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get PPCA  
(see week 2)

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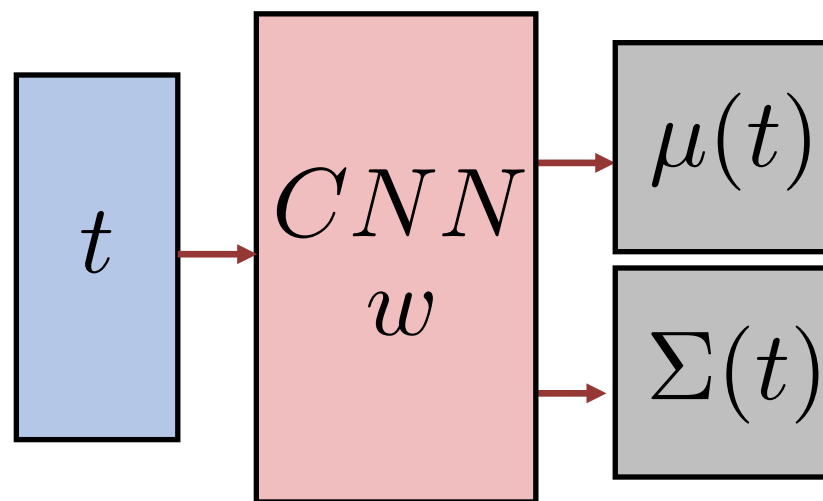
But if  $x$  is image, why not  $\mu(t) = \text{CNN}_1(t)$   
 $\Sigma(t) = \text{CNN}_2(t)$

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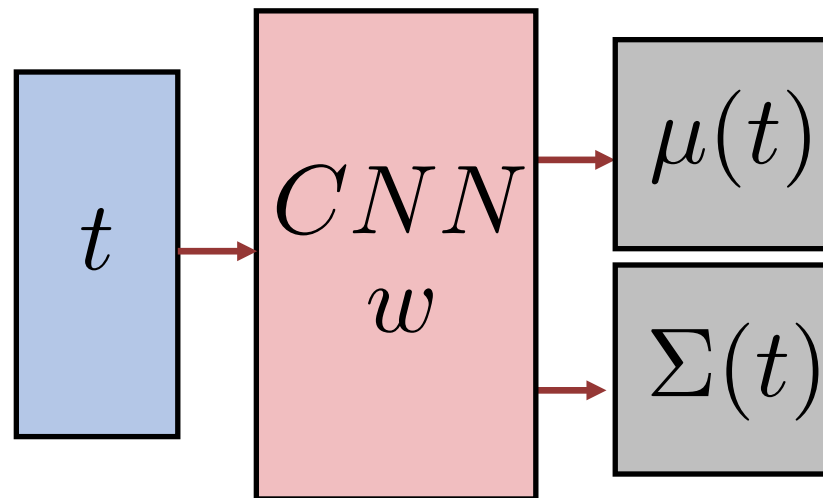


# Continuous mixture of Gaussians

$$p(x \mid \textcolor{red}{w}) = \int p(x \mid t, \textcolor{red}{w}) p(t) dt$$

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$$p(x \mid t, \textcolor{red}{w}) = \mathcal{N}(\mu(t, \textcolor{red}{w}), \Sigma(t, \textcolor{red}{w}))$$

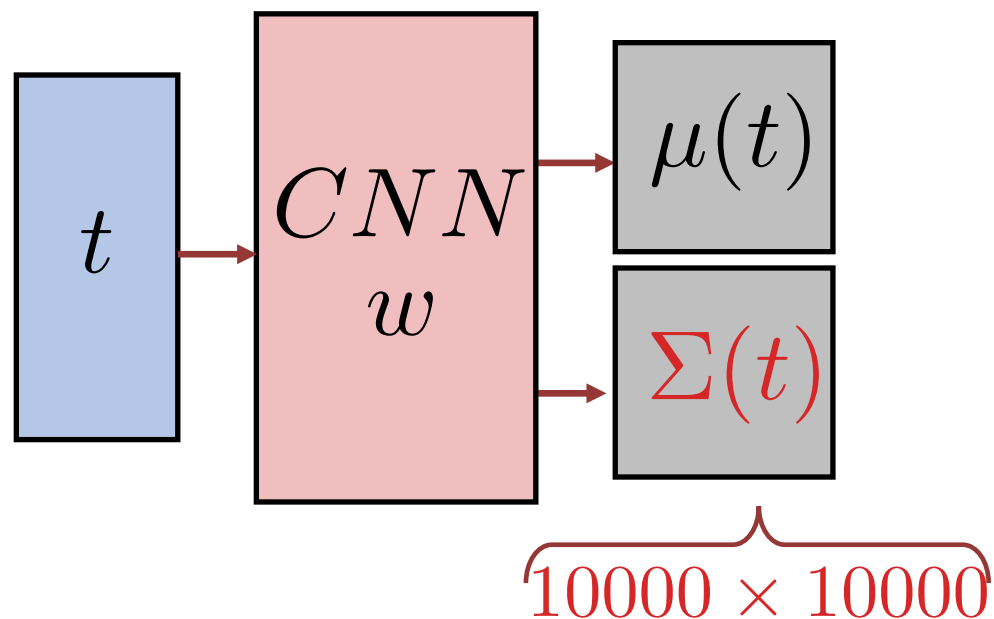


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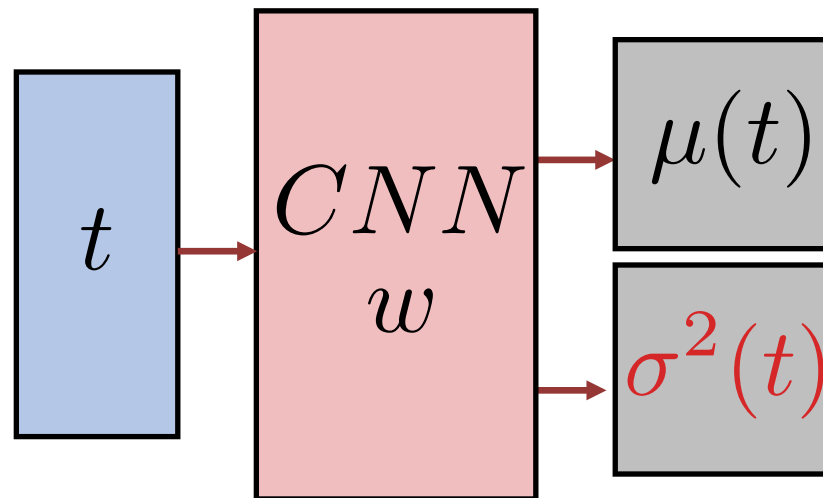


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$$p(t) = \mathcal{N}(0, I)$$

$$p(x \mid t, w) = \mathcal{N}(\mu(t, w), \text{diag}(\sigma^2(t, w)))$$



# Scaling up Expectation Maximization

$$\max_w p(X \mid w) = \int p(X \mid T, w) p(T) dt$$

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$$\log p(X \mid w) \geq \mathcal{L}(w, q)$$

$$\underset{w, q}{\text{maximize}} \quad \mathcal{L}(w, q)$$

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Latent Variable model — use EM! But E-step is intractable

Need to compute  $p(T \mid X, w)$

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$$T_s \sim q(T)$$

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Then Variational EM! **But again intractable.**

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