CHEME 132 Module 1: Lattice Models of Equity Share Price

Jeffrey D. Varner
Smith School of Chemical and Biomolecular Engineering
Cornell University, Ithaca NY 14853

Introduction

A lattice model discretizes the potential future states of the world into a finite number of options. For instance, a binomial lattice model has two future states: `up` and `down`, while a ternary lattice model has three: `up`, `down`, and `flat`. To make predictions, we must assign values and probabilities to each of these future states and then calculate the expected value and variance of future values. Thus, we do not know quantities such as share price exactly because we are projecting into the future. Instead, we have only a probabilistic model of the possible future values. We'll begin with the simplest possible lattice model, a binomial lattice (Fig. 1).

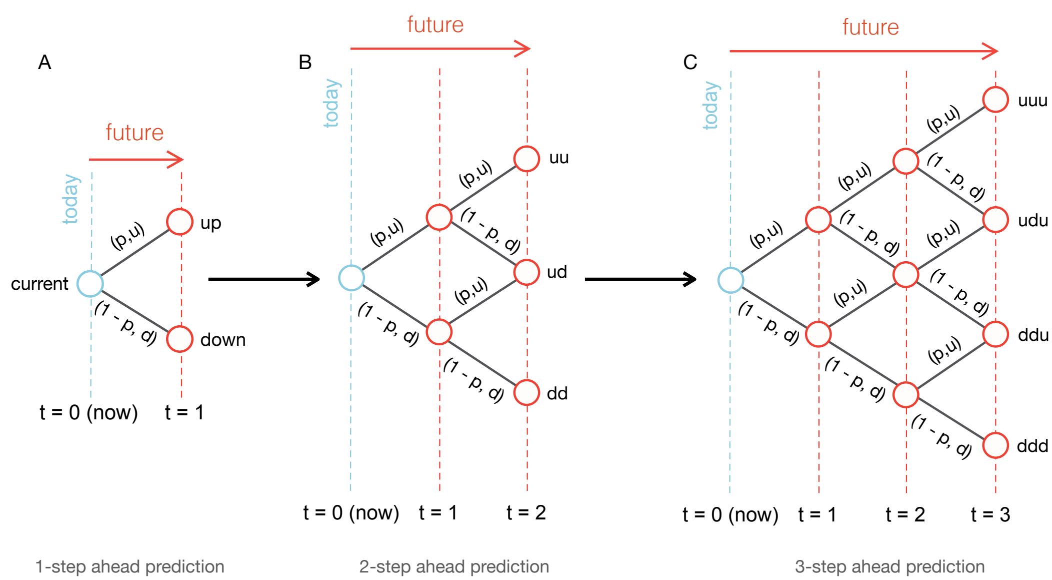

Fig. 1: Binomial lattice model schematic. At each node, the share price can either go `up` by a factor of u or `down` by a factor of d. The probability of going `up` is p and the probability of going `down` is $1-p$. **A**: Single time-step lookahead. **B**: Two time-step lookahead. **C**: Three time-step lookahead. At level of the tree l, the potential share price can take on $l+1$ values.

Let's start with a single time-step lookahead, where we have two possible future states (Fig. 1A). Let the initial share price at time `0` be $S_{\circ}$ and the share price at future time `1` be S_1. During the transition from time `0`$\rightarrow$`1` the world transitions from the current state, to one of two possible future states: `up` or `down`. We move to the `up` state with probability p or the `down` state with probability $(1-p)$. Thus, at the time `1`, the share price S_1 can take on one of two possible values: $S^{u}=u\cdot S_{\circ}$ if the world moves to the `up` state, or $S^{d}=d\cdot S_{\circ}$ if the world moves to the `down` state. As we move to the future, we can continue to build out the lattice model by adding additional time-steps, for example consider a two-step ahead prediction (Fig. 1B). At time `2`, the share price can take on one of three possible values: $S^{uu} = u^2 \cdot S_\circ$ if the world moves to the `up-up` state, $S^{ud} = ud \cdot S_\circ$ if the world moves to the `up-down` state, or $S^{dd} = d^2 \cdot S_\circ$ if the world moves to the `down-down` state. We can continue to build out the lattice model by adding additional time-steps, for example consider a three-step ahead prediction (Fig. 1C).

