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The standard MC estimator is:

$$\widehat{CVaR}_\alpha^{(MC)}(L) = \frac{1}{\sum_{i=1}^{n} I_{(q_\alpha,+\infty)}(L^{(i)})} \sum_{i=1}^{n} L^{(i)} I_{(q_\alpha,+\infty)}(L^{(i)}),$$

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$\widehat{CVaR}_\alpha^{(MC)}(L)$ is unstable, i.e. it has a very high variance, if the number of simulation runs is not very high.

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Let X be a r.v. in a probability space $(\Omega, \mathcal{F}, P)$ with absolutely continuous distribution function and density function f.

Goal: Determine $\theta = E(h(X)) = \int_{-\infty}^{\infty} h(x)f(x)dx$ for some given function h.

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In case of rare events, e.g. $h(x) = I_A(x)$ with $P(A) << 1$, the convergence is very slow.

Importance sampling (contd.)

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Let g be a probability density function, such that $f(x) > 0 \Rightarrow g(x) > 0$.

We define the *likelihood ratio* as: $r(x) := \begin{cases} \frac{f(x)}{g(x)} & g(x) > 0 \\ 0 & g(x) = 0 \end{cases}$

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g is called *importance sampling density* (IS density).

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Goal: choose an IS density g such that the variance of the IS estimator is much smaller than the variance of the standard MC-estimator.

$$var\left(\hat{\theta}_n^{(IS)}\right) = \frac{1}{n}(E_g(h^2(X)r^2(X)) - \theta^2)$$

$$var\left(\hat{\theta}_n^{(MC)}\right) = \frac{1}{n}(E(h^2(X)) - \theta^2)$$

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For $g^*(x) = f(x)h(x)/E(h(x))$ we get : $\hat{\theta}_1^{(IS)} = h(X_1)r(X_1) = E(h(X))$.

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Goal: choose g such that $E_g(h^2(X)r^2(X))$ becomes small, i.e. such that $r(x)$ is small for $x \geq c$. Aquivalently, the event $X \geq c$ should be more probable under density g than under density f.

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For example for the estimation of the tail probability?

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(A unique solution of the above equality exists for all relevant values of c, see e.g. Embrechts et al. for a proof).

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Let X be a r.v. in $(\Omega, \mathcal{F}, P)$ such that $M_X(t) = E^P(\exp\{tX\}) < \infty$, $\forall t$.

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We have $\frac{dP}{dQ_t} = M_X(t)\exp(-tX) =: r_t(X)$.
The IS algorithm does not change: Simulate independent realisations of X_i in $(\Omega, \mathcal{F}, Q_t)$ and set $\hat{\theta}_n^{(IS)} = (1/n)\sum_{i=1}^n X_i r_t(X_i)$.

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Y_i are the loss indicators with default probability $\bar{p}_i$ and $e_i = (1 - \lambda_i) L_i$ are the positive deterministic exposures in the case that a corresponding loss happens. λ_i are the recovery rates and L_i are the credit nominals, for $i = 1, 2, \ldots, m$.

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Consider the loss function of a credit portfolio $L = \sum_{i=1}^{m} e_i Y_i$.

Y_i are the loss indicators with default probability $\bar{p}_i$ and $e_i = (1 - \lambda_i) L_i$ are the positive deterministic exposures in the case that a corresponding loss happens. λ_i are the recovery rates and L_i are the credit nominals, for $i = 1, 2, \ldots, m$.

Let Z be a vector of economical impact factors, such that $Y_i | Z$ are independent and $Y_i | (Z = z) \sim Bernoulli(p_i(z))$, $\forall i = 1, 2, \ldots, m$.

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Simplified case: Y_i are independent for $i = 1, 2, \ldots, m$.
Let $\Omega = \{0, 1\}^m$ be the state space of the random vector Y.
Consider the probability measure P in Ω:

$$P(\{y\}) = \prod_{i=1}^{m} \bar{p}_i^{y_i}(1-\bar{p}_i)^{1-y_i},\ y \in \{0,1\}^m.$$

The moment generating function of L is $M_L(t) = \prod_{i=1}^{m}(e^{te_i}\bar{p}_i + 1 - \bar{p}_i)$.

