CS598 PS Machine Learning for Signal Processing

Fixed Features and their Origins

2 September 2020

Today's overview

- Features and their importance
- Human perception of signals
- Fixed features for machine perception

Why features?

- Features are a very important subject
  - Bad features make problems unsolvable
  - Good features make problems trivial

- Learning how to pick features is the key
  - So is understanding what they mean

A simple example

- How do we compare two numbers?

Case 1

$$x = 3$$
$$y = 3$$

Case 2

$$x = 3$$
$$z = 100$$

A simple example

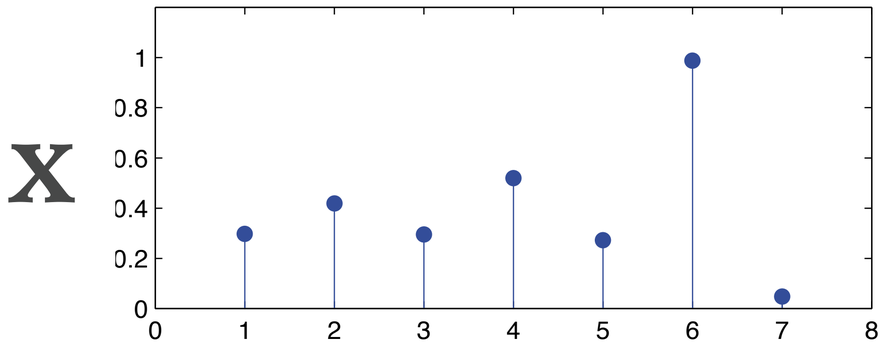
- We can use their distance:

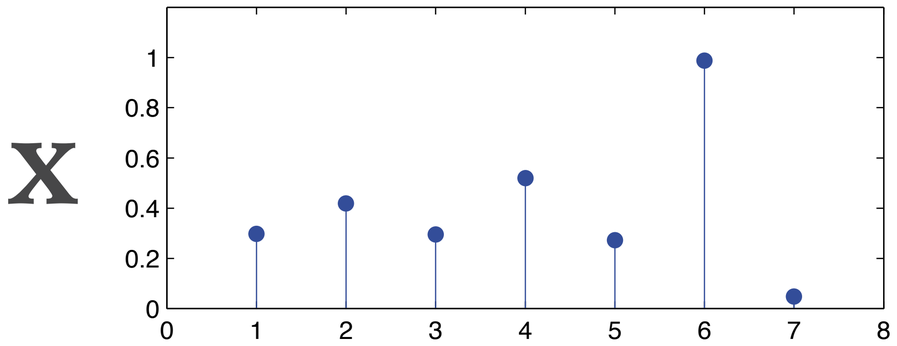
$$\left\|x - y\right\| = 0 \qquad \left\|x - z\right\| = 97$$

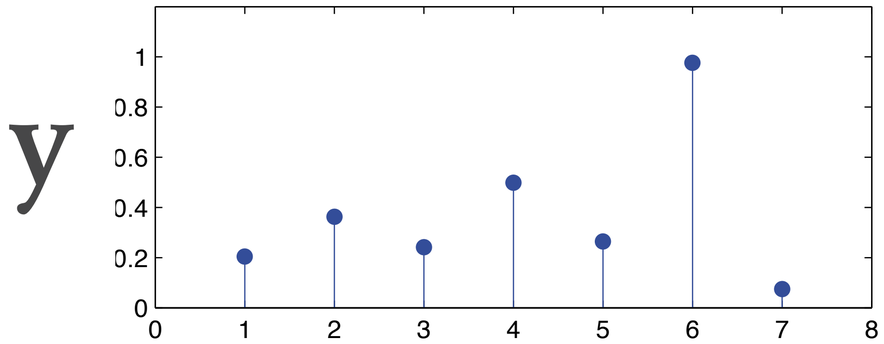
  - x,y similar but x,z not so much
- Best way to represent a number is itself!

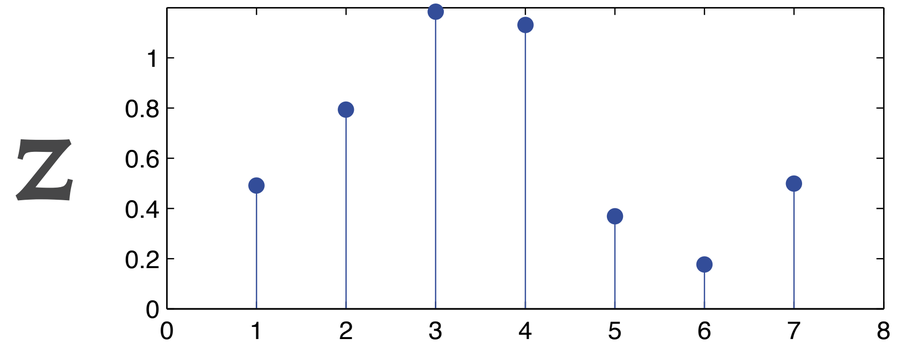
Moving up a level

- Comparing two vectors:









Moving up a level

- Make up a distance measure:

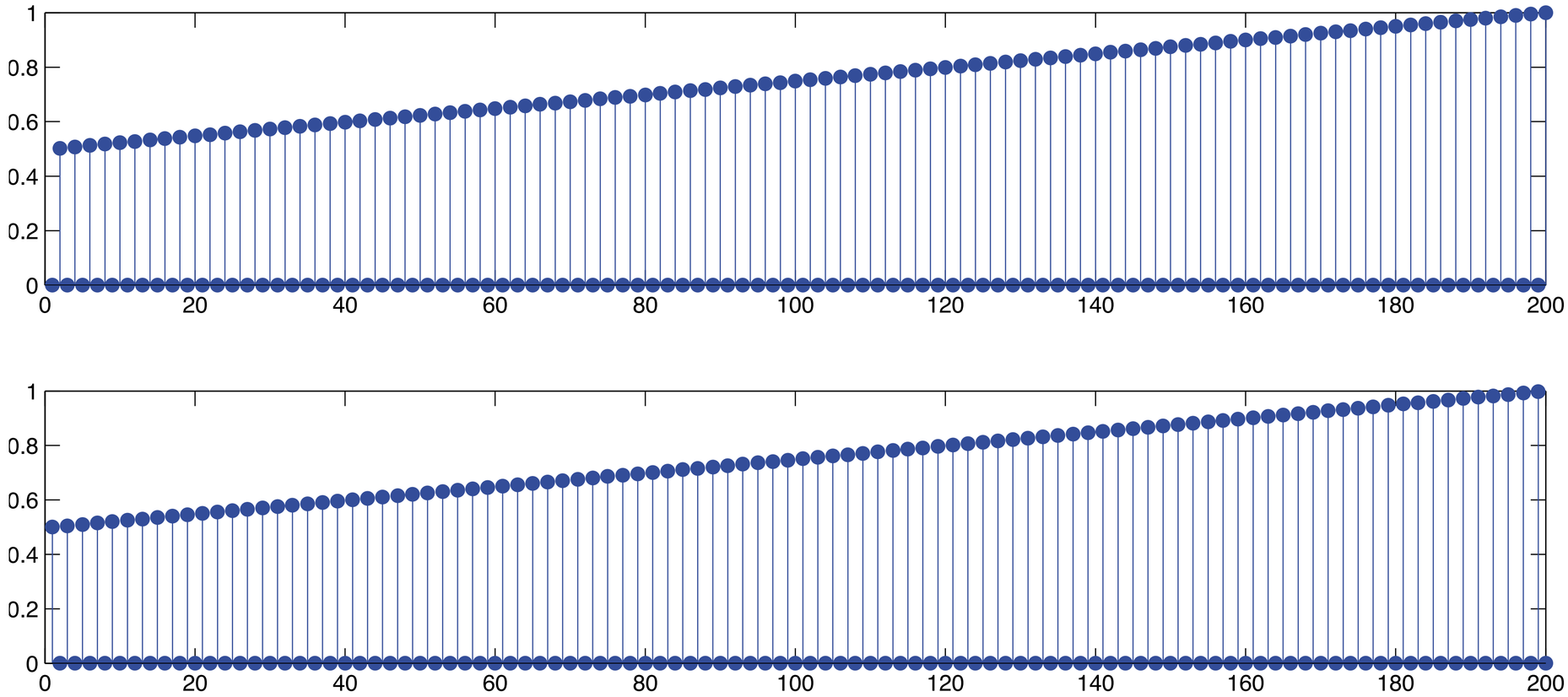
$$\angle \mathbf{x}, \mathbf{y} = 4.9^\circ \qquad \angle \mathbf{x}, \mathbf{z} = 48.2^\circ$$