Analytical solution

Let's consider a binomial lattice model with n time-steps. At each time-step, the share price can either go `up` by a factor of u or `down` by a factor of d. Then, at time `n`, the share price can take on $n+1$ possible values:

$$S_n = S_\circ \times D_1 \times D_2 \times D_3 \times \cdots \times D_n \tag{1}$$

where D_i is a random variable that can take on one of two values: u or d, with probabilities p and $(1-p)$ respectively. Thus, at each time-step, the world flips a coin and lands in either the `up` state with probability p or the `down` state with probability $(1-p)$. For a single time-step, we model this random process as a Bernoulli trial, where the probability of success is p and the probability of failure is $(1-p)$. As the number of time-steps increases we have a series of Bernoulli trials, which is a binomial distribution (Defn: 1):

Definition 1: Binomial Share Price and Probability

Let $S_\circ$ denote the current share price at t = `0`, u and d denote the `up` and `down` factors, and p denote the probability of going `up`. At time t, the binomial lattice model predicts the share price S_t is given by:

$$S_t = S_\circ \cdot u^{t-k} \cdot d^k \qquad \text{for} \quad k = 0, 1, \dots, t$$

The probability that the share price takes on a partiuclar value at time t is given by:

$$P(S_t = S_\circ \cdot u^{t-k} \cdot d^k) = \binom{t}{k} \cdot (1-p)^k \cdot p^{t-k} \qquad \text{for} \quad k = 0, 1, \dots, t$$

where $\binom{t}{k}$ denotes the binomial coefficient.

Models of u, d and p

The `up` and `down` factors u and d, and the probability p can be defined in various ways. For example, we can estimate them from historical data, or we can propose models for their values.

Historical data

Suppose we have a historical share price dataset from time $1, \dots, T$ for some ticker j denoted as $\mathcal{D}_j = \left\{S_1^{(j)}, S_2^{(j)}, \dots, S_T^{(j)}\right\}$, where $S_i^{(j)}$ denotes the share price of ticker j at time i. We can use different values for the share price, e.g., the opening price, closing price, high price, low price, etc. In our case, when dealing with historical data we will typically use the volume weighted average price (VWAP) for the time period, e.g., the VWAP for the day, week, month, etc. Over the time range of the dataset $\mathcal{D}_j$, we can calculate the number of `up` and `down` moves occuring between time $i-1$ and i, and the magnitude of these moves. Then, the fraction of `up` moves is an estimate of the probability p, while some measured of the magnitude of the `up` and `down` moves, e.g., the average value are estimates of u and d respectively.

Estimating u, d and p from historical data. Suppose we assume the share price of ticker j is continously compounded with an instantaneous discount (interest) rate of $r_{i,i-1}^{(j)} \equiv \mu_{i,i-1}^{(j)} \cdot \Delta t$, i.e., we split the return into a growth rate $\mu_{i,i-1}^{(j)}$ and a time step size Δt. Then, the share price at time i is goverenved by an expression of the form:

$$S_i^{(j)} = \exp\left(\mu_{i,i-1} \cdot \Delta t\right) \cdot S_{i-1}^{(i)} \tag{2}$$

where $\mu_{i,i-1}^{(j)}$ denotes the *growth rate* (units: 1/time) for ticker j, and Δt (units: time) is the time step size during the time period $(i-1) \rightarrow i$. Solving for the growth rate (and dropping the ticker j superscript for simplicity) gives:

$$\mu_{i,i-1} = \left(\frac{1}{\Delta t}\right) \cdot \ln\left(\frac{S_i}{S_{i-1}}\right) \tag{3}$$

We'll often use daily price data; thus, the natural time frame between S_{i-1} and S_i is a single trading day. However, subsequently, it will be easier to use an annualized value for the μ parameter; thus, we let $\Delta t = 1/252$, i.e., the fraction of an average trading year that occurs in a single trading day; thus, our base time will be years. We compute the growth rate for each trading day i in a collection of datasets $\mathcal{D}$ using Algorithm 1. Then we can estimate the `up` and `down` factors u and d from

Algorithm 1 Logarithmic excess growth rate

Require: Collection of price datasets $\mathcal{D}$, where $\mathcal{D}_j \in \mathcal{D}$. All datasets have the same length N.
Require: list of stocks $\mathcal{L}$, where $\dim \mathcal{L} = M$.
Require: time step size Δt between t and $t-1$ (units: years),
Require: risk-free rate r_f (units: inverse years).

