

Dynamic Programming Deconstructed

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Introduction

Consider a worker who observes wage offer w_t and either

- **rejects**, gets unemployment compensation η_t , waits for next period
- **accepts**, works forever at current offer w_t

Bellman's equation, assuming IID shocks:

$$v(w, \eta) = \max \left\{ \frac{u(w)}{1 - \beta}, u(\eta) + \beta \mathbb{E} v(w', \eta') \right\}$$

We can simplify this problem by a “time shift”

Examples. Start the clock when

- agent has received current offer and rejected it
- agent has received current offer, rejected it and received unemployment compensation

Leads to alternative “versions” of the Bellman equation

Benefit: we have **multiple angles of attack** on the same problem

In fact economists have come up with many tricks to simplify Bellman equations in different applications

Collectively, we call them “plan factorizations”

The basic idea:

- rearrange the Bellman equation into a more advantageous form. . .
- while preserving its link to optimality

Examples from a variety of applications:

- Jovanovic (1982)
- Rust (1987)
- Aguirregabiria and Mira (2002)
- \vdots ← insert many names
- Fajgelbaum, Schaal and Taschereau-Dumouchel (2017)
- Winberry (2018)
- Kristensen, Mogensen, Moon and Schjerning (2018)
- etc., etc.

We compose a theoretical framework for plan decomposition that

- contains all of the existing manipulations as special cases
- extends to nonseparable preferences
 - recursive preferences
 - risk-sensitive control
 - desire for robustness, ambiguity, etc.
- provides a full set of optimality results
- obtains relative rates of convergence
- obtains new results by exploiting plan factorizations in novel ways

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Examples from the Literature

Recall the Bellman equation of the McCall model discussed above:

$$v(w, \eta) = \max \left\{ \frac{u(w)}{1 - \beta}, u(\eta) + \beta \mathbb{E} v(w', \eta') \right\}$$

A functional equation in **two** dimensions...

Now let

$$g(\eta) := u(\eta) + \beta \mathbb{E} v(w', \eta') \quad (1)$$

Then Bellman's equation becomes

$$v(w, \eta) = \max \left\{ \frac{u(w)}{1 - \beta}, g(\eta) \right\} \quad (2)$$

Combining (1) and (2) to eliminate v gives

$$g(\eta) = u(\eta) + \beta \mathbb{E} \max \left\{ \frac{u(w')}{1 - \beta}, g(\eta') \right\}$$

A functional equation in **one** dimension

We can do still better using **Rust's** “expected value” approach

Let $h := \beta \mathbb{E} v(w', \eta')$, so that

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

Now eliminate v to get

$$h = \beta \mathbb{E} \max \left\{ \frac{u(w')}{1 - \beta}, u(\eta') + h \right\}$$

A functional equation in **zero** dimensions

Example. (Optimal savings) Consider

$$v(w, z, \eta) = \max_{c, w', \ell} \{u(c, \ell) + \beta \mathbb{E}_z v(w', z', \eta')\}$$

subject to

$$w' + c \leq R w + q(z, \eta) \ell, \quad c, w' \geq 0 \quad \text{and} \quad 0 \leq \ell \leq 1.$$

Here

- $\{\eta_t\}$ are IID innovations and $\{z_t\}$ is Markov
- \mathbb{E}_z conditions on current state z

The BE is a three dimensional functional equation

Analogous to Winberry (2018), let

$$h(w, z) := \mathbb{E}_z v(w, z, \eta)$$

Use the law of iterated expectations to write the BE as

$$v(w, z, \eta) = \max_{c, w', \ell} \{u(c, \ell) + \beta \mathbb{E}_z \mathbb{E}_{z'} v(w', z', \eta')\}$$

and rearrange to get

$$h(w, z) = \mathbb{E}_z \max_{c, w', \ell} \{u(c, \ell) + \beta \mathbb{E}_z h(w', z')\}$$

subject to

$$w' + c \leq R w + q(z, \eta) \ell, \quad c, w' \geq 0 \quad \text{and} \quad 0 \leq \ell \leq 1$$

A two dimensional functional equation...

Questions!

- At what point does the standard theory break down?
- Does contractivity imply optimality?
- Does iteration converge at the same rate?
- Might one sequence converge while another does not?
- Do the answers to these questions change if we have
 - EZ preferences?
 - ambiguity?
 - desire for robustness?
 - risk-sensitive preferences?

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New Applications of Plan Factorizations

Plan factorizations have been used in the past to

- reduce dimension
- obtain more smoothness
- simplify estimation

Can they help us in **other** ways???

