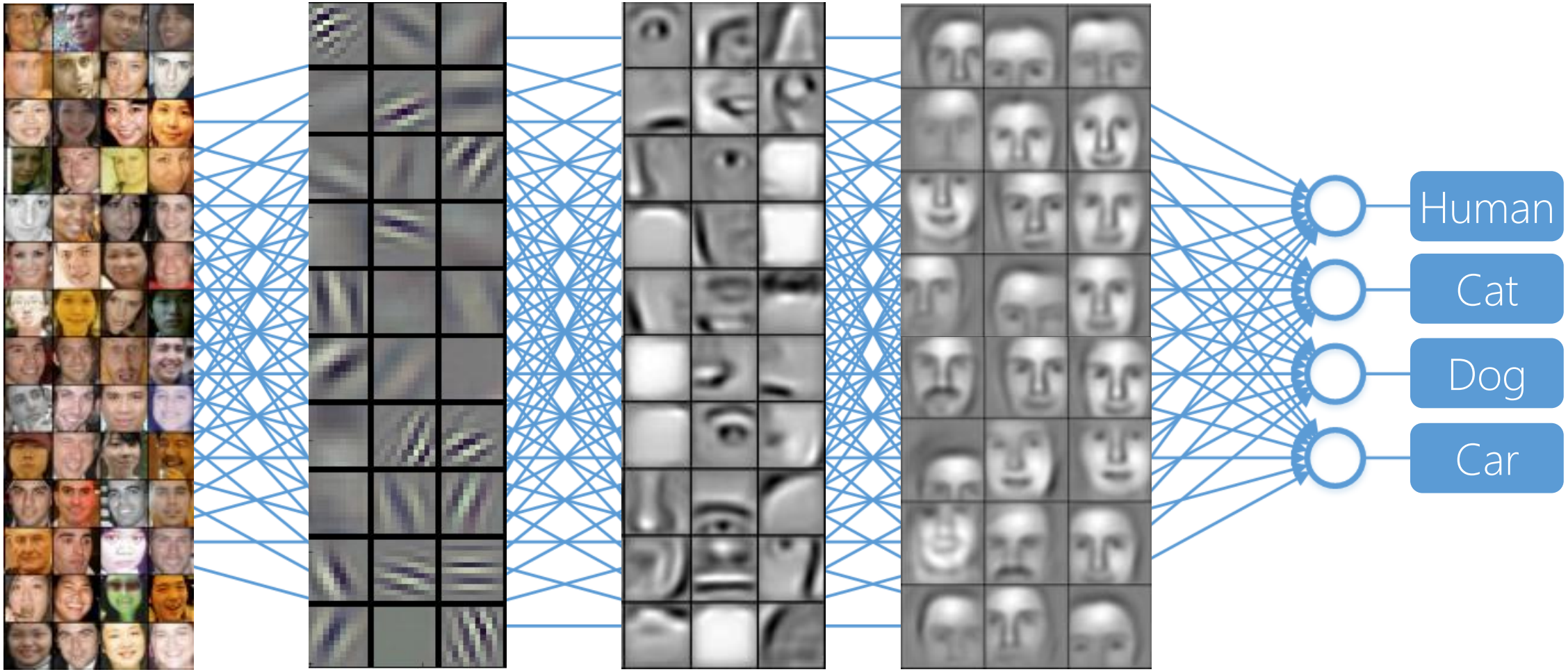
Practical Machine Learning with Python

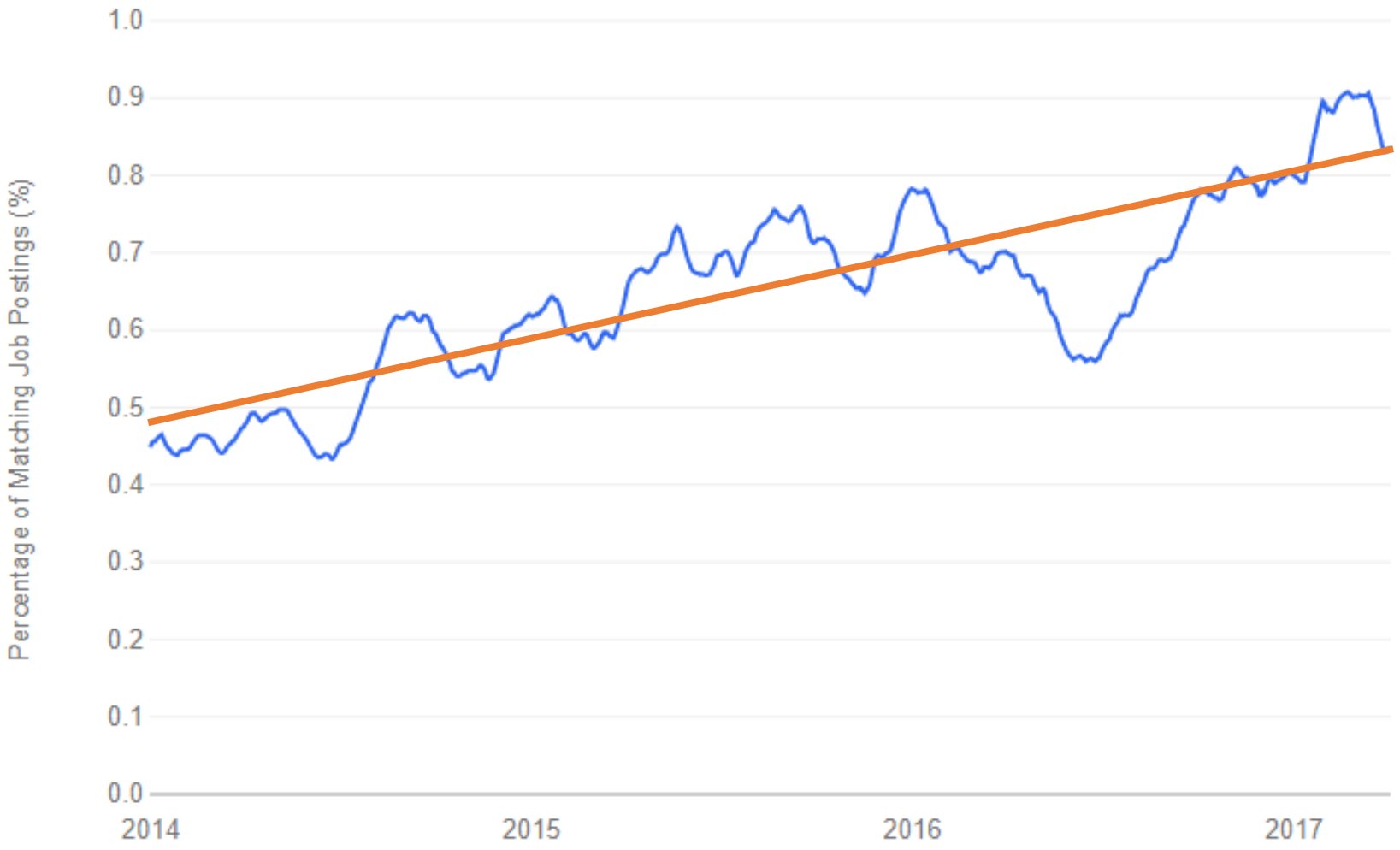
@MatthewRenze

#IndyCode

```
function updatePhotoDescription() {
    if (descriptions.length > (page * 9) + (currentImage.substring(1) - 1)) {
        document.getElementById('bigImageDesc').innerHTML = descriptions[(page * 9) + currentIma
    }
}

function updateAllImages() {
    var i = 1;
    while (i < 10) {
        var elementId = 'foto' + i;
        var elementIdBig = 'bigImage' + i;
        if (page * 9 + i - 1 < photos.length) {
            document.getElementById( elementId ).src = 'images/mini' + photos[page * 9 + i
            document.getElementById( elementIdBig ).src = 'images/medium' + photos[page
        } else {
            document.getElementById( elementId ).src = '';
```

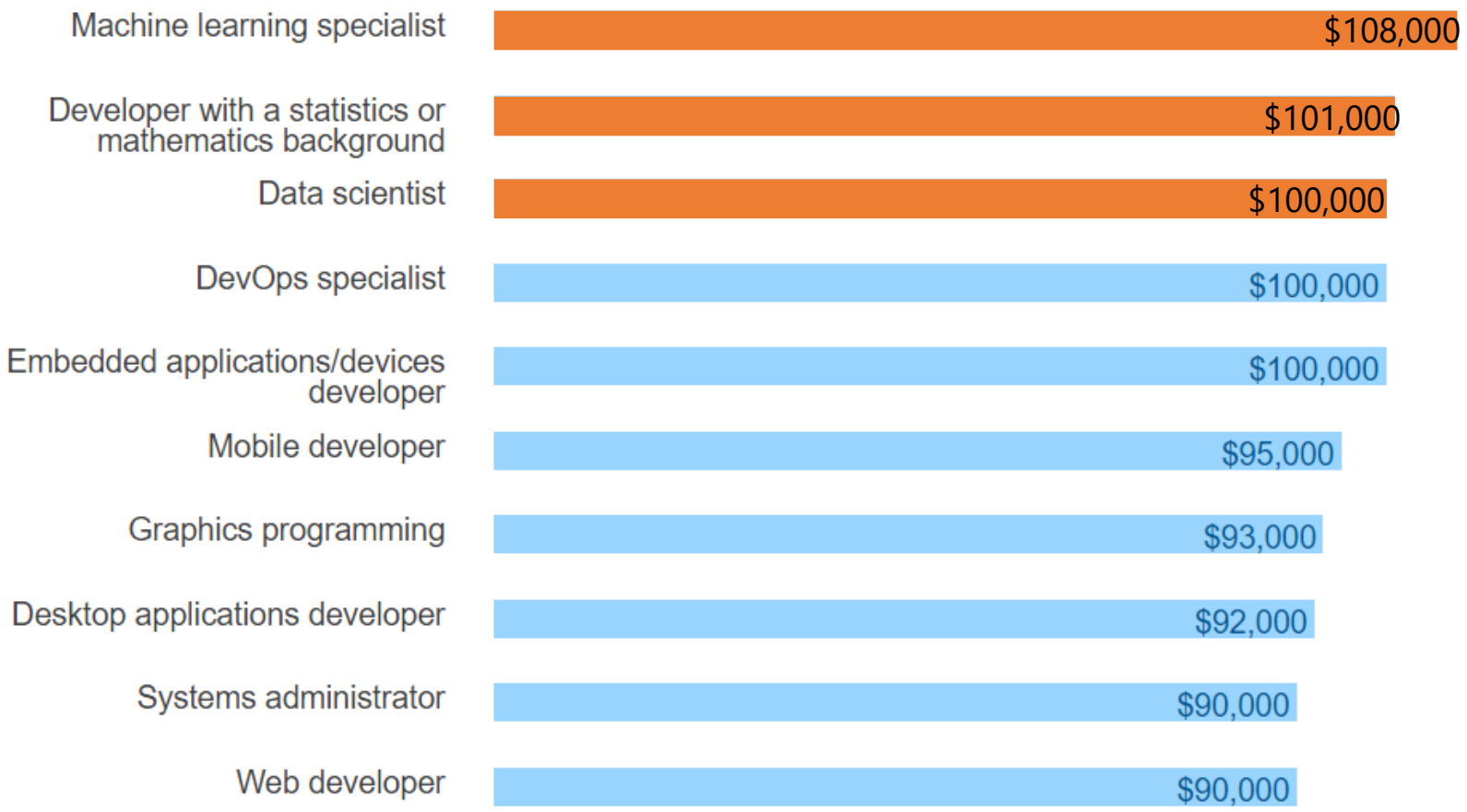

Human
Cat
Dog
Car

Job Postings for Machine Learning



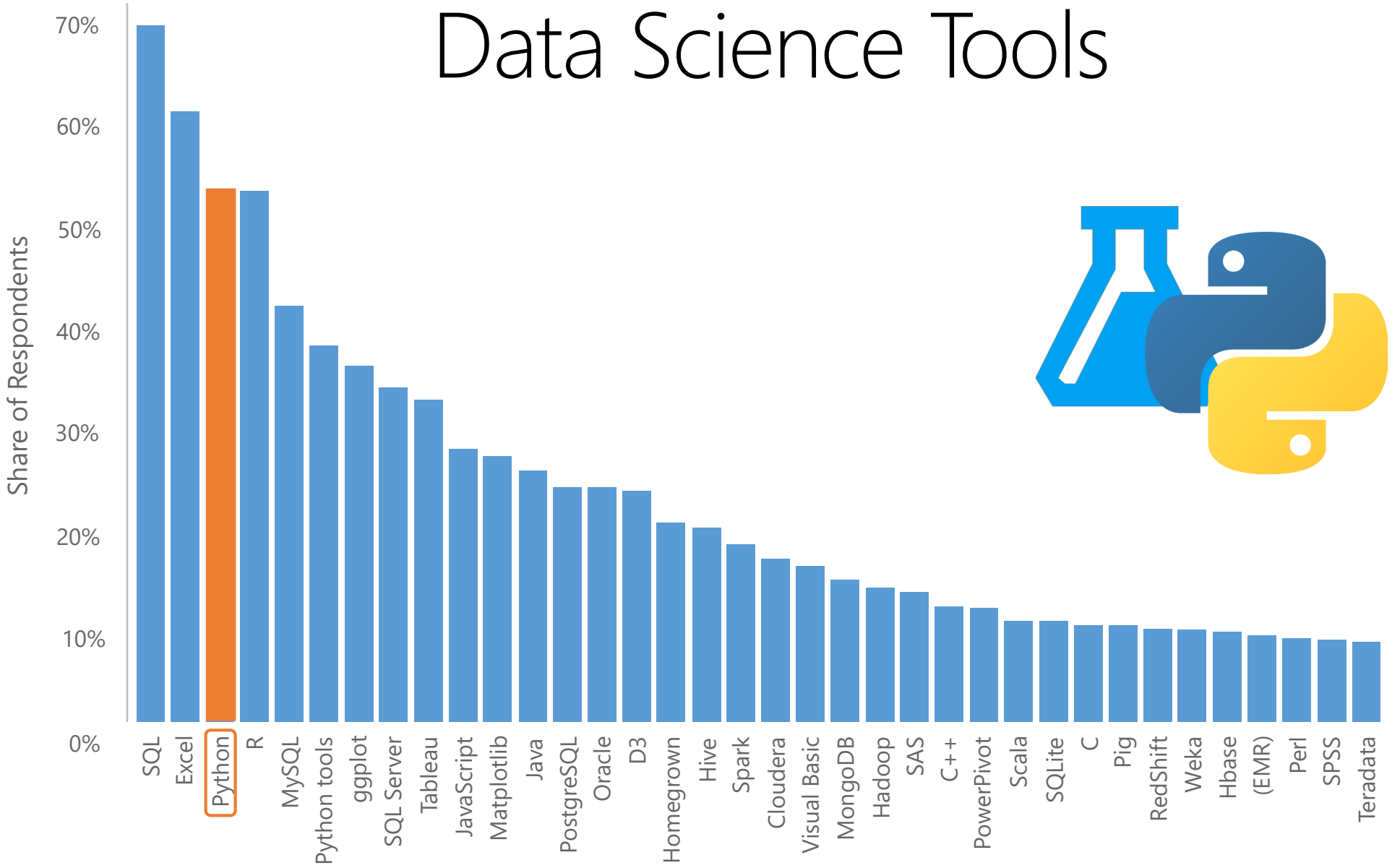
Source: Indeed.com

Average Salary by Job Type (USA)



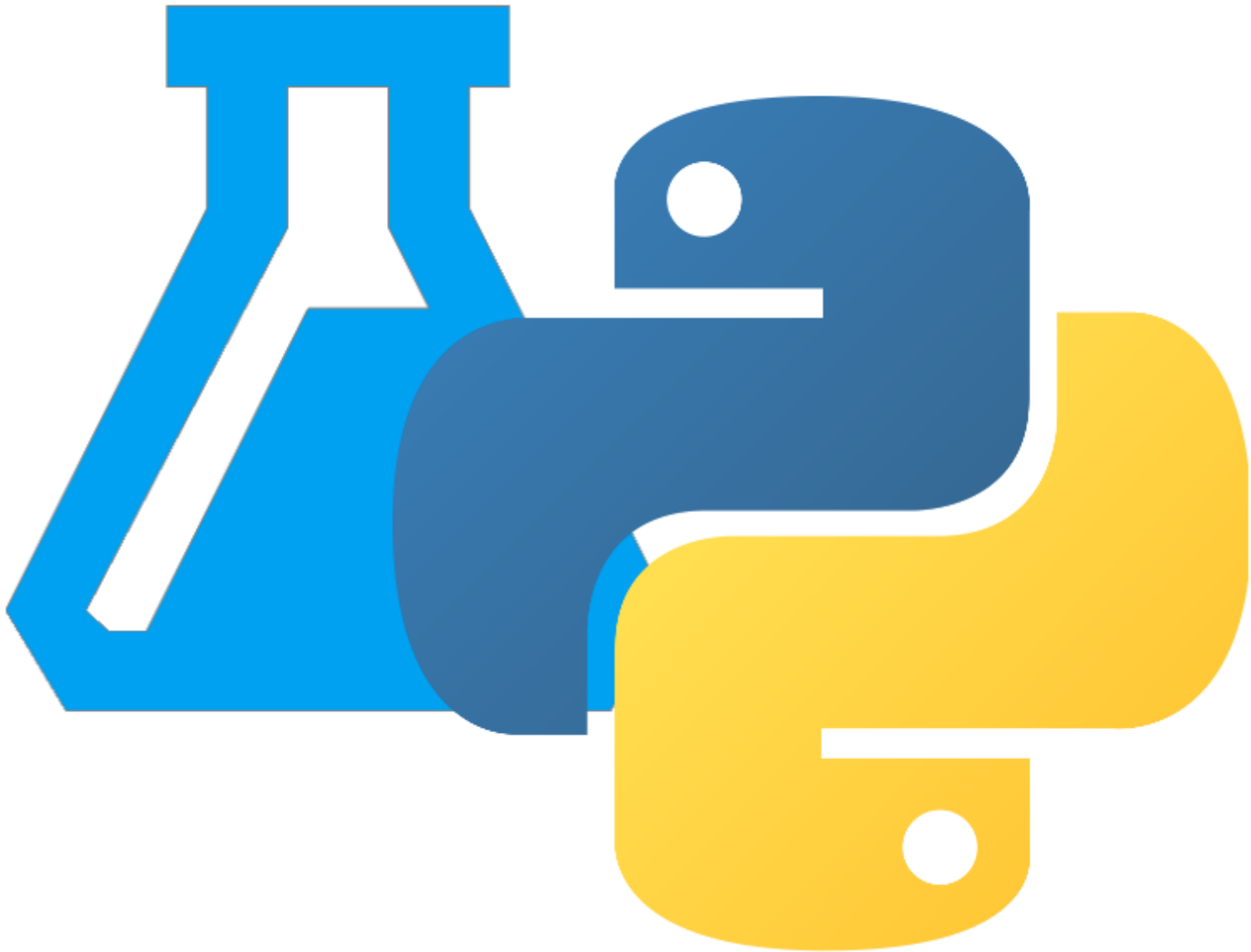
Source: Stack Overflow 2017

Data Science Tools



Tool: language, platform, analytics

Source: O'Reilly 2015 Data Science Salary Survey



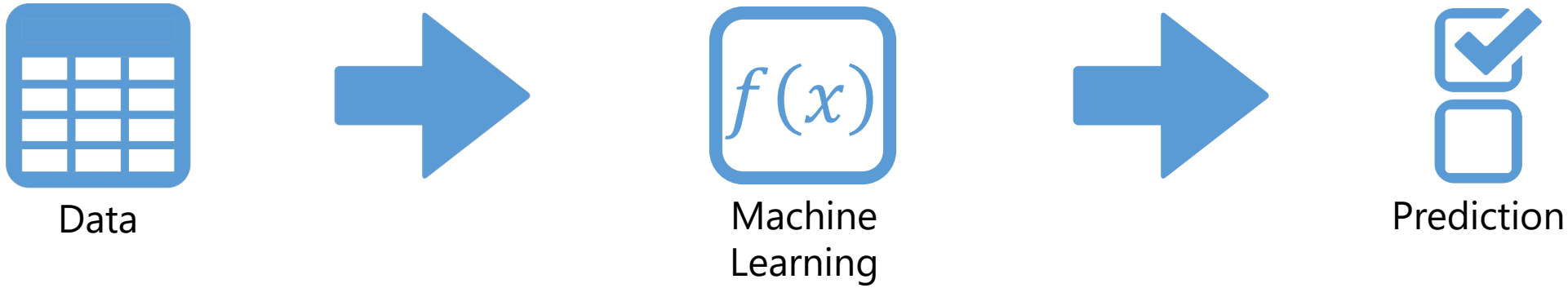
Overview

1. Intro to ML and Python
2. Classification
3. Regression
4. Clustering
5. ML in Practice

How Does This Apply to Me?

- ☑ Make decisions using data
- ☑ Make predictions using data
- ☑ Make recommendations using data
- ☑ Automate these with code

Conceptual Model



About Me

Data Science Consultant

Education

- B.S. in Computer Science
- B.A. in Philosophy
- Data Science specializations

Community

- Public speaker
- Pluralsight author
- Microsoft MVP
- Open source

IOWA STATE UNIVERSITY

PLURALSIGHT

MVP Microsoft® Most Valuable Professional

ASP INSIDERS

Schedule

Lectures (15 min)

Demos (10 min)

Labs (30 min)

Breaks (5 min)

Logistics

Pairing for labs is optional

Ask questions if needed

Come and go as needed

Feedback at the end

Labs

Labs

A

(Easy)

Labs

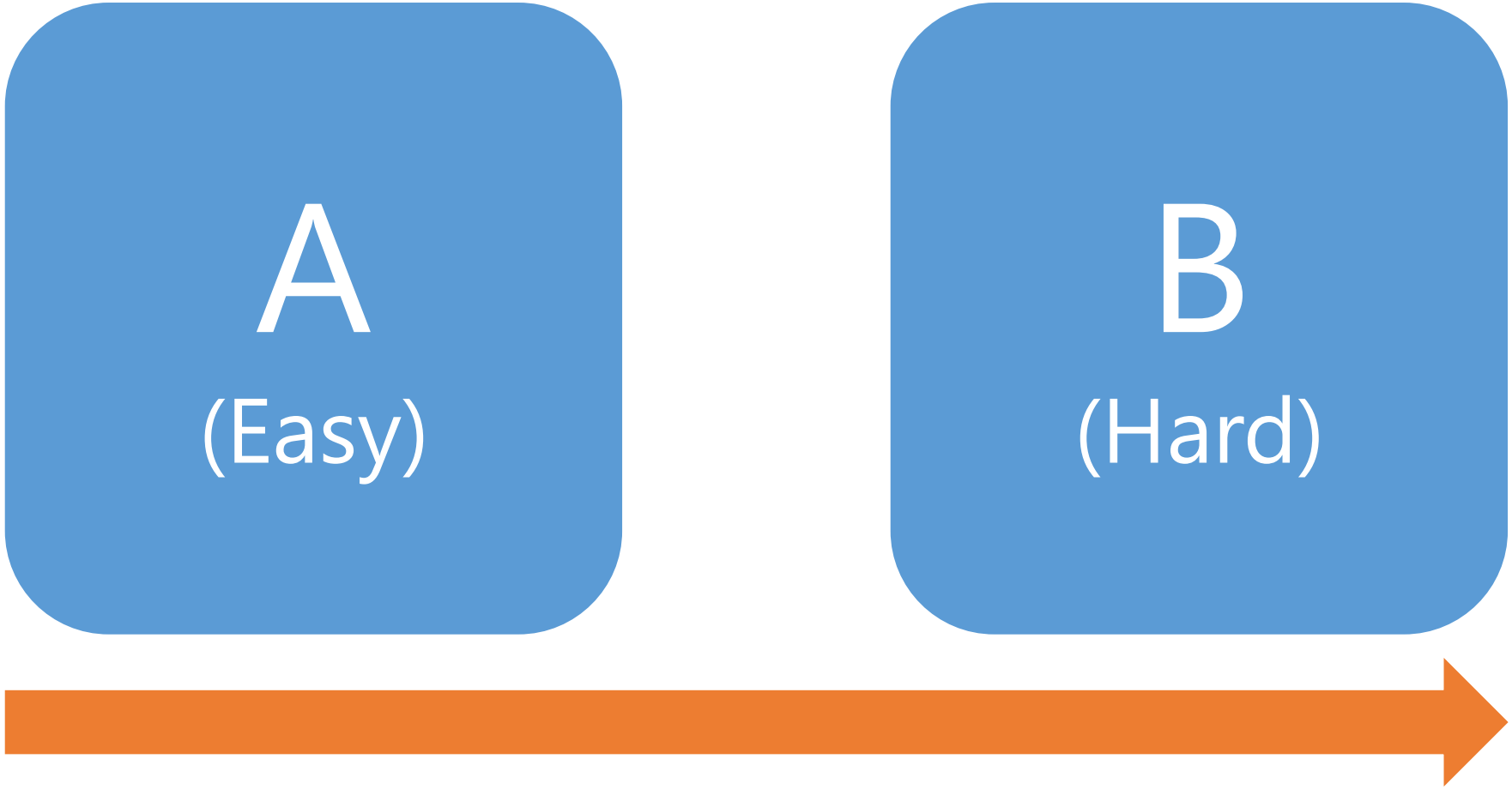
A

(Easy)

B

(Hard)

Labs

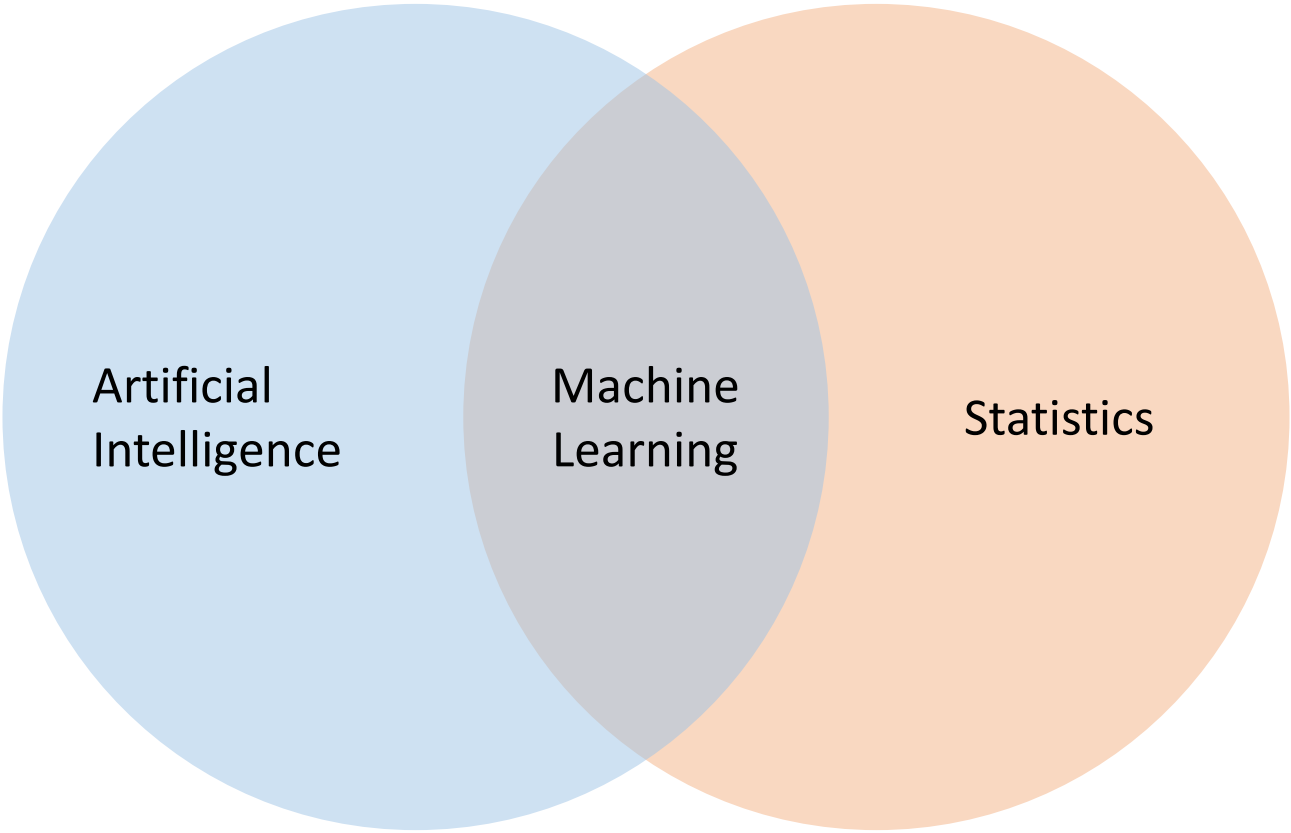


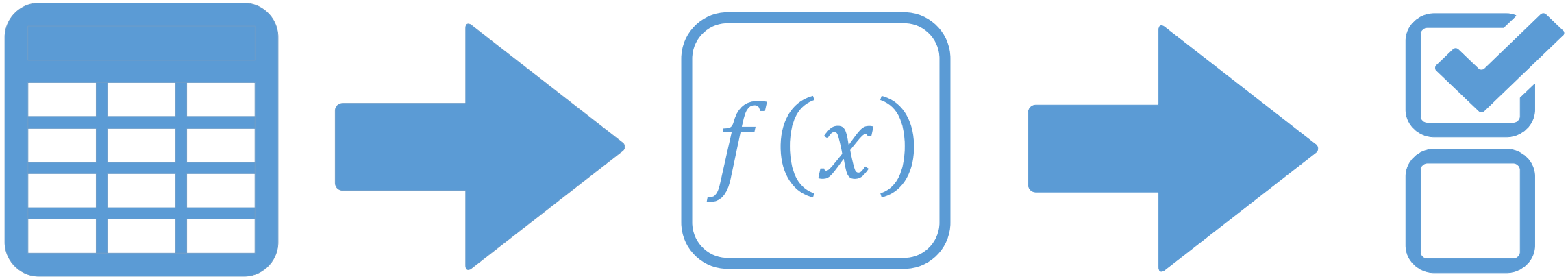
Workshop URL

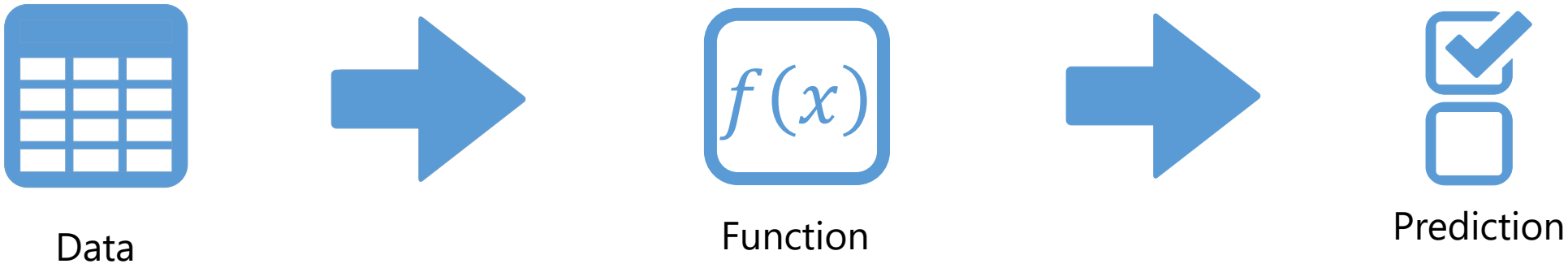
http://www.matthewrenze.com/workshops/practical-machine-learning-with-python/

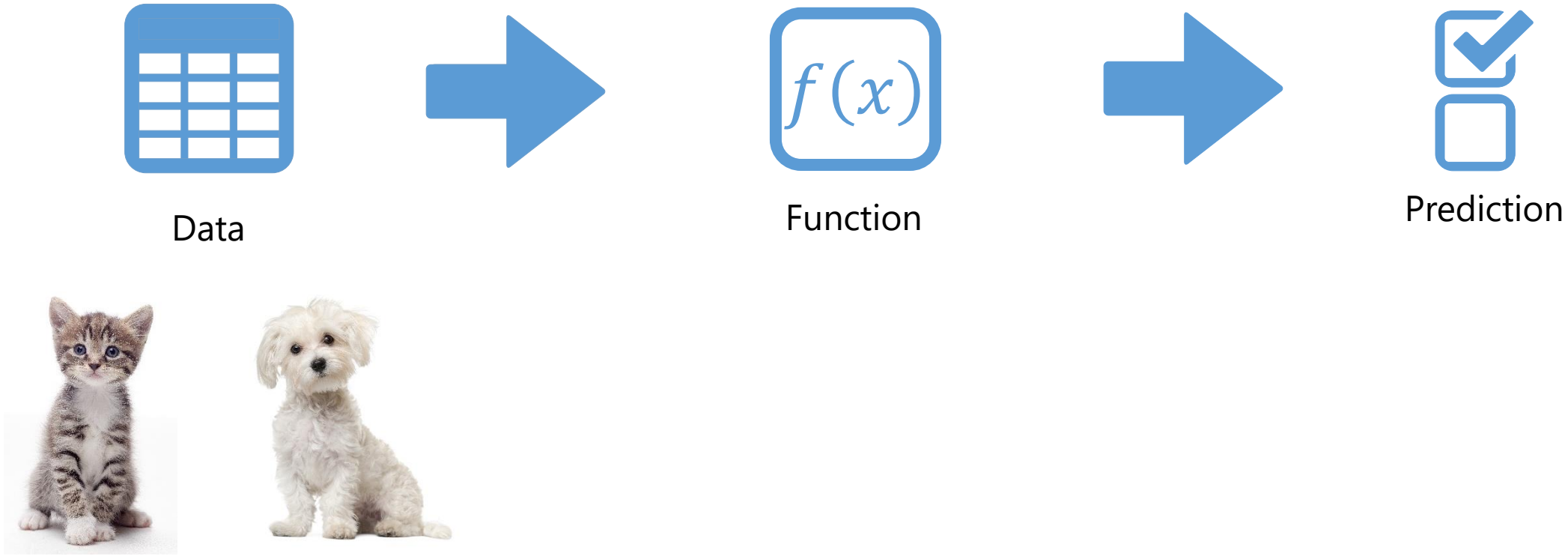
Introduction to Machine Learning

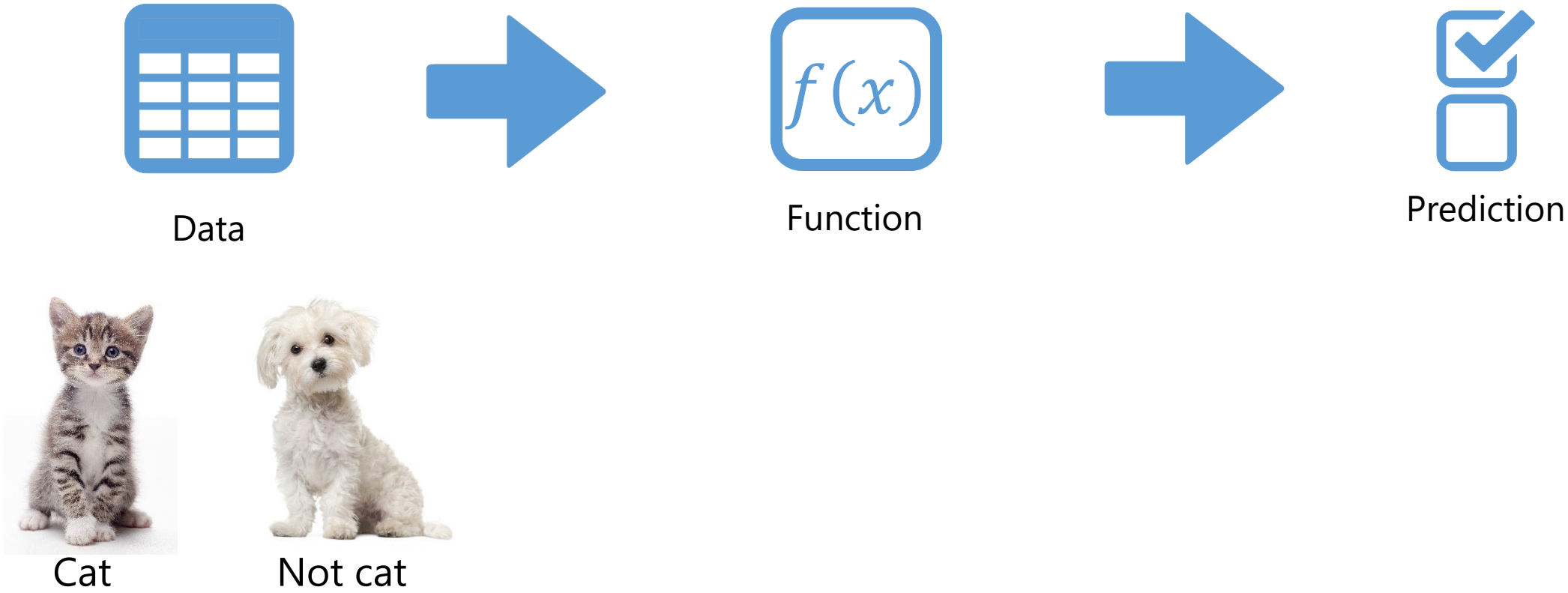
What is machine learning?

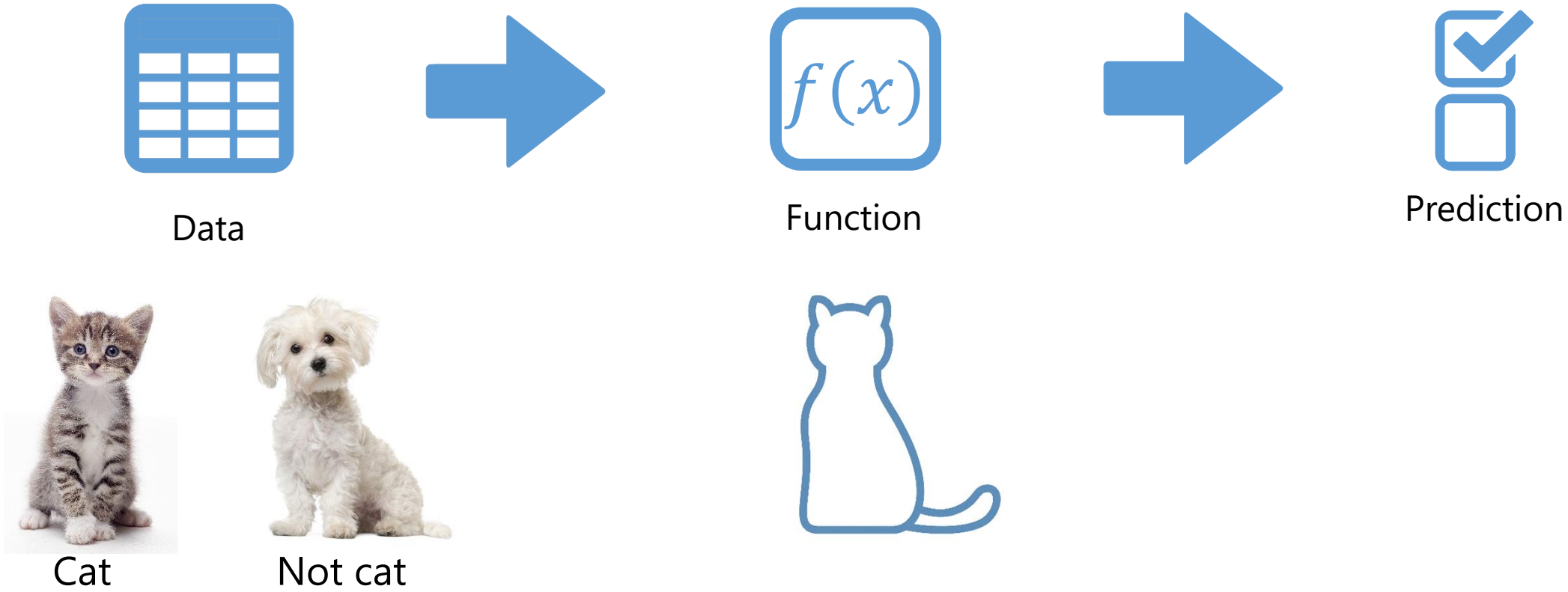

Artificial Intelligence
Machine Learning
Statistics

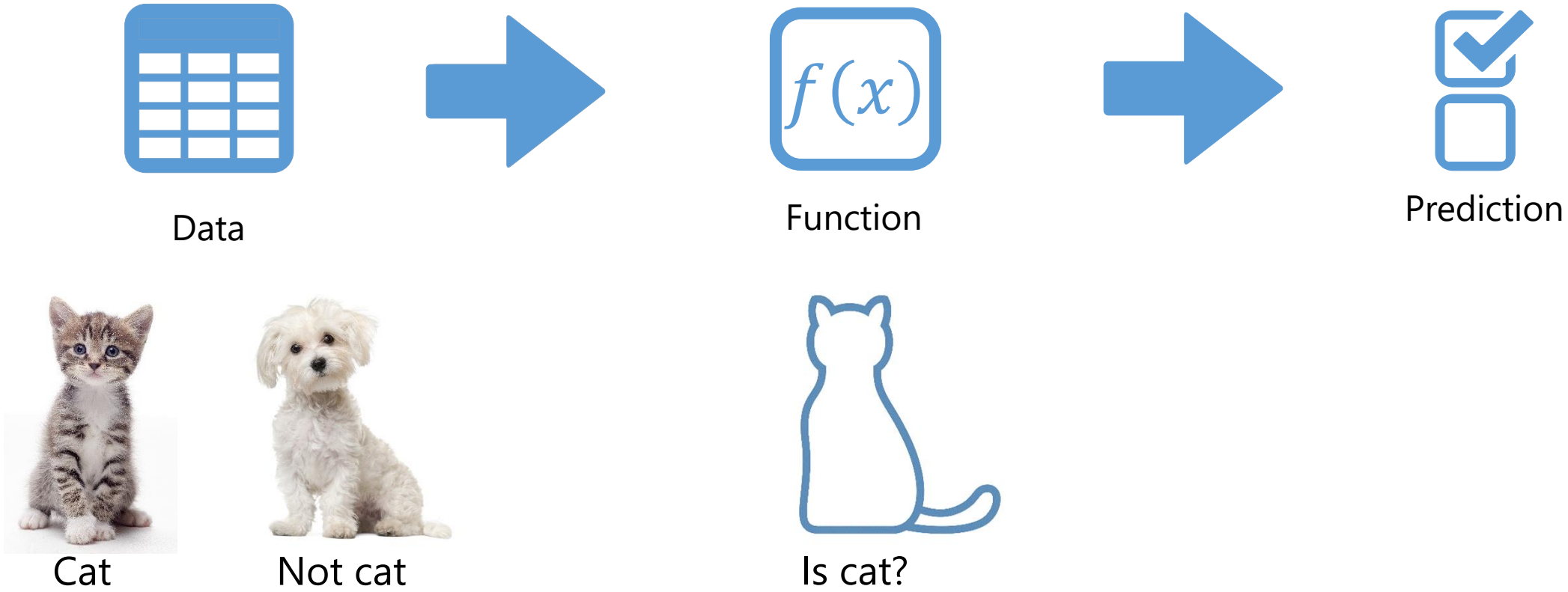

$f(x)$

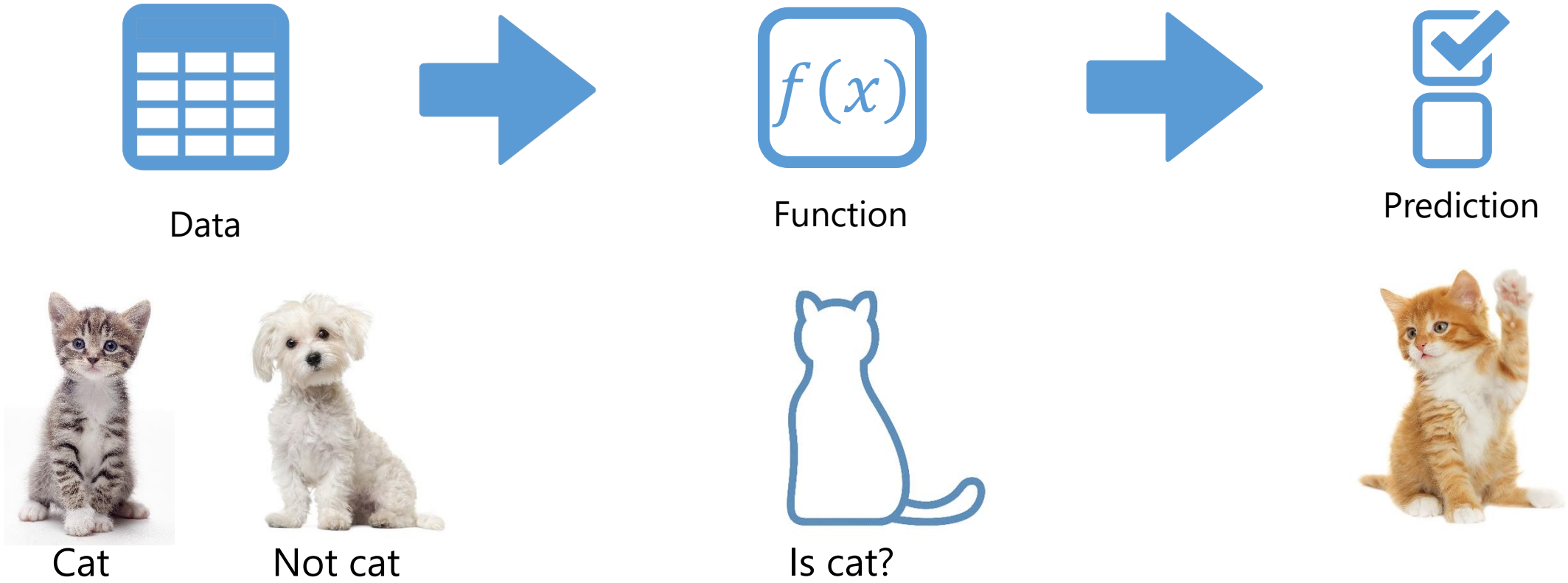

Data
$f(x)$
Function
Prediction

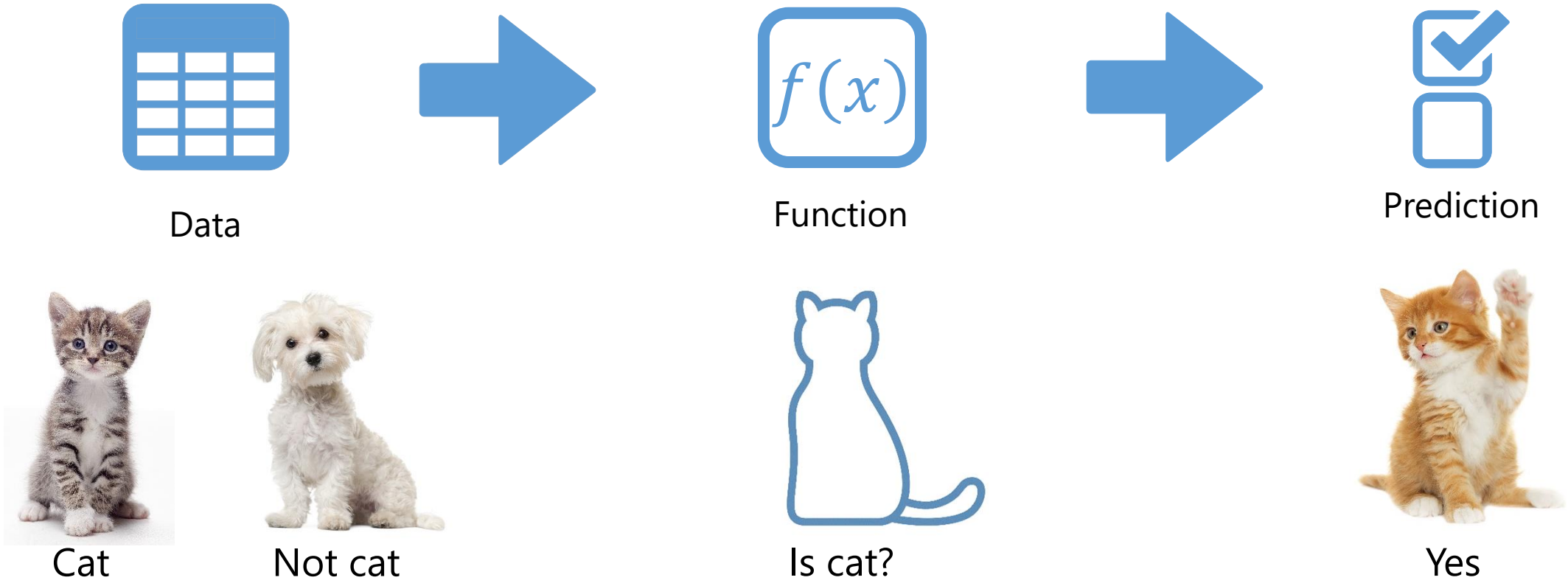

Data
$f(x)$
Function
Prediction


Data
$f(x)$
Function
Prediction
Cat
Not cat


Data
$f(x)$
Function
Prediction
Cat
Not cat

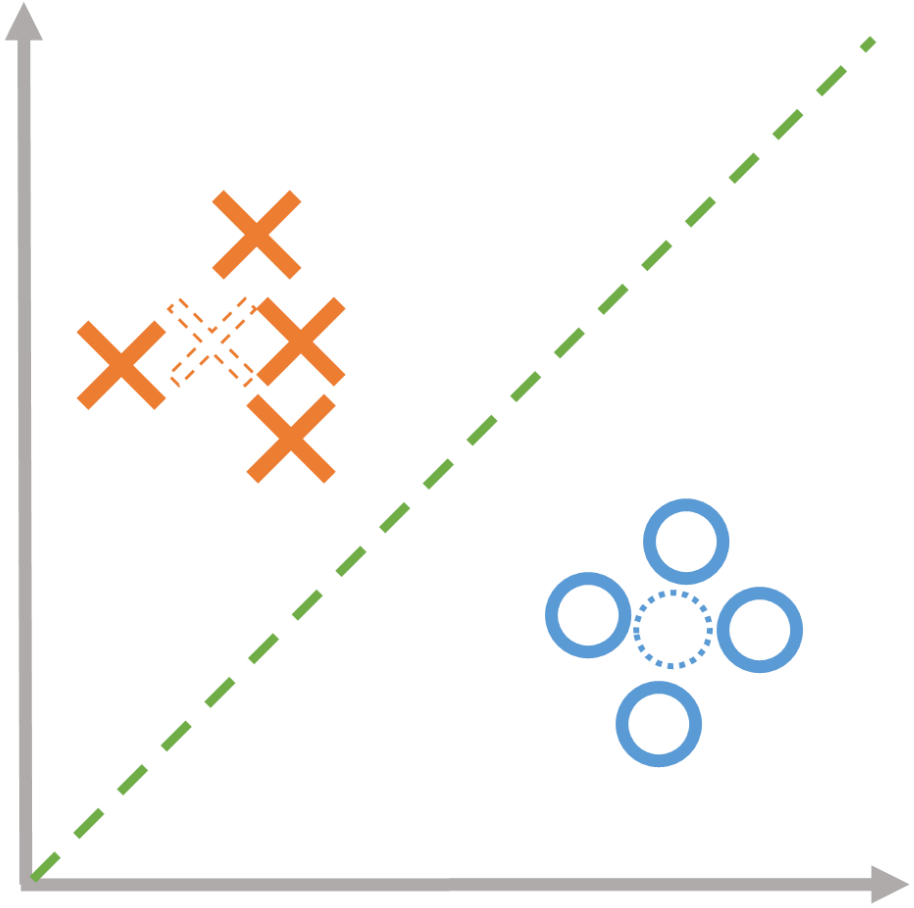

Data
$f(x)$
Function
Prediction
Cat
Not cat
Is cat?


Data
$f(x)$
Function
Prediction
Cat
Not cat
Is cat?

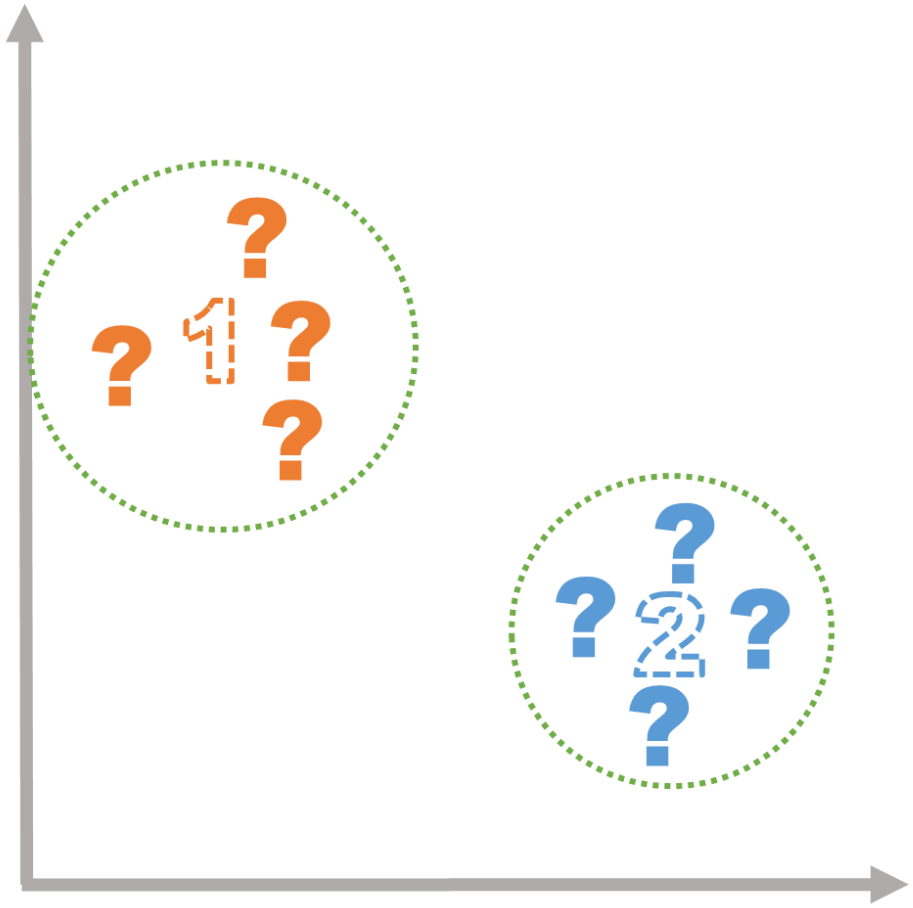

Data
$f(x)$
Function
Prediction
Cat
Not cat
Is cat?
Yes

What types of machine learning exist?

Types of Machine Learning

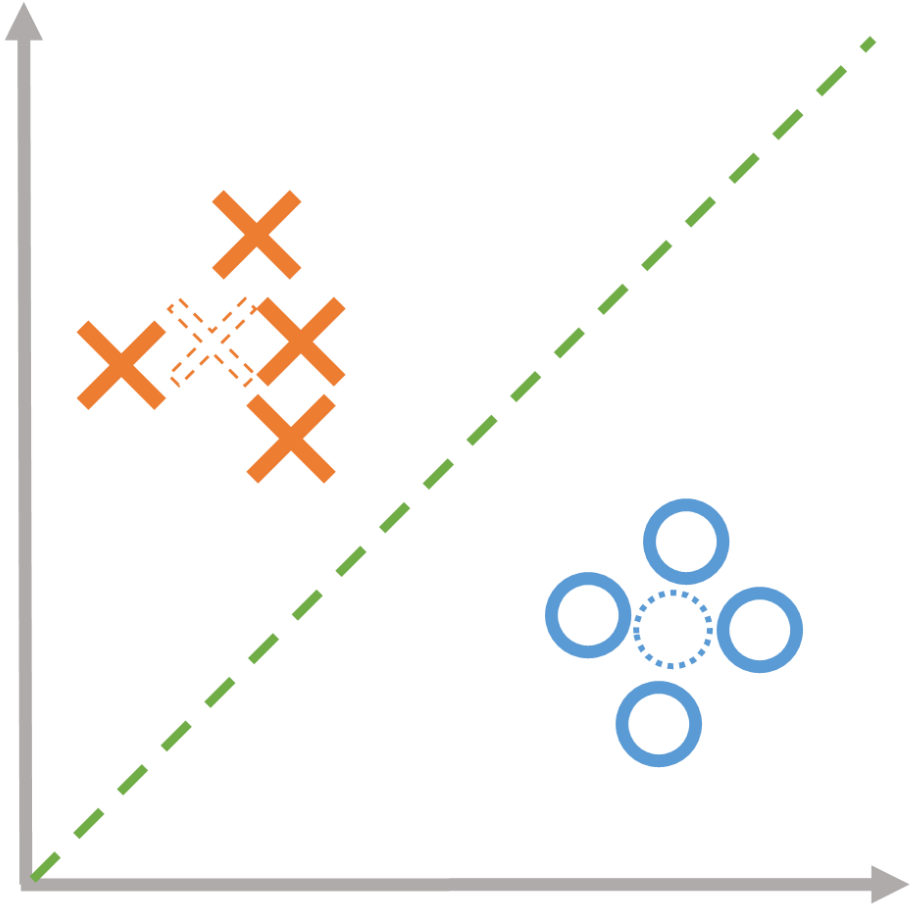


Supervised Learning



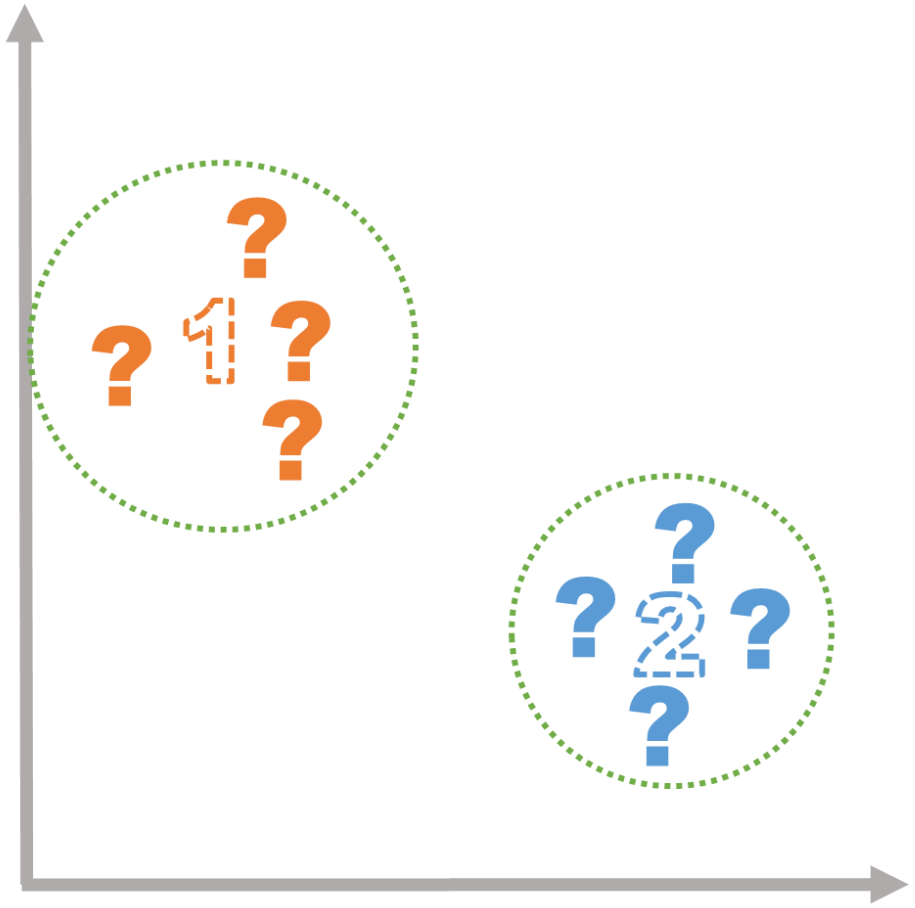
Unsupervised Learning

Types of Machine Learning



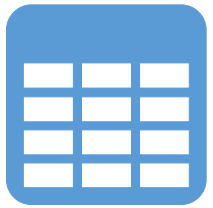
Supervised Learning

Types of Machine Learning

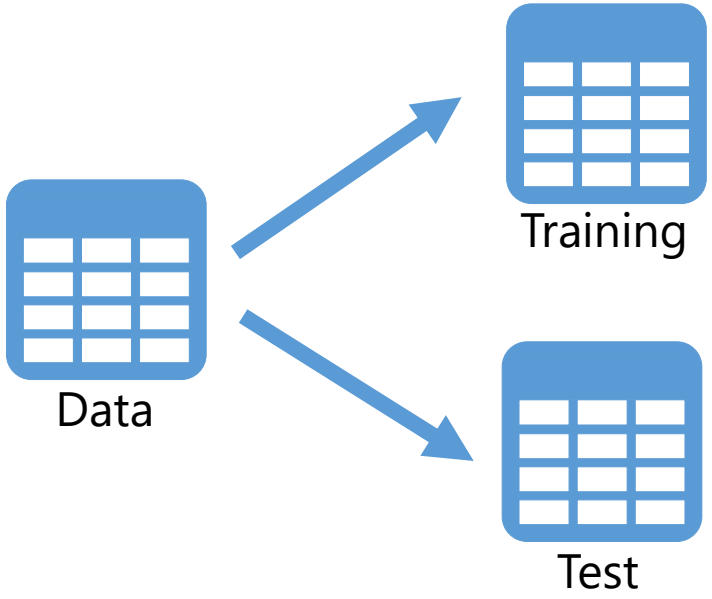


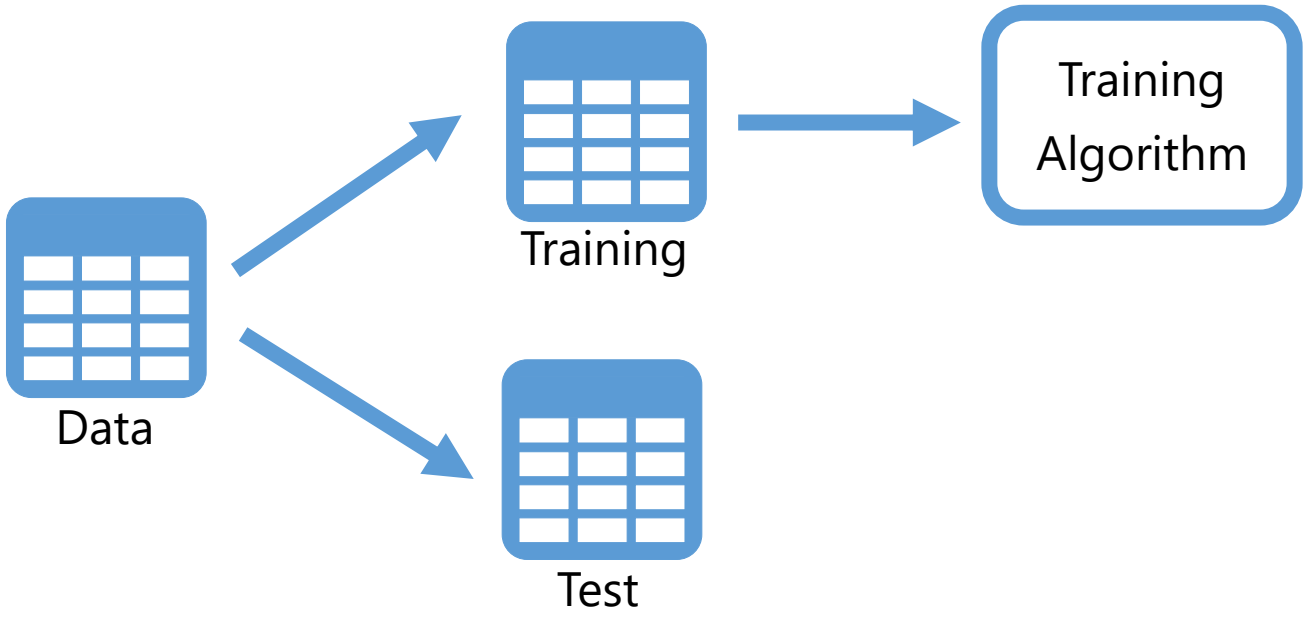
Unsupervised Learning

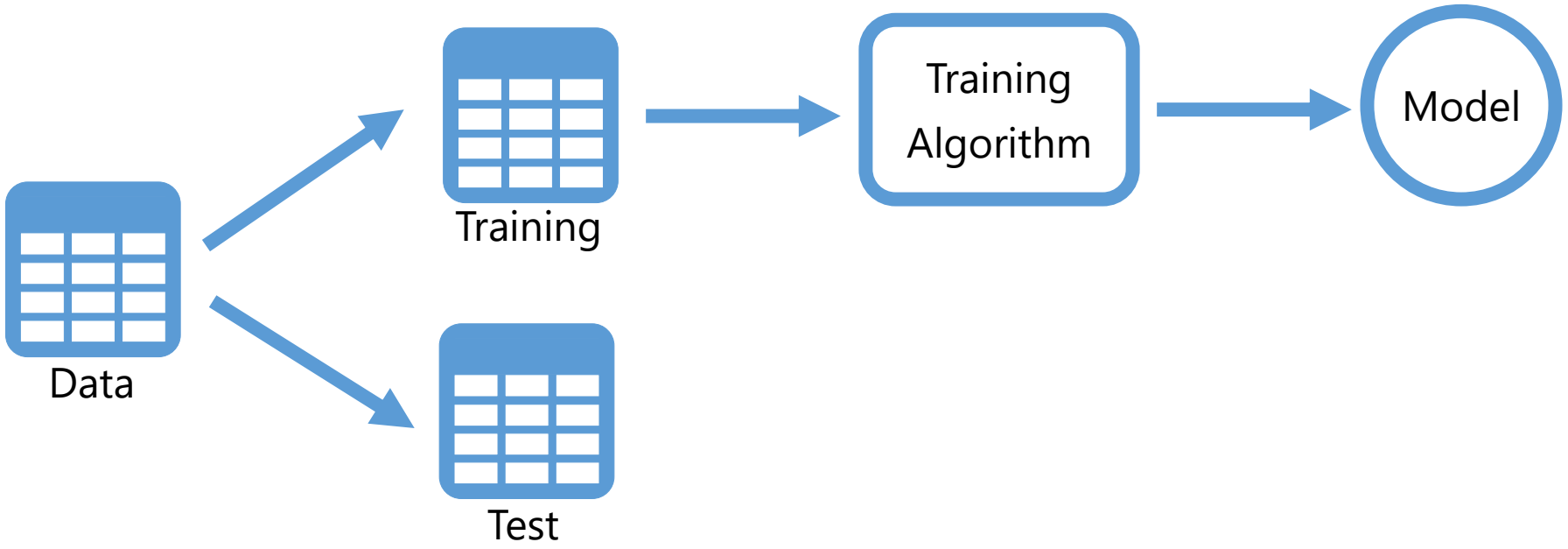
How does machine learning work?

