

# Applying the importance sampling to regression

---

Jieun Shin

December 15, 2021

1. Introduction
2. Methodology
3. Choice the optimal reference parameter
4. Simulation

## 1. Introduction

---

# 1. Introduction

- Objective: Comparison of variance reduction methods for estimating extreme event probability,  $\ell = \mathbb{E}[Y > \gamma]$ , in simple linear regression.
- Let  $Y$  be the response variable of simple linear regression:

$$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i \quad \text{where } \epsilon \sim N(0, \sigma^2),$$

for  $i = 1, \dots, n$ .

- Importance sampling using least square estimator.
- Comparison of results when using two suggested distributions in regression.
- Check if variance reduction occur.

## 2. Methodology

---

### Estimation of rare-event probabilities

- Let the parameter set for target distribution as  $\boldsymbol{\theta}^* = (\sigma^{*2}, \beta_0^*, \beta_1^*)$  and proposed distribution as  $\boldsymbol{\theta} = (\sigma^2, \beta_0, \beta_1)$ .
- We want to estimate of

$$\ell = \mathbb{P}_{\boldsymbol{\theta}^*}(Y \geq \gamma) = \mathbb{E}_{\boldsymbol{\theta}^*}[I\{Y \geq \gamma\}] \quad (1)$$

for some fixed level  $\gamma$ .

- $Y$  is a random vector with pdf  $f(\cdot, \boldsymbol{\theta}^*)$  belonging to parametric family  $\{f(\cdot, \boldsymbol{\theta}), \boldsymbol{\theta} \in \boldsymbol{\Theta}\}$ , and  $\{Y \geq \gamma\}$  is assumed to be a rare event.

### Importance sampling estimator

- The importance sampling estimator  $\hat{\ell}_{IS}$  is defined as

$$\hat{\ell}_{IS} = \frac{1}{N} \sum_{k=1}^N I(Y_k > \gamma) W(Y_k; \boldsymbol{\theta}^*, \boldsymbol{\theta}), \quad (2)$$

where  $W(Y_k; \boldsymbol{\theta}^*, \boldsymbol{\theta}) = f(Y_k; \boldsymbol{\theta}^*)/f(Y_k; \boldsymbol{\theta})$  is the likelihood ratio.

- We consider two methods to choose the *optimal reference parameter*  $\boldsymbol{\theta}$ .
  1. Cross-entropy method
  2. Least square estimator

### 3. Choice the optimal reference parameter

---



### 3. Choice the optimal reference parameter

#### Cross-entropy (CE) method

- The optimal CE reference parameter  $\hat{\theta}_{CE}$  is defined as

$$\hat{\theta}_{CE} = \operatorname{argmax}_{\theta} \mathbb{E}_{\tilde{\theta}} \left[ I(Y_k > \gamma) W(Y_k; \theta^*, \tilde{\theta}) \ln f(Y_k; \theta) \right], \quad (3)$$

where  $\tilde{\theta}$  is an *arbitrary tilting parameter*.

- We can estimate  $\hat{\theta}_{CE}$  as the solution of the stochastic program

$$\hat{\theta}_{CE} = \operatorname{argmax}_{\theta} \frac{1}{N} \sum_{k=1}^N I(Y_k > \gamma) W(Y_k; \theta^*, \tilde{\theta}) \ln f(Y_k; \theta), \quad (4)$$

where  $Y_1, \dots, Y_N$  is a random sample from  $f(Y_k; \tilde{\theta})$ .

### 3. Choice the optimal reference parameter

#### Cross-entropy (CE) method

1. Find the optimal  $\hat{\sigma}_{CE}^2$  as the solution of the stochastic program

$$\hat{\sigma}_{CE}^2 = \operatorname{argmax}_{\sigma^2} \frac{1}{N} \sum_{k=1}^N I(\varepsilon_k > \gamma) W(\varepsilon_k; \sigma^{*2}, \tilde{\sigma}^2) \ln f(\varepsilon_k; \sigma^2) \quad (5)$$

$$= \frac{\sum_{k=1}^N I(\varepsilon_k > \gamma) W(\varepsilon_k; \sigma^{*2}, \tilde{\sigma}^2) \varepsilon_k^2}{\sum_{k=1}^N I(\varepsilon_k > \gamma) W(\varepsilon_k; \sigma^{*2}, \tilde{\sigma}^2)}, \quad (6)$$

where the error  $\varepsilon_k \sim N(0, \tilde{\sigma}^2)$ .

