Lecture Notes 3: Scale Mixture Distribution

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Notice: In this lecture note, $X \sim \mathcal{N}(a, b)$ means that $\mu = a, \sigma^2 = b$. Prof.Zhang sometimes means $\mu = a, \sigma = b$ in the class. So the notation or results may be a little different with your notes.

2.4 Scale Mixture Distribution

We will show several distributions can be seen as the scale mixture of distributions, which is defined as follows,

$$\begin{aligned} X &\sim F(\theta) \\ \theta &\sim G(\lambda) \end{aligned}$$

, So, $T(x) = \int_\theta F(\theta)G(\lambda)d\theta$ can be seen as a scale mixture of F, where the scale has distribution G.

2.4.1 Student's t-distribution

The Student's t-distribution is a scale mixture of Gaussian distribution, where the scale has a Gamma distribution. Let $X \sim \mathcal{N}(\mu, \frac{\sigma^2}{r})$, $r \sim \text{Gamma}(\frac{\nu}{2}, \frac{\nu}{2})$, then the integral will be:

$$\begin{aligned} &\int_0^\infty \frac{r^{1/2}}{\sqrt{2\pi}\sigma} e^{-\frac{r(x-\mu)^2}{2\sigma^2}} \frac{(\frac{\nu}{2})^{\frac{\nu}{2}}}{\Gamma(\frac{\nu}{2})} r^{\frac{\nu}{2}-1} e^{-\frac{\nu}{2}r} \mathrm{d}r \\ =& \frac{(\frac{\nu}{2})^{\frac{\nu}{2}}}{\Gamma(\frac{\nu}{2})\sigma\sqrt{2\pi}} \int_0^\infty r^{\frac{\nu+1}{2}-1} e^{-\frac{r}{2}(\frac{(x-\mu)^2}{\sigma^2}+\nu)} \mathrm{d}r \\ =& \frac{(\frac{\nu}{2})^{\frac{\nu}{2}}\Gamma(\frac{\nu+1}{2})}{\sigma\sqrt{2\pi}\Gamma(\frac{\nu}{2})} \left[\frac{(x-\mu)^2}{2\sigma^2} + \frac{\nu}{2}\right]^{-\frac{\nu+1}{2}} \\ =& \frac{\Gamma(\frac{\nu+1}{2})}{\sigma\sqrt{\nu\pi}\Gamma(\frac{\nu}{2})} \left[\frac{(x-\mu)^2}{\nu\sigma^2} + 1\right]^{-\frac{\nu+1}{2}} \\ =& t_\nu(\mu, \sigma^2) \end{aligned}$$

Note that during the integral, we use a mathematical trick. Since we have

$$\int_0^\infty \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x} dx = 1$$

from Gamma distribution, so we can get $\int_0^\infty x^{\alpha-1}e^{-\beta x}dx = \frac{\Gamma(\alpha)}{\beta^\alpha}$. This trick will be often used in the follows.

2.4.2 Laplace Distribution

Laplace distribution is:

$$f(x) = \frac{1}{4\sigma}\exp(-\frac{|x-\mu|}{2\sigma})$$

Let we see 2σ as σ for convenience, that is:

$$f(x) = \frac{1}{2\sigma}\exp(-\frac{|x-\mu|}{\sigma})$$

The Laplace distribution is a scale mixture of Gaussian distribution, where the scale has a exponential distribution. Let $X \sim \mathcal{N}(\mu, r)$, $r \sim \text{Exponential}(\frac{1}{2\sigma^2})$, then we can get the mixture distribution:

$$\begin{aligned}
&\int_0^\infty \frac{1}{\sqrt{2\pi r}} e^{-\frac{(x-\mu)^2}{2r}} \frac{1}{2\sigma^2} e^{-\frac{r}{2\sigma^2}} \mathrm{d}r \\
=&\frac{1}{2\sigma^2\sqrt{2\pi}} \int_0^\infty r^{\frac{1}{2}-1} e^{-\frac{1}{2}\left(\frac{(x-\mu)^2}{r}+\frac{r}{\sigma^2}\right)} \mathrm{d}r \\
=&\frac{1}{2\sigma^2\sqrt{2\pi}} \frac{2K_{1/2}\left(\sqrt{(\frac{1}{\sigma^2}(x-\mu)^2)}\right)}{(\frac{1}{\sigma^2(x-\mu)^2})^{\frac{1}{4}}} \\
=&\frac{1}{2\sigma} e^{-\frac{|x-\mu|}{\sigma}}
\end{aligned}$$

The integral term is a integral of generalized inverse Gaussian distribution, $\text{GIG}(\frac{1}{2}, \frac{1}{\sigma^2}, (x-\mu)^2)$.