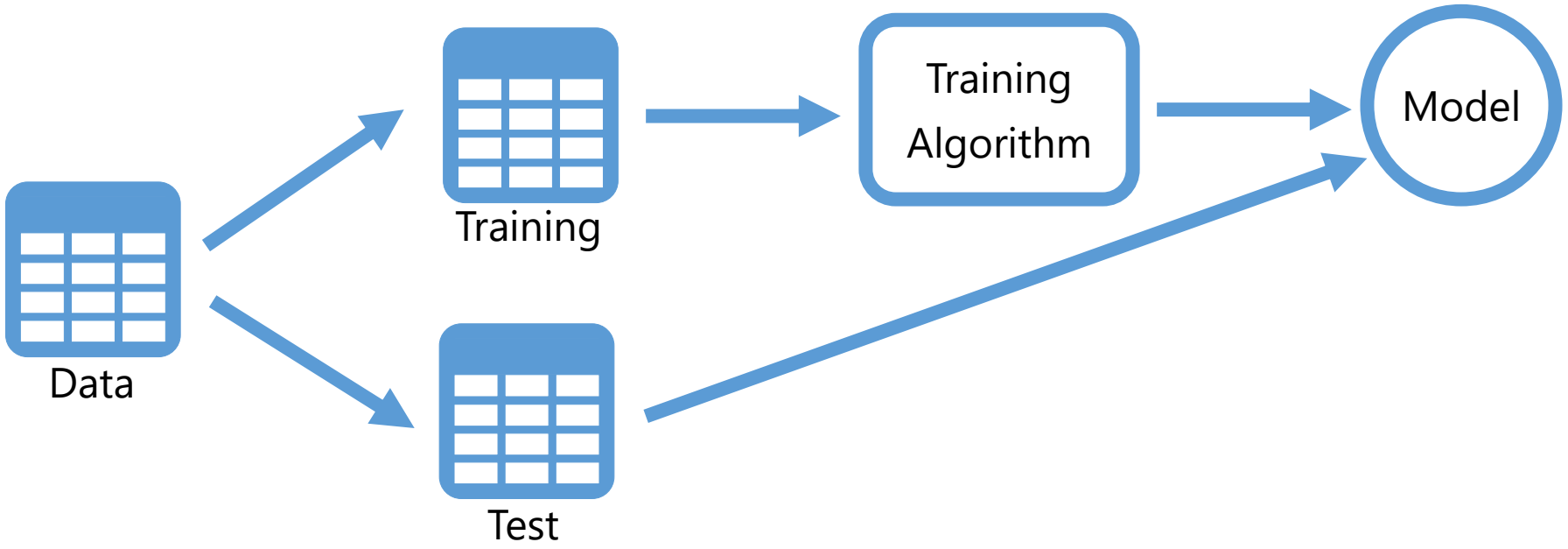


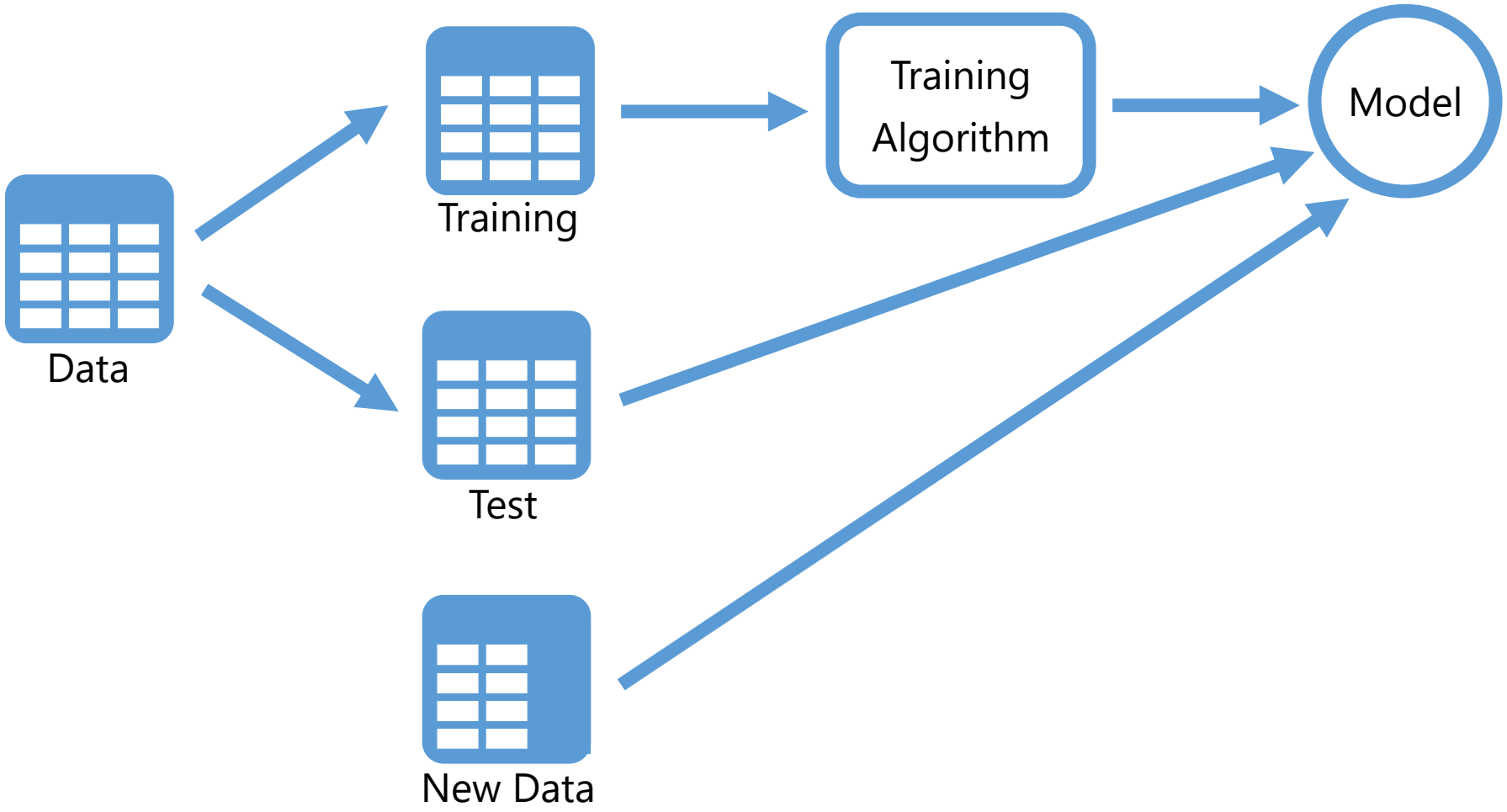
Data

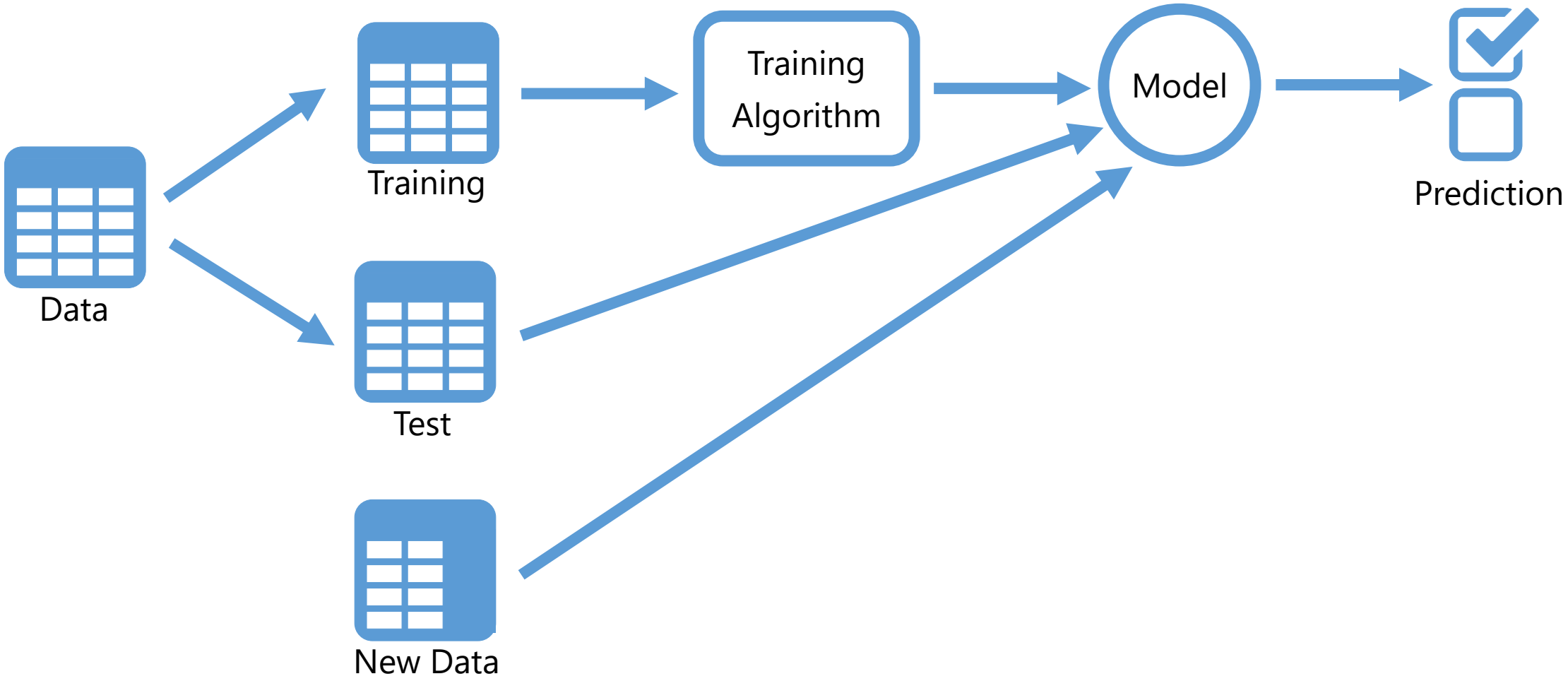

Training
Data
Test

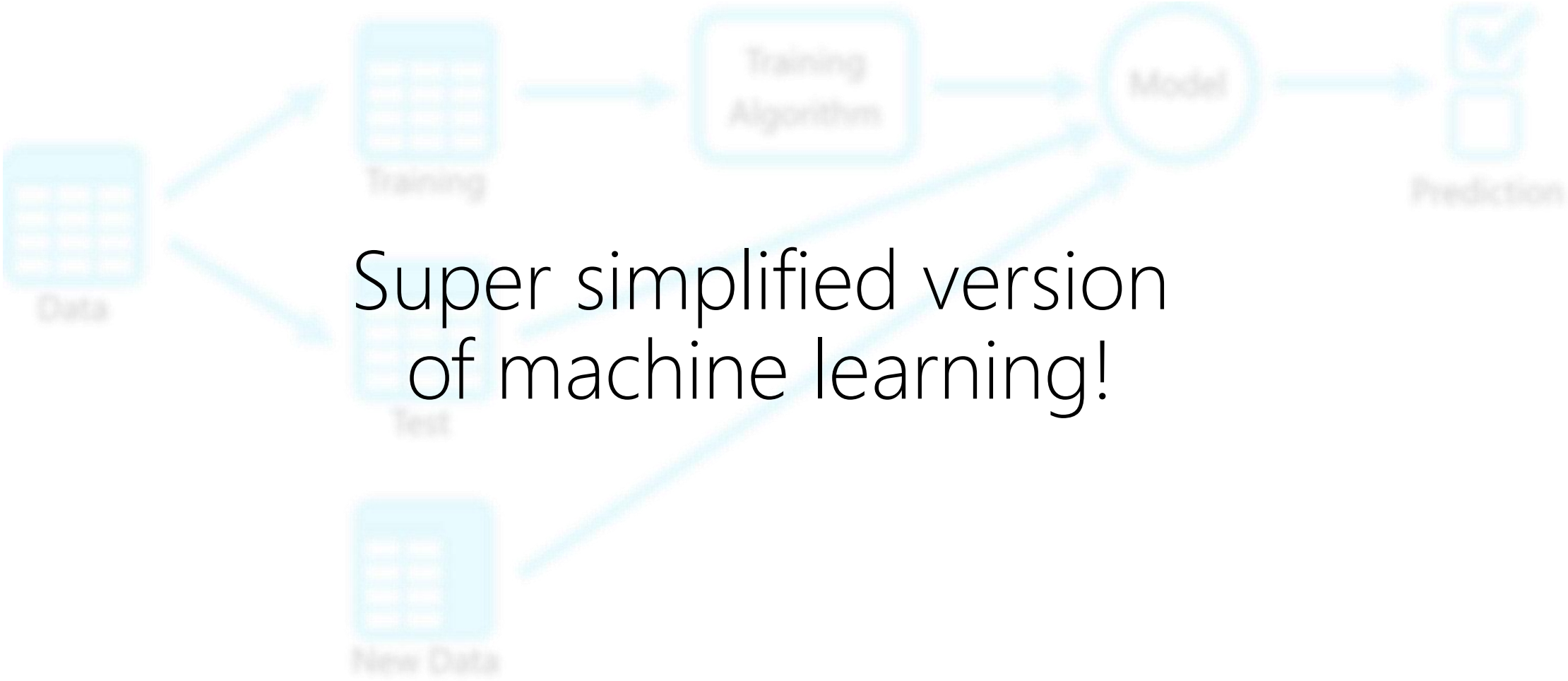

Training
Algorithm
Training
Data
Test


Data
Training
Test
Training
Algorithm
Model


Data
Training
Test
Training
Algorithm
Model

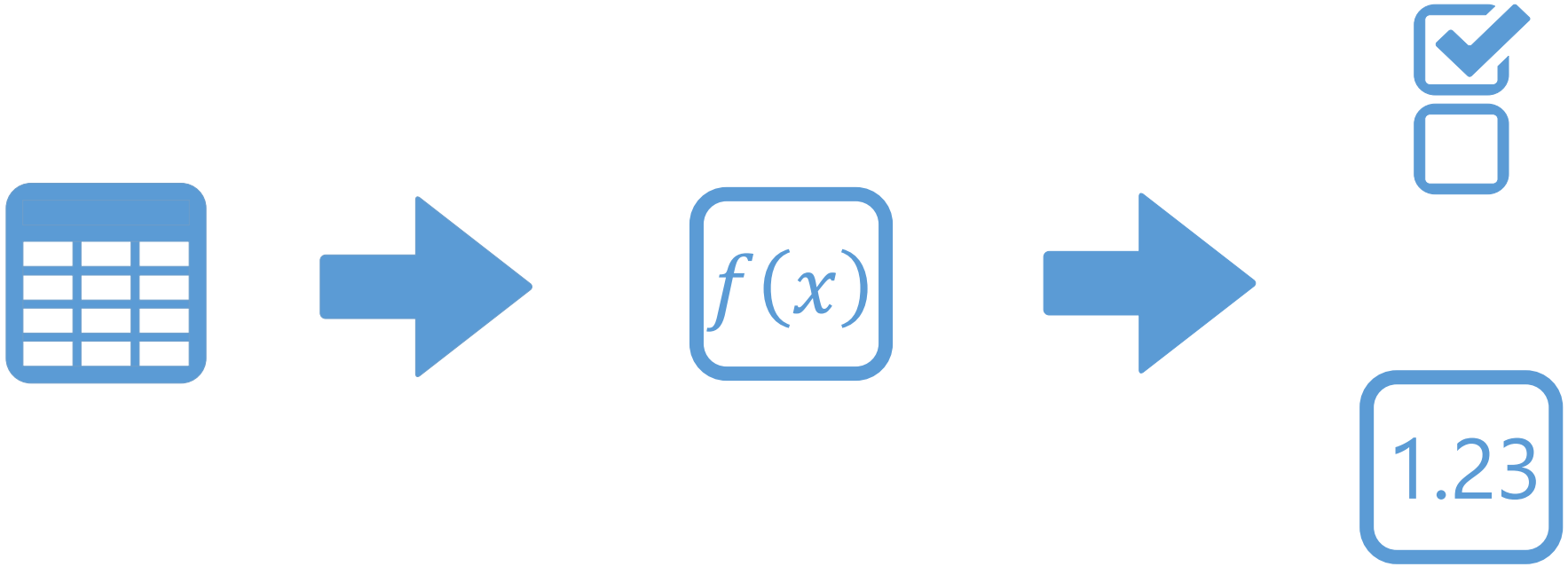

Data
Training
Test
New Data
Training
Algorithm
Model

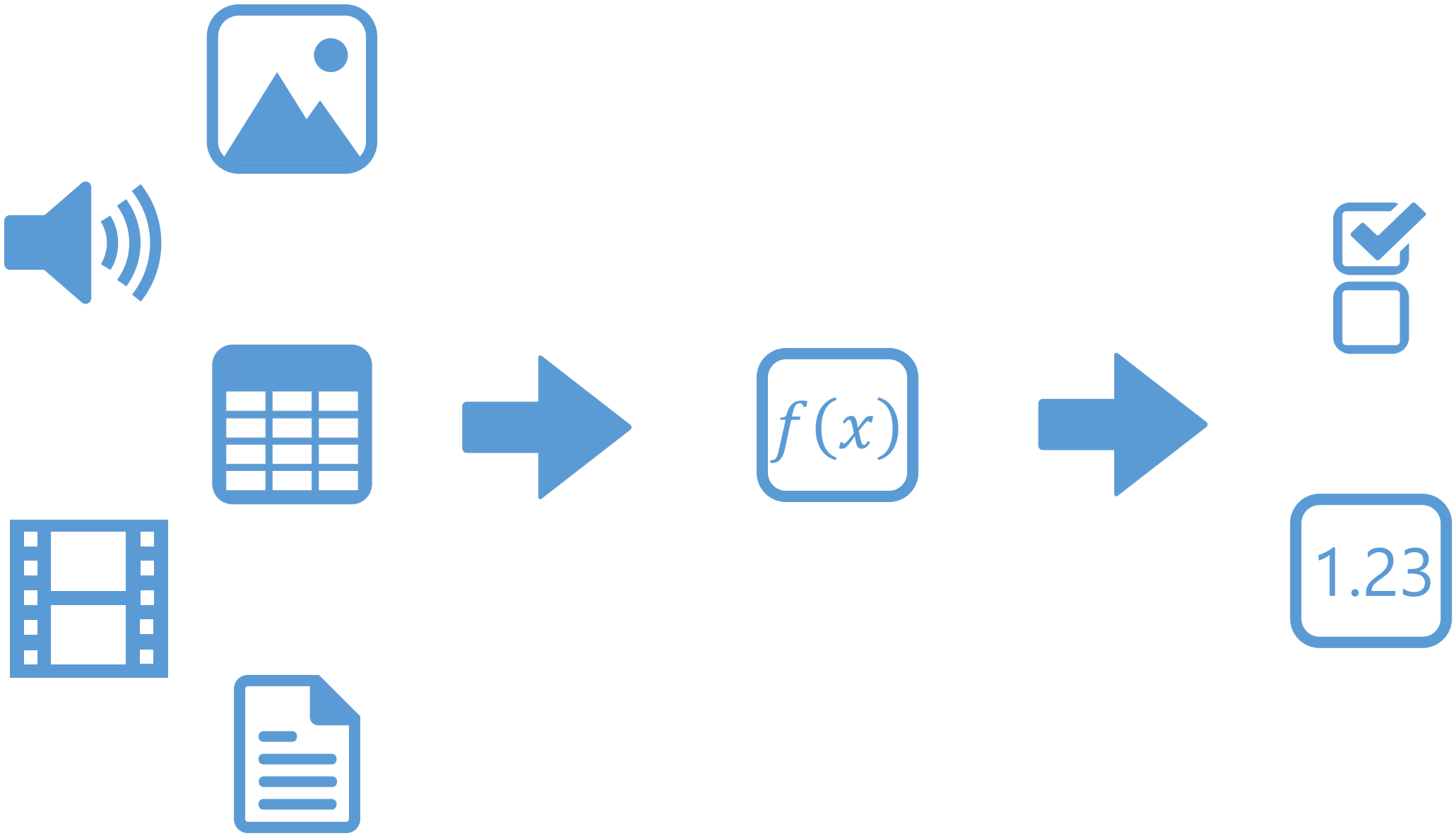

Data
Training
Test
New Data
Training Algorithm
Model
Prediction

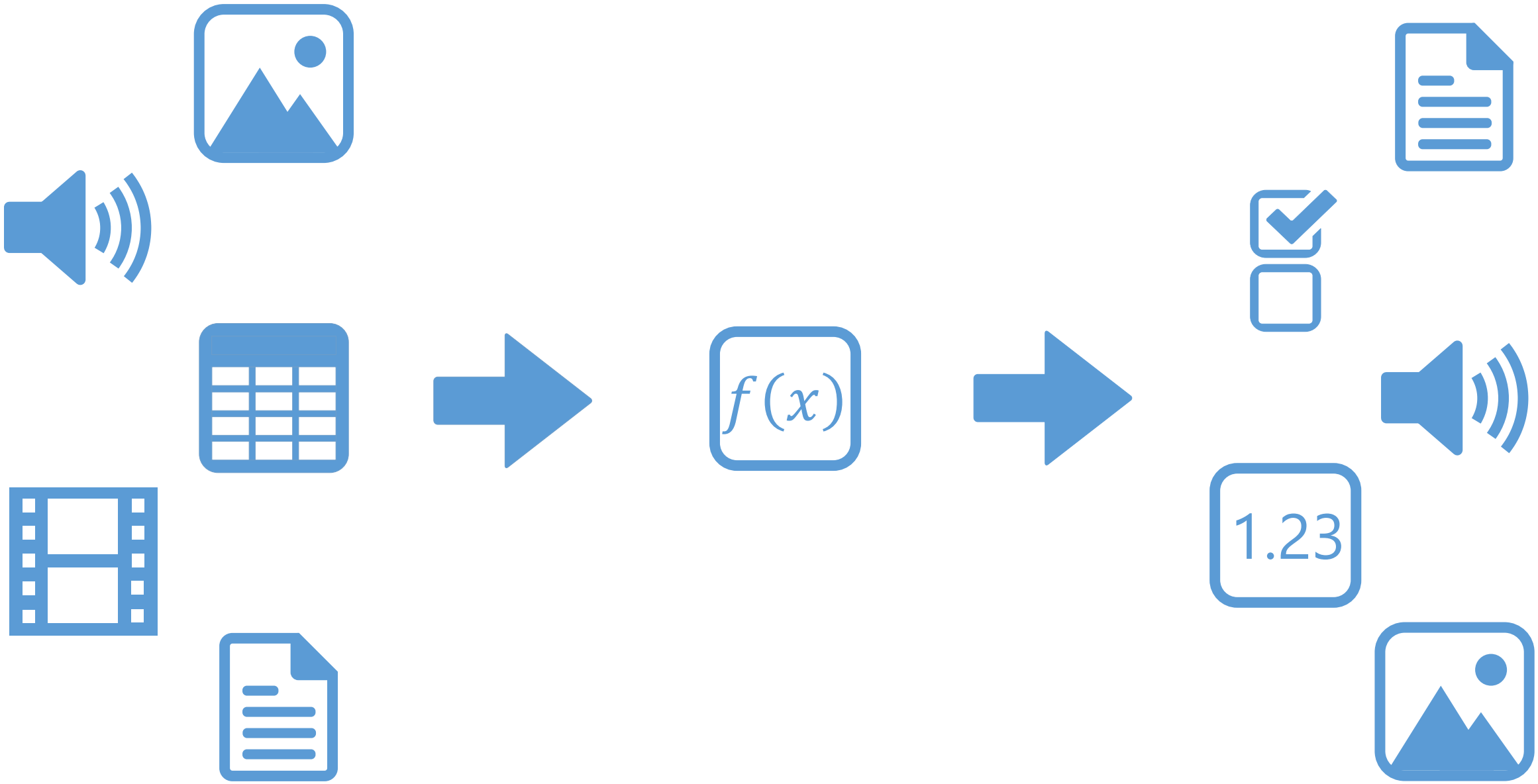


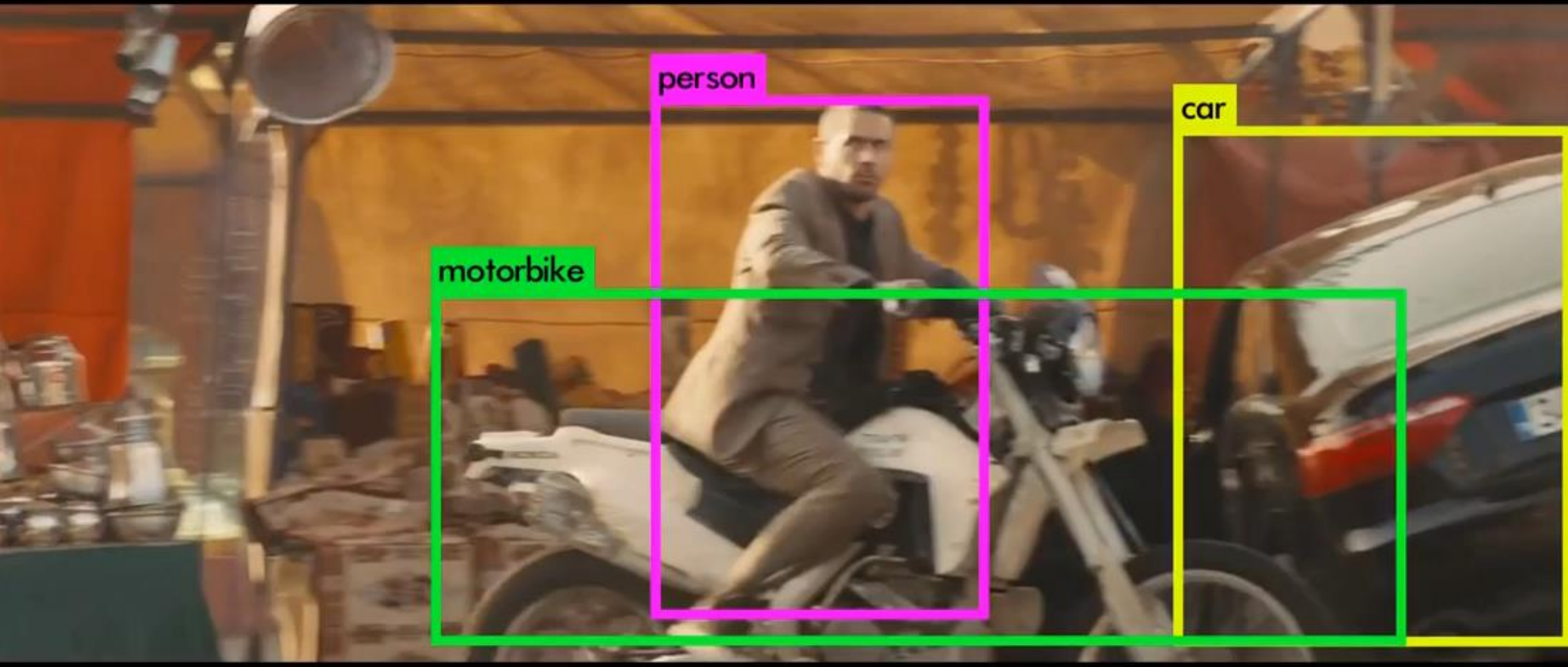
Super simplified version of machine learning!

What can machine learning do?


$f(x)$
1.23


$f(x)$
1.23


$f(x)$
1.23

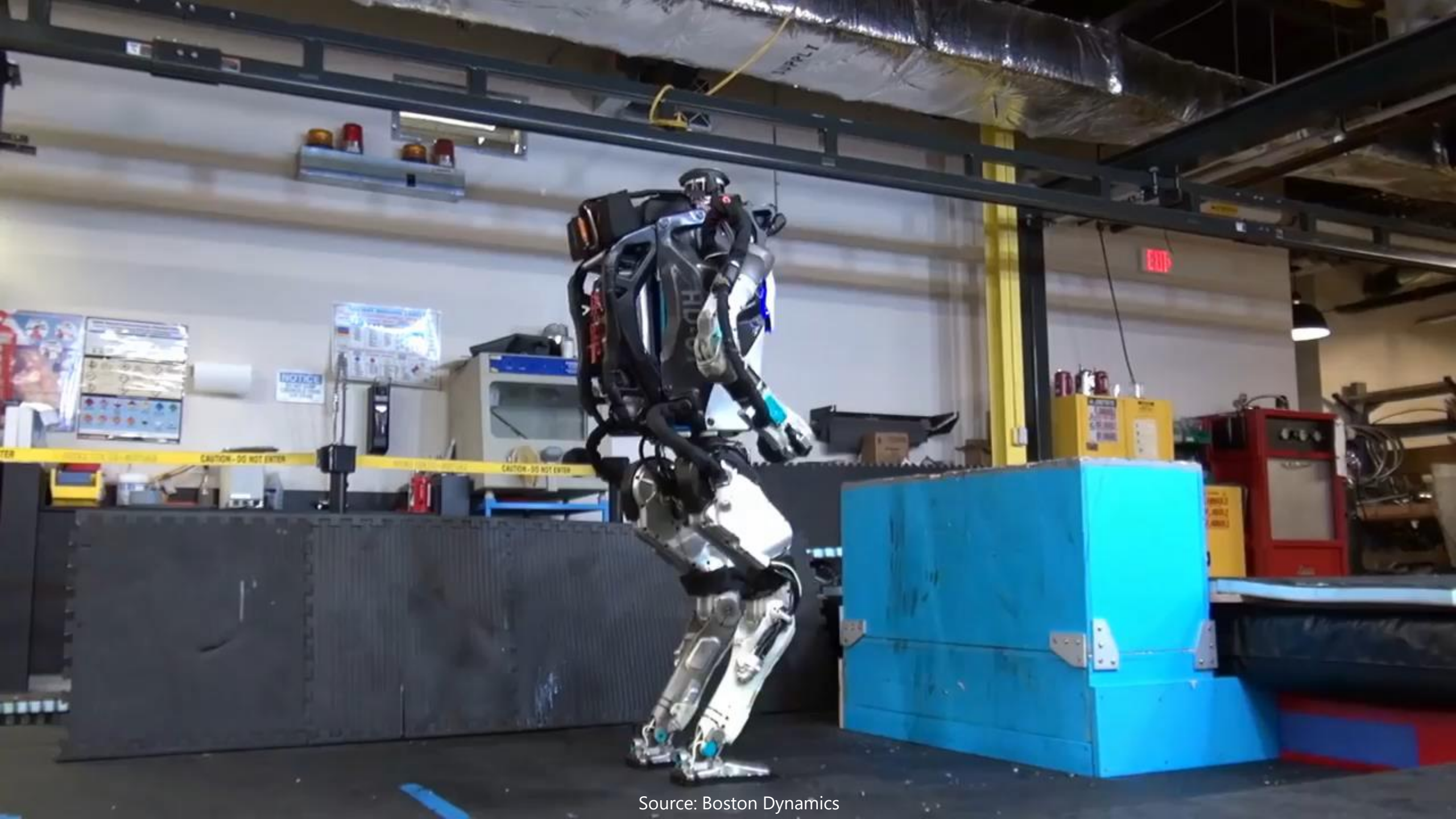


Source: YOLO: Real-Time Object Detection

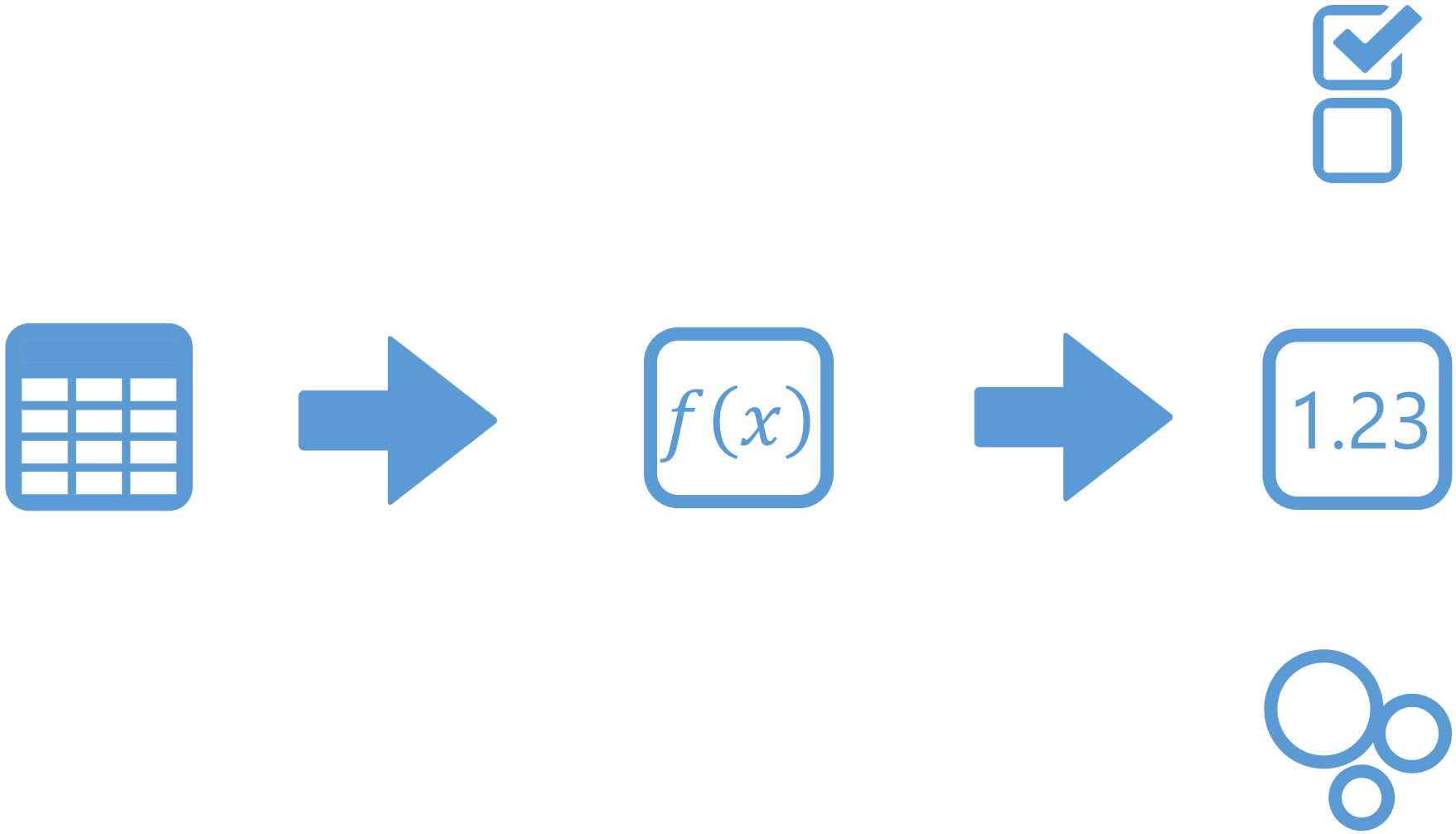

Source: Nvidia

Source: http://grail.cs.washington.edu/projects/AudioToObama/

Source: Google Deep Mind



Source: Boston Dynamics


$f(x)$
1.23

Disclaimer

Introduction to Python

What is Python?

Open source
Interpreted
Readability
Cross platform

What is Python?

Active development

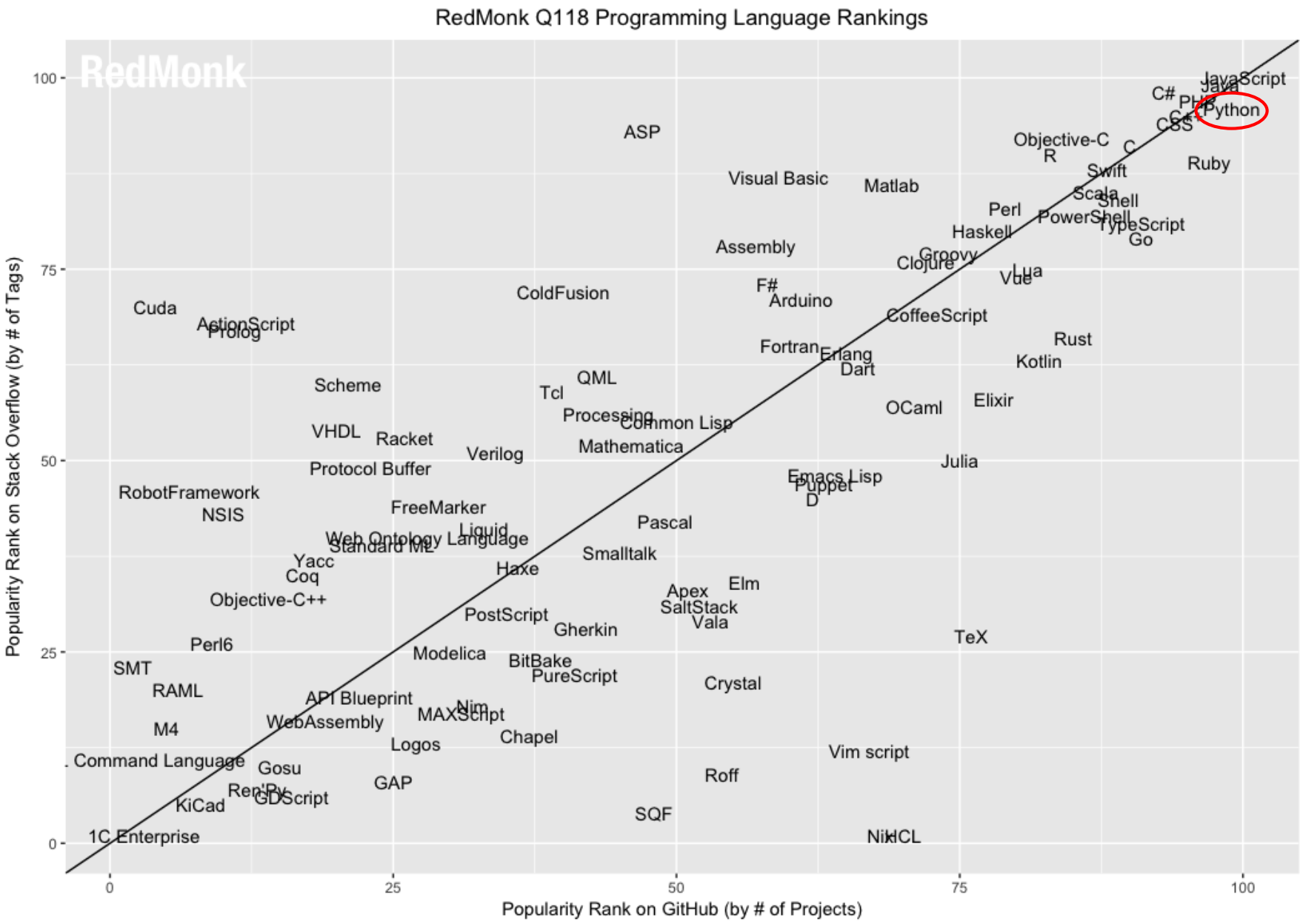
Large user community

Modular and extensible

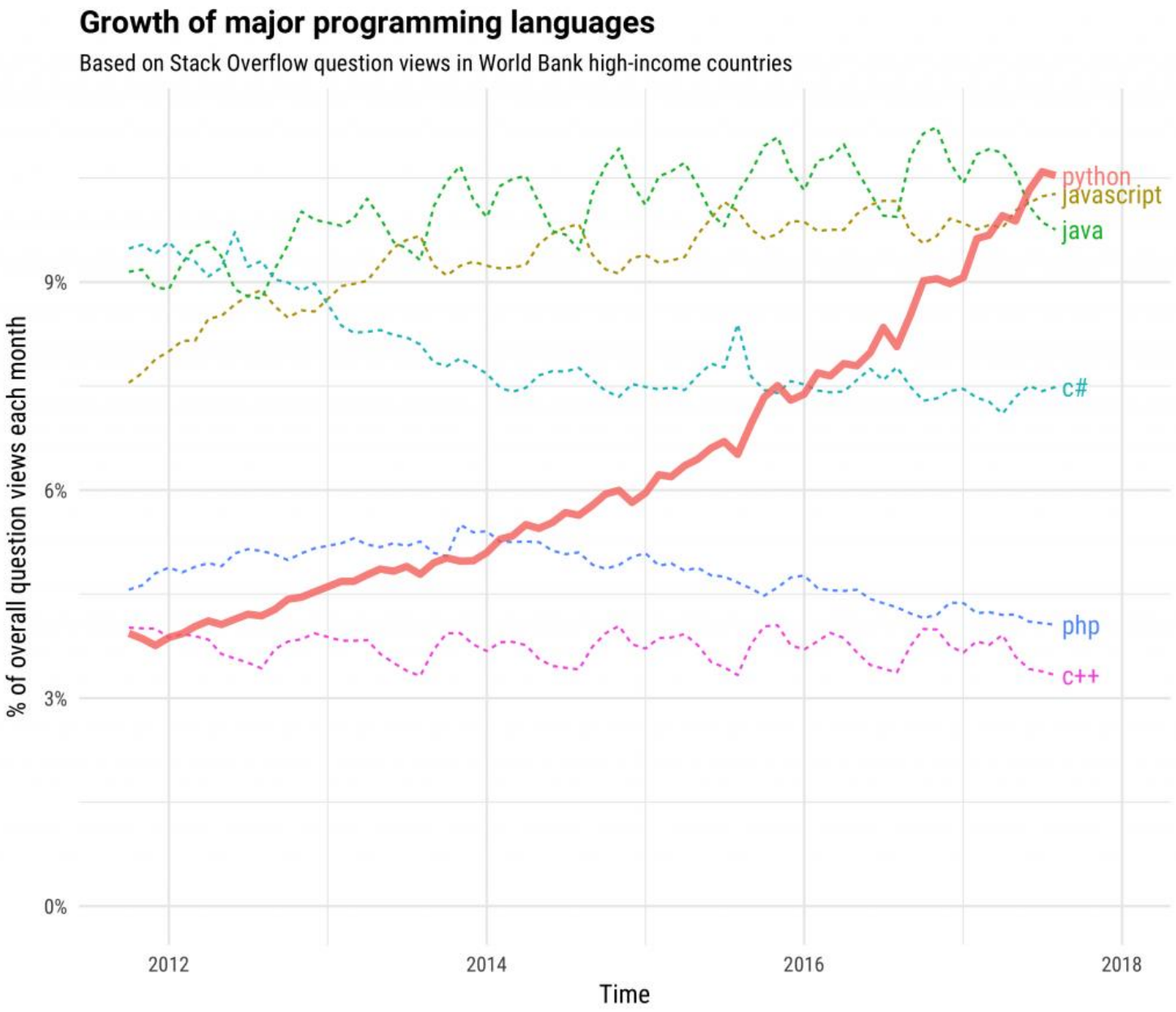
135,000+ packages


FREE


FREE

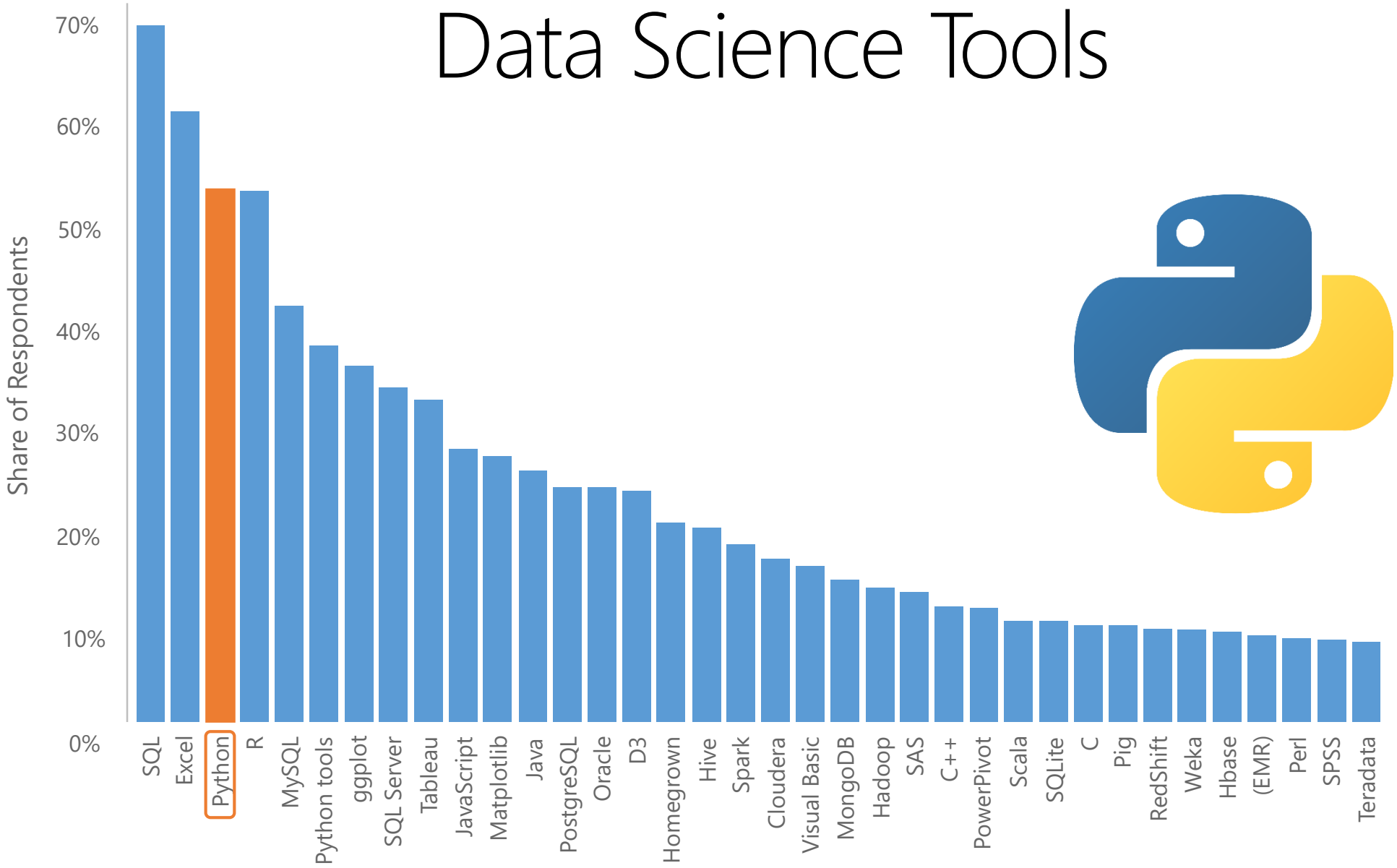


http://sogrady-media.redmonk.com/sogrady/files/2018/03/lang.rank_.118.png



Source: Stack Overflow

Data Science Tools



Tool: language, platform, analytics

Source: O'Reilly 2015 Data Science Salary Survey

Python 3.6 (64-bit)

```
Python 3.6.3 (v3.6.3:2c5fed8, Oct  3 2017, 18:11:49) [MSC v.1900 64 bit (AMD64)] on win32
Type "help", "copyright", "credits" or "license" for more information.
>>> x = "Hello World"
>>> print(x)
Hello World
>>> 
```

Spyder (Python 3.5)

File Edit Search Source Run Debug Consoles Tools View Help

C:\Users\stevek

Editor - C:\temp\plot_bayesian_ridge.py

plot_bayesian_ridge.py

```python
"""
=========================
Bayesian Ridge Regression
=========================

Computes a Bayesian Ridge Regression on a synthetic data

See :ref:`bayesian_ridge_regression` for more informatio

Compared to the OLS (ordinary least squares) estimator,
weights are slightly shifted toward zeros, which stabili

As the prior on the weights is a Gaussian prior, the his
estimated weights is Gaussian.

The estimation of the model is done by iteratively maxim
marginal log-likelihood of the observations.
"""
print(__doc__)

import numpy as np
import matplotlib.pyplot as plt
from scipy import stats

from sklearn.linear_model import BayesianRidge, LinearRe

#######################################################
# Generating simulated data with Gaussian weigths
np.random.seed(0)
n_samples, n_features = 100, 100
X = np.random.randn(n_samples, n_features)  # Create Gau
# Create weigts with a precision lambda_ of 4.
lambda_ = 4.
w = np.zeros(n_features)
# Only keep 10 weights of interest
relevant_features = np.random.randint(0, n_features, 10)
for i in relevant_features:
```

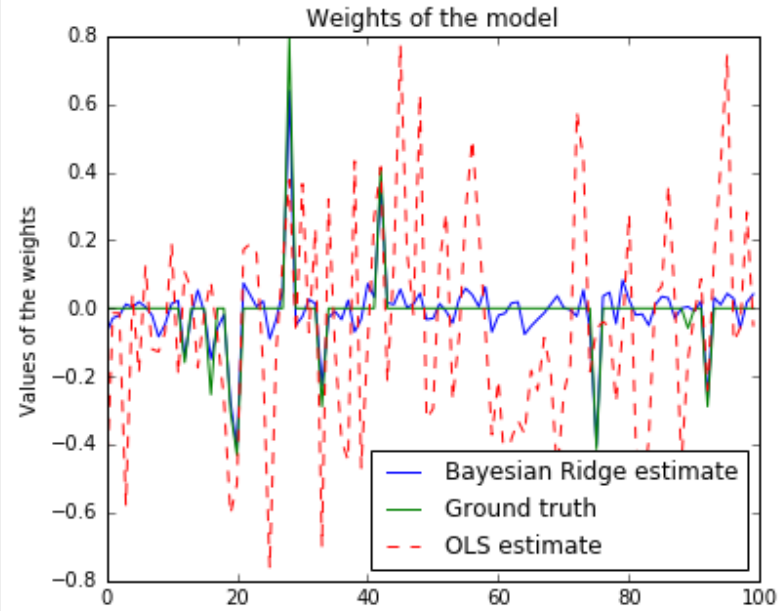
Variable explorer

Name	Type	Size	Value
X	float64	(100, 100)	array([[1.7640… 0.1269…
alpha_	float	1	50.0
digits	datasets.base.Bunch	5	{'target': ar... 1., 0.]])}
i	int32	1	42
iris	datasets.base.Bunch	5	{'target': ar... 5.1, 1.8]])}

Object inspector | Variable explorer | File explorer

IPython console

Console 1/A



Console | History log | IPython console

Permissions: RW | End-of-lines: LF | Encoding: UTF-8-GUESSED | Line: 1 | Column: 1 | Memory: 40 %

15-Preview-of-Data-Science-Tools.py - Microsoft Visual Studio

File Edit View Project Debug Team Tools Test Analyze Window Help

Steve Dower

Quick Launch (Ctrl+Q)

Attach...

15-Preview-of-Data-Science-Tools.py

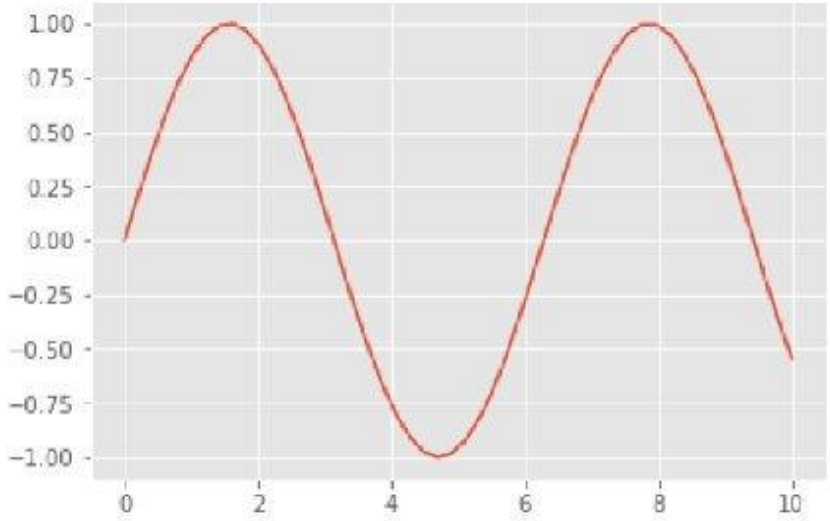
```
# In[14]:

import matplotlib.pyplot as plt
plt.style.use('ggplot')  # make graphs in the


# Now let's create some data (as NumPy arrays

# In[15]:

x = np.linspace(0, 10)  # range of values frc
y = np.sin(x)           # sine of these value
plt.plot(x, y);         # plot as a line


# If you run this code live, you will see an


# What we see is a smooth interpolation betwe

# ## Other Data Science Packages
#
# Built on top of these tools are a host of c
#
```

100 %

Anaconda 4.3.0 Interactive

Environment: Anaconda 4.3.0

```
In [18]: # Now let's create some data (as NumPy
    ....:
    ....: # In[15]:
    ....:
    ....: x = np.linspace(0, 10)  # range of valu
    ....: y = np.sin(x)           # sine of these
    ....: plt.plot(x, y);         # plot as a lin
```




```
In [19]:
```

100 %

Python Environments

Ln 153 Col 1 Ch 1 INS

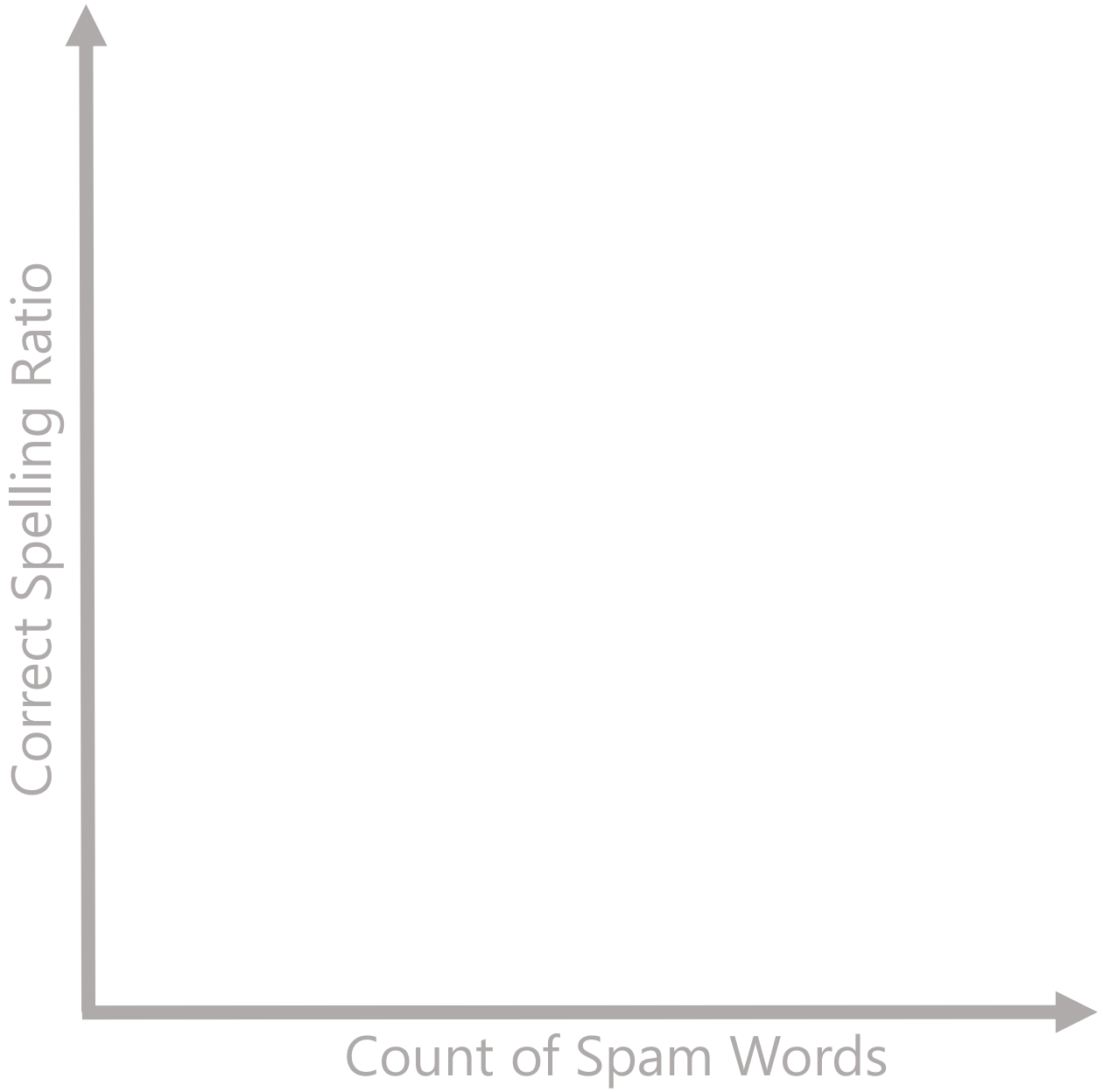
Add to Source Control

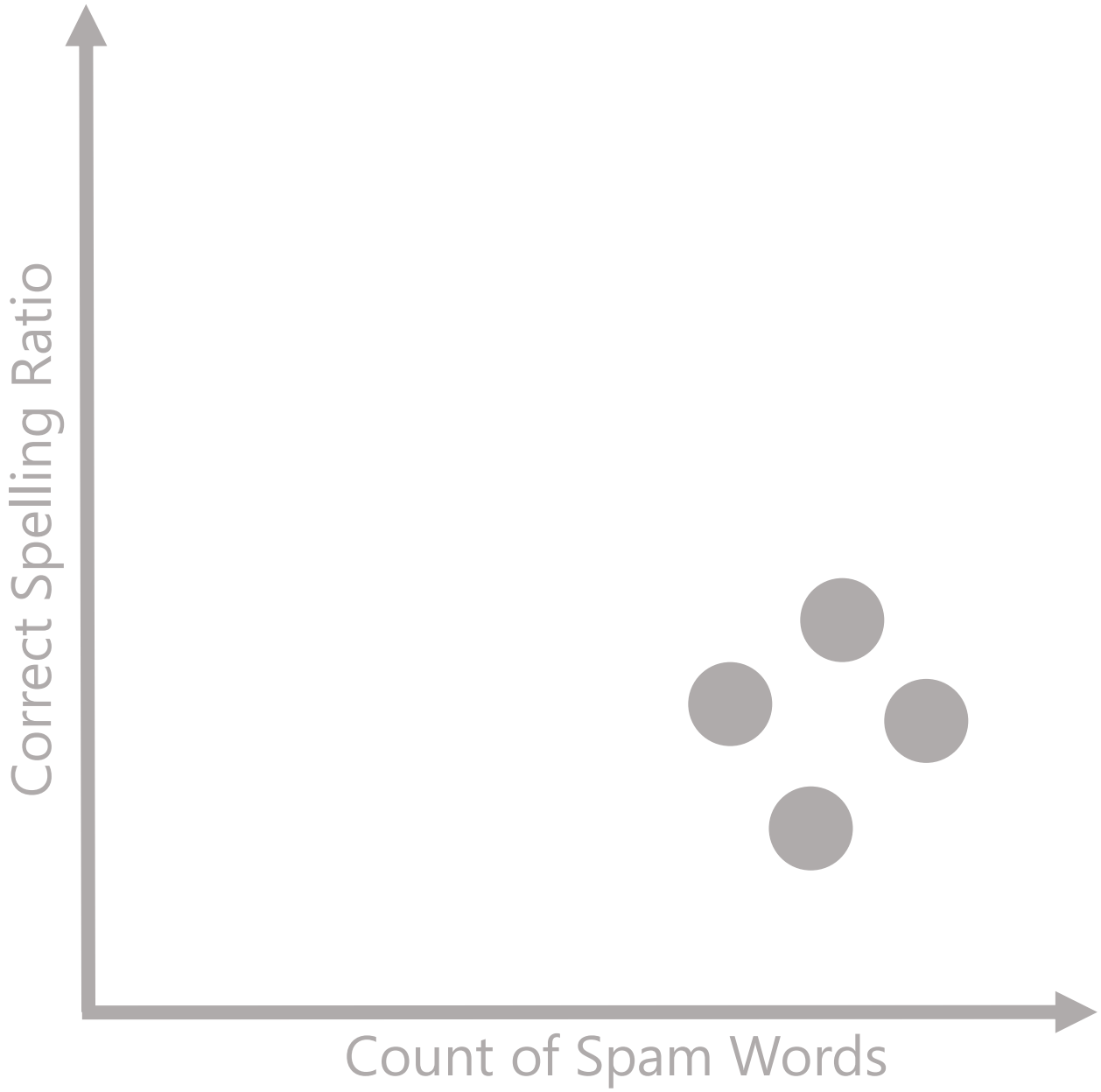
Demo 1
Python Language Basics

Lab 1
Python Language Basics

Classification


Ingredients:
Pork with Ham,
Salt, Water,
Modified Potato
Starch, Sugar,
Sodium Nitrite
SPAM®
Classic
U.S.
INSPECTED
AND PASSED BY
DEPARTMENT OF
AGRICULTURE
Serving
Suggestion
NET WT
12 OZ
(340g)


Correct Spelling Ratio
Count of Spam Words


Correct Spelling Ratio
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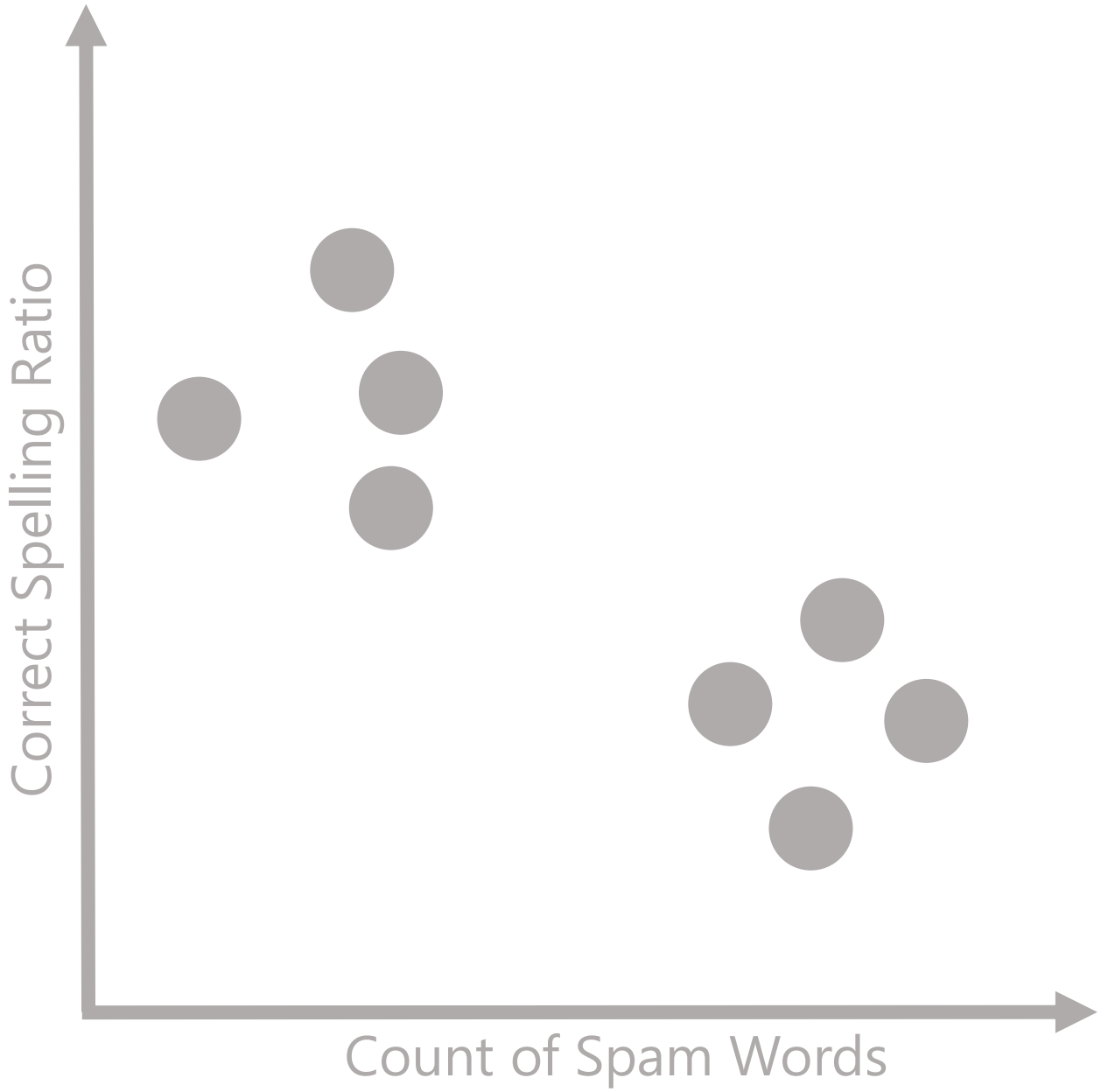
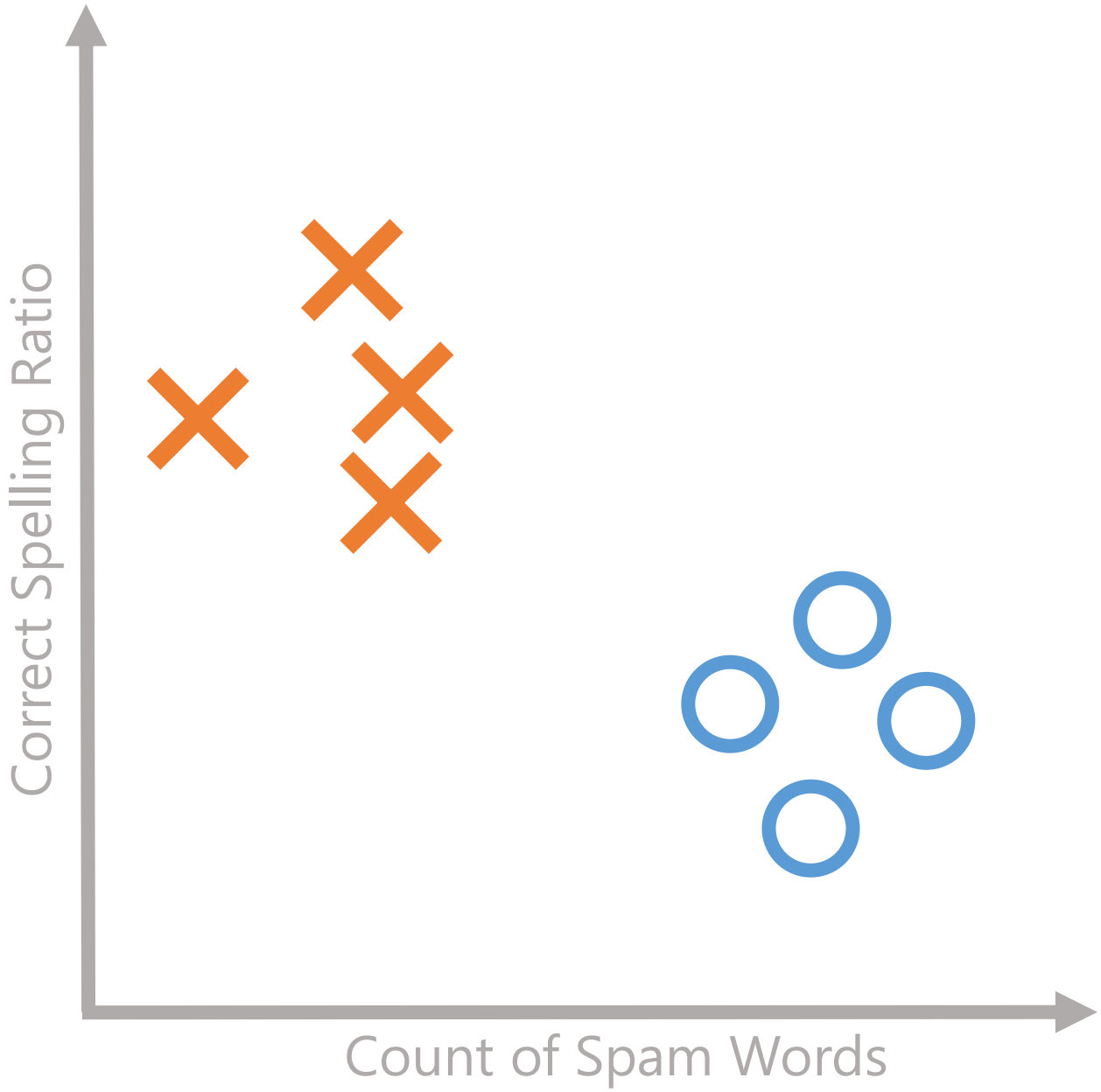

Correct Spelling Ratio
Count of Spam Words


Correct Spelling Ratio
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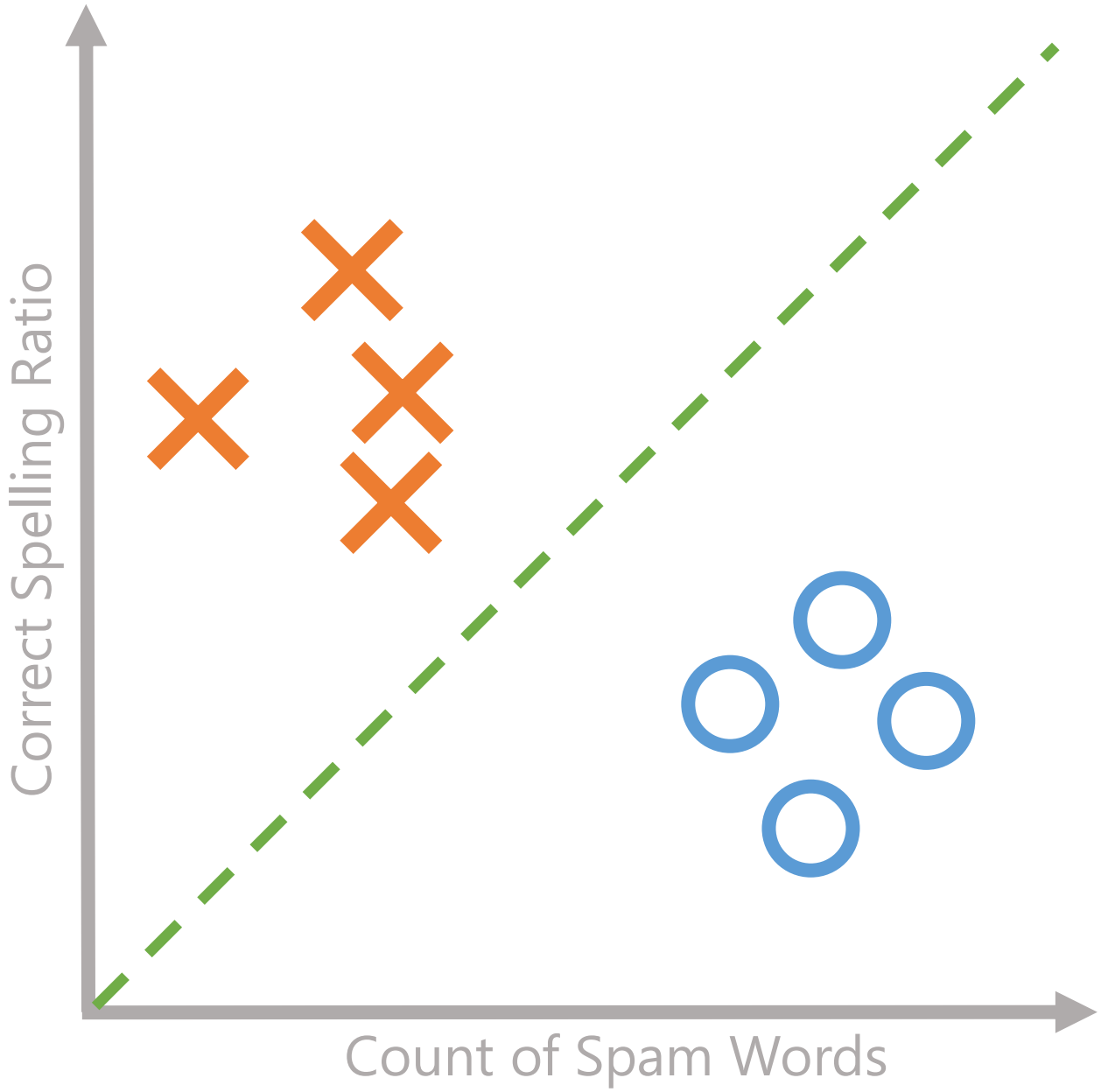
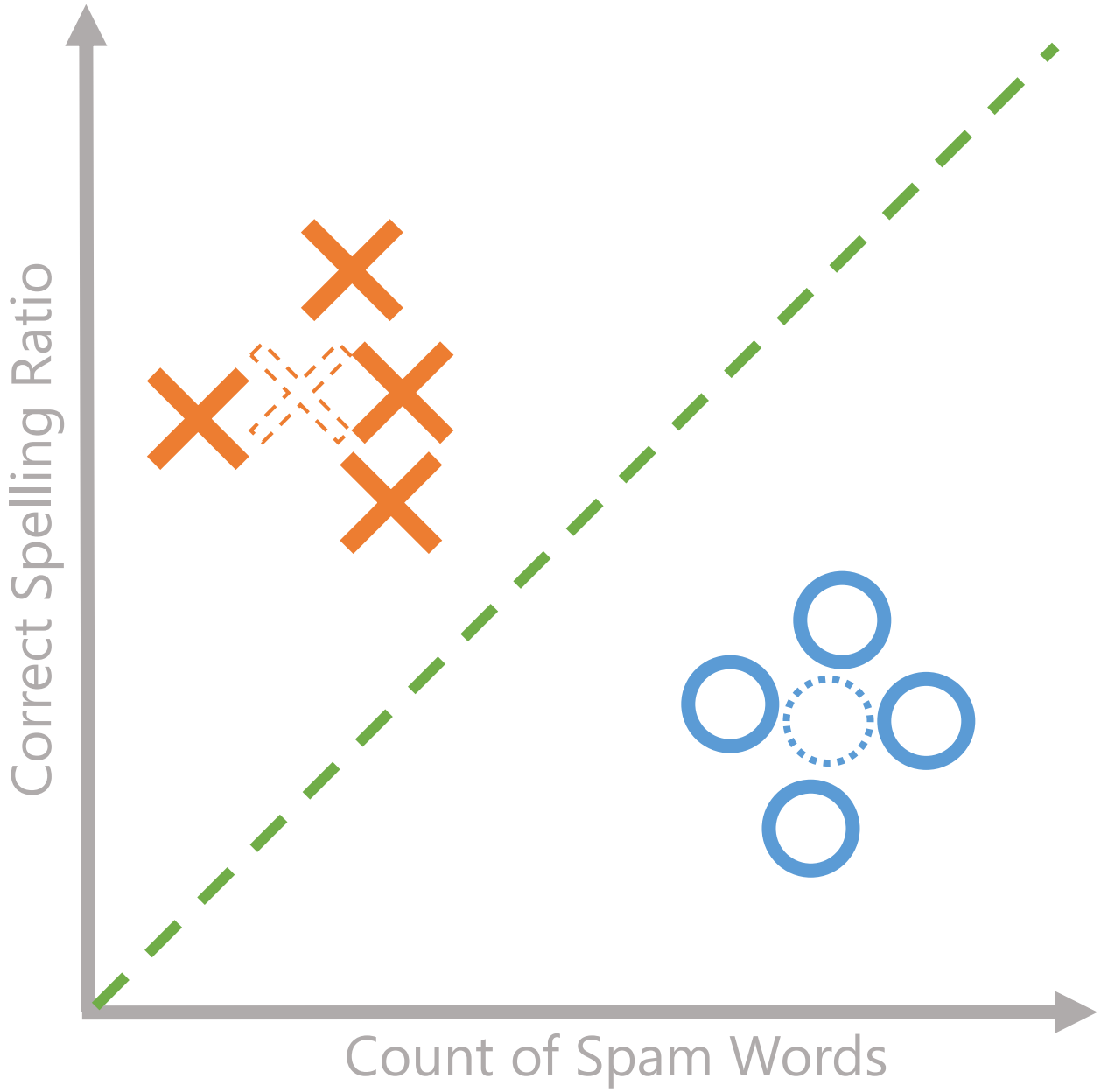
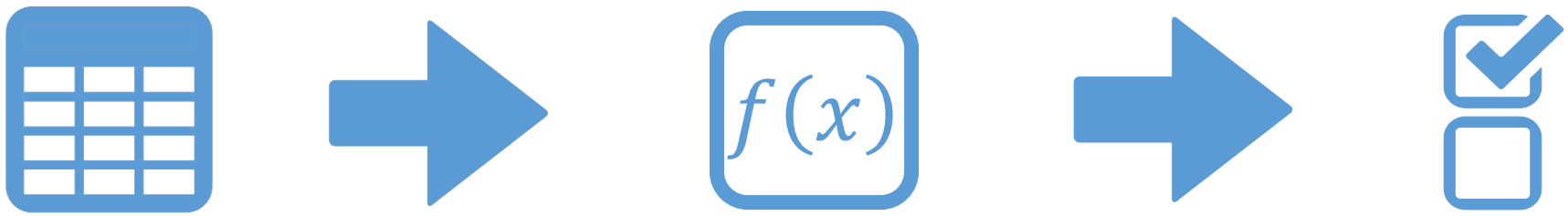
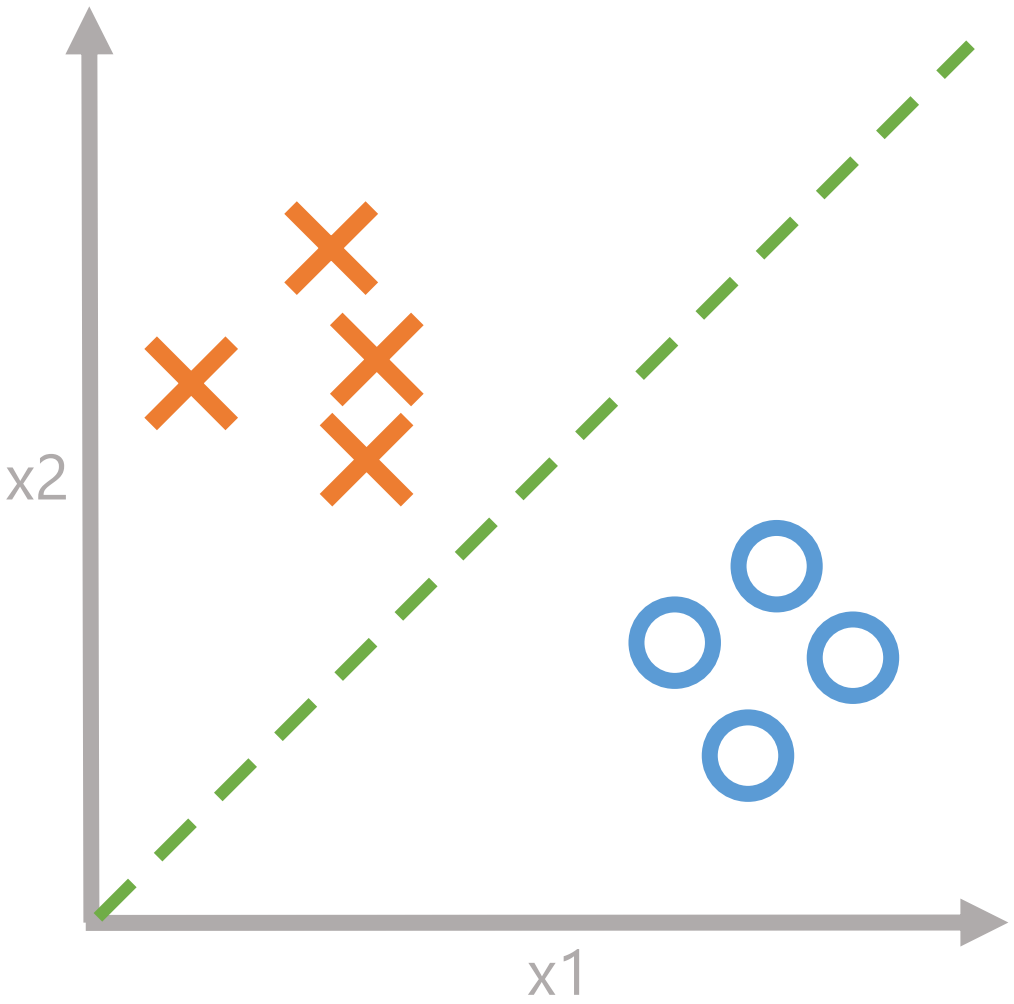

