Notes on Bayesian Logistic Regression

Max Leung

April 11, 2023

1 Laplace Approximation

$$
\begin{aligned}
lnf(\boldsymbol{z}) &\approx lnf(\boldsymbol{z}_0) + \overbrace{\nabla lnf(\boldsymbol{z}_0)'}^{\boldsymbol{0}'}(\boldsymbol{z}-\boldsymbol{z}_0) + \frac{1}{2}(\boldsymbol{z}-\boldsymbol{z}_0)'\overbrace{\nabla\nabla lnf(\boldsymbol{z}_0)}^{-\boldsymbol{A}}(\boldsymbol{z}-\boldsymbol{z}_0) \\
&= lnf(\boldsymbol{z}_0) - \frac{1}{2}(\boldsymbol{z}-\boldsymbol{z}_0)'\boldsymbol{A}(\boldsymbol{z}-\boldsymbol{z}_0)
\end{aligned}
$$

$$
\begin{aligned}
f(\boldsymbol{z}) &\approx exp(lnf(\boldsymbol{z}_0) - \frac{1}{2}(\boldsymbol{z}-\boldsymbol{z}_0)'\boldsymbol{A}(\boldsymbol{z}-\boldsymbol{z}_0)) \\
&= exp(lnf(\boldsymbol{z}_0))exp(-\frac{1}{2}(\boldsymbol{z}-\boldsymbol{z}_0)'\boldsymbol{A}(\boldsymbol{z}-\boldsymbol{z}_0)) \\
&= f(\boldsymbol{z}_0)exp(-\frac{1}{2}(\boldsymbol{z}-\boldsymbol{z}_0)'\boldsymbol{A}(\boldsymbol{z}-\boldsymbol{z}_0))
\end{aligned}
$$

If we approximate $f(.)$ by $N(\boldsymbol{z}_0, \boldsymbol{A}^{-1})$, we have

$$
\begin{aligned}
&\approx \frac{1}{(2\pi)^{M/2}|\boldsymbol{A}|^{-1/2}}\underbrace{exp\{-\frac{1}{2}(\boldsymbol{z}_0-\boldsymbol{z}_0)'\boldsymbol{A}(\boldsymbol{z}_0-\boldsymbol{z}_0)\}}_{1}exp(-\frac{1}{2}(\boldsymbol{z}-\boldsymbol{z}_0)'\boldsymbol{A}(\boldsymbol{z}-\boldsymbol{z}_0)) \\
&= N(\boldsymbol{z}|\boldsymbol{z}_0, \boldsymbol{A}^{-1}) = q(\boldsymbol{z})
\end{aligned}
$$

where $\boldsymbol{z}_0 = arg\ max_{\boldsymbol{z}} lnf(\boldsymbol{z})$ and $\boldsymbol{A} = -\nabla\nabla lnf(\boldsymbol{z}_0)$

2 Bayesian Logistic Regression

2.1 Posterior Distribution of Parameters

Assume we have prior density $p(\boldsymbol{w}) = N(\boldsymbol{w}|\boldsymbol{m}_0, \boldsymbol{S}_0)$
Likelihood function is $p(\boldsymbol{t}|\boldsymbol{w}) = \prod_{n=1}^{N} p(C_1|\boldsymbol{x}_n;\boldsymbol{w})^{t_n}(1-p(C_1|\boldsymbol{x}_n;\boldsymbol{w}))^{1-t_n}$ where $p(C_1|\boldsymbol{x}_n;\boldsymbol{w}) = \sigma(\boldsymbol{w}'\boldsymbol{x}_n)$
Posterior density is

$$
\begin{aligned}
p(\boldsymbol{w}|\boldsymbol{t}) &\propto p(\boldsymbol{t}|\boldsymbol{w})p(\boldsymbol{w}) \\
&= \prod_{n=1}^{N} \sigma(\boldsymbol{w}'\boldsymbol{x}_n)^{t_n}(1-\sigma(\boldsymbol{w}'\boldsymbol{x}_n))^{1-t_n} N(\boldsymbol{w}|\boldsymbol{m}_0, \boldsymbol{S}_0)
\end{aligned}
$$

