

# Computational Methods

Wenlan Luo  
Tsinghua University

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## About the course

Goal:

- ▶ Prepare students to solve Huggett-Aiyagari type models.

Approach:

- ▶ Step-by-step guidance to replicate papers.

For beginners:

- ▶ Review literature developed based on the framework.
- ▶ Review dynamic programming, equilibrium definitions, properties, etc.
- ▶ Review basic algorithms and numerical routines.

For advanced users:

- ▶ Learn how to fine-tune. Compare different algorithms for efficiencies.
- ▶ Introduce integration of C++ into Matlab for fast development with decent performances.

## What do Huggett-Aiyagari type models do?

- ▶ **Inequality:**

**Aiyagari (1994)**, Huggett (1996), Cagetti and De Nardi (2006), Huggett et al. (2011), Kaymak and Poschke (2015), Hubmer et al. (2016)

- ▶ **Consumer behavior:**

Kaplan and Violante (2010), Berger and Vavra (2015), Kaplan and Violante (2014), Telyukova (2013), Heathcote et al. (2009)

- ▶ **Aggregate fluctuation:**

**Krusell and Smith (1998)**, Heathcote (2005), Khan and Thomas (2013), Bachmann and Bai (2013), Winberry (2014)

- ▶ **Taxation:**

Conesa et al. (2009), Guner et al. (2014), **Badel et al. (2014)**

- ▶ **Monetary policy with heterogeneity:**

**McKay et al. (2016)**, Auclert (2014), Kaplan et al. (2015), Gornemann et al. (2014), Vavra (2013)

## Resources

- ▶ Books:
  - Recursive Methods in Economic Dynamics - Stokey and Lucas (1989)
  - Numerical Methods in Economics - Judd (1998)
  - Dynamic Programming - Rust (2006)
  - Numerical Recipes: The Art of Scientific Computing, Third Edition (2007)
- ▶ Others' lecture notes:
  - Mark Huggett
  - Dirk Krueger
  - Victor Rios-Rull
  - Tony Smith

## Aiyagari (1994)

Decision problem:

$$\begin{aligned}v(\epsilon, k) &= \max_{k'} u(c) + \beta E v[(\epsilon', k') | \epsilon] \\ \text{s.t. } c + k' &\leq k(1+r) + \epsilon w \\ k' &\geq 0, l = 1\end{aligned}$$

Primitives:  $u(\cdot)$ ,  $\beta$ ,  $\epsilon' | \epsilon \sim \phi(\cdot | \epsilon)$ ,  $F, \delta$

Equilibrium:  $k'(\epsilon, k)$ ,  $\Gamma, K, L, r, w$ , s.t.

- ▶  $k'(\epsilon, k)$  solves the decision problem.
- ▶ Stationary distribution:

$$\Gamma(\mathcal{E}, \mathcal{K}) = \int \mathbf{1}(k'(\epsilon, k) \in \mathcal{K}, \epsilon' \in \mathcal{E}) \phi(d\epsilon' | \epsilon) \Gamma(d\epsilon, dk)$$

- ▶ Aggregation:

$$K = \int k \Gamma(dk, d\epsilon), L = \int \epsilon \Gamma(dk, d\epsilon)$$

- ▶ Price determination:

$$r = F_K(K, L) - \delta, w = F_N(K, L)$$

## Aiyagari (1994), solve the decision problem

Input:  $w, r$ . Output:  $k'(\epsilon, k)$

Approach: global method. Time iteration until convergence.

Algorithms:

- ▶ Grid search
- ▶ Solve optimization problem by approximating future value off-grid
- ▶ Solve the Euler equation
- ▶ Endogenous grid method based on the Euler equation

## Aiyagari (1994), solve the decision problem, preliminaries

Parameterizations:

$$u(c) = c^{1-\gamma}/(1-\gamma), F = K^\alpha L^{1-\alpha}$$

$$\epsilon' = \rho\epsilon + \sigma(1-\rho^2)^{1/2}u, u \sim N(0, 1)$$

Preliminaries:

- ▶ Discrete shock process
- ▶ Choose asset grid

## Aiyagari (1994), solve the decision problem, grid search

### Algorithms

- ▶ Discretize  $(\epsilon, k)$  over finite grids. Choose discrete grid for  $k'$  the same as  $k$ .
- ▶ Initialize  $v(\epsilon, k)$ .
- ▶ Given  $v$ ,
  - ▶ For each  $(\epsilon, k)$ , for each discrete  $k'$ , compute  $c(k', \epsilon, k)$
  - ▶ Compute  $\tilde{v}(k', \epsilon, k) = u(c(k', \epsilon, k)) + \beta E[v(\epsilon', k') | \epsilon]$
  - ▶ Compute  $v_{new}(\epsilon, k) = \max_{k'} \tilde{v}(k', \epsilon, k)$ .  $k'(\epsilon, k) = \arg \max$
  - ▶ Check convergence of  $v_{new}$  and  $v$ . Update  $v$ .