Correct Spelling Ratio
Count of Spam Words


Correct Spelling Ratio
Count of Spam Words

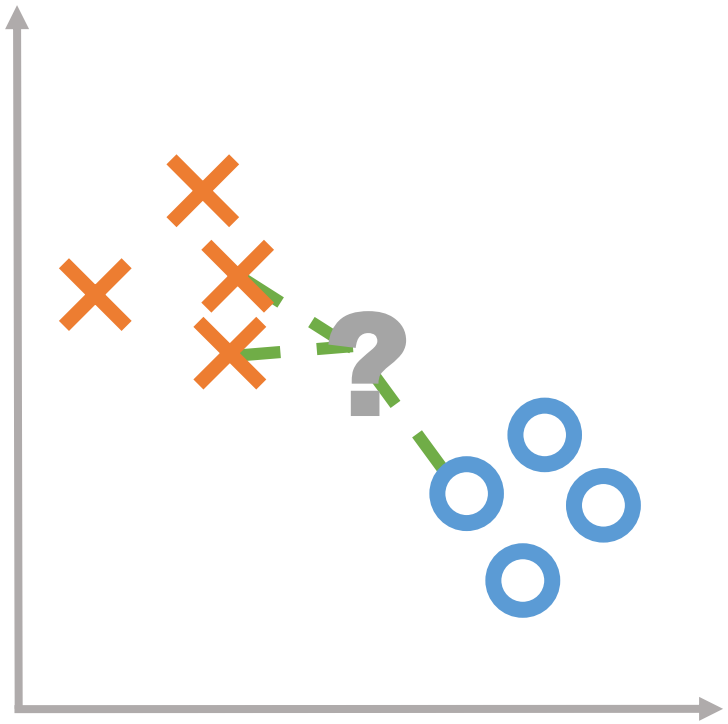

$f(x)$

Classification Algorithms

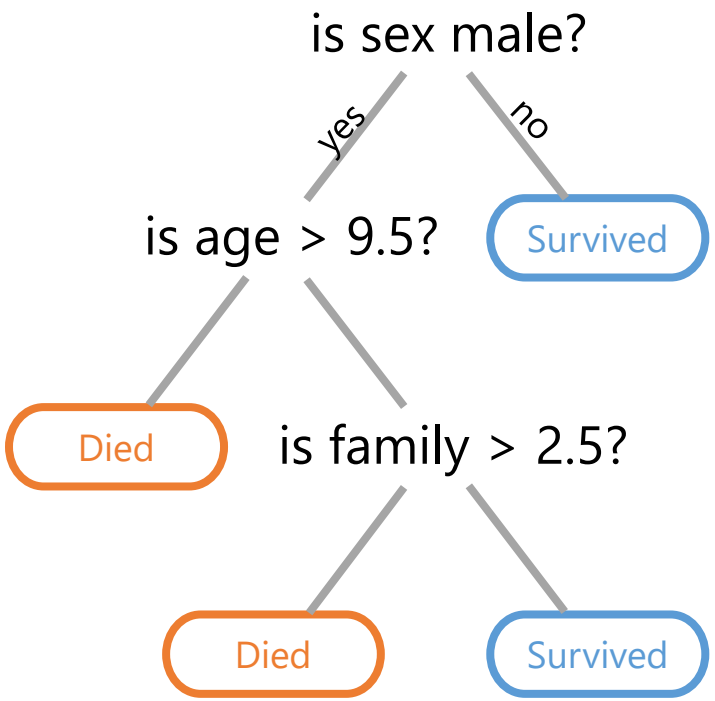
k-Nearest Neighbors
Decision Tree Classifier
Naïve Bayes Classifier
Support Vector Machine
Neural Network Classifier



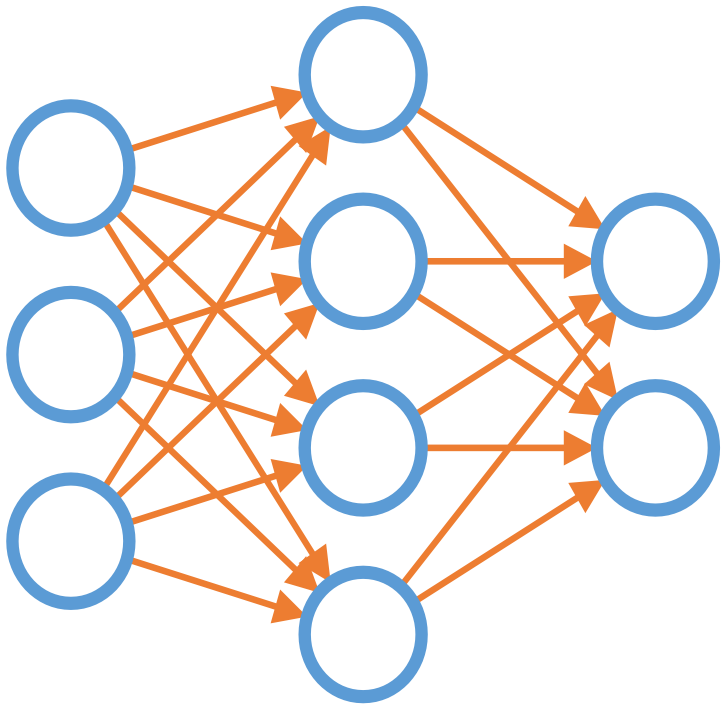
Classification Algorithms



k-Nearest Neighbors

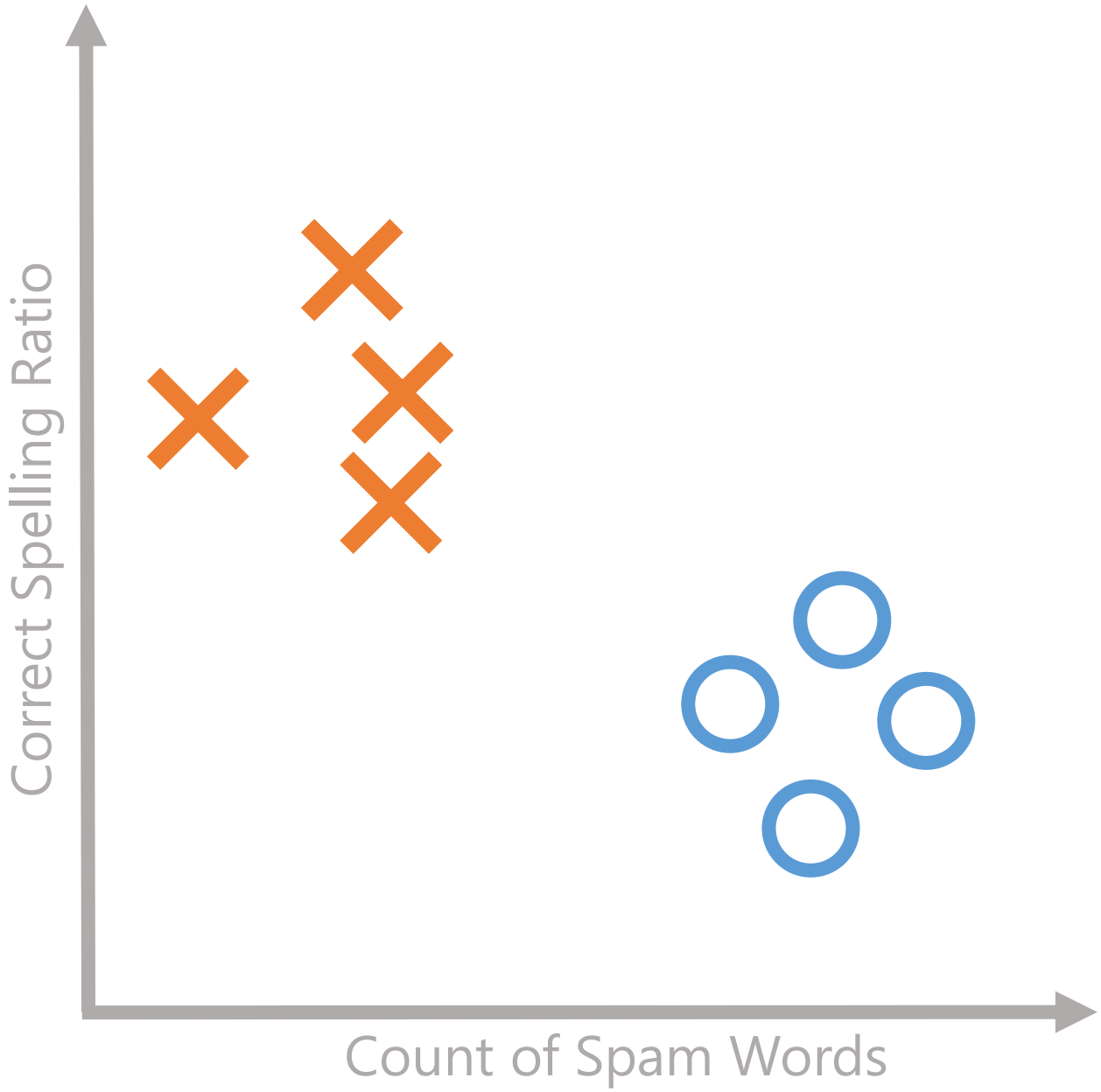


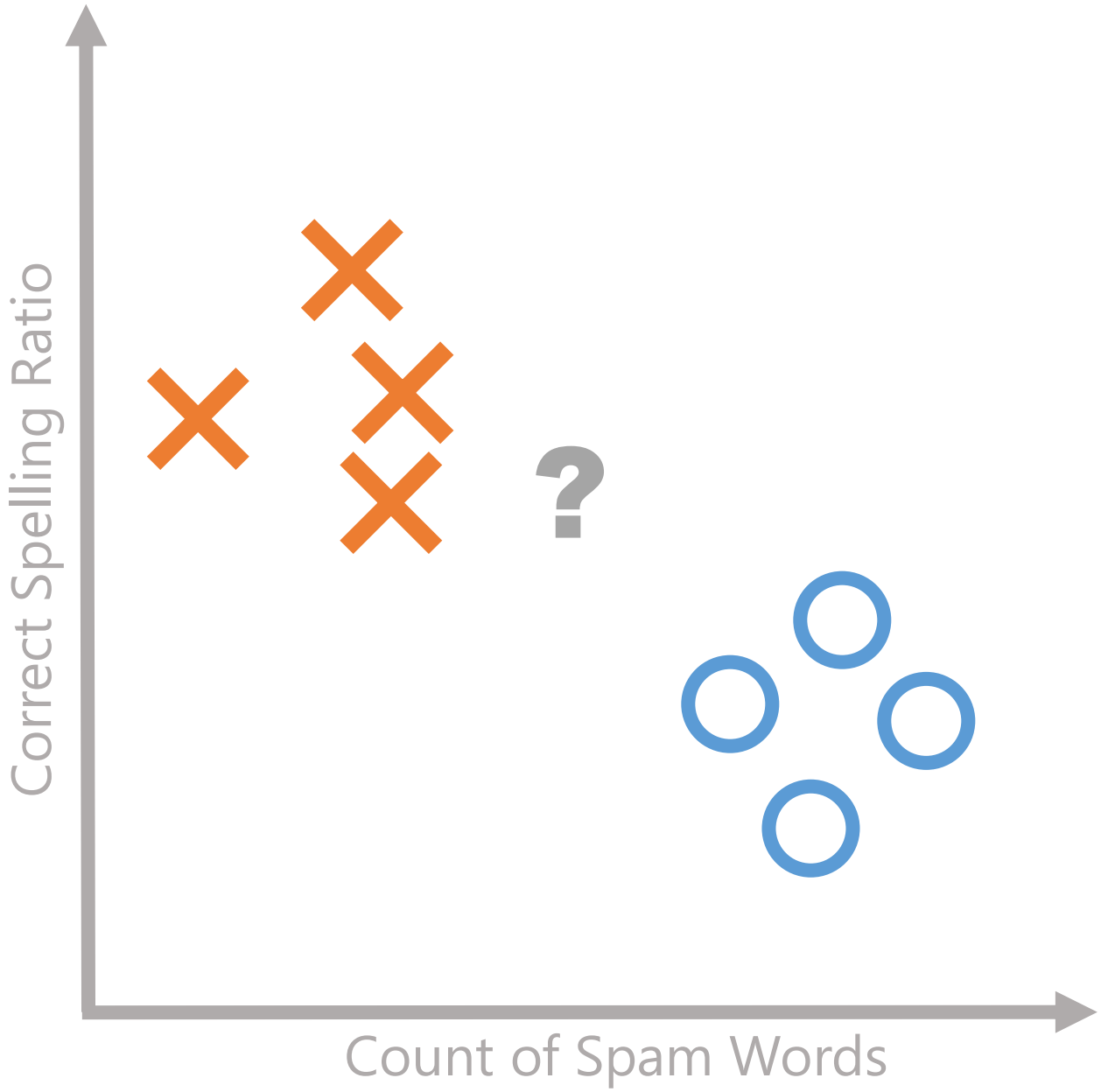
Decision Tree

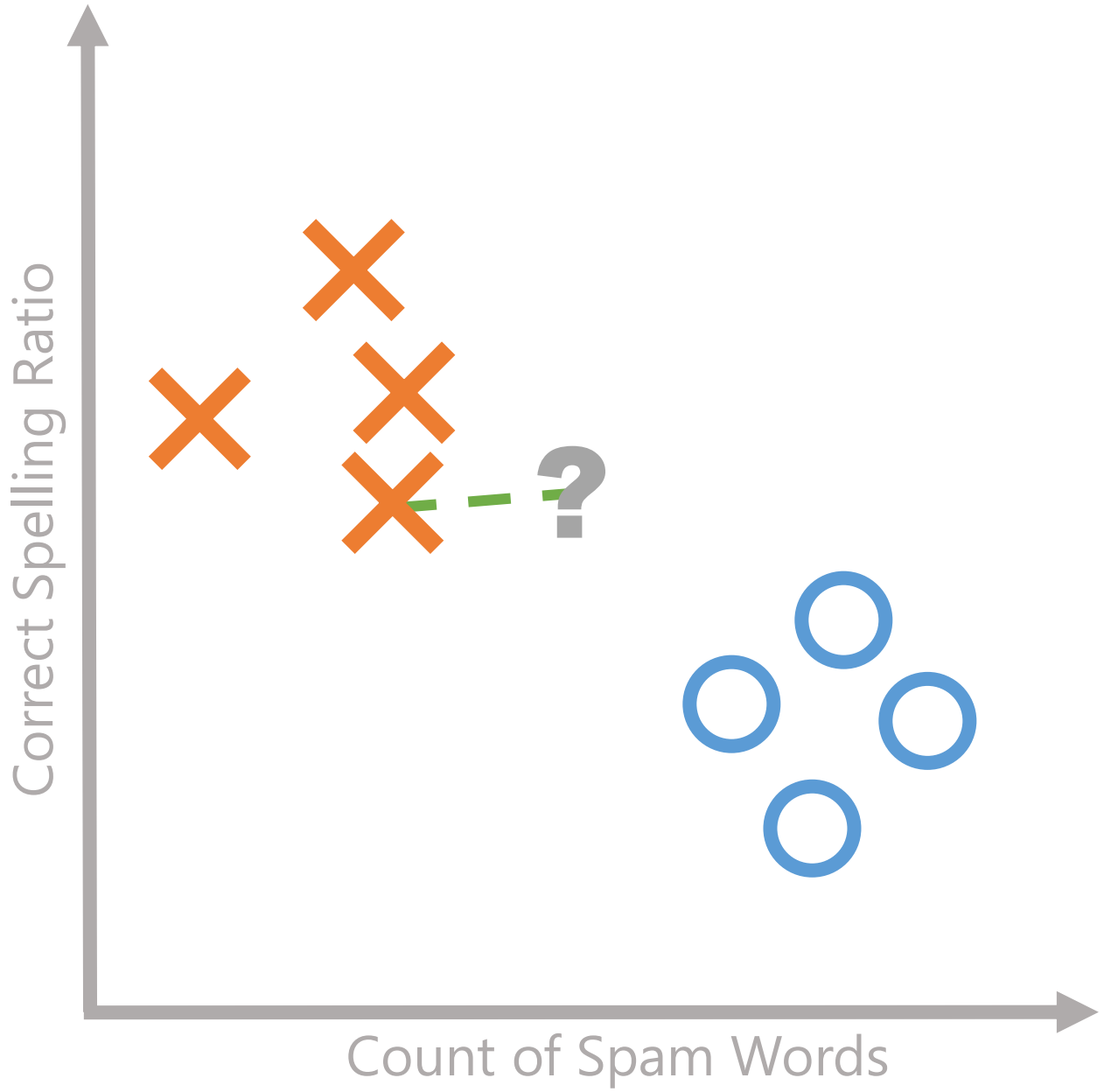


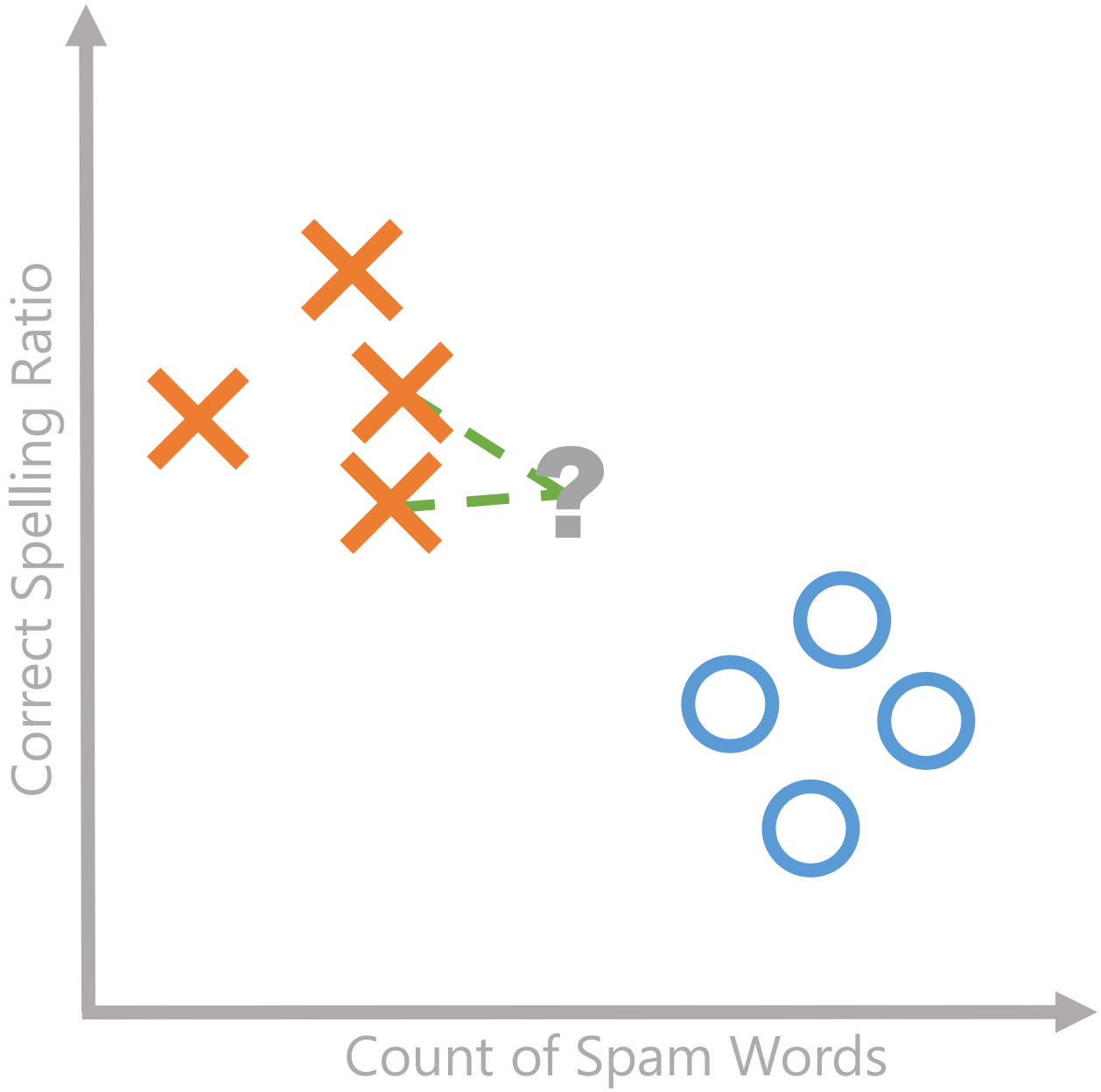
Neural Network

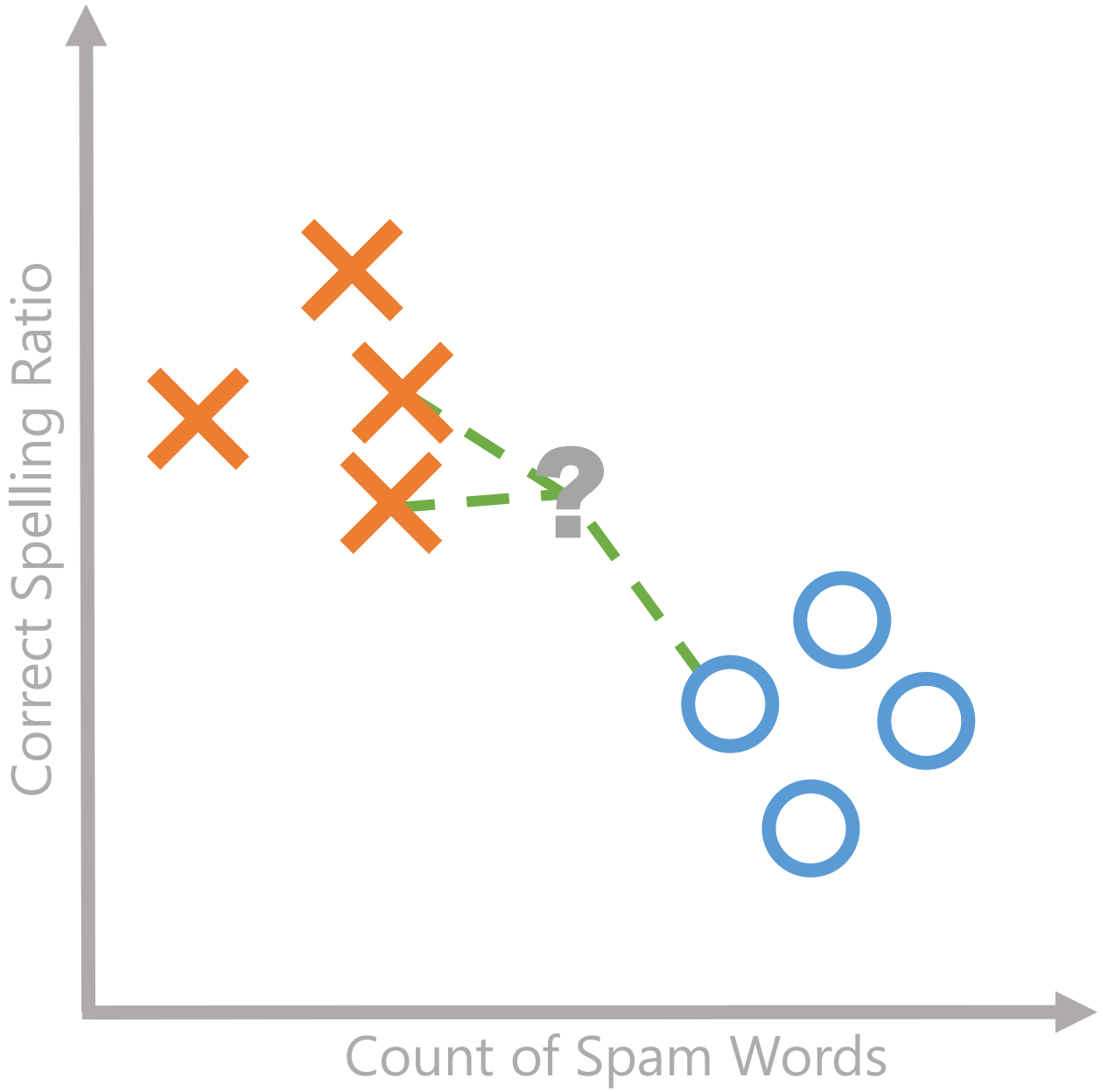
k-Nearest Neighbors Classifier

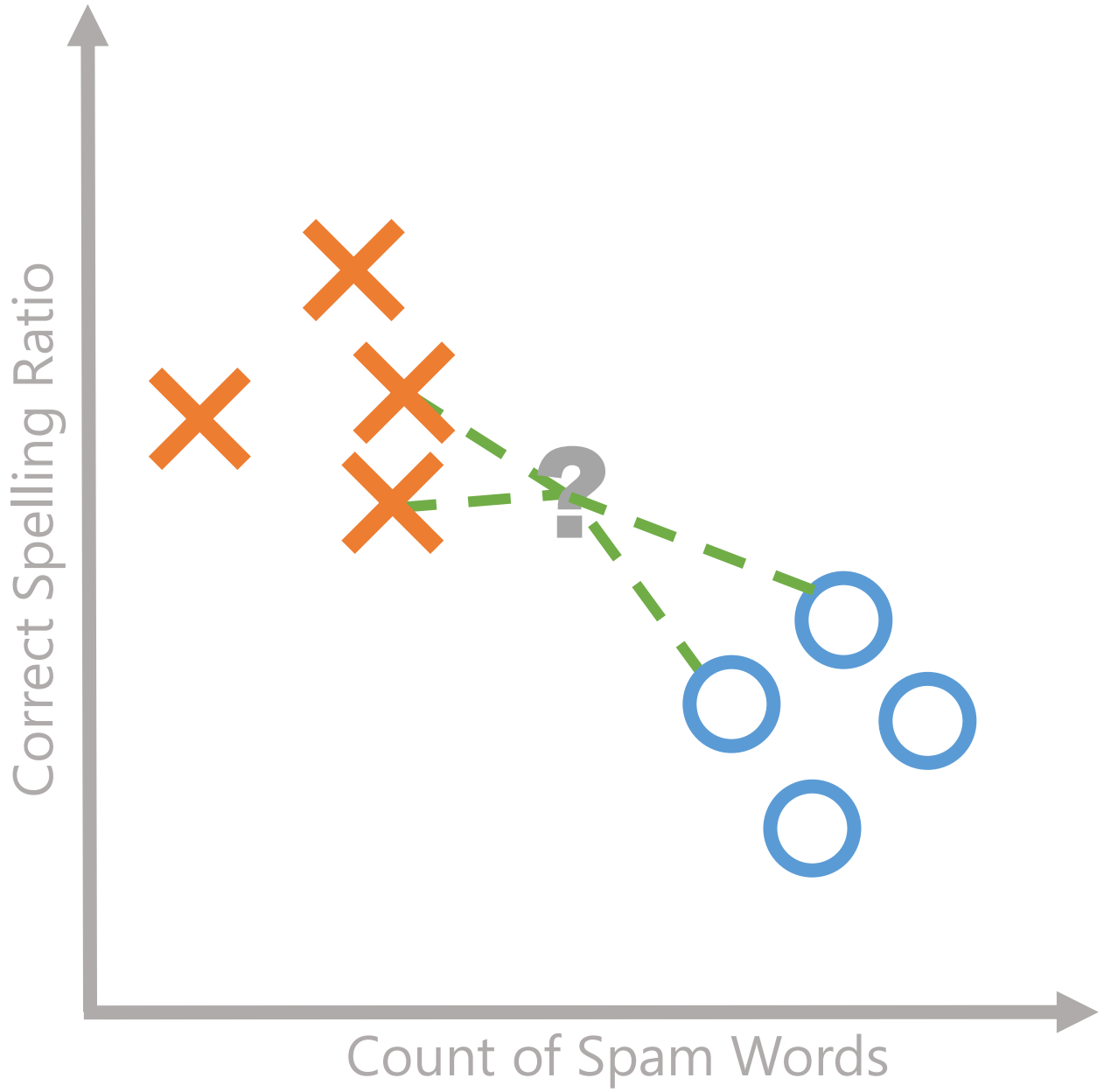

Correct Spelling Ratio
Count of Spam Words


Correct Spelling Ratio
?
Count of Spam Words


Correct Spelling Ratio
?
Count of Spam Words

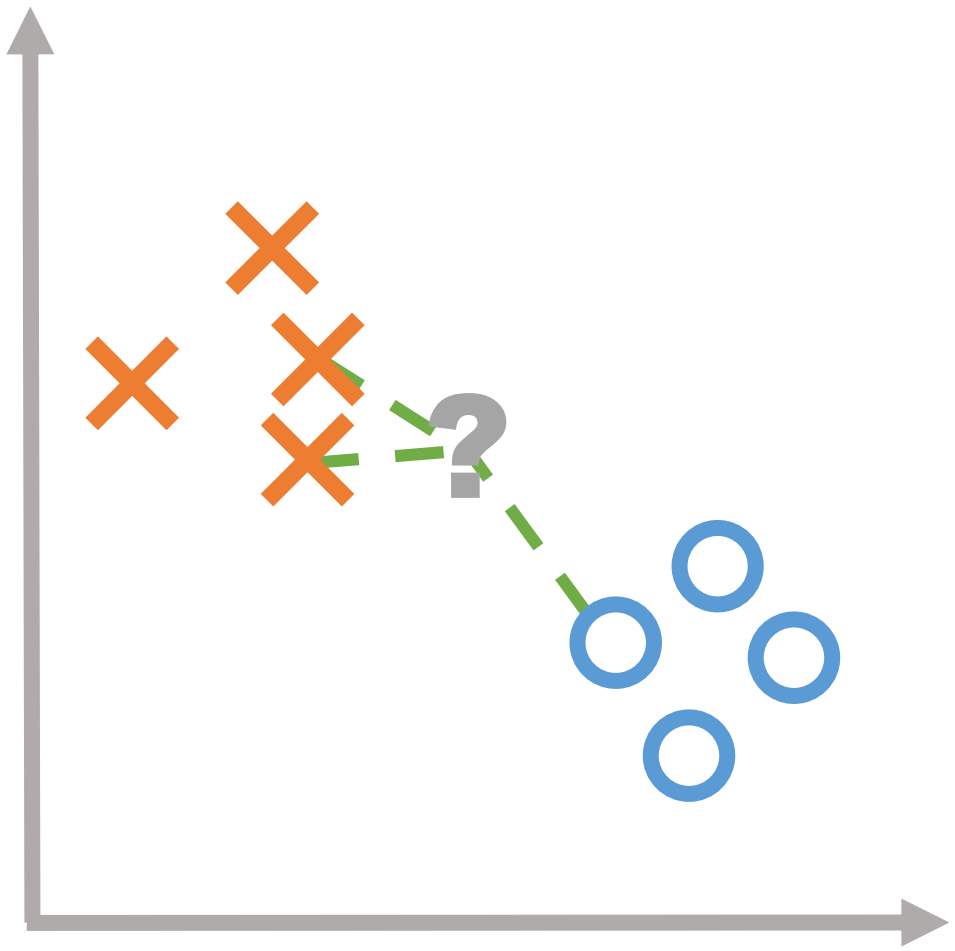

Correct Spelling Ratio
?
Count of Spam Words


Correct Spelling Ratio
?
Count of Spam Words


Correct Spelling Ratio
?
Count of Spam Words

K-Nearest Neighbors Classifier

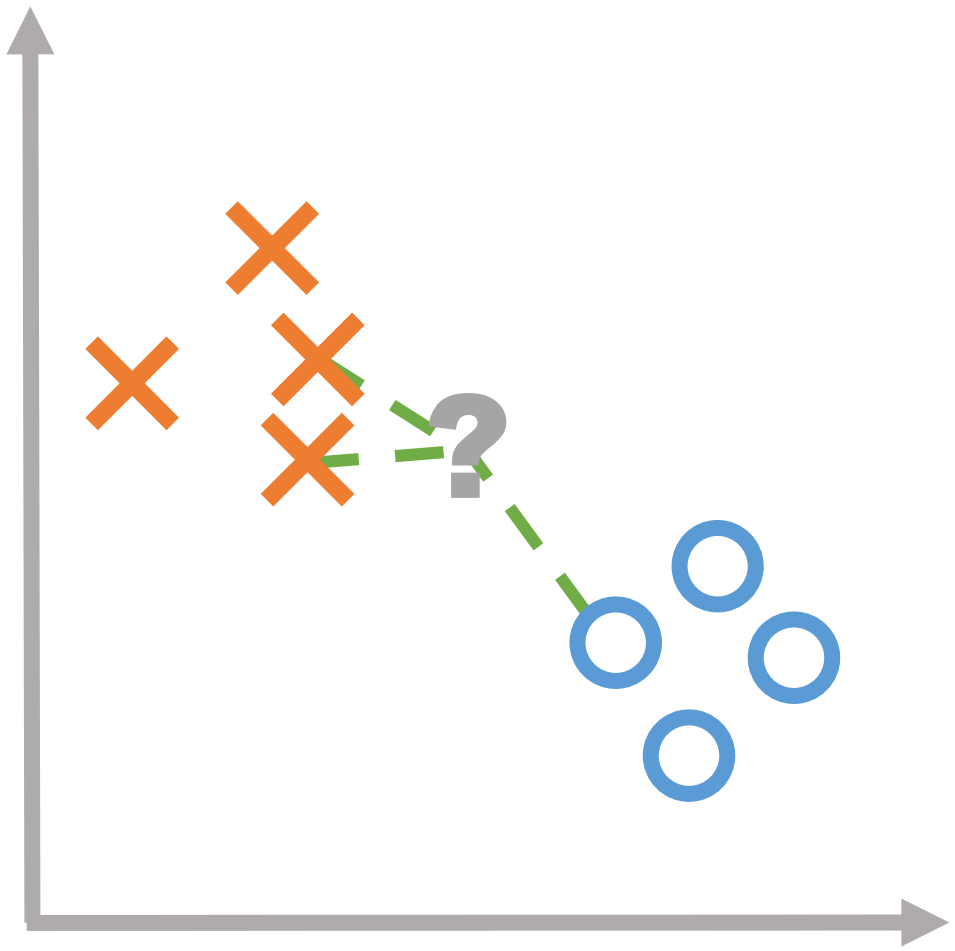
Supervised learning



K-Nearest Neighbors Classifier

Supervised learning

Uses class of neighbors

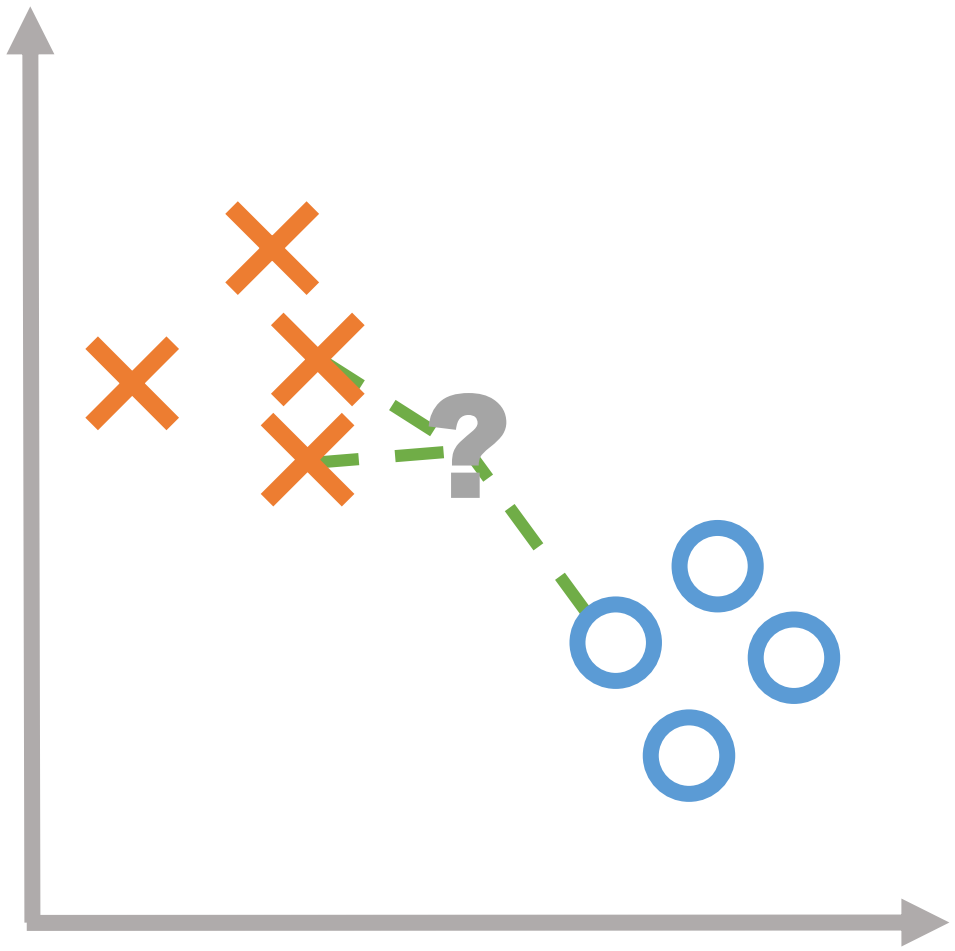


K-Nearest Neighbors Classifier

Supervised learning

Uses class of neighbors

k specifies how many



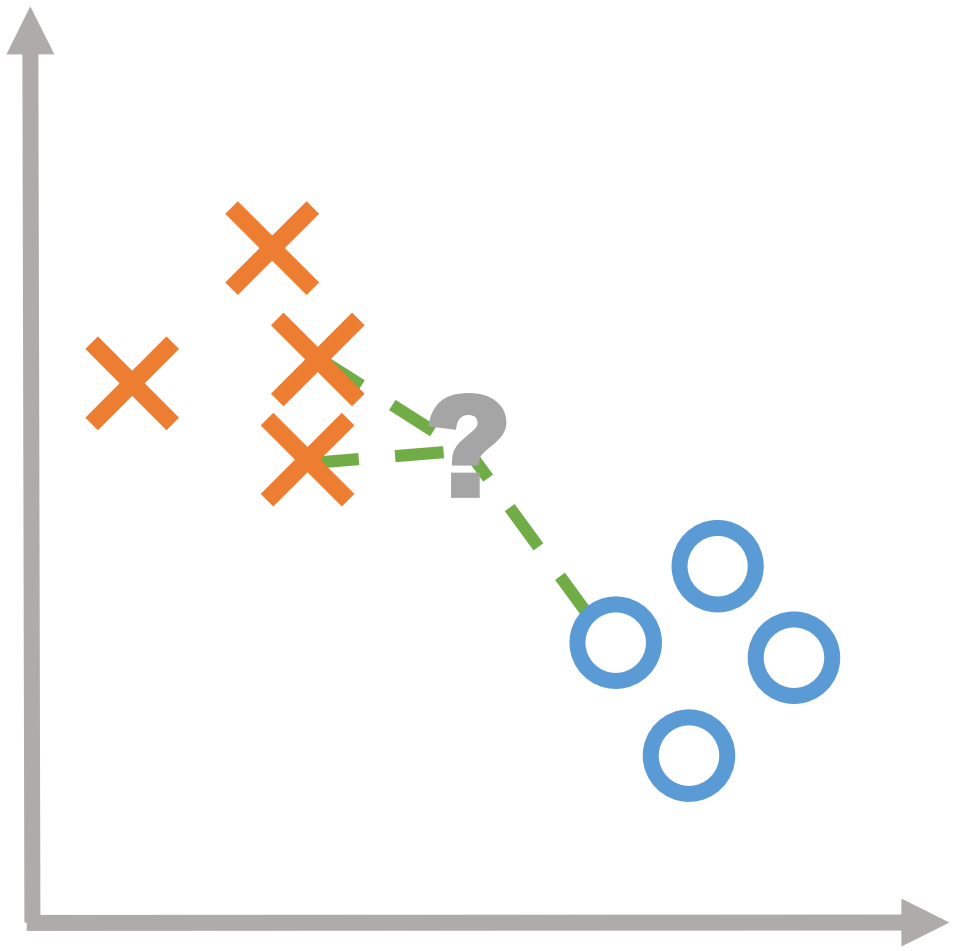
K-Nearest Neighbors Classifier

Supervised learning

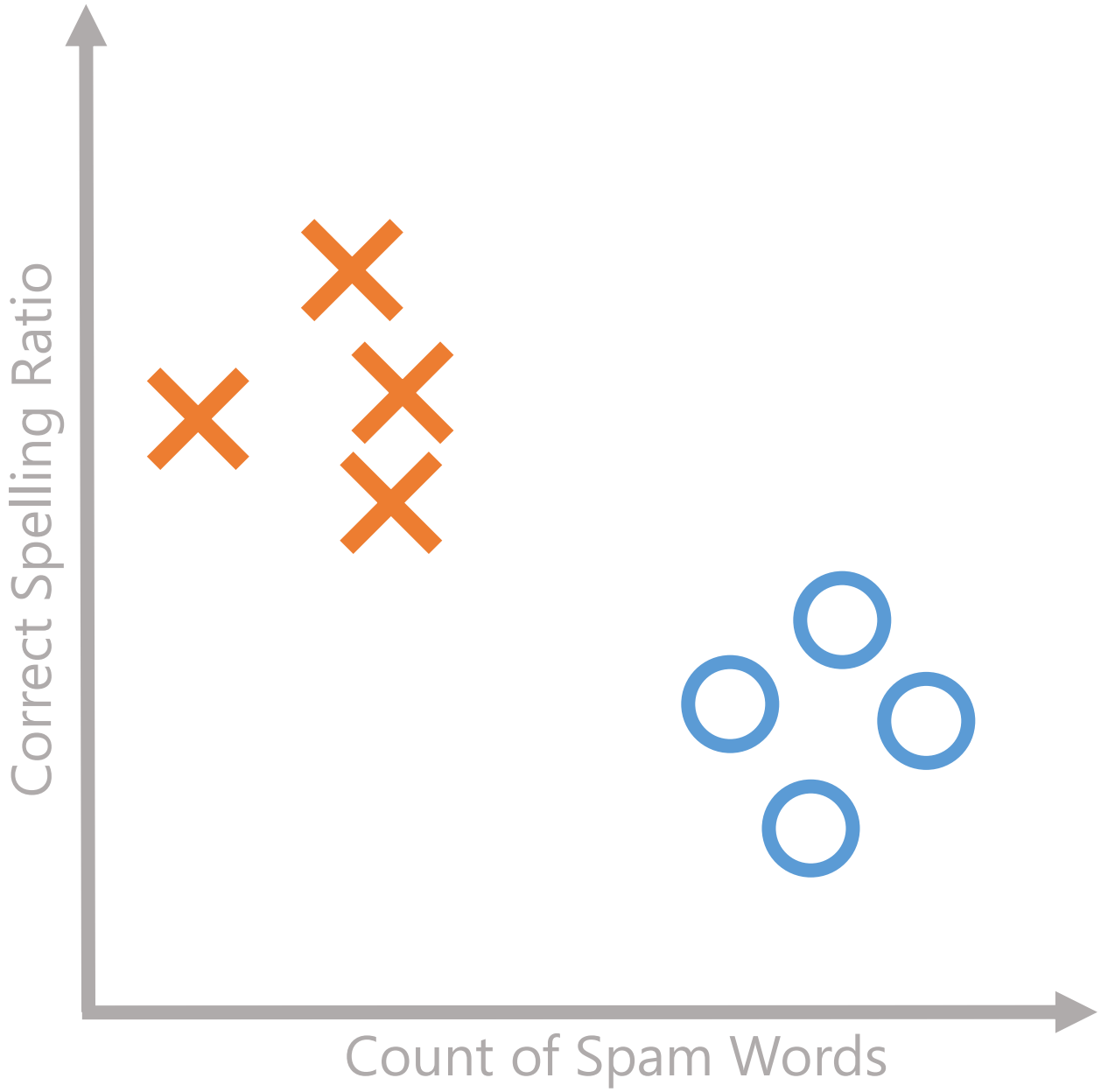
Uses class of neighbors

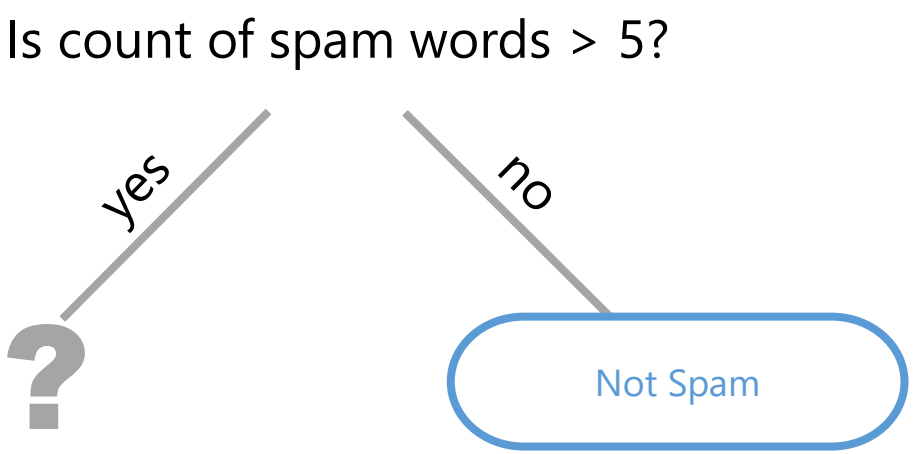
k specifies how many

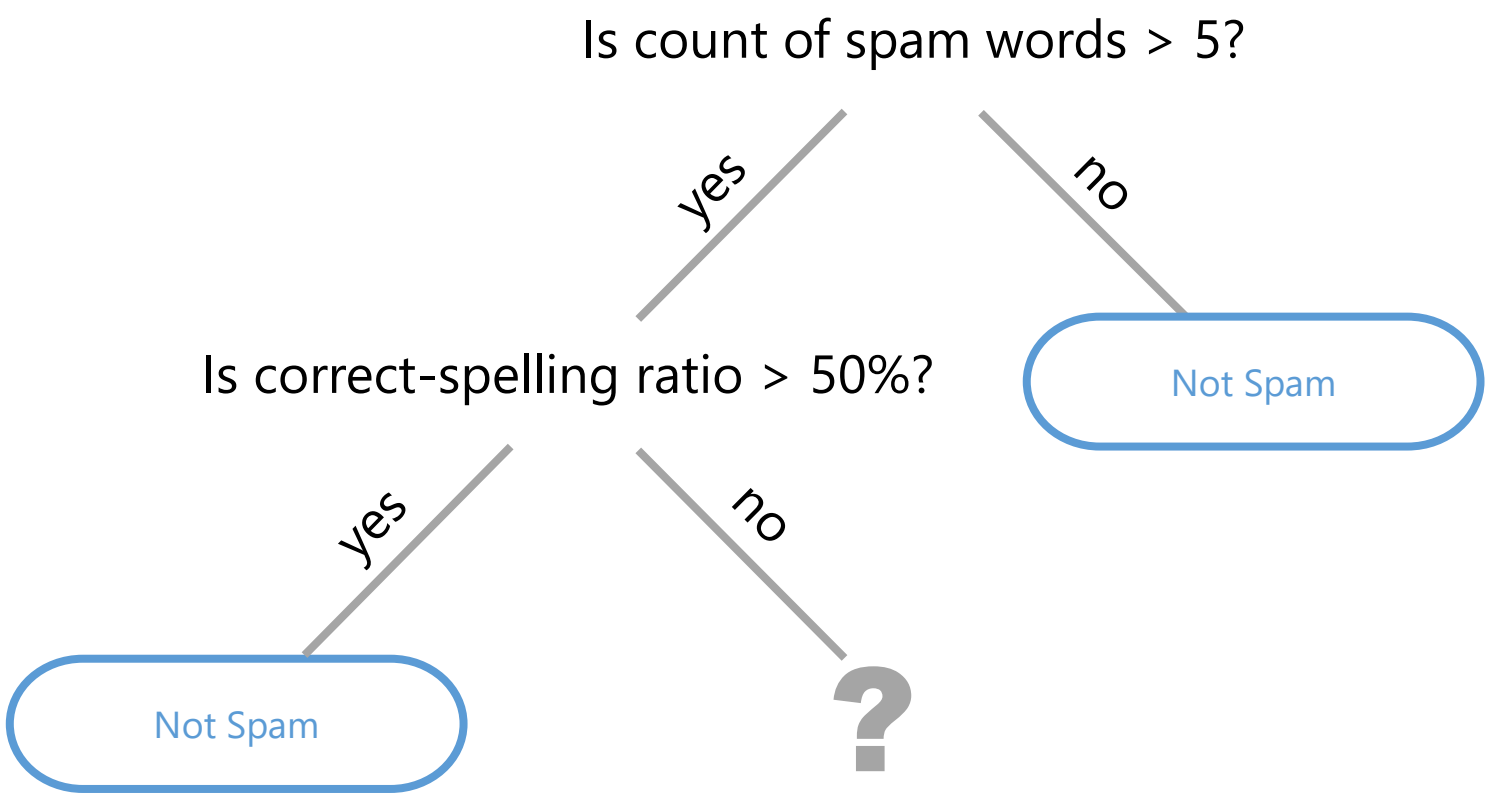
Simple and easy

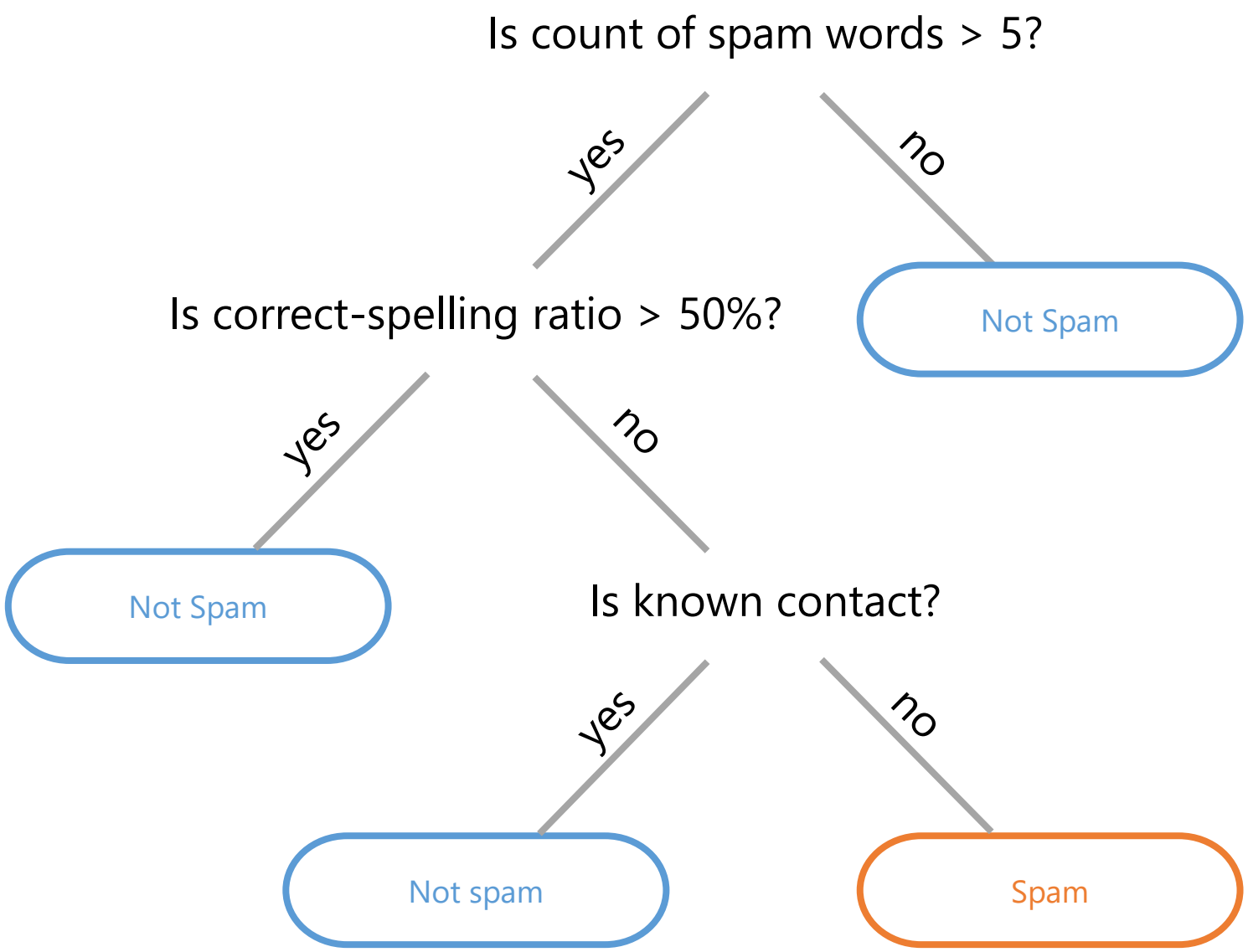


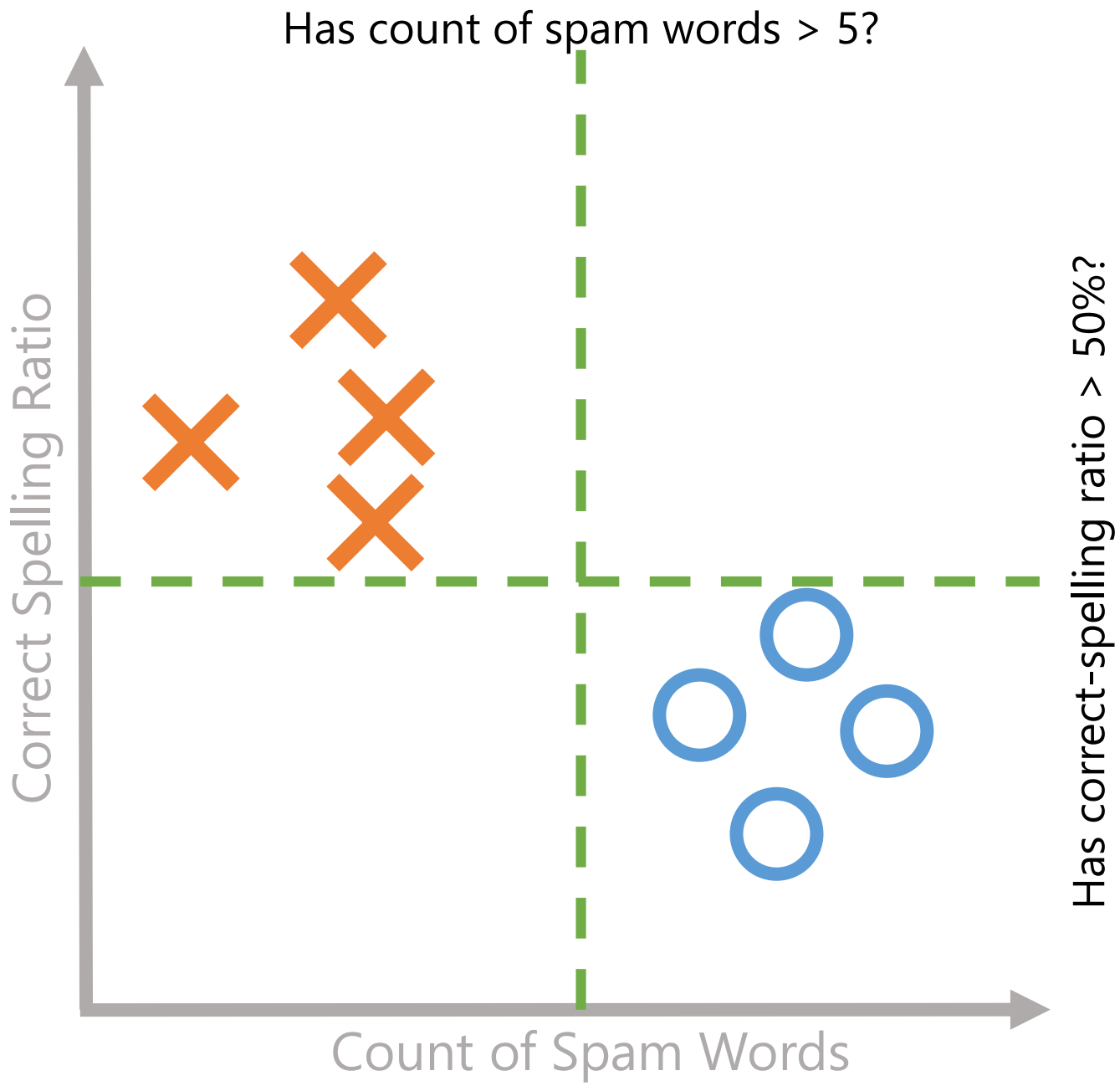
Decision Tree Classifier


Correct Spelling Ratio
Count of Spam Words


Is count of spam words > 5?
yes
no
?
Not Spam

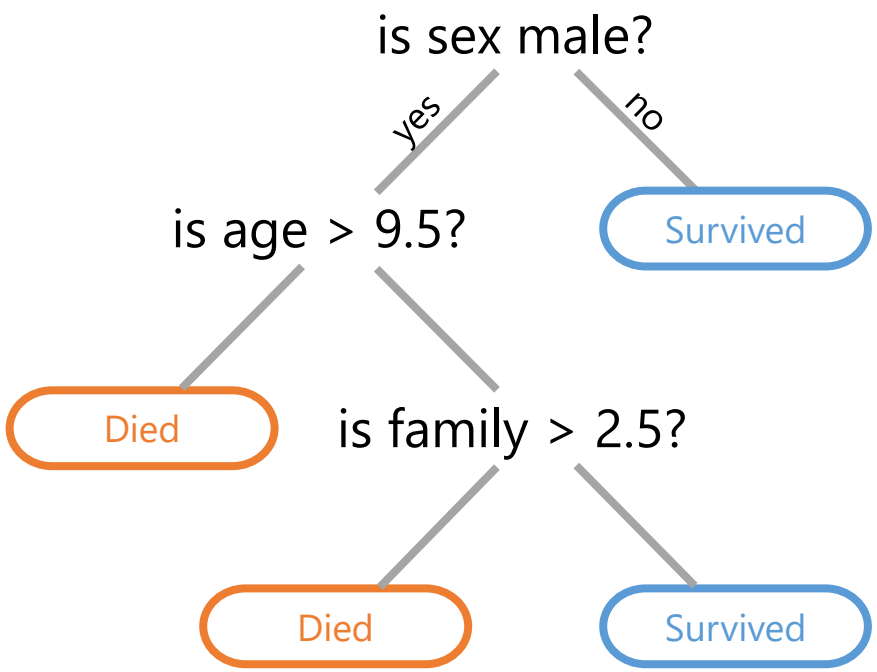

Is count of spam words > 5?
yes
no
Not Spam
Is correct-spelling ratio > 50%?
yes
no
Not Spam
?


Is count of spam words > 5?
yes
no
Not Spam
Is correct-spelling ratio > 50%?
yes
no
Not Spam
Is known contact?
yes
no
Not spam
Spam


Has count of spam words > 5?
Has correct-spelling ratio > 50%?
Correct Spelling Ratio
Count of Spam Words

