A Guided Tour of Chapter 7: Derivatives Pricing and Hedging

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Brief Overview of Derivatives

- Term *Derivative* comes from the word *Derived*
- Financial product whose structure (and hence, *value*) is derived from the *performance* of an *underlying* entity
- Technically a legal contract between buyer and seller that is either:
  - *Lock-type*: *Entitles* buyer to future contingent-cashflow (*payoff*)
  - *Option-type*: Buyer has future *choices*, leading to contingent-cashflow
- Some common derivatives:
  - Forward - Contract to deliver/receive asset on future date for fixed cash
    
    Forward Payoff: \( f(X_t) = X_t - K \)
  
  - European Option - *Right* to buy/sell on future data at agreed price
    
    Call and Put Option Payoff: \( \max(X_t - K, 0) \) and \( \max(K - X_t, 0) \)
  
  - American Option - Can exercise option on *any day* before expiration
- Why do we need derivatives?
  - To protect against adverse market movements (*risk-management*)
  - To express a market view *cheaply* (leveraged trade)
Derivatives Pricing and Hedging problems as MDPs

- **Pricing**: Determination of fair value of an asset or derivative
- **Hedging**: Protect against market movements with “opposite” trades
- **Replication**: Clone payoff of a derivative with trades in other assets

We consider two applications of Stochastic Control here:
- Optimal Exercise of American Options in an idealized setting
- Optimal Hedging of Derivatives Portfolio in a real-world setting

Both problems enable us to price the respective derivatives

Expressing these problems as MDP Control brings ADP/RL into play

- Optimal Exercise of American Options is Optimal Stopping problem
- So we start by learning about Stopping Time and Optimal Stopping
Stopping Time

- Stopping time $\tau$ is a “random time” (random variable) interpreted as time at which a given stochastic process exhibits certain behavior.
- Stopping time often defined by a “stopping policy” to decide whether to continue/stop a process based on present position and past events.
- Random variable $\tau$ such that $Pr[\tau \leq t]$ is in $\sigma$-algebra $F_t$, for all $t$.
- Deciding whether $\tau \leq t$ only depends on information up to time $t$.
- Hitting time of a Borel set $A$ for a process $X_t$ is the first time $X_t$ takes a value within the set $A$.
- Hitting time is an example of stopping time. Formally,

$$T_{X,A} = \min\{t \in \mathbb{R} | X_t \in A\}$$

eg: Hitting time of a process to exceed a certain fixed level.
Optimal Stopping Problem

- Optimal Stopping problem for Stochastic Process $X_t$:

$$W(x) = \max_\tau \mathbb{E}[H(X_\tau)|X_0 = x]$$

where $\tau$ is a set of stopping times of $X_t$, $W(\cdot)$ is called the Value function, and $H$ is the Reward function.

- Note that sometimes we can have several stopping times that maximize $\mathbb{E}[H(X_\tau)]$ and we say that the optimal stopping time is the smallest stopping time achieving the maximum value.

- Example of Optimal Stopping: Optimal Exercise of American Options
  - $X_t$ is risk-neutral process for underlying security’s price
  - $x$ is underlying security’s current price
  - $\tau$ is set of exercise times corresponding to various stopping policies
  - $W(\cdot)$ is American option price as function of underlying’s current price
  - $H(\cdot)$ is the option payoff function, adjusted for time-discounting
We formulate Stopping Time problems as Markov Decision Processes

- **State** is $X_t$
- **Action** is Boolean: Stop or Continue
- **Reward** always 0, except upon Stopping (when it is $= H(X_\tau)$)
- **State**-transitions governed by the Stochastic Process $X_t$

For discrete time steps, the Bellman Optimality Equation is:

$$V^*(X_t) = \max(H(X_t), \mathbb{E}[V^*(X_{t+1})|X_t])$$

For finite number of time steps, we can do a simple backward induction algorithm from final time step back to time step 0
Mainstream approaches to American Option Pricing

- American Option Pricing is Optimal Stopping, and hence an MDP
- So can be tackled with Dynamic Programming or RL algorithms
- But let us first review the mainstream approaches
- For some American options, just price the European, eg: vanilla call
- When payoff is not path-dependent and state dimension is not large, we can do backward induction on a binomial/trinomial tree/grid
- Otherwise, the standard approach is Longstaff-Schwartz algorithm
- Longstaff-Schwartz algorithm combines 3 ideas:
  - Valuation based on Monte-Carlo simulation
  - Function approximation of continuation value for in-the-money states
  - Backward-recursive determination of early exercise states
- RL is an attractive alternative to Longstaff-Schwartz algorithm
Binomial Tree for Backward Induction
Classical Pricing and Hedging of Derivatives

- Classical Pricing/Hedging Theory is based on a few core concepts:
  - **Arbitrage-Free Market** - where you cannot make money from nothing
  - **Replication** - when the payoff of a Derivative can be constructed by assembling (and rebalancing) a portfolio of the underlying securities
  - **Complete Market** - where payoffs of all derivatives can be replicated
  - **Risk-Neutral Measure** - Altered probability measure for movements of underlying securities for mathematical convenience in pricing

- Assumptions of **arbitrage-free and completeness** lead to (dynamic, exact, unique) replication of derivatives with the underlying securities.

