BC COMS 2710: Computational Text Analysis

Lecture 18 – Clustering

Announcements – Assignments

- Readings 05:
  - link posted to course site
  - due Sunday
- HW 03:
  - Released last Friday
  - Optional – has anyone looked at it?
- HW04/Tutorial 5.1
  - Releasing today or Friday
  - Based on last Thursday’s and this week’s material

Final Project – Deliverables

- Project ideation – Friday May 28st
  - 5 points
- Project proposal – Sunday June 6th
  - 9 points
- Project presentations – Monday June 14th
  - 6 points
- Project submissions – Friday June 18th
  - 15 points
- http://coms2710.barnard.edu/final_project

Final Project – Proposal due Sunday June 6th

Beefed up version of project ideation

1. Research Question
2. Detailed source of data:
    1. List of twitter user’s, subreddits, etc
3. Detailed methods you plan on applying for exploratory data analysis
    1. Tf-idf, topic modeling, …
4. Prediction

Logistic Regression

Summary of Logistic Regression

- Optimizes $\mathrm{P}(Y\,|X)$ directly
- Define the features
- Learn a vector of weights for each label $y \in Y$
  - Gradient descent, update weights based on error
- Multiple feature vector by weight vector
- Output is $\mathrm{P}(Y = y\,|X)$ after normalizing
- Choose the most probable Y

Slide from Nate Chambers

Parameters

Parameters in …

- Logistic Regression:
  - Weights

- Naive Bayes:
  - Priors – $P(Y)$
  - Likelihoods - $P(x_i|Y)$

- Values that are estimated from data

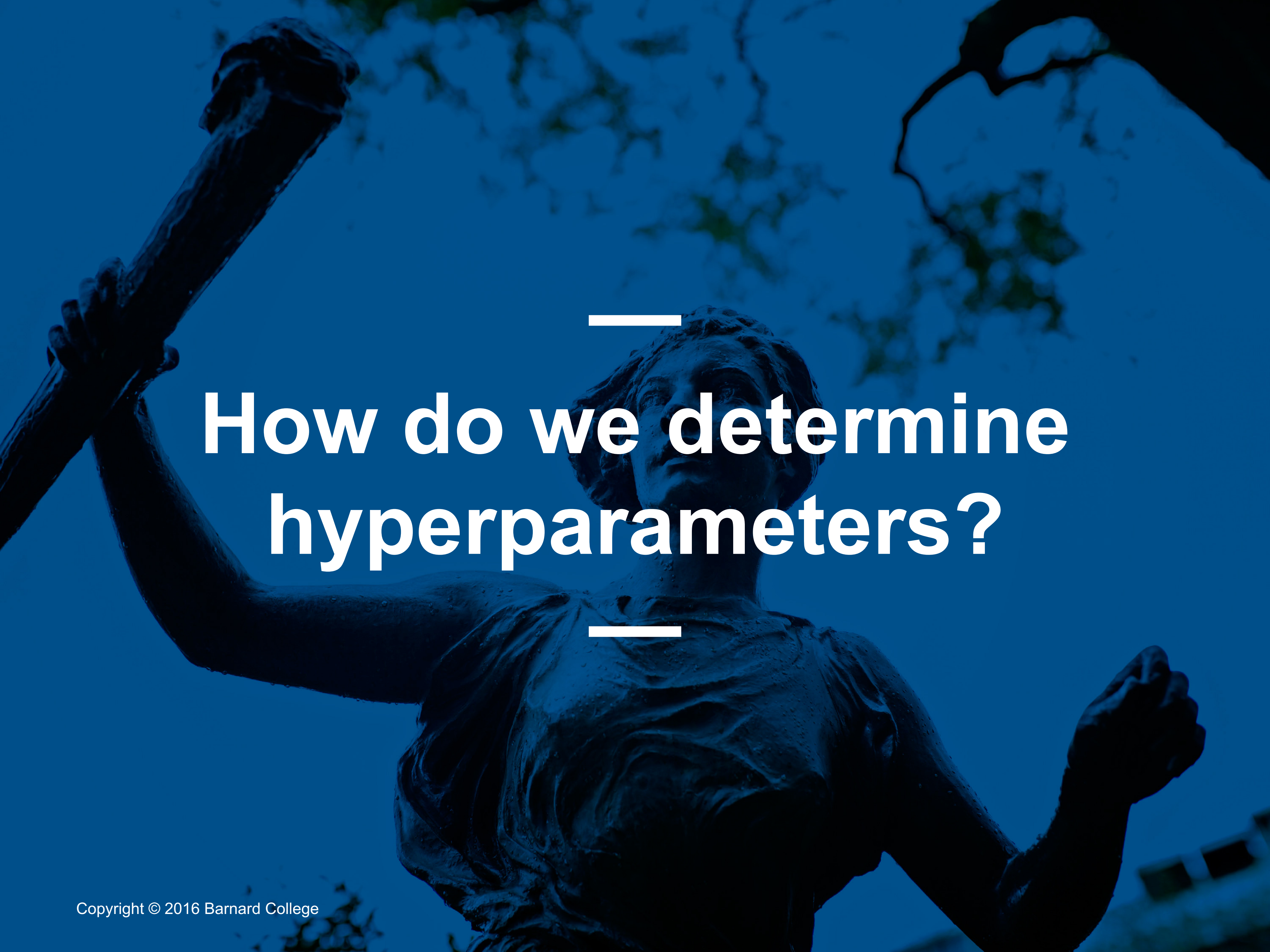
Hyperparameters

- a configuration that is external to the model and whose value cannot be estimated from data
- ***"If you have to specify a value manually, then it is probably a model hyperparameter"***

