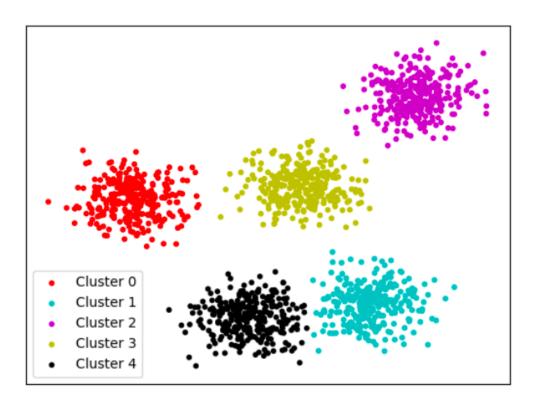
# 349:Machine Learning

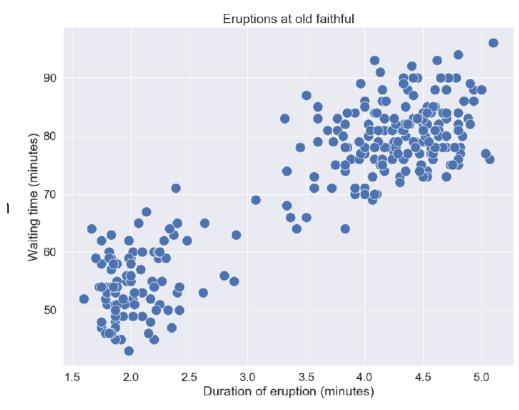
k-Means Clustering

#### **Reasons for k-Means Clustering**

- Unsupervised ML task:
   Labels are expensive!
- Common use cases
   Social network analysis
   Anomaly detection
   Media recommendation
   Speaker recognition
   Many more ...



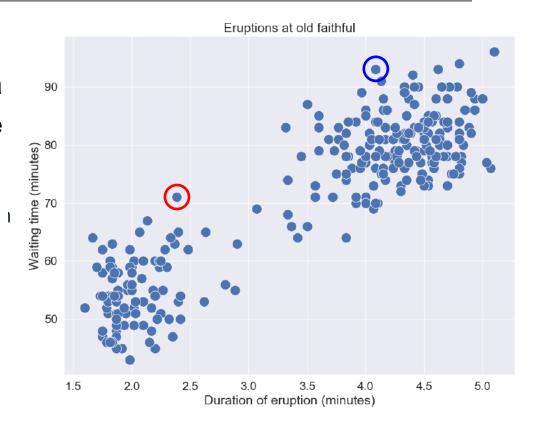
Raw data from Old Faithful
 Captures some phenomena
 How could you possibly use this?



· Raw data from Old Faithful

Captures some phenomena How could you possibly use this?

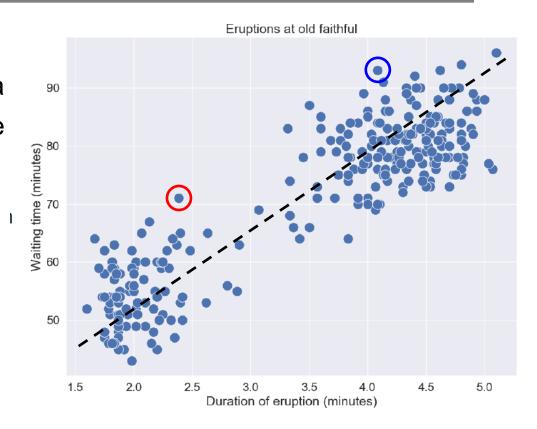
What is the underlying relationship?



· Raw data from Old Faithful

Captures some phenomena How could you possibly use this?

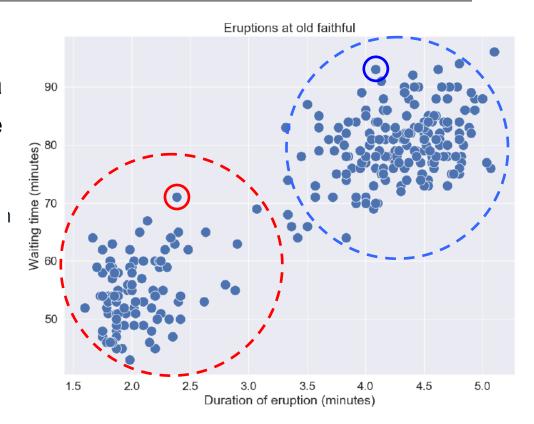
What is the underlying relationship?



