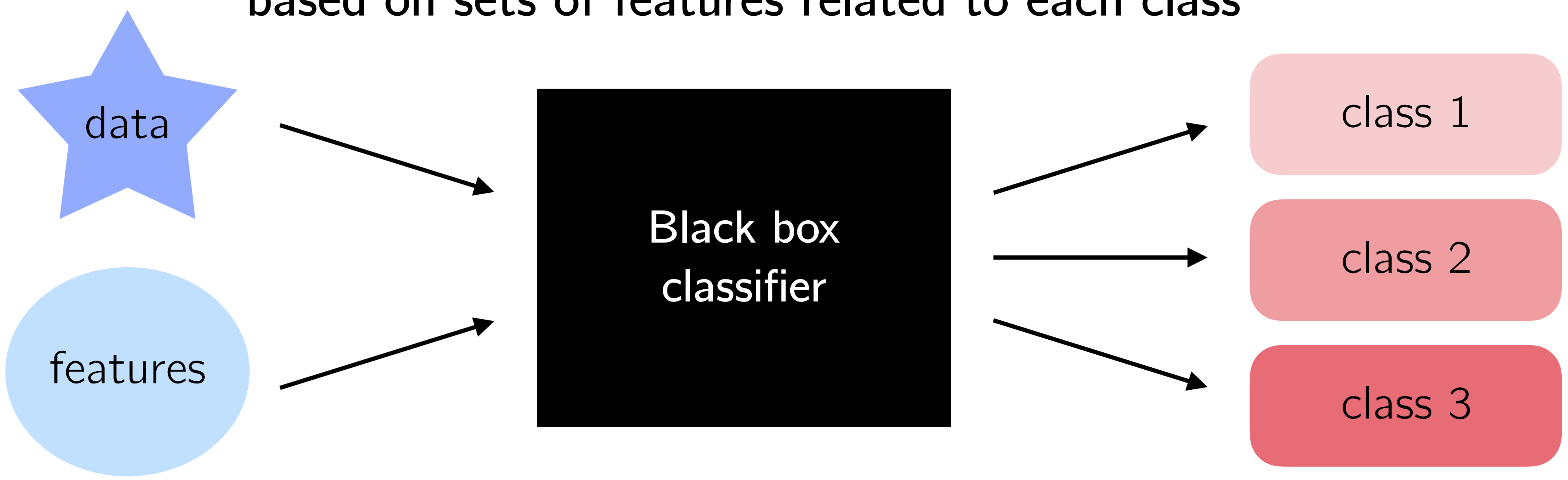
Generative Classification

Katie Chamberlain

What is a classifier?

categorizes data into predefined sets of classes
based on sets of features related to each class



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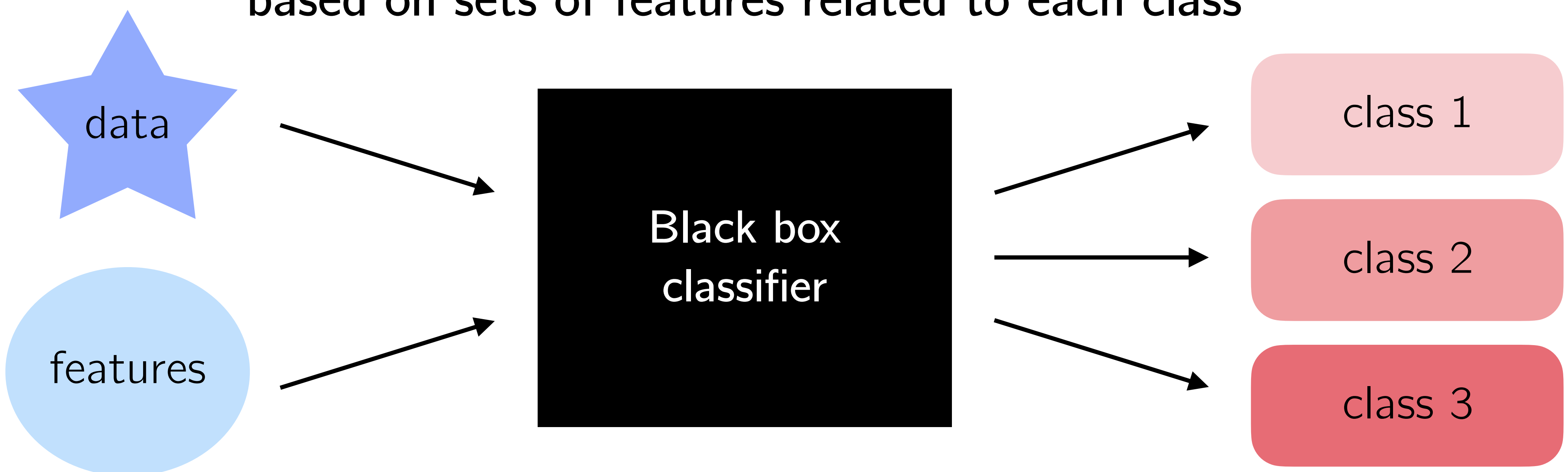
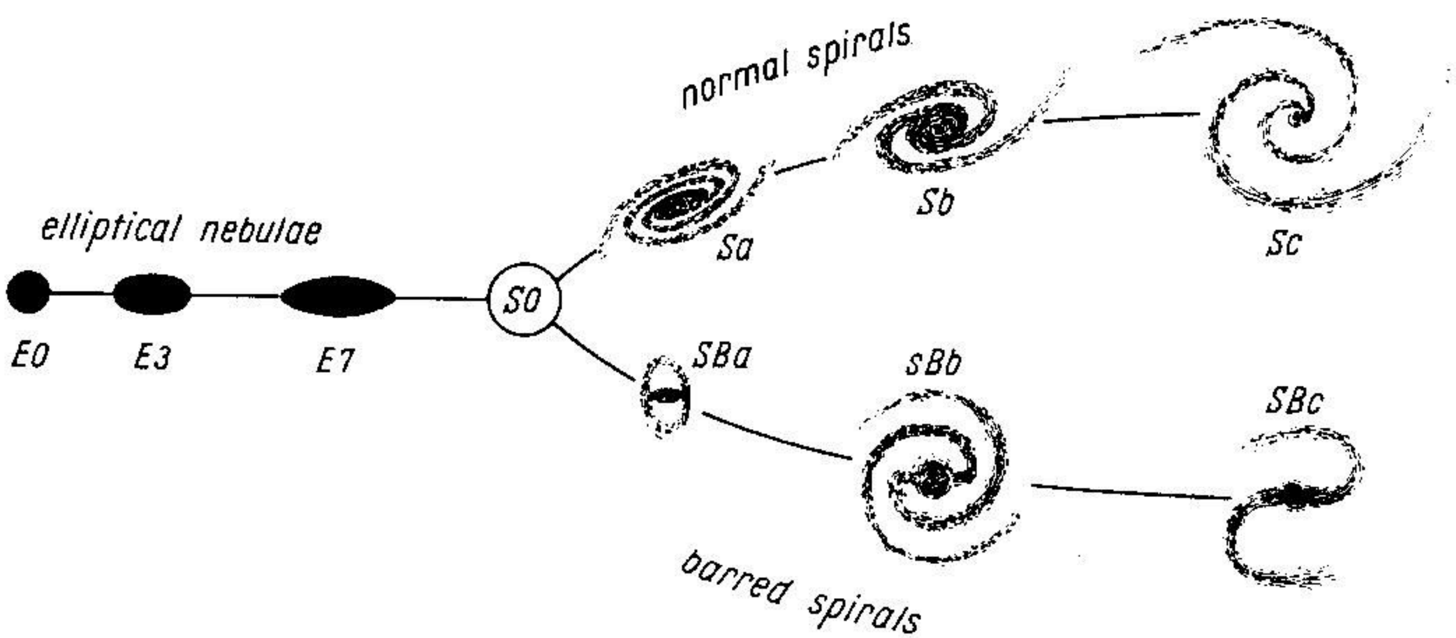


Edwin Hubble was a classifier!

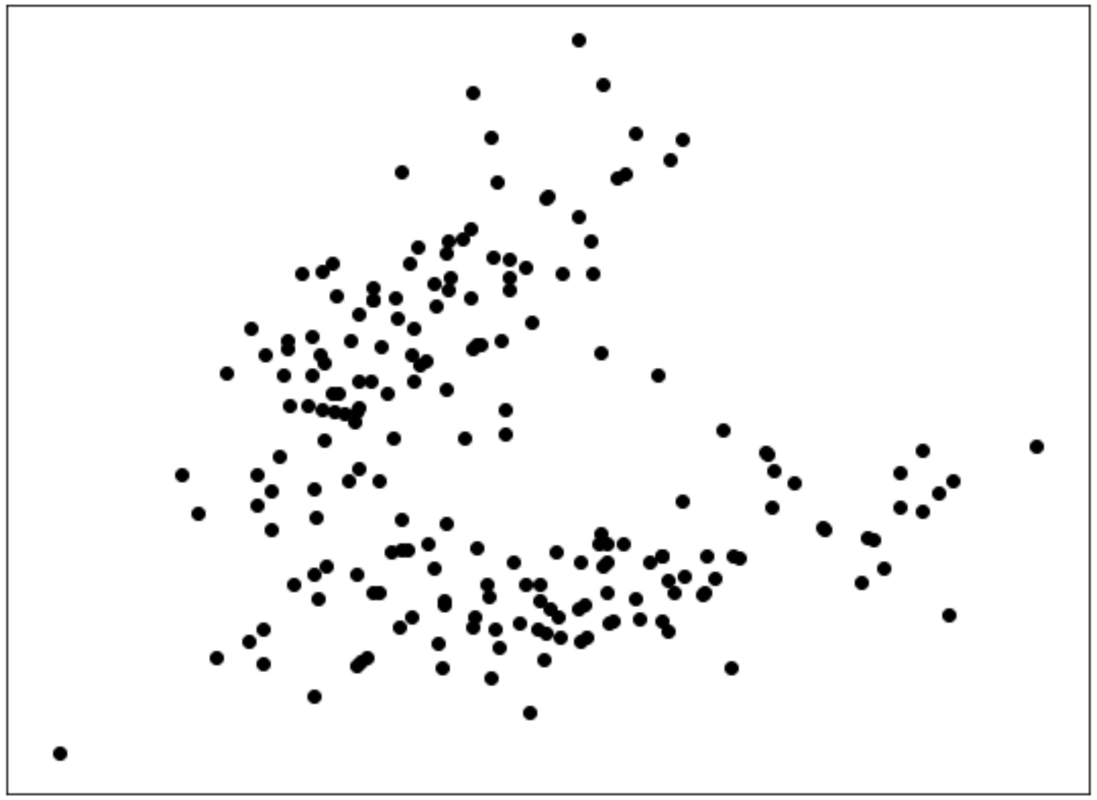


He separated observed galaxies into different classes

(spiral, elliptical, etc)

Unsupervised vs. supervised classification

Unsupervised



Supervised

Unsupervised vs. supervised classification

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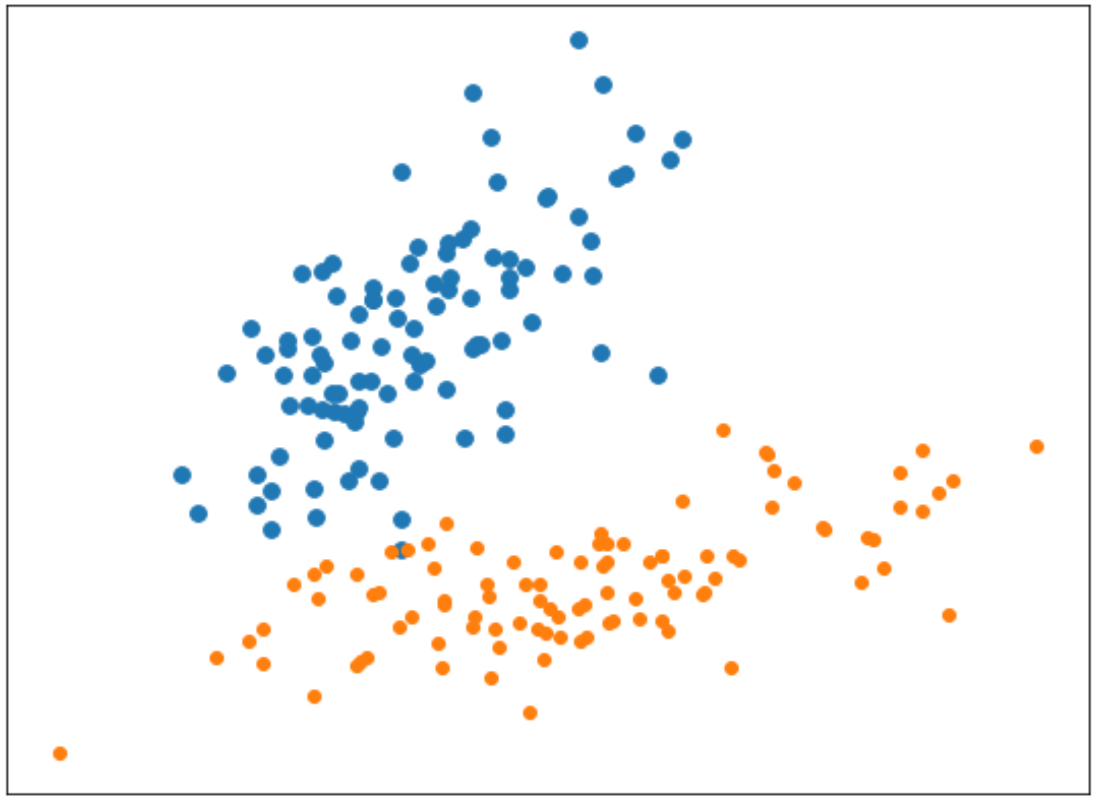