IS in the case of Bernoulli mixture models (contd.)

Consider a probability measure Q_t:

$$Q_t(\{y\}) = \prod_{i=1}^{n} \left(\frac{\exp\{te_i y_i\}}{\exp\{te_i\}\bar{p}_i + 1 - \bar{p}_i} \bar{p}_i^{y_i} (1 - \bar{p}_i)^{1-y_i} \right).$$

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Let $\bar{q}_{t,i}$ be new default probabilities

$$\bar{q}_{t,i} := \exp\{te_i\}\bar{p}_i / (\exp\{te_i\}\bar{p}_i + 1 - \bar{p}_i).$$

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$\lim_{t\to\infty} \bar{q}_{t,i} = 1$ and $\lim_{t\to-\infty} \bar{q}_{t,i} = 0$ imply that $E^{Q_t}(L)$ takes all values in $(0, \sum_{i=1}^{m} e_i)$ for $t \in \mathbb{R}$.

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Choose t, such that $\sum_{i=1}^{m} e_i \bar{q}_{t,i} = c$.

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The general case: Y_i are independent conditional on Z

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Algorithm: IS for the conditional loss distribution

(1) For a given z compute the conditional default probabilities $p_i(z)$ (as in the simplified case) and solve the equation

$$\sum_{i=1}^{m} e_i \frac{\exp\{te_i\} p_i(z)}{\exp\{te_i\} p_i(z) + 1 - p_i(z)} = c\,.$$

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(2) Generate n_1 conditional realisations of the vector of default indicators $(Y_1, \ldots, Y_m)$, Y_i are simulated from *Bernoulli*(q_i), $i = 1, 2, \ldots, m$, with

$$q_i = \frac{\exp\{t(c, z)e_i\}p_i(z)}{\exp\{t(c, z)e_i\}p_i(z) + 1 - p_i(z)}\,.$$

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(3) Let $M_L(t,z) := \prod[\exp\{t(c,z)e_i\}p_i(z) + 1 - p_i(z)]$ be the conditional moment generating function of L. Let $L^{(1)}$, $L^{(2)}$,...,$L^{(n_1)}$ be the n_1 conditional realisations of L for the n_1 simulated realisations of $Y_1, Y_2, \ldots, Y_m$. Compute the *IS*-estimator for the tail probability of the conditional loss distribution:

$$\hat{\theta}_{n_1}^{(IS)}(z) = M_L(t(c,z),z)\frac{1}{n_1}\sum_{j=1}^{n_1} I_{L^{(j)}\geq c}\exp\{-t(c,z)L^{(j)}\}L^{(j)}.$$

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Naive approach: Generate many realisations z of the impact factors Z and compute $\hat{\theta}_{n_1}^{(IS)}(z)$ for every one of them. The required estimator is the average of $\hat{\theta}_{n_1}^{(IS)}(z)$ over all realisations z.
This is not the most efficient approach, see Glasserman and Li (2003).

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A better alternative: IS for the impact factors.

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The likelihood ratio:

$$r_\mu(Z) = \frac{\exp\{-\frac{1}{2}Z^t\Sigma^{-1}Z\}}{\exp\{-\frac{1}{2}(Z-\mu)^t\Sigma^{-1}(Z-\mu)\}} = \exp\{-\mu^t\Sigma^{-1}Z + \frac{1}{2}\mu^t\Sigma^{-1}\mu\}$$

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(3) compute the IS estimator for the independent excess probability:

$$\hat{\theta}_n^{(IS)} = \frac{1}{n}\sum_{i=1}^{n} r_\mu(z_i)\hat{\theta}_{n_1}^{(IS)}(z_i)$$

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Glasserman und Li (2003) propose some numerical solution approaches.