ECON 899b: Problem Set 1

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Overview: For this assignment, the goal is to apply different methods of optimization for discrete choice models. In particular, we use the public use microdata on mortgages to study the log-likelihood of the loan being pre-paid within the first-year.

Findings: The attached code ("main_program.jl" and "helper_functions.jl") produces the results described below. In the first step, I wrote functions to evaluate log-likelihood, the score of the log-likelihood function (approximation of the FOC), and the Hessian matrix (approximation of SOC) given some β vector. Specifically, $\beta_0 = -1$ and all other β values in the vector are 0. Then, I use the numerical derivative method in Julia to calculate the FOC and SOC of the log-likelihood function at the same β values. The comparison between the score and Hessian, and the numerical derivatives, are summarized in Tables 1, 3, 4. It appears that the approximations and numerical derivatives are very similar and/or identical.

Then, I wrote a Newton algorithm that solves for maximum likelihood, and compared the resulting coefficients to that of the BFGS (Quasi-Newton) and Simplex algorithms. Using the initial guess, the Newton algorithm converged in 37 iterations and approximately 12 seconds. The results of the algorithm are summarized in Table 2 below.

The implementation of the BFGS algorithm was slightly more complicated. Without providing a gradient function, the algorithm took a very long time to converge. When I input the score of the log-likelihood as the gradient and used the resulting β values from the Newton algorithm as the initial guess, the algorithm converged in 3 iterations and approximately 1 second. I used an educated guess for the initial value, because the simple initial values result in nonsensical results.

Similar to the BFGS algorithm, I was only able to get the Simplex algorithm to converge when I used the Newton algorithm results as the initial values. When I attempted to run the optimization without a refined initial guess, the optimization package returned a "failed line search" message. With an educated guess, the Simplex algorithm converged in 694 iterations, and approximately 140 seconds. Comparing the β results from all 3 algorithms, the coefficients appear to be very similar.

^{*}I collaborated with Anya Tarascina and Claire Kim on this assignment.

Table 1: Comparison of Log Likelihood Score and Numerical First Derivative

Score of Log Likelihood	Numerical First Derivative
-556.32	-556.32
-2835.5	-2835.5
-666.47	-666.47
-1992.44	-1992.44
-2537.75	-2537.75
-4381.48	-4381.48
-1980.73	-1980.73
-10436.78	-10436.78
-9360.45	-9360.45
-39586.27	-39586.27
-39185.51	-39185.51
-2111.58	-2111.58
-940.03	-940.03
-1045.49	-1045.49
-1126.38	-1126.38
-1031.63	-1031.63

Table 2: Comparison of Coefficients

β_{newton}	β_{bfgs}	$\beta_{simplex}$
0.89	0.89	0.89
0.52	0.52	0.52
0.5	0.5	0.5
0.08	0.08	0.08
0.6	0.6	0.6
-0.9	-0.9	-0.9
-0.1	-0.1	-0.1
0.08	0.08	0.08
0.21	0.21	0.21
-0.48	-0.48	-0.48
0.0	0.0	0.0
0.63	0.63	0.63
1.0	1.0	1.0
0.62	0.62	0.62
0.24	0.24	0.24
0.07	0.07	0.07

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Table 3: Hessian Matrix for Log Likelihood Function

-880.4	-0.0	-10.1	-404.2	-421.3	-686.3	-332.0	-1720.7	-1655.1	-6608.0	-6563.0	-390.1	-163.8	-189.3	-211.6	-170.1
-0.0	-1816.2	-210.1	-712.5	-859.5	-1515.9	-692.6	-3555.2	-3244.0	-13367.3	-13260.3	-746.2	-360.8	-392.8	-380.8	-339.0
-10.1	-210.1	-855.7	-235.2	-238.3	-409.1	-192.0	-989.2	-877.3	-3472.3	-3448.4	38.8	-77.7	-130.5	-114.5	-97.2
-404.2	-712.5	-235.2	-1550.5	-824.9	-1158.3	-596.2	-3035.1	-3077.9	-11335.2	-11372.4	-590.5	-256.3	-345.1	-351.5	-228.1
-421.3	-859.5	-238.3	-824.9	-967.0	-1478.0	-700.8	-3622.3	-3394.8	-13681.8	-13590.3	-788.6	-375.8	-390.7	-386.2	-337.6
-686.3	-1515.9	-409.1	-1158.3	-1478.0	-2677.0	-1190.9	-6153.7	-5527.5	-23043.4	-22841.3	-1476.4	-657.7	-661.1	-642.5	-570.3
-332.0	-692.6	-192.0	-596.2	-700.8	-1190.9	-633.0	-2837.2	-2588.6	-10605.8	-10519.4	-667.3	-298.9	-307.6	-300.6	-262.4
-1720.7	-3555.2	-989.2	-3035.1	-3622.3	-6153.7	-2837.2	-14925.4	-13444.9	-55598.2	-55158.9	-3253.8	-1563.4	-1594.9	-1564.1	-1353.3
-1655.1	-3244.0	-877.3	-3077.9	-3394.8	-5527.5	-2588.6	-13444.9	-12906.6	-50808.4	-50436.9	-2877.7	-1404.3	-1458.9	-1435.2	-1228.6
-6608.0	-13367.3	-3472.3	-11335.2	-13681.8	-23043.4	-10605.8	-55598.2	-50808.4	-211160.9	-209177.6	-12006.5	-5906.9	-5995.0	-5889.2	-5087.2
-6563.0	-13260.3	-3448.4	-11372.4	-13590.3	-22841.3	-10519.4	-55158.9	-50436.9	-209177.6	-208012.6	-11907.2	-5837.5	-5948.3	-5859.1	-5058.2
-390.1	-746.2	38.8	-590.5	-788.6	-1476.4	-667.3	-3253.8	-2877.7	-12006.5	-11907.2	-1680.6	-352.0	-367.2	-362.3	-319.4
-163.8	-360.8	-77.7	-256.3	-375.8	-657.7	-298.9	-1563.4	-1404.3	-5906.9	-5837.5	-352.0	-800.3	-0.0	-0.0	-0.0
-189.3	-392.8	-130.5	-345.1	-390.7	-661.1	-307.6	-1594.9	-1458.9	-5995.0	-5948.3	-367.2	-0.0	-815.6	-0.0	-0.0
-211.6	-380.8	-114.5	-351.5	-386.2	-642.5	-300.6	-1564.1	-1435.2	-5889.2	-5859.1	-362.3	-0.0	-0.0	-800.1	-0.0
-170.1	-339.0	-97.2	-228.1	-337.6	-570.3	-262.4	-1353.3	-1228.6	-5087.2	-5058.2	-319.4	-0.0	-0.0	-0.0	-695.1

