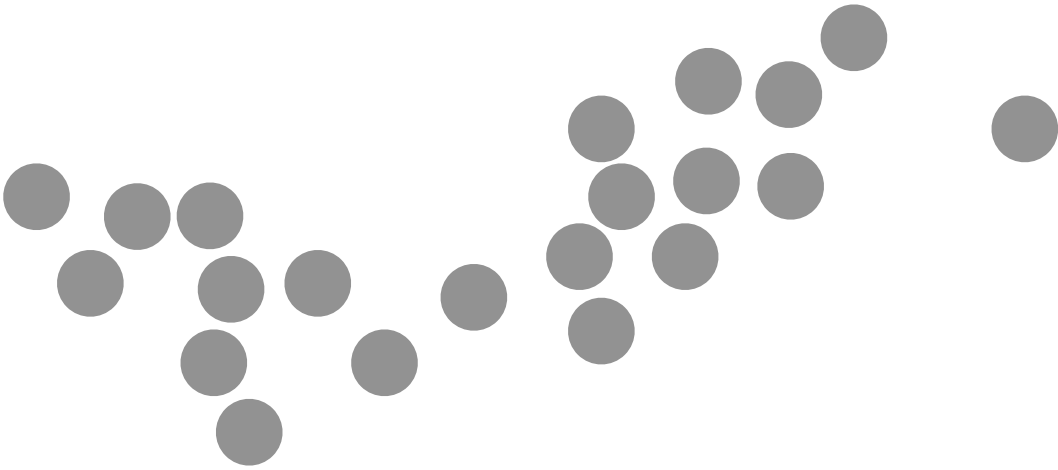


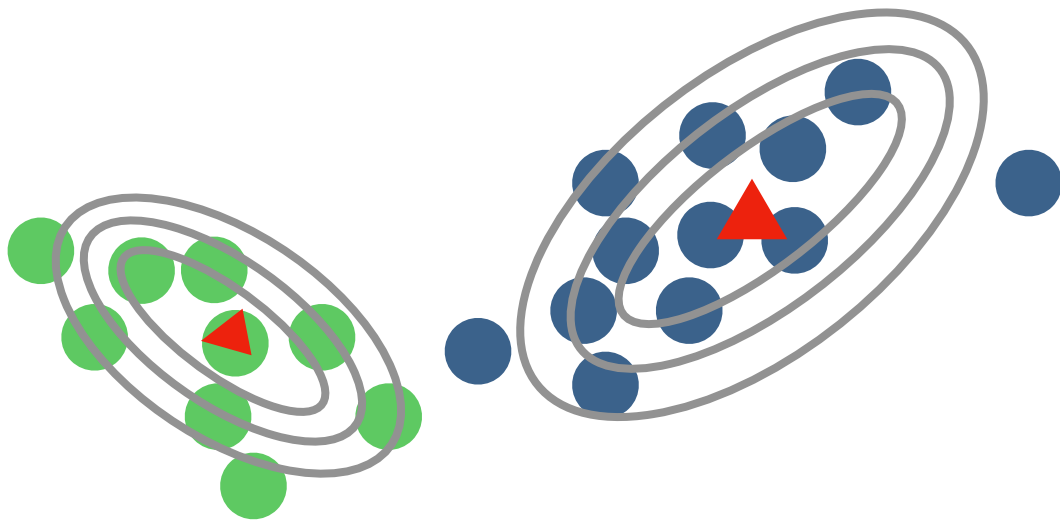
Background: Bayesian inference





have some data

$$y_n \sim v_1 N(\mu_1, \Sigma_1) + v_2 N(\mu_2, \Sigma_2)$$




wish to infer parameters
and z_n , the cluster label
for each datum:

$$x = (w_1, w_2, \mu_1, \mu_2, \Sigma_1, \Sigma_2, (z_n))$$

Bayesian inference:
compute conditional
distribution of parameters
given data

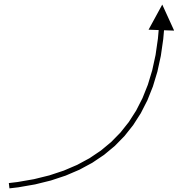
posterior distribution

(beliefs after observing data)


$$p(x \mid y)$$

$$p(x | y) \propto p(y | x) p(x)$$

likelihood
(GMM)



prior



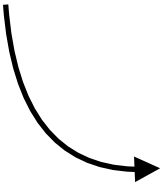
(beliefs before data)

problem: $p(x|y)$ intractable

solution: approximate it with
some $q(x)$ (*variational inference*)

- lots of work if \mathcal{X} is continuous
(e.g., normalizing flows)

- little work for discrete x



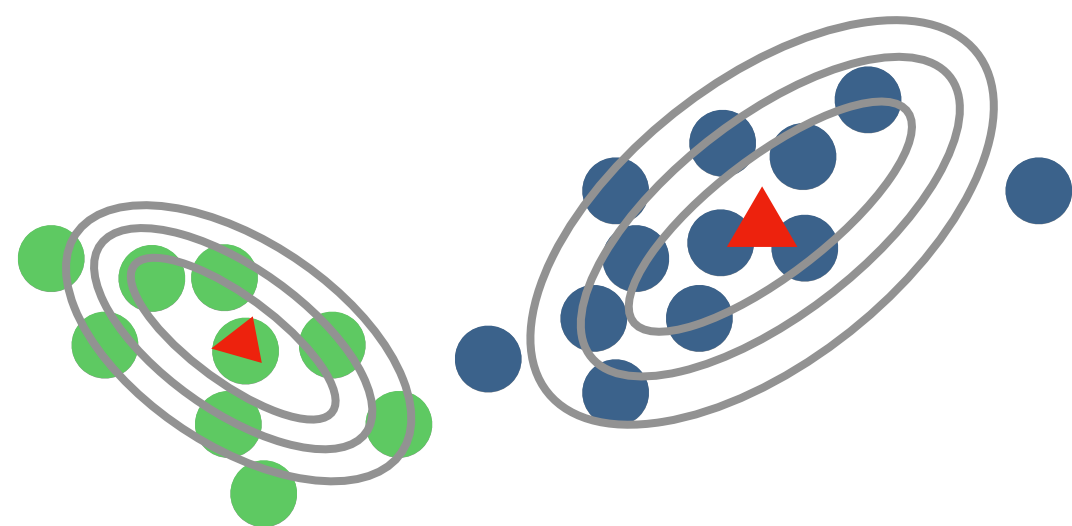
usually, embed x in a
continuous space and use
known methods

this talk: variational inference
for discrete posteriors without
continuous embedding

Background: Bayesian inference

have some data

$$y_n \sim w_1 \mathcal{N}(\mu_1, \Sigma_1) + w_2 \mathcal{N}(\mu_2, \Sigma_2)$$



wish to infer parameters
and z_n , the cluster label
for each datum:

$$x = (w_1, w_2, \mu_1, \mu_2, \Sigma_1, \Sigma_2, (z_n))$$

Bayesian inference:
compute conditional
distribution of parameters
given data

posterior distribution
(beliefs after observing data)

$$p(x | y) \propto p(y | x)p(x)$$

likelihood (GMM) prior (beliefs before data)

problem: $p(x | y)$ intractable

solution: approximate it with
some $q(x)$ (*variational inference*)

- lots of work if x is continuous
(e.g., normalizing flows)
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Background: normalizing flows