

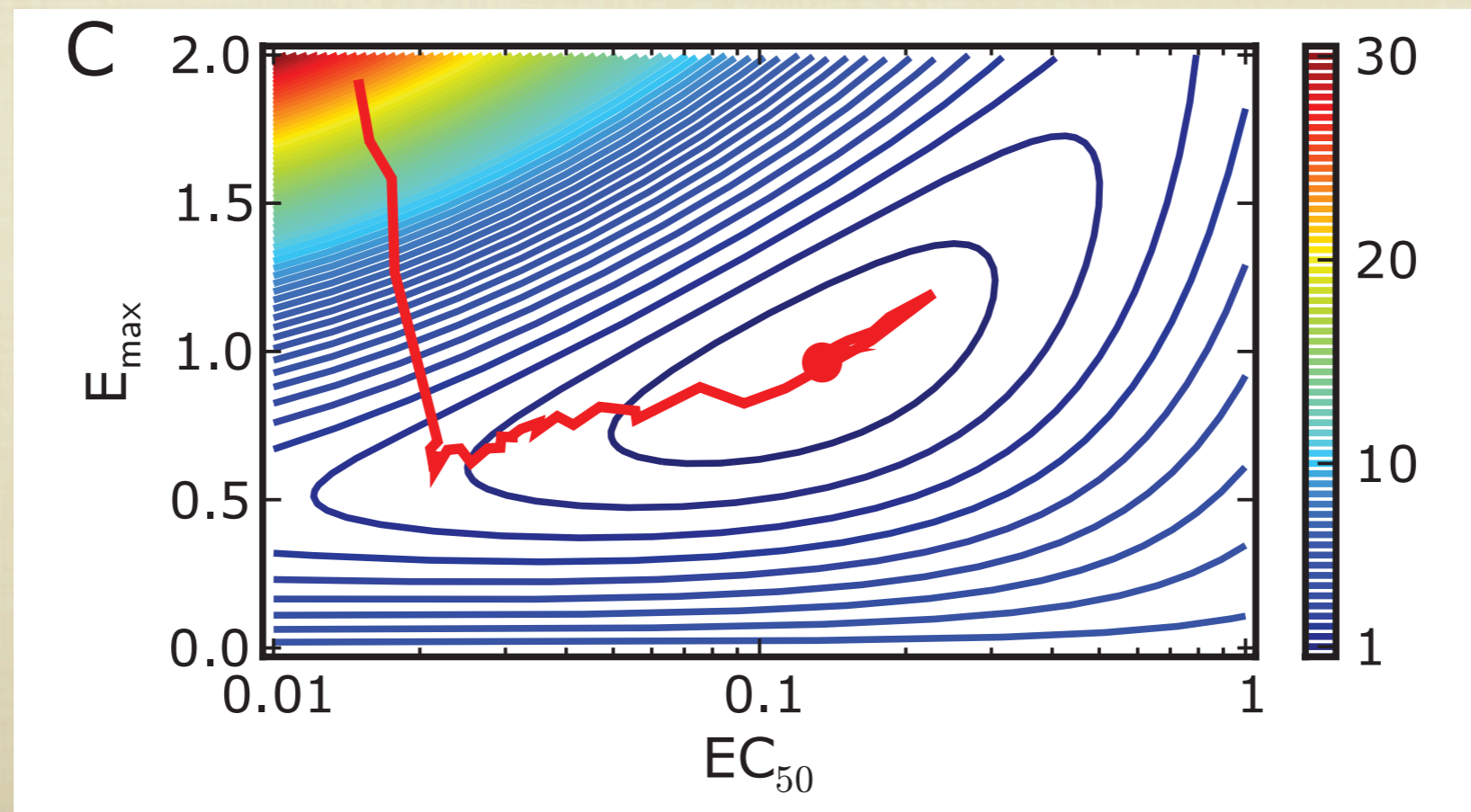
# Experimental data analysis

## Lecture 3: Confidence intervals

Dodo Das

## Review of lecture 2

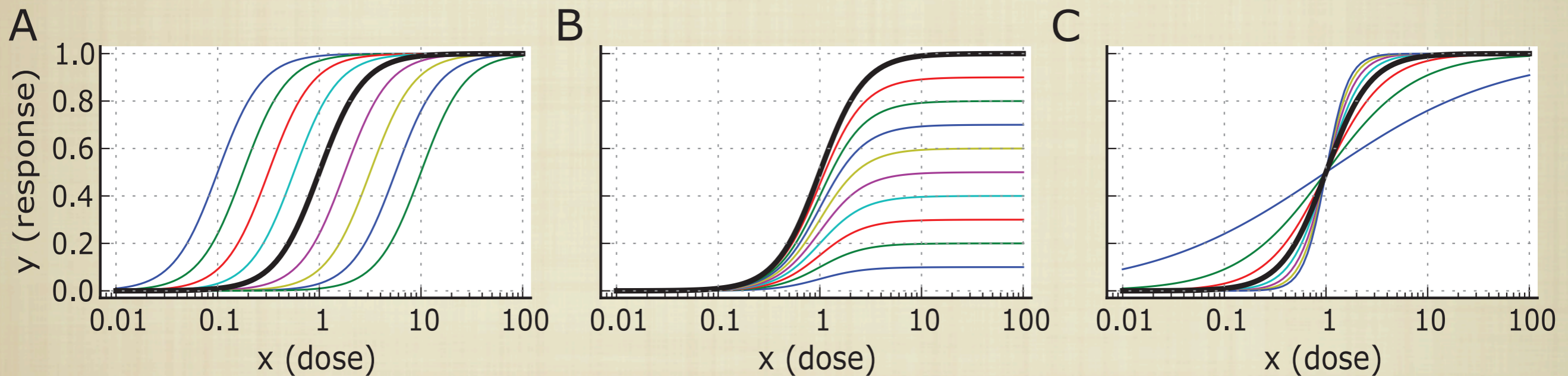
- Nonlinear regression - Iterative likelihood maximization
- Levenberg-Marquardt algorithm (Hybrid of steepest descent and Gauss-Newton)
- Stochastic optimization - MCMC, Simulated annealing.