Decision Tree Classifier

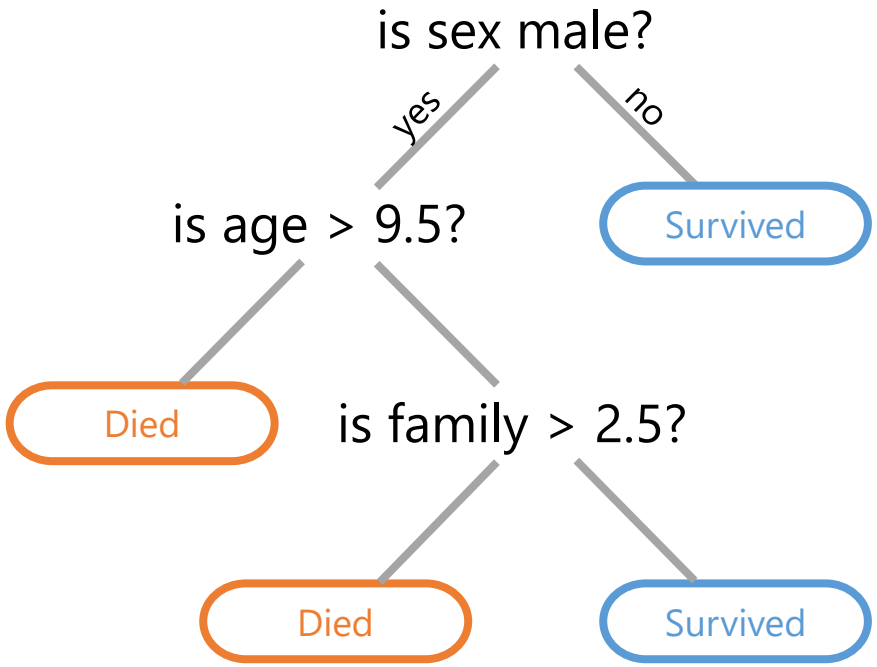
Supervised learning



Decision Tree Classifier

Supervised learning

Tree of decisions

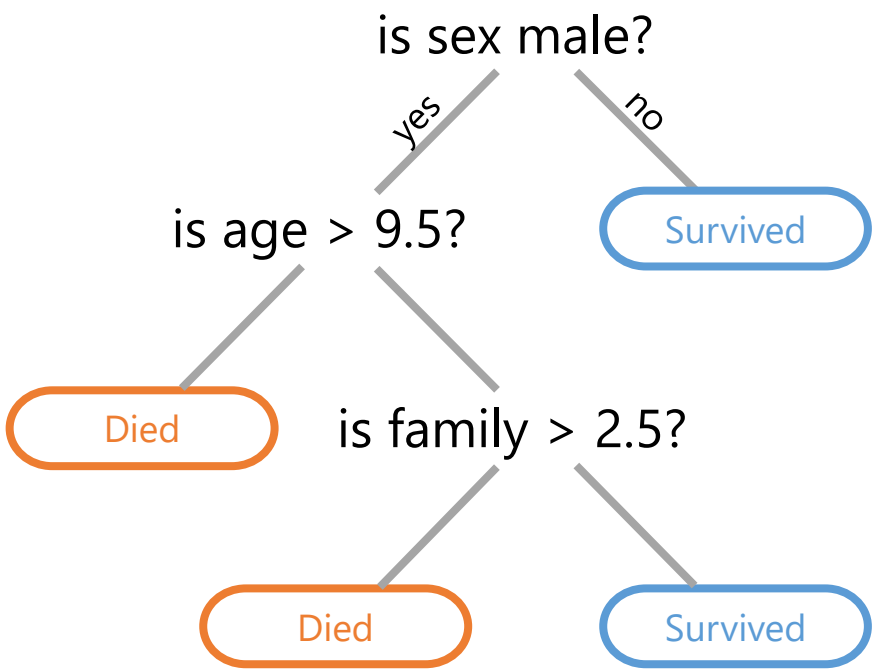


Decision Tree Classifier

Supervised learning

Tree of decisions

Information gain



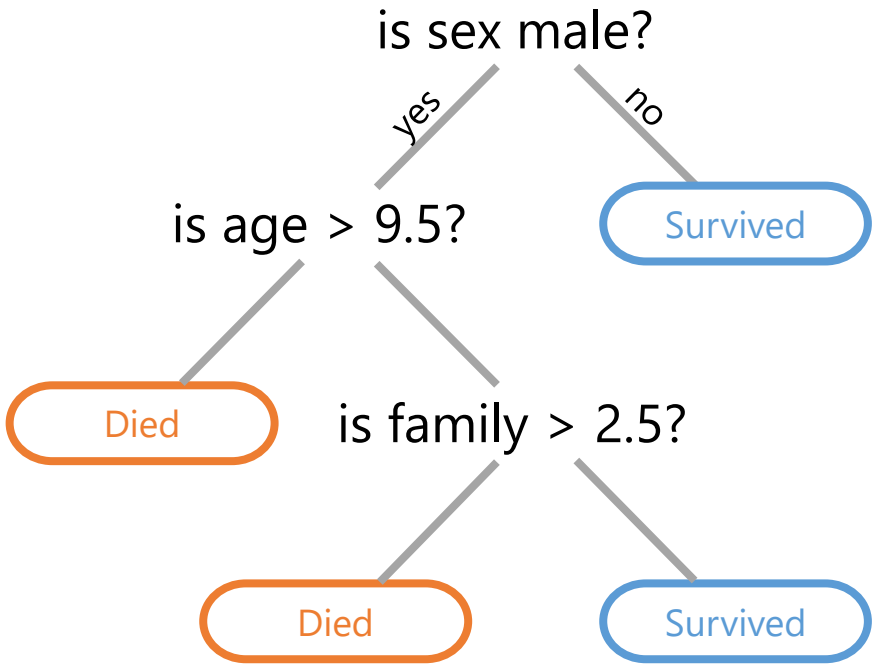
Decision Tree Classifier

Supervised learning

Tree of decisions

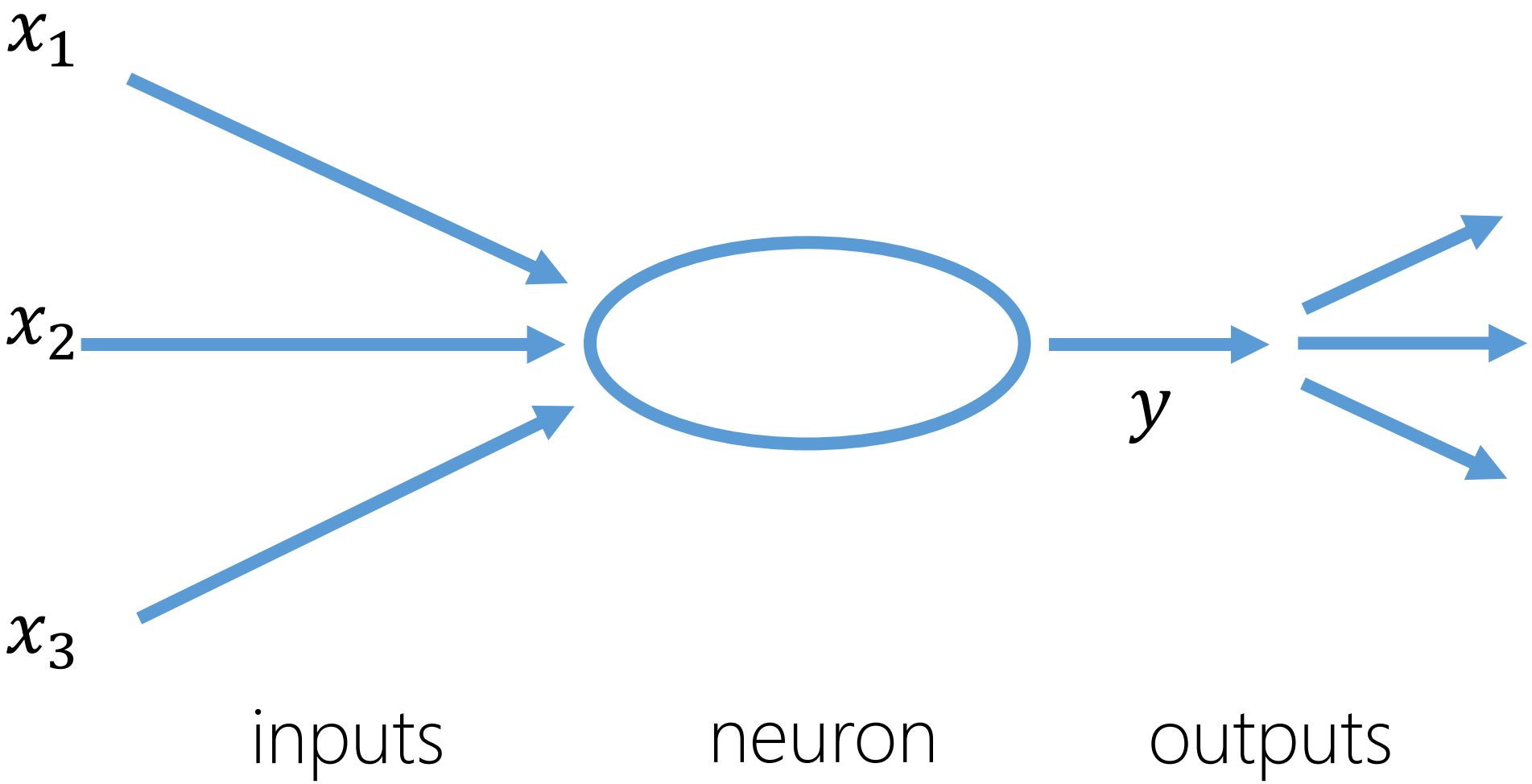
Information gain

Simple and easy

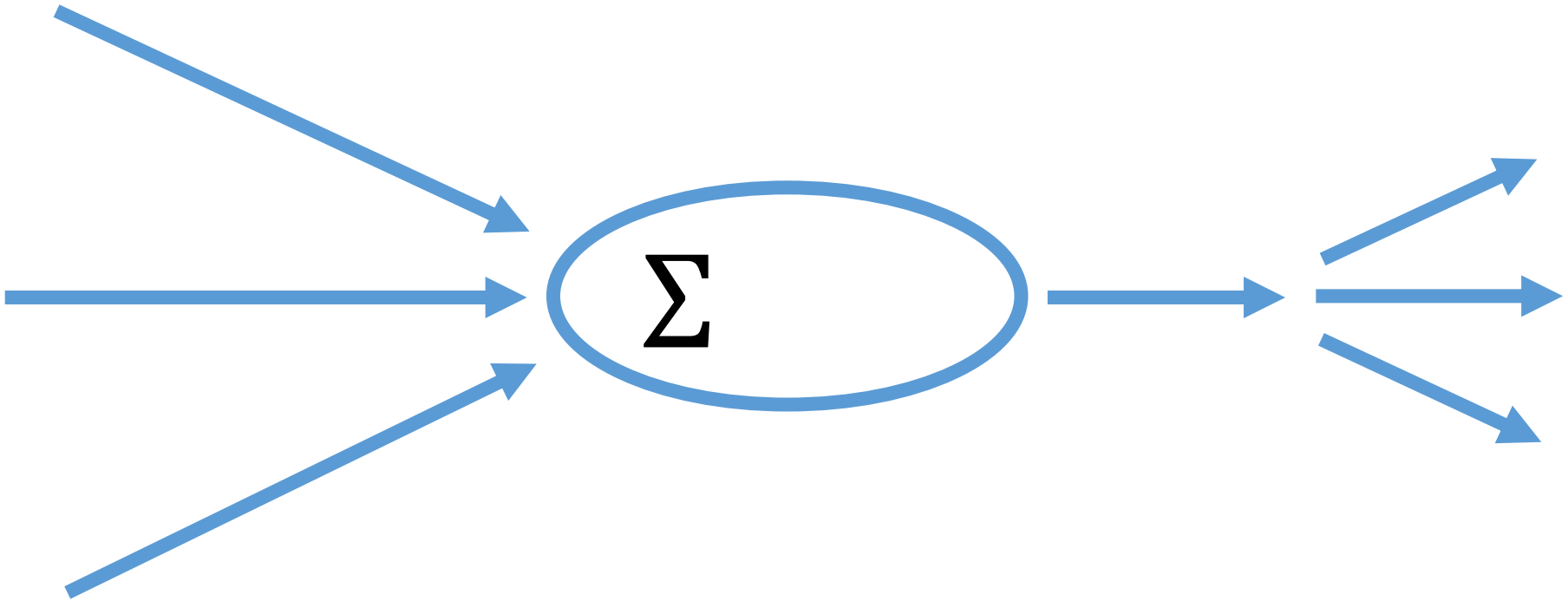


Neural Network Classifier

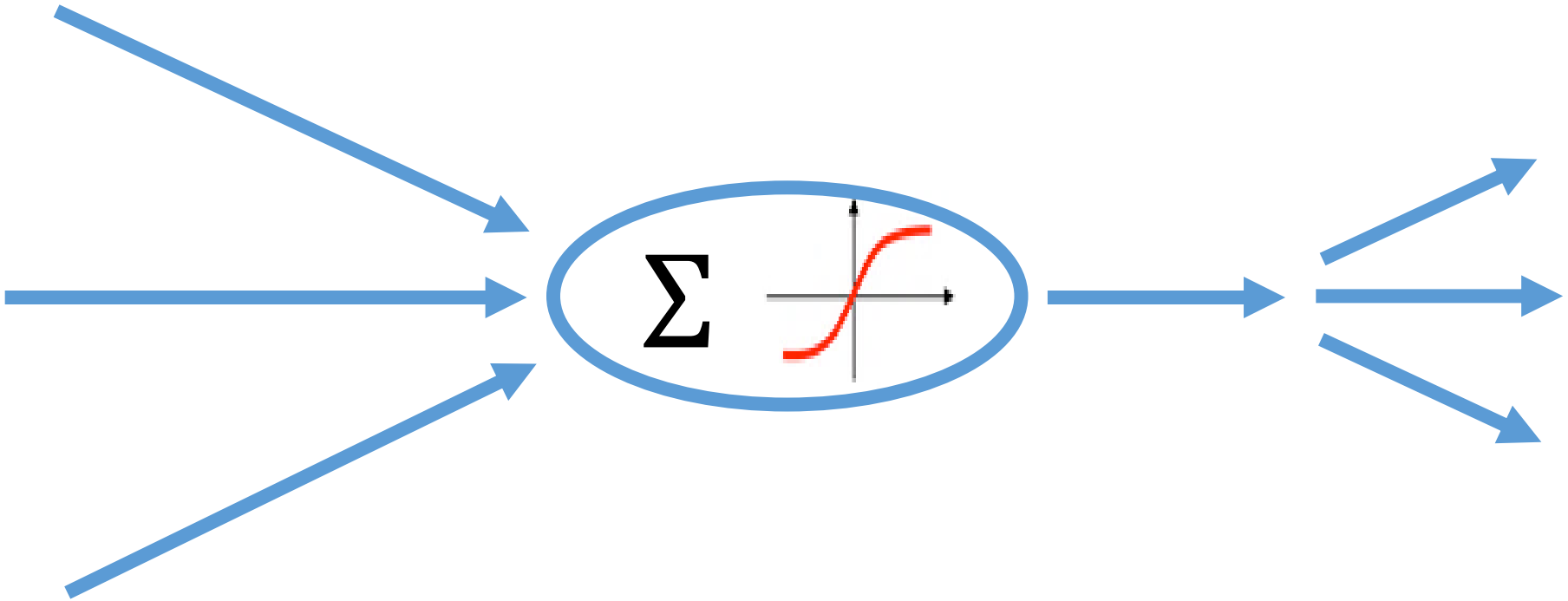
Artificial Neuron



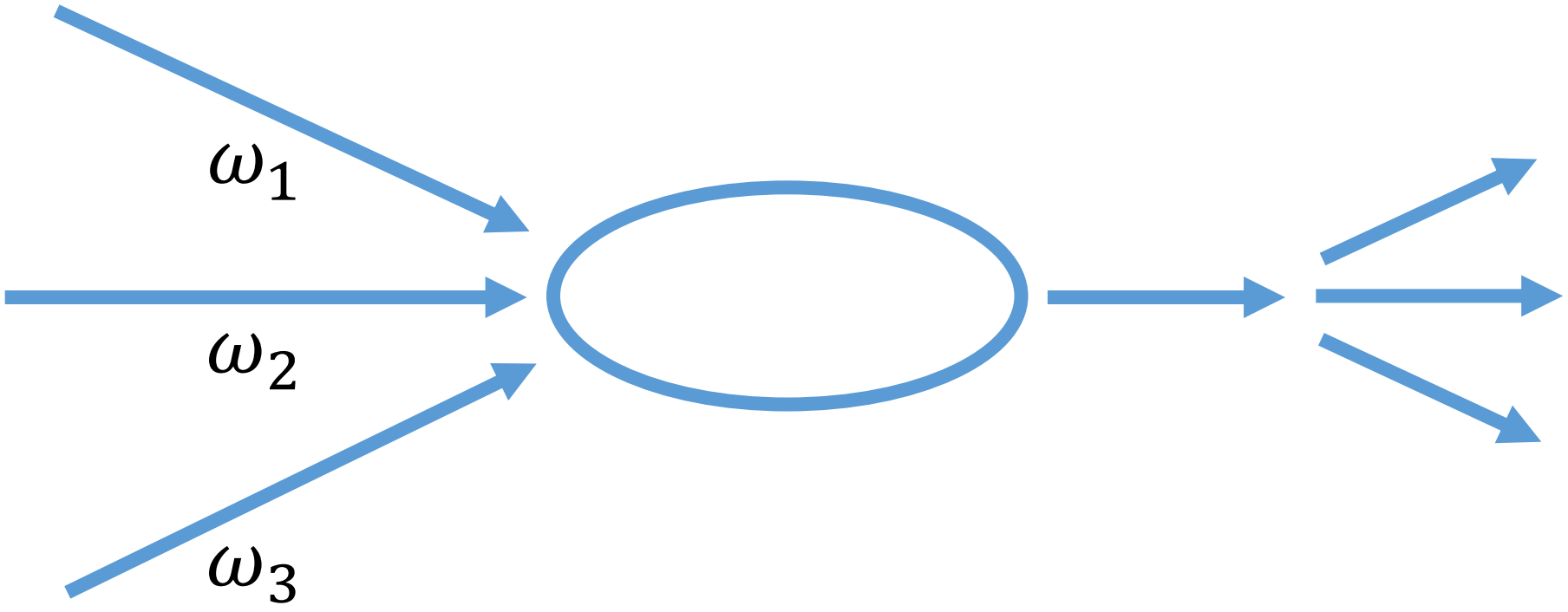
Artificial Neuron



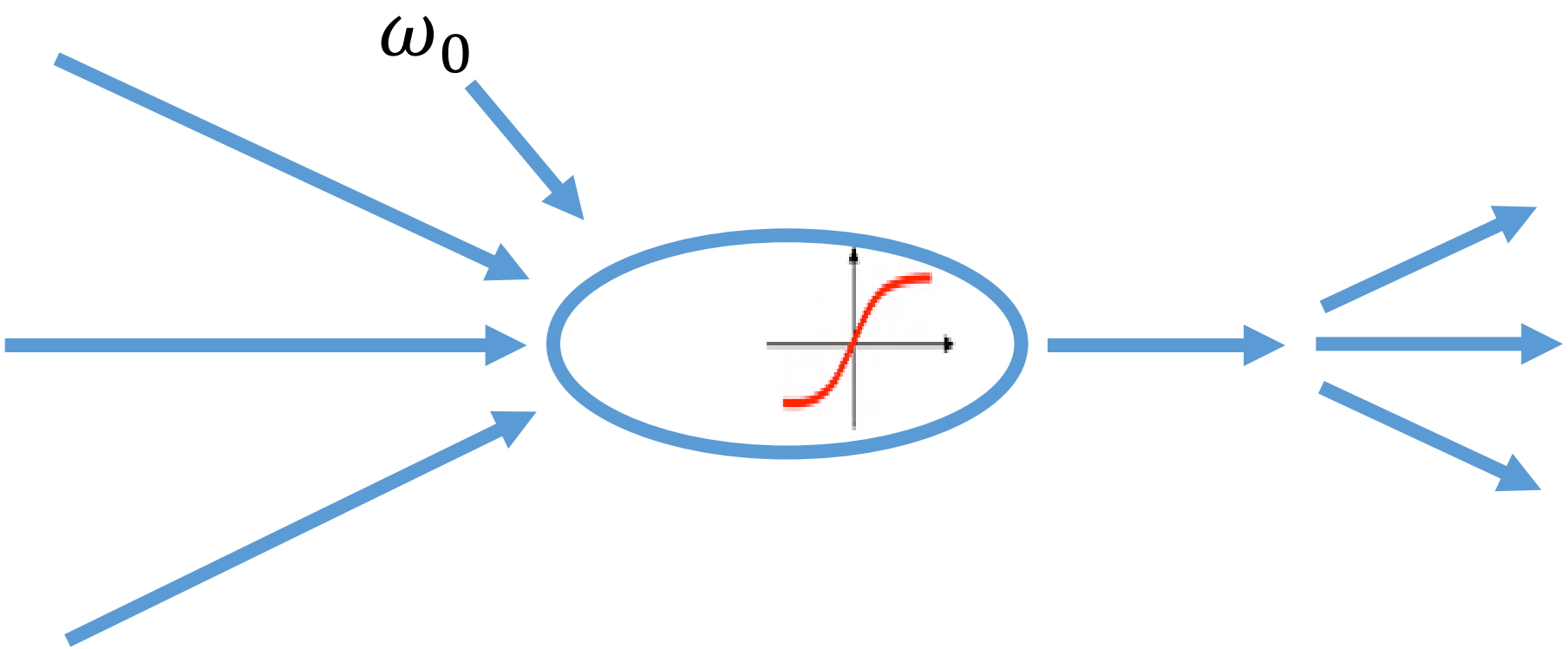
Artificial Neuron



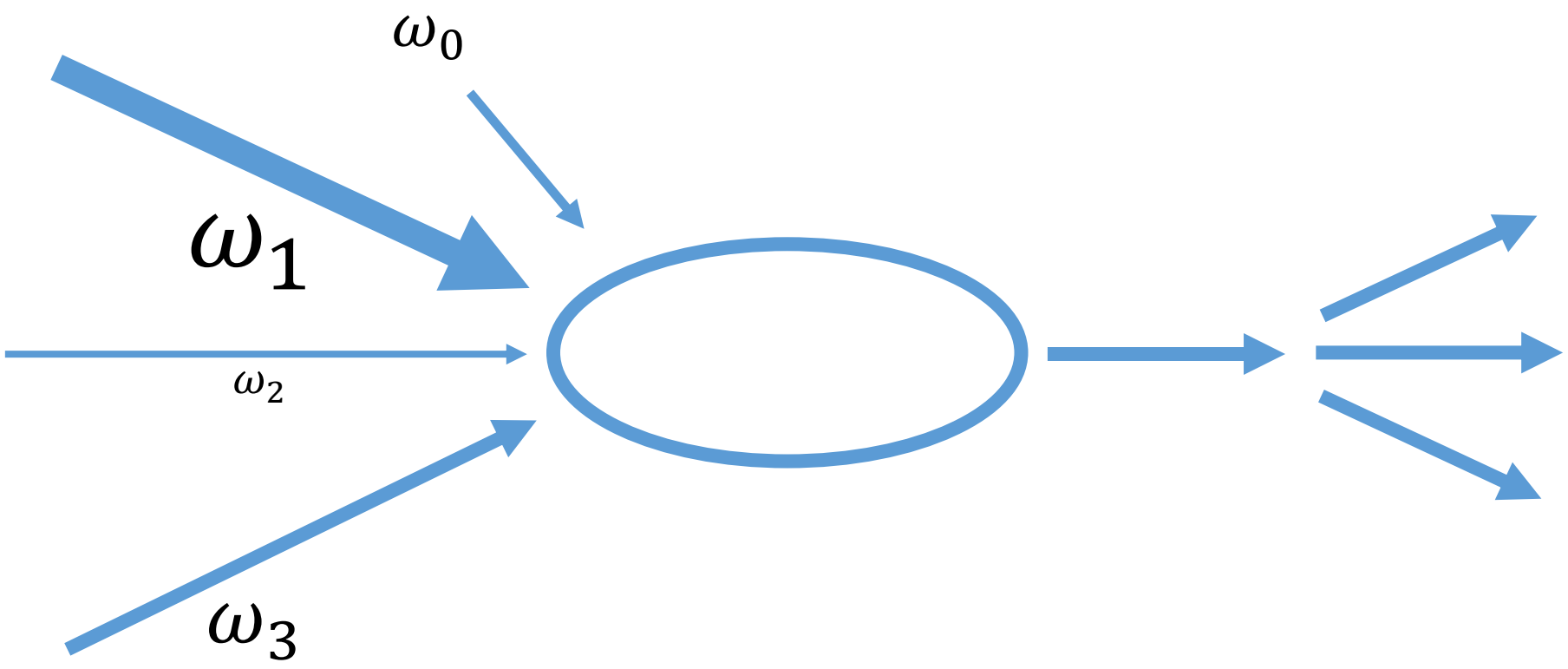
Artificial Neuron



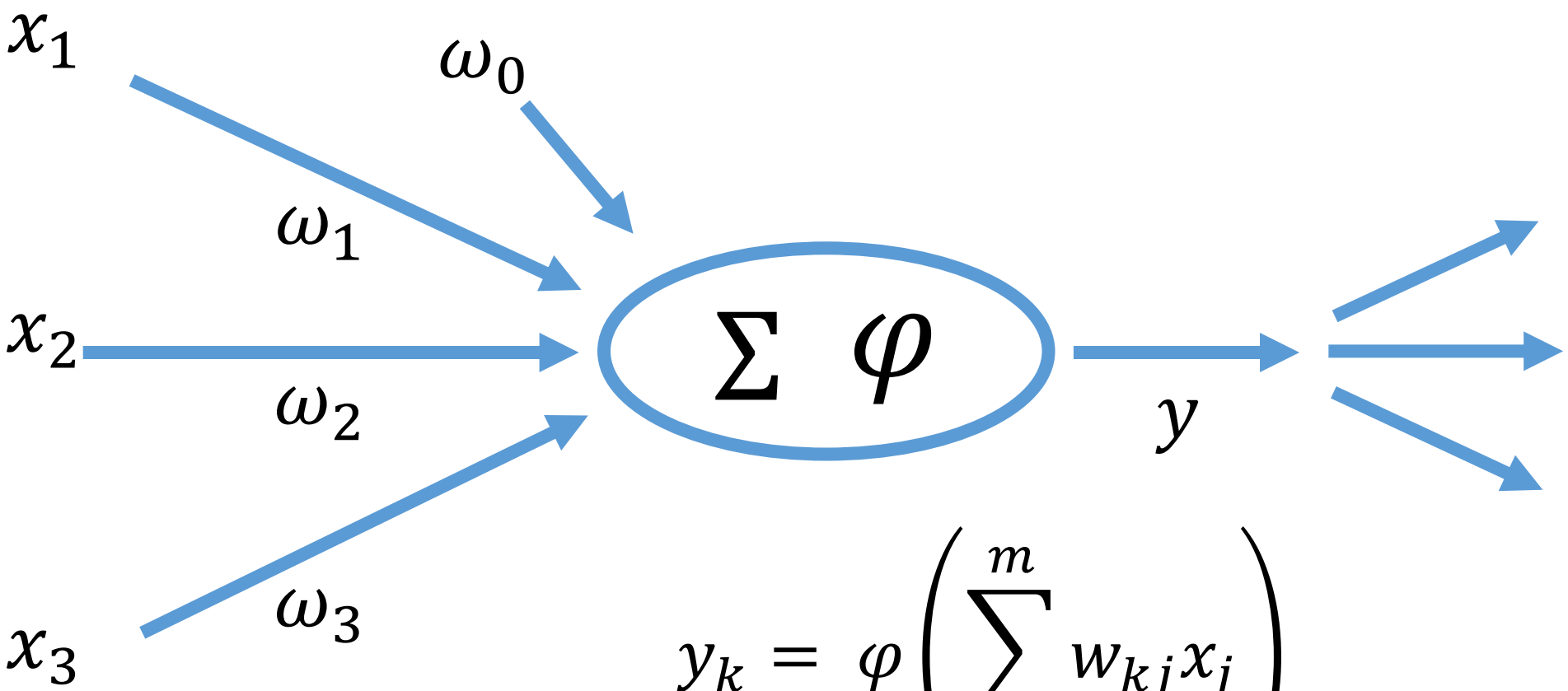
Artificial Neuron



Artificial Neuron

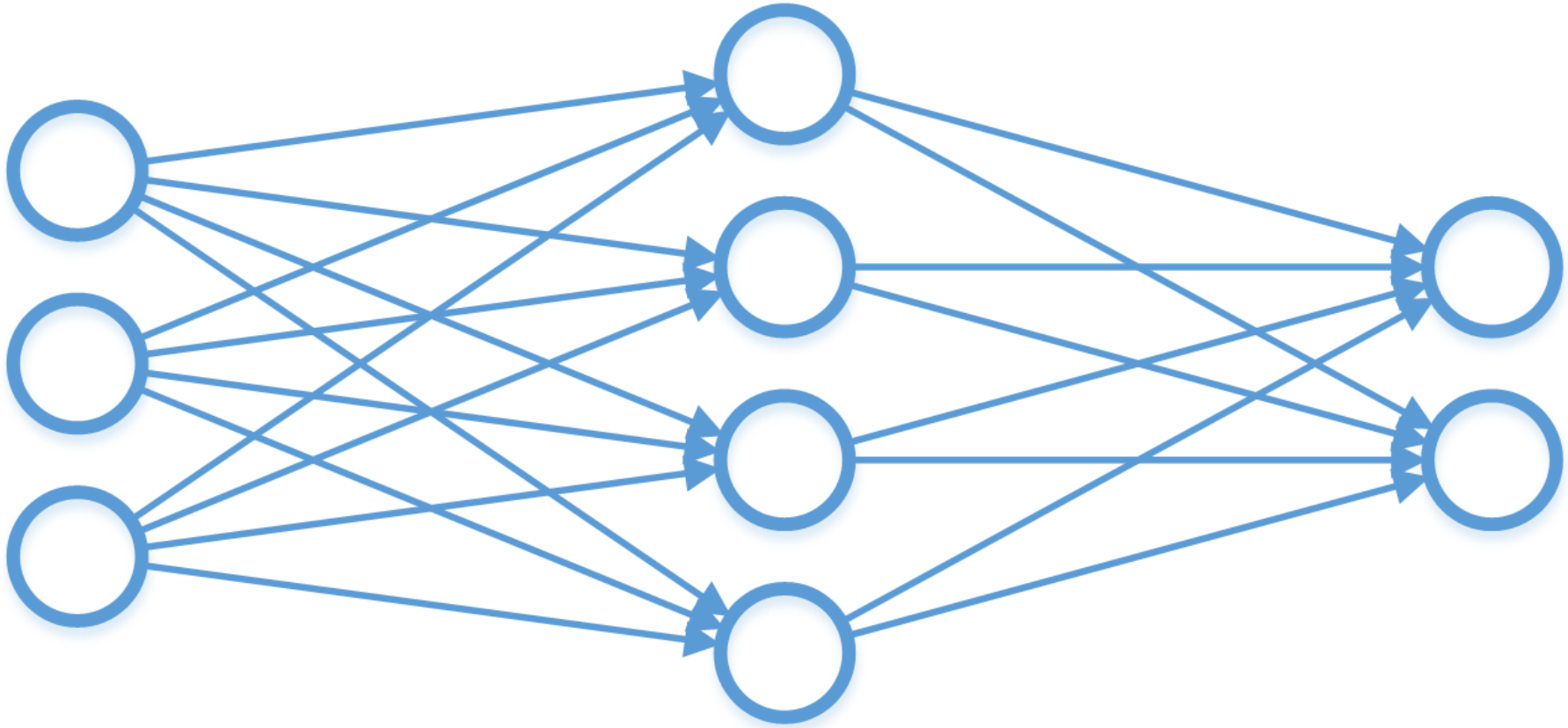


Artificial Neuron

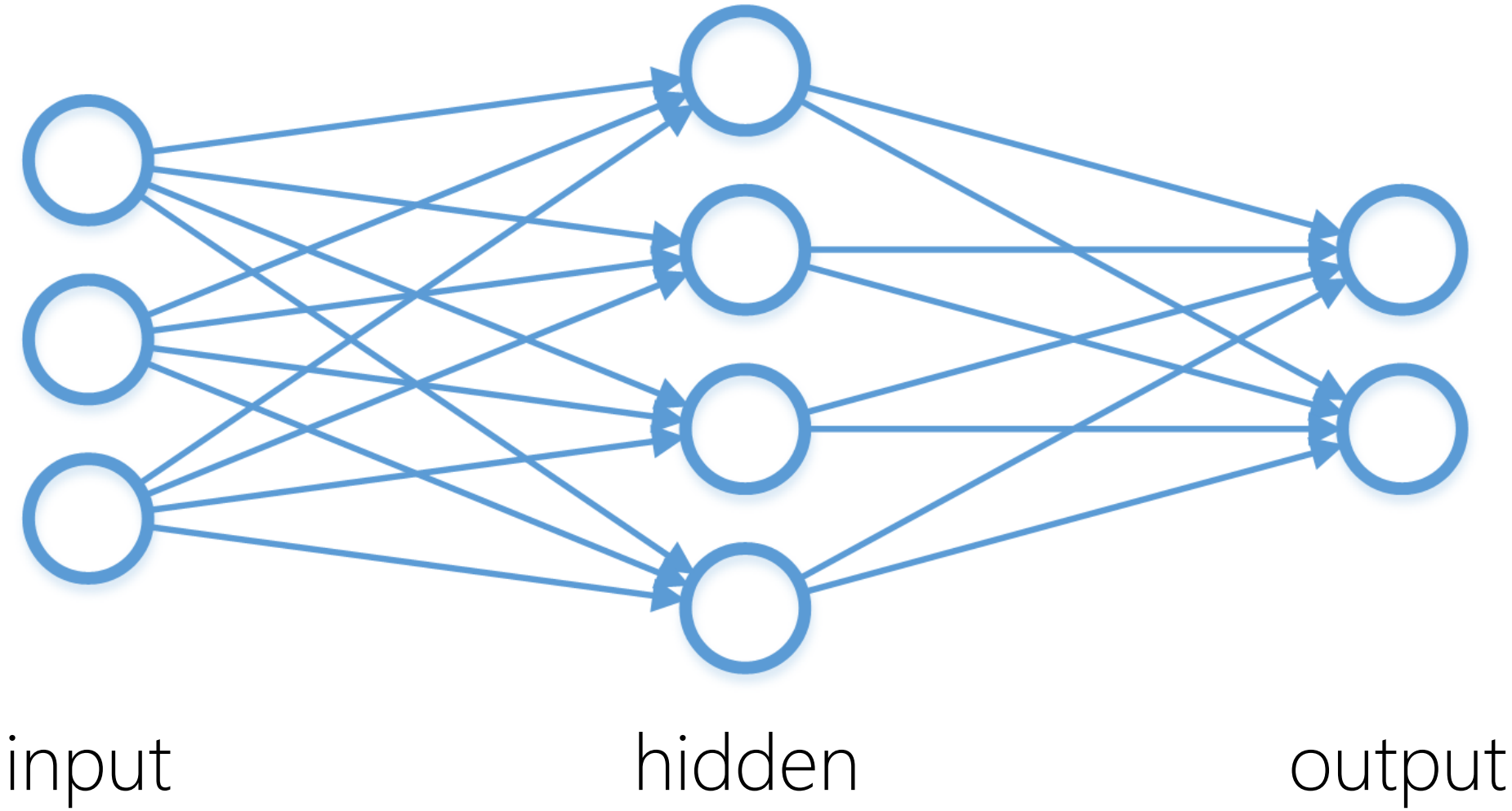


$$y_k = \varphi\left(\sum_{j=0}^{m} w_{kj} x_j\right)$$

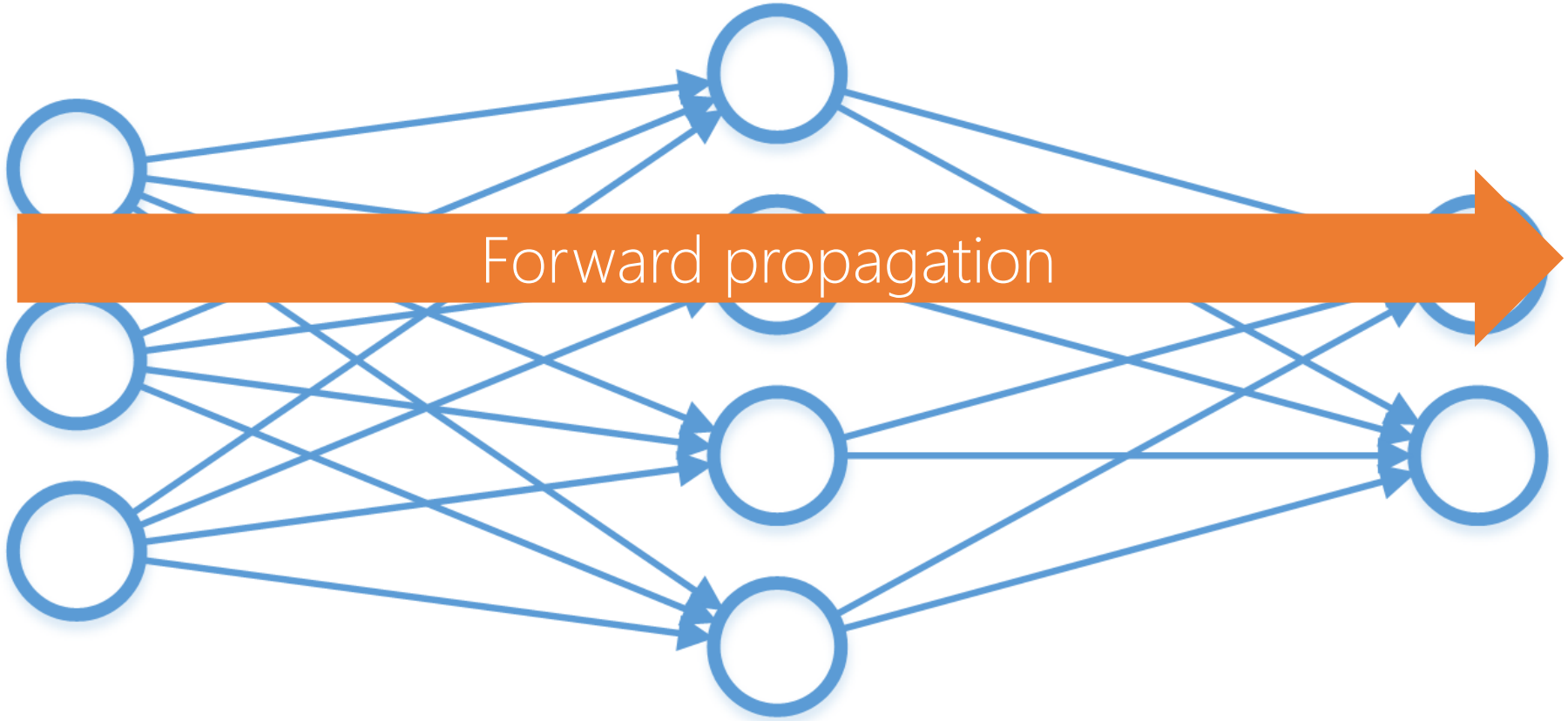
Artificial Neural Network



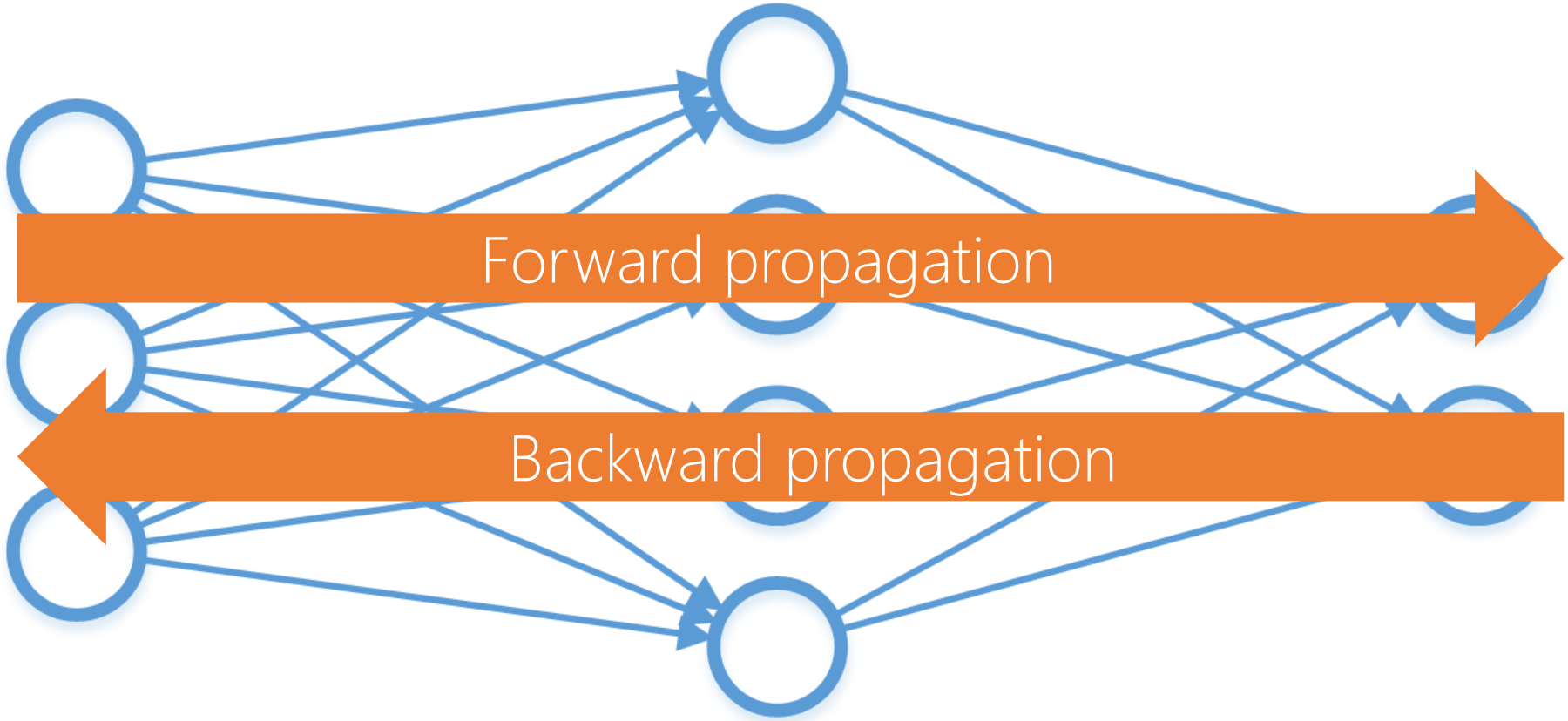
Artificial Neural Network



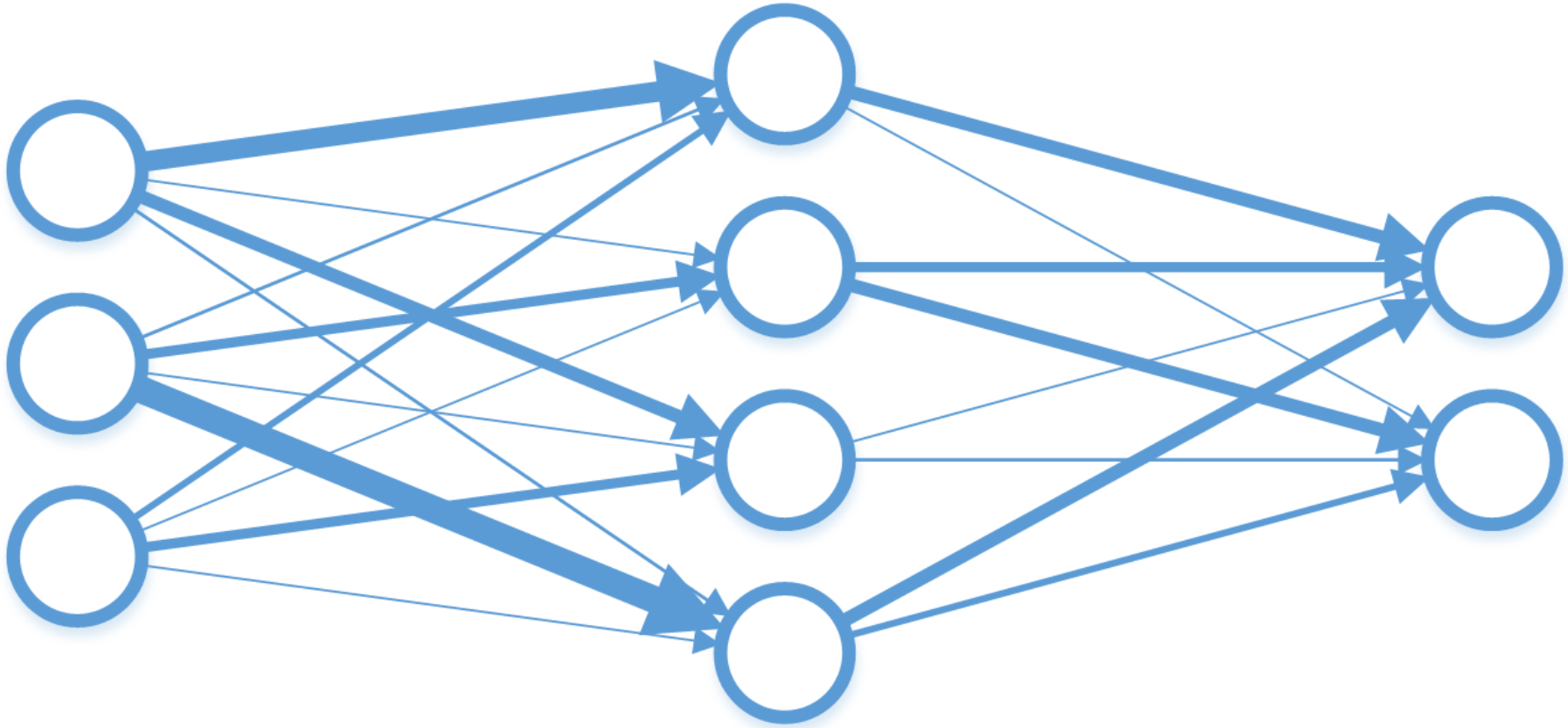
Artificial Neural Network



Artificial Neural Network

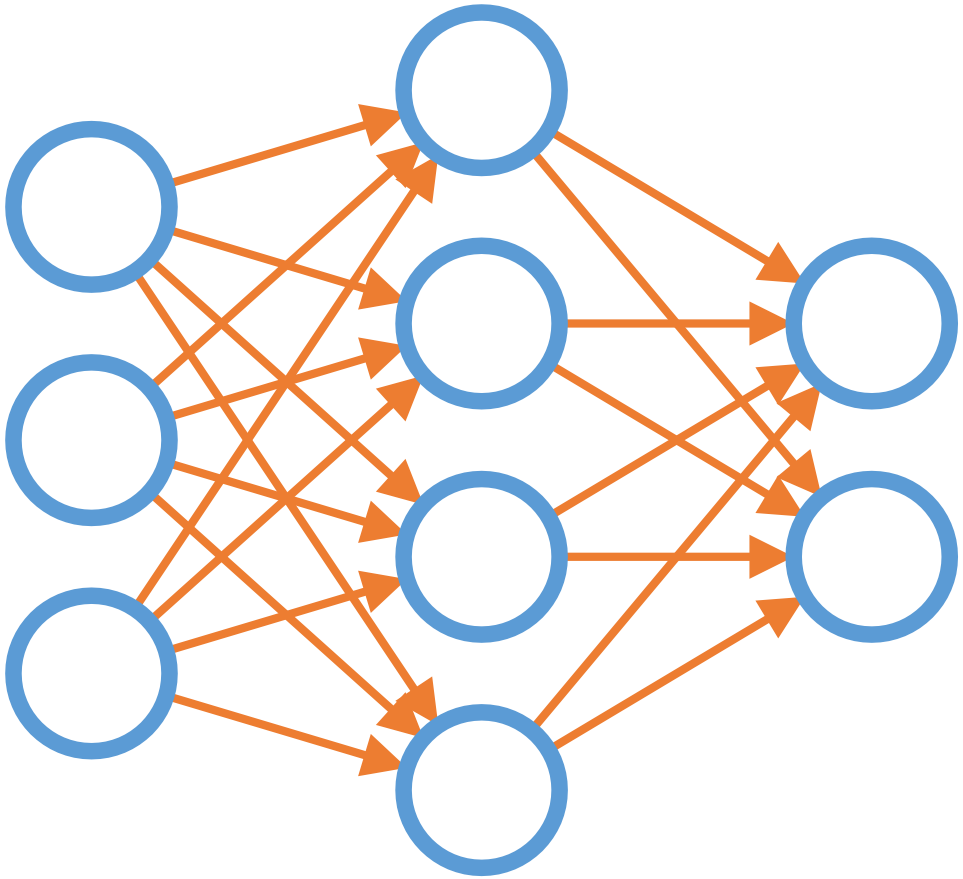


Artificial Neural Network



Neural Network Classifier

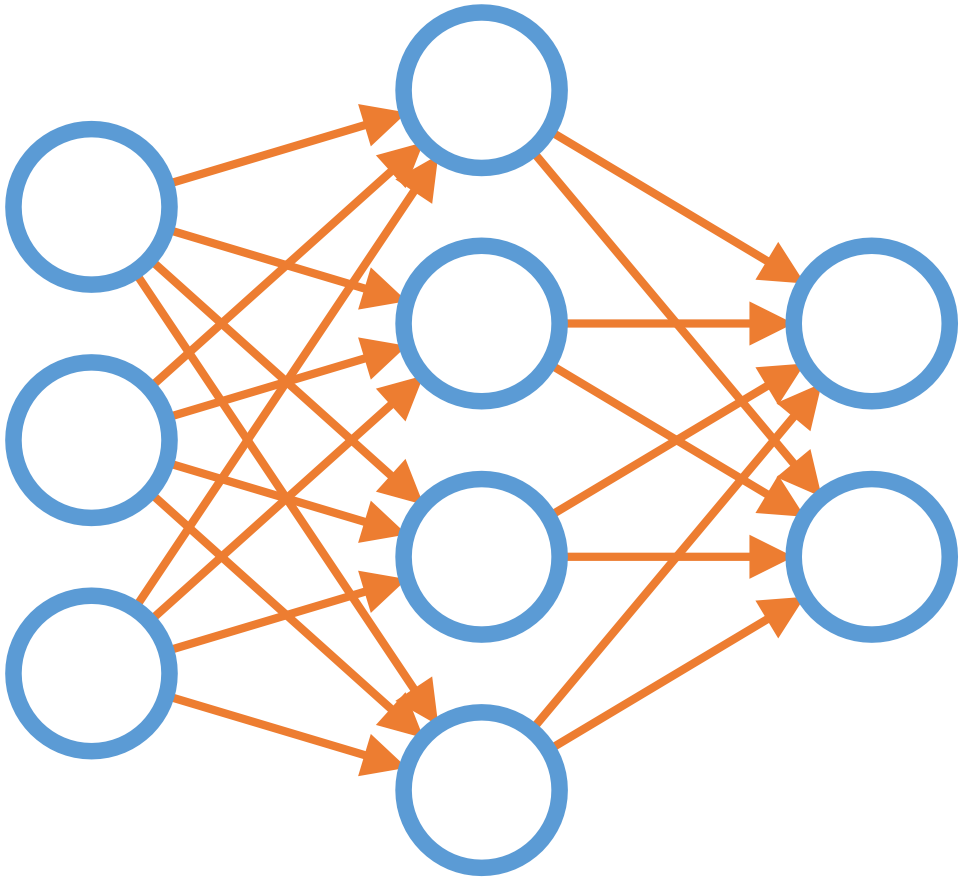
Supervised learning



Neural Network Classifier

Supervised learning

Neurons in a brain

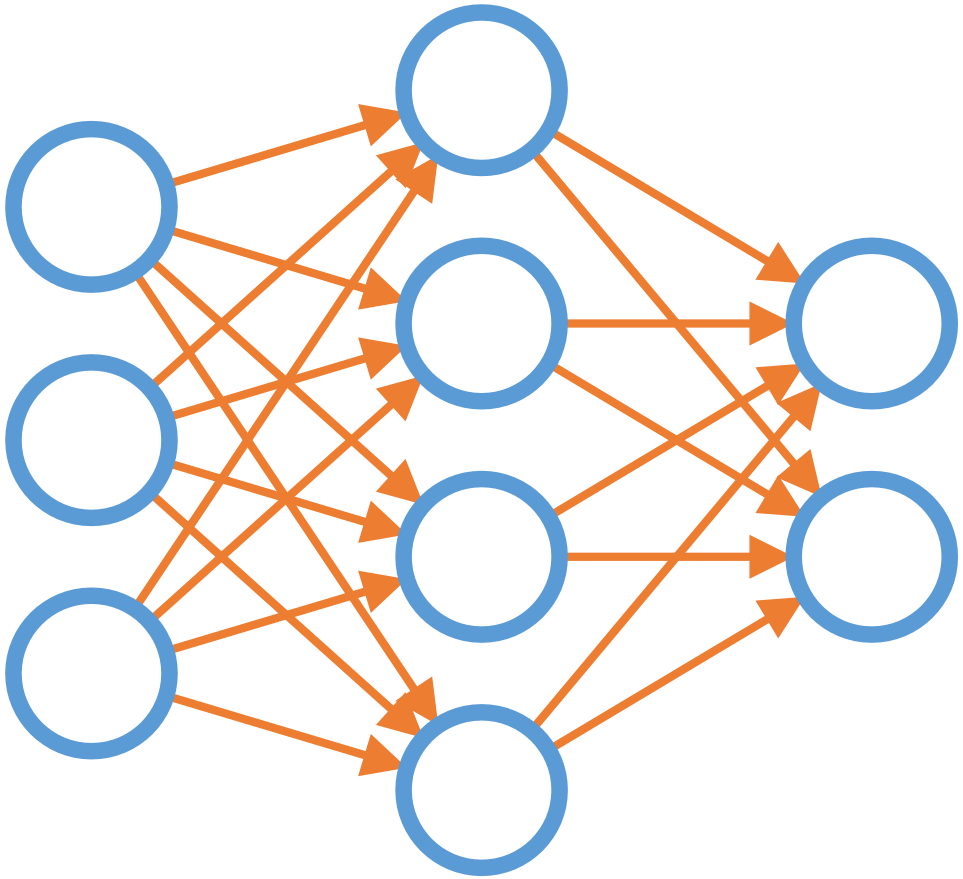


Neural Network Classifier

Supervised learning

Neurons in a brain

Weighted connections



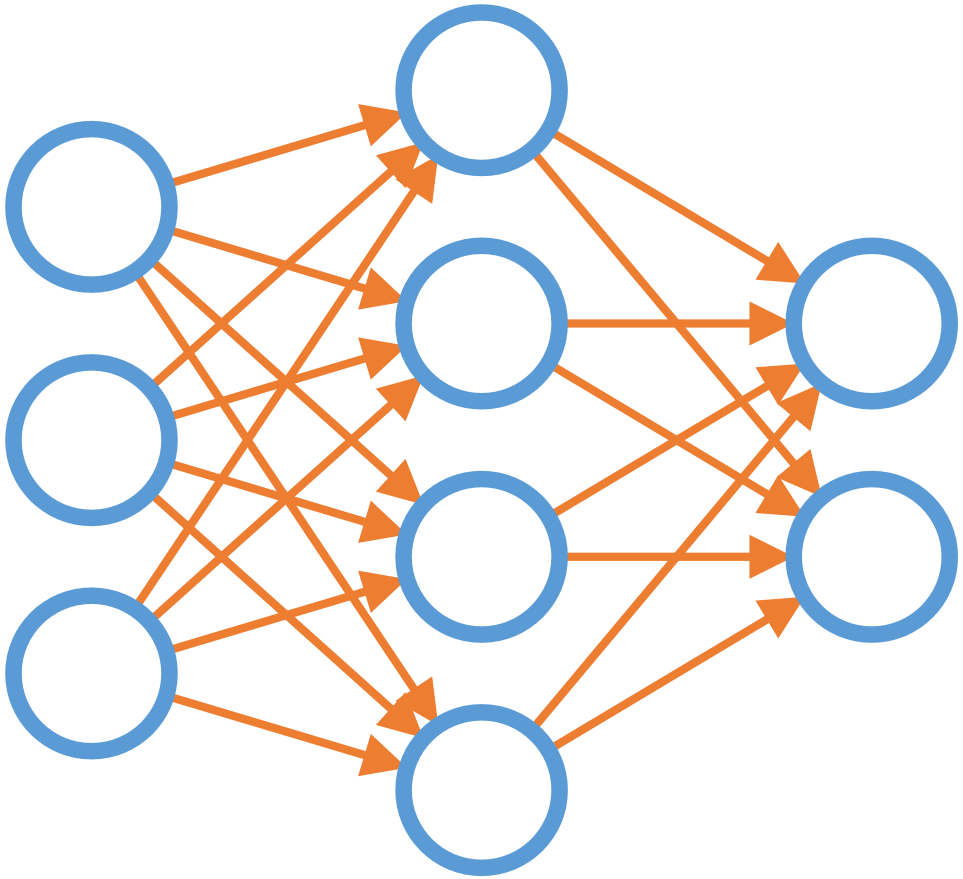
Neural Network Classifier

Supervised learning

Neurons in a brain

Weighted connections

Complex



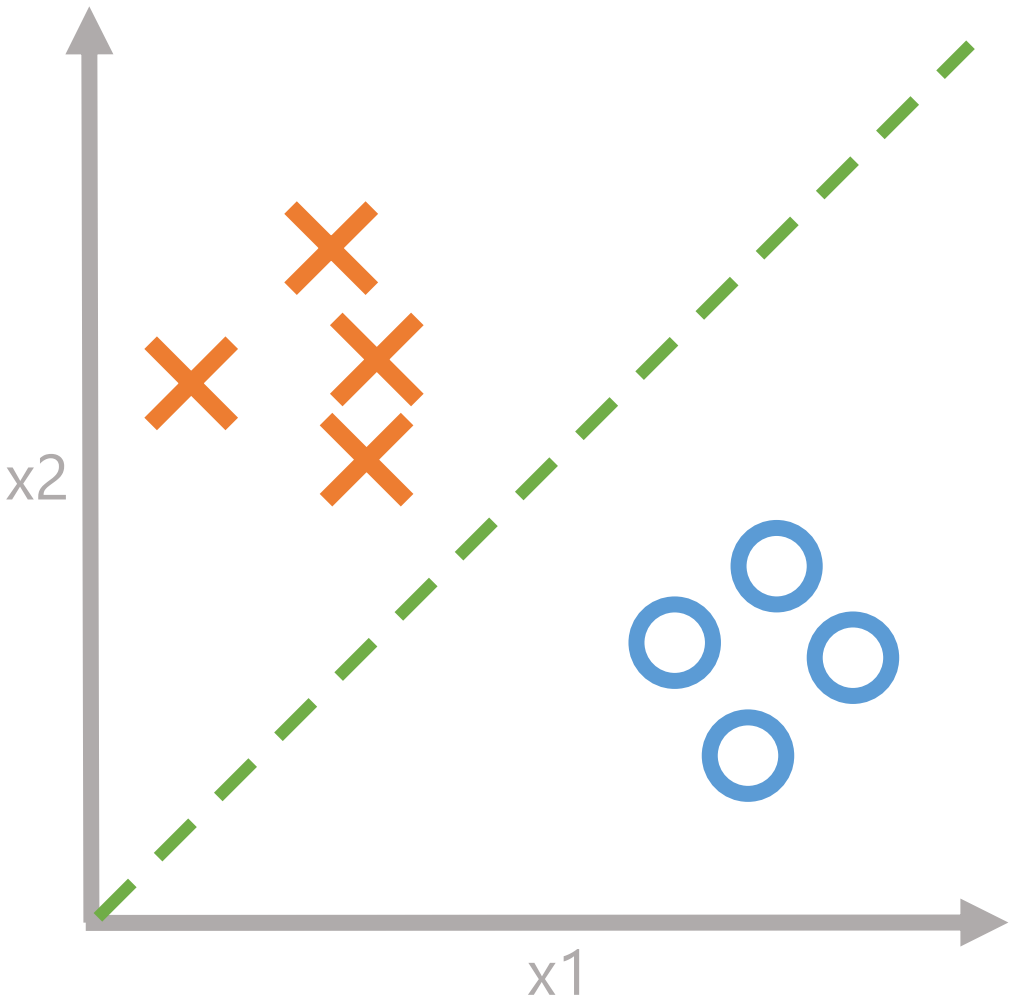
Real-World Examples

Should we approve this loan?

Will this customer buy from us?

Should we replace this part?

Does this person have cancer?



Iris Data Set

Iris Setosa

Iris Versicolor

Iris Virginica

Photos by Radomił Binek, Danielle Langlois, and Frank Mayfield

Iris Data Set

Fisher's Iris Data				
Species	Petal Length	Petal Width	Sepal Length	Sepal Width
setosa	1.1	0.1	4.3	3
setosa	1.4	0.2	4.4	2.9
setosa	1.3	0.2	4.4	3
setosa	1.3	0.2	4.4	3.2
setosa	1.3	0.3	4.5	2.3
…		…	…	…

Demo 2 - Classification

Goal: Predict species based on petal and sepal measurements

Insurance Policy Risk Data Set

Insurance Policy Risk							
Gender	State	State Rate	Height	Weight	BMI	Age	Risk
Male	MA	0.01	184	67.8	20.0	77	High
Male	VA	0.14	163	89.4	33.6	82	High
Female	NY	0.09	170	81.2	28.1	31	Low
Male	TN	0.12	175	99.7	32.6	39	Low
Female	FL	0.11	184	72.1	21.3	68	High
…		…	…	…	…	…	…

Insurance Policy Rates Data Set

Insurance Policy Rates							
Gender	State	State Rate	Height	Weight	BMI	Age	Rate
Male	MA	0.01	184	67.8	20.0	77	0.33
Male	VA	0.14	163	89.4	33.6	82	0.87
Female	NY	0.09	170	81.2	28.1	31	0.01
Male	TN	0.12	175	99.7	32.6	39	0.02
Female	FL	0.11	184	72.1	21.3	68	0.15
…		…	…	…	…	…	…

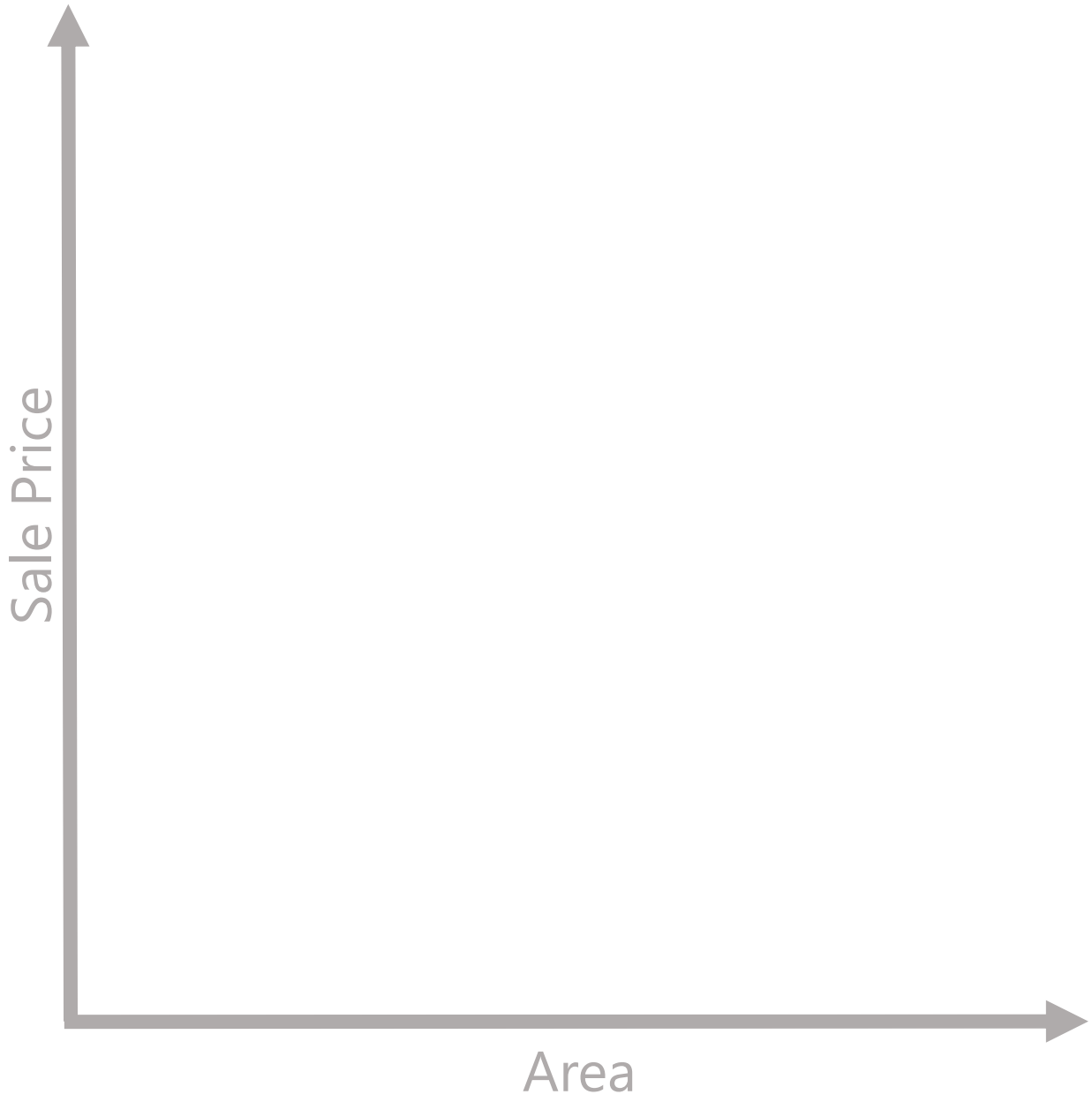
Lab 2A – Classification (Easy)

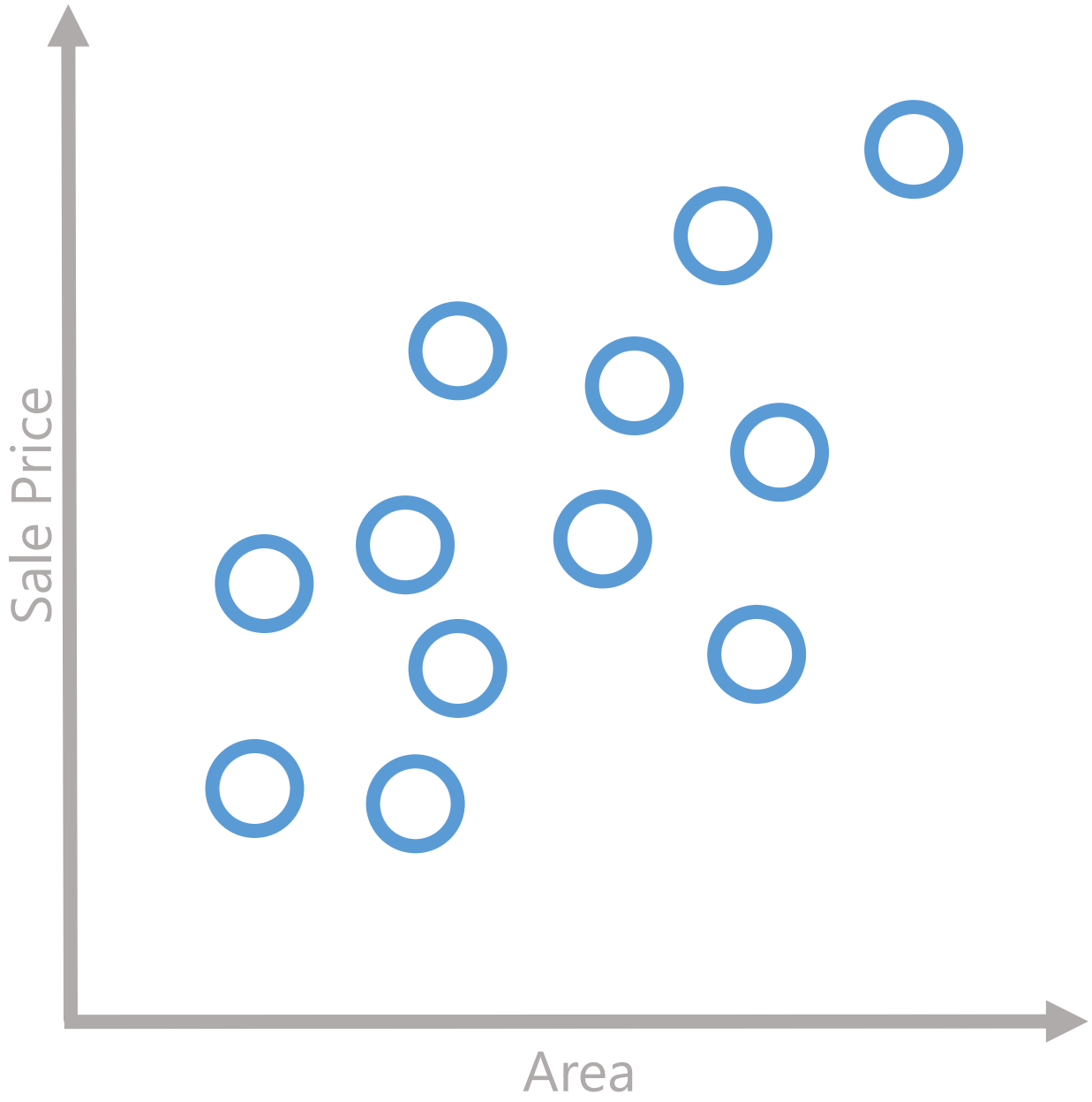
Goal: Predict species based on petal and sepal measurements

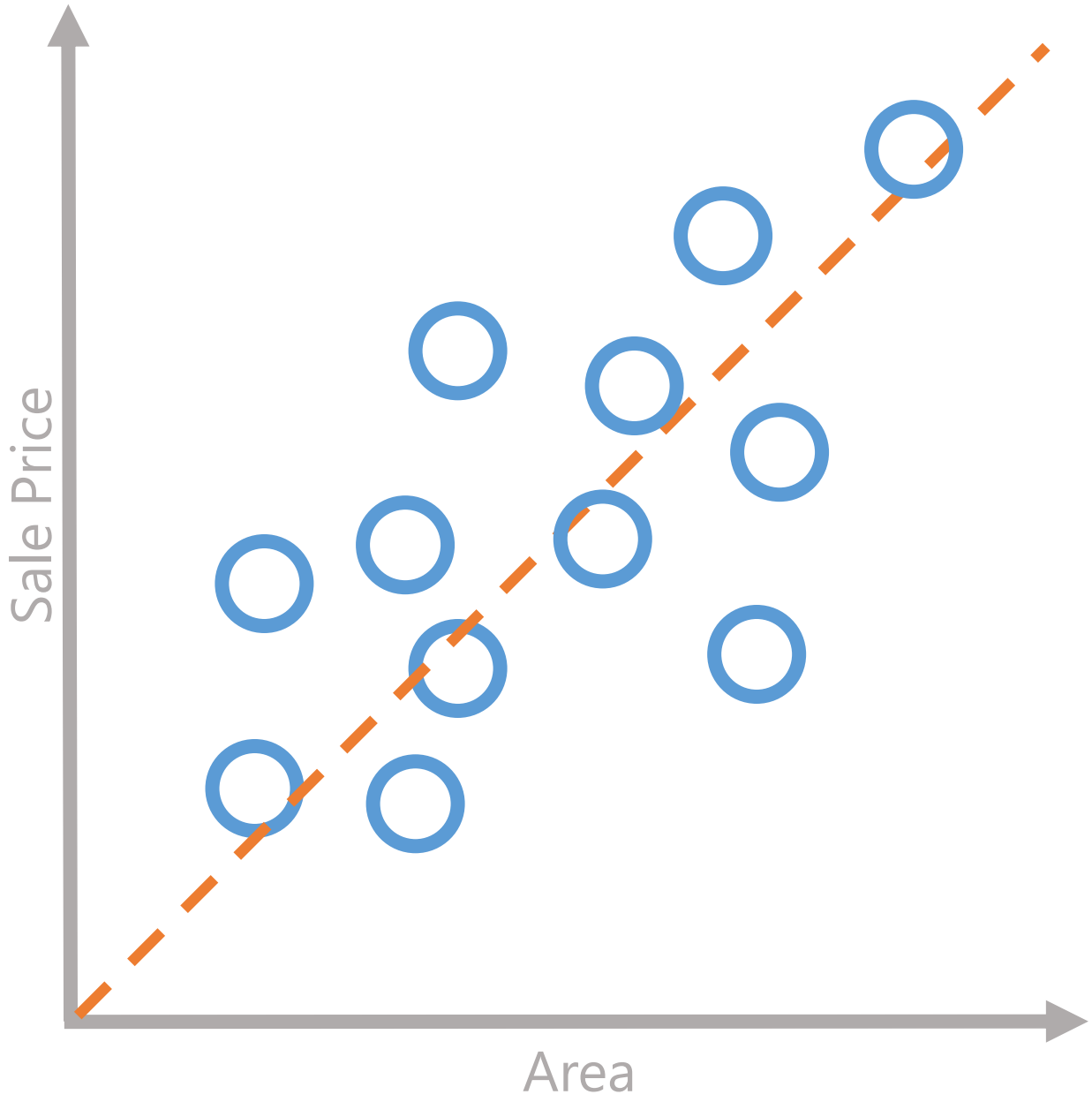
Lab 2B – Classification (Hard)

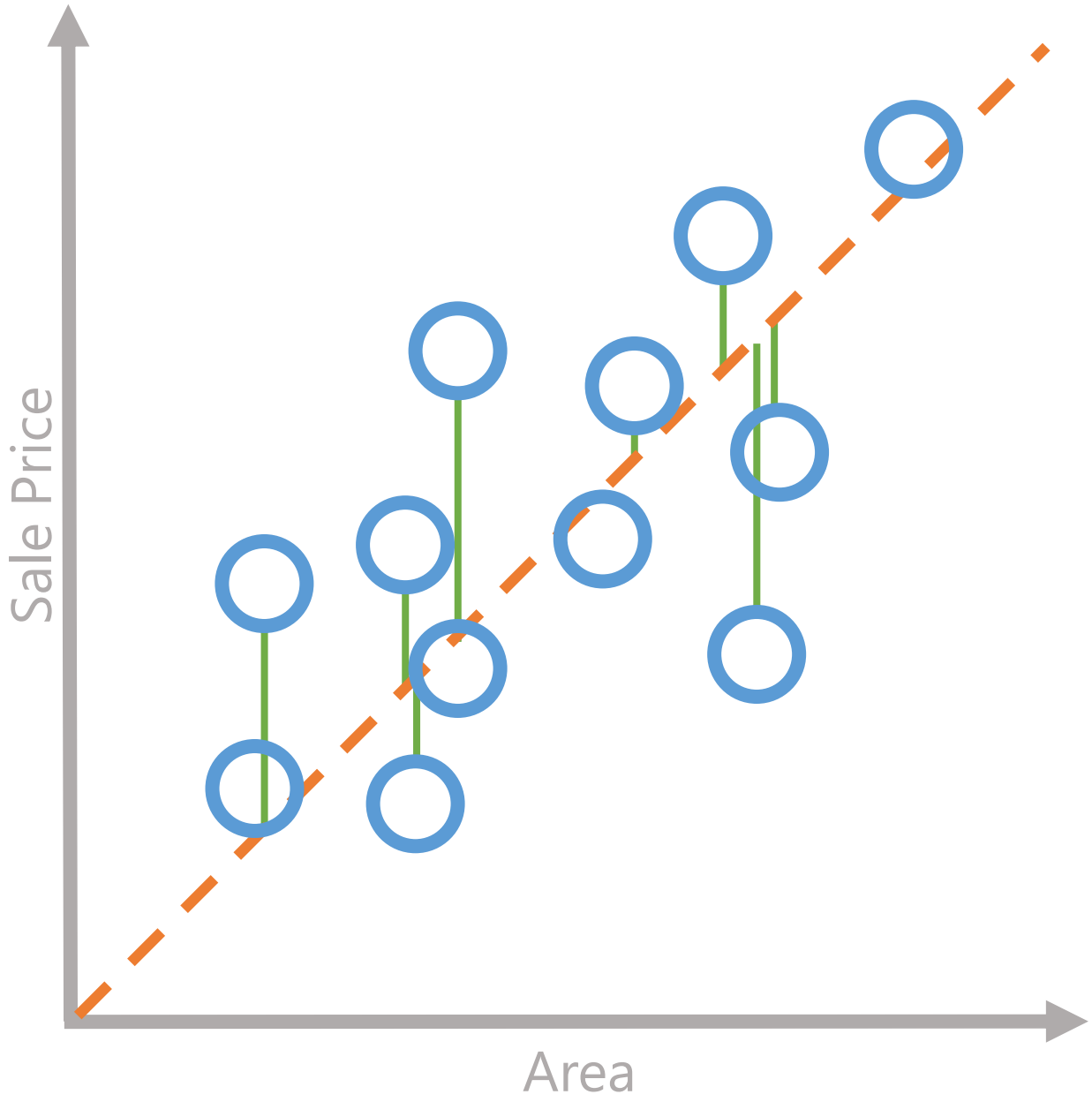
Goal: Predict the risk of
an insurance policy

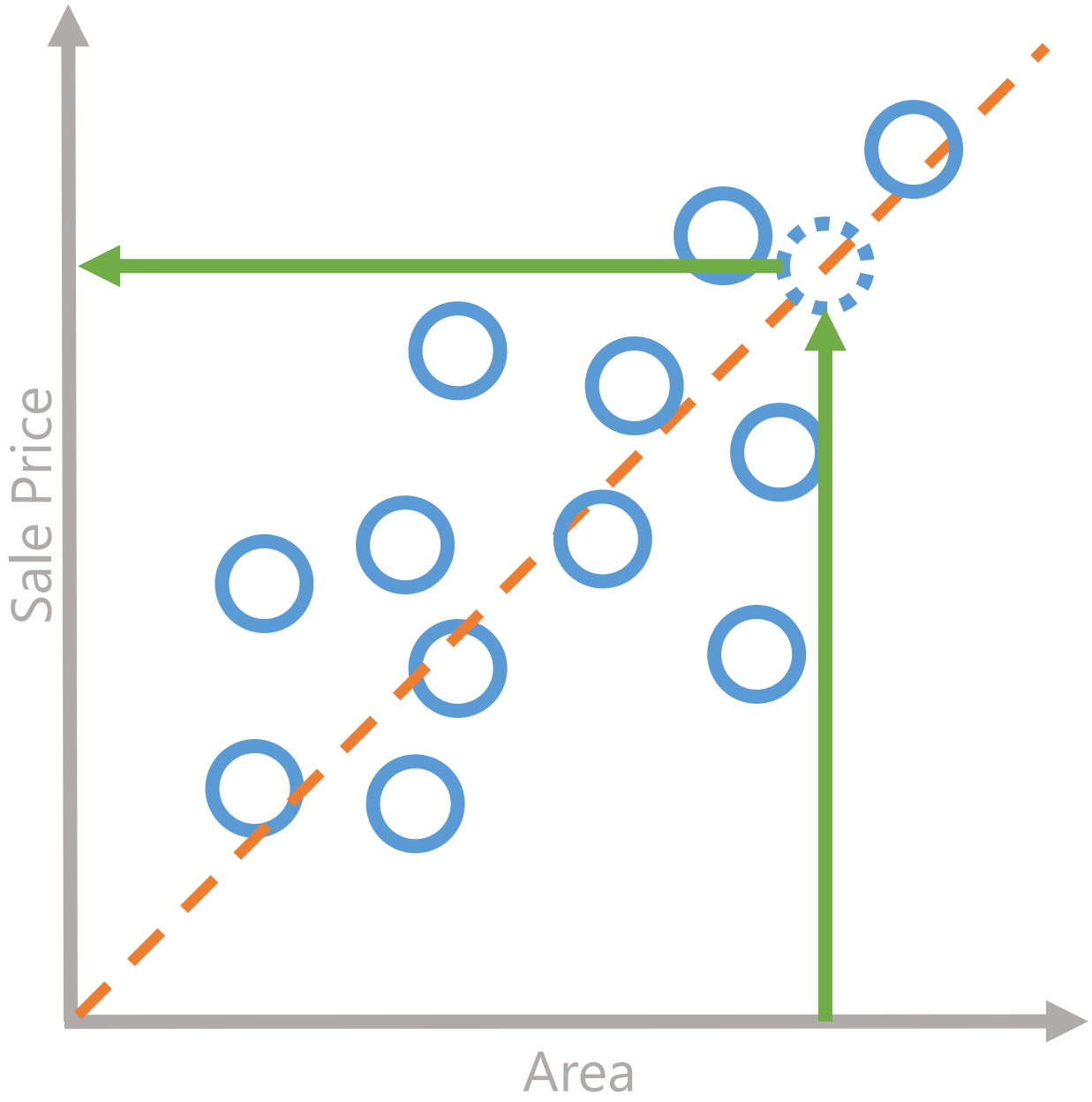
Regression

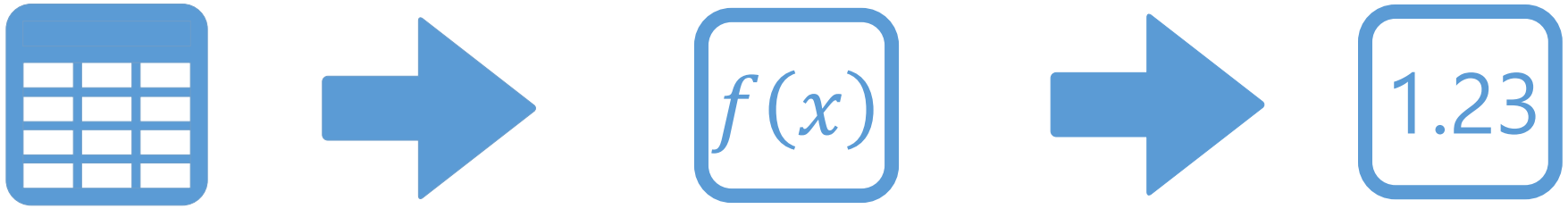

Sale Price
Area


Sale Price
Area


Sale Price
Area

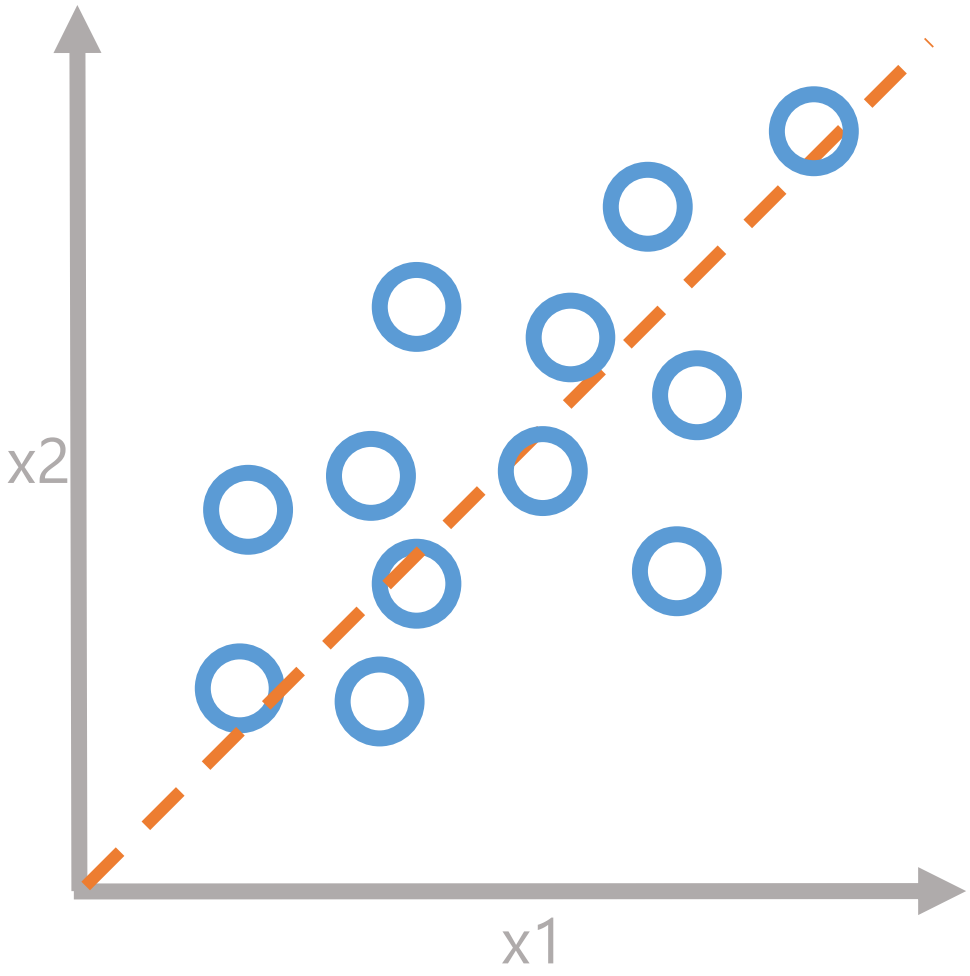

Sale Price
Area


Sale Price
Area

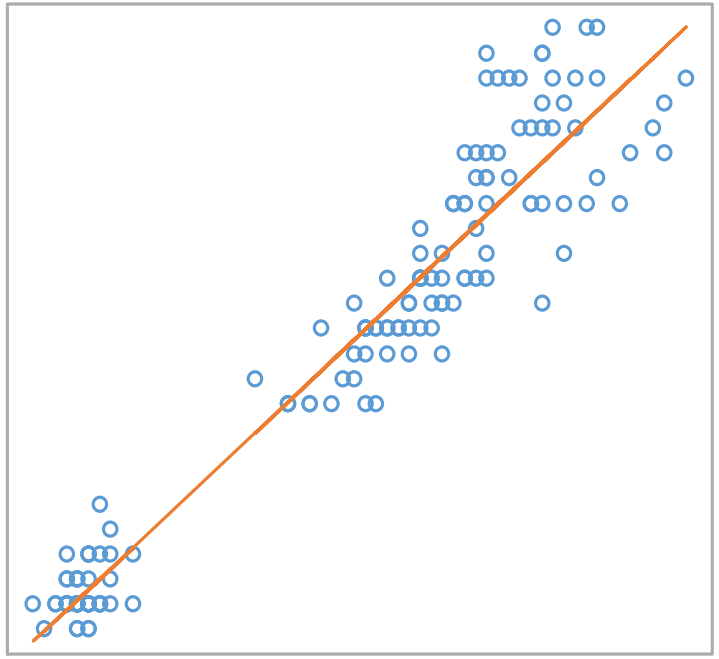

$f(x)$
1.23

Regression Algorithms

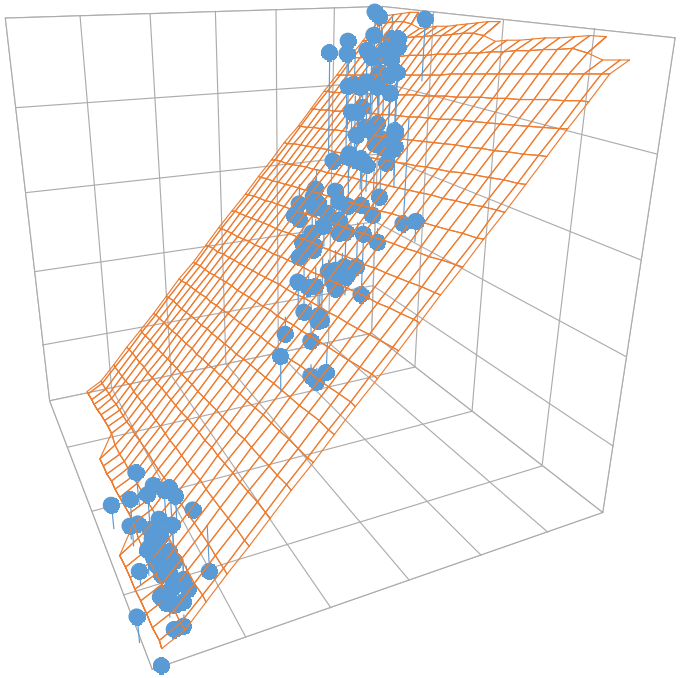
Linear Regression
Polynomial Regression
Lasso Regression
ElasticNet Regression
Neural Network Regression



