Carnegie Mellon University
Heinz College

# 94-775 Unstructured Data Analytics

## Lecture 10: Wrap up topic modeling & clustering; intro to predictive data analytics

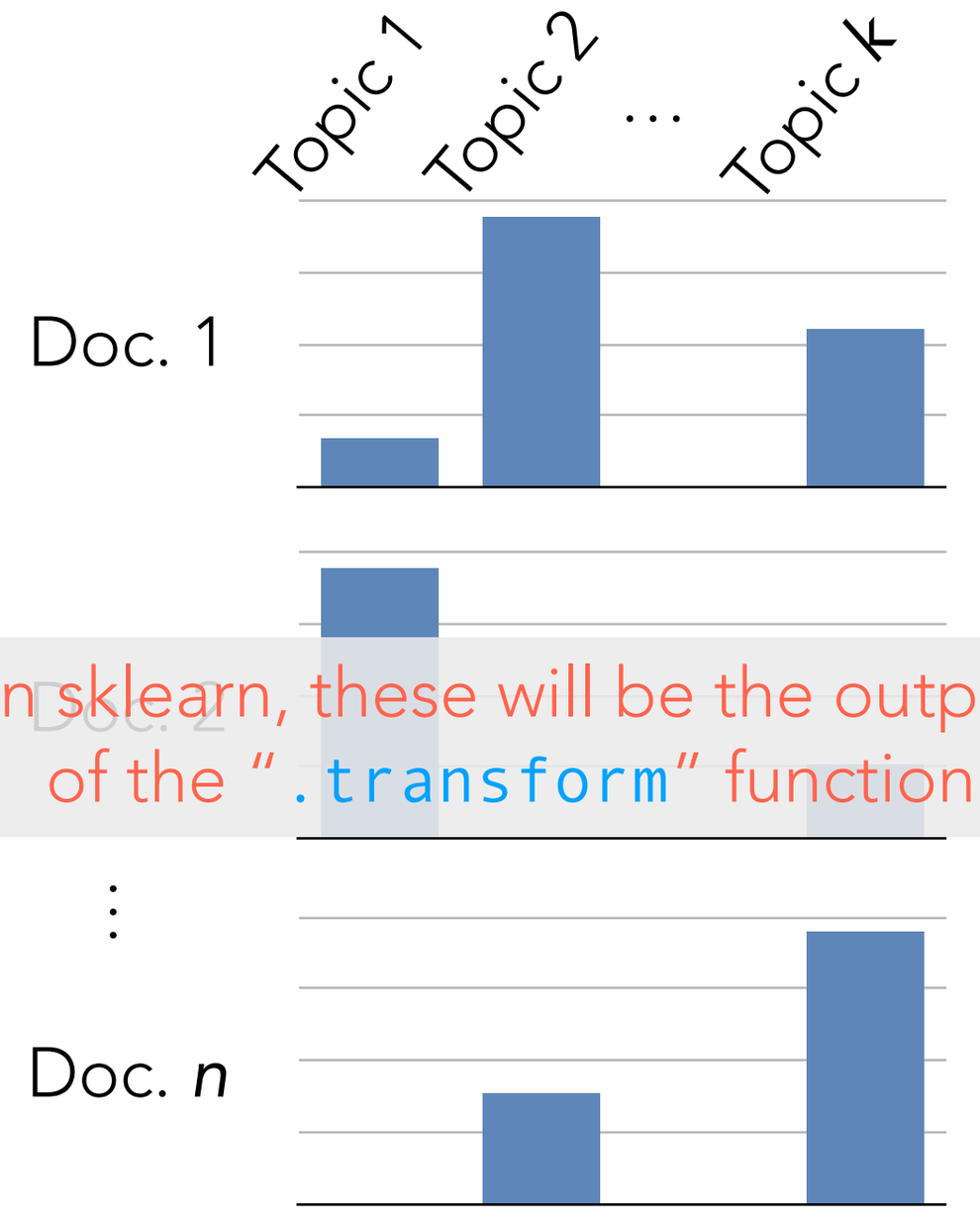
Slides by George H. Chen

# Administrivia

- Reminder: Quiz 2 is tomorrow 11:00am during the recitation slot 😱
  - Coverage: weeks 3 + 4 as well as the lecture on Tue April 8 (“Lecture 9”)
  - Given the relatively short time between Quiz 1 & Quiz 2, I’ve intentionally tried to dial down the difficulty compared to Quiz 1 (we’ll find out tomorrow how you feel about Quiz 2’s difficulty level!)

- Reminder: no formal Quiz 2 review session but I have an extra office hour slot today 7pm-8pm over Zoom
  - See Canvas announcement I sent out Mon April 7 for the Zoom link

# (Flashback) LDA Generative Model




In sklearn, these will be the output of the "`.transform`" function


Goal: Learn these distributions

In sklearn, these will be in "`.components_`"

LDA models each word in document *i* to be generated as:

1. Randomly choose a topic *Z* (use topic distribution for doc *i*)
2. Randomly choose a word (use word distribution for topic *Z*)

# How to choose the number of topics *k*?

# How "Coherent" is a Topic?

Let's look at top-20 word lists (the ones from the demo)

```
[Topic 0]
good : 0.01592254908129389
like : 0.01584763067117222
just : 0.015714974597809874
think : 0.014658035148150044
don : 0.01336602502776772
time : 0.012159230893303024
year : 0.011442050656933937
new : 0.009768217977593912
years : 0.00843922077825026
game : 0.0084164825794737 57
make : 0.008318270139852606
ve : 0.00805613381872604
know : 0.00786552901690738
going : 0.007357414502894818
better : 0.007305177940555176
really : 0.007282768897233162
got : 0.007100242166187475
way : 0.007020258221618519
team : 0.006901091494924322
car : 0.006860678090522195
```

If we see the word "good", how likely are we to see the word "years"?

