Machine Learning for Signal Processing

Lecture 1: Introduction

Representing sound and images

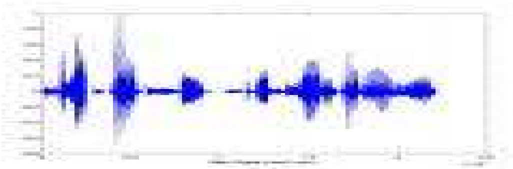
Class 1. 31 Aug 2021

Instructor: Bhiksha Raj

What is a signal

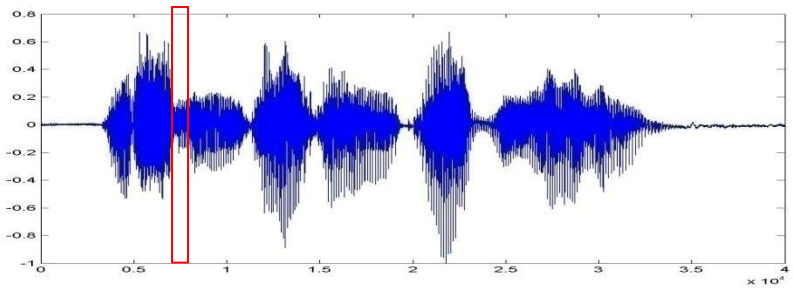
- A mechanism for conveying information
  - Semaphores, gestures, traffic lights..

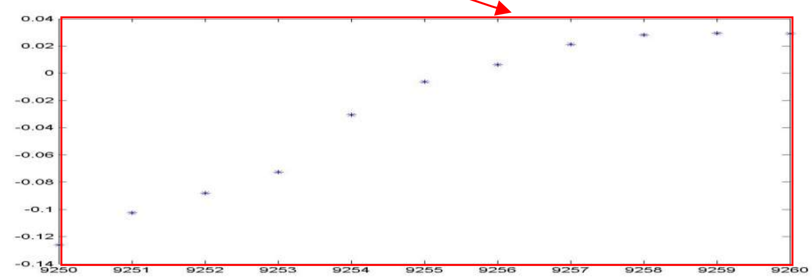
- In Electrical Engineering: currents, voltages



- Digital signals: Ordered collections of numbers that convey information
  - from a source to a destination
  - about a real world phenomenon

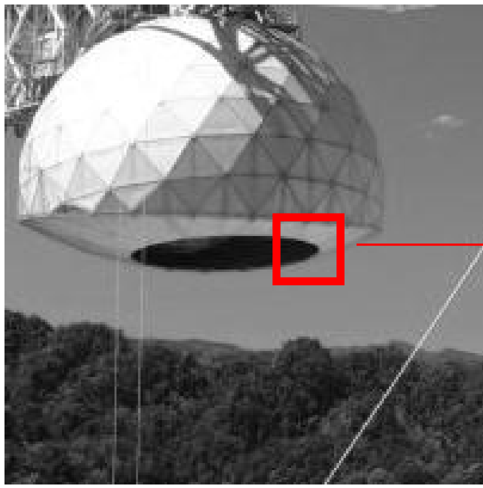
Signal Examples: Audio

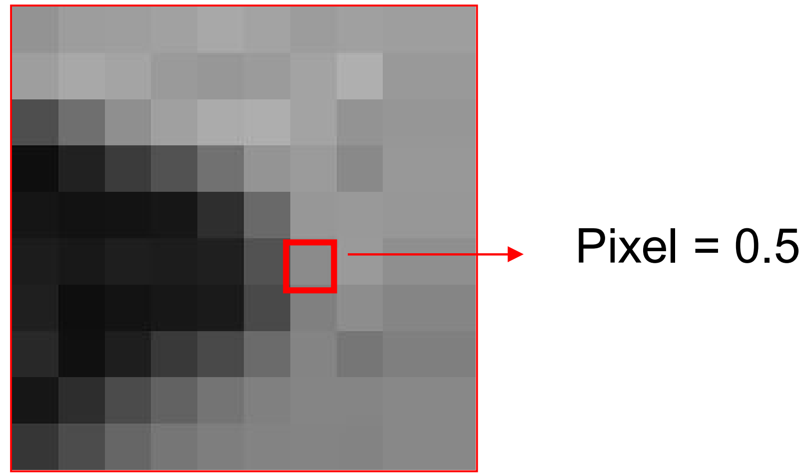




- A sequence of numbers
  - $[n_1\ n_2\ n_3\ n_4\ \ldots]$
  - The order in which the numbers occur is important
    - Ordered
    - In this case, a *time series*
  - Represent a perceivable sound

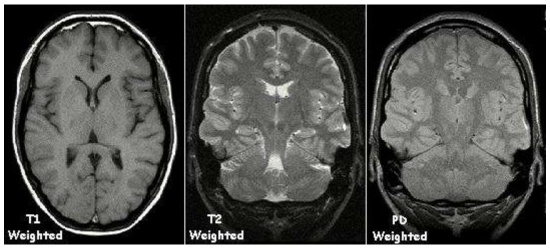
Example: Images





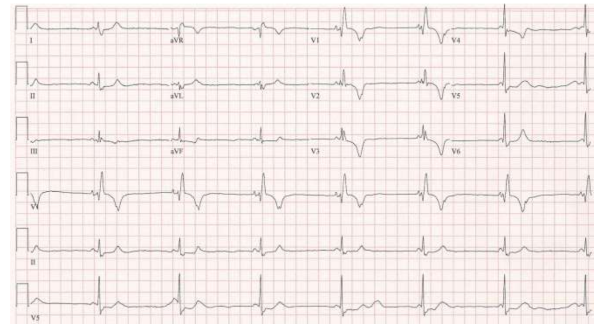
- A rectangular arrangement (matrix) of numbers
  - Or sets of numbers (for color images)
- Each pixel represents a visual representation of one of these numbers
  - 0 is minimum(black), 1 is maximum(white)
  - Position / order is important
- Represent a visual scene

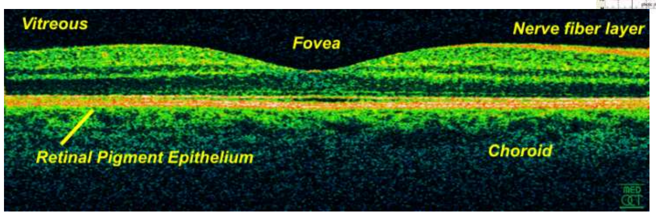
Example: Biosignals



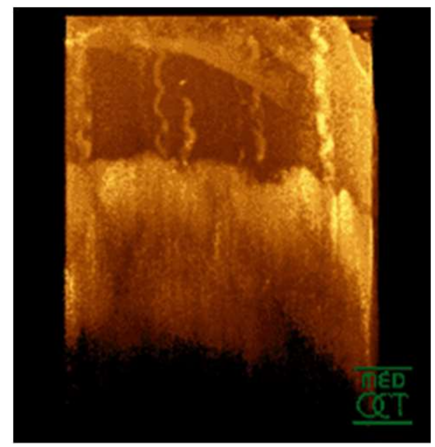
MRI


EEG


ECG

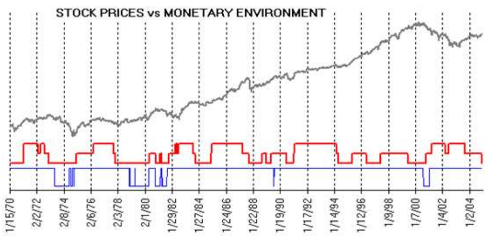


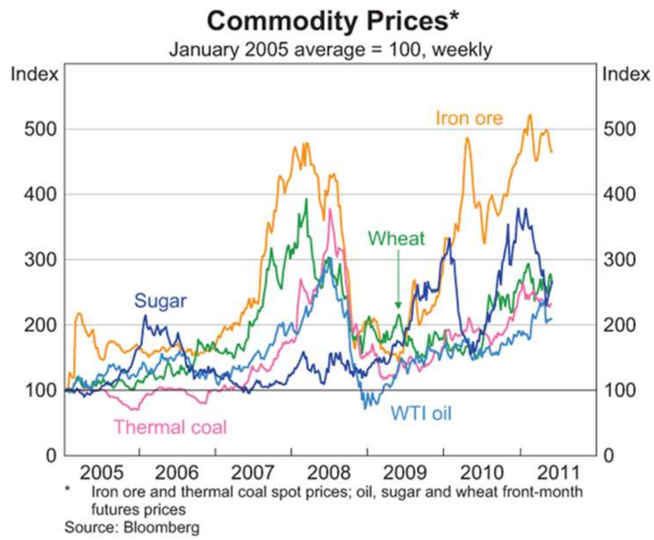
Optical Coherence Tomography


OCT of fingertip
(from Wikipedia)

- Biosignals
  - MRI: "k-space" → 3D Fourier transform
    - Invert to get image
  - EEG: Many channels of brain electrical activity
  - ECG: Cardiac activity
  - OCT, Ultrasound, Echo cardiogram: Echo-based imaging
  - Others..
- Represent body readings

Financial Data





- Stocks, options, other derivatives
- The numbers represent market trends

- Special Issues on Signal Processing Methods in Finance and Electronic Trading from various journals

Many others

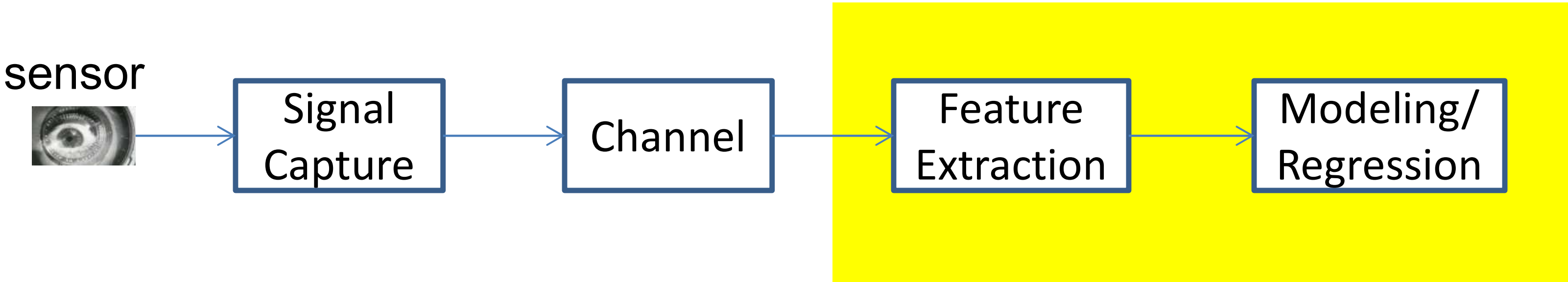
- Network data..
- Weather..
- Any stochastic time series
- Etc.

- In each case: Ordered arrangements of numbers that represent some real-world phenomenon

What is Signal Processing

- Acquisition, Analysis, Interpretation, and Manipulation of signals.
  - Acquisition:
    - Sampling, sensing
  - Analysis:
    - Decomposition: Separating signals into basic "building" blocks
  - Manipulation:
    - Denoising
    - Coding
    - Synthesis
  - Interpretation:
    - Detection: Radars, Sonars
    - Pattern matching: Biometrics, Iris recognition, fingerprint recognition
    - Prediction: Financial prediction, speech coding, etc.
  - Etc.
- Boundaries between these categories of operations are fuzzy

The Tasks in a typical Signal Processing Paradigm



- Capture: Recovery, enhancement
- Channel: Coding-decoding, compression-decompression, storage
- Pattern analysis
  - Feature extraction
  - Regression: Prediction, classification

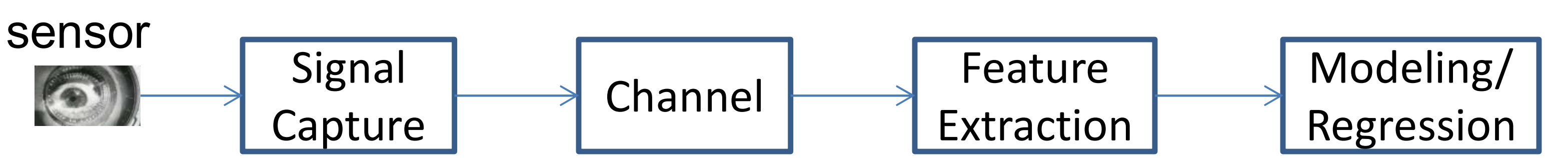
What is Machine Learning

- The science that deals with the development of algorithms that can learn from data
  - Learning the structure of data
    - Feature extraction
  - Learning patterns in data
    - Automatic text categorization; Market basket analysis
  - Learning to classify between different kinds of data
    - Is that picture a flower or not?
  - Learning to predict data
    - Weather prediction, movie recommendation

- Focus: *Learning* (from data and other information sources)

MLSP

- Application of Machine Learning techniques to the analysis of signals



- *Can be applied to each component of the chain*

MLSP

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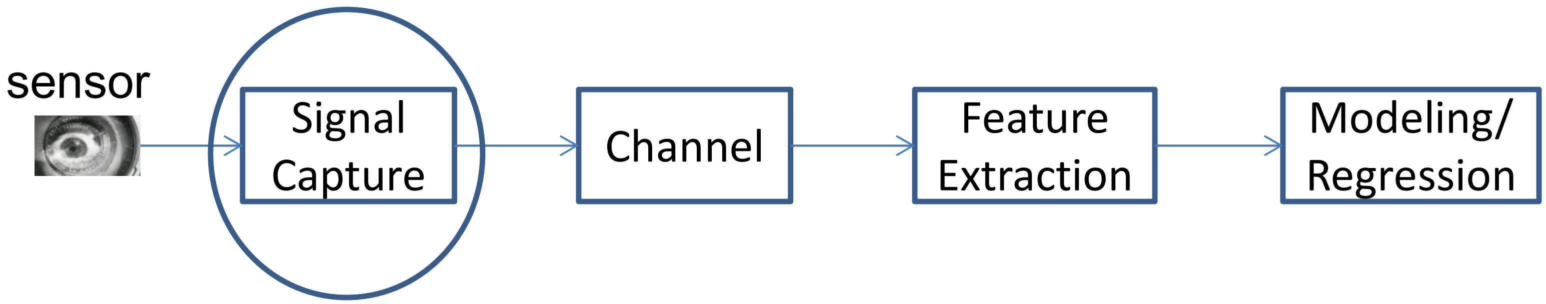
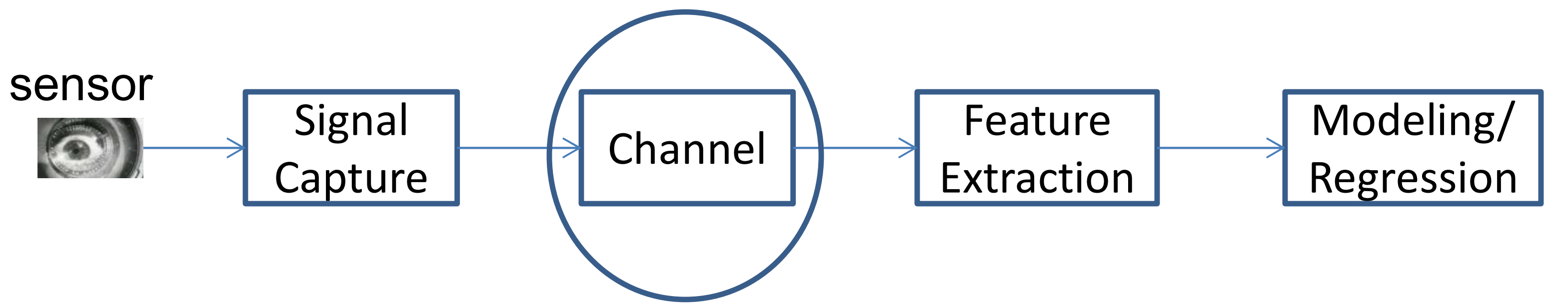


- *Can be applied to each component of the chain*
- Sensing
  - Compressed sensing, dictionary-based representations
- Denoising
  - ICA, filtering, separation

MLSP

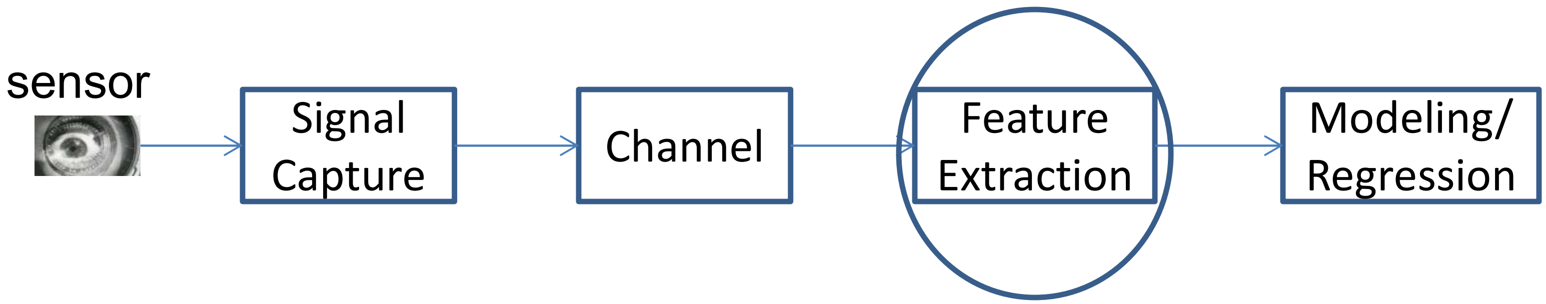
- Application of Machine Learning techniques to the analysis of signals



