
Machine Learning

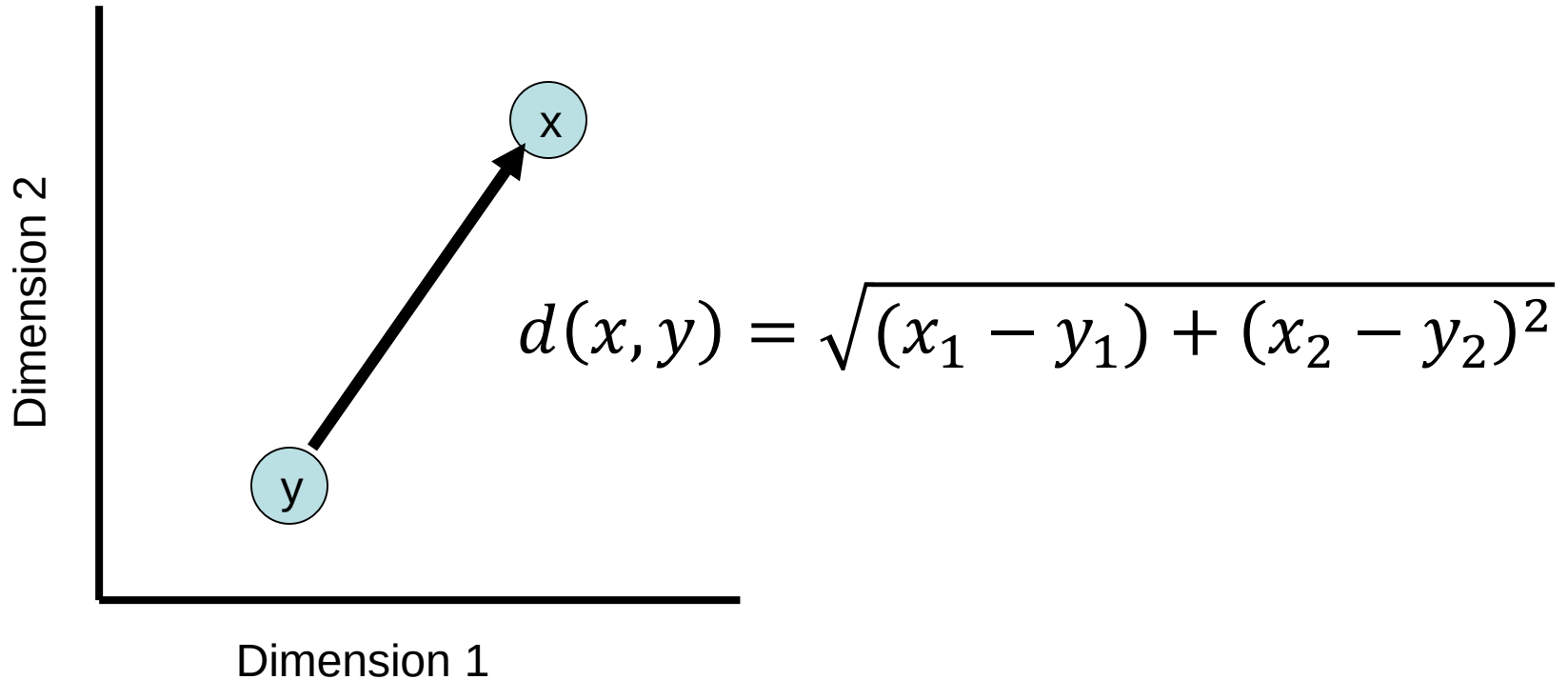
Measuring Distance

Why measure distance?

- Nearest neighbor requires a distance measure
- Also:
 - Local search methods require a measure of “locality” (Friday)
 - Clustering requires a distance measure (later)
 - Search engines require a measure of similarity, etc.

Euclidean Distance

- What people intuitively think of as “distance”



Generalized Euclidean Distance

n = the number of dimensions


$$d(\vec{x}, \vec{y}) = \left[\sum_{i=1}^n |x_i - y_i|^2 \right]^{1/2}$$

where $\vec{x} = \langle x_1, x_2, \dots, x_n \rangle$,

$\vec{y} = \langle y_1, y_2, \dots, y_n \rangle$

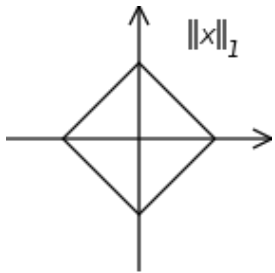
and $\forall i (x_i, y_i \in \mathbb{R})$