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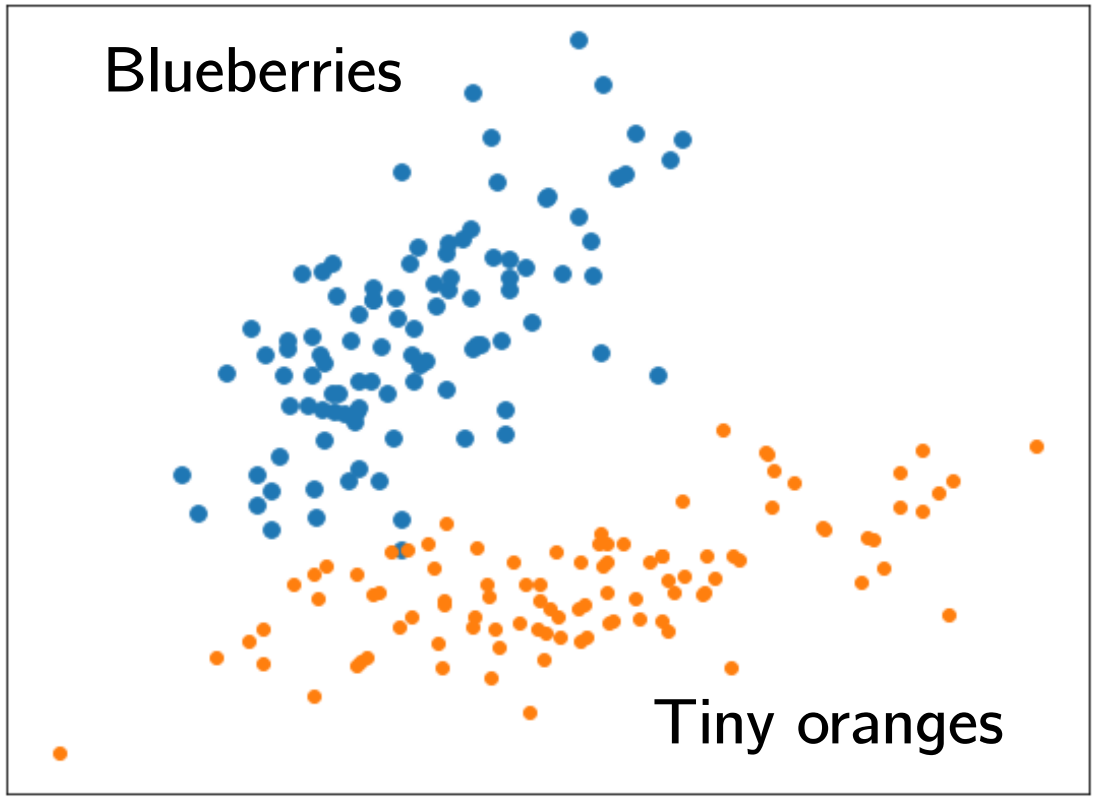

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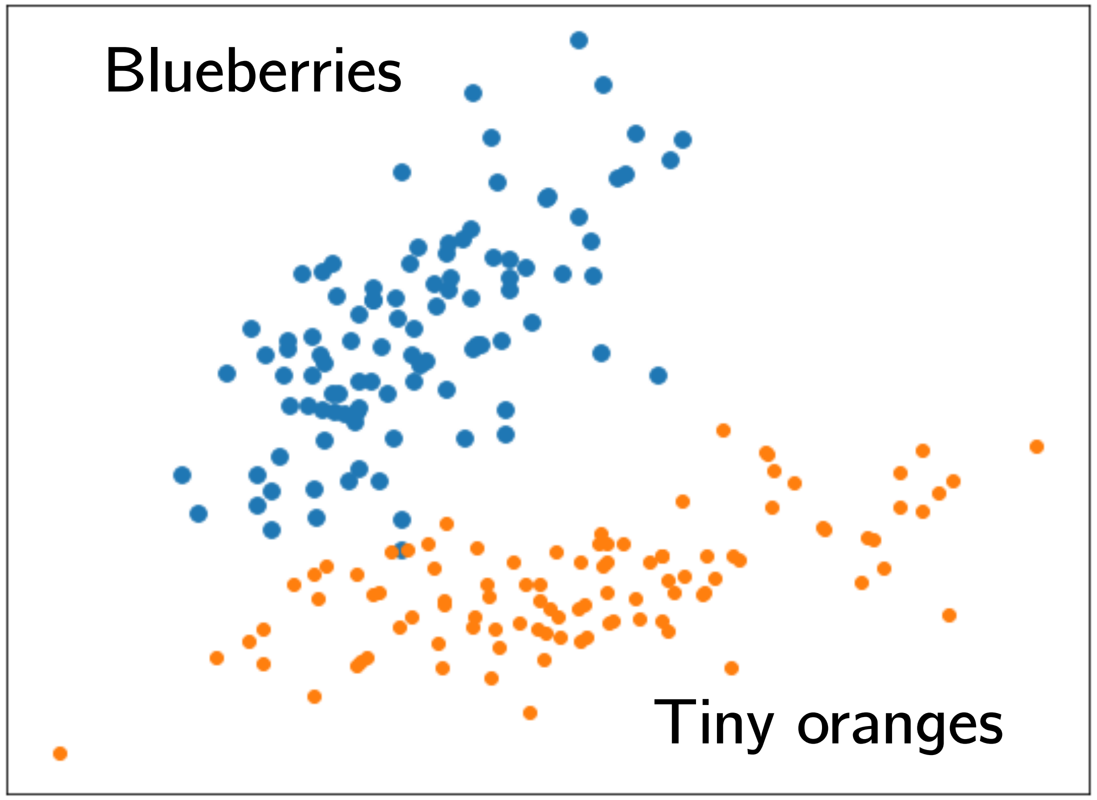

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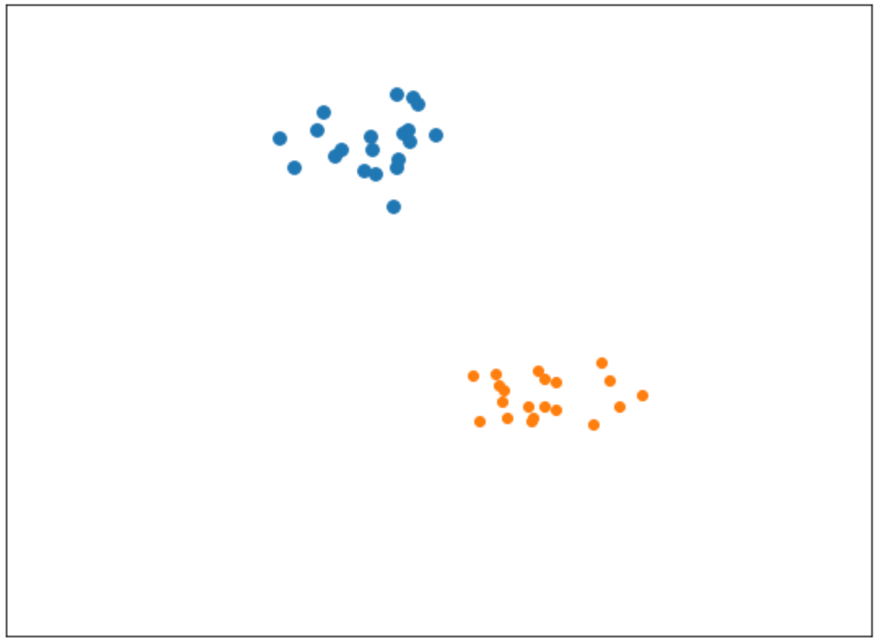

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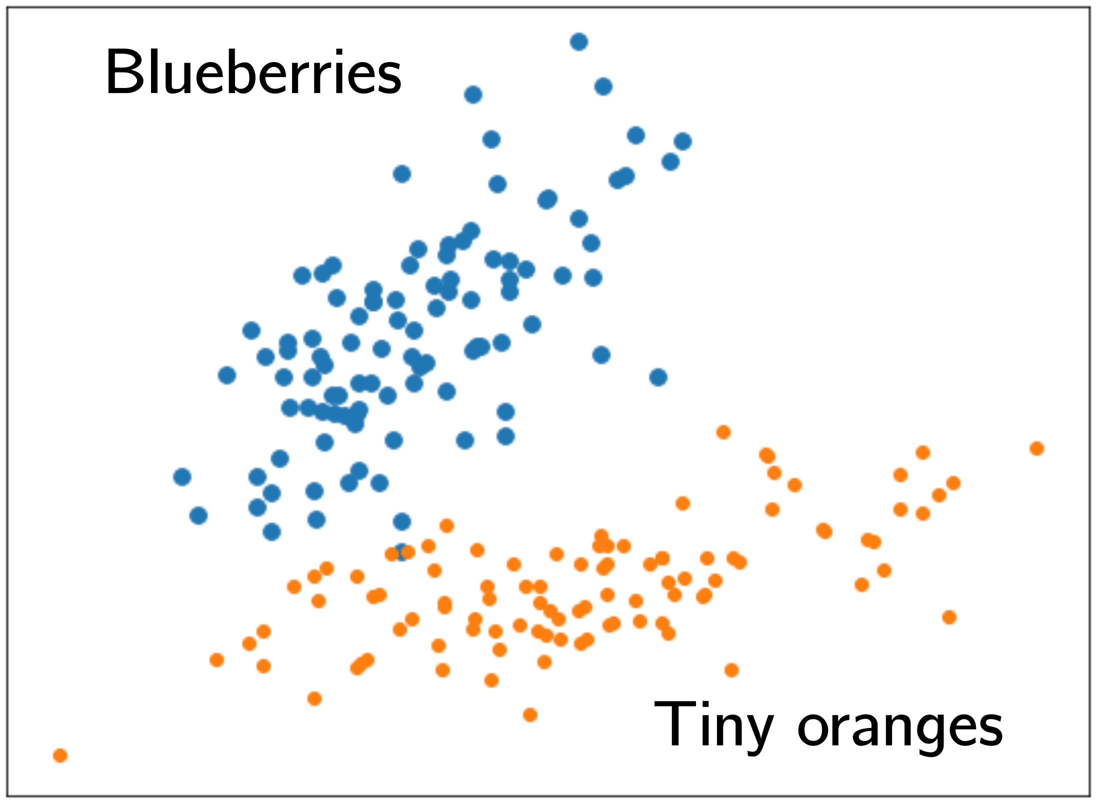

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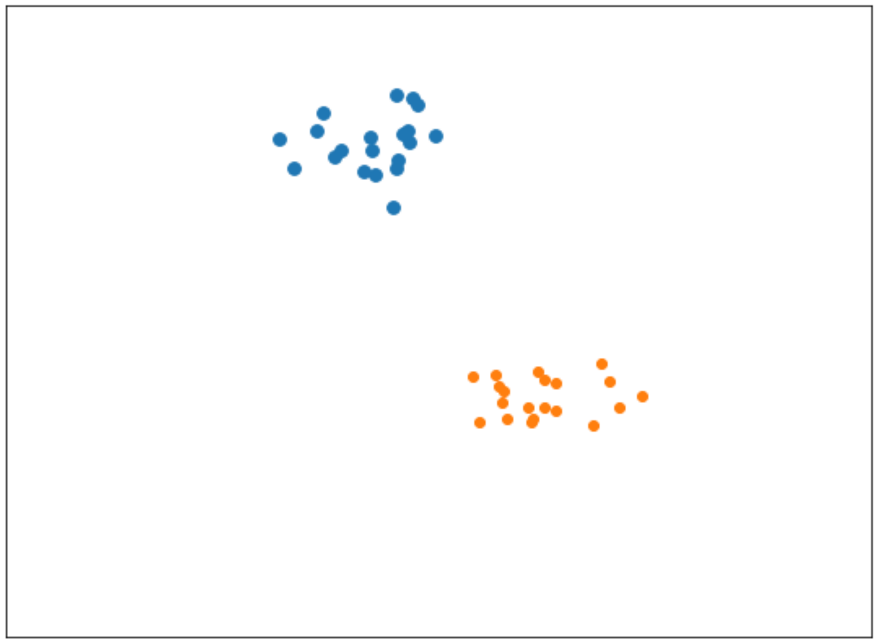

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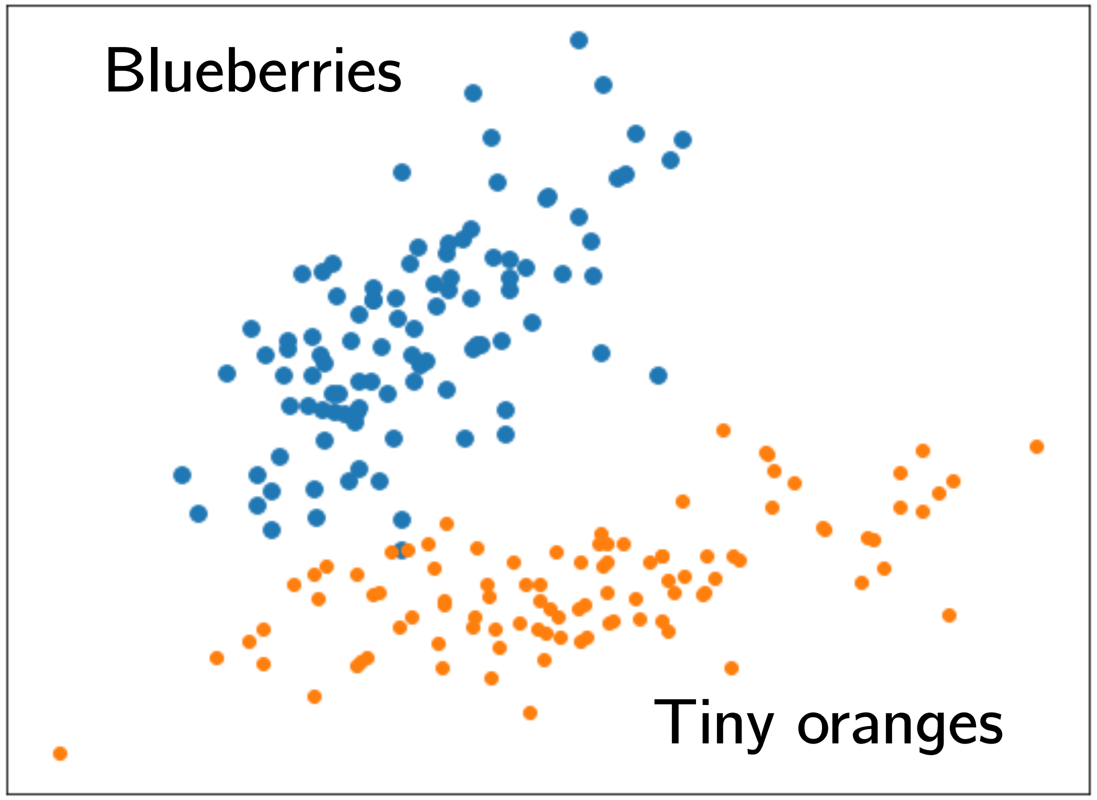