### Disadvantages:

- ▶ Slow.
- ▶ Inaccurate. Policy function is not continuous in  $(w, r)$  or parameters.

# Aiyagari (1994), solve the decision problem, approximating $v$ function

## Algorithms

- ▶ Discretize  $(\epsilon, k)$ .
- ▶ Initialize  $v(\epsilon, k)$ .
- ▶ Given  $v$ , loop over  $(\epsilon, k)$ 
  - ▶ For each  $(\epsilon, k)$ , solve problem

$$v_{new}(\epsilon, k) = \max_{k'} u(c(k', \epsilon, k)) + \beta E[\tilde{v}(\epsilon', k') | \epsilon],$$

where  $\tilde{v}$  approximates  $v$ .

- ▶ Check convergence of  $v_{new}$  and  $v$ . Update  $v$ .

## Choice of numerical methods:

- ▶ Approximation: piece-wise (linear/spline/pchip)
- ▶ Optimization: bracketing-based method

# What is Matlab slow at?

An introduction to different languages

- ▶ Compiled languages: C, C++, Fortran
  - ▶ What you write e.g. "1+1" is executed as "1+1" by machine directly
  - ▶ Need to compile after code changes. Costly to develop and debug.
- ▶ Interpreted languages: Matlab, Python
  - ▶ Everything is stored as an object internally (Matlab's mxArray, Python's PyObject)
  - ▶ When you call "1+1", the machine does the following:
    - ▶ The interpreter splits the expression as "object", "operator", "object"
    - ▶ Check the type and size of two objects and select the operator "scalar plus"
    - ▶ Read two scalars from two objects.
    - ▶ Allocate space for the result
    - ▶ Do the "1+1".
    - ▶ Wrap the result "2" into an object with its type and size.
  - ▶ When you call "A\*B" for two large matrix, the same procedure goes but the bottleneck is now to do the "A\*B", which is calling some external library by both C++ and Matlab. Overhead of other parts is thus less important.
  - ▶ That's why doing loops and function calls is extremely slow in Matlab.
- ▶ JIT: Julia, Matlab (partial), Java/C# (partial), Python (numba)

# Aiyagari (1994), solve the decision problem, approximating $v$ function

A **vectorized** implementation

## Algorithms

- ▶ Discretize  $(\epsilon, k)$ .
- ▶ Initialize  $v(\epsilon, k)$ .
- ▶ Given  $v$ , **vectorize** over  $(\epsilon, k)$ 
  - ▶ For each  $(\epsilon, k)$ , solve problem

$$v_{new}(\epsilon, k) = \max_{k'} u(c(k', \epsilon, k)) + \beta E[\tilde{v}(\epsilon', k') | \epsilon],$$

where  $\tilde{v}$  approximates  $v$ .

- ▶ Check convergence of  $v_{new}$  and  $v$ . Update  $v$ .

## Disadvantages:

- ▶ Write code in vectorized fashion is hard!
- ▶ Still slow!

# Combining Matlab and C++: an introduction to mex

## Why Matlab, not Julia or Python?

- ▶ Matlab has well-maintained libraries, version stability, free of bugs.
- ▶ Fast if used in a good way. (Built-in MKL for linear algebra and function approximation, state-of-art optimization libraries)
- ▶ Super easy integration with C++ for computation-intensive parts, while still use Matlab's other convenient utilities (debug, plot, output, etc.)

## Preparations:

- ▶ Visual Studio Community 2015 on Windows. It's free for academic use.
- ▶ g++ 4.8 on Linux and Mac.
- ▶ run "mex -setup C++" in Matlab.