P(see word "years" | see word "good")

If this probability is high for every pair of words in the top-20 list, then in some sense the topic is more "coherent"

Focus on a single topic at a time

Coherence of topic:

$$\sum_{\text{top words } v,w \text{ that are not the same}} \log \mathbb{P}(\text{see word } v | \text{see word } w)$$

$$\frac{\#\text{ documents that mention both } v \text{ and } w}{\#\text{ documents that mention } w} \quad +0.1$$

avoid numerical issues

# How Different is a Topic from the Others?

Let's look at top-20 word lists (the ones from the demo)

```
[Topic 0]
good : 0.01592254908129389
like : 0.01584763067117222
just : 0.015714974597809874
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new : 0.008768217977593912
years : 0.00843922077825026
game : 0.008416482579473757
make : 0.008318270139852606
ve : 0.00805613381872604
know : 0.00786552901690738
going : 0.007357414502894818
better : 0.007305177940555176
really : 0.007282768897233162
got : 0.007100242166187475
way : 0.007020258221618519
team : 0.006901091494924322
car : 0.006860678090522195
```

```
[Topic 1]
drive : 0.025114459755967225
card : 0.01904504522714293
scsi : 0.01574807346309645
disk : 0.015086151949241311
use : 0.01311205775591249
output : 0.012487568705565076
file : 0.011474974819227298
bit : 0.011450491727323115
hard : 0.010426435918865882
entry : 0.009962381704950415
memory : 0.009892936703385204
mac : 0.009531449582937765
video : 0.009451338641933656
drives : 0.009074000962777757
pc : 0.0090703286112168
windows : 0.008135023862197355
16 : 0.00798823814975238
bus : 0.007927283819698584
controller : 0.007902057876189581
program : 0.00784268458596016
```

```
[Topic 2]
10 : 0.0320292203
00 : 0.0269643305
25 : 0.0218296912
15 : 0.0206063577
11 : 0.0206043503
20 : 0.0204957609
12 : 0.0203766844
14 : 0.0180554708
16 : 0.0164602656
13 : 0.0160230124
17 : 0.0160189031
18 : 0.0159314160
30 : 0.0134871298
50 : 0.0133230831
24 : 0.0131269045
19 : 0.0125205615
55 : 0.0125002331
21 : 0.0122642479
40 : 0.0119281525
22 : 0.0112072317
```

If "good" only shows up in the top-20 word list for topic 0, then it is considered a unique top word for topic 0

Each topic has a # of unique top words

# How to Choose Number of Topics *k*?

Compute:

| | |
|---|---|
| Topic 0's coherence score | Topic 0's # unique top words |
| Topic 1's coherence score | Topic 1's # unique top words |
| ⋮ | ⋮ |
| Topic (k-1)'s coherence score | Topic (k-1)'s # unique top words |
| Compute average coherence | Compute average # unique top words |

Can plot average coherence vs *k*, and average # unique top words vs *k*
(for values of *k* you are willing to try)

# How to Choose Number of Topics *k*?

Demo

# Topic Modeling: Last Remarks

- There are score functions aside from coherence & # unique top words (e.g., normalized-mutual-information coherence, (log) lift score, …)
- There are *many* topic models, not just LDA
  (e.g., Hierarchical Dirichlet Process, correlated topic models, SAGE, anchor word topic models, Scholar, embedded topic model, …)
- *Dynamic* topic models can track how topics change *over time*
  - Requires time stamp for every text document we fit the model to
- **Warning:** learning topic models is very sensitive to random initialization
  - Can try fitting data multiple times using different random seeds & seeing which topics consistently show up across random seeds
- There are variants of topic models where users provide supervision (e.g., user specifies what some topics should be about in terms of top words, or where a topic should predict some outcome)
- On the course webpage, I posted a link to Maria Antoniak's practical guide for using LDA (very helpful if you want to use LDA in the future!)

# A similar strategy could be used for choosing the number of clusters

Look at top word lists

Can compute average coherence across clusters

Can compute average # unique top words across clusters

Make the same plots as in the demo you just saw
(replace topics with clusters)

# Another Strategy for Choosing the Number of Clusters

I'm presenting this just so that you know about it but it often does not work well for unstructured data like text…

For $k$ = 2, 3, … up to some user-specified max value:

Fit model ($k$-means or GMM) using $k$

Compute a score for the model

Many score functions (CH index, silhouette, …)

**No single score function is the "best"!**

Use whichever $k$ has the best score

In practice, even if you use this strategy, it's important to visualize the clusters to see whether they make any sense

The "clustering on text" lecture demo has an example of using CH index as the score function

# 94-775

Part I: Exploratory data analysis

*Identify structure present in "unstructured" data*

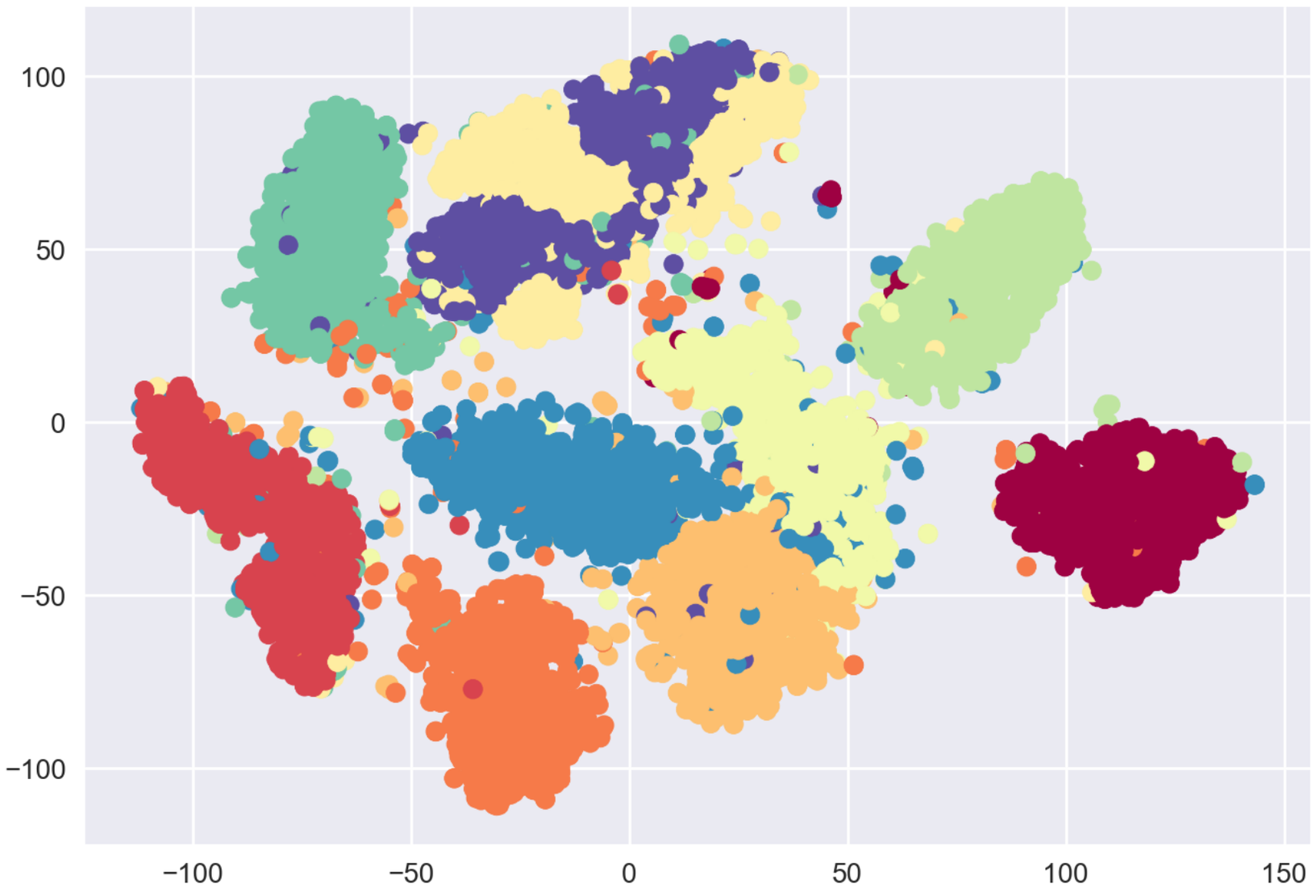
- Frequency and co-occurrence analysis
- Visualizing high-dimensional data/dimensionality reduction
- Clustering
- Topic modeling

