$Y_i \mid X_i \sim N(\beta_0 + X_i^T \beta, \sigma^2)$ ←

Cíl 1: predikce ceny má'h vybr. auta

$X_i \sim N(\mu, \Sigma)$

→ máme model pro (Y_i, X_i)

→ budeme muset zjišťovat samotné λ

$\beta \mid \lambda \sim N(0, \lambda^{-1} I_p)$

$\lambda \to \beta$

$$p(\beta \mid \lambda) \propto \exp\left(-\frac{\lambda}{2} \beta^T \beta\right) =$$

$$= \exp\left(-\frac{\lambda}{2} \sum_j \beta_j^2\right)$$

$$p(y \mid \beta, \sigma^2, x) \propto \exp\left(-\frac{1}{2\sigma^2} \sum (y_i - x_i^T \beta)^2\right)$$

$$p(y \mid \beta) \propto \exp\left(-\frac{1}{2\sigma^2} \sum (y_i - x_i^T \beta)^2\right)$$

$$p(\beta \mid \lambda) \propto \exp\left(-\frac{\lambda}{2} \sum_j \beta_j^2\right)$$

$$p(\beta | y) \propto \exp\left(-\frac{1}{2\sigma^2}\sum (y_i - x_i^T \beta)^2 - \frac{\lambda}{2}\sum_j \beta_j^2\right)$$

tedy

$$\hat\beta = \operatorname{argmax} p(\beta | y)$$

$$\hat\beta = \operatorname{argmin} \frac{1}{2\sigma^2} \underbrace{\sum (y_i - x_i^T\beta)^2}_{SS(\beta)} + \frac{\lambda}{2}\sum_j \beta_j^2$$

zjednodušení

$$\hat\beta \approx \operatorname{argmin} \sum (y_i - x_i^T\beta)^2 + \frac{\lambda}{2}\sum_j \beta_j^2$$

$$\tilde\beta(\text{LASSO}) = \operatorname{argmin} \sum (y_i - x_i^T\beta)^2 + \frac{\lambda}{2}\sum |\beta_j|$$

$$\min\left(SS(\beta) + \frac{\lambda}{2}\sum_j \beta_j^2\right) \to \hat\beta_\lambda$$

penalizace

= ridge regrese

$$MSE(\hat\beta) = var(\hat\beta) + bias(\hat\beta)\, bias(\hat\beta)^T$$

pro ~~$\lambda\in(0,$~~ pro $\lambda \in (0, \bar\lambda)$

je $MSE(\hat\beta_\lambda) < var(\hat\beta_{LSE})$

$\lambda \to \infty$

$\hat\beta_j \to 0$

$$\min \left(SS(\beta) + \frac{1}{2} \sum_j |\beta_j| \right)$$

$\rightarrow$ LASSO odhad

$\downarrow$

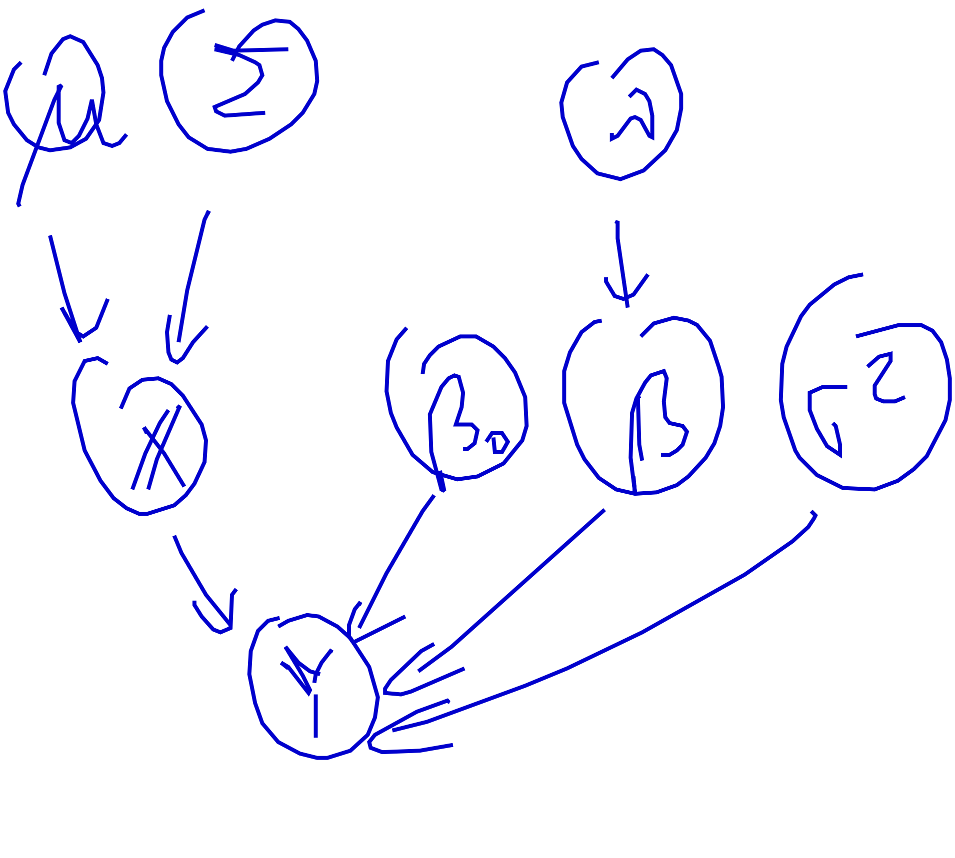
může ~~ale~~ mít minimum v bodech $(\neq 0, \neq 0, \neq 0)$

