# What is machine learning?

UNDERSTANDING MACHINE LEARNING

**Lis Sulmont**
Curriculum Manager, DataCamp

datacamp

**AlphaZero beat humans at Chess and StarCraft, now it's working with quantum computers**

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Machine Learning Gives Rise to Better Lung Disease Models from Stem Cells

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Amazon is injecting Alexa with more artificial intelligence than ever

How Google Maps uses machine learning to predict bus traffic delays in real time

# This A.I. Bot Writes Such Convincing Ads, Chase Just 'Hired' It to Write Marketing Copy

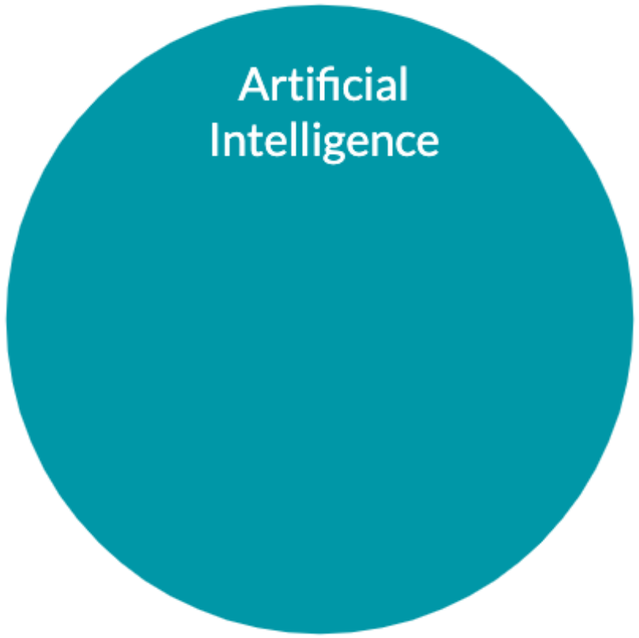
During a trial run, JPMorgan Chase found ads written by the machine learning platform got far more clicks than ads written by humans.

# A.I. is transforming the job interview—and everything after


Waymo's Self-Driving Technology Gets Smarter, Recognizes Billions of Objects Thanks To Content Search
New machine learning algorithm produces "near-perfect" fake human faces
The AI-Art Gold Rush Is Here
An artificial-intelligence "artist" got a solo show at a Chelsea gallery. Will it reinvent art, or destroy it?

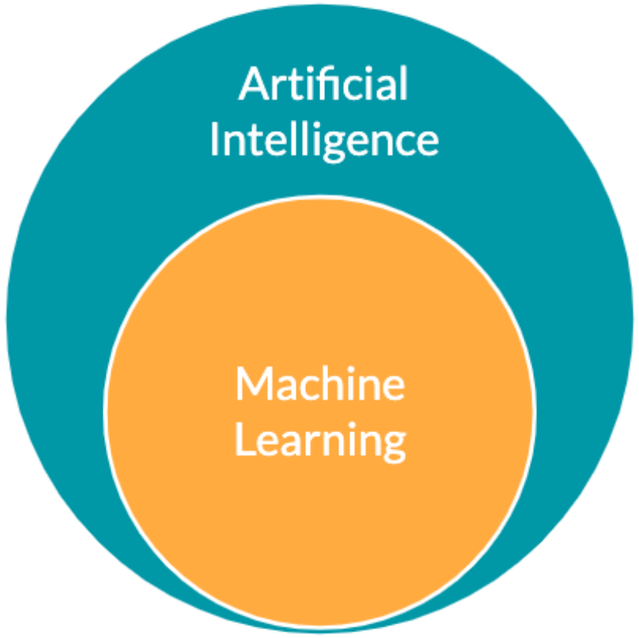

White House reportedly aims to double AI research budget to $2B
Finland seeks to teach 1% of all Europeans basics on AI