2.4.3 Negative Binomial Distribution

Negative Binomial Distribution is a scale of Poisson distribution, where the scale has a Gamma distribution. Let $K \sim \text{Poisson}(\lambda)$, $\lambda \sim \text{Gamma}(r, \frac{1-p}{p})$, then we can get the mixture distribution:

$$\begin{aligned}
&\int_0^\infty \frac{\lambda^k}{k!} e^{-\lambda} \frac{\lambda^{r-1} e^{-\frac{1-p}{p}\lambda}}{\Gamma(r)(\frac{p}{1-p})^r} \mathrm{d}\lambda \\
=&\frac{1}{k!\Gamma(r)(\frac{p}{1-p})^r} \int_0^\infty \lambda^{k+r-1} e^{-\frac{\lambda}{p}} \mathrm{d}\lambda \\
=&\frac{\Gamma(r+k)p^k(1-p)^r}{\Gamma(r)k!} \\
=&\binom{k+r-1}{k} p^k (1-p)^r
\end{aligned}$$

Homework 1: $\sum\limits_{k=0}^{\infty} \text{Gamma}(x|k+\rho+1, \beta)\text{Poisson}(k|\lambda), \rho$ is a constant, $\rho > -1$.

3 Statistical Inference (I)

Statistical inference is the process of deducing properties of an underlying distribution by analysis of data. **Maximum-likelihood estimation(MLE)** and **Maximum a posteriori probability(MAP) estimate** are two improtant methods.

Assume that we want to estimate an unobserved population parameter θ on the basis of observations x. Let f be the sampling distribution of x, so that $f(x|\theta)$ is the probability of x when the underlying population parameter is θ.And the MLE of θ is

$$\hat{\theta}_{ML}(x) = \underset{\theta}{\operatorname{argmax}} f(x|\theta)$$

Now assume that a prior distribution g over θ exists. This allows us to treat θ as a random variable as in Bayesian statistics. Then the posterior distribution of θ is $f(\theta|x) = \frac{f(x|\theta)g(\theta)}{f(x)}$. And the MAP of θ is

$$\hat{\theta}_{MAP}(x) = \underset{\theta}{\operatorname{argmax}} f(x|\theta)g(\theta)$$

Example 3.1. *In **Logistic regression**, $y \sim Bernoulli(\frac{1}{1+\exp(-a^T x)})$*

Example 3.2. *In **Least square Estimation**, $y \sim \mathcal{N}(a^T x, \sigma^2)$, $p(y) = \frac{1}{\sqrt{2\pi}\sigma}\exp(-\frac{(y-a^T x)^2}{2\sigma^2})$.*

$$\max \frac{1}{\sqrt{2\pi}\sigma}\exp(-\frac{(y-a^T x)^2}{2\sigma^2}) \Leftrightarrow \max -\frac{(y-a^T x)^2}{2\sigma^2} - log(\sigma) \Leftrightarrow \min \frac{(y-a^T x)^2}{2\sigma^2} + log(\sigma)$$

Example 3.3. *In **Ridge regression**, $p(y|a) \sim \mathcal{N}$, $p(a) \sim \mathcal{N}(0, \tau^2)$, then*

$$\min - log(p(y|a)) - log(p(a)) \Leftrightarrow \min \frac{1}{2}[(y - a^T x)^2 + \lambda||a||_2^2]$$

3.1 Jeffreys Prior

In order to show Jeffrey prior, we first introduce **Fisher information**. In mathematical statistics, the Fisher information is a way of measuring the amount of information that an observable random variable X carries about an unknown parameter θ upon which the probability of X depends.