# Demo 3: Nonlinear regression in MATLAB

- Objective: Using a Hill function to model dose-response data.

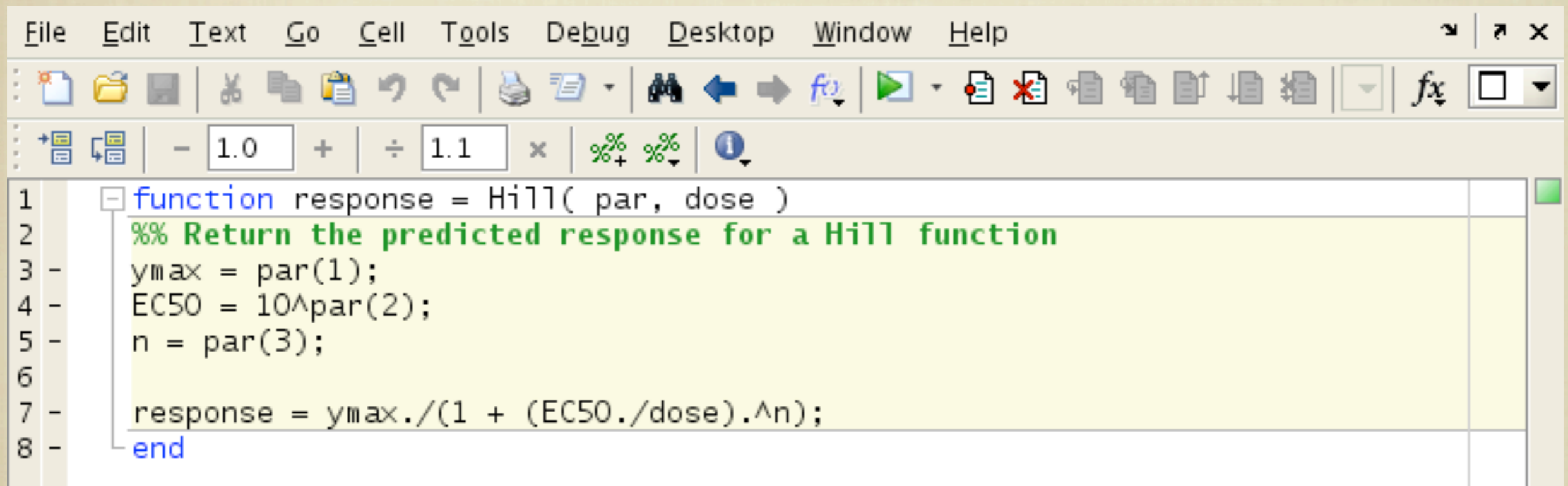
$$y = f(x; y_{\max}, EC_{50}, n) = \frac{y_{\max}}{1 + (EC_{50}/x)^n}$$



# Demo 3: Nonlinear regression in MATLAB

Need the statistics toolbox which contains the function `nlinfit`

i) Write a MATLAB function to compute the Hill function for a given set of parameter values.



```
File Edit Text Go Cell Tools Debug Desktop Window Help
[Icons]
- 1.0 + ÷ 1.1 x % %
1 function response = Hill( par, dose )
2 %% Return the predicted response for a Hill function
3 - ymax = par(1);
4 - EC50 = 10^par(2);
5 - n = par(3);
6
7 - response = ymax./(1 + (EC50./dose).^n);
8 - end
```

# Demo 3: Nonlinear regression in MATLAB

ii) Choose some model parameters to simulate data [or collect data from experiments]

```
File Edit Text Go Cell Tools Debug Desktop Window Help
[Icons] [fx]
- 1.0 + ÷ 1.1 x % % %
1 %% Nonlinear regression. Generate data for a dose response curve by adding
2 %% some normally distributed noise to a Hill function. Use nlinfit to
3 %% perform nonlinear regression
4 |
5 %% Specify model parameters. The Hill function is given by
6 %%  $y(x) = y_{max}/(1 + (EC50/dose)^n)$ 
7 - ymax = 1;
8 - Lec50 = 0;
9 - n = 2;
10 - modelpar = [ymax Lec50 n];
11
12 %% Generate some data
13 - dose = (logspace(-1, 1, 15))';
14 - yTrue = Hill(modelpar, dose);
15
16 %% Add normal error to simulate experimental noise
17 - NoiseStd = 0.1; % The standard deviation of the noise
18 - err = NoiseStd*randn(length(yTrue), 1);
19 - yExpt = yTrue + err;
20
```

# Demo 3: Nonlinear regression in MATLAB

iii) Pick an initial guess and call nlinfit

```
20
21 %% Call nlinfit to perform nonlinear regression. Add an option to see the
22 %% SSR value after each iteration
23 - options = statset('Display', 'iter');
24 - betaGuess = [1, 1, 1] % Initial guess for parameter values
25 - betaHat = nlinfit(dose, yExpt, @Hill, betaGuess, options)
26
27 %% Not all initial guesses work. This one fails to find the minimum.
28 - betaGuess = [0.1, 1, 4]
29 - nlinfit(dose, yExpt, @Hill, betaGuess, options)
30
31 %% Plot data and fit
32 - semilogx(dose, yExpt, 'ro', 'MarkerSize', 8)
33 - hold on
34 - doseFit = (logspace(-1, 1, 201))';
35 - yFit = Hill(betaHat, doseFit);
36 - plot(doseFit, yFit, 'b-', 'LineWidth', 2)
37 - plot(doseFit, Hill(modelpar, doseFit), 'b--', 'LineWidth', 1)
38 - xlim([0.09, 11])
39 - ylim([-0.05, 1.15])
40 - xlabel('dose')
41 - ylabel('response')
42 - grid on
43 - legend('Data', 'Nonlinear fit', 'True model', 'Location', 'NW')
```