# Artificial intelligence (AI)




A huge set of tools for making computers behave intelligently

# Artificial intelligence (AI)

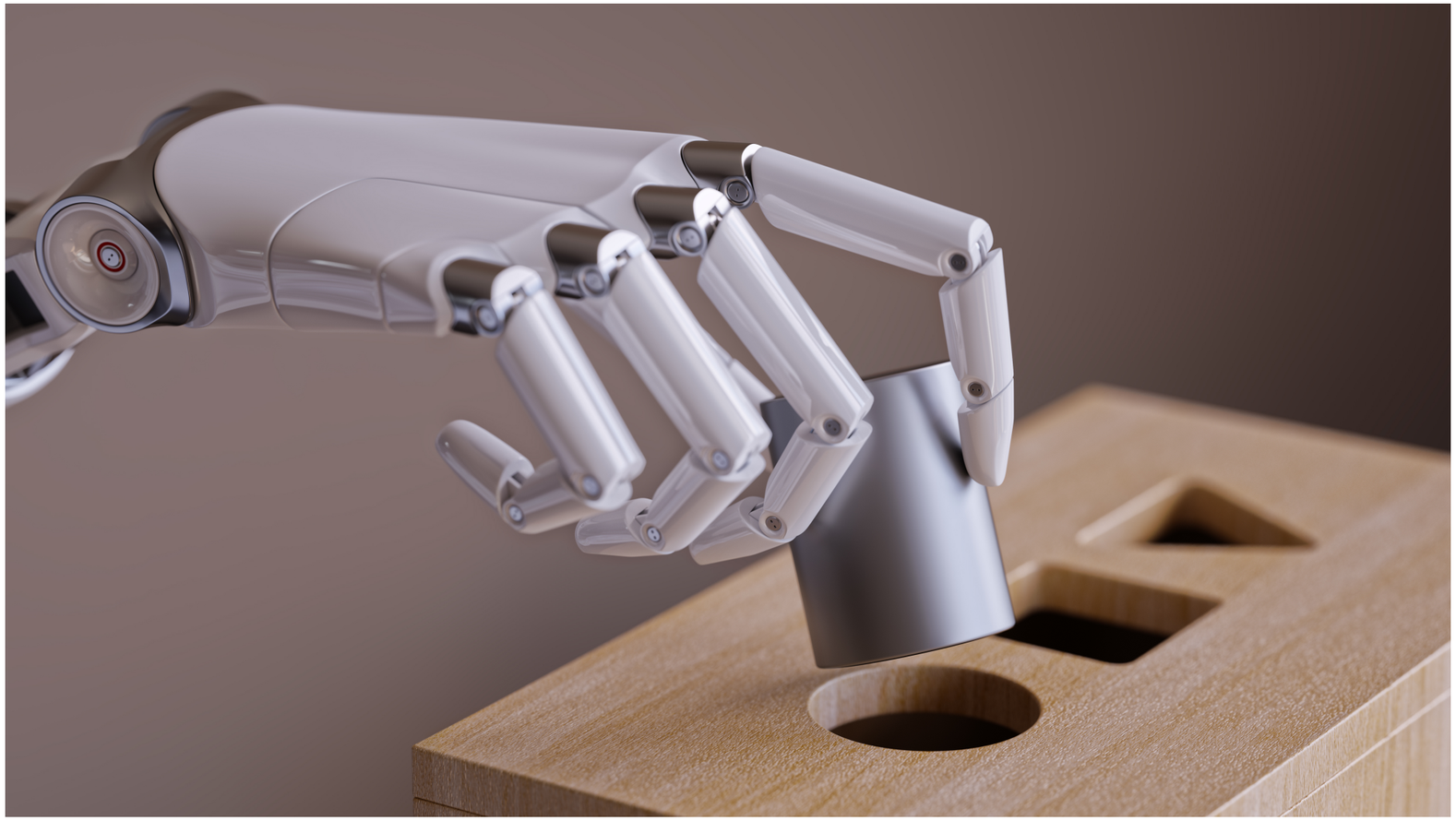



A huge set of tools for making computers behave intelligently

Machine learning is the most prevalent subset of AI

# Defining machine learning:

A set of tools for making inferences and predictions from data



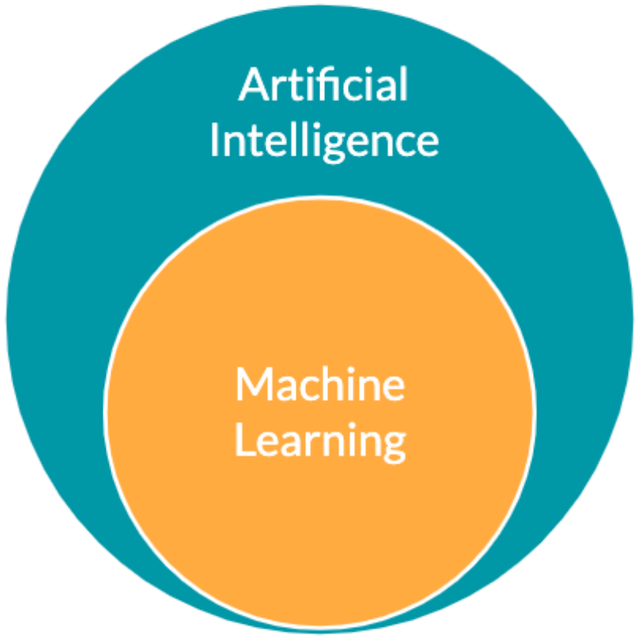
# Defining machine learning: what can it do?

- **Predict** future events
  - *Will it rain tomorrow?*
    - Yes (75% probability)
- **Infer** the causes of events and behaviors
  - *Why does it rain?*
    - Time of the year, humidity levels, temperature, location, etc
- **Infer** patterns
  - *What are the different types of weather conditions?*
    - Rain, sunny, overcast, fog, etc

# Defining machine learning: how does it work?

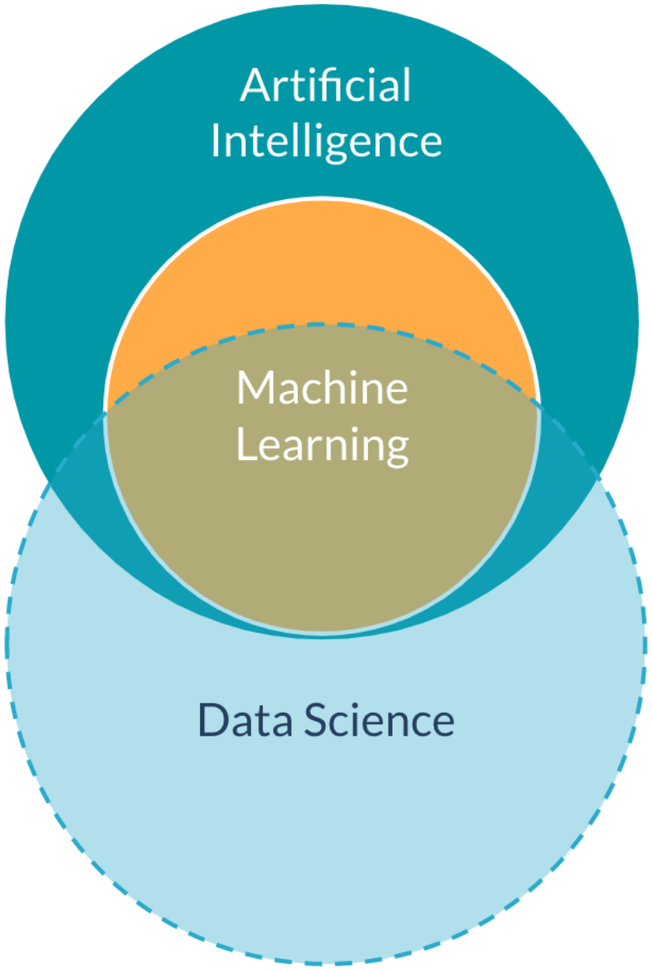
- Interdisciplinary mix of statistics and computer science
- Ability to learn without being explicitly programmed
- Learn patterns from existing data and applies it to new data
- Relies on high-quality data
- ... more to come throughout the course!