$$\left\| \mathbf{x} - \mathbf{y} \right\| = 0.12 \qquad \left\| \mathbf{x} - \mathbf{z} \right\| = 1.48$$

  - We simply generalize the scalar approach

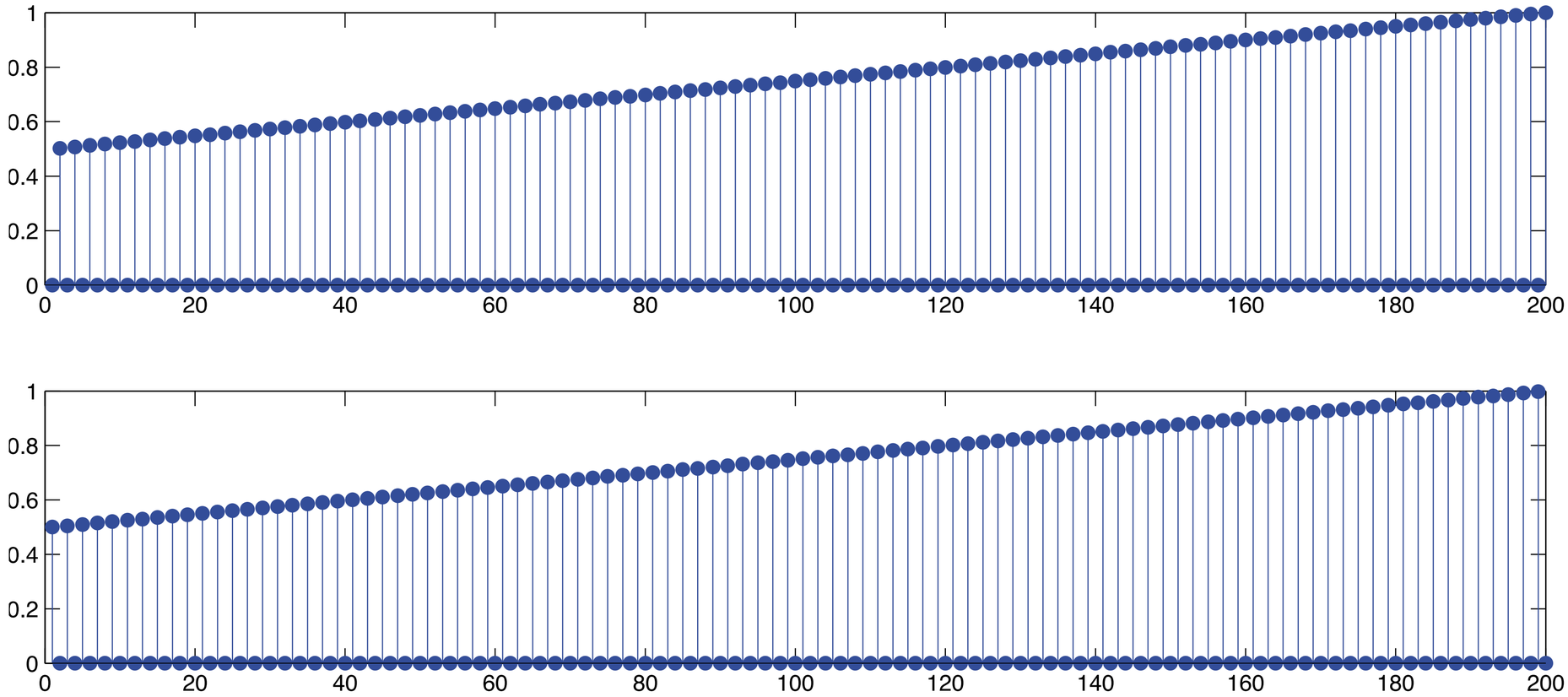
Moving up again

- Compare two longer vectors:



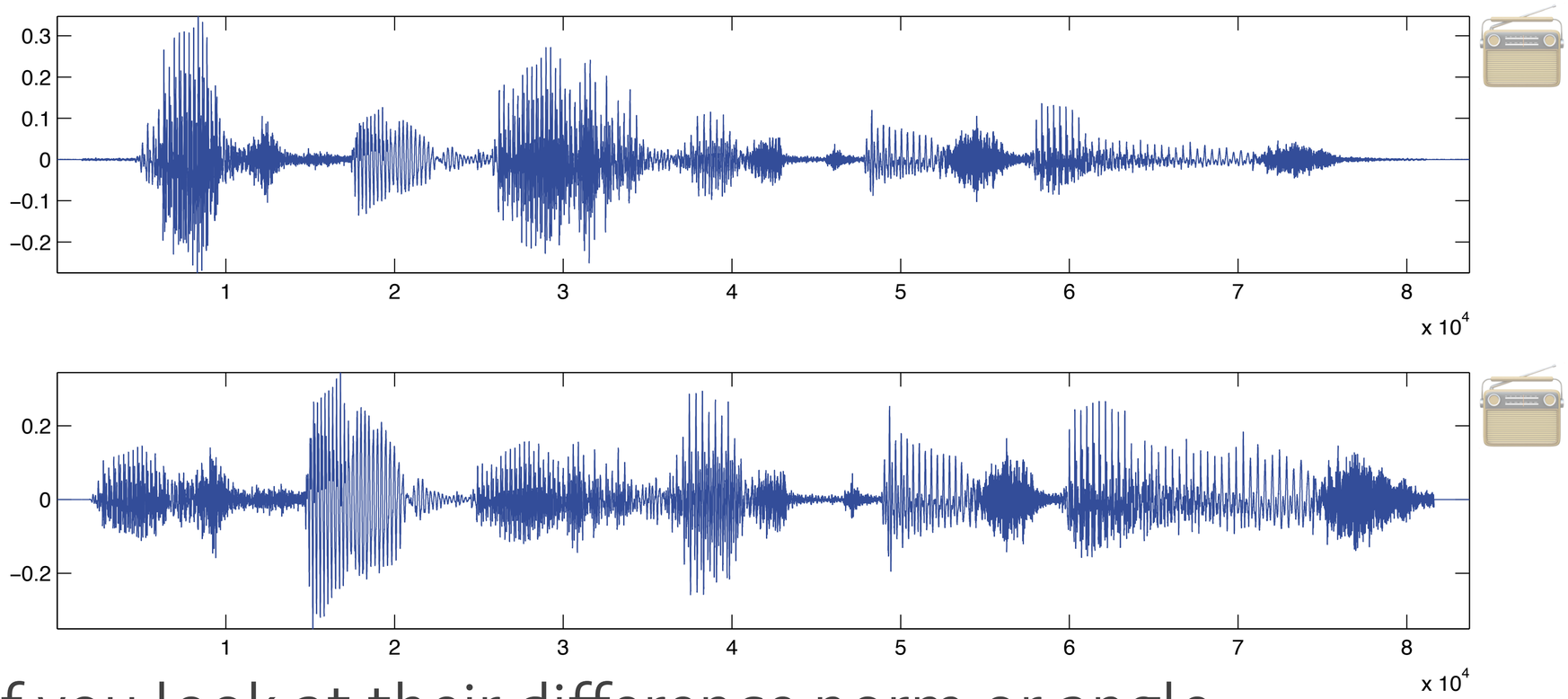
Look similar but are not!

