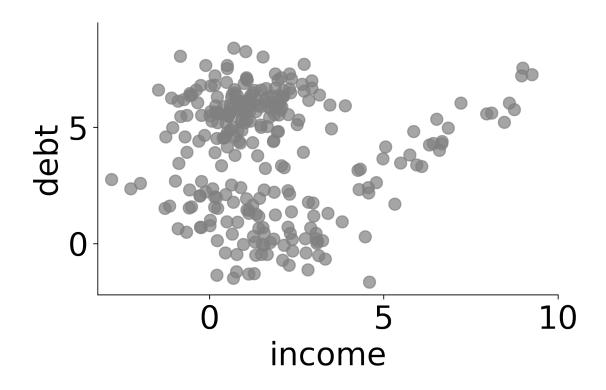
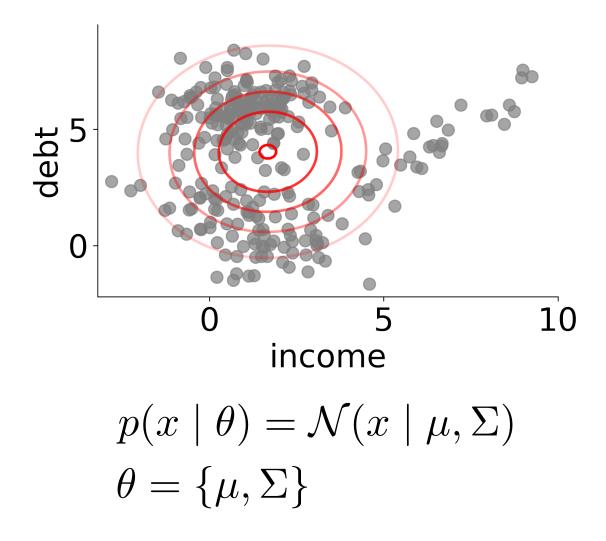
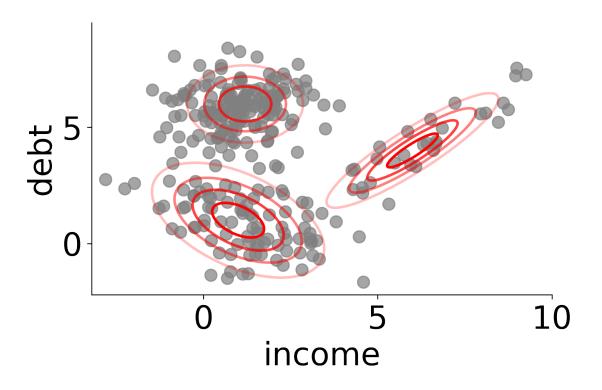
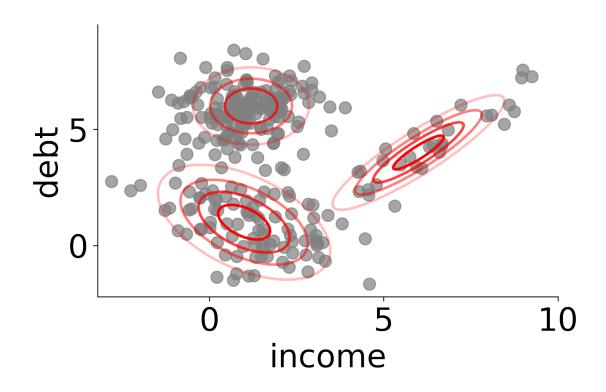
# **Probabilistic model of data**



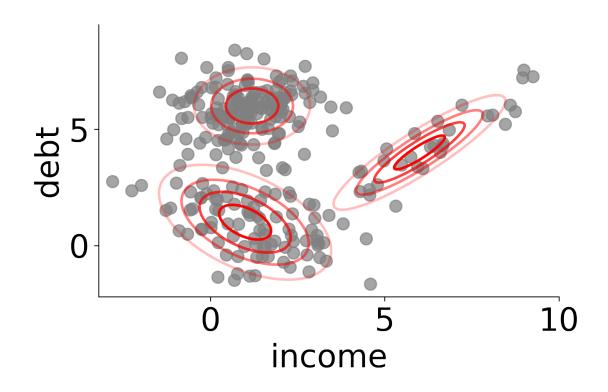
#### **Probabilistic model of data**







$$p(x \mid \theta) = \pi_1 \mathcal{N}(x \mid \mu_1, \Sigma_1) + \pi_2 \mathcal{N}(x \mid \mu_2, \Sigma_2) + \pi_3 \mathcal{N}(x \mid \mu_3, \Sigma_3)$$



$$p(x \mid \theta) = \pi_1 \mathcal{N}(x \mid \mu_1, \Sigma_1) + \pi_2 \mathcal{N}(x \mid \mu_2, \Sigma_2) + \pi_3 \mathcal{N}(x \mid \mu_3, \Sigma_3)$$

$$\theta = \{\pi_1, \pi_2, \pi_3, \mu_1, \mu_2, \mu_3, \Sigma_1, \Sigma_2, \Sigma_3\}$$

