GENERAL ASSEMBLY

# INTRO TO DATA SCIENCE

## MACHINE LEARNING / KNN

# I. WHAT IS MACHINE LEARNING?
# II. MACHINE LEARNING PROBLEMS
# III. CLASSIFICATION WITH K NEAREST NEIGHBORS

# I. WHAT IS MACHINE LEARNING?

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from Wikipedia:

“Machine learning, a branch of artificial intelligence, is about the construction and study of systems that can *learn from data*.”

*source: http://en.wikipedia.org/wiki/Machine_learning*

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# WHAT IS MACHINE LEARNING?



from Wikipedia:

“Machine learning, a branch of artificial intelligence, is about the construction and study of systems that can *learn from data*.”

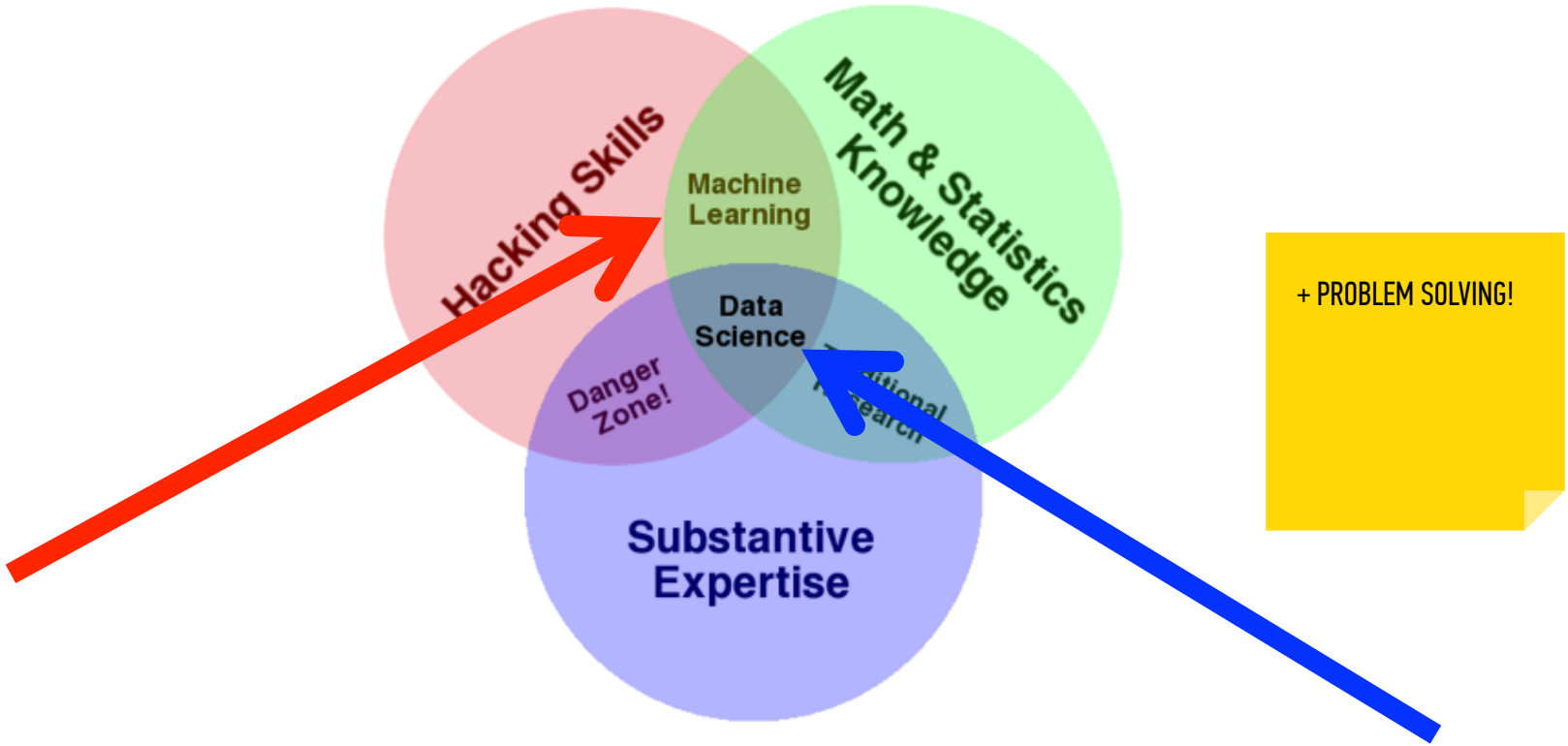
“The core of machine learning deals with *representation* and *generalization*…”