- Oops! $\angle \mathbf{x}, \mathbf{y} \approx 90^\circ, \quad \left\| \mathbf{x} - \mathbf{y} \right\| = 10.8$



How about this?

- Are these two vectors the same?



- Not if you look at their difference norm or angle …

And with matrices

- Comparing:

$$\mathbf{X} = \begin{bmatrix} 1. & 1.98 \\ 3.05 & 4. \end{bmatrix} \text{ and } \mathbf{Y} = \begin{bmatrix} 1.1 & 2. \\ 3. & 3.9 \end{bmatrix}$$

$$\mathbf{X} = \begin{bmatrix} 1. & 1.98 \\ 3.05 & 4. \end{bmatrix} \text{ and } \mathbf{Z} = \begin{bmatrix} 100 & 200 \\ 300 & 400 \end{bmatrix}$$

- Use the norm again:

$$\left\|\mathbf{X} - \mathbf{Y}\right\| = 0.13, \quad \left\|\mathbf{X} - \mathbf{Z}\right\| = 541$$

Image matrices

- Similar images, but the distances don't say so!

X

Y

Z

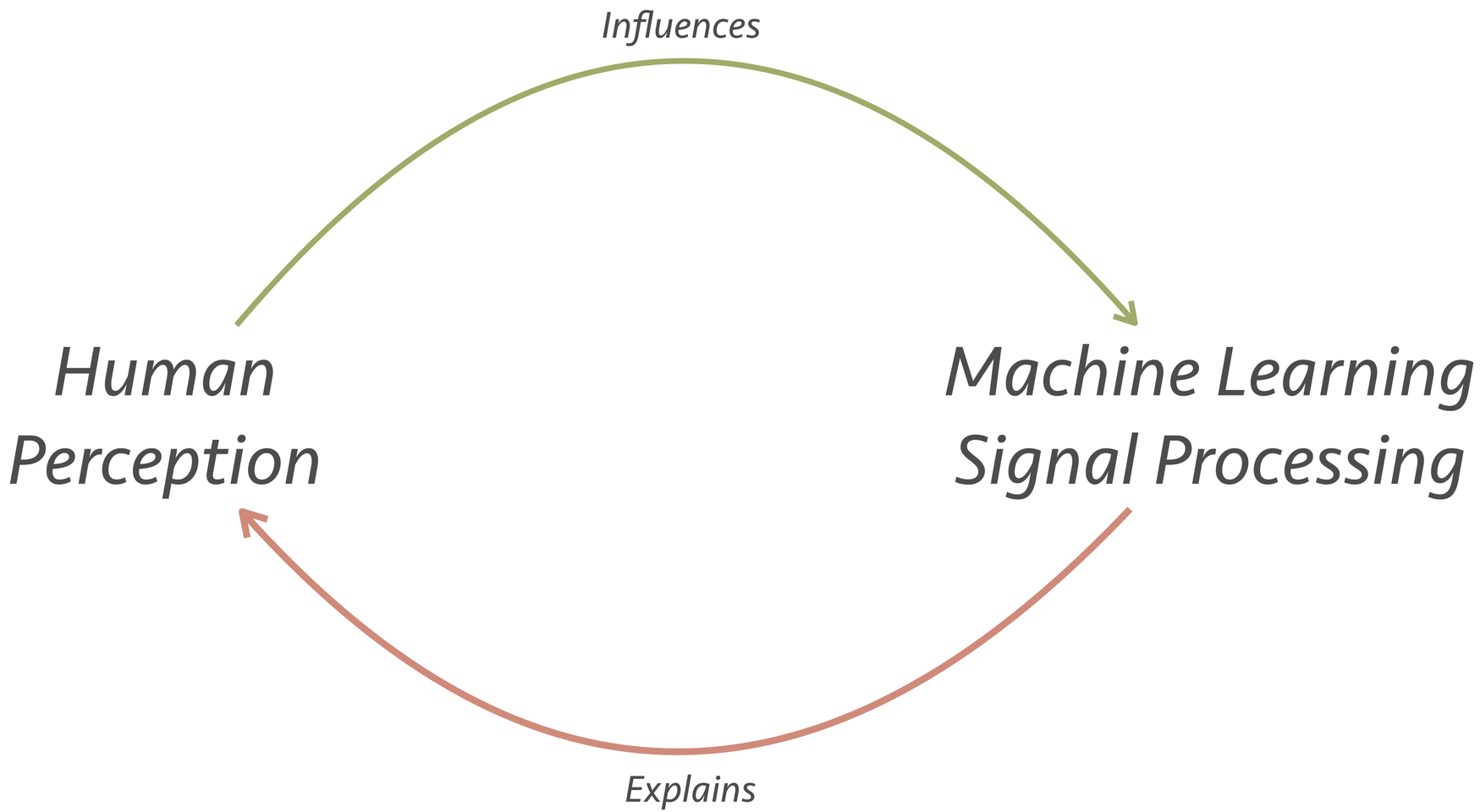
Difference norms won't get you far!