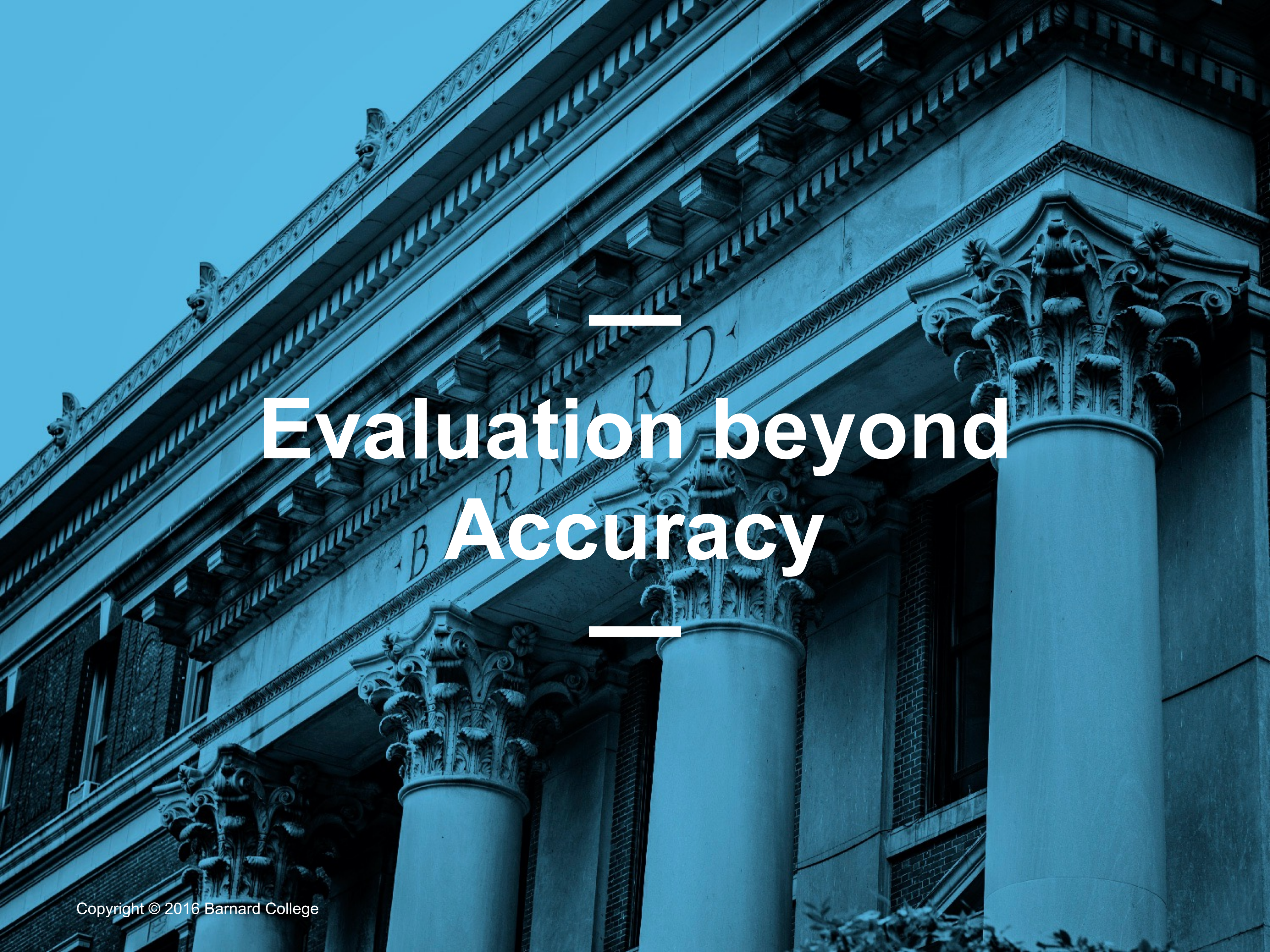
[Machine Learning Mastery]

Hyperparameters in …

- Logistic Regression:
  - max_iters
- Naive Bayes:
  - Value for smoothing
    - Add-one smoothing (Laplacian smoothing)
- LDA
  - ***k*** – the number of topics



How do we determine hyperparameters?



Evaluation beyond Accuracy

Confusion Matrix

	gold positive	gold negative
positive prediction	True Positive **(TP)**	False Positive **(FP)**
negative prediction	False Negative **(FN)**	True Negative **(TN)**

Metrics from the confusion matrix: accuracy

	gold positive	gold negative
positive prediction	True Positive **(TP)**	False Positive **(FP)**
negative prediction	False Negative **(FN)**	True Negative **(TN)**

Accuracy: $\frac{TP+TN}{TP+FP+TN+FN}$

Metrics from the confusion matrix: precision

	gold positive	gold negative
positive prediction	True Positive **(TP)**	False Positive **(FP)**
negative prediction	False Negative **(FN)**	True Negative **(TN)**

% of items the system detected (i.e., items the system labeled as positive) that are in fact positive (according to the human gold labels)

Precision: $\frac{TP}{TP+FN}$

Definition from Dan Jurafsky

Metrics from the confusion matrix: recall

	gold positive	gold negative
positive prediction	True Positive **(TP)**	False Positive **(FP)**
negative prediction	False Negative **(FN)**	True Negative **(TN)**

% of items actually present in the input that were correctly identified by the system.

Recall: $\frac{TP}{TP+FP}$

Definition from Dan Jurafsky

Metrics from the confusion matrix: F1

	gold positive	gold negative
positive prediction	True Positive **(TP)**	False Positive **(FP)**
negative prediction	False Negative **(FN)**	True Negative **(TN)**

Combine precision and recall

$$F_1 = \frac{2PR}{P+R}$$

Clustering

Different Types of Machine Learning

- Supervised Learning
  - Given labeled examples, learn rules

- Unsupervised Learning
  - Given unlabeled example, learn patterns

Slide from Tony Liu

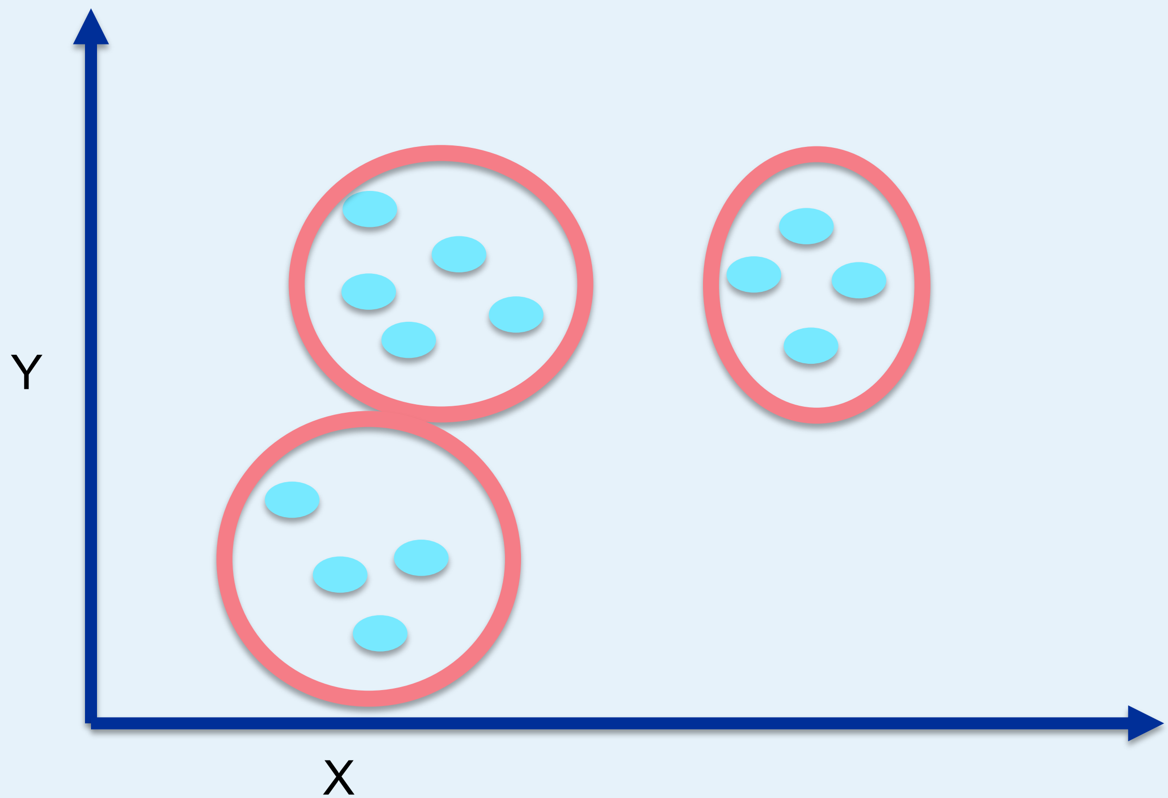
Clustering

- Unsupervised learning
  - Requires data, but no labels
- Detect patterns e.g. in
  - Group emails
  - Group obituaries
  - Group any documents
- Useful when don't know what you're looking for
- Good way to explore your data

