Clustering

Introduction to Clustering

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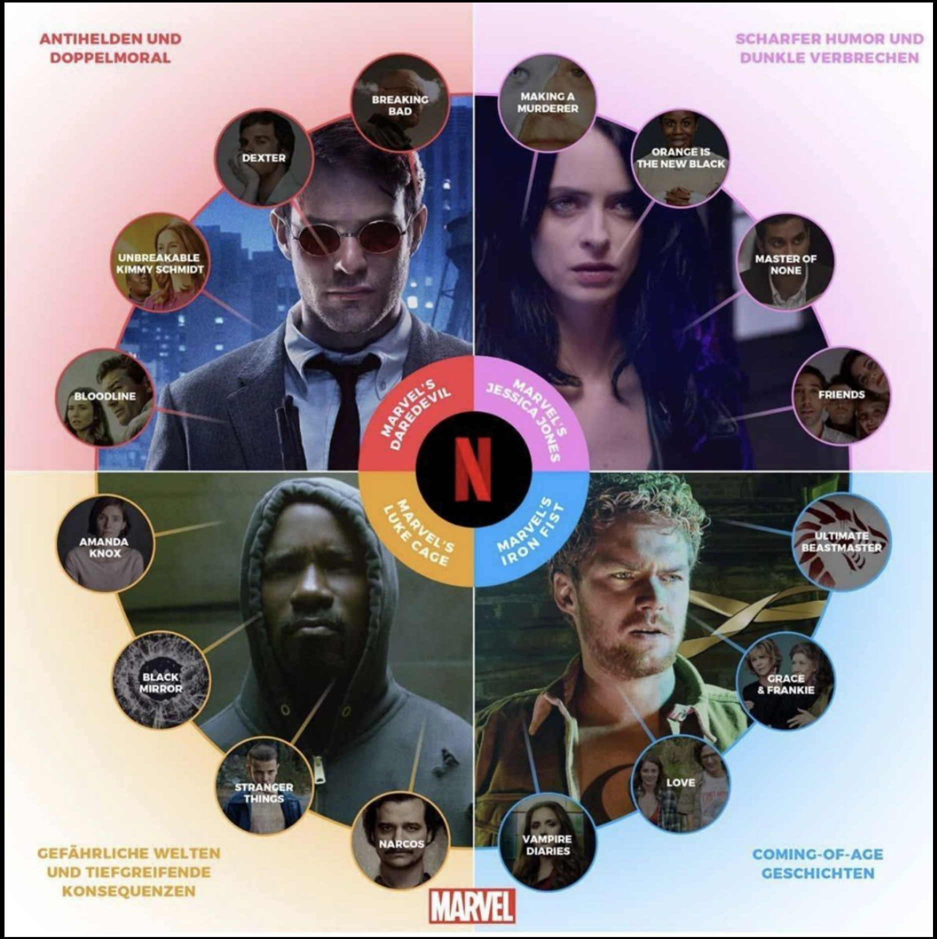
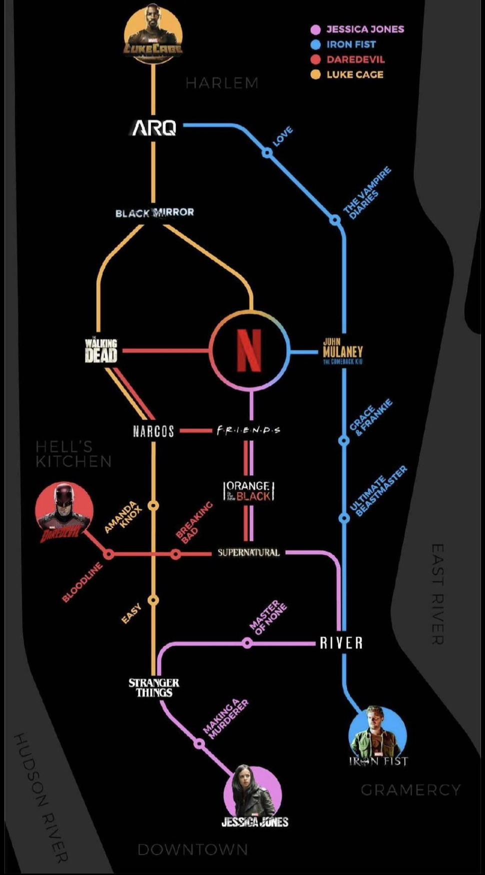
HdM Stuttgart