$M \leftarrow$ length$(\mathcal{D}_1)$ ▷ Number of trading days in the dataset $\mathcal{D}_j$
$N \leftarrow$ length$(\mathcal{L})$ ▷ Number of stocks in the dataset $\mathcal{D}$
$\mu \leftarrow$ Array$(M-1, N)$ ▷ Initialize empty array of growth rates

for $i \in \mathcal{L}$ **do**
  $\mathcal{D}_i \leftarrow \mathcal{D}[i]$ ▷ Get dataset for stock i
  for $t = 2 \rightarrow N$ **do**
    $S_1 \leftarrow$ VWAP$(\mathcal{D}_i[t-1])$ ▷ Get volume weighted average price for stock i at time $t-1$
    $S_2 \leftarrow$ VWAP$(\mathcal{D}_i[t])$ ▷ Get volume weighted average price for stock i at time t
    $\mu[t-1, i] \leftarrow \left(\frac{1}{\Delta t}\right) \cdot \ln\left(\frac{S_2}{S_1}\right) - r_f$ ▷ Set $r_f = 0$ for regular growth rate
  end for
end for

the growth rate array generated using something like Algorithm 2. While this strategy is simple, it may not be robust. For example, if the dataset $\mathcal{D}_j$ is short, i.e., only a few trading days, then the number of `up` and `down` moves will be small, and the estimates of u, d and p will be poor. If a

Algorithm 2 Estimating u, d and p from the μ-array

Require: μ-array from Algorithm 1.

$\mu \leftarrow$ sort$(\mu_{i,i-1})$
$N \leftarrow$ length(μ) ▷ Number of growth rates

$i_{+} \leftarrow$ findall$(\mu > 0)$ ▷ Find the indices of all `positive` growth rates
for $i \in i_{+}$ **do**
  $\mu[i] \rightarrow (\mu \rightarrow \text{push!}(\text{up}, \exp(\mu \cdot \Delta t)))$ ▷ Push the `positive` return $\mu \cdot \Delta t$ onto up-array
end for
$u \leftarrow$ mean$(\texttt{up})$ ▷ mean is our estimate of the `up` factor u

$i_{-} \leftarrow$ findall$(\mu < 0)$ ▷ Find the indices of all `negative` growth rates
for $i \in i_{i}$ **do**
  $\mu[i] \rightarrow (\mu \rightarrow \text{push!}(\text{down}, \exp(\mu \cdot \Delta t)))$ ▷ Push the `negative` return $\mu \cdot \Delta t$ onto down-array
end for
$d \leftarrow$ mean$(\texttt{down})$ ▷ mean is our estimate of the `down` factor d

$N_{+} \leftarrow$ length(i_{+}) ▷ Number of `positive` growth rates
$p \leftarrow N_{+}/N$ ▷ Estimate of the probability p
return u, d and p

precise estimate of u, d and p is required, the number of trading days in the dataset $\mathcal{D}_j$ should be large. Furthermore, the estimates of u, d and p are not robust to outliers in the dataset $\mathcal{D}_j$. Thus, we may want to consider other models for computing u, d and p.