which is not a well known joint density function

$$
\begin{aligned}
lnp(\boldsymbol{w}|\boldsymbol{t}) &= ln[\prod_{n=1}^{N} \sigma(\boldsymbol{w}'\boldsymbol{x}_n)^{t_n}(1-\sigma(\boldsymbol{w}'\boldsymbol{x}_n))^{1-t_n} N(\boldsymbol{w}|\boldsymbol{m}_0, \boldsymbol{S}_0)] \\
&= \sum_{n=1}^{N}[t_n ln\sigma(\boldsymbol{w}'\boldsymbol{x}) + (1-t_n)ln(1-\sigma(\boldsymbol{w}'\boldsymbol{x}))] + ln[N(\boldsymbol{w}|\boldsymbol{m}_0, \boldsymbol{S}_0)] \\
&= \sum_{n=1}^{N}[t_n ln\sigma(\boldsymbol{w}'\boldsymbol{x}) + (1-t_n)ln(1-\sigma(\boldsymbol{w}'\boldsymbol{x}))] + ln[\frac{1}{(2\pi)^{D/2}|\boldsymbol{S}_0|^{1/2}}exp\{-\frac{1}{2}(\boldsymbol{w}-\boldsymbol{m}_0)'\boldsymbol{S}_0^{-1}(\boldsymbol{w}-\boldsymbol{m}_0)\}] \\
&= \sum_{n=1}^{N}[t_n ln\sigma(\boldsymbol{w}'\boldsymbol{x}) + (1-t_n)ln(1-\sigma(\boldsymbol{w}'\boldsymbol{x}))] + ln[\frac{1}{(2\pi)^{D/2}|\boldsymbol{S}_0|^{1/2}}] - \frac{1}{2}(\boldsymbol{w}-\boldsymbol{m}_0)'\boldsymbol{S}_0^{-1}(\boldsymbol{w}-\boldsymbol{m}_0)
\end{aligned}
$$

We can approximate $p(\boldsymbol{w}|\boldsymbol{t})$ by Laplace Approximation. As a result, our posterior follows multivariate normal distribution.

$$p(\boldsymbol{w}|\boldsymbol{t}) \approx q(\boldsymbol{w}) = N(\boldsymbol{w}|\boldsymbol{w}_{MAP}, \boldsymbol{S}^{-1})$$

where $\boldsymbol{w}_{MAP} = arg\ max_{\boldsymbol{w}} lnp(\boldsymbol{w}|\boldsymbol{t})$

$$\frac{\partial lnp(\boldsymbol{w}|\boldsymbol{t})}{\partial \boldsymbol{w}}|_{\boldsymbol{w}_{MAP}} = \boldsymbol{0}$$

$$\frac{\partial \sum_{n=1}^{N}[t_n ln\sigma(\boldsymbol{w}'\boldsymbol{x}) + (1-t_n)ln(1-\sigma(\boldsymbol{w}'\boldsymbol{x}))] + ln[\frac{1}{(2\pi)^{D/2}|\boldsymbol{S}_0|^{1/2}}] - \frac{1}{2}(\boldsymbol{w}-\boldsymbol{m}_0)'\boldsymbol{S}_0^{-1}(\boldsymbol{w}-\boldsymbol{m}_0)}{\partial \boldsymbol{w}}|_{\boldsymbol{w}_{MAP}} = \boldsymbol{0}$$

$$\boldsymbol{X}'(\boldsymbol{t}-\boldsymbol{p}) - \boldsymbol{S}_0^{-1}(\boldsymbol{w}_{MAP}-\boldsymbol{m}_0) = \boldsymbol{0}$$

where $\boldsymbol{p} = (\sigma(\boldsymbol{w}'_{MAP}\boldsymbol{x}_1), \cdots, \sigma(\boldsymbol{w}'_{MAP}\boldsymbol{x}_D))'$

There is no closed form solution for $\boldsymbol{w}_{MAP}$

$$\begin{aligned}
\boldsymbol{S} &= -\nabla\nabla lnp(\boldsymbol{w}_{MAP}|\boldsymbol{t}) \\
&= -\nabla\nabla\{\sum_{n=1}^{N}[t_n ln\sigma(\boldsymbol{w}'\boldsymbol{x}) + (1-t_n)ln(1-\sigma(\boldsymbol{w}'\boldsymbol{x}))] + ln[\frac{1}{(2\pi)^{D/2}|\boldsymbol{S}_0|^{1/2}}] - \frac{1}{2}(\boldsymbol{w}-\boldsymbol{m}_0)'\boldsymbol{S}_0^{-1}(\boldsymbol{w}-\boldsymbol{m}_0)\} \\
&= -(-\boldsymbol{X}'\boldsymbol{W}\boldsymbol{X} - S_0^{-1}) \\
&= \boldsymbol{X}'\boldsymbol{W}\boldsymbol{X} + S_0^{-1}
\end{aligned}$$

where $(\boldsymbol{W})_{ii} = \sigma(\boldsymbol{w}'_{MAP}\boldsymbol{x}_i)(1-\sigma(\boldsymbol{w}'_{MAP}\boldsymbol{x}_i))$ and $(\boldsymbol{W})_{ij} = 0$ for $i \neq j$

3 Reference

Bishop, C. M. (2006). Pattern Recognition and Machine Learning. New York :Springer.