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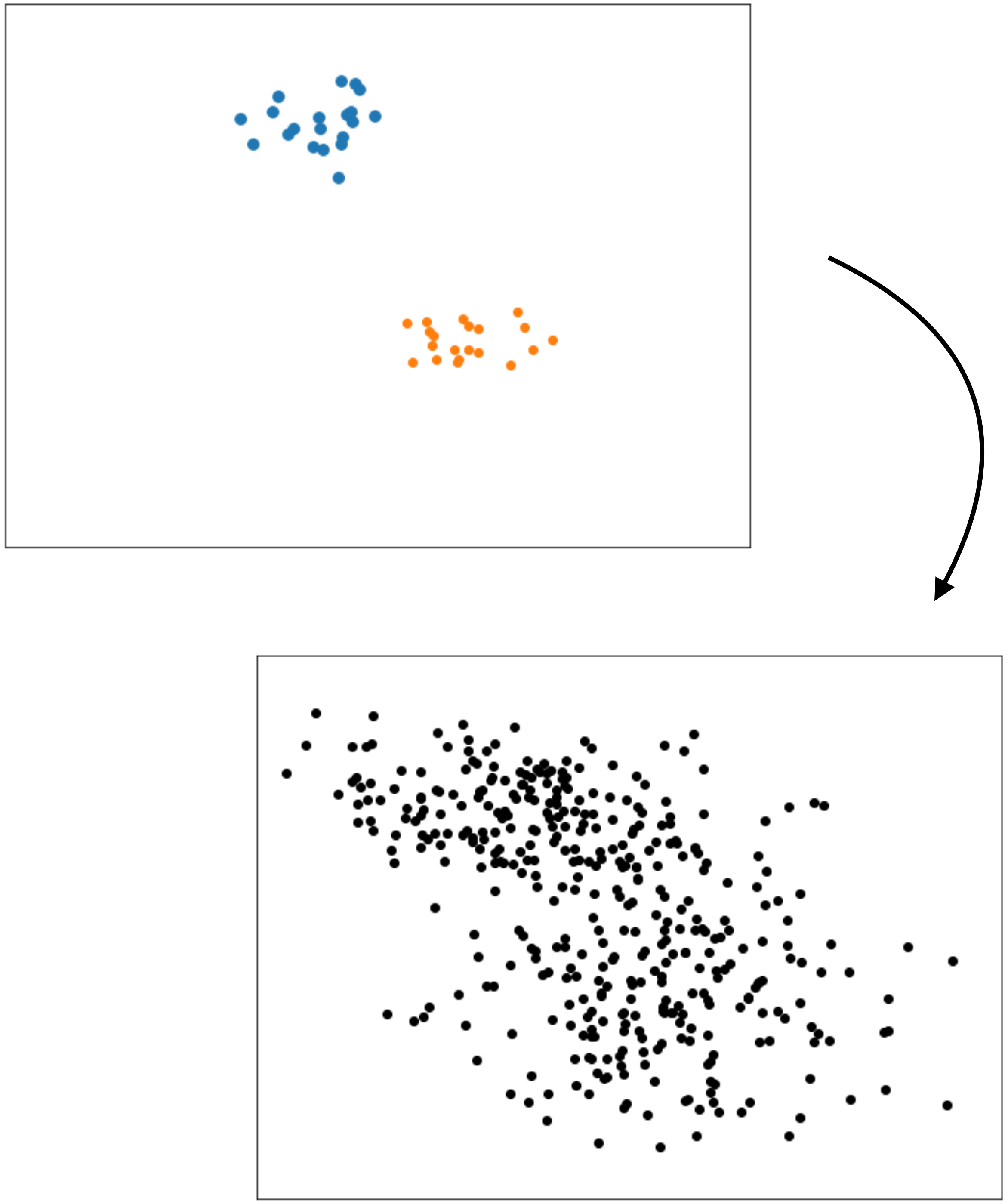

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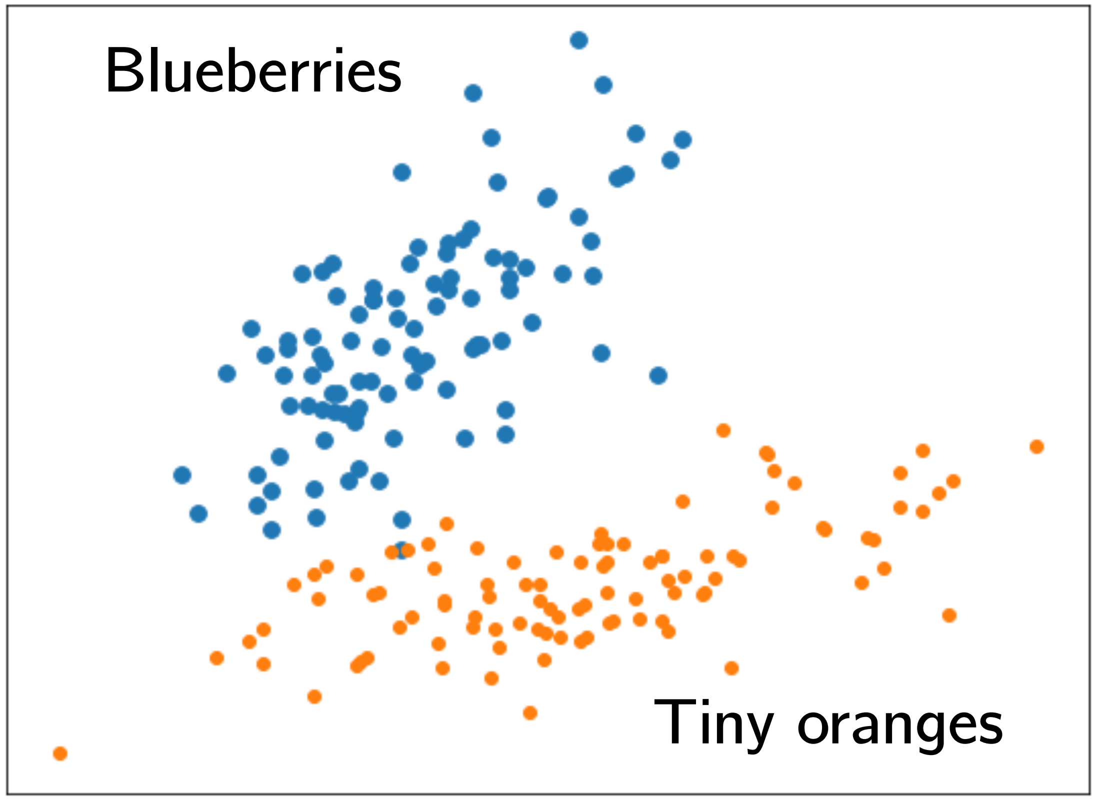

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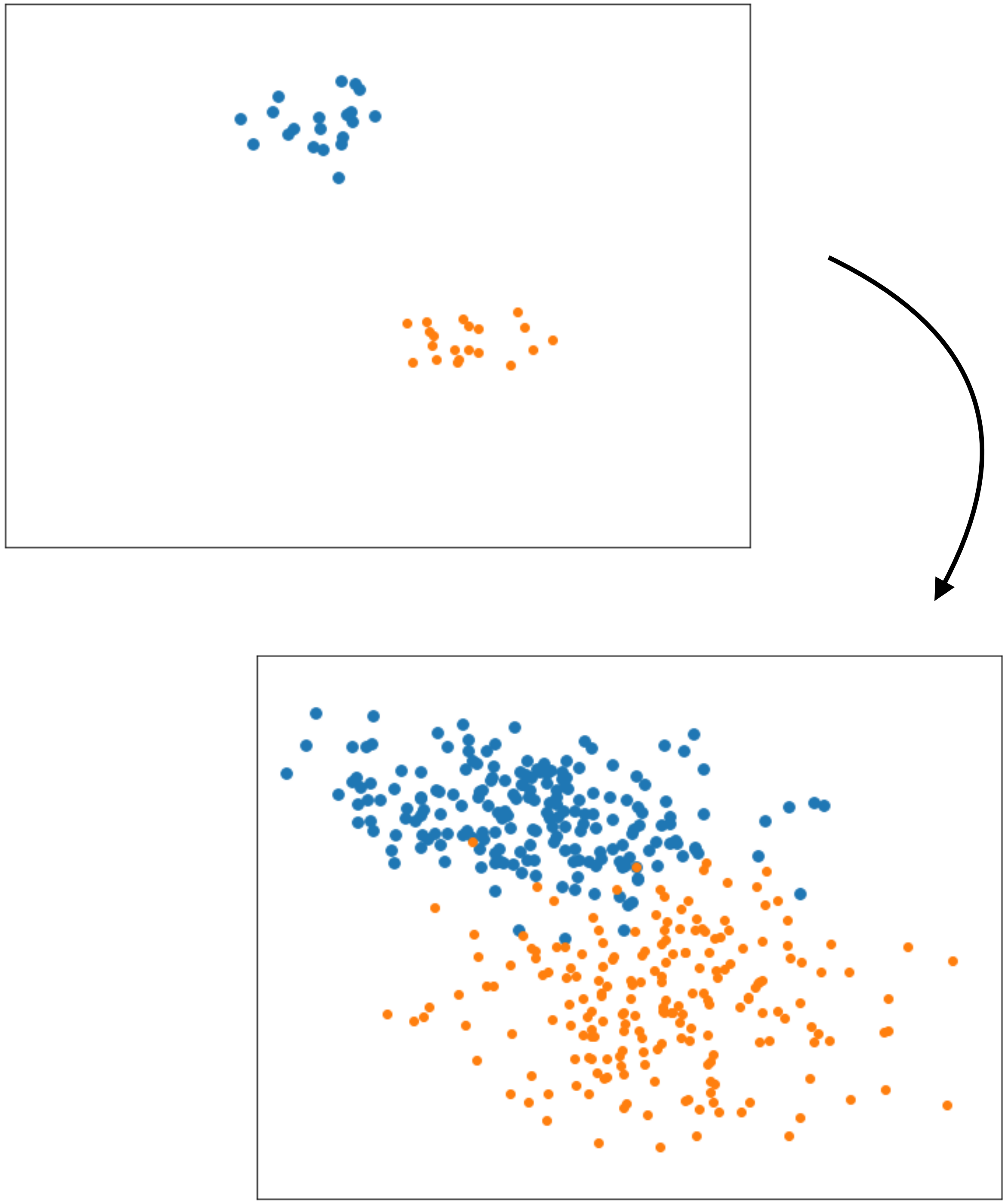


Unsupervised vs. supervised classification

Unsupervised

Supervised

<u>Our goal</u>

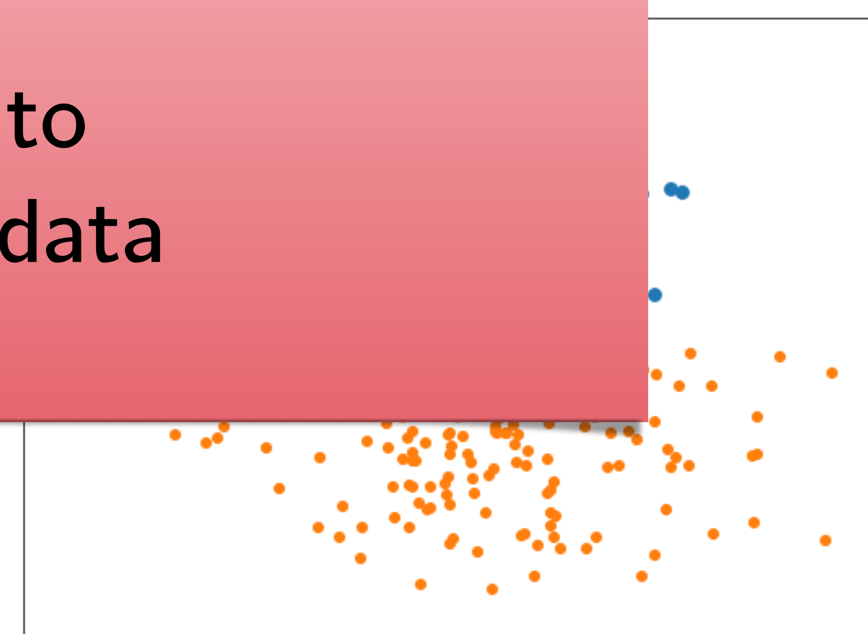
characterize the relation between:

• features in the data

• their classes

apply classifications to

large set of unlabeled data



What is a generative model?