Risk-neutral probability q

Another approach to computing the parameters in the lattrice is to use the risk-neutral probability q. Let's consider a single-step binomial lattice model (Fig. 1A). The expected value of the share price at time `1` for a single step is given by:

$$\mathbb{E}_{\mathbb{Q}}(S_1|S_{\circ}) = q \cdot S^{u} + (1-q) \cdot S^{d}$$

where $\mathbb{E}_{\mathbb{Q}}(\dots)$ denotes the expectation operator written with respect to the risk-neutral probability measure $\mathbb{Q}$, the term q denotes the risk-neutral probability of the `up` state, and S^u and S^d are the share prices in the `up` and `down` states respectively. The hypothetical probability q is used to price derivatives (as we shall see later), however, we could also think of it as a tool to compute a *fair* price for a share of stock. Suppose we rewrite Eqn. (2) as:

$$\mathcal{D}_{1,0}(\bar{r}) \cdot S_{\circ} = \mathbb{E}_{\mathbb{Q}}\left(S_1|S_{\circ}\right) \tag{4}$$

where $\mathcal{D}_{1,0}(\bar{r})$ is the continuous discount factor between period $0 \rightarrow 1$, and $\bar{r}$ is the effective (constant) risk-free rate. Thus, unlike the previous case, where the share price S_i was discounted by the return $\mu_{i,i-1} \cdot \Delta t$ (which could vary in time), here we discount the share price S_i by an effective (constant) risk-free rate $\bar{r}$. The expectation operator $\mathbb{E}_{\mathbb{Q}}(\dots)$ can be matched with the expansion:

$$\mathcal{D}_{1,0}(\bar{r}) \cdot S_{\circ} = q \cdot S^{u} + (1-q) \cdot S^{d} \tag{5}$$

The share prices in the `up` and `down` states are the product of the `up` factor u (or a `down` factor d) and the initial share price, i.e., $S^{u} = u \cdot S_{\circ}$ and $S^{d} = d \cdot S_{\circ}$. Substiuting these price values into Eqn. (5) and solving for q gives:

$$q = \frac{\mathcal{D}_{1,0}(\bar{r}) - d}{u - d} \tag{6}$$

Thus, we can compute the risk-neutral probability q from the `up` and `down` factors u and d and the effective risk-free rate $\bar{r}$.

Binomial lattice trade strategy

Suppose we purchase n_{o} share of ticker `XYZ` at time $t = 0$ for S_{o} USD/share. Then, at some later date $t = T$, we sell all n_{o} shares for S_{T} USD/share. The NPV of this trade is:

$$\text{NPV}(\bar{r}, T) = -n_{o} \cdot S_{o} + n_{o} \cdot S_{T} \cdot \mathcal{D}_{T,0}^{-1}(\bar{r})$$

where $\mathcal{D}_{T,0}^{-1}(\bar{r})$ is the inverse of the continuous discount factor for period $0 \rightarrow T$ with effective discount rate $\bar{r}$. Factoring out n_{o} gives:

$$\text{NPV}(\bar{r}, T) = n_{o} \cdot \left(S_{T} \cdot \mathcal{D}_{T,0}^{-1}(\bar{r}) - S_{o}\right)$$

The term in the parenthesis is the net change in the share price, i.e., the change in the share price S_{T} discounted by the effective discount rate $\bar{r}$. However, if we hold the shares for a short period, e.g., on order days or months, then we approximate as $\mathcal{D}_{T,0}^{-1}(\bar{r}) \approx 1$, which simplifies to:

$$\text{NPV}(\bar{r}, T) \simeq n_{o} \cdot (S_{T} - S_{o})$$

Dividing by the initial investment $n_{o} \cdot S_{o}$ gives the return on investment (ROI) as a fraction:

$$\frac{\text{NPV}(\bar{r}, T)}{n_{o} \cdot S_{o}} \simeq \frac{S_{T} - S_{o}}{S_{o}} = \frac{S_{T}}{S_{o}} - 1 \tag{7}$$

Equation (7) is the fractional return on investment. At time $t = T$, the share price S_{T} is a random variable which takes the form (from Defn. 1):

$$S_{T} \in \left\{S_{\circ} \cdot u^{t-k} \cdot d^{k}\right\}_{k=0}^{T}$$

where $S_{\circ}$ is the initial share price, u and d are the `up` and `down` factors, and p is the probability of going `up`. Substiuting this expression into Eqn. (7) gives:

$$\frac{\text{NPV}(\bar{r}, T)}{n_{o} \cdot S_{o}} \in \left\{u^{T-k} \cdot d^{k} - 1\right\}_{k=0}^{T} \tag{8}$$