# Data science




Data science is about discovering and communicating insights from data

# Data science

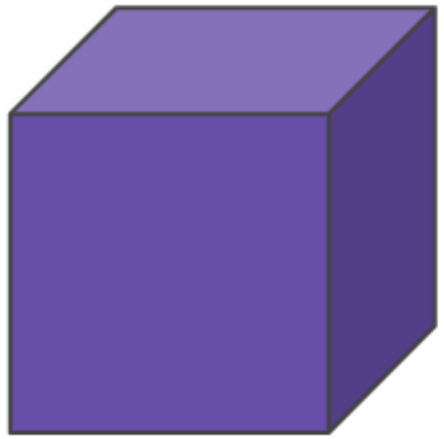



Data science is about making discoveries and creating insights from data

Machine learning is often an important tool for data science work

# Machine learning model

A statistical representation of a real-world process based on data



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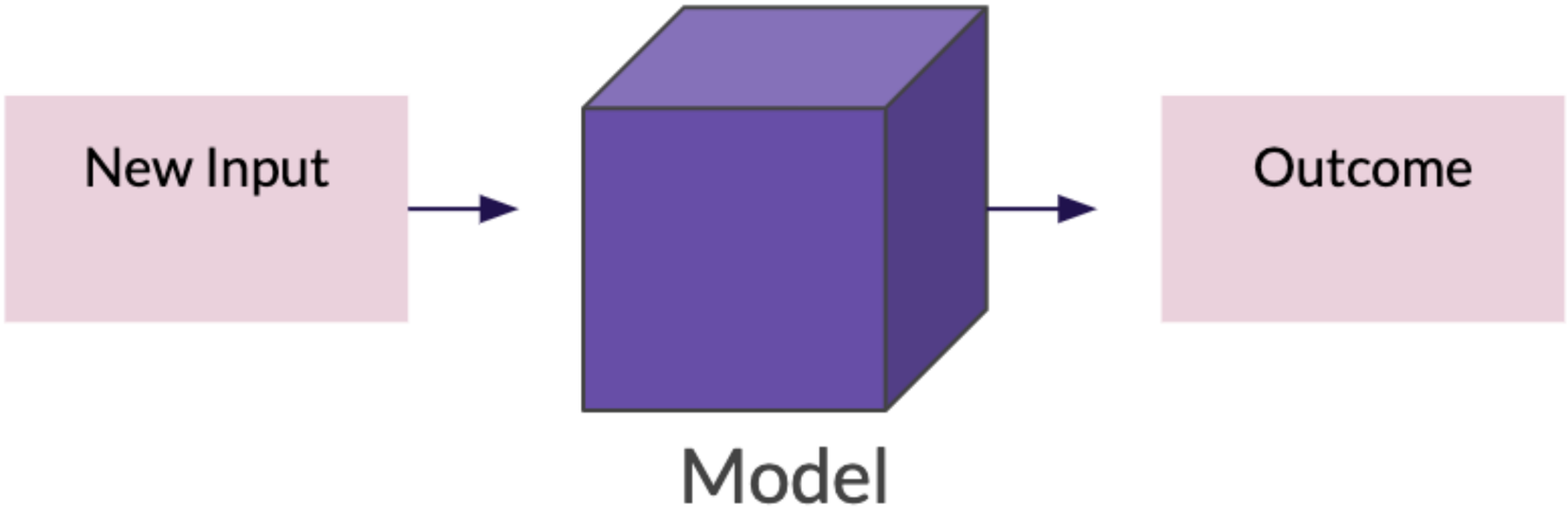

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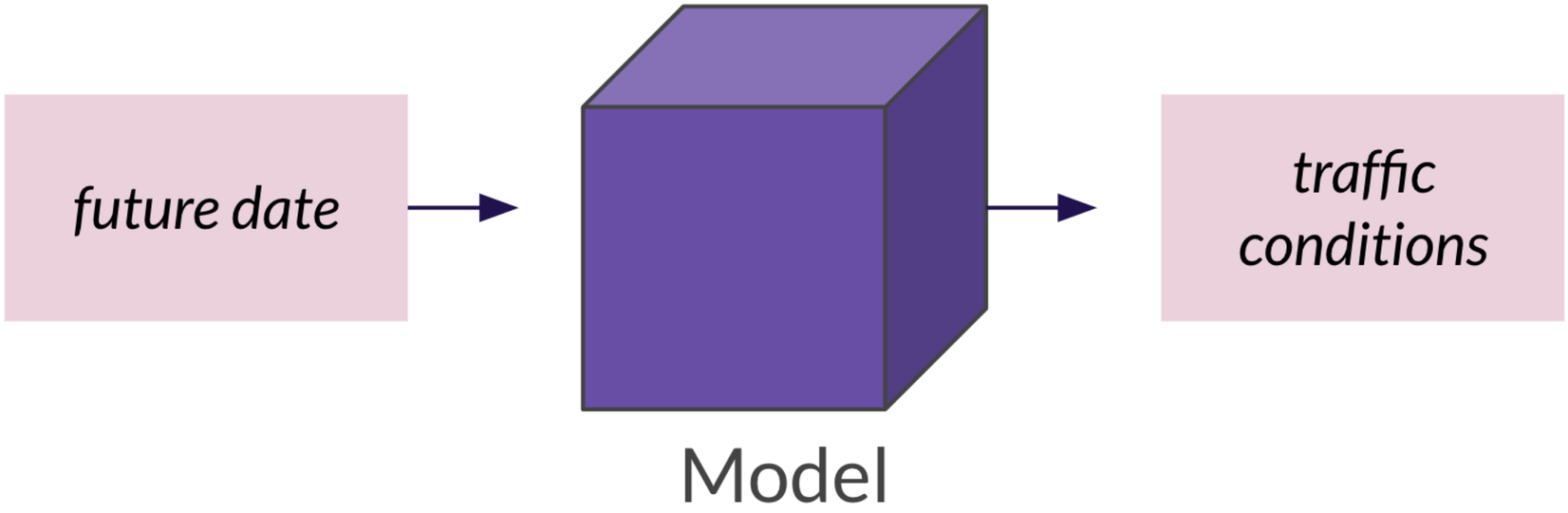

