Experimental Design for Machine Learning on Multimedia Data

See: http://www.icsi.berkeley.edu/~fractor/fall2020/

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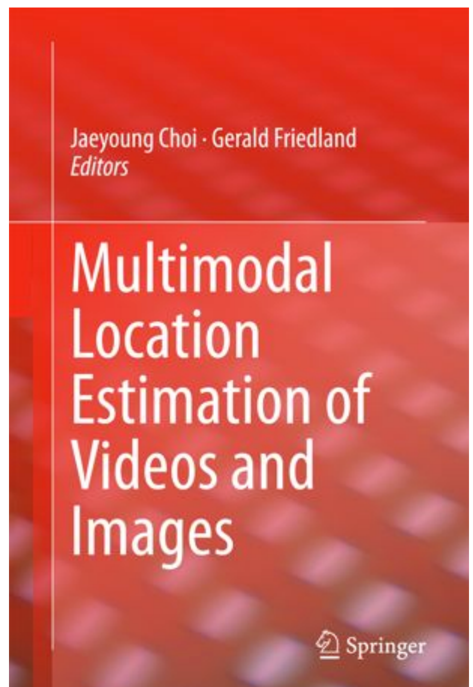
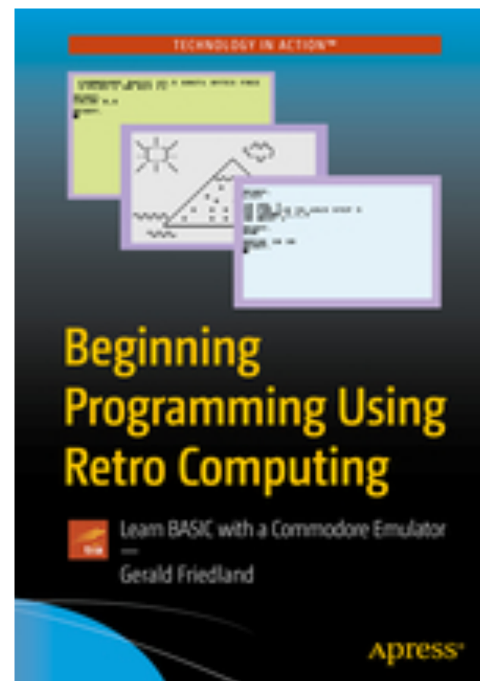
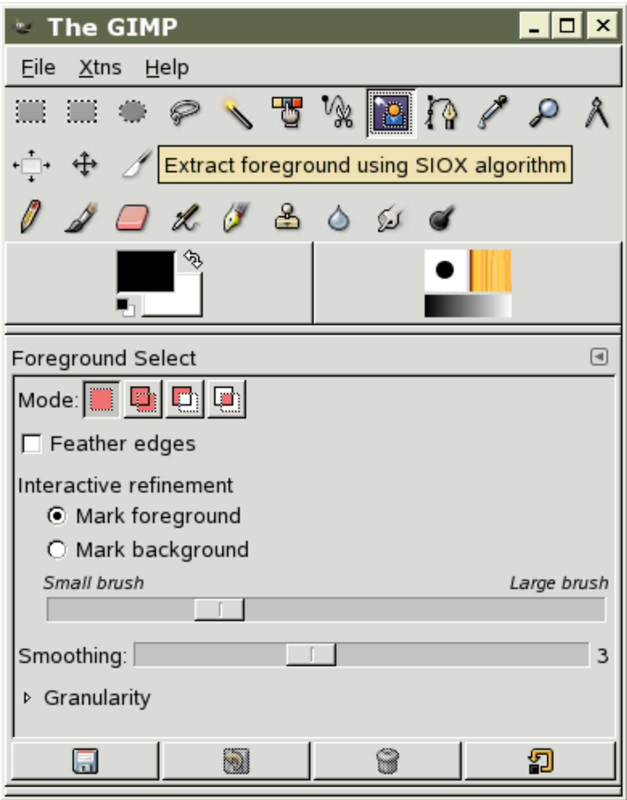
About Me….