### 3. Choice the optimal reference parameter

#### Cross-entropy (CE) method

2. Find the optimal  $\hat{\beta}_{0CE}$  as the solution of the stochastic program:

$$\hat{\beta}_{0CE} = \underset{\beta_0}{\operatorname{argmax}} \frac{1}{N} \sum_{k=1}^N I(Y_k > \gamma) W(Y_k; \beta_0^*, \tilde{\beta}_0) \ln f(Y_k; \beta_0) \quad (7)$$

$$= \frac{\sum_{k=1}^N I(Y_k > \gamma) W(Y_k; \beta_0^*, \tilde{\beta}_0) (Y_k - \tilde{\beta}_1 X_k)}{\sum_{k=1}^N I(Y_k > \gamma) W(Y_k; \beta_0^*, \tilde{\beta}_0)}, \quad (8)$$

where the response variable  $Y_k \sim N(\tilde{\beta}_0 + \tilde{\beta}_1 X_k, \tilde{\sigma}^2)$ .

### 3. Choice the optimal reference parameter

#### Cross-entropy (CE) method

3. Find the optimal  $\hat{\beta}_{1CE}$  as the solution of the stochastic program:

$$\hat{\beta}_{1CE} = \underset{\beta_1}{\operatorname{argmax}} \frac{1}{N} \sum_{k=1}^N I(Y_k > \gamma) W(Y_k; \beta_1^*, \tilde{\beta}_1) \ln f(Y_k; \beta_1) \quad (9)$$

$$= \frac{\sum_{k=1}^N I(Y_k > \gamma) W(Y_k; \beta_1^*, \tilde{\beta}_1) X_k (Y_k - \tilde{\beta}_0)}{\sum_{k=1}^N I(Y_k > \gamma) W(Y_k; \beta_1^*, \tilde{\beta}_1) X_k^2}, \quad (10)$$

where the response variable  $Y_k \sim N(\tilde{\beta}_0 + \tilde{\beta}_1 X, \tilde{\sigma}^2)$ .

### 3. Choice the optimal reference parameter

#### Least square estimator

We choose the optimal reference parameter as least square estimator as follows:

$$\hat{\sigma}_{LS}^2 = \operatorname{argmin}_{\sigma^2} \sum_{k=1}^N \varepsilon_k^2, \quad (11)$$

$$\hat{\beta}_{0LS} = \operatorname{argmin}_{\beta_0} \sum_{k=1}^N (Y_k - \tilde{\beta}_0 - \tilde{\beta}_1 X_k)^2, \quad (12)$$

$$\hat{\beta}_{1LS} = \operatorname{argmin}_{\beta_1} \sum_{k=1}^N (Y_k - \tilde{\beta}_0 - \tilde{\beta}_1 X_k)^2, \quad (13)$$

where the response variable  $\varepsilon_k \sim N(0, \tilde{\sigma}^2)$ ,  $Y_k \sim N(\tilde{\beta}_0 + \tilde{\beta}_1 X_k, \tilde{\sigma}^2)$ .

## 4. Simulation

---

### Simulation setting

- Set the parameter of target distribution as  $\sigma^{*2} \in \{\sqrt{0.4}, \sqrt{12}\}$ ,  $\beta_0^* = 5$ ,  $\beta_1^* = 3$ .  
and  $X_k \sim U(0, 1)$  and  $\varepsilon_k \sim N(0, \sigma^{*2})$  then  
 $Y_k = \beta_0^* + \beta_1^* X_k + \varepsilon_k, k = 1, \dots, N$ .
- Set the large value  $\gamma$  is 99.95% quantile value of  $Y$ .
- Sample size:  $N = 10^6$ .

## 4. Simulation

**Table 1:**  $\sigma^{*2} = \sqrt{0.4}$ ,  $\tilde{\sigma}^2 = 1$ ,  $\tilde{\beta}_0 = 7$ ,  $\tilde{\beta}_1 = 7$

Method	$\hat{\sigma}^2$	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\ell}$	$\text{Var}(\hat{\ell})$	relative error
CMC	-	-	-	0.000500	0.0000223551	0.0447102
IS-CE	0.40025	3.048124	6.999594	0.000464	0.0000032378	0.0069722
IS-LS	0.99992	6.999022	7.000913	0.000349	0.0000972918	0.2782808

**Table 2:** Table2.  $\sigma = \sqrt{12}$ ,  $\tilde{\sigma}^2 = 1$ ,  $\tilde{\beta}_0 = 10$ ,  $\tilde{\beta}_1 = 10$

Method	$\hat{\sigma}^2$	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\ell}$	$\text{Var}(\hat{\ell})$	relative error
CMC	-	-	-	0.000500	0.0000223551	0.0447102
IS-CE	7.86831	10.14025	9.936445	0.000520	0.0000020892	0.0040148
IS-LS	0.99992	9.999022	10.00091	0.000440	0.0000105115	0.0238859