# Aiyagari (1994), solve the decision problem, approximating $v$ function

A C-mex implementation

## Algorithms

- ▶ Discretize  $(\epsilon, k)$ .
- ▶ Initialize  $v(\epsilon, k)$ .
- ▶ Given  $v$ , loop over  $(\epsilon, k)$  in C++
  - ▶ For each  $(\epsilon, k)$ , solve problem

$$v_{new}(\epsilon, k) = \max_{k'} u(c(k', \epsilon, k)) + \beta E[\tilde{v}(\epsilon', k') | \epsilon],$$

where  $\tilde{v}$  approximates  $v$ .

- ▶ Check convergence of  $v_{new}$  and  $v$ . Update  $v$ .

## Advantages:

- ▶ Write code in natural ways, no need to spend extra mental cost on vectorization
- ▶ Extremely fast and parallel scalable.

## Cost:

- ▶ Need to know basics about C++
- ▶ Need to be familiar with basic numerical routines (optimization, function approximation) in C++, but most are available online.

## Aiyagari (1994), solve the decision problem, solve Euler equation

Decision problem:

$$\begin{aligned} v(\epsilon, k) &= \max_{k'} u(c) + \beta E[v(\epsilon', k')|\epsilon] \\ \text{s.t. } c + k' &\leq k(1+r) + \epsilon w_l \\ k' &\geq 0, l = 1 \end{aligned}$$

FOC w.r.t.  $k'$

$$-u'(k(1+r) + \epsilon w_l - k') + \beta E[v_k(\epsilon', k')|\epsilon] + \lambda_{k' \geq 0} = 0$$

or

$$u'(k(1+r) + \epsilon w_l - k') \geq \beta E[v_k(\epsilon', k')|\epsilon]$$

Equality holds iff  $k' > 0$ .

Aiyagari (1994), solve the decision problem, solve Euler equation

$$u'(k(1+r) + \epsilon w l - k') \geq \beta E[v_k(\epsilon', k')|\epsilon]$$

### Algorithms

- ▶ Discretize  $(\epsilon, k)$ .
- ▶ Initialize  $v_k(\epsilon, k)$ .
- ▶ Given  $v_k$ , loop over  $(\epsilon, k)$ 
  - ▶ For each  $(\epsilon, k)$ , check if

$$u'(k(1+r) + \epsilon w l - 0) > \beta E[v_k(\epsilon', 0)|\epsilon]$$

if yes, then you have a corner,  $k'(\epsilon, k) = 0$ . Else, solve  $k'$  s.t.

$$u'(k(1+r) + \epsilon w l - k') = \beta E[\tilde{v}_k(\epsilon', k')|\epsilon]$$

where  $\tilde{v}_k$  approximates  $v_k$ .

Since  $u'(0) = \infty > \beta E[v_k(\epsilon', k(1+r) + \epsilon w l)|\epsilon]$  and  $u'(k(1+r) + \epsilon w l - 0) \leq \beta E[v_k(\epsilon', 0)|\epsilon]$ , we have a solution.

Since  $v_{kk} < 0$  and  $u''(\cdot) < 0$ , the solution is unique.

- ▶ Compute  $v_{k,new}$  using Envelope theorem

$$v_{k,new}(\epsilon, k) = (1+r)u'(k(1+r) + \epsilon w l - k'(\epsilon, k))$$

- ▶ Check convergence of  $v_k$  and update  $v_k$ .

## Aiyagari (1994), solve the decision problem, endogenous grid method

$$u'(k(1+r) + \epsilon w l - k') \geq \beta E[v_k(\epsilon', k')|\epsilon]$$

Algorithm:

- ▶ Discretize  $(\epsilon, k)$  over  $eGrid, kGrid$ .
- ▶ Initialize  $v_k(\epsilon, k)$ .
- ▶ Given  $v_k$ 
  - ▶ For each  $(\epsilon, k')$  on grids, compute

$$\tilde{k}(\epsilon, k') = \frac{u'^{-1}(\beta E[v_k(\epsilon', k')|\epsilon]) + k' - \epsilon w l}{1+r}$$

- ▶ Interpolate  $k'$  over  $\tilde{k}$  and evaluate interpolation at  $k \in kGrid$  for  $k \geq \tilde{k}(\epsilon, 0)$ . This gives  $k'(\epsilon, k)$  for  $k \geq \tilde{k}(\epsilon, 0)$ .
- ▶ We know  $k'$  is increasing in  $k$ , and therefore  $k'(\epsilon, k) = 0, \forall k \leq \tilde{k}(\epsilon, 0)$ .
- ▶ Update using envelope theorem. Check convergence.