Part II: Predictive data analysis

*Make predictions using known structure in data*

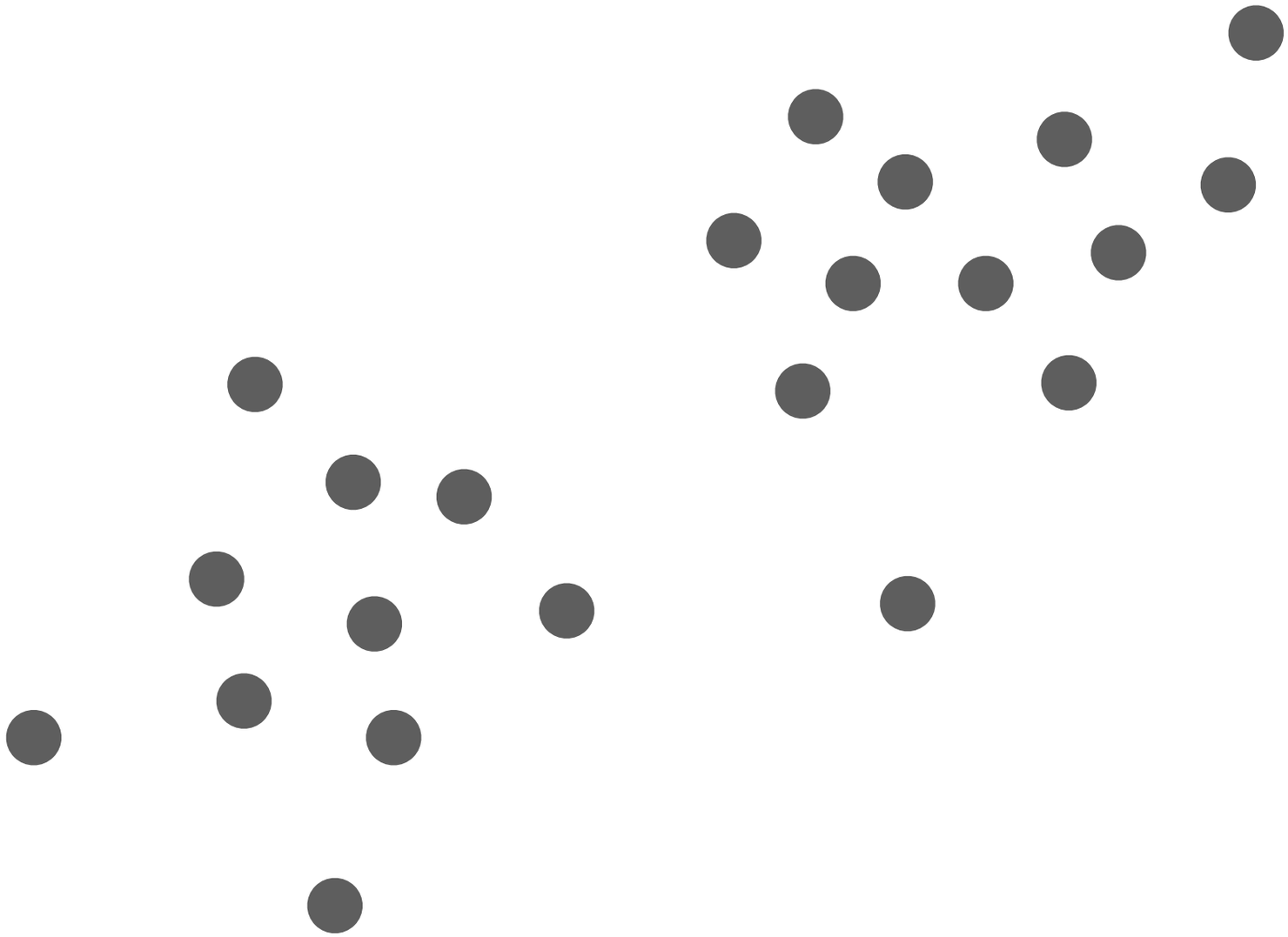
- Basic concepts and how to assess quality of prediction models
- Neural nets and deep learning for analyzing images and text

