Written Exam Economics Summer 2020

Introduction to Programming and Numerical Analysis

Date 16th – 18th May 2019

This exam question consists of 6 pages in total.

(An electronic version of the notebook with the exam questions is also available).

Answers only in English.

You should hand-in a single zip-file named with your groupname only. The zip-file should contain:

- 1. A general README.md for your portfolio
- 2. A Feedback.txt file with a list of the groups each group member have given peer feedback to
- 3. Your inaugural project (in the folder /inauguralproject)
- 4. Your data analysis project (in the folder /dataproject)
- 5. Your model analysis project (in the folder /modelproject)
- 6. Your exam project (in the folder /examproject)

Be careful not to cheat at exams!

Exam cheating is for example if you:

- Copy other people's texts without making use of quotation marks and source referencing, so that it may appear to be your own text
- Use the ideas or thoughts of others without making use of source referencing, so it may appear to be your own idea or your thoughts
- Reuse parts of a written paper that you have previously submitted and for which you have received a
 pass grade without making use of quotation marks or source references (self-plagiarism)
- Receive help from others in contrary to the rules laid down in part 4.12 of the Faculty of Social Science's common part of the curriculum on cooperation/sparring

You can read more about the rules on exam cheating on your Study Site and in part 4.12 of the Faculty of Social Science's common part of the curriculum.

Exam cheating is always sanctioned by a written warning and expulsion from the exam in question. In most cases, the student will also be expelled from the University for one semester.

```
import numpy as np
```

Linear regression

Consider the following linear equation:

$$y_i = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \epsilon_i$$

Assume you have access to data of the **independent variables** $(x_{1,i}, x_{2,i})$ and the **dependent variable** (y_i) for N individuals, where i indexes individuals. The variable ϵ_i is a mean-zero **stochastic shock**.

Assume the data generating process is given by:

In [2]:

```
def DGP(N):
    # a. independent variables
    x1 = np.random.normal(0,1,size=N)
    x2 = np.random.normal(0,1,size=N)

# b. errors
    eps = np.random.normal(0,1,size=N)

extreme = np.random.uniform(0,1,size=N)
    eps[extreme < 0.05] += np.random.normal(-5,1,size=N)[extreme < 0.05]
    eps[extreme > 0.95] += np.random.normal(5,1,size=N)[extreme > 0.95]

# c. dependent variable
    y = 0.1 + 0.3*x1 + 0.5*x2 + eps

return x1, x2, y
```

The data you have access to is:

In [3]:

```
np.random.seed(2020)
x1,x2,y = DGP(10000)
```

Question 1: Estimate the vector of coefficients $\beta=(\beta_0,\beta_1,\beta_2)$ using ordinary least squares (OLS) implemented with matrix algebra by

$$\hat{\beta} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$$

where \mathbf{X}' is the transpose of \mathbf{X} and

$$\mathbf{y} = egin{pmatrix} y_1 \ y_2 \ dots \ y_N \end{pmatrix}, \quad \mathbf{X} = egin{pmatrix} 1 & x_{1,1} & x_{2,1} \ 1 & x_{1,2} & x_{2,2} \ dots & dots \ 1 & x_{1,N} & x_{2,N} \end{pmatrix}$$

Question 2: Construct a 3D plot, where the data is plotted as scattered points, and the prediction of the model is given by the plane

$${\hat y}_i = {\hat eta}_0 + {\hat eta}_1 x_{1,i} + {\hat eta}_2 x_{2,i}$$

Question 3: Esimtate the vector of coefficients $\beta = (\beta_0, \beta_1, \beta_2)$ using a **numerical solver** to solve the ordinary least square problem, shown below, directly. Compare your results with the matrix algebra results.

$$\min_{eta} \sum_{i=1}^N (y_i - (eta_0 + eta_1 x_{1,i} + eta_2 x_{2,i}))^2$$

Question 4: Estimate the vector of coefficients $\beta=(\beta_0,\beta_1,\beta_2)$ using least absolute deviations (LAD) using a numerical solver to solve the following problem directly:

$$\min_{eta} \sum_{i=1}^N |y_i - (eta_0 + eta_1 x_{1,i} + eta_2 x_{2,i})|$$

where |z| is the absolute value of z.

Question 5: Set N=50. Repeat the estimation using the OLS and LAD methods K=5000 times, drawing a new random sample from the data generating process each time. Compare the estimates from each method using histograms. Which method do you prefer? Explain your choice.

Durable purchases

Consider a household living in two periods.

In the second period it gets utility from non-durable consumption, c, and durable consumption, $d + \chi x$:

$$egin{aligned} v_2(m_2,d) &= \max_c rac{(c^lpha(d+\chi x)^{1-lpha})^{1-
ho}}{1-
ho} \ ext{s.t.} \ &x &= m_2 - c \ &c &\in [0,m_2] \end{aligned}$$

where

- m_2 is cash-on-hand in the beginning of period 2
- c is non-durable consumption
- d is pre-committed durable consumption
- ullet $x=m_2-c$ is extra durable consumption
- ho > 1 is the risk aversion coefficient
- $lpha \in (0,1)$ is the utility weight on non-durable consumption
- $\chi \in (0,1)$ implies that extra durable consumption is *less* valuable than pre-comitted durable consumption
- the second constraint ensures the household cannot die in debt

The **value function** $v_2(m_2,d)$ measures the household's value of having m_2 at the beginning of period 2 with precomitted durable consumption of d. The optimal choice of non-durable consumption is denoted $c^*(m_2,d)$. The optimal extra durable consumption function is $x^*(m_2,d)=m_2-c^*(m_2,d)$.

