# Dynamic Programming: Infinite State

4.2.3 Job Search with Learning

Thomas J. Sargent and John Stachurski

#### Introduction

This section we consider a job search model where wage offer distribution is unknown.

The agent learns about  $\phi$  by starting with a prior and updating it in light of the wage offer sequence.

### Learning about the Wage Distribution

- two candidate continuous distributions f and g over wage offers;
- nature chooses  $\varphi$  from f or g, and the entire wage offer sequence is drawn from  $\varphi$ ;
- agent does not know the true  $\varphi$ , and starts with an initial guess  $\pi_0 f(w) + (1 \pi_0) g(w)$ ;
- agent observes a sequence of wage offers w<sub>1</sub>, w<sub>2</sub>, ... and updates her beliefs about φ according to Bayes' rule:

$$\pi_{t+1} = \frac{f(W_{t+1})\pi_t}{f(W_{t+1})\pi_t + g(W_{t+1})(1 - \pi_t)}$$
(1)

### A bit more on Bayes' rule

The update rule (1) is updating the probability that  $\varphi = f$  based on the observation  $W_{t+1}$ .

More generally, we can write the update rule as

$$\mathbb{P}\{\varphi = f \mid W_{t+1}\} = \frac{\mathbb{P}\{W_{t+1} \mid \varphi = f\} \mathbb{P}\{\varphi = f\}}{\mathbb{P}\{W_{t+1}\}}$$

where

$$\mathbb{P}\{\,W_{t+1}\} = \sum_{\psi \in \{f,g\}} \mathbb{P}\{\,W_{t+1} \mid \varphi = \psi\} \mathbb{P}\{\varphi = \psi\}.$$

### Belief State

Now we can formulate the problem as an ADP by incorpreting the belief state.

#### Assumption 1: Support of Wage Distribution

The densities f and g are positive on (0, M) and zero elsewhere.

let  $\varphi_{\pi} \coloneqq \pi f + (1 - \pi)g$  represent the estimate of the wage offer distribution given belief  $\pi$  and let

$$\kappa(w,\pi) \coloneqq \frac{\pi f(w)}{\pi f(w) + (1-\pi)g(w)} \qquad (w \in (0,M) \ \pi \in (0,1)).$$

 $\kappa(w,\pi)$  is the updated belief  $\pi'$  of  $\pi$  having observed draw w, e.g.  $\kappa:(0,M)\times(0,1)\to(0,1).$ 

#### ADP Formulation

The state is  $(w, \pi) \in (0, M) \times (0, 1) := X$  and  $\pi$  is referred to as the **belief state**. The action space is  $A = \{0, 1\}$ :

The policy operator is given by

$$(T_{\sigma} v)(w, \pi) = \sigma(w, \pi) \frac{w}{1 - \beta}$$

$$+ (1 - \sigma(w, \pi)) \left[ c + \beta \int v(w', \kappa(w', \pi)) \varphi_{\pi}(w') dw' \right].$$

Let  $\mathbb{T} = \{ T_{\sigma} : \sigma \in A \}$ , and  $V \coloneqq bmX$ . Evidently,  $T_{\sigma}$  is order preserving selfmap on V. Hence  $(V, \mathbb{T})$  is an ADP.

### ADP Formulation

Similar to the traditional job search model, it is easy to check that given  $v \in V$ , show that  $\sigma$  defined by

$$\sigma(w) = \mathbb{1}\left\{\frac{w}{1-\beta} \ge c + \beta \int v(w', \kappa(w', \pi)) \varphi_{\pi}(w') dw'\right\}$$

is v-greedy for  $(V, \mathbb{T})$ .

The Bellman operator is given by

$$v(w,\pi) = \max\left\{\frac{w}{1-\beta}, c+\beta \int v(w',\kappa(w',\pi)) \varphi_{\pi}(w') dw'\right\}. \tag{2}$$

### Factor ADP

Similar to the conventional model, we can formulate the problem as a factor ADP to reduce the dimensionality.

 $h(\pi)$  be the corresponding reservation wage at belief state  $\pi$ , which is the wage level at which the worker is indifferent between accepting and rejecting. This value satisfies

$$\frac{h(\pi)}{1-\beta} = c + \beta \int v(w', \kappa(w', \pi)) \, \varphi_{\pi}(w') \, \mathrm{d}w'. \tag{3}$$

We combine (2) and (3) to obtain

$$v(w,\pi) = \max\left\{\frac{w}{1-\beta}, \frac{h(\pi)}{1-\beta}\right\}$$

and then use this expression to eliminate v in (2), obtaining

$$h(\pi) = (1 - \beta)c + \beta \int \max\{w', h[\kappa(w', \pi)]\} \varphi_{\pi}(w') dw'.$$
 (4)

Equation (4) can be understood as a functional equation in h. Equivalently, the map h is the fixed point of the operator  $\hat{T}$  given by

$$(\hat{T}h)(\pi) = (1-\beta)c + \beta \int \max\{w', h[\kappa(w', \pi)]\} \varphi_{\pi}(w') dw'.$$
 (5)

When this fixed point is well-defined we call it the **optimal reservation** wage function. The value  $h(\pi)$  will indicate the smallest wage offer at which the worker is willing to accept, given her current belief state  $\pi$ .

### **FDP** Formulation

We adapt the model to the factored dynamic program (FDP) framework  $(V, \hat{V}, \mathbb{G}, F)$ .

- State:  $(w, \pi)$ , where w is the wage offer and  $\pi$  is the belief state.
- V = bmX
- $\hat{V} = bm\Pi$ , where  $\pi \in \Pi := (0,1)$ 
  - Related to reservation wage  $h_{\rm res}(\pi)$  in (3) by  $h(\pi) = \frac{h_{\rm res}(\pi)}{1-\beta}$ .