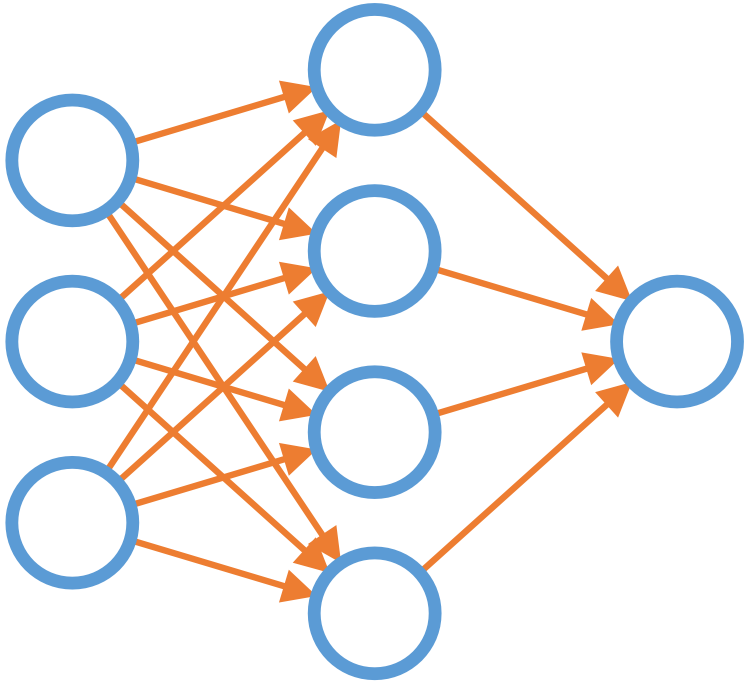
Regression Algorithms



Simple Linear



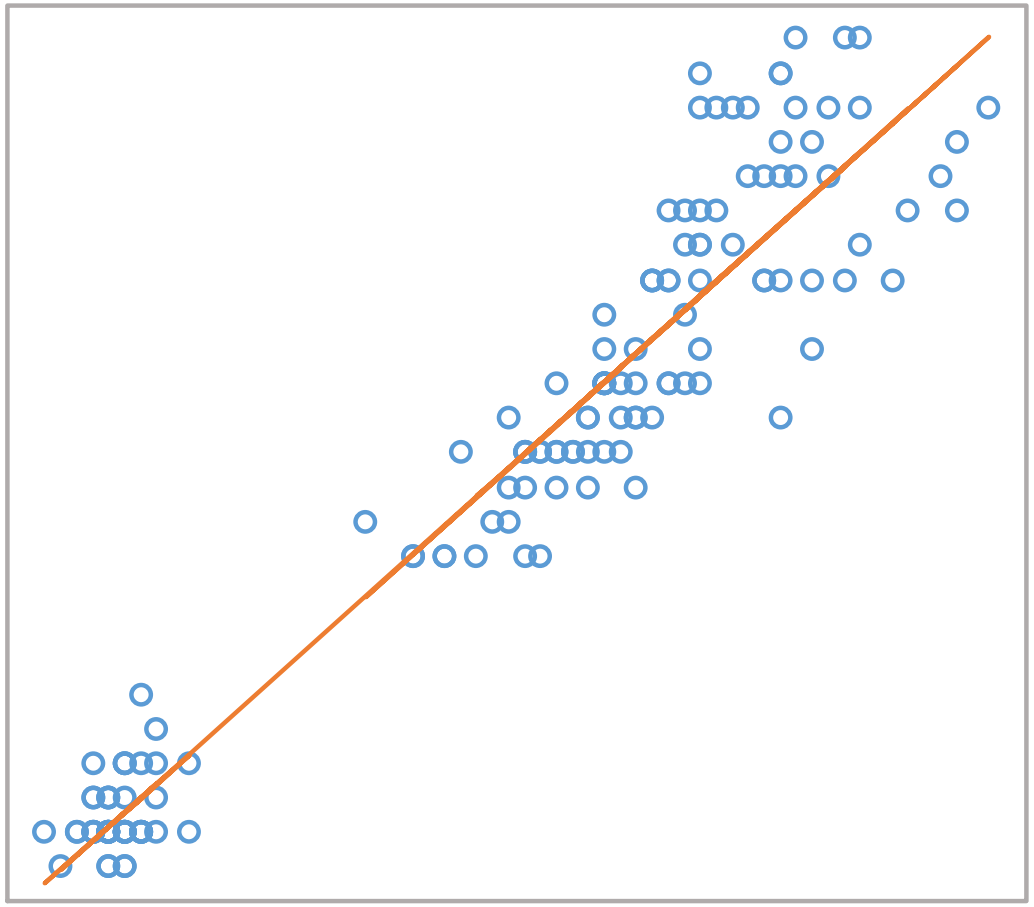
Multiple Linear



Neural Network

Simple Linear Regression

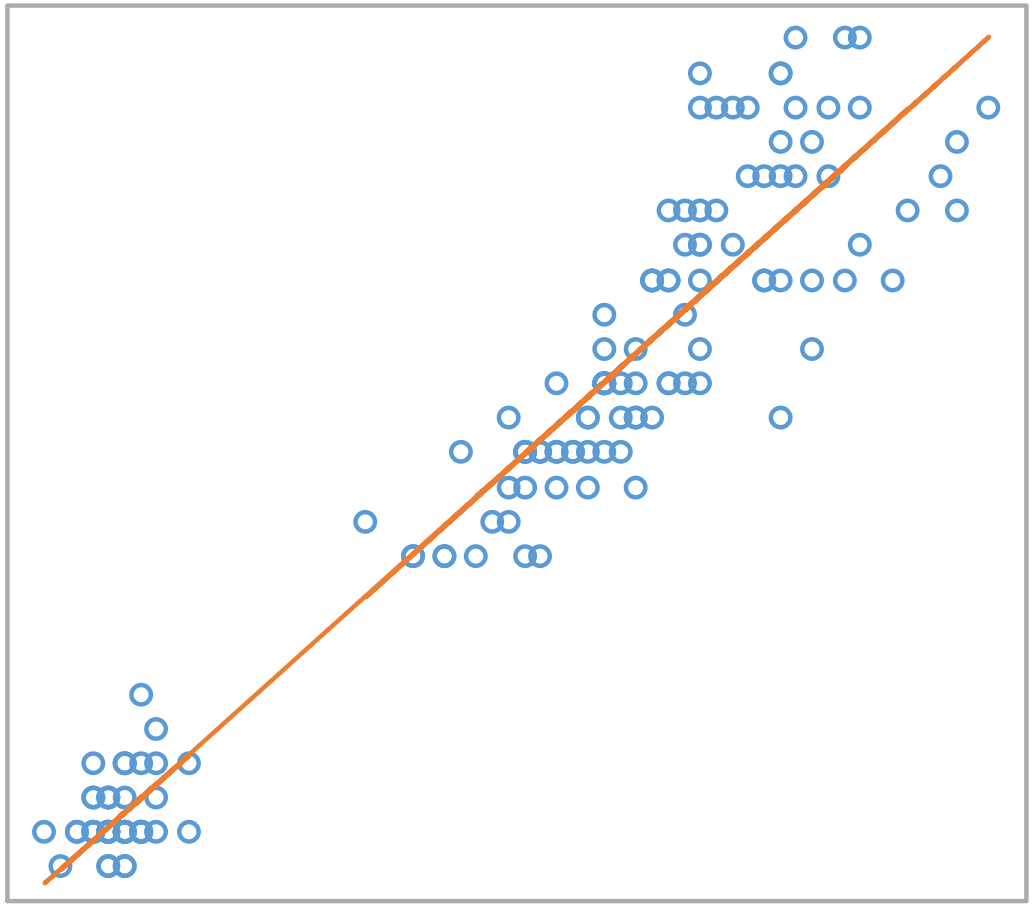
Relationship



Simple Linear Regression

Relationship

Linear model

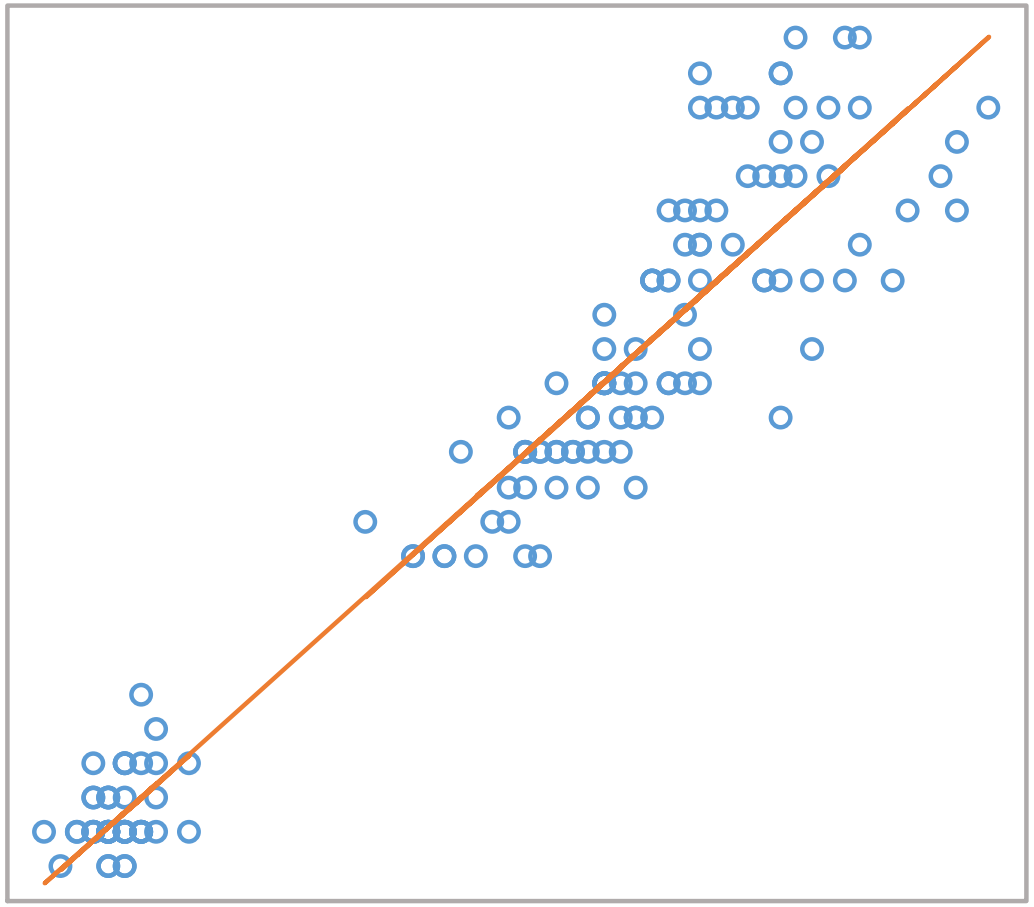


Simple Linear Regression

Relationship

Linear model

$y = m \cdot x + b$



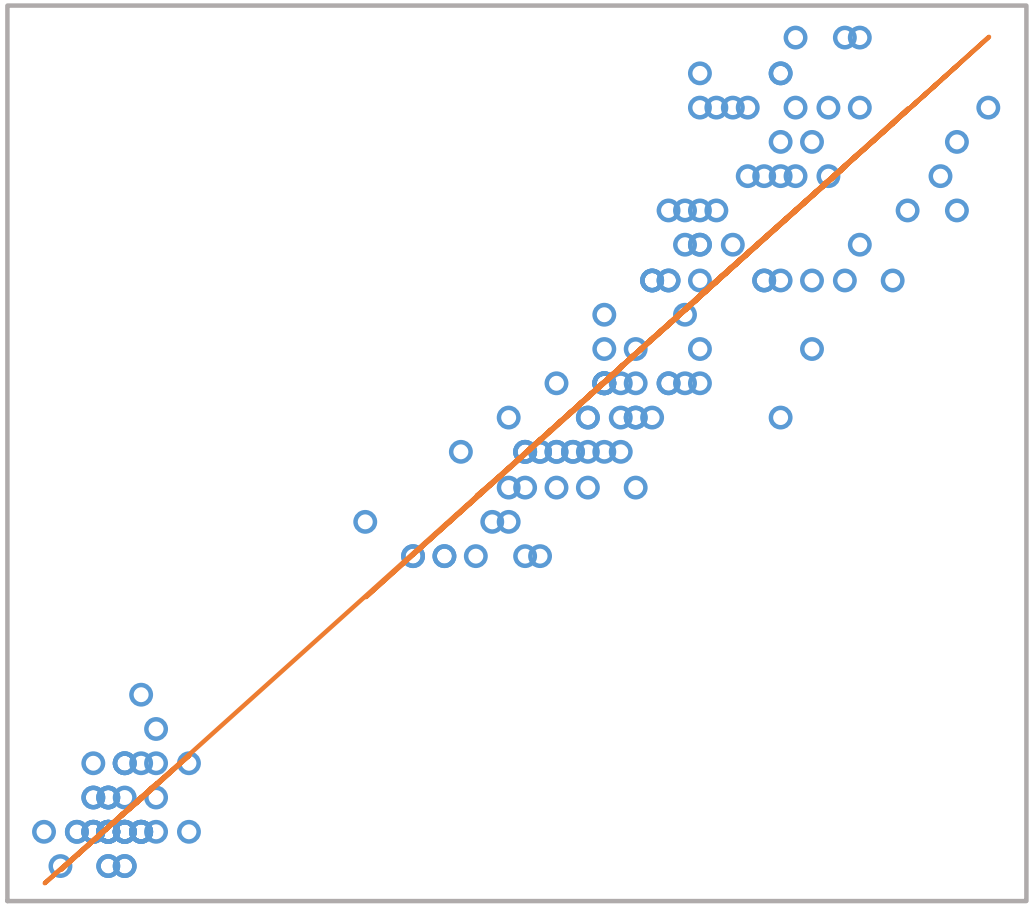
Simple Linear Regression

Relationship

Linear model

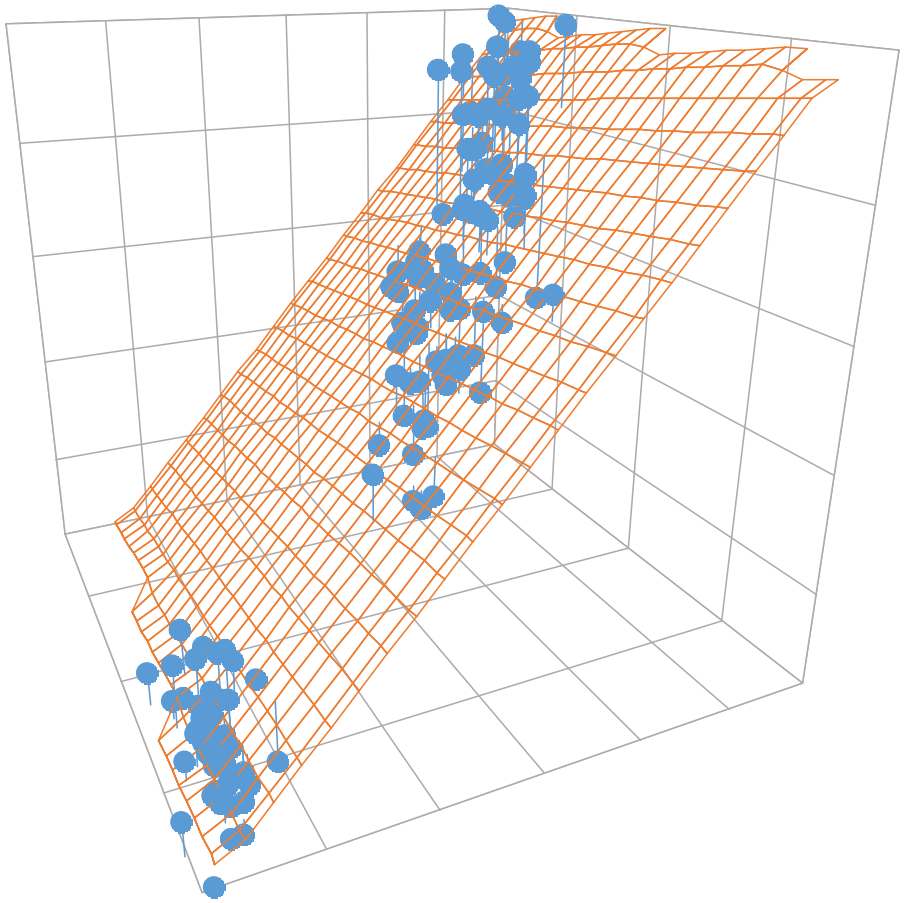
$y = m \cdot x + b$

Parameters estimated



Multiple Linear Regression

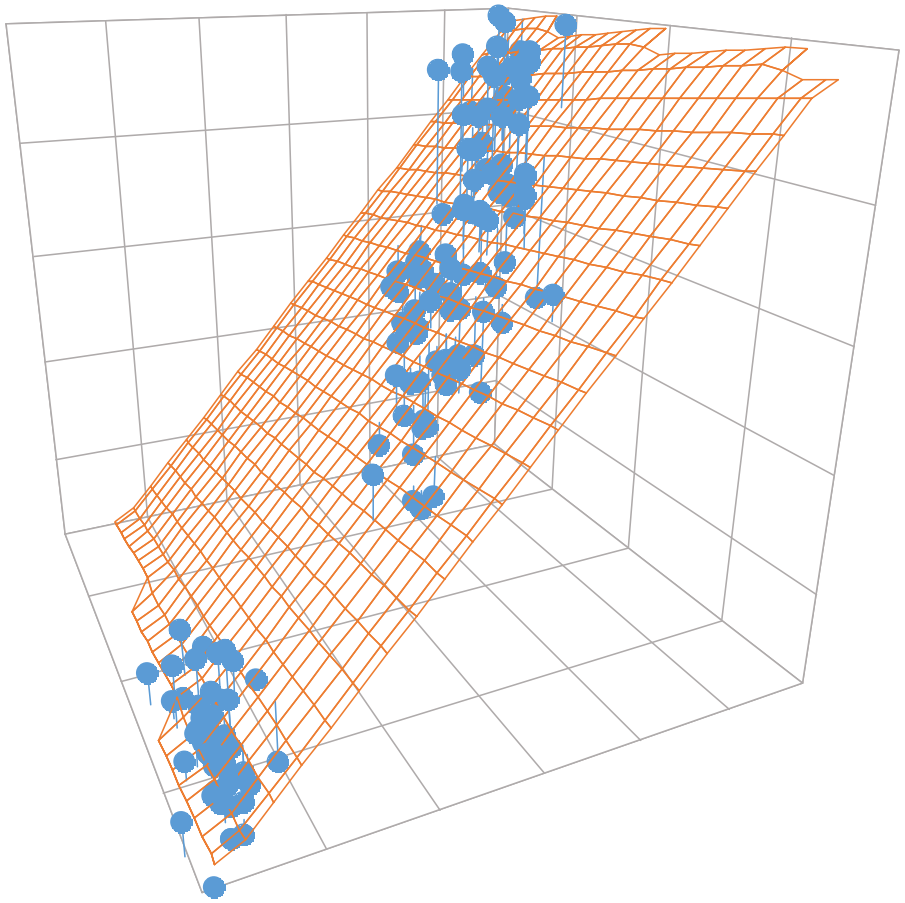
Similar to SLR



Multiple Linear Regression

Similar to SLR

Multiple variables

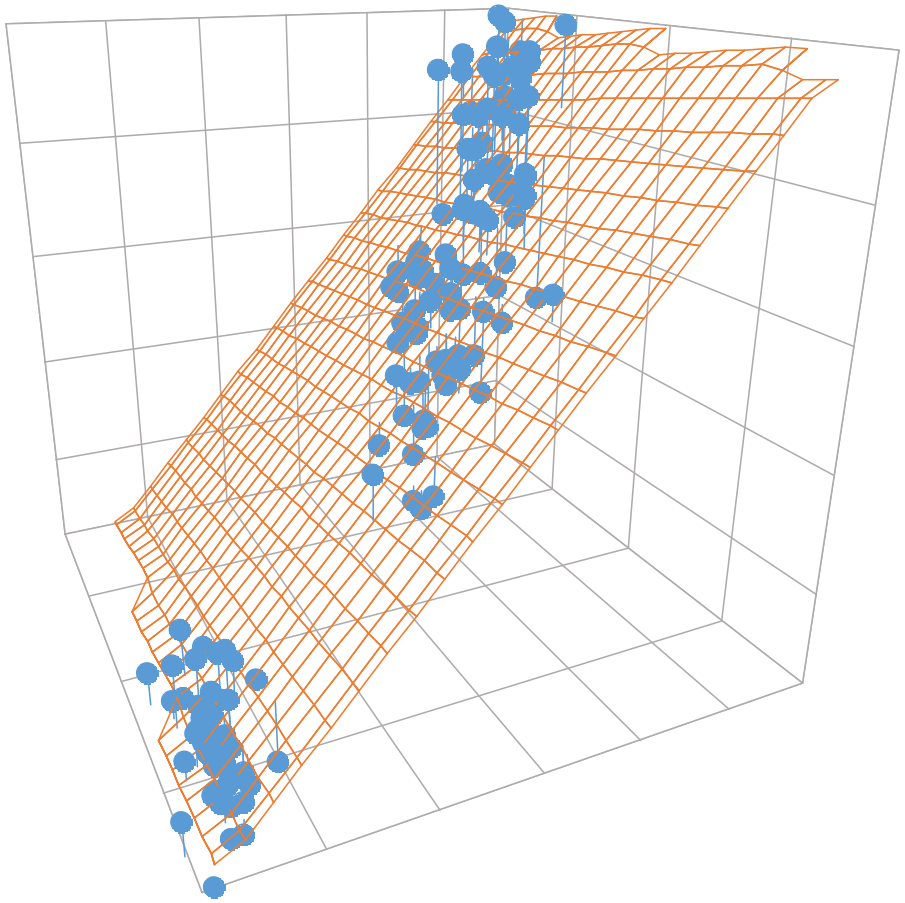


Multiple Linear Regression

Similar to SLR

Multiple variables

Multiple slopes



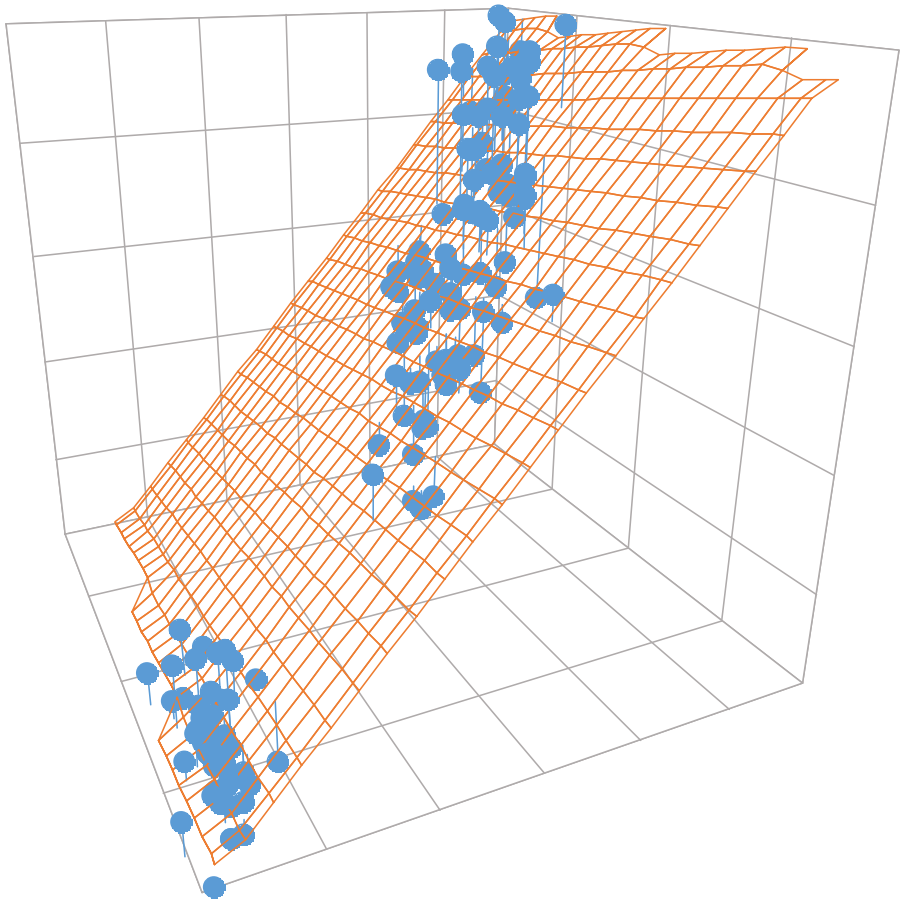
Multiple Linear Regression

Similar to SLR

Multiple variables

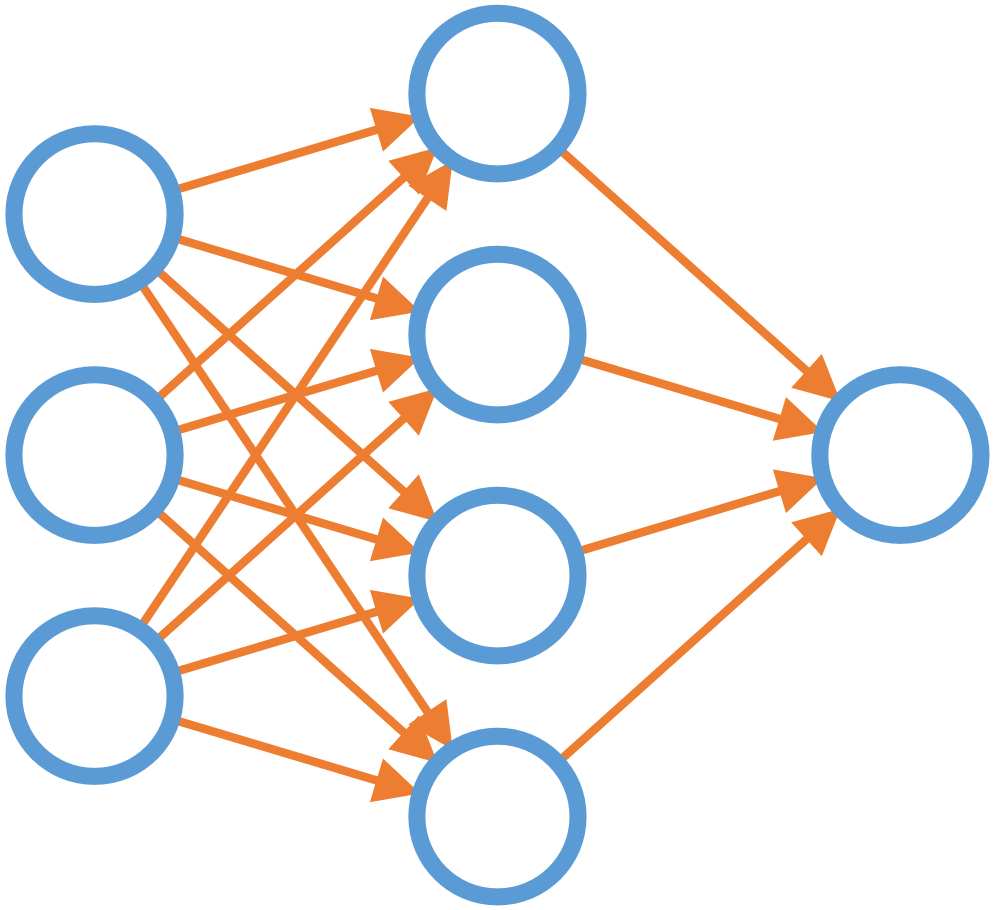
Multiple slopes

Categorical variables



Neural Network Regression

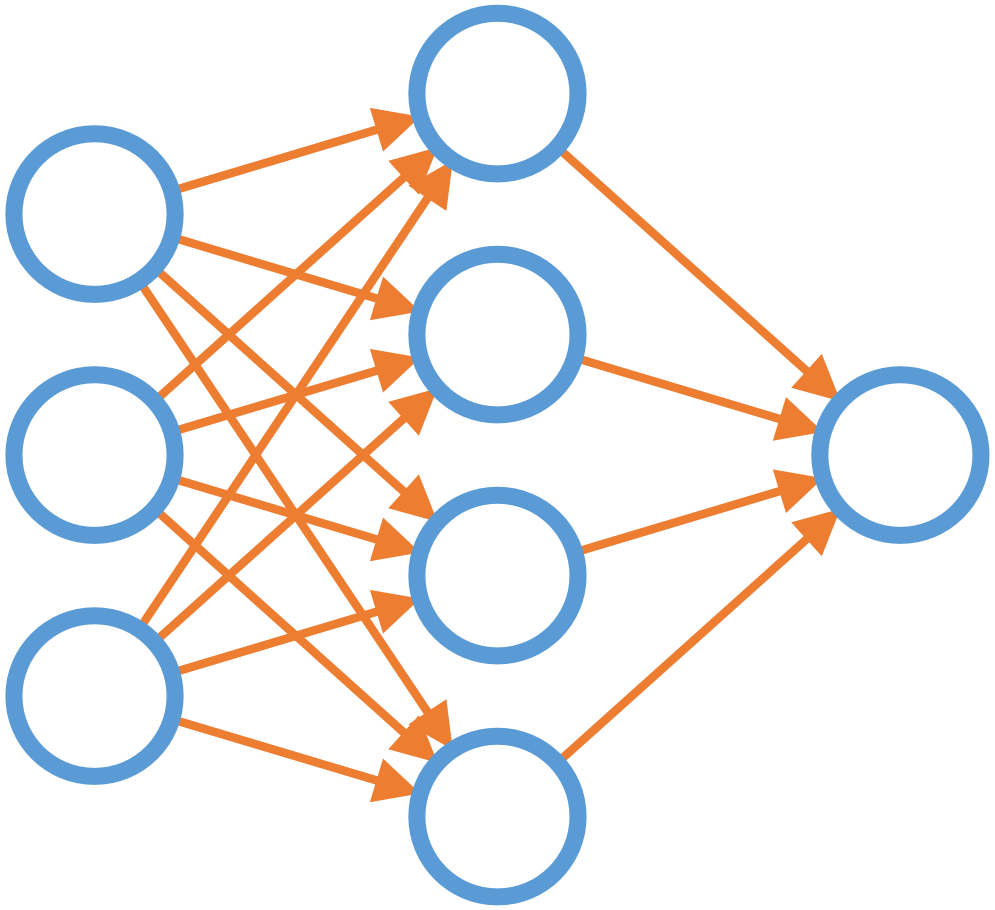
Similar to NN classifier



Neural Network Regression

Similar to NN classifier

Numeric output



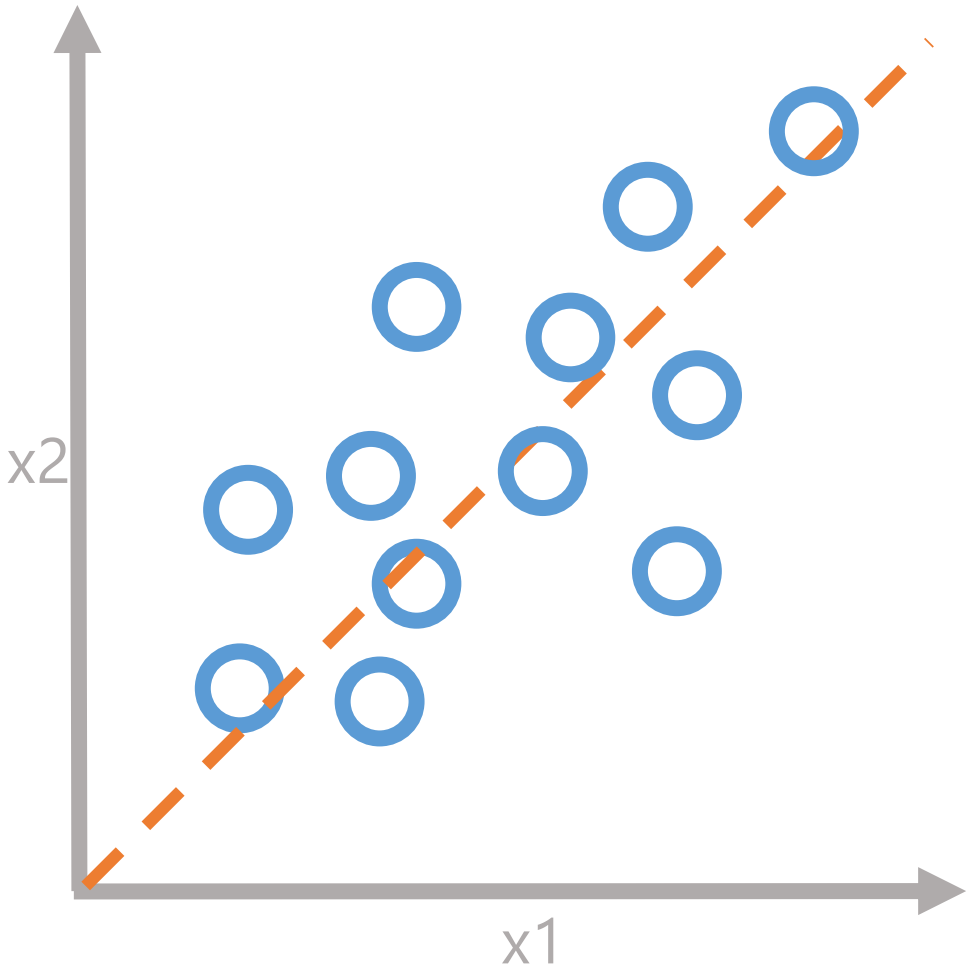
Real-World Examples

How much profit will we make?

What will the price be tomorrow?

How many units will they buy?

How long until this part fails?



Demo 3 - Regression

Goal: Predict petal width
based on petal length

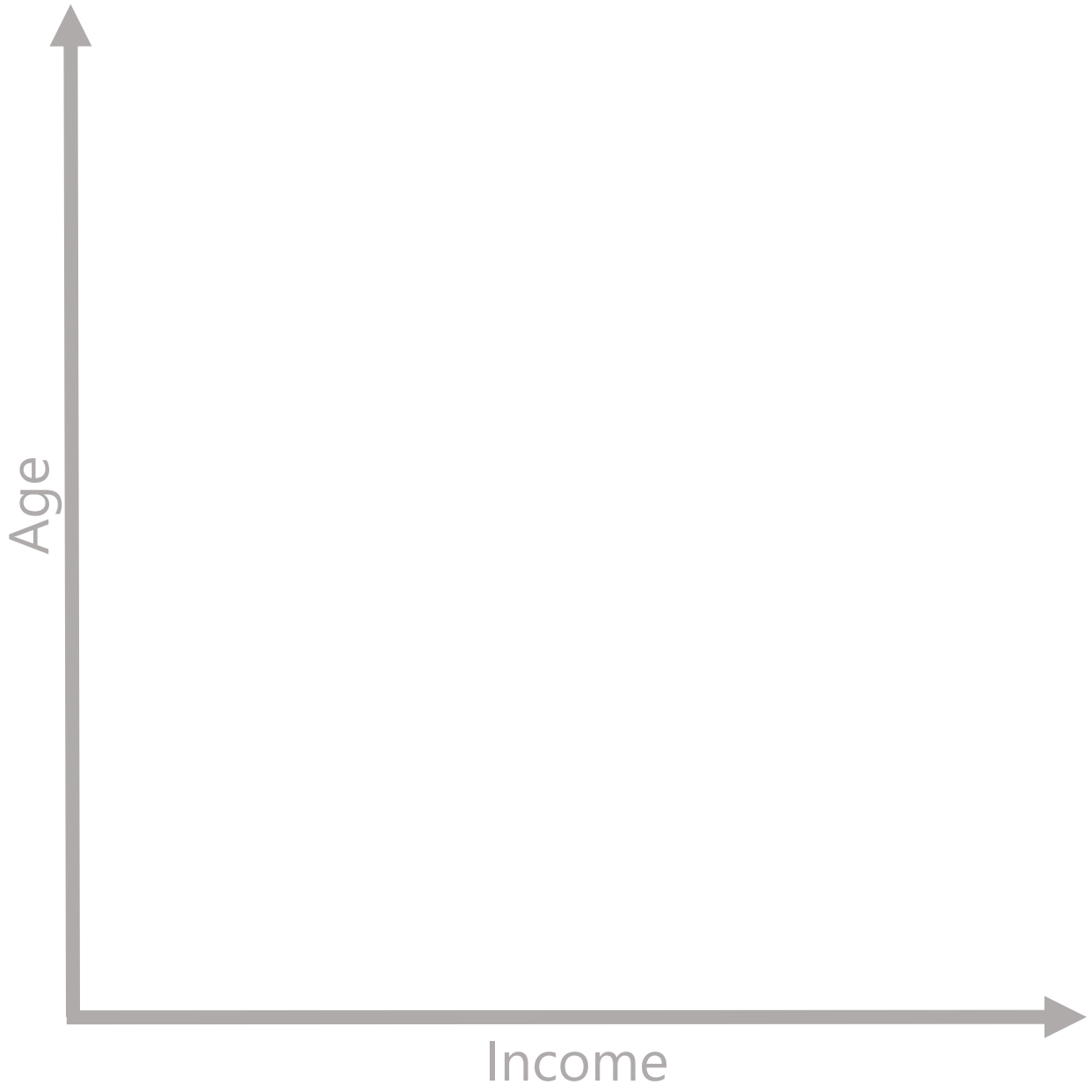
Lab 3A – Regression (Easy)

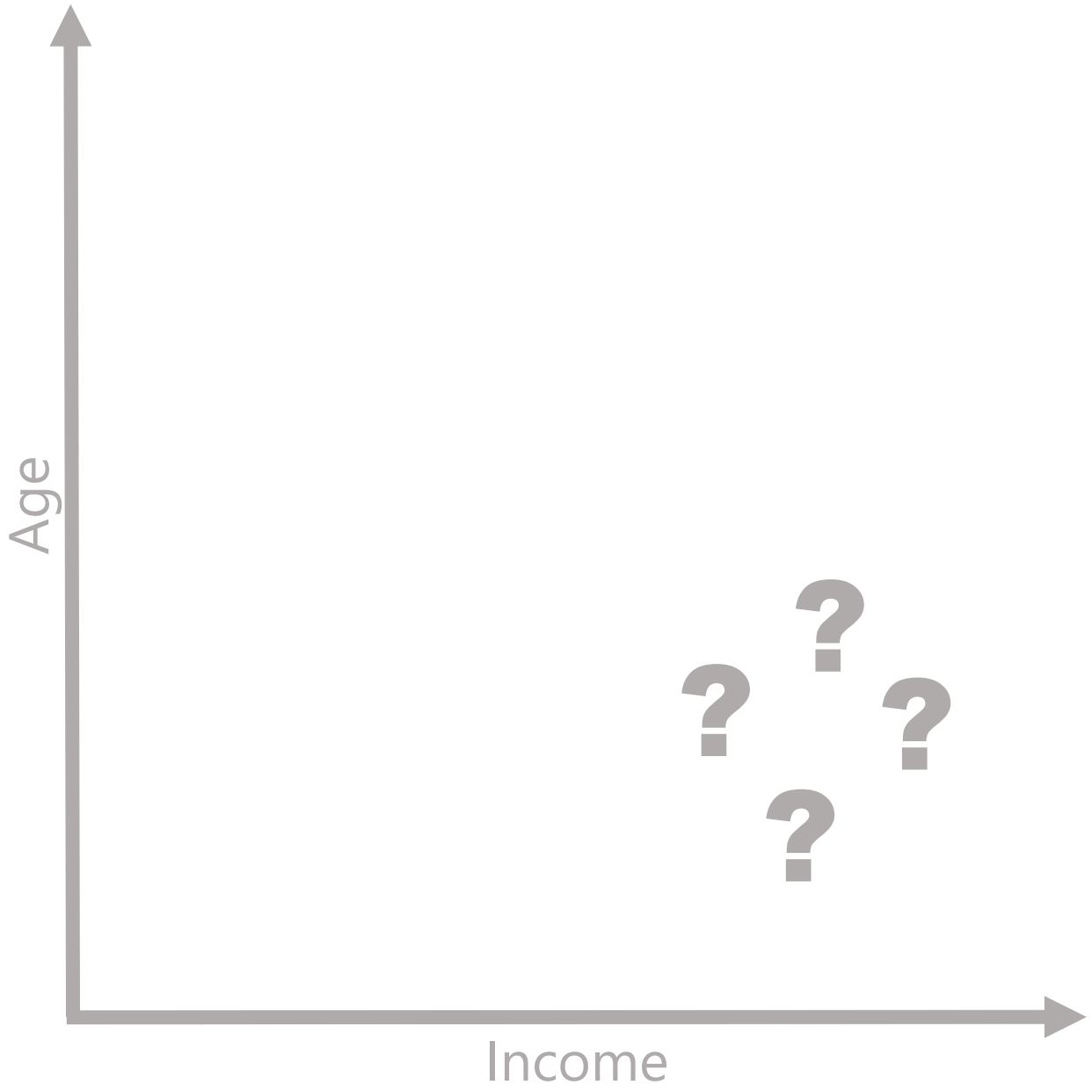
Goal: Predict petal width

Lab 3B – Regression (Hard)

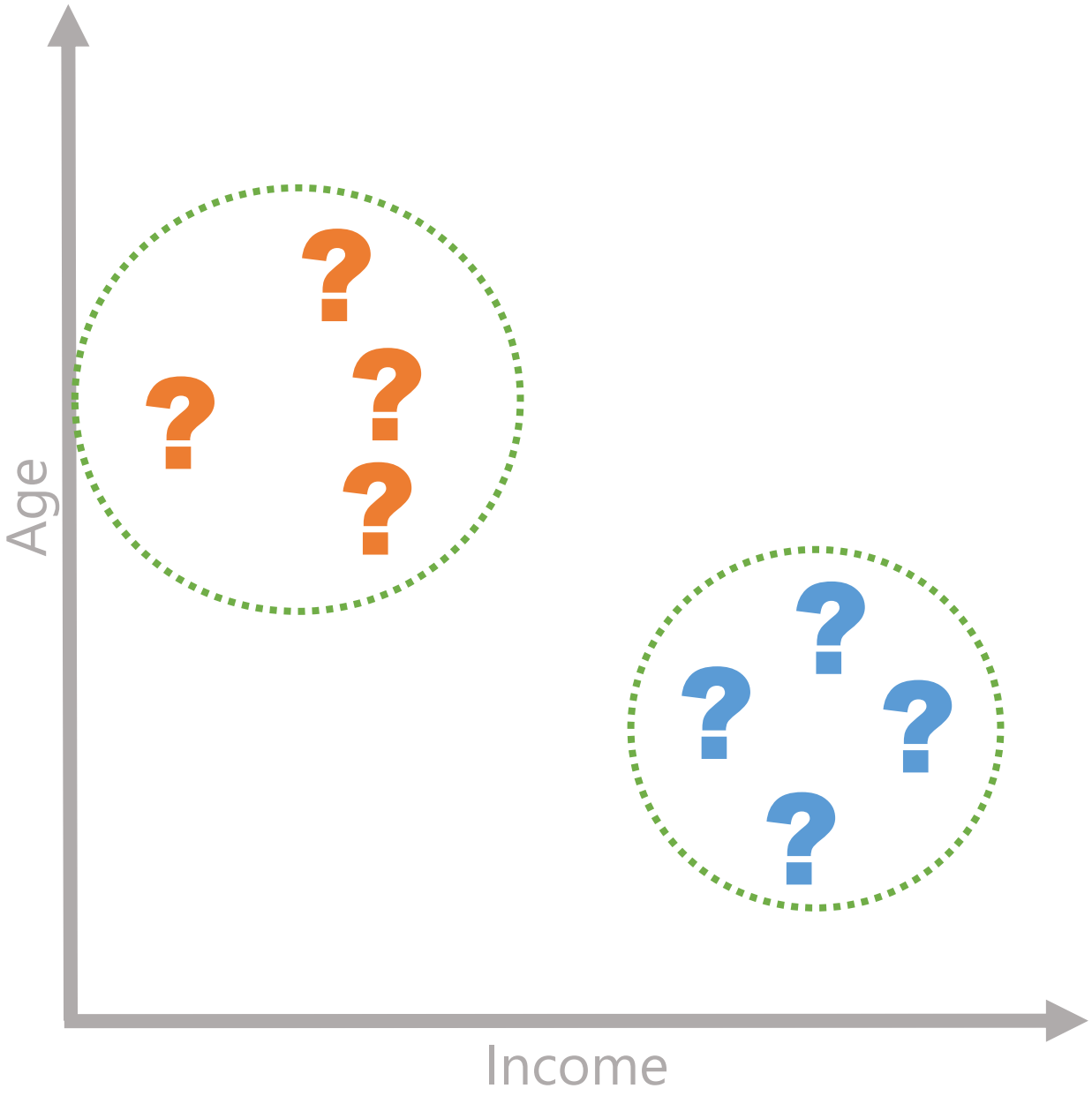
Goal: Predict mortality rate

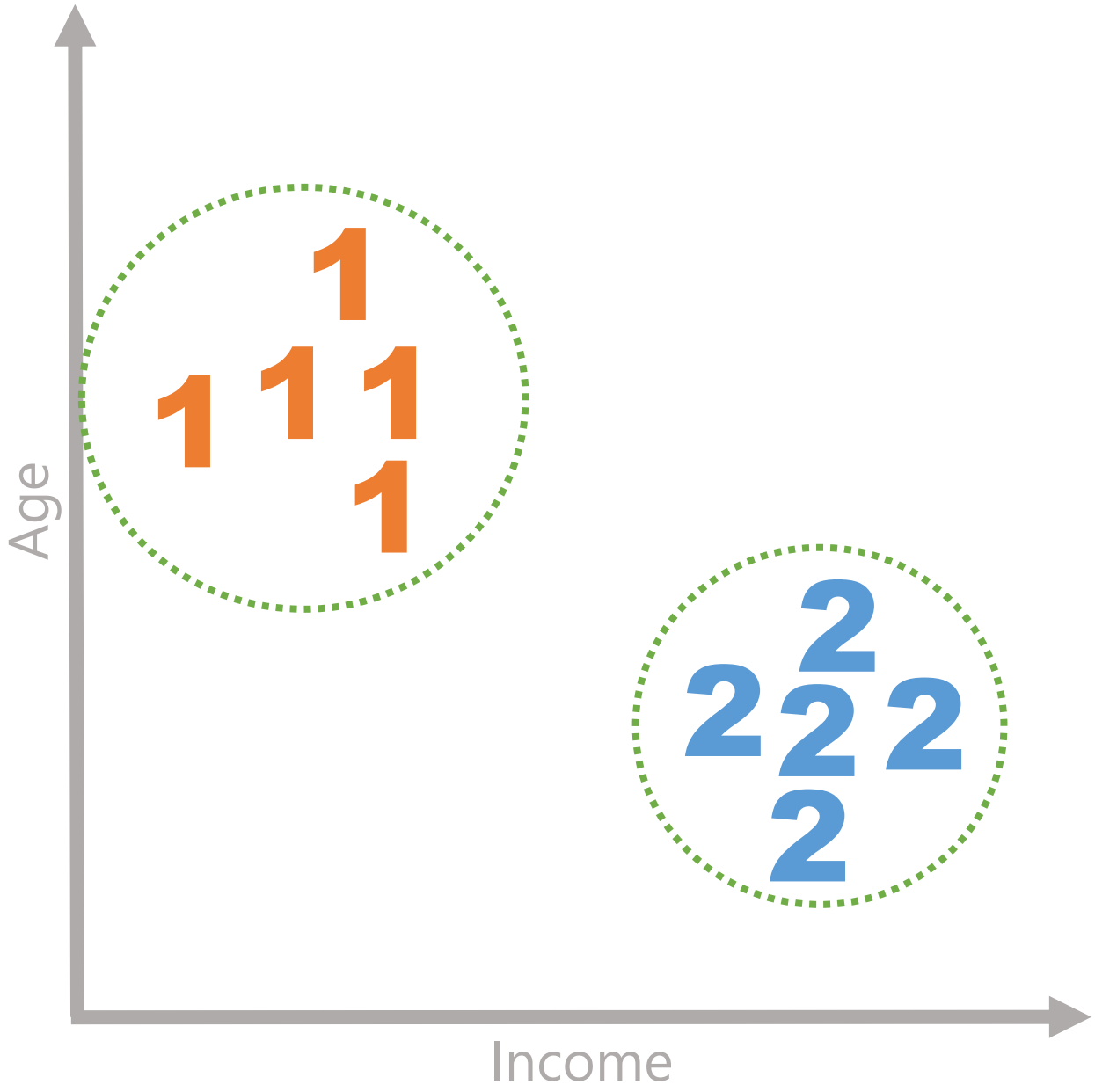
Clustering

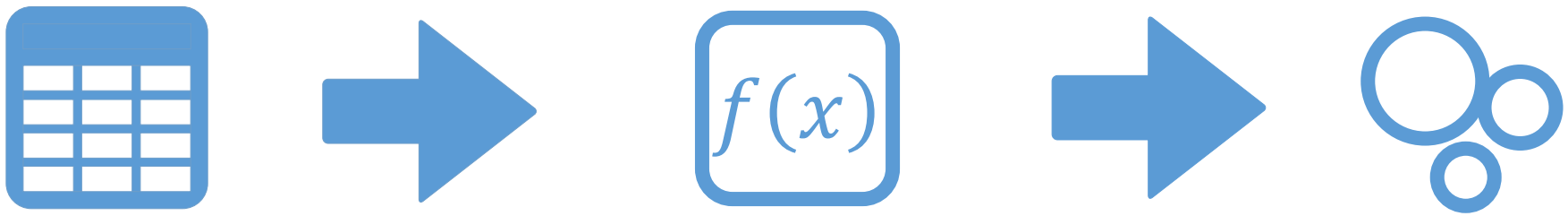

Age
Income


Age
Income


Age
Income


Age
Income


1
1 1 1
1
2
2 2 2
2
Age
Income

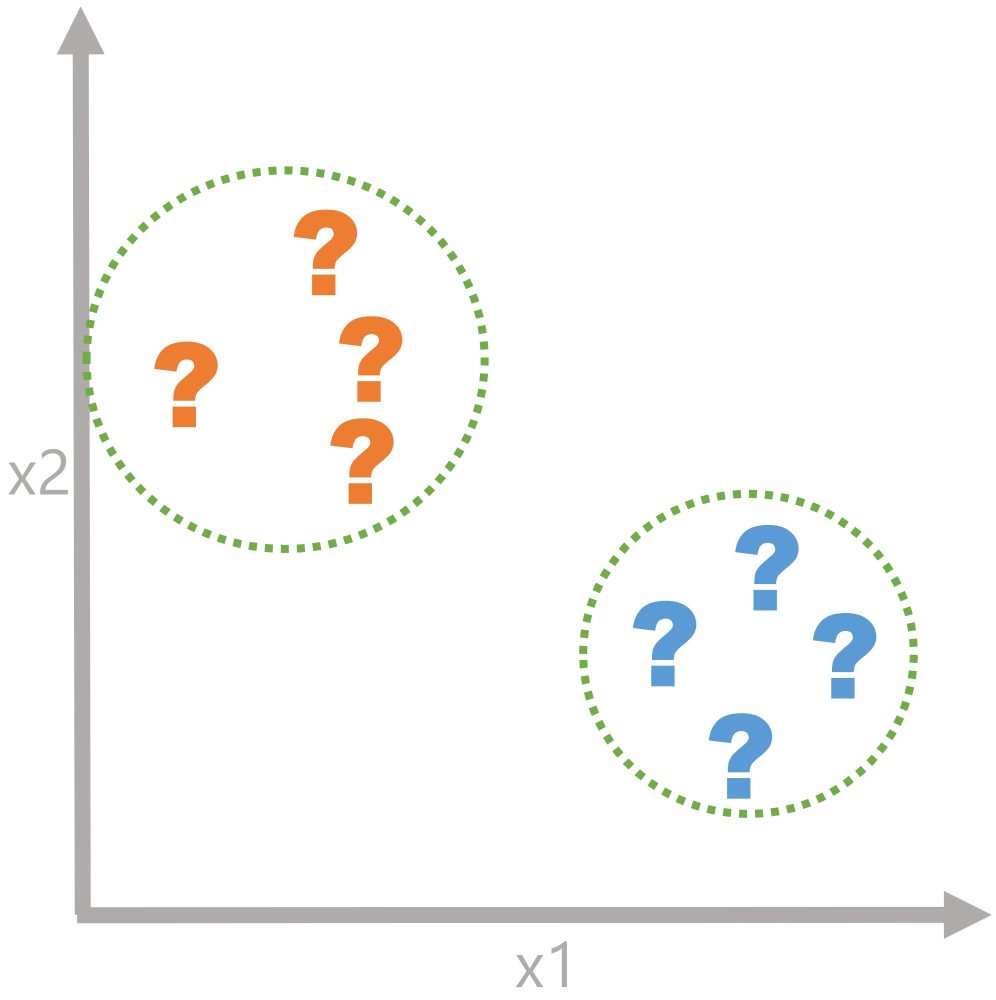

$f(x)$

Clustering Algorithms

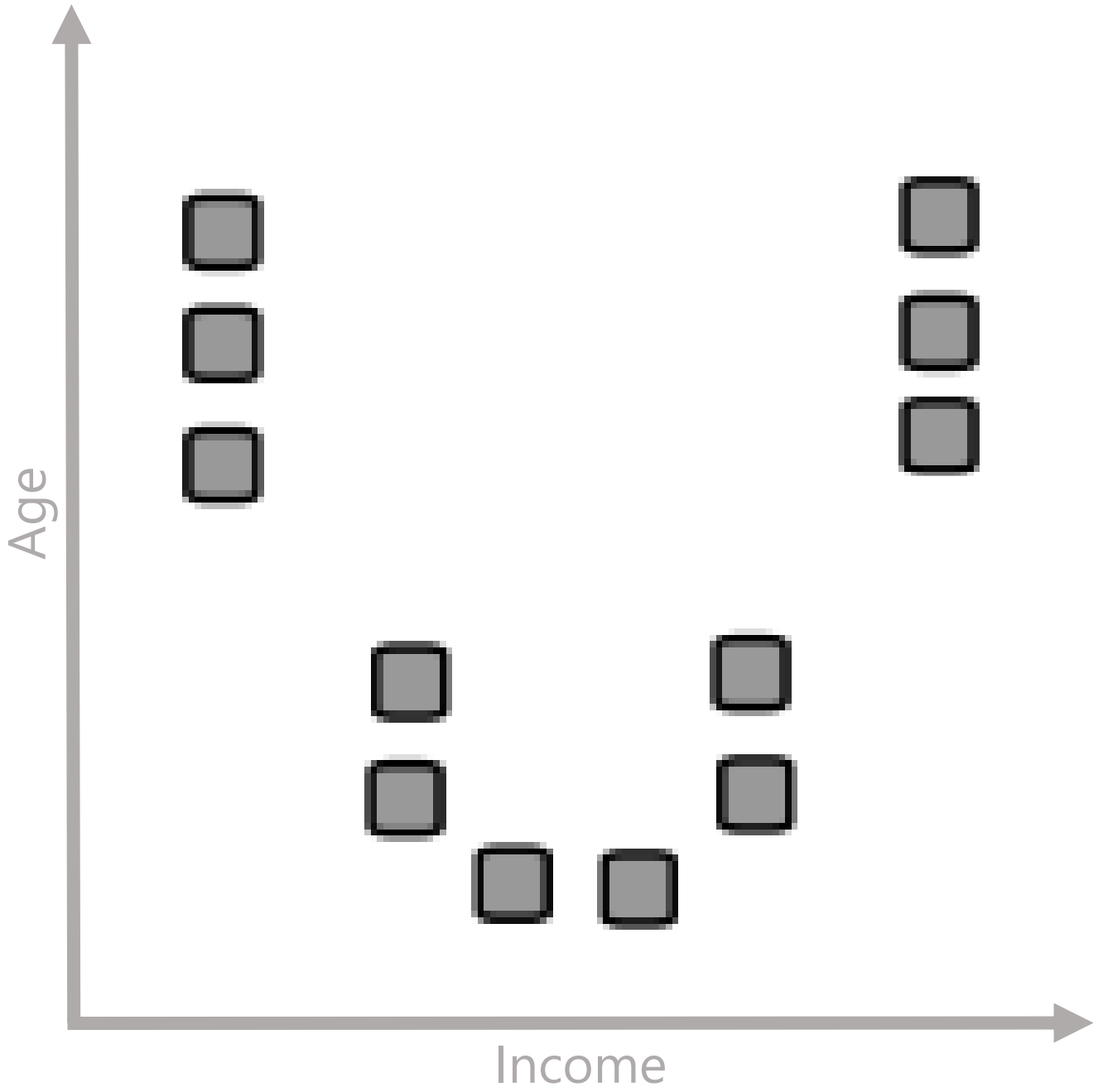
K-means

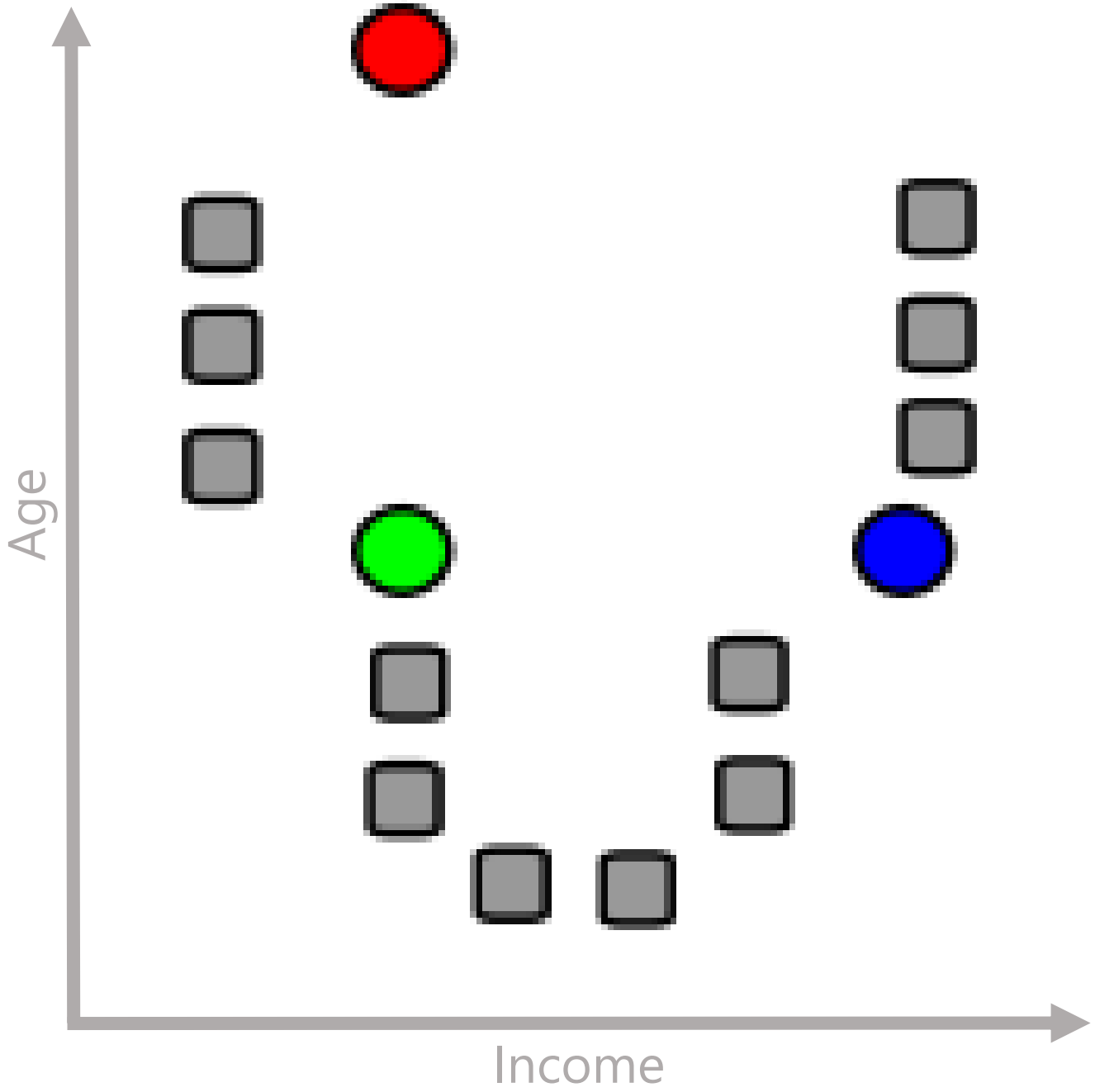
Hierarchical clustering

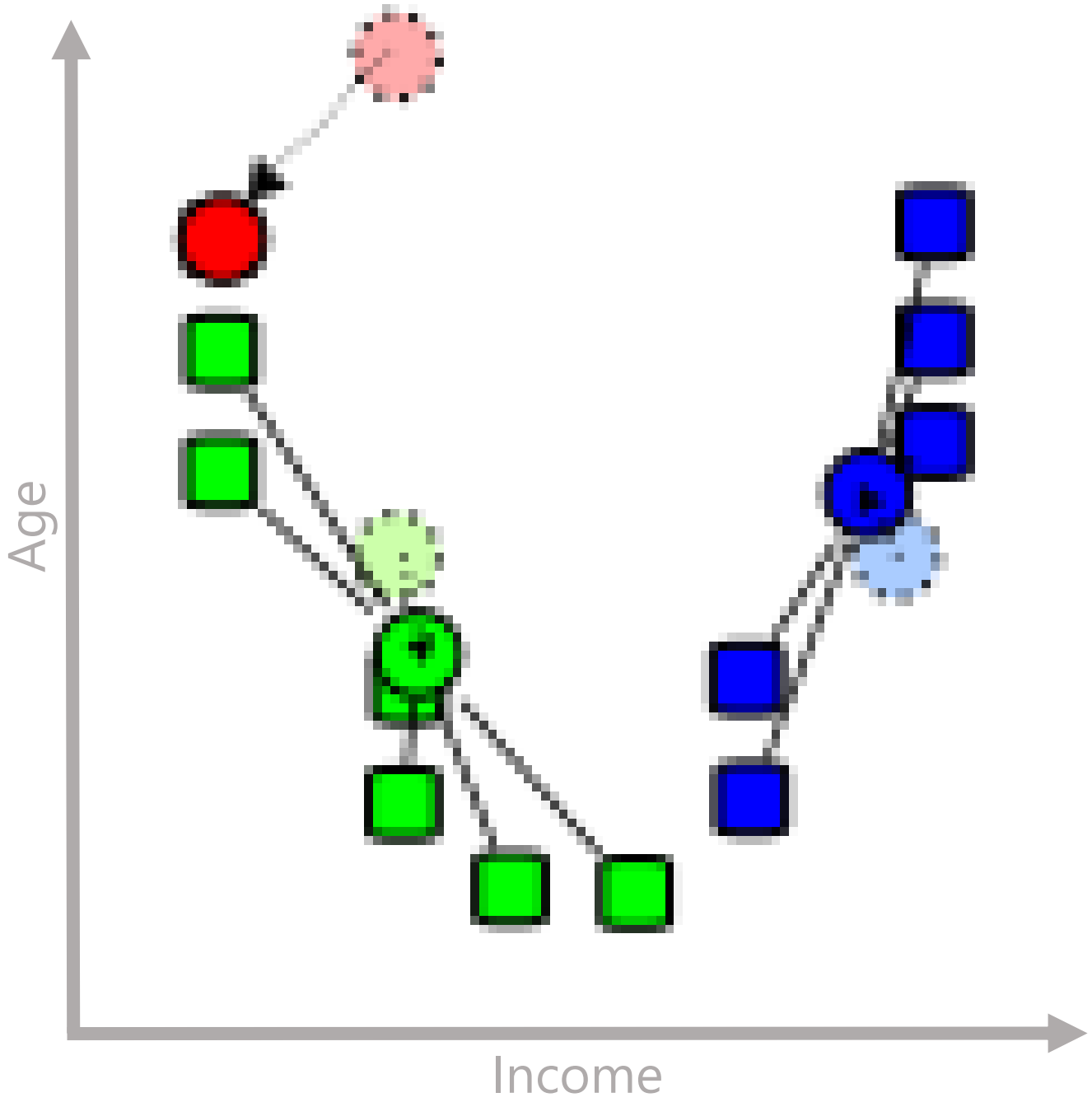
Expectation maximization

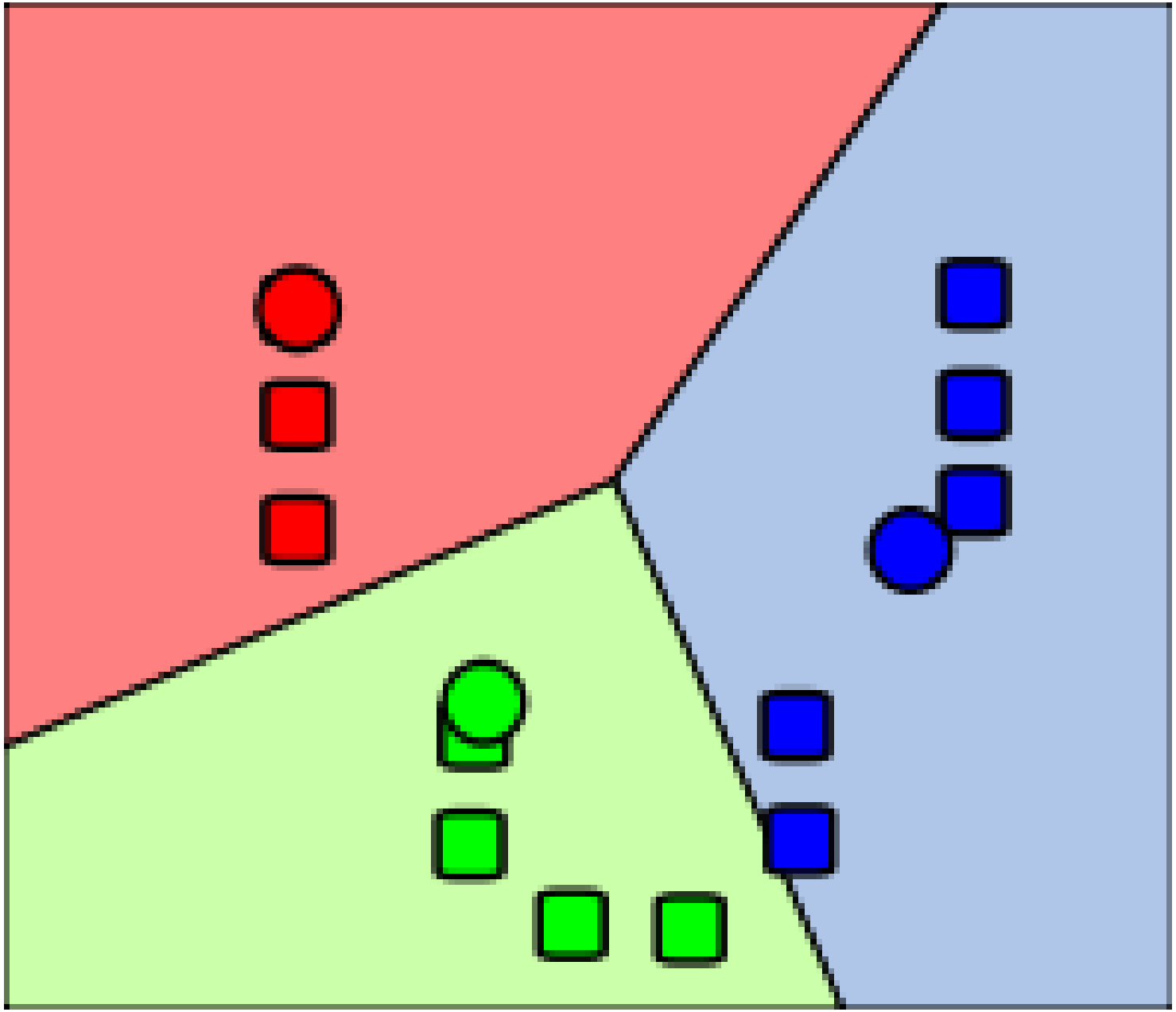


k-Means Clustering


Age
Income

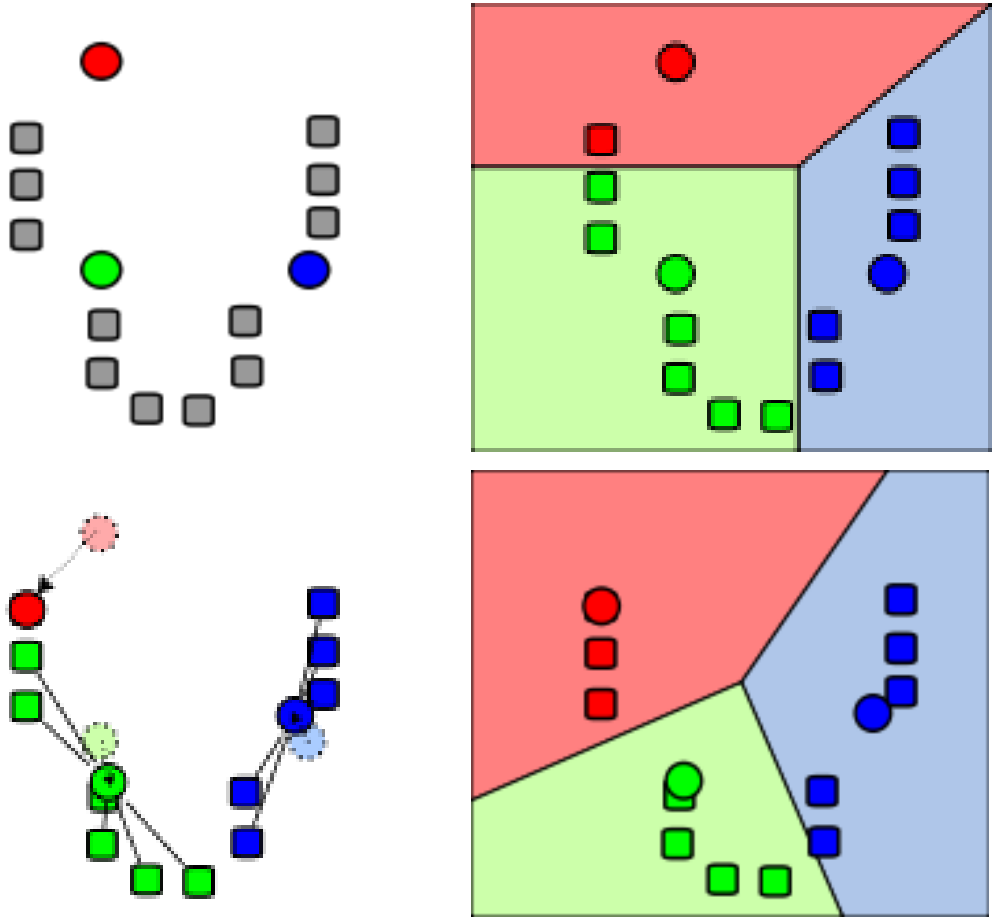

Age
Income


Age
Income



k-Means Clustering

Unsupervised learning

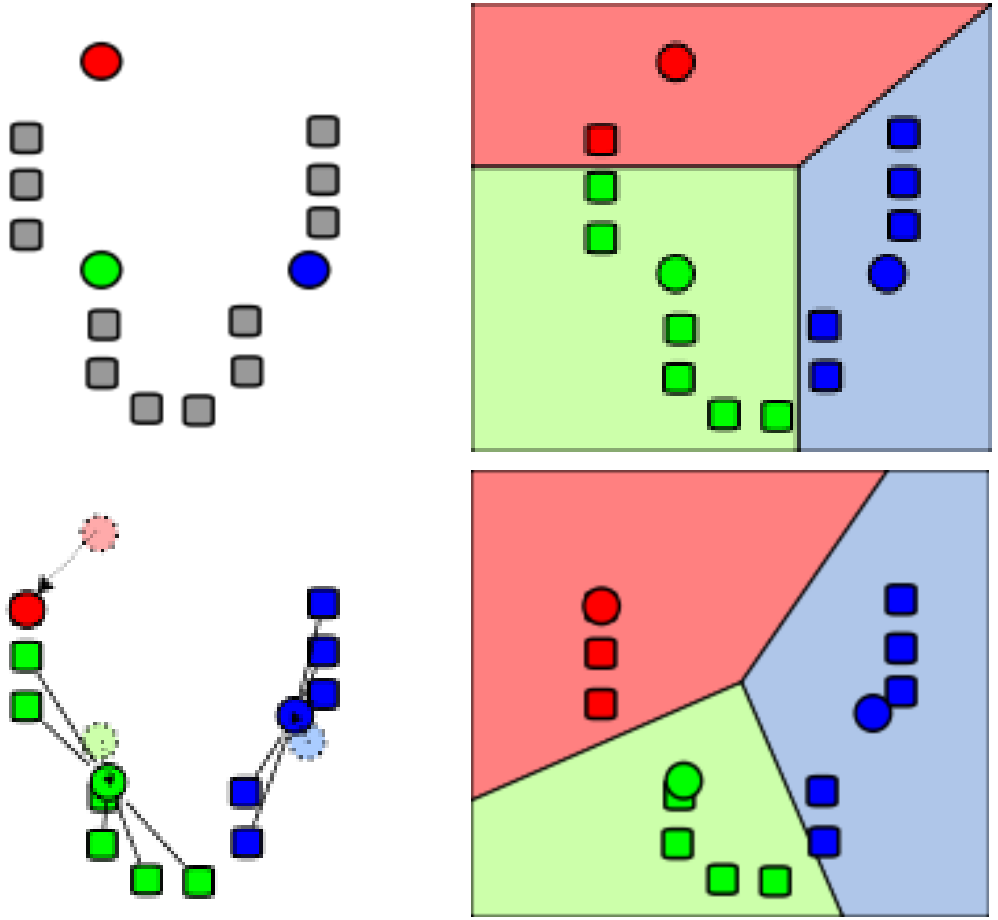


Source: Wikipedia

k-Means Clustering

Unsupervised learning

Specify k (# of clusters)