- *representation* – extracting structure from data
- *generalization* – making predictions from data

*source: http://en.wikipedia.org/wiki/Machine_learning*

# YOU WANT TO GO HERE

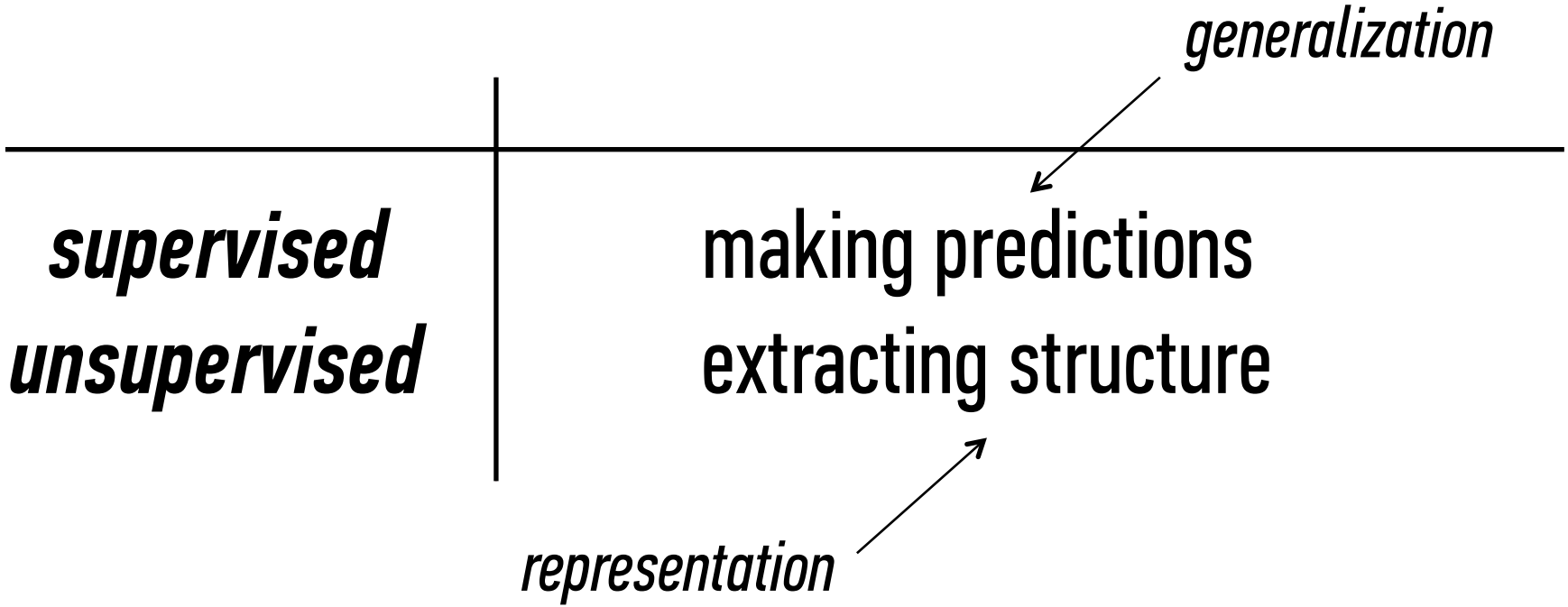





*source: http://www.dataists.com/2010/09/the-data-science-venn-diagram/*

# II. MACHINE LEARNING PROBLEMS

| | |
|---|---|
| ***supervised*** | making predictions |
| ***unsupervised*** | extracting structure |