The probability function for X, which is also the likelihood function for θ, is a function $f(X;\theta)$; it is the probability mass (or probability density) of the random variable X conditional on the value of θ. Then we define Fisher information:

Definition 3.1. *Fisher Information:*

$$I(\theta) = \mathbb{E}((\frac{\partial \log f(x;\theta)}{\partial\theta})^2) = \int (\frac{\partial \log f(x;\theta)}{\partial\theta})^2 f(x;\theta)dx$$

Lemma 3.1. *If $\log f(x;\theta)$ is twice differentiable with respect to θ and under certain regularity conditions, then*

$$I(\theta) = -\mathbb{E}(\frac{\partial^2 \log f}{\partial\theta^2})$$

Proof. first

$$\begin{aligned}\frac{\partial^2 \log f}{\partial\theta^2} &= \frac{\partial}{\partial\theta}(\frac{\partial log(f)}{\partial\theta}) \\ &= \frac{\partial}{\partial\theta}(\frac{\frac{\partial f}{\partial\theta}}{f}) \\ &= \frac{\frac{\partial^2 f}{\partial\theta^2}}{f} - \frac{(\frac{\partial f}{\partial\theta})^2}{f^2} \\ &= \frac{\frac{\partial^2 f}{\partial\theta^2}}{f} - (\frac{\partial \log f}{\partial\theta})^2\end{aligned} \tag{1}$$

then

$$\begin{aligned}\mathbb{E}(\frac{\partial^2 \log f}{\partial\theta^2}) &= \int \frac{\partial^2 \log f}{\partial\theta^2} f \mathrm{d}x \\ &= \int \frac{\partial^2 f}{\partial\theta^2}\mathrm{d}x - I(\theta)\end{aligned}$$

if $\int \frac{\partial^2 f}{\partial\theta^2}\mathrm{d}x = \frac{\partial^2}{d\theta^2}\int f\mathrm{d}x = \frac{\partial^2}{\partial\theta}1 = 0$(the certain condition),then we had proved the lemma. □

Definition 3.2. *Jeffreys prior is defined in terms of Fisher information*

$$p(\theta) \propto \sqrt{I(\theta)}$$

Remark: It has the key feature that it is **invariant under reparametrization** of parameter θ. For an alternate parametrization φ we can derive

$$p(\varphi) \propto \sqrt{I(\varphi)}$$

from

$$p(\theta) \propto \sqrt{I(\theta)}$$

where θ and φ exist a one-to-one mapping.

Proof.

$$\begin{aligned}p(\varphi) = p(\theta)|\frac{d\theta}{d\varphi}| \propto \sqrt{I(\theta)(\frac{d\theta}{d\varphi})^2} \propto \sqrt{\mathbb{E}((\frac{d\log f}{d\theta})^2)(\frac{d\theta}{d\varphi})^2} \\ \propto \sqrt{\mathbb{E}((\frac{d\log f}{d\theta}\frac{d\theta}{d\varphi})^2)} = \sqrt{\mathbb{E}((\frac{d\log f}{d\varphi})^2)} \propto \sqrt{I(\varphi)}\end{aligned}$$

□

Example 3.4. $X \sim \mathcal{N}(\mu, \sigma^2)$.

Case 1: Fix σ, the only parameter is μ. The likelihood is:

$$f(X|\mu) = \frac{1}{\sqrt{2\pi}\sigma}\exp(-\frac{1}{2\sigma^2}(x-\mu)^2)$$

so

$$\log f = -\frac{(x-\mu)^2}{2\sigma^2} + \ln(\frac{1}{\sqrt{2\pi}\sigma})$$

So we can get:

$$\begin{aligned} I(\mu) &= \mathbb{E}\left[\left(\frac{\partial \log f}{\partial \mu}\right)^2\right] \\ &= \mathbb{E}\left[\left(\frac{x-\mu}{\sigma^2}\right)^2\right] \\ &= \frac{\mathbb{E}(x-\mu)^2}{\sigma^4} \\ &= \frac{1}{\sigma^2} \end{aligned}$$

Thus the Jeffreys prior $p(\mu) \propto \sqrt{I(\mu)} = \frac{1}{\sigma}$. As σ is fixed, so $p(\mu) \propto 1$.

Remark: Although $p(\mu) = 1$ is a improper prior, as $\int_{-\infty}^{\infty} 1dx = \infty$, the posterior is proper. The prior is also called **uninformative prior**.