- *Can be applied to each component of the chain*
- Channel: Compression, coding

MLSP

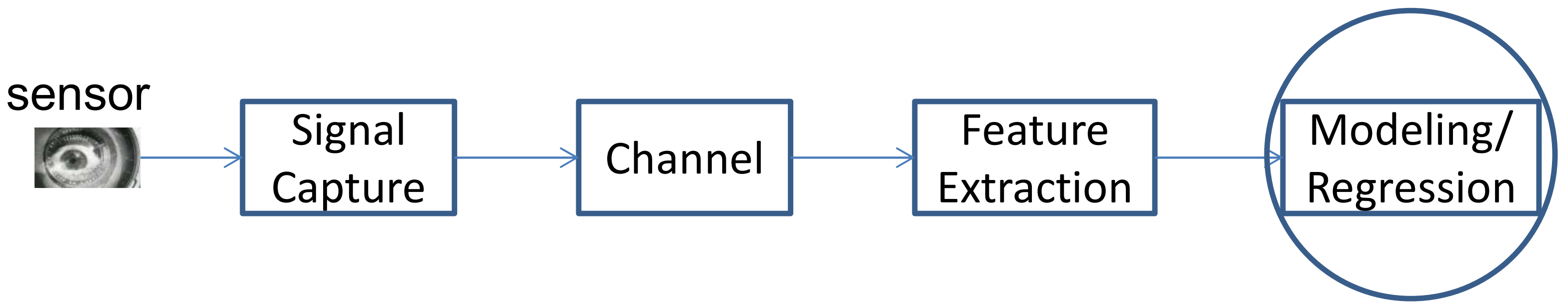
- Application of Machine Learning techniques to the analysis of signals



- *Can be applied to each component of the chain*
- Feature Extraction:
  – Dimensionality reduction
    - Linear models, non-linear models

MLSP

- Application of Machine Learning techniques to the analysis of signals



- *Can be applied to each component of the chain*
- Classification, Modelling and Interpretation, Prediction

Poll 1

Poll 1

- **Q1 -- How many blocks do we have in the complete signal processing chain**
  - 1
  - 2
  - 3
  - **4**

- **Q2 -- Which of the blocks of the signal processing chain can we apply ML techniques to** (choose all that apply)
  - **signal capture**
  - **channel**
  - **feature extraction**
  - **modelling**

In this course

- The four "aspects" of MLSP:
  - **Representation**: How best to represent signals for effective downstream or upstream processing
  - **Modelling**: How to *model* the systematic and statistical characteristics of the signal
  - **Classification**: How do we assign a class to the data?
  - **Prediction**: How do we predict new or unseen values or attributes of the data

What we will cover

- **Representations**: Algebraic methods for extracting information from signals
  - Deterministic representations
  - Data-driven characterization
    - PCA
    - ICA
    - NMF
    - Factor Analysis
    - LGMs

What we will cover

- **Representations/Modelling**: Learning-based approaches for modeling data
  - Dictionary representations
  - Sparse estimation
    - Sparse and over-complete characterization, Compressed sensing
  - Regression
  - ~~Neural networks~~

- **Modelling**: Latent variable characterization
  - Clustering, K-means
  - Expectation Maximization
  - Probabilistic Latent Component Analysis

What we will cover

- **Modeling/Prediction**: Time Series Models
  - Markov models and Hidden Markov models
  - Linear and non-linear dynamical systems
    - Kalman filters, particle filtering
    - Non-linear models
- **Classification and Prediction:**
  - Binary classification. Meta-classifiers
- Wish list: Additional topics
  - Privacy in signal processing
  - Extreme value theory
  - Dependence and significance

Recommended Background

- DSP
  - Fourier transforms, linear systems, basic statistical signal processing
- Linear Algebra
  - Definitions, vectors, matrices, operations, properties
- Probability
  - Basics: what is a random variable, probability distributions, functions of a random variable
- Machine learning
  - Learning, modelling and classification techniques

Guest Lectures (not finalized)

- Ashwin Shankarnarayanan
  - Professor, ECE
  - Compressive sensing

- TBD
  - Unlikely to have more because this is a shortened semester

Schedule of Other Lectures

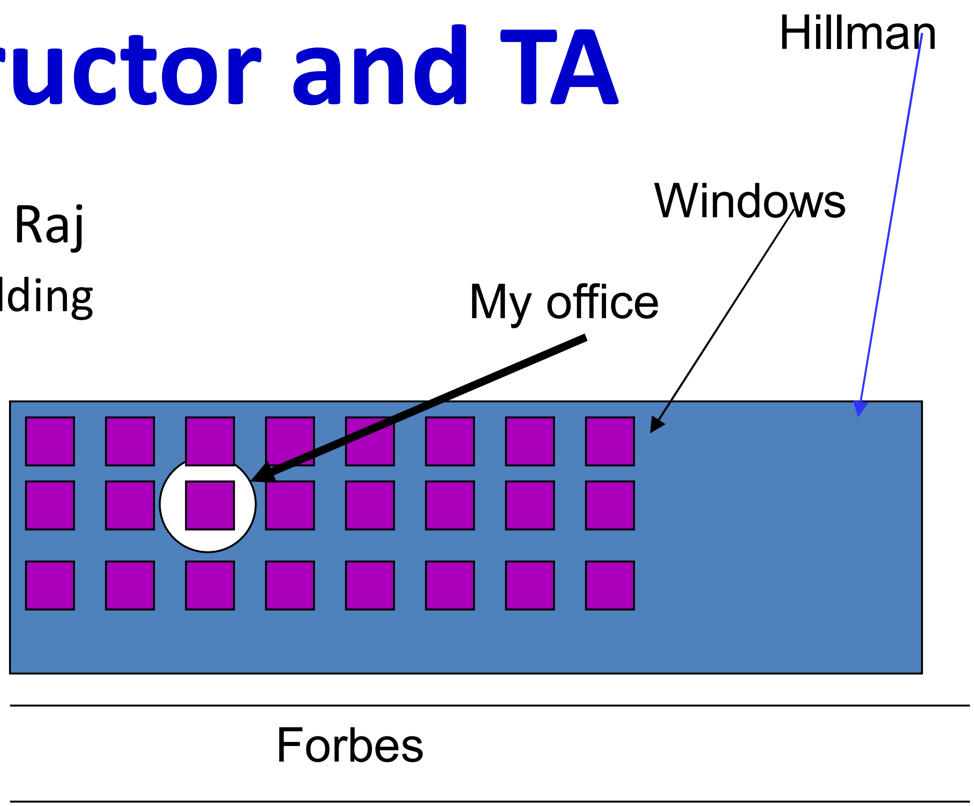
- Tentative Schedule on Website
- https://mlsp2021.cs.cmu.edu

Grading

- Mini quizzes : 24%
  - Ten multiple-choice questions on the topics of the week
  - Weekly
  - Will be open on Friday, closed on Saturday night
- Homework assignments : 50%
  - Mini projects
  - Will be assigned during course
  - Expect four
  - You *will not catch up* if you slack on any homework
    - Those who didn't slack will also do the next homework
- Final project: 25%
  - Will be assigned early in course
  - Dec 10 (approx): Video presentations
    - Evaluated in part by peers
- 1% for class participation
  - Attendance as measured by responses to in-class polls
    - Alternately, viewership of Panopto videos for Kigali students

Instructor and TA

- Instructor: Prof. Bhiksha Raj
  - Room 6705 Hillman Building
  - bhiksha@cs.cmu.edu
  - 412 268 9826



- TAs:
  - Mohammed Danish (mohamme2@andrew)
  - Yinghao Ma (yinghaom@andrew)
  - Kigali: Charles Yusuf (cyusuf@Africa.cmu.edu)
- Office Hours:
  - Check course website

Additional Administrivia

- Website:
  – https://mlsp2021.cs.cmu.edu
  – Lecture material will be posted on the day of each class on the website
  – Reading material and pointers to additional information will be on the website

- We will use Piazza
  – Please join piazza for 11-755/18-797

Continuing..

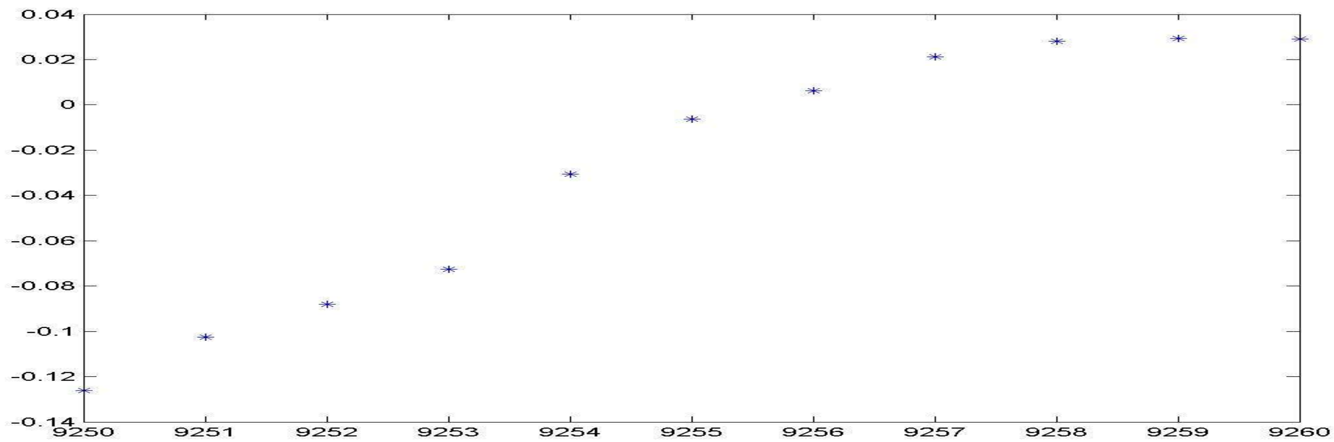
- Story so far:
  - What is a signal
  - Some types of signals
  - What is SP
  - What is ML
    - And where does it apply in the SP chain
- Continuing – some additional concepts..
  - More on signals
  - More on what we *do* with signals
    - Representation, Regression, classification, prediction
  - And how
    - Supervision

More on Signals

- Principles of signal *capture* and what the numbers mean
- Explained through examples
  - Sound, images
    - Signals where the purpose of signal capture is to recreate stimulus
    - Signals we emphasize a bit in course
    - But also because of easily interpretable principles that extend to all signals
  - Also MRI
    - Signal, where the purpose is to make inferences about an underlying system or process
    - Illustrates capture in *transform* domain

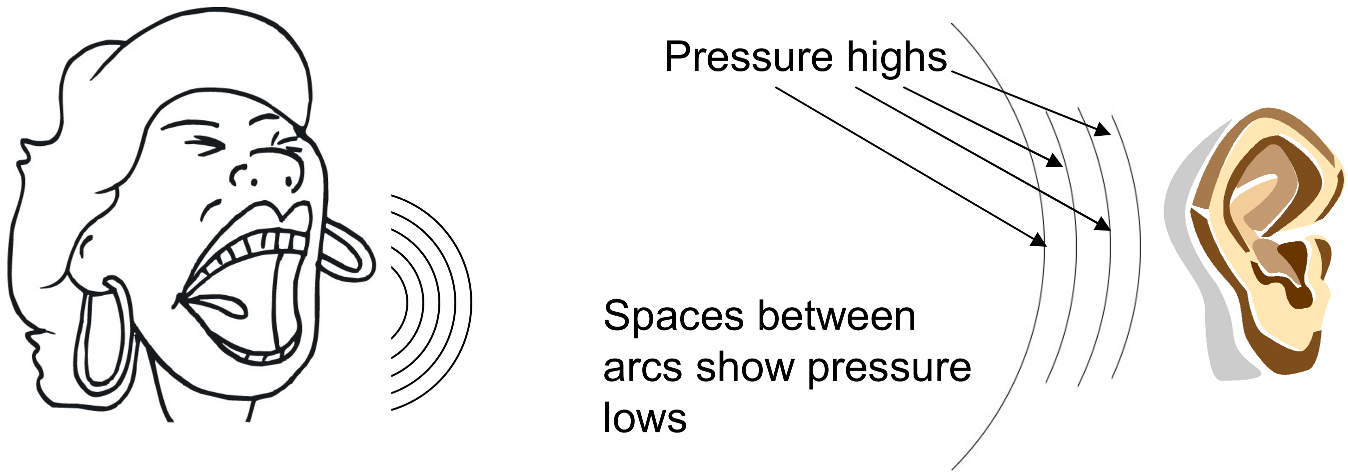
E.g. Audio Signals

- A typical digital audio signal
  - It's a sequence of numbers



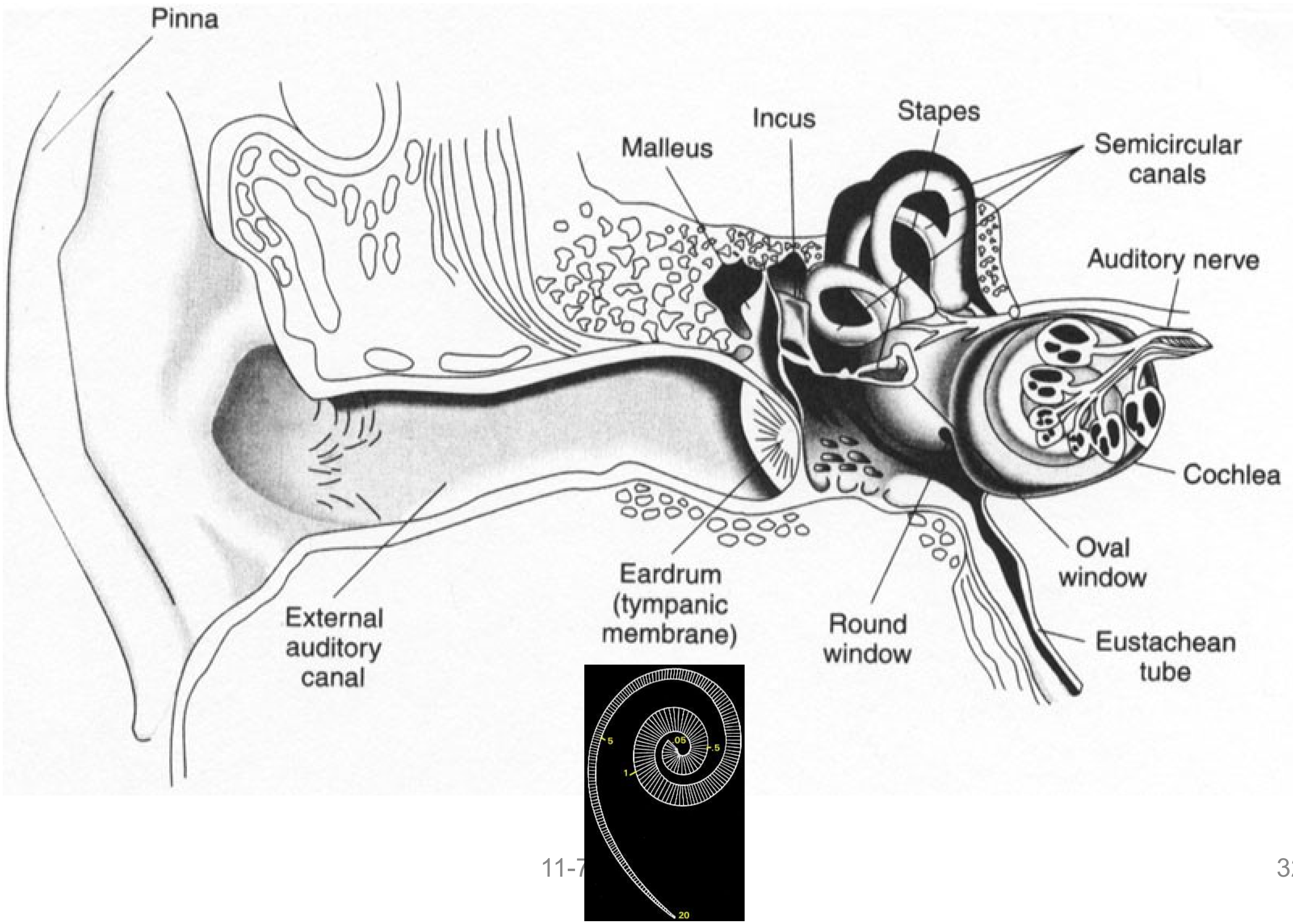
  - Must represent a quantity that enables near-perfect recreation of sound stimulus