# Demo 3: Nonlinear regression in MATLAB

```
Command Window
New to MATLAB? Watch this Video, see Demos, or read Getting Started.

betaGuess =

    1    1    1

Iteration          SSE          Norm of Gradient          Norm of Step
-----
    0          3.36869
    1          2.41072          1.09421          1.13207
    2          1.29038          2.7598          0.717239
    3          0.737374          4.97887          1.03529
    4          0.315402          1.19888          1.09758
    5          0.151169          0.253951          0.412226
    6          0.115426          0.0941071          0.336512
    7          0.108014          0.0424598          0.247683
    8          0.107063          0.00288839          0.0328246
    9          0.106997          0.000564608          0.0306803
   10          0.106991          1.90122e-05          0.00157004
   11          0.10699          5.20445e-06          0.00286241
   12          0.10699          1.79044e-07          0.000198578
   13          0.10699          4.70273e-08          0.000264638
   14          0.10699          2.26291e-09          3.04801e-05

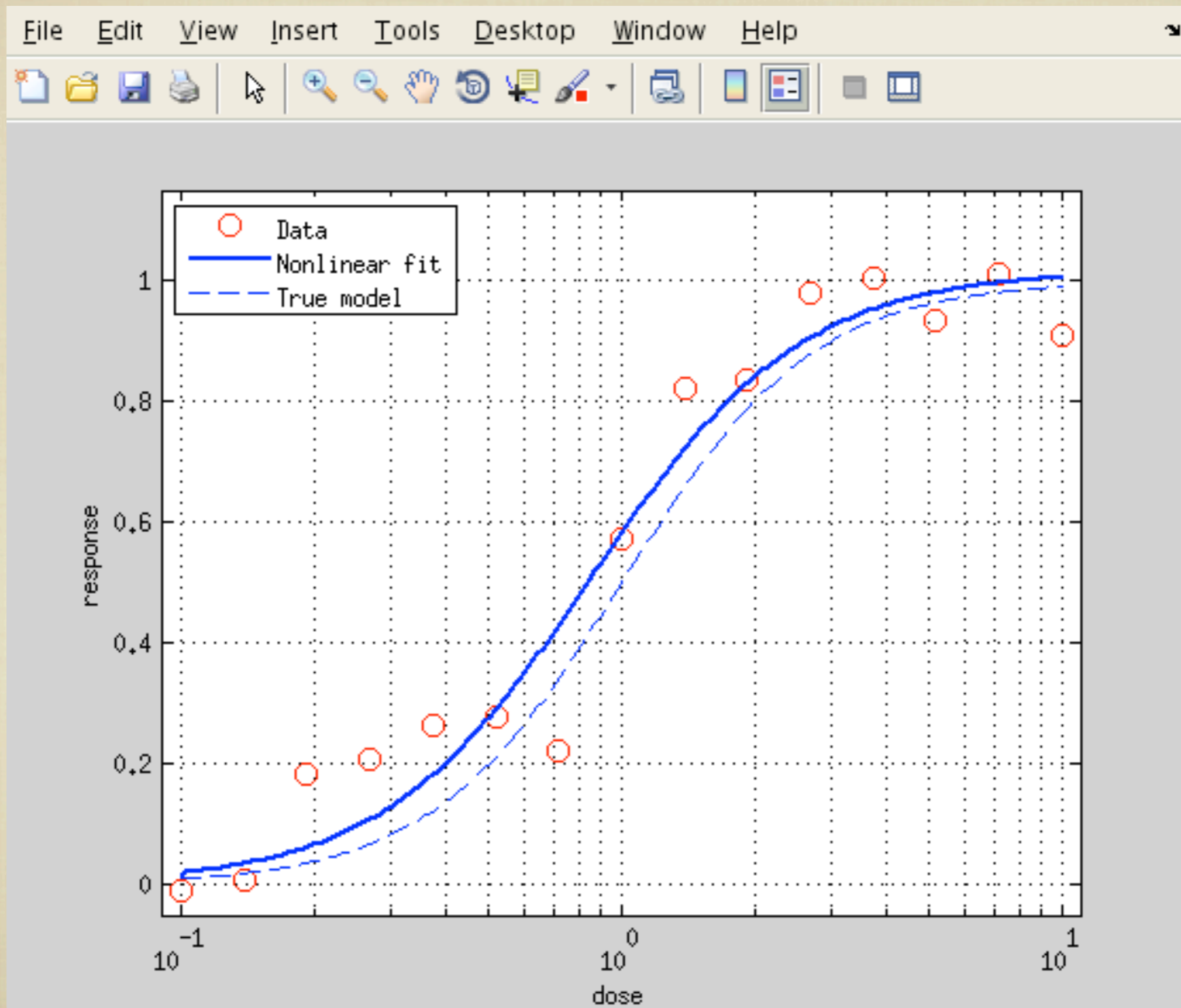
Iterations terminated: relative change in SSE less than OPTIONS.ToIFun

betaHat =

    1.0164   -0.0697    1.8357

fx >> |
```

# Demo 3: Nonlinear regression in MATLAB





# Demo 3: Nonlinear regression in MATLAB

Convergence can be sensitive to the initial guess.

```
27 %% Not all initial guesses work. This one fails to find the minimum.  
28 - betaGuess = [0.1, 1, 4]  
29 - nlinfit(dose, yExpt, @Hill, betaGuess, options)
```