Advantages:

- ▶ No need to solve equations (avoid function calls).
- ▶ Easy to vectorize (avoid loops).

References: Carroll (2005), Barillas and Fernández-Villaverde (2007)

## Aiyagari (1994), solve the decision problem, summary

### Summary

- ▶ Endogenous grid method avoids repetitive function calls in optimization or root-finding. Should be the first choice whenever possible. But usually only applies to a few problems.
- ▶ Vectorized golden search deals with more general problems (1-D) and still makes computation feasible.
- ▶ For non-standard problems (any problems with states or controls go beyond 1-D) and best performances consider C-mex.

## Aiyagari (1994), Monte Carlo simulations

Algorithm:

- ▶ Generate history of shocks  $\epsilon_i^t$ 
  - ▶ Theorem:  $F$  is a cdf, then  $F^{-1}(u) \sim F$  if  $u \sim Un[0, 1]$
  - ▶ For discrete distribution that  $F$  is a "step" function, first generate  $u \sim Un[0, 1]$ , then look up which "step"  $u$  falls in.
  - ▶ For Markovian process, generate  $\epsilon_i^{t+1}$  base on  $\phi(\cdot|\epsilon_i^t)$
- ▶ Generate initial distribution  $k_0$ .
- ▶ Simulate forward using  $k'(\epsilon, k)$ , approximating the policy function for  $k$  off-grid.

The choice of  $I$  and  $T$ ?

- ▶ Moments of distribution become stationary.

## Aiyagari (1994), solve equilibrium

Algorithm:

- ▶ Search over  $r \in [r_{min}, r_{max}]$  using bracketing method:
  - ▶ Given  $r$ , solve policies, simulate stationary distribution.
  - ▶ Compute aggregate  $K$  and  $L$  from stationary distribution. Compute implied  $r_{new}$ .
- ▶ Until  $r$  and  $r_{new}$  are close enough.

## Aiyagari (1994), non-stochastic simulations

Algorithm:

- ▶ Approximate distribution of states  $\Gamma$  with distribution  $\tilde{\Gamma}$  over discrete grids  $(\epsilon, k)$ .
- ▶ The markovian process induced by the exogenous shock and policy function gives a transition  $H : \tilde{\Gamma} \rightarrow \tilde{\Gamma}'$ . Usually the approximation and transition are constructed such that the transition can be directly computed.

Example Young (2010):

- ▶ Approximate  $\Gamma$  as histogram over discrete grid  $(\epsilon, k)$ .
- ▶ Assume if  $k'(\epsilon, k)$  is off-grid, it is allocated between  $k'_{left}$  and  $k'_{right}$  uniformly.

Advantages:

- ▶ No need to generate random numbers. Remove randomness of aggregate variables.
- ▶ Convenient to check convergence of distributions.

## Krusell and Smith (1998): dealing with aggregate uncertainty

Decision problem:

$$\begin{aligned} v(\epsilon, k; z, \Gamma) &= \max_{k'} u(c) + \beta Ev[(\epsilon', k'; z', \Gamma') | \epsilon, z] \\ \text{s.t. } c + k' &\leq k(1 + r(z, \Gamma)) + \epsilon w(z, \Gamma) l \\ k' &\geq 0, l = 1 \\ \Gamma' &= H(z, \Gamma) \end{aligned}$$

Primitives:  $u(\cdot)$ ,  $\beta$ ,  $(\epsilon', z') | (\epsilon, z) \sim \phi(\cdot | \epsilon, z)$ ,  $F, \delta$

Equilibrium:  $k'(\epsilon, k; z, \Gamma)$ ,  $H : (z', z, \Gamma) \rightarrow \Gamma'$ ,  $K(z, \Gamma)$ ,  $L(z, \Gamma)$ ,  $r(z, \Gamma)$ ,  $w(z, \Gamma)$ ,  
s.t.

- ▶  $k'(\epsilon, k; z, \Gamma)$  solves the decision problem.
- ▶ Transition rule of measure:

$$H(z', z, \Gamma)(\mathcal{K}, \mathcal{E}) = \int \mathbf{1}(k'(\epsilon, k; z, \Gamma) \in \mathcal{K}, \epsilon' \in \mathcal{E}) \phi(d\epsilon', dz' | \epsilon, z) \Gamma(d\epsilon, dk)$$

- ▶ Aggregation:

$$K(z, \Gamma) = \int k \Gamma(dk, d\epsilon), L(z, \Gamma) = \int \epsilon \Gamma(dk, d\epsilon)$$

- ▶ Price determination:

$$r(z, \Gamma) = F_K(z, K, L) - \delta, w(z, \Gamma) = F_N(z, K, L)$$

## Krusell and Smith (1998): dealing with aggregate uncertainty

Challenge:  $\Gamma$  is an infinite-dimension object.