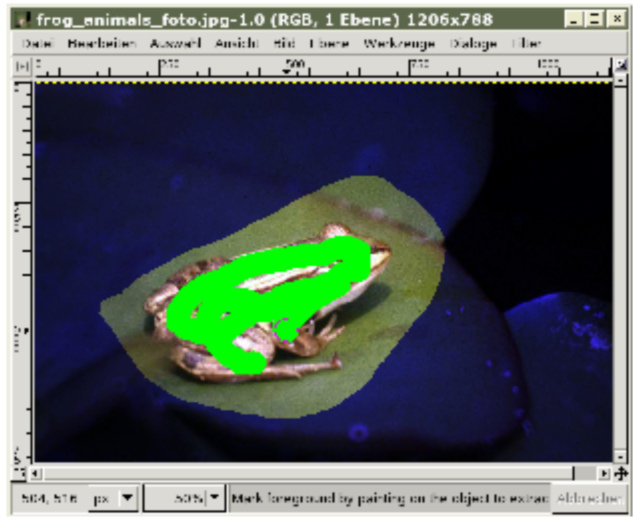
- **Adjunct Assistant Professor**
- **CTO, Brainome Inc**
- **Started work in Machine Learning in 2001**

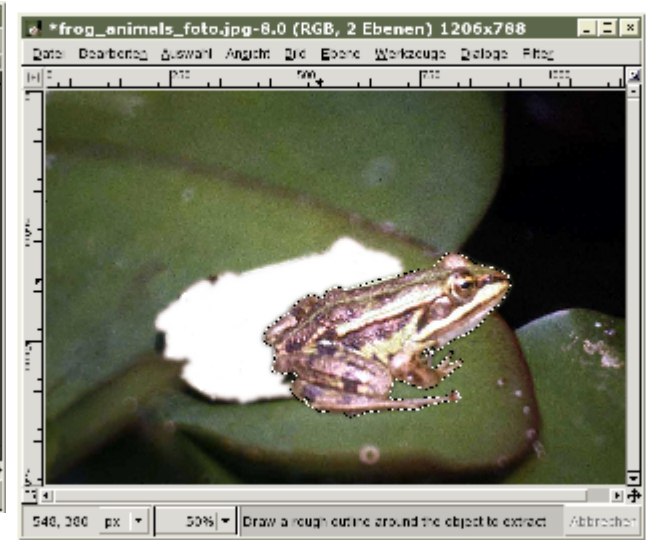




About Me…





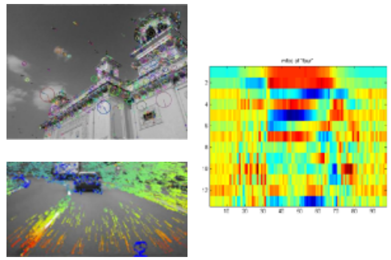


G. Friedland, K. Jantz, T. Lenz, F. Wiesel, R. Rojas: *A Practical Approach to Boundary-Accurate Multi-Object Extraction from Still Images and Videos*, to appear in Proceedings of the IEEE International Symposium on Multimedia (ISM2006) San Diego (California), December, 2006

http://www.siox.org

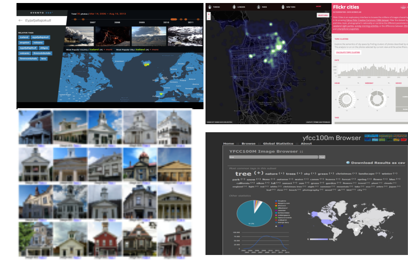
The Multimedia Commons (YFCC100M)

100.2M Photos
800K Videos



Features for Machine Learning
(Visual, Audio, Motion, etc.)