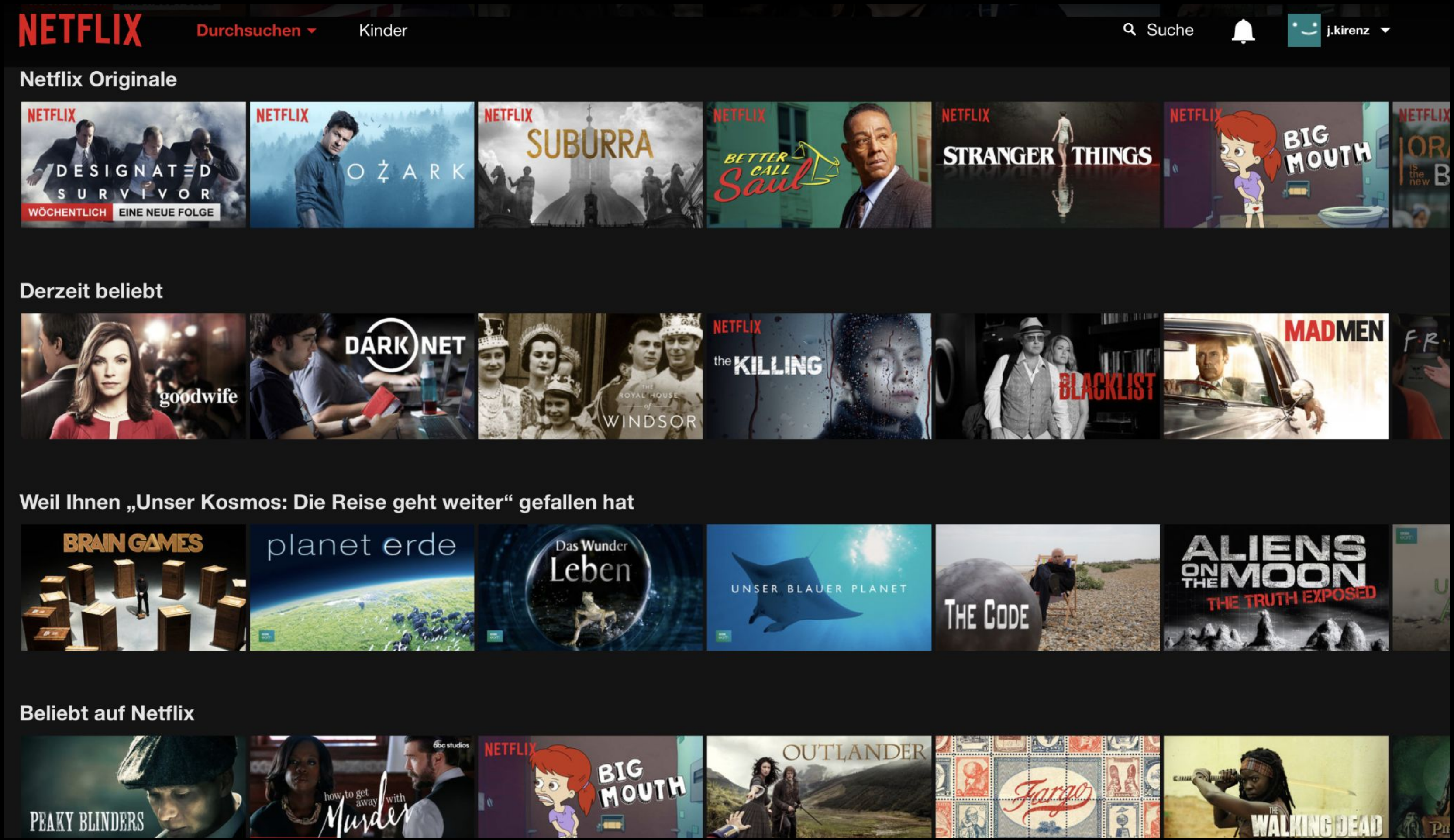


ANTIHELDEN UND DOPPELMORAL
BREAKING BAD
DEXTER
UNBREAKABLE KIMMY SCHMIDT
BLOODLINE
MARVEL'S DAREDEVIL
SCHARFER HUMOR UND DUNKLE VERBRECHEN
MAKING A MURDERER
ORANGE IS THE NEW BLACK
MASTER OF NONE
FRIENDS
MARVEL'S JESSICA JONES
N
MARVEL'S LUKE CAGE
MARVEL'S IRON FIST
AMANDA KNOX
BLACK MIRROR
STRANGER THINGS
NARCOS
ULTIMATE BEASTMASTER
GRACE & FRANKIE
LOVE
VAMPIRE DIARIES
GEFÄHRLICHE WELTEN UND TIEFGREIFENDE KONSEQUENZEN
COMING-OF-AGE GESCHICHTEN
MARVEL

DER WEG ZU MARVEL'S DEFENDERS

Auf dem Weg zum Marvel-Binge gibt es einige unerwartete Haltepunkte, aber die Reise durch die Serienwelt bringt genauso viel Spaß wie die Ankunft bei den Defenders.




NETFLIX
Durchsuchen
Kinder
Suche
j.kirenz
Netflix Originale
DESIGNATED SURVIVOR
WÖCHENTLICH
EINE NEUE FOLGE
OZARK
SUBURRA
BETTER CALL Saul
STRANGER THINGS
BIG MOUTH
Derzeit beliebt
goodwife
DARK NET
THE ROYAL HOUSE of WINDSOR
the KILLING
BLACKLIST
MADMEN
Weil Ihnen „Unser Kosmos: Die Reise geht weiter“ gefallen hat
BRAIN GAMES
planet erde
Das Wunder Leben
UNSER BLAUER PLANET
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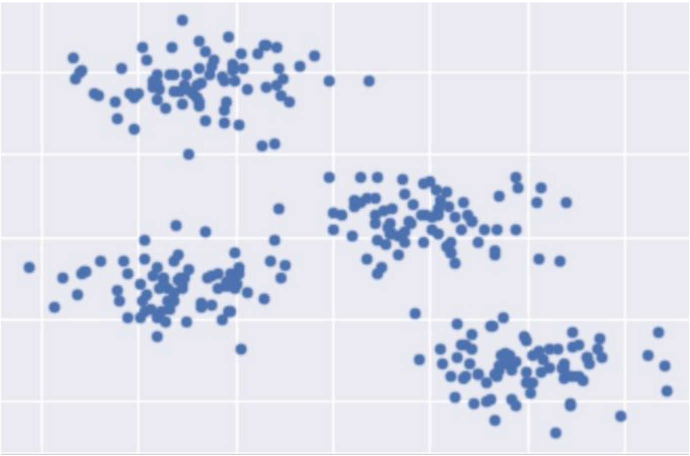
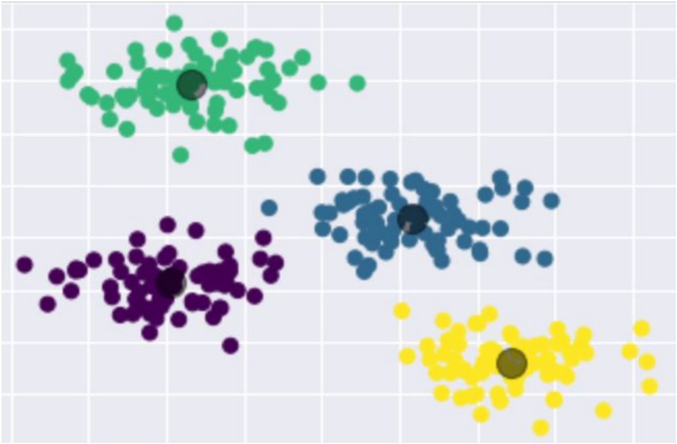
OUTLANDER
Fargo
THE WALKING DEAD

Discover unknown subgroups in data.

Unlabeled examples (observations)



Grouping unlabeled examples is called clustering.