Slide from David Sontag

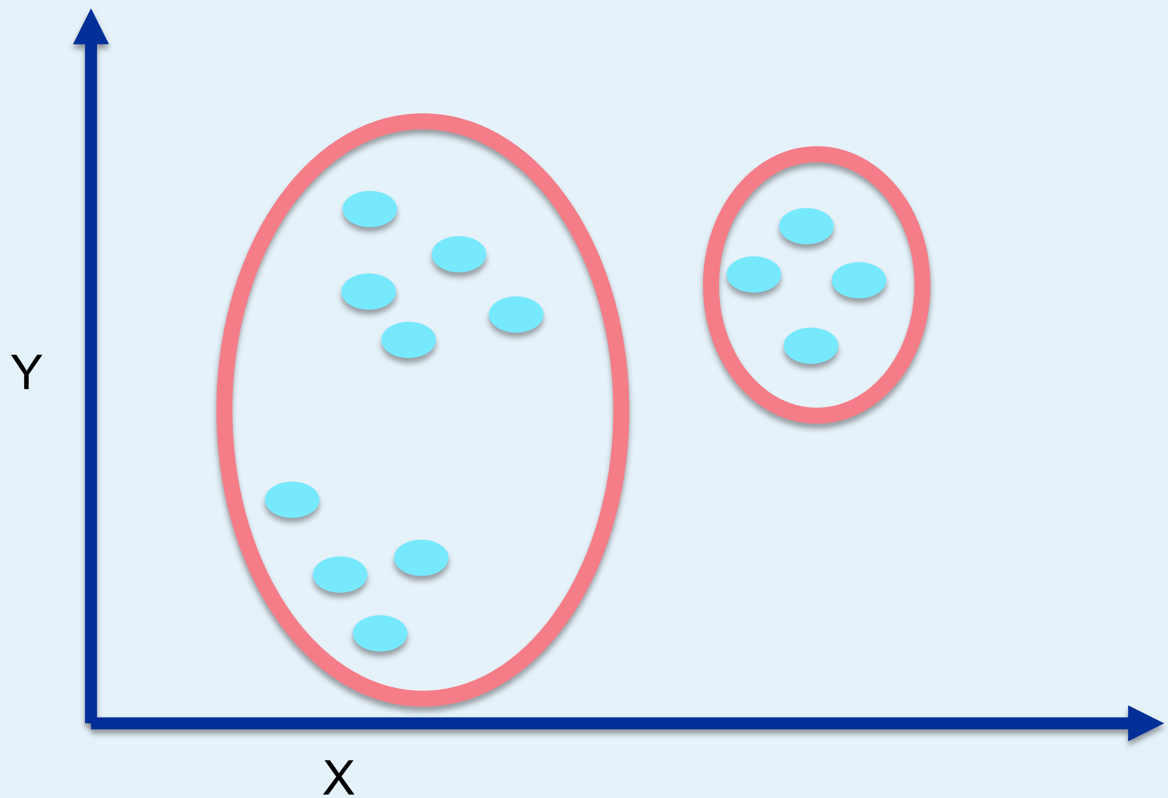
Idea: group together similar instances

- Example: 2D point patterns



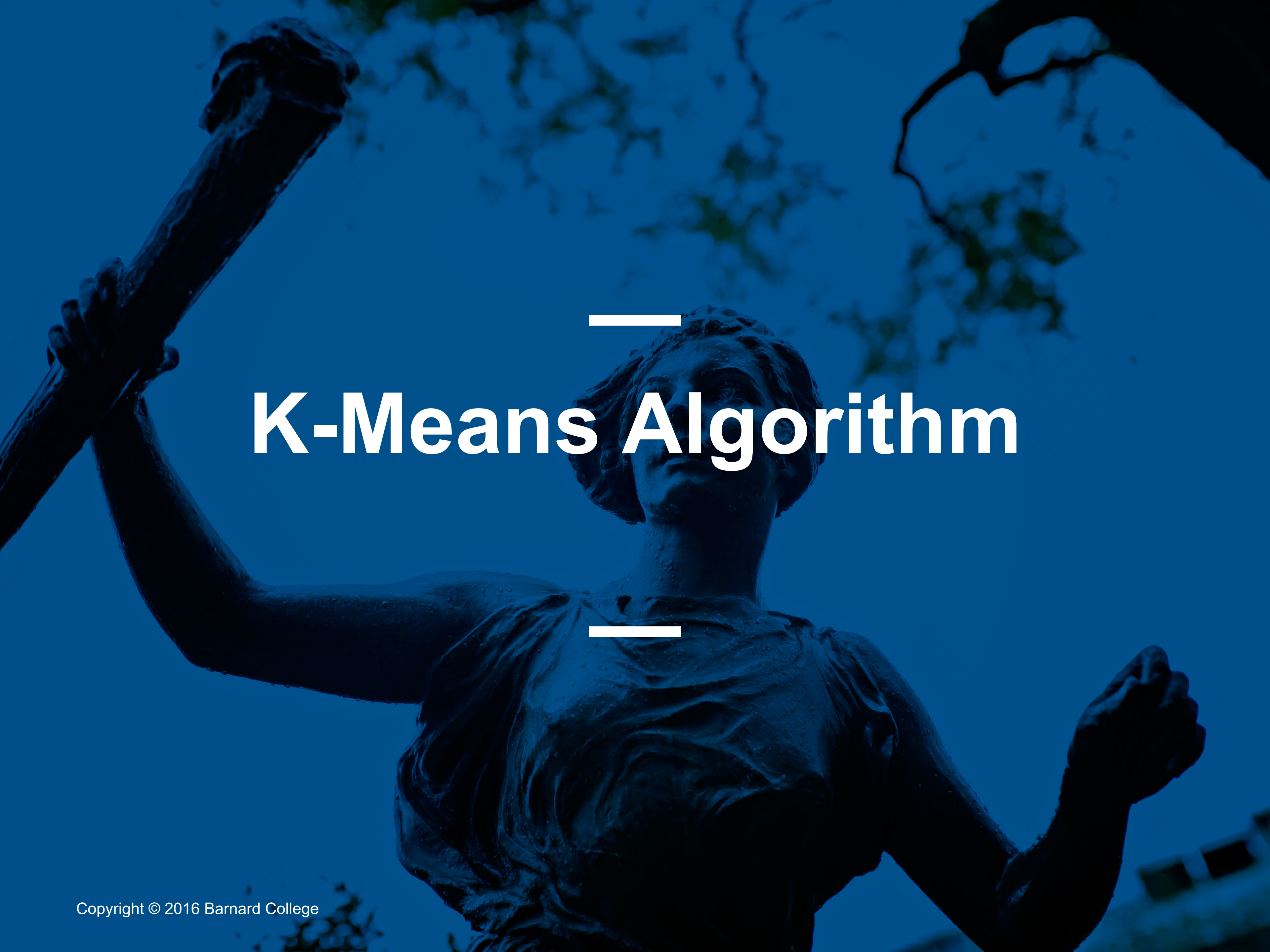
Idea: group together similar instances

- Example: 2D point patterns



Clustering HW02

- HW02 analyzed obits
- Why might we want to cluster obits?
  - Find groups of similar obituaries
  - Find topics of obituaries
  - …