Table 4: Numerical Second Derivative

-880.3	0.0	-10.1	-404.2	-421.3	-686.3	-332.0	-1720.7	-1655.1	-6608.0	-6563.0	-390.1	-163.8	-189.3	-211.5	-170.0
0.0	-1816.2	-210.1	-712.5	-859.5	-1515.9	-692.6	-3555.2	-3244.0	-13367.3	-13260.3	-746.2	-360.8	-392.8	-380.8	-339.0
-10.1	-210.1	-855.4	-235.2	-238.4	-409.0	-192.0	-989.2	-877.3	-3472.3	-3448.4	38.8	-77.7	-130.5	-114.6	-97.2
-404.2	-712.5	-235.2	-1550.4	-824.9	-1158.3	-596.2	-3035.1	-3077.9	-11335.2	-11372.4	-590.5	-256.3	-345.1	-351.5	-228.0
-421.3	-859.5	-238.4	-824.9	-966.7	-1478.0	-700.8	-3622.3	-3394.8	-13681.8	-13590.3	-788.6	-375.8	-390.7	-386.2	-337.6
-686.3	-1515.9	-409.0	-1158.3	-1478.0	-2676.7	-1191.0	-6153.7	-5527.5	-23043.4	-22841.3	-1476.4	-657.8	-661.1	-642.5	-570.3
-332.0	-692.6	-192.0	-596.2	-700.8	-1191.0	-632.8	-2837.2	-2588.6	-10605.8	-10519.4	-667.3	-298.9	-307.6	-300.6	-262.4
-1720.7	-3555.2	-989.2	-3035.1	-3622.3	-6153.7	-2837.2	-14925.2	-13444.8	-55598.2	-55158.9	-3253.8	-1563.4	-1594.9	-1564.1	-1353.3
-1655.1	-3244.0	-877.3	-3077.9	-3394.8	-5527.5	-2588.6	-13444.8	-12906.4	-50808.4	-50436.9	-2877.7	-1404.3	-1458.9	-1435.2	-1228.6
-6608.0	-13367.3	-3472.3	-11335.2	-13681.8	-23043.4	-10605.8	-55598.2	-50808.4	-211160.6	-209177.6	-12006.6	-5906.8	-5995.0	-5889.2	-5087.2
-6563.0	-13260.3	-3448.4	-11372.4	-13590.3	-22841.3	-10519.4	-55158.9	-50436.9	-209177.6	-208012.2	-11907.2	-5837.5	-5948.3	-5859.1	-5058.2
-390.1	-746.2	38.8	-590.5	-788.6	-1476.4	-667.3	-3253.8	-2877.7	-12006.6	-11907.2	-1680.5	-352.0	-367.2	-362.3	-319.3
-163.8	-360.8	-77.7	-256.3	-375.8	-657.8	-298.9	-1563.4	-1404.3	-5906.8	-5837.5	-352.0	-800.3	-0.0	0.0	-0.0
-189.3	-392.8	-130.5	-345.1	-390.7	-661.1	-307.6	-1594.9	-1458.9	-5995.0	-5948.3	-367.2	-0.0	-815.6	0.0	-0.0
-211.5	-380.8	-114.6	-351.5	-386.2	-642.5	-300.6	-1564.1	-1435.2	-5889.2	-5859.1	-362.3	0.0	0.0	-800.0	0.0
-170.0	-339.0	-97.2	-228.0	-337.6	-570.3	-262.4	-1353.3	-1228.6	-5087.2	-5058.2	-319.3	-0.0	-0.0	0.0	-695.0