L^p norms

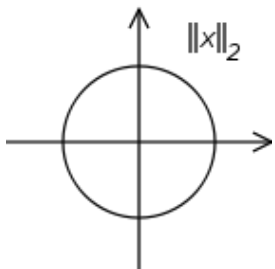
- L^p norms are all special cases of this:

$$d(\vec{x}, \vec{y}) = \left[\sum_{i=1}^n |x_i - y_i|^p \right]^{1/p}$$

p changes the norm



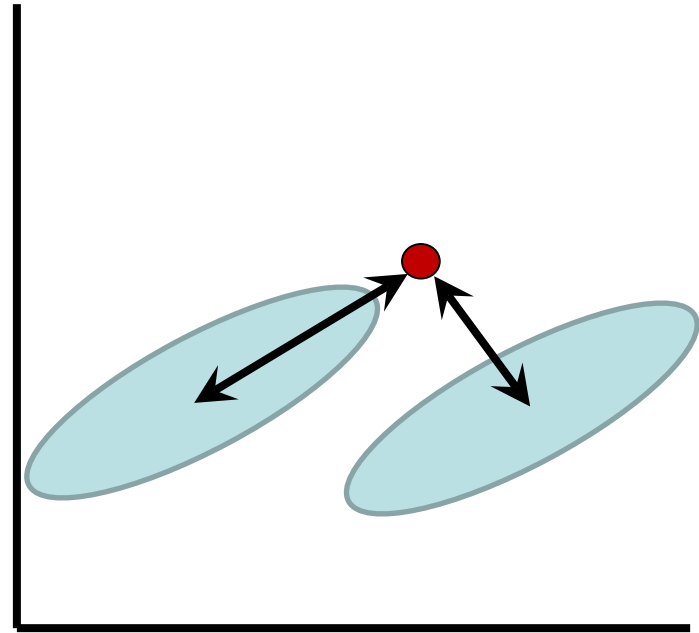
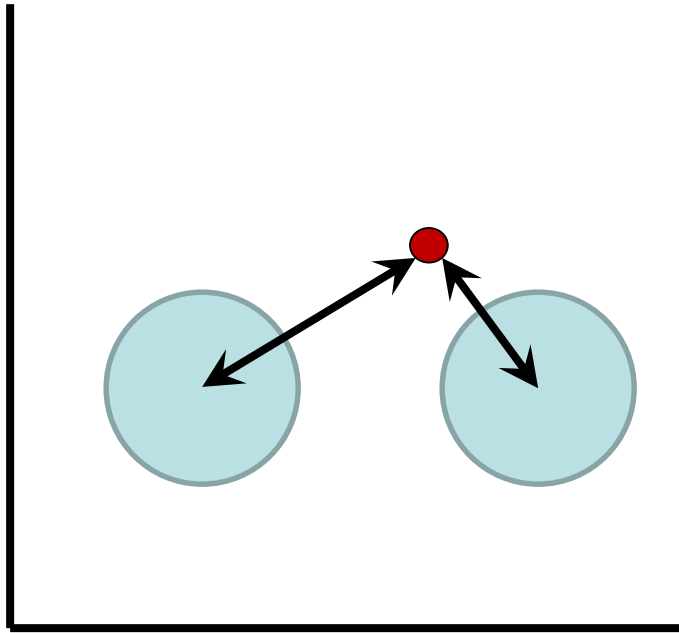
$\|x\|_1 = L^1$ norm = Manhattan Distance: $p = 1$



$\|x\|_2 = L^2$ norm = Euclidean Distance: $p = 2$

Hamming Distance: $p = 1$ and $x_i, y_i \in \{0,1\}$

Weighting Dimensions

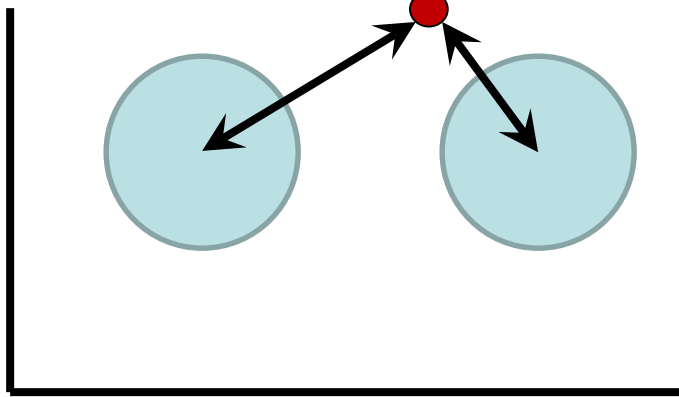


- Put point in cluster with the closest center of gravity?
- Which cluster should the red point go in?
- How do I measure distance in a way that gives the “right” answer for both situations?