Generative classification is based on density estimation:

This just means that we have a model that
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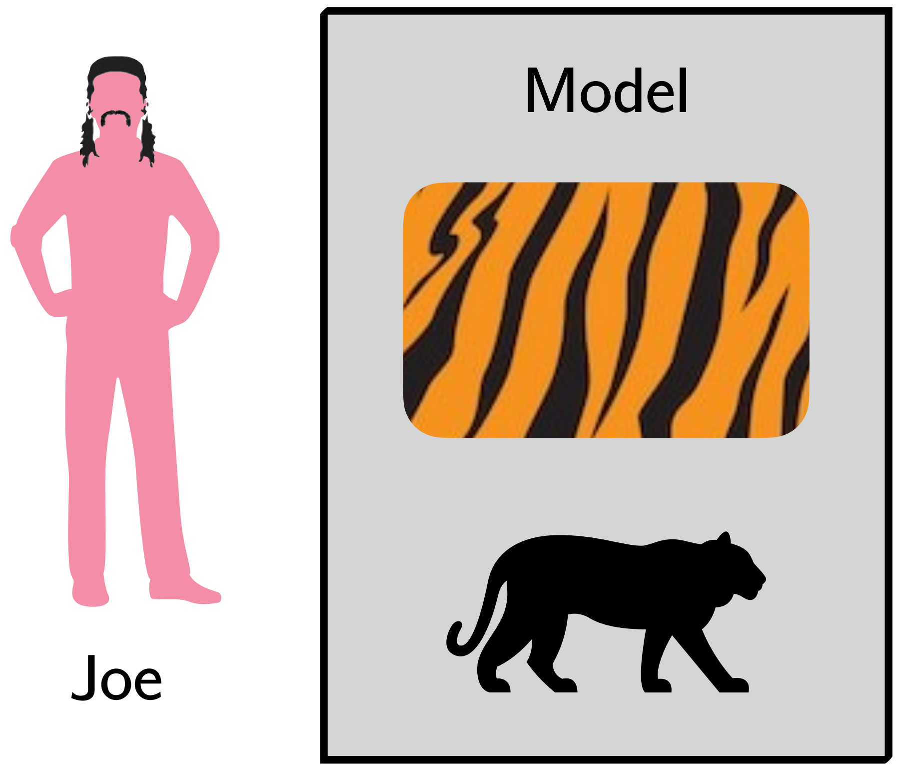

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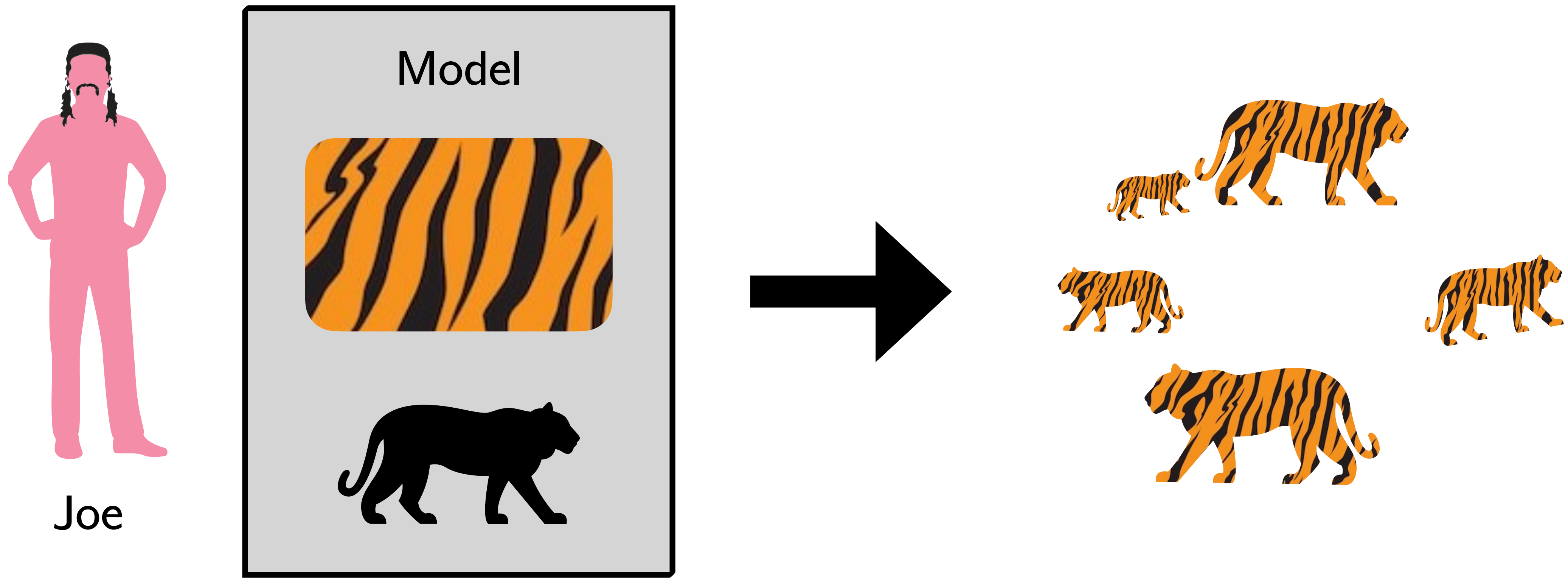

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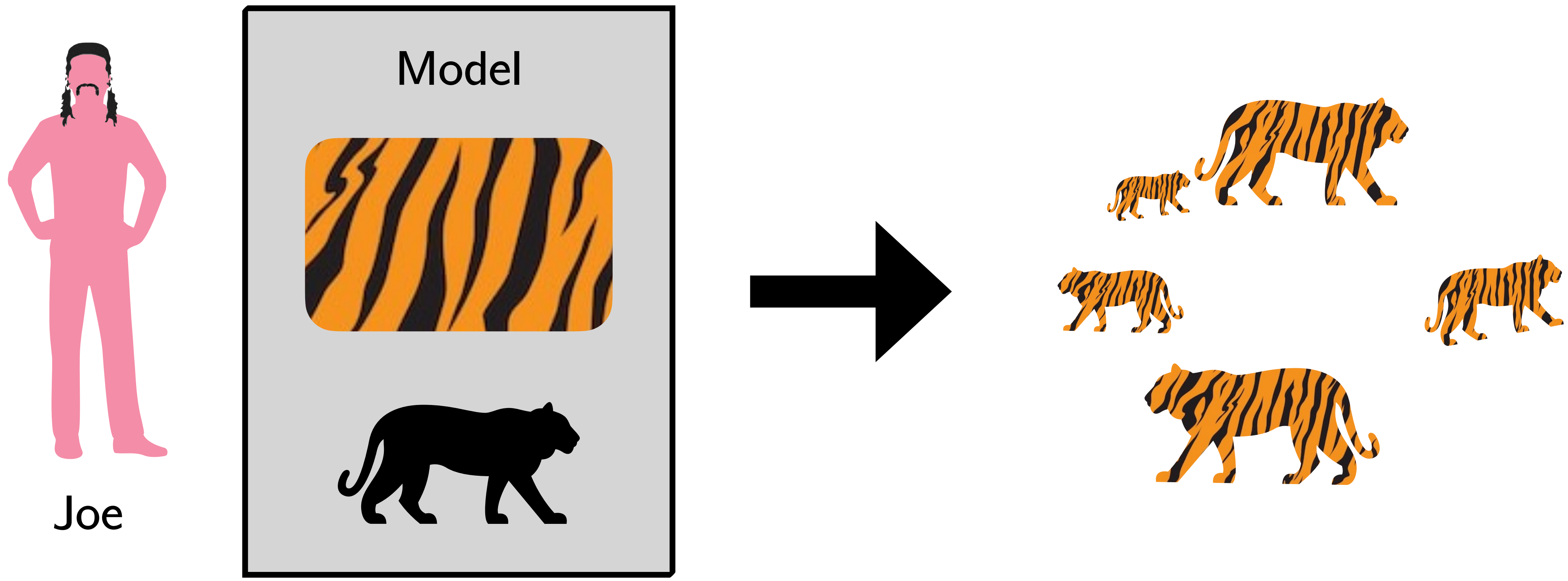


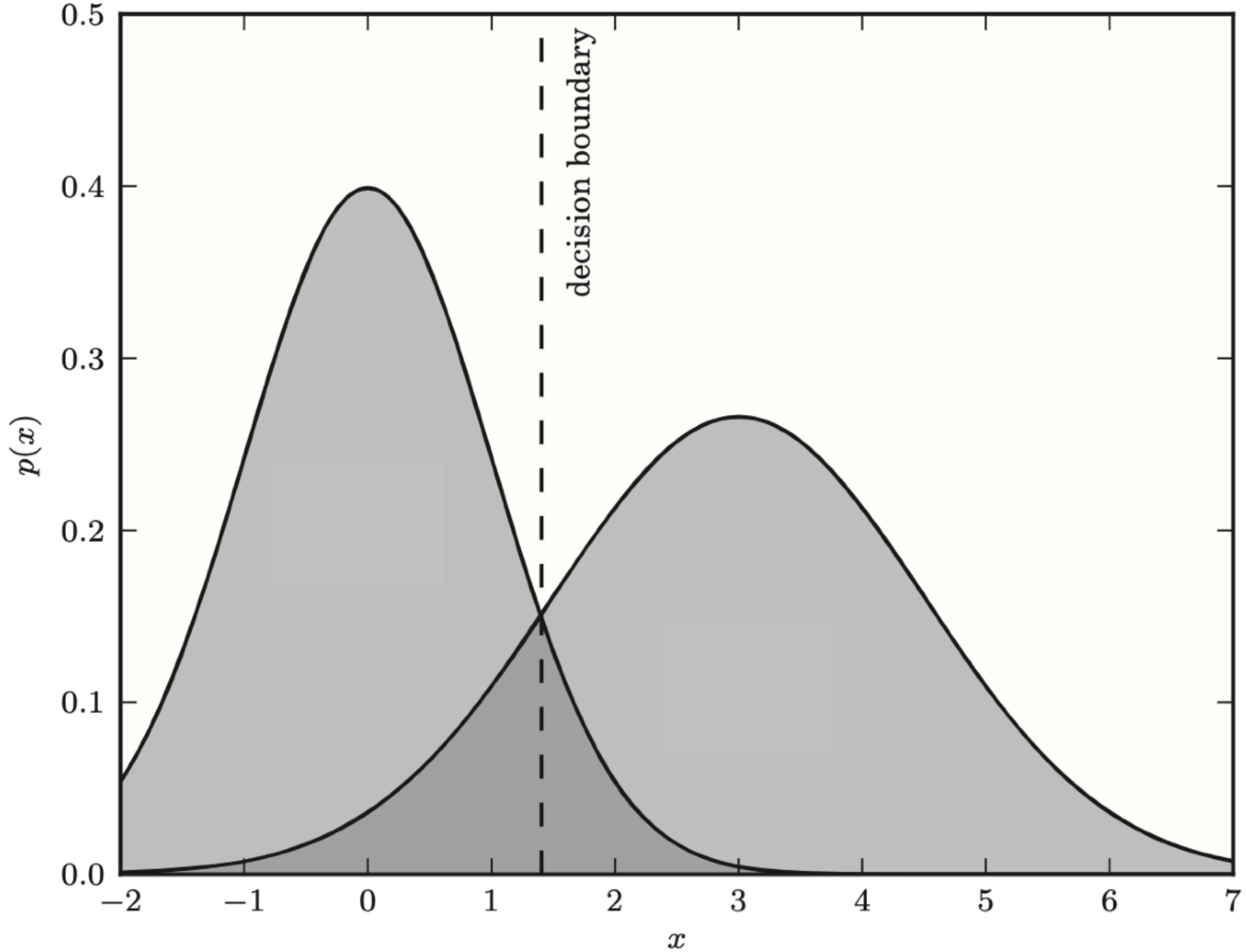
Generative classifiers are:

classifiers that utilize a generative model

Bayes Classifier and Models

<u>Bayes classifier:</u>

how we determine
which class an object belongs to



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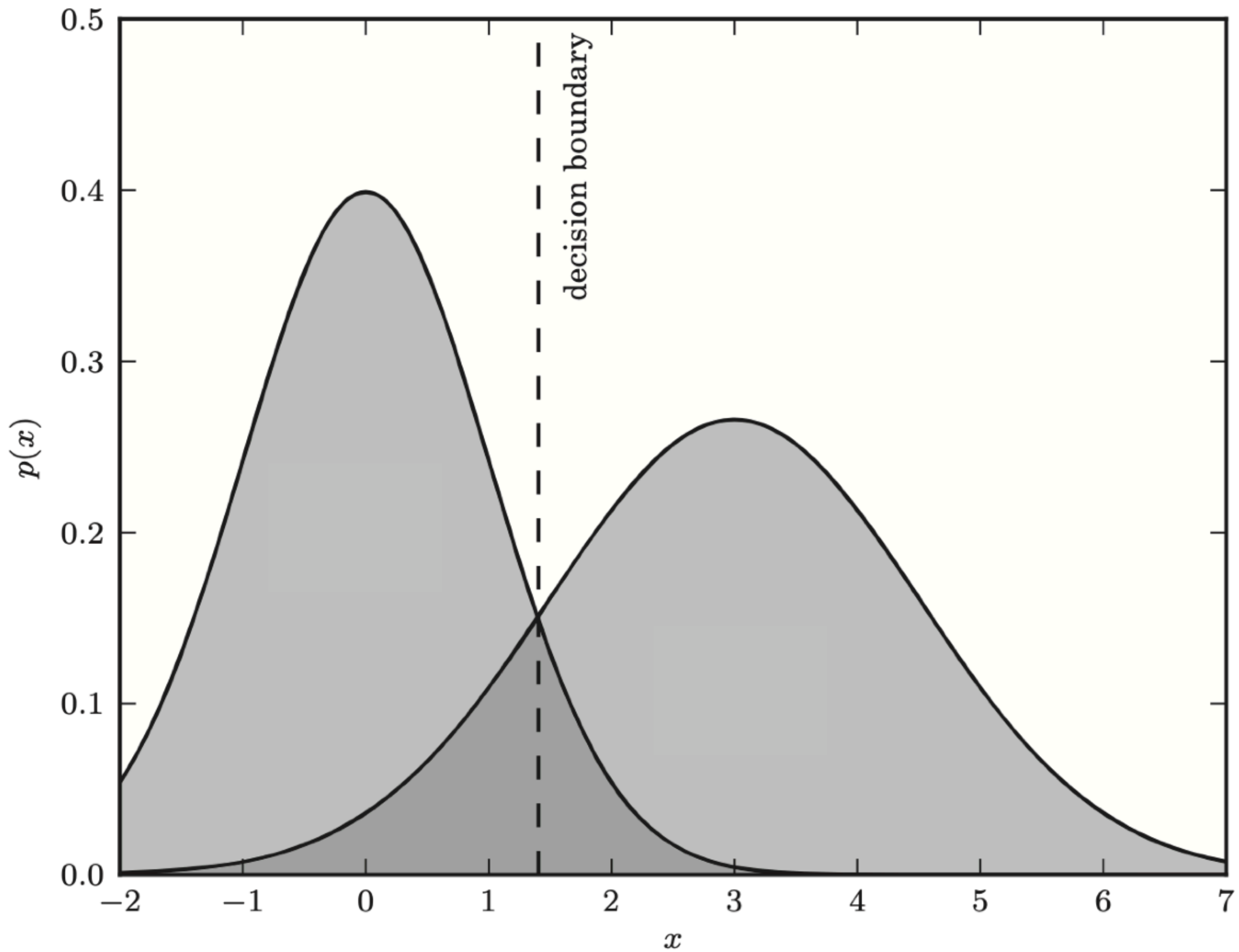

