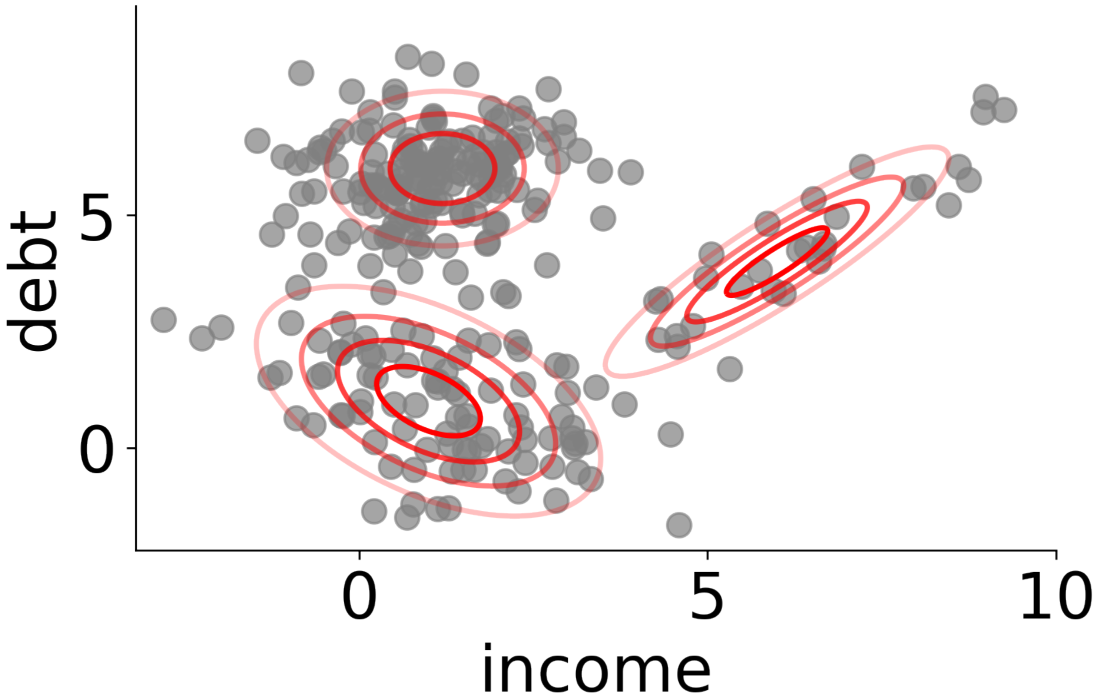
Gaussian Mixture Model revisited



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

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

Gaussain Mixture Model connection

E-step

EM: For each point compute

$$q(t_i) = p(t_i \mid x_i, \theta)$$

GMM: For each point compute

$$p(t_i \mid x_i, \theta)$$

M-step

EM: Update parameters to maximize

$$\max_\theta \mathbb{E}_q \log p(X, T \mid \theta)$$

GMM: Update Gaussian parameters to fit points assigned to them

$$\mu_1 = \frac{\sum_i p(t_i = 1 \mid x_i, \theta)\, x_i}{\sum_i p(t_i = 1 \mid x_i, \theta)}$$

NOTE: there is a proof for this ^. But it is up to us if we want to study it.
Basically, set the partial derivative w.r.t. the mu we want to get, to 0.Then find this mu value.