User-Supplied Metadata
and New Annotations



Tools for Searching,
Processing, and Visualizing

100M videos and images, and a growing pool of **tools** for research with **easy access** through **Cloud Computing**

Collaboration Between Academia and Industry:

ICSI International Computer Science Institute

Lawrence Livermore National Laboratory

Yahoo! Labs

amazon web services

Berkeley University of California

Benchmarks & Grand Challenges:

Digital Video Retrieval at NIST

ACM mm

2016 ICMR

MediaEval Benchmark

Creative Commons or
Public Domain

Supported in part by NSF Grant 1251276
"BIGDATA: Small: DCM: DA: Collaborative Research:
SMASH: Scalable Multimedia content AnalysiS in a High-level language"

Jupyter Integration

YFCC100M+MMCommons+Amazon’s MXNet

jupyter predict_geolocation Last Checkpoint: 10 hours ago (autosaved)

Logout

File Edit View Insert Cell Kernel Widgets Help

Trusted

Python 2

Markdown

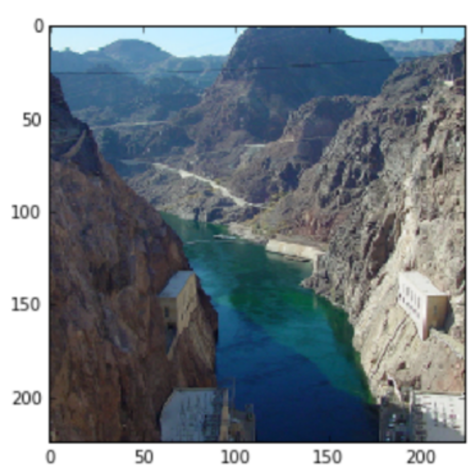
```
        statinfo = os.stat(filepath)
        print('Succesfully downloaded', imgname, statinfo.st_size, 'bytes.')
    return filepath
```

Now we can predict an image's location. We use images from Placing Task 2016 dataset to evaluate the result.

In [77]:

```
imgname = 'd661b83d659af4d818ddd6edf54096.jpg'
result = predict_and_evaluate(imgname)
```

```
('Ground truth: ', (36.016233, -114.737316))
rank=1, prob=0.462128, lat=36.0164119656, lng=-114.737289028, dist from groundtruth=0.020047 km
rank=2, prob=0.260691, lat=36.0141364684, lng=-114.733238705, dist from groundtruth=0.434543 km
rank=3, prob=0.236675, lat=36.0164436503, lng=-114.740746605, dist from groundtruth=0.309436 km
rank=4, prob=0.006943, lat=35.9723883996, lng=-113.791496647, dist from groundtruth=85.229922 km
rank=5, prob=0.006833, lat=36.8630814967, lng=-111.561140839, dist from groundtruth=299.302093 km
```



Why do we care?

- Consumer-Produced Multimedia allows empirical studies at never-before seen scale in various research disciplines such as sociology, medicine, economics, environmental sciences, computer science...

- Recent buzzword: BIGDATA

Problem

How can YOU effectively work on large scale multimedia data (without working at Google)?

Amazon EC2/HPC: Practical Question

— How much money (cpu time, memory, IO) do I need to budget for my deep learning experiment?

— State of the Art: No answer.
For example, ImageNet models vary significantly:

- AlexNet: 238MB model, 2.27Bn Ops
- DarkNet: 28MB model, 0.96Bn Ops
- VGG-16: 528 MB, 30.94Bn Ops

— Source: https://pjreddie.com/darknet/imagenet/

What is this class about?

- Introduction to systematic experimental design of Machine Learning Experiments
- Covers some theory but is also hands on.
- Covers different modalities: Visual, Audio, Tags, Sensor Data
- Covers different side topics, such as adversarial examples

Content of 2012 Class

- Visual methods for video analysis
- Acoustic methods for video analysis
- Meta-data and tag-based methods for video analysis
- Inferring from the social graph and collaborative filtering
- Information fusion and multimodal integration
- Coping with memory and computational issues
- Crowd sourcing for ground truth annotation
- Privacy issues and societal impact of video retrieval

