

Random Tree Method

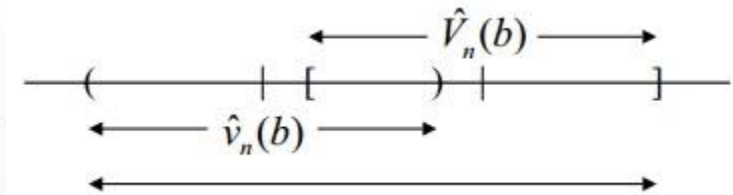
Monte Carlo Methods in Financial Engineering

What is it for?

- solve full optimal stopping problem & estimate value of the American option
 - simulate paths of underlying Markov chain
 - produces two consistent estimators: one **biased high** and one **biased low** **converging to the wanted Value V_0**
 - renders a **confidence interval for the „true“ Value V_0**
 - control error
 - **but only for small m** (e.g. $m = 5$), limits the scope of the method
 - computing time grows exponentially (in the number of exercise dates)
-

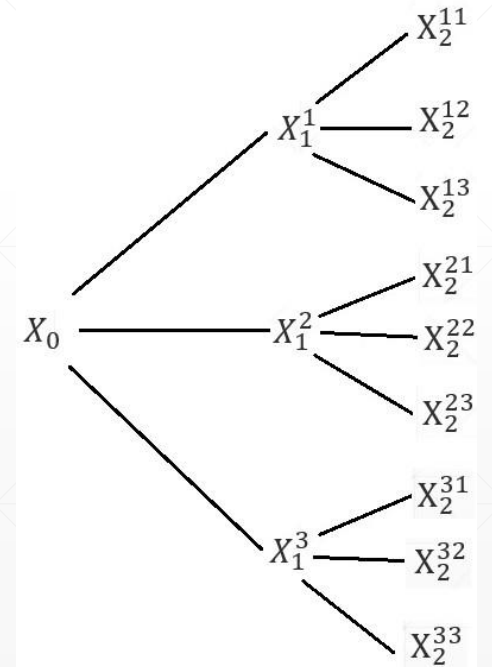
Find the interval

- simulation parameter b , time parameter m
- $\hat{V}(b)$ and $\hat{v}(b)$ sample means of n independent replications for some V_0
- so that: $E[\hat{V}(b)] \geq V_0 \geq E[\hat{v}(b)]$
- we need some halfwidths $L_n(b)$ for low bias and $H_n(b)$ for high bias
- confidence interval $\hat{v}_n(b) - L_n(b), \hat{V}_n(b) + H_n(b)$
- for $n \rightarrow \infty$ the halfwidths shrink to 0 and our estimators come really close to V_0 for $b \rightarrow \infty$



