

- **Problem Descriptions**

We generate N paths of the MCMC sampling for the CIR bond prices $B_{CIR}(t), t = 1, 2, \dots, T$ and contingent payoffs $\{P_{CAT}(Y_t), t = 1, 2, \dots, T\}$, denote them by

$$\left\{ \left({}_1B_{CIR}^{(i)}, {}_1P_{CAT}^{(i)} \right), \left({}_2B_{CIR}^{(i)}, {}_2P_{CAT}^{(i)} \right), \dots, \left({}_TB_{CIR}^{(i)}, {}_TP_{CAT}^{(i)} \right), i = 1, 2, \dots, N \right\}$$

Let π denote the *physical* distribution of the N paths of the MCMC sampling with equal probability of $1/N$ on each path. We convert π into the risk-neutral version π^* with a constraint such that

$$\sum_{i=1}^N \pi_i^* \sum_{t=1}^T \exp(\delta t) \left({}_tB_{CIR}^{(i)} \cdot {}_tP_{CAT}^{(i)} \right) = V_o$$

where V_o is a vector of N equally probable (under the *physical* distribution, π) market prices of the bond at some time $t = 0$

$$V_o = \sum_{i=1}^N \pi_i \sum_{t=1}^T {}_tB_{CIR}^{(i)} \exp(\delta t) {}_tP_{CAT}^{(i)} \text{ for } i = 1, \dots, N \quad (1)$$

where,

$$\pi_i = \frac{1}{N}$$

Based on the maximum entropy principle the risk-neutral distribution π^* should minimize the Kullback-Leibler information divergence

$$KL(\mathbb{P} \parallel \mathbb{Q}) : \arg \min \sum_{i=1}^N \pi_i^* \ln \left(\frac{\pi_i^*}{\pi_i} \right)$$

with the following additional constraints

$$\pi_i^* > 0, \text{ for } i = 1, \dots, N,$$

$$\sum_{i=1}^N \pi_i^* = 1$$

$$\sum_{i=1}^N \pi_i^* \sum_{t=1}^T \exp(\delta t) \left({}_tB_{CIR}^{(i)} \cdot {}_tP_{CAT}^{(i)} \right) = V_o$$

● Lagrange Dual Function

This KL divergence minimization problem is a convex optimization problem, and it can be solved by the method of Lagrange multipliers as follows.

$$\mathcal{L} = \sum_{i=1}^N \pi_i^* \ln\left(\frac{\pi_i^*}{\pi_i}\right) - \gamma \left(\sum_{i=1}^N \pi_i^* - 1 \right) - \lambda \left[\left\{ \sum_{i=1}^N \pi_i^* \sum_{t=1}^T \exp(\delta t) \left({}_tB_{CIR}^{(i)} \cdot {}_tP_{CAT}^{(i)} \right) \right\} - V_o \right]$$

$$\gamma \in R, \lambda \in R$$

Taking first order conditions with respect to π_i^* , we get

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial \pi_i^*} &= \ln \frac{\pi_i^*}{\pi_i} + 1 - \gamma - \lambda \left[\sum_{t=1}^T \exp(\delta t) \left({}_tB_{CIR}^{(i)} \cdot {}_tP_{CAT}^{(i)} \right) \right] = 0 \\ \exp \left(\ln \frac{\pi_i^*}{\pi_i} + 1 - \gamma - \lambda \left[\sum_{t=1}^T \exp(\delta t) \left({}_tB_{CIR}^{(i)} \cdot {}_tP_{CAT}^{(i)} \right) \right] \right) &= 1 \\ \exp \left(\ln \pi_i^* - \ln \pi_i + 1 - \gamma - \lambda \left[\sum_{t=1}^T \exp(\delta t) \left({}_tB_{CIR}^{(i)} \cdot {}_tP_{CAT}^{(i)} \right) \right] \right) &= 1 \\ \pi_i^* &= \pi_i \exp \left(-1 + \gamma + \lambda \left[\sum_{t=1}^T \exp(\delta t) \left({}_tB_{CIR}^{(i)} \cdot {}_tP_{CAT}^{(i)} \right) \right] \right) \\ \pi_i^* &= \exp(-1 + \gamma) \pi_i \exp \left(\lambda \sum_{t=1}^T \exp(\delta t) \left({}_tB_{CIR}^{(i)} \cdot {}_tP_{CAT}^{(i)} \right) \right) \quad (2) \end{aligned}$$

Since $\sum_{i=1}^N \pi_i^* = 1$ and $\sum_{i=1}^N \pi_i = 1$, it follows that

$$\sum_{i=1}^N \pi_i^* = \exp(-1 + \gamma) \sum_{i=1}^N \pi_i \exp \left(\lambda \sum_{t=1}^T \exp(\delta t) \left({}_tB_{CIR}^{(i)} \cdot {}_tP_{CAT}^{(i)} \right) \right) = 1$$

Dividing through, we get

$$\exp(-1 + \gamma) = \frac{1}{\sum_{i=1}^N \pi_i \exp \left(\lambda \sum_{t=1}^T \exp(\delta t) \left({}_tB_{CIR}^{(i)} \cdot {}_tP_{CAT}^{(i)} \right) \right)} \quad (3)$$