Gaussian

**GMM** 

**Flexibility** 





# **GMM vs Guassian**

	Gaussian	GMM
Flexibility		(??)
# of parameters	77	
Parameters	$\mu, \Sigma$	$\{\pi_1, \pi_2, \pi_3\}$ $\{\mu_1, \mu_2, \mu_3\}$ $\{\Sigma_1, \Sigma_2, \Sigma_3\}$

$$\max_{\theta} p(X \mid \theta)$$

$$\max_{\theta} p(X \mid \theta) = \prod_{i=1}^{N} p(x_i \mid \theta)$$

$$\max_{\theta} \prod_{i=1}^{N} p(x_i \mid \theta) = \prod_{i=1}^{N} (\pi_1 \mathcal{N}(x_i \mid \mu_1, \Sigma_1) + \ldots)$$

$$\max_{\theta} \prod_{i=1}^{N} p(x_i \mid \theta) = \prod_{i=1}^{N} (\pi_1 \mathcal{N}(x_i \mid \mu_1, \Sigma_1) + \ldots)$$

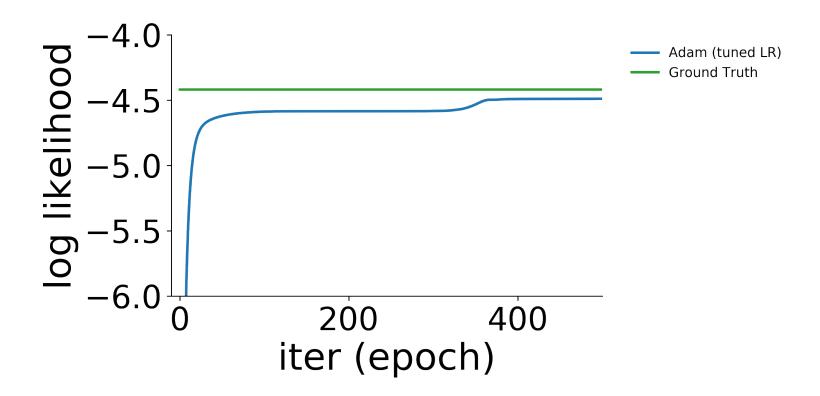
subject to 
$$\pi_1 + \pi_2 + \pi_3 = 1$$
;  $\pi_k \ge 0$ ;  $k = 1, 2, 3$ .

$$\max_{\theta} \prod_{i=1}^{N} p(x_i \mid \theta) = \prod_{i=1}^{N} (\pi_1 \mathcal{N}(x_i \mid \mu_1, \Sigma_1) + \ldots)$$
subject to  $\pi_1 + \pi_2 + \pi_3 = 1; \ \pi_k \ge 0; \ k = 1, 2, 3.$ 

$$\sum_{k} \ge 0;$$

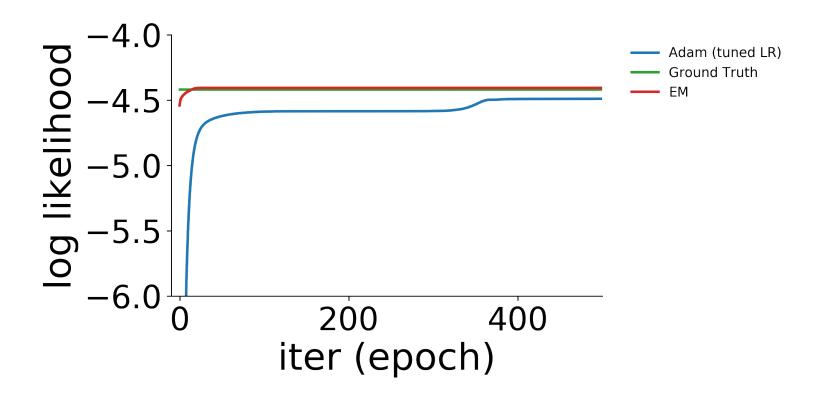
$$\max_{\theta} \prod_{i=1}^{N} p(x_i \mid \theta) = \prod_{i=1}^{N} (\pi_1 \mathcal{N}(x_i \mid \mu_1, \Sigma_1) + \ldots)$$

subject to 
$$\pi_1 + \pi_2 + \pi_3 = 1$$
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$$\max_{\theta} \prod_{i=1}^{N} p(x_i \mid \theta) = \prod_{i=1}^{N} (\pi_1 \mathcal{N}(x_i \mid \mu_1, \Sigma_1) + \ldots)$$

subject to 
$$\pi_1 + \pi_2 + \pi_3 = 1$$
;  $\pi_k \ge 0$ ;  $k = 1, 2, 3$ .



# **Summary**

Gaussian Mixture Model is a flexible probability distribution

It is hard to fit (train) with SGD