generalization
supervised
unsupervised
making predictions
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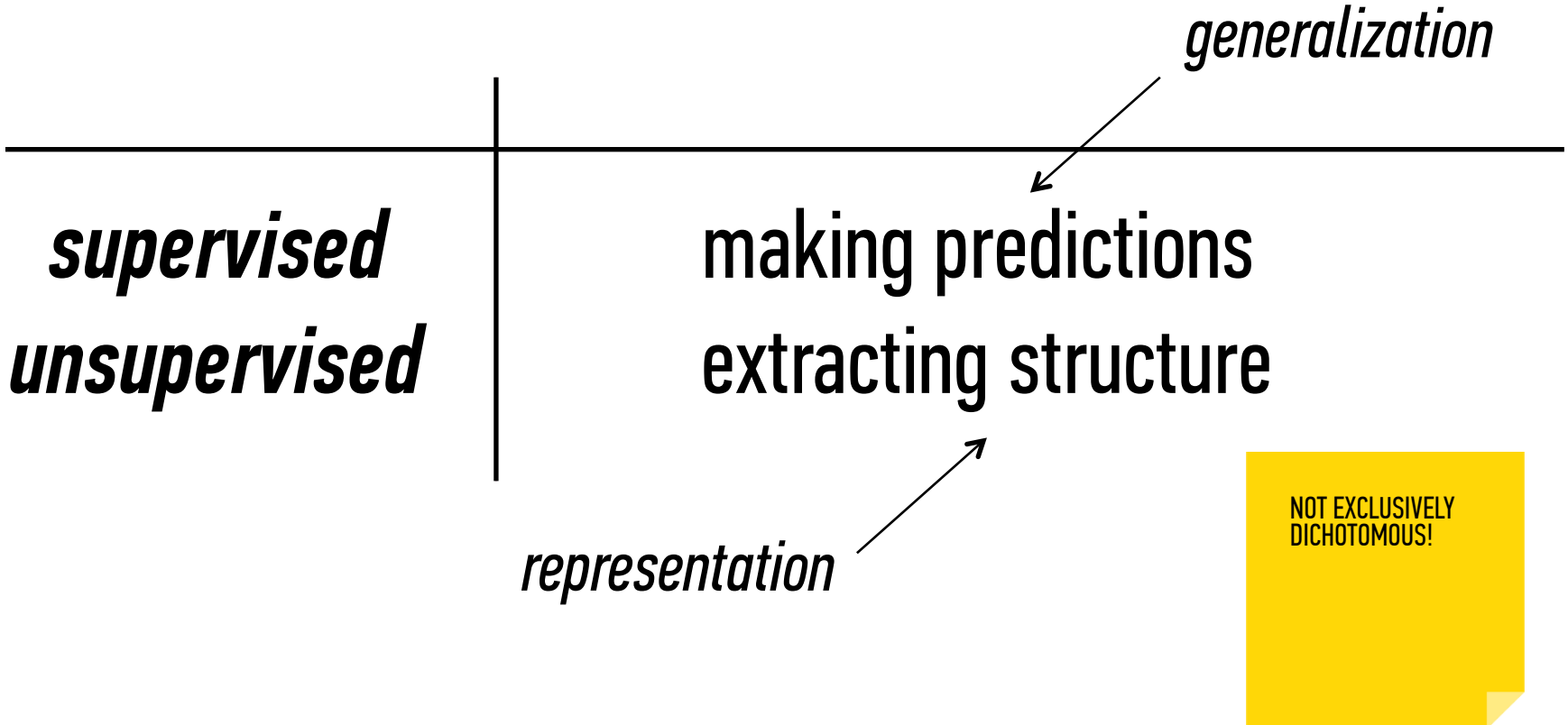
representation


generalization
supervised
unsupervised
making predictions
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representation
NOT EXCLUSIVELY
DICHOTOMOUS!

| | *continuous* | *categorical* |
|---|---|---|
| | quantitative | qualitative |

| | *continuous* | *categorical* |
|---|---|---|
| *color* | *RGB-values* | *{red, blue}* |
| *ratings* | *1 – 10 rating* | *1-5 star rating* |

| | *continuous* | *categorical* |
|---|---|---|
| | quantitative | qualitative |

NOTE

The space where data live is called the *feature space*.

Each point in this space is called a *record*.

| | *continuous* | *categorical* |
|---|---|---|
| ***supervised*** | regression | classification |
| ***unsupervised*** | dimension reduction | clustering |

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NOTE

We will implement solutions using *models* and *algorithms.*

Each will fall into one of these four buckets.

QUESTION

# WHAT IS THE GOAL OF MACHINE LEARNING?

| | |
|---|---|
| *supervised* | making predictions |
| *unsupervised* | extracting structure |

Academic goal: make good predictions by some metric.

Practical goal: provide insight and solve problems.

The goal is determined by the type of problem.

QUESTION

# HOW DO YOU DETERMINE THE RIGHT APPROACH?

| | *continuous* | *categorical* |
|---|---|---|
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ANSWER

The right approach is determined by the desired solution **and the data available**.

What type of problem is this?

Music Recommendation

What type of problem is this?

**Music Recommendation**

*It could be either.*

# TYPES OF ML SOLUTIONS



What type of problem is this?

**Music Recommendation as Supervised Learning**

Predict which songs a user will ‘thumbs-up’

What type of problem is this?