- You need to articulate what matters
  - You need to know what matters
- *Features* are the means to do so
- Let's examine what matters to us
  - Sounds and images
    - And we can then generalize based on this

Human perception

- It is important to know what we perceive
  - We've had a few billion years of MLSP refinement!
- Use that knowledge to design features
- Applies to domains we directly perceive
  - Vision, audition, touch, olfaction
  - But helps in figuring out the rest too
    - bio signals, network data, communications, etc

The bigger picture

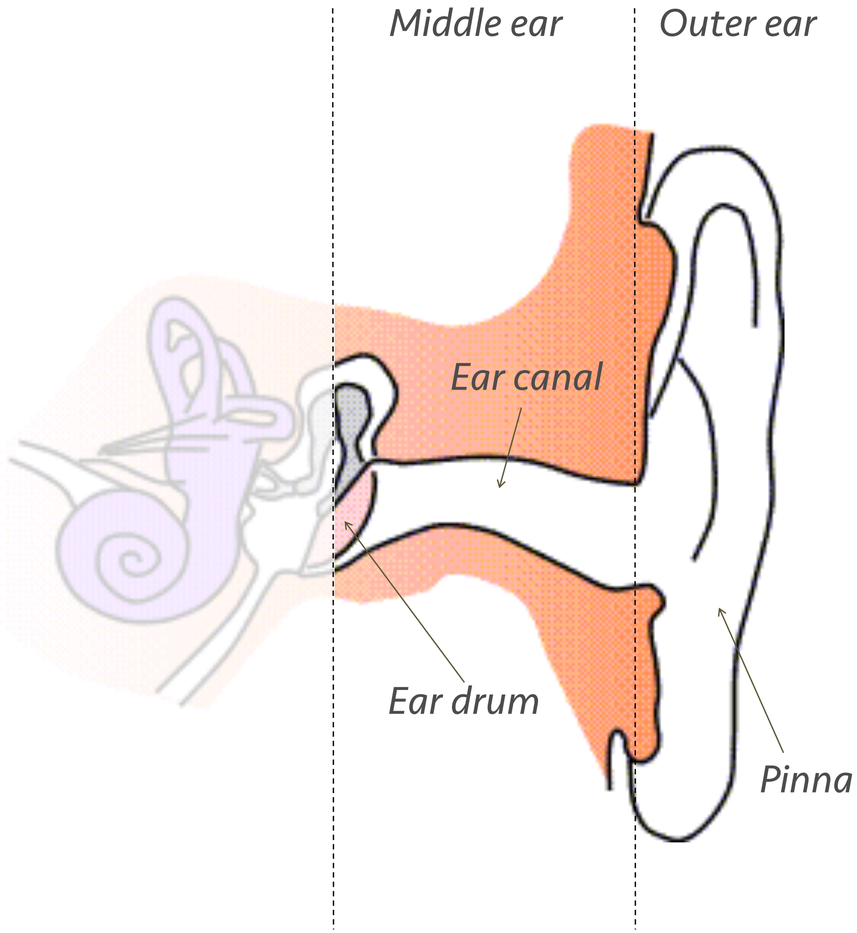


A bit of hearing

- Sounds and hearing
  - Easy 1D signals to start with
- Human hearing aspects
  - Physiology and psychology
- Lessons learned

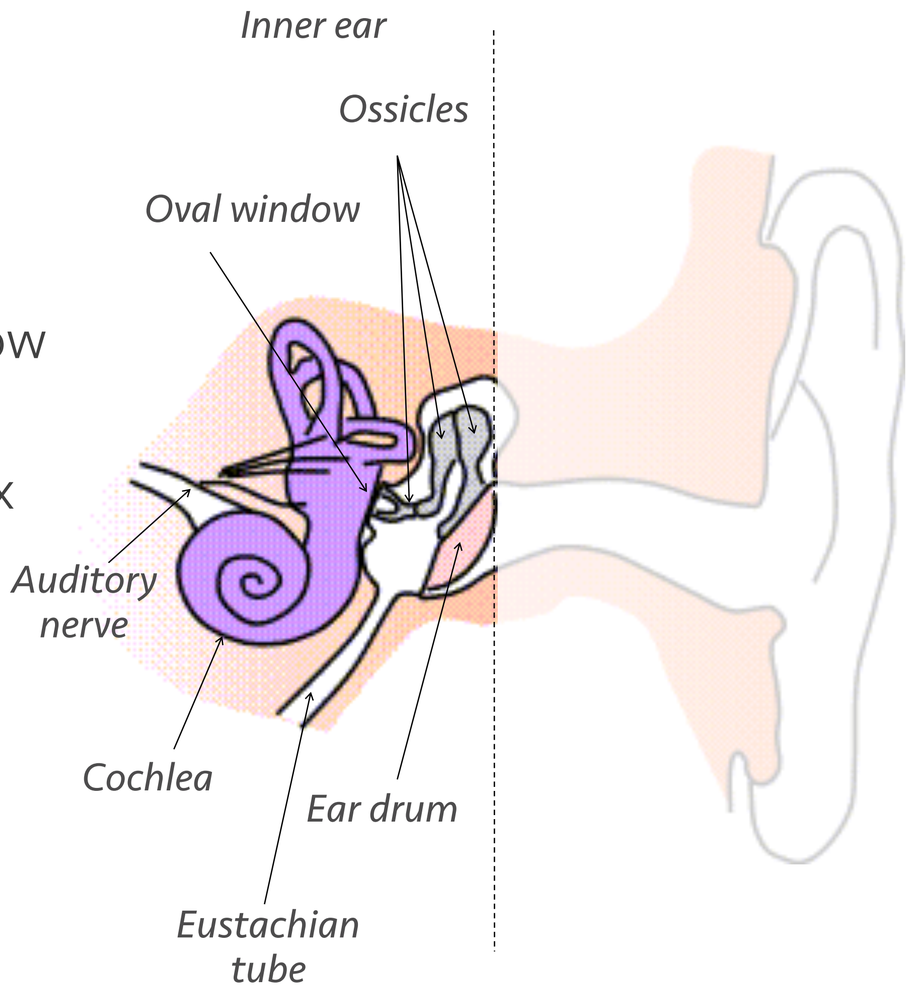
The hardware (outer/middle ear)

- The pinna (auricle)
  - Aids sound collection
  - Does directional filtering
  - Holds earrings, etc ...
- The ear canal
  - About 25mm x 7mm
  - Amplifies sound at ~3kHz by ~10dB
  - Helps clarify a lot of sounds!
- Ear drum
  - End of middle ear, start of inner ear
  - Transmits sound as a vibration to the inner ear



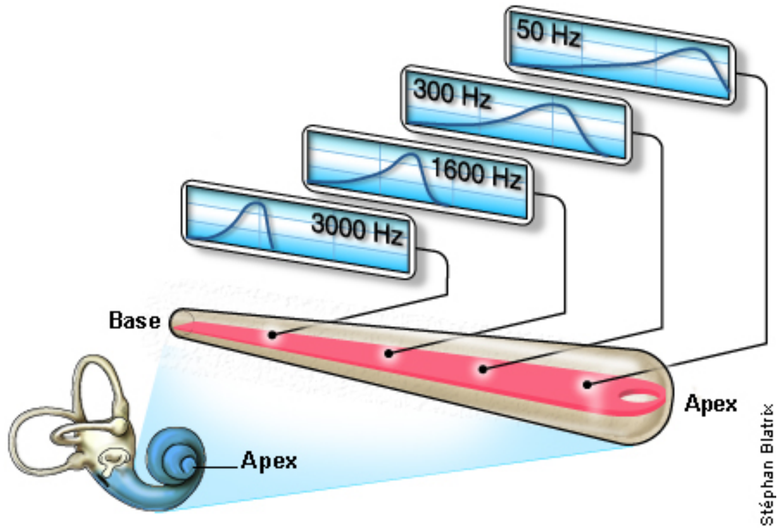
More hardware (inner ear)