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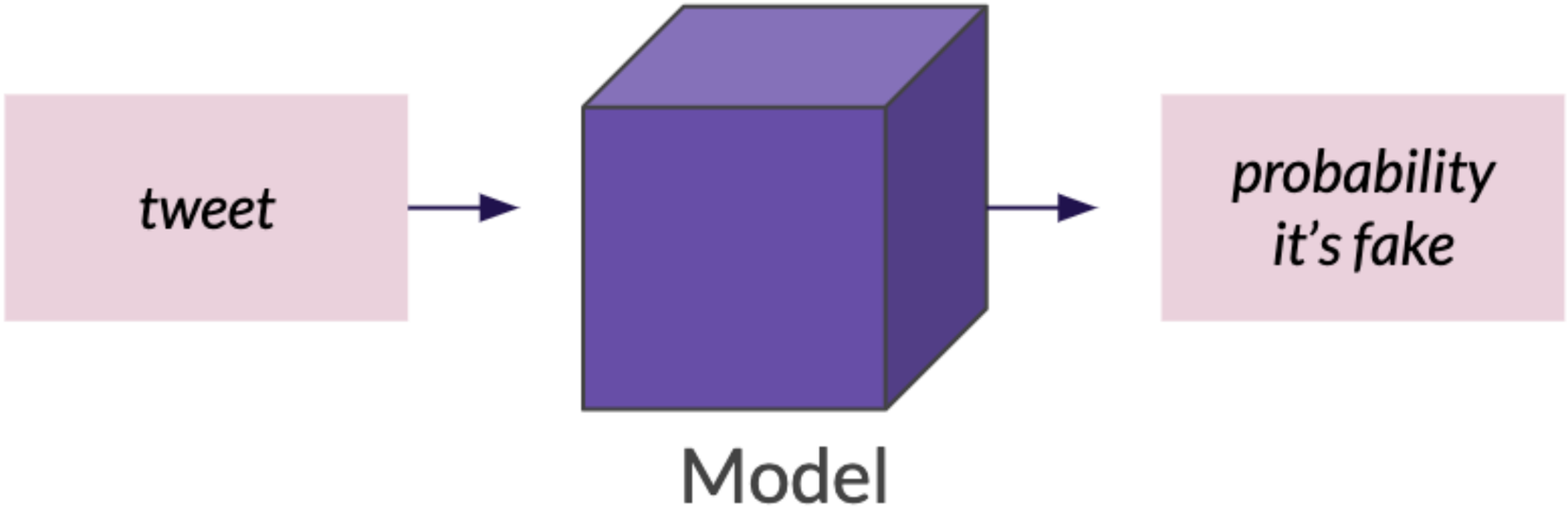

# Let's practice!

UNDERSTANDING MACHINE LEARNING

# Machine learning concepts

## UNDERSTANDING MACHINE LEARNING

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# Three types of machine learning

1) Reinforcement learning

2) Supervised learning

3) Unsupervised learning

# Training data

- **Training data:** existing data to learn from
- **Training a model:** when a model is being built from training data
  - Can take nanoseconds to weeks

# Supervised learning training data

| Age | Sex | Cholesterol | Cigarettes per day | Family history of heart disease | Chest pain type | Blood sugar | Heart disease |
|---|---|---|---|---|---|---|---|
| 55 | M | 221 | 5 | True | typical angina | 118 | True |
| 50 | F | 196 | 0 | False | non-anginal pain | 98 | False |
| 53 | F | 215 | 0 | True | asymptomatic | 110 | True |
| 62 | M | 245 | 3 | False | typical angina | 126 | True |
| 48 | M | 190 | 0 | True | non-anginal pain | 99 | False |
| 70 | M | 201 | 0 | True | typical angina | 105 | False |

# Supervised learning training data

Target Variable

| Age | Sex | Cholesterol | Cigarettes per day | Family history of heart disease | Chest pain type | Blood sugar | Heart disease |
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Labels

# Supervised learning training data

Observations *or* Examples

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# Supervised learning training data

Features

| Age | Sex | Cholesterol | Cigarettes per day | Family history of heart disease | Chest pain type | Blood sugar | Heart disease |
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# After training (supervised learning)

| Age | Sex | Cholesterol | Cigarettes per day | Family history of heart disease | Chest pain type | Blood sugar | Heart disease |
|---|---|---|---|---|---|---|---|
| 65 | F | 208 | 2 | False | typical angina | 105 | ??? |

# After training (supervised learning)

| Age | Sex | Cholesterol | Cigarettes per day | Family history of heart disease | Chest pain type | Blood sugar | Heart disease |
|---|---|---|---|---|---|---|---|
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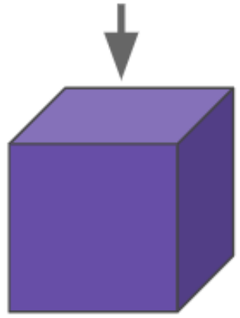

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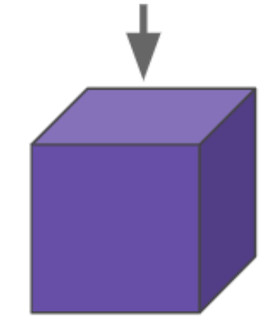

| Heart disease |
|---|
| False |

# Supervised vs unsupervised learning

- **Supervised learning**
  - Training data is "labeled"
- **Unsupervised learning**
  - Training data only has features
  - Useful for:
    - Anomaly detection
    - Clustering, e.g., *dividing data into groups*

Target Variable

| Blood sugar | Heart disease |
|---|---|
| 118 | True |
| 98 | False |
| 110 | True |
| 126 | True |
| 99 | False |
| 105 | False |

Labels

# Unsupervised learning training data

| Age | Sex | Cholesterol | Cigarettes per day | Family history of heart disease | Chest pain type | Blood sugar | Heart disease |
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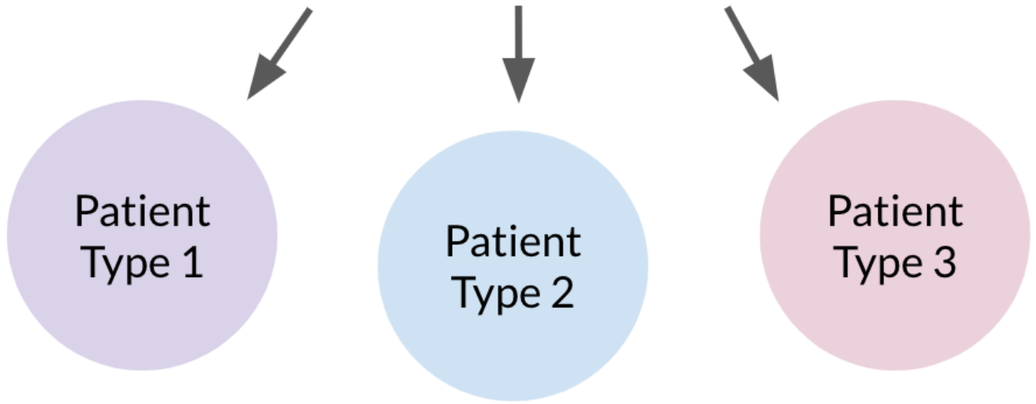

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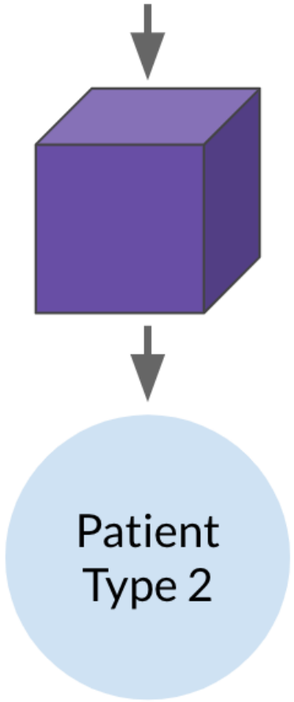

