

9.07 Matlab Tutorial

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Aim

- Transform students into Matlab ninjas!

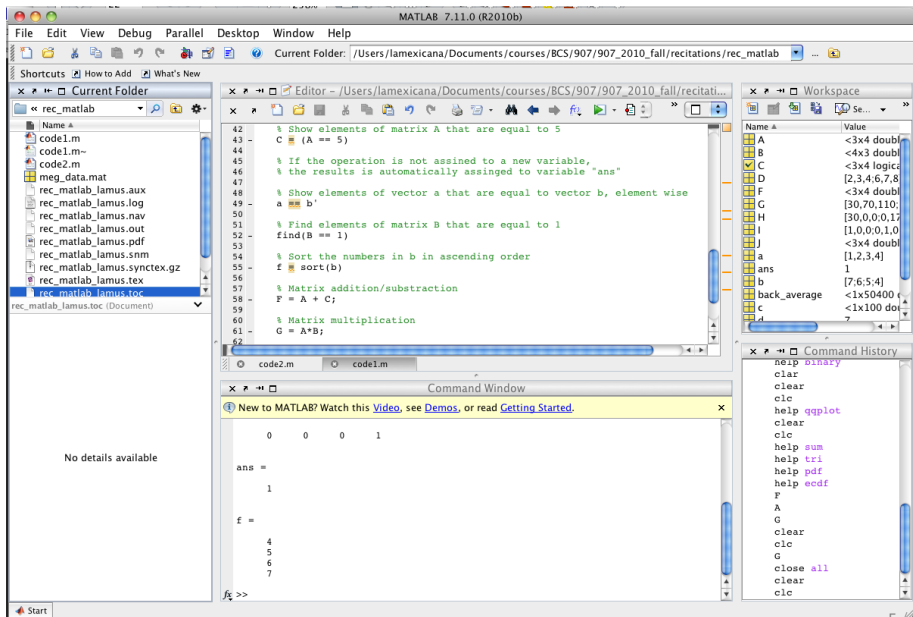


- Matrix operations: `a + b`, `a*b`, `A.*B`, `A.^B`, `sort`, etc
- Loops: `for i=1:n`, `while "statement is true"`
- Some useful functions: `rand`, `randn`, `min`, `max`, etc
- Function for displaying results:
`figure`, `plot`, `subplot`, `bar`, `hist`, `title`, `xlabel`, etc
- Translating algorithms into Matlab code.

Getting started

- Getting Matlab: <http://web.mit.edu/student-matlab/>
- Matlab support: <http://www.mathworks.com/support/>, in search support box select “Function list for all products”
- Matlab support: Goto Help>Product Help
- In command prompt type: `help <name of funct>`

The Matlab interface



Constructing matrices

- Generate the (1×4) row vector $a = [1 \ 2 \ 3 \ 4]$

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- Generate the row vector $c = [1 \ 2 \ \dots \ 100]$

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- Generate the 3×4 matrix $A = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 5 & 6 & 7 & 8 \\ 9 & 10 & 11 & 12 \end{bmatrix}$

```
A = [1 2 3 4; 5 6 7 8; 9 10 11 12];
```

Constructing matrices

- Accessing a portion of the matrix A

- Take the element in the 2nd row and 3rd column of matrix A

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d = A(2,3);
```

- Take the elements in the 1st through 2nd rows and 2nd through 4th columns

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D = A(1:2,2:4);
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- Load data from a “.mat” file meg_data.mat

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load meg_data
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- Find elements of matrix B that are equal to 1

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find(B == 1)
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- Sort the numbers in b in ascending order

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f = sort(b)
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- Add matrices A and C , i.e., $F = A + C$

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- Multiply the matrices A and B , i.e., $G = A * B$

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G = A*B;
```

Matrix operations

- Multiply element-wise matrix G and the identity matrix I , i.e.,

$$G = \begin{bmatrix} 130 & 70 & 110 \\ 70 & 174 & 278 \\ 110 & 278 & 446 \end{bmatrix}, I = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$H = \begin{bmatrix} h_{1,1} & h_{1,2} & h_{1,3} & h_{1,4} \\ h_{2,1} & h_{2,2} & h_{2,3} & h_{2,4} \\ h_{3,1} & h_{3,2} & h_{3,3} & h_{3,4} \end{bmatrix} = \begin{bmatrix} 130 * 1 & 70 * 0 & 110 * 0 \\ 70 * 0 & 174 * 1 & 278 * 0 \\ 110 * 0 & 278 * 0 & 446 * 1 \end{bmatrix}$$