- Ear drum (tympanum)
  - Excites the ossicles (ear bones)
- Ossicles
  - Malleus (hammer), incus (anvil), stapes (stirrup)
  - Transfers vibrations from the ear drum to the oval window
  - Amplify sound by ~14dB (peak at ~1kHz)
  - Muscles connected to ossicles control the acoustic reflex (damping in presence of loud sounds)
- The oval window
  - Transfers vibrations to the cochlea
- Eustachian tube
  - Used for pressure equalization



The cochlea

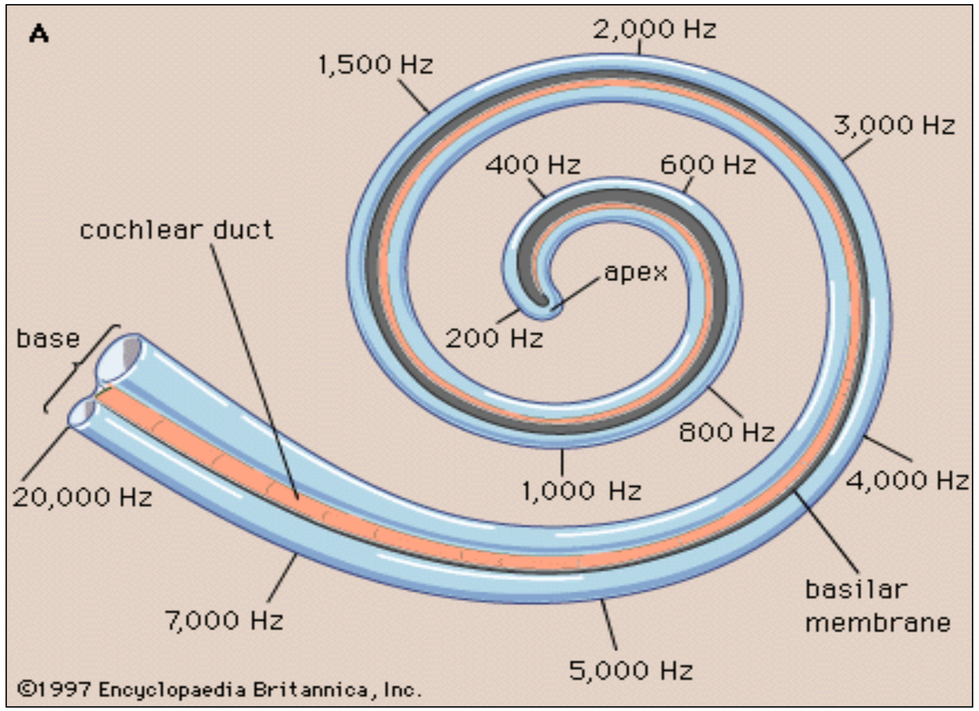
- The “mechanical to electrical” converter
  - Translates oval window vibrations to a neural signal
  - Fluid filled with the basilar membrane in the middle
  - Each section of the basilar membrane resonates with a different sound frequency
  - Vibrations of the basilar membrane move sections of hair cells which send off neural signals to the brain
- The cochlea acts like the equalizer display in your music player 
  - Frequency domain decomposition
- Neural signals from the hair cells go to the auditory nerve

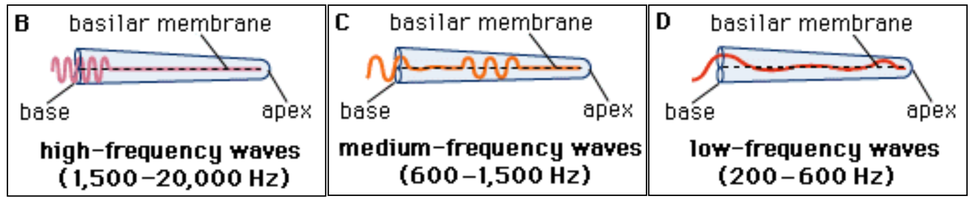


Microscope photograph of hair cells (yellow)

Masking & critical bands

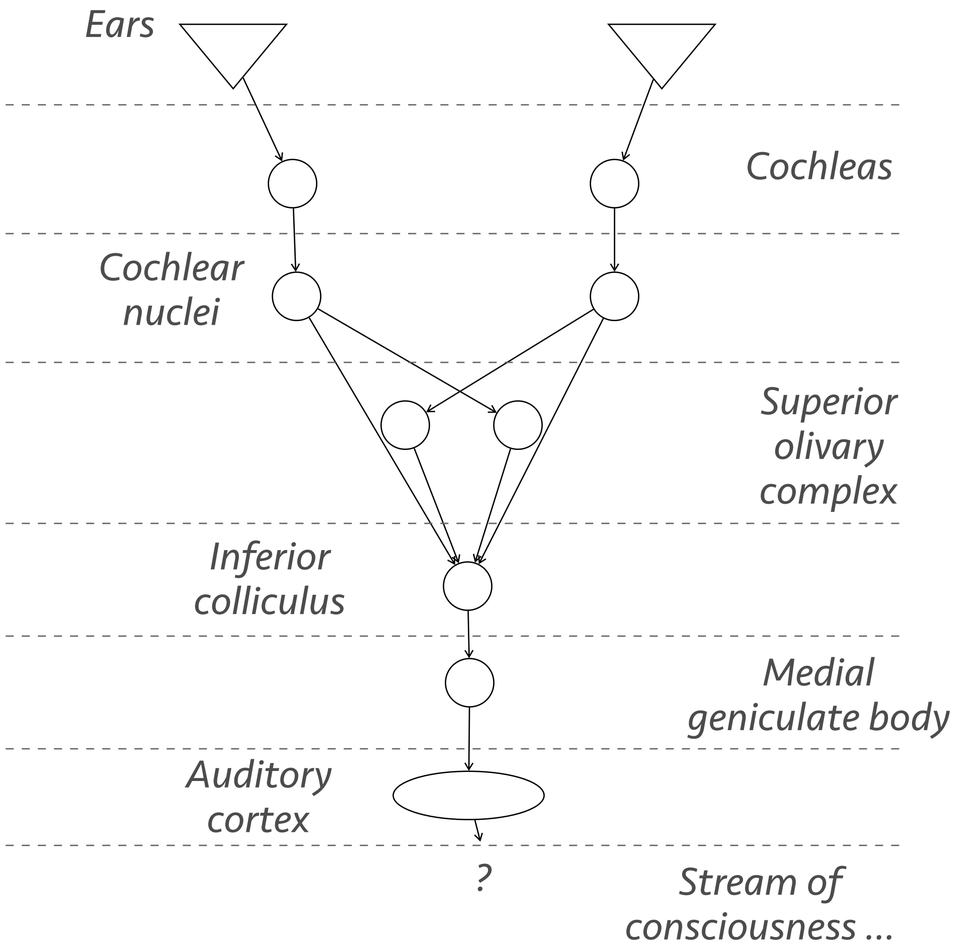
- When the basilar membrane is excited by two tones in the same region, the softest of the two will be masked
  - E.g. two sinusoids at 150Hz and 170Hz, if one sinusoid is loud enough the other will be inaudible
- There are 24 such “critical bands”
  - Simultaneous excitation on a band by multiple sources results in some masking
- There is also temporal masking
  - Preceding sounds mask what’s next