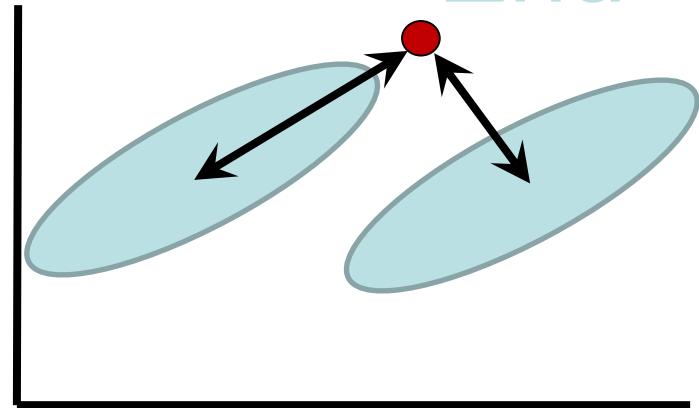
Weighting Dimensions

| Think

Start

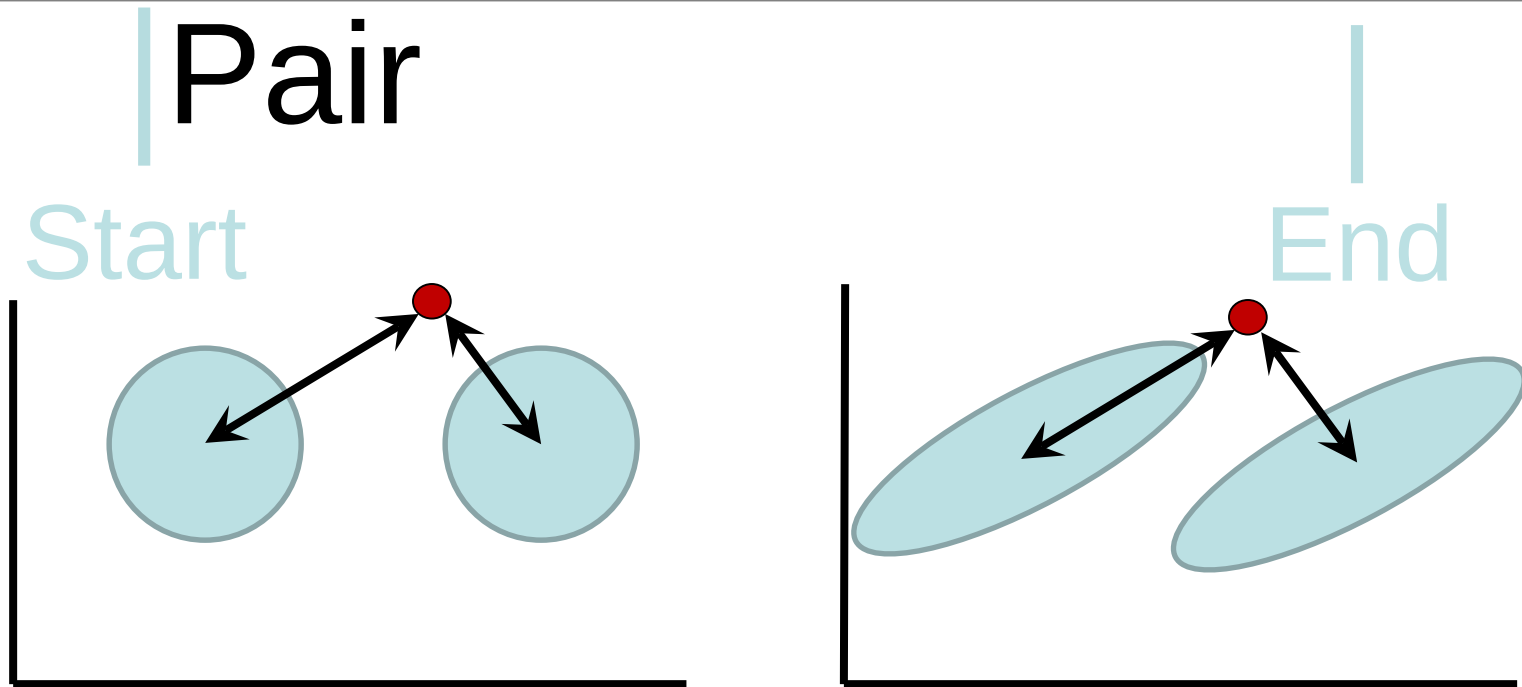


| End



- Put point in cluster with the closest center of gravity?
- Which cluster should the red point go in?
- How do I measure distance in a way that gives the “right” answer for both situations?

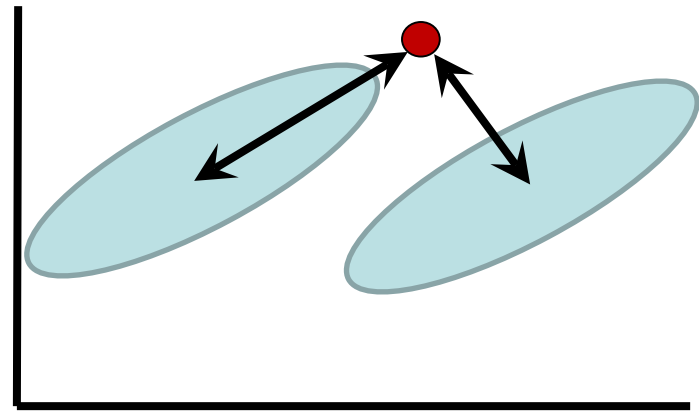
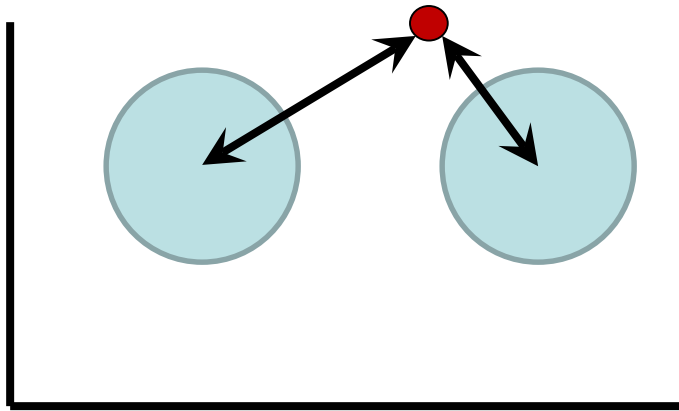
Weighting Dimensions



- Put point in cluster with the closest center of gravity?
- Which cluster should the red point go in?
- How do I measure distance in a way that gives the “right” answer for both situations?