Content of 2020 Class

- Less anecdotal
- More systematic
- Adds: Concepts for Machine Learning measurements
- See: Machine Learning Cheat Sheet and Design Process

Course Overview

- The scientific process and how to think about it in the age of Machine Learning
- The machine learning scientific process
- Measurements beyond accuracy:
  - Capacity
  - Generalization
- Types of Training, Regularization, Occam's Razor
- Reproducibility vs Repeatability
- Experimental Setup: Annotator Agreement, which machine lear to chose
- Adversarial Examples
- Evaluating success beyond accuracy
- Intrinsics of audio data
- Intrinsics of Image and Video data

Lecture Material

- Some background material for lectures:
  G. Friedland, R. Jain: Introduction to Multimedia Computing, Cambridge University Press, 2014.

- More material as we go…

How do you receive Credit?

- Attend Lecture Regularly
- Measure out a project. More information: http://www.icsi.berkeley.edu/~fractor/fall2020/
- Weekly homework is optional but will improve your understanding, which will improve your grade!
- Final exam is optional unless you are MEng.

Typical Homework/Final Exam

- Calculate capacity for different networks
  - How do you deal with convolutional layers?
  - How does regularization count?
- Given a task:
  - Describe what happens if you have too many neurons
  - Describe what happens if you layer too deep
  - Describe what happens if you use features

Project

- Chose a project, either yours or somebody else's or some project of the past.
- Write a report to answers 10 questions that
  - require you to measure best-case accuracy, capacity, generalization and other quantities
  - and then ask you to judge the success of the project
  - and comment on its reproducibility.

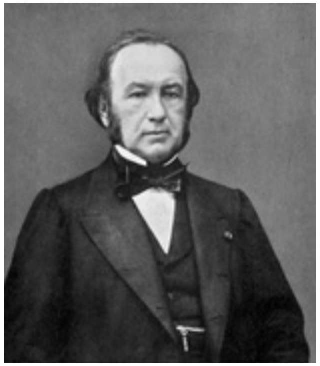
Due 1 week after the end of the semester.

Questions?

A Warning!

What we <u>think</u> we know:

- Neural Networks can be trained to be more intelligent than humans e.g., beat Go masters
- Deep Learning is better than „shallow“ Learning
- There is no data like more data
- AI is going to take over the world soon
- Let’s pray to AI!