Case 2: Fix μ, the only parameter is σ. For convenience, let $\tau = \frac{1}{\sigma^2}$. So $f(x) = \frac{\tau^{\frac{1}{2}}}{\sqrt{2\pi}}e^{-\frac{\tau(x-\mu)^2}{2}}$. The likelihood is denoted by $f(\tau)$:

$$\begin{aligned} & f(\tau) = \tfrac{\tau^{\frac{1}{2}}}{\sqrt{2\pi}}\exp(-\tfrac{\tau(x-\mu)^2}{2}) \\ \Longrightarrow\quad & \log f \propto \tfrac{1}{2}\log\tau - \tfrac{\tau}{2}(x-\mu)^2 + C \\ \Longrightarrow\quad & \tfrac{\partial \log f}{\partial \tau} \propto \tfrac{1}{2\tau} - \tfrac{(x-\mu)^2}{2} \end{aligned}$$

Hence,

$$\begin{aligned} I(\tau) &= \mathbb{E}\left[\left(\frac{\partial \log f}{\partial \tau}\right)^2\right] \\ &= \mathbb{E}\left[\frac{1}{4}\left(\frac{1}{\tau} - (x-\mu)^2\right)^2\right] \\ &= \mathbb{E}\left[\frac{1}{4\tau^2} - \frac{(x-\mu)^2}{2\tau} + \frac{(x-\mu)^4}{4}\right] \\ &= \frac{1}{4\tau^2} - \frac{1}{2\tau^2} + \frac{1}{4}\mathbb{E}(x-\mu)^4 \\ &= \frac{1}{4\tau^2} - \frac{1}{2\tau^2} + \int_{-\infty}^{\infty}\frac{1}{4}(x-\mu)^4\mathcal{N}(x|\mu,\tau^{-1})dx \\ &= \frac{1}{2\tau^2} \end{aligned}$$

where the integral can be computed from variance :

$$
\begin{aligned}
&\int (x-\mu)^2 \frac{\tau^{\frac{1}{2}}}{\sqrt{2\pi}} \exp(-\frac{\tau(x-\mu)^2}{2})dx = \tau^{-1} \\
\Longrightarrow &\int (x-\mu)^2 \frac{1}{\sqrt{2\pi}} \exp(-\frac{\tau(x-\mu)^2}{2})dx = \tau^{-\frac{3}{2}} \\
&\text{(taking the derivate of both side)} \\
\Longrightarrow &\int (x-\mu)^4 \frac{1}{\sqrt{2\pi}} \exp(-\frac{\tau(x-\mu)^2}{2})dx = 3\tau^{-\frac{5}{2}} \\
\Longrightarrow &\int (x-\mu)^4 \frac{\tau^{\frac{1}{2}}}{\sqrt{2\pi}} \exp(-\frac{\tau(x-\mu)^2}{2})dx = 3\tau^{-2} \\
\Longrightarrow &\mathbb{E}\left((x-\mu)^4\right) = \frac{3}{\tau^2}
\end{aligned}
$$

So Jeffreys prior is $\pi(\tau) \propto \frac{1}{\tau}$. Note that $p(\sigma) = \pi(\tau)|d\tau/d\theta|$, hence,

$$
\begin{aligned}
p(\sigma) \propto &\quad \tfrac{1}{\tau}|-2\sigma^{-3}| \\
\propto &\quad \sigma^2|-2\sigma^{-3}| \\
\propto &\quad \tfrac{1}{\sigma}
\end{aligned}
$$

Homework 2: Compute the following integrals:

1. $u_0 = \int_{-\infty}^{\infty} \Phi(x)\mathcal{N}(x|\mu,\sigma^2)dx$
2. $u_1 = \int_{-\infty}^{\infty} \Phi(x)\mathcal{N}(x|\mu,\sigma^2)xdx$
3. $u_2 = \int_{-\infty}^{\infty} \Phi(x)\mathcal{N}(x|\mu,\sigma^2)(x-m_1)^2dx$

   where $\Phi(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}}e^{-\frac{t^2}{2}}dt$

Example 3.5. $X \sim Poisson(n;\lambda)$

$$\log f = -\lambda + n\log\lambda$$

Fisher information is:

$$
\begin{aligned}
I(\lambda) &= \mathbb{E}\left[\left(\frac{n}{\lambda}-1\right)^2\right] \\
&= 1 + \frac{\mathbb{E}(n^2)}{\lambda^2} - 2 \\
&= \frac{\lambda+1}{\lambda} - 1 \\
&= \frac{1}{\lambda}
\end{aligned}
$$

So Jeffreys prior is:

$$p(\lambda) \propto \sqrt{\frac{1}{\lambda}}.$$

Homework 3: $f(x;\theta) = \theta^x(1-\theta)^{1-x}$, $0 < \theta < 1$.