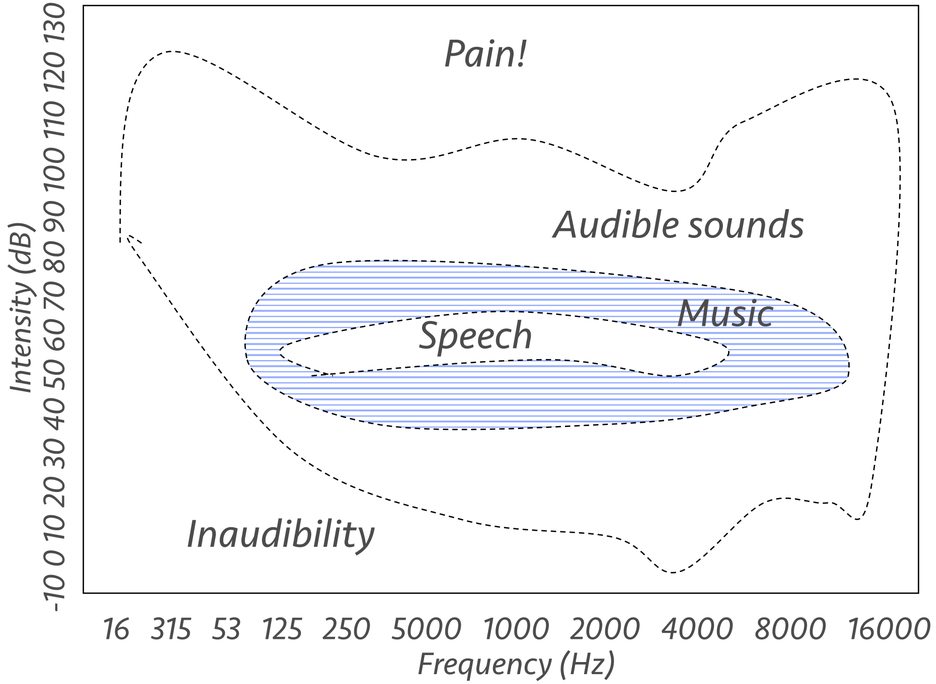
The neural pathways

- Cochlear nuclei
  - Prepping/distribution of neural data from cochlea
- Superior Olivary Complex
  - Coincidence detection across ear signals
  - Localization functions
- Inferior Colliculus
  - Last place where we have most original data
  - Probably initiates first auditory images in brain
- Medial Geniculate Body
  - Relays various sound features (frequency, intensity, etc) to the auditory cortex
- Auditory Cortex
  - Reasoning, recognition, identification, etc
  - High-level processing



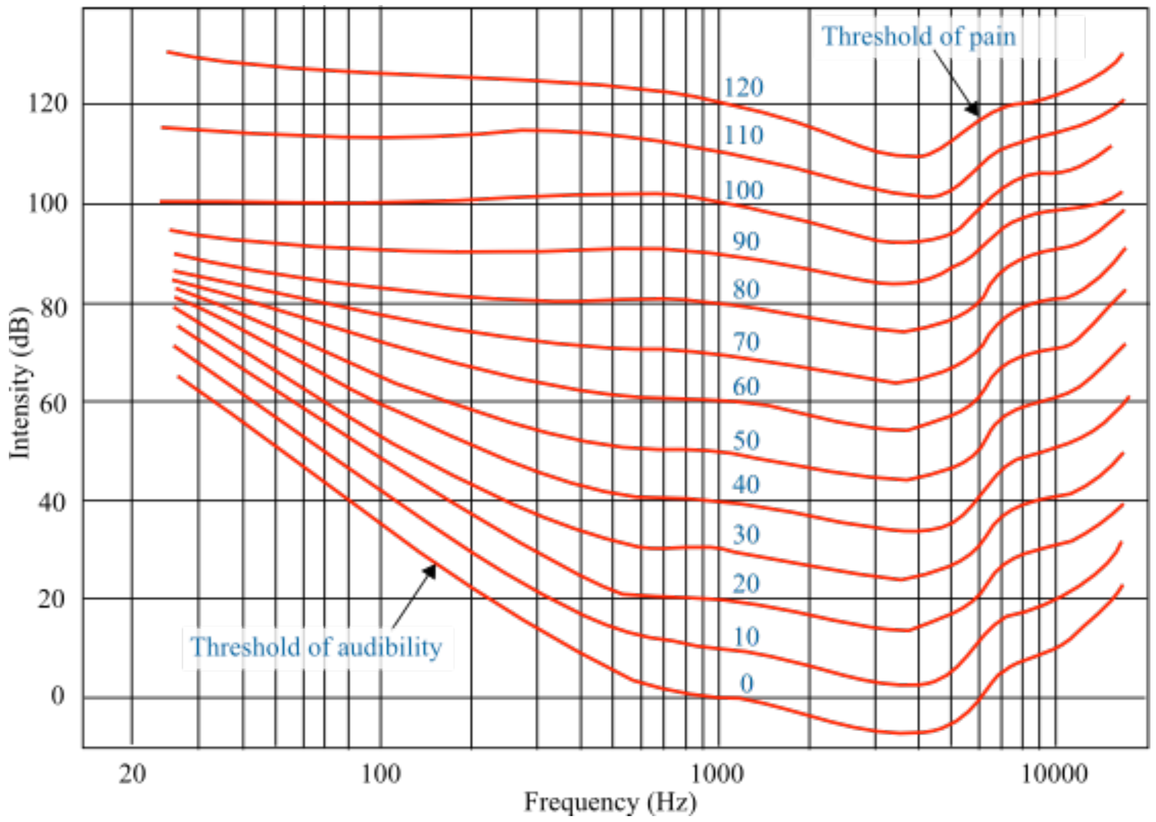
The limits of hearing

- Frequency
  - 20Hz to 20kHz (upper limit decreases with age/trauma)
  - Infrasound (< 20Hz) can be felt through skin
  - Ultrasound (> 20kHz) can be "emotionally" perceived (discomfort, nausea, etc)
- Loudness
  - Low limit is 2×10^{-10} atm
  - 0dB SPL to 130dB SPL (frequency dependent)
    - A dynamic range of 3,000,000 to 1!
  - 130dB SPL threshold of pain
  - 194dB SPL is definition of a shock wave, sounds stops!