# Demo 3: Nonlinear regression in MATLAB

Convergence can be sensitive to the initial guess.

```
Command Window
New to MATLAB? Watch this Video, see Demos, or read Getting Started.

betaGuess =
    0.1000    1.0000    4.0000

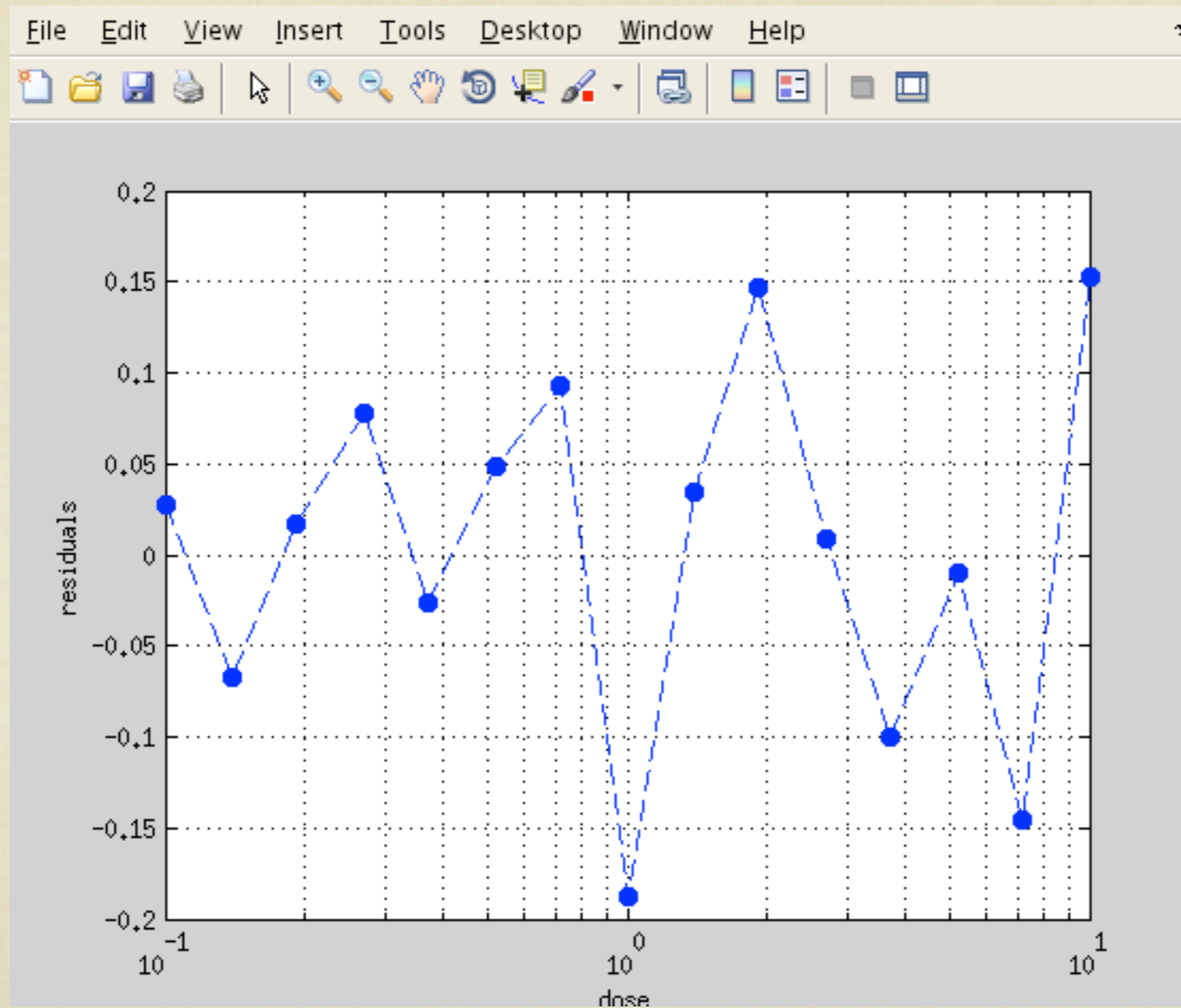
Iteration      SSE      Norm of Gradient      Norm of Step
-----
0             6.52615
1             4.77415      1.74131      20.0928
2             4.5339      4.89515      26.4957
3             3.82728      2.56718      251.139
Warning: Rank deficient, rank = 1, tol = 1.5114e-14.
> In nlinfit>LMfit at 294
  In nlinfit at 166
4             3.62008      0.299641      0.115246
Warning: Rank deficient, rank = 1, tol = 1.4483e-14.
> In nlinfit>LMfit at 294
  In nlinfit at 166
5             3.61836      0.00296674      0.0114105
Warning: Rank deficient, rank = 1, tol = 1.4418e-14.
> In nlinfit>LMfit at 294
  In nlinfit at 166
6             3.61836      2.96377e-06      0.000113991
Warning: Rank deficient, rank = 1, tol = 1.4411e-14.
> In nlinfit>LMfit at 294
  In nlinfit at 166
7             3.61836      2.96349e-10      1.1398e-07
Iterations terminated: relative norm of the current step is less than OPTIONS.To1X
Warning: The Jacobian at the solution is ill-conditioned, and some
model parameters may not be estimated well (they are not identifiable).
Use caution in making predictions.
> In nlinfit at 223

ans =
    0.4849    0.7968 -293.7222

fx >>
```

# Demo 3: Nonlinear regression in MATLAB

Compute and plot residuals



# Parameter confidence intervals

- Question: What does a 95% confidence interval mean?
- eg: Say, a best fit parameter estimate is  $\hat{a} = 1$ , and we have estimated the 95% CI to be  $[0.5, 1.5]$ . How can we interpret this result?

# Parameter confidence intervals

- Question: What does a 95% confidence interval mean?
- eg: Say, a best fit parameter estimate is  $\hat{a} = 1$ , and we have estimated the 95% CI to be  $[0.5, 1.5]$ . How can we interpret this result?
- If we repeat our experiment and the fitting procedure many times, 95% of the times the true (but unknown) parameter value will lie within this CI.

