Experimental Design for Machine Learning on Multimedia Data

See: http://www.icsi.berkeley.edu/~fractor/fall2019/

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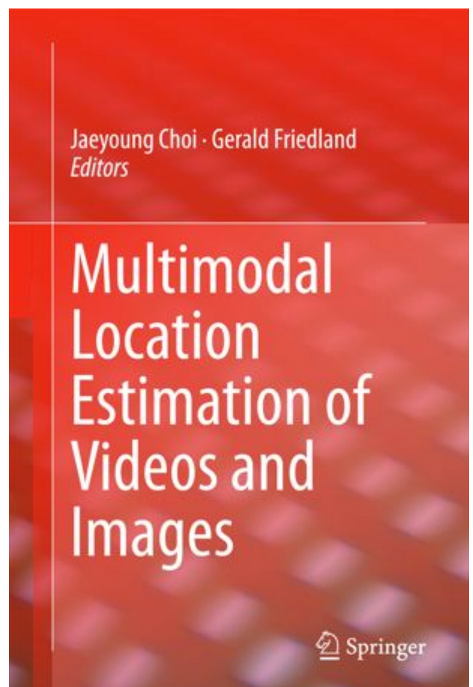
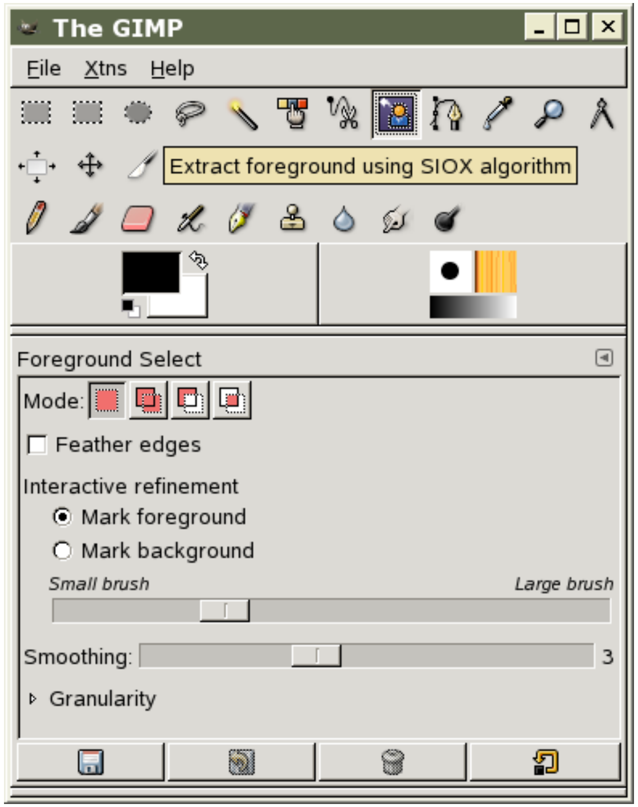
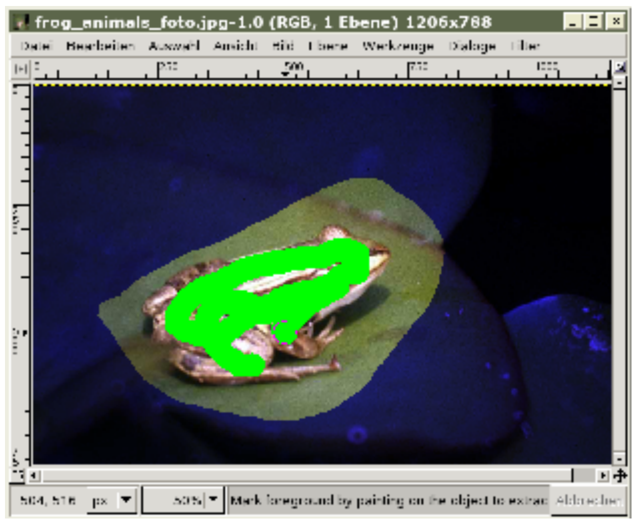
About Me….