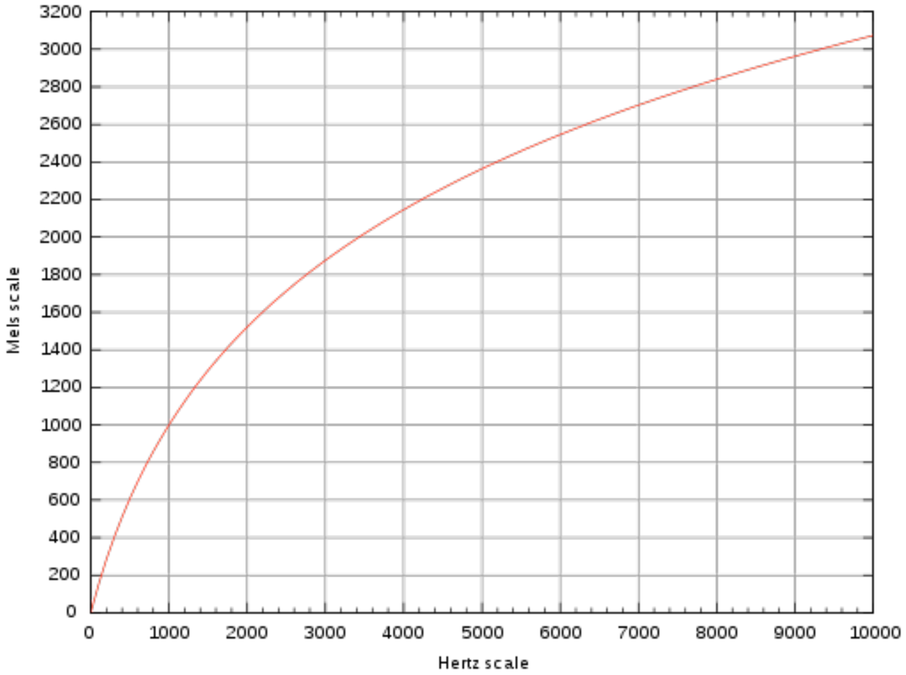
Perception of loudness

- Loudness is subjective
  - Perceived loudness changes with frequency
  - Perception of “twice as loud” is not really that!
- Fletcher-Munson curves
  - Equal perceived loudness over frequencies
- Just noticeable difference is about 1dB SL
- 1kHz to 5kHz are best heard frequencies
  - What the ear canal and ossicles amplify!
- Low limit shifts up with age!



Perception of pitch

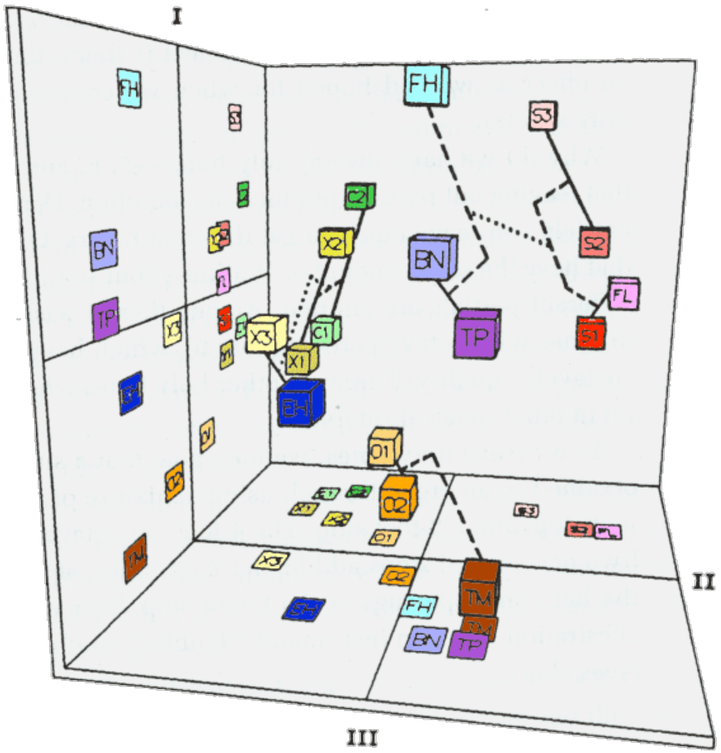
- Pitch is also a subjective (and arbitrary) measure
- Perceived doubling of pitch doesn't imply a real doubling of frequency
  - Mel scale is the perceptual pitch scale
  - 2× Mels correspond to a perceived pitch doubling
- Musically useful range varies from 30Hz to 4kHz
- Just noticeable difference is about 0.5% of frequency
  - Varies with training though



"Pitch is that attribute of auditory sensation in terms of which sounds may be ordered from low to high"
- American National Standards Institute

Perception of timbre

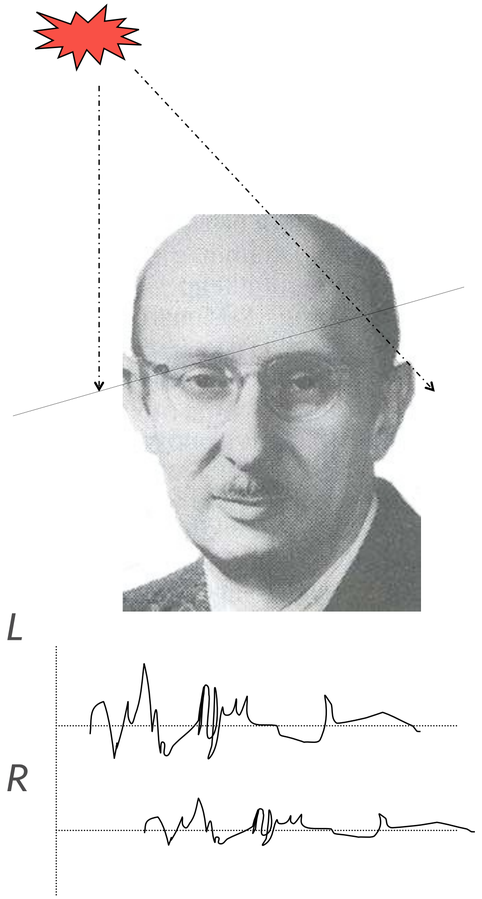
- Timbre is what distinguishes sounds outside of loudness & pitch
  - Another bogus ANSI description!
- Timbre is dynamic and can have many facets which often include pitch and loudness
- There is not a coherent body of literature examining human timbre perception
  - But there is a huge bibliography on computational timbre perception!



Gray's timbre space of musical instruments

Binaural hearing

- Having two ears is good!
  - We can localize sounds around us
  - We can wear glasses …
- Interaural differences provide the cues
  - Interaural time diff (ITD)
  - Interaural intensity diff (IID)
  - Other extra filtering by pinnae, head, and torso
- Detecting these creates a *spatial* percept
- Borrowing these ideas we can design sensor arrays



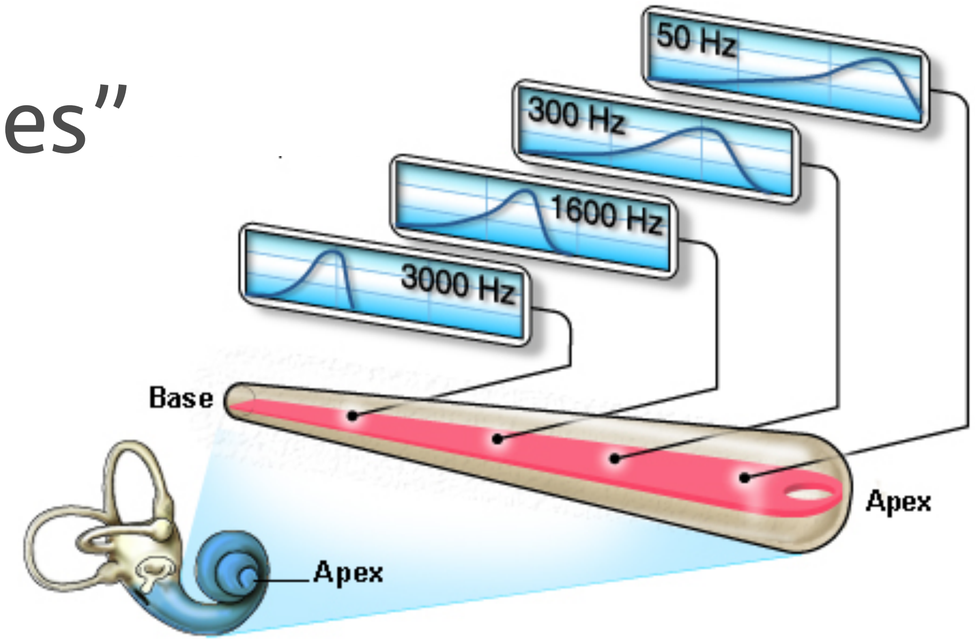
This is a CS class, why all this?