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$$H = G .* I;$$

- Find the cube of the elements of matrix A

$$J = A.^3;$$

- Load the MEG data from `meg_data.mat` and compute the sample mean of the first 500 samples with a `for` loop: $\bar{y} = \frac{1}{500} \sum_{i=1}^{500} y_i$

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```
% load the meg data
load('meg_data.mat');
% Take the required values
y = back_average(1:500);
% Initialize a variable accumulate the sum
acum = 0;
for i=1:500
    % Accumulates the sum of the data
    acum = acum + y(i);
end
% Divide by number of samples
y_bar1 = acum / 500;
```


Loops

- Compute the sample mean again using a `while` loop

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```
% Initialize a temporary variable
acum = 0;
counter = 0;
while counter < 500
    % Updates the counter
    counter = counter + 1;
    % Accumulates the sum of the data
    acum = acum + y(counter);
end
% Divide by number of samples
y_bar2 = acum / 500;
```

Some useful functions

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```
% Draw 500 samples from Bernoulli distribution  
p = 0.5;  
b = rand(1,500) > 0.5;
```


Some useful functions

- Computed the minimum, maximum, mean, standard deviation, and variance from simulated sample from the standard Gaussian distribution: $x_i, i = 1, 2, \dots, 500$, where the sample variance is $\hat{\sigma}^2 = \frac{1}{500} \sum_{i=1}^{500} (x_i - \bar{x})^2$, and the sample standard deviation is $\hat{\sigma}$

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```
% The minimum
x_min = min(x);

% The maximum
x_max = max(x);

% The sample mean
x_bar = mean(x);

% The sample variance
sigma2_hat = var(x);

% The sample standard deviation
sigma_hat = sigma2_hat^(1/2);
```