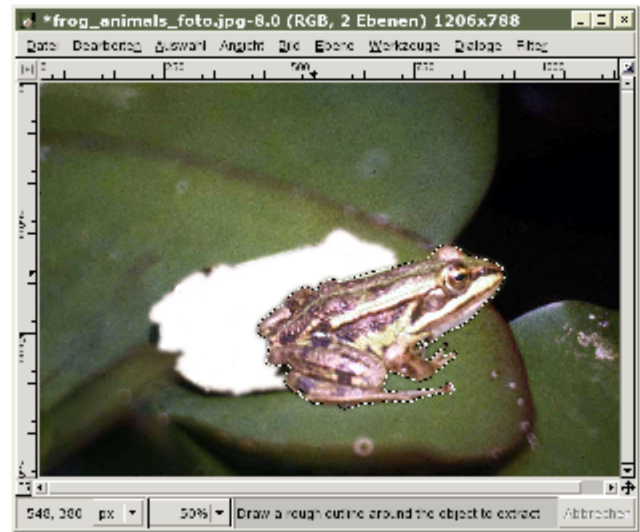
- **Adjunct Assistant Professor**
- **Data Scientist at National Lab**
- **Started work in Machine Learning in 2001**



About Me…





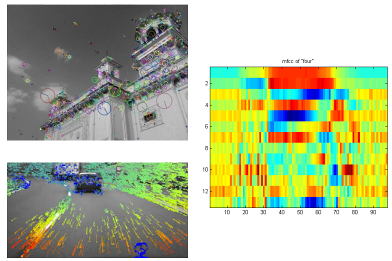


http://www.siox.org

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

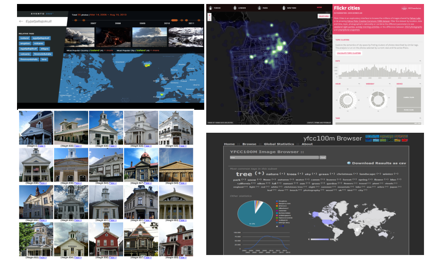
The Multimedia Commons (YFCC100M)

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 · ICMR 2016 · 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

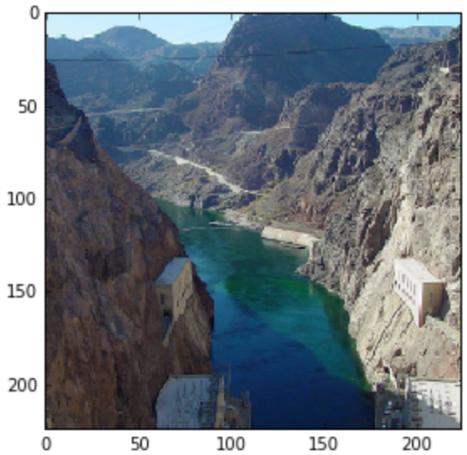
```
        statinfo = os.stat(filepath)
        print('Succesfully downloaded', imgname, statinfo.st_size, 'bytes.')
    return filepath
```

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 2019 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 lea 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/fall2019/
- 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.

Help

- Jaeyoung Choi (EC2)

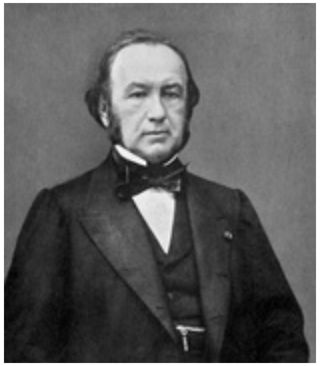
- Rishi Puri (TA)

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!