# Unsupervised Learning

- In reality, data doesn't always come with labels
  - Requires manual labor to label
  - Labels are unknown
- No labels: model is unsupervised and finds its own patterns

# Let's practice!

UNDERSTANDING MACHINE LEARNING

# Machine learning workflow

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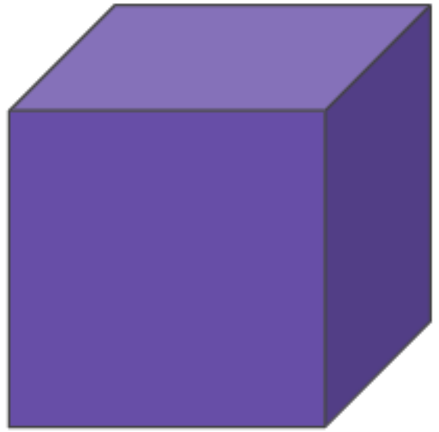
# Machine learning workflow

Historical data

?



Machine learning model

# Our scenario

**Our dataset:** NYC property sales from 2015-2019

Includes:

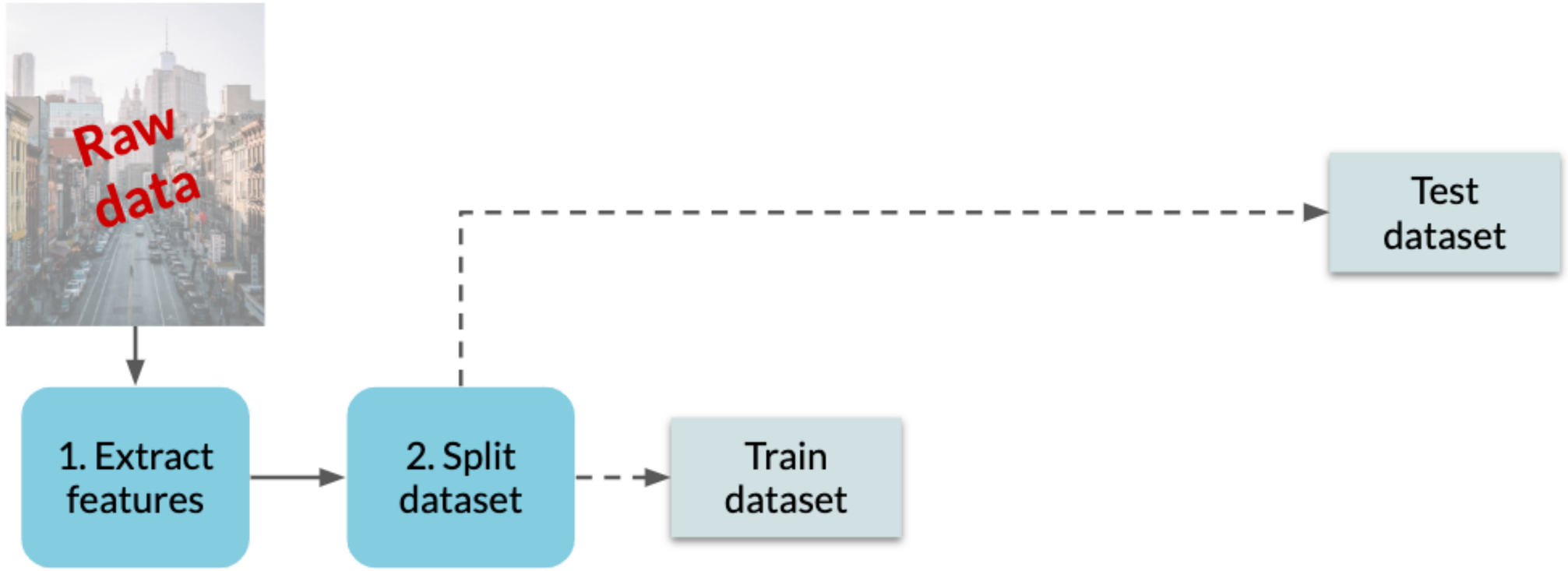
- Square feet
- Neighborhood
- Year built
- Sale price
- And more!