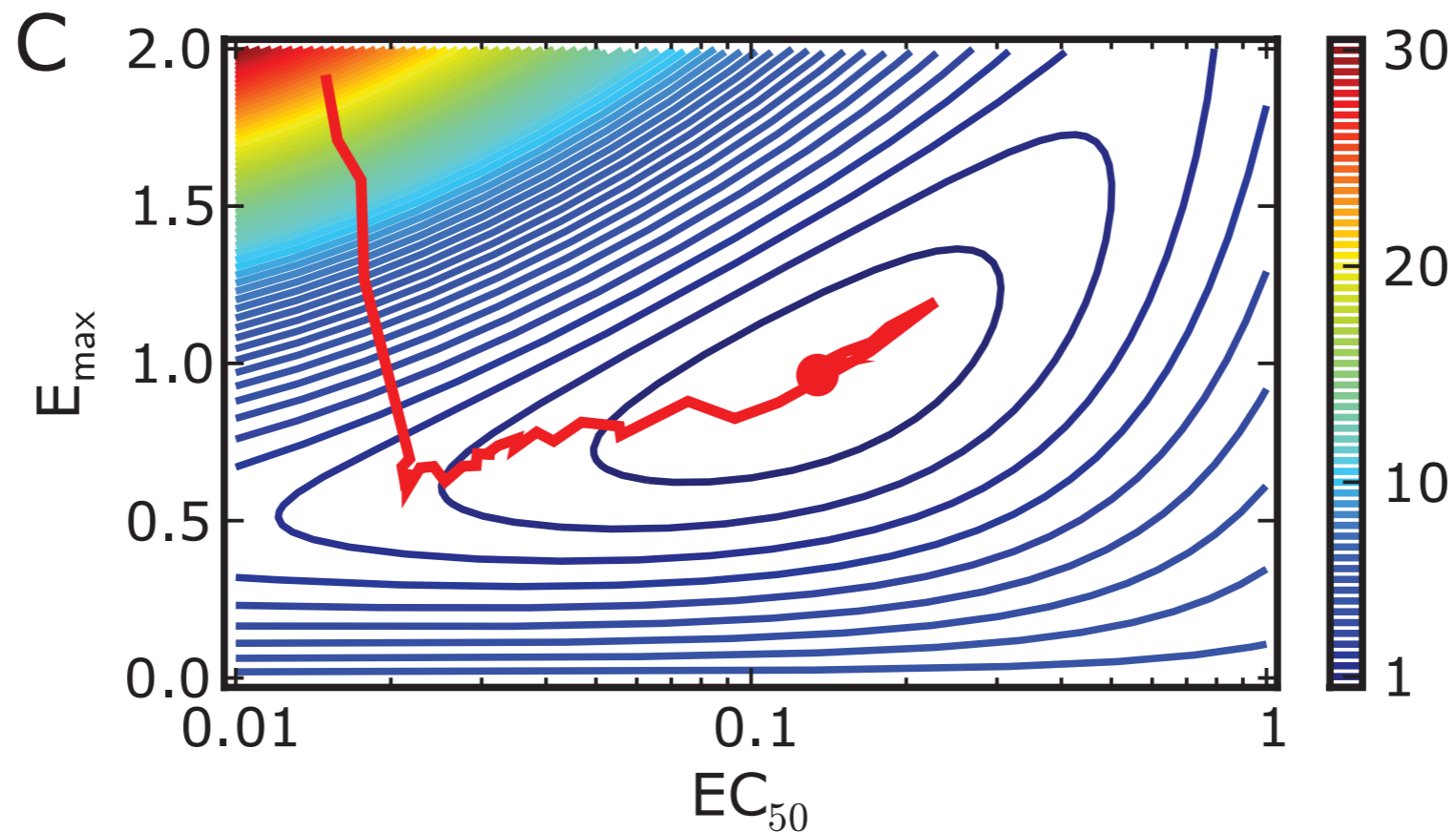
# Computing parameter confidence intervals

■ Two approaches:

1. **Asymptotic confidence intervals:** Based on an analytical approximation.
2. **Bootstrap confidence intervals:** Computational technique based on resampling the errors.

# Asymptotic confidence intervals

- Use a local approximation of the SSR landscape to estimate the curvature (covariance matrix).
- Assuming that the errors are normally distributed, this covariance matrix can be used to compute a confidence interval around each parameter.



# Demo 4: Computing asymptotic CIs in MATLAB

Use the `nlparci` command in the Statistics toolbox

```
File Edit Text Go Cell Tools Debug Desktop Window Help
- 1.0 + ÷ 1.1 × %>% %>% ⓘ
1 %% Estimate asymptotic confidence intervals for a nonlinear regression
2 %% fit using nlparci (Statistics toolbox)
3
4 %% Fit simulated dose-response data to a Hill function, given by
5 %%  $y(x) = y_{\max}/(1 + (EC50/dose)^n)$ 
6
7 %% Load data
8 - DoseResponse = load('DoseResponseData.dat', '-ascii');
9 - dose = DoseResponse(:,1);
10 - yExpt = DoseResponse(:,2);
11
12 %% Call nlinfit to perform nonlinear regression.
13 - betaGuess = [1, 1, 1]; % Initial guess for parameter values
14 - [betaHat, res, Jac, Cov, mse] = nlinfit(dose, yExpt, @Hill, betaGuess);
15
16 %% Supply output to nlparci to estimate asymptotic 95% CIs.
17 - asympCI = nlparci(betaHat, res, 'covar', Cov);
18
19 %% Print parameter estimates and asymptotic CIs
20 - [betaHat' asympCI]
21
```



# Demo 4: Computing asymptotic CIs in MATLAB

Use the `nlparci` command in the Statistics toolbox

```
File Edit Text Go Cell Tools Debug Desktop Window Help
- 1.0 + ÷ 1.1 x % % %
1 %% Estimate asymptotic confidence intervals for a nonlinear regression
2 %% fit using nlparci (Statistics toolbox)
3
4 %% Fit simulated dose-response data to a Hill function, given by
5 %%  $y(x) = y_{\max}/(1 + (EC50/dose)^n)$ 
6
7 %% Load data
8 - DoseResponse = load('DoseResponseData.dat', '-ascii');
9 - dose = DoseResponse(:,1);
10 - yExpt = DoseResponse(:,2);
11
12 %% Call nlinfit to perform nonlinear regression.
13 - betaGuess = [1, 1, 1]; % Initial guess for parameter values
14 - [betaHat, res, Jac, Cov, mse] = nlinfit(dose, yExpt, @Hill, betaGuess);
15
16 %% Supply output to nlparci to estimate asymptotic 95% CIs.
17 - asympCI = nlparci(betaHat, res, 'covar', Cov);
18
19 %% Print parameter estimates and asymptotic CIs
20 - [betaHat' asympCI]
21
```

```
Command Window
New to MATLAB? Watch this Video, see Demos, or read Getting Started.

ans =

    1.0268    0.9040    1.1497
    0.0058   -0.0930    0.1045
    2.8238    1.2890    4.3585

fx >>
```

# Bootstrapping: The principle

- A computational approach that addresses the following question:
- Given a limited number of observations, how can we estimate some quantity, eg: mean, median etc. for the population from which the observations are drawn?
- If we 'resample' from the observations, we can, in some sense, simulate the population distribution.