Example

Two classes:

Bayes Classifier and Models

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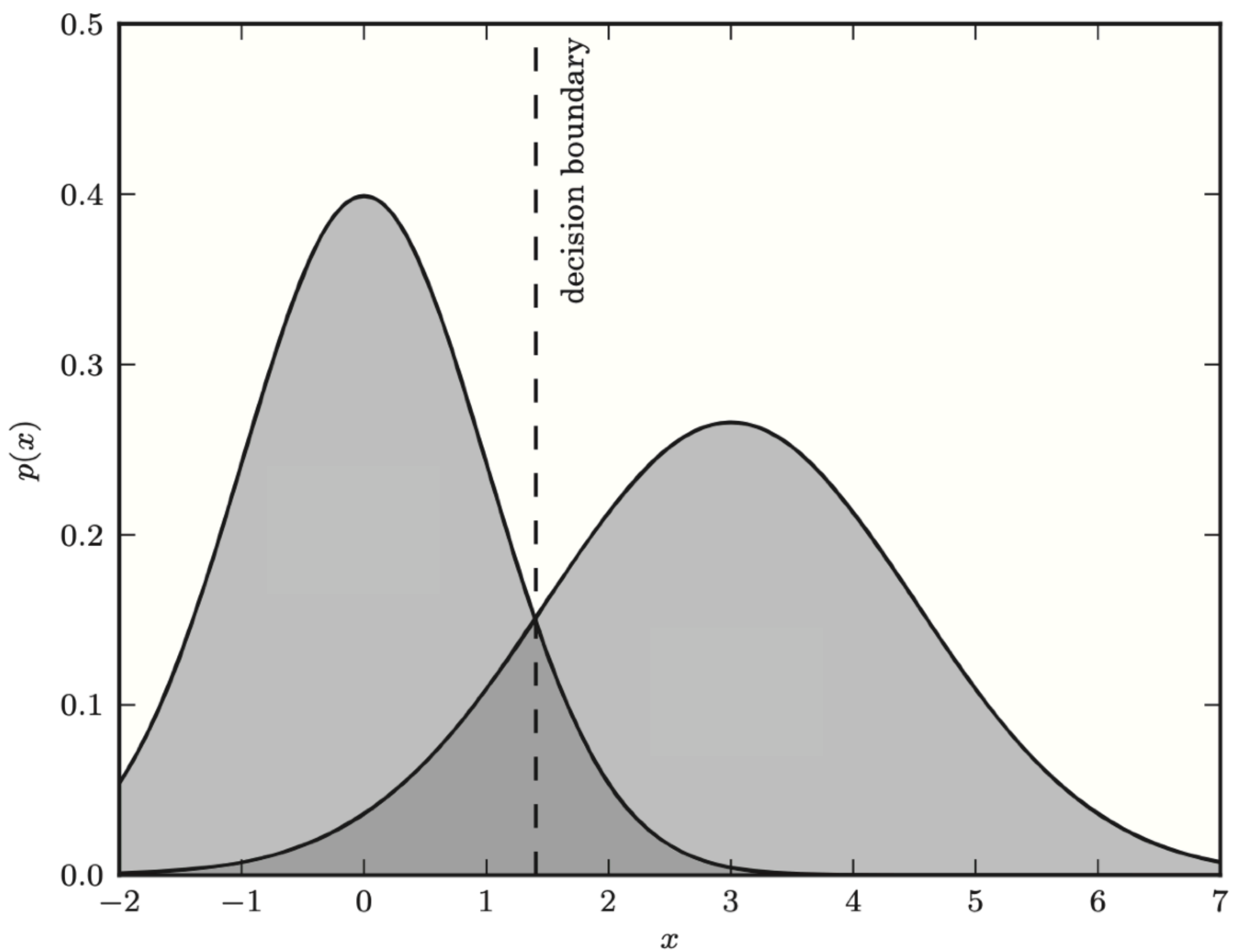

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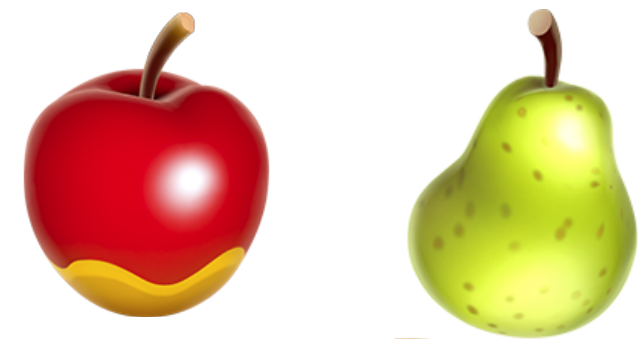

$$\widehat{y} = \begin{cases} 1 & \text{if } \pi_1 p_1(\mathbf{x}) > \pi_0 p_0(\mathbf{x}) \\ 0 & \text{otherwise} \end{cases}$$

π_1 - probability of being apple

$p_1(x)$ - probability of finding x in your bushel of apples

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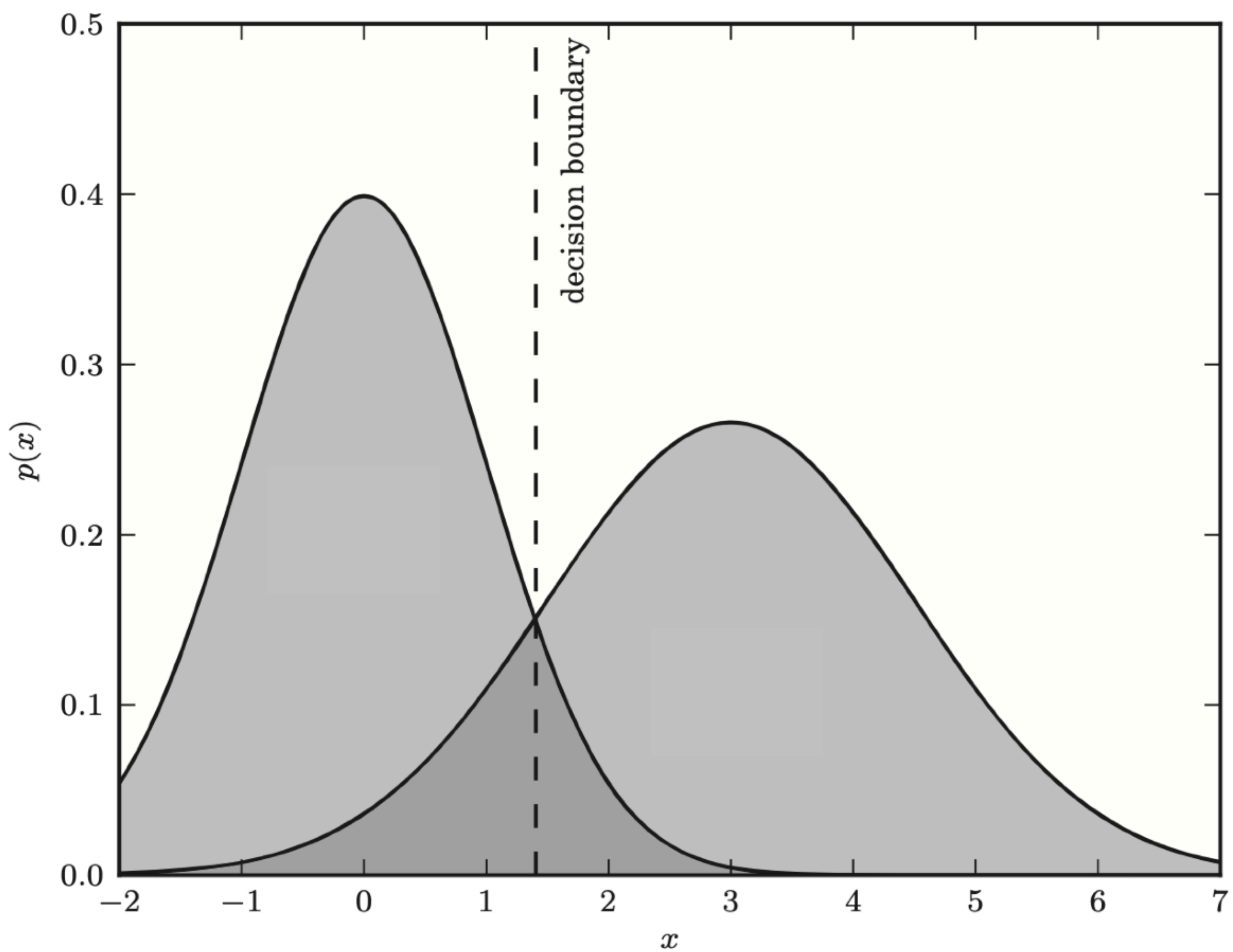

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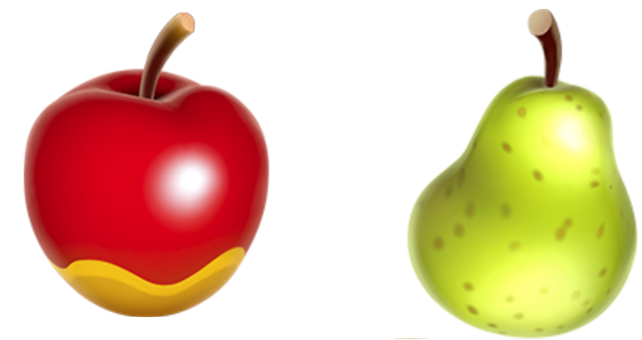

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$\hat{y} = 1$ - best fit is class 'apple'

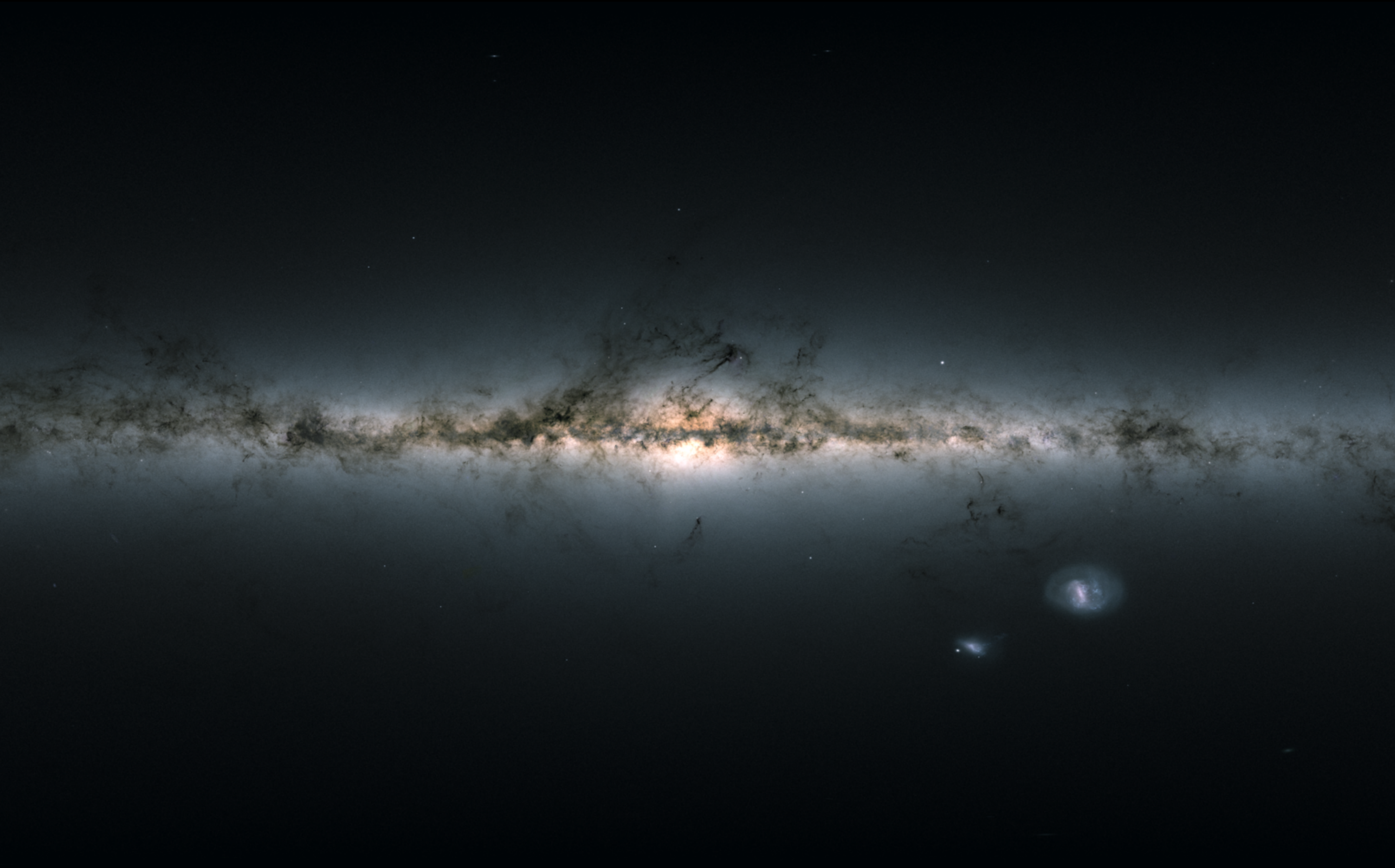
$\hat{y} = 0$ - best fit is class 'pear'

Brief intro to my research

Dwarf galaxies!

They are numerous!

