The GEModelTools for Solving HANK Models in Python

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Abstract

This note provides an overview of the GEModelClass Python-package for solving general equilibrium models.

Code:

Package: github.com/JeppeDruedahl/GEModelTools

 ${\bf Examples: \ github.com/JeppeDruedahl/GEModelToolsNotebooks}$

1 Overview

The GEModelClass is an add-on to the basic EconModelClass (see here).

A model consists of the following list of namespaces:

- 1. Parameters: .par
- 2. Solution: .sol
- 3. Simulation: .sim
- 4. Steady state: .ss
- 5. Transition path: .path
- 6. Jacobians for household problem: .jac_hh
- 7. Full Jacobians: . jac

The user is required to specify some variable lists in .settings() for:

- 1. Aggregate variables: .varlist. Used as path.VARNAME.
- 2. Household variables: .varlist_hh

Used as sol. VARNAME and sol.path_VARNAME

Extra: i and w are used for saving indices and weights for use in simulation.

- 3. Household grids: .grid_hh. Used as par.VARNAME_grid.
- 4. Household policy functions: .pols_hh. Should be in .varlist_hh.
- 5. Household inputs: .inputs_hh. Should be in .varlist.
- 6. Household outputs: .outputs_hh. Should be in .varlist_hh.
- 7. Exogenous inputs: .inputs_exo. Should be in .varlist.
- 8. Endogenous inputs: .inputs_endo. Should be in .varlist.
- 9. Targets: .targets. Should be in .varlist.

And in .setup() choose the following settings:

- 1. Number of exogenous states: par.Nz
- 2. **Number of grid points:** par.Nendo1, par.Nendo2,... where endo1, endo2,..., is in .grids_hh
- 3. Length of transition period: par.transition_T
- 4. For each exogenous input:

```
Initial jump: par.jump_VARNAME
Persistence: par.rho_VARNAME
```

5. Optional solver settings:

```
par.max_iter_solve, par.max_iter_simulate, par.max_iter_broyden
par.tol_solve, par.tol_simulate, tol_broyden
```

In in .allocate() the internal method .allocate_GE(sol_shape) can now be called to allocate:

1. Exogenous grids and transition matrices:

```
par.z_grid_ss, shape=(par.Nz,)
par.z_trans_ss, shape=(par.Nz,)
par.z_ergodic_ss, shape=(par.Nz,)
par.z_grid_path, shape=(par.transition_T,par.Nz)
par.z_trans_path, shape=(par.transition_T,par.Nz,par.Nz)
```

2. Distribution:

```
sim.D, shape=sol_shape
sim.path_D, shape=(par.transition_T,*sol_shape)
```

3. All variables in .sol

```
sol.VARNAME, shape=sol_shape
sol.path_VARNAME, shape=(par.transition_T,*sol_shape)
```

4. All variables in .path

```
path.VARNAME, shape=(par.transition_T,)
ss.VARNAME, scalar
```

5. All variables in .jac_hh OUTPUTNAME.upper()_INPUTNAME, shape=(par.transition_T,par.transition_T)

The user must also provide the following **functions**:

- 1. grids.py must contain create_grids(model) which at a minimum creates the grids for the endogenous variables and the grids and transition matrices for the exogenous variable.
- 2. household_problem.py must contain the jitted¹ functions: solve_hh_ss(par,sol,ss), result in sol.VARNAME. solve_hh_path(par,sol,path), result in sol.path_VARNAME.
- 3. find_strady_state.py must contain the function find_ss(model,do_print), which fills ss, and solve and simulate the household problem in steady state.
- 4. transition_path.py must contain the jitted function evaluate_transition_path(par,sol,sim,ss,path,jac_hh,use_jac_hh), where use_jac_hh is a boolean for whether or not to use the household Jacobians when evaluating household behavior (used when calculating the full Jacobian).