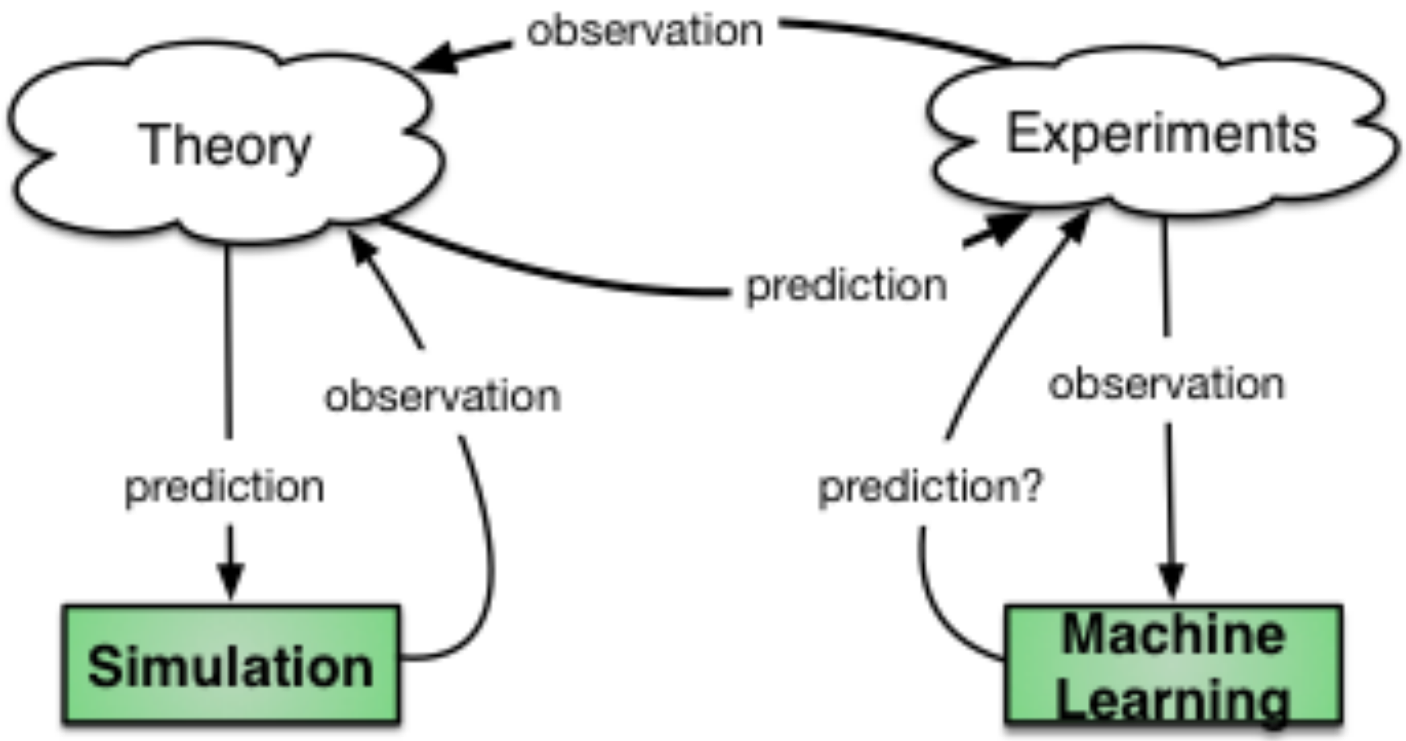
It is what we think we know already that often prevents us from learning.

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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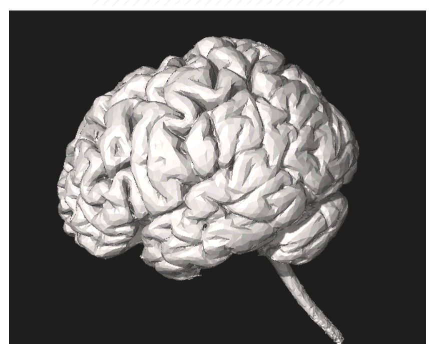

$$E = mc^2$$

The Scientific Method: Practical (new)

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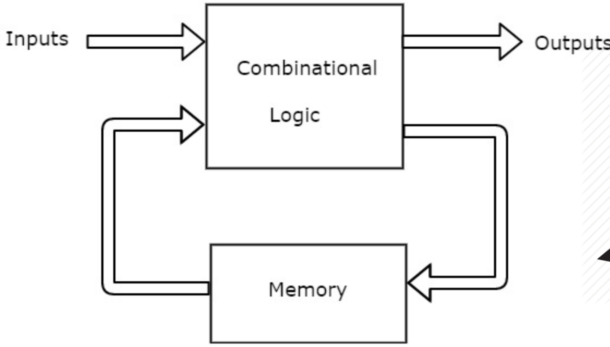

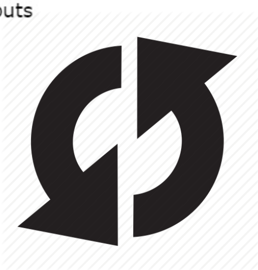

$$E = mc^2$$

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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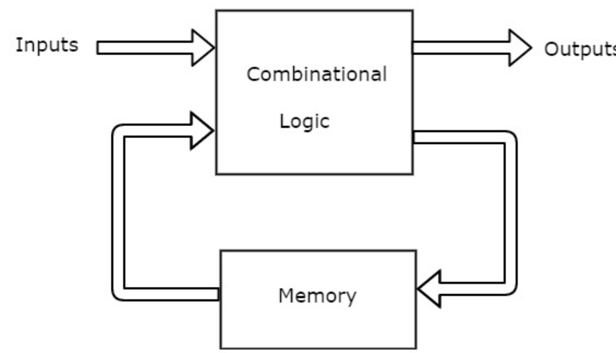


- Question:

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

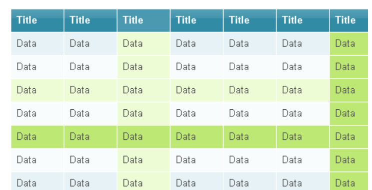
Thought Framework: Machine Learning

Assume

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

(binary classifier)

Question:



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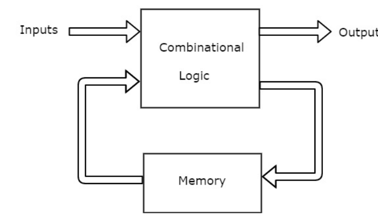


How many state transitions does *M* need to model the training data?