Weighting Dimensions

Share



- Put point in cluster with the closest center of gravity?
- Which cluster should the red point go in?
- How do I measure distance in a way that gives the “right” answer for both situations?

Weighted Norms

- You can compensate by weighting your dimensions....

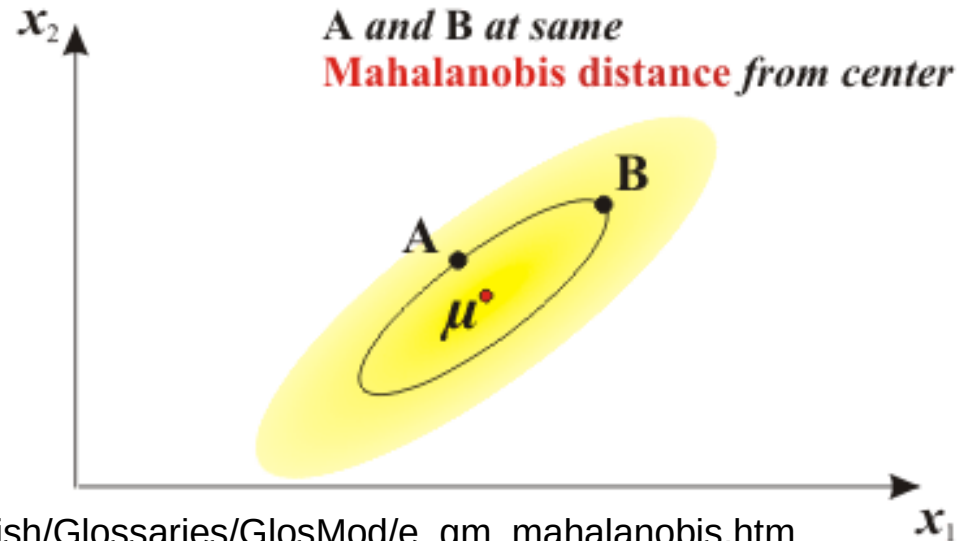
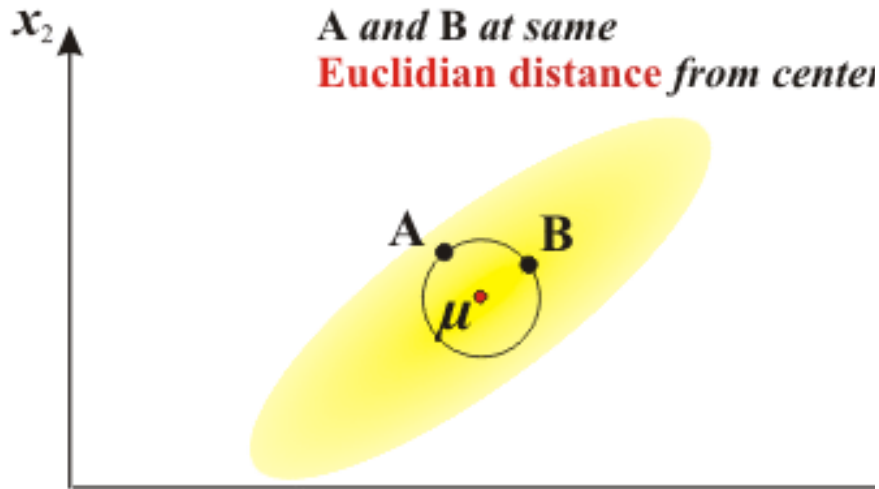
$$d(\vec{x}, \vec{y}) = \left[\sum_{i=1}^n w_i |x_i - y_i|^p \right]^{1/p}$$

This lets you turn your circle of equal-distance into an ellipse with axes parallel to the dimensions of the vectors.

Mahalanobis distance

The region of constant Mahalanobis distance around the mean of a distribution forms an ellipsoid.