1. Compute Jeffreys prior about θ.
2. If $\theta = \sin^2\alpha$, compute Jeffreys prior about α.

3.2 Compute Posterior Probability

Assume we have a model $x = \theta + \epsilon$, where x is data which we observed or predict, θ is the parameters, $\epsilon \sim \mathcal{N}(0,\tau)$ is the error term. So given θ, $X \sim \mathcal{N}(\theta,\tau)$. When we use MAP(maximum a posteriori) to estimate parameter θ, we will get $p(\theta|x) \propto p(x|\theta)p(\theta)$. We will discuss this problem under several different conditions in the following.

Case 1 Fix τ. The only parameter is θ. And we set the prior about θ is $\mathcal{N}(\theta|0,\lambda)$. So

$$\begin{aligned}
p(\theta|x) &\propto p(x|\theta)p(\theta) \\
&\propto \frac{1}{\sqrt{2\pi\tau}}e^{-\frac{(x-\theta)^2}{2\tau}}\frac{1}{\sqrt{2\pi\lambda}}e^{-\frac{\theta^2}{2\lambda}} \\
&\propto \frac{1}{2\pi\sqrt{\tau\lambda}}e^{-\frac{1}{2}[(\frac{1}{\tau}+\frac{1}{\lambda})(\theta-\frac{\lambda x}{\tau+\lambda})^2+\frac{x^2}{\tau+\lambda}]} \\
&\propto \mathcal{N}(\frac{\lambda x}{\lambda+\tau},\frac{\lambda\tau}{\lambda+\tau})
\end{aligned}$$

Then we can get the estimation about θ from MAP, $\hat{\theta} = \frac{\lambda x}{\lambda+\tau}$.

Case 2 Let θ and τ both be parameters. In order to get MAP, we may make three solutions.

Solution 1 Assume that τ, λ are independent. $p(\theta,\tau) = p(\theta)p(\tau)$ and we use a new τ,λ here, $\tau = \tau_{old}^{-1}, \lambda = \lambda_{old}^{-1}$ for convenience of computing(It is different with the τ,λ used in case 1). Suppose $\tau \sim \text{Gamma}(\alpha/2,\beta/2)$

$$\begin{aligned}
p(\theta,\tau|x) &\propto p(x|\theta,\tau)p(\theta,\tau) = p(x|\theta,\tau)p(\theta)p(\tau) \\
&\propto \frac{1}{\sqrt{2\pi}}\tau^{\frac{1}{2}}\exp(-\frac{\tau(x-\theta)^2}{2})\frac{\lambda^{\frac{1}{2}}}{\sqrt{2\pi}}\exp(-\frac{\lambda\theta^2}{2})(\frac{\beta}{2})^{\frac{\alpha}{2}}\exp(-\frac{\beta\tau}{2})\frac{\tau^{\frac{\alpha}{2}-1}}{\Gamma(\alpha/2)}
\end{aligned}$$

To get maximum posterior, let

$$L = \tau^{\frac{\alpha+1}{2}-1}\exp(-\frac{\tau}{2}((x-\theta)^2+\beta)-\frac{\lambda\theta^2}{2})$$

then

$$\ln L = (\frac{\alpha+1}{2}-1)\ln\tau - \frac{\tau}{2}((x-\theta)^2+\beta)-\frac{\lambda\theta^2}{2}$$

Let

$$Q = -2\ln L = -(\alpha - 1)\ln \tau + \tau((x-\theta)^2 + \beta) + \lambda\theta^2$$

We need to solve equations:

$$\begin{cases} \frac{\partial Q}{\partial \theta} & = -2\tau(x-\theta) + 2\lambda\theta = 0 \\ \frac{\partial Q}{\partial \tau} & = \frac{1-\alpha}{\tau} + (x-\theta)^2 + \beta = 0 \end{cases}$$

It is a difficult problem to solve, especially when θ is a vector.

