

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,

$$X \sim F(\theta)$$

$$\theta \sim G(\lambda)$$

, 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:

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

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:

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

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

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

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:

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

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:

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

Homework 1: $\sum_{k=0}^{\infty} \text{Gamma}(x|k + \rho + 1, \beta) \text{Poisson}(k|\lambda)$, ρ 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 important 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*, $y \sim \text{Bernoulli}(\frac{1}{1+\exp(-a^T x)})$

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

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

then

$$\begin{aligned}
\mathbb{E} \left(\frac{\partial^2 \log f}{\partial \theta^2} \right) &= \int \frac{\partial^2 \log f}{\partial \theta^2} f dx \\
&= \int \frac{\partial^2 f}{\partial \theta^2} dx - I(\theta)
\end{aligned}$$

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

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.

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

\square

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

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

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

so

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

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 $f(\tau)$:

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

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 :

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

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

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

Homework 2: Compute the following integrals:

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

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

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

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

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:

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

Then the corresponding L is given by:

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

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)