$$P(\underline{\beta}, \underline{\lambda}, \ldots \mid y)$$

$\downarrow$

$$P(\beta \mid y)$$

$$P(\beta \mid \ldots) \propto P(y \mid \beta_0, \beta, X, \sigma^2) \cdot P(\beta \mid \lambda)$$



$Y_{new} \sim (Y, X)$, kde

$Y|X \sim N(\ldots)$

$X \sim N(\ldots)$

Chci

$p(y_{new}|Y,X) \neq$

Chci vygenerovat

$\forall \theta$

$y_{new}^{(1)}, y_{new}^{(2)}, \ldots$ z

$$p(y_{new}|DATA) =$$

$$= \int p(y_{new}, \cancel{\theta}_{x_{new}} | DATA) \, d\theta \, dx_{new} =$$

$$= \int p(y_{new} | \theta, \cancel{DATA}_{x_{new}}) \, p(\theta|DATA) \, d\theta \, dx_{new} =$$

$p(x_{new}|\theta, DA\cancel{TA})$

$$= \int p(y_{new}|\theta, x_{new}) \, p(\theta|DATA) \, p(x_{new}|\theta) \, d\theta \, dx_{new}$$

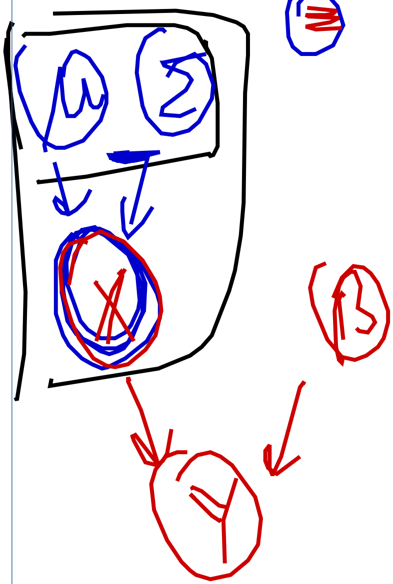
$$p(y_{new}|\theta) \stackrel{?}{=} \int p(y_{new}|x_{new}, \theta) \, p(x_{new}|\theta) \, dx_{new}$$

$\sim N(\ldots)$

$$p(y_{new} \mid \underline{DATA}) = \int p(y_{new} \mid x_{new}, \theta)\, p(x_{new} \mid \theta)\, p(\theta \mid DATA)\, d\theta\, dx_{new}$$

$X_i = (X_{i1}, \ \ , X_{ip})^T$

chybí



při znalosti všeho je primární apost.

$= p(\beta, \beta_0, \sigma^2, \mu, \Sigma, \nu \mid Y, X)$

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neznám-li nějaké X i řekneme a že neznáme $X_{11}, \ , X_{10,1}$

=> prim. aposterior. rozděl. je

$$p(X_{1,1}, .., X_{10,1}, \beta, \beta_0, \sigma^2, \mu, \Sigma, \nu \mid \underline{DATA})$$

"data" bez 10-ti X_1

JAGS:

```
for (i=1:10){
  -> Xi1 ~ N(μ1, σ1²)
     Yi ~ N(β0 + β1 Xi1 + β2 Xi2 + ... + βp Xip, σ²)
}
```

```
for ( i := 1 : n ) {
      yi ~ N( β0 + . . . . , σ² )
}
```