Remark : One way to solve the problem above is to compute one parameter, for example θ, while fixing the other parameter, i.e. τ. Then fix θ, compute θ. Hold on until they get convergent. Well, then we need to think about the convergence problem.

Solution 2 Assume $p(\theta, \tau) = p(\theta|\tau)p(\tau)$, and $p(\theta|\tau) \sim \mathcal{N}(0, (\lambda\tau)^{-1})$, suppose $\tau \sim \text{Gamma}(\alpha/2, \beta/2)$, follow the same steps in solution 1, we get:

$$\begin{aligned} p(\theta, \tau|x) &\propto p(x|\theta, \tau)p(\theta|\tau)p(\tau) \\ &\propto \frac{\tau^{\frac{1}{2}}}{\sqrt{2\pi}} e^{-\frac{\tau(x-\theta)^2}{2}} \frac{(\lambda\tau)^{\frac{1}{2}}}{\sqrt{2\pi}} e^{-\frac{\lambda\tau\theta^2}{2}} (\frac{\beta}{2})^{\frac{\alpha}{2}} e^{(-\frac{\beta\tau}{2})} \frac{\tau^{\frac{\alpha}{2}-1}}{\Gamma(\alpha/2)} \end{aligned}$$

Then the corresponding L is given by:

$$L = \tau^{\frac{\alpha+1}{2}-1}(\lambda\tau)^{\frac{1}{2}} \exp(-\frac{\tau}{2}((x-\theta)^2 + \beta) - \frac{\lambda\tau\theta^2}{2}).$$

Then the Q is

$$Q = -2\ln L = -(\alpha - 1)\ln \tau + \tau((x-\theta)^2 + \beta) - \ln(\lambda\tau) + \lambda\tau\theta^2$$

To get the estimation of θ and τ, we need to solve:

$$\begin{cases} \frac{\partial Q}{\partial \theta} = 0 \\ \frac{\partial Q}{\partial \tau} = 0 \end{cases}$$

Then we will get:

$$\begin{cases} -\tau(x-\theta) + \tau\lambda = 0 \\ \beta - \frac{\alpha-1}{\tau} - \frac{1}{\tau} + (x-\theta)^2 + \lambda\theta^2 = 0 \end{cases}$$

We can easily solve θ and τ. It is called **decouple**.

Solution 3 From the two sub-cases above, we can find the major problem is computing complexity. Another problem will occurs if there are too many hyper-parameters. As we need to search the best hyper-parameters by grid search. So if there are 2 hyper-parameters, the search space is 2-dimensional. If there are 3 hyper-parameters, the search space is 3-dimensional... It will cost too much time when the search space is high dimensional.

Simply, we can give an uninformative prior to τ, $p(\tau) \propto 1$. Or we can consider Jeffreys prior for τ. According to Example 3.1, case 2,we get $p(\tau) \propto \frac{1}{\tau}$. So we will have:

$$
\begin{aligned}
p(\theta, \tau|x) &\propto p(x|\theta, \tau)p(\theta|\tau)p(\tau) \\
&\propto \frac{1}{\sqrt{2\pi\tau}} e^{-\frac{(x-\theta)^2}{2\tau}} \frac{1}{\sqrt{2\pi\lambda\tau}} e^{-\frac{\theta^2}{2\lambda\tau}} \frac{1}{\tau} = L
\end{aligned}
$$

Removing constants, we will get:

$$
Q = -2\ln L = 3\ln\tau + \ln(\lambda\tau) + \frac{(x-\theta)^2}{\tau} + \frac{\theta^2}{\lambda\tau}
$$

Then according to $\frac{\partial Q}{\partial \theta} = 0$ and $\frac{\partial Q}{\partial \tau} = 0$, we will get the followings:

$$
\begin{cases}
-2(x-\theta) + \frac{2\theta}{\lambda} = 0 \\
\frac{3}{\tau} + \frac{1}{\tau} - \frac{1}{\tau^2}\left(\frac{(x-\theta)^2}{2} + \frac{\theta^2}{\lambda}\right) = 0
\end{cases}
$$

We can see it is easy to solve and there is no extra parameter.(Solution 2 has two new parameters, α and β)