Lecture 7 Function approximation

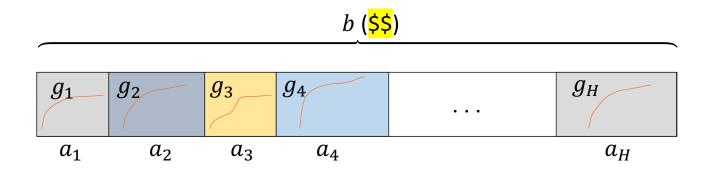
# Year 1963

#### Polynomial Approximation—A New Computational Technique in Dynamic Programming: Allocation Processes

By Richard Bellman, Robert Kalaba, and Bella Kotkin

Mathematics and Computation 17:155—161, 1963

The problem & the dynamic programming formulation

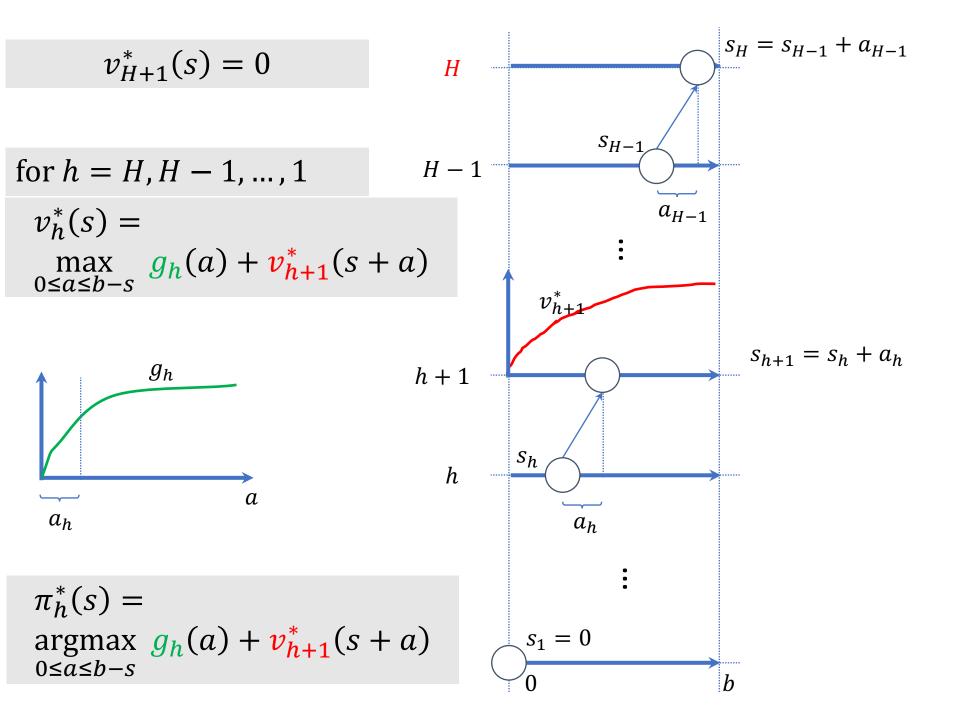


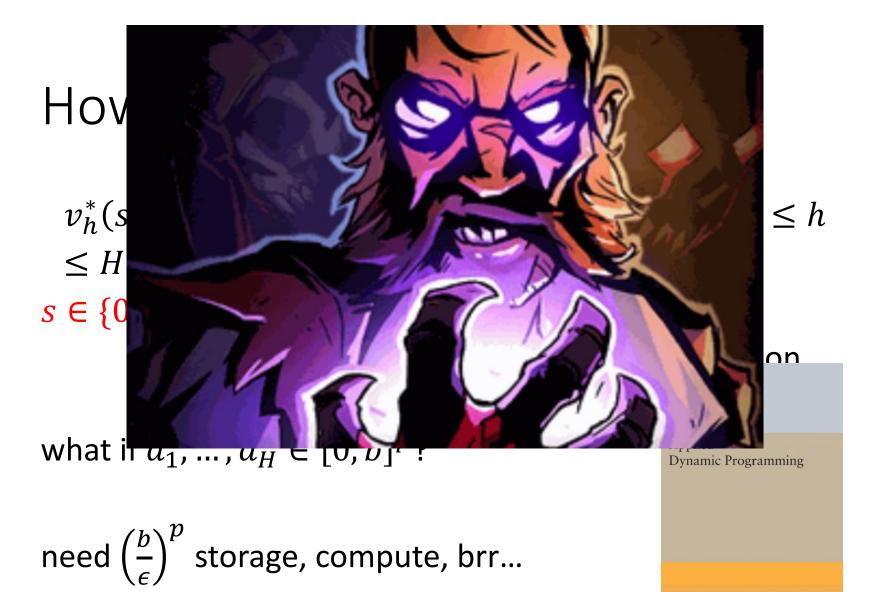
$$v_1^*(0) = \max\{ \sum_{i=1}^H g_i(a_i) : a_1, \dots a_H \ge 0, a_1 + \dots + a_H = b \} = ?$$
  