The axes of this ellipsoid don't have to be parallel to the dimensions describing the vector



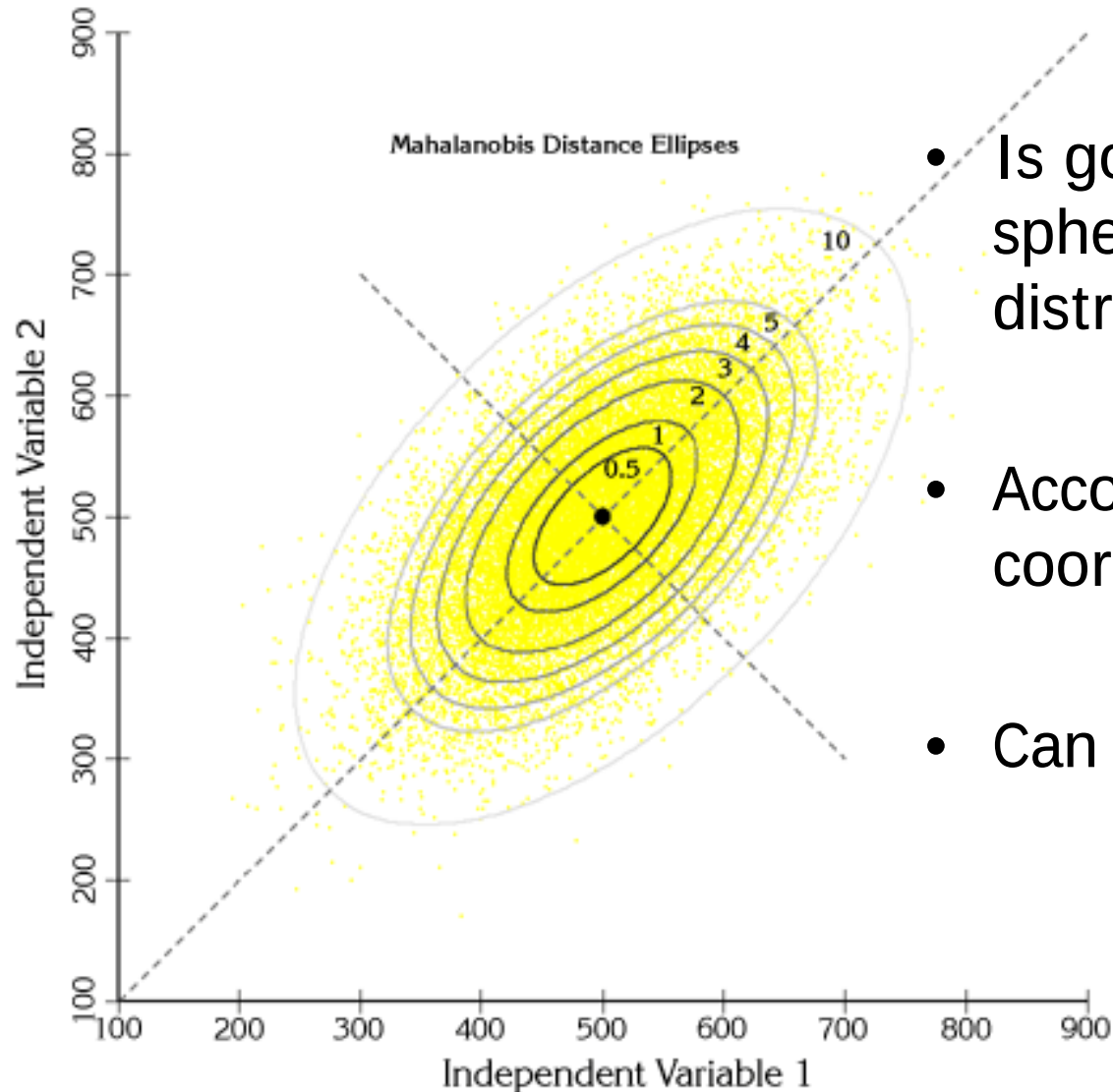
Images from: http://www.aiaccess.net/English/Glossaries/GlosMod/e_gm_mahalanobis.htm

Calculating Mahalanobis

$$d(\vec{x}, \vec{y}) = \sqrt{(\vec{x} - \vec{y})^T S^{-1} (\vec{x} - \vec{y})}$$

- This matrix S is called the “covariance” matrix and is calculated from the data distribution

Take-away on Mahalanobis



- Is good for non-spherically symmetric distributions.
- Accounts for scaling of coordinate axes
- Can reduce to Euclidean

What is a “metric”?

- A metric has these four qualities.

$$d(x, y) = 0 \quad \text{iff} \quad x = y \quad (\text{reflexivity})$$

$$d(x, y) \geq 0 \quad (\text{non - negative})$$

$$d(x, y) = d(y, x) \quad (\text{symmetry})$$

$$d(x, y) + d(y, z) \geq d(x, z) \quad (\text{triangle inequality})$$

- ...otherwise, call it a “measure”

Metric, or not?

- Driving distance with 1-way streets



- Categorical Stuff :
 - Is distance (Jazz to Blues to Rock) no less than distance (Jazz to Rock)?

Categorical Variables

- Consider feature vectors for genre & vocals:
 - Genre: {Blues, Jazz, Rock, Hip Hop}
 - Vocals: {vocals, no vocals}

$s1 = \{\text{rock, vocals}\}$

$s2 = \{\text{jazz, no vocals}\}$

$s3 = \{\text{rock, no vocals}\}$

- Which two songs are more similar?