### **FDP Operators**

• Operator  $F \colon V \to \hat{V}$ : Maps full value v to continuation value h = Fv.

$$(\mathit{Fv})(\pi) = c + \beta \int v(w', \kappa(w', \pi)) \, \varphi_{\pi}(w') \, dw'. \quad (\mathsf{from} \ (3))$$

• Family  $\mathbb{G} = \{G_{\sigma} \mid \sigma \in \Sigma\}$ : Maps  $h \in \hat{V}$  to value  $v = G_{\sigma}h$  under policy  $\sigma$ .

$$(G_{\sigma}h)(w,\pi) = \frac{\sigma(w,\pi)w}{1-\beta} + (1-\sigma(w,\pi))h(\pi)$$

where  $\sigma(w, \pi) \in \{0, 1\}$  (0=reject, 1=accept).

•  $G \colon \hat{V} \to V$ : Defined as  $G = \sup_{\sigma \in \Sigma} G_{\sigma}$ . This yields:

$$(Gh)(w,\pi) = \max\left\{\frac{w}{1-\beta},h(\pi)\right\}.$$

This corresponds to using the policy  $\sigma^*$  that is greedy w.r.t. h.

$$T_{\sigma} := G_{\sigma}F \colon V \to V :$$

$$(T_{\sigma}v)(w,\pi) = (G_{\sigma}(Fv))(w,\pi)$$

$$= \frac{\sigma(w,\pi)w}{1-\beta} + (1-\sigma(w,\pi))(Fv)(\pi)$$

$$= \frac{\sigma(w,\pi)w}{1-\beta}$$

$$+ (1-\sigma(w,\pi)) \left[ c + \beta \int v(w',\kappa(w',\pi)) \varphi_{\pi}(w') dw' \right]$$

This is the standard policy operator for policy  $\sigma$  in the original state space V.

$$\begin{split} \hat{T}_{\sigma} &:= FG_{\sigma} \colon \hat{V} \to \hat{V} \colon \\ &(\hat{T}_{\sigma}h)(\pi) = (F(G_{\sigma}h))(\pi) \\ &= c + \beta \int (G_{\sigma}h)(w', \kappa(w', \pi)) \, \varphi_{\pi}(w') \, dw' \\ &= c + \beta \int \left[ \frac{\sigma(w', \kappa(w', \pi))w'}{1 - \beta} \right. \\ &+ (1 - \sigma(w', \kappa(w', \pi))) h(\kappa(w', \pi)) \right] \varphi_{\pi}(w') \, dw' \end{split}$$

This operator updates the continuation value function h under policy  $\sigma$ .

- It is easy to verify that F and  $G_{\sigma}$  are order preserving, and
- according to the discussion on v-greedy policies in the previous section, the set  $\{G_{\sigma}\hat{v}\}$  has the greatest element for each  $\hat{v}\in\hat{V}$ .
- Hence,  $(V, \hat{V}, \mathbb{G}, F)$  is indeed a factored dynamic program.

Recall the operator  $\hat{T}$  from (5) acting on the reservation wage function h:

$$(\hat{T}h)(\pi) = (1 - \beta)c + \beta \int \max\{w', h[\kappa(w', \pi)]\} \varphi_{\pi}(w') dw'.$$

Goal: Show  $\hat{T}$  maps bc(0,1) (bounded, continuous functions on (0,1)) to itself. If  $h \in bc(0,1)$ , is  $\hat{T}h$  also continuous?

## Applying Dominated Convergence

Let  $\pi_n \to \pi$  in (0,1). We need to show  $(\hat{T}h)(\pi_n) \to (\hat{T}h)(\pi)$ . Requires showing convergence of the integral term:

$$\int \underbrace{\max\{w', h[\kappa(w', \pi_n)]\} \ \phi_{\pi_n}(w')}_{H_n(w')} \, \mathrm{d}w' \to$$

$$\int \max\{w', h[\kappa(w', \pi)]\} \ \phi_{\pi}(w') \, \mathrm{d}w'$$

We use the Dominated Convergence Theorem (DCT). Check conditions:

- 1. Pointwise Convergence:  $H_n(w') \to H(w')$  a.e.
- 2. Domination:  $\sup_n |H_n(w')| \leq H(w')$  for some integrable H.

## **Checking DCT Conditions**

Assume  $h \in bc(0, 1)$ . Let  $||h||_{\infty} = \sup |h(\pi)|$ .

#### 1. Pointwise Convergence:

- $\kappa(w',\pi)$  and  $\varphi_{\pi}(w')$  are continuous in  $\pi \in (0,1)$  for  $w' \in (0,M)$ .
- Since h is continuous,  $h[\kappa(w', \pi_n)] \to h[\kappa(w', \pi)]$ .
- Thus  $H_n(w') \to \max\{w', h[\kappa(w', \pi)]\} \varphi_\pi(w')$  pointwise for  $w' \in (0, M)$ .

#### 2. Domination:

- $\max\{w', h[\kappa(w', \pi_n)]\} \leq \max\{M, ||h||_{\infty}\}.$
- $\varphi_{\pi_n}(w') = \pi_n f(w') + (1 \pi_n) g(w') \le f(w') + g(w')$ .
- $|H_n(w')| \leq \max\{M, ||h||_{\infty}\} (f(w') + g(w')).$

 $\bullet \ \int H(w') \,\mathrm{d}w' = \max\{M, \|h\|_\infty\} (\int f + \int g) = 2 \max\{M, \|h\|_\infty\} < \infty.$ 

Conclusion: By DCT, the integral converges. Thus  $\hat{T}h$  is continuous.