

Problem Set 2 Solutions

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1 Main Problem Set Code

```
1 clear all;
2 clc;
3 load nlsw88
4 options = optimset('Disp','iter-detailed','MaxFunEvals',1e12,'MaxIter',1e6);
5 rand('seed',1234); randn('seed',1234);
6 %% Problem 1(a)
7 %%% Set up the data:
8 y = log(wage);
9 X = [ones(size(wage)) age race==2 race==3 collgrad];
10 %%% create a vector that is 1 if all obs are there; 0 otherwise:
11 subset = ~...
    ~isnan(wage)&~isnan(age)&~isnan(race)&~isnan(married)&~isnan(grade)&~isnan(collgrad);
12 y = log(wage(subset)); %drop missing observations from y
13 X = X(subset,:); %drop missing observations from X
14 nb = size(X,2); %initialize the number of regressors for later use
15
16
17 % (i) Estimate  $\hat{\beta}$  and  $s^2$  (variance of  $\epsilon_i$ ) ...
    using fminsearch with default convergence tolerances
18 [bOLSsearch,SSEsearch]=fminsearch('OLS1',rand(nb,1),options,X,y);
19 s2OLSsearch = SSEsearch/(length(y)-size(X,2));
20
21
22 % (ii) Estimate  $\hat{\beta}$  and  $s^2$  (variance of  $\epsilon_i$ ) ...
    using fminunc with default convergence tolerances
23 [bOLSunc,SSEunc]=fminunc('OLS1',rand(nb,1),options,X,y);
24 s2OLSunc = SSEunc/(length(y)-size(X,2));
25
26
27 % (iii) Estimate  $\hat{\beta}$  and  $s^2$  (variance of  $\epsilon_i$ ) ...
    using fmincon with default convergence tolerances and with  $\beta_3 < 0$  ...
    as the only restriction
28 %%% Initialize fmincon constraints to be empty (i.e. no constraint ...
    inputs), except for an upper bound on beta3
29 A = [];
30 b = [];
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31 Aeq = [];
32 beq = [];
33 lb = [];
34 ub = 10*ones(size(X,2),1);
35 ub(3) = 0; %(set the upper bound at 0 for beta3, but no upper bound for ...
    the rest)
36 nonlcon = [];
37 [bOLScon,SSEcon]=fmincon('OLS1',rand(nb,1),A,b,Aeq,beq,lb,ub,nonlcon,options,X,y);
38 s2OLScon = SSEcon/(length(y)-size(X,2));
39
40
41 % (iv) How do your answers differ when using each of the optimizers?
42 ansA = (X'*X)\X'*y;
43 SSEansA = (y-X*ansA)'*(y-X*ansA);
44 ansA = [ansA; (y-X*ansA)'*(y-X*ansA)/(length(y)-size(X,2))];
45 compareA = [[bOLSsearch;s2OLSsearch;SSEsearch] [bOLSunc;s2OLSunc;SSEunc] ...
    [bOLScon;s2OLScon;SSEcon] [ansA;SSEansA]]
46 %% Problem 1(b)
47
48
49 % (i) Estimate  $\hat{\beta}$  and  $\hat{\sigma}^2$  (variance of ...
     $\text{varepsilon}_i$ ) using fminsearch with default convergence tolerances
50 [bMLEsearch,likeSearch]=fminsearch('normalMLE',rand(nb+1,1),options,X,y);
51 bMLEsearch(end) = bMLEsearch(end)^2; %recover sigma2, not sigma
52
53
54 % (ii) Estimate  $\hat{\beta}$  and  $\hat{\sigma}^2$  using fminunc with ...
    default convergence tolerances
55 [bMLEunc,likeUnc]=fminunc('normalMLE',rand(nb+1,1),options,X,y);
56 bMLEunc(end) = bMLEunc(end)^2;
57
58
59 % (iii) Estimate  $\hat{\beta}$  and  $\hat{\sigma}^2$  using fmincon with ...
    default convergence tolerances and with  $\beta_3 < 0$  as the only ...
    restriction
60 lb = -10*ones(size(X,2)+1,1);
61 lb(end)=0;
62 ub = 10*ones(size(X,2)+1,1);
63 [bMLEcon,likeCon]=fmincon('normalMLE',.5*rand(nb+1,1)-.25,A,b,Aeq,beq,lb,ub,nonlcon,options,X,y);
64 bMLEcon(end) = bMLEcon(end)^2;
65
66
67 % (iv) How sensitive is  $\hat{\beta}$  to the normal distribution ...
    assumption? How close are  $s^2$  and  $\hat{\sigma}^2$ 
68 compareA
69 compareB = [[bMLEsearch;-likeSearch] [bMLEunc;-likeUnc] [bMLEcon;-likeCon] ...
    [ansA;SSEansA]]
70 %% Problem 1(c)
71 %%% Set up the data:
72 y = log(wage);
73 X = [ones(size(wage)) age race==2 race==3 collgrad grade married south...
    c_city union ttl_exp tenure age.^2 hours never_married];