# What if we have labels?




Example: MNIST handwritten digits have known labels

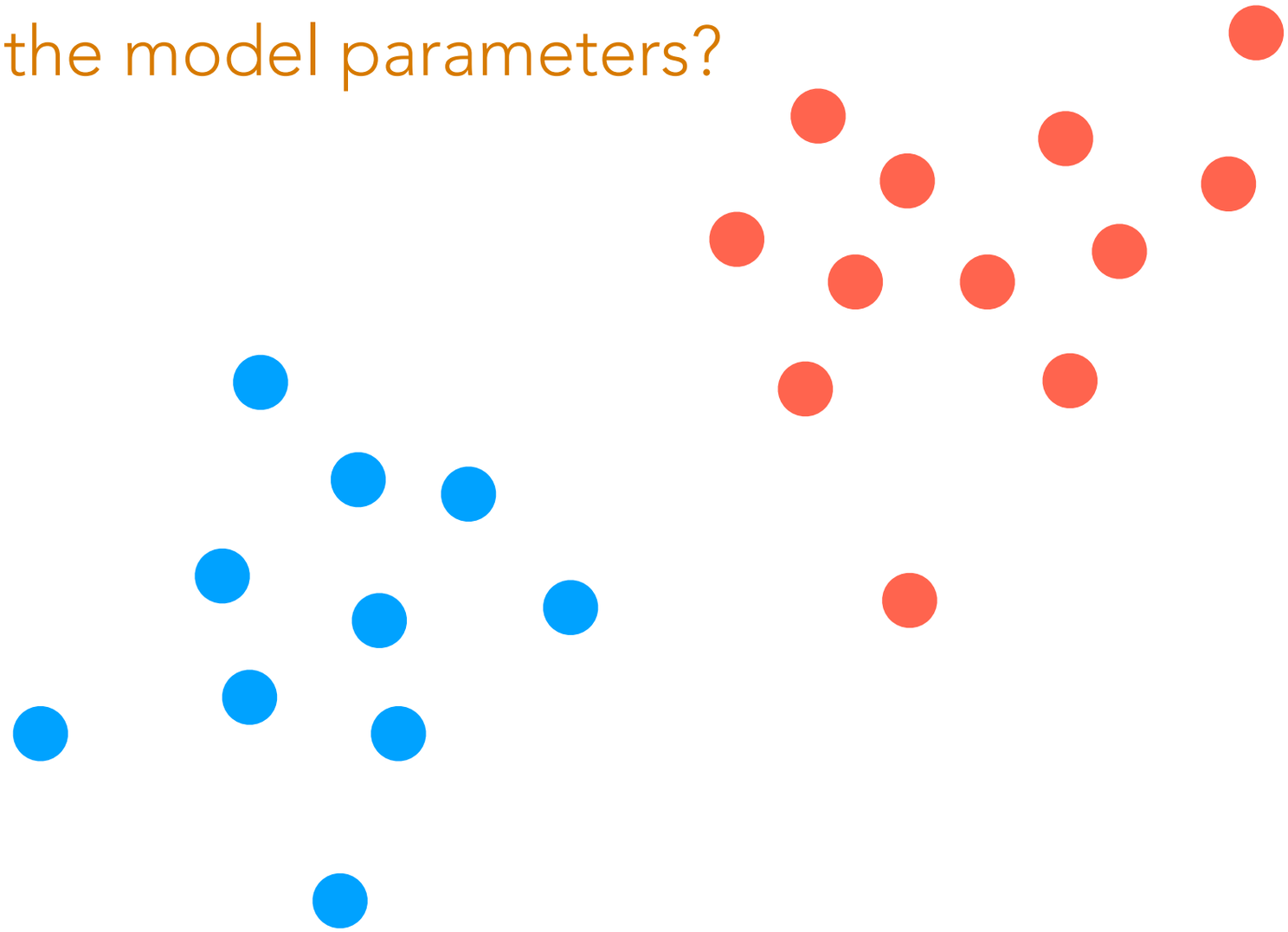
If the labels are known…



If the labels are known…

And we assume data generated by GMM…

What are the model parameters?



# (Flashback) Learning a GMM

Don't need this top part if we know the labels!

Step 0: Guess $k$

Step 1: Guess cluster probabilities, means, and covariances

(often done using $k$-means)

**Repeat until convergence:**

Step 2: Compute probability of each point being in each of the $k$ clusters

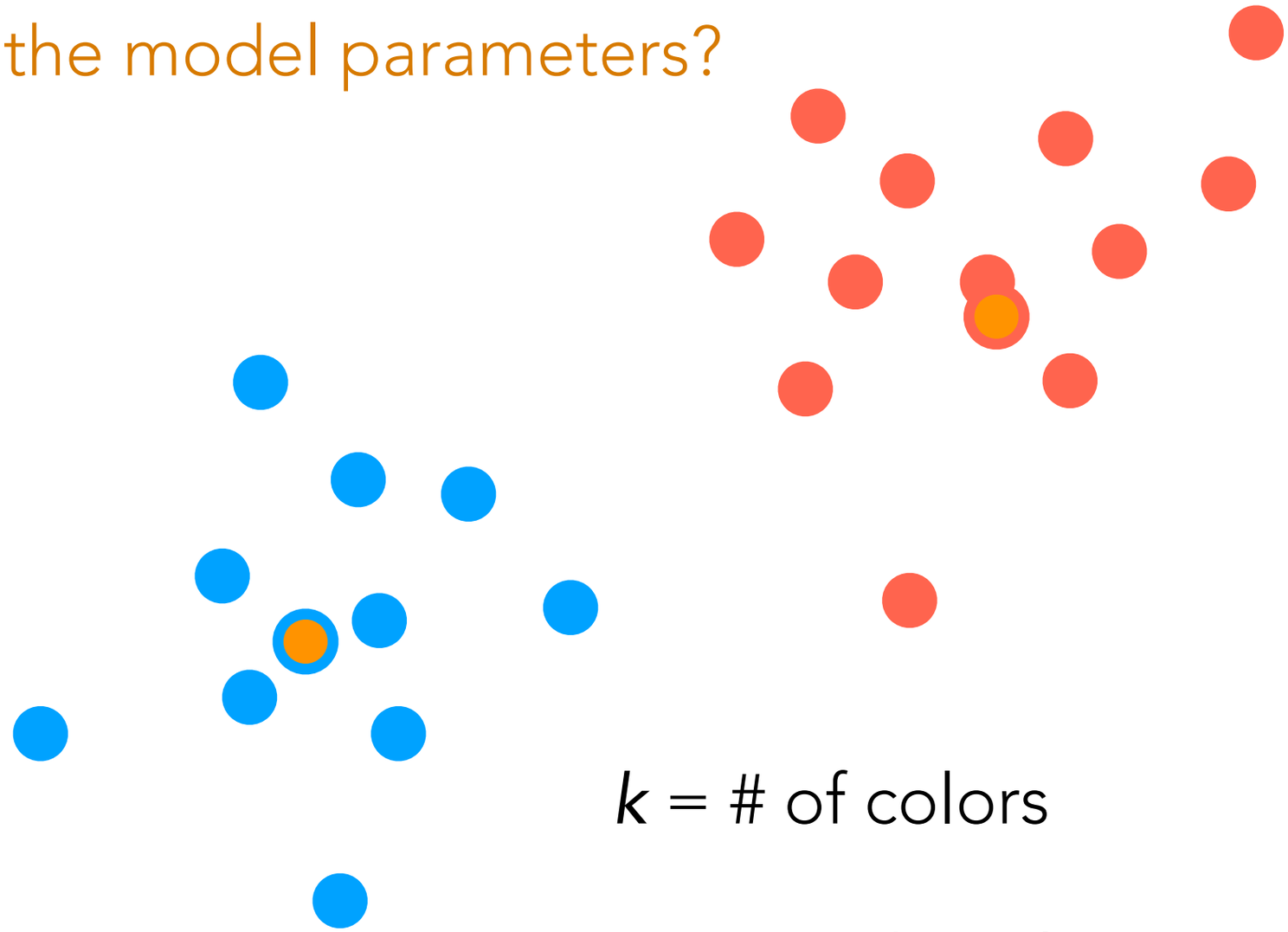
Step 3: Update cluster probabilities, means, and covariances accounting for probabilities of each point belonging to each of the clusters