· Raw data from Old Faithful

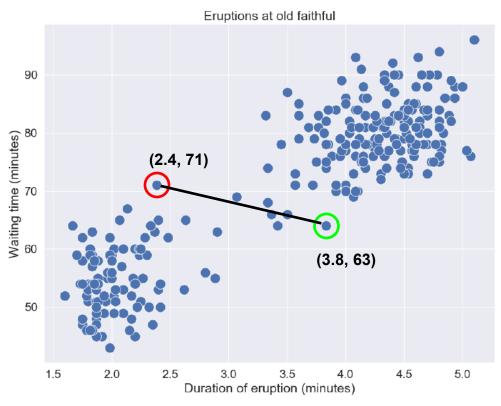
Captures some phenomena How could you possibly use this?

What is the underlying relationship?

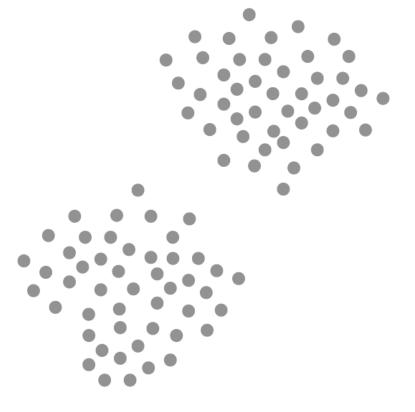


- Raw data from Old Faithful
  - Captures some phenomena How could you possibly use this?
  - What is the underlying relationship?
- Distance Metric can be used to measure pair-wise relations

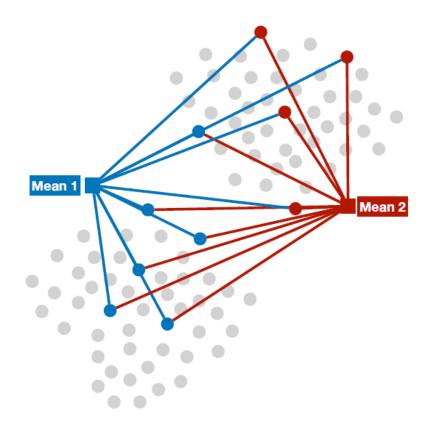
$$d(p_i, p_j) = \sqrt{\sum_{A} (p_{i,a} - p_{j,a})^2}$$
$$= \sqrt{(71 - 63)^2 + (2.4 - 3.8)^2}$$
$$= 8.13$$



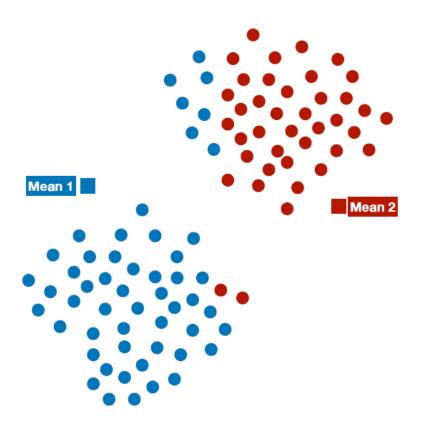
· We start with unlabeled data



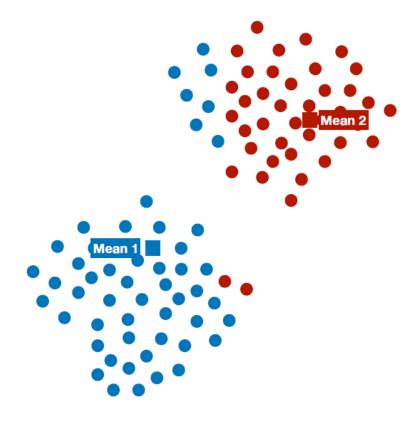
- We start with unlabeled data
  - 1. Randomly select means
  - 2. Calculate distance to means for every data point
  - 3. Assign class labels based upon shortest distance
  - 4. Update means and repeat



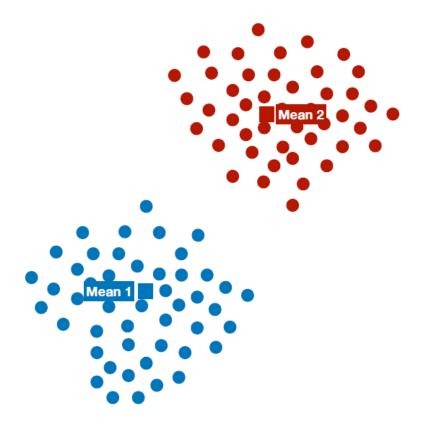
- We start with unlabeled data
  - 1. Randomly select means
  - 2. Calculate distance to means for every data point
  - 3. Assign class labels based upon shortest distance
  - 4. Update means and repeat



- We start with unlabeled data
  - 1. Randomly select means
  - 2. Calculate distance to means for every data point
  - 3. Assign class labels based upon shortest distance
  - 4. Update means and repeat



- We start with unlabeled data
  - 1. Randomly select means
  - 2. Calculate distance to means for every data point
  - 3. Assign class labels based upon shortest distance
  - 4. Update means and repeat until *convergence*