High redshift dwarfs are the progenitors of z=0 galaxies like ours



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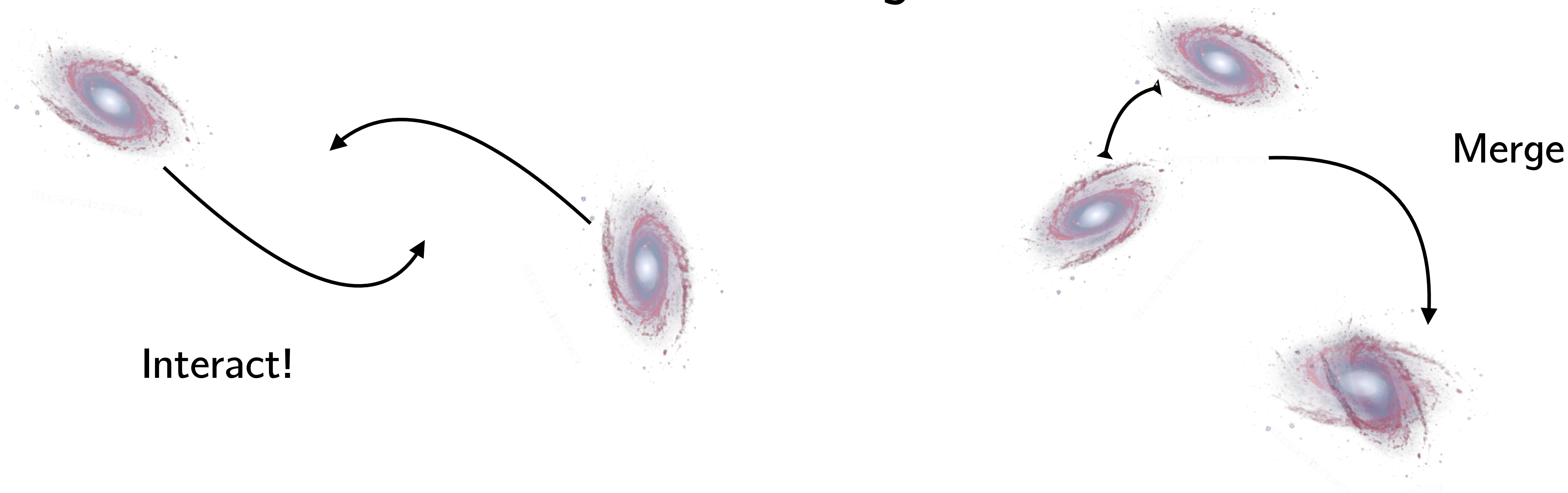
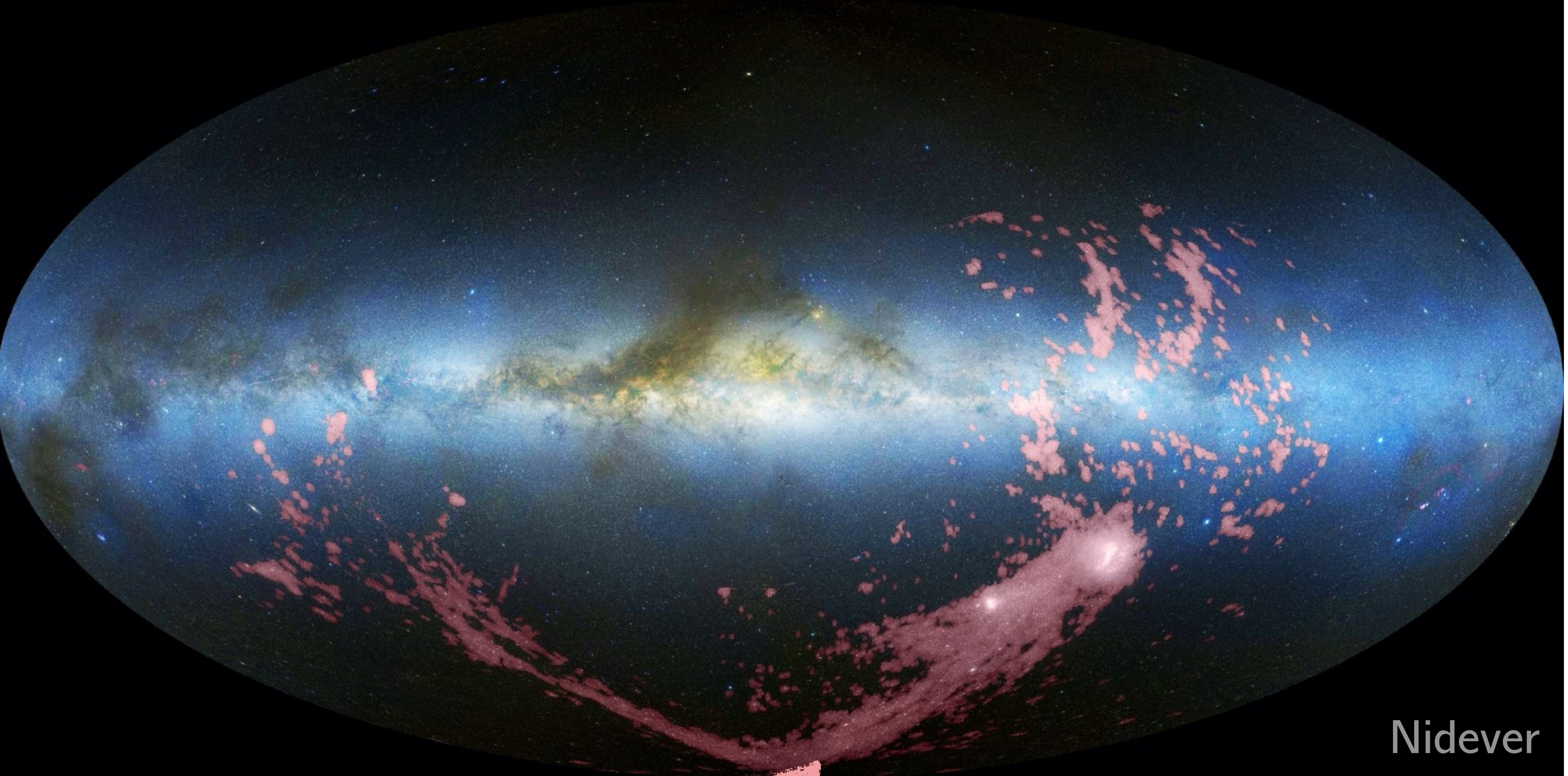
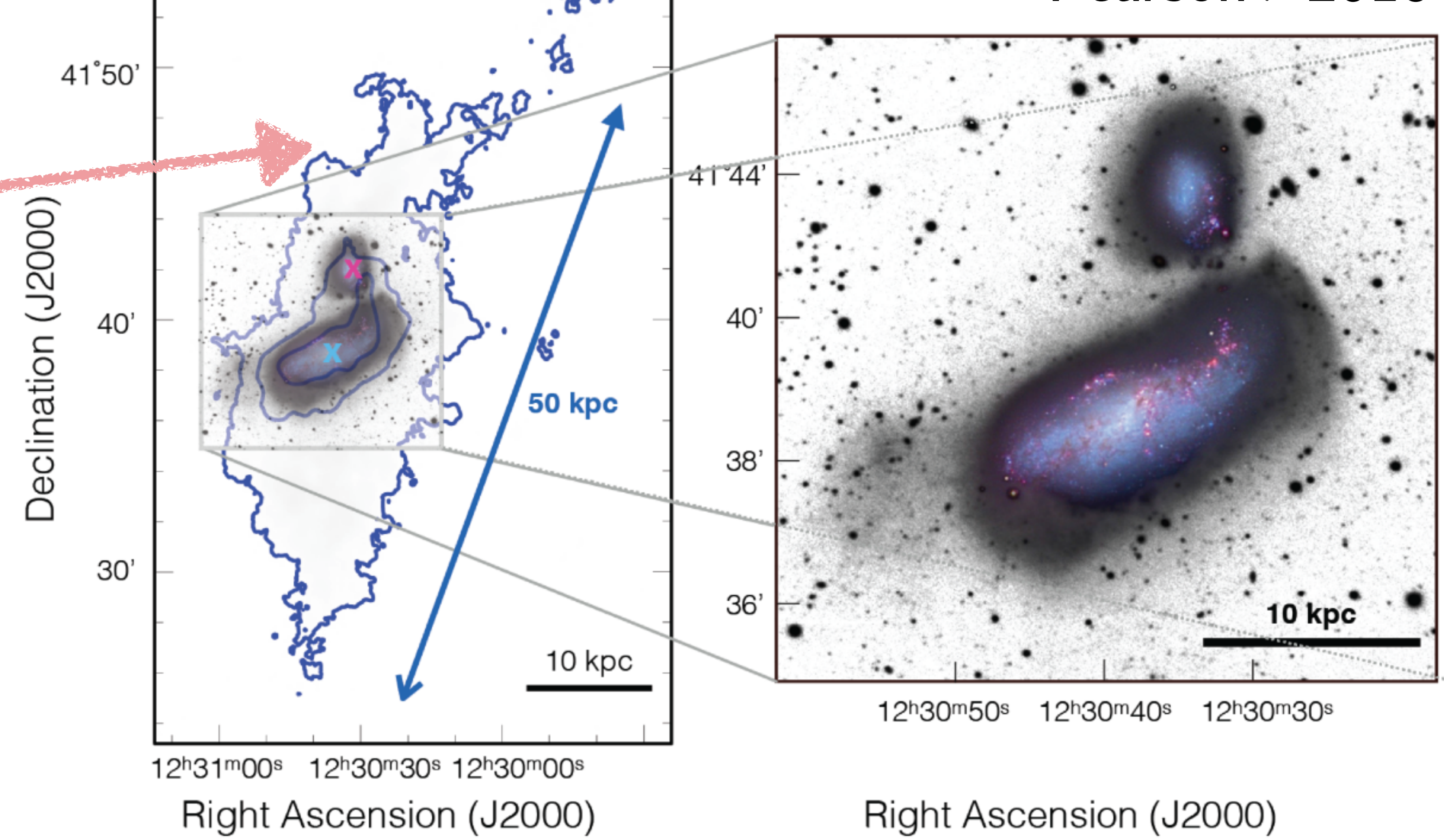
Pairs of dwarf galaxies





Extended
gas features in HI

Pearson+ 2018



Naïve Bayes Classifier + Example

Say we track 8 dwarf galaxies in a simulation, and find the following properties for each one!

Star Formation	Gas Envelope	Asymmetry	Recent Merger?
Extremely enhanced	No Envelope	Asymmetric	Yes
Extremely enhanced	Envelope	Asymmetric	No
Enhanced	Envelope	Asymmetric	Yes
Enhanced	Envelope	Symmetric	No
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If we find a galaxy that has:

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- A large gas envelope
- Symmetry

What can we say about whether our galaxy has likely been through a merger or not?

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- **Independent**
- **Equally important**

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Naïve Bayes Classifier + Example

Probabilities by trait

Star Formation	Yes	No	P(Yes)	P(No)
Extremely Enhanced	1	1	1/5	1/3
Enhanced	2	1	2/5	1/3
Normal	2	1	2/5	1/3

Gas Envelope	Yes	No	P(Yes)	P(No)
Envelope	3	2	3/5	2/3
No envelope	2	1	2/5	1/3

Asymmetry	Yes	No	P(Yes)	P(No)
Asymmetric	4	2	4/5	2/3
Symmetric	1	1	1/5	1/3

$$\mathrm{P}(\mathrm{Yes}|[\mathrm{Ext.Enhanced}, \mathrm{Envelope}, \mathrm{Symmetric}]) = \frac{\mathrm{P}(\mathrm{Ext.Enhanced}|\mathrm{Yes}) * \mathrm{P}(\mathrm{Envelope}|\mathrm{Yes}) * \mathrm{P}(\mathrm{Symmetric}|\mathrm{Yes}) * \mathrm{P}(\mathrm{Yes})}{\mathrm{P}([\mathrm{Ext.Enhanced}, \mathrm{Envelope}, \mathrm{Symmetric}])}$$

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Naïve Bayes Classifier + Example

$$\mathrm{P}(\mathrm{Yes}|[\mathrm{Ext.Enhanced}, \mathrm{Envelope}, \mathrm{Symmetric}]) = 0.35$$

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According to this model, it's likely that this new galaxy has NOT recently undergone a merger!

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Great, except a lot of variables in astronomy are *not* discrete!
Such as: colors, ages, masses, redshift, etc.

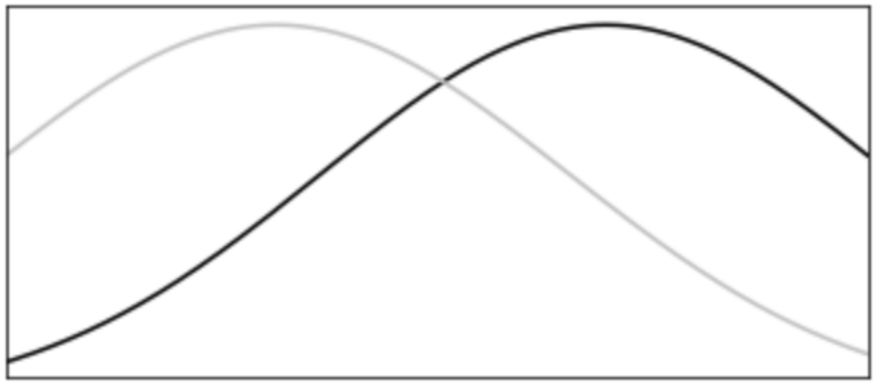
→ *What about continuous variables?* ←

Gaussian Naïve Bayes Classifier

This is a frequentist technique which:

Models the distribution with a Gaussian!