Clustering is **unsupervised learning**

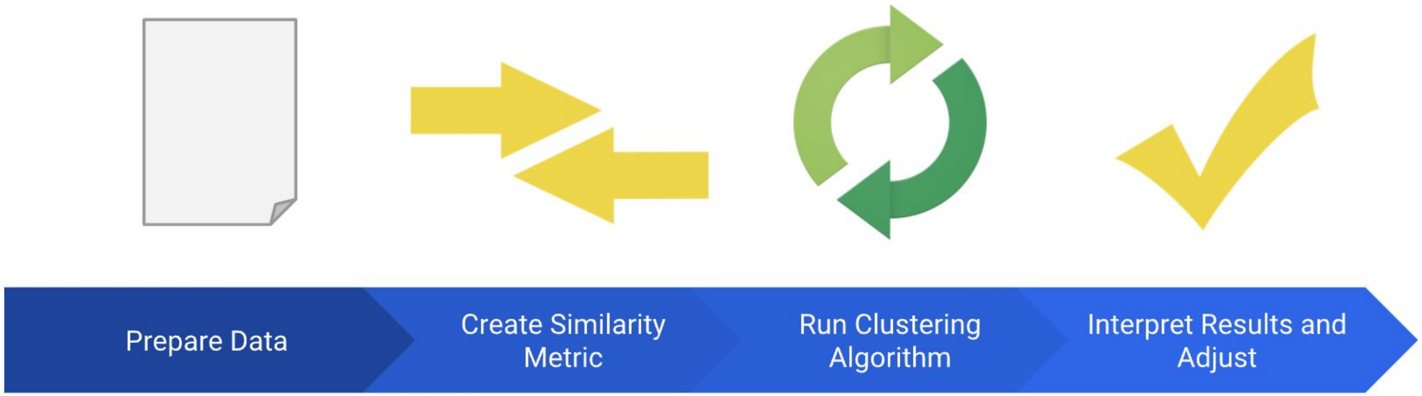
The goal is to discover interesting things about the observations:

- is there an informative way to **visualize** the data?
- Can we **discover subgroups** among the variables or among the observations?

Use cases for cluster analysis

- **Customer segmentation** (understanding different customer segments to devise marketing strategies)
- **Recommender systems** (grouping together users with similar viewing patterns on Netflix, in order to recommend similar content)
- **Anomaly detection** (fraud detection, detecting defective mechanical parts)

To cluster your data, you'll follow these steps:



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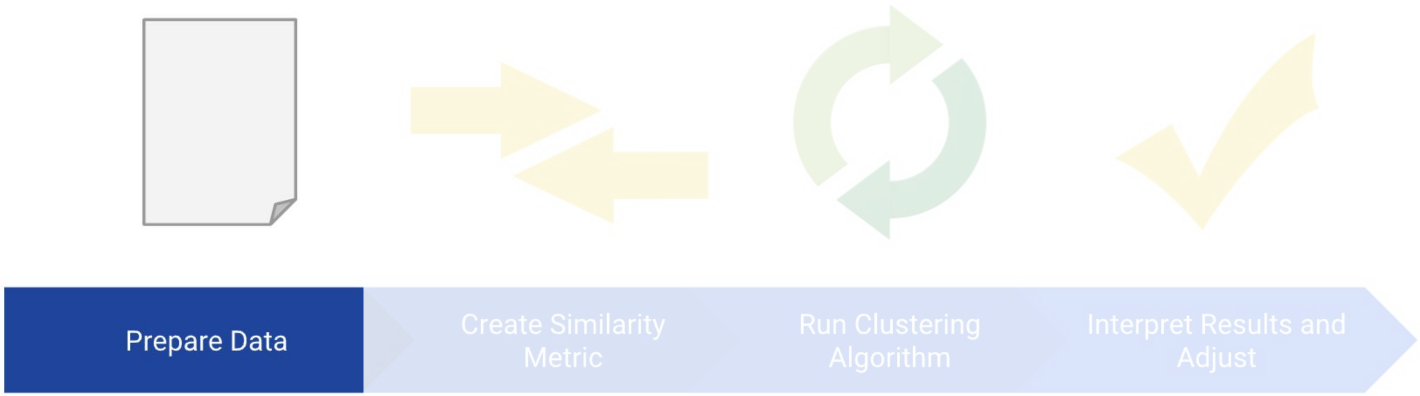

Exclude all missing values and outliers

Normalizing data

If you only have a few values, you could use this simple rule:

$$x' = \frac{x}{\max(x)}$$

Normalizing data by rescaling (min-max normalization)

Typically, we use rescaling like this:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

Rescalin results in a range [0, 1]

Source: Google Developers https://developers.google.com/machine-learning/clustering/prepare-data

Standardization with **z-score**

Another alternative:

$$x' = (x - \mu)/\sigma$$

$$\text{where:} \quad \mu = \text{mean}$$

$$\sigma = \text{standard deviation}$$

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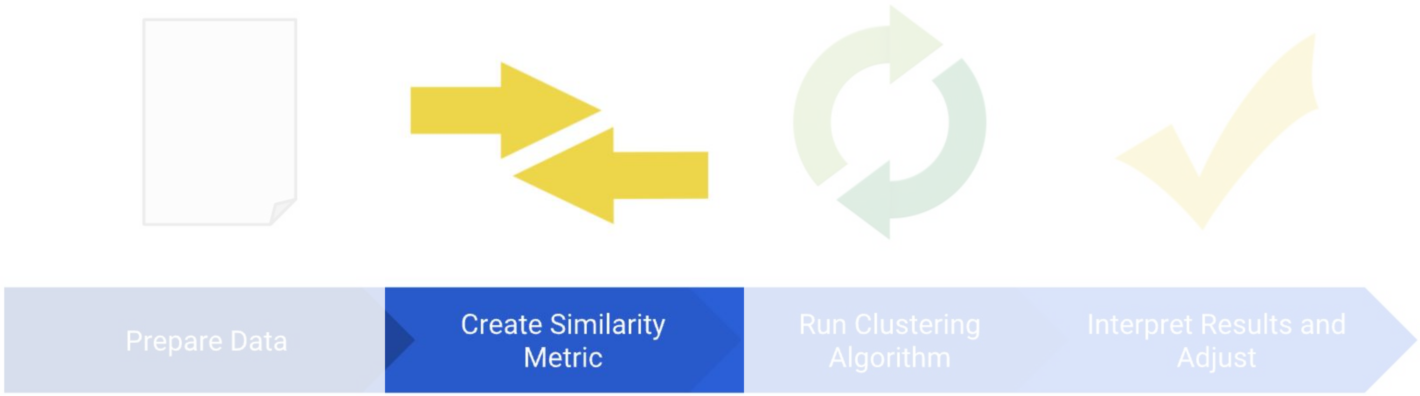

Source: Google Developers https://developers.google.com/machine-learning/clustering/workflow

How to create a similarity measure for a numeric feature?

- Feature X_1: shoe size

Shoe A

size: 8

Shoe B

size: 11

Picture source: Allbirds

How to create a similarity measure for a numeric feature?