# Bootstrapping in practice for nonlinear regression.

1. Use the nonlinear least squares regression to determine the best-fit estimates of the model parameters, and the predicted model response  $(y_i)_{\text{predicted}}$  at each value of the independent variable  $x_i$ .
2. Calculate the residuals  $\epsilon_i = (y_i)_{\text{observed}} - (y_i)_{\text{predicted}}$  at each of the  $N$  data points.
3. Resample the residuals **with replacement** to generate a new set of residuals  $\{\epsilon_i^*\}$ . What this means is that we generate a new set of  $N$  residuals where each of  $N$  values is one of the original residuals chosen with equal probability. Typically, some of the original residuals will be chosen more than once, while some will not be chosen at all. For example, say we have three data points and we calculate the residuals to be 0.1, -0.2 and 0.3. Then some possible sets of resampled residuals are:  $\{-0.2, 0.1, -0.2\}$ ,  $\{0.1, 0.3, -0.2\}$ ,  $\{0.3, -0.2, -0.2\}$ , and so on.
4. Add the resampled residuals to the predicted response to generate a **bootstrap data set**,  $\{x_i, y_i^*\} = \{x_i, (y_i)_{\text{predicted}} + \epsilon_i^*\}$
5. Treat the bootstrap dataset as an independent replicate experiment, and fit it to the model to calculate new estimates of model parameters.
6. Repeat steps 3-5 many times - typically 500 to 1000 times - each time generating a new bootstrap data set, and fitting it to the model. Store the resulting best-fit parameter estimates. These independent estimates constitute a sample from the bootstrap distribution of the model parameters.
7. For each parameter, calculate the standard deviation of the bootstrap sample. This standard deviation is the estimated bootstrap standard error for that parameter.
8. To calculate the 95% bootstrap CIs, compute the 97.5<sup>th</sup> and the 2.5<sup>th</sup> percentile values of each parameter from the bootstrap distributions. (There are other prescriptions for calculating bootstrap CIs, but this one is the simplest.)

# Demo 5: Estimating bootstrap CIs in MATLAB

```
File Edit Text Go Cell Tools Debug Desktop Window Help
- 1.0 + ÷ 1.1 x %>% %>% i
1 %% Construct bootstrap samples for a nonlinear regression and estimate
2 %% bootstrap confidence intervals.
3
4 %% Fit simulated dose-response data to a Hill function, given by
5 %%  $y(x) = y_{\max}/(1 + (EC50/dose)^n)$ 
6
7 %% Load data
8 - DoseResponse = load('DoseResponseData.dat', '-ascii');
9 - dose = DoseResponse(:,1);
10 - yExpt = DoseResponse(:,2);
11
12 %% Call nlinfit to perform nonlinear regression.
13 - betaGuess = [1, 1, 1]; % Initial guess for parameter values
14 - [betaHat, residuals, Jac, Cov, mse] = nlinfit(dose, yExpt, @Hill, betaGuess);
15
16 %% Resample the residuals using the bootstrap function
17 - nboot = 200; % Number of bootstrap replicates
18 - [~, bootIndices] = bootstrap(nboot, [], residuals);
19 - bootIndices(:,1:3) % Print the first 3 columns of bootIndices
20 - bootResiduals = residuals(bootIndices);
21 - bootResiduals(:, 1:3) % Print the first 3 columns of bootResiduals
22
23 %% Generate bootstrap datasets by adding the resampled residuals
24 %%to the best fit curve
25 - yMod = Hill(betaHat, dose);
26 - yBoot = repmat(yMod, 1, nboot) + bootResiduals;
27
28 %% Fit each of the bootstrap datasets to the Hill function to
29 %% build up the bootstrap distributions of parameter estimates
30 - betaBoot = zeros(nboot, 3);
31 - for i=1:nboot
32 -     betaBoot(i,:) = nlinfit(dose, yBoot(:,i), @Hill, betaGuess);
33 - end
34
35 % Estimate 95% CIs
36 - bootCI = prctile(betaBoot,[2.5 97.5]);
37
```

# Demo 5: Estimating bootstrap CIs in MATLAB

```
Command Window
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%% Resample the residuals using the bootstrap function
nboot = 200; % Number of bootstrap replicates
[~, bootIndices] = bootstrap(nboot, [], residuals);
bootIndices(:,1:3) % Print the first 3 columns of bootIndices
bootResiduals = residuals(bootIndices);
bootResiduals(:, 1:3) % Print the first 3 columns of bootResiduals

ans =

    13     13     11
    12     9     10
     6     4     15
     6    14     6
    15    13     2
    13     9    14
     2     1    12
    10     8    13
    12    12    13
    12    14    15
     8     2     5
    12     8     4
     9     1     3
    12     3     1
    10     6     4

ans =

-0.0097 -0.0097  0.0089
-0.1002  0.0342  0.1473
 0.0486  0.0772  0.1527
 0.0486 -0.1453  0.0486
 0.1527 -0.0097 -0.0670
-0.0097  0.0342 -0.1453
-0.0670  0.0276 -0.1002
 0.1473 -0.1874 -0.0097
-0.1002 -0.1002 -0.0097
-0.1002 -0.1453  0.1527
-0.1874 -0.0670 -0.0260
-0.1002 -0.1874  0.0772
 0.0342  0.0276  0.0171
-0.1002  0.0171  0.0276
 0.1473  0.0486  0.0772

fx >>
```

# Demo 5: Estimating bootstrap CIs in MATLAB

```
File Edit Text Go Cell Tools Debug Desktop Window Help
[Icons] [fx] [ ]
+ [1.0] + [1.1] x [%] [%] [i]
1 %% Construct bootstrap samples for a nonlinear regression and estimate
2 %% bootstrap confidence intervals.
3
4 %% Fit simulated dose-response data to a Hill function, given by
5 %%  $y(x) = y_{\max}/(1 + (EC50/dose)^n)$ 
6
7 %% Load data
8 - DoseResponse = load('DoseResponseData.dat', '-ascii');
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20 - bootResiduals = residuals(bootIndices);
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23 %% Generate bootstrap datasets by adding the resampled residuals
24 %%to the best fit curve
25 - yMod = Hill(betaHat, dose);
26 - yBoot = repmat(yMod, 1, nboot) + bootResiduals;
27
28 %% Fit each of the bootstrap datasets to the Hill function to
29 %% build up the bootstrap distributions of parameter estimates
30 - betaBoot = zeros(nboot, 3);
31 - for i=1:nboot
32 -     betaBoot(i,:) = nlinfit(dose, yBoot(:,i), @Hill, betaGuess);
33 - end
34
35 % Estimate 95% CIs
36 - bootCI = prctile(betaBoot,[2.5 97.5]);
37
```