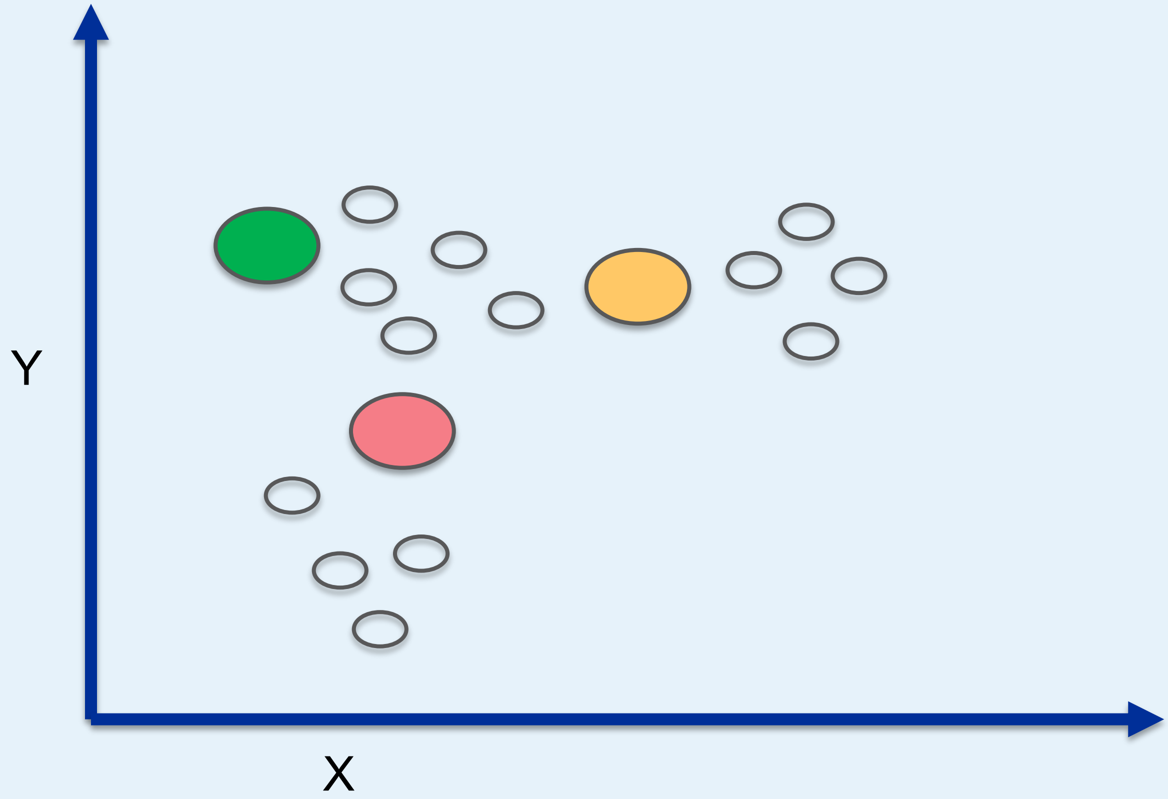
K-Means Algorithm

K-means Algorithms

1. Initialize: Randomly pick K points as cluster centers

Randomly pick K points as centers

- Example: 2D point patterns



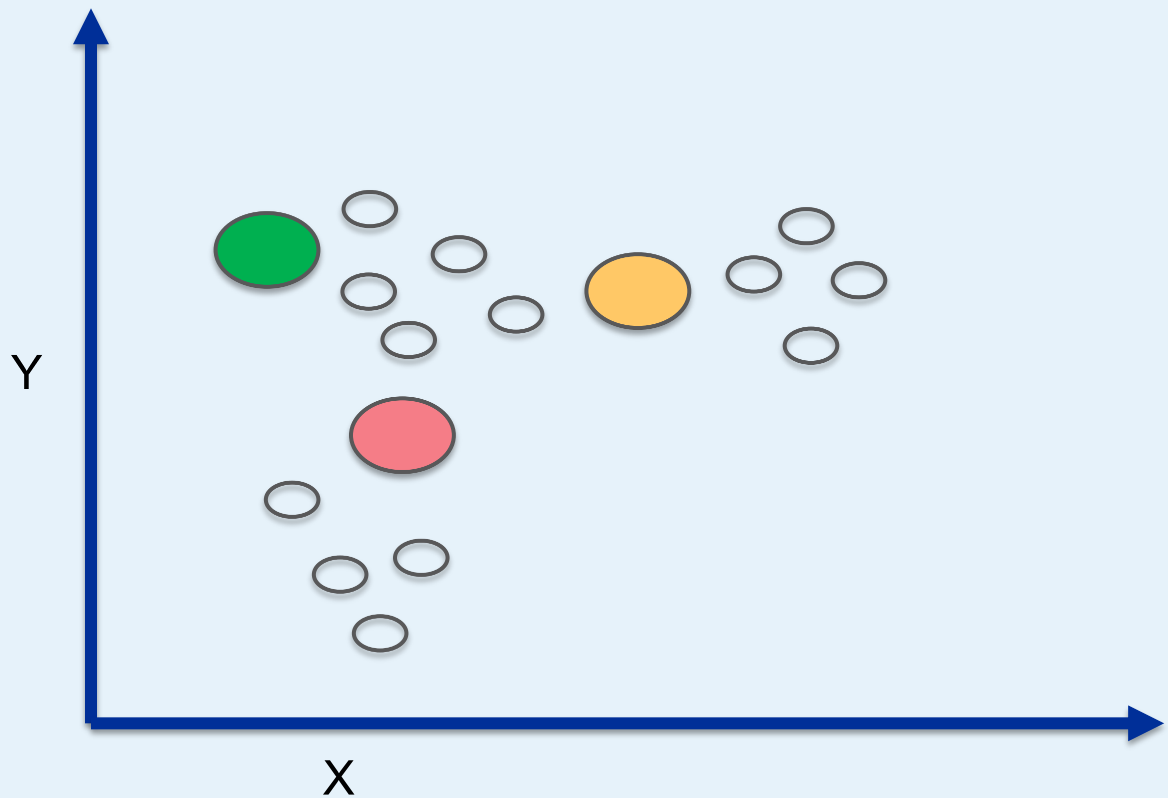
K-means Algorithms

1. Initialize: Randomly pick K points as cluster centers

2. Assign data points to each cluster
    1. Based on distance between point and cluster's center

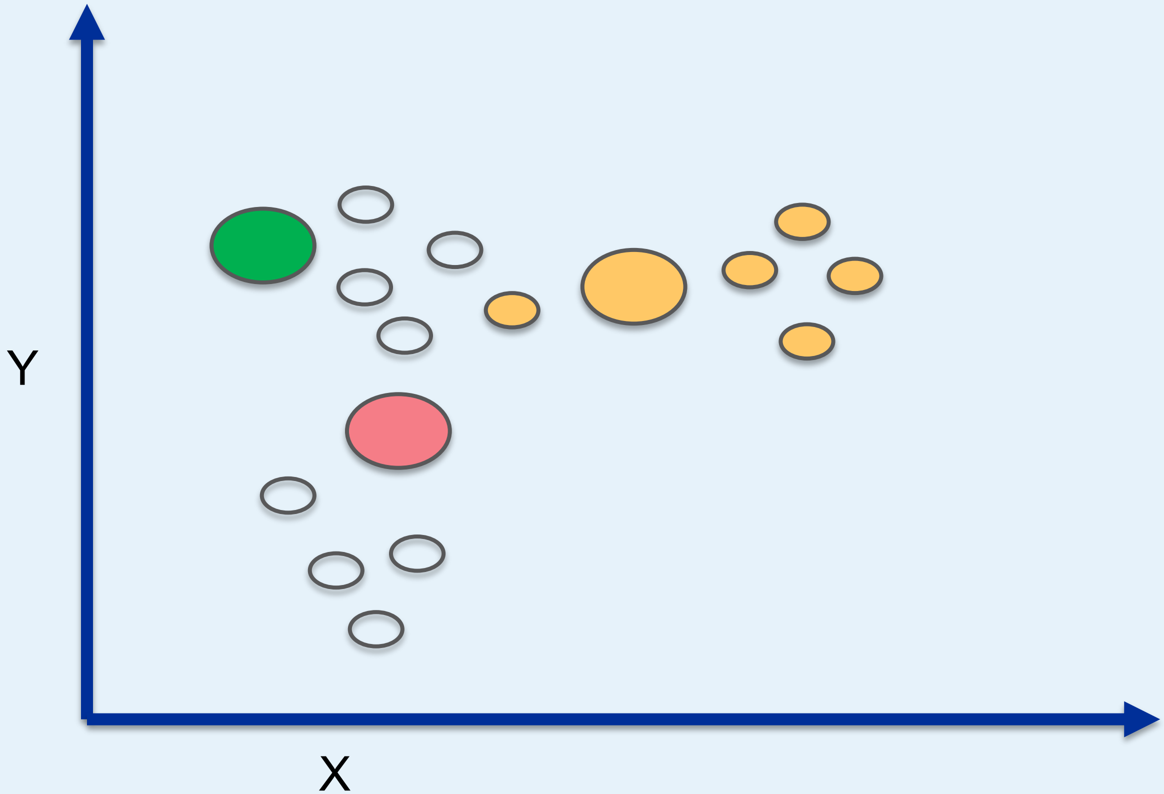
Assign data points to each cluster

- Example: 2D point patterns



Assign data points to each cluster

- Example: 2D point patterns



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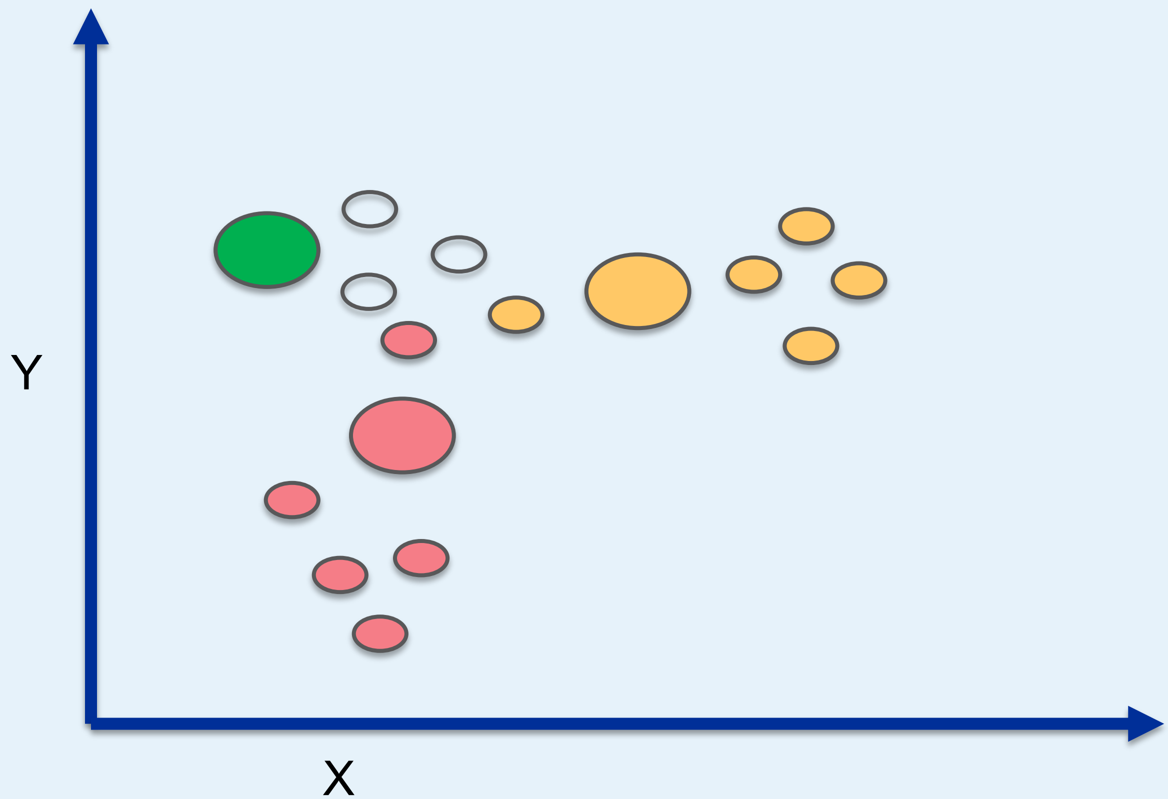

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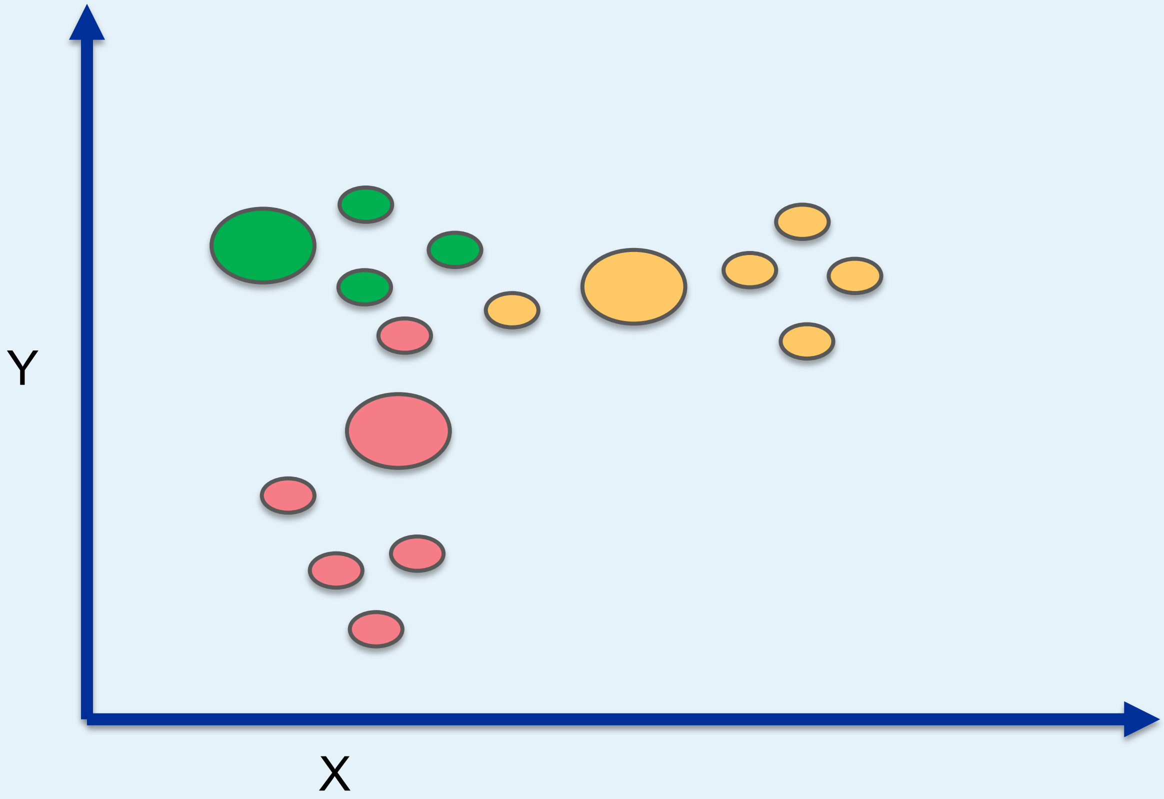

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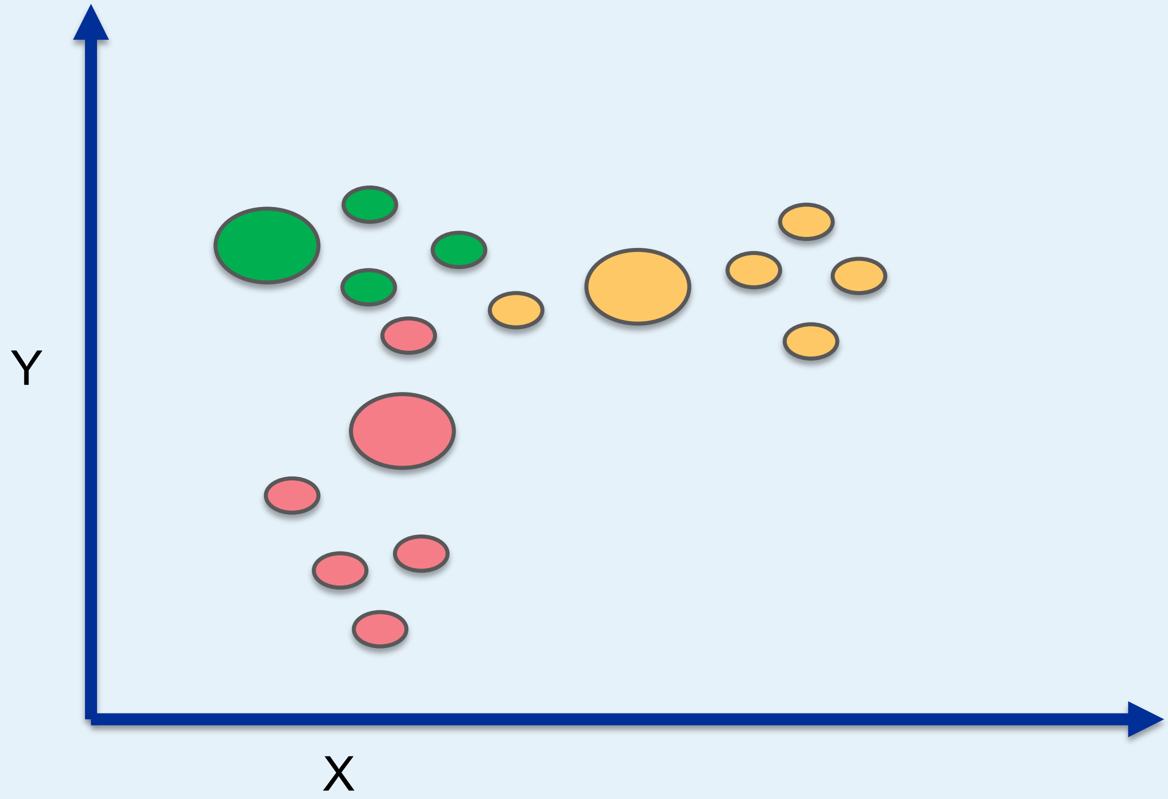
3. Update the center of each cluster
   1. The average of its assigned points

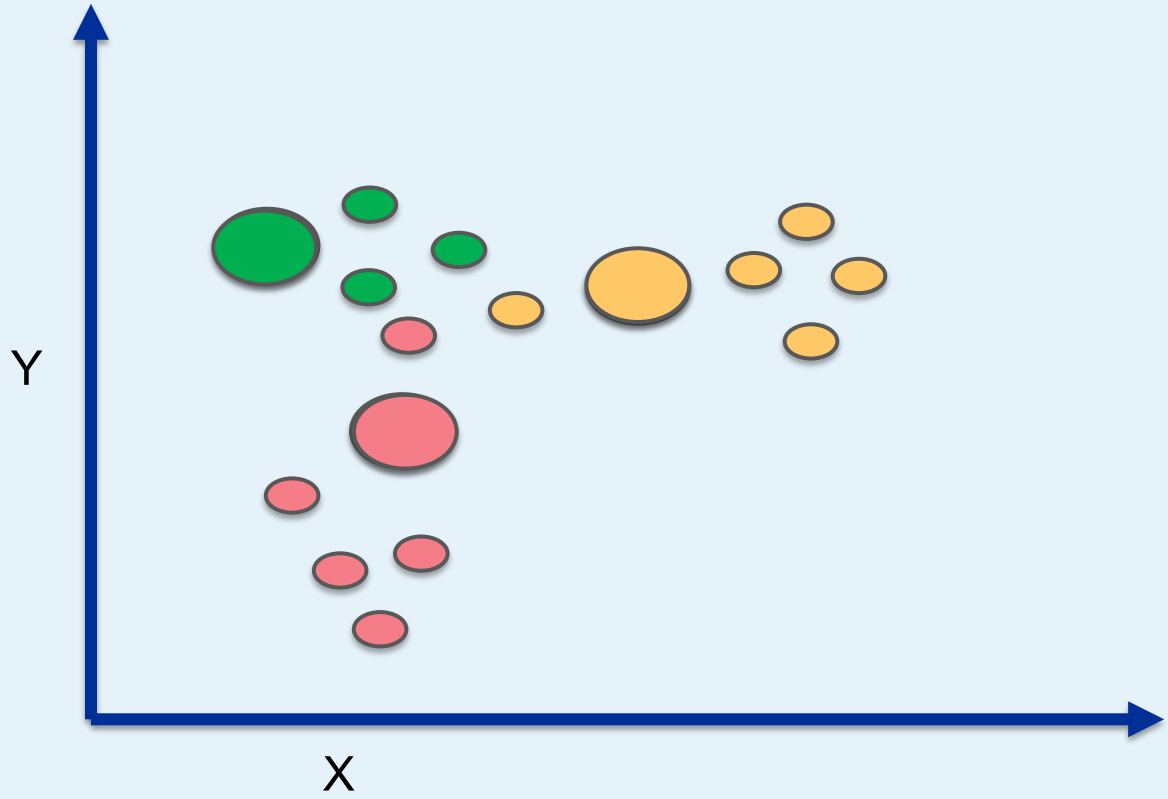
Update Centers

- Example: 2D point patterns



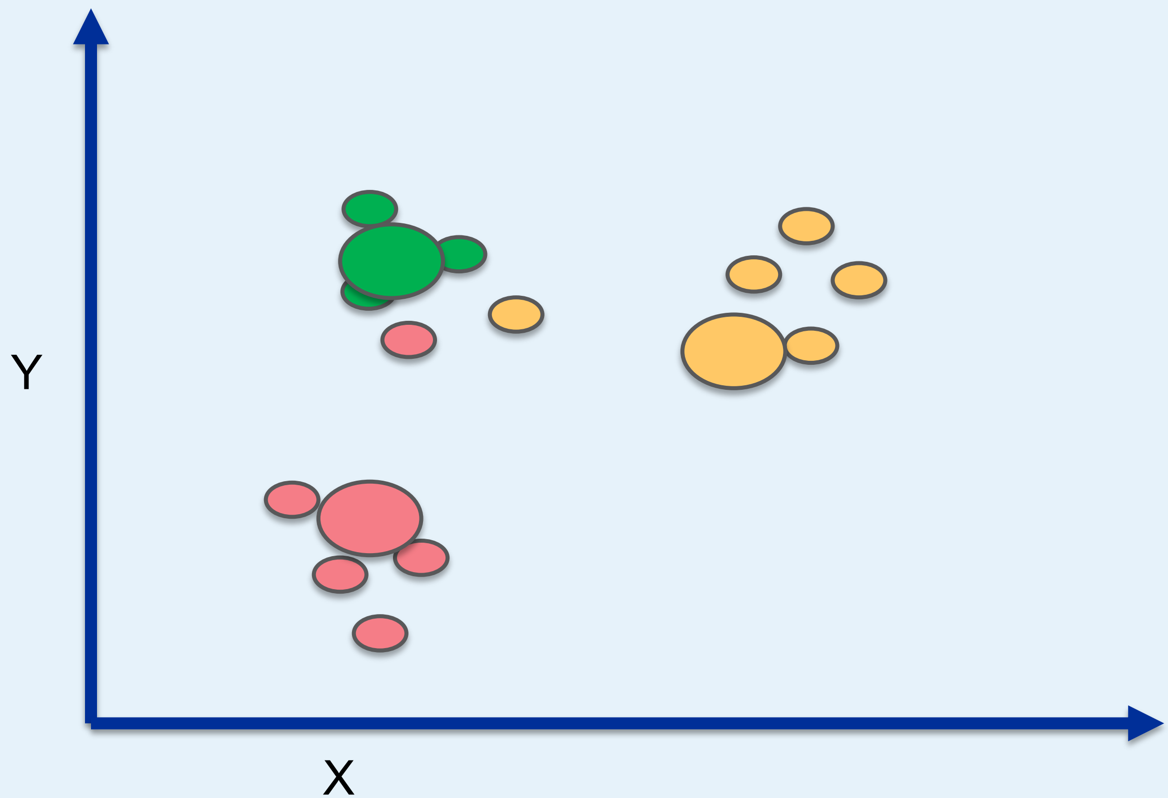
Update Centers

- Example: 2D point patterns



Updated Centers

- Example: 2D point patterns



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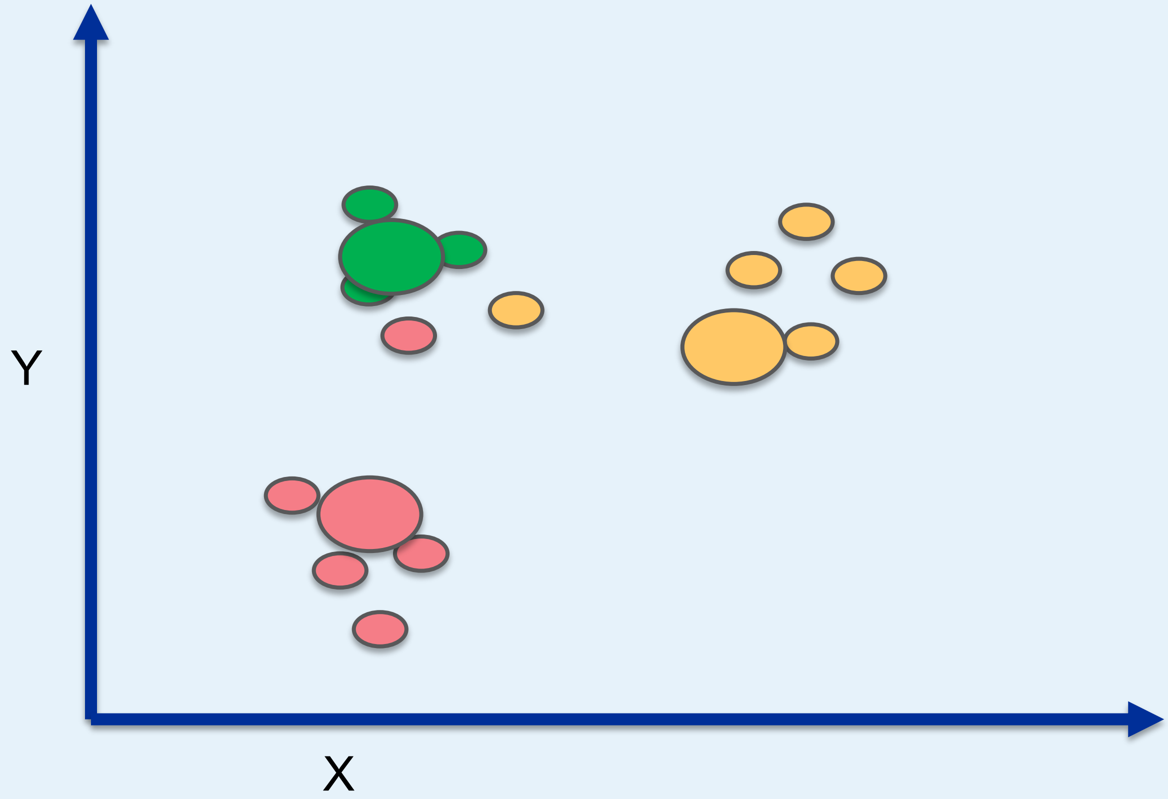
4. Repeat 2 & 3 until the assignments stop changing

Reassign data points to each cluster

- Example: 2D point patterns



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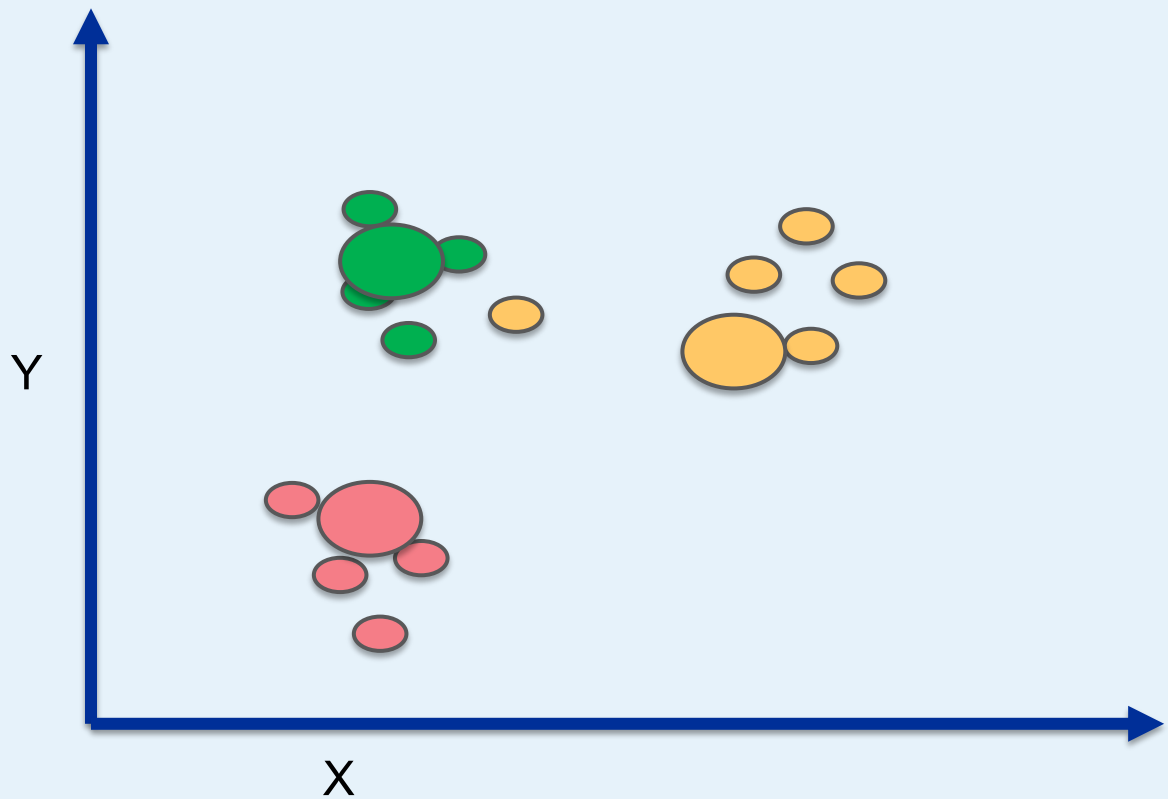

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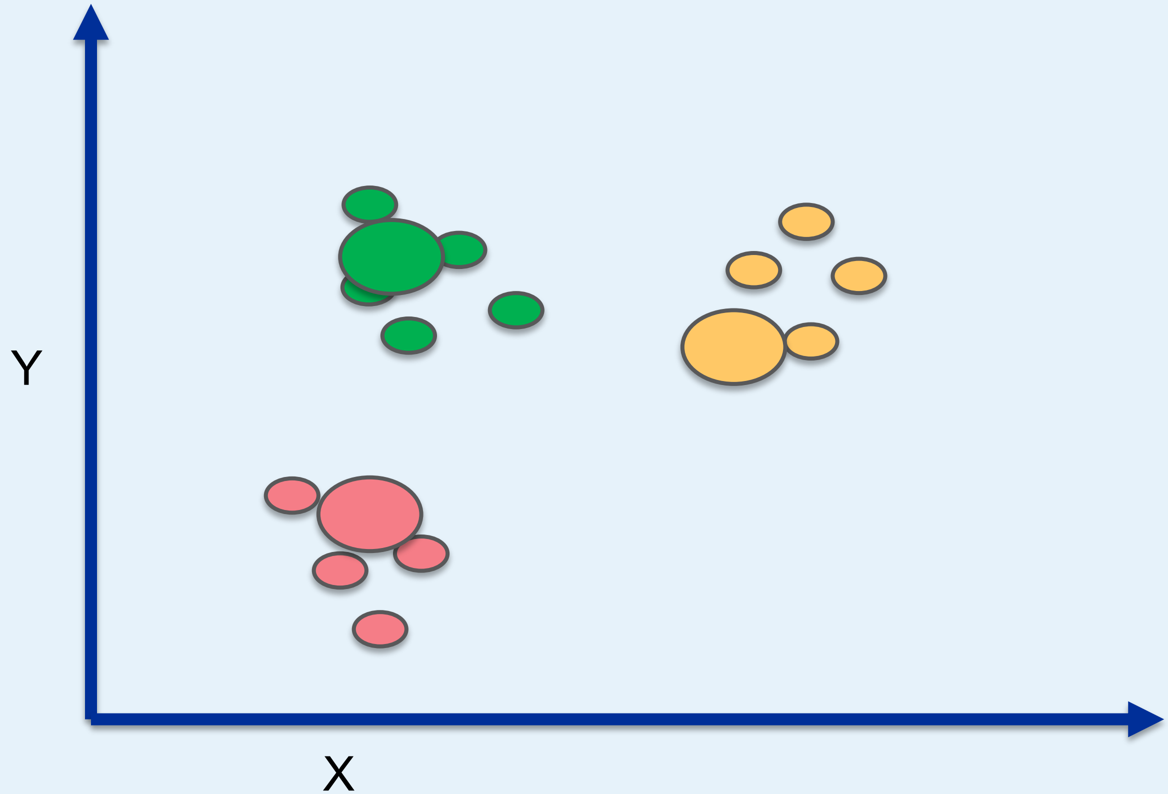

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How do we quantify similarity/distance?

We need to define similarity/distance

Similarity metrics we've seen so far:

cos similarity

Euclidian distance between two documents x_1 and x_2

$$D = \sqrt{\sum_i (x_{1_i} - x_{2_i})^2}$$

Week 6

- Monday 06/07 - Matrix Factorization
- Tuesday 06/08 – Word Embeddings
- Wednesday 06/09 – Guest Lecture
  - Attendance required
- Thursday 06/10 - TBA