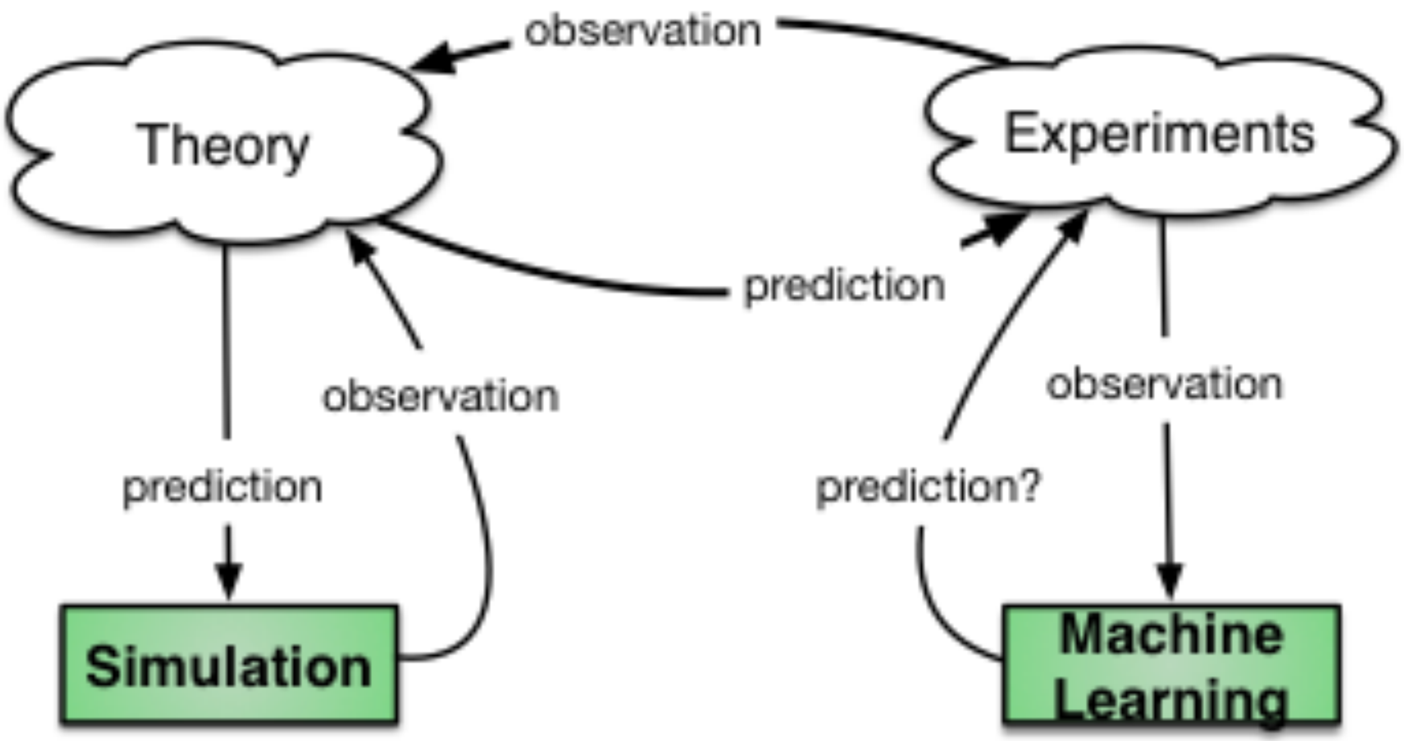
It is what we think we know already that often prevents us from learning.

Claude Bernard

A game…

- Continue the sequence:
  - 2, 4, 6, 8, ….
  - 6, 5, 1, 3, …..
- What is the next number?
  - 100000 (sequence 1)
  - 100000 (sequence 2)
- Why?

The Scientific Method



Data Science: The Science of Automating the Scientific Method

The Scientific Method: Practical (traditional)

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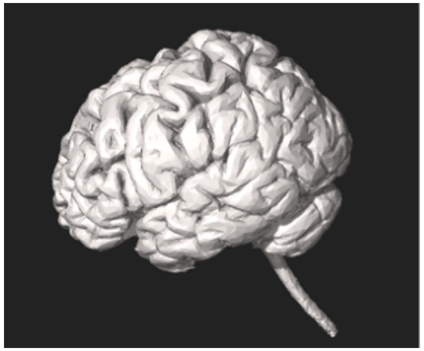

$$E = mc^2$$

The Scientific Method: Practical (new)

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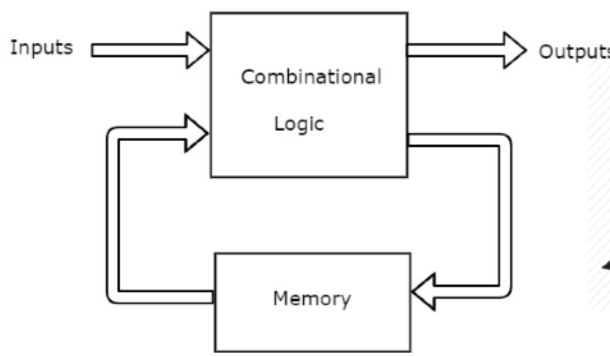

$$E = mc^2$$

Thought Framework: Machine Learning

- Intelligence: *The ability to adapt* (Binet and Simon, 1904)

- Machine learning *adapts a finite state machine M to an unknown function based on observations*.

- Input: *n* rows of observations (instances) in a table with header:

$$(x_1, x_2, \ldots, x_m, f(\overrightarrow{x}))$$

  where $f(\overrightarrow{x})$ is a column with labels we call target function.