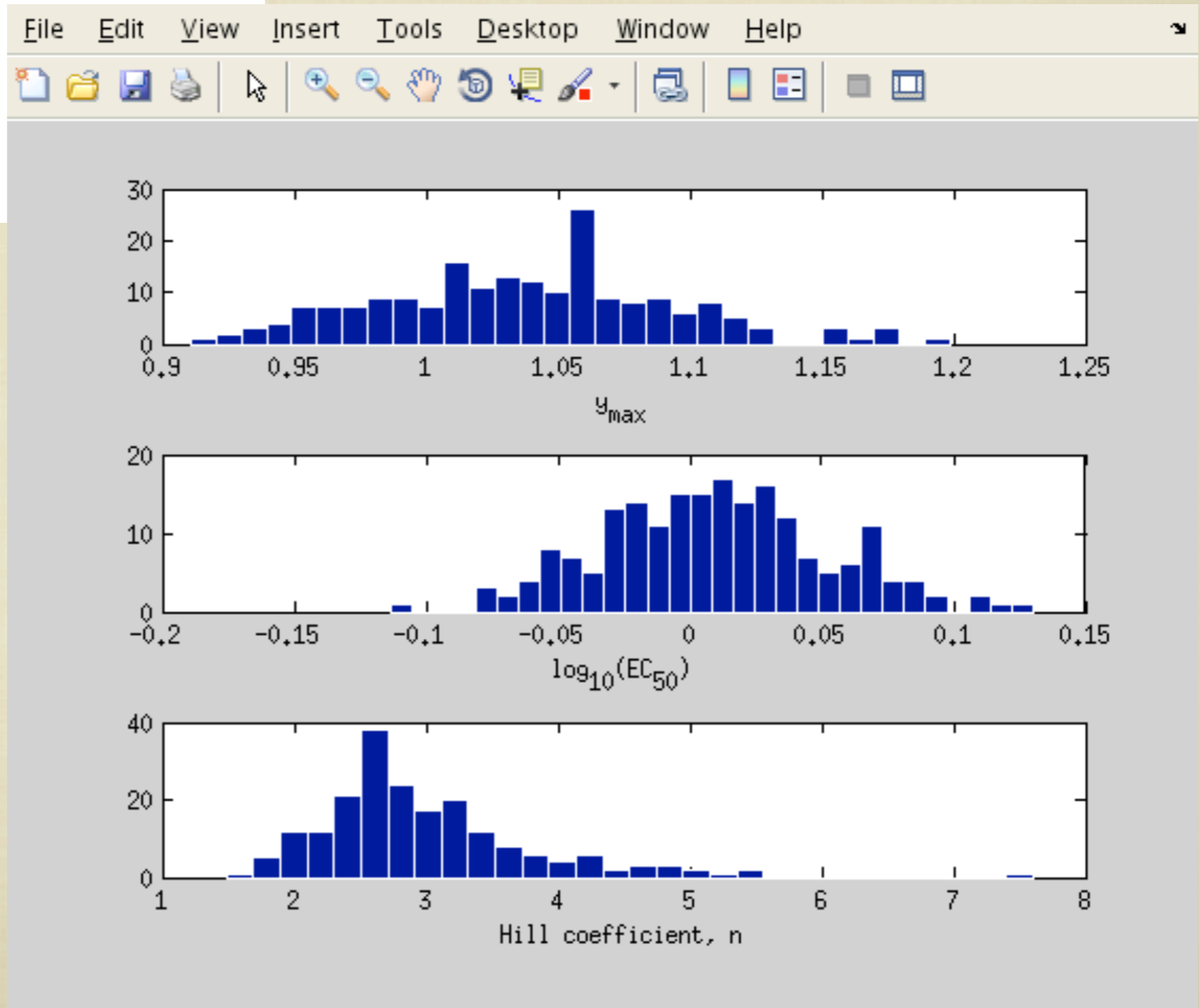
# Demo 5: Estimating bootstrap CIs in MATLAB

```
Command Window
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betaHat =
    1.0268    0.0058    2.8238

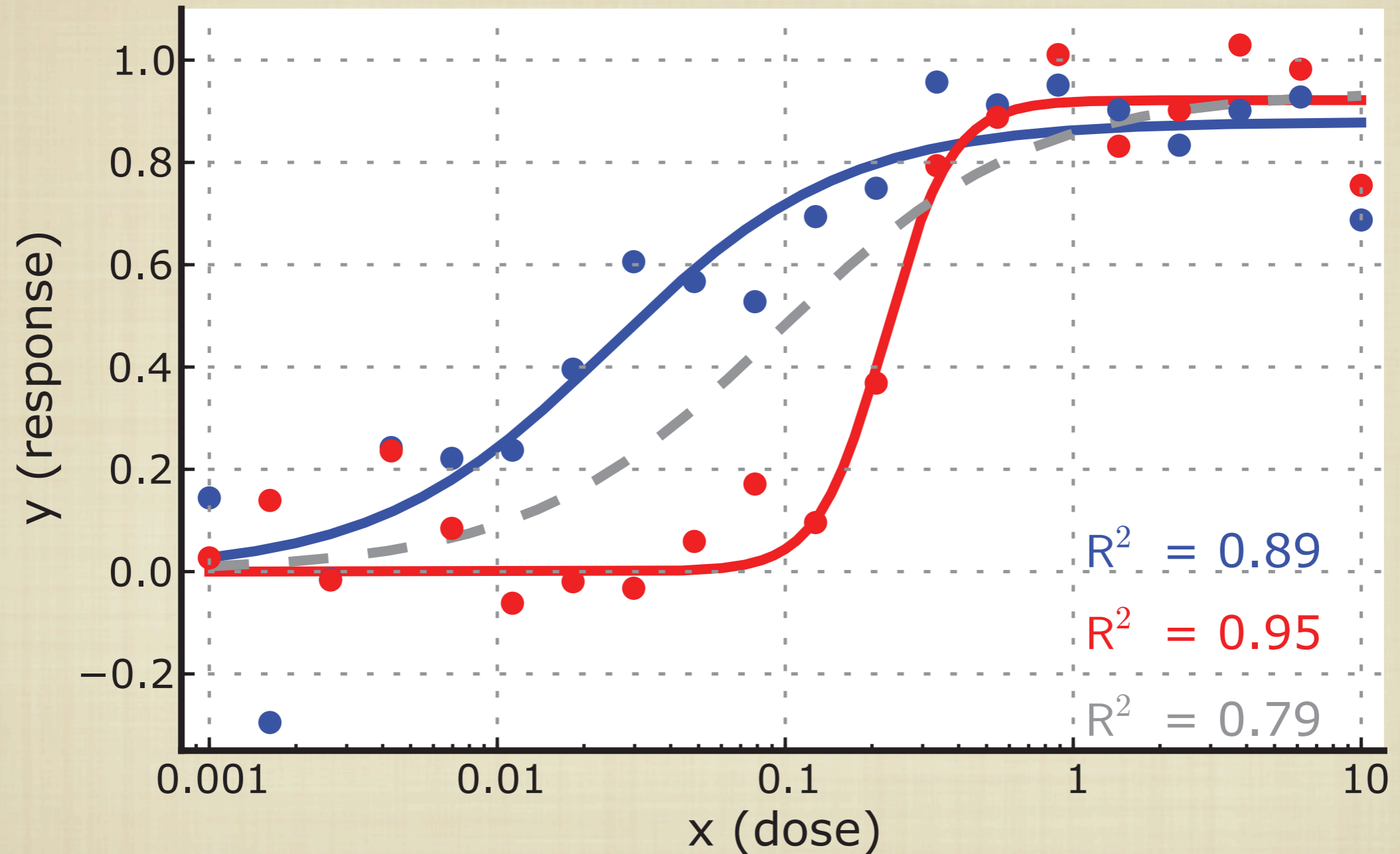
bootCI =
    0.9347   -0.0668    1.8171
    1.1601    0.0922    5.1005

fx >>
```