- Feature X_1: shoe size

Picture source: Allbirds

Create a manual **similarity measure** for two numeric features

- Feature X_1: shoe size (numeric)
- Feature X_2: price (numeric)

size: 8
price: 120

size: 11
price: 150

Picture source: Allbirds

Create a manual similarity measure for two numeric features

- Feature X_1: shoe size (numeric)
- Feature X_2: price (numeric)

Picture source: Allbirds

Create a manual similarity measure for two numeric features

Since we don't have enough data, we'll simply scale the data without normalizing

Action	Method
Scale the size.	Assume a maximum possible shoe size of 20. Divide 8 and 11 by the maximum size 20 to get 0.4 and 0.55.
Scale the price.	Divide 120 and 150 by the maximum price 150 to get 0.8 and 1.
Find the difference in size.	$0.55 - 0.4 = 0.15$
Find the difference in price.	$1 - 0.8 = 0.2$
Find the RMSE.	$\sqrt{\frac{0.2^2+0.15^2}{2}} = 0.17$

$$x' = \frac{x}{\max(x)}$$

Source: Google Developers: https://developers.google.com/machine-learning/clustering/similarity/manual-similarity

Create a manual similarity measure for two numeric features

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Create a manual similarity measure for a categorical feature

- Feature X_3: color (categorical)

color: black

color: blue

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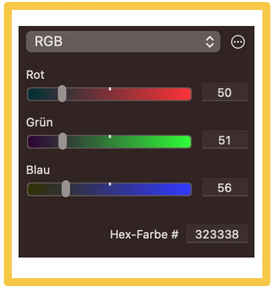
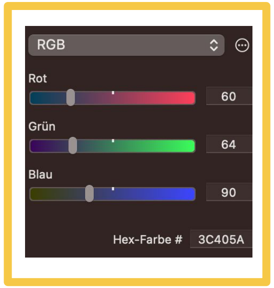




color: blue

Picture source: Allbirds

Create a manual **similarity** measure for a **categorical** feature

Feature with **multiple levels** (multivalent)

- Movie genres:
  - comedy,
  - action,
  - drama,
  - non-fiction,
  - biographical
- Can be "action" and "comedy" simultaneously, or just "action"

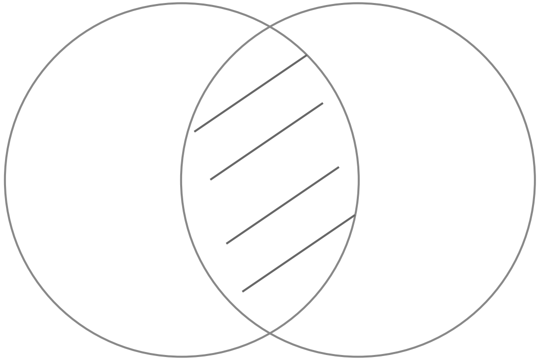
How to measure similarity?

1: [comedy, action]

2: [action, drama]

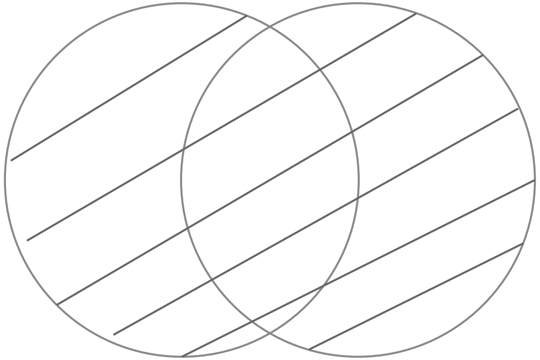
Intersection & union

Intersection



A ∩ B

Union

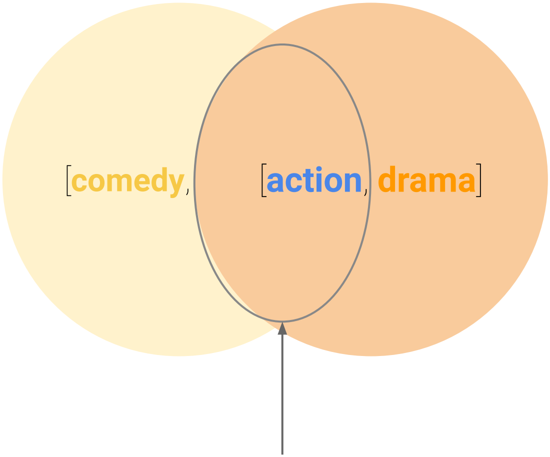


A ∪ B

Jaccard distance

[comedy, action]

[action, drama]



Union:
[comedy, action, drama]

Intersection:
action

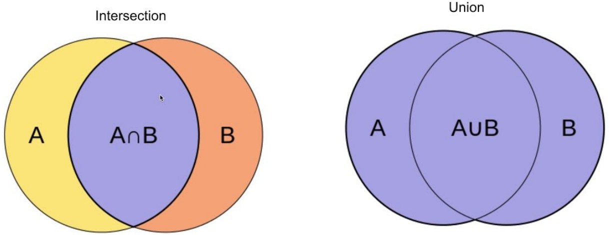
Jaccard distance

$$\frac{\textbf{Intersection}\ \text{action}}{\textbf{Union}\ [\text{comedy, action, drama}]}$$

$$\frac{A \cap B}{A \cup B}$$

Create a manual similarity measure for a categorical feature

- A: [“comedy”,”action”] and B: [“comedy”,”action”] = 1
- A: [“comedy”,”action”] and B: [“action”] = ½
- A: [“comedy”,”action”] and B: [“action”, "drama"] = ⅓
- A: [“comedy”,”action”] and B: [“non-fiction”,”biographical”] = 0