The sound stimulus

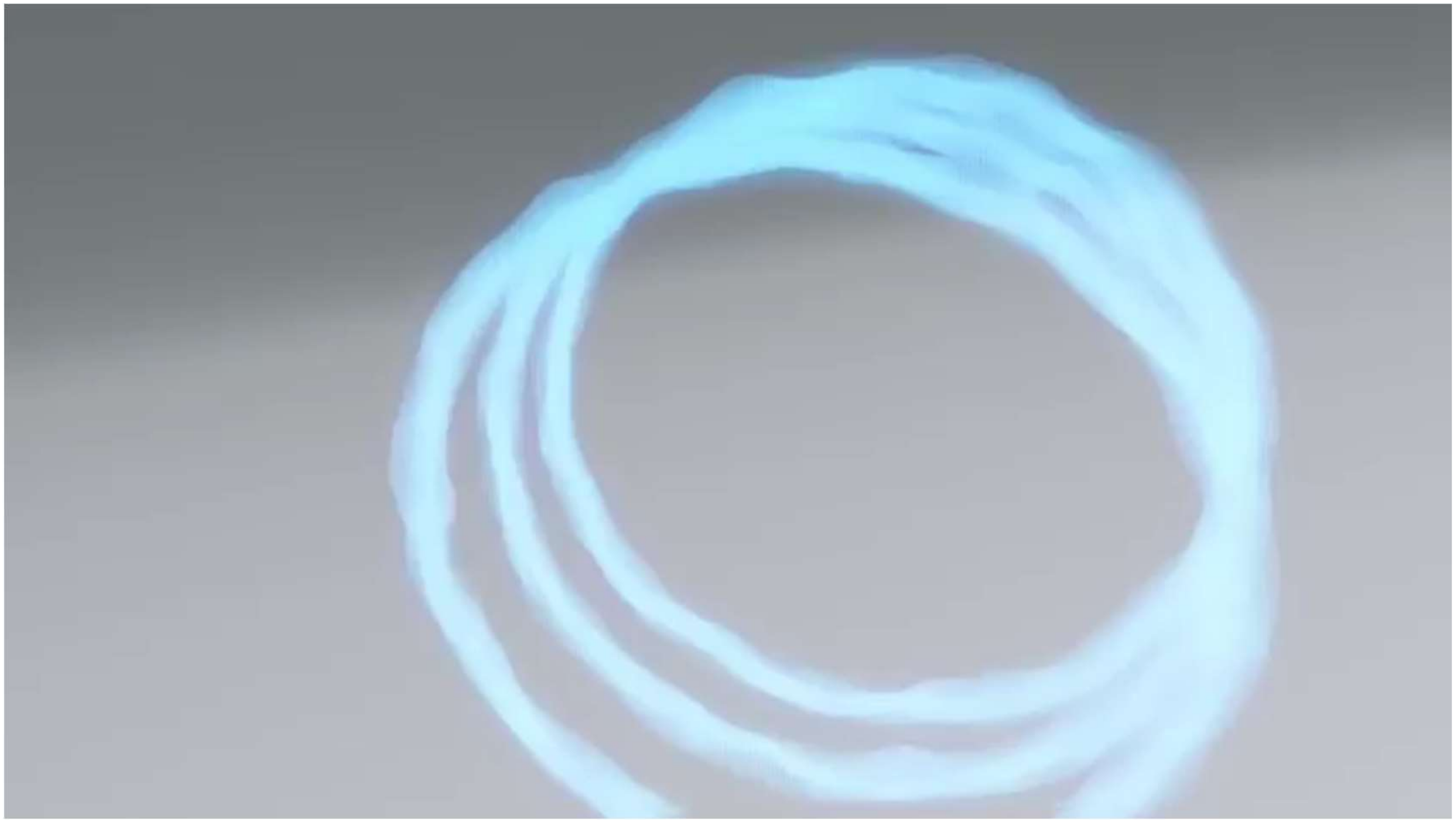


- Any sound is a pressure wave: alternating highs and lows of air pressure moving through the air
- When we speak, we produce these pressure waves
  - Essentially by producing puff after puff of air
  - Any sound producing mechanism actually produces pressure waves
- These pressure waves move the eardrum
  - Highs push it in, lows suck it out
  - We sense these motions of our eardrum as “sound”

SOUND PERCEPTION

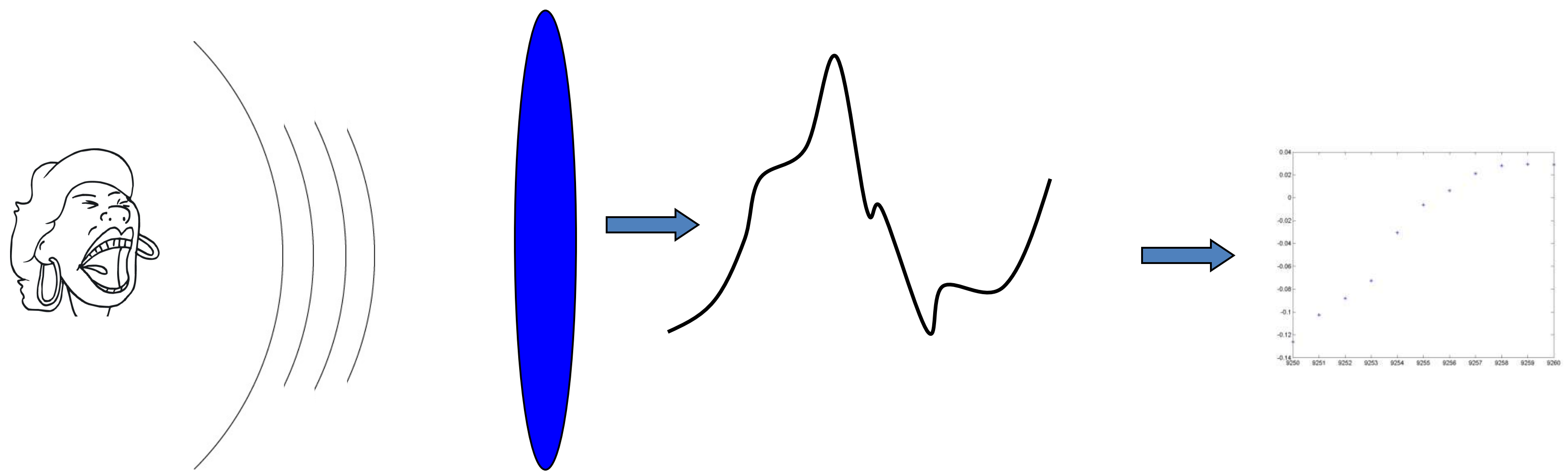


SOUND PERCEPTION



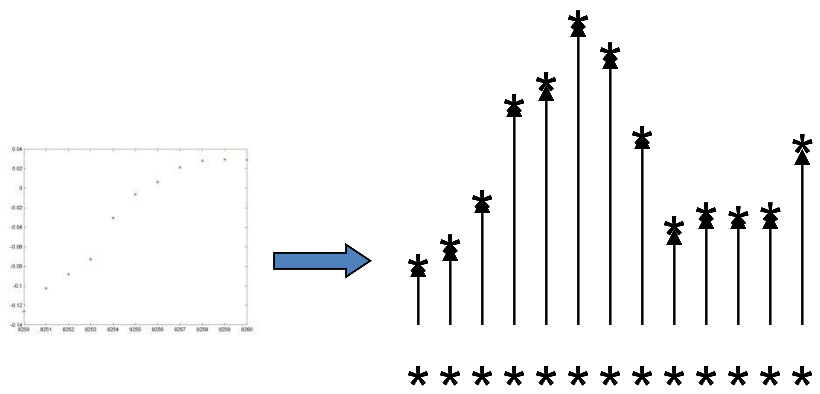
Storing pressure waves on a computer

- The pressure wave moves a diaphragm
  - On the microphone
- The motion of the diaphragm is converted to continuous variations of an electrical signal
  - Many ways to do this
- A "sampler" samples the continuous signal at regular intervals of time and stores the numbers



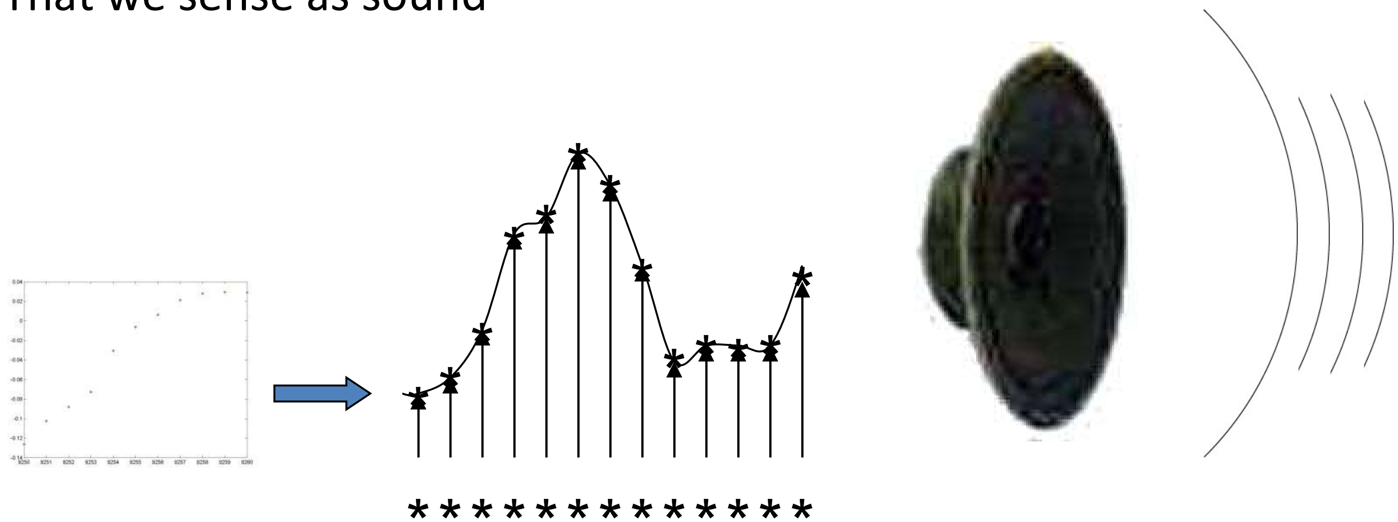
Are these numbers sound?

- How do we even know that the numbers we store on the computer have anything to do with the recorded sound really?
  - Recreate the sense of sound
- The numbers are used to control the levels of an electrical signal



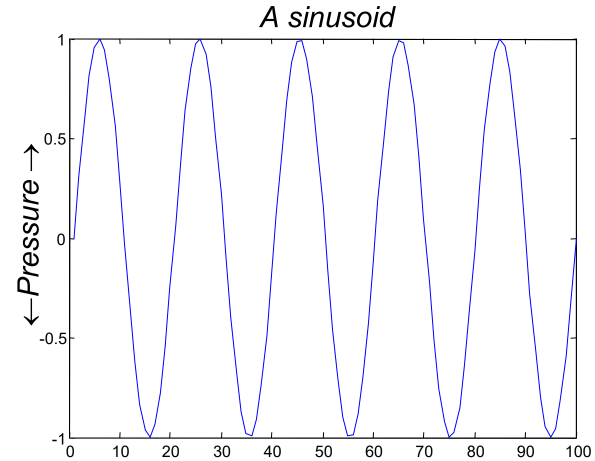
Are these numbers sound?

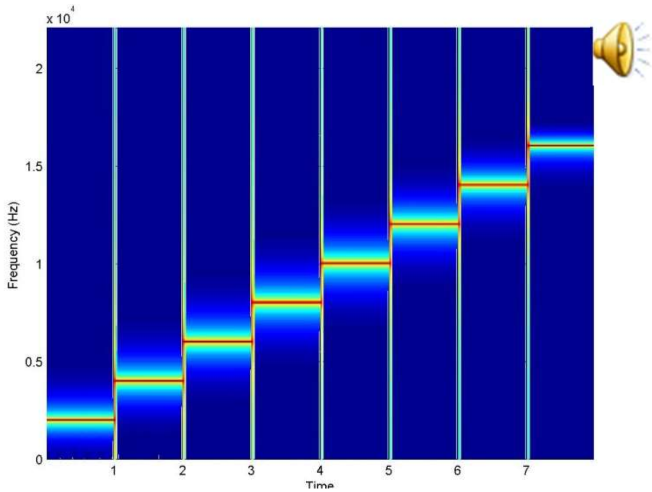
- How do we even know that the numbers we store on the computer have anything to do with the recorded sound really?
  - Recreate the sense of sound
- The numbers are used to control the levels of an electrical signal
- The electrical signal moves a diaphragm back and forth to produce a pressure wave
  - That we sense as sound



How many samples a second

- Convenient to think of sound in terms of sinusoids with frequency
- Sounds may be modelled as the sum of many sinusoids of different frequencies
  - Frequency is a physically motivated unit
  - Each hair cell in our inner ear is tuned to specific frequency
- Any sound has many frequency components
  - We can hear frequencies up to 16000Hz
    - Frequency components above 16000Hz can be heard by children and some young adults
    - Nearly nobody can hear over 20000Hz.

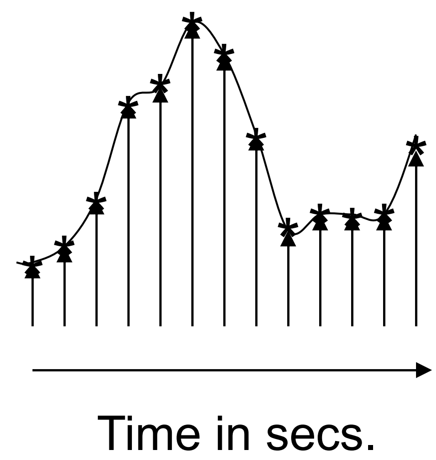




Signal representation - Sampling

- *Sampling frequency* (or *sampling* rate) refers to the number of samples taken a second

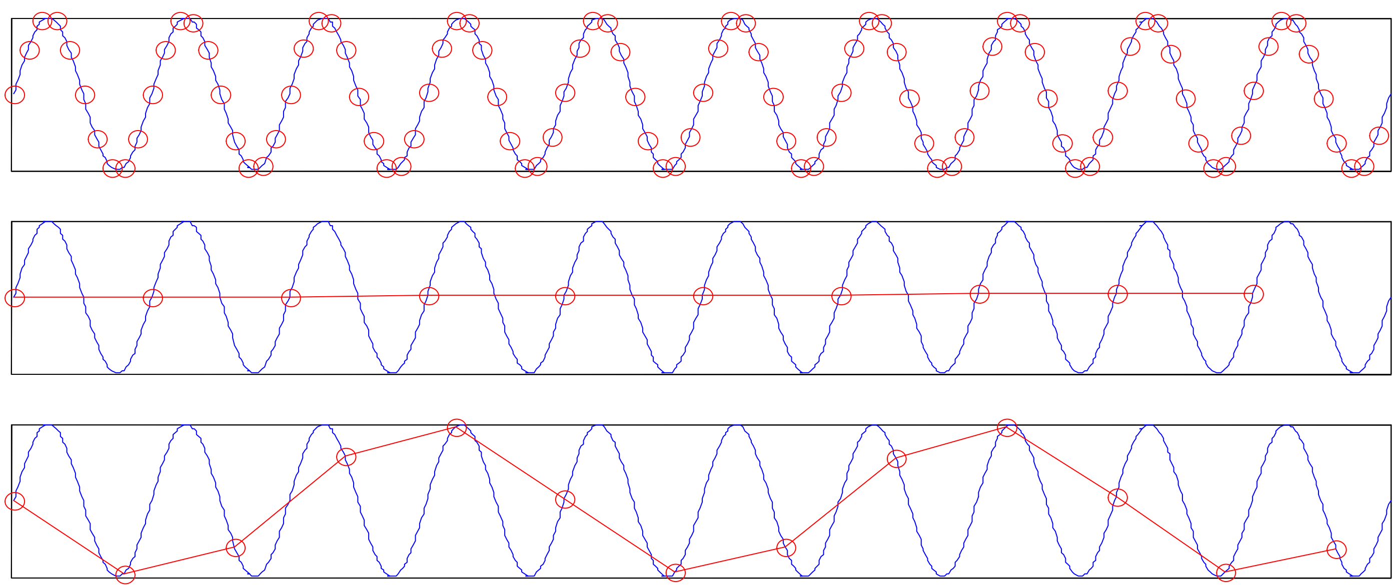
- Sampling rate is measured in Hz
  - We need a sample rate twice as high as the highest frequency we want to represent (Nyquist freq)



- For our ears this means a sample rate of at least 40kHz
  - Because we hear up to 20kHz

Aliasing

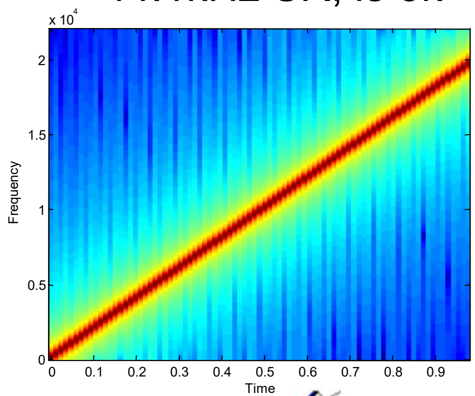
- Low sample rates result in *aliasing*
  - High frequencies are misrepresented
  - Frequency f_1 will become (sample rate – f_1)
  - In video also when you see wheels go backwards



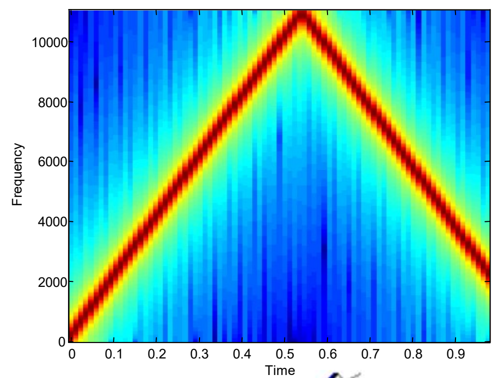
Aliasing examples

Sinusoid sweeping from 0Hz to 20kHz

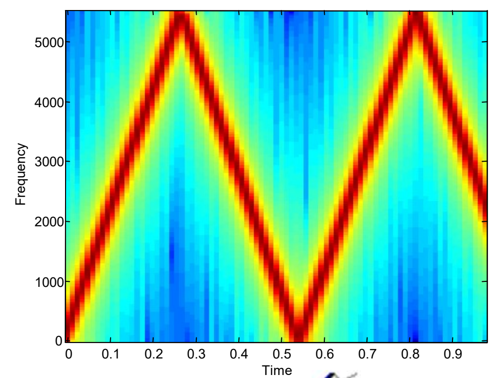
44.1kHz SR, is ok



22kHz SR, aliasing!



11kHz SR, double aliasing!