We don't even need to repeat until convergence

If the labels are known…

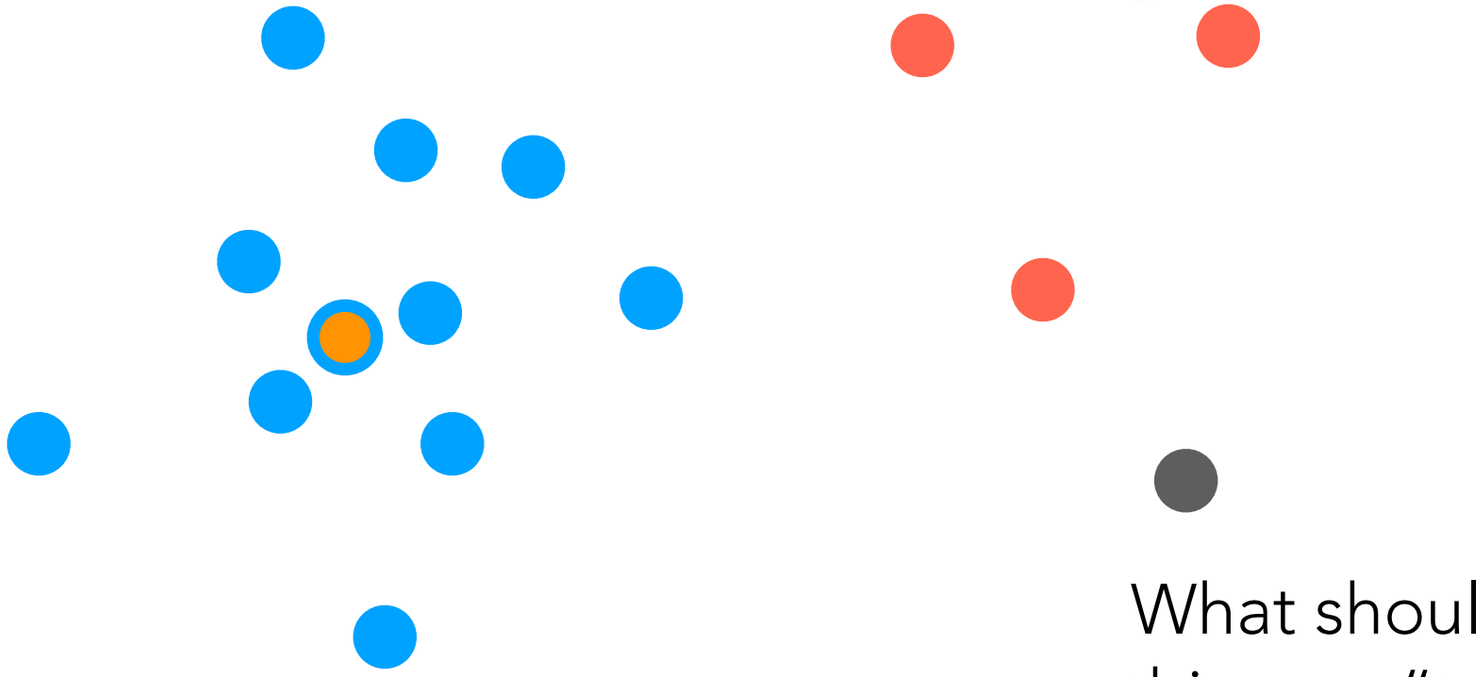
And we assume data generated by GMM…

What are the model parameters?



$k$ = # of colors

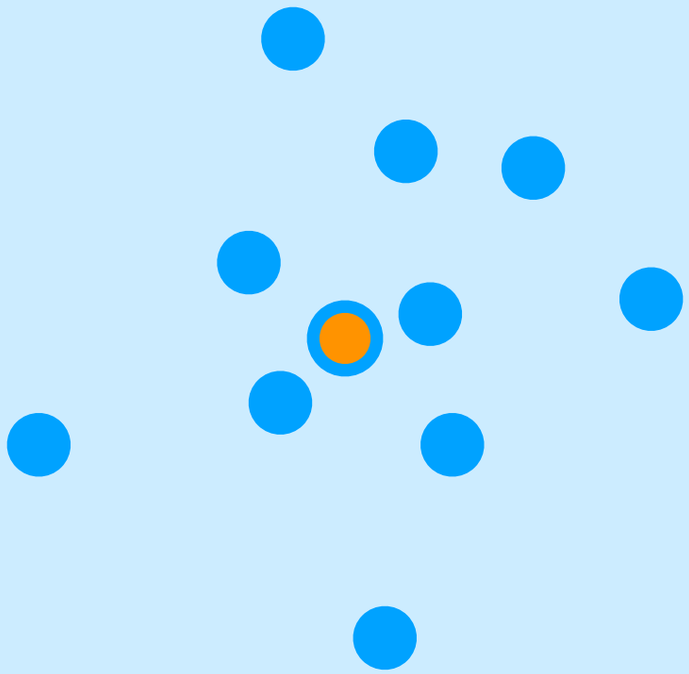
We can directly estimate cluster means, covariance matrices



What should the label of this new “test” point be?

Whichever cluster has higher probability!