74 %%% create a vector that is 1 if all obs are there; 0 otherwise:
75 subset1 = ~isnan(wage)&~isnan(age)&~isnan(race)&~isnan(married)...

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77         &¬isnan(grade)&¬isnan(collgrad)&¬isnan(south)&¬isnan(c_city)...
78         &¬isnan(union)&¬isnan(ttl_exp)&¬isnan(tenure)&¬isnan(hours)...
79         &¬isnan(never_married);
80 y = log(wage(subset1)); %drop missing observations from y
81 X = X(subset1,:);      %drop missing observations from X
82 nb = size(X,2);        %initialize the number of regressors for later use
83 %%% Initialize the baseline closed-form OLS formulas (for later comparison)
84 ansC = (X'*X)\X'*y;
85 sseC = (y-X*ansC)'*(y-X*ansC);
86 s2C = (y-X*ansC)'*(y-X*ansC)/(length(y)-size(X,2));
87 %%% Initialize the width of the OLS+noise for starting values:
88 alpha = .75;
89
90
91 % (i) Estimate \hat{\beta} and s^{2} using fminsearch with default ...
92 % convergence tolerances, assuming \varepsilon_{i} is mean-zero
93 % I'm going to write a function called OLS1 that minimizes the sum of the ...
94 % squared errors for any vector Y and matrix X
95 [bOLSsearch,SSEsearch,eOLSsearch]=fminsearch('OLS1',ansC+(2*alpha*ansC.*rand(size(ansC))-alpha*ansC),options,X,y);
96 s2OLSsearch = SSEsearch/(length(y)-size(X,2));
97
98 % (ii) Estimate \hat{\beta} and s^{2} using fminunc with default ...
99 % convergence tolerances, assuming \varepsilon_{i} is mean-zero
100 [bOLSunc,SSEunc,eOLSunc]=fminunc('OLS1',ansC+(2*alpha*ansC.*rand(size(ansC))-alpha*ansC),options,X,y);
101 s2OLSunc = SSEunc/(length(y)-size(X,2));
102
103 % (iii) Estimate \hat{\beta} and \hat{\sigma}^{2} using fminsearch with ...
104 % default convergence tolerances, assuming ...
105 % \varepsilon_{i} \overset{iid}{\sim} N\left(0,\sigma\right)
106 [bMLEsearch,likeSearch,eMLEsearch]=fminsearch('normalMLE',[ansC+(2*alpha*ansC.*rand(size(ansC))-alpha*ansC),ones(size(ansC))],options,X,y);
107 bMLEsearch(end) = bMLEsearch(end)^2; %recover sigma2, not sigma
108
109 % (iv) Estimate \hat{\beta} and \hat{\sigma}^{2} using fminunc with ...
110 % default convergence tolerances, assuming ...
111 % \varepsilon_{i} \overset{iid}{\sim} N\left(0,\sigma\right)
112 [bMLEunc,likeUnc,eMLEunc]=fminunc('normalMLE',[ansC+(2*alpha*ansC.*rand(size(ansC))-alpha*ansC),ones(size(ansC))],options,X,y);
113 bMLEunc(end) = bMLEunc(end)^2;
114
115 % (v) How does fminsearch compare to fminunc when the dimension of the ...
116 % parameter vector increases?
117 exitFlags = [eOLSsearch eOLSunc eMLEsearch eMLEunc]
118 compareC = [[bOLSsearch;s2OLSsearch;SSEsearch] [bOLSunc;s2OLSunc;SSEunc] ...
119 [bMLEsearch;-likeSearch] [bMLEunc;-likeUnc] [ansC; s2C; sseC]]
120 compareA
121 compareB
122
123 % (vi) How do the estimators in (i) through (iv) perform when the ...

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    starting values are 0.01 for all parameters?
122 [bOLSsearch, SSEsearch, eOLSsearch]=fminsearch('OLS1', .01*ones(nb,1), options, X, y);
123 s2OLSsearch = SSEsearch/(length(y)-size(X,2));
124
125 [bOLSunc, SSEunc, eOLSunc]=fminunc('OLS1', .01*ones(nb,1), options, X, y);
126 s2OLSunc = SSEunc/(length(y)-size(X,2));
127
128 [bMLEsearch, likeSearch, eMLEsearch]=fminsearch('normalMLE', .01*ones(nb+1,1), options, X, y);
129 bMLEsearch(end) = bMLEsearch(end)^2; %recover sigma2, not sigma
130
131 [bMLEunc, likeUnc, eMLEunc]=fminunc('normalMLE', .01*ones(nb+1,1), options, X, y);
132 bMLEunc(end) = bMLEunc(end)^2;
133 exitFlags2 = [eOLSsearch eOLSunc eMLEsearch eMLEunc]
134 compareC2 = [[bOLSsearch; s2OLSsearch; SSEsearch] [bOLSunc; s2OLSunc; SSEunc] ...
    [bMLEsearch; -likeSearch] [bMLEunc; -likeUnc] [ansC; s2C; sseC]]
135 compareC
136 %% Problem 2(a)
137 clear all;
138 load nhanes2d
