Bayesian Deep Learning 1

- Machine Learning Models
  - measure of uncertainty : not point estimates, distribution of possible outcomes
  - deep learning models: deterministic + probability theory → Bayesian Deep Learning

- Bayesian Probability Theory
  - Formalism : rational beliefs = probability theory
  - Bayesian Probabilistic Modelling

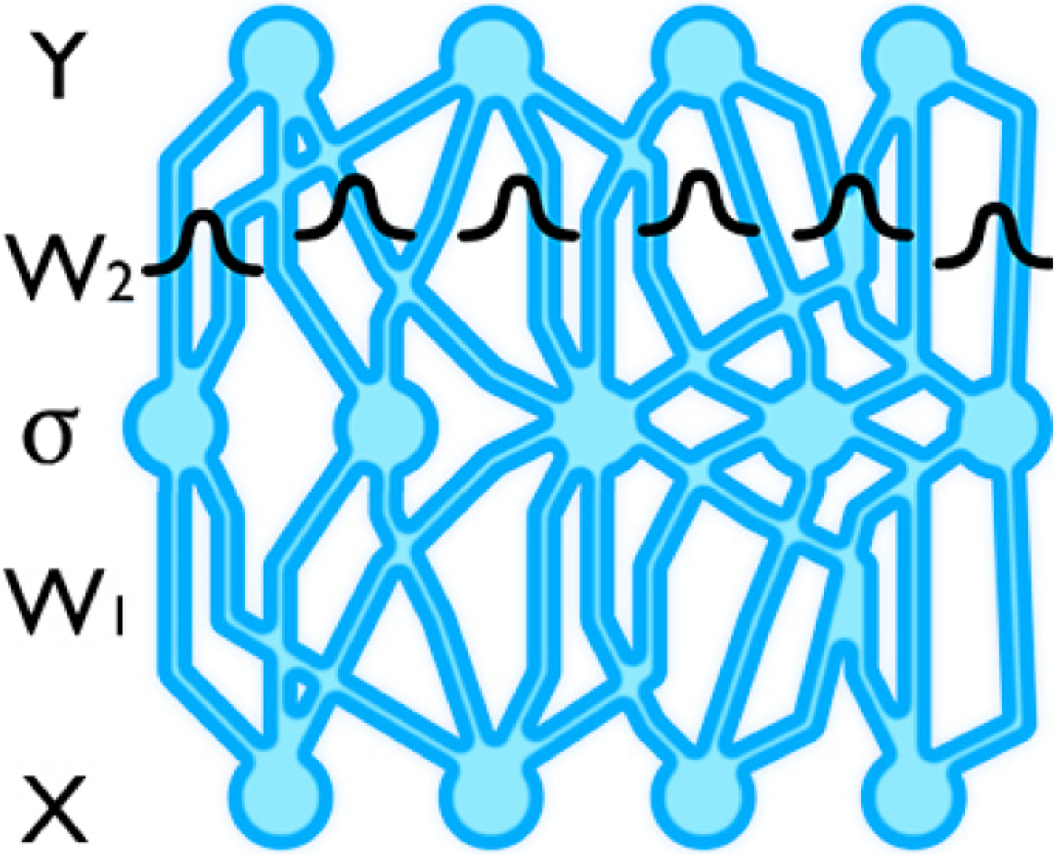
    "assumptions" about underlying process
    - prior: belief about parameters (μ)
    - likelihood: belief in how data was generated with parameters $(X_n|\mu, \sigma^2 \; N(\mu, \sigma^2))$

    → update prior belief on parameters conditioned on data

    Bayes Rule

    $P(X = x|Y = y, \mathcal{H}) = \frac{P(Y=y|X=x,\mathcal{H})P(X=x|\mathcal{H})}{P(Y=y|\mathcal{H})}$

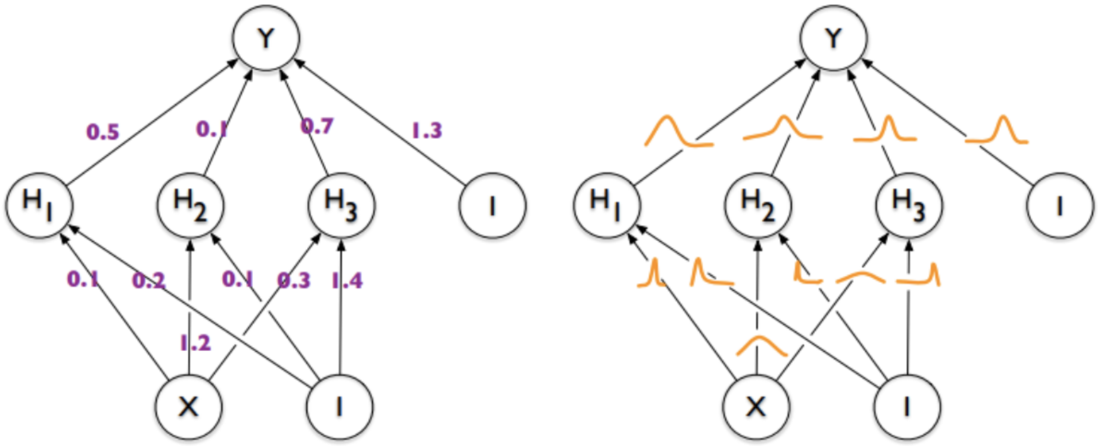
    $P(\mu|\mathcal{D}, \sigma, \mathcal{H}) = \frac{P(\mathcal{D}|\mu,\sigma,\mathcal{H})P(\mu|\sigma,\mathcal{H})}{P(\mathcal{D}|\sigma,\mathcal{H})}$: posterior = likelihood * prior / model evidence
  - Basis function $\phi_k(x)$
    - linear regression on $\phi_k(x)$, not on x : basis function regression
  - Parameterised basis functions $\phi_k^{w_k, b_k}$
    - ϕ_k applied to inner product $w_k^T x + b_k$
    - Hierarchy in parametrised basis functions: input→hidden layers→output



- Bayesian Deep Learning Model
  - prior distribution over parameters W

    $p(W) = N(W; 0_k, s^2 l_k)$
  - likelihood conditioned on W generated observations with gaussian noise added

    $p(y|W, x) = N(y; W^T\phi(x), \sigma^2), y_n = W^T\phi(x_n) + \epsilon_n, \epsilon_n\ N(0, \sigma^2)$



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학습을 통해 고정된 W 값을 찾는 것이 아니라, W의 확률분포를 찾아가는 것!