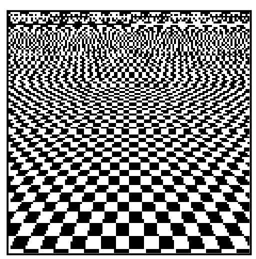


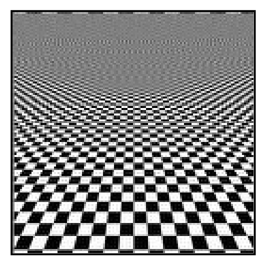
On real sounds

at 44kHz *at 11kHz* *at 4kHz*

at 22kHz *at 5kHz* *at 3kHz*

On images





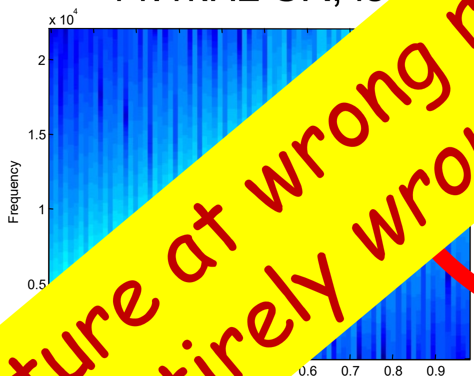
On video

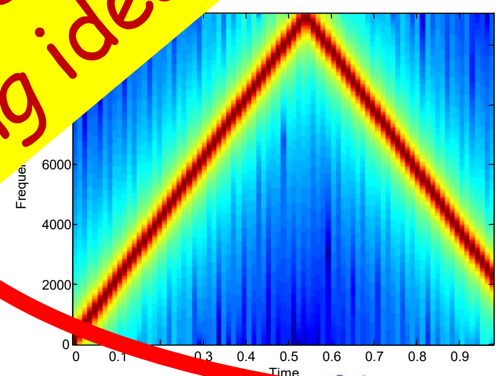
Aliasing ... mples

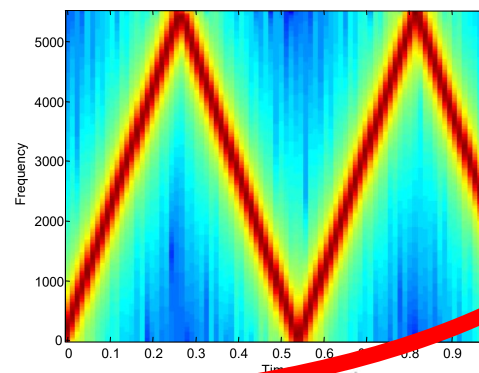
Capture at wrong rate can give you entirely wrong idea of signal

Sinusoid s... m 0Hz to 20kHz

44.1kHz SR, is ... SR, aliasing! 11kHz SR, double aliasing!





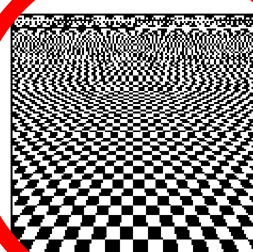


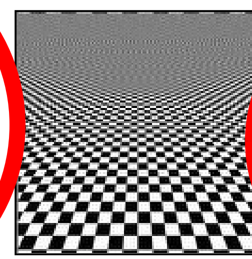
...n real sounds

at 44kHz at 11kHz at 4kHz

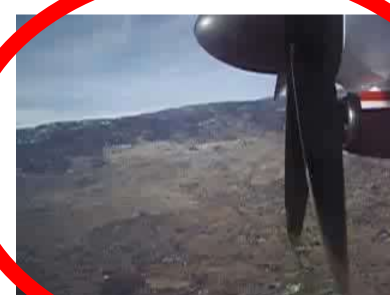
at 22kHz at 5kHz at 3kHz

On images

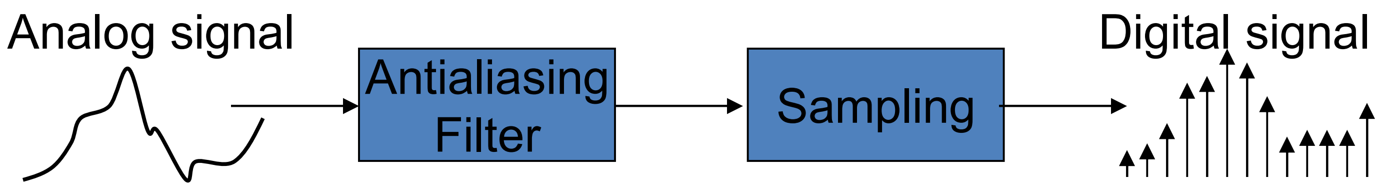


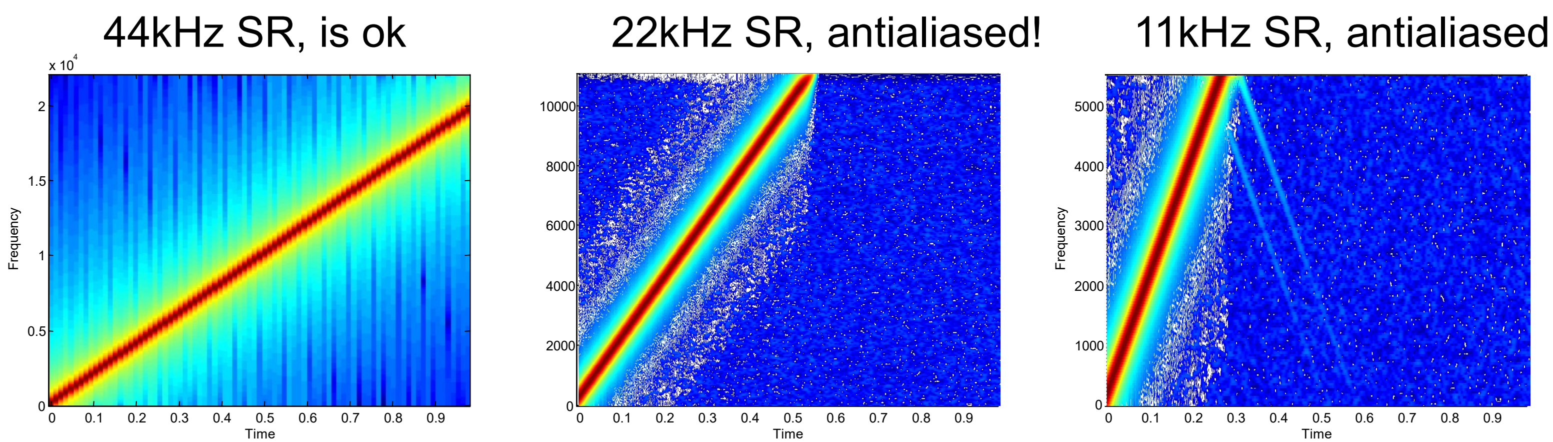


On video



Avoiding Aliasing



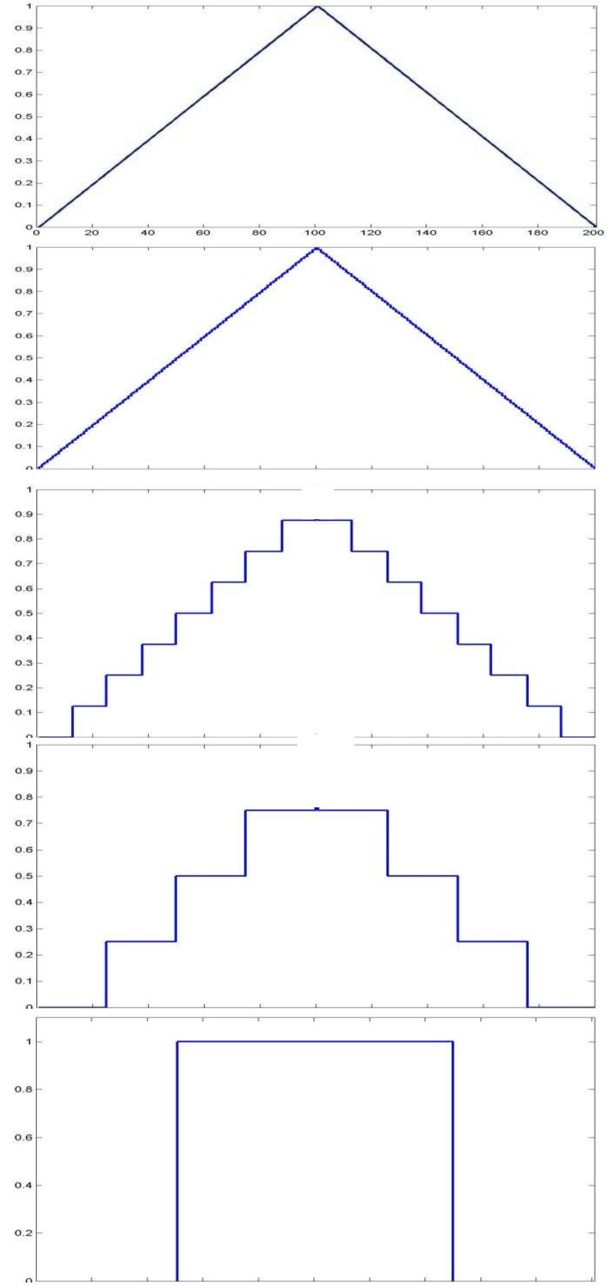


- Solution: *Filter the signal* before sampling it
  - Cut off all frequencies above sampling.frequency/2
  - E.g., to sample at 44.1Khz, filter the signal to eliminate all frequencies above 22050 Hz
- Will only lose information, but not distort existing information

Problem 2: Resolution

- Sound is the outcome of a continuous range of variations
  - The pressure wave can take any value (within limits)
- A computer has finite resolution
  - Numbers can only be stored to finite resolution
  - E.g. a 16-bit number can store only 65536 values, while a 4-bit number can store only 16 unique values
- Low-resolution storage results in loss of information

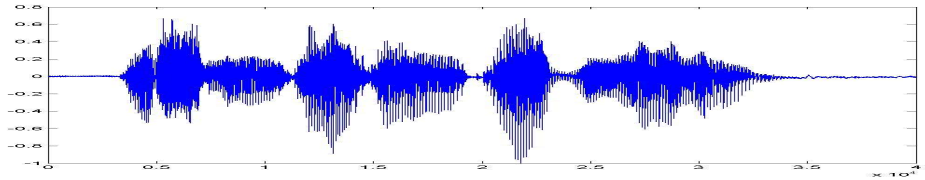
Storing the signal on a computer



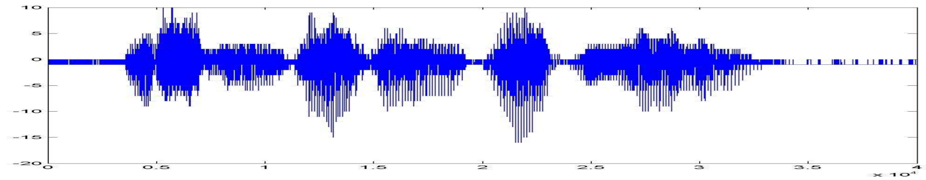
- The original signal
- 8 bit quantization
- 3 bit quantization
- 2 bit quantization
- 1 bit quantization

Tom Sullivan Says his Name

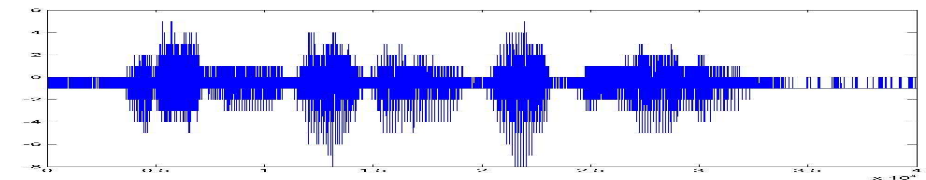
- 16 bit sampling



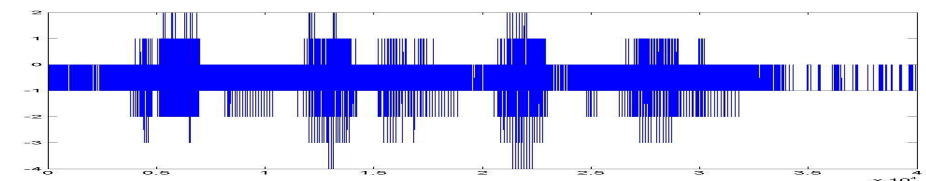
- 5 bit sampling



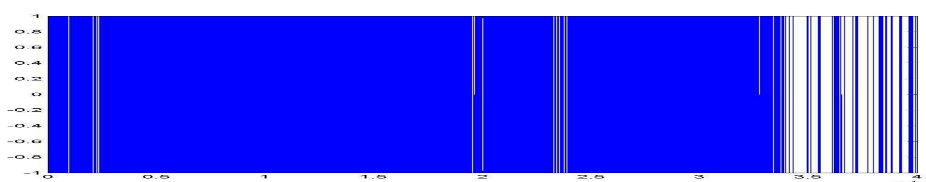
- 4 bit sampling



- 3 bit sampling

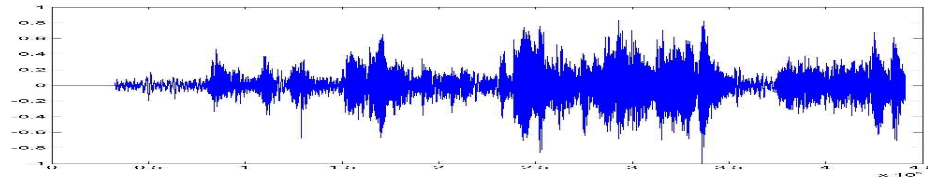


- 1 bit sampling

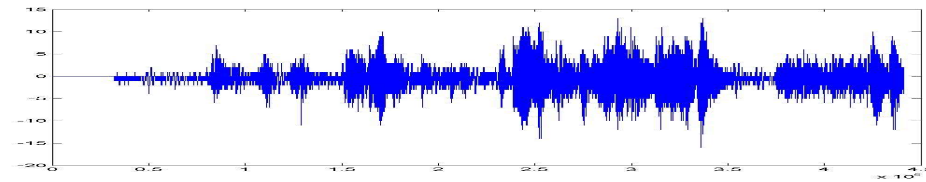


A Schubert Piece

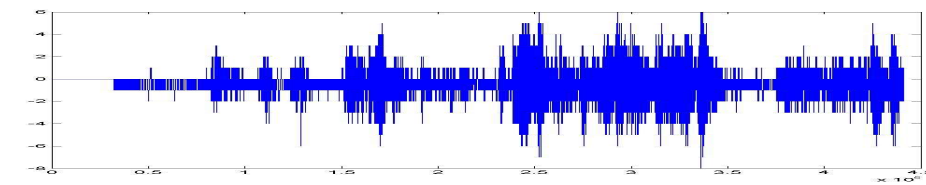
- 16 bit sampling



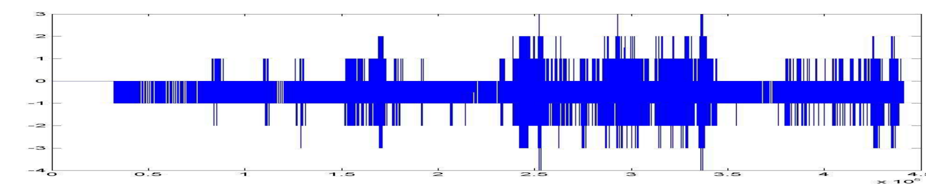
- 5 bit sampling



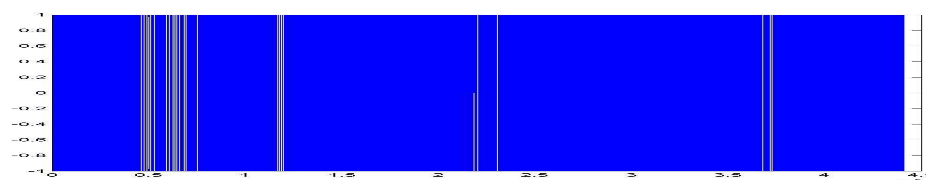
- 4 bit sampling



- 3 bit sampling



- 1 bit sampling



Lessons (for any signal)