$$a_1^*, \dots, a_H^* = ?$$

 $v_h^*(s)$ : optimal value achievable over [h, H]when  $s \in [0, b]$  of the resource is used beforehand

$$v_{H+1}^*(s) = 0$$

$$v_h^*(s) = \max_{0 \le a \le b-s} g_h(a) + v_{h+1}^*(s+a) \qquad 1 \le h \le H$$





"curse of dimensionality"

https://www.rand.org/content/dam/rand/pubs/reports/2006/R352.pdf

### New idea (in 1963): Generalized polynomial approximation

-0.75

-1.00

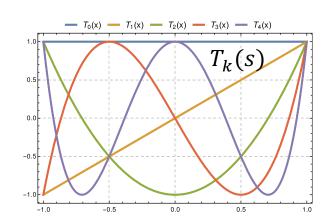
-1.00

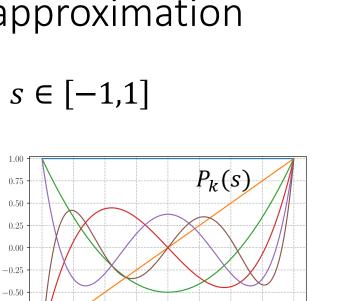
$$f(x) = \sum_{k=1}^{d} \theta_k \varphi_k(s), \qquad s \in \mathbb{R}$$

If using  $\{P_k\}$ , orthonormal set w.r.t. uniform measure on [-1,1]

$$\theta_k = \int_{-1}^1 f\varphi_k$$

+Gauss quadratures: eval f at  $\{s_i\}_{i \in [r]}$ 





 $- P_4$ 

 $-P_5$ 

0.50

0.75

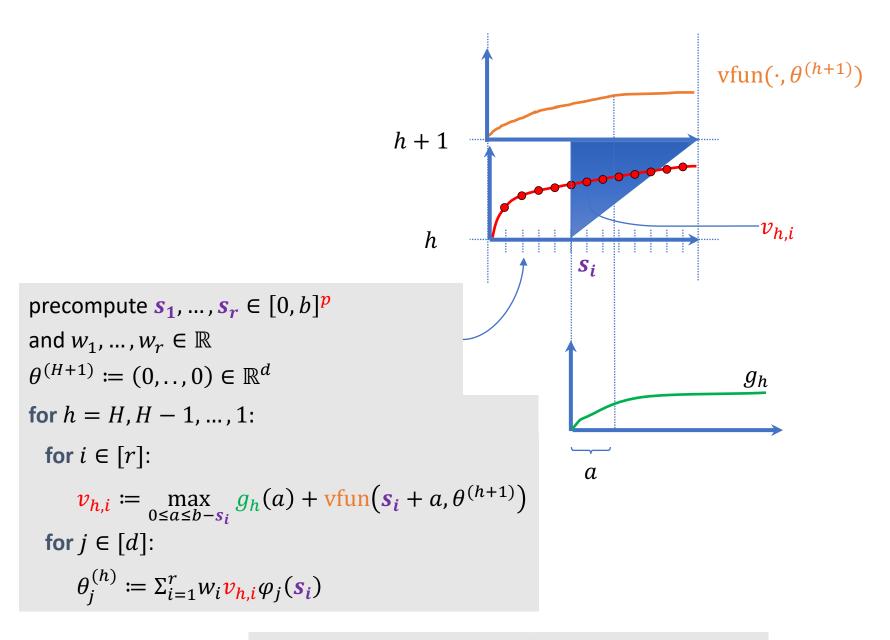
1.00

0.25

 $-P_2$ 

0.00

-0.75 -0.50 -0.25



**vfun**(*s*,  $\theta$ ): =  $\sum_{k=1}^{d} \theta_k \varphi_k(s)$ 

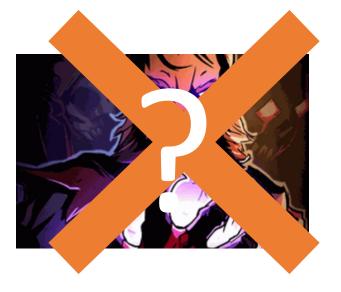




## What did we gain?

Storage: O(H(d + r))Compute cost: O(H(d + r OptCost))

Compare with  $\left(\frac{b}{\epsilon}\right)^p!$ 



Gain?