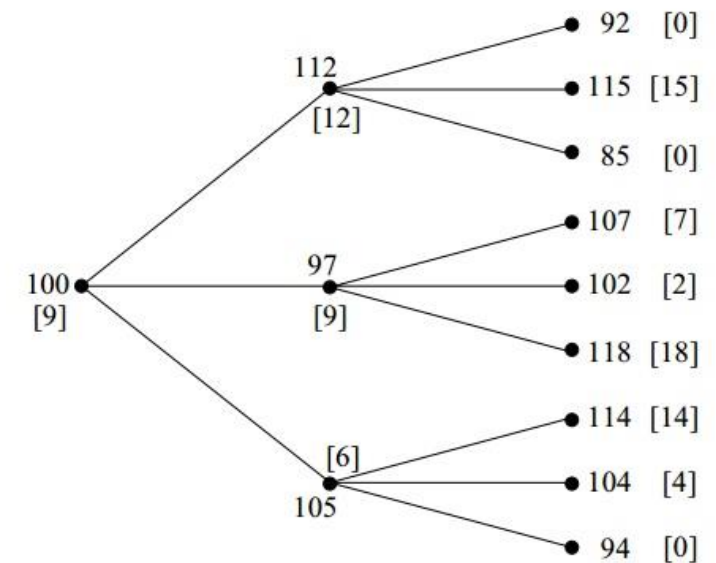
The Tree

- for simulating a tree of paths need underlying *Markov chain* $X_0, \dots, X_m$
- *branching parameter* b , *time/date* $0, \dots, m$
- from initial state X_0 simulate b *i.i.d. successor states* $X_1^1, \dots, X_1^b$ all having law of X_1 . From each X_1^i simulate b *i.i.d. successors* $X_2^{i1}, \dots, X_2^{ib}$ with law of X_2 *given* $X_1 = X_1^i$. From each $X_2^{i_1 i_2}$ generate b *more successors* $X_3^{i_1 i_2 1}, \dots, X_3^{i_1 i_2 b}$ and so on...
- denote generic node at step time i by $X_i^{j_1, \dots, j_i}$
- superscript indicates, that the node is reached by following the j_1 branch out of X_0 , the j_2 branch out of $X_1^{j_1}$ etc.
- not essential, that branching parameter b is fixed across the time steps, but it's a convenient simplification



High Estimator

- from random tree define high & low estimators at each node by
backward induction: $V_{i-1}(x) = \max\{ h_{i-1}(x), E[V_i(X_i)|X_{i-1} = x] \}$
- $h_i(x) = (x - 100)^+$ is the discounted **payoff function** with strike price 100 at the i 'th exercise date and $V_m = h_m$ is satisfied from the discounted **option value**
- high estimator**: $V_i(x) = \max\{ h_i(x), E[V_{i+1}(X_{i+1})|X_i = x] \}$ $i = 0, \dots, m-1$
- write for the high estimator: $\hat{V}_i^{j_1 \dots j_i}$ for each node $X_i^{j_1, \dots, j_i}$.
 Set at the **terminal nodes** $\hat{V}_m^{j_1 \dots j_m} = h_m(X_i^{j_1, \dots, j_m})$. Working backward: $\hat{V}_i^{j_1 \dots j_i} = \max\{ h_i(X_i^{j_1, \dots, j_i}), \frac{1}{b} \sum_{j=1}^b \hat{V}_{i+1}^{j_1 \dots j_i j} \}$
- first term inside max.: immediate exercise
 second term: continuation value
 ➡ choosing the max the estimator is deciding whether to exercise or continue!



High Estimator – confidence interval

- under modest conditions **each** $\widehat{V}_i^{j_1 \dots j_i}$ **converges** in probability (and in norm) as $b \rightarrow \infty$ to the **true value** $V_i(X_i^{j_1, \dots, j_i})$ given $h_i(X_i^{j_1, \dots, j_i})$, this holds at all terminal nodes because V_m is initialized to $h_i = V_m$. (The continuation value at the $(m - 1)$ th step is the average of i.i.d. replications and converges by the law of large numbers.)
- primarily interested in $\widehat{V}_0$, the estimate of the option price at the current time and state
- let $\bar{V}_0(n, b)$ denote the sample mean ($\bar{x}$) of the n replications of $\bar{V}_0$, let $s_V(n, b)$ denote their sample standard deviation. With $z_{\frac{\alpha}{2}}$ denoting the $1 - \frac{\alpha}{2}$ quantile of the normal distribution

$$\Rightarrow \bar{V}_0(n, b) \pm z_{\frac{\alpha}{2}} \frac{s_V(n, b)}{\sqrt{n}} \Leftarrow \text{(first half of wanted interval for the true value } V_0)$$

- provides (for large n) an asymptotically valid $1 - \frac{\alpha}{2}$ - confidence interval for $E[\widehat{V}_0]$
 - the high estimator is based on successor nodes (unfairly peeking into future)
-

Low Estimator

- to remove „successor-based“ source of bias: separate exercise decision from continuation value

- at all **terminal nodes** set: $\hat{v}_m^{j_1 \dots j_m} = h_m(X_i^{j_1, \dots, j_m})$. At nodes $j_1, \dots, j_i$ at time step i and for

$$k = 1, \dots, b \text{ set for the } \underline{\text{low estimator}}: \hat{v}_{ik}^{j_1 \dots j_i} = \begin{cases} h_i(X_i^{j_1 \dots j_i}) & \text{if } \frac{1}{b-1} \sum_{j=1, j \neq k}^b \hat{v}_{i+1}^{j_1 \dots j_i j} \leq h_i(X_i^{j_1 \dots j_i}) \\ \hat{v}_{i+k}^{j_1 \dots j_i k} & \text{otherwise} \end{cases}$$