One Solution: Hamming distance

Blues	Jazz	Rock	Hip Hop	Vocals
0	0	1	0	1
0	1	0	0	0
0	0	1	0	0

s1 = {rock, vocals}

s2 = {jazz, no_vocals}

s3 = { rock, no_vocals}

Hamming Distance = number of different bits
in two binary vectors

Hamming Distance

$$d(\vec{x}, \vec{y}) = \sum_{i=1}^n |x_i - y_i|$$

where $\vec{x} = \langle x_1, x_2, \dots, x_n \rangle$,

$$\vec{y} = \langle y_1, y_2, \dots, y_n \rangle$$

and $\forall i (x_i, y_i \in \{0, 1\})$

Defining your own distance

(an example)

How often does artist x quote artist y ?

Quote Frequency

	Beethoven	Beatles	Liz Phair
Beethoven	7	0	0
Beatles	4	5	0
Liz Phair	?	1	2

Let's build a distance measure!

Defining your own distance (an example)

	Beethoven	Beatles	Liz Phair
Beethoven	7	0	0
Beatles	4	5	0
Liz Phair	?	1	2

Quote frequency $Q_f(x, y)$ = value in table

$$\text{Distance } d(x, y) = 1 - \frac{Q_f(x, y)}{\sum_{z \in \text{Artists}} Q_f(x, z)}$$

Missing data

- What if, for some category, on some examples, there is no value given?
- Approaches:
 - Discard all examples missing the category
 - Fill in the blanks with the mean value
 - Only use a category in the distance measure if both examples give a value

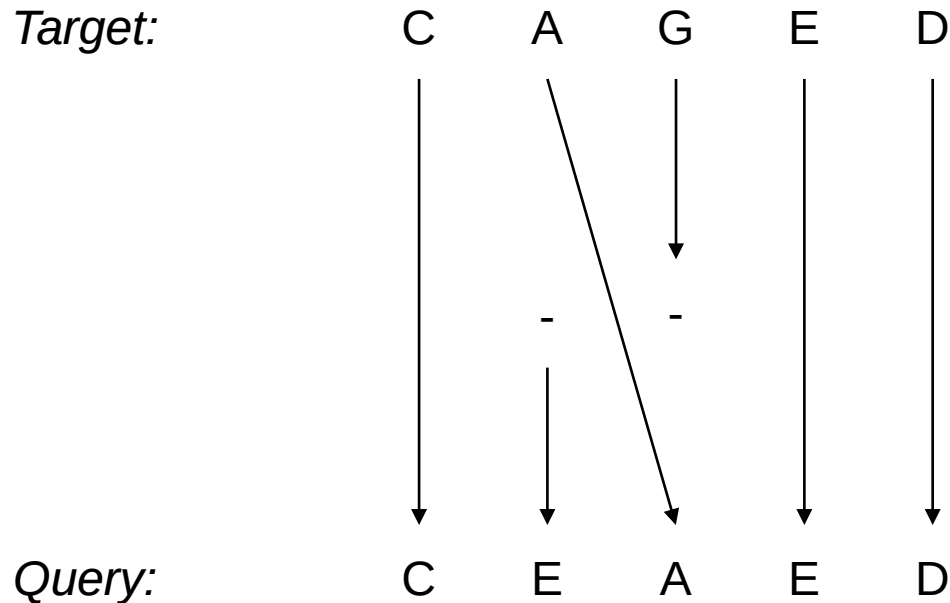
Dealing with missing data

$$w_i = \begin{cases} 1, & \text{if both } x_i \text{ and } y_i \text{ are defined} \\ 0, & \text{otherwise} \end{cases}$$

$$d(\vec{x}, \vec{y}) = \frac{n}{\sum_{i=1}^n w_i} \left[\sum_{i=1}^n w_i \phi(x_i, y_i) \right]$$

Edit Distance

- Query = string from finite alphabet
- Target = string from finite alphabet
- Cost of Edits = Distance



Semantic Relatedness

$d(\text{Portland, Hippies})$

$< <$

$d(\text{Portland, Monster trucks})$

Semantic Relatedness

- Several measures have been proposed
- One that works well: “Milne-Witten”

$SR_{MW}(x, y) \propto$ fraction of Wikipedia
in-links to either x or y
that link to both

Ad-hoc Reference Systems

Country
music

Rock
music

Hip
hop
music

Ad-hoc Reference Systems

Country
music



Category

[Talk](#)

[Read](#)

[Edit](#)

[View history](#)