Assign class labels based upon distance to the means

$$c_i \equiv \underset{m}{\operatorname{arg\,min}} \|x_i - \mu_m\|_2$$

• Update the means:

$$\mu_{m,a} \equiv \frac{\sum_{c \in m} \mathbf{1} \cdot \mathbf{x}_{i,a}}{\sum_{c \in m} \mathbf{1}}$$

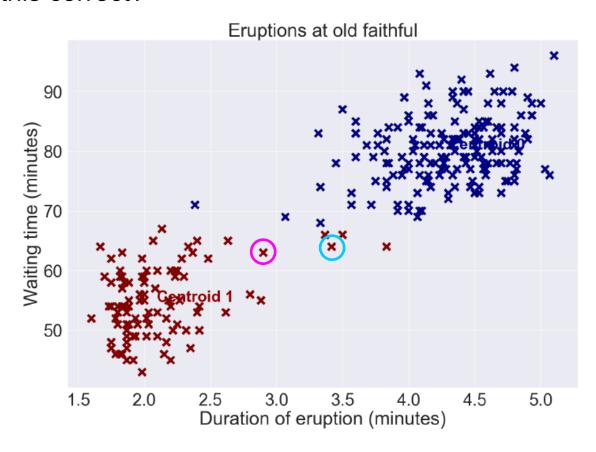
where:

a is the attribute, m is the class label, and  $\mu=(a_1,a_2,\dots a_A) \text{ is a vector in the attribute-space}$ 

# **Back to Old Faithful Example**

 The k-Means algorithm classifies Old Faithful data into two clusters:

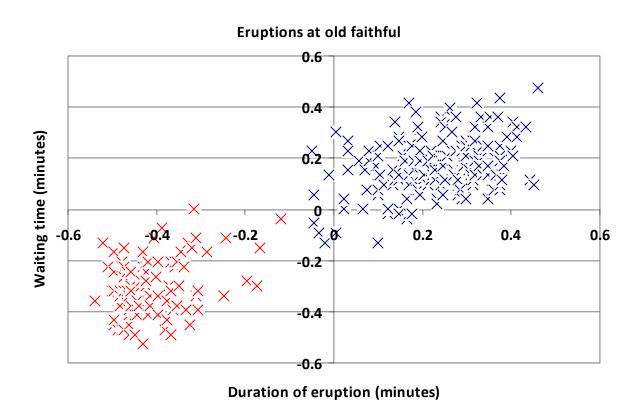
But is this correct?



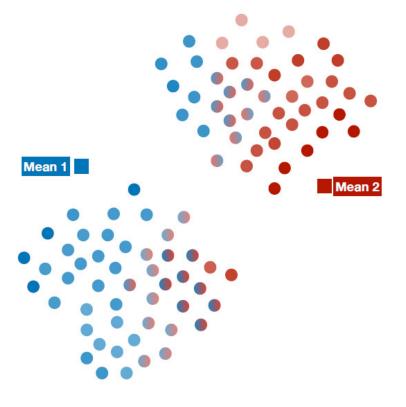
# **Old Faithful Example -- Revisited**

 Normalizing data allows but attributes to be considered

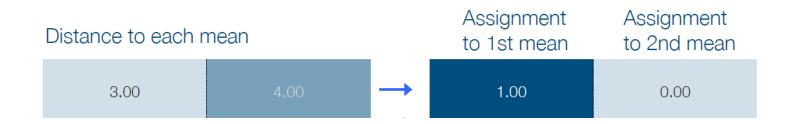
$$x_{i}^{'} = \frac{x_{i} - \min(x)}{\max(x) - \min(x)}$$



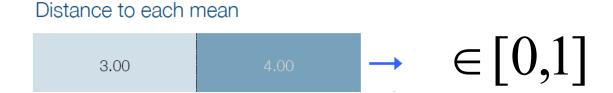
 Soft decision is based on how much closer an observation is to one means versus others.



A hard-margin classifier assigns an atomic class label



A soft-margin classifier will assign a probability



Probability is assigned to each class using the softmax function

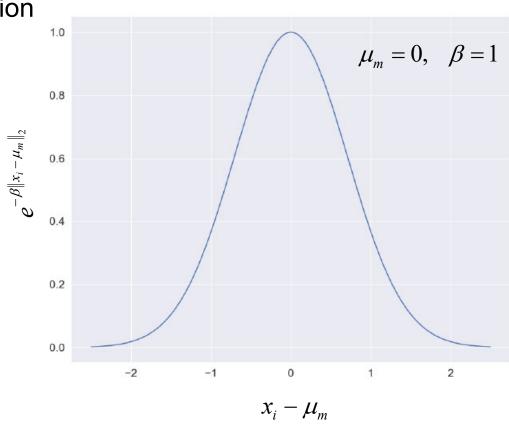
$$P(x_i \in m) = \operatorname{softmax}(z_{im}) = \frac{e^{z_{im}}}{\sum_{m} e^{z_{im}}}$$

where:

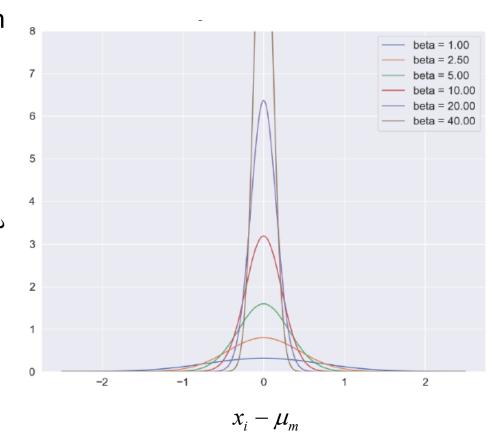
$$z_{im} = -\beta \|x_i - \mu_m\|_2$$

and  $\beta$  controls the **sharpness** of the distribution

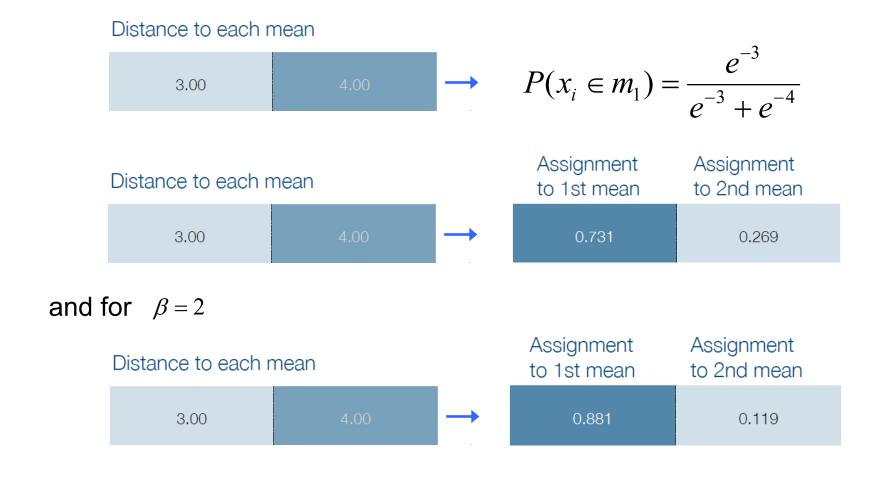
 Resulting probability distribution is a Gaussian function of the distance between an observation and a mean



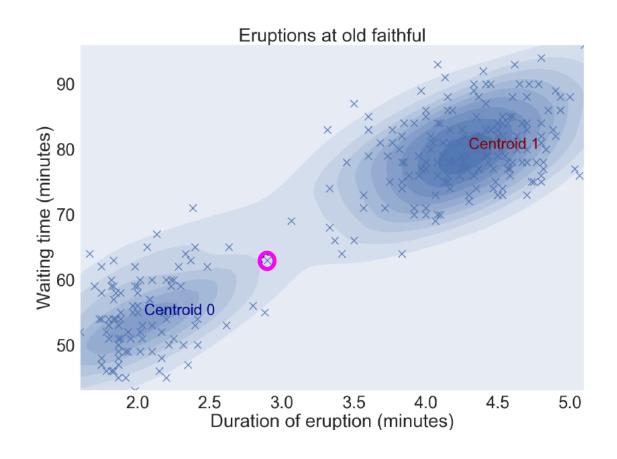
- Resulting probability distribution is a Gaussian function of the distance between an observation and a mean
- β is sometimes called the temperature



• Applying this to the previous example with  $\beta = 1$ 



 Applying Soft k-Means to Old Faithful resolves ambiguity



#### **Take Aways**

- We learned how to classify unlabeled data k-Means clustering
- We formulated a Soft k-Means to handle uncertainty (and express confidence)

#### **Precision vs Recall**

Classifiers are often evaluated with an eye towards their being search engines. (e.g. labeling documents as either relevant or not to a search query). In this case people often use the following measures:

precision	$p = \frac{tp}{tp + fp}$
recall	$r = \frac{tp}{tp + fn}$
F-measure	$F = 2\frac{p \cdot r}{p + r}$

	• •	ac Giassii	ioation
Classification		True	False
	True	True positive (tp)	False positive (fp)
Machine's	False	False negative (fn)	True negative (tn)

True Classification

#### **Confusion Matrix**

Lets us see which things the classifier is mixing up. Helps direct improvement.

#### **Correct Classification**

Machine's Classification

	Dog	Coyote	Cactus	Road Runner
Dog	8	5	0	2
Coyote	2	5	0	2
Cactus	0	0	8	2
Road Runner	0	0	2	4