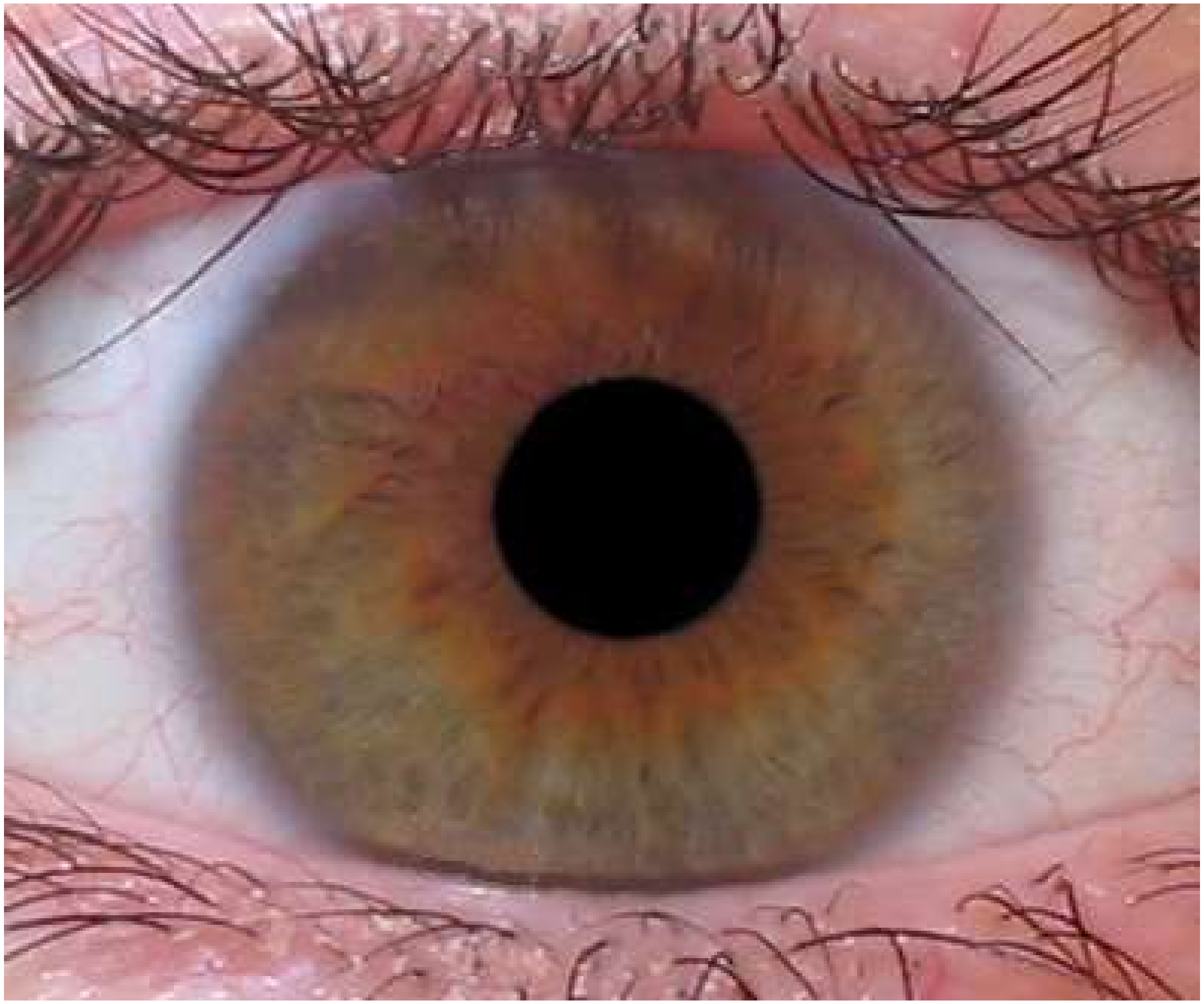
- *Transduce* signal in meaningful manner
  - For sound and images, must be able to recreate original stimulus from signal
- Sample fast enough to capture highest frequency variations
- Store with sufficient resolution
- For audio
  - Common sample rates
    - For speech 8kHz to 16kHz
    - For music 32kHz to 44.1kHz
    - Pro-equipment 96kHz
  - Common bit resolution
    - 12-bit equivalent for speech
    - 16 bits for high-fidelity speech
    - 24 bits for music

Poll 2

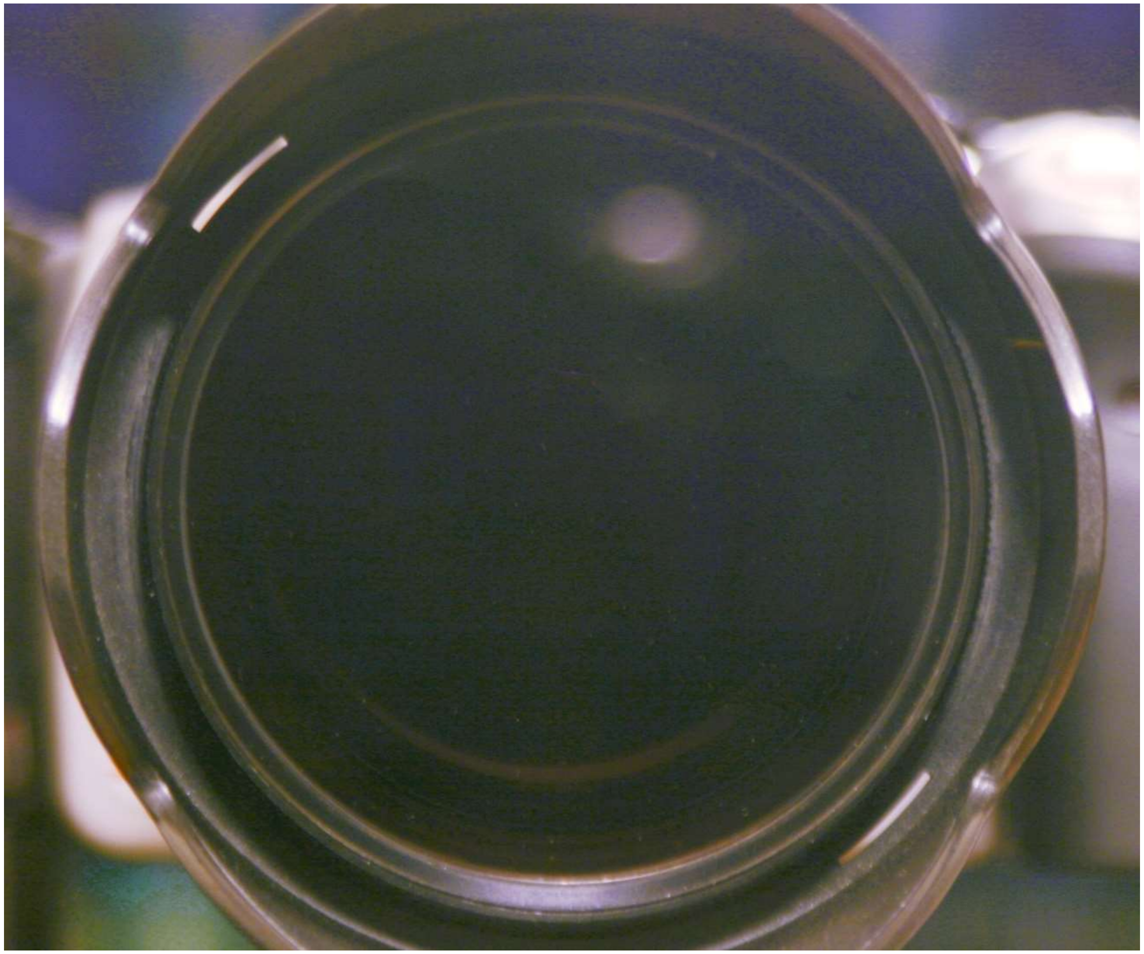
Poll 2

- What is the only true test to verify that you have digitally captured a sound perfectly
  - If your sampling rate is greater than the nyquist rate
  - If you have anti-aliased the signal before sampling
  - If the bit resolution of the samples is large enough
  - If it is possible to recreate the original sound signal perfectly from the digitally captured signal

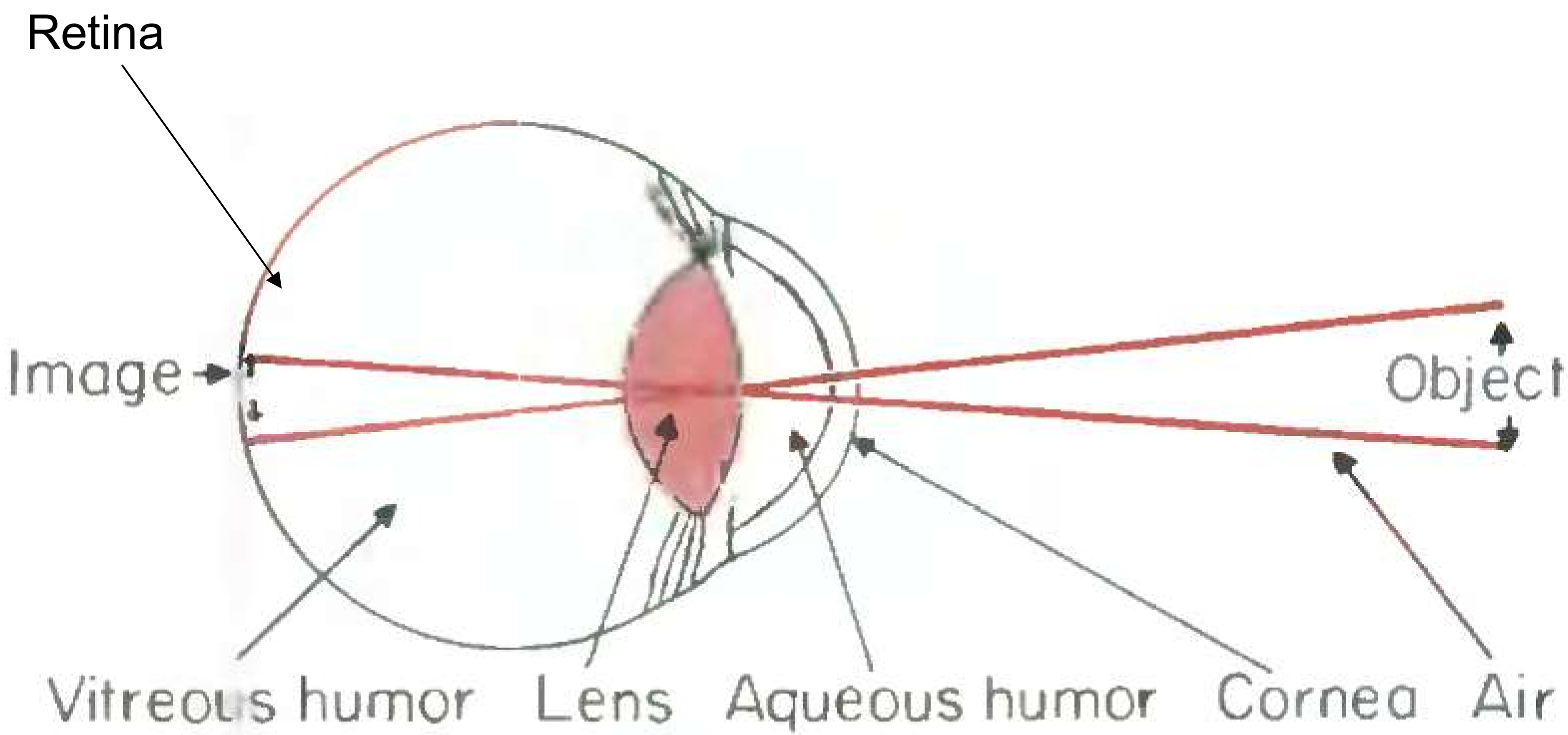
Images



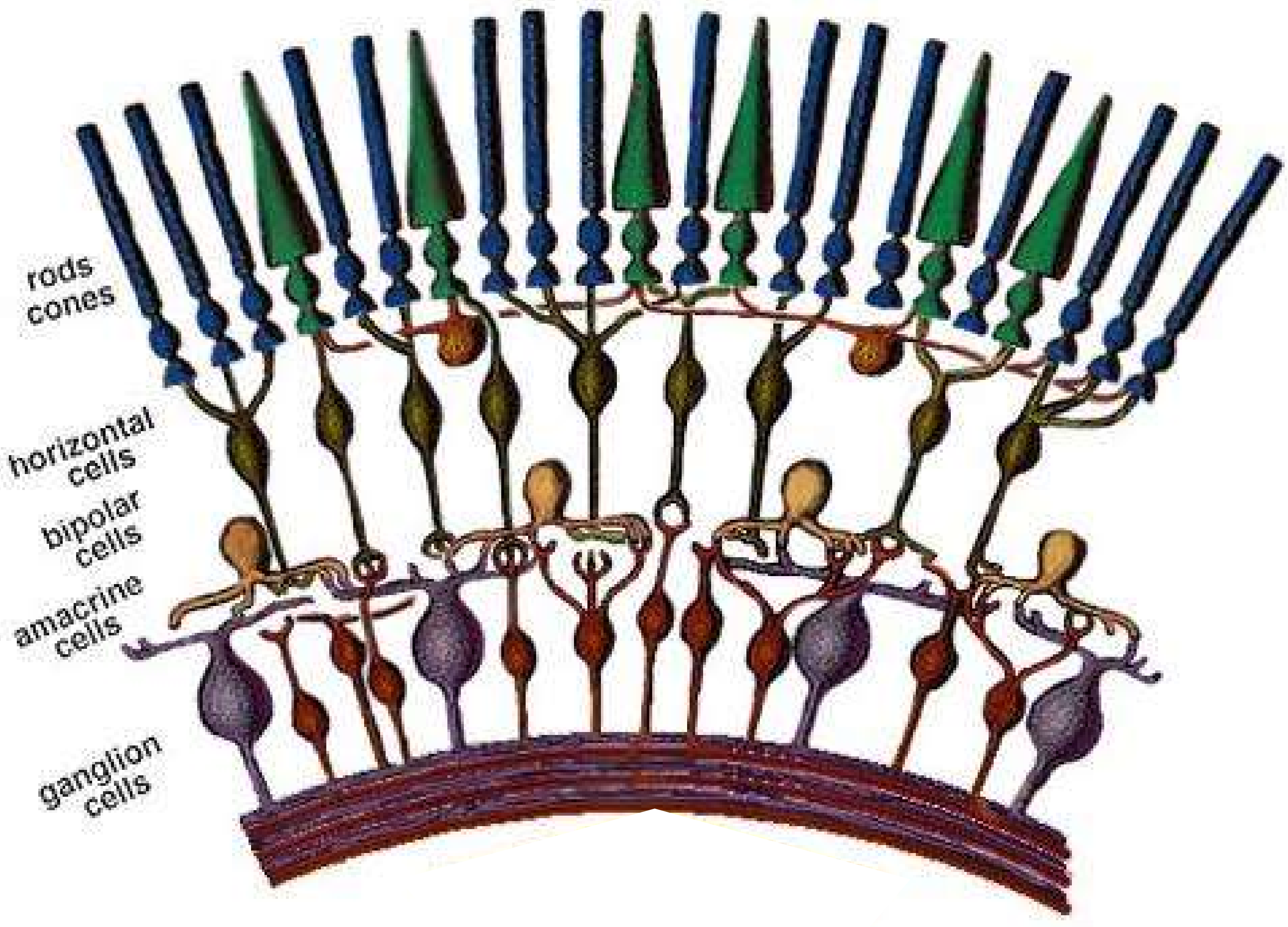
Images



The Eye



Basic Neuroscience: Anatomy and Physiology Arthur C. Guyton, M.D. 1987 W.B.Saunders Co.



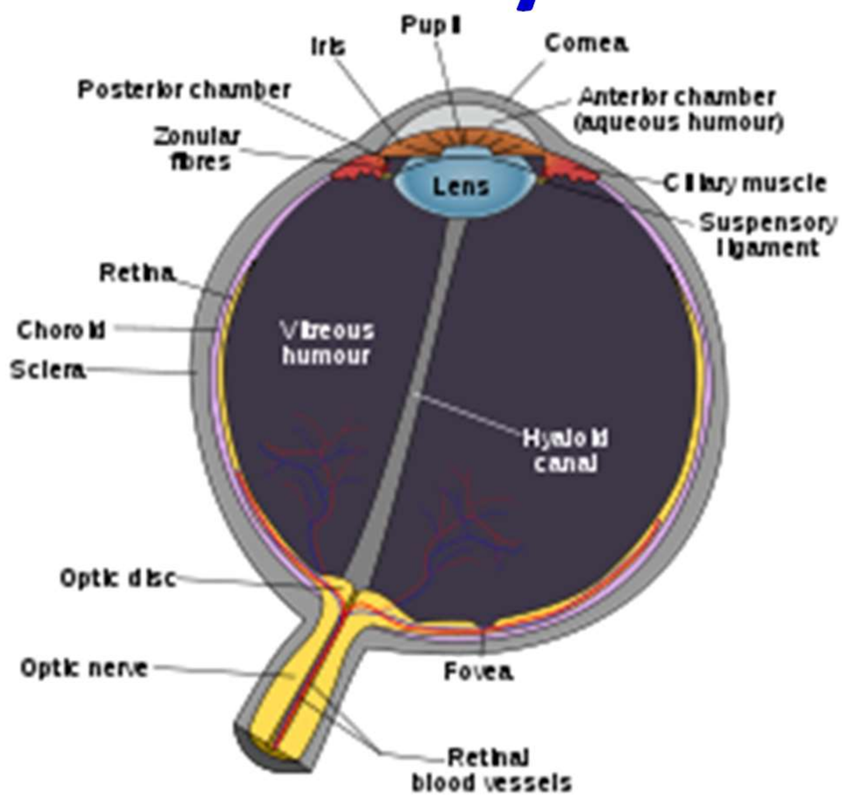
http://www.brad.ac.uk/acad/lifesci/optometry/resources/modules/stage1/pvp1/Retina.html

Rods and Cones

- Separate Systems
- Rods
  - Fast
  - Sensitive
  - Grey scale
  - predominate in the periphery
- Cones
  - Slow
  - Not so sensitive
  - Fovea / Macula
  - COLOR!