# Comparing fits from two different experiments

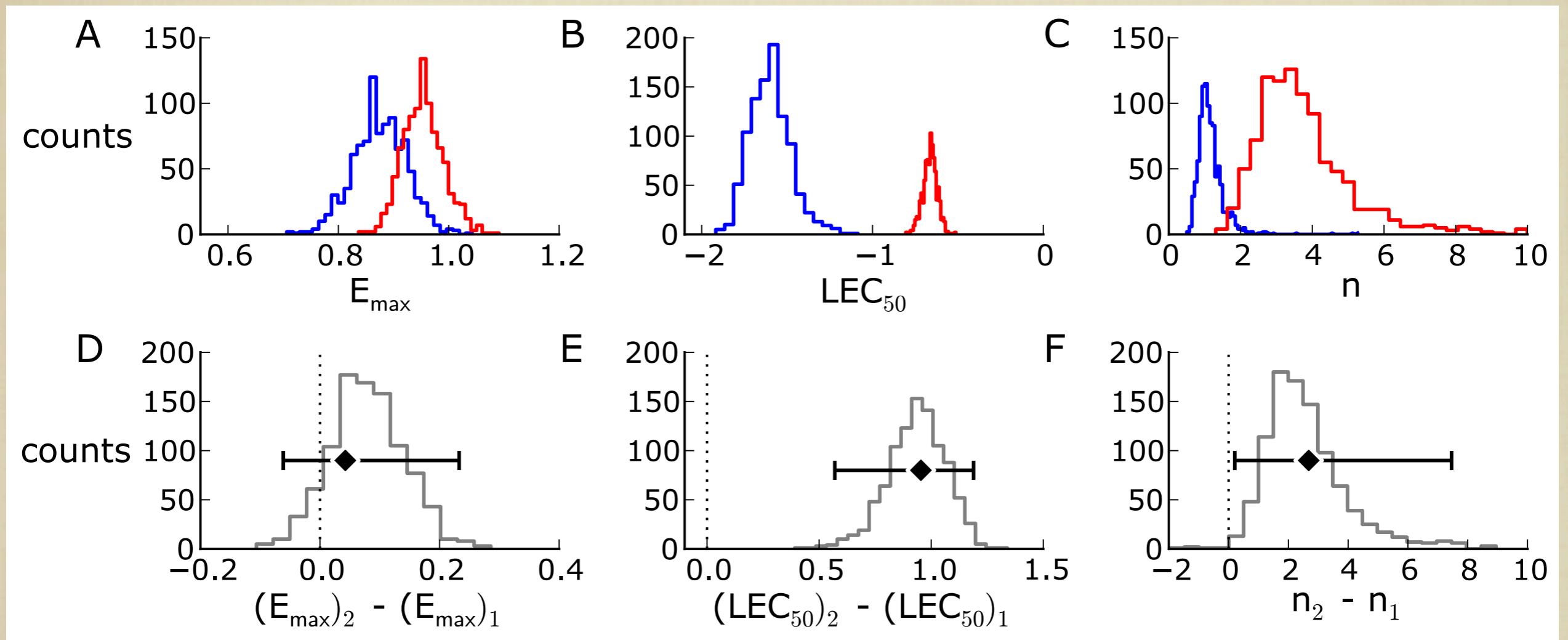
A



- Which parameters are different between the two datasets?



# Bootstrap-based hypothesis testing



- $E_{\max}$  is not (the 95% CI of the difference distribution crosses 0), but  $EC_{50}$  and  $n$  are different.

# Friday

- How to pick the best model from a set of proposed models?
- Bias-variance tradeoff
- F-test
- Akaike's information criterion (AIC)