

Appendix

```
t = [3.4935 4.2853 5.1374 5.8181 6.8632 8.1841]';
```

```
x = [6 10.1333 14.2667 18.4000 22.5333 26.6667]';
```

```
sig = 0.1;
```

```
m = length(t);
```

```
G = [ones(m,1) x]; % matrix G
```

No.1

Use IRLS to find 1-norm estimates for t_0 and s_2 .

```
tolr = 1e-8;
```

```
tolx = 1e-16;
```

```
p = 1;
```

```
maxiter = 5;
```

```
W = (1/sig)*eye(m);
```

```
Gw = W*G;
```

```
tw = W*t;
```

```
ML1 = irls(Gw, tw, tolr, tolx, p, maxiter); % irls function
```

```
to = ML1(1)
```

```
s2 = ML1(2)
```

Plot the data and the fitted model on the same graph

```
err = sig*ones(size(t));
```

```
% fitted model
```

```
T = zeros(m,1);
```

```
for i = 1:m
```

```
    T(i) = to + s2*x(i);
```

```
end
```

```
%plot
```

```
figure1=figure(1);
```

```
%L1 estimate
```

```
%subplot(2,1,1)
```

```
plot(x,t,'.','MarkerSize',20)
```

```
hold on
```

```
errorbar(x,t,err,'LineStyle','none')
```

```
hold on
```

```
plot(x,T,'r',LineWidth=2)
```

```
hold off
```

```
legend('data','Error bound','fitted model','Location','southeast')
```

```
ylabel('Arrival times')
```

```
xlabel('Distance (km)')
```

```
title('L1 estimate')
```

No.2

Create an ensemble of q data sets

$q = 1e4$; % no of monte carlo simulations

$n = 2$; % no of parameters

```
noise = sig*randn(m,q);
```

```
db = G*ML1;
```

```
M = zeros(q,n);
```

```
for i = 1:q
```

```
    di = (db + noise(:,i));
```

```
    dw = di./sig;
```

```
    ML1i = irls(Gw, dw, tolr, tolX, p, maxiter);
```

```
    M(i,1) = ML1i(1); M(i,2) = ML1i(2);
```

```
end
```

Create a Q-Q plot for each of the two parameter estimates.

```
%figure2=figure('Position', [100, 100, 1024, 1200]);
```

```
figure(2)
```

```
subplot(2,1,1)
```

```
qqplot(M(:,1))
```

```
ylabel('Quantiles of Input Sample');
```

```
xlabel('Standard Normal Quantiles');
```

```
title('Q-Q plot for to')
```

```
subplot(2,1,2)
```

```
qqplot(M(:,2))
```

```
ylabel('Quantiles of Input Sample');
```

```
xlabel('Standard Normal Quantiles');
```

```
title('Q-Q plot for s2')
```

No.3

Estimate the uncertainty in your L_1 parameter estimates from 1. using confidence intervals, with two different approaches:

(a). Find a range where 95% of the ensemble L_1 parameter estimates lie, relative to the mean.

```
mbar = mean(M); % mean
```

```
A = M - repmat(mbar,[q],[1]);
```

```
Ai = sort(A);
```

```
sigi = Ai(0.95*q,:);
```

```
%for to
```

```
ct1 = to - sigi(1);
```

```
ct2 = to + sigi(1);
```

```
Confidence_interval_to = [ct1 ct2]
```

```
%for s2
```

```
ct11 = s2 - sigi(2);
```

```
ct22 = s2 + sigi(2);
```

```
Confidence_interval_s2 = [ct11 ct22]
```

(b). Use the empirical estimate of the covariance given by (2.110).

```
C = (A'*A)/q; % empirical estimate
```

```
%for to
```

```
z = 1.96;
```

```
ct1 = to - sqrt(C(1,1))*z;%/sqrt(n);
```

```
ct2 = to + sqrt(C(1,1))*z;%/sqrt(n);
```

```
Confidence_interval_to = [ct1 ct2]
```

```
%for s2
```

```
ct11 = s2 - sqrt(C(2,2))*z;%/sqrt(n);
```

```
ct22 = s2 + sqrt(C(2,2))*z;%/sqrt(n);
```

```
Confidence_interval_s2 = [ct11 ct22]
```