The following internal methods are now available:

- 1. .solve_ss(): Solve household problem at steady state, sol.VARNAME.
- 2. .simulate_ss(): Simulate household problem at steady state, sim.D.
- 3. .solve_path(): Solve household problem along transition path, sol.path_VARNAME
- 4. .simulate_path():Simulate household problem along transition path, sim.path_D.
- 5. .compute_jac_hh(): Compute the Jacobians of household problem, jac_hh.
- 6. .compute_jac(): Compute the full Jacobian, jac.
- 7. .find_transition_path(): Find transition for path for exogenous inputs, everything in path.

¹ The function should be decorated with @numba.njit.

2 Example

```
1
2 from EconModel import EconModelClass
3 from GEModelTools import GEModelClass
4
5 class HANKModelClass(EconModelClass, GEModelClass):
6
7
      def settings(self):
           """ fundamental settings """
8
9
10
           self.grids_hh = [] # grids
           self.pols_hh = [] # policy functions
11
12
           self.inputs_hh = [] # inputs to household problem
13
           self.outputs_hh = [] # output of household problem
14
           self.varlist_hh = [] # variables in household problem
15
           self.inputs_exo = [] # exogenous inputs
16
           self.inputs_endo = [] # endogenous inputs
17
           self.targets = [] # targets
           self.varlist = [] # all variables
18
19
20
      def setup(self):
           """ set baseline parameters """
21
22
23
           par = self.par
24
           par.NVARNAME = 100 # number of grid points
           par.jump_VARNAME = -0.01 # initial jump in %
25
           par.rho_VARNAME = 0.8 # AR(1) coefficeint
26
27
           par.transition_T = 500 # length of path
28
29
      def allocate(self):
           """ allocate model """
30
31
32
           par = self.par
33
           sol_shape = (par.Nfix,par.Nz,par.Nendo1)
34
           self.allocate_GE(sol_shape)
35
```

Listing 1: Example: Setup

3 Solution method

In this section, we explain the non-linear sequence space solution method implemented in the package for a simple model.

3.1 Model

Overview. There is a continuum of measure one households who

- 1. Own stocks, a_{t-1} (measured end-of-period)
- 2. Supply labor with productivity z_t (exogenous and stochastic)

$$z_{t} = \rho z_{t-1} + \varepsilon_{t}^{z}. \tag{1}$$

$$\mathbb{E}[z_{t}] = 1.$$

$$\operatorname{Var}[\varepsilon_{t}^{z}] = \sigma_{z}^{2}.$$

3. Consume, c_t

Firms rent capital, K_{t-1} , and hire labor, L_t to produce goods,

$$Y_t = Z_t K_{t-1}^{\alpha} L_t^{1-\alpha}, \tag{2}$$

where Z_t is technology. Capital depreciates with the rate δ .

Both households are firms are **price takers** and

- 1. r_t^k is the (real) rental rate for capital
- 2. $r_t = r_t^k \delta$ is the implied (real) interest rate
- 3. w_t is the (real) wage rate

Firms. Firms maximize profits implying the standard pricing equations

$$r_t^k = \alpha Z_t (K_{t-1}/L_t)^{\alpha - 1} \equiv r^k (Z_t, K_{t-1}, L_t)$$
 (3)

$$w_t = (1 - \alpha)Z_t(K_{t-1}/L_t)^{\alpha} \tag{4}$$

$$= (1 - \alpha) Z_t \left(\frac{r_t^k}{\alpha Z_t} \right)^{\frac{\alpha}{\alpha - 1}} \equiv w(r_t^k, Z_t)$$

Households. Households have *perfect foresight* wrt. to the interest rate and the wage rate, $\{r_t, w_t\}_{t=0}^{\infty}$, and solve the problem

$$V_{t}(z_{t}, a_{t-1}) = \max_{c_{t}} \frac{c_{t}^{1-\sigma}}{1-\sigma} + \beta \mathbb{E}_{t} \left[V_{t+1}(z_{t+1}, a_{t}) \right]$$
s.t.
$$a_{t} + c_{t} = (1 + r_{t})a_{t-1} + w_{t}z_{t}$$