**Music Recommendation**
**As Unsupervised Learning**

Cluster songs based on attributes
and recommend songs in the same group

## QUESTION

# *HOW DO YOU KNOW IF YOU'RE DOING WELL?*

| | |
|---|---|
| ***supervised*** | *making predictions* |
| ***unsupervised*** | *extracting structure* |

| | |
|---|---|
| ***supervised*** | *test out your predictions* |

| | |
|---|---|
| ***supervised*** | *test out your predictions* |
| ***unsupervised*** | *...* |

| | |
|---|---|
| *supervised*<br>*unsupervised* | *test out your predictions*<br>*...* |

ALSO

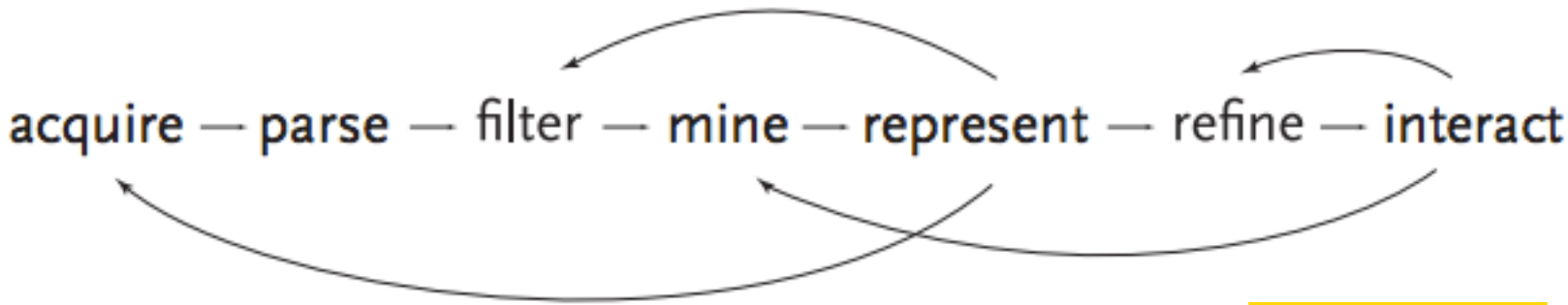
There may be external sources of feedback, for example conversion rates in production systems.

## QUESTION

# *WHAT DO YOU DO WITH YOUR RESULTS?*

# THE DATA SCIENCE WORKFLOW





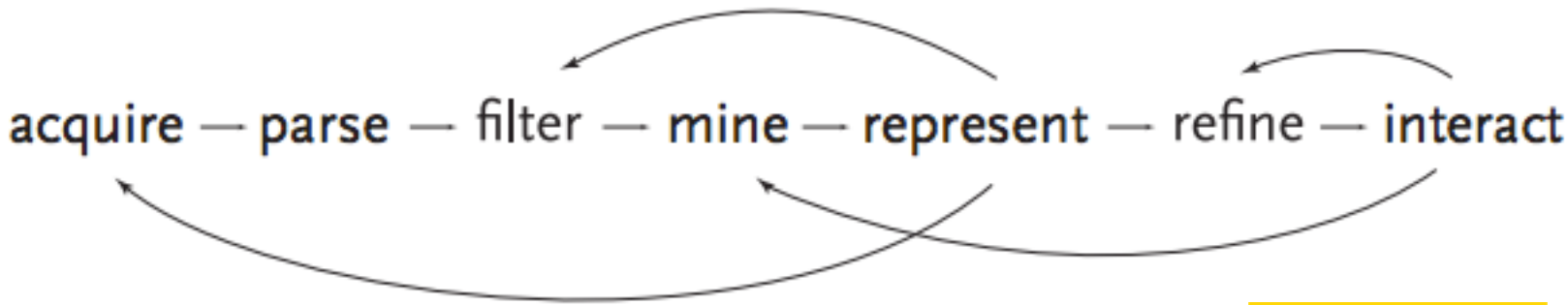

ANSWER

Interpret them and react accordingly - *application*.

*source: http://benfry.com/phd/dissertation-110323c.pdf*

# THE DATA SCIENCE WORKFLOW






ANSWER

In
re

NOTE

This also relies on your problem solving skills!

*source: http://benfry.com/phd/dissertation-110323c.pdf*

# III.
# CLASSIFICATION WITH KNN

| | *continuous* | *categorical* |
|---|---|---|
| ***supervised*** | ??? | ??? |
| ***unsupervised*** | ??? | ??? |

| | *continuous* | *categorical* |
|---|---|---|
| ***supervised*** | regression | classification |
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# Here's (part of) an example dataset:

**Fisher's *Iris* Data**

| Sepal length | Sepal width | Petal length | Petal width | Species |
|---|---|---|---|---|
| 5.1 | 3.5 | 1.4 | 0.2 | *I. setosa* |
| 4.9 | 3.0 | 1.4 | 0.2 | *I. setosa* |
| 4.7 | 3.2 | 1.3 | 0.2 | *I. setosa* |
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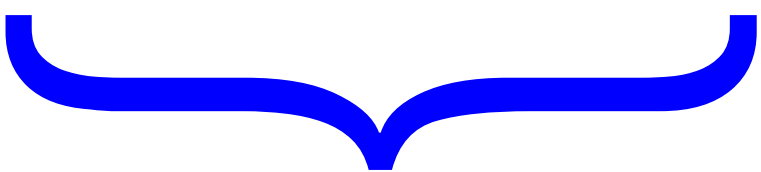
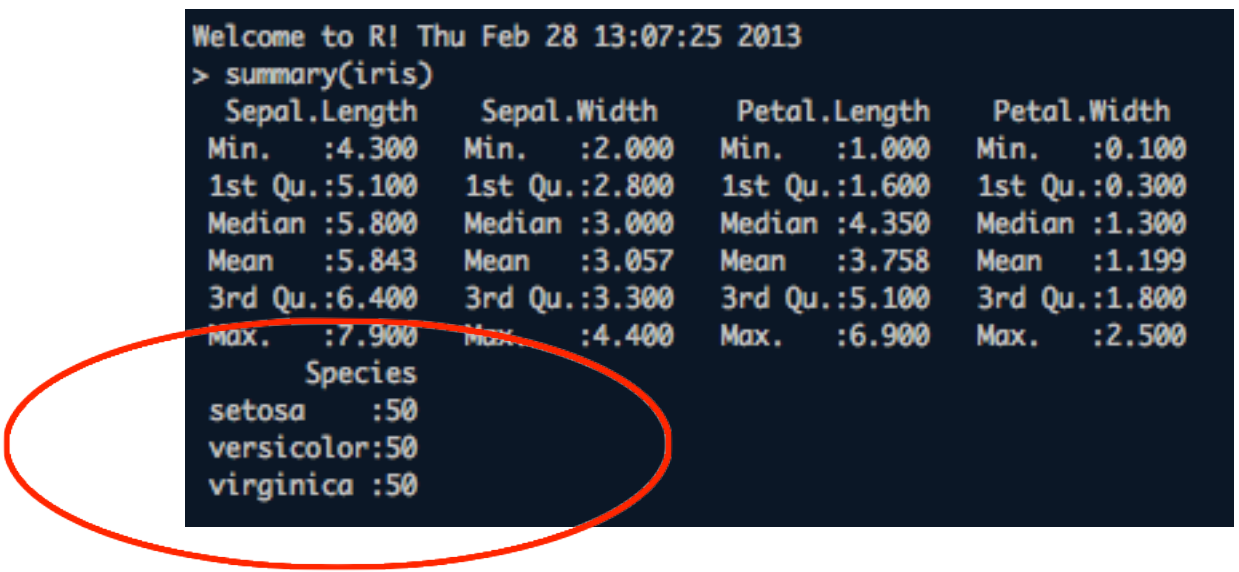


class labels *(categorical)*

Q: What does “supervised” mean?

Q: What does “supervised” mean?

A: We know the labels.



Q: How does a classification problem work?

Q: How does a classification problem work?

A: Data in, predicted labels out.

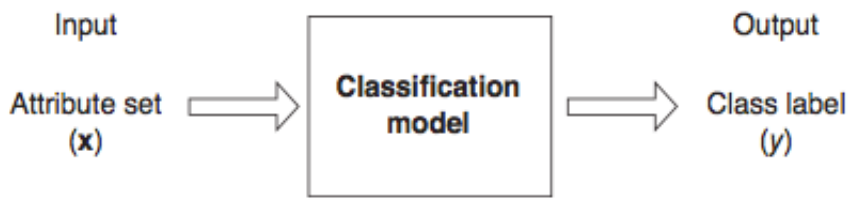
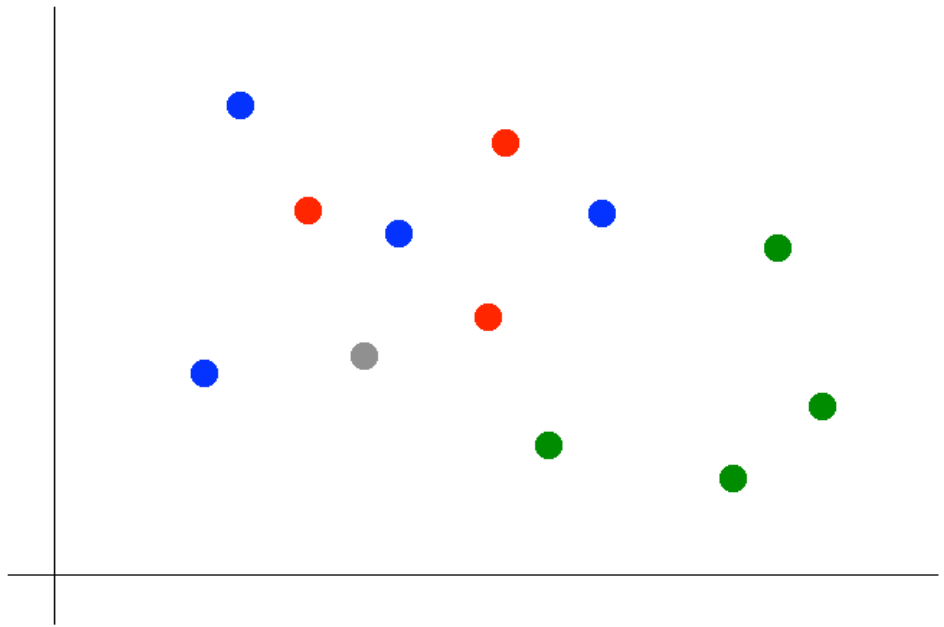