For fixed OptCost, the cost is independent of the dimension p

At least we can run the procedure: Fine-grained error control through the choice of  $\{\phi_k\}_k, r$  and OptCost

Relevance?  

$$v_h^*(s) = \max_{0 \le a \le b-s} g_h(a) + v_{h+1}^*(s+a)$$

### $\Rightarrow$

# $v_{h}^{*}(s) = \max_{a \in \mathcal{A}_{h}(s)} r_{h}(s, a) + \mathbb{E}_{\xi}[v_{h+1}^{*}(f_{h}(s, a, \xi))]$

**Markov Decision Processes** 

### The RL Hypothesis

Dynamic programming + function approximation

key technique to solve large scale control problems

Markov Decision Problems



"Finally, if we combine these techniques – polynomial approximations and Lagrange multipliers – with that of successive approximations, there should be very few allocation processes which still resist our efforts."





### But.. does this work ..?

**1.** Approximation: How large should be the degree of polynomials used to approximate  $v^*$ ?

Smoothness, approximation theory, systems theory..

#### 2. Computation:

Given that we can approximate well  $v^*$ , say,

 $v^*(s) = \Sigma_{i=1}^d \theta_i^* \varphi_i(s),$ 

how much computation is needed to get  $\theta^* = (\theta_1^*, \dots, \theta_d^*)$ ?

Can we do it in  $poly(A, H, d, 1/\varepsilon)$  regardless of dimension (state space size)?

#### O' Curse of Dimensionality, Where is Thy Sting?

Kenneth L. Judd Hoover Institution and NBER April 11, 2008

https://kenjudd.org/wp-content/uploads/2017/02/Curse\_in\_Dallas.pdf

#### Math Tool II: Efficient Function Approximation

• Linear polynomial methods:

 $f\left(x,y,z,\ldots\right)=\sum_{i=1}^{m}a_{i}\phi_{i}\left(x,y,z,\ldots\right),\,\phi_{i}\text{ multivariate polynomials}$ 

- Simple tensor product approach produces approximations like

$$\sum_{i=0}^m \sum_{j=0}^m \sum_{k=0}^m a_{ij} x^i y^j z^k$$

- Proper notion of "degree" in multivariate context is sum of powers

degree 
$$\left(x^{i}y^{j}z^{k}\right) = i + j + k$$

– Complete polynomials like

$$\sum_{i+j+k\leq m}a_{ijk}x^iy^jz^k$$

have far fewer terms by a ratio of nearly d!, but are almost as good

- See Gaspar-Judd (1997)

https://kenjudd.org/wp-content/uploads/2016/09/jgasweb.pdf https://www.cambridge.org/core/journals/macroeconomic-dynamics/article/abs/solvinglargescale-rationalexpectations-models/A484F77266454AA52B535BF8B28257B8

## Modeling assumptions

- $v^* \in \mathcal{F}$  realizable
- $q^* \in \mathcal{F}'$ realizable
- $v^{\pi} \in \mathcal{F}$  for any deterministic/stochastic ML  $\pi$
- $q^{\pi} \in \mathcal{F}'$  for any deterministic/stochastic ML  $\pi$
- $T^{\pi}\mathcal{F} \subset \mathcal{F}, T^{\pi}\mathcal{F}' \subset \mathcal{F}'$  for any deterministic/stochastic ML  $\pi$
- $T\mathcal{F} \subset \mathcal{F}, T\mathcal{F}' \subset \mathcal{F}'$
- $T^{\pi}\mathbb{R}^{S} \subset \mathcal{F}, T^{\pi}\mathbb{R}^{S \times A} \subset \mathcal{F}'$  for any deterministic/stochastic ML  $\pi$
- $T\mathbb{R}^{\mathcal{S}} \subset \mathcal{F}, T\mathbb{R}^{\mathcal{S} \times A} \subset \mathcal{F}'$

# Questions from slack

### Matthew Pietrosanu 19 hours ago

I'll bite since this relates to some of my research in functional data analysis. The choice of basis {phi\_j: j=1,...,d} isn't discussed much in the notes. Are there any particularly common choices in RL? (I can only speak to statistics, so I'm curious.) Or am I reading too much into what will ultimately be just a "toy" model (e.g., with the bases obtained by other means, say, NN?)

+9

Matthew Pietrosanu 19 hours ago

As a followup, though this involves infinite-dimensional state spaces.. Are there any settings where estimating this basis is a primary concern? (e.g., a smooth basis that describes some "optimal" d-dimensional subset of the infinite-dimensional space of functions.) In such a setting, estimating Phi (as a matrix) along some grid in S might not be adequate (e.g., the basis described by Phi may be non-smooth). Are there any approaches in RL to deal with this? (Again, maybe this isn't even a relevant problem.)

+2