Functions for displaying results

- Load and plot the MEG data

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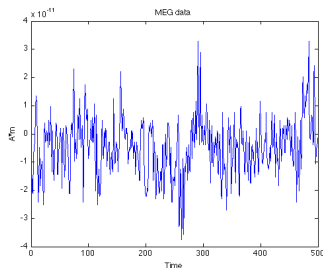
- Load and plot the MEG data

```
load('meg_data.mat');  
% Take the required values  
y = back_average(1:500);  
figure, plot(y)  
title('MEG data')  
xlabel('Time'), ylabel('A*m')
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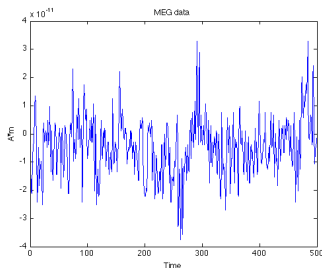
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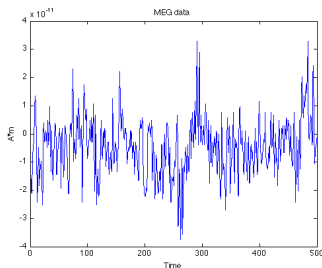
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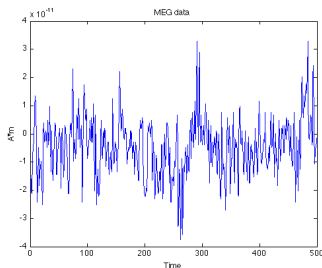
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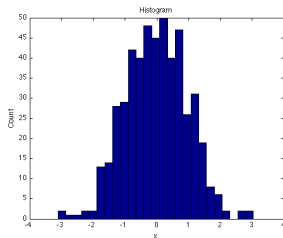
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Translating a problem to an algorithm to a code

- Simulate 500 independent samples from the exponential distribution with a “fair” coin

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- Simulate 500 independent samples from the exponential distribution with a “fair” coin
 - With the “fair” coin we can obtain a samples from the Bernoulli distribution with parameter $p = 0.5$. Recall that the pdf of the Bernoulli is given by:
 $f_{ber}(b) = p^b(1 - p)^{(1-b)}$, where $b \in \{0, 1\}$

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- And from the uniform sample simulate a new sample of the exponential distribution using the Inverse Transform method!

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- It is possible if we could generate a sample from the uniform distribution using a coin
- And from the uniform sample simulate a new sample of the exponential distribution using the Inverse Transform method!
 - Find an algorithm
 - Write the code

From the problem to an algorithm

- To find the algorithm we should note that a number u between 0 and 1 can be represented with the binary expansion $0.b_1b_2b_3\dots$, i.e:

$$u = \sum_{i=1}^{\infty} b_i/2^i, \text{ where } b_i \in \{0, 1\}$$

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- For example:
 - If $u = 0.75$ then $b_1 = 1, b_2 = 1, b_j = 0, j = 3, 4, \dots$, since $u = 1/2 + 1/2^2 + 0/2^3 + \dots$

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 - If $u = 0.958$ then $0.b_1b_2b_3\dots = 0.1111010101\bar{0}$

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 - If $u = 0.75$ then $b_1 = 1, b_2 = 1, b_j = 0, j = 3, 4, \dots$, since $u = 1/2 + 1/2^2 + 0/2^3 + \dots$
 - If $u = 0.958$ then $0.b_1b_2b_3\dots = 0.1111010101\bar{0}$
 - If $u = 0.3288$ then $0.b_1b_2b_3\dots = 0.01010100001010010010\bar{0}$

From the problem to an algorithm

- The million dollar question: If the binary coefficients b_i in expansion $u = \sum_{i=1}^{\infty} b_i/2^i$ come from a Bernoulli distribution with $p = 0.5$ (the “fair” coin), what is the distribution of u ?

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- The answer is: u is a uniform random variable. But this is difficult to show!

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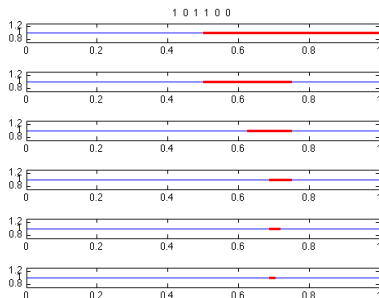
- The million dollar question: If the binary coefficients b_i in expansion $u = \sum_{i=1}^{\infty} b_i/2^i$ come from a Bernoulli distribution with $p = 0.5$ (the “fair” coin), what is the distribution of u ?
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- The answer is: u is a uniform random variable. But this is difficult to show!
- We will use a heuristic argument to convince our selves
- If $b_1 = 1 \rightarrow u \geq 0.5$ and if $b_1 = 0 \rightarrow u < 0.5$
- More generally, with a figure we see that:



From the algorithm to the code

- Simulate a sample of size 1000 from the uniform distribution using samples from the Bernoulli distribution with parameter $p = 0.5$:

$$u_j = \sum_{i=1}^{500} b_{i,j}/2^i, \text{ where } j = 1, 2, \dots, 1000, i = 1, 2, \dots, 500$$

and $b_{i,j}$ are iid Bernoulli with parameter p

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and $b_{i,j}$ are iid Bernoulli with parameter p

```
% Sample size
n = 1000;
% Compute the denominators expansion
m = 500;
d = 1./2.^[1:m];
% For loop to obtain the 500 uniform rvs
for i =1:n
    % Simulate 100 Bernoulli rvs (b-{i,j})
    b = rand(1,m)>0.5;
    % Compute the summation
    u(i) = sum(b.*d);
end
```

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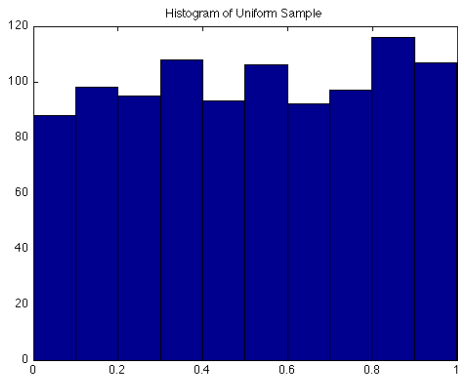
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Make change in variable $w = -\lambda \tau \rightarrow d\tau = -dw/\lambda$

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- Now we can obtain F_{exp}^{-1} as:

$$F_{exp}^{-1}(u) = -\frac{\log(1-u)}{\lambda}$$

From the algorithm to the code

- Generate a sample of size 1000 of the exponential distribution with parameter $\lambda = 3$ using a sample from the uniform distribution (u_j) using the Inverse Transform method:

$$t_j = -\frac{\log(1 - u_j)}{3}, \text{ where } j = 1, 2, \dots, 1000$$

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```
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```

- Make a histogram of the sample simulated from the exponential distribution

```
figure, hist(t)  
title('Histogram of Exponential Sample')
```

Did it WORK???

- Raise your hand if you think it did work

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