**Figure 4.2.** Classification as the task of mapping an input attribute set $\mathbf{x}$ into its class label $y$.

*source: http://www-users.cs.umn.edu/~kumar/dmbook/ch4.pdf*

Suppose we want to predict the color of the grey dot.



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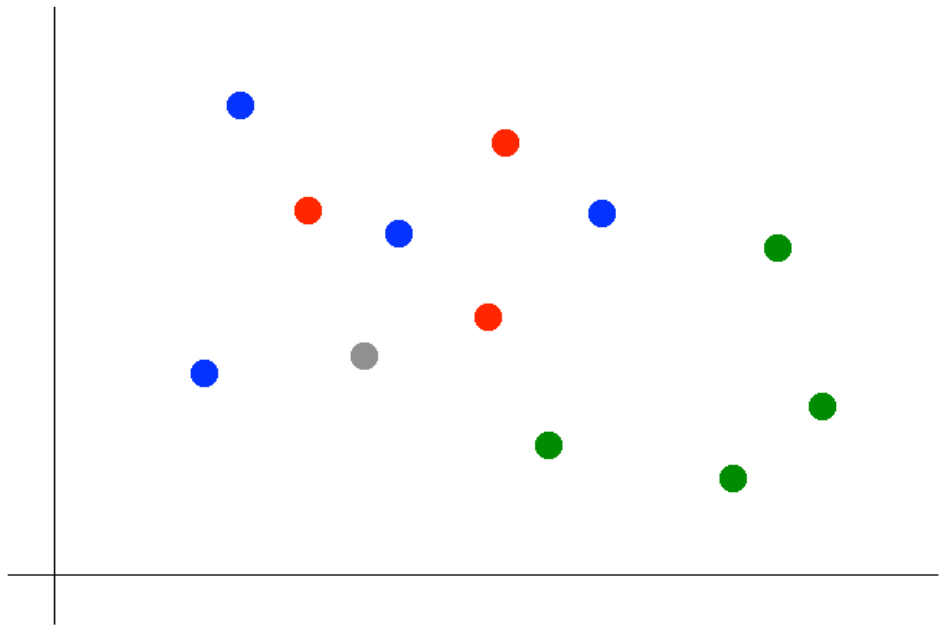
QUESTION:

What are the features?
What are the labels?



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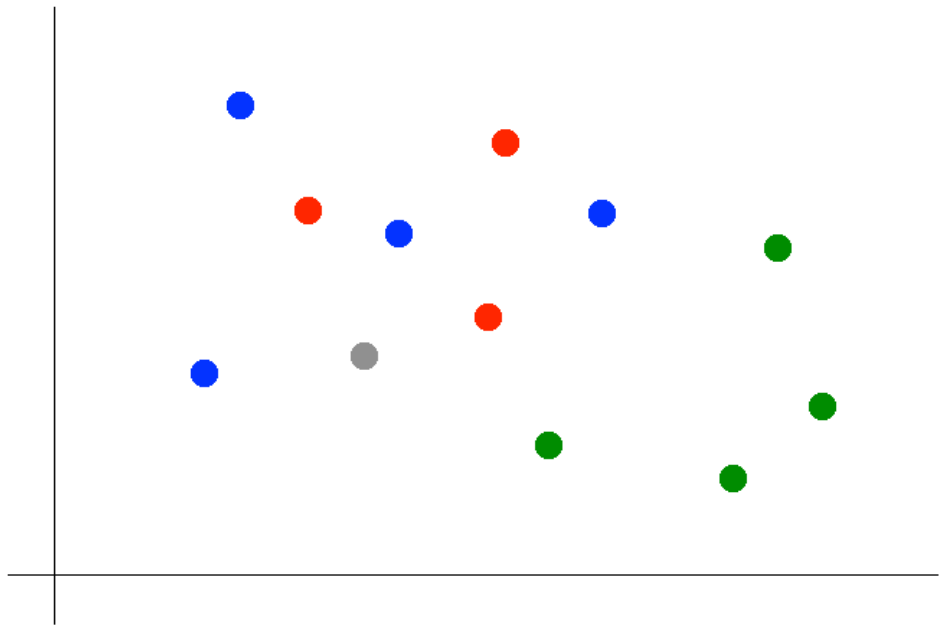