Solution by Krusell and Smith (1998): approximate  $\Gamma$  using finite moments.

Findings:

- ▶ First moment of  $k$  is sufficient to approximate the distribution. Why?
  - ▶  $r$  and  $w$  are only determined by  $\bar{k}$
  - ▶ Households' decision rules for saving are almost linear in  $k$  when  $k$  is large. Nonlinearity of decision rules happens when  $k$  is low, but in equilibrium the mass of people with low  $k$  is small.
- ▶ Transition rule for distribution  $H(z', z, \Gamma)$  can be well approximated by

$$\log(\bar{k}') = \alpha_0(z) + \alpha_1(z) \log(\bar{k})$$

## Krusell and Smith (1998): dealing with aggregate uncertainty

Decision problem:

$$\begin{aligned}v(\epsilon, k; z, \bar{k}) &= \max_{k'} u(c) + \beta E v[(\epsilon', k'; z', \bar{k}') | \epsilon, z] \\ \text{s.t. } c + k' &\leq k(1 + r(z, \bar{k})) + \epsilon w(z, \bar{k})/l \\ k' &\geq 0, l = 1 \\ \log(\bar{k}') &= \alpha_0(z) + \alpha_1(z) \log(\bar{k})\end{aligned}$$

Primitives:  $u(\cdot)$ ,  $\beta$ ,  $(\epsilon', z') | (\epsilon, z) \sim \phi(\cdot | \epsilon, z)$ ,  $F$ ,  $\delta$

Equilibrium:  $k'(\epsilon, k; z, \bar{k})$ ,  $\alpha_0(z)$ ,  $\alpha_1(z)$ ,  $K(z, \bar{k})$ ,  $L(z, \bar{k})$ ,  $r(z, \bar{k})$ ,  $w(z, \bar{k})$ , s.t.

- ▶  $k'(\epsilon, k; z, \bar{k})$  solves the decision problem.
- ▶ Transition rule of moment is consistent with the transition of distribution.
- ▶ Aggregation:

$$\bar{k} = \int k \Gamma(dk, d\epsilon), L(z, \bar{k}) = \int \epsilon \Gamma(dk, d\epsilon)$$

- ▶ Price determination:

$$r(z, \bar{k}) = F_K(z, \bar{k}, L) - \delta, w(z, \bar{k}) = F_N(z, \bar{k}, L)$$

## Krusell and Smith (1998): solve the decision problem

$$\begin{aligned}v(\epsilon, k; z, \bar{k}) &= \max_{k'} u(c) + \beta E v[(\epsilon', k'; z', \bar{k}') | \epsilon, z] \\ \text{s.t. } c + k' &\leq k(1 + r(z, \bar{k})) + \epsilon w(z, \bar{k})l \\ k' &\geq 0, l = 1 \\ \log(\bar{k}') &= \alpha_0(z) + \alpha_1(z) \log(\bar{k})\end{aligned}$$

Challenges: how to interp over two dimensions  $(k', \bar{k}')$ .

Algorithm:

- ▶ Given  $(z, \bar{k})$ , compute  $\bar{k}'$  using the transition rule.
- ▶ Interpolate over  $\bar{k}'$ , get  $(E\tilde{v})_{z, \bar{k}', \epsilon}(k')$ . That is, when we solve individual's problem varying  $k'$ ,  $(z, \bar{k}')$  are always fixed.
- ▶ Solve individual's optimization problem.

## Krusell and Smith (1998): simulations and aggregation

Algorithm:

- ▶ Simulate  $k_t$  forward using policy function  $k'(\epsilon, k; z, \bar{k})$ . Construct  $\bar{k}_t$  along the way.
- ▶ Run regressions for samples  $z_t = B$  and  $z_t = G$ .

$$\log(\bar{k}_{t+1}) = \alpha_0(z_t) + \alpha_1(z_t) \log(\bar{k}_t)$$

- ▶ Update coefficients. Resolve the decision problem, simulation, regression.

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