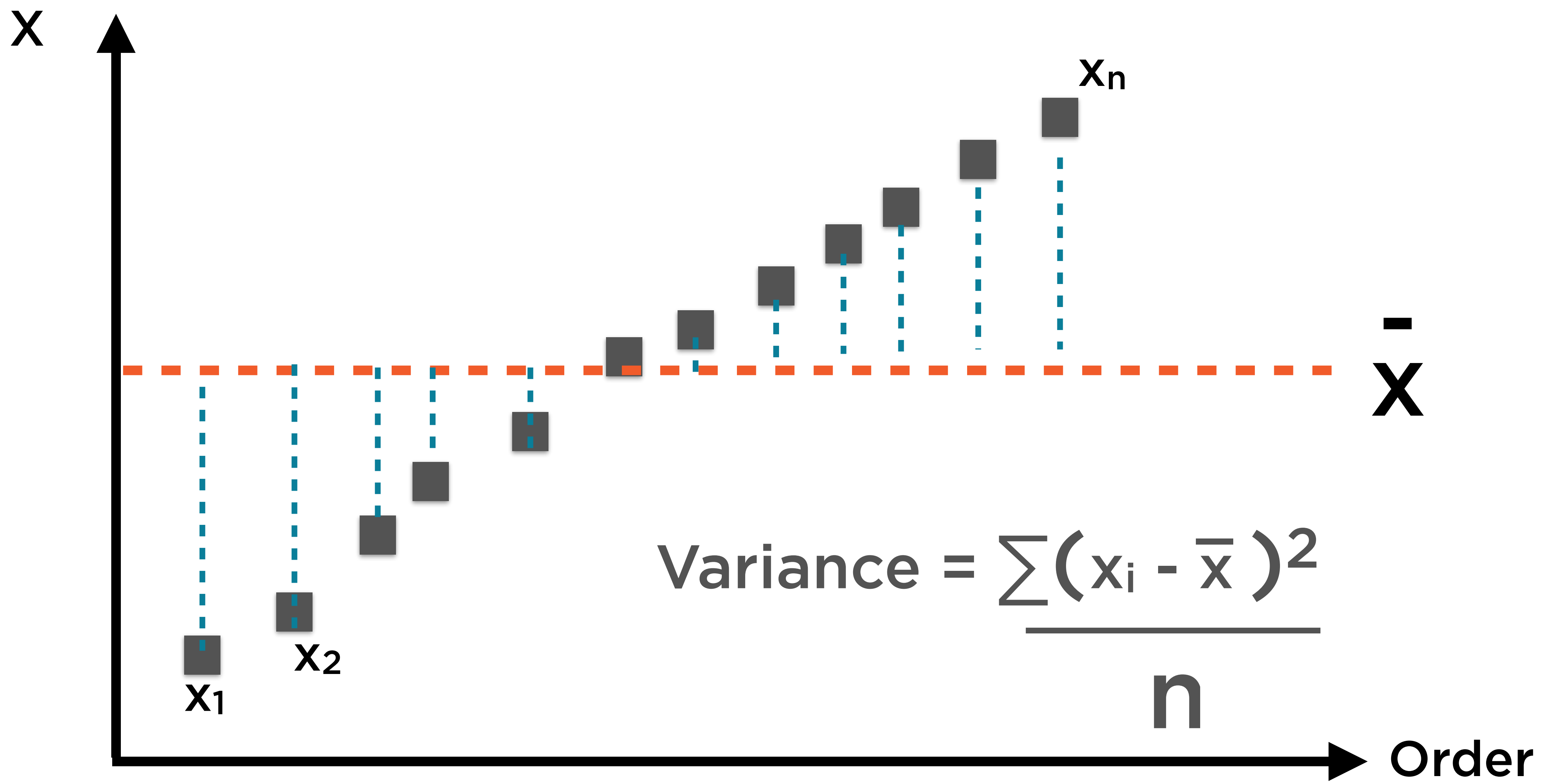

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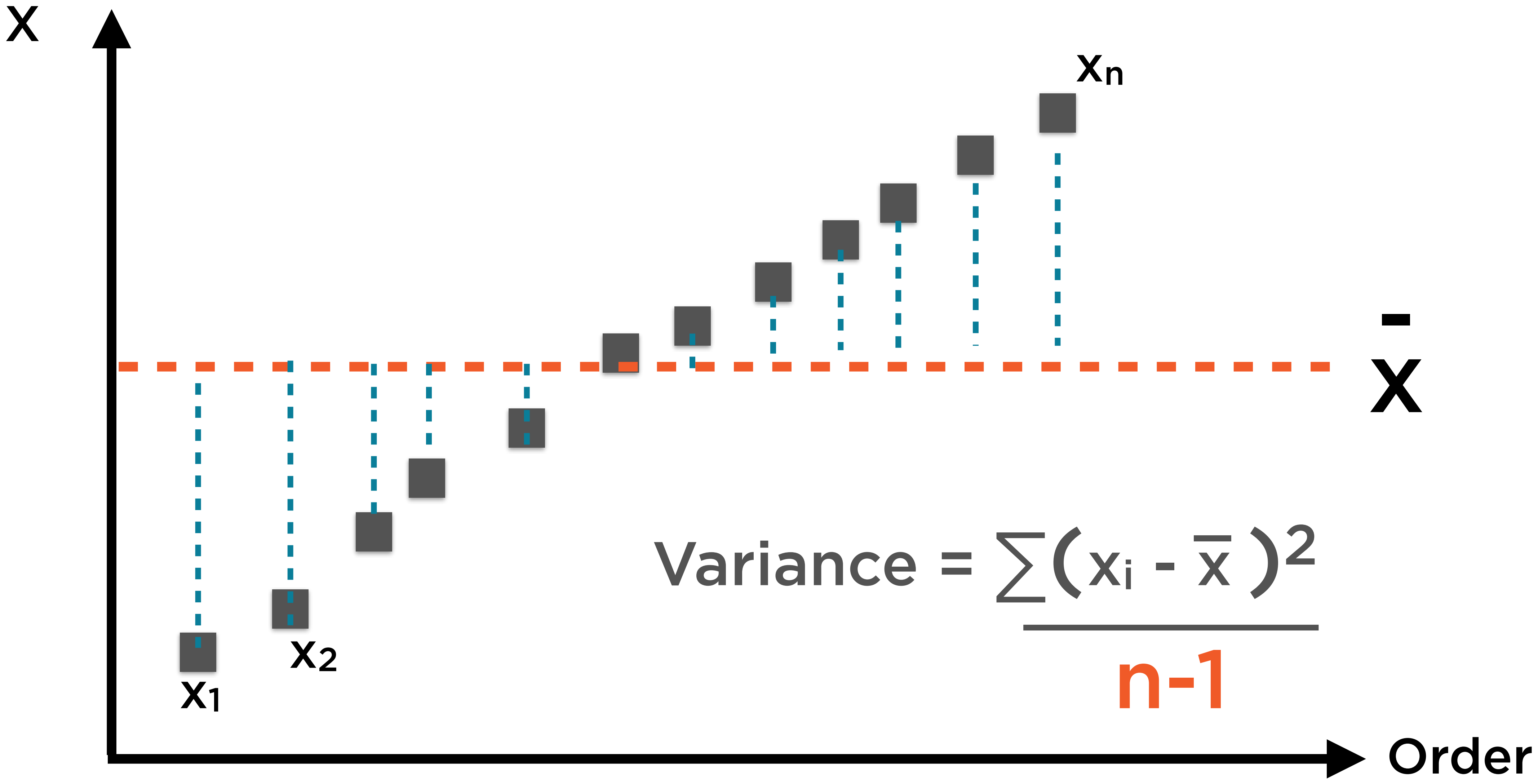


$$\text{Variance} = \frac{\sum(x_i - \bar{x})^2}{n-1}$$

We can improve our estimate of the variance by tweaking the denominator - this is called Bessel's Correction

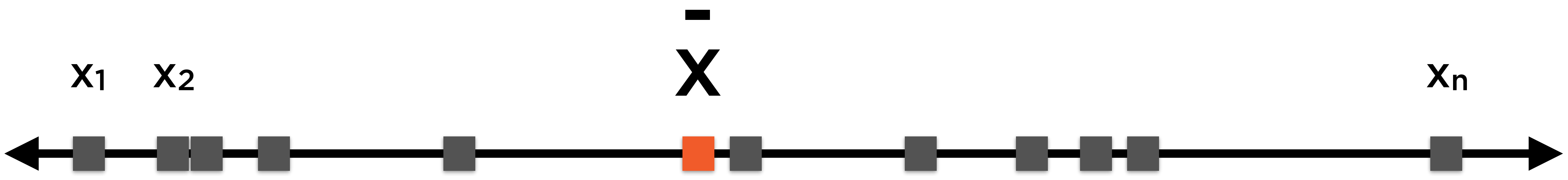
Mean and Variance

Mean and variance succinctly summarize a set of numbers

$$\bar{x} = \frac{x_1 + x_2 + \ldots + x_n}{n}$$

$$\text{Variance} = \frac{\sum (x_i - \bar{x})^2}{n-1}$$

Variance and Standard Deviation



Standard deviation is the square root of variance

$$\text{Variance} = \frac{\sum (x_i - \bar{x})^2}{n-1}$$

$$\text{Std Dev} = \sqrt{\frac{\sum (x_i - \bar{x})^2}{n-1}}$$

Standardizing Data

$$
\left[\begin{array}{ccc}
X_{11} & & X_{1k} \\
X_{21} & & X_{2k} \\
X_{31} & \cdots & X_{3k} \\
\cdots & & \cdots \\
X_{n1} & & X_{nk}
\end{array}\right]
$$

$$
\begin{array}{ccc}
\text{avg}(X_1) & \cdots & \text{avg}(X_k) \\
\text{stdev}(X_1) & \cdots & \text{stdev}(X_k)
\end{array}
$$

Standardizing Data

$$\begin{bmatrix} \dfrac{x_{11} - avg(X_1)}{stdev(X_1)} & \dots & \dfrac{x_{1k} - avg(X_k)}{stdev(X_k)} \\ \dots & & \dots \\ \dfrac{x_{n1} - avg(X_1)}{stdev(X_1)} & & \dfrac{x_{nk} - avg(X_k)}{stdev(X_k)} \end{bmatrix}$$

Each column of the standardized data has mean 0 and variance 1

Standardized Data

Many techniques work best on standardized data

Standardization prevents some (high-variance) data series from dominating

Examples:

- Principal Components Analysis
- Lasso/Ridge Regression

Continuous and Categorical Variables

Continuous	Categorical
Can take an infinite set of values (height, weight, income…)	Can take a finite set of values (Male/ Female, Day of week…)

Categorical Data

- Continuous data can be ordered, categorical data can not
- ML algorithms only operate on numbers
- Categorical data need to be encoded as numbers
- Numerical encodings of categorical data should never be ordered

Categorical Data

Continuous data can be ordered, categorical data can not

ML algorithms only operate on numbers

Categorical data need to be encoded as numbers

Numerical encodings of categorical data should never be ordered

One-hot Encoding

Sunday

Monday

Tuesday

Wednesday

Thursday

Friday

Saturday

One-hot Encoding

	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Monday	0	1	0	0	0	0	0
Thursday	0	0	0	0	1	0	0
Saturday	0	0	0	0	0	0	1