$$z_{t+1} \sim \Gamma_{z}(z_{t})$$

$$a_{t} \geq 0,$$

where

$$V_t(z_t, a_{t-1}) = V(z_t, a_{t-1}; \{r_\tau, w_\tau\}_{\tau=t}^{\infty}).$$

The FOC is $c_t^{-\sigma} = \beta \mathbb{E}_t[v_{a,t+1}]$ and the envelope condition is $v_{a,t} = (1+r_t)c_t^{-\sigma}$. The optimal saving and consumption functions $a_t^*(a_{t-1}, z_t)$ and $c_t^*(a_{t-1}, z_t)$ can be found using e.g. the EGM. These solutions live on the discretized grids, $z_t \in \{z^0, \ldots, z^{\#z^{-1}}\}$ and $a_t \in \{a^0, \ldots, a^{\#a^{-1}}\}$. In grids.py the user must supply the function create_grids(model) to setup these grids.

The user should provide two jiited functions in household_problem.py:

- 1. solve_hh_ss(par,sol,ss): Solve for $a_{ss}^*(\bullet)$ and $c_{ss}^*(\bullet)$ in sol.a and sol.c.
- 2. solve_hh_path(par,sol,path): Solve for $\{a_t^*(\bullet)\}_{t=0}^{T-1}$ and $\{c_t^*(\bullet)\}_{t=0}^{T-1}$ for arbitrary sequences $\{r_t, w_t\}_{t=0}^T$, where $a_T^*(\bullet) = a_{ss}^*(\bullet)$ and $c_T^*(\bullet) = c_{ss}^*(\bullet)$, in sol.path_a and sol.path_c.

Distribution. Let D_t be the distribution of households over z_t and a_{t-1} . The supply of capital then is

$$\mathcal{K}_{t} = \int a_{t}^{*}(a_{t-1}, z_{t})dD_{t} = \int a_{t}dD_{t+1}$$
(5)

The household problem implies a time-varying but non-stochastic law of motion for D_t denoted $\Gamma_{t,D}$.

In practice, this simulation problem is generic. It is beneficial to use a simulation method, where households are always on the grid. The idea here is to re-distribute

mass to grid points based on optimal decision. More precisely we calculate

$$D_{t+1}(e^k, a^l) = \sum_{i=0}^{\#_e - 1} \Pr[e^k | e^i] \sum_{j=0}^{\#_a - 1} D_t(e^i, a^j) \omega(a_t^*(e^i, a^j), a^{\max\{l-1, 0\}}, a^l, a^{\min\{l+1, \#_a - 1\}}),$$
(6)

where ω is a weight calculated using linear interpolation

$$\omega(a,\underline{a},\tilde{a},\overline{a}) = 1\{a \in [\underline{a},\overline{a}]\} \begin{cases} \frac{\overline{a}-a}{\overline{a}-\tilde{a}} & \text{if } a \geq \tilde{a} \\ \frac{a-\underline{a}}{\overline{a}-a} & \text{if } a < \tilde{a} \end{cases}.$$

Extension to higher dimensions are straightforward. This is provided in the package as the methods .simulate_ss() and .simulate_path().

Market clearing. Market clearing requires

Capital:
$$K_t = \mathcal{K}_t = \int a_t dD_{t+1} = \int a_t^*(z_t, a_{t-1}) dD_t$$

Labour: $L_t = \int e_t dD_t = 1$
Goods: $Y_t = \int c_t^*(z_t, a_{t-1}) dD_t + K_t - K_{t-1} + \delta K_{t-1}$

3.2 Stationary equilibrium

A stationary equilibrium for a given Z_{ss} is one where

- 1. Quantities K_{ss} and L_{ss} ,
- 2. prices r_{ss} and w_{ss} ,
- 3. a distribution D_{ss} over a_{t-1} and z_t
- 4. and policy functions $a_{ss}^*(z_t, a_{t-1})$ and $c_{ss}^*(z_t, a_{t-1})$

are such that

- 1. $a_{ss}^*(\bullet)$ and $c_{ss}^*(\bullet)$ solves the household problem with $\{r_{ss}, w_{ss}\}_{t=0}^{\infty}$
- 2. D_{ss} is the invariant distribution implied by the household problem
- 3. Firms maximize profits, $r_{ss} = r(Z_{ss}, K_{ss}, L_{ss})$ and $w_{ss} = w(r_{ss}, Z_{ss})$
- 4. The labor market clears, i.e. $L_{ss} = \int e_t dD_{ss} = 1$

