### Tools:

git: lewrn it.

you can "version" your code, make changes, recall past versions and settings (called: history").

File-by-file and line-by-line changes to track "ditts".

An (almost) perfect audit of your work.

- Not required to learn but 3% grade extra credit it all your projects

  (with history) available in git. Note: cannot do it all at the end,

  must have evidence throughout course.
- I will post a link to tutorial but basic idea is:

Add file, commit, edit, add, commit.

- Distributions for Windows and Linux (and Mac).

latex: not required but fast and efficient layout (typesetting) tool. You can automatically generate document w/ latest images, etc. You can also break your reports into bitesize pieces.

Benefit: All text based so you can version (and search) your project reports right along with your code.

PhD: you will eventually need.

Masters: good skill to have.

"The not so short introduction to later" (Ch: 1,2,3)

## Languages:

Matlab: free for students (software. usc. edu).

most class examples will use Matlab because it allows rapid prototyping. Both TAS are strong with Matlab.

Java, C/C++: some of my favorites but I don't recommend for this class. Very useful for the same problems during research due to execution speed.

Python: Powerful general purpose computing language. A good skill to develop, and relatively easy to learn.

I recomend python v3.6 unless you have specific compatibility needs (its complicated).

Recomended packages: scipy, numpy, matplotlib
"scientific" computing array processing plotting library.

R: powerful statistics tool. Very practical resume builder.

The "lingua franca" in many big data and information processing fields.

For beginners, I suggest: RStudio. It provides a nice command window interface and simplifies dealing with graphics and packages.

Others: Excel, Perl, ... whatever you like.

# Coding Style:

#1 Rule: make it readable. It should be clear enough even to someone not familian with the syntax for a particular language.

#### Hints:

- 1. Comment code, document reasoning, describe assumptions, numeric considerations (valid ranges, etc.).
  - \* \* required for EESII \* \*
- 2. Make code readable
  - comment should be helpful, not superflowous.
  - nice industing
  - descriptive variable names

see syllabus: not necessarily marked down it not but it the grader cannot follow/parse your code they will deduct.

help with general methods; but they might not be able to diagnose specific failures, compilation issues, etc. Post to Piazza.

"Know your gear" before you start and

"Know what you expect" before every experiment.

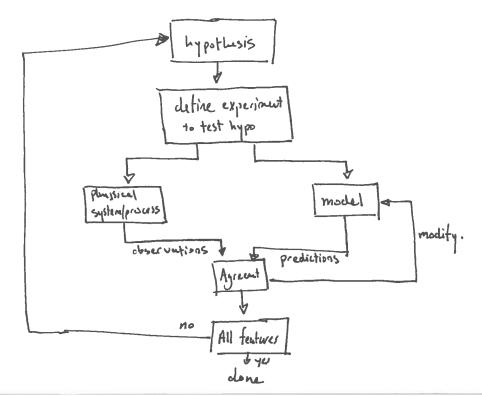
To encourage new efforts:

receive +2% to overall grade for submitting a different (anguage than your previous projects (max: 472).

So submitting project 1 with Mutles, Project 2 with C/CH, and project 3 with python gives +4% class grade.

### Some theory:

Mathematical models: explain observed behavior using simple and understandable rules with measurable properties.



EESII

Each of these steps require modeller input and each decision requires an expert opinion.

For EESII: you are the expert.

Iterative process continues until model is sufficient (or run out of funding)
(good enough)

## Types of models:

1. Deterministic model.

exact inputs produce same output.

Consider electrical circuit:  $V=i\cdot R$ . In this model knowing i and R.
gives the "exact" (theoretical) voltage.

Note: repeating the experiment yields the exact same model prediction.

2. Probability models

exact inputs produce different outputs (usually).

Detn: A random experiment is an experiment in which the outcome vanies in an impredictable fashion when the experiment is repeated und the same condition.

4 You cannot generally use a deterministic model for random experiments.

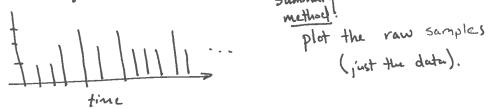
Ex: 3-ball un experiment.



- 2. record Mumber and return

experiment outcome: number from set 5= {1,2,3}.

Repeat the experiment many times: 1,1,2,3,2,3,2...



In this class we take advantage of Statistical Regularity regularity is a means to quantify predictability.

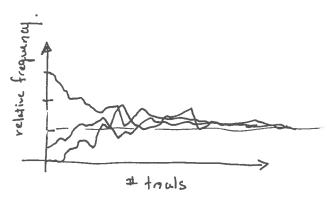
Many models rely on the fact that averages of long sequences of experiments (each called a "trial") will yield approximately the same value.

Ex: Let NI(n), N2(n), and Ng(n) be the number of times the experimental outcome is 1,2, and 3 respectively.

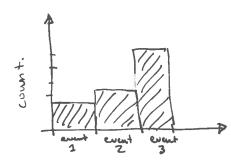
Define: the relative frequency  $f_K(n) = \frac{N_K(n)}{n}$ 

Statistical regularity means that  $f_{\kappa}(n)$  varies less-and-less as n gets large Specifically: lim  $f_K(n) = P_K$ A constant  $P_K$  is called the probability of outcome K.

EE211



summary method: plut relative frequency (or count) vs # trials.



summary method: plot counts for each louteune (or range of outcomes).

Statistical regularity means we could re-run the trials \*\*HISTOGRAM\*\*
and each may start with very different relative frequencies but they
will eventually all converge to the same point.

By simulation result, PK -> 1/3 for each outcome (agrees with intuition).

Consider: modify experiment and add additional #1 to urn. then  $P_1 = \frac{1}{2}$ ,  $P_2 = \frac{1}{4}$ ,  $P_3 = \frac{1}{4}$ .

EESII considerations: Project #1.

Just flipping a coin ... as "easy" as it gets (0 or 1).

Bernoulli trial

Hint: Use the rand () function in your preferred language.

Assiming X~ U[0,1].

1

random experiment with two passible outcomes

O, 1 / H, T. | etc.

then threshold:

 $rand() \ge 0.5 \leftarrow Head$  $rand() < 0.5 \leftarrow Tail$  D: Does it matter if you switch?

# Coding hints:

1. Put your experiment in a function (or large equivalent)

- you can easily invoke with different parameters without having to disrupt your algorithm code.

Naming: Bad: experiments () 11 return 0 or 1.

Better: flip-coin ()

Better: flip-usin (0.5) 11 H" probability.

Best: flip-coin-n (0.5, 50) Il multiple flips.

(may be faster in some languages).

2. Start building a "library" of useful functions for re-use.

e.g. flip-fair-coin ()
return flip-coin (0.5).

] -> within reason, note the "factorial problem" in the extreme.