Define the so-called end-of-period 1 value function as:

$$w(a,d) \equiv eta \mathbb{E}_1 \left[v_2(m_2,d)
ight]$$

where

$$m_2 = (1+r)a + y \ y = egin{cases} 1-\Delta & ext{with prob. } rac{1}{3} \ 1 & ext{with prob. } rac{1}{3} \ 1+\Delta & ext{with prob. } rac{1}{3} \end{cases}$$

and

- a is assets at the end of period 1
- $\beta > 0$ is the discount factor
- ullet \mathbb{E}_1 is the expectation operator conditional on information in period 1
- y is income in period 2
- $\Delta \in (0,1)$ is the level of income risk (mean-preserving)
- r is the return on savings

In the first period, the household chooses it's pre-comitted level of durable consumption for the next-period,

$$egin{aligned} v_1(m_1) &= \max_d w(a,d) \ ext{s.t.} \ a &= m_1 - d \ d &\in [0,m_1] \end{aligned}$$

where m_1 is cash-on-hand in period 1. The second constraint ensures the household *cannot* borrow. The **value function** $v_1(m_1)$ measures the household's value of having m_1 at the beginning of period 1. The optimal choice of pre-committed durable consumption is denoted $d^*(m_1)$.

The **parameters** and **grids** for m_1 , m_2 and d should be:

In [4]:

```
# a. parameters
rho = 2
alpha = 0.8
beta = 0.96
r = 0.04
Delta = 0.25

# b. grids
m1_vec = np.linspace(1e-8,10,100)
m2_vec = np.linspace(1e-8,10,100)
d_vec = np.linspace(1e-8,5,100)
```

Question 1: Find and plot the functions $v_2(m_2,d)$, $c^*(m_2,d)$, and $x^*(m_2,d)$. Comment.

Question 2: Find and plot the functions $v_1(m_1)$ and $d^*(m_1)$. Comment.

Hint: For interpolation of $v_2(m_2,d)$ consider using interpolate.RegularGridInterpolator([GRID-VECTOR1,GRID-VECTOR2],VALUE-MATRIX,bounds_error=False,fill_value=None) .

Next, consider an **extension** of the model, where there is also a **period 0**. In this period, the household makes a choice whether to stick with the level of durables it has, z=0, or adjust its stock of durables, z=1. If adjusting, the household loses a part of the value of its durable stock; more specifically it incurs a proportional loss of $\Lambda \in (0,1)$.

Mathematically, the household problem in period 0 is:

$$v_0(m_0,d_0) = \max_{z \in \{0,1\}} egin{cases} w(m_0,d_0) & ext{if } z = 0 \ v_1(m_0 + (1-\Lambda)d_0) & ext{if } z = 1 \end{cases}$$

The **parameters** and **grids** for m_0 and d_0 should be:

In [5]:

```
Lambda = 0.2

m0_vec = np.linspace(1e-8,6,100)

d0_vec = np.linspace(1e-8,3,100)
```

Question 3: For which values of m_0 and d_0 is the optimal choice not to adjust, i.e. z=0? Show this in a plot. Give an interpretion of your results.

Gradient descent

Let $oldsymbol{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$ be a two-dimensional vector. Consider the following algorithm:

Algorithm: gradient descent()

Goal: Minimize the function f(x).

- 1. Choose a tolerance $\epsilon>0$, a scale factor $\Theta>0$, and a small number $\Delta>0$
- 2. Guess on $oldsymbol{x}_0$ and set n=1
- 3. Compute a numerical approximation of the jacobian for f by

$$abla f(oldsymbol{x}_{n-1}) pprox rac{1}{\Delta} \left[f\left(oldsymbol{x}_{n-1} + \left[egin{array}{c} \Delta \ 0 \end{array}
ight] - f(oldsymbol{x}_{n-1}) \ f\left(oldsymbol{x}_{n-1} + \left[egin{array}{c} 0 \ \Delta \end{array}
ight]
ight) - f(oldsymbol{x}_{n-1})
ight]$$

- 4. Stop if the maximum element in $|\nabla f(\boldsymbol{x}_{n-1})|$ is less than ϵ
- 5. Set $\theta = \Theta$
- 6. Compute $f_n^{ heta} = f(oldsymbol{x}_{n-1} heta
 abla f(oldsymbol{x}_{n-1}))$
- 7. If $f_n^{ heta} < f(oldsymbol{x}_{n-1})$ continue to step 9
- 8. Set $\theta = \frac{\theta}{2}$ and return to step 6
- 9. Set $x_n = x_{n-1} \theta \nabla f(\boldsymbol{x}_{n-1})$
- 10. Set n=n+1 and return to step 3

Question: Implement the algorithm above such that the code below can run.

Optimizer function:

```
In [6]:
```

```
def gradient_descent(f,x0,epsilon=1e-6,Theta=0.1,Delta=1e-8,max_iter=10_000):
    pass
```

Test case:

```
In [7]:
```

```
def rosen(x):
    return (1.0-x[0])**2+2*(x[1]-x[0]**2)**2

x0 = np.array([1.1,1.1])
try:
    x,it = gradient_descent(rosen,x0)
    print(f'minimum found at ({x[0]:.4f},{x[1]:.4f}) after {it} iterations')
    assert np.allclose(x,[1,1])
except:
    print('not implemented yet')
```

not implemented yet