- 5. The capital market clears, i.e. $K_{ss} = \int a_{ss}^*(z_t, a_{t-1}) dD_{ss}$
- 6. The goods market clears, i.e. $Y_{ss} = \int c_{ss}^*(z_t, a_{t-1}) dD_{ss} + \delta K_{ss}$

We can find the stationary equilibrium by solving a root-finding problem

- 1. Guess on r_{ss}
- 2. Calculate $w_{ss} = w(r_{ss}, Z_{ss})$
- 3. Solve the infinite horizon household problem
- 4. Simulate until convergence of D_{ss}
- 5. Calculate supply $\mathcal{K}_{ss} = \int a_{ss}^*(z_t, a_{t-1}) dD_{ss}$
- 6. Calculate demand $K_{ss} = \left(\frac{r_{ss} + \delta}{\alpha Z_{ss}}\right)^{\frac{1}{\alpha 1}} L_{ss}$
- 7. If for some tolerance ϵ

$$|\mathcal{K}_{ss} - K_{ss}| < \epsilon$$

then stop, otherwise update r_{ss} appropriately and return to step 2

In find_strady_state.py the user must supply the function find_ss(model,do_print) to solve the problem. In practice we guess on r_{ss} and w_{ss} and derive Z_{ss} and δ_{ss} from the implied household problem.

3.3 Transition path

A transition path for $t \in \{0, 1, 2, ...\}$, given an initial distribution D_0 and a path of Z_t , is paths of quantities K_t and L_t , prices r_t and w_t , policy functions $a_t^*(\bullet)$ and $c_t^*(\bullet)$, distributions D_t , such that for all t

- 1. $a_t^*(\bullet)$ and $c_t^*(\bullet)$ solve the household problem given price paths
- 2. D_t are implied by the household problem given price paths and D_0
- 3. Firms maximize profit, $r_t = r(Z_t, K_{t-1}, L_t)$ and $w_t = w(r_t, Z_t)$
- 4. The labor market clears, i.e. $L_t = \int z_t dD_t = 1$
- 5. The capital market clears, i.e. $K_{t-1} = \int a_{t-1} dD_t$
- 6. The goods market clears, i.e. $Y_t = \int c_t^*(\bullet) dD_t + K_t K_{t-1} + \delta K_{t-1}$

This is also called an MIT-shock \equiv »shock in a world without shocks«.

In practice we consider a truncated transition path of length T, and everything is back to steady state afterwards.

3.4 Sequence space method

We can think of the model in terms of inputs are targets:

1. 1 exogenous input: $\{Z_t\}_{t=0}^{T-1}$

2. 1 endogenous input: $\{K_t\}_{t=0}^{T-1}$

3. 1 target: Asset market clearing

The model is then captured by the equation system

$$\boldsymbol{H}(\{K_t, Z_t\}_{t=0}^T) = \boldsymbol{0} \Leftrightarrow$$

$$\begin{bmatrix} \text{Asset market clearing } \end{bmatrix} = \boldsymbol{0}$$

$$\begin{bmatrix} K_t - \mathcal{K}_t \end{bmatrix} = \begin{bmatrix} 0 \end{bmatrix}$$

$$\forall t \in \{0, 1, \dots, T-1\}$$

where we have

$$L_t = 1$$

$$r_t = \alpha Z_t (K_{t-1}/L_t)^{\alpha - 1}$$

$$w_t = (1 - \alpha) Z_t \left(\frac{r_t + \delta}{\alpha Z_t} \right)^{\frac{\alpha}{\alpha - 1}}$$

$$D_t = \Gamma_{t-1, D}(D_{t-1}), \forall t > 0$$

$$\mathcal{K}_t = \int a_t^* (z_t, a_{t-1}) dD_t$$

$$K_{-1} = K_{ss}$$

$$D_0 = D_{ss}$$

In evaluate_transition_path.py the user must supply the jitted function evaluate_transition_path_distribution(...), which given the inputs updates the value of all targets.