**Our target:** Sale price

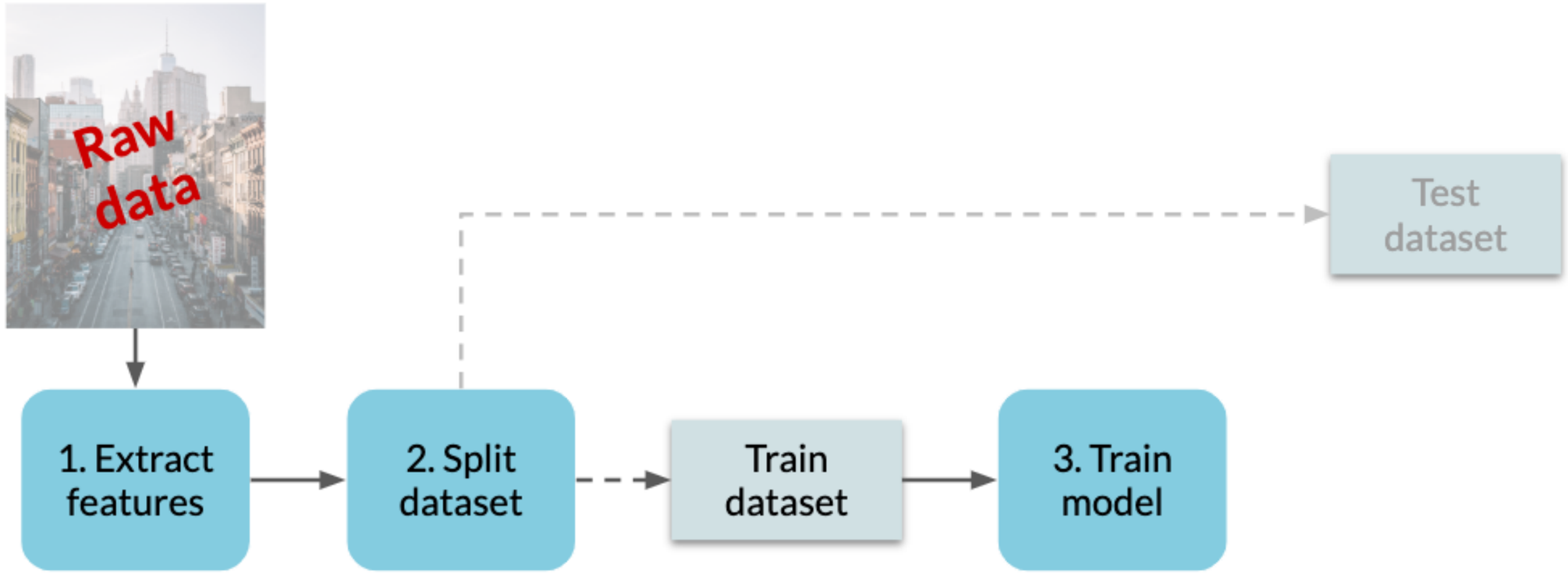
# Step 1: Extract features


1. Extract features

# Step 2: Split dataset



# Step 3: Train model



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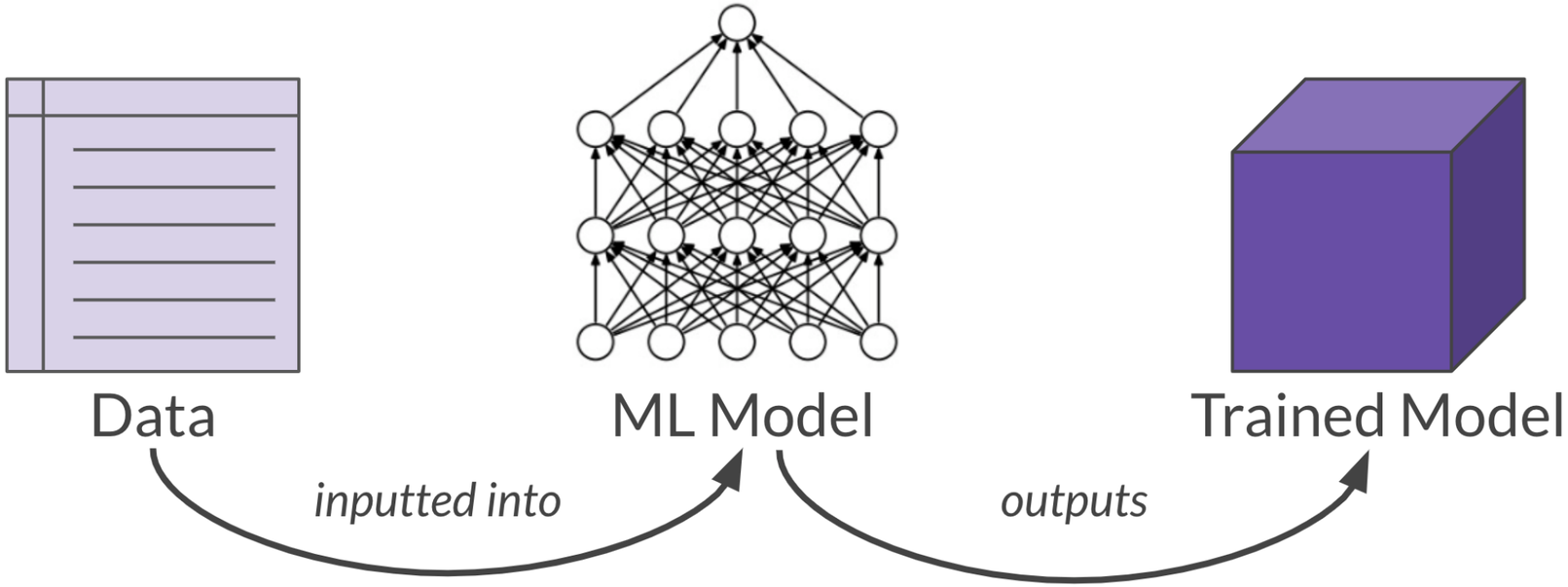
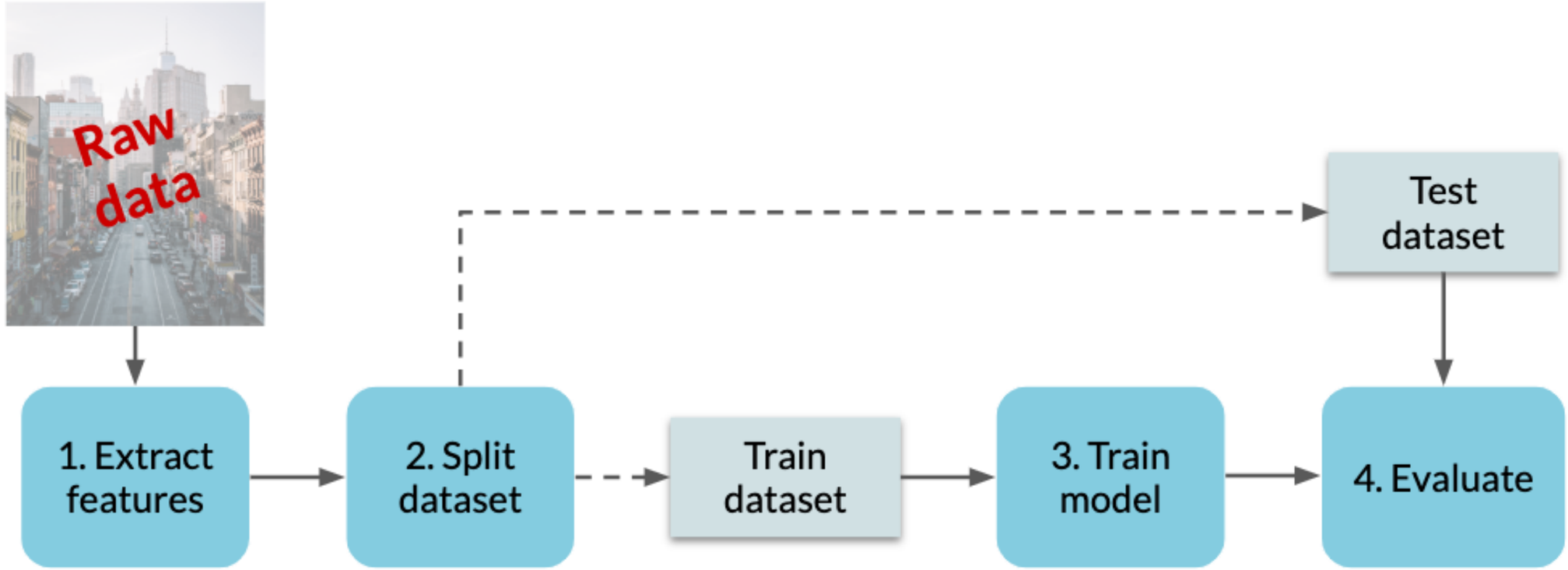