Insert equation (3) in to equation (2) to get

$$\pi_i^* = \frac{\pi_i \exp \left(\lambda \sum_{t=1}^T \exp(\delta t) \left({}_t B_{CIR}^{(i)} \cdot {}_t P_{CAT}^{(i)} \right) \right)}{\sum_{i=1}^N \pi_i \exp \left(\lambda \sum_{t=1}^T \exp(\delta t) \left({}_t B_{CIR}^{(i)} \cdot {}_t P_{CAT}^{(i)} \right) \right)} \text{ for } i = 1, \dots, N, t = 1, \dots, T. \quad (4)$$

Let $\alpha_i \triangleq \sum_{t=1}^T \exp(\delta t) \left({}_t B_{CIR}^{(i)} \cdot {}_t P_{CAT}^{(i)} \right)$ then (4) can be simplified as
i.e.

$$\pi_i^* = \frac{\pi_i \exp(\lambda \alpha_i)}{\sum_{i=1}^N \pi_i \exp(\lambda \alpha_i)} \quad (5)$$

Let $\Gamma = \max_{i=1, \dots, N} \lambda \alpha_i$

Then (5) is equivalent to

$$\pi_i^* = \frac{\pi_i \exp(\lambda \alpha_i - \Gamma)}{\sum_{i=1}^N \pi_i \exp(\lambda \alpha_i - \Gamma)}$$

This can be used to calculate π_i^* once λ is known, in order to avoid overflow in the numerical calculation of exp.

● Solving the dual problem by equivalence to another minimization problem

The followings are steps to calculate λ .

First, (1) can be simplified as

$$\sum_{i=1}^N \pi_i^* \alpha_i = V_o \quad (6)$$

Substituting (5) into (6), it comes to

$$\sum_{i=1}^N \frac{\pi_i \exp(\lambda \alpha_i)}{\sum_{i=1}^N \pi_i \exp(\lambda \alpha_i)} \alpha_i = V_o$$

Remember that $\pi_i = \frac{1}{N}$, so

$$\frac{\sum_{i=1}^N \alpha_i \exp(\lambda \alpha_i)}{\sum_{i=1}^N \exp(\lambda \alpha_i)} = V_o \quad (7)$$

This happens to be the minimizer of the following minimization problem

$$\min_{\lambda} \sum_{i=1}^N \exp[\lambda\{\alpha_i - V_o\}] \quad (8)$$

This can be proved by the following steps:

$$\text{Let } f(\lambda) = \sum_{i=1}^N \exp[\lambda\{\alpha_i - V_o\}]$$

Then

$$\begin{aligned} \frac{df}{d\lambda} &= \sum_{i=1}^N \{\alpha_i - V_o\} \exp[\lambda\{\alpha_i - V_o\}] \\ &= \exp[-\lambda V_o] \sum_{i=1}^N \{\alpha_i - V_o\} \exp[\lambda\alpha_i] \end{aligned}$$

Let $\frac{df}{d\lambda} = 0$, leading to

$$\exp[-\lambda V_o] \sum_{i=1}^N \{\alpha_i - V_o\} \exp[\lambda\alpha_i] = 0$$

i.e.

$$\begin{aligned} \sum_{i=1}^N \{\alpha_i - V_o\} \exp[\lambda\alpha_i] &= 0 \\ \sum_{i=1}^N \alpha_i \exp[\lambda\alpha_i] &= V_o \sum_{i=1}^N \exp[\lambda\alpha_i] \end{aligned}$$

i.e.

$$\frac{\sum_{i=1}^N \alpha_i \exp[\lambda\alpha_i]}{\sum_{i=1}^N \exp[\lambda\alpha_i]} = V_o$$

That is the same form as (7). So solving the minimization problem (8) is the identical to solving the equation (7).

The minimization problem can be solved by **scipy.optimize.minimize_scalar**.

● Domain of δ

The domain of δ should be depending on $\{\alpha_i\}$, this can be proved from the followings:

Note that,

$$\sum_{i=1}^N \pi_i^* \alpha_i = V_o$$

$$\sum_{i=1}^N \pi_i^* = 1$$

So

$$\max_{\pi_i^*} \sum_{i=1}^N \pi_i^* \alpha_i = \max\{\alpha_1, \alpha_2, \dots, \alpha_N\}$$

Then it requires that

$$V_o \leq \max\{\alpha_1, \alpha_2, \dots, \alpha_N\}$$

Howeve, from Eq. (1.1)

$$V_o = \frac{1}{N} \sum_{i=1}^N \sum_{t=1}^T \exp(\delta t) {}_tB_{CIR}^{(i)} {}_tP_{CAT}^{(i)} \text{ for } i = 1, \dots, N$$

So the choice of δ should satisfy that

$$\frac{1}{N} \sum_{i=1}^N \sum_{t=1}^T \exp(\delta t) {}_tB_{CIR}^{(i)} {}_tP_{CAT}^{(i)} \leq \max\{\alpha_1, \alpha_2, \dots, \alpha_N\}$$

Let function $f(\delta) = \frac{1}{N} \sum_{i=1}^N \sum_{t=1}^T \exp(\delta t) {}_tB_{CIR}^{(i)} {}_tP_{CAT}^{(i)}$

It is a function of δ and its is increasing function when δ is increasing

Let function $h(\delta) = \frac{1}{N} \sum_{i=1}^N \sum_{t=1}^T \exp(\delta t) {}_tB_{CIR}^{(i)} {}_tP_{CAT}^{(i)} - \max\{\alpha_1, \alpha_2, \dots, \alpha_N\}$

So the root of $h(\delta)$, i.e. δ^* to satisfy $h(\delta^*) = 0$ is the solution we need.