Example. Benhabib et al. (JET, 2015) study a Bewley model with financial income risk and Bellman equation

$$v(w) = \max_{0 \leq s \leq w} \{u(w - s) + \beta \mathbb{E} v(R's + y')\}$$

Here

- $\{R_t\}$ and $\{y_t\}$ are nonnegative and IID
- CRRA utility $u(c) = c^{1-\gamma}/(1-\gamma)$ with $\gamma > 1$

One difficulty: v unbounded below, so can't use

- standard DP arguments with sup norms...
- or even weighted sup norm methods

Can a plan factorization help?

Let

$$g(s) := \beta \mathbb{E} v(R's + y')$$

so that

$$v(w) = \max_{0 \leq s \leq w} \{u(w - s) + g(s)\}$$

Manipulating to eliminate v gives

$$g(s) = \beta \mathbb{E} \max_{0 \leq s' \leq R's + y'} \{u(R's + y' - s') + g(s')\}$$

Corresponding “Bellman-like” operator is

$$Sg(s) = \beta \mathbb{E} \max_{0 \leq s' \leq R's + y'} \{u(R's + y' - s') + g(s')\}$$

If $g(s) \geq M$, then

$$Sg(s) = \beta \mathbb{E} \max_{0 \leq s' \leq R's + y'} \{u(R's + y' - s') + g(s')\}$$

$$\geq \beta \mathbb{E} \max_{0 \leq s' \leq R's + y'} \{u(R's + y' - s') + M\}$$

$$= \beta \mathbb{E} \{u(R's + y') + M\}$$

$$\therefore Sg(s) \geq \beta \mathbb{E} u(y') + M$$

Thus, $\mathbb{E} u(y') > -\infty \implies$

- Sg also bounded below!
- and a sup norm contraction...

Questions!

- S is a contraction but what does this imply?
- If one Bellman-like equation has a unique fixed point, do all?
- Does this lead us to optimality?
 - After all, the original Bellman op. is not a sup norm contraction
- Is that still true if we add in, say, risk sensitivity?
- Are there more plan factorizations we should try?
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Theory

In what follows, a dynamic programming problem consists of

- a **state space** \mathbb{X}
- an **action space** \mathbb{A}
- a **feasible correspondence** Γ
- a set of **candidate value functions** \mathbb{V}
- a **state-action aggregator** Q

The Bellman equation:

$$v(x) = \max_{a \in \Gamma(x)} Q(x, a, v) \quad \text{for all } x \in \mathbb{X}$$

The **Bellman operator** is

$$T v(x) = \max_{a \in \Gamma(x)} Q(x, a, v)$$

A **v -greedy** policy is a feasible policy σ such that, for all x ,

$$\sigma(x) \in \operatorname{argmax}_{a \in \Gamma(x)} Q(x, a, v)$$

- Treats v as the value function and makes best choice

Can accommodate

- recursive preferences
- risk-sensitive preferences
- robustness
- ambiguity
- etc.

Just modify the definition of Q ...

Example. Benhabib et al. (JET, 2015) continued:

- $x = w$
- $a = s$
- $\Gamma(w) = [0, w]$
- $Q(w, s, v) = u(w - s) + \beta \mathbb{E} v(R's + y')$

Example. Benhabib et al. with CES aggregator:

Same, except

$$Q(w, s, v) = \left\{ (1 - \beta)u(w - s)^\rho + \beta [\mathbb{E} v(R's + y')]^\rho \right\}^{1/\rho}$$

We define a **plan factorization** to be a pair of operators (W_0, W_1) be such that

$$(W_1 W_0 v)(x, a) = Q(x, a, v), \quad \forall \text{ feasible } (x, a) \text{ and } \forall v \in \mathbb{V}$$

- $W_0 \circ W_1$ represents future value conditional on current action
- An arbitrary decomposition

Letting

$$Mh(x) := \max_{a \in \Gamma(x)} h(x, a)$$

the Bellman operator can be written as

$$T = M \circ W_1 \circ W_0$$

Example. Recall that in Benhabib et al. (JET, 2015),

$$Q(w, s, v) = u(w - s) + \beta \mathbb{E} v(R's + y')$$

Our plan factorization is (W_0, W_1) where

- $(W_0 v)(s) = g(s) := \beta \mathbb{E} v(R's + y')$
- $(W_1 g)(w, s) := u(w - s) + g(s)$