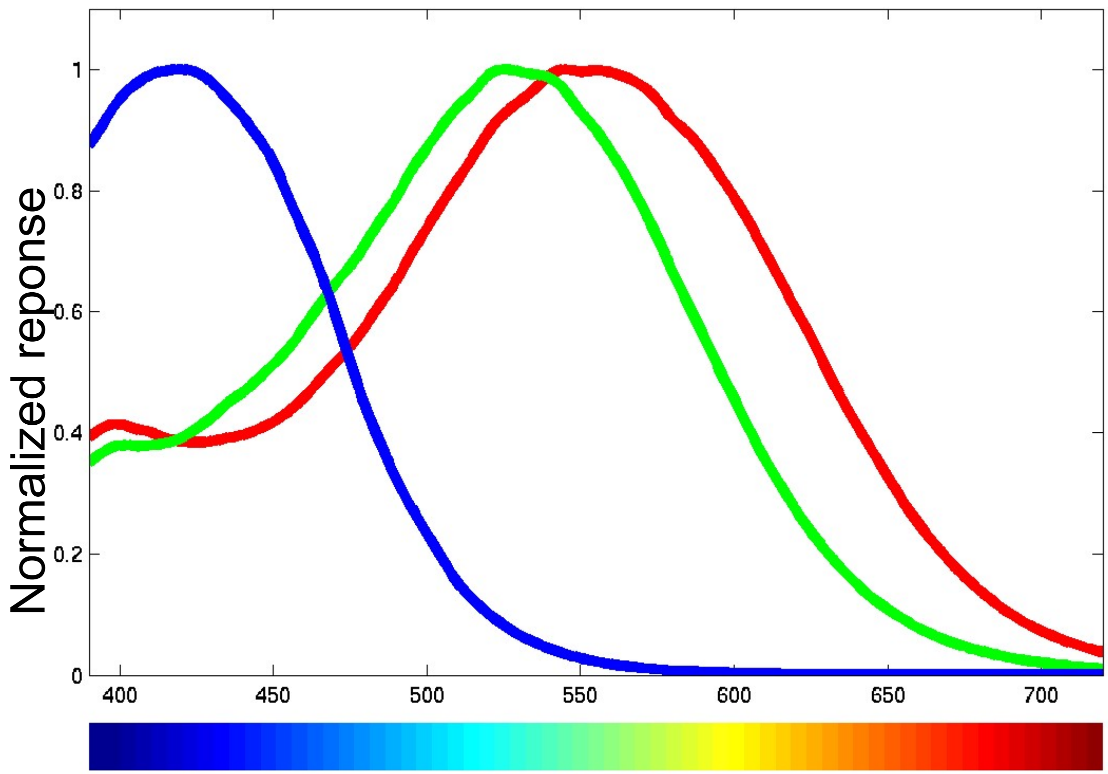
Basic Neuroscience: Anatomy and Physiology Arthur C. Guyton, M.D. 1987 W.B.Saunders Co.

The Eye



- The density of cones is highest at the fovea
  - The region immediately surrounding the fovea is the macula
    - The most important part of your eye: damage == blindness
- Peripheral vision is almost entirely black and white
- Eagles are bifoveate
- Dogs and cats have no fovea, instead they have an elongated slit

Three Types of Cones (trichromatic vision)



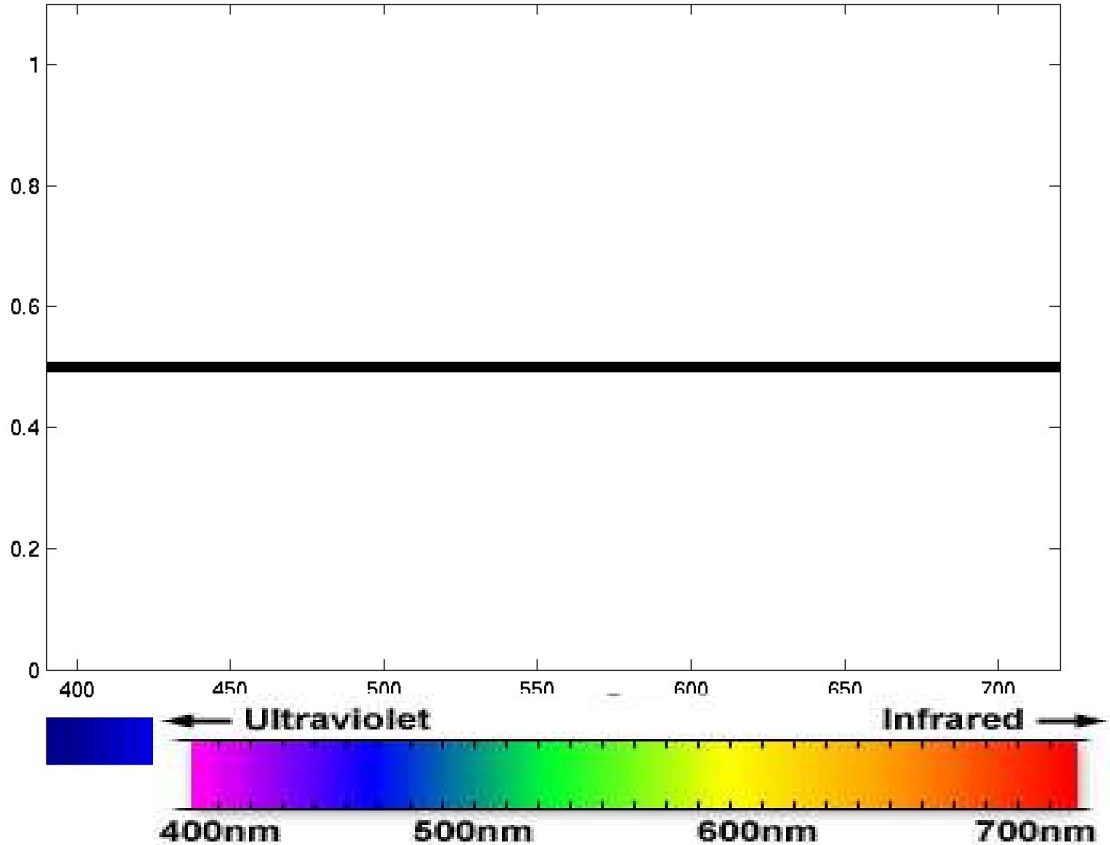
Wavelength in nm

Trichromatic Vision

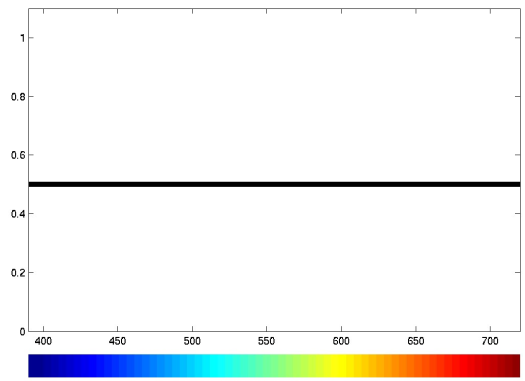
- So-called “blue” light sensors respond to an entire range of wavelengths
  - Including in the so-called “green” and “red” regions

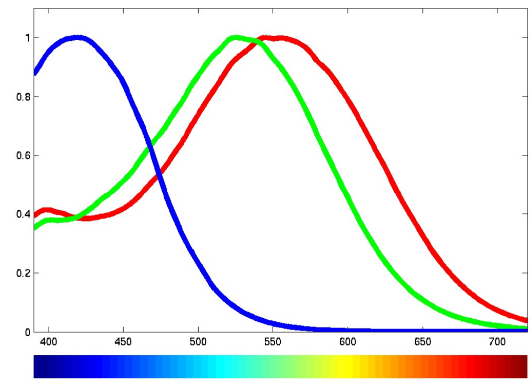
- The difference in response of “green” and “red” sensors is small
  - Varies from person to person
    - Each person really sees the world in a different color
  - If the two curves get too close, we have color blindness
    - Ideally traffic lights should be red and blue

White Light


1
0.8
0.6
0.4
0.2
0
400
450
500
550
600
650
700
Ultraviolet
Infrared
400nm
500nm
600nm
700nm

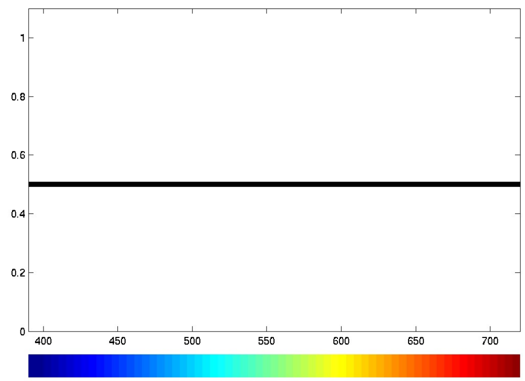
Response to White Light

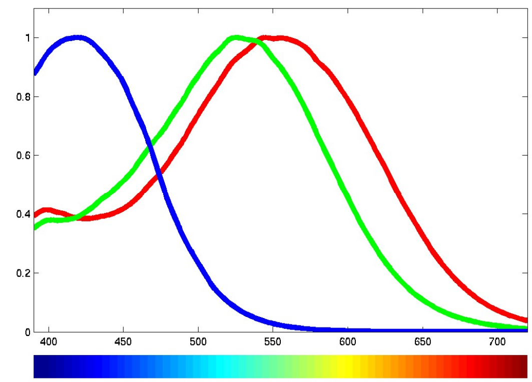


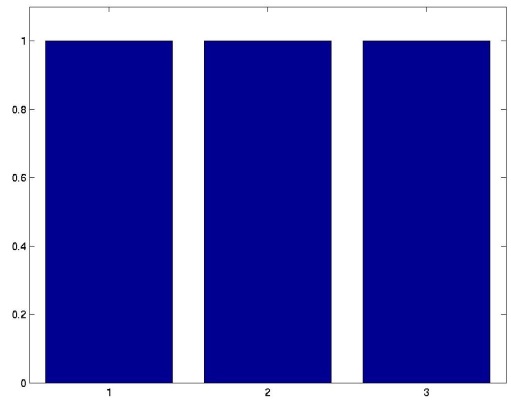


?