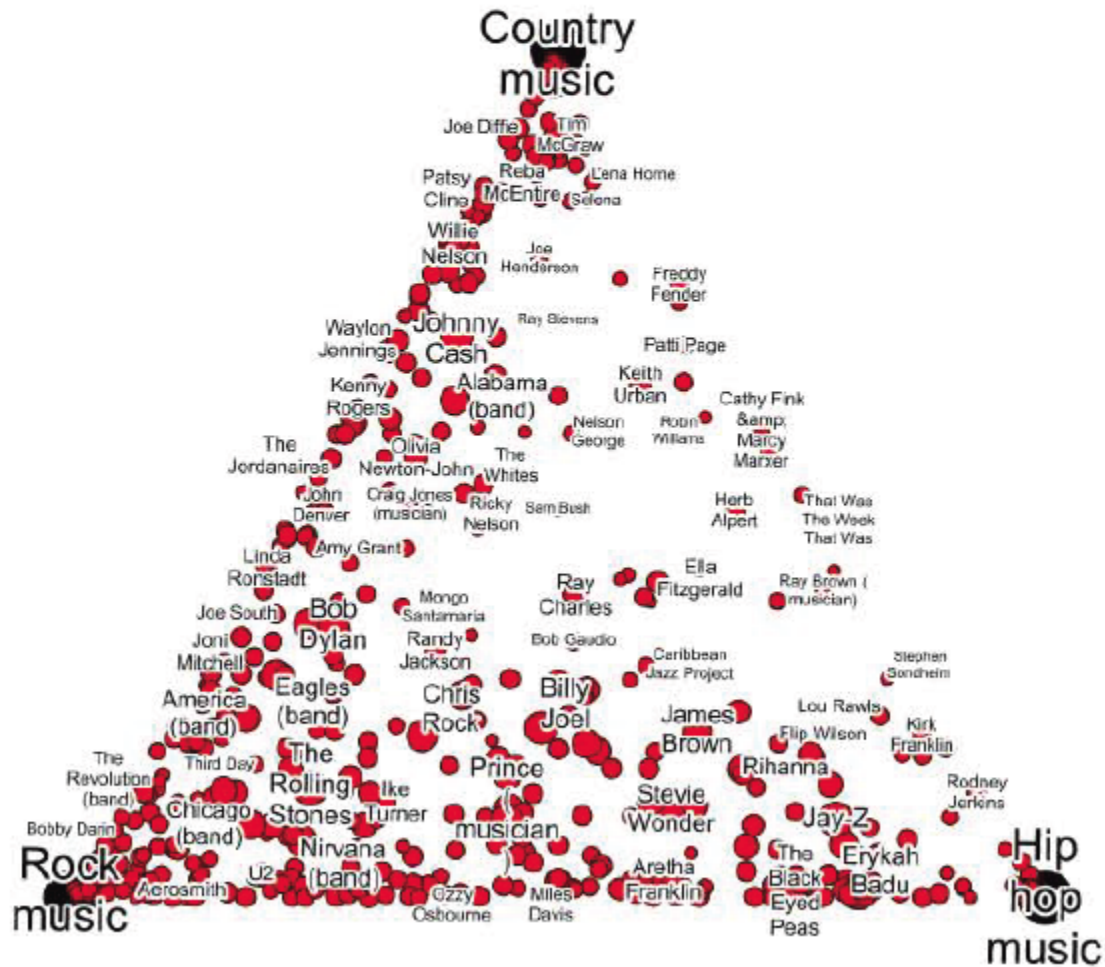
Category:Grammy Award winners

From Wikipedia, the free encyclopedia

Rock
music

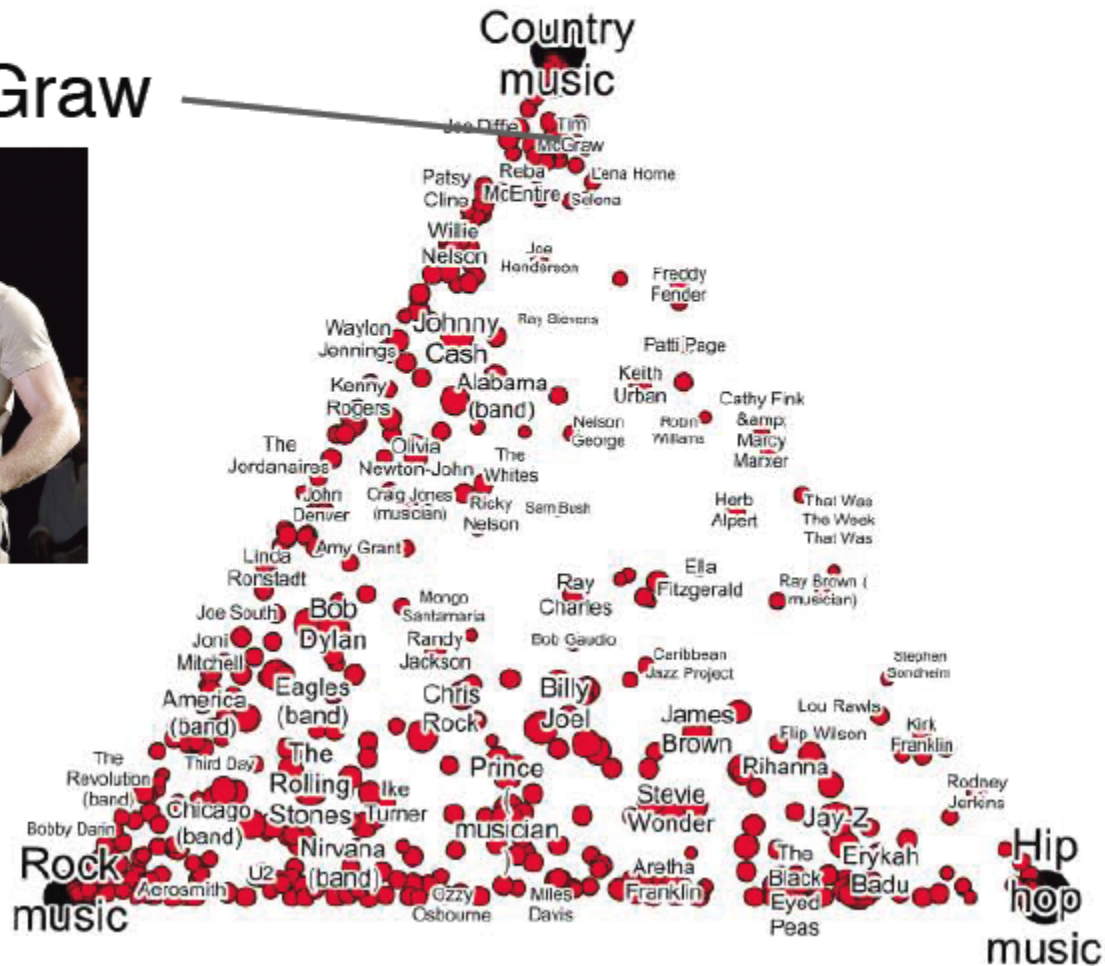
Hip
hop
music

Ad-hoc Reference Systems



Ad-hoc Reference Systems

Tim McGraw

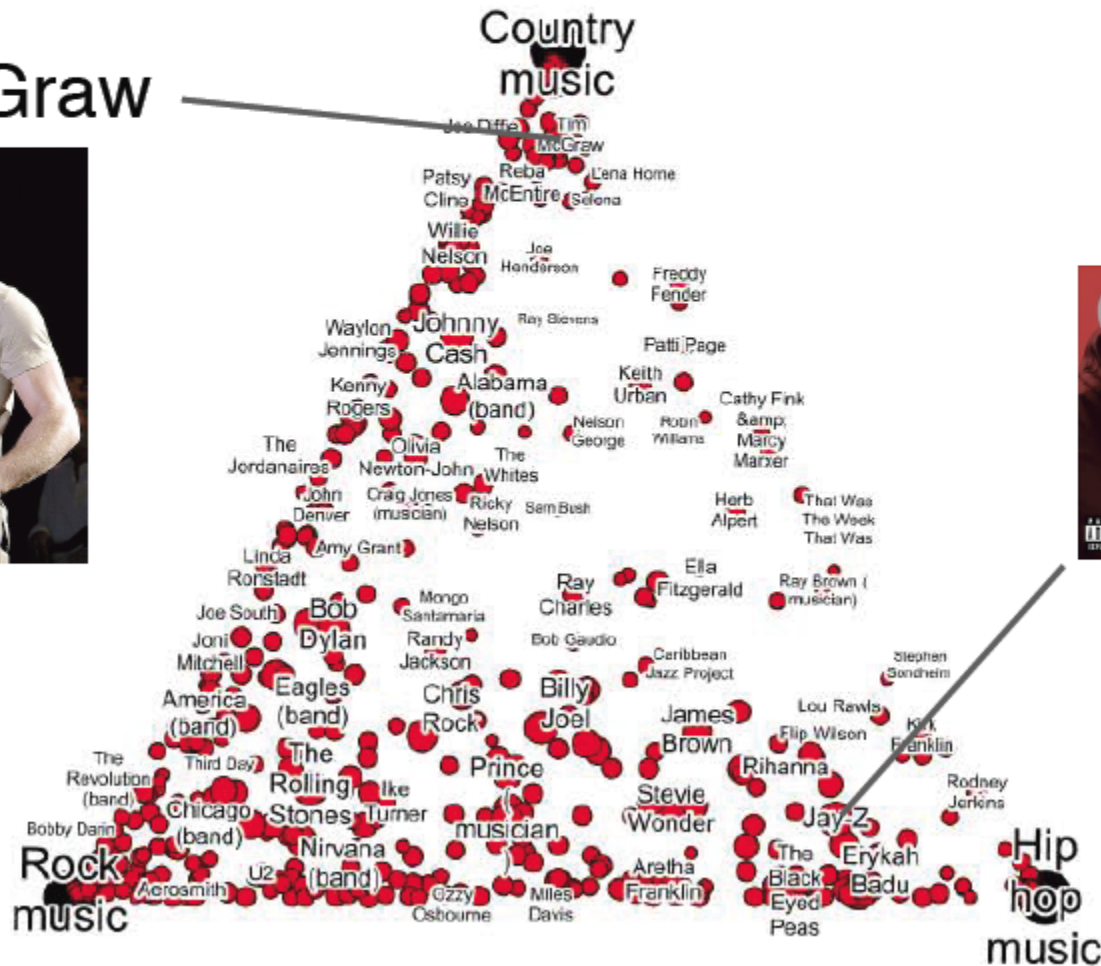


Ad-hoc Reference Systems

Tim McGraw



Jay-Z



One more distance measure

- Kullback–Leibler divergence
 - Related to entropy & information gain
 - not a metric, since it is not symmetric
 - Take **EECS 428:Information Theory** to find out more