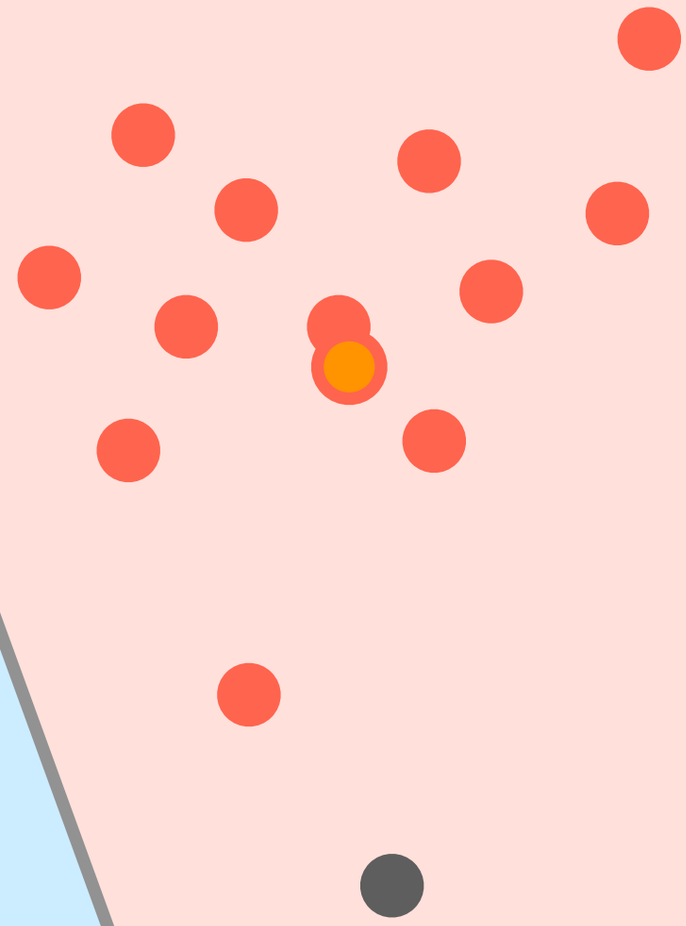
Decision boundary



This classifier we've created assumes a *generative model*

We just created a **classifier**

(a procedure that given a test data point tells us what "class" it belongs to)



What should the label of this new "test" point be?

Whichever cluster has higher probability!

# Predictive Data Analysis

Training data

$$(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$$

**Goal:** Given new test feature vector $x$, predict label $y$

- $y$ is discrete (such as colors red and blue)
  ➔ prediction is referred to as **classification**
- $y$ is continuous (such as a real number)
  ➔ prediction is referred to as **regression**

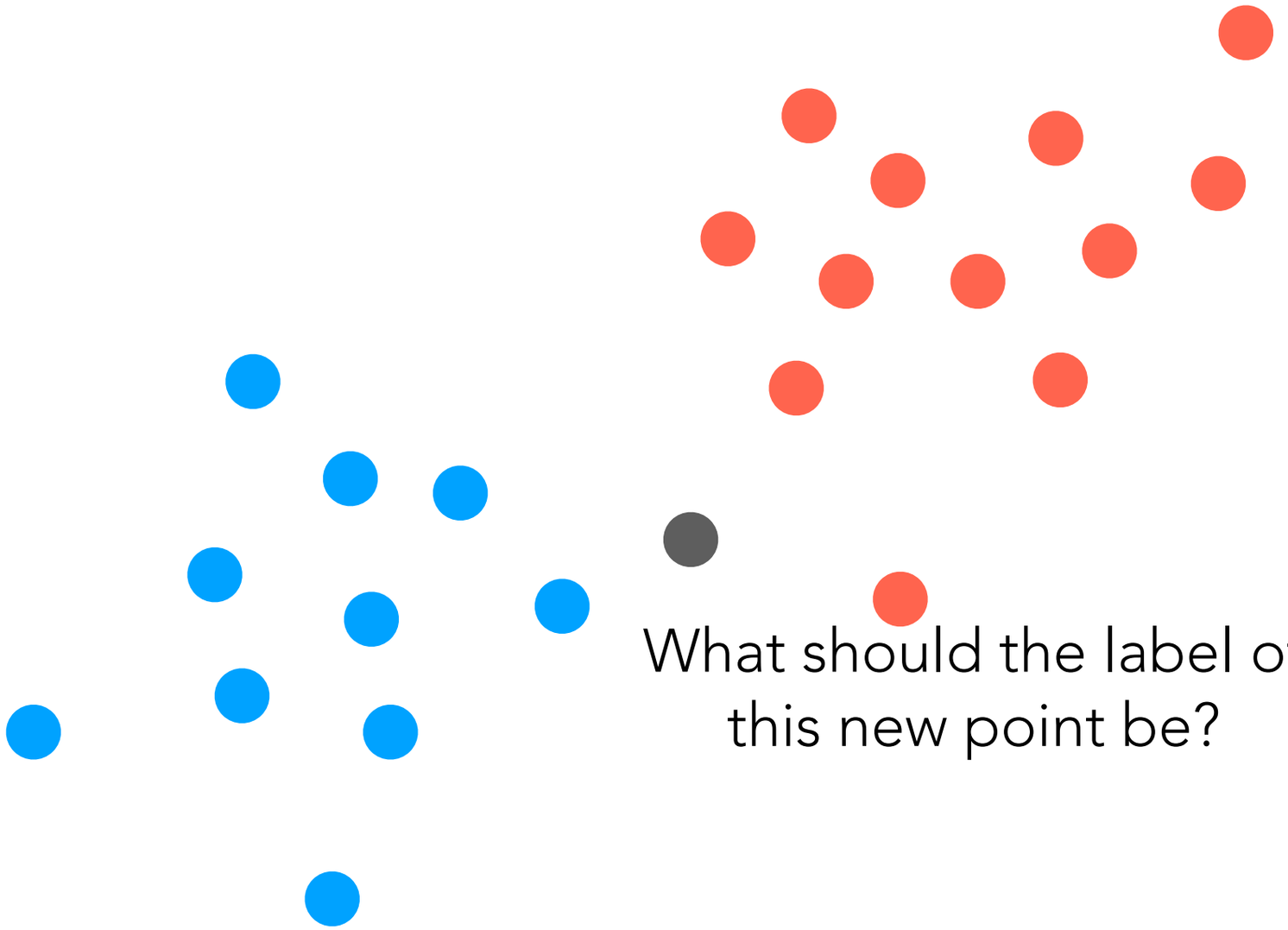
We could have many such test feature vectors, which we collectively refer to as *test data*