# Step 4: Evaluate



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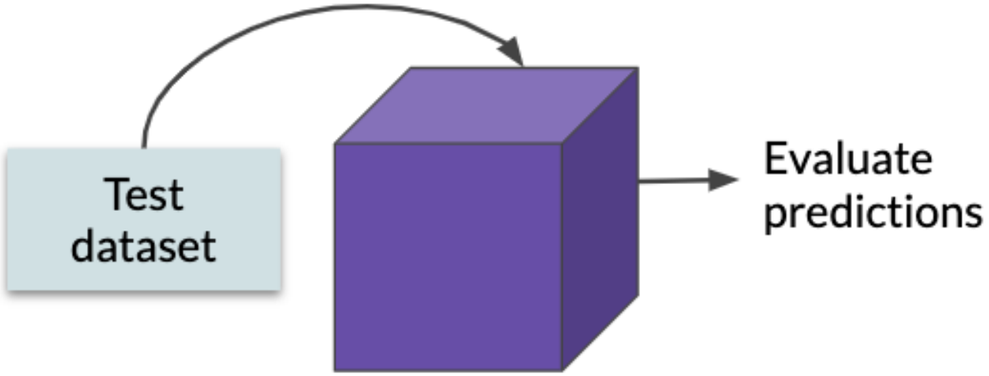
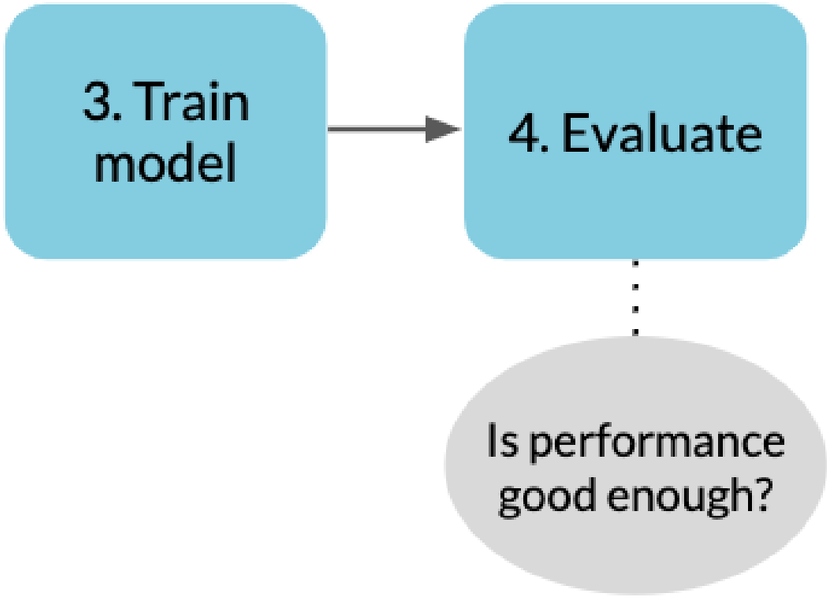



- Test dataset: "unseen" data
- Many ways to evaluate:
  - What is the average error of the predictions?
  - What percent of apartments did the model accurately predict within a 10% margin?

# Step 4: Evaluate



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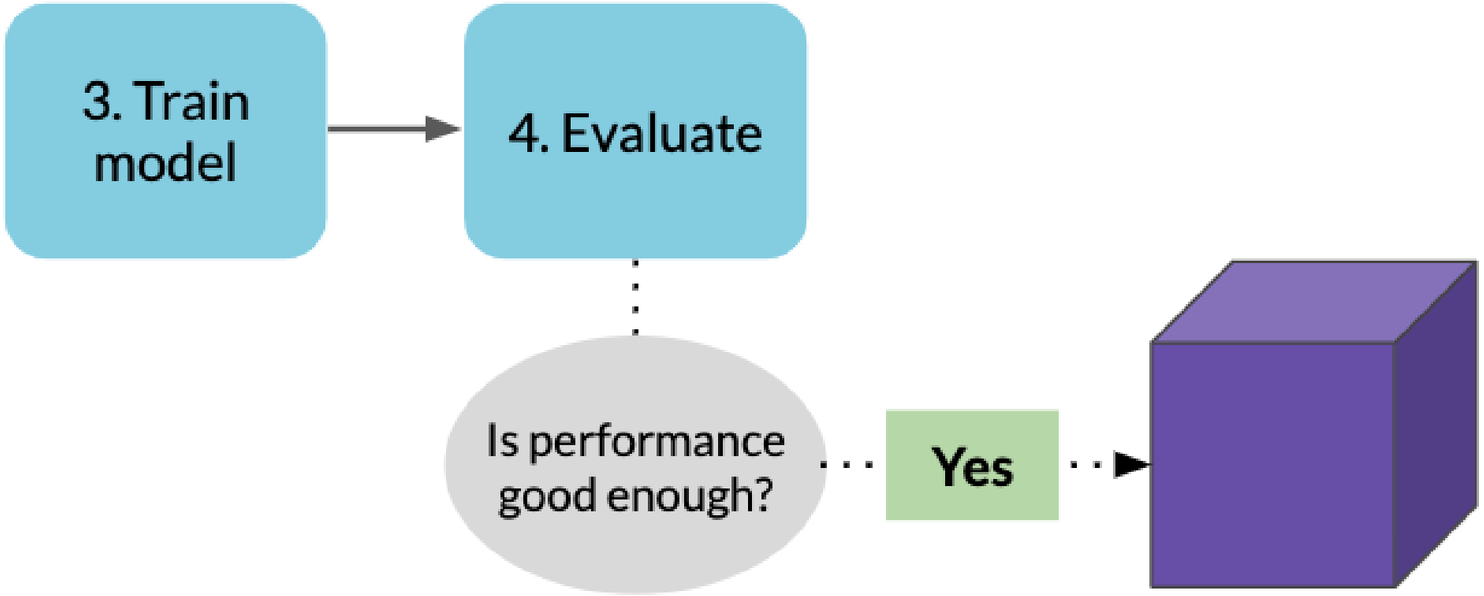

