# MA668: Algorithmic and High Frequency Trading Lecture 22

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- ① The running penalty/reward may, in general, be dependent on time t, the current position of the controlled process  $\mathbf{X}^{\mathbf{u}}_t$  and the control itself  $\mathbf{u}_t$ .
  - ② On the other hand, the terminal reward depends solely on the terminal value of the controlled process.
- **③** For simplicity, the functions G and F are assumed to be uniformly bounded and the vector of drifts  $\mu_t$  and volatilities  $\sigma_t$  are, as usual, Lipschitz continuous.
- The integrability assumption on the controls, drift and volatility are necessary to ensure that the steps outlined below can be made rigorous.
- The predictability assumption on the controls is necessary, since otherwise the agent may be able to peek into the future to optimise her/his strategy, and strategies which do peek into the future cannot be implemented in the real world.

- The value function (equation (10) of previous lecture) has the interpretation that the agent wishes to maximize the total of terminal reward function G and running reward/penalty F, by acting in an optimal manner
- $oldsymbol{\Theta}$  Her/his actions  $oldsymbol{u}$  affect the dynamics of the underlying system in some generic way given by (equation (11) of previous lecture).
- Thus, her/his past actions affect the future dynamics and she/he must therefore adapt and tune her/his actions to account for this feedback effect.

 $oldsymbol{0}$  For an arbitrary admissible control  $oldsymbol{u}$ , we define the so-called performance criteria  $H^u(x)$  by:

by:
$$H^{\mathsf{u}}(\mathsf{x}) = \mathbb{E}\left[G\left(\mathsf{X}_{T}^{\mathsf{u}}\right) + \int_{s}^{T} F\left(s, \mathsf{X}_{s}^{\mathsf{u}}, \mathsf{u}_{s}\right) ds\right]. \tag{1}$$

The agent therefore seeks to maximise this performance criteria, and
naturally:

naturally: 
$$H(\mathbf{x}) = \sup_{\mathbf{u} \in \mathcal{A}_{0,T}} H^{\mathbf{u}}(\mathbf{x}). \tag{2}$$

- As mentioned earlier, rather than optimizing H<sup>u</sup>(x) directly, it is more convenient (and powerful) to introduce a time-indexed collection of optimization problems on which a dynamic programming principle (DPP) can be derived.
- The DPP in infinitesimal form leads to a Dynamic Programming Equation (DPE) or the Hamilton-Jacobi-Bellman (HJB) equation: This is a non-linear PDE whose solution is a tentative solution to the original problem.
- If a classical solution a to the DPE exists, then it is possible to prove, through a verification argument, that it is in fact the solution to the original control.
- We discuss the three preceding points in the next three topics of discussion

<sup>&</sup>lt;sup>a</sup>Here, a classical solution means that the solution is once differentiable in time and twice in all (diffusive) state variables, so that the infinitesimal generator can be applied to it

#### The Dynamic Programming Principle

- ① The usual trick to solving stochastic (and deterministic!) control problems is to embed the original problem into a larger class of problems indexed by time  $t \in [0, T]$  but equal to the original problem at t = 0.
- 2 To this end, first define (with a slight abuse of notation):

$$H(t,\mathbf{x}) := \sup_{\mathbf{u} \in \mathcal{A}_{t,T}} H^{\mathbf{u}}(t,\mathbf{x}), \tag{3}$$

and

$$H^{\mathbf{u}}(t,\mathbf{x}) := \mathbb{E}_{t,\mathbf{x}} \left[ G\left(\mathbf{X}_{T}^{\mathbf{u}}\right) + \int_{0}^{T} F\left(s,\mathbf{X}_{s}^{\mathbf{u}},\mathbf{u}_{s}\right) ds \right], \tag{4}$$

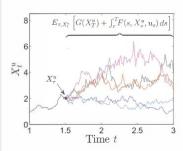
where the notation  $\mathbb{E}_{t,x}[\cdot]$  represents the expectation conditional on  $\mathbf{X}^u_t = \mathbf{x}$ .

- These two objects are the time indexed analog of the original control problem and the performance criteria.
- **1** In particular,  $H(0, \mathbf{x})$  coincides with the original control (equation (10) of previous lecture) and  $H^{\mathbf{u}}(0, \mathbf{x})$  with the performance criteria (1).

# The Dynamic Programming Principle (Contd ...)

- **1** Next, we take an arbitrary admissible strategy  $\mathbf{u}$  and imagine flowing the  $\mathbf{X}$  process forward in time from t to an arbitrary stopping time  $\tau \leq T$ .
- ② Then, conditional on  $\mathbf{X}_{\tau}^{\mathbf{u}}$ , the contribution of the running reward/penalty from  $\tau$  to T and the terminal reward can be viewed as the performance criteria starting from the new value of  $\mathbf{X}_{\tau}^{\mathbf{u}}$  (see Figure 5.1).
- **3** This allows the value function to be written in terms of the expectation of its future value at  $\tau$  plus the reward between now and  $\tau$ .