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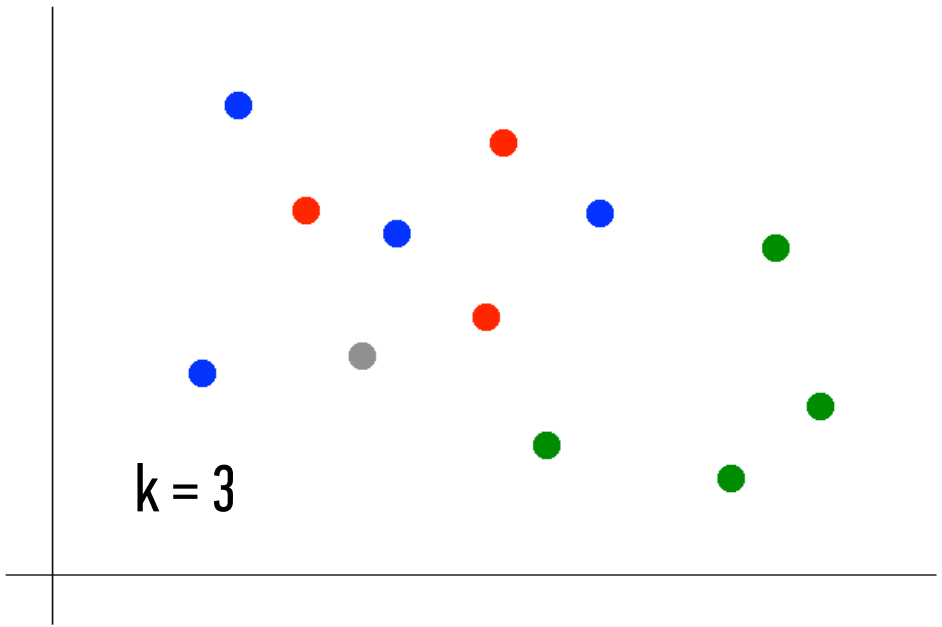
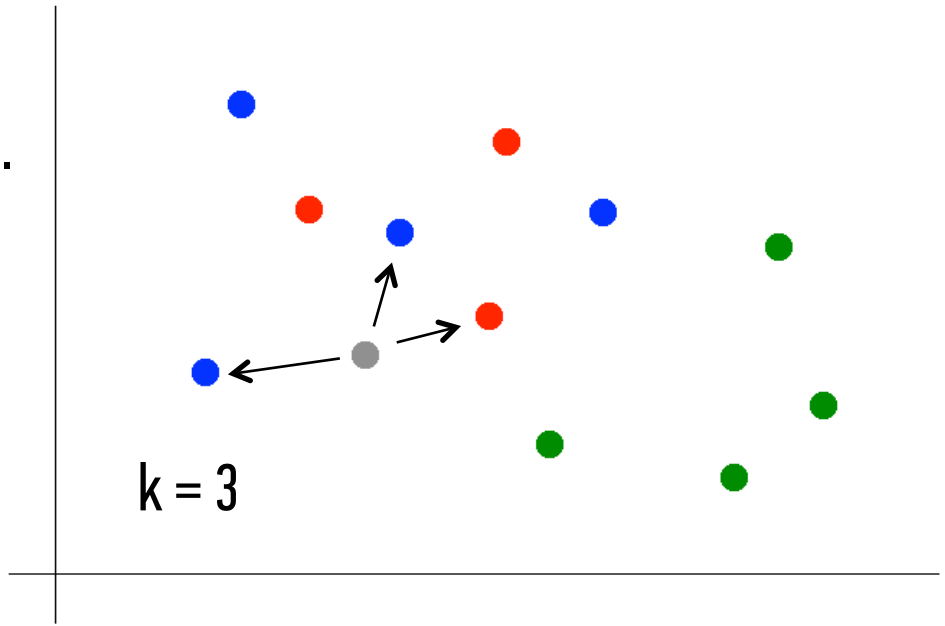