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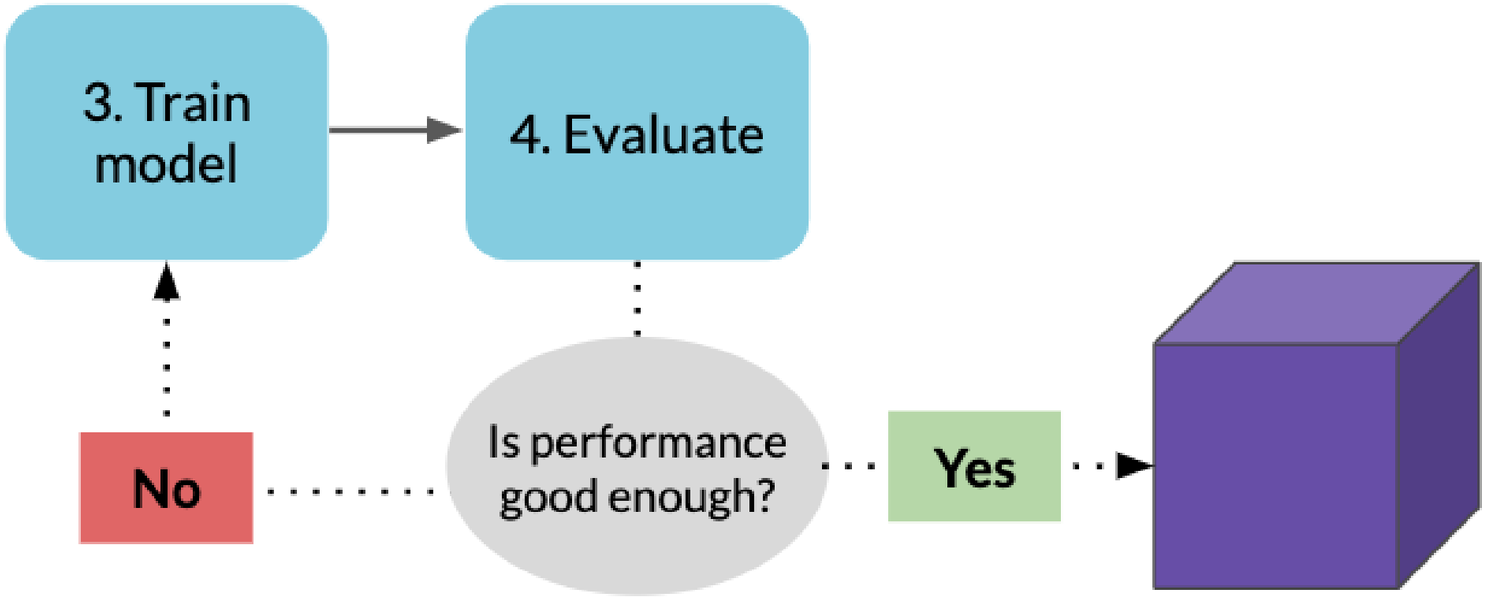
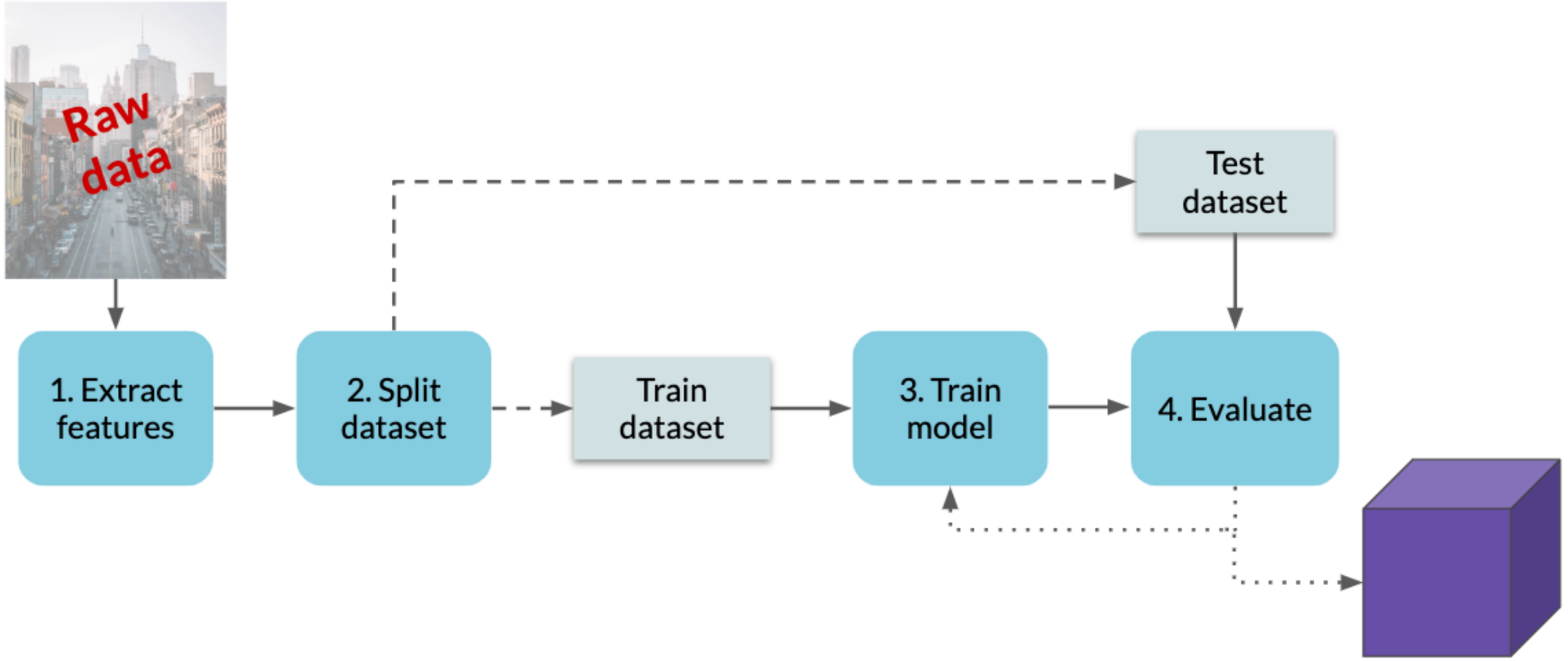



- If not, tune the model and re-train it:
  - e.g., change the model's options, add/remove features

# Machine learning workflow



# Summary of steps

1. **Extract features**
   - Choosing features and manipulating the dataset
2. **Split dataset**
   - Train and test dataset
3. **Train model**
   - Input train dataset into a machine learning model
4. **Evaluate**
   - *If desired performance isn't reached:* tune the model and repeat Step 3

# Let's practice!

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