- Output: State machine *M* that maps a point

$$(x_1, x_2, \ldots, x_m) \implies f(\overrightarrow{x})$$

Thought Framework: Machine Learning

- Assume

$$x_i \in \mathbb{R}, f(\overrightarrow{x}) \in \{0,1\}$$

(binary classifier)

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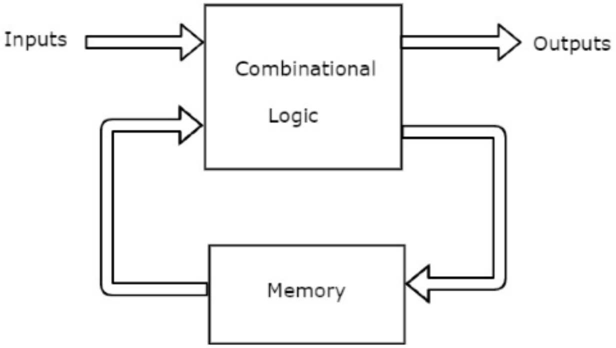


- Question:

How many state transitions does *M* need to model the training data?

Refresh: Memory Arithmetic

- *Information is reduction of uncertainty*:
  $H = -\log_2 P = -\log_2 \frac{1}{\#states} = \log_2 \#states$
  measured in bits.

- Information: $\log_2 \#states$ (positive bits)
  Uncertainty: $\log_2 P = \log_2 \frac{1}{\#states}$ (negative bits)

- If states are not equiprobable, *Shannon Entropy* provides tighter bound.
  Math: Assumptions needed! (infinity, distribution)
  Engineering: Estimate using binning

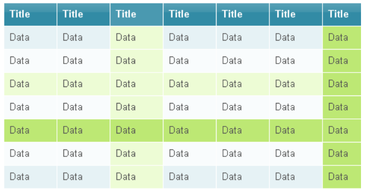
Thought Framework: Machine Learning

Assume

$$x_i \in \mathbb{R}, f(\overrightarrow{x}) \in \{0,1\}$$

(binary classifier)

Question:



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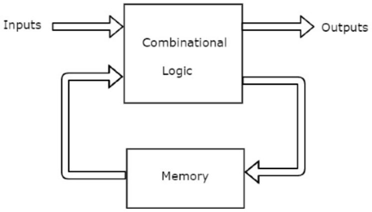


How many state transitions does *M* need to model the training data?

Maximally: #rows (lookup table)
Minimally: ?

Thought Framework: Machine Learning

- ***Intellectual Capacity:*** *The number of unique target functions a machine learner is able to represent (as a function of the number of model parameters).*

- ***Memory Equivalent Capacity (MEC):*** *A machine learner's intellectual capacity is memory-equivalent to N bits when the machine learner is able to represent all 2^N binary labeling functions of any N inputs.*

- At MEC or higher, *M* is able to **memorize** all possible state transitions from the input to the output.

Important Engineering Trick

Memorization is worst-case generalization

- If we deduce nothing from data, the only thing we can do is memorize the observations verbatim.
- Using as many parameters as needed for memorization is therefore an indicator that the machine learner did not deduce anything (overfitting).
- Reducing parameters below memorization capacity will, in the best case, make the machine learner forget what's not relevant with regards to the target function: **generalization**.

Generalization in Machine Learning (balanced binary classifier)