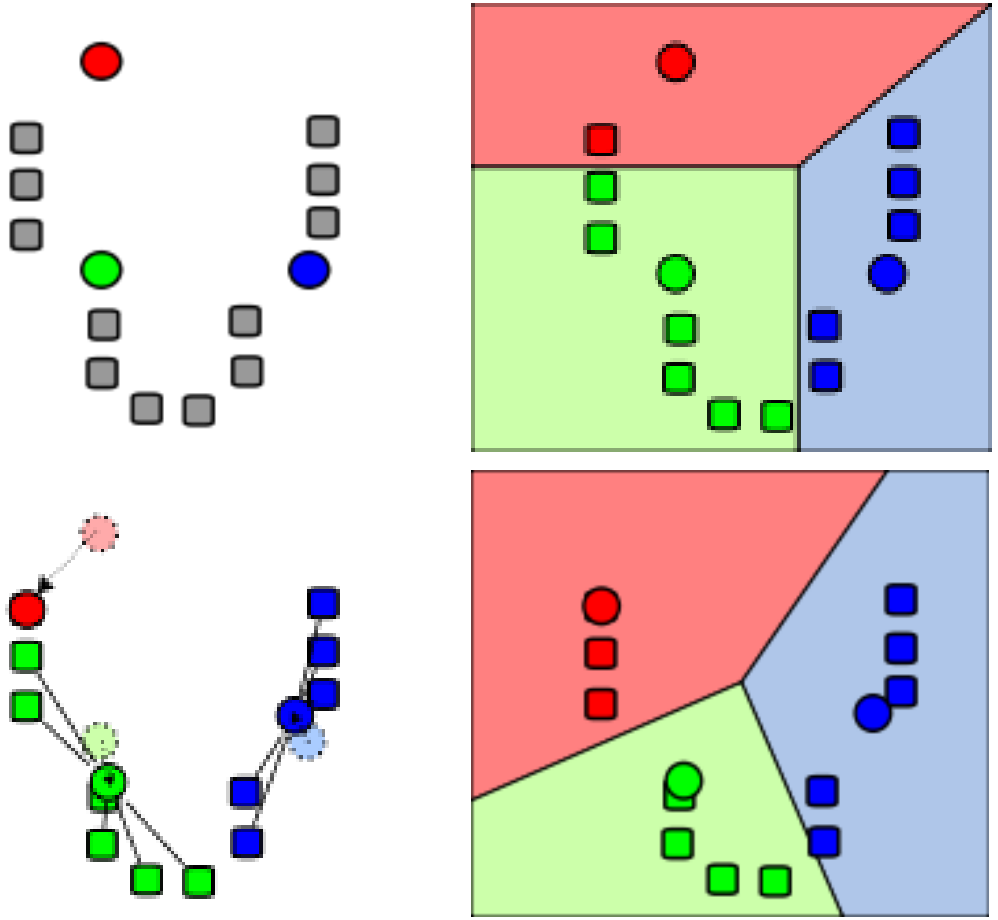
Source: Wikipedia

k-Means Clustering

Unsupervised learning

Specify k (# of clusters)

Algorithm finds centers



Source: Wikipedia

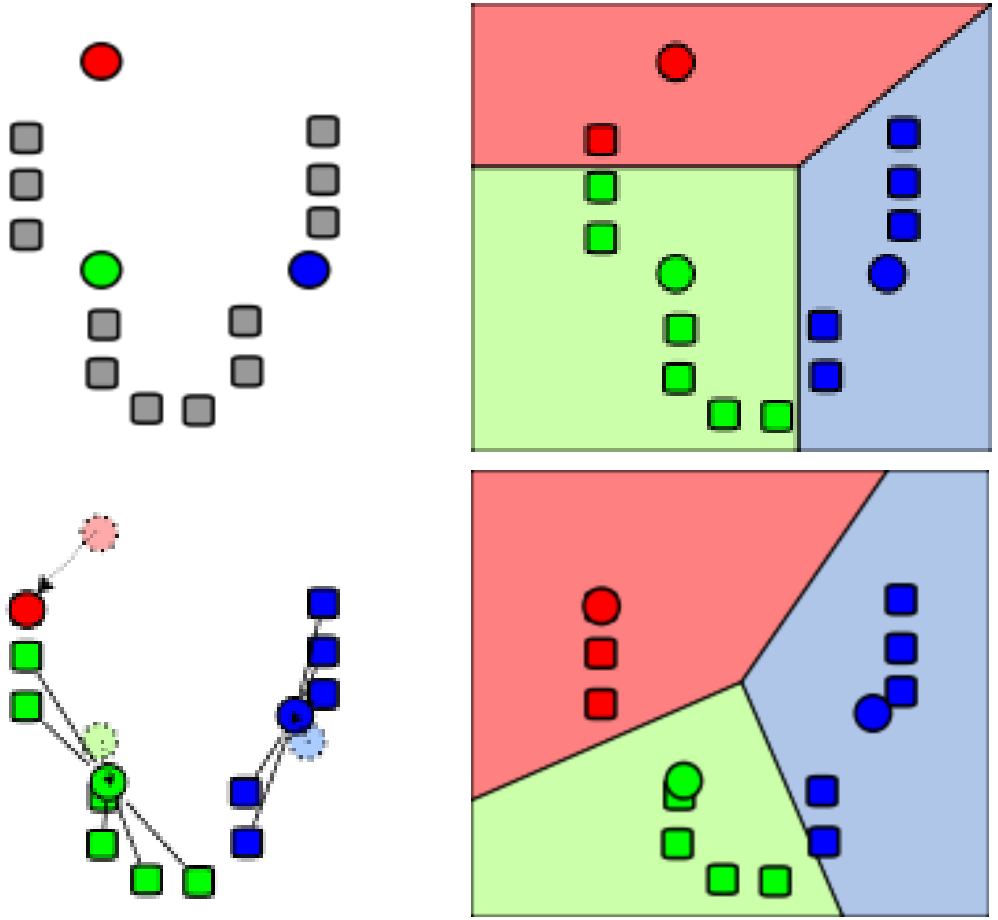
k-Means Clustering

Unsupervised learning

Specify k (# of clusters)

Algorithm finds centers

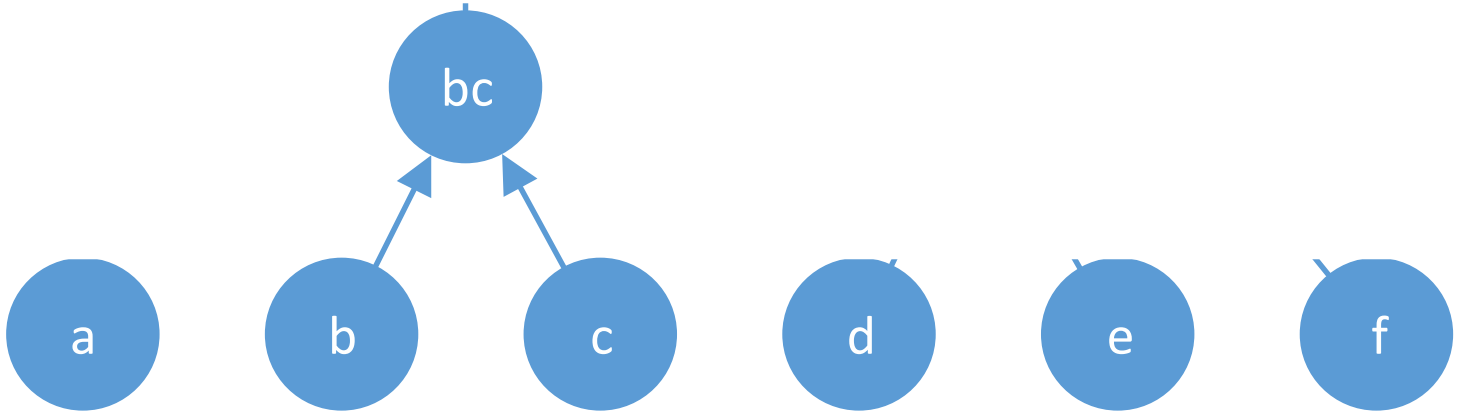
Random restarts

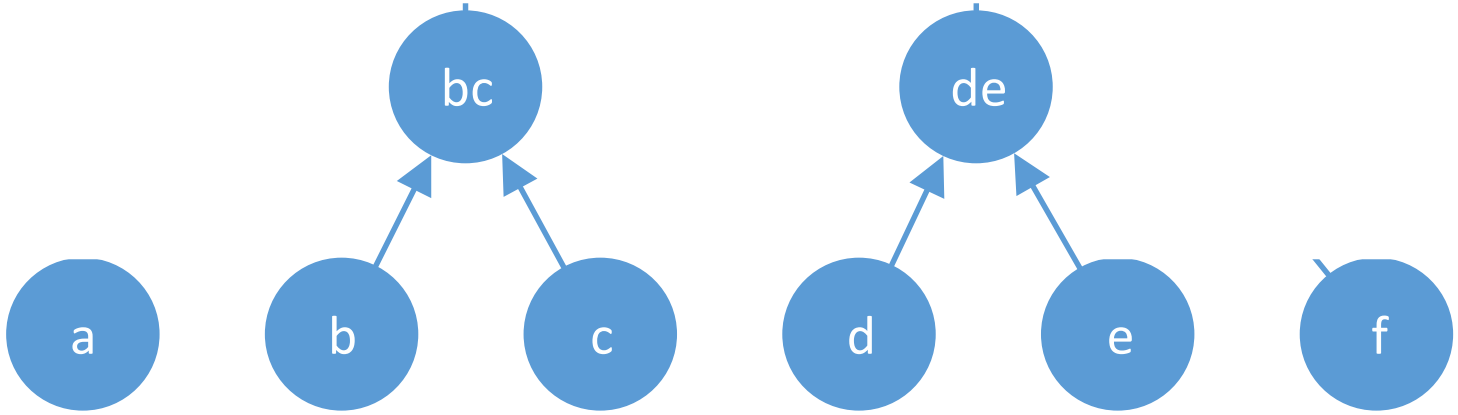


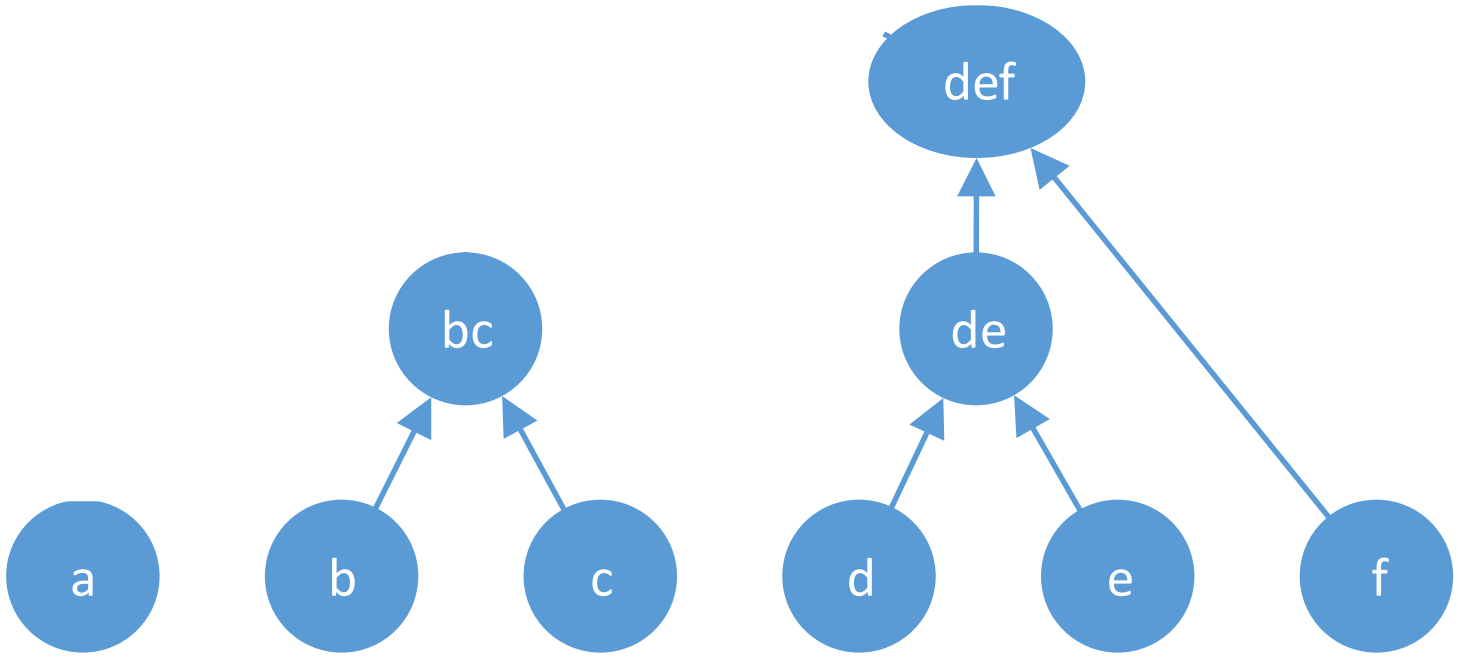
Source: Wikipedia

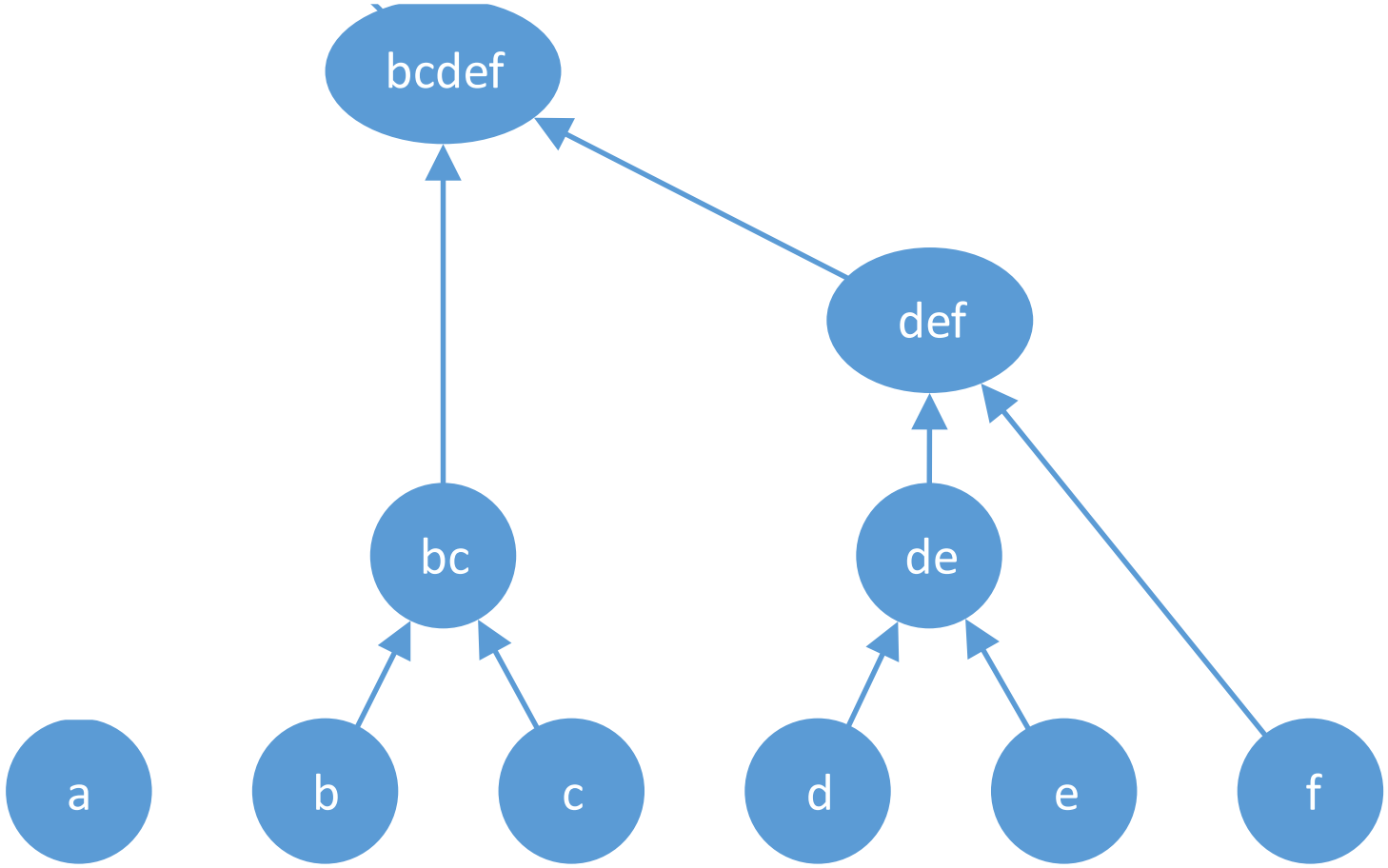
Hierarchical Clustering

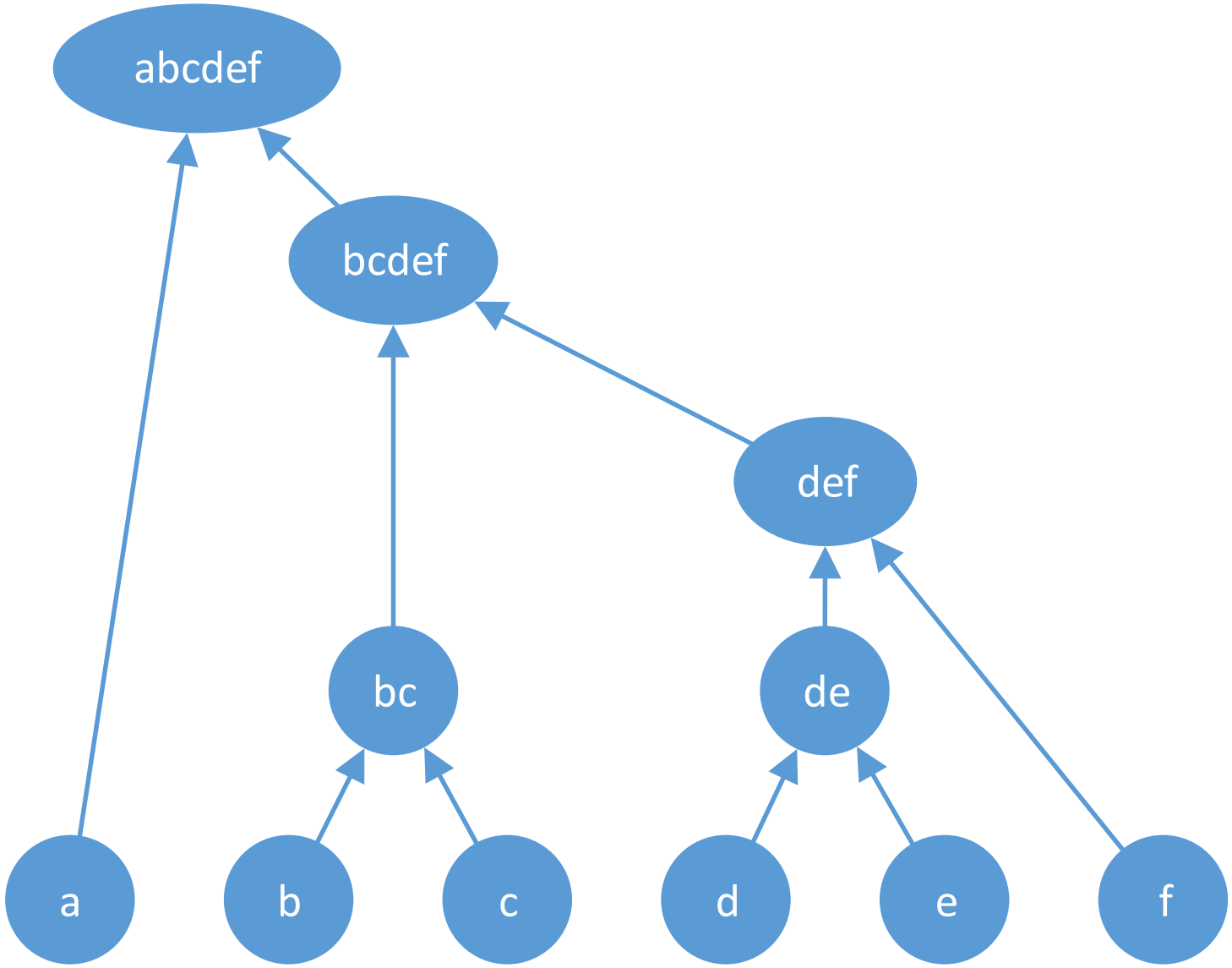

a
b
c
d
e
f

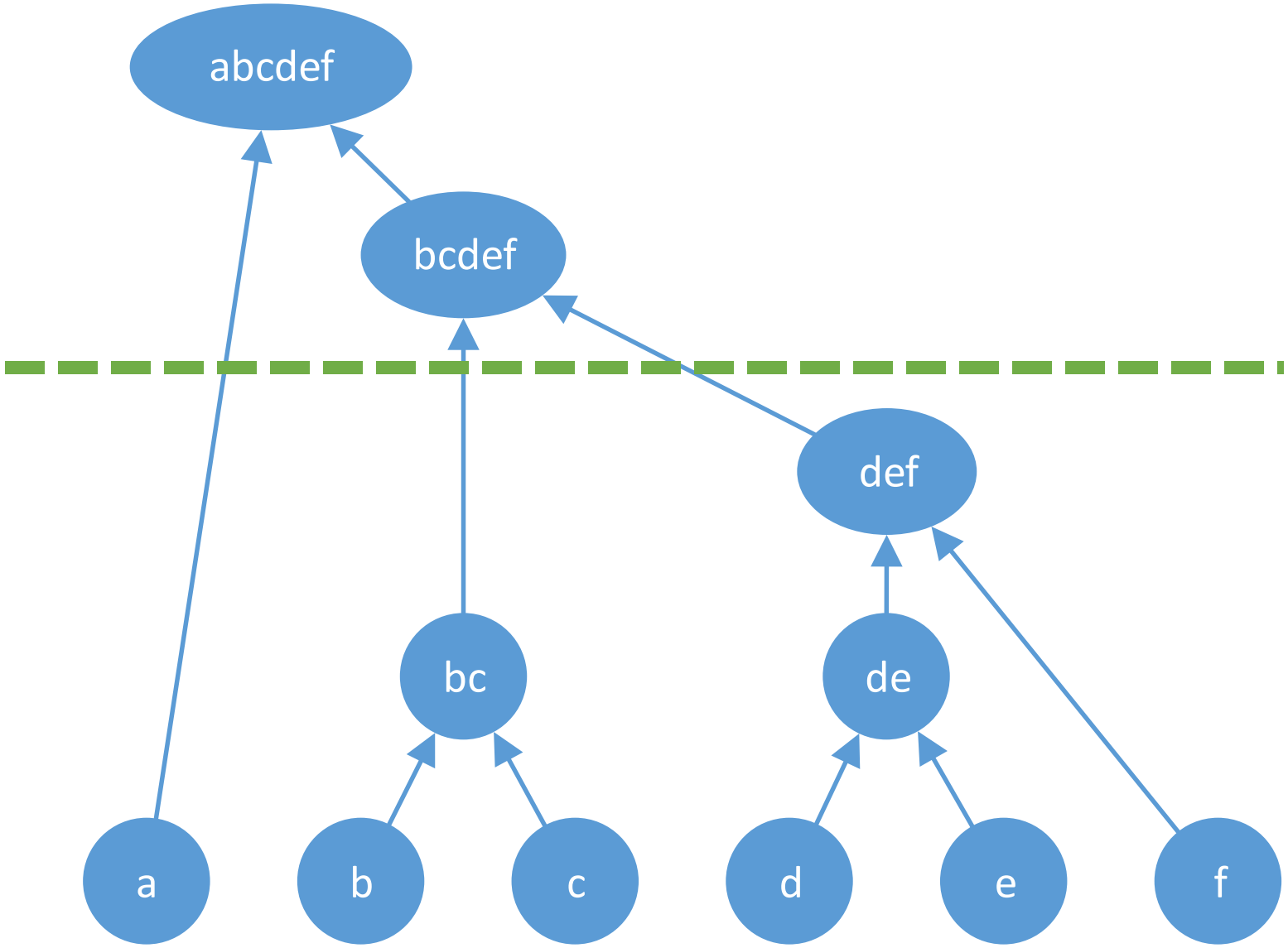

bc
a
b
c
d
e
f


bc
de
a
b
c
d
e
f


def
bc
de
a
b
c
d
e
f

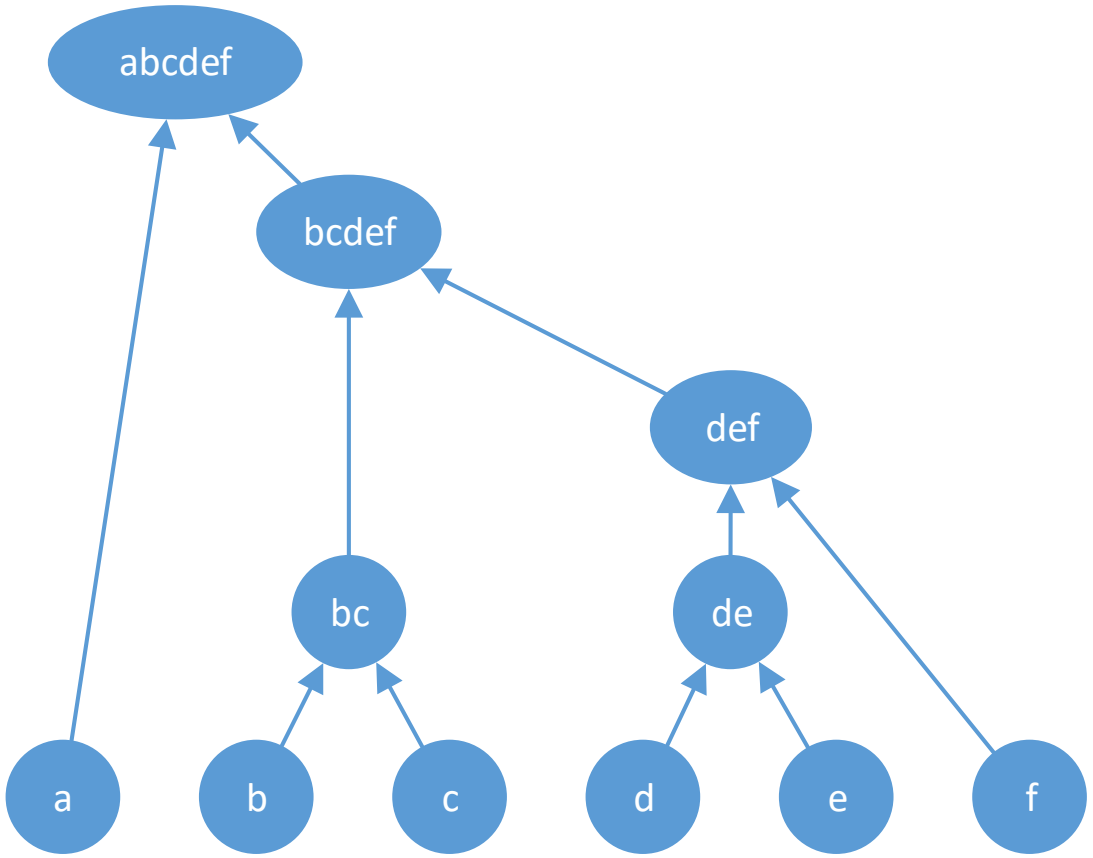

bcdef
def
bc
de
a
b
c
d
e
f


abcdef
bcdef
def
bc
de
a
b
c
d
e
f


abcdef
bcdef
def
bc
de
a
b
c
d
e
f

Hierarchical Clustering

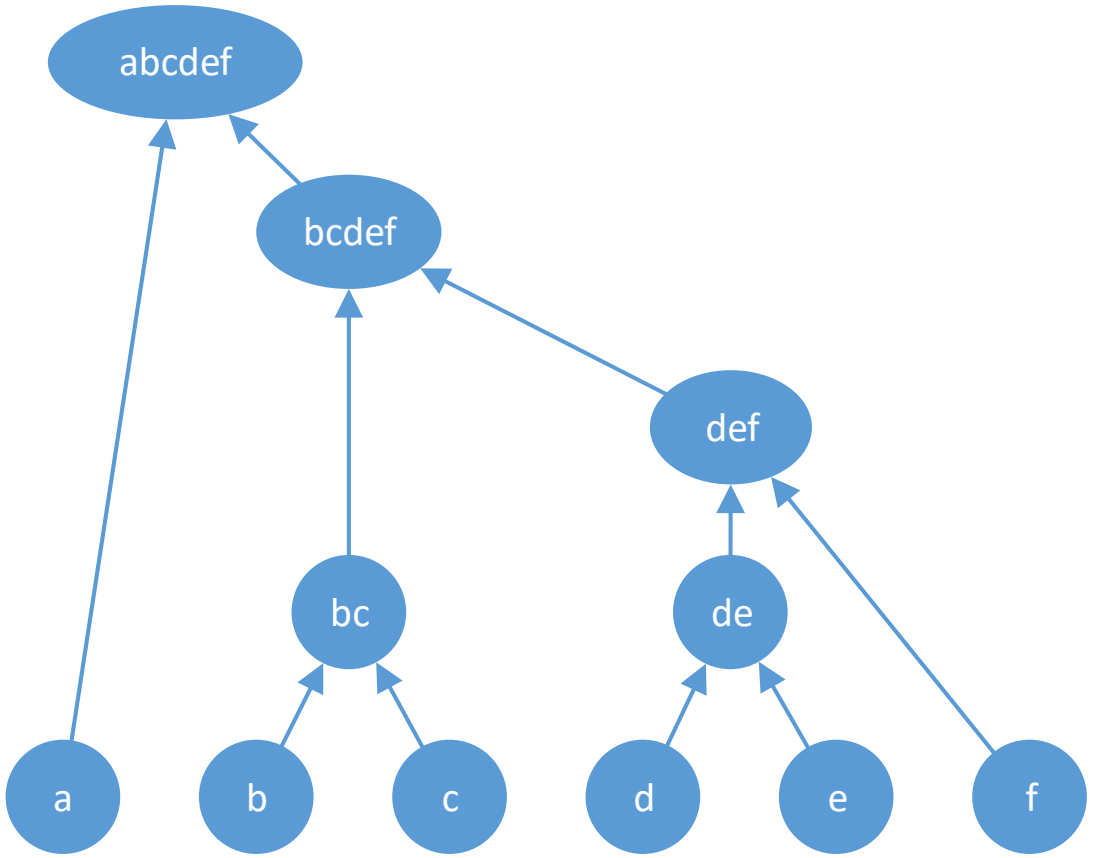
Unsupervised learning



Hierarchical Clustering

Unsupervised learning

Tree of connectedness

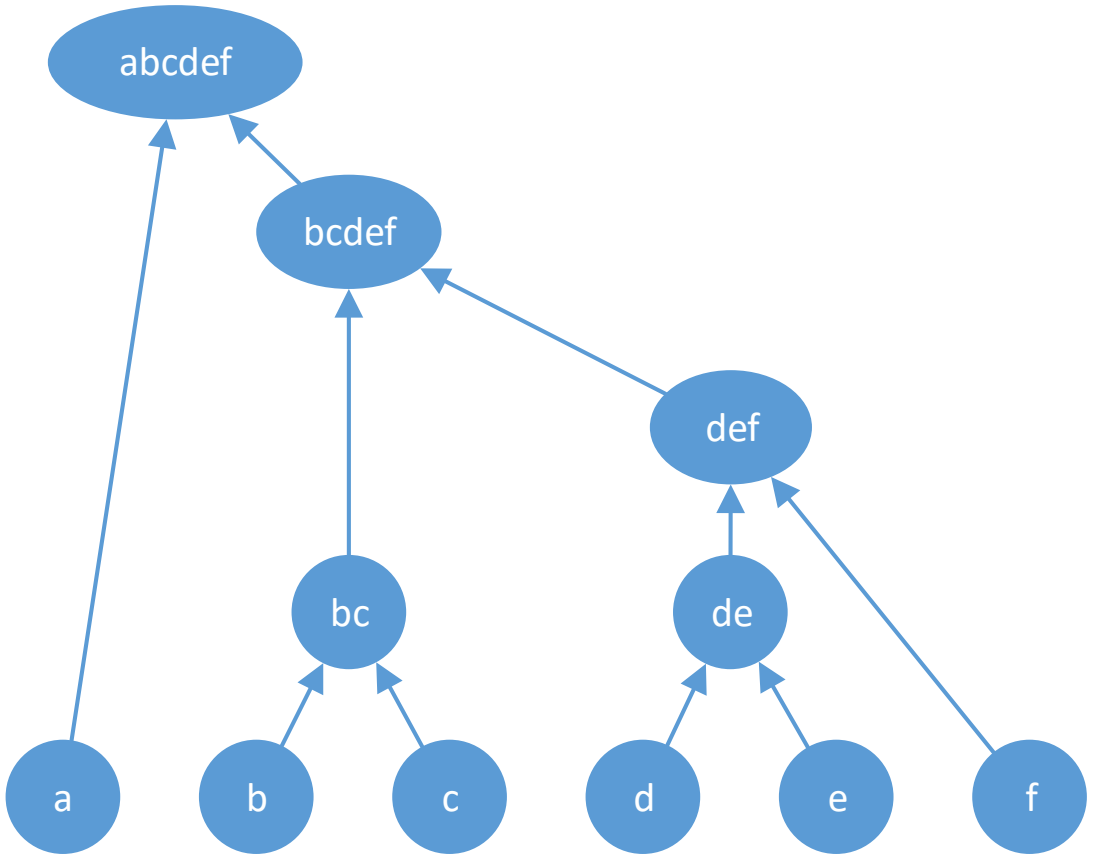


Hierarchical Clustering

Unsupervised learning

Tree of connectedness

Cuts create clusters

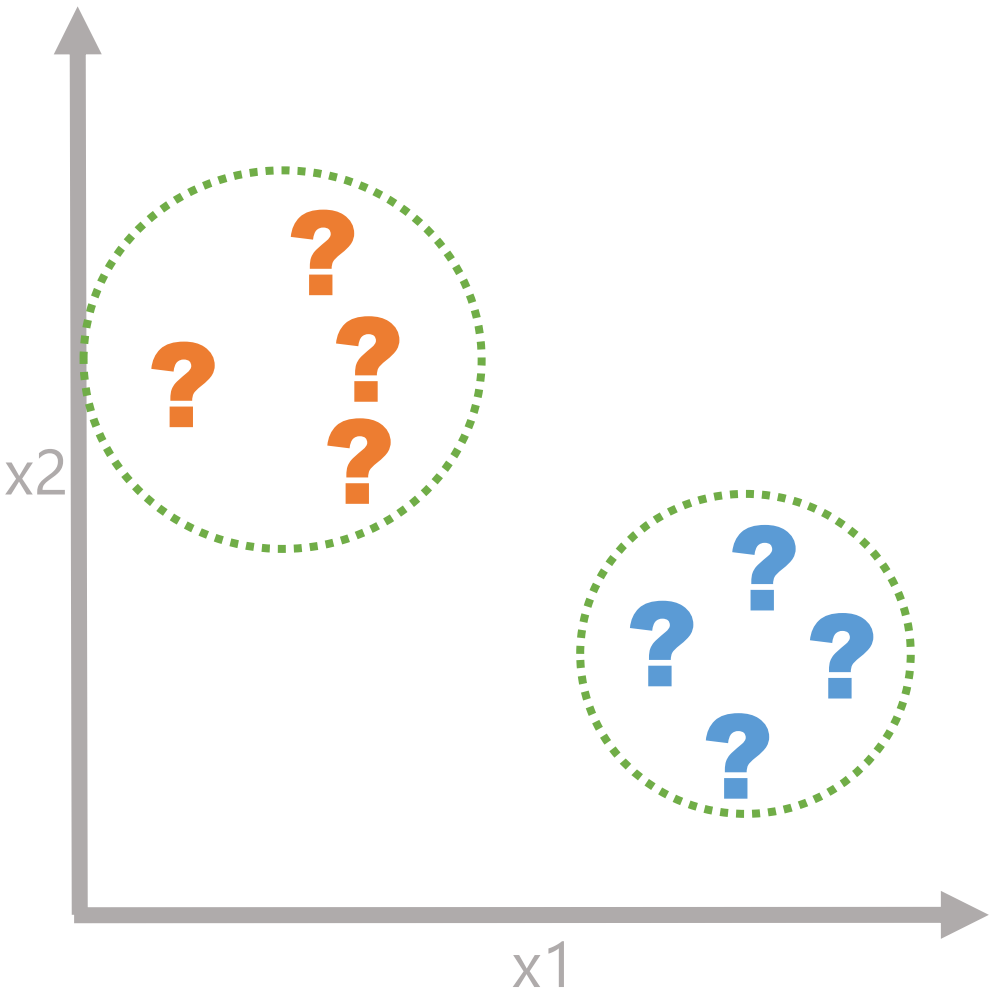


Real-world Examples

What are our market segments?

How to group our documents?

Which products to recommend?



Demo 4 - Clustering

Goal: Group flowers by similarity

Lab 4A – Clustering (Easy)

Goal: Group flowers by similarity

Lab 4B – Clustering (Hard)

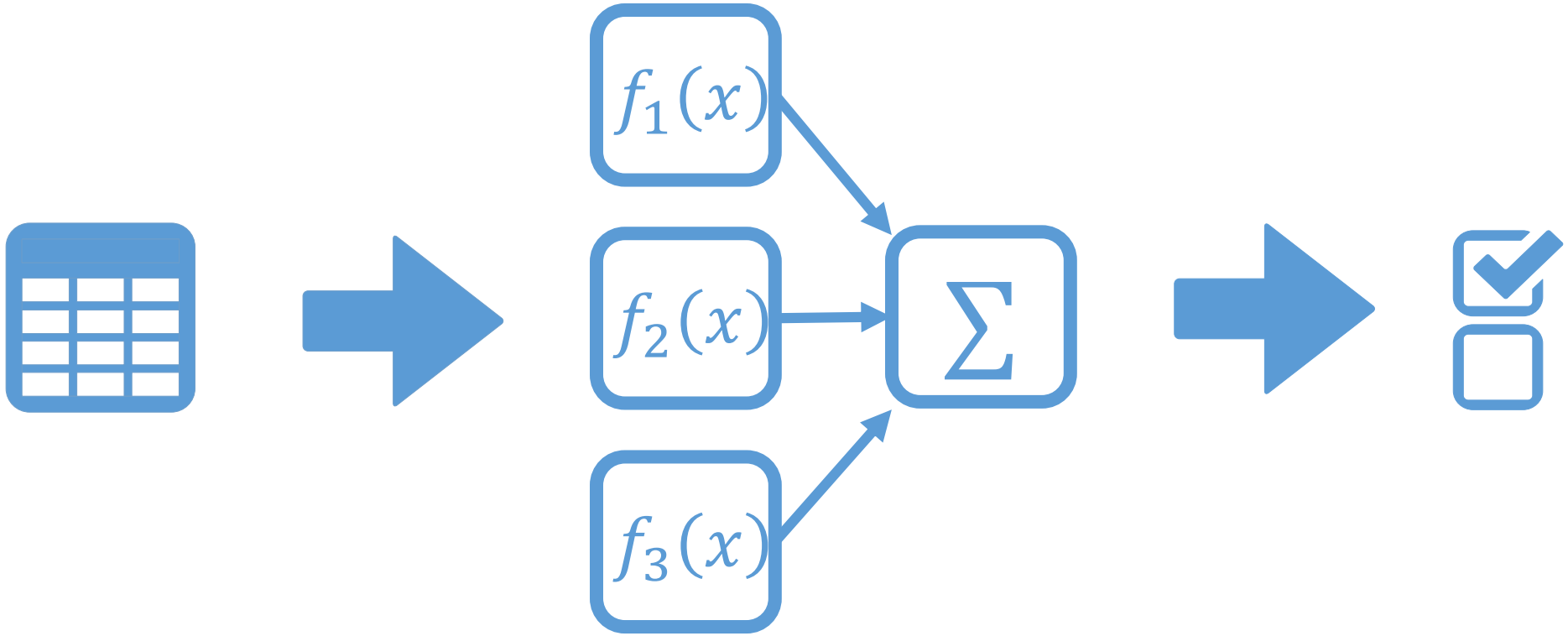
Goal: Group insurance policies

Ensemble Learning

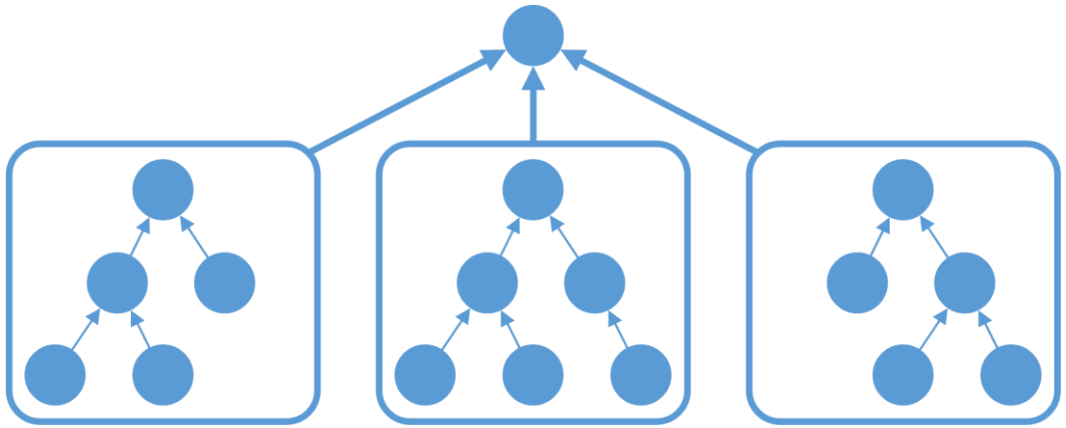
Wisdom of the Crowds


HOORAY! OUR SPORTS TEAM WON!
LET'S CELEBRATE
BY DESTROYING OUR OWN CITY!

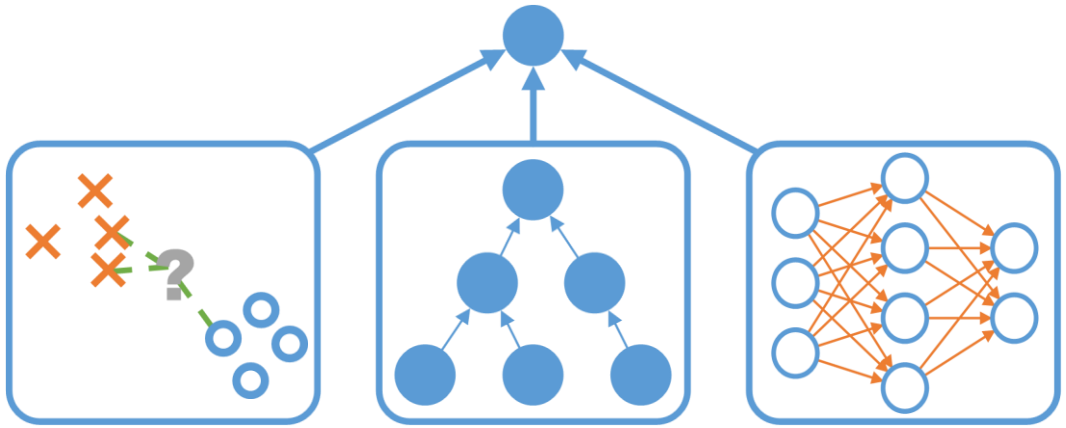
Ensemble Learning



Types of Ensembles



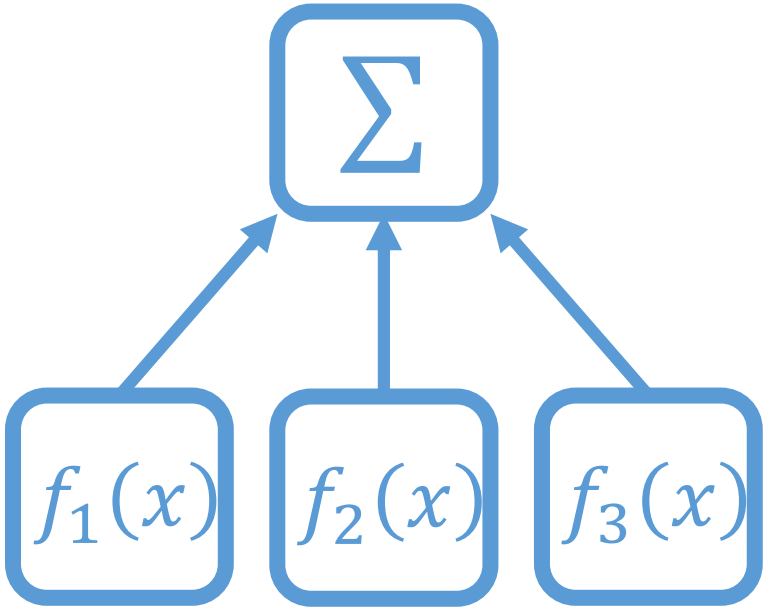
Same Type of Model



Different Types of Models

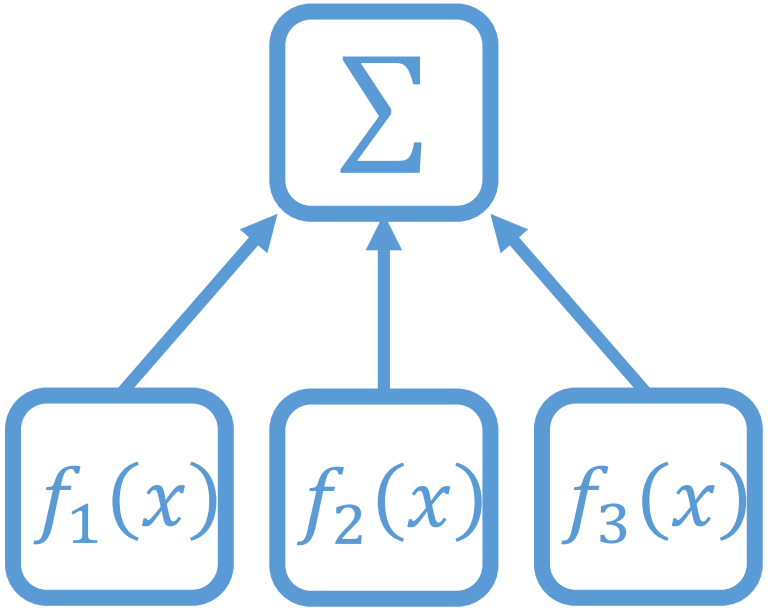
Ensemble Creation Techniques

Bagging
Boosting
Stacking

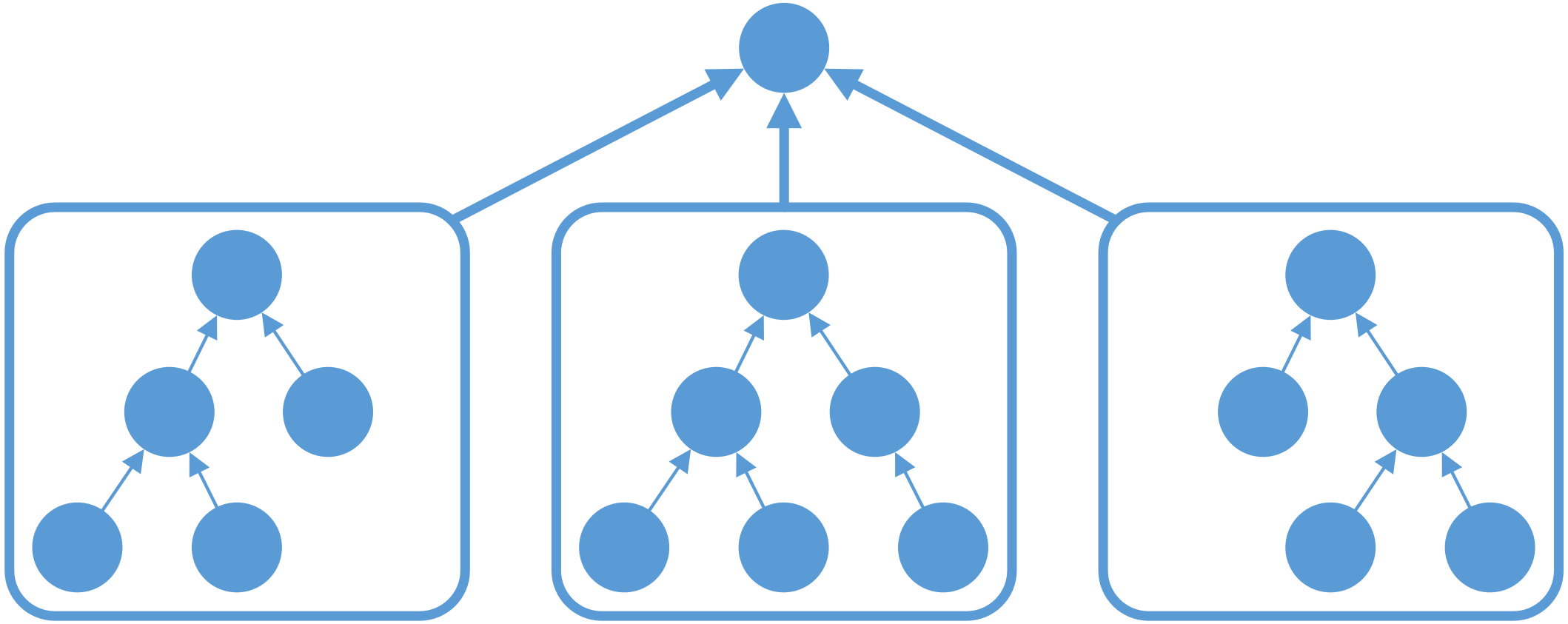


Ensemble Aggregation Techniques

Averaging
Majority Vote
Weighted Average
Weighted Majority Vote

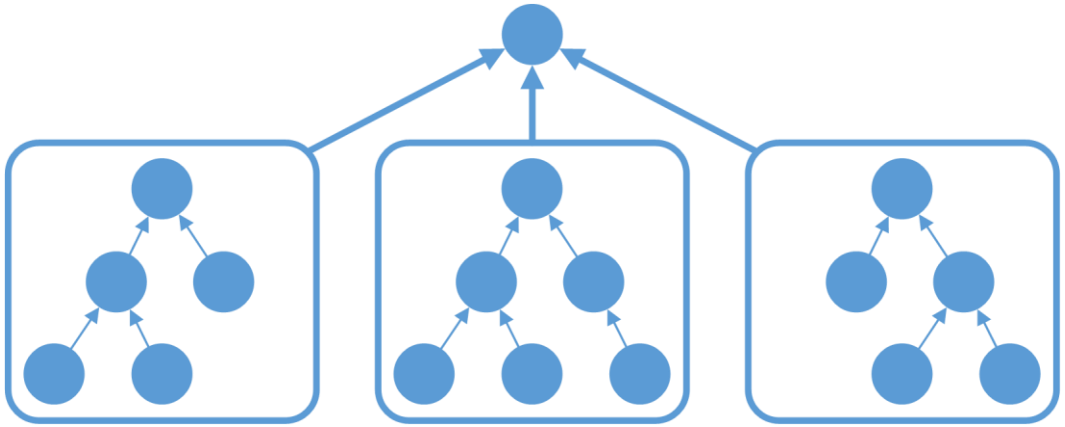


Random Forest Classifier



Random Forest Classifier

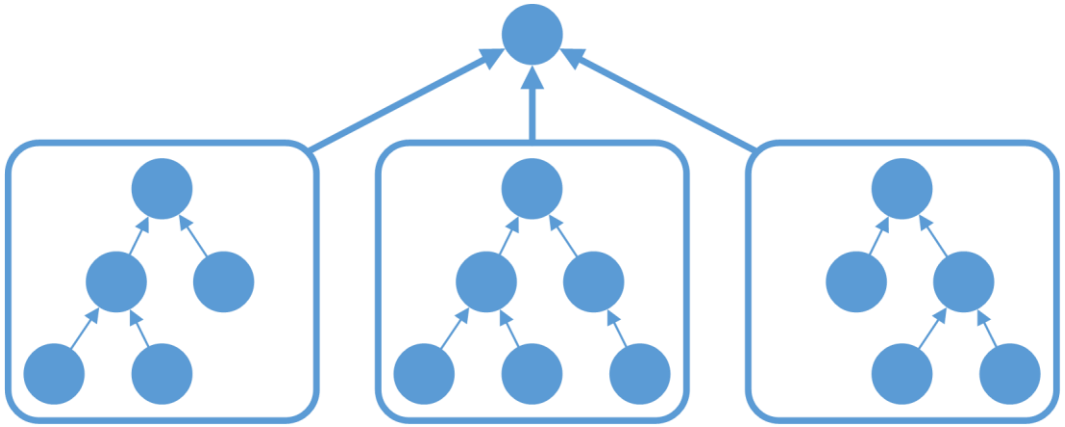
Multiple trees



Random Forest Classifier

Multiple trees

Created by bagging

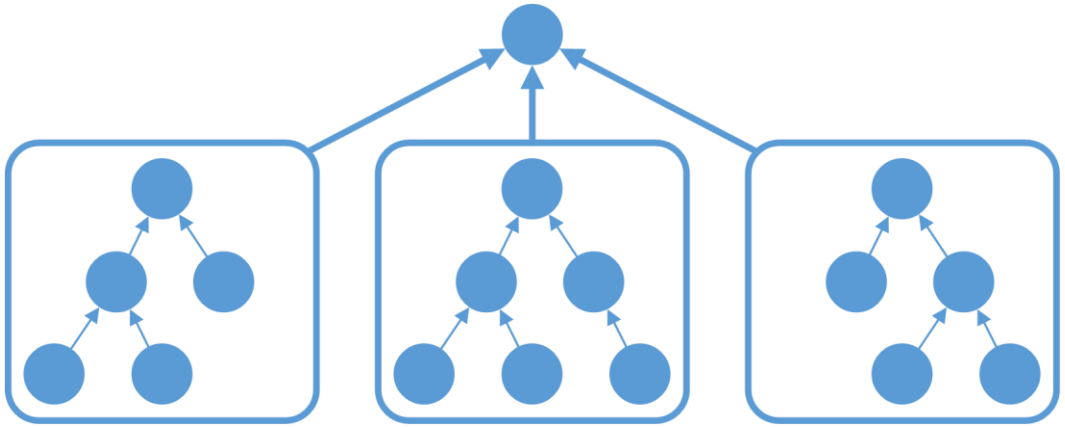


Random Forest Classifier

Multiple trees

Created by bagging

Majority vote



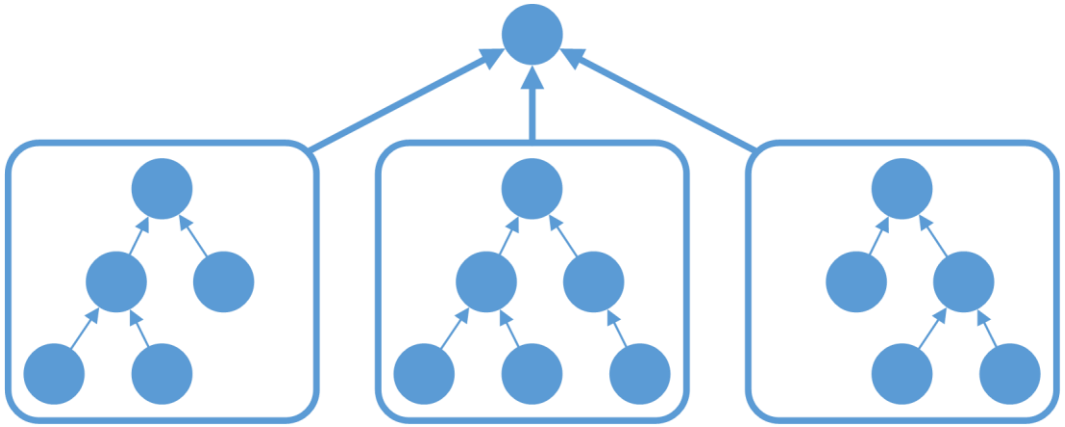
Random Forest Classifier

Multiple trees

Created by bagging

Majority vote

More robust



Why Use Ensemble Learning?

Pros

More accurate

More robust

More stable

Why Use Ensemble Learning?