Jacobian. Defining $K = (K_0, K_1, ...)$ and $Z = (Z_0, Z_1, ...)$ we can write the equation system in time-stacked form

$$\boldsymbol{H}(\boldsymbol{K},\boldsymbol{Z})=\boldsymbol{0}$$

Total differentiation implies

$$\boldsymbol{H}_{\boldsymbol{K}}d\boldsymbol{K} + \boldsymbol{H}_{\boldsymbol{Z}}d\boldsymbol{Z} = 0 \Leftrightarrow d\boldsymbol{K} = -\boldsymbol{H}_{\boldsymbol{K}}^{-1}\boldsymbol{H}_{\boldsymbol{Z}}d\boldsymbol{Z}$$

where

$$m{H}_{m{K}} = \left[egin{array}{cccc} rac{\partial H_0}{\partial K_0} & rac{\partial H_0}{\partial K_1} & \cdots \\ rac{\partial H_1}{\partial K_0} & \ddots & \ddots \\ dots & \ddots & \ddots \end{array}
ight], \ m{H}_{m{Z}} = \left[egin{array}{cccc} rac{\partial H_0}{\partial Z_0} & rac{\partial H_0}{\partial Z_1} & \cdots \\ rac{\partial H_1}{\partial Z_0} & \ddots & \ddots \\ dots & \ddots & \ddots \end{array}
ight]$$

and

$$egin{aligned} oldsymbol{H}_K &= \mathcal{J}^{\mathcal{K},r} \mathcal{J}^{r,K} + \mathcal{J}^{\mathcal{K},w} \mathcal{J}^{w,K} - oldsymbol{I} \ oldsymbol{H}_Z &= \mathcal{J}^{\mathcal{K},r} \mathcal{J}^{r,Z} + \mathcal{J}^{\mathcal{K},w} \mathcal{J}^{w,Z} \end{aligned}$$

where generically

$$\mathcal{J}^{x,y} = \begin{bmatrix} \frac{\partial x_0}{\partial y_0} & \frac{\partial x_0}{\partial y_1} & \cdots \\ \frac{\partial x_1}{\partial y_0} & \ddots & \ddots \\ \vdots & \ddots & \ddots \end{bmatrix}$$

Once the Jacobians H_K and H_Z , collectively referred to as "the full Jacobian", are both calculated, the equation system can be solved with a quasi-Newton equation solver such as the Broyden-solver. This is provided in the package with the method .find_transition_path().

In the package there are two methods which both needs to be run to calculate the Jacobian:

- 1. .compute_jac_hh(): Compute the Jacobians of household problem $(\mathcal{J}^{\mathcal{K},r}, \mathcal{J}^{\mathcal{K},w})$ using the fast fast news algorithm (see below).
- 2. .compute_jac(): Compute the full Jacobian using simple numerical differentiation relying on the Jacobians of the household problem.

3.5 Fake new algorithm

Consider the following notation:

1. **Productivity:** z_t , indexed by i, lives on $\mathcal{G}_z = \{z^0, z^1, \dots, z^{\#_z - 1}\}$ with transition matrix Π^e with elements

$$\pi_{[i,i+]}^z = \Pr[z_{t+1} = z^{i+1} | z_t = z^i].$$

- 2. **Assets:** a_t , indexed by j, lives on $\mathcal{G}_a = \{a^0, a^1, \dots, a^{\#_a 1}\}.$
- 3. Value and policy functions: v, a^* and c^* lives on $\mathcal{G}_z \times \mathcal{G}_a$ with

$$\boldsymbol{v}_{[i,j]} = u(\boldsymbol{c}_{[i,j]}^*) + \sum_{j_+=0}^{\#_a-1} \boldsymbol{Q}_{[j,j_+]}^i \beta \sum_{k=0}^{\#_z-1} \pi_{[i,i_+]}^e v_{[i_+j_+]},$$