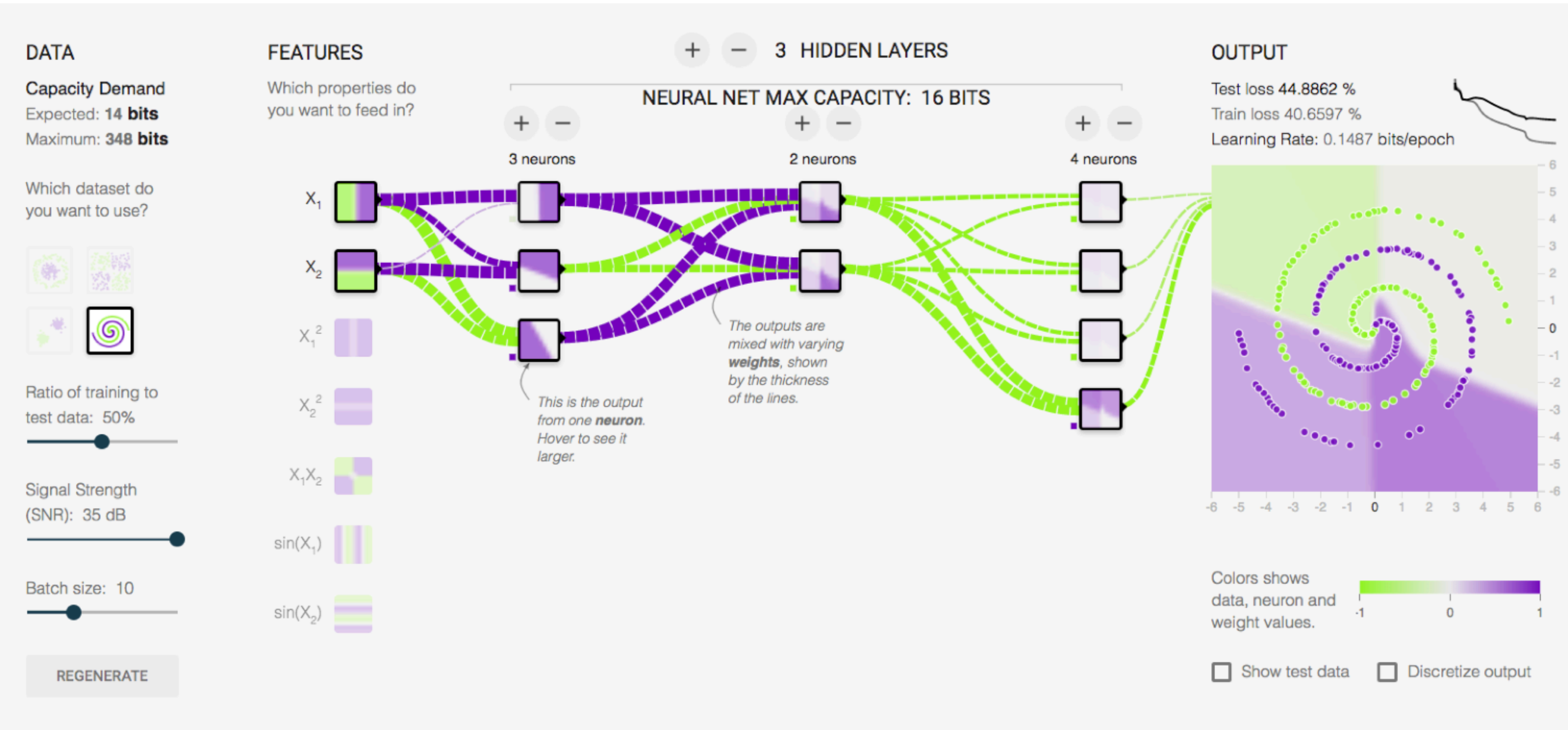
Memorization is worst-case generalization.

For binary classifiers:

$$G = \frac{\#correctly\ classified\ instances}{Memory\ Equivalent\ Capacity} \quad [\frac{bits}{bit}]$$

$G<1$ => *M* needs more training/data (not even memorizing)
$G=1$ => *M* is memorizing = overfitting
$1<G<G_{MEM}$ => M could be implementing a lossless compression (and still overfit)
$G>G_{MEM}$ => *M* is generalizing (no chance for overfitting)

Hands-On Intuition:
Experimental Design for TensorFlow



http://tfmeter.icsi.berkeley.edu

Homework this week:

- Please watch lecture explaining generalization:

https://www.youtube.com/watch?v=UZ5vhqDKyrY&list=PL17CtGMLr0Xz3vNK31TG7mJIzmF78vsFO