

Beta - Bernoulli

$$X_i \sim \text{Ber}(\theta)$$

$$N = N_1 + N_0$$

$$P(D|\theta) = \theta^{N_1} (1-\theta)^{N_0}$$

$$N_1 = \sum_{i=1}^N \mathbb{I}(X_i=1); \quad N_0 = \sum_{i=1}^N \mathbb{I}(X_i=0)$$

$$P(\theta) = \text{Beta}(\theta|a, b) \propto \theta^{a-1} (1-\theta)^{b-1}$$

$$P(\theta|D) \propto P(D|\theta) \cdot P(\theta)$$

$$\Rightarrow P(\theta|D) \propto \theta^{N_1} (1-\theta)^{N_0} \theta^{a-1} (1-\theta)^{b-1}$$

$$\Rightarrow P(\theta|D) \propto \theta^{N_1+a-1} (1-\theta)^{N_0+b-1}$$

$$\Rightarrow P(\theta|D) \sim \text{Beta}(N_1+a, N_0+b)$$

$$\text{Beta}(a, b) = \int_0^1 t^{a-1} (1-t)^{b-1} dt$$

Normalizing constant for Beta distribution

Marginal likelihood

$$P(y|\alpha) = \int P(y|\theta, \alpha) \cdot d\theta$$

$$= \int P(y|\theta) \cdot P(\theta|\alpha) \cdot d\theta$$

$$= \int \boxed{\text{Ber}(\theta) \cdot \text{Beta}(a, b) \cdot d\theta} \rightarrow$$

$\beta(a, b)$

equal to normalizing constant for posterior

$$\frac{\beta(N_1+a, N_0+b)}{\beta(a, b)}$$

$$\beta(a, b)$$

Normalizing constant for Posterior
normalizing constant for prior

1.3 Posterior mean

$$E_{\theta}[\theta_i] = \int \theta \cdot P(\theta | y, a) \cdot d\theta$$

$$= \int \theta \cdot P(\theta | D, a, b) \cdot d\theta$$

$$= \int \theta \cdot \frac{\theta^{N_1 + a - 1} (1 - \theta)^{N_0 + b - 1}}{\beta(a, b)} d\theta$$

$$\beta(a, b) \quad \beta(a + N_1, b + N_0)$$

$$= \frac{\tau(a) \cdot \tau(b)}{\tau(a + b)}$$

$$\Rightarrow E_{\theta}[\theta_i] = \frac{\int \theta^{N_1 + a} (1 - \theta)^{N_0 + b - 1} d\theta}{\beta(a + N_1, b + N_0)}$$

$$= \frac{\beta(a + N_1 + 1, b + N_0)}{\beta(a + N_1, b + N_0)}$$

$$= \left[\frac{\tau(a + N_1 + 1) \tau(b + N_0)}{\tau(a + b + N + 1)} \right] \left[\frac{\tau(a + b + N)}{\tau(a + N) \tau(b + N_0)} \right]$$

$$\tau(a + 1) = a \tau(a)$$

$$\Rightarrow E_{\theta}[\theta_i] = \frac{a + N_1}{a + b + N} //$$

1.4 Posterior Predictive

$$P(\hat{y} | y, a) = \int P(\hat{y} | \theta | y, a) \cdot d\theta$$

$$= \int P(\hat{y}, \theta | D, a, b) \cdot d\theta$$

$$= \int P(\hat{y} | \theta, D, a, b) \cdot P(\theta | D, a, b) \cdot d\theta$$

$$= \int \frac{\theta^{I(\hat{y}=1)} (1-\theta)^{I(\hat{y}=0)} \theta^{N_1+a-1} (1-\theta)^{N_0+b-1}}{\beta(a, N_0+b)} \cdot d\theta$$

$$P(\hat{y} | D, a, b) = \frac{1}{\beta(N_1+a, N_0+b)} \int \theta^{I(\hat{y}=1) + N_1+a-1} (1-\theta)^{N_0+b-1 + I(\hat{y}=0)} \cdot d\theta$$

$$P(\hat{y}=1 | D, a, b) = \frac{1}{\beta(N_1+a, N_0+b)} \int \theta^{N_1+a-1} (1-\theta)^{N_0+b-1} \cdot d\theta$$
$$= E[\theta]$$

$$\Rightarrow P(\hat{y}=1 | D, a, b) = \frac{N_1+a}{N+a+b}$$