#### Figure 5.1



**Figure 5.1** The DPP allows the value function to be written as an expectation of the future value function. The key idea is to flow the dynamics of the controlled process from t to  $\tau$  and then rewrite the remaining expectation as the future performance criteria.

Figure: Figure 5.1

## The Dynamic Programming Principle (Contd ...)

More precisely, by iterated expectations, the time-indexed performance

criteria becomes: 
$$H^{\mathbf{u}}(t,\mathbf{x}) = \mathbb{E}_{t,\mathbf{x}} \left[ G\left(\mathbf{X}_{T}^{\mathbf{u}}\right) + \int_{\tau}^{T} F\left(s,\mathbf{X}_{s}^{\mathbf{u}},\mathbf{u}_{s}\right) ds + \int_{t}^{\tau} F\left(s,\mathbf{X}_{s}^{\mathbf{u}},\mathbf{u}_{s}\right) ds \right],$$

$$= \mathbb{E}_{t,x} \left[ \mathbb{E}_{\tau,x_{\tau}^{\mathbf{u}}} \left[ G\left(\mathbf{X}_{T}^{\mathbf{u}}\right) + \int_{\tau}^{T} F\left(s,\mathbf{X}_{s}^{\mathbf{u}},\mathbf{u}_{s}\right) ds \right] + \int_{t}^{\tau} F\left(s,\mathbf{X}_{s}^{\mathbf{u}},\mathbf{u}_{s}\right) ds \right],$$

$$H^{\mathbf{u}}(t, \mathbf{x}) = \mathbb{E}_{t, \mathbf{x}} \left[ G(\mathbf{X}_{T}^{\mathbf{u}}) + \int_{\tau} F(s, \mathbf{X}_{s}^{\mathbf{u}}, \mathbf{u}_{s}) ds + \int_{t} F(s, \mathbf{X}_{s}^{\mathbf{u}}, \mathbf{u}_{s}) ds \right]$$

$$= \mathbb{E}_{t, \mathbf{x}} \left[ \mathbb{E}_{\tau, \mathbf{x}_{\tau}^{\mathbf{u}}} \left[ G(\mathbf{X}_{T}^{\mathbf{u}}) + \int_{\tau}^{T} F(s, \mathbf{X}_{s}^{\mathbf{u}}, \mathbf{u}_{s}) ds \right] + \int_{\tau}^{\tau} F(s, \mathbf{X}_{s}^{\mathbf{u}}, \mathbf{u}_{s}) ds \right],$$

 $= \mathbb{E}_{t,x} \left| H^{\mathsf{u}}(\tau, \mathbf{X}_{\tau}^{\mathsf{u}}) + \int_{-\tau}^{\tau} F(s, \mathbf{X}_{s}^{\mathsf{u}}, \mathbf{u}_{s}) ds \right|.$ 

(5)

## The Dynamic Programming Principle (Contd ...)

- Now,  $H(t, \mathbf{x}) \geq H^{\mathbf{u}}(t, \mathbf{x})$  for an arbitrary admissible control  $\mathbf{u}$  (with equality holding if  $\mathbf{u}$  is the optimal control  $\mathbf{u}^*$  assuming that  $\mathbf{u}^* \in \mathcal{A}_{t,T}$ , i.e., the supremum is attained by an admissible strategy  $^a$  and an arbitrary  $\mathbf{x}$ .
- ② Hence, on the right-hand side of (5) the performance criteria  $H^{\mathbf{u}}(\tau, \mathbf{X}_{\tau}^{\mathbf{u}})$  at the stopping time T is bounded above by the value function  $H(\tau, \mathbf{X}_{\tau}^{\mathbf{u}})$ .
- The equality can then be replaced by an inequality with the value function (and not the performance criteria) showing up under the expectation:

$$H^{\mathbf{u}}(t,\mathbf{x}) \leq \mathbb{E}_{t,\mathbf{x}} \left[ H(\tau,\mathbf{X}^{\mathbf{u}}_{\tau}) + \int_{t}^{\tau} F(s,\mathbf{X}^{\mathbf{u}}_{s},\mathbf{u}_{s}) ds \right],$$

$$\leq \sup_{\mathbf{u} \in \mathcal{A}} \mathbb{E}_{t,\mathbf{x}} \left[ H(\tau,\mathbf{X}^{\mathbf{u}}_{\tau}) + \int_{t}^{\tau} F(s,\mathbf{X}^{\mathbf{u}}_{s},\mathbf{u}_{s}) ds \right].$$

This provides us with a first inequality.

<sup>&</sup>lt;sup>a</sup>It may be the case that the supremum is obtained by a limiting sequence of admissible strategies for which the limiting strategy is in fact not admissible