(instead of discrete probabilities
in the previous example)



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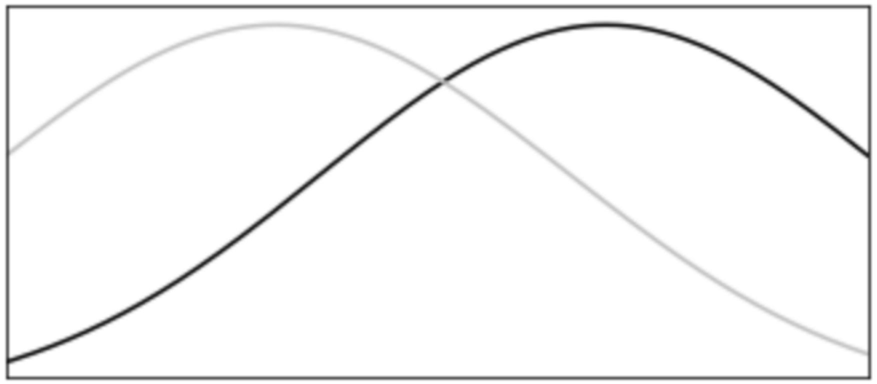

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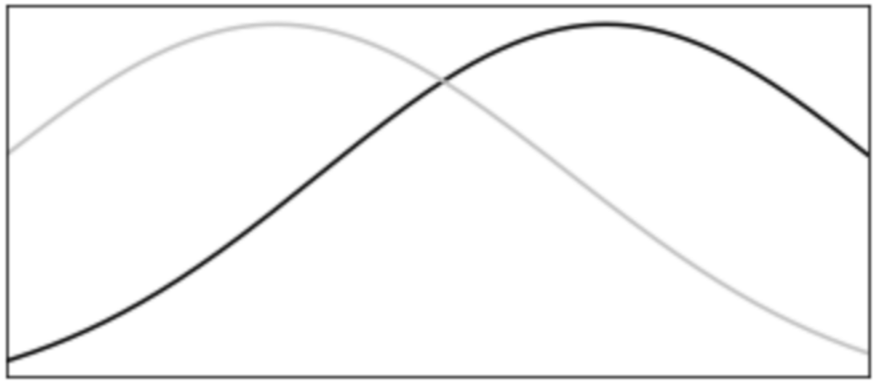

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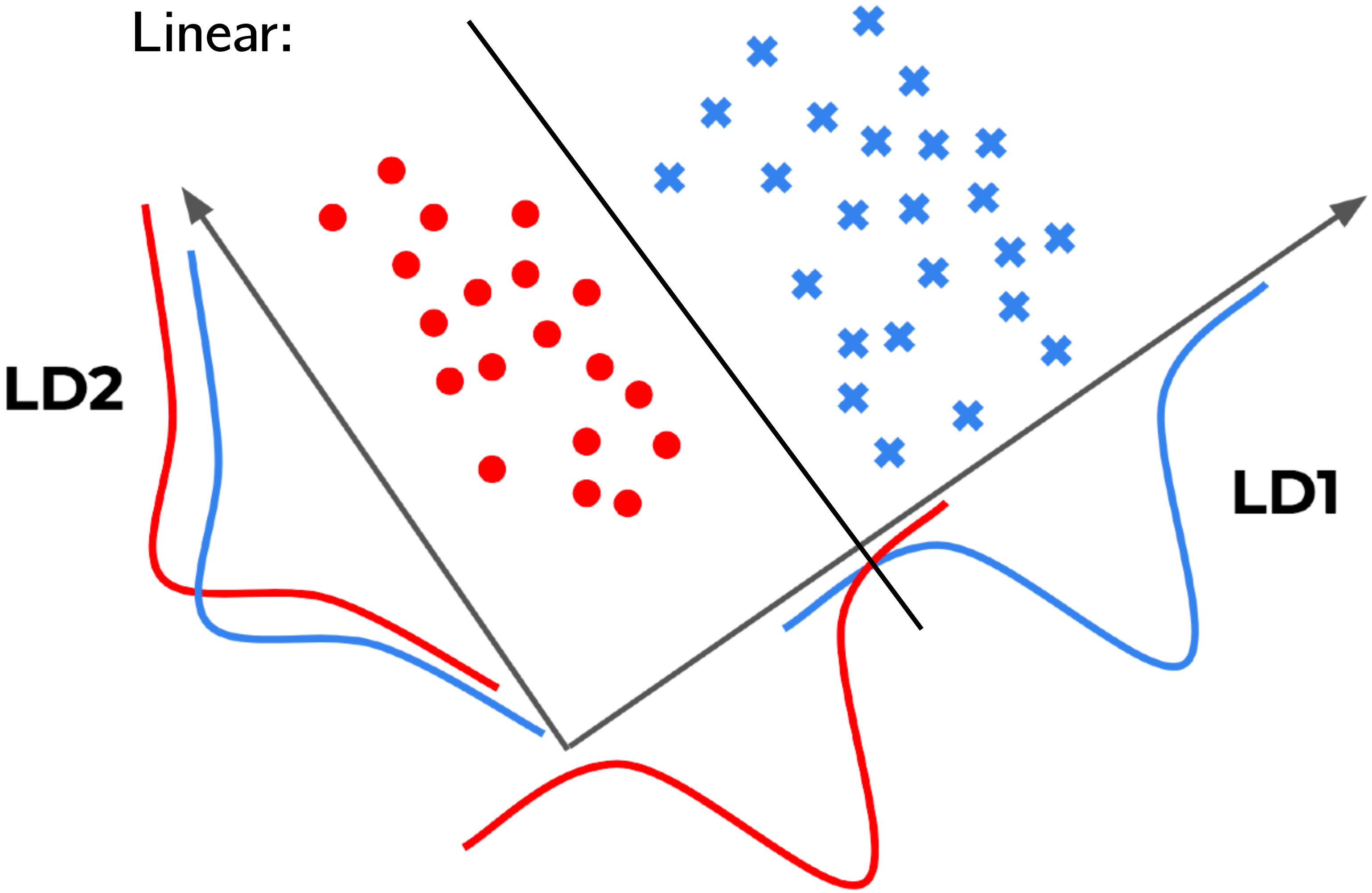
Note: if there are covariances between the variables in your distributions, then you need to use the *Gaussian Bayes Classifier* which accounts for those dependencies.

Linear/Quadratic Discriminant Analysis

Linear:



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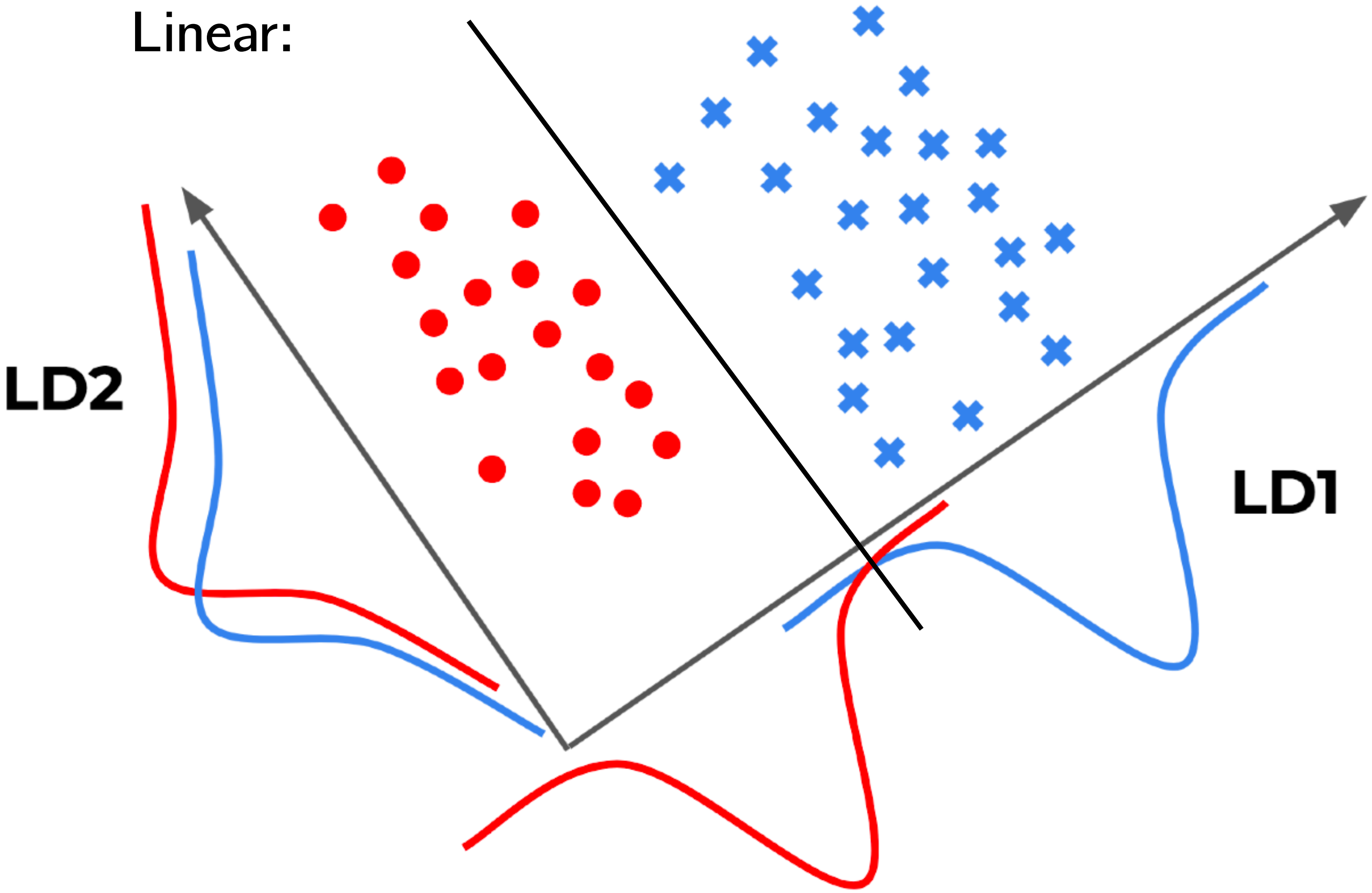

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Decreases the dimensionality of the data by:

- Maximizing the separation between gaussians
- Minimizing the spread of each gaussian

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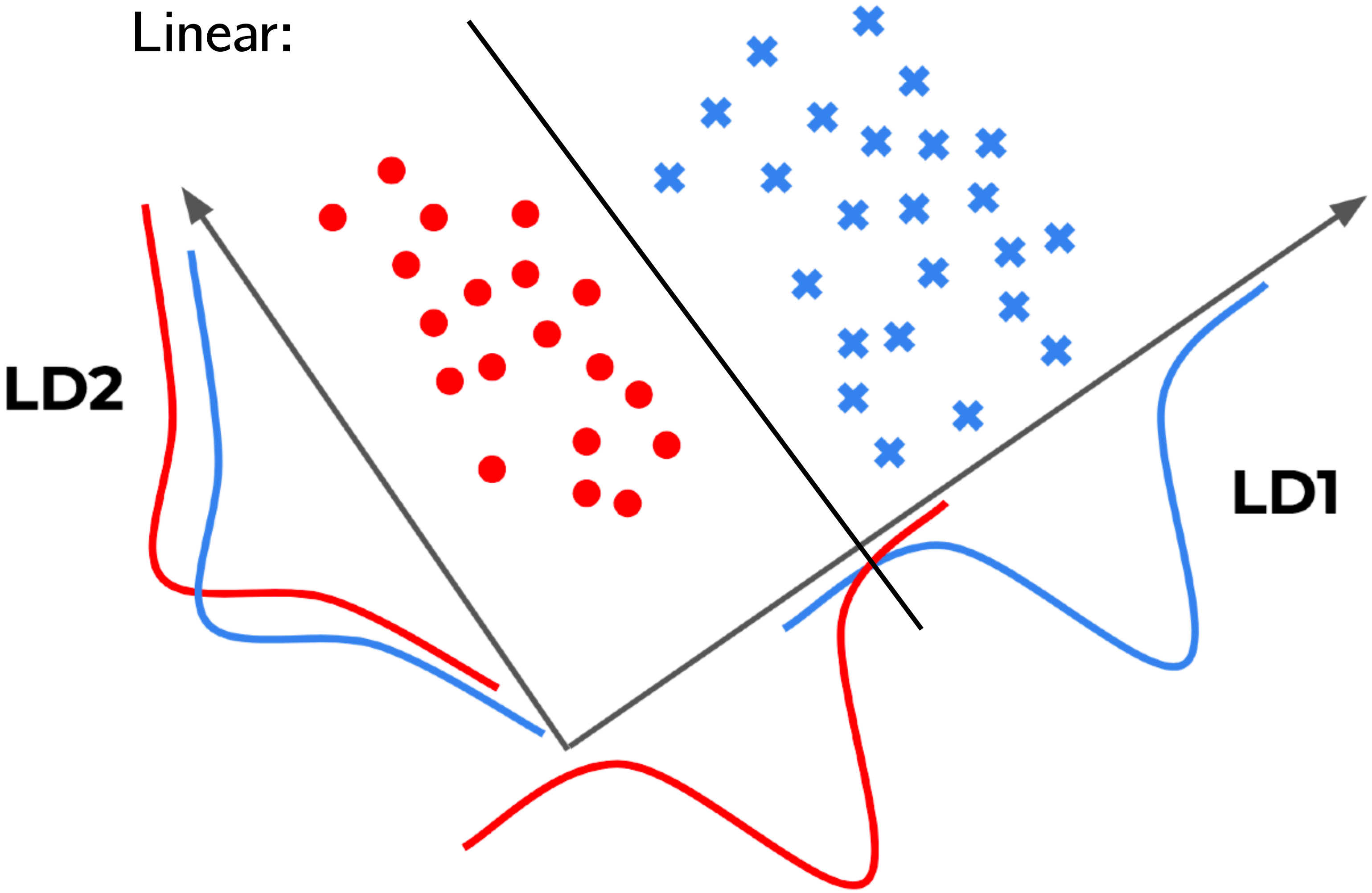