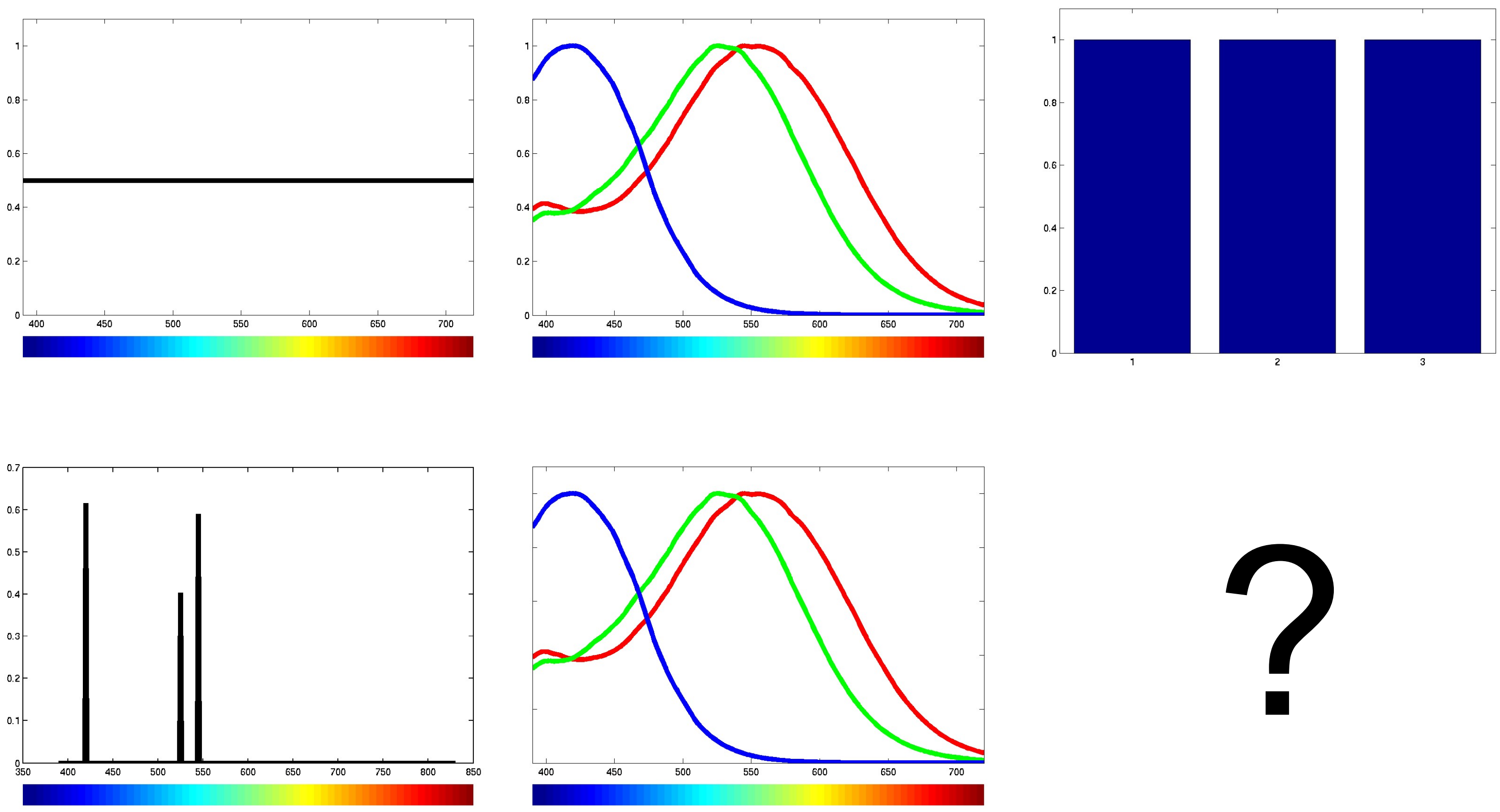
Response to White Light



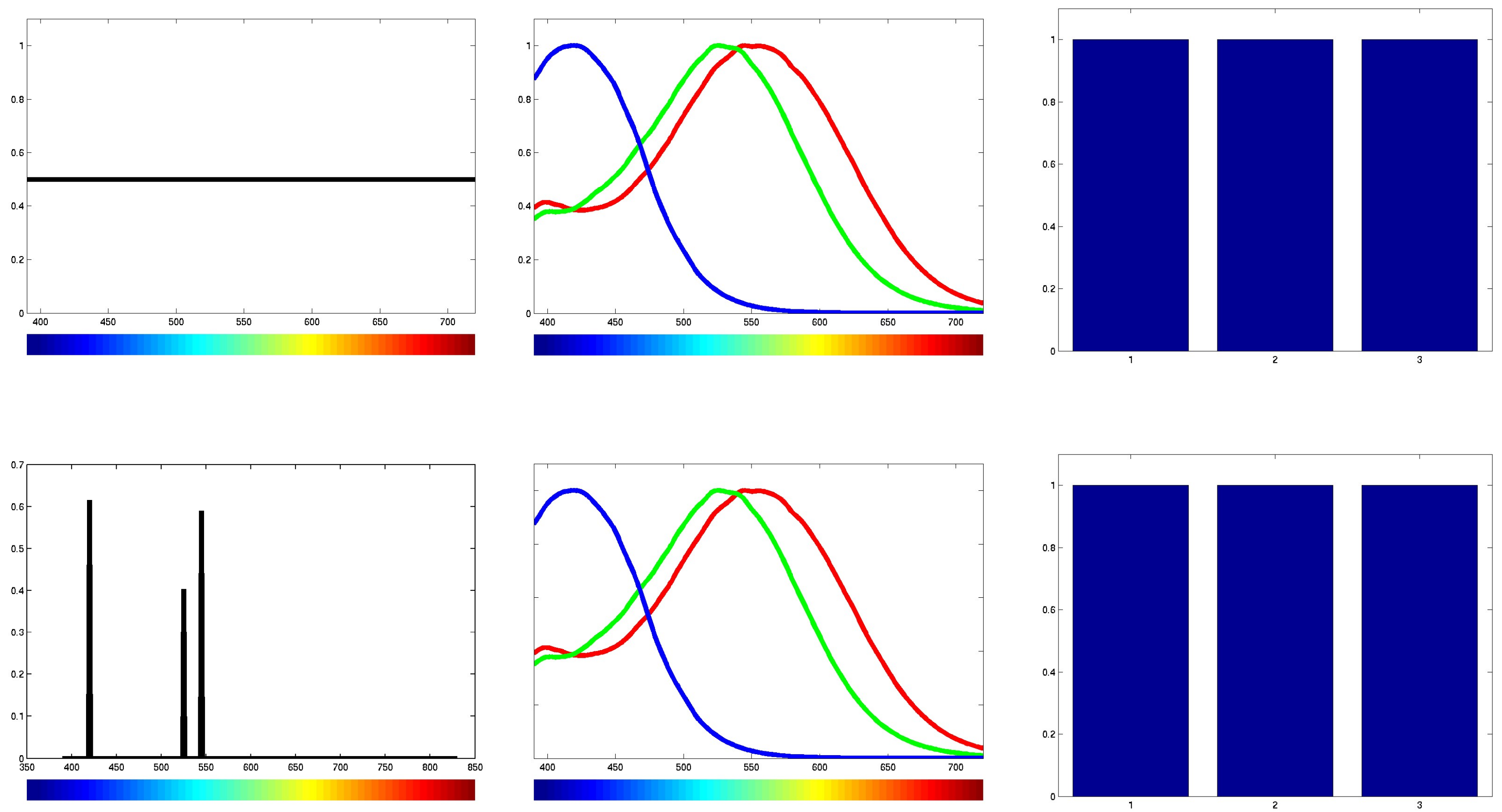




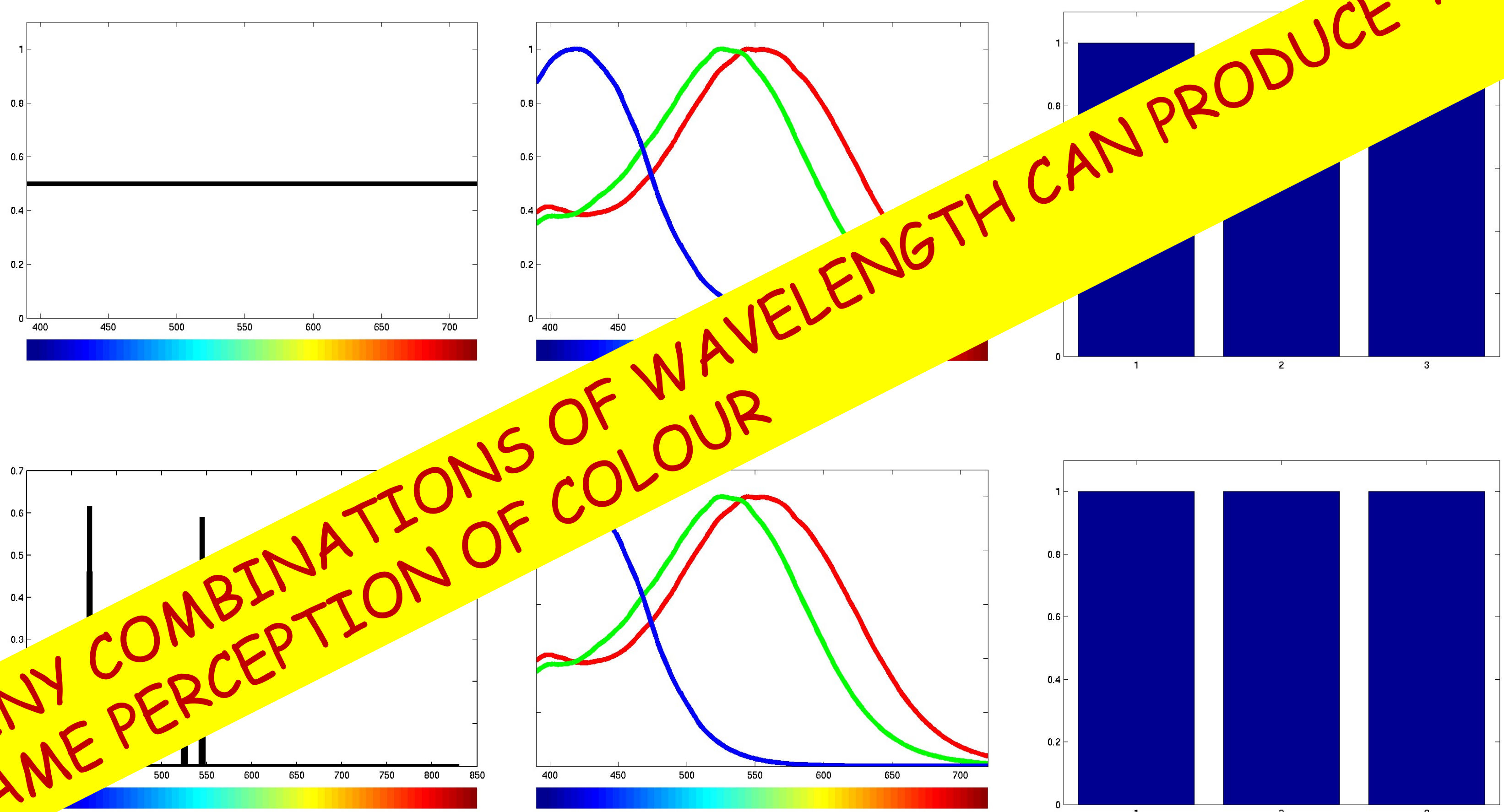
Response to Sparse Light



Response to Sparse Light

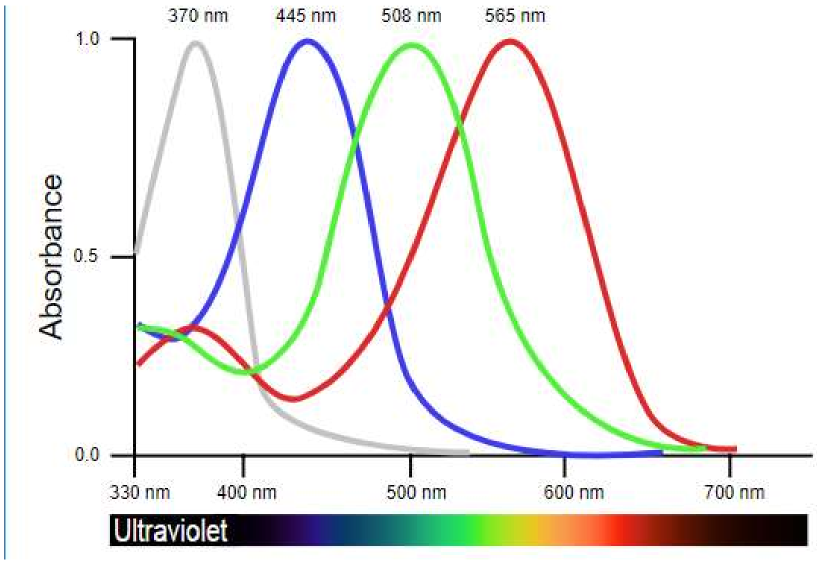


Response to Sparse Light



MANY COMBINATIONS OF WAVELENGTH CAN PRODUCE THE SAME PERCEPTION OF COLOUR

Tetrachromats..



By L. Shyamal - Own work, Public Domain, https://commons.wikimedia.org/w/index.php?curid=6308626

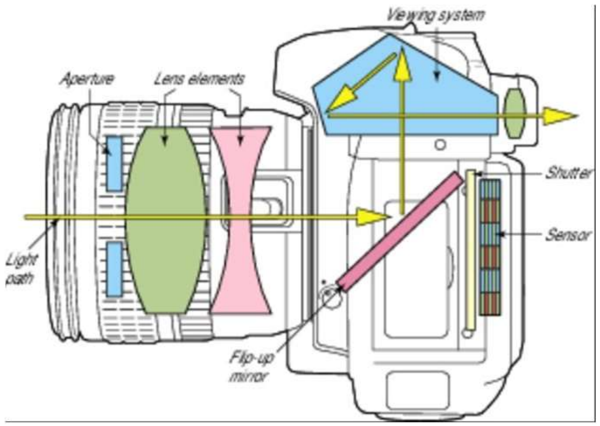
Estrildid finches

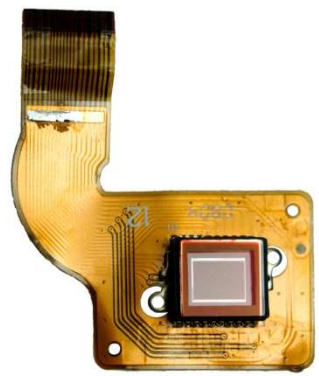
Goldfish

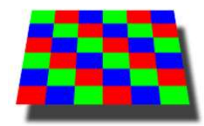
Several types of animals are *tetrachromatic*

(including at least one human)

Digital Capture of Images

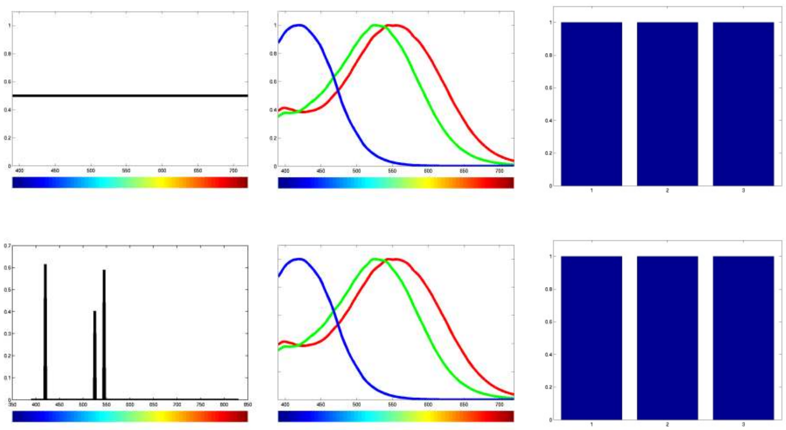






- Lens projects image on sensor
  - Typically CCD or CMOS
- Sensor comprises sensing elements of 3 colors
  - Different strategies for arrangement of color sensors
- Limited number of sensing elements
  - 200-600 ppi
  - The camera generally includes an anti-aliasing filter to eliminate aliasing in the image

Representing Images

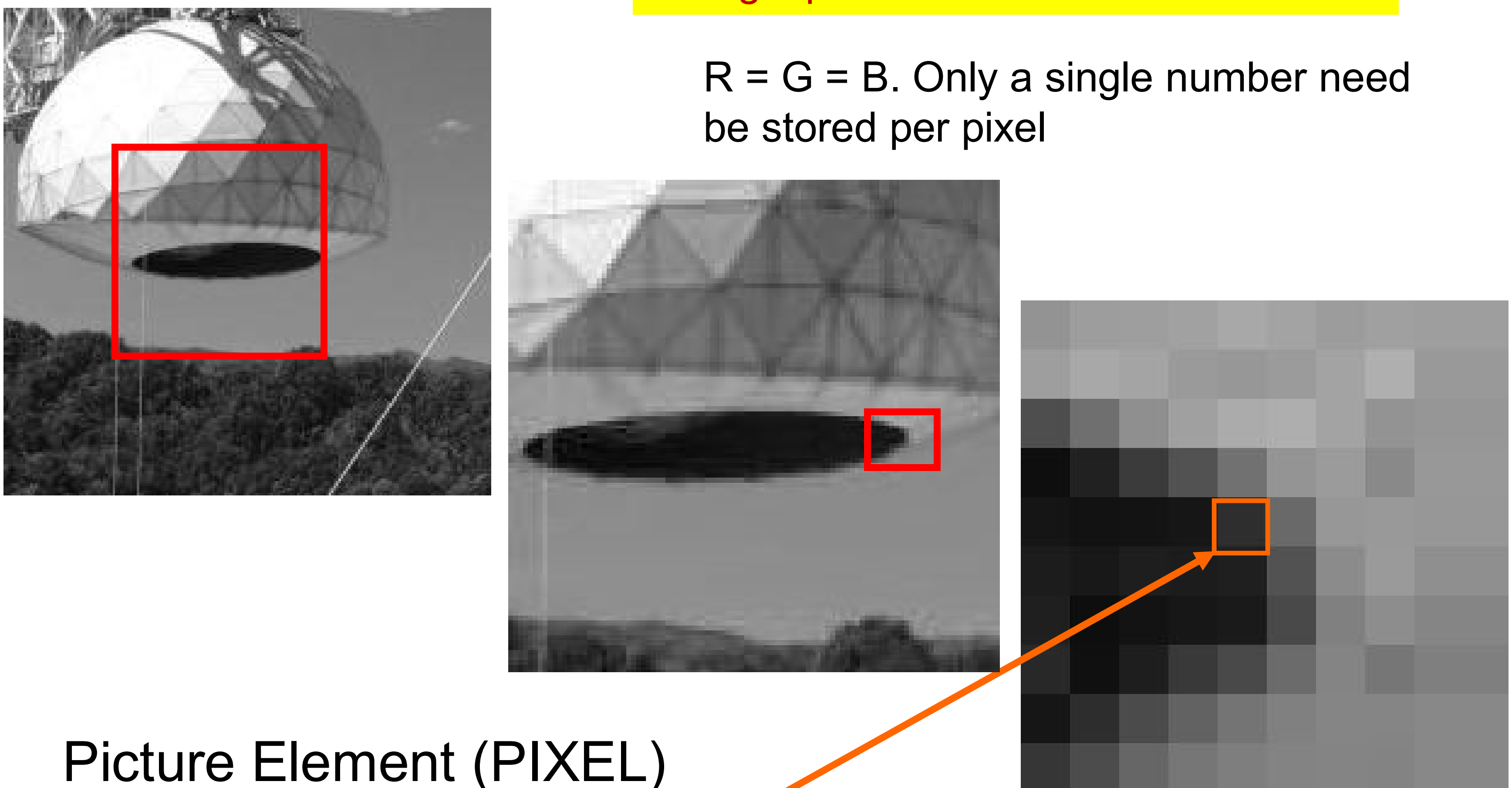


- Utilize trichromatic nature of human vision
  - Trigger the three cone types to produce a sensation approximating desired color
    - A *tetrachromatic* animal would be very confused by our computer images
- The three “chosen” colors are red (650nm), green (510nm) and blue (475nm)
- Can still only represent a small fraction of the 10 million colors that humans can sense

Computer Images: Grey Scale

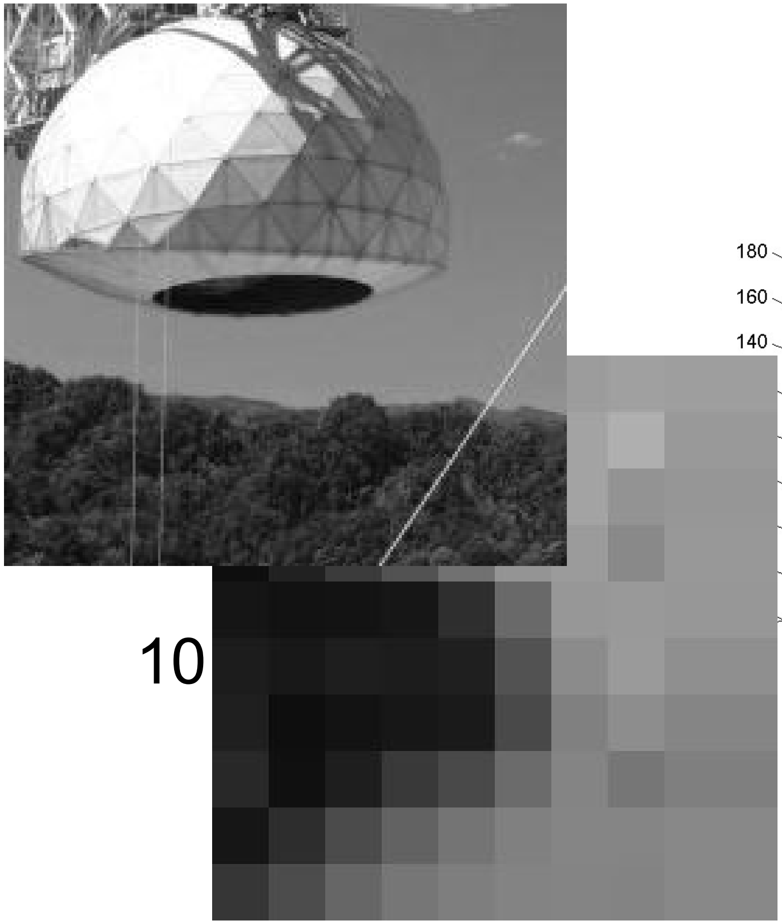
Signal: Each stored number represents a single pixel

R = G = B. Only a single number need be stored per pixel

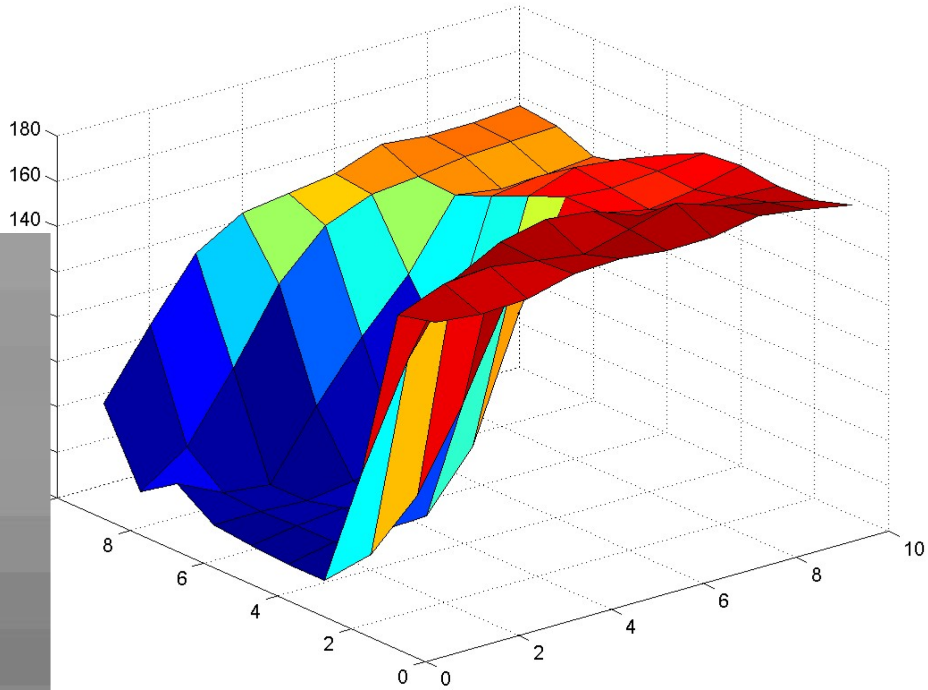


Picture Element (PIXEL)
Position & gray value (scalar)

What we see

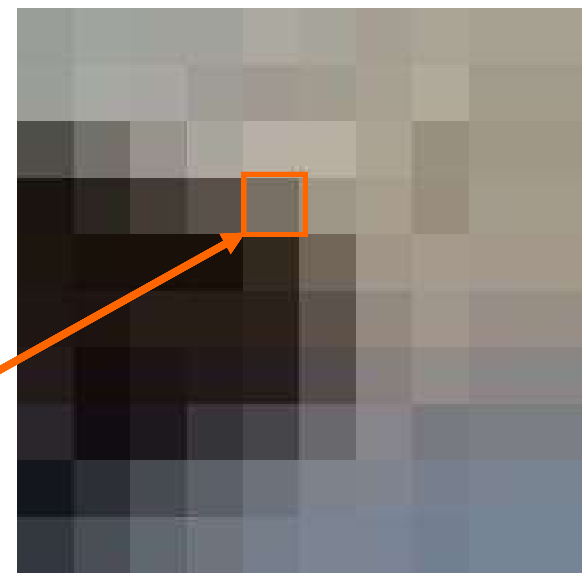


What the computer “sees”



Color Images

Signal: Each triad of stored numbers represents a single pixel



Picture Element (PIXEL)
Position & color value (red, green, blue)