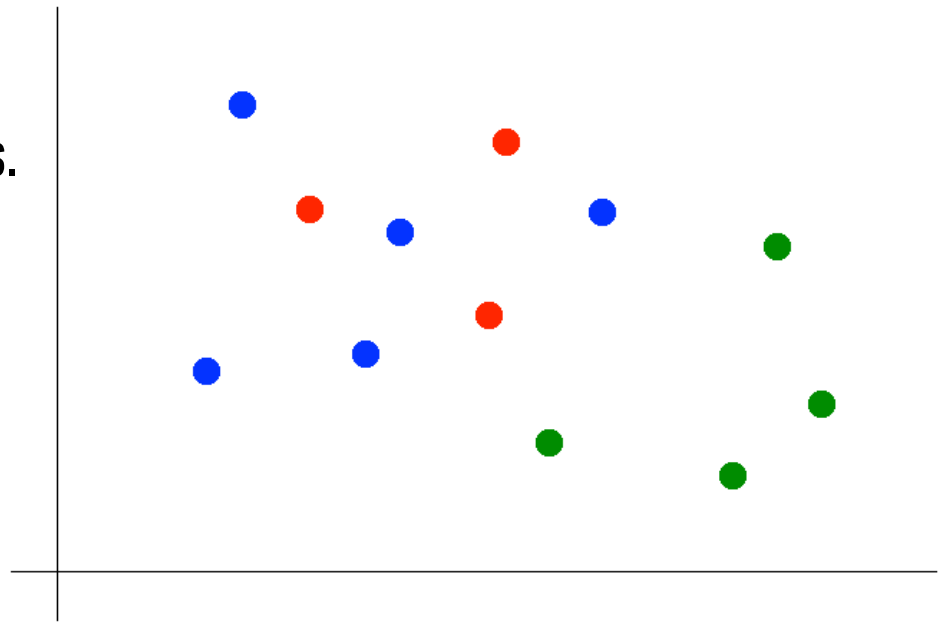
Suppose we want to predict the color of the grey dot.

1) Pick a value for k.
2) Find colors of k nearest neighbors.



Suppose we want to predict the color of the grey dot.

1) Pick a value for k.
2) Find colors of k nearest neighbors.
3) Assign the most common color to the grey dot.



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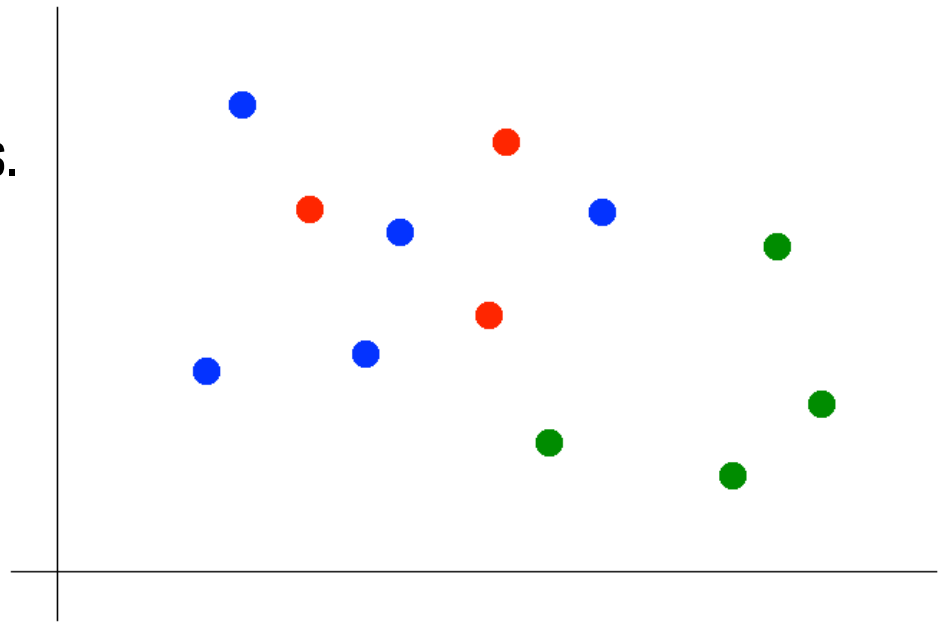

NOTE:

Our definition of "nearest" implicitly uses the *Euclidean distance function*.

# INTRO TO DATA SCIENCE