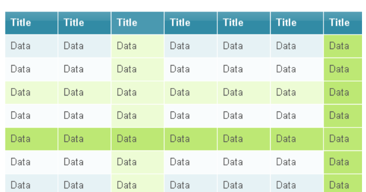
Maximally: #rows (lookup table)
Minimally: ?

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 N uniformly random inputs.*

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



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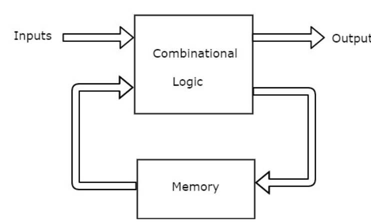


Important trick

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

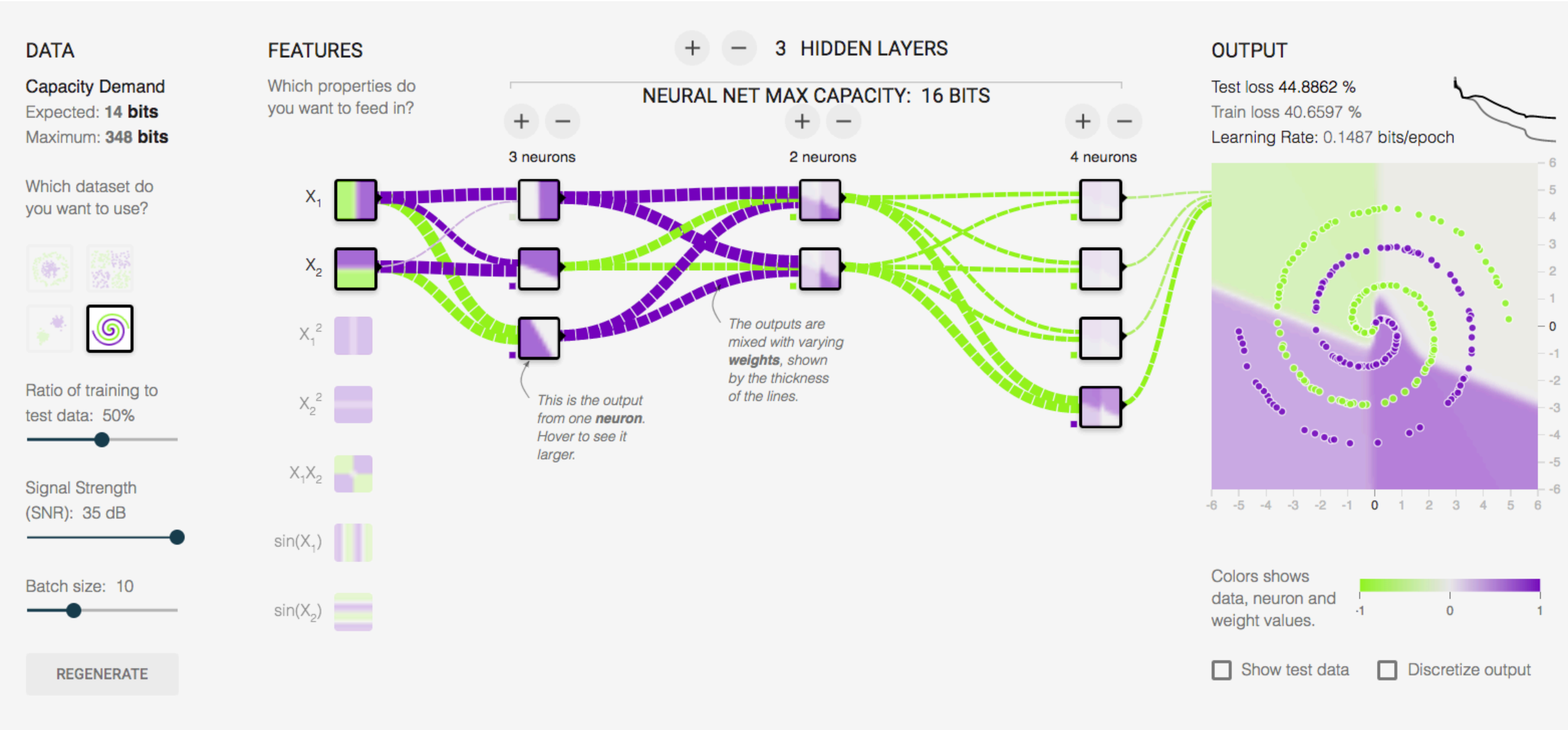
Memorization is worst-case generalization.

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

No Homework this week!