139 options = optimset('Disp', 'iter-detailed', 'MaxFunEvals', 1e12, 'MaxIter', 1e6);
140 options2 = ...
    optimset('Disp', 'iter-detailed', 'MaxFunEvals', 1e12, 'MaxIter', 1e6, 'TolX', 1e-8, 'TolFun', 1e-8);
141 %% Set up the data:
142 y = hct;
143 X = [ones(size(hct)) age race==2 race==3 heartatk sex==2 highbp region==1 ...
    region==2 region==3 smsa==2 smsa==4 height weight houssiz];
144
145 %% create a vector that is 1 if all obs are there; 0 otherwise:
146 subset2 = ~isnan(hct) & ~isnan(age) & ~isnan(race) & ~isnan(heartatk) ...
    & ~isnan(sex) & ~isnan(highbp) & ~isnan(region) & ~isnan(smsa) ...
    & ~isnan(height) & ~isnan(weight) & ~isnan(houssiz);
147
148 y = hct(subset2); %drop missing observations from y
149 X = X(subset2, :); %drop missing observations from X
150 nb = size(X,2); %initialize the number of regressors for later use
151 %% Initialize the baseline closed-form OLS formulas (for later comparison)
152 ans2A = (X'*X)\X'*y;
153 sse2A = (y-X*ans2A)'*(y-X*ans2A);
154 s22A = (y-X*ans2A)'*(y-X*ans2A)/(length(y)-size(X,2));
155 %% Initialize the width of the OLS+noise for starting values:
156 alpha = 1.5;
157
158
159
160 % i. Estimate  $\hat{\beta}$  and  $\hat{\sigma}^2$  using fminsearch with ...
    default convergence tolerances, assuming ...
     $\text{varepsilon}_{i|\text{overset{iid}}{\sim} N\left(0, \sigma\right)}$  . Use the ...
    same starting values as in part (i) of 1(c), but now with  $\alpha=1.5$  .
161 [bMLEsearch1, likeSearch1, eMLEsearch1]=fminsearch('normalMLE', [ans2A+(2*alpha*ans2A.*rand(s
162 bMLEsearch1(end) = bMLEsearch1(end)^2; %recover sigma2, not sigma
163
164
165 % ii. Estimate  $\hat{\beta}$  and  $\hat{\sigma}^2$  using fminsearch with ...
    TolX and TolFun each set to  $10^{-8}$  (instead of the default), ...
    assuming  $\text{varepsilon}_{i|\text{overset{iid}}{\sim} N\left(0, \sigma\right)}$  . ...
    Use the same starting values as in part (i) of 2(a).
166 [bMLEsearch2, likeSearch2, eMLEsearch2]=fminsearch('normalMLE', [ans2A+(2*alpha*ans2A.*rand(s

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```

167 bMLEsearch2(end) = bMLEsearch2(end)^2;
168
169
170 % iii. Estimate  $\hat{\beta}$  and  $\hat{\sigma}^2$  using fminunc with ...
      default convergence tolerances, assuming ...
       $\text{N} \left( 0, \sigma \right)$  . Use the ...
      same starting values as in part (i) of 2(a).
171 [bMLEunc1,likeUnc1,eMLEunc1]=fminunc('normalMLE',[ans2A+(2*alpha*ans2A.*rand(size(ans2A))-
172 bMLEunc1(end) = bMLEunc1(end)^2;
173
174
175 % iv. Estimate  $\hat{\beta}$  and  $\hat{\sigma}^2$  using fminunc with TolX ...
      and TolFun each set to  $10^{-8}$  (instead of the default), assuming ...
       $\text{N} \left( 0, \sigma \right)$  . Use the ...
      same starting values as in part (i) of 2(a).
176 [bMLEunc2,likeUnc2,eMLEunc2]=fminunc('normalMLE',[ans2A+(2*alpha*ans2A.*rand(size(ans2A))-
177 bMLEunc2(end) = bMLEunc2(end)^2;
178
179
180 % v. How do your answers change when the convergence tolerance changes? ...
      How many more iterations did the optimization require under the ...
      stricter tolerances? How different are your answers depending on the ...
      optimizer?
181 exitFlags = [eMLEsearch1 eMLEsearch2 eMLEunc1 eMLEunc2]
182 compareTol = [[bMLEsearch1;-likeSearch1] [bMLEsearch2;-likeSearch2] ...
      [bMLEunc1;-likeUnc1] [bMLEunc2;-likeUnc2] [ans2A; s22A; sse2A]]

```

2 OLS Function Code

```
1 function SSE = OLS1(beta,X,Y)
2 SSE = (Y-X*beta)'*(Y-X*beta);
3 end
```

3 MLE Function Code

```
1 function [like]=normalMLE(b,X,Y)
2 beta      = b(1:end-1);
3 wagesigma = b(end);
4 like = sum(.5*log(2*pi*(wagesigma^2))+.5*((Y-X*beta)/wagesigma).^2);
5 end
```