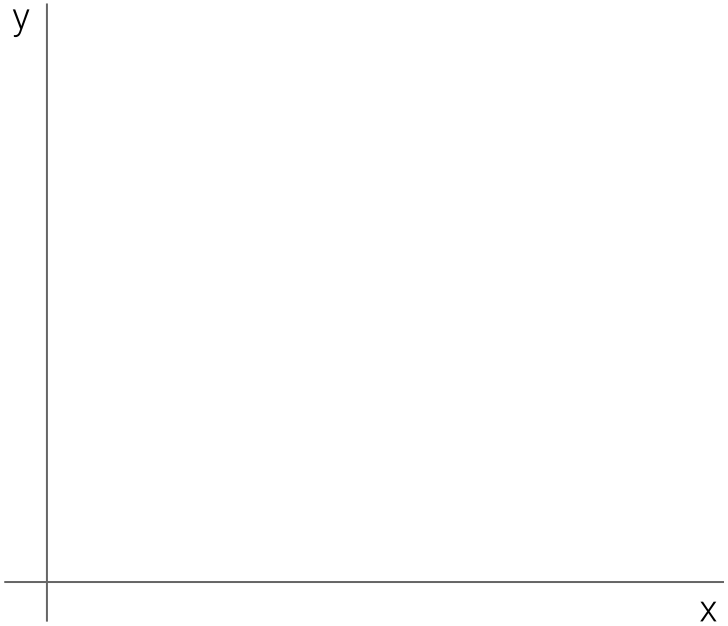


$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}$$

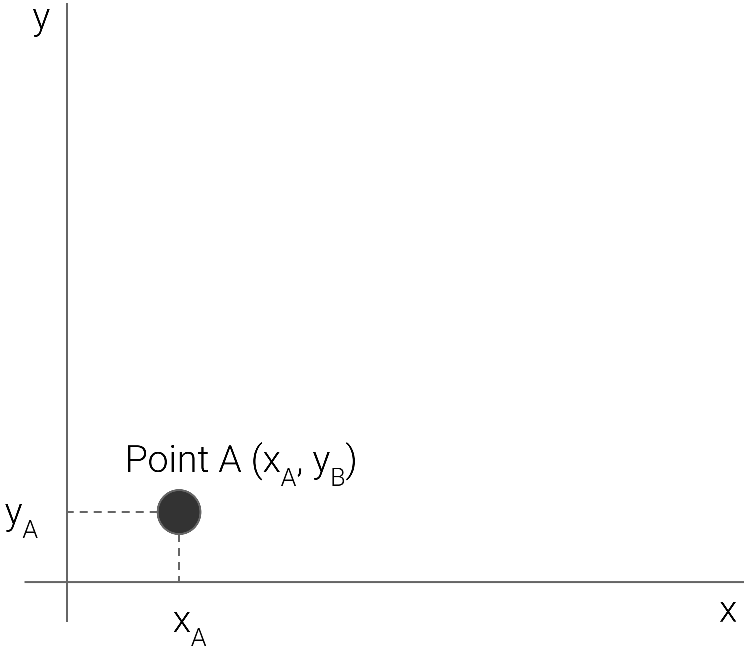
- **Jaccard similarity**. Calculate similarity using the ratio of common values
- **Jaccard distance**. Calculate distance using (1- Jaccard similarity)

Popular distance metrics for numerical features

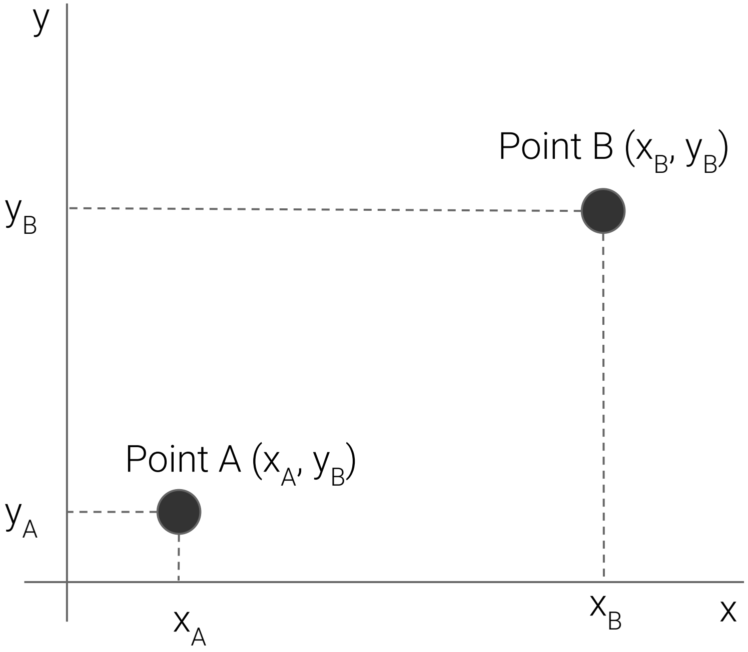
Let's start with a simple coordinate system (CS)



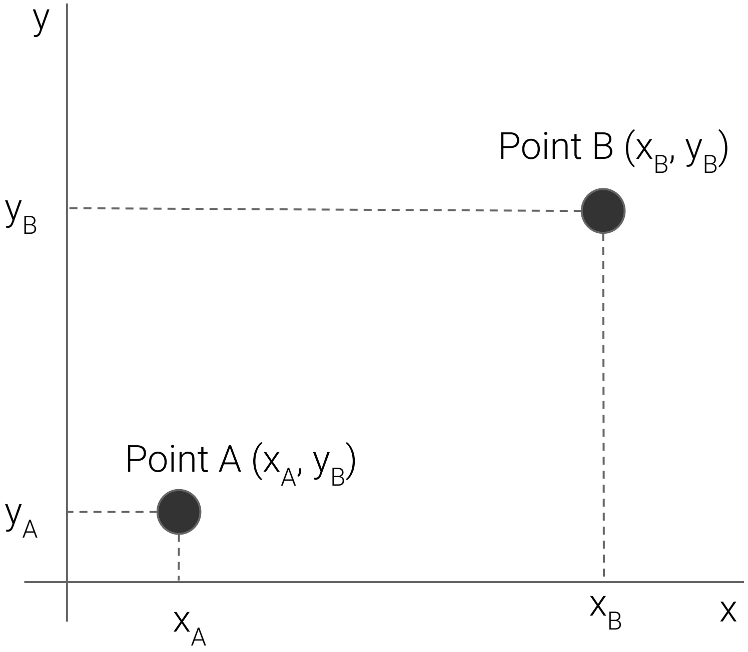
We include one observation “A”