A giant zoo of methods

- Generative models (like what we just described)
- Discriminative models (just care about learning prediction rule; after training model, we don't have a way to generate data)

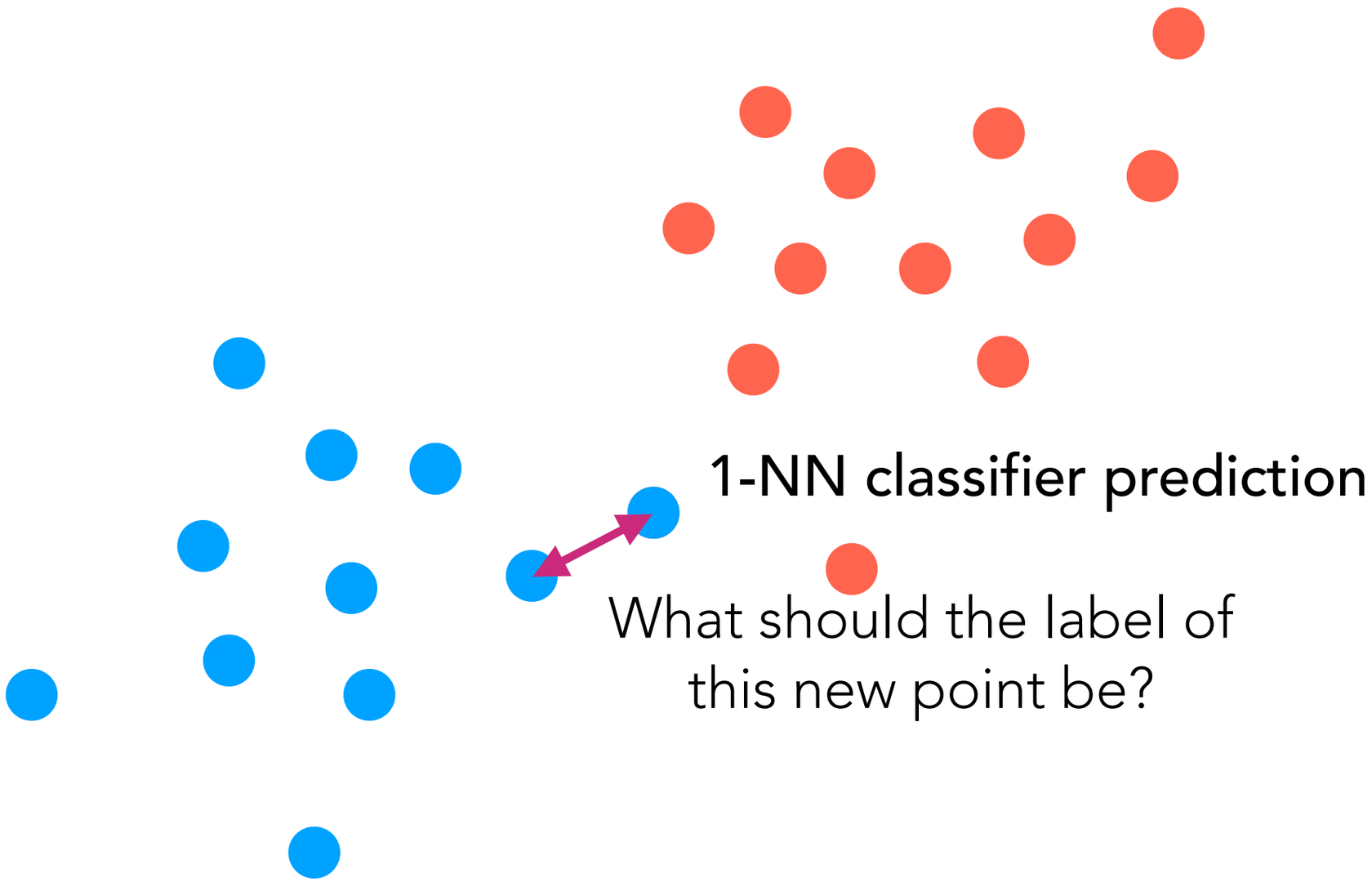
# Example of a Discriminative Method: *k*-NN Classification