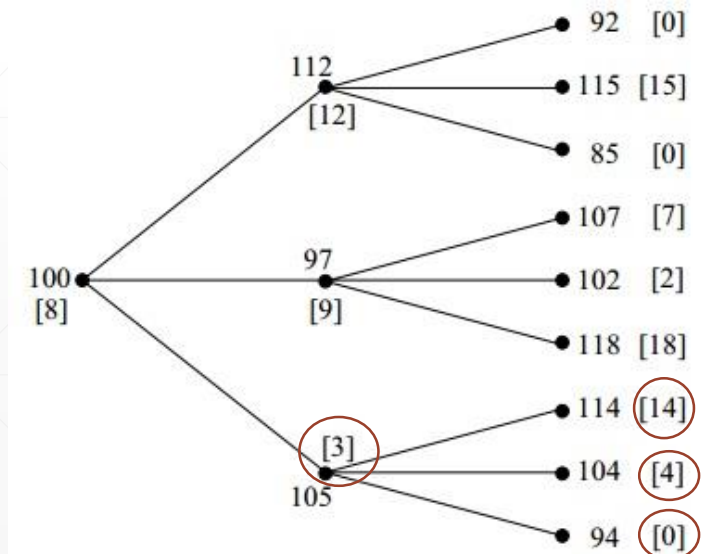
- example: leave out first successor node:

$\frac{1}{2}(4 + 0) = 2 \leq 5 = h_i(X_i^{j_1, \dots, j_i})$, so we exercise and get 5

leave out second one: $\frac{1}{2}(14 + 0) = 7 \geq 5$, continue and get 4

leave out third: $\frac{1}{2}(14 + 4) = 9 \geq 5$, continue and get 0

averaging payoffs: $\frac{1}{3}(5 + 4 + 0) = 3$, so we get a low estimator of 3 at that node. ([3])



Low Estimator – confidence interval

- $\hat{v}_0$ converges in probability and in norm as $b \rightarrow \infty$ to the true value $V_0(X_0)$
- $\hat{v}_0$ estimator of the option price at the current time and state
- let $\bar{v}_0(n, b)$ denote the sample mean ($\bar{x}$) of the n replications of $\bar{v}_0$, let $s_v(n, b)$ denote their sample standard deviation. With $z_{\frac{\alpha}{2}}$ denoting the $1 - \frac{\alpha}{2}$ quantile of the normal distribution

$$\Rightarrow \bar{v}_0(n, b) \pm z_{\frac{\alpha}{2}} \frac{s_v(n, b)}{\sqrt{n}} \Leftarrow \text{(second half of wanted interval for the true value } V_0)$$

- finally found interval for $V_0(X_0)$:

$$\left(\bar{v}_0(n, b) \pm z_{\frac{\alpha}{2}} \frac{s_v(n, b)}{\sqrt{n}}, \bar{V}_0(n, b) \pm z_{\frac{\alpha}{2}} \frac{s_V(n, b)}{\sqrt{n}} \right)$$

by increasing n and b see that $E[\hat{V}_0]$ and $E[\hat{v}_0]$ approach $V_0(X_0)$ and the confidence interval can be made as tight as we need.