As required,

$$(W_1 W_0 v)(w, s) = Q(w, s, v)$$

Rearranging the Bellman Operator

Recall that

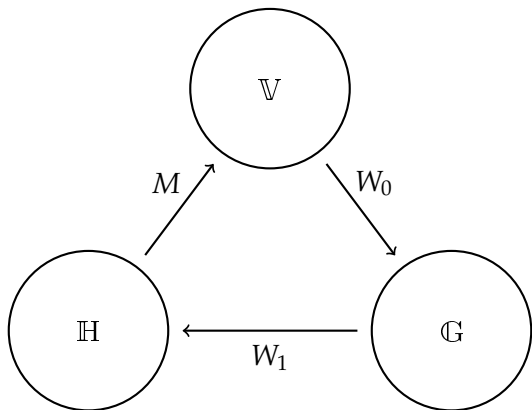
$$T = M \circ W_1 \circ W_0 \text{ on } \mathbb{V}$$

Now consider

$$S = W_0 \circ M \circ W_1 \text{ on } \mathbb{G}$$

Here $\mathbb{G} := W_0\mathbb{V}$

We call S the **refactored Bellman operator**



Example. Recall again **Benhabib et al.** (JET, 2015), with “Bellman-like” operator

$$Sg(s) = \beta \mathbb{E} \max_{0 \leq s' \leq R's + y'} \{u(R's + y' - s') + g(s')\} \quad (3)$$

Our plan factorization was

- $(W_0v)(s) = g(s) := \beta \mathbb{E} v(R's + y')$
- $(W_1g)(w, s) := u(w - s) + g(s)$

It follows that S in (3) can be expressed as the factorized Bellman operator

$$S = W_0 \circ M \circ W_1 \text{ on } \mathbb{G}$$

For each $\sigma \in \Sigma :=$ **feasible policies**, define

$$M_\sigma v(x) := v(x, \sigma(x))$$

Policy operators

$$T_\sigma = M_\sigma \circ W_1 \circ W_0 \text{ on } \mathbb{V}$$

$$S_\sigma = W_0 \circ M_\sigma \circ W_1 \text{ on } \mathbb{G}$$

Let

- $v_\sigma :=$ fixed point of T_σ and $v^* := \sup_\sigma v_\sigma =$ **value function**
- $g_\sigma :=$ fixed point of S_σ
- $g^* := \sup_\sigma g_\sigma =$ **refactored value function**

Question: Does the refactored Bellman operator have “equal rights”?

For example, suppose we obtain contraction results for S

Does this mean we can

- proceed as we would for T and
- be confident that the result is approximately optimal?

Answer: Yes, if W_0 is isotone on \mathbb{V} and W_1 is isotone on \mathbb{G}

Let's call this **joint isotonicity**

Main Results

Thm. Under joint isotonicity, the next two statements are equivalent:

1. v^* satisfies the Bellman equation
2. g^* satisfies refactored Bellman equation

In particular, if g^* satisfies refactored Bellman equation, then

- Bellman's principle of optimality holds
- set of optimal policies is nonempty

So when does $Sg^* = g^*$?

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So when does $Sg^* = g^*$?

Thm. Assume joint isotonicity. If \exists a topology τ on \mathbb{G} under which

- the pointwise partial order is closed and
- S and $\{S_\sigma\}_{\sigma \in \Sigma}$ are asymptotically stable on \mathbb{G} ,

then g^* satisfies the refactored Bellman equation

Moreover,

1. A feasible policy is optimal if and only if it is g^* -greedy
2. $S^k g \rightarrow g^*$ as $k \rightarrow \infty$ for all $g \in \mathbb{G}$
3. At least one optimal policy exists

Translation: Under joint monotonicity, refactored version has equal rights

You can

- pick the pick the factorization you want to work with
- establish contraction (or similar) results in that setting
- proceed in the obvious way

We also prove that iterates are “conjugate”

Translation: Freely use the factorization that produces the most efficient Bellman operator

Joint isotonicity not required for above

Plus other results on algorithms, optimality... see paper

Application

Bäuerle and Jaśkiewicz (JET, 2018) study a growth model with **risk-sensitive preferences**

The Bellman equation is

$$v(x) = \sup_{y \in [0, x]} \left\{ u(x - y) - \frac{\beta}{\gamma} \log \int \exp(-\gamma v[f(y, z)]) \mu(dz) \right\}$$

They provide conditions for the validity of

- value function iteration
- Bellman's principle of optimality

One short-coming: utility must be bounded below

We generalize their results to include utility unbounded below

Method:

1. Implement a plan factorization to obtain the refactored Bellman equation

$$g(y) = -\frac{1}{\gamma} \times$$

$$\log \int \exp \left\{ -\gamma \sup_{y' \in [0, f(y, z)]} [u(f(y, z) - y') + \beta g(y')] \right\} \mu(dz)$$

2. Establish the conditions of the preceding theorem

In doing so we exploit the fact that the solution g is naturally bounded below