Pros

More accurate

More robust

More stable

Cons

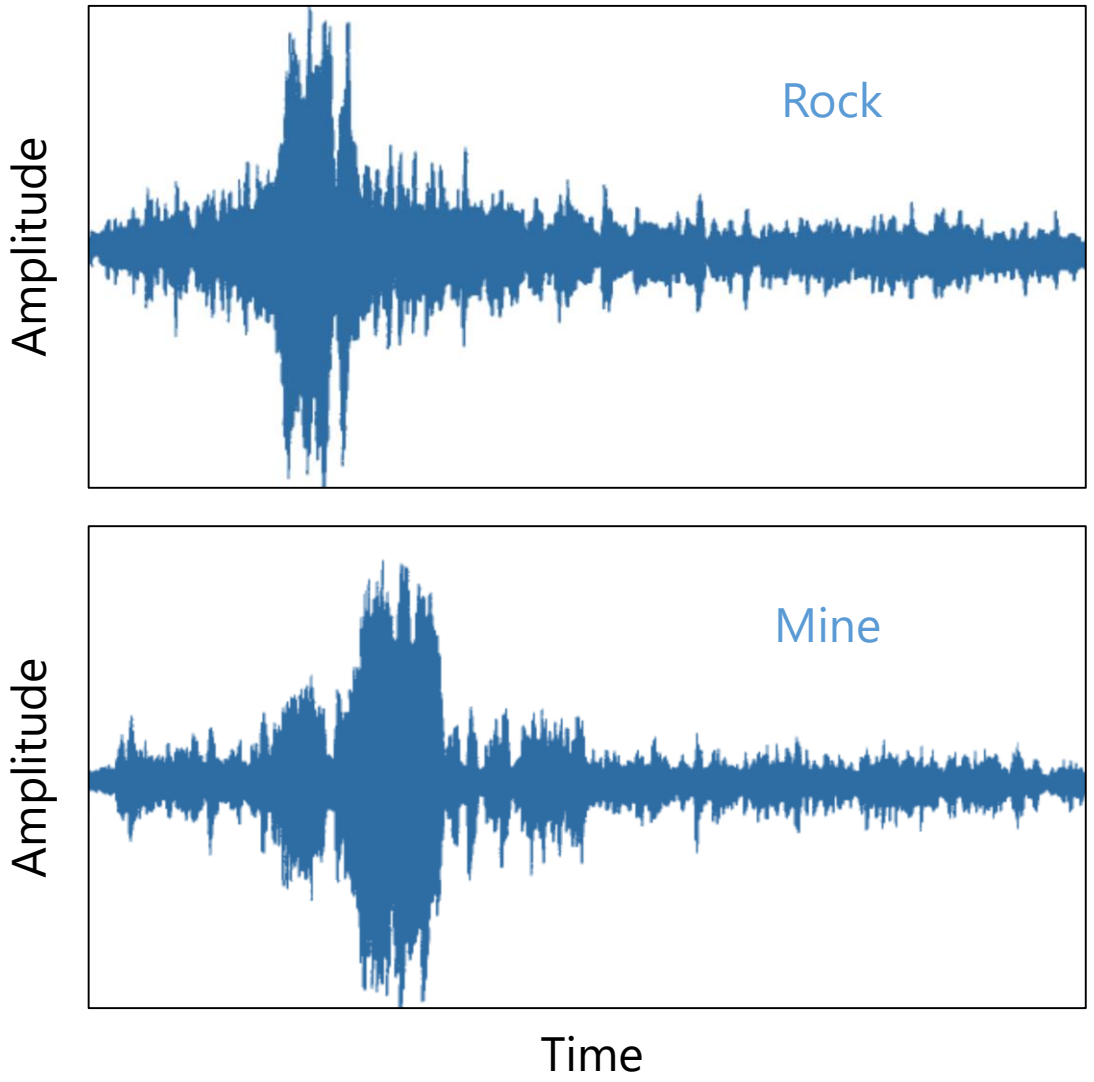
More complex

More CPU time

More art than science

Ensemble Learning Demo


8


Rock
Amplitude
Mine
Amplitude
Time

Sonar							
V1	V2	V3	…	V58	V59	V60	Class
0.02	0.03	0.04	…	0.00	0.01	0.00	rock
0.04	0.05	0.08	…	0.00	0.01	0.00	mine
0.02	0.05	0.10	…	0.01	0.01	0.01	rock
0.01	0.01	0.06	…	0.00	0.00	0.01	rock
0.07	0.06	0.04	…	0.00	0.01	0.01	mine
0.02	0.04	0.02	…	0.00	0.01	0.00	rock
…	…	…	…	…	…	…	…


Minesweeper
Game
Help

Demo 5 – ML in Practice

Goal: Predict rock or mine

Lab 5A – ML in Practice (Easy)

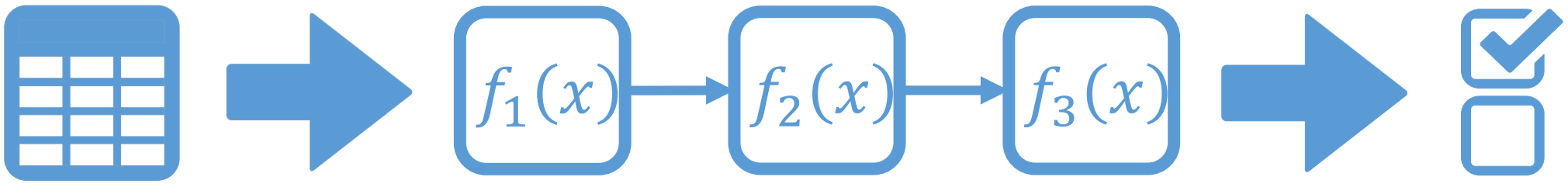
Goal: Predict rock or mine

Lab 5B – ML in Practice (Hard)

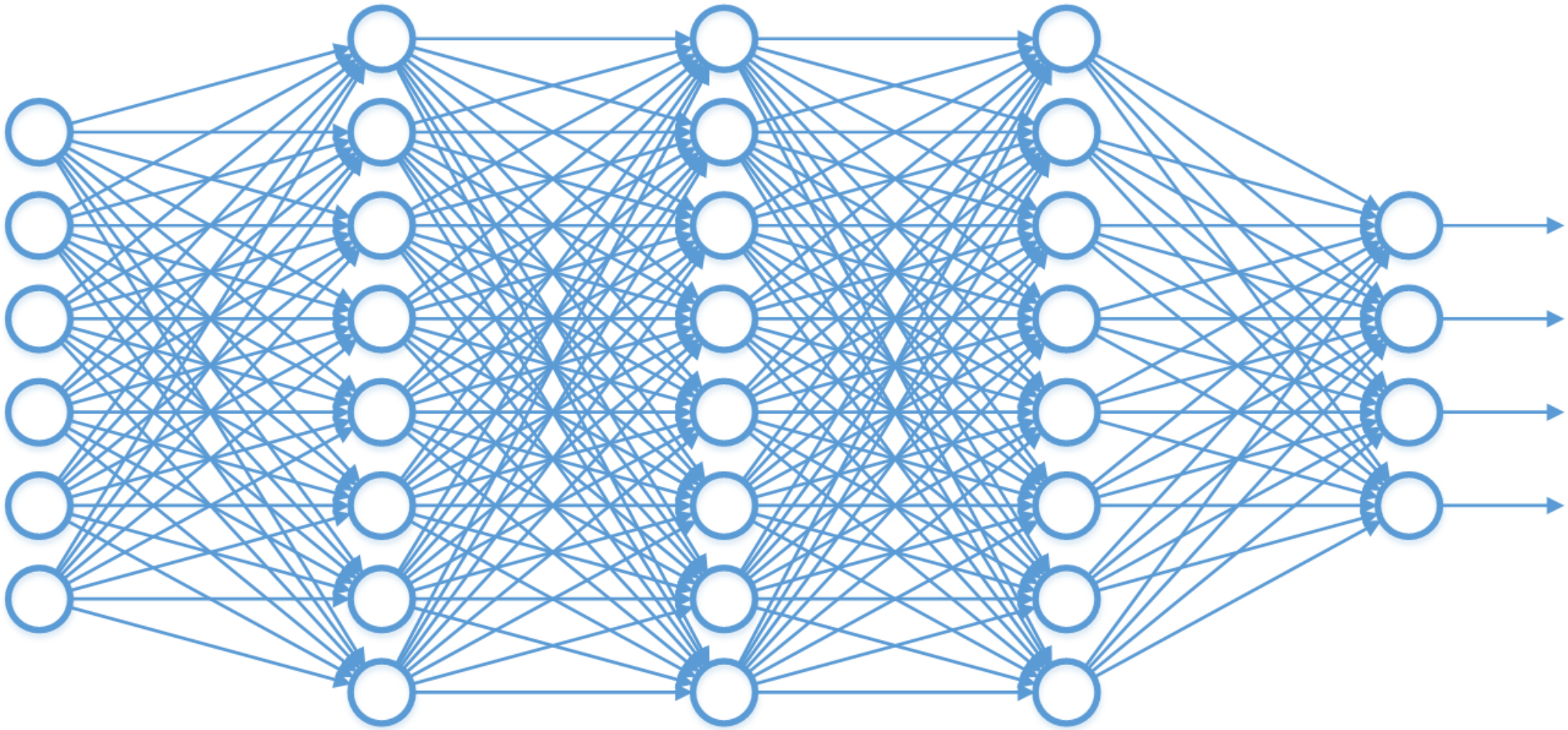
Goal: Predict risk class

Deep Learning

Deep Learning

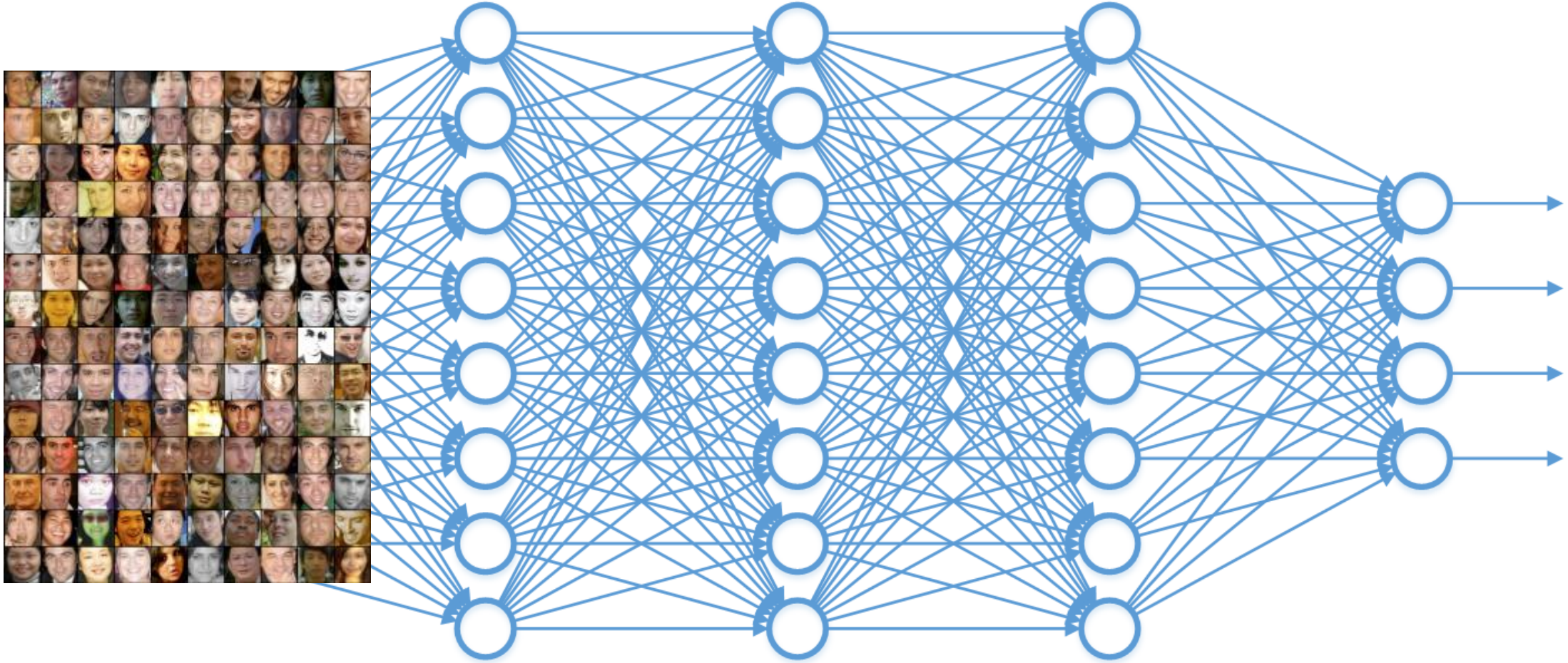


Deep Neural Network



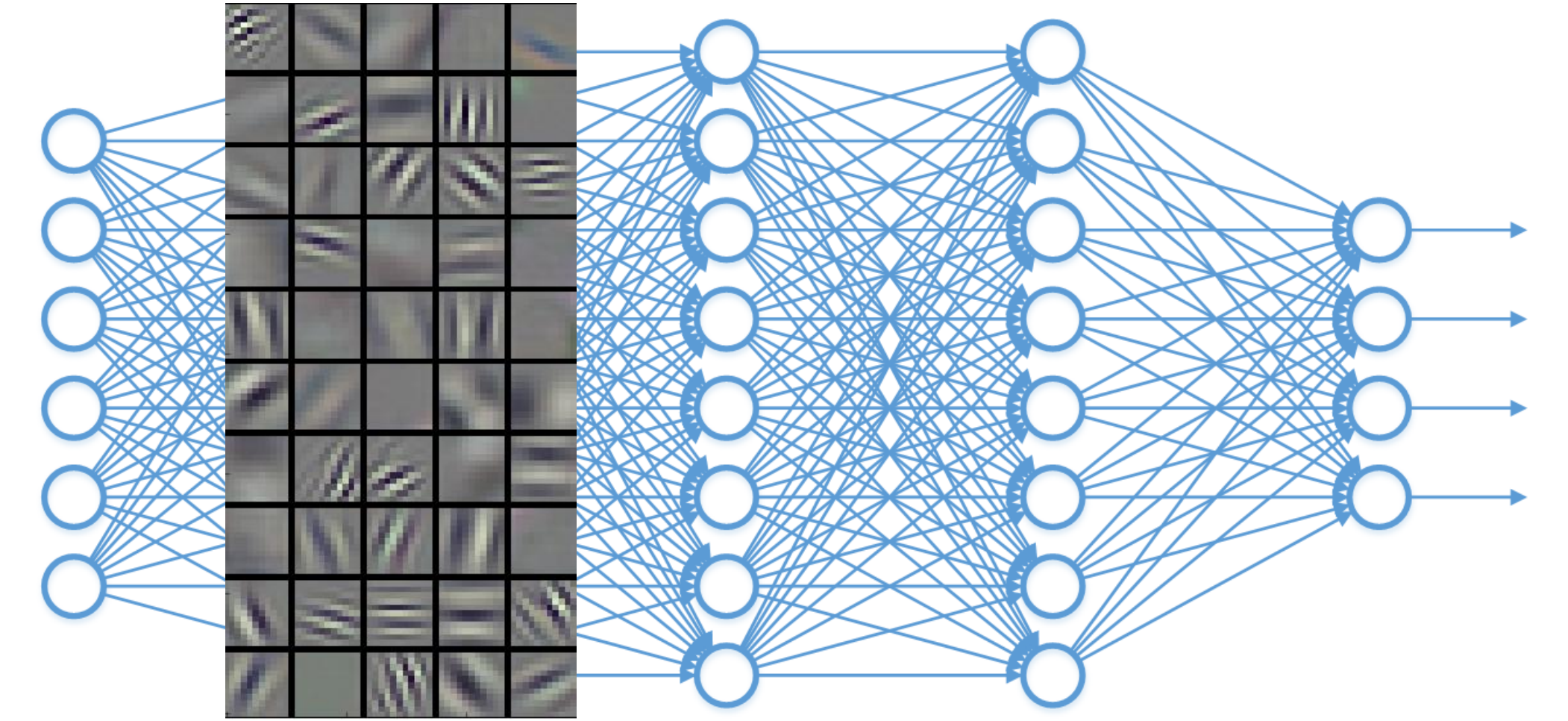
input hidden 1 hidden 2 hidden 3 output

Deep Neural Network

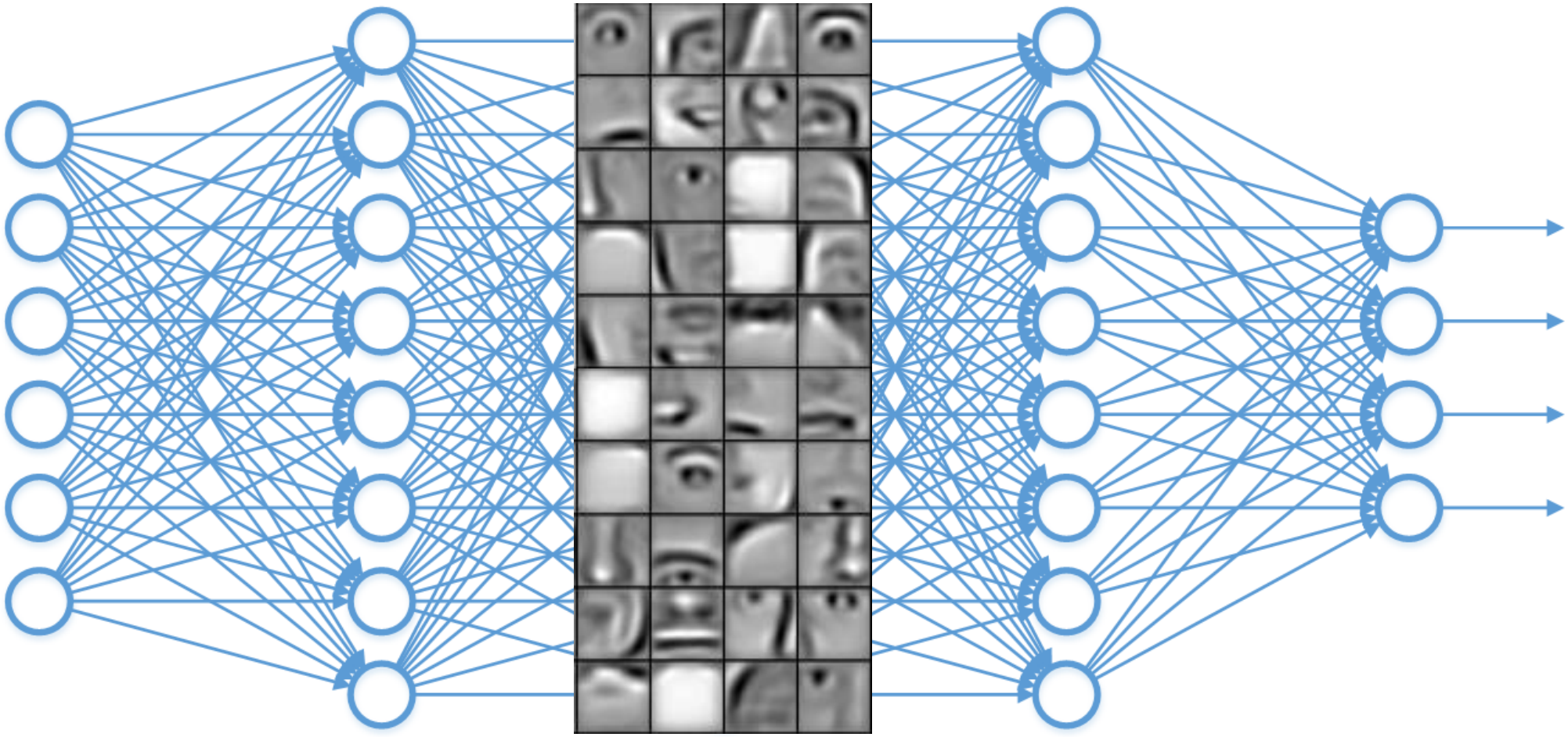


input hidden 1 hidden 2 hidden 3 output

Deep Neural Network

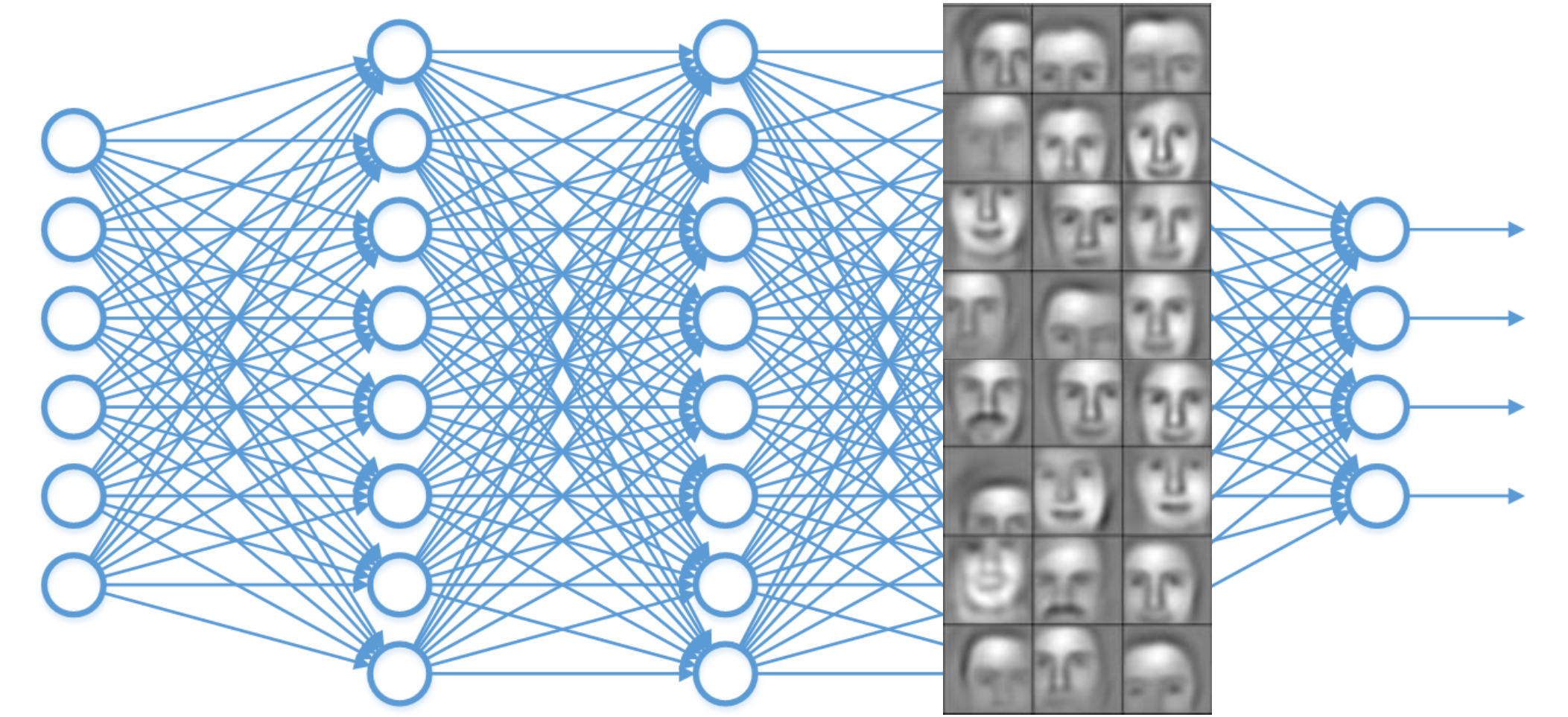


Deep Neural Network

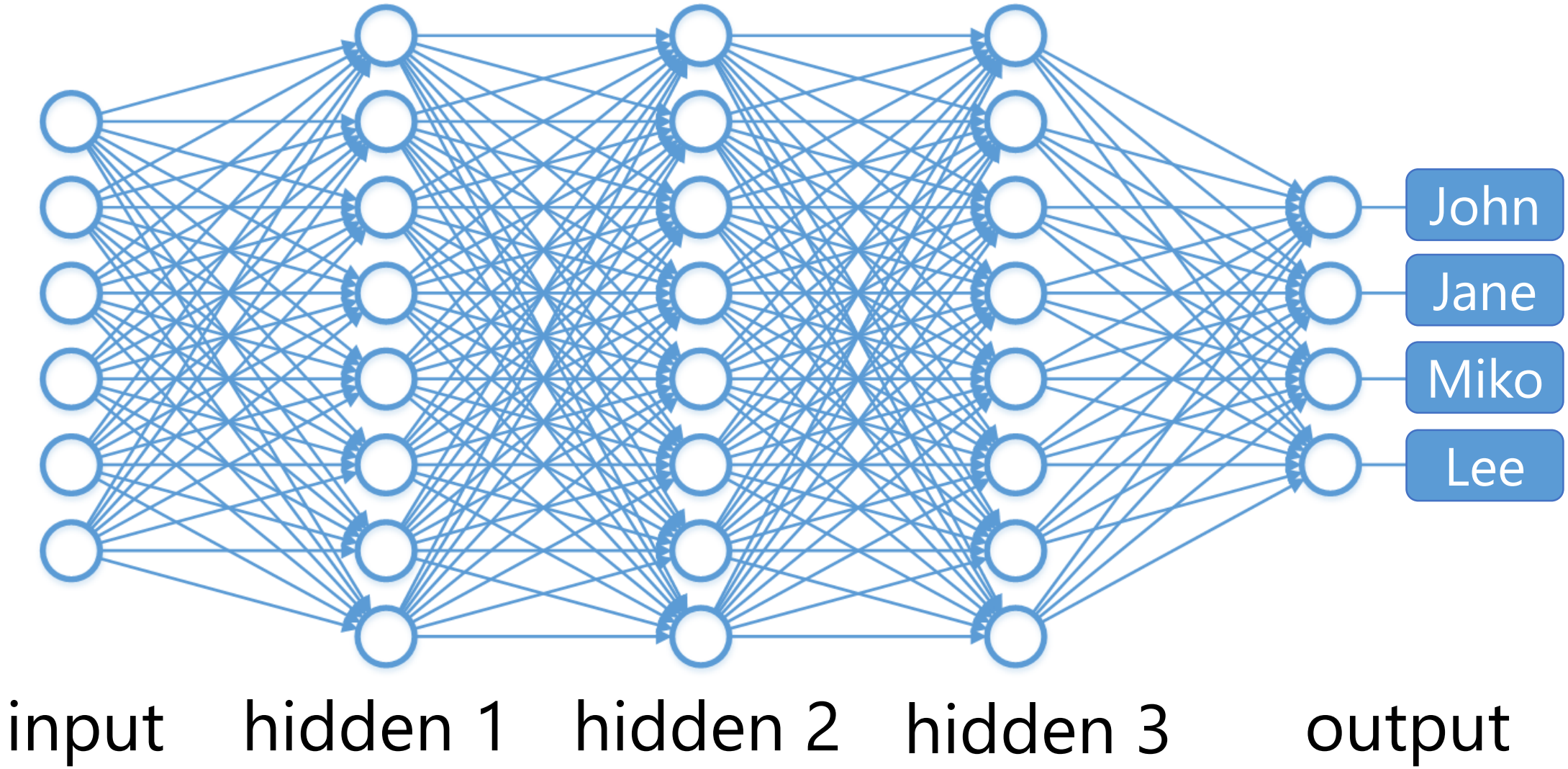


input hidden 1 hidden 2 hidden 3 output

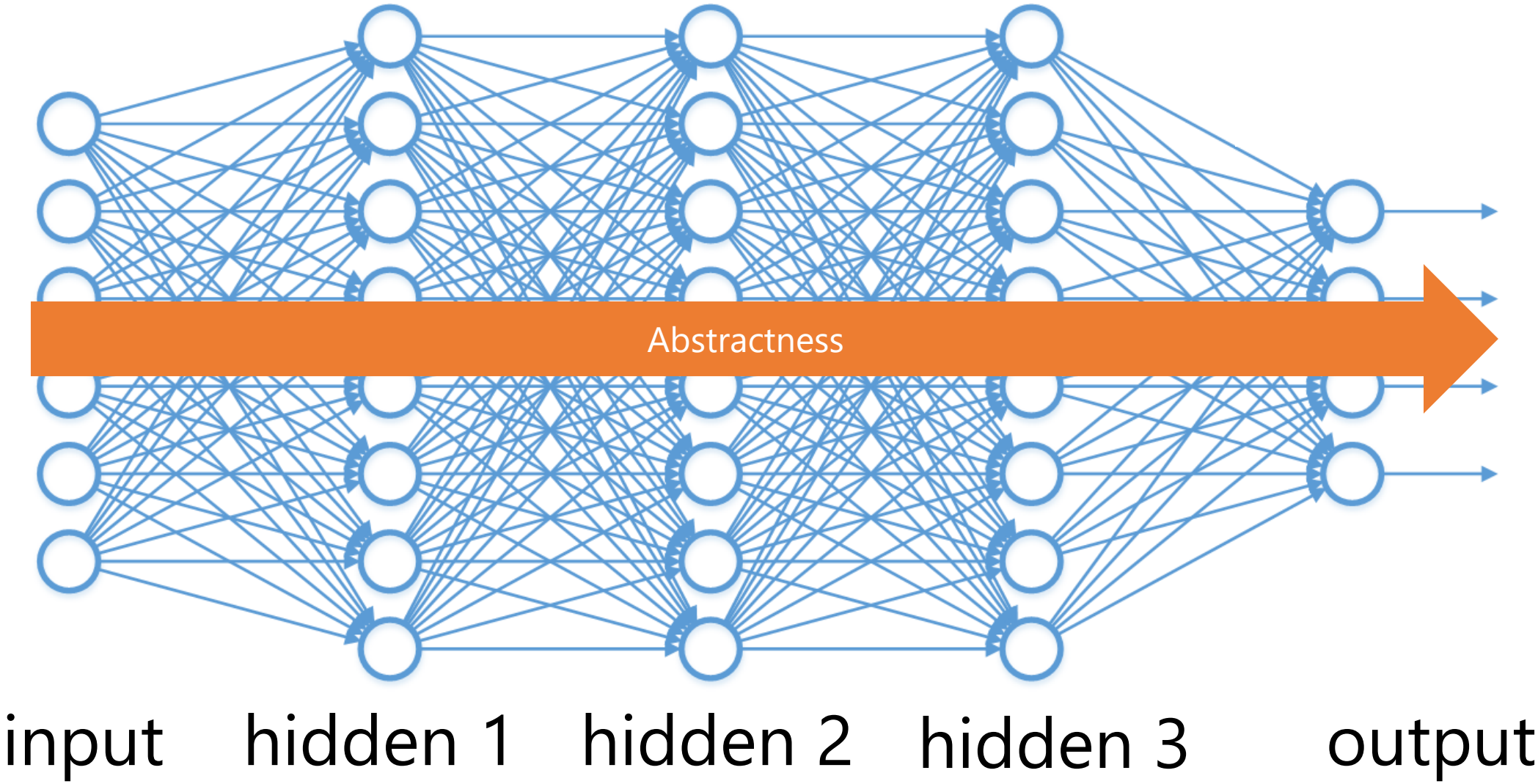
Deep Neural Network



Deep Neural Network



Deep Neural Network



Deep Learning Techniques

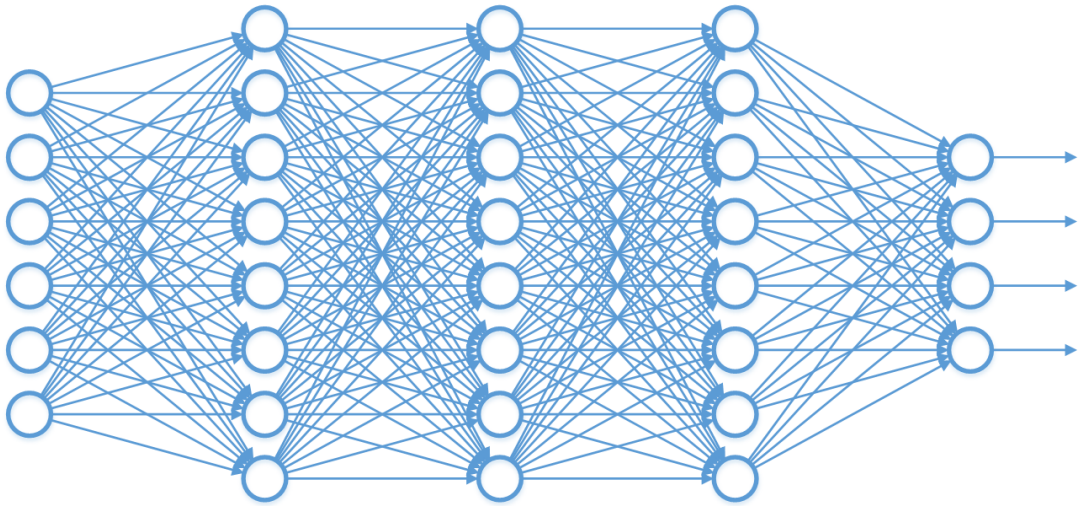
Fully connected (DNN)

Convolutional (CNN)

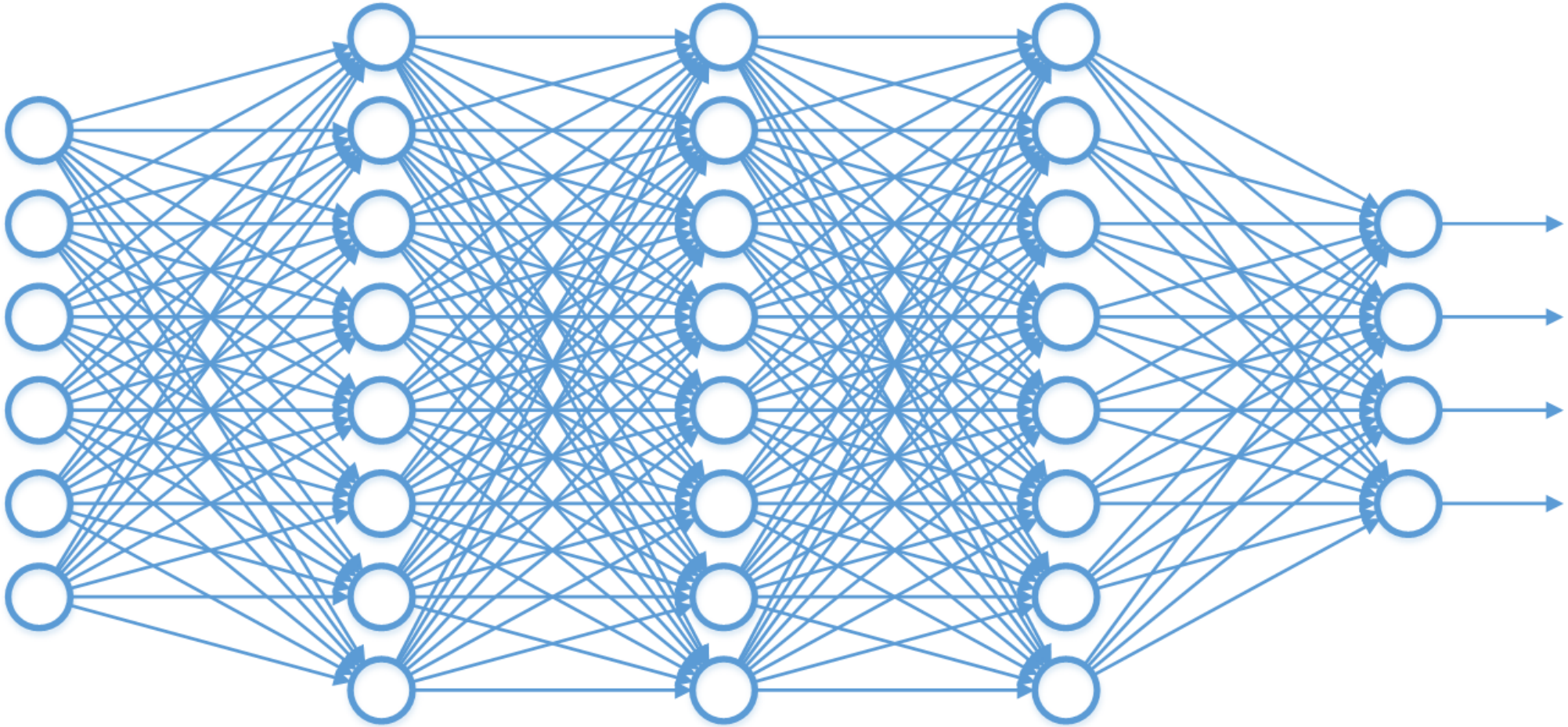
Recurrent (RNN)

Generative Adversarial (GAN)

Deep Q Learning (DQN)

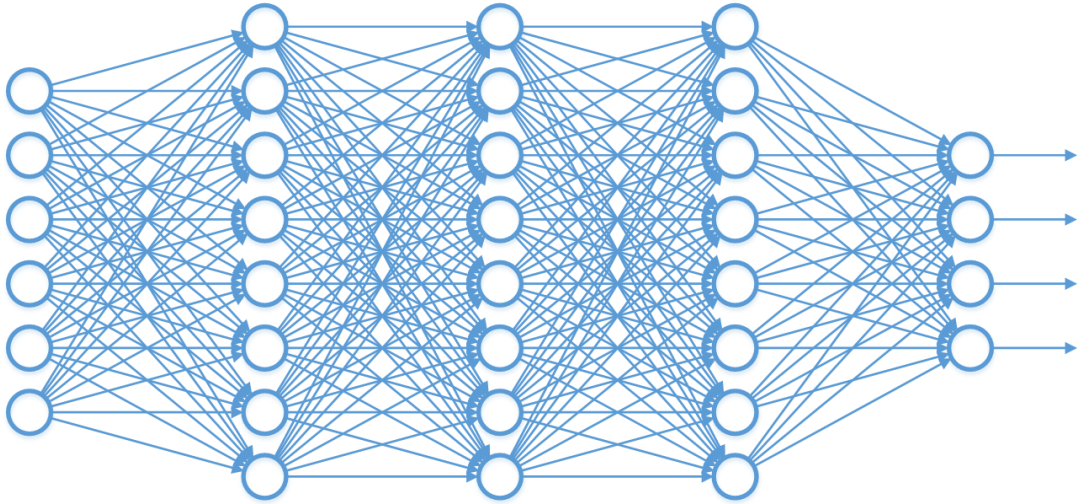


Deep Neural Network



Deep Neural Network

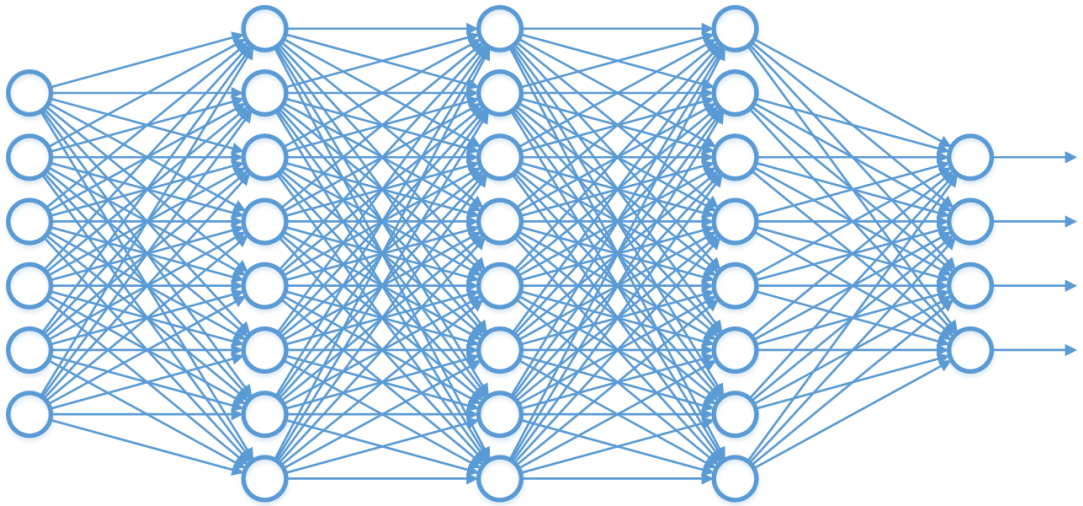
Neural network



Deep Neural Network

Neural network

Multiple hidden layers

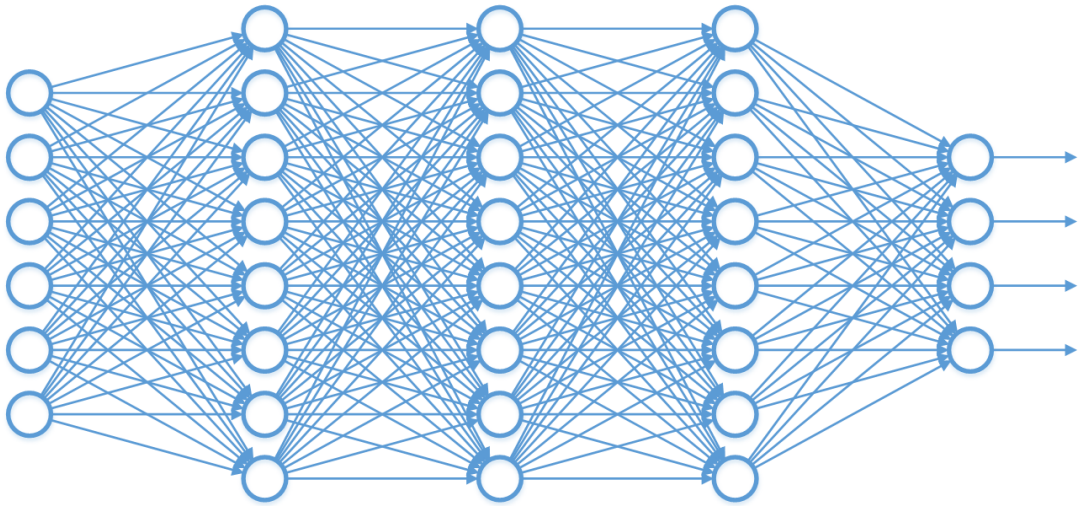


Deep Neural Network

Neural network

Multiple hidden layers

Non-linear activation



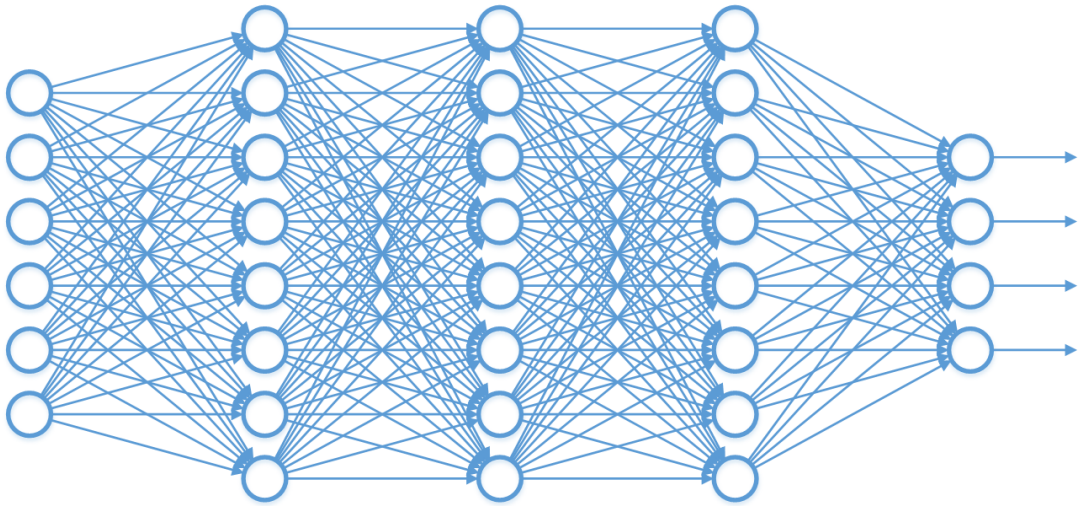
Deep Neural Network

Neural network

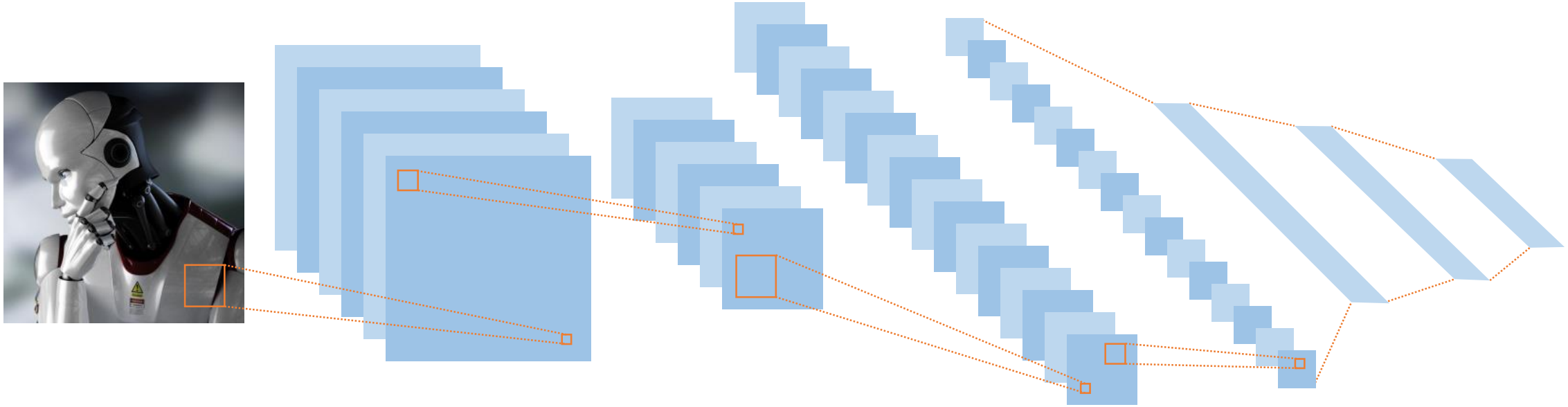
Multiple hidden layers

Non-linear activation

Fully connected

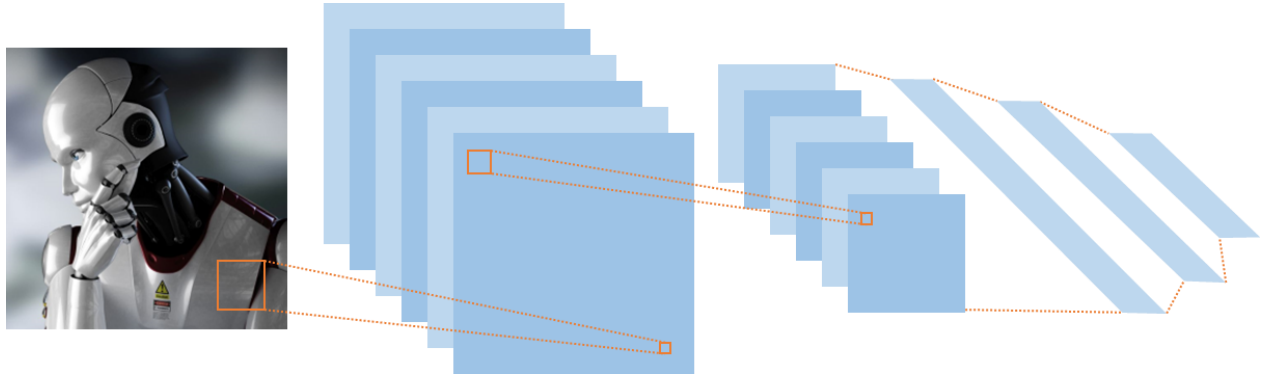


Convolutional Neural Networks (CNN)



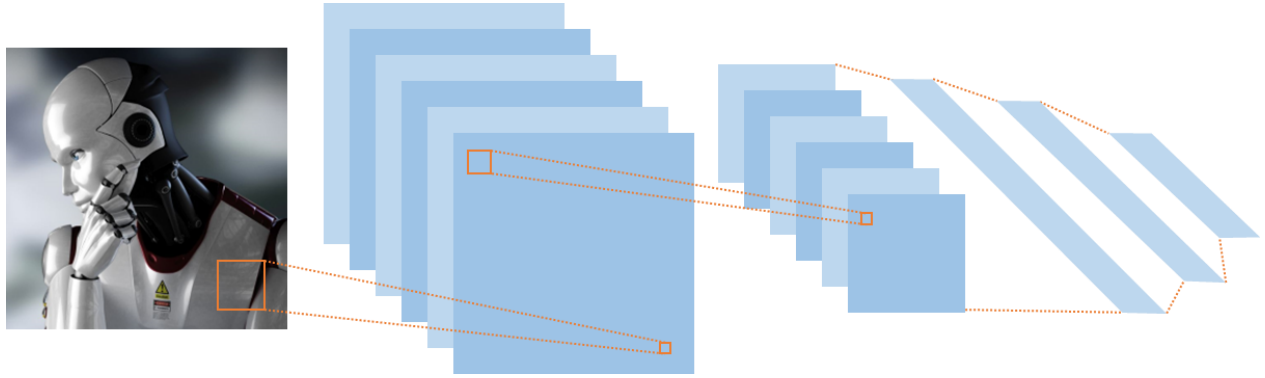
Convolutional Neural Network (CNN)

Sparse



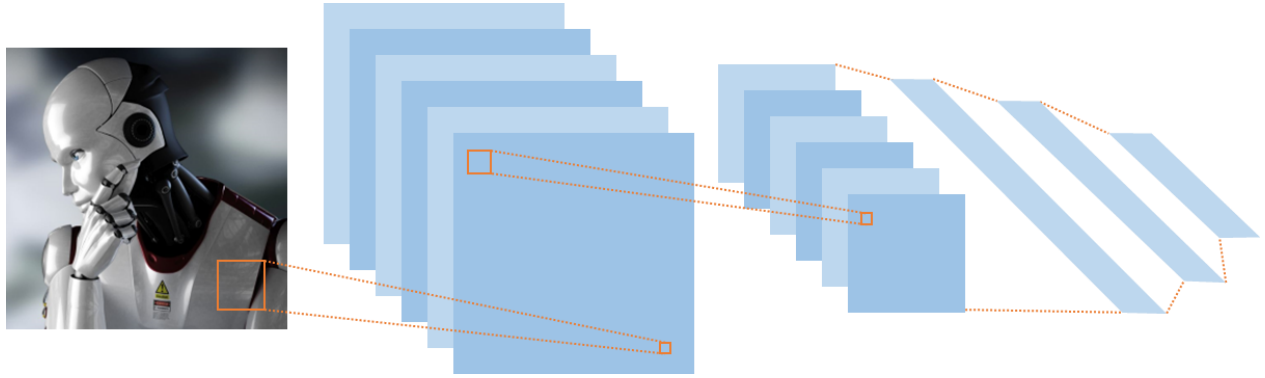
Convolutional Neural Network (CNN)

Sparse
Convolutions



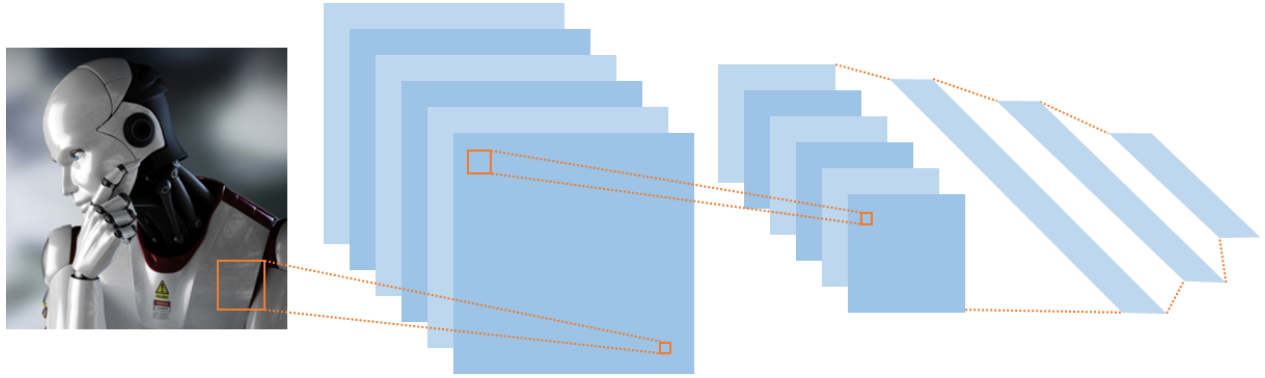
Convolutional Neural Network (CNN)

Sparse
Convolutions
Filters

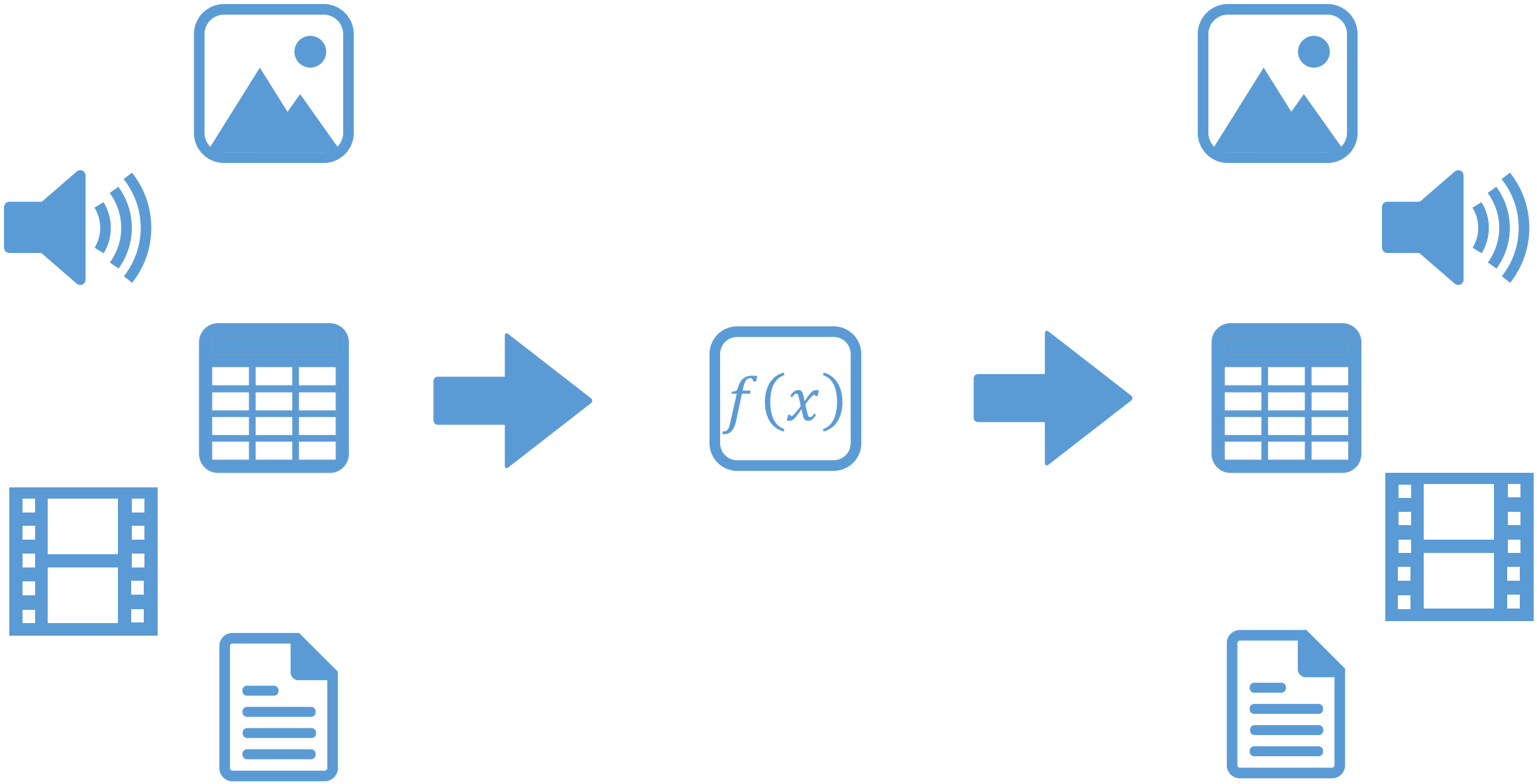


Convolutional Neural Network (CNN)

Sparse
Convolutions
Filters
Pooling




$f(x)$


$f(x)$

Why Use Deep Learning?

Pros

More powerful

More accurate

Data synthesis

Why Use Deep Learning?

Pros

More powerful

More accurate

Data synthesis

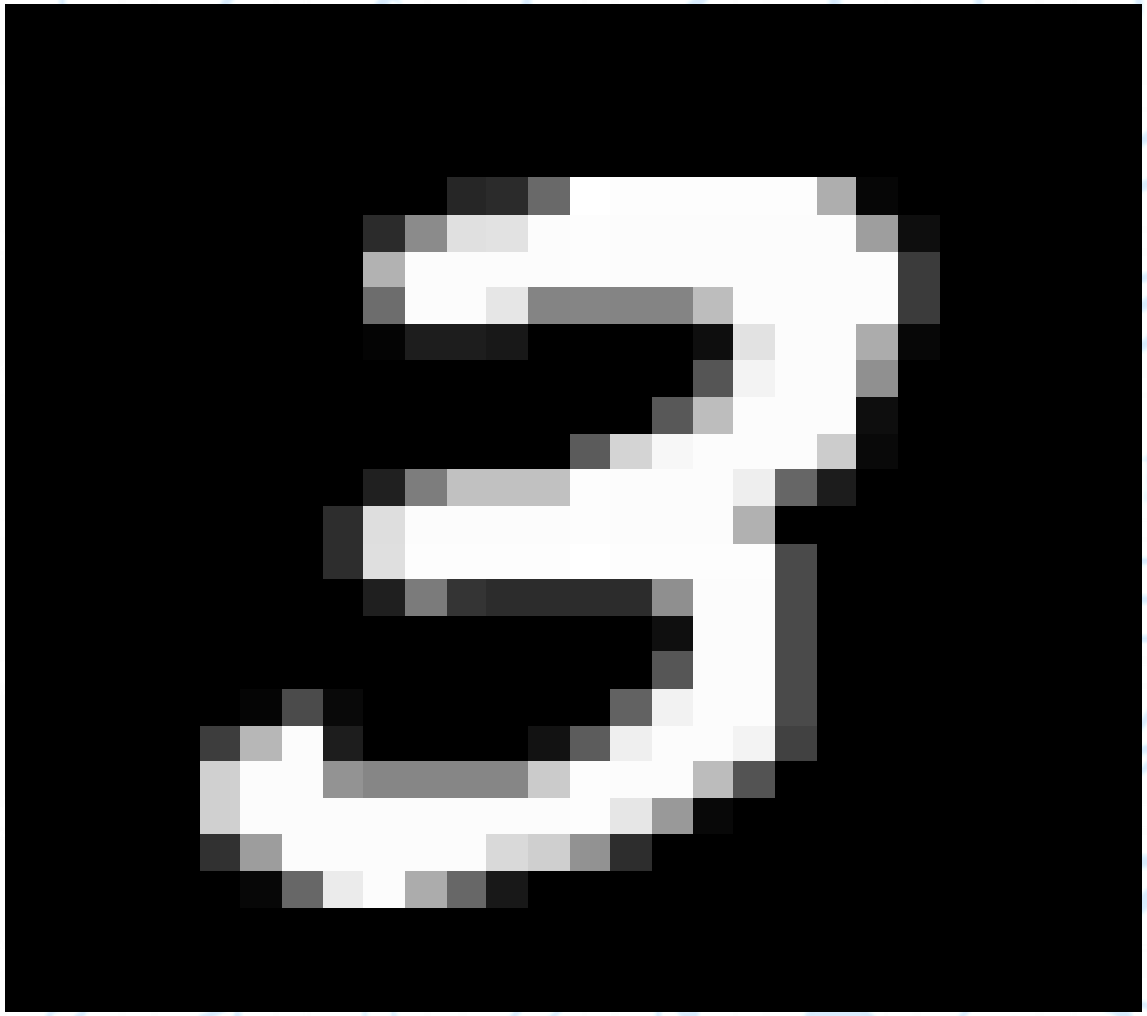
Cons

More complex

More training

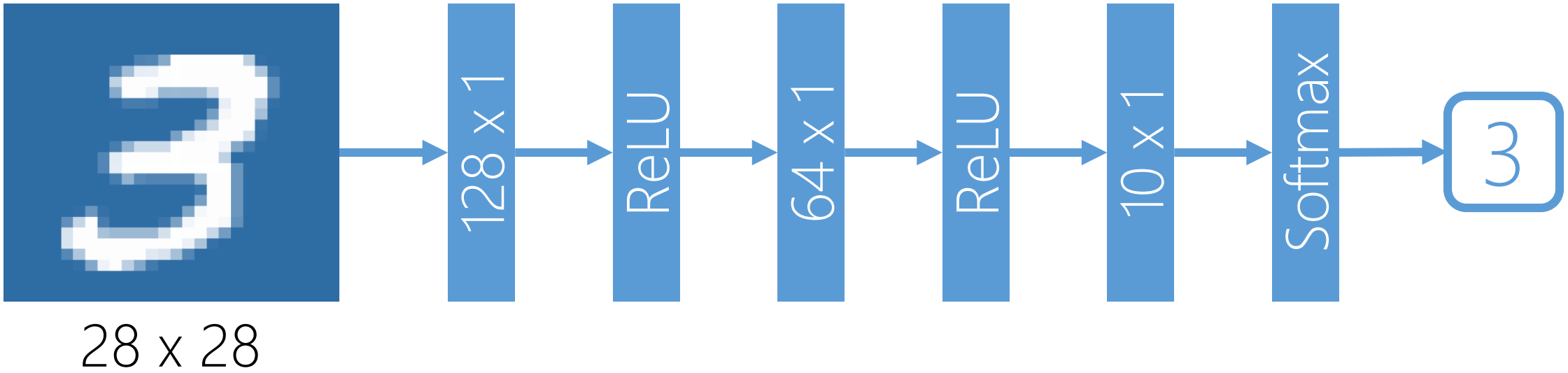
Less transparent

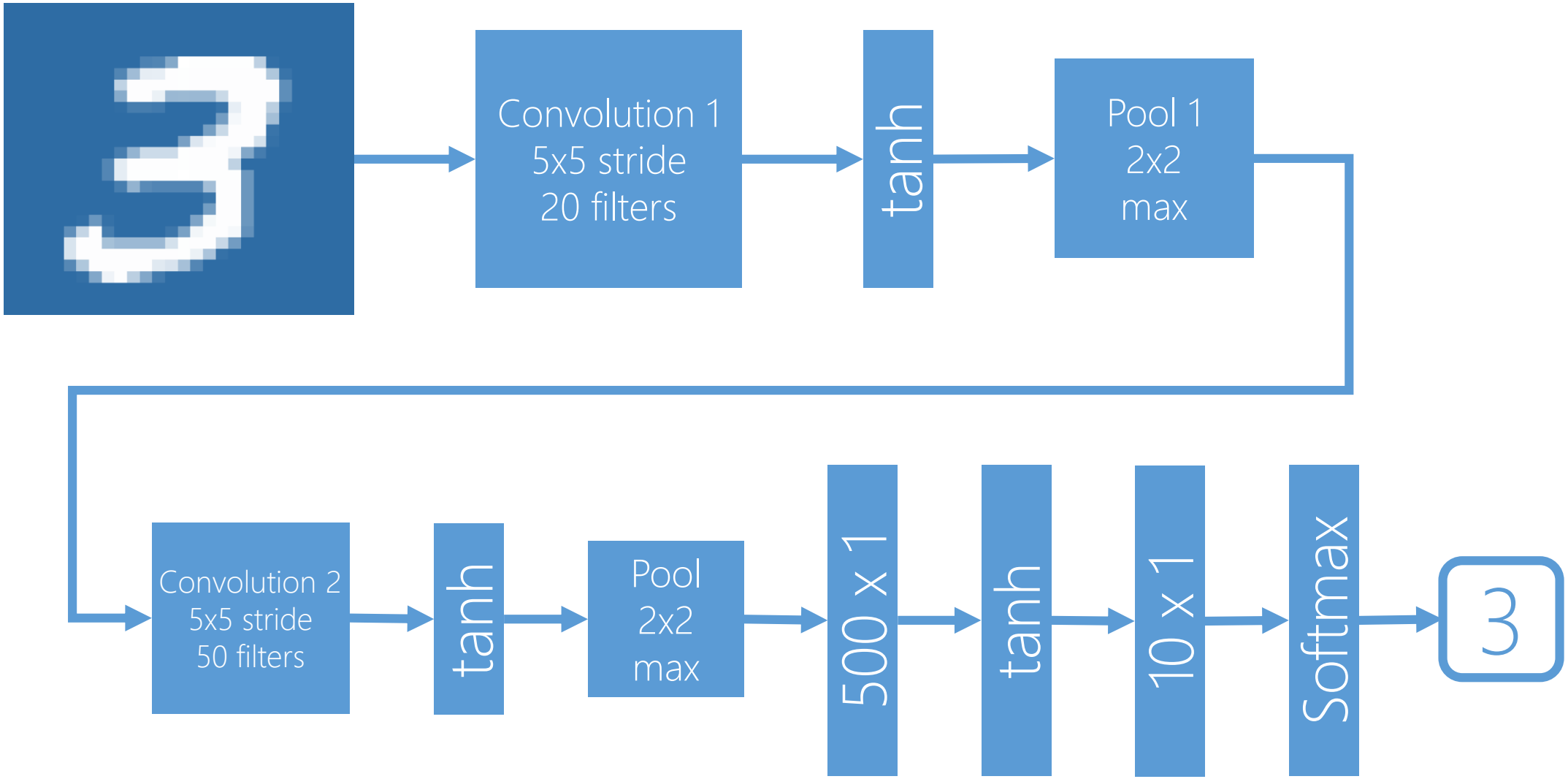
Deep Learning Demo



28 x 28

MNIST							
Label	Pixel 0	Pixel 1	Pixel 2	…	Pixel 781	Pixel 782	Pixel 783
3	0	0	0	…	0	0	0
5	0	0	0	…	0	0	0
0	0	0	0	…	0	0	0
4	0	0	0	…	0	0	0
1	0	0	0	…	0	0	0
9	0	0	0	…	0	0	0
…	…	…	…	…	…	…	…


28 x 28
128 x 1
ReLU
64 x 1
ReLU
10 x 1
Softmax
3


Convolution 1
5x5 stride
20 filters
tanh
Pool 1
2x2
max
Convolution 2
5x5 stride
50 filters
tanh
Pool
2x2
max
500 x 1
tanh
10 x 1
Softmax
3

Demo 6 – Deep Learning

Goal: Predict handwritten digits
with a deep neural network

Lab 6A – Deep Learning (Easy)

Goal: Predict handwritten digits
with a deep neural network

Lab 6B – ML in Practice (Hard)

Goal: Predict handwritten digits
with CNN (LeNet)

Lab 6B – ML in Practice (Hard)

Goal: Predict handwritten digits
with CNN (LeNet)

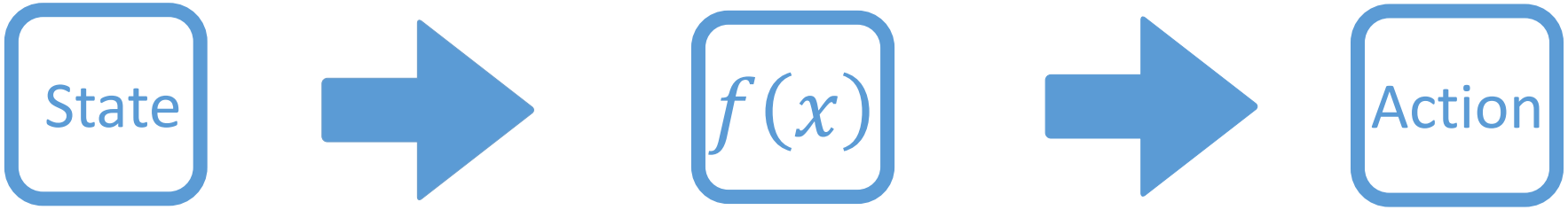
Lab 6B – ML in Practice (Hard)

Goal: Predict handwritten digits
with CNN (LeNet)