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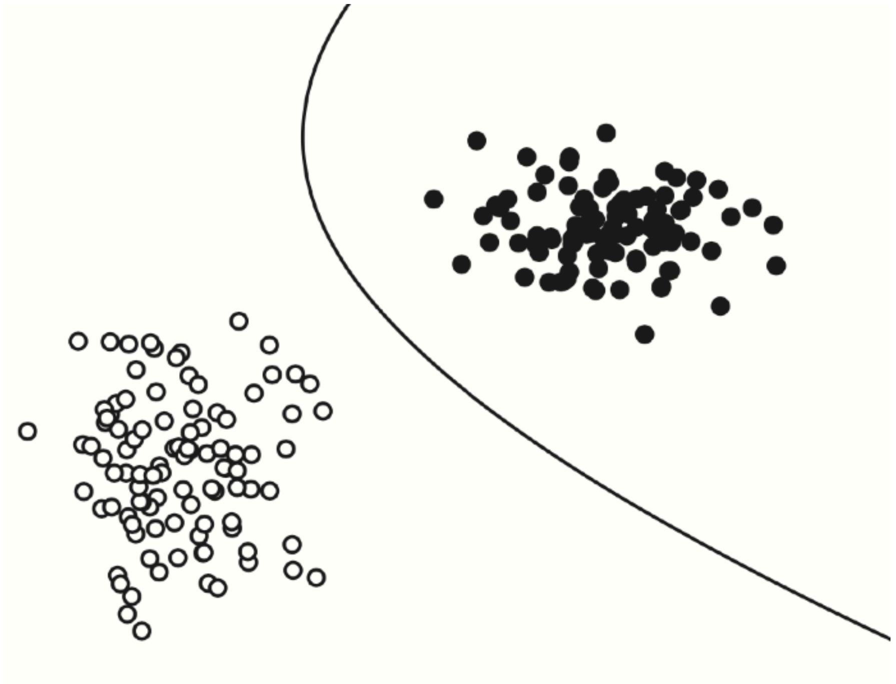
Quadratic:



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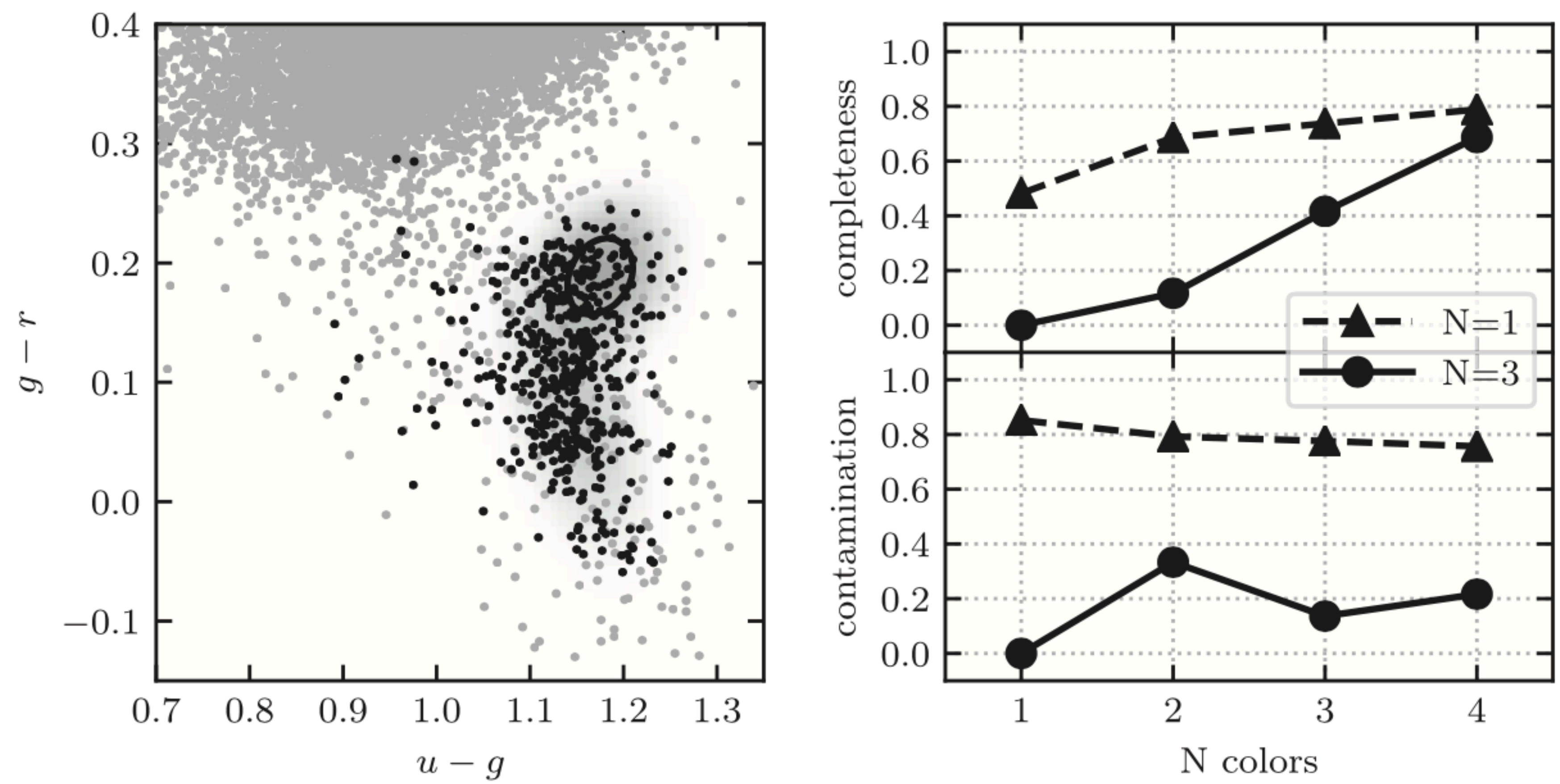
Gaussian Mixture Model Bayes Classifier

A step up from the
Gaussian Bayes classifier:
Use Gaussian mixture model



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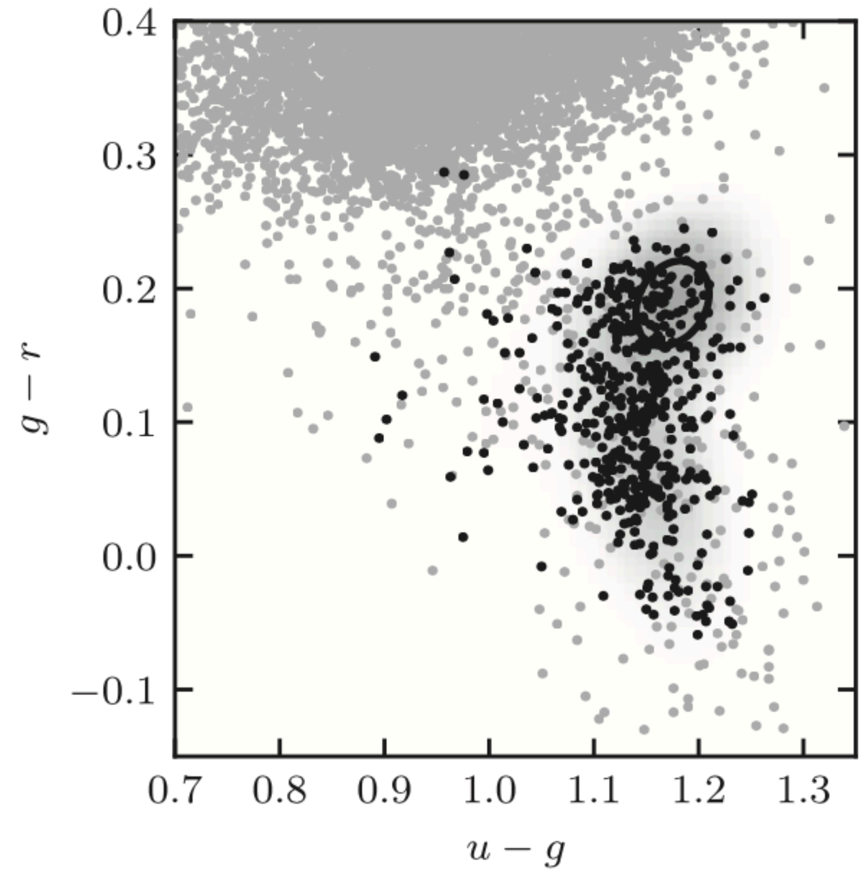

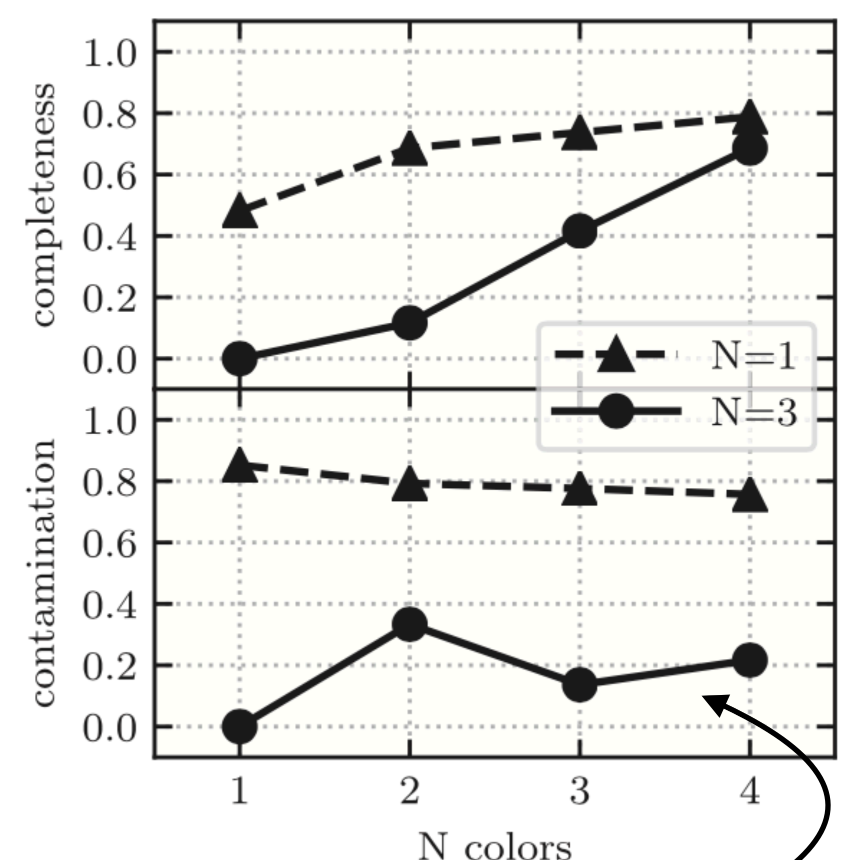

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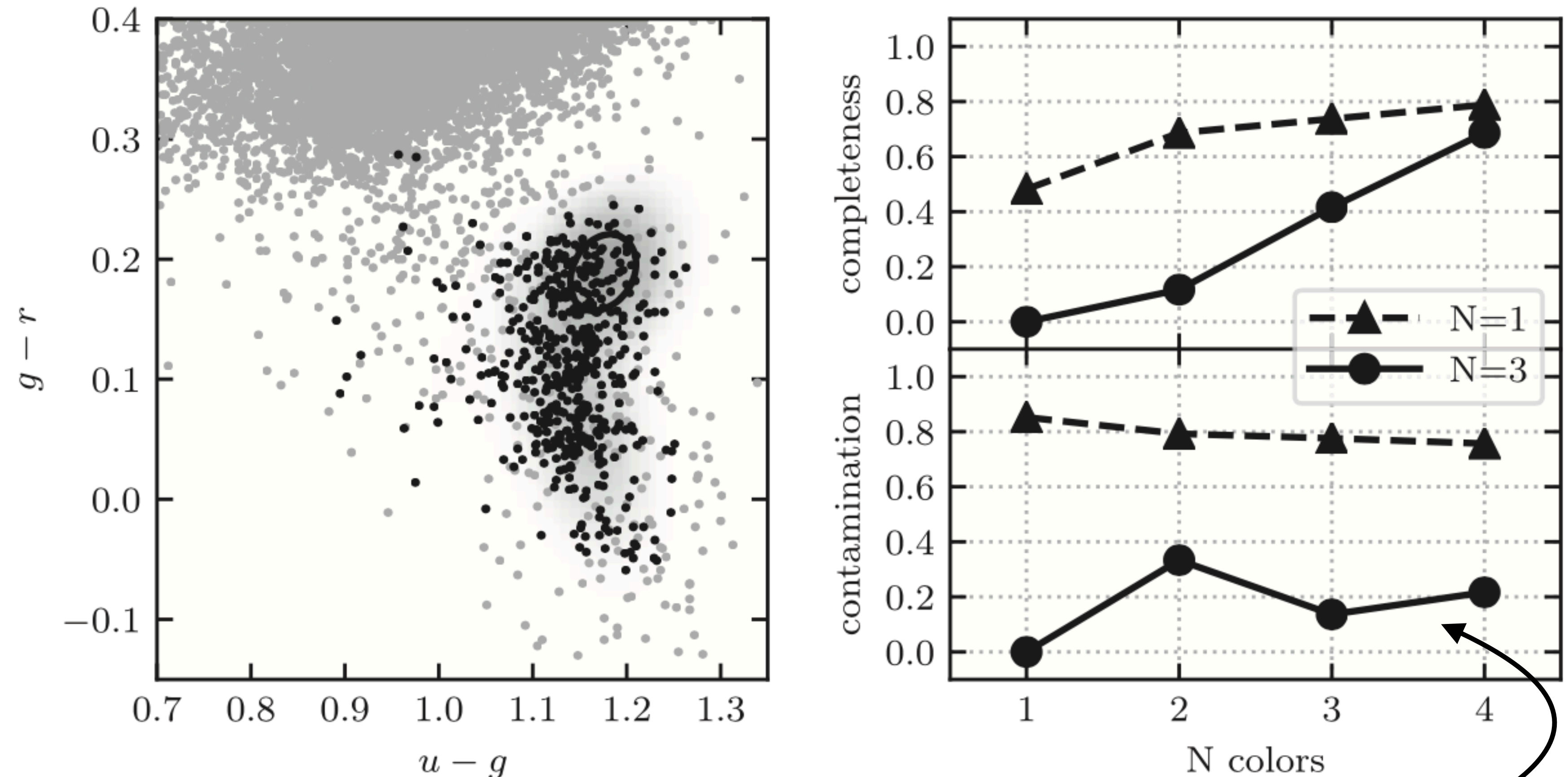

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Pick your classifier based on what's most important to you:
Completeness or low contamination