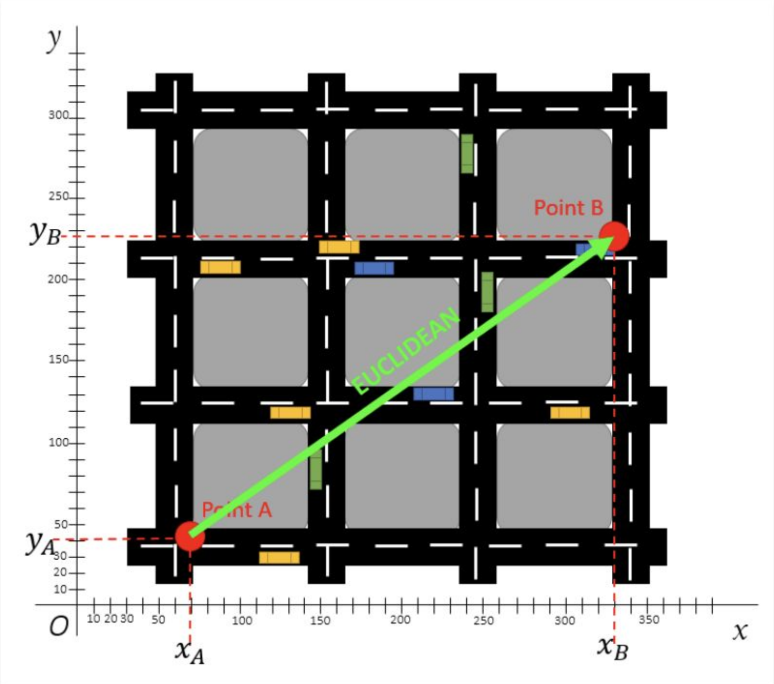
And another observation "B"



How can we measure the distance between A and B?



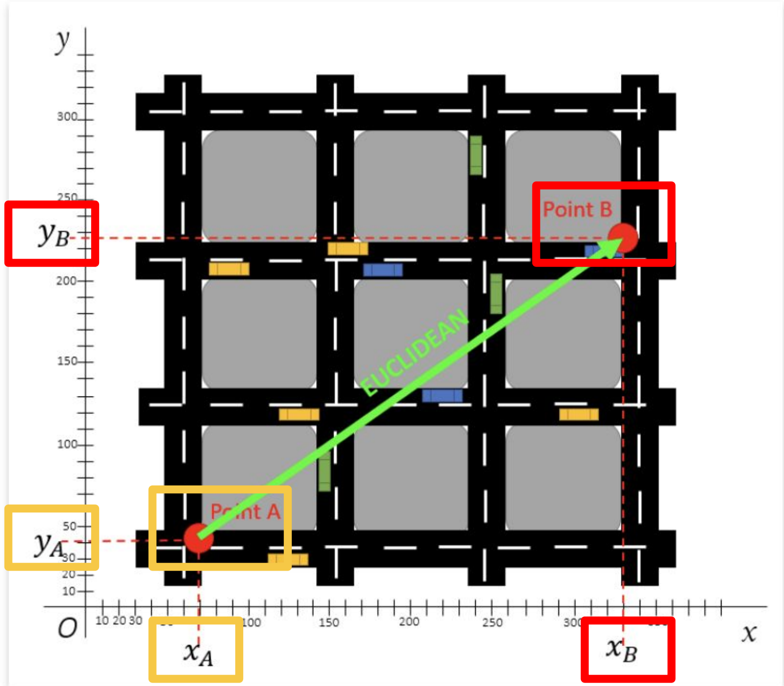
Imagine there are streets on the CS



This would be the shortest distance

$$d(A,B) = \sqrt{\sum_{i=1}^{n}(A_i - B_i)^2}$$

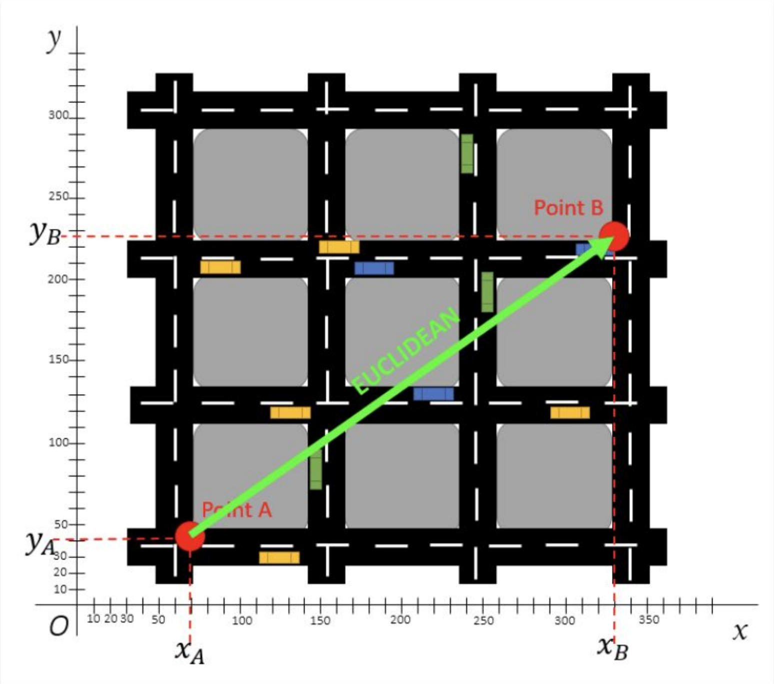
- x_A = 70
- x_B = 330
- y_A = 40
- y_B = 228



Euclidean distance (L_2 distance)

$$d(A,B) = \sqrt{\sum_{i=1}^{n}(A_i - B_i)^2}$$

- x_A = 70
- x_B = 330
- y_A = 40
- y_B = 228



$$d(A,B) = \sqrt{(x_A - x_B)^2 + (y_A - y_B)^2}$$

$$d(A,B) = \sqrt{(70 - 330)^2 + (40 - 228)^2}$$

$$d(A,B) = \sqrt{(-260)^2 + (-188)^2}$$

$$d(A,B) = \sqrt{(76600 + 35344)}$$

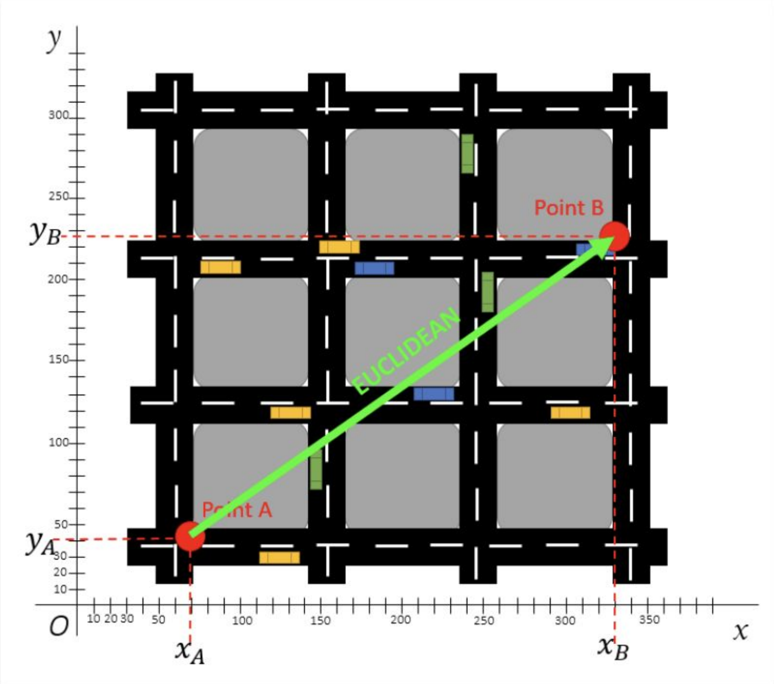
$$d(A,B) = \sqrt{(112225)}$$

$$d(A,B) = 335$$

Squared Euclidean distance (L_2)