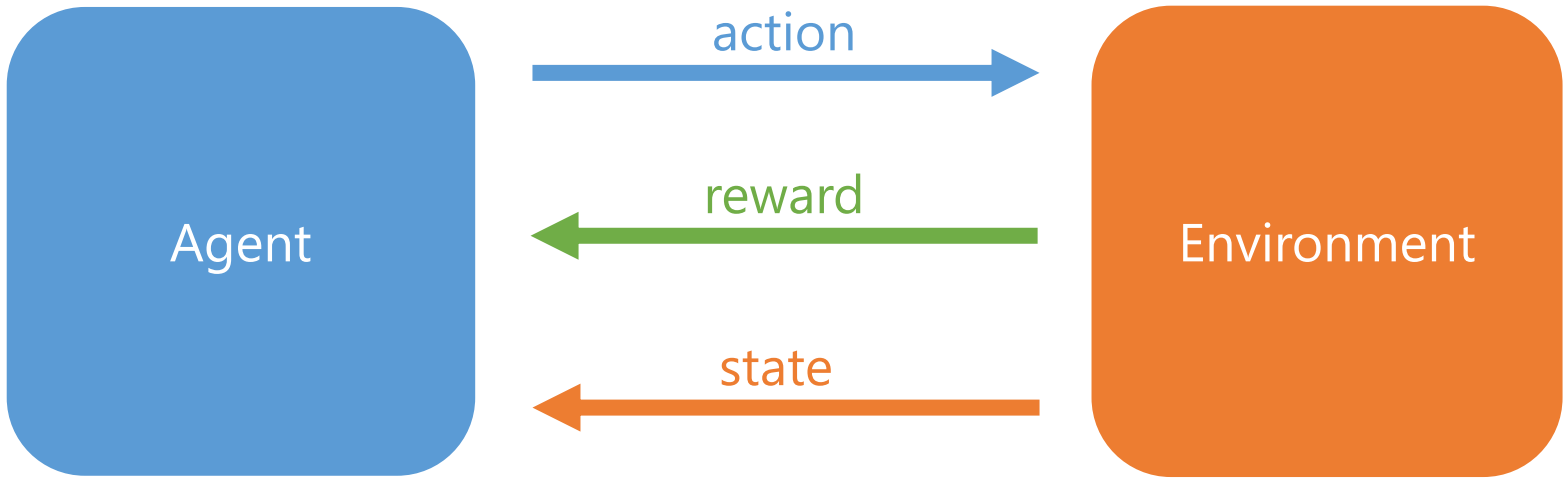
Reinforcement Learning

NOTE: Add video of RL playing video game

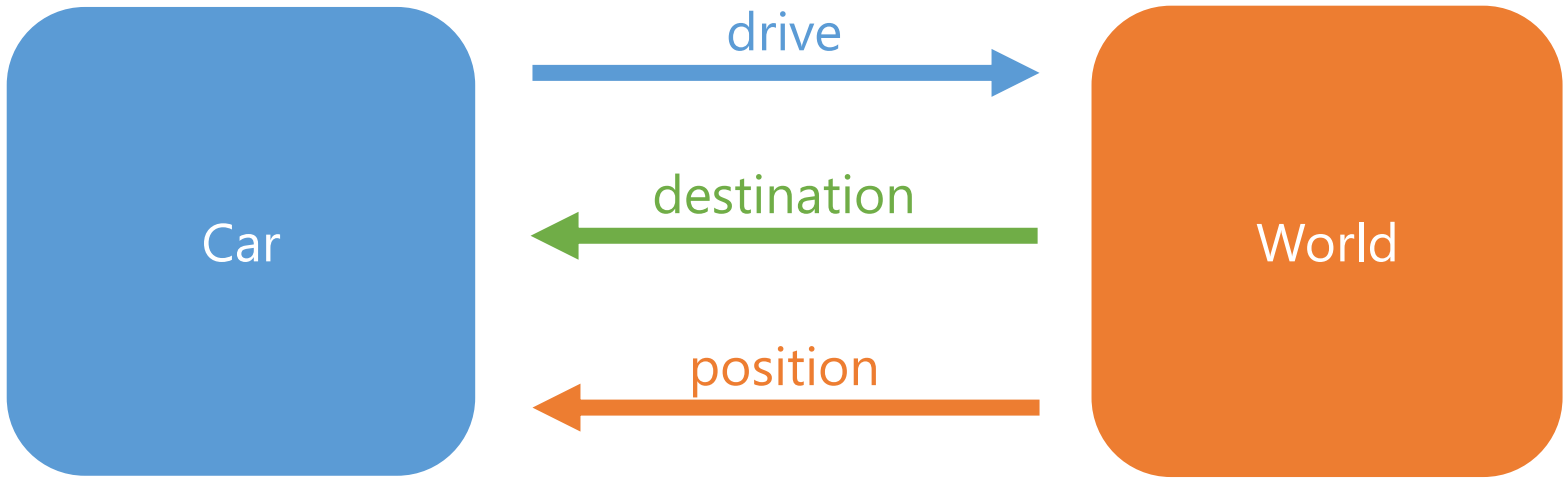
Reinforcement Learning



Reinforcement Learning

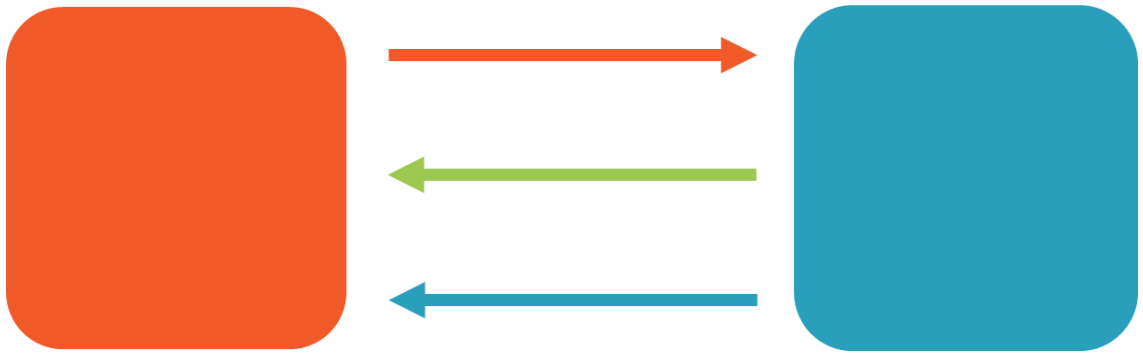


Reinforcement Learning



Reinforcement Learning

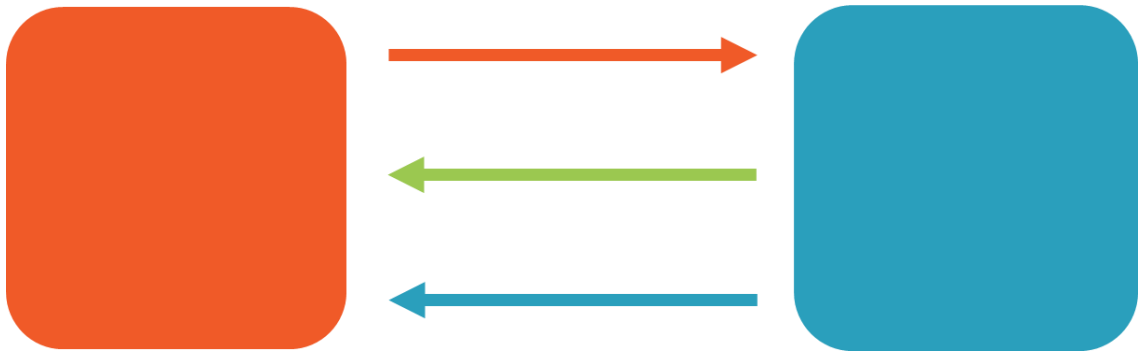
Action replay



Reinforcement Learning

Action replay

Optimal policy

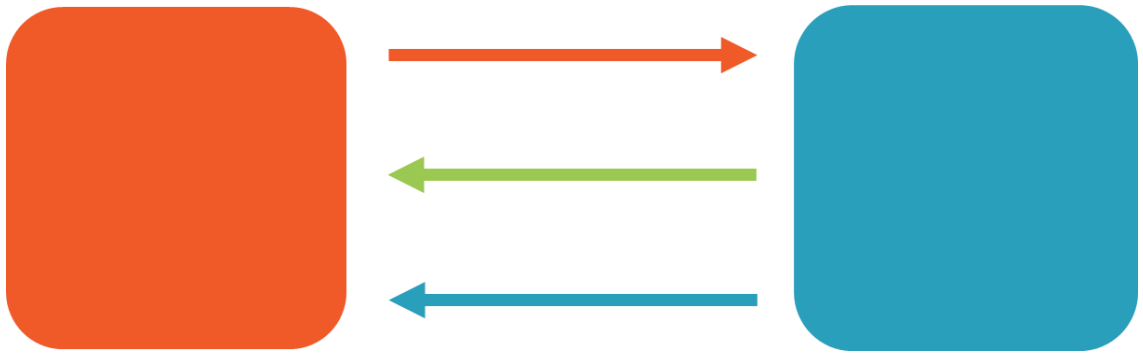


Reinforcement Learning

Action replay

Optimal policy

Discounted reward



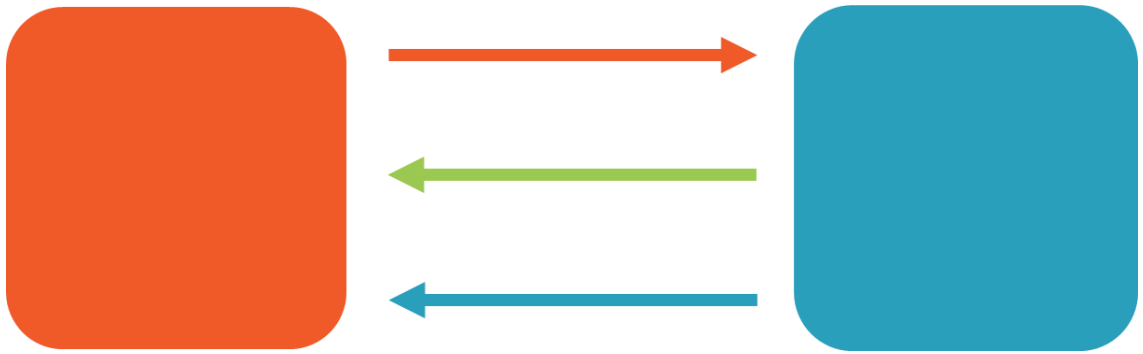
Reinforcement Learning

Action replay

Optimal policy

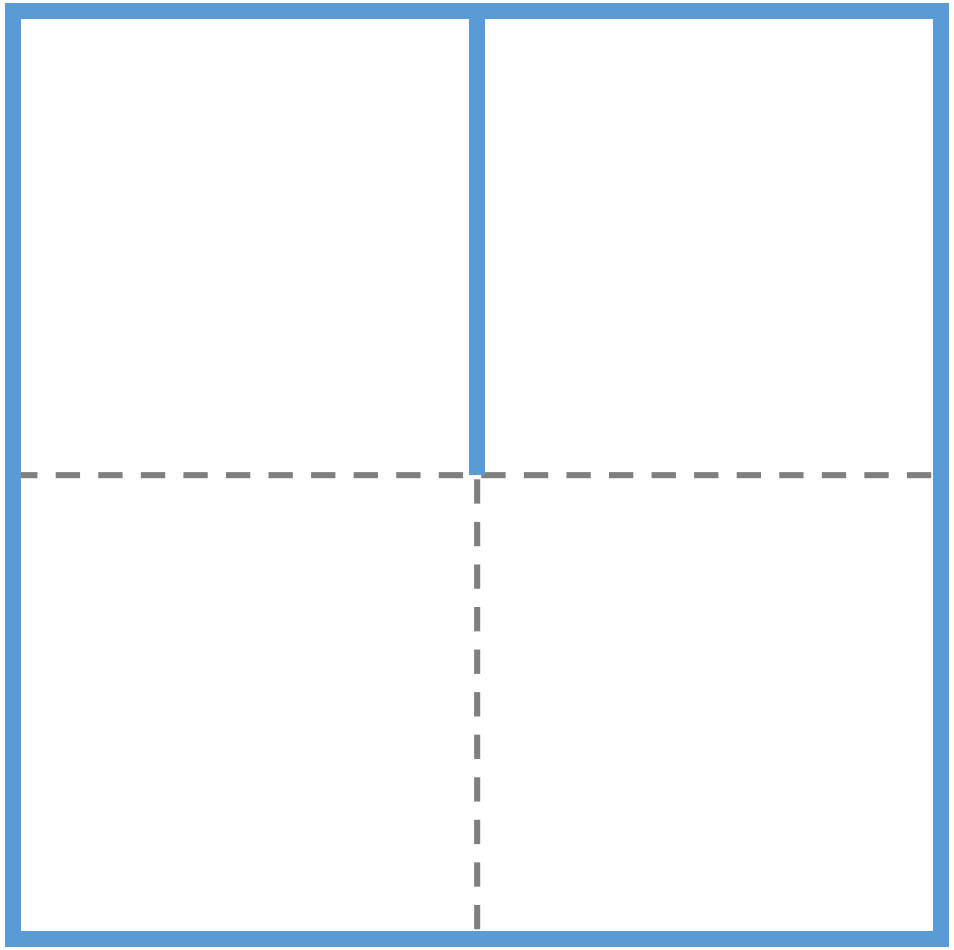
Discounted reward

Markov decision process

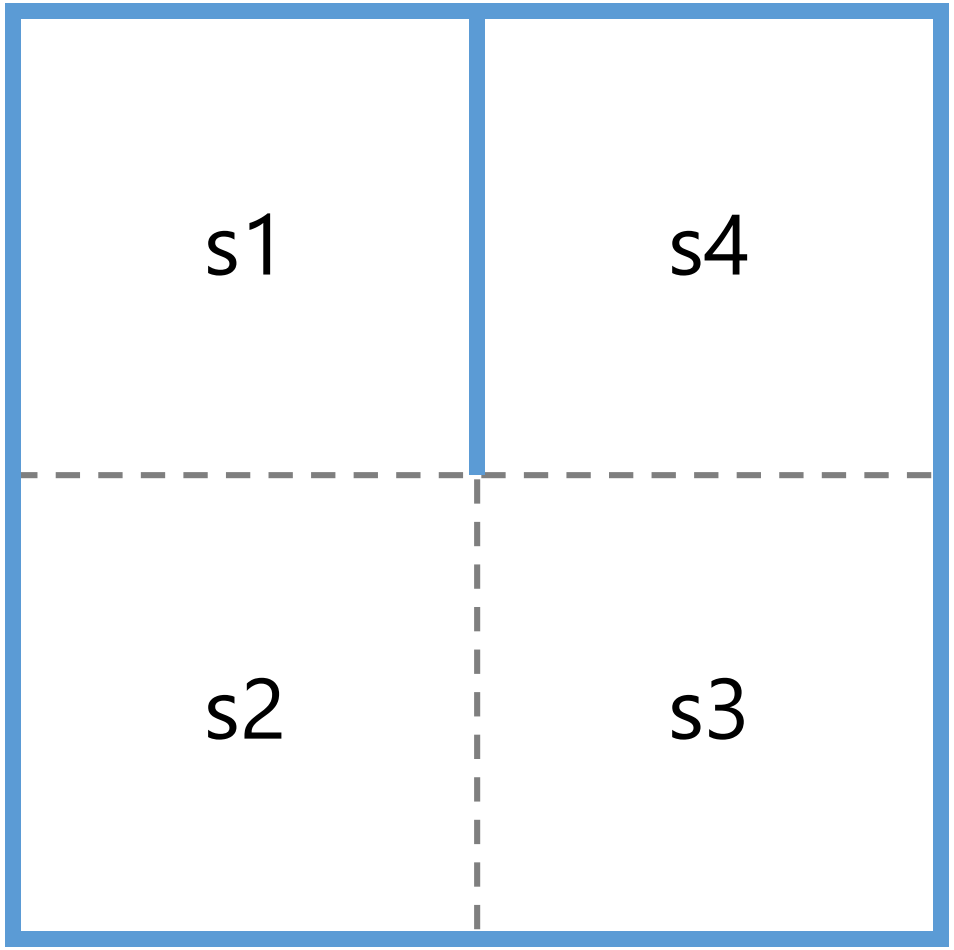


Reinforcement Learning Demo

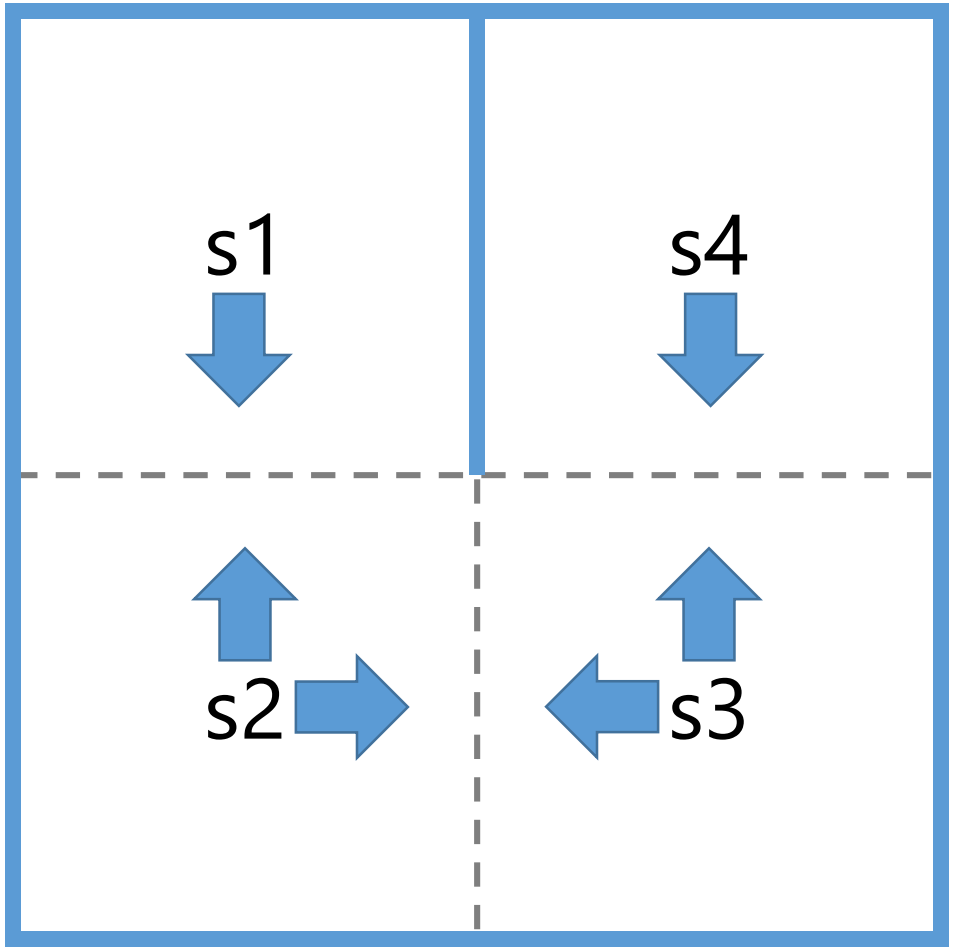
Grid World



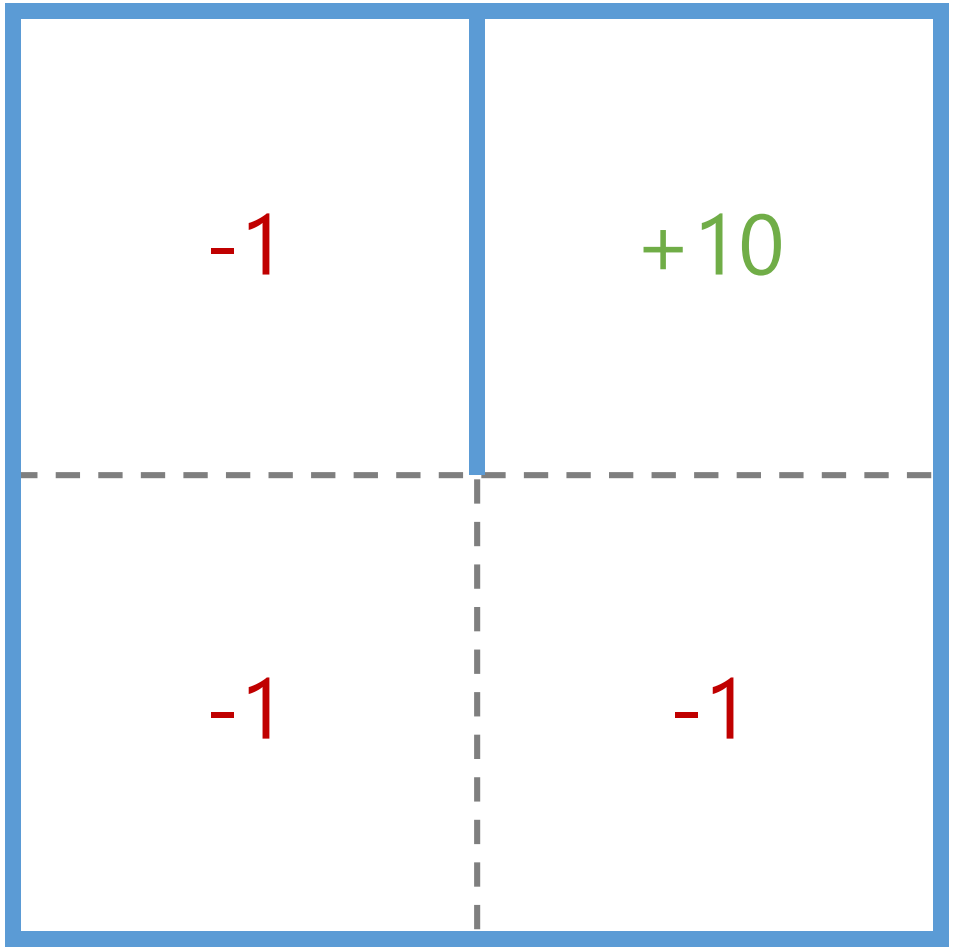
States



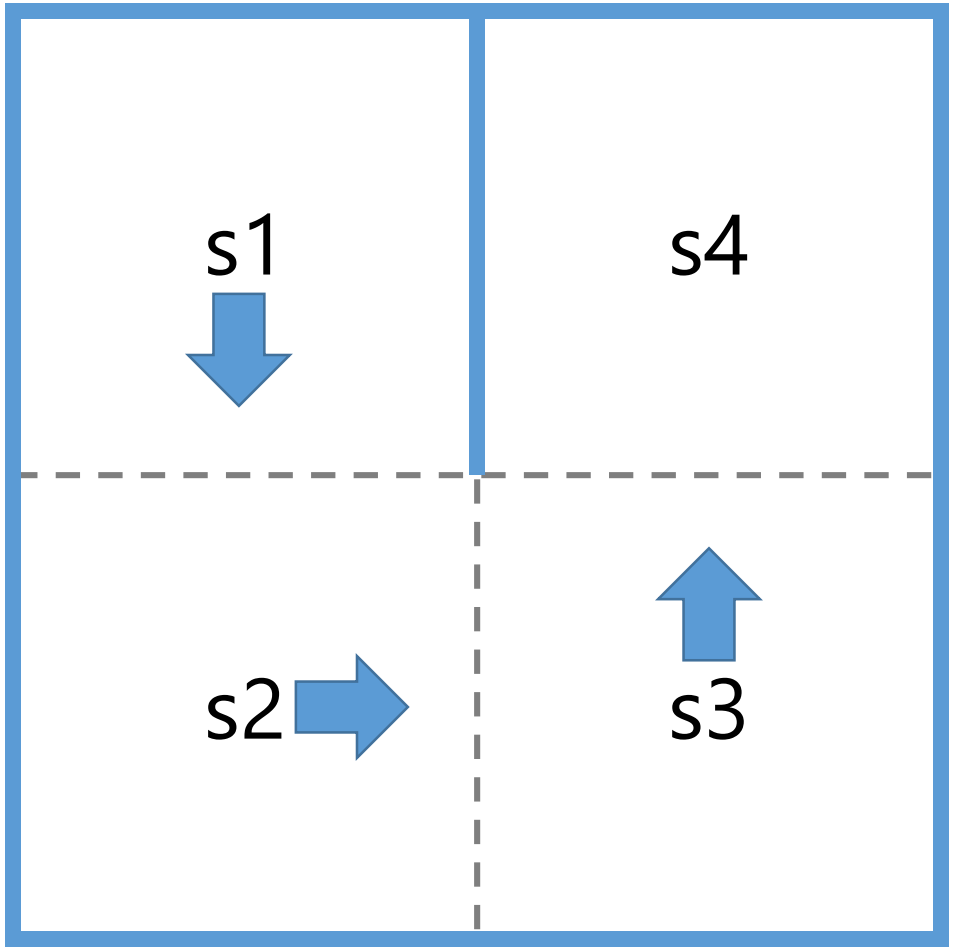
Actions



Rewards



Optimal Policy



Recap

States: s1, s2, s3, s4

Actions: up, down, left, right

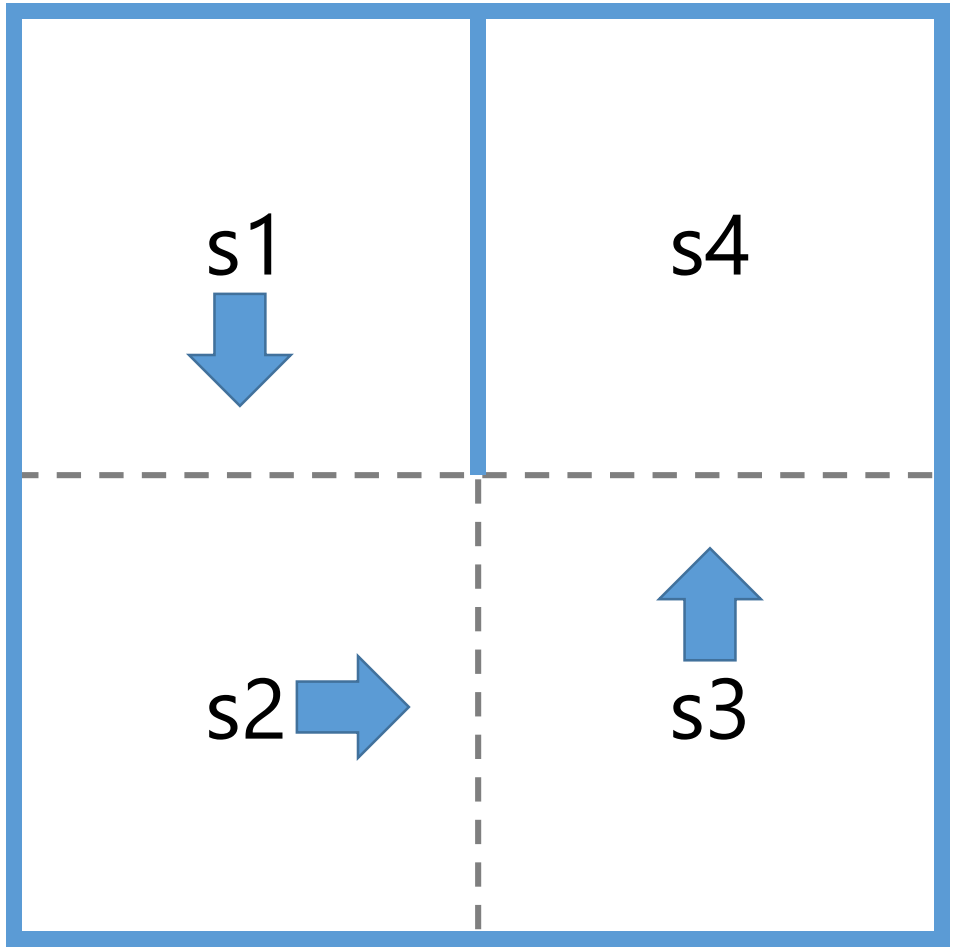
Rewards: s1, s3, s3 = -1;

s4 = 10

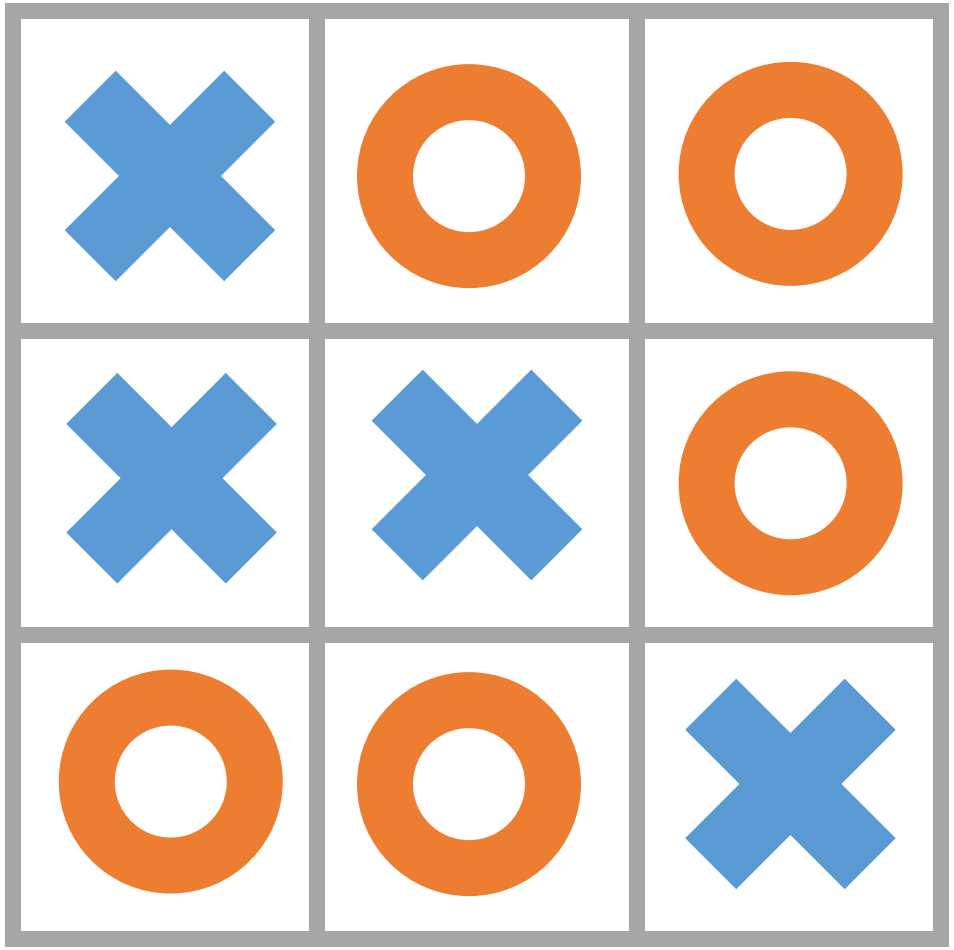
Policy: s1 = down

s2 = right

s3 = up



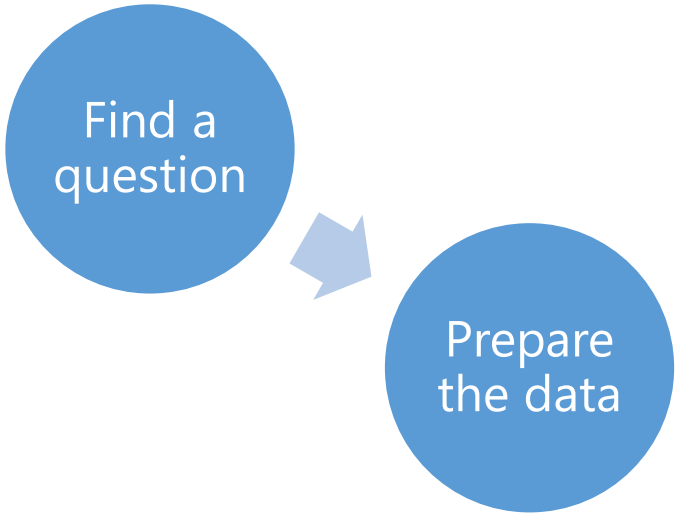
Tic-Tac-Toe

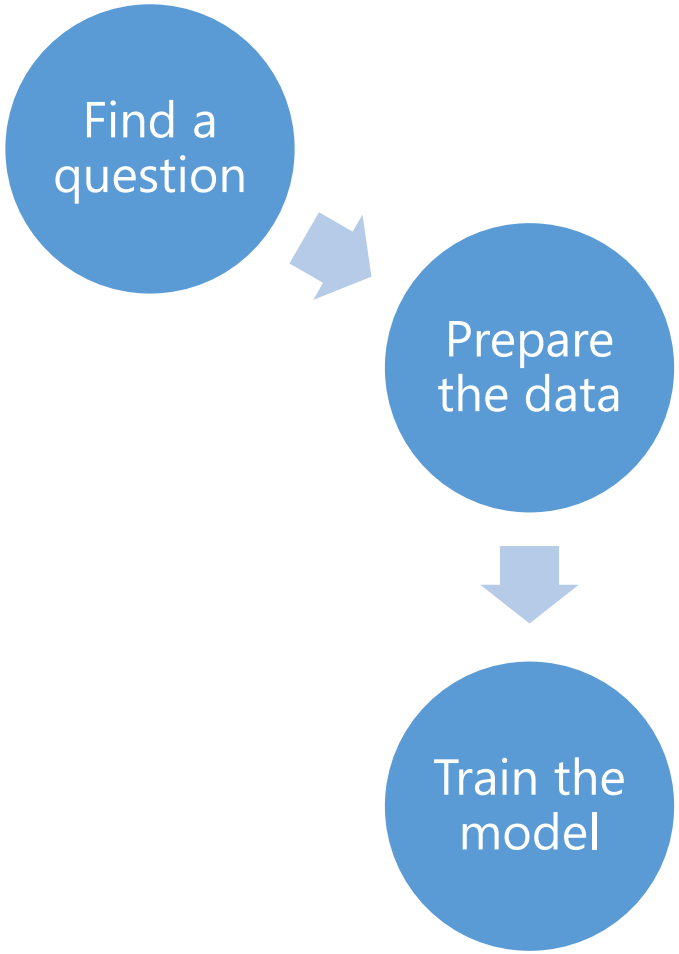


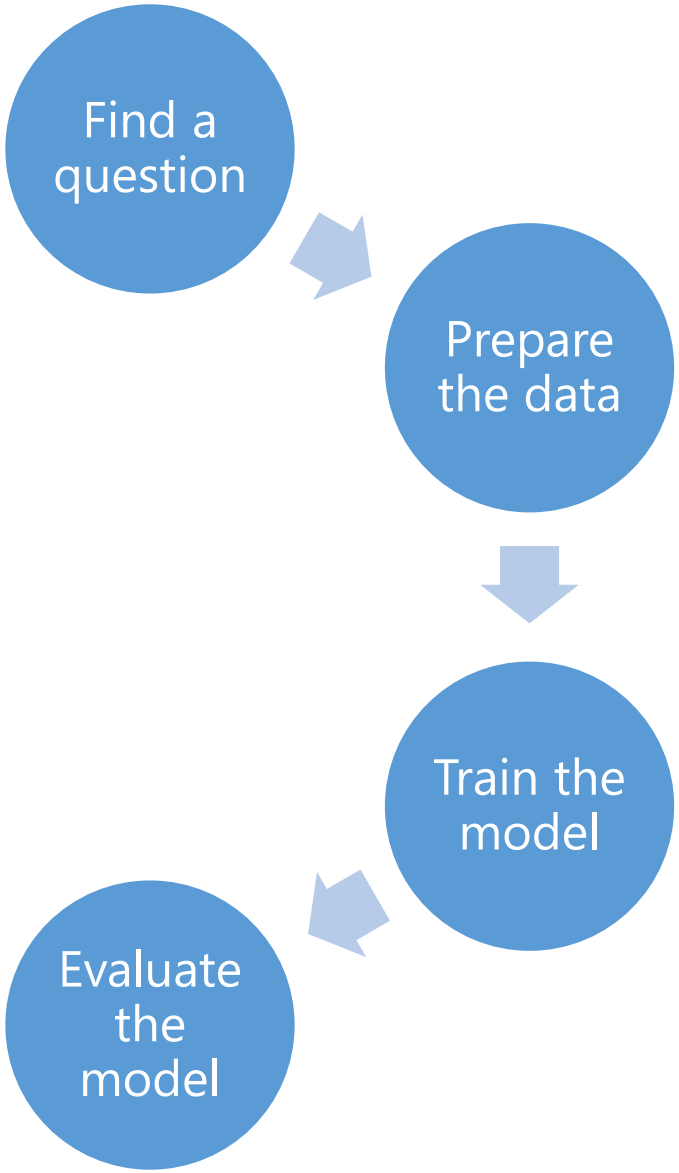
ML in Practice

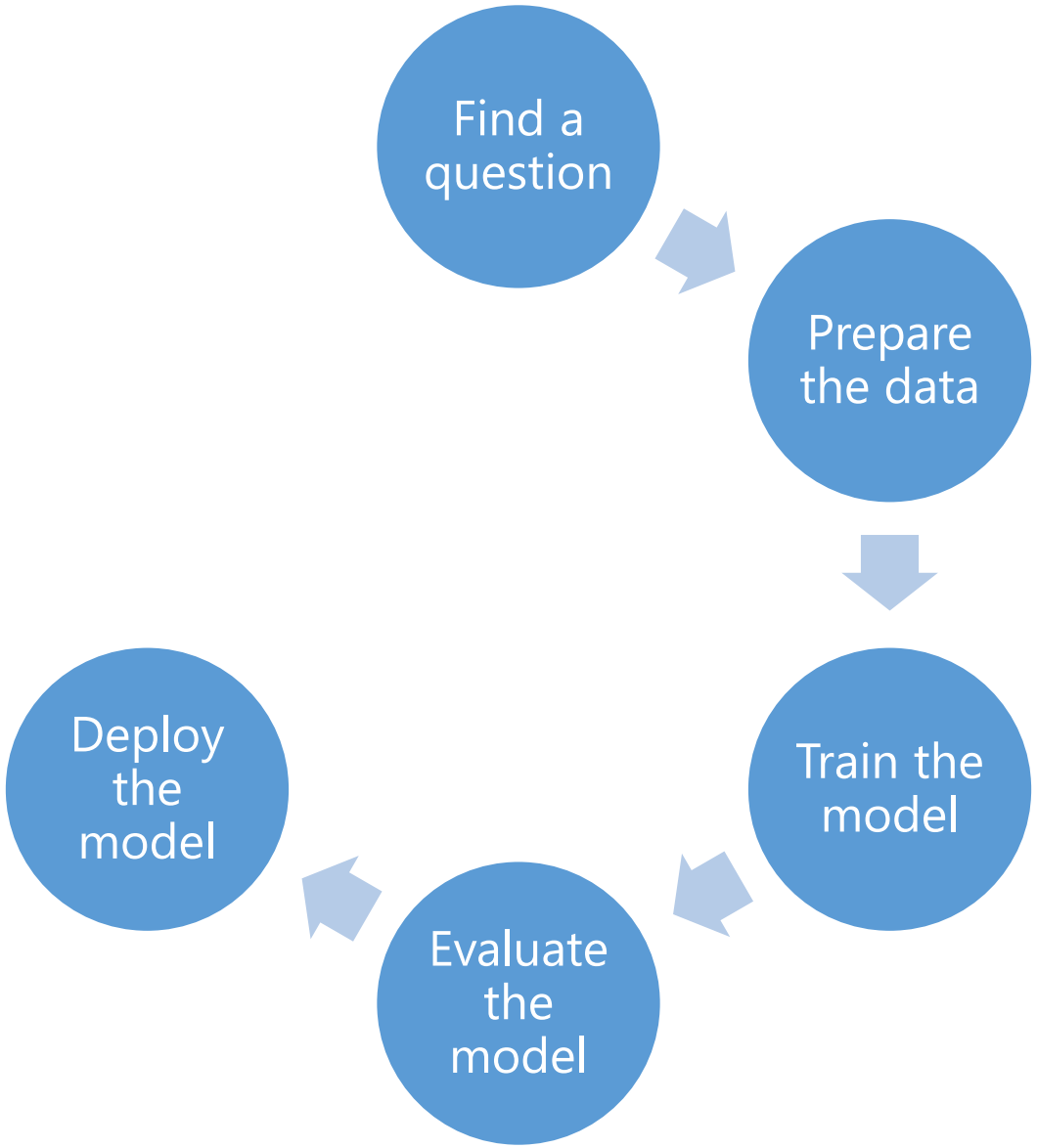
What is the machine learning process?

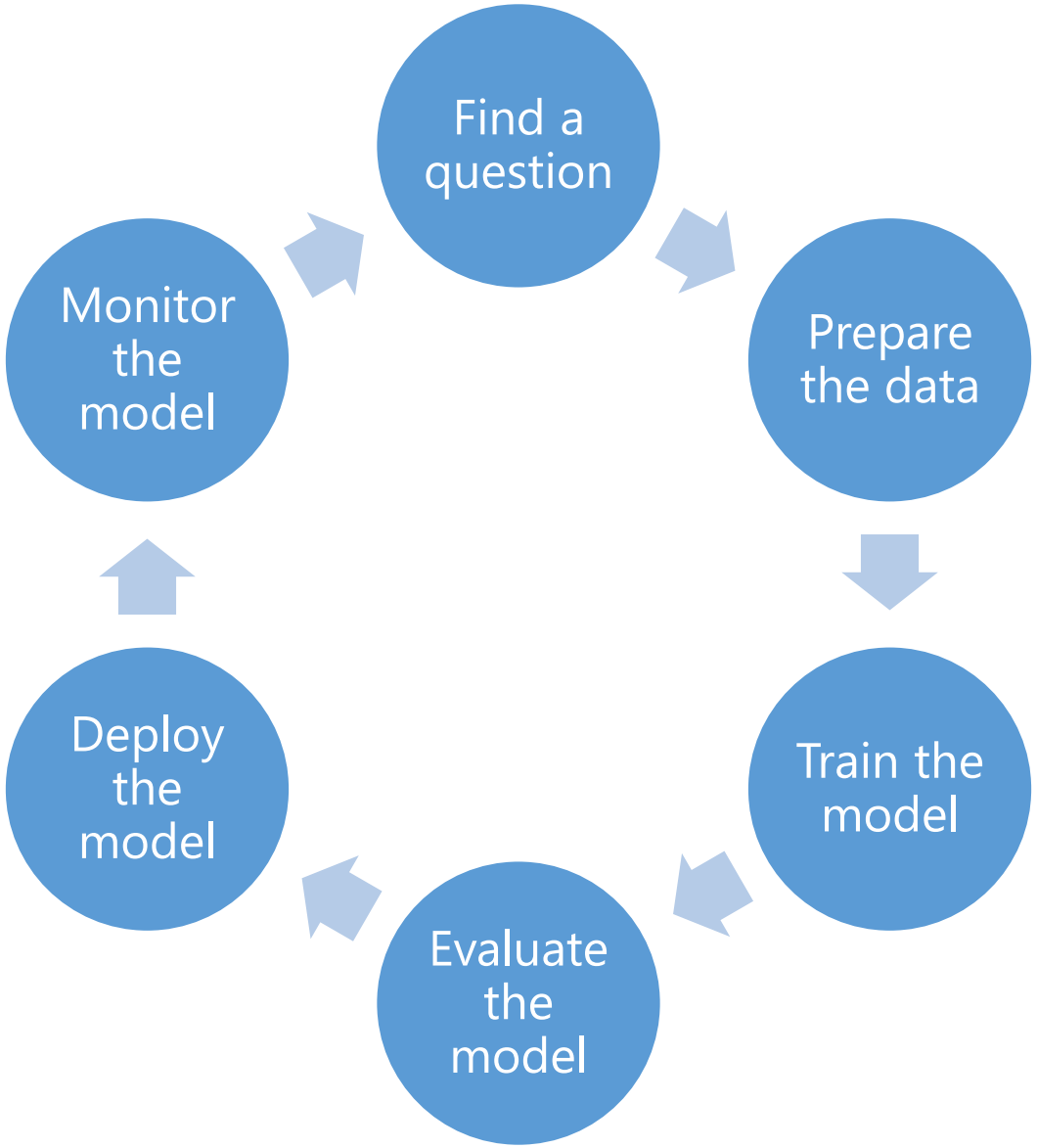
Find a question

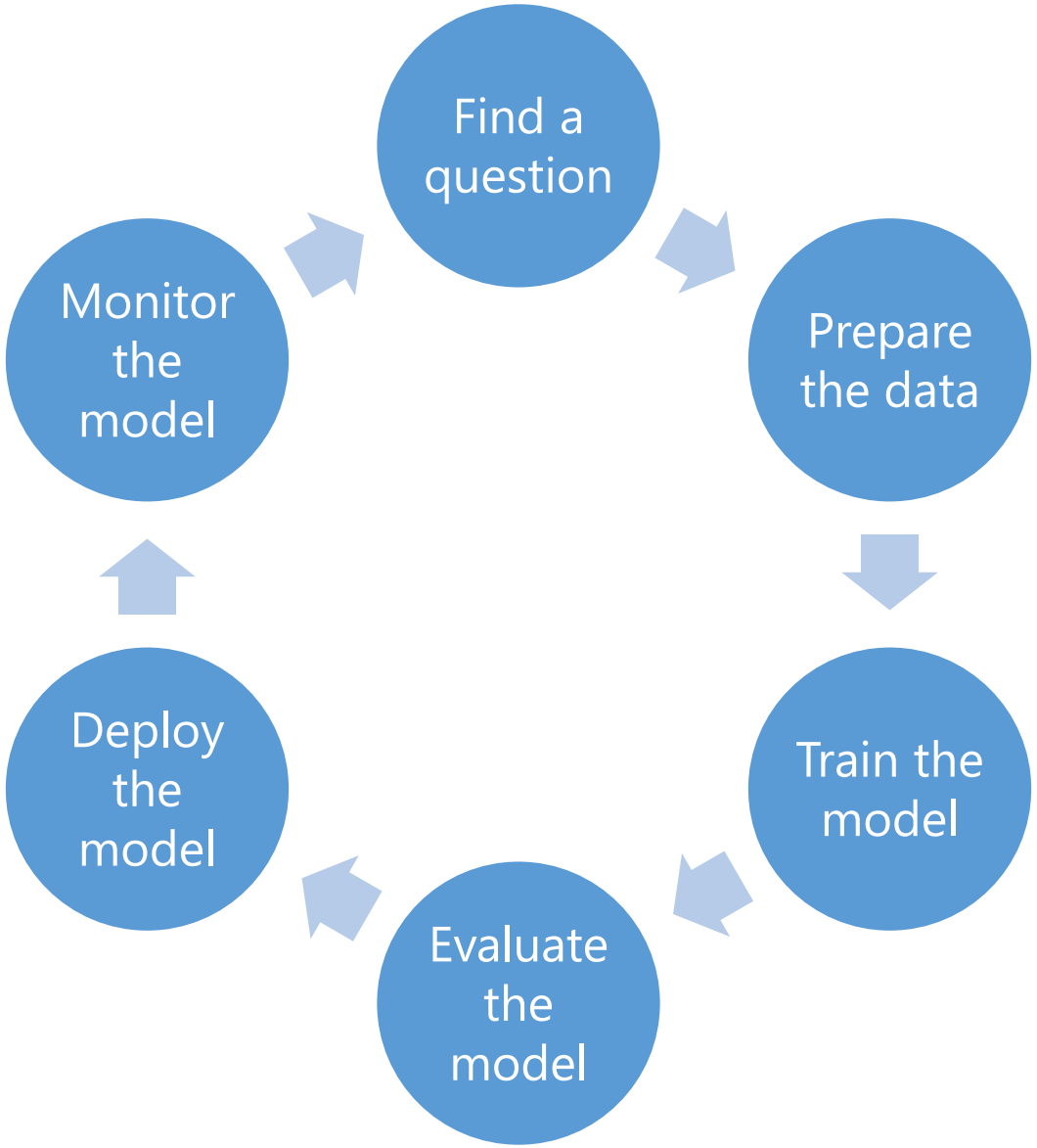

Find a question
Prepare the data

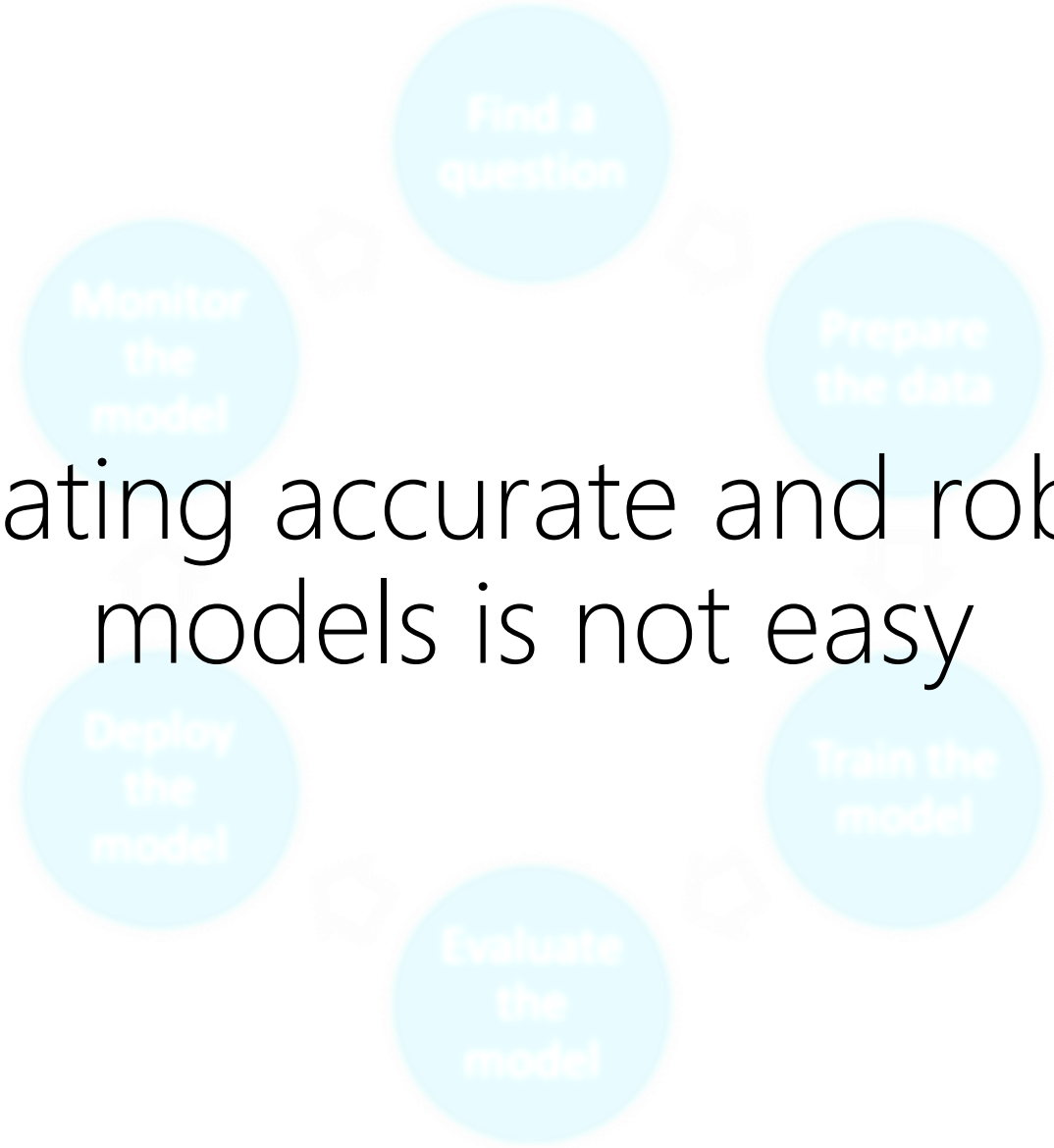

Find a question
Prepare the data
Train the model


Find a question
Prepare the data
Train the model
Evaluate the model


Find a question
Prepare the data
Train the model
Evaluate the model
Deploy the model


Find a question
Prepare the data
Train the model
Evaluate the model
Deploy the model
Monitor the model

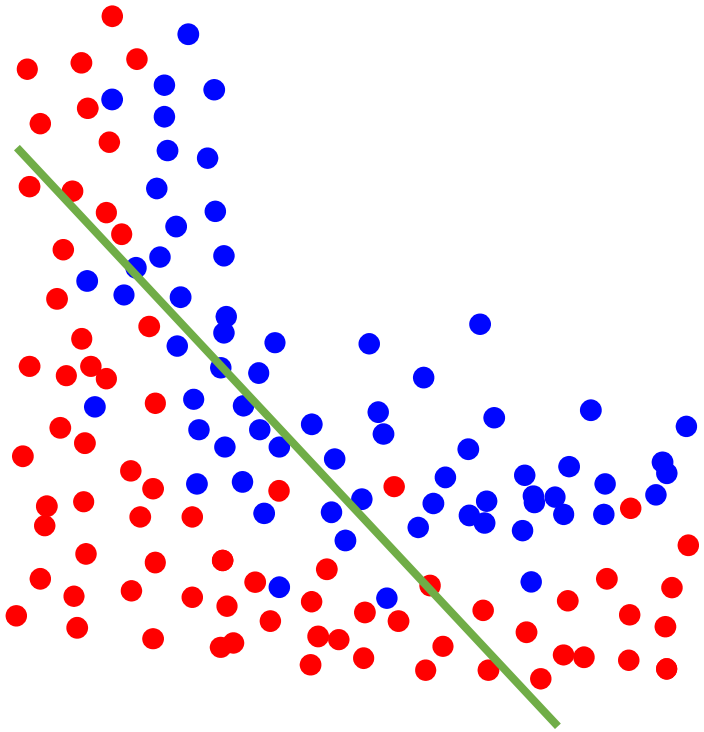

Find a question
Prepare the data
Train the model
Evaluate the model
Deploy the model
Monitor the model



Creating accurate and robust models is not easy

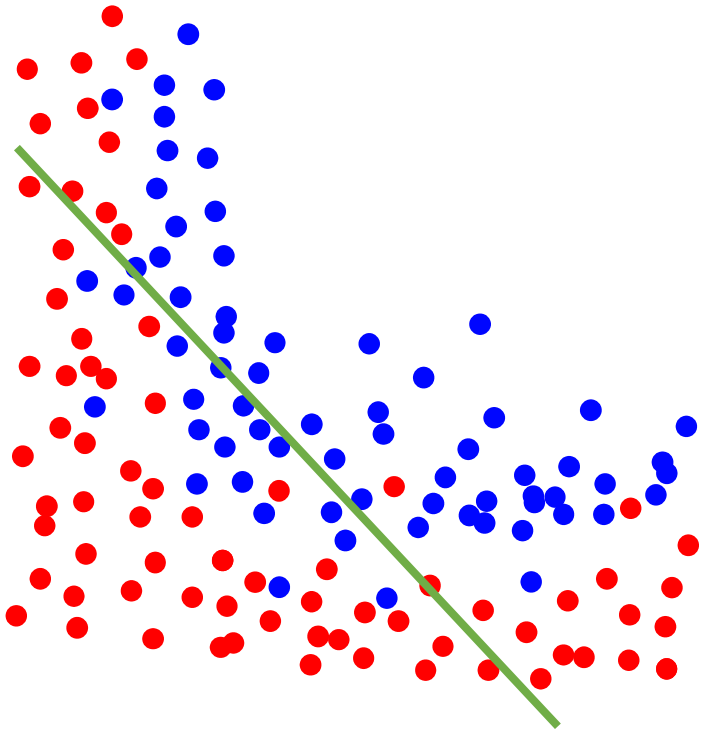
Goodness of Fit

Goodness of Fit

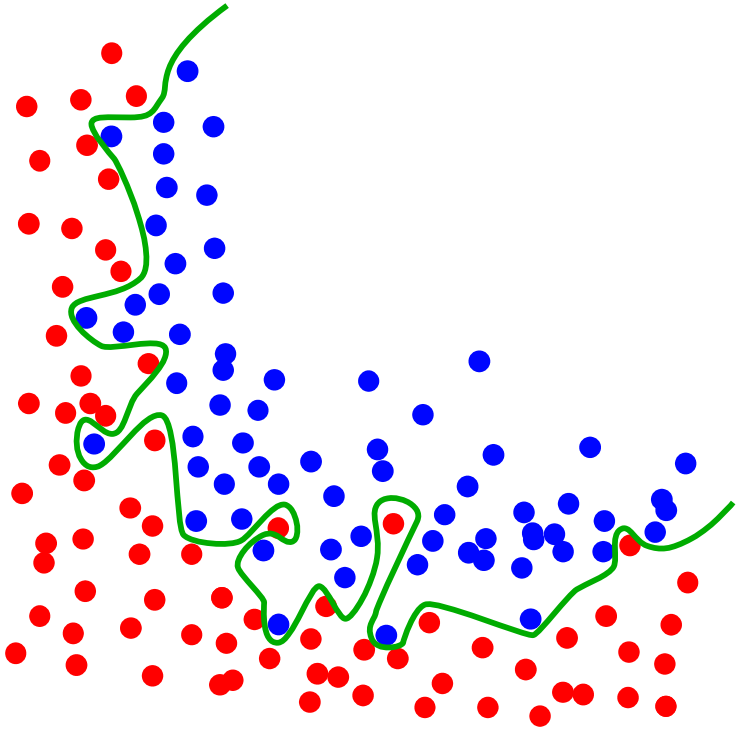


Underfit

Goodness of Fit

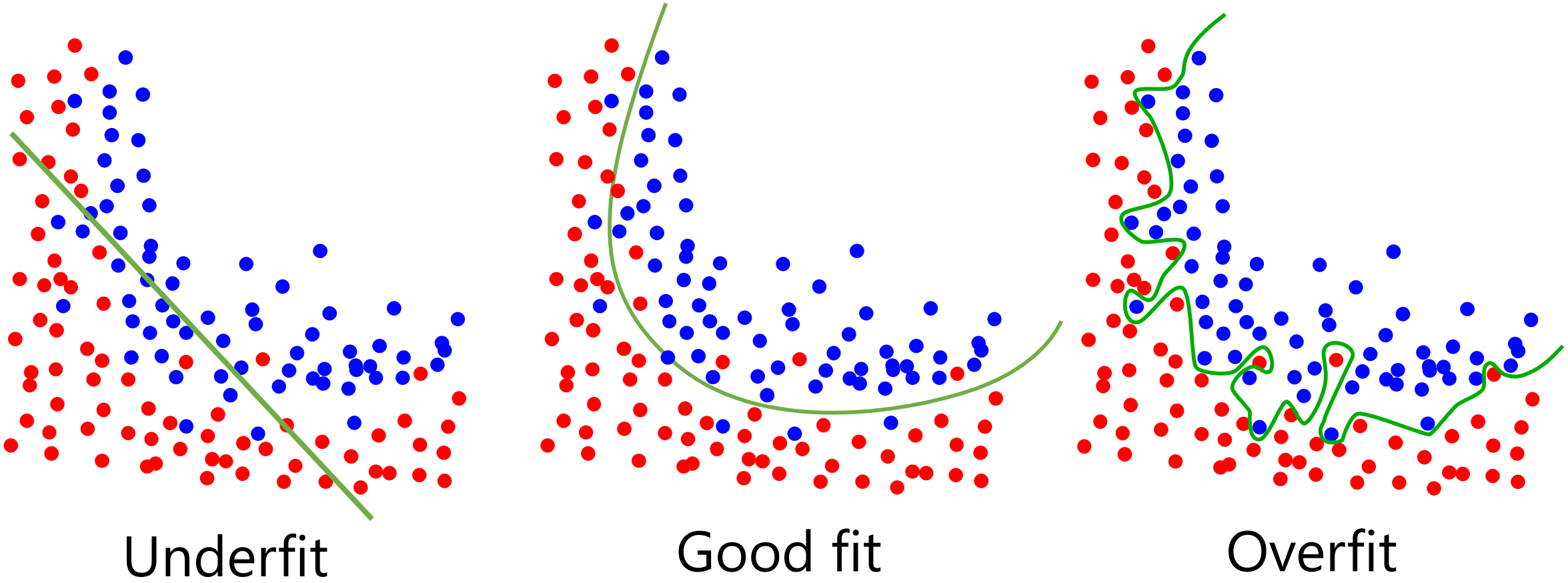


Underfit



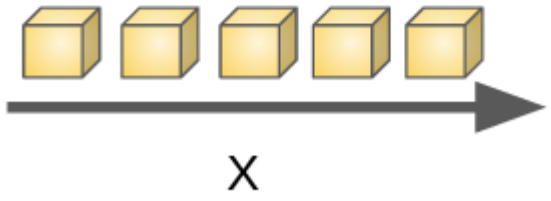
Overfit

Goodness of Fit

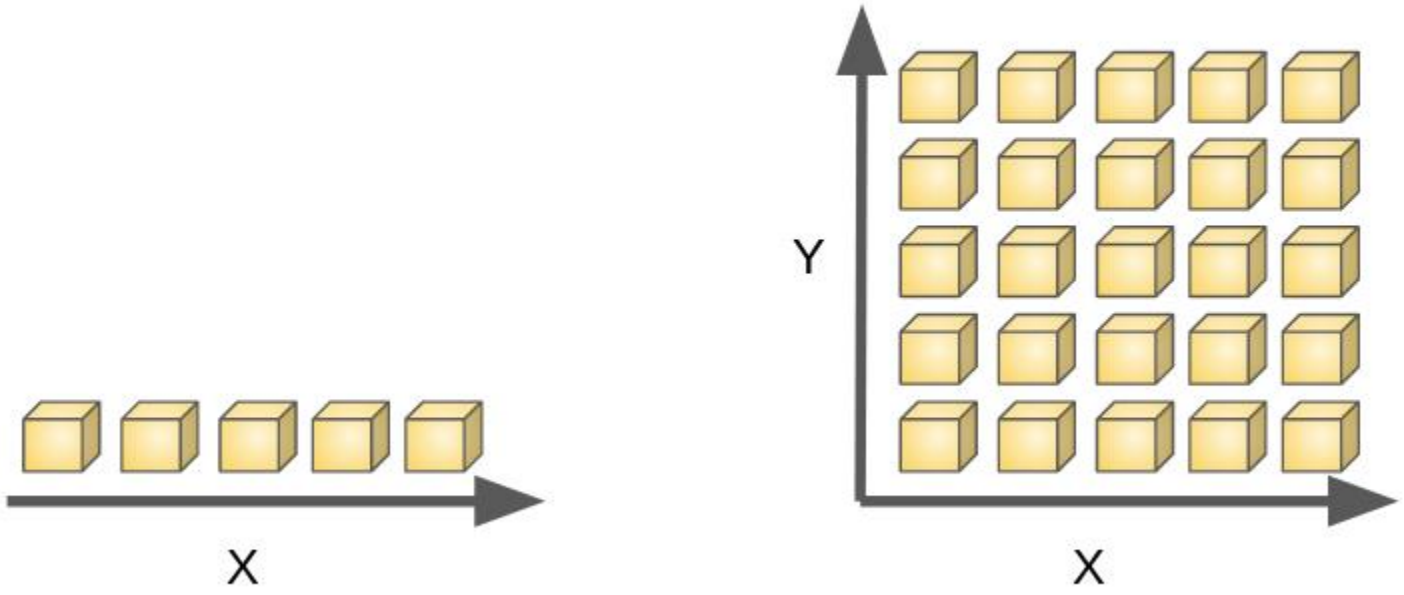


Curse of Dimensionality

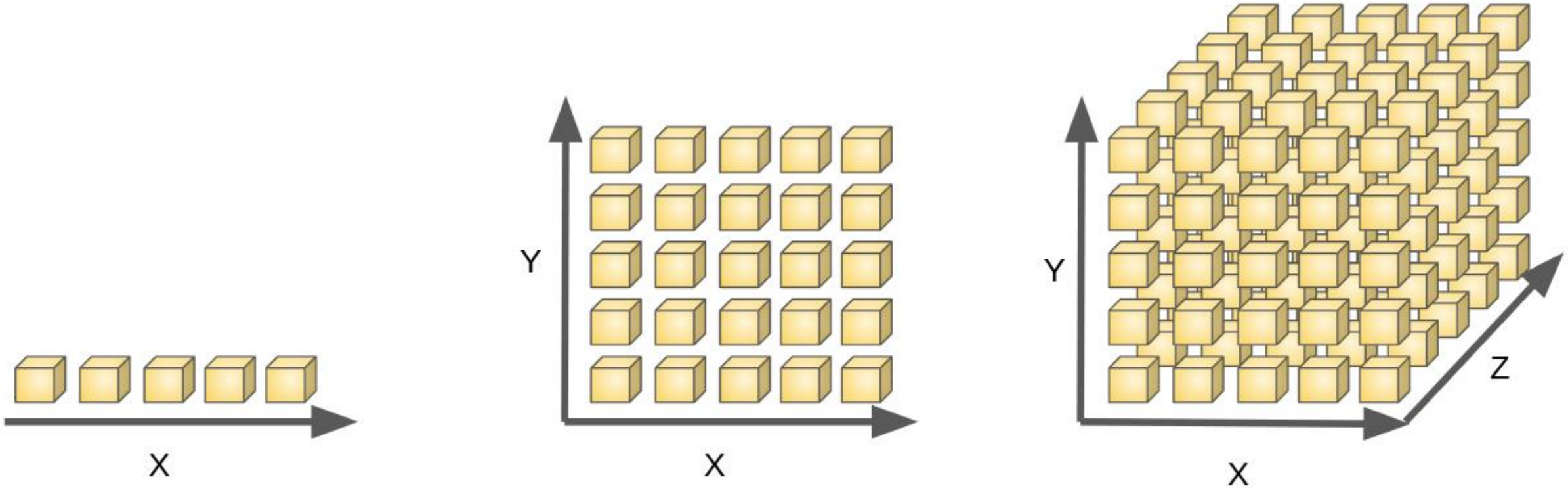
Curse of Dimensionality



Curse of Dimensionality



Curse of Dimensionality




Movie Break

Demo 8 – ML in Practice

Goal: Predict survivors
of the Titanic

Lab 8A – ML in Practice (Easy)

Goal: Predict survivors
of the Titanic

Lab 8B – ML in Practice (Hard)

Goal: Predict risk in practice

ML in Production

How to Deploy to Production

Deploy to web app (Shiny)
Deploy to cloud (Azure ML)
Deploy to server (ML Server)
Deploy to any app (ONNX)

C:/Workshop/Data - Shiny

http://127.0.0.1:4017 | Open in Browser | Publish

Iris Species Predictor

Petal Length (cm)

1 4 7

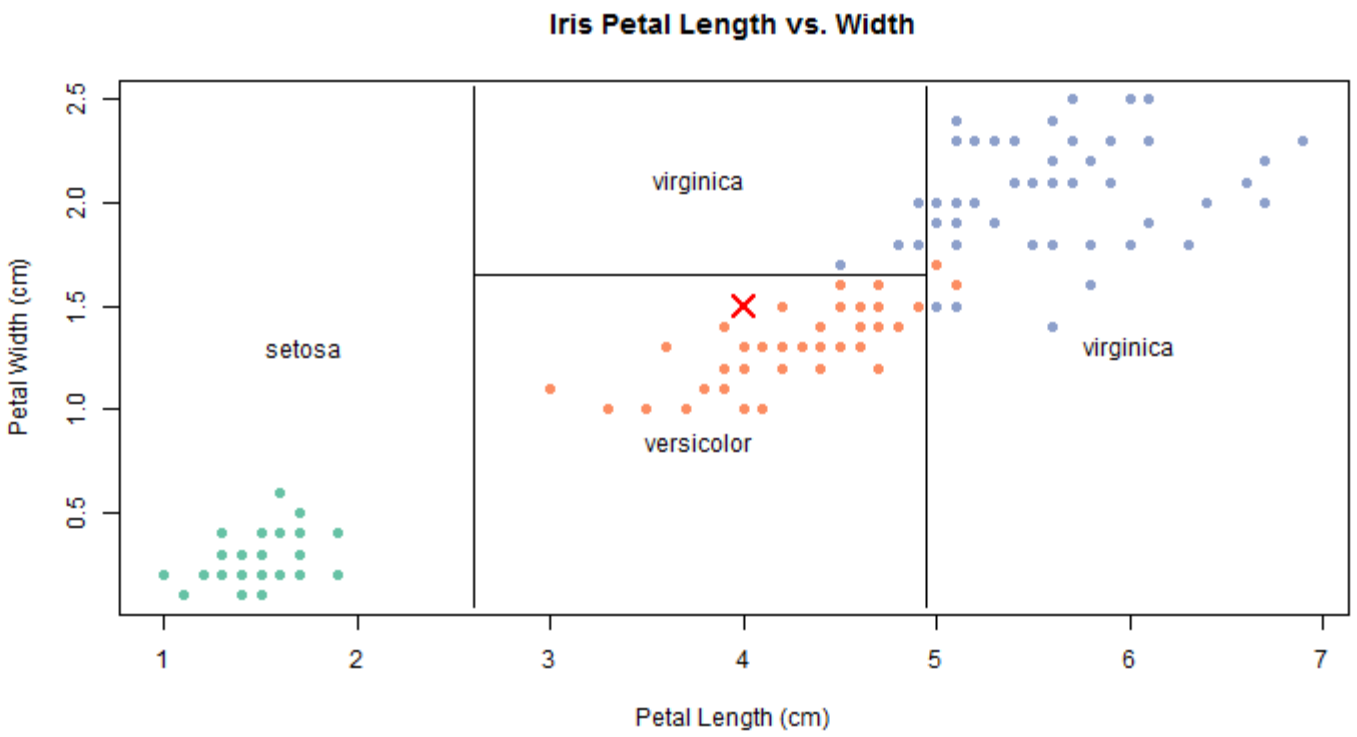
1 2 3 4 5 6 7

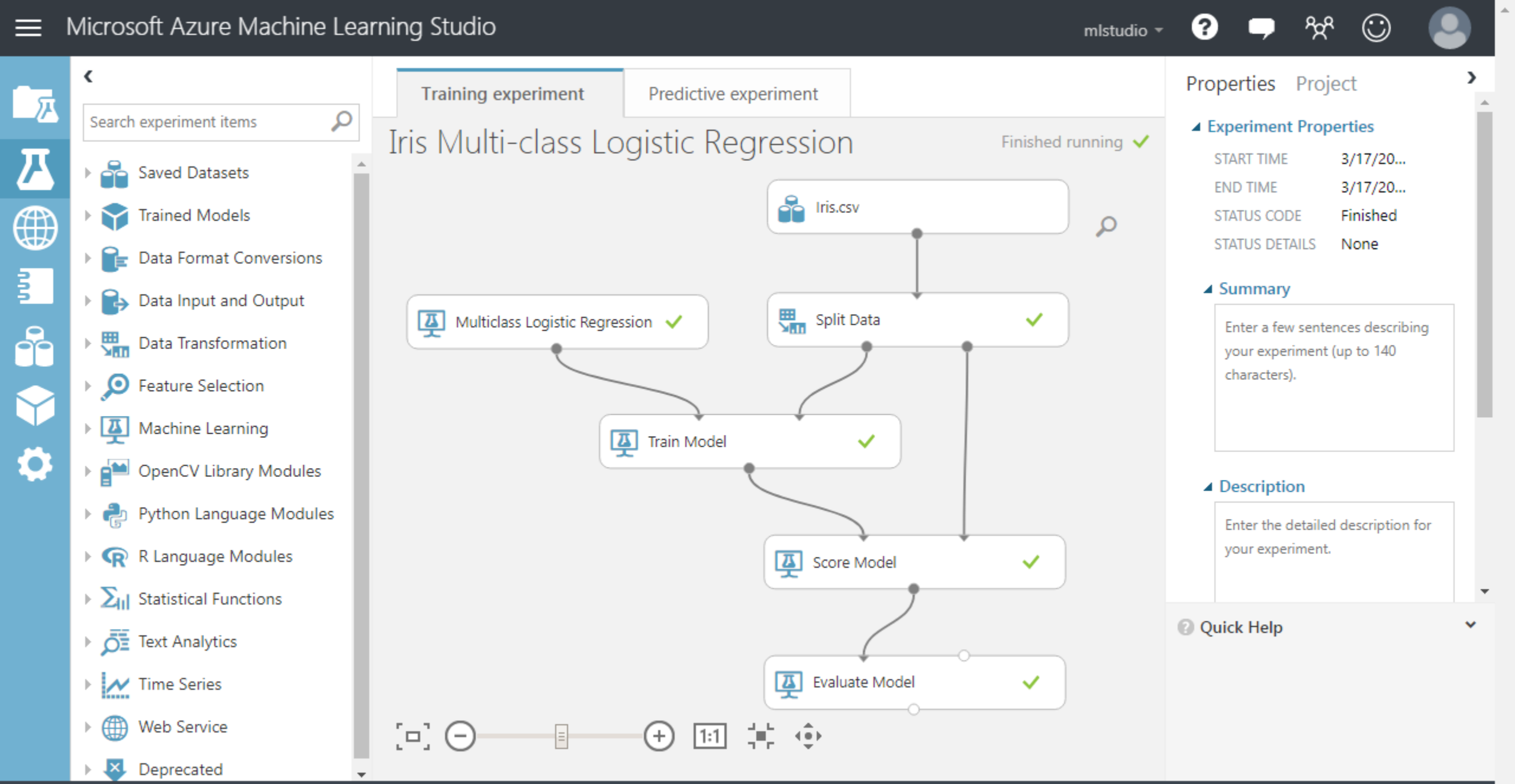
Petal Width (cm)

0 1.5 2.5

0 0.5 1 1.5 2 2.5

The predicted species is versicolor

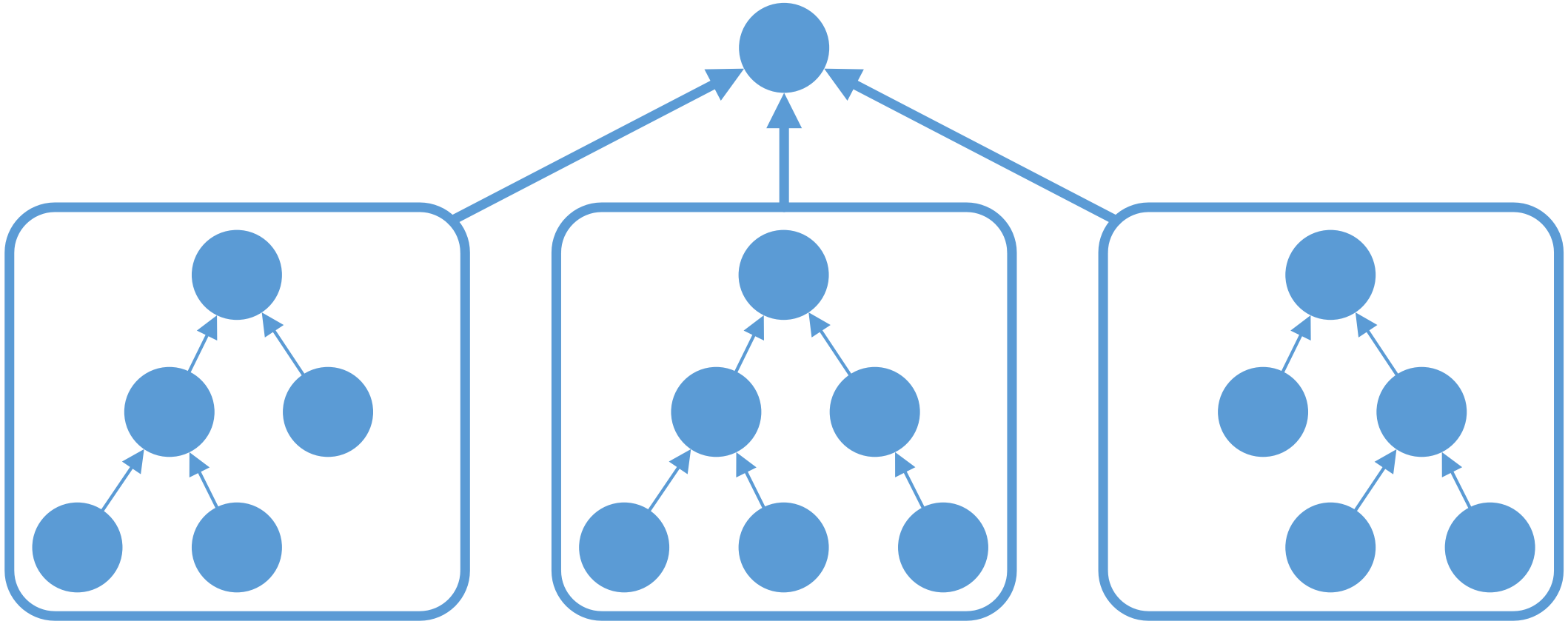



Microsoft Azure Machine Learning Studio
mlstudio
Training experiment
Predictive experiment
Iris Multi-class Logistic Regression
Finished running
Search experiment items
Saved Datasets
Trained Models
Data Format Conversions
Data Input and Output
Data Transformation
Feature Selection
Machine Learning
OpenCV Library Modules
Python Language Modules
R Language Modules
Statistical Functions
Text Analytics
Time Series
Web Service
Deprecated
Iris.csv
Multiclass Logistic Regression
Split Data
Train Model
Score Model
Evaluate Model
1:1
Properties
Project
Experiment Properties
START TIME
3/17/20...
END TIME
3/17/20...
STATUS CODE
Finished
STATUS DETAILS
None
Summary
Enter a few sentences describing your experiment (up to 140 characters).
Description
Enter the detailed description for your experiment.
Quick Help
NEW
RUN HISTORY
SAVE
SAVE AS
DISCARD CHANGES
RUN
SET UP WEB SERVICE
PUBLISH TO GALLERY

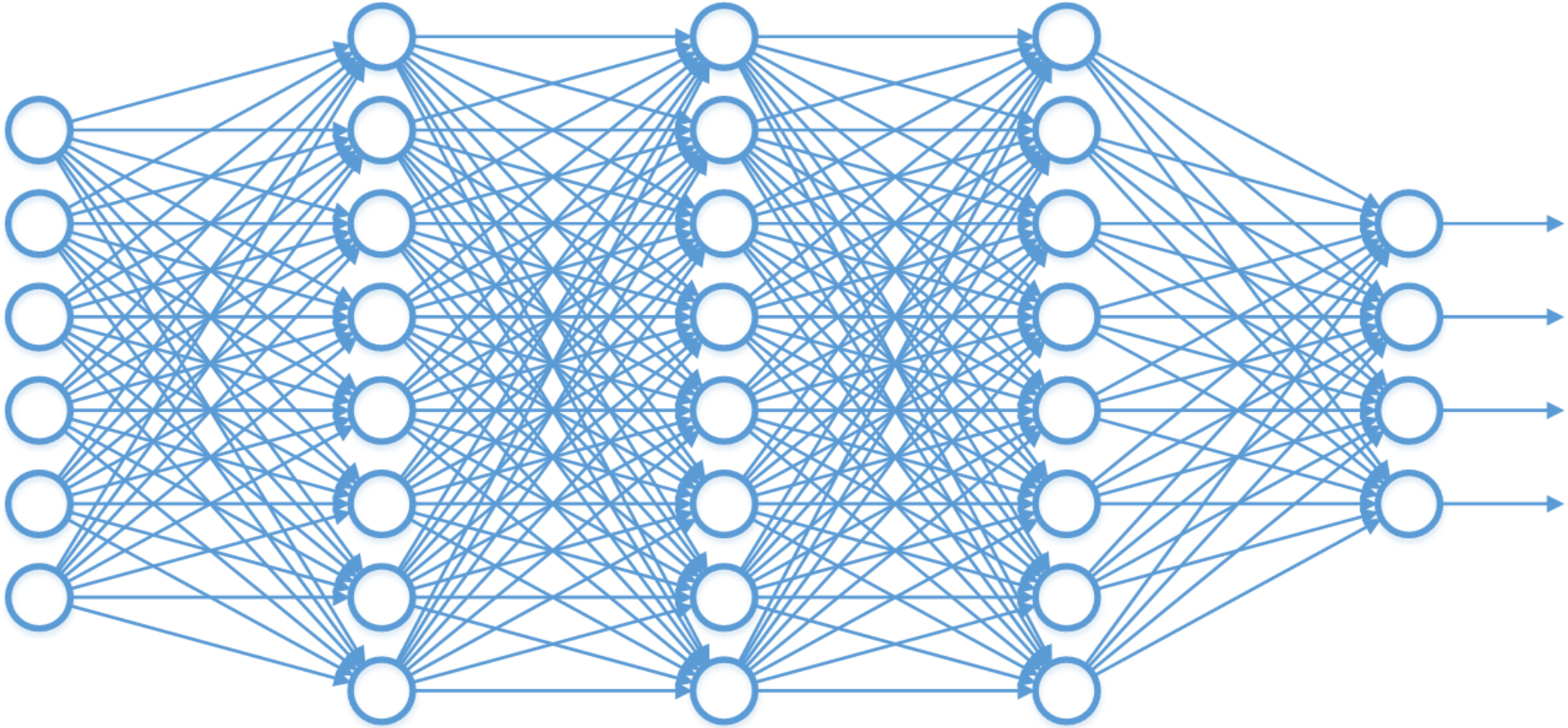
Conclusion


This is just the tip of the iceberg!

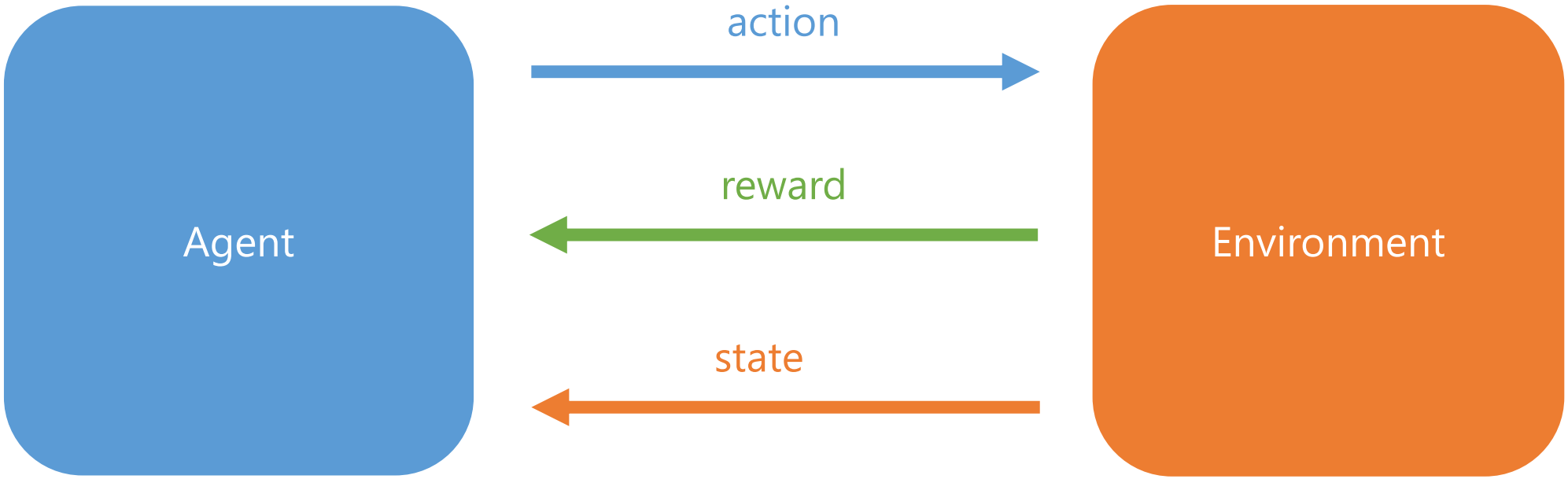
Ensemble Learning



Deep Learning



Reinforcement Learning



Where do we go from here?

Where to Go Next

Data Camp: https://www.datacamp.com

Pluralsight: https://www.pluralsight.com

Coursera: https://www.coursera.org

Pluralsight Courses

Data Science with R

Data Science: The Big Picture

Deep Learning: The Big Picture

Exploratory Data Analysis with R

Data Visualization with R (3-part)

https://www.pluralsight.com/authors/matthew-renze

Matthew Renze

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News

2017-08-25 - Invitation to Speak at Devoxx Morocco

Very excited to announce that I've been invited to give a keynote in Casablanca at Devoxx Morocco in November. My keynote presentation will be on Artificial Intelligence.

2017-08-16 - Invitation to Speak at Microsoft Ignite

I've been invited to speak at Microsoft Ignite in Orlando, Florida in September. This will be my first time speaking at Ignite. Talks will include both Data Science and Machine Learning with R.

2017-08-14 - Dev on Fire Interview

Matthew is a data science consultant, author for Pluralsight, international public speaker, a Microsoft MVP, ASPInsider, and open-source software contributor.

www.matthewrenze.com

Feedback

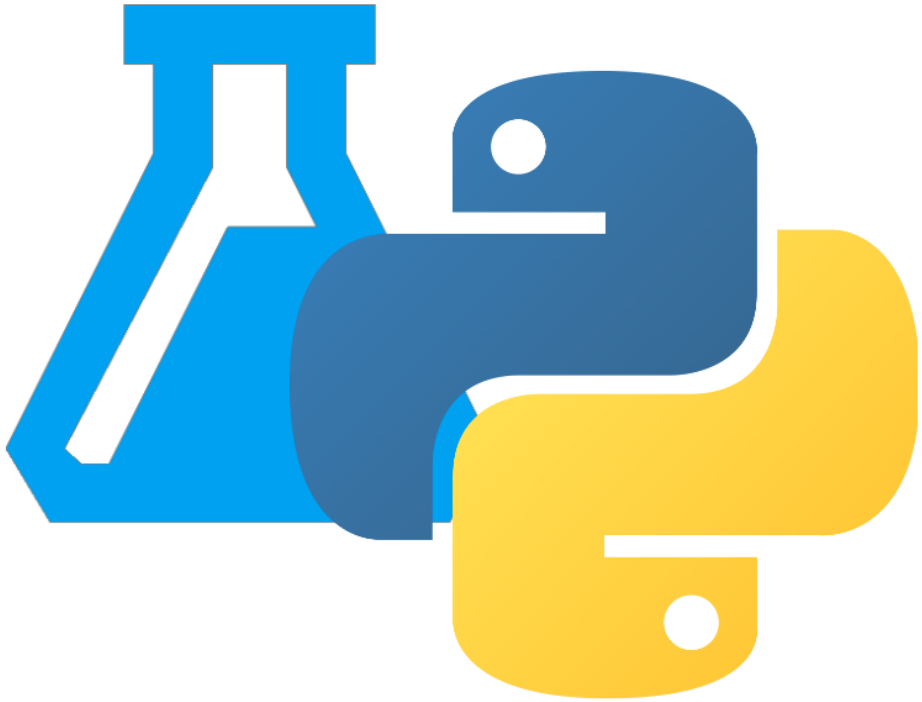
Very important to me!

What did you like?

What could I improve?

Conclusion

1. Intro to ML and Python
2. Classification
3. Regression
4. Clustering
5. ML in Practice




Caution
WARNING
ELECTRICITY

Are you prepared?

Is your organization?

Is our world prepared?


Caution
WARNING
ELECTRICITY

Contact Info

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Thank You! :)