VAEs

Variational autoencoders have the following graph structure. The inputs are encoded into some latent distribution decoded to match the output as closely as possible.



Linear Regression



My Approach

I restructure the graph such that both the inputs and outputs are generated from some latent space.



Ideal Characteristics Linear Regression

- Ability to use an unlimited number of inputs
- Adding variables does not neccisarily improve the likelihood, but can also decrease the likelihood
- Exploit all information in the variables (e.g. do not test on significance)

Review

Process

 $\$ \begin{aligned} X_i & = AZ_i + \epsilon_i \ Y_i & = BZ_i + \epsilon'_i \ \epsilon & \sim N(\mu, \sigma) \ \epsilon' & \sim N(\mu', \sigma') \ \end{aligned}

Parameters

 $$\ \end{tabular} $$ \Big\{ X \& : \operatorname{(M \times N)} : \operatorname{(M \times N)} : \operatorname{(M \times N)} : \operatorname{(F \times N)} : \operatorname{(F \times N)} : \operatorname{(P \times N)} : \operatorname{(M \times 1)} \setminus \operatorname{(M \times N)} : \operatorname{(M \times N)} \setminus \operatorname{(M \times N)} \setminus$

\$\$

Derivation

\$\$ \begin{aligned} \textrm{Objective : } \argmax_{\theta} p(Y|X;\theta) \end{aligned}

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 $\$ \begin{aligned} p(Z) & = (2\pi)^{-\frac{k}{2}} det(\Sigma)^{-\frac{1}{2}}e^{-\frac{1}{2}} Z'Z} \ & \propto e^{Z'Z}\

 $p(X|Z) \& = \frac{1}^T (2 \pi)^{-\frac{M}{2}} \det(\sum_X)^{-\frac{1}{2}} e^{-\frac{1}{2}} e$

\$\$

 $$$ \left(\frac{1}{2} e^{-\frac{1}{2}} e$

\$\$

\$\$

 $\label{eq:continuous} $$ \frac{1}{2}e^{-\frac{1}{2}(X-A \hat{Z})'Sigma_X^{-1}(X - A \hat{Z}) -\frac{1}{2}(Z-\hat{Z})'A' Sigma_X^{-1} A(Z - \hat{Z})) e^{-\frac{1}{2} Z'Z} \end{aligned}$

\$\$

 $\ \phi_{\alpha} \in P(Y|Z)p(Z|X)p(Z) dZ \ \rho_{\alpha_{1}{2} Z'Z} \rho_{t=1}^T \det(\Sigma_X)^{-\frac{1}{2}} \det(\Sigma_Y)^{-\frac{1}{2}} \det(\Sigma_Y)^{-\frac{1}{2}} \det(\Sigma_Y)^{-\frac{1}{2}}$

 $\& = \det(\Sigma_X)^{-\frac{T}{2}} \det(\Sigma_Y)^{-\frac{T}{2}} \det(\Sigma_Y)^{-\frac{$

 $\& = \det(\Sigma_X)^{-\frac{T}{2}} \det(\Sigma_Y)^{-\frac{T}{2}} \det(\Sigma_Y)^{-\frac{$

 $$$ \operatorname{CT}_{2} \det(\Sigma_T)^{-\frac{T}{2}} \det(\Sigma_T)^{-\frac{T}{$

\$\$

 $\label{thm:linear} $$ \left[p(Y|X; \right] & = \frac{\pi_{X}} e^{\int a_X, \sigma_Y, \hat{Z}} & = \frac{T}{2} p(X|Z)p(Z)dZ}{p(X)} \ & \rho(X) &$

\$\$

 $\label{logp} $$ \left(X^{-1} \right) - \frac{T}{2} \log(|Sigma_Y^{-1}|) - \frac{T}{2} \log(|I + A' Sigma_X^{-1} A + B' Sigma_Y^{-1} B|) + \frac{T}{2} \log(|I + A' Sigma_X^{-1} A|) - \frac{1}{2} \sum_{t=1}^T (Y_t - B + T_{2}t) \leq X^{-1}(Y_t - B +$

\$\$

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first order deriviative

example with trace

derivatives in a trace (first order approximation)

 $\$ \begin{aligned} \frac{\pi_Y^{-1} (Y_t - B \hat{Z}_t)B' \end{aligned}

\$\$

 $\$ \begin{aligned} \frac{\pi P(Y|X)}{\pi A} & = ... + \frac{1}{2} \sum_{t=1}^T 2 \leq P(Y_t - B) \

\$\$

 $\begin{aligned} \frac{\log\{p(Y|X)\}}{\operatorname{Sigma_Y^{-1}} & = \frac{T}{2} \simeq 1}{2} \sum_{t=1}^T (Y_t - B \hat{Z}_t)' \end{array}$

\$\$

 $\$ \begin{aligned} \frac{\pi(Y|X)}}{\pi(Z)} & = \end{aligned}

\$\$

Decomposition Rule

 $\$ \begin{aligned} (Y-XB)'(Y-XB) & = (Y-X \hat{B})'(Y-X \hat{B}) + (B - \hat{B})'X'X (B - \hat{B}) \end{aligned}

\$\$

 $\$ \begin{aligned} X & : \textrm{M x N}\ A & : \textrm{M x F}\ Z & : \textrm{F x N}\ \end{aligned}

\$\$

 $$$ \Big\{ p(Z|X) & p(Z|X) & p(Z|X) p(Z|X) p(Z|X) p(Z|X) p(Z|X) p(Z|X) p(Z|X) p(Z|X) p(Z|X) p(X|Z) p(X|X) p(X|Z) p(X|X) p(X|Z) p(X$

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Parameters:

\$\$ A, B, \Sigma, \Sigma', \mu, \mu'

\$\$

Multivariate Gaussian Distribution

 $\label{ligned} $$ \left(\sum_{e^{-\frac{1}{2}}e^{-\frac{1}{2}}e^{-\frac{1}{2}(x-\mu)'} \right) \left(\sum_{e^{-\frac{1}{2}}$

\$\$

Bayesian Regression

Univariate

Process

\$\$ \begin{aligned} y &= X \beta + \epsilon \end{aligned}

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Assume flat priors

\$\$ \begin{aligned} p(\beta) & \propto 1 \ p(\sigma^2) & \propto \sigma^{-2} \end{aligned}

\$\$

Bayesian prediction

 $\$ \begin{aligned} y & = X \beta + \epsilon\ p(y|X) & = \int p(Y, \beta, \sigma^2|X) d\beta d\sigma^2 \ & = \int p(Y|X, \beta, \sigma^2) p(\beta, \sigma^2 | X) d\beta d\sigma^2 \end{aligned}

\$\$

 $\ \phi^{-(N+2-k)} e^{-frac{1}{2 \simeq^2}(y - X \hat \)'(y - X\hat \)} \end{aligned} \ \$

\$\$

Singular Value Decomposition

\$\$ \begin{aligned}

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Estimating Covariance matrix

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