$$d^2(A,B) = \sum_{i=1}^{n}(A_i - B_i)^2$$

- x_A = 70
- x_B = 330
- y_A = 40
- y_B = 228



$$d^2(A,B) = (x_A - x_B)^2 + (y_A - y_B)^2$$

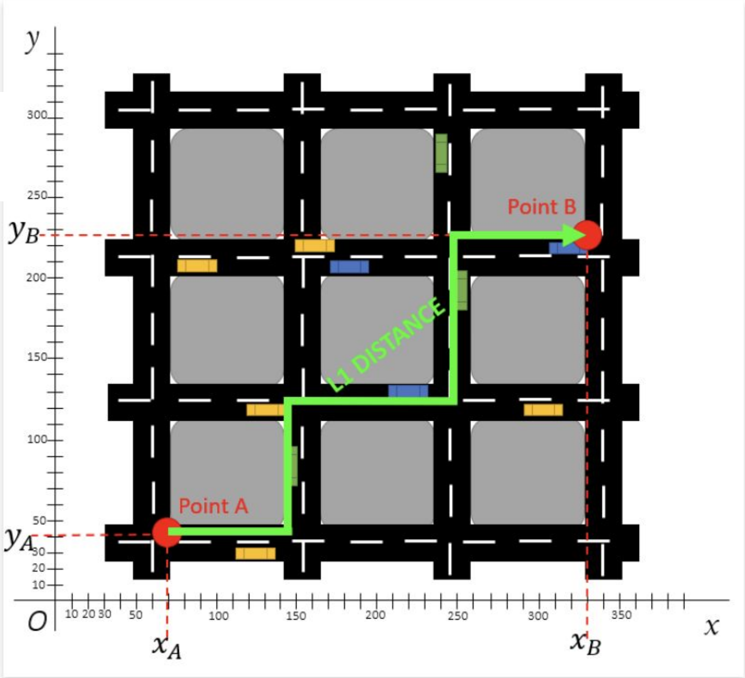
$$d^2(A,B) = (70 - 330)^2 + (40 - 228)^2$$

$$d^2(A,B) = 112225$$

L_1 distance (Manhattan distance)

$$d(A,B) = \sum_i |A_i - B_i|$$

- x_A = 70
- x_B = 330
- y_A = 40
- y_B = 228



$$d(A,B) = |x_A - x_B| + |y_A - y_B|$$

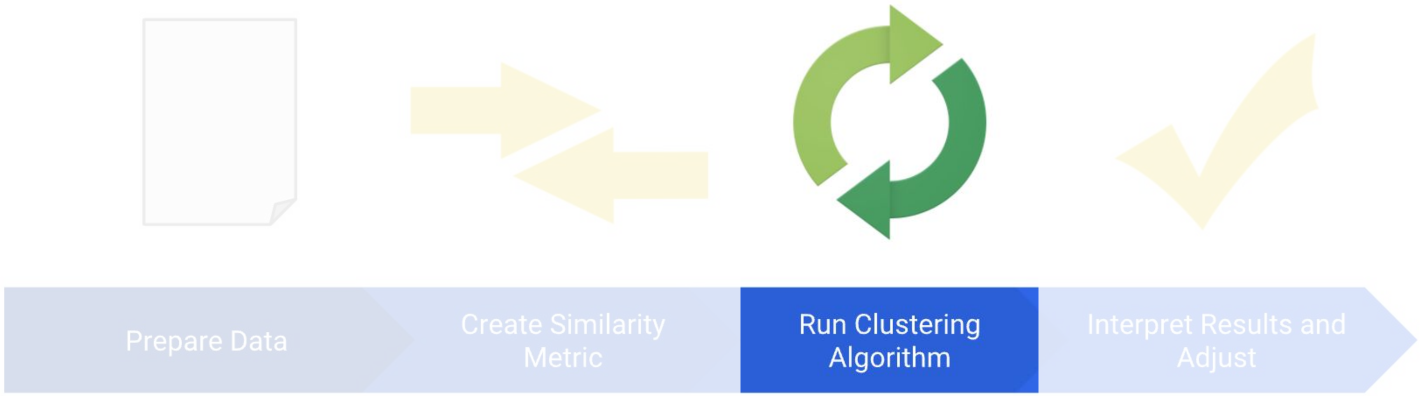
$$d(A,B) = |70 - 330| + |40 - 228|$$

$$d(A,B) = |-260| + |-188|$$

$$d(A,B) = 260 + 188$$

$$d(A,B) = 448$$

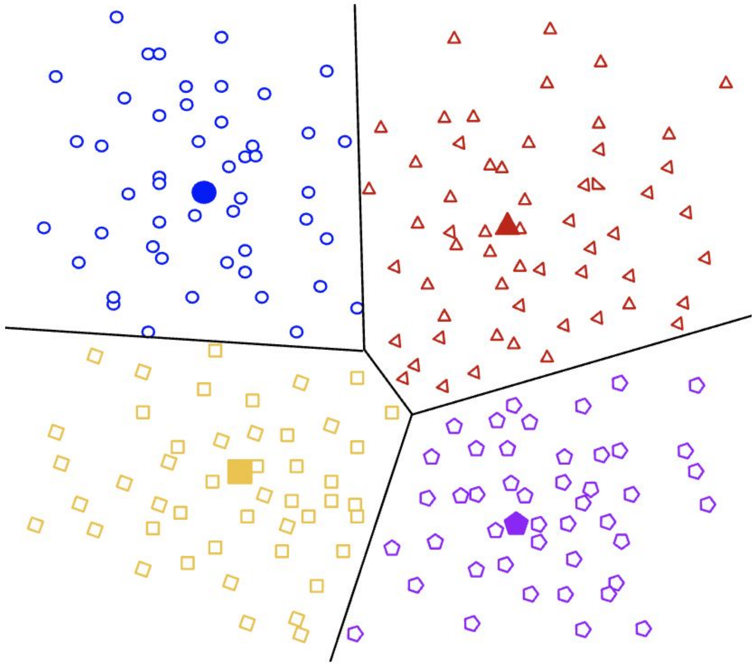
To cluster your data, you'll follow these steps:



Source: Google Developers https://developers.google.com/machine-learning/clustering/workflow

Centroid-based Clustering

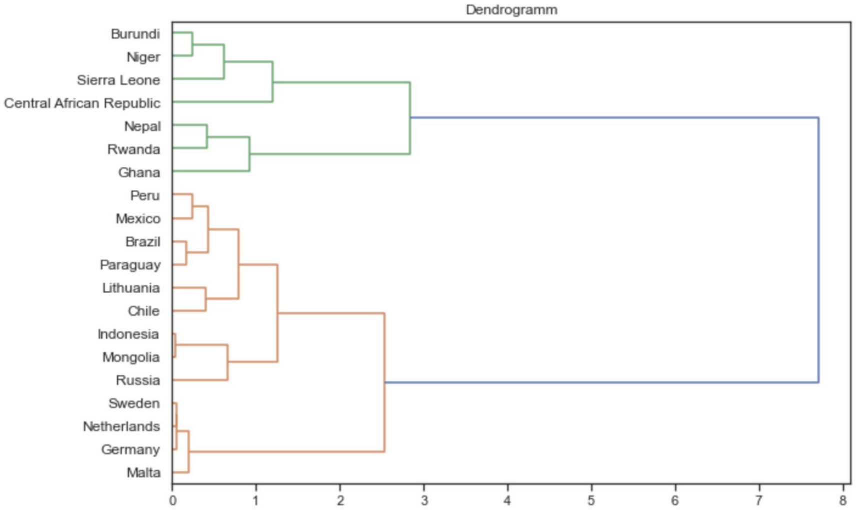
- Centroid-based algorithms are **efficient**
- But sensitive to **initial conditions** and **outliers**.
- **k-means** is the most widely-used centroid-based clustering algorithm.



Source: Google Developers https://developers.google.com/machine-learning/clustering/clustering-algorithms

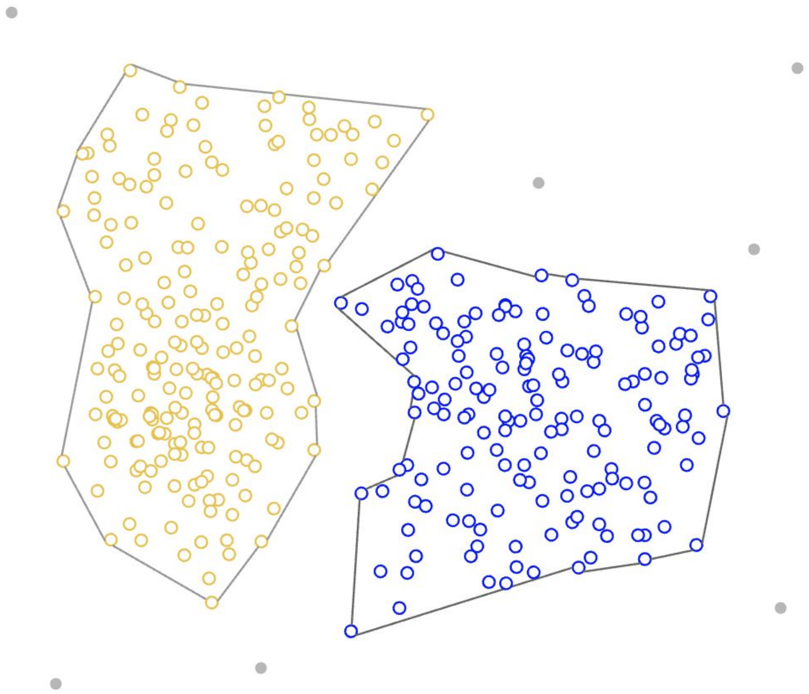
Hierarchical Clustering

- Hierarchical clustering creates a **tree** of clusters.
- One advantage is that any number of clusters can be chosen by cutting the tree at the right level.



Density-based Clustering

- Density-based clustering connects areas of high example **density** into clusters
- Advantage:
    - they do not assign outliers to clusters.
- Disadvantage:
    - have difficulty with data of varying densities and high dimensions.



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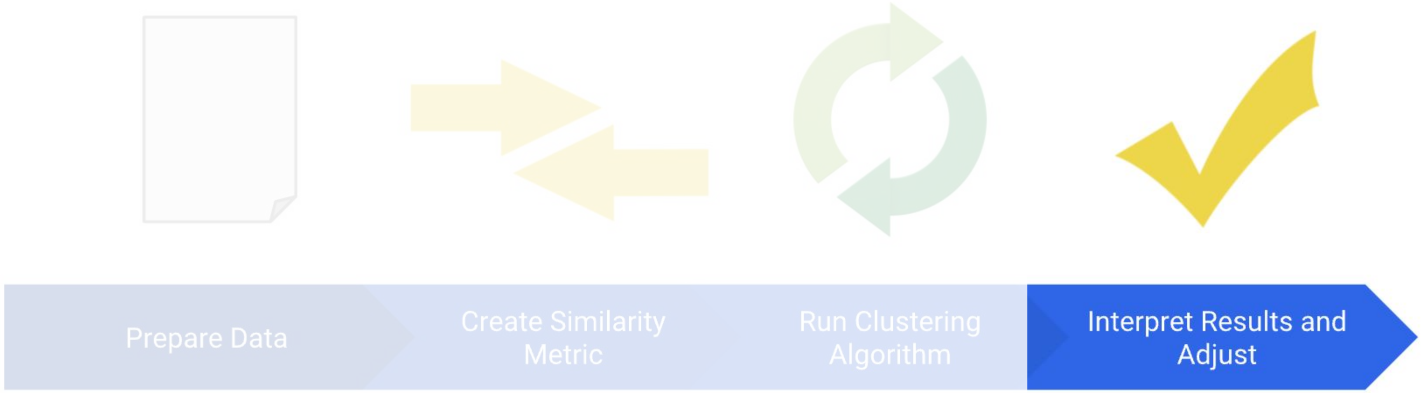

Because clustering is unsupervised, no “truth” is available to verify results

- It mainly depends on the **subjective interpretability**
- We have some kind of quality measures for some algorithms (like k-Means)