RGB Representation

original

R

G

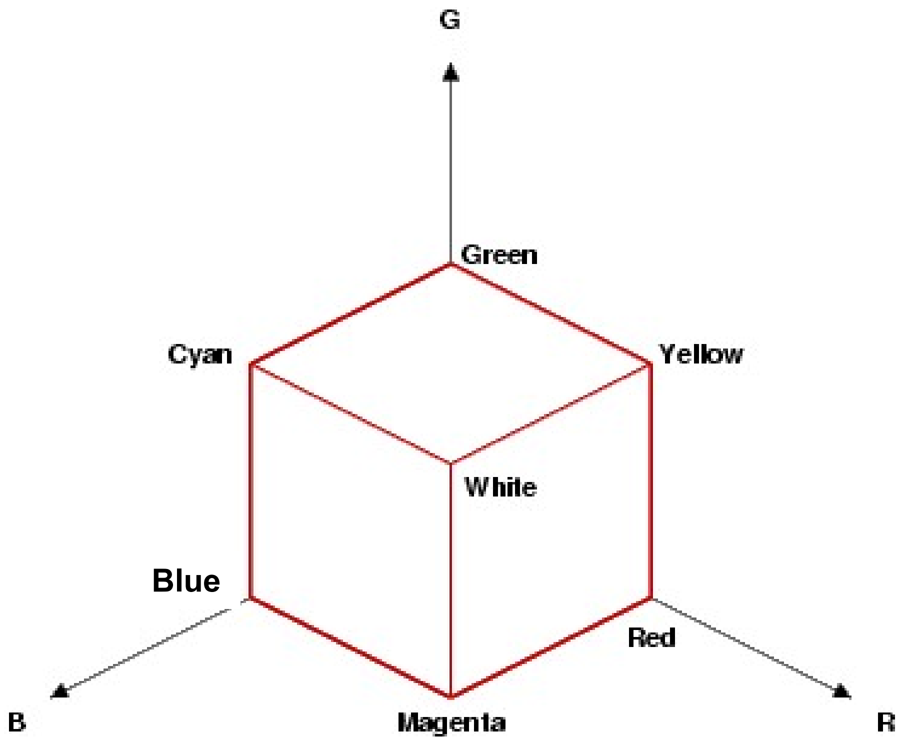
B

Poll 3

Poll 3

- How many different combinations of colors (wavelengths) are there to create the impression of white color to the human eye
  - one
  - two
  - three
  - infinite

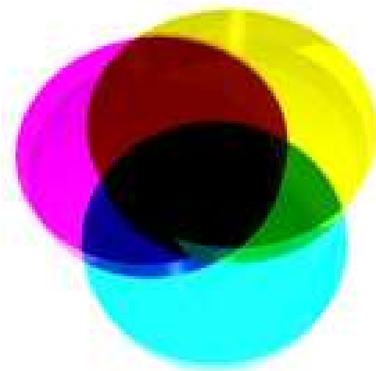
The CMYK color space

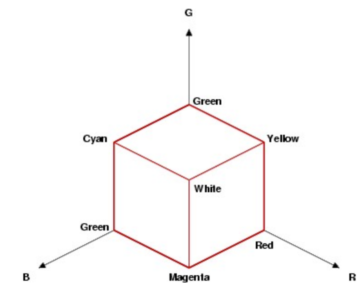


Represent colors in terms of cyan, magenta, and yellow

- The “K” stands for “Key”, not “black”

CMYK is a *subtractive* representation





- RGB is based on *composition*, i.e. it is an additive representation
  - Adding equal parts of red, green and blue creates white
- What happens when you mix red, green and blue paint?
  - Clue – paint colouring is subtractive..
- CMYK is based on *masking,* i.e. it is subtractive
  - The base is white
  - Masking it with equal parts of C, M and Y creates Black
  - Masking it with C and Y creates Green
    - Yellow masks blue
  - Masking it with M and Y creates Red
    - Magenta masks green
  - Masking it with M and C creates Blue
    - Cyan masks green
  - Designed specifically for *printing*
    - As opposed to rendering

An Interesting Aside

- Paints create subtractive coloring
  - Each paint masks out some colours
  - Mixing paint subtracts combinations of colors
  - Paintings represent subtractive colour masks

- In the 1880s Georges-Pierre Seurat pioneered an *additive-colour* technique for painting based on "pointilism"
  - How do you think he did it?

Quantization and Saturation

- Captured images are typically quantized to 8 bits
- 8-bits is not very much ~250:1
- Humans can easily accept 100,000:1
- And most cameras will give you only 6-bits anyway…
  - Truth in advertising!

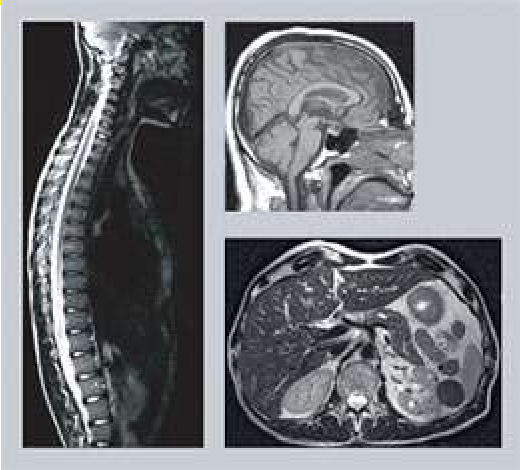
Processing Colour Images

- Typically work only on the Grey Scale image
  - Decode image from whatever representation to RGB
  - GS = R + G + B
- For specific algorithms that deal with colour, individual colours may be maintained
  - Or any linear combination that makes sense may be maintained.

Signals..

- Speech and Images are examples of signals where the digitized signal is a facsimile of the stimulus to be represented
  - Many other signals of this kind, including bio-signals, network traffic, etc.
- Next up : a signal where the digitized signal is *not* a direct facsimile of the data to be represented
  - Signal captured in a *transform* domain

Magnetic Resonance Imaging

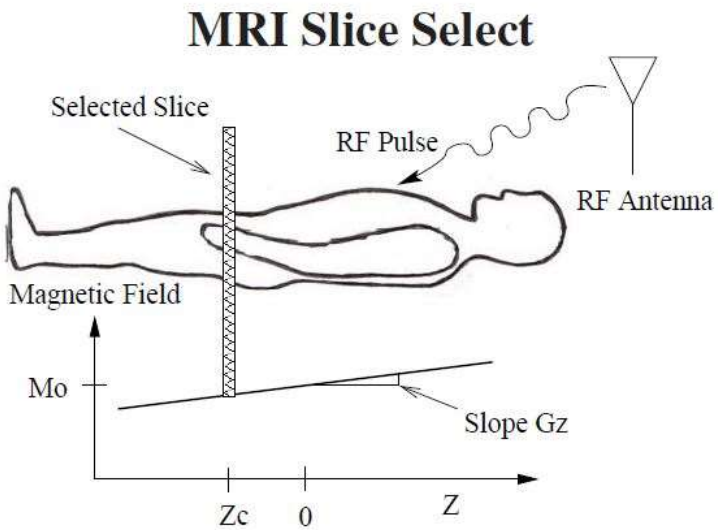


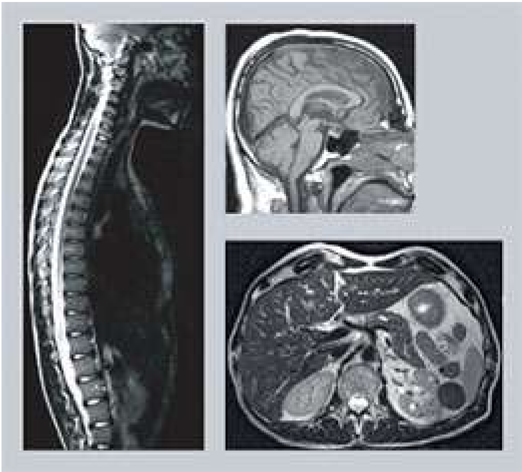
- Attempts to image *interior structure* of soft tissue
- Does so by imposing a magnetic field and measuring resonance of protons (Hydrogen atoms)

Cross-section of a body

- Image changes left to right, top to bottom at different rates at different locations
  - Different tissue densities…
  - … which show up as a range of “spatial frequencies”

MRI





- Takes *slice-wise* measurements in the *Fourier domain*
- A single "gradient field" derives response from a single "spatial frequency" component
  - Which can be measured
- Sequence of *gradient fields* derive resonant response of different *spatial frequencies* of tissue slice
  - Effectively a 2D Fourier transform
- Must invert transform to create image
- "Join" slices for full 3-D reconstruction

Poll 4

Poll 4

- What is the key difference between MRI imaging and and XRAY
  - MRI using EM waves, while Xrays use XRays
  - MRI is very similar to XRays
  - **MRIs are captured in a transform domain and must be decoded to obtain the image, while XRays are captured directly in the image domain**
  - MRIs are captured are multiple images, while XRays only capture a single image

What we *do* with signals

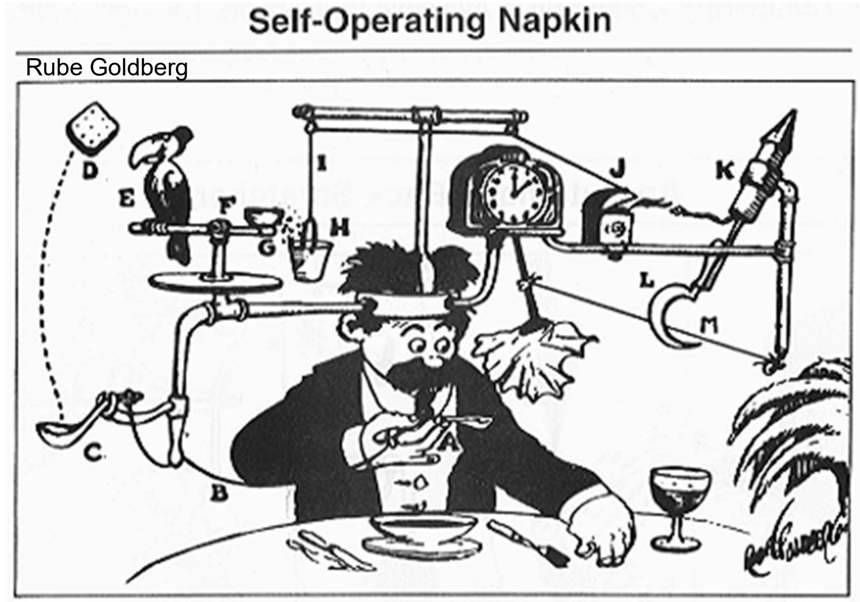
- Have seen examples of signals and caveats of signal capture
- Next: Machine Learning challenges in dealing with the data

Representation

- Signals can be *decomposed* into combinations of building blocks
  - Different signals of any category composed as different combinations of the same building blocks
  - Knowing the composing combination informs us about the properties of the signal
    - But requires knowing the building blocks
    - Using the wrong building blocks will give us imprecise or meaningless conclusions

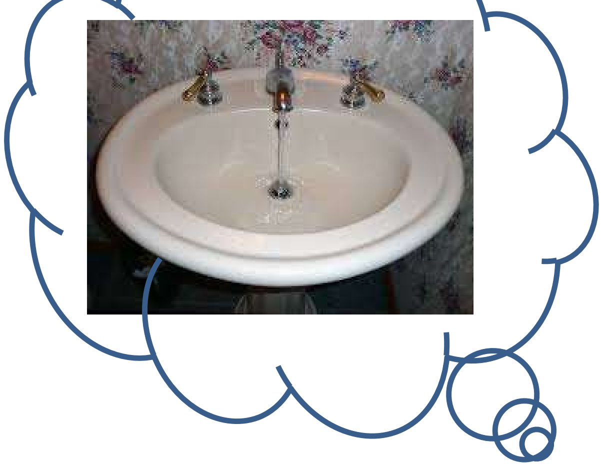
- **ML challenge**: Find building blocks from analysis of signals
  - Mathematically: $\mathbf{S} = f(\mathbf{B},\mathbf{W})$, find $\mathbf{B}$ and $\mathbf{W}$ from $\mathbf{S}$
  - $\mathbf{S}$ = signal, $\mathbf{B}$ = building blocks, $\mathbf{W}$ = combination parameters, $\mathbf{f}$ = combination function

Modelling



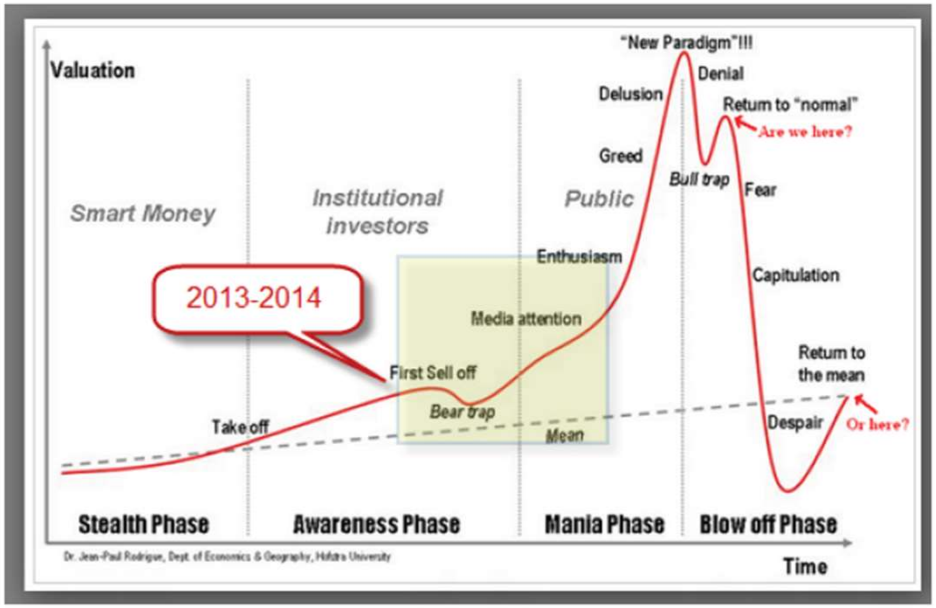
- Signals are produced by *processes*
  - Which are generally partially or fully unknown
- Knowledge of the process is often crucial for additional processing
  - Control, prediction, analysis
- **ML challenge**: Characterizing the process underlying the signal
  - Characterization through statistical properties of the signal
  - Characterization through an abstract parametric model

Classification



- Signals may arise from different classes of stimuli/processes
- Often needed to identify underlying process/stimulus
- **ML challenge**: Identify underlying "class" of the signal

Prediction



- Signals can be analyzed to make predictions about the future of the signal or the underlying process
- **ML challenge**: How to make the "best" predictions

Supervision

- Learning representations and modeling are often preliminary steps to classification and prediction
- Can be performed *without* reference to the actual classification/prediction task
  - *Unsupervised* learning
- Can be explicitly optimized

Supervision

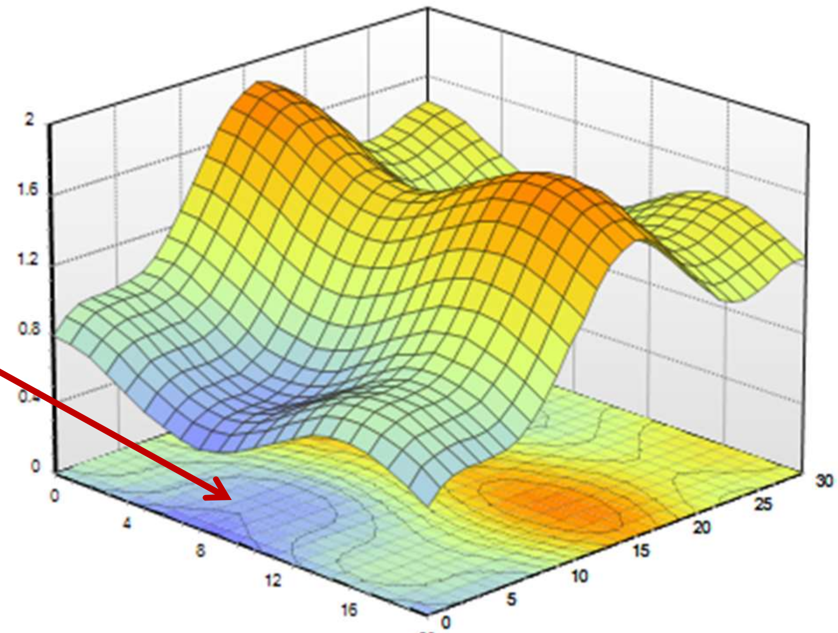
- Task: Detect if it’s a face
- Unsupervised representation: characterize edges, gradation
  – Does not specifically help with problem
- Supervised representation: characterize nose-like features, eyebrow-like features, mouth-like features…
  – Better suited to detect faces

Primary tools of the trade..

- Linear algebra
  - Some calculus
- Optimization
- Probability…

Optimization

Find this spot!



- Machine learning problems often require finding parameters/values that "optimize" an objective
- Typical objectives
  - Error of constructing a signal
  - Accuracy of predicting future
  - Error in classifying signal
- Problem: Given only variation of objective w.r.t. parameters of algorithm, find the optimal set of parameters

Optimization: Formulation

- In the majority of machine learning task, a set of samples is provided $z_1, z_2, \ldots, z_n$
- Supervised learning

$$z = (x, y)$$

$$h \textit{ is predictor function } h : X \to Y$$

$$\min imize\ f(h;(x,y)) = loss\ function\,(h(x), y)$$

- Unsupervised learning (k-mean clustering)

$$z = x \in \Re^d$$

$$h = (\mu_1, \ldots., \mu_k) \in \Re^{d \times k},\ \textit{which corresponds to cluster centers}$$

$$\min imize\ f((\mu_1, \ldots., \mu_k); x) = \min_j \left\| \mu_j - x \right\|^2$$

Next Class..

- Review of linear algebra..