where $\mathbf{c}_{[i,j]}^* = c^*(z_i, a_j)$ and $\mathbf{Q}_{[j,k]}^i$ are the weights implied by linear interpolation of $a^*(z_t, a_{t-1})$ at $\mathbf{a}_{[i,j]}^* = a^*(z_i, a_j)$ given by

$$\boldsymbol{Q}_{[j,k]}^{i} = \begin{cases} \frac{a_{ij}^{*} - a^{j+-1}}{a^{j} + a^{j} + 1} & \text{if } j_{+} > 0, \text{and } a_{ij}^{*} \in [a^{j+-1}, a^{j+}] \\ \frac{a_{ij}^{*} - a^{j+}}{a^{j} + 1 - a^{j+}} & \text{if } j_{+} < \#_{a} - 1, \text{and } a_{ij}^{*} \in [a^{j+}, a^{j+1}] \\ 0 & \text{else} \end{cases}$$

Let \overrightarrow{x} be the row-stacked version of the matrix x. The Bellman equation can be written

$$\overrightarrow{\boldsymbol{v}}_{t} = u(\overrightarrow{\boldsymbol{c}}_{t}^{*}) + \beta \boldsymbol{Q}_{t} \widetilde{\boldsymbol{\Pi}}^{e} \overrightarrow{\boldsymbol{v}}_{t+1} m \tag{7}$$

where $\tilde{\Pi} = \Pi \otimes \boldsymbol{I}_{\#_a \times \#_a}$ and Q_t is the policy matrix given by

$$\boldsymbol{Q}_{t} = \begin{bmatrix} \boldsymbol{Q}_{t}^{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \ddots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \boldsymbol{Q}_{t}^{\#_{e}-1} \end{bmatrix}, \boldsymbol{Q}_{t}^{i} = \begin{bmatrix} \ddots & \vdots & \ddots \\ \cdots & q_{[j,j_{+}]}^{i} & \cdots \\ \vdots & \vdots & \ddots \end{bmatrix}.$$
(8)

Simulation is now the inverse operation:

$$\overrightarrow{D}_{t+1} = \widetilde{\Pi}^{e'} \mathbf{Q}_t' \overrightarrow{D}_t, \tag{9}$$

where ' denoted transpose.

The fake new algorithm now is:

Step 1: Solve backwards T-1 periods from a shock Δ_x to price x. $\boldsymbol{a}_s^{*,x}$ is the optimal saving policy with s periods until shock arrival \boldsymbol{Q}_s^x is the associated policy matrix

Step 2: Numerical derivatives,

$$\Delta_{D,x}^{s} = \frac{\widetilde{\Pi}^{e\prime} \boldsymbol{Q}_{s}^{x\prime} \overrightarrow{D}_{ss} - \overrightarrow{D}_{ss}}{\Delta_{x}}, \Delta_{a,x}^{s} = \frac{\overrightarrow{\boldsymbol{a}}_{s}^{*,x\prime} \overrightarrow{D}_{ss} - \overrightarrow{\boldsymbol{a}_{ss}^{*,*\prime}} \overrightarrow{D}_{ss}}{\Delta_{x}}$$

Step 3: Expectation factors,
$$\mathcal{E}_t = \begin{cases} \boldsymbol{a}_{ss}^* & \text{if } t = 0\\ \boldsymbol{Q}_{ss} \tilde{\Pi}^e \mathcal{E}_{t-1} & \text{else} \end{cases}$$

Step 4: Fake news matrix,
$$\mathcal{F}^{a}_{[t,s]} = \begin{cases} \Delta^{s}_{a,x} & \text{if } t = 0 \\ \overrightarrow{\mathcal{E}}_{t-1} \Delta^{s}_{D,x} & \text{else} \end{cases}$$

Step 5: Jacobian,
$$\mathcal{J}_{[t,s]}^{\mathcal{K},x} = \begin{cases} \mathcal{F}_{[t,s]}^a & \text{if } t = 0 \lor s = 0\\ \sum_{k=0}^{\min\{t,s\}} \mathcal{F}_{[t-k,s-k]}^a & \text{else} \end{cases}$$