- All these processes provide an insight
  - They encapsulate important statistics of sounds
    - Which is what machine learning all is about!
  - They suggest features and scales that we should use

- To make machines that cater to our needs
  - We need to learn from our perception

Lessons learned from the cochlea

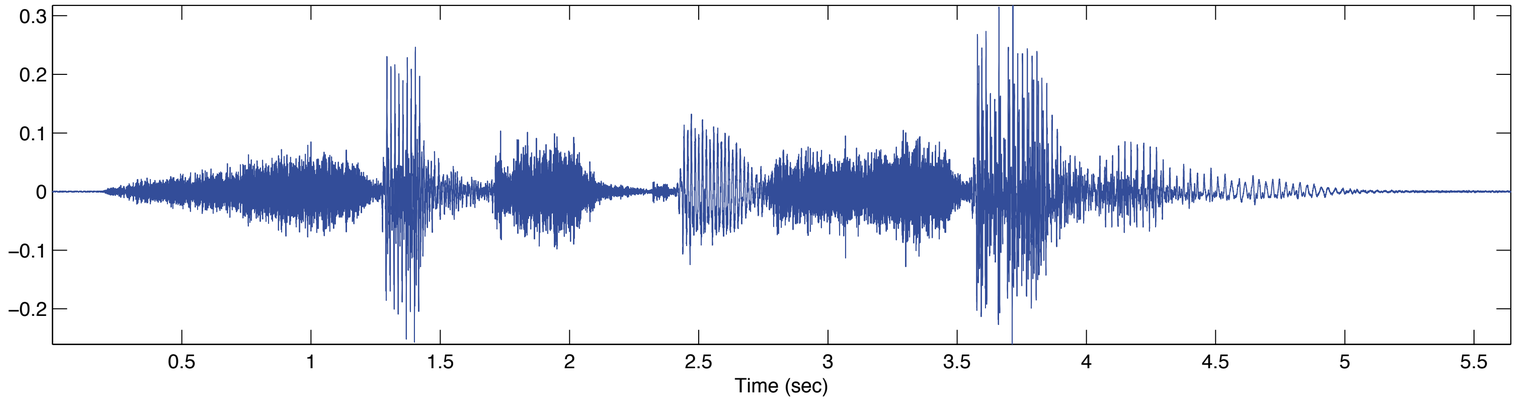
- Sounds are not vectors of samples
  - This is not what we process when we hear
- Sounds are “groups of frequencies”
  - That is the perceptual feature used
- Frequency representations are what we should use

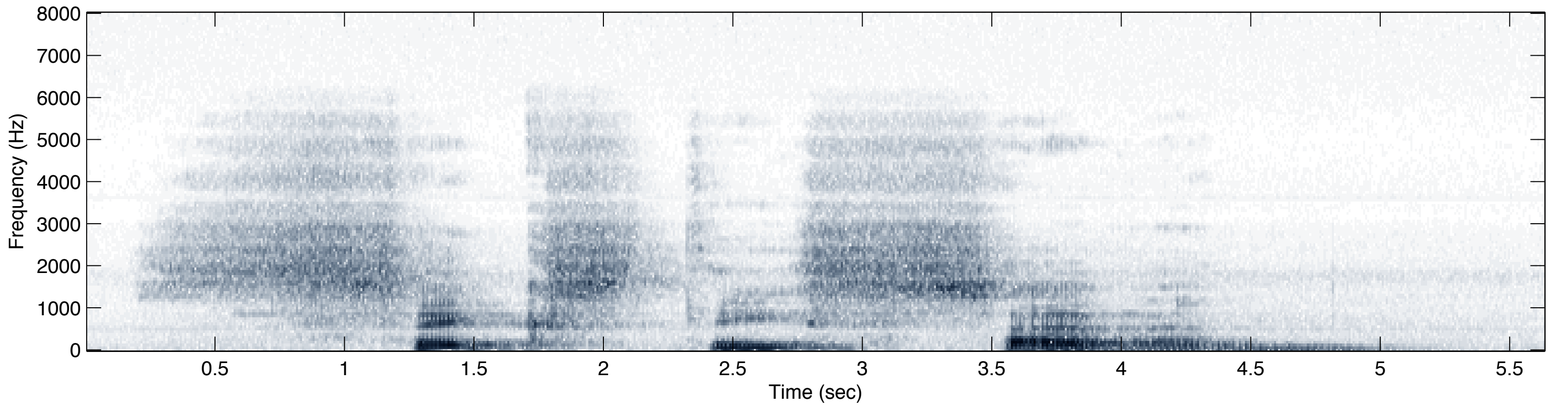


Emulating the cochlea

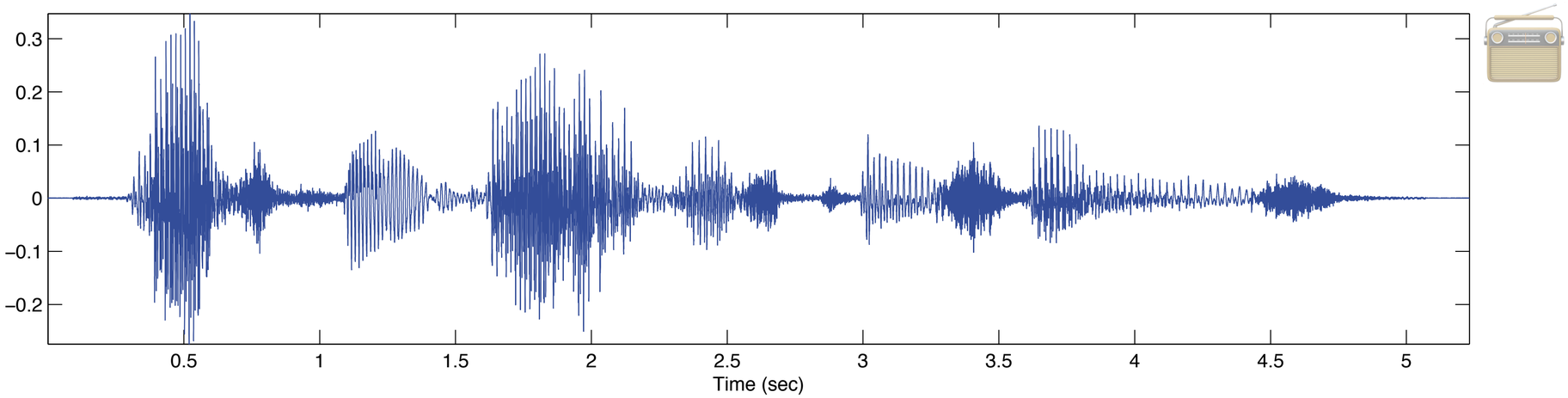