- Assumptions of frictionless trading provide these idealistic conditions.
- Frictionless := continuous trading, any volume, no transaction costs
- Replication strategy gives us the pricing and hedging solutions.
- This is the foundation of the famous Black-Scholes formulas.
- However, the real-world has many frictions ⇒ **Incomplete Market**
- ... where derivatives cannot be exactly replicated.
In an incomplete market, we have multiple risk-neutral measures. So, multiple derivative prices (each consistent with no-arbitrage). The market/trader “chooses” a risk-neutral measure (hence, price). This “choice” is typically made in ad-hoc and inconsistent ways. Alternative approach is for a trader to play *Portfolio Optimization*. Maximizing “risk-adjusted return” of the derivative plus hedges, based on a specified preference for trading risk versus return. This preference is equivalent to specifying a *Utility function*. Reminiscent of the Portfolio Optimization problem we’ve seen before. Likewise, we can set this up as a stochastic control (MDP) problem, where the decision at each time step is: *Trades in the hedges*. So what’s the best way to solve this MDP?
Dynamic Programming not suitable in practice due to:
  - Curse of Dimensionality
  - Curse of Modeling

So we solve the MDP with Deep Reinforcement Learning (DRL)

The idea is to use real market data and real market frictions
Developing realistic simulations to derive the optimal policy
The optimal policy gives us the (practical) hedging strategy
The optimal value function gives us the price (valuation)
Formulation based on Deep Hedging paper by J.P.Morgan researchers
More details in the prior paper by some of the same authors
Problem Setup

- We will simplify the problem setup a bit for ease of exposition
- This model works for more complex, more frictionful markets too
- Assume time is in discrete (finite) steps $t = 0, 1, \ldots, T$
- Assume we have a position (portfolio) $D$ in $m$ derivatives
- Assume each of these $m$ derivatives expires in time $\leq T$
- Portfolio-aggregated *Contingent Cashflows* at time $t$ denoted $X_t \in \mathbb{R}$
- Assume we have $n$ underlying market securities as potential hedges
- Hedge positions (units held) at time $t$ denoted $\alpha_t \in \mathbb{R}^n$
- Cashflows per unit of hedges held at time $t$ denoted $Y_t \in \mathbb{R}^n$
- Prices per unit of hedges at time $t$ denoted $P_t \in \mathbb{R}^n$
- Trading account position at time $t$ is denoted as $\beta_t \in \mathbb{R}$
States and Actions

- Denote state space at time $t$ as $S_t$, state at time $t$ as $s_t \in S_t$
- Among other things, $s_t$ contains $\alpha_t, P_t, \beta_t, D$
- $s_t$ will include any market information relevant to trading actions
- For simplicity, we assume $s_t$ is just the tuple $(\alpha_t, P_t, \beta_t, D)$
- Denote action space at time $t$ as $A_t$, action at time $t$ as $a_t \in A_t$
- $a_t$ represents units of hedges traded (positive for buy, negative for sell)
- Trading restrictions (eg: no short-selling) define $A_t$ as a function of $s_t$
- State transitions $P_{t+1} | P_t$ available from a simulator, whose internals are estimated from real market data and realistic assumptions
Sequence of events at each time step $t = 0, \ldots, T$

1. Observe state $s_t = (\alpha_t, P_t, \beta_t, D)$
2. Perform action (trades) $a_t$ for account position change $= -a_t^T \cdot P_t$
3. Trading transaction costs, eg. $= -\gamma \cdot \text{abs}(a_t^T) \cdot P_t$ for some $\gamma > 0$
4. Update $\alpha_t$ as: $\alpha_{t+1} = \alpha_t + a_t$ (force-liquidation at $T \Rightarrow a_T = -\alpha_T$)
5. Realize cashflows (from updated positions) $= X_{t+1} + \alpha_{t+1}^T \cdot Y_{t+1}$
6. Update trading account position $\beta_t$ as:
   \[
   \beta_{t+1} = \beta_t - a_t^T \cdot P_t - \gamma \cdot \text{abs}(a_t^T) \cdot P_t + X_{t+1} + \alpha_{t+1}^T \cdot Y_{t+1}
   \]
7. Reward $r_t = 0$ for all $t = 0, \ldots, T - 1$ and $r_T = U(\beta_{T+1})$ for an appropriate concave Utility function $U$ (based on risk-aversion)
8. Simulator evolves hedge prices from $P_t$ to $P_{t+1}$
Assume we now want to enter into an incremental position (portfolio) $D'$ in $m'$ derivatives (denote the combined position as $D \cup D'$).

We want to determine the Price of the incremental position $D'$, as well as the hedging strategy for $D'$.

Denote the Optimal Value Function at time $t$ as $V^*_t : S_t \rightarrow \mathbb{R}$.

Pricing of $D'$ is based on the principle that introducing the incremental position of $D'$ together with a calibrated cashflow (Price) at $t = 0$ should leave the Optimal Value (at $t = 0$) unchanged.

Precisely, Price of $D'$ is the value $x$ such that

$$V^*_0((\alpha_0, P_0, \beta_0 - x, D \cup D')) = V^*_0((\alpha_0, P_0, \beta_0, D))$$

This Pricing principle is known as the principle of Indifference Pricing.

The hedging strategy at time $t$ for all $0 \leq t < T$ is given by the Optimal Policy $\pi^*_t : S_t \rightarrow \mathcal{A}_t$. 
DRL Approach a Breakthrough for Practical Trading?

- The industry practice/tradition has been to start with Complete Market assumption, and then layer ad-hoc/unsatisfactory adjustments.
- There is some past work on pricing/hedging in incomplete markets.
- But it’s theoretical and not usable in real trading (e.g., Superhedging).
- My view: This DRL approach is a breakthrough for practical trading.
- Key advantages of this DRL approach:
  - Algorithm for pricing/hedging independent of market dynamics.
  - Computational cost scales efficiently with size $m$ of derivatives portfolio.
  - Enables one to faithfully capture practical trading situations/constraints.
  - Deep Neural Networks provide great function approximation for RL.