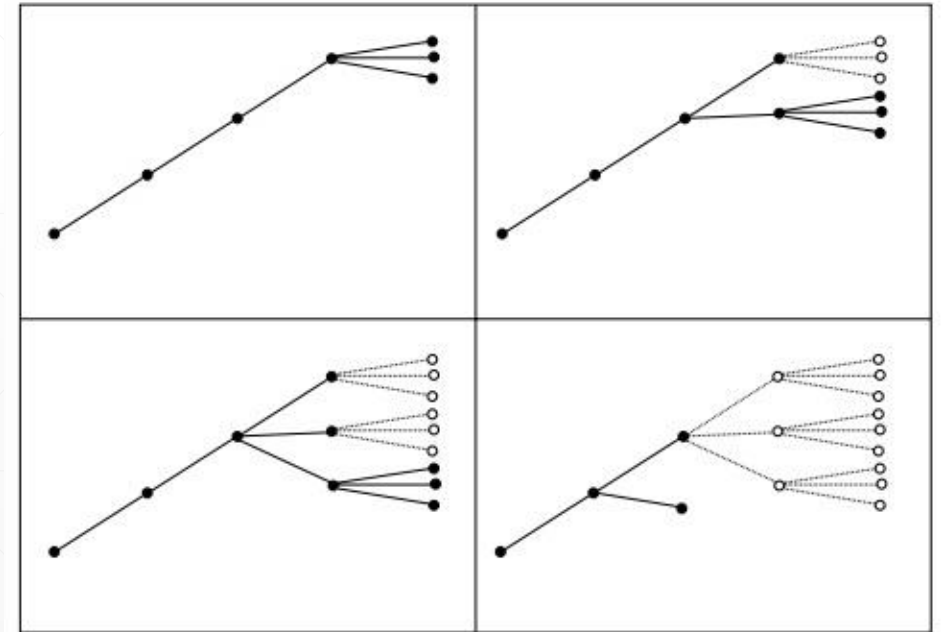
- simple technique for error control
-

Implementation

- won't generate naive all m^b nodes. Each node depends only on subtree
→ reduce storage requirements of the method, so it's never necessary to store more than $mb + 1$ nodes at a time.

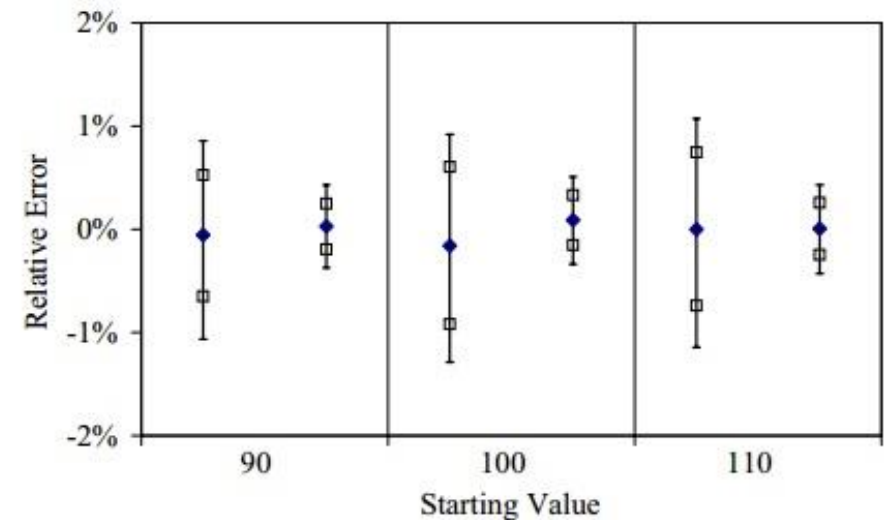
Depth-First Processing

- indices $j_1, \dots, j_i$ taking values in $\{1, \dots, b\}$. The string $j_1, \dots, j_i$ labels the node reached by following the branches...
- in depth-first algorithm we follow a single branch rather than generating all branches at once
- **like:** generate **1, 11, 111, 1111**. At this point we reached the terminal step and can go no deeper, so generate nodes **1112, ..., 111b**. From these values we calculate high and low biased estimators at (for) node **111**. Next, generate **112** and its successors: **1121, 1122, ..., 112b** using them to calculate high and low estimators at **112**, then discard and repeat...
113, ..., 11b → node 11
12, ..., 1b → node 1
2, ..., b → root node



Prunning and Variance Conrol

- branching is needed only *when the optimal exercise decision is unknown*. If we know at which time it is optimal not to exercise, than it *would already suffice to generate just a single branch out of that node*. Working, then, backward through the tree the value we assign to that node is for both (high and low) estimators the (discounted) value of the corresponding estimator at the unique successor node.
- And **this** is an ordinary simulation to price an European option, where we *never have the choice to exercise early*. For that we compare European options with American options and use antithetic variates. If the value of the *European option exceeds the payoff of the American option it is optimal to continue*. In case, that the European option can be prised quickly, then the size of the tree *reduces by a factor of b* .
- e.g. pruning, antithetic branching and control variate interval closer to the exact value.
 - first: 100 replications; but second: several thousands
 - GBM=0.30 || 5=% || strike price=100 || b=50 || 90% coverage
- random tree method producing high and low estimators and render **estimates exact to within about 1%!**



Thank you

for your attention!

Jana Frank