# Example: *k*-NN Classification

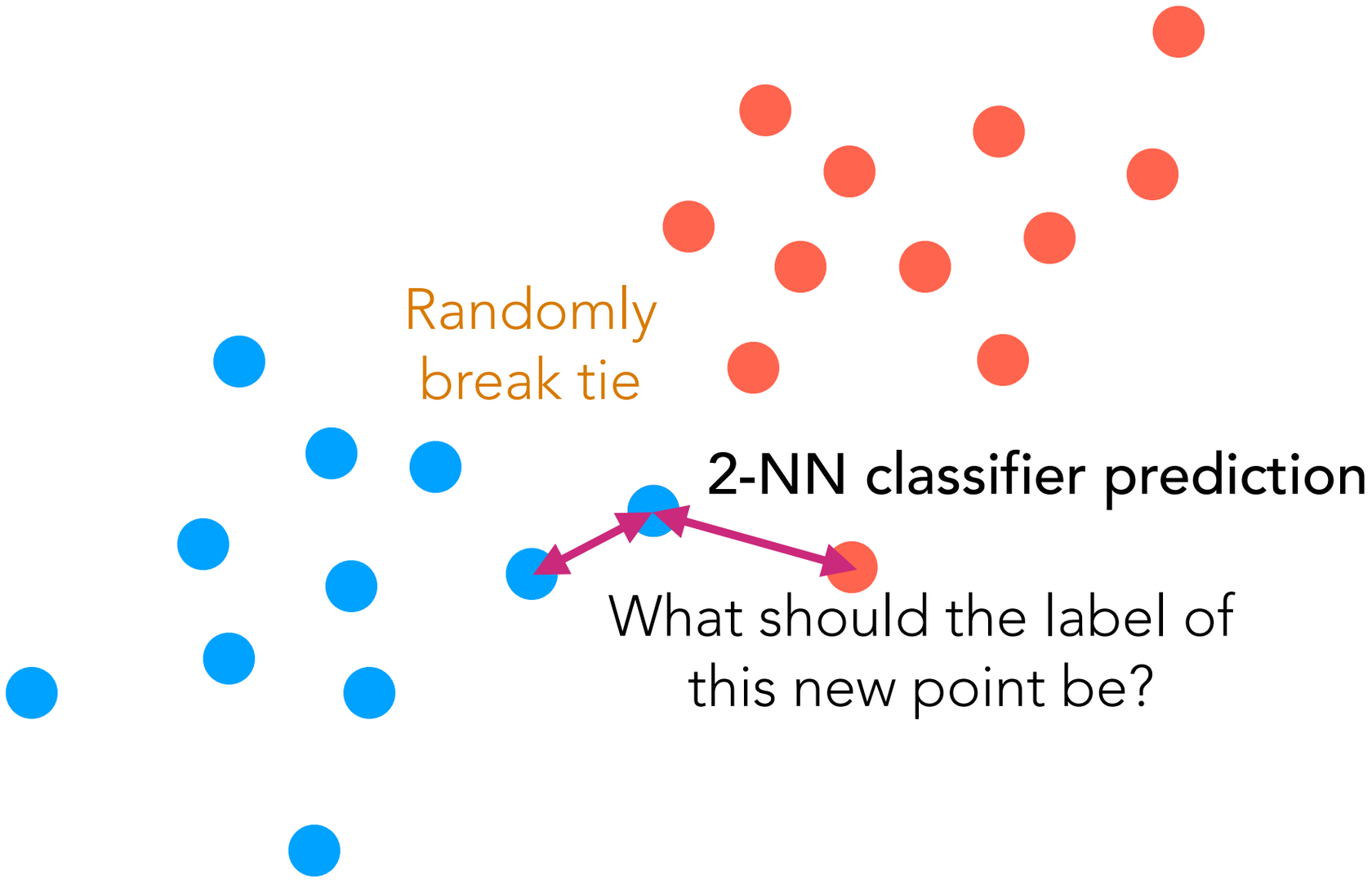


What should the label of this new point be?

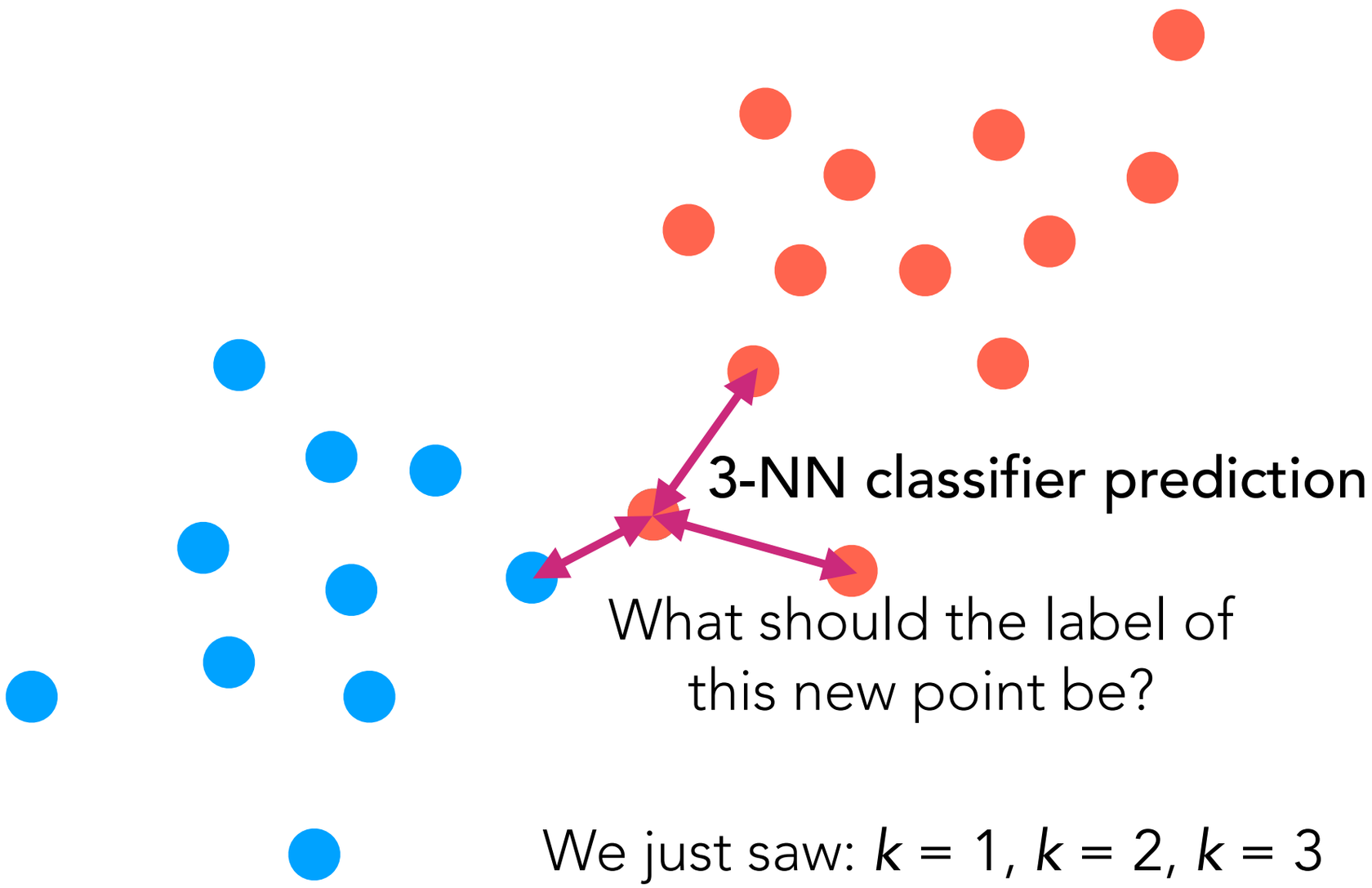
# Example: *k*-NN Classification



# Example: *k*-NN Classification



# Example: *k*-NN Classification




What should the label of this new point be?

We just saw: $k = 1$, $k = 2$, $k = 3$

What happens if $k = n$?

# How do we choose *k*?

What I'll describe next can be used to select hyperparameter(s) for any prediction method

Fundamental question:
How do we assess how good a prediction method is?

# Hyperparameters vs. Parameters

- We fit a model's parameters to training data
  (terminology: we "learn" the parameters)

- We pick values of hyperparameters and they do *not* automatically get fit to training data

- Example: Gaussian mixture model
  - Hyperparameter: number of clusters *k*
  - Parameters: cluster probabilities, means, covariance matrices

- Example: *k*-NN classification
  - Hyperparameters: number of nearest neighbors *k*
  - Parameters: N/A

Actually, there's another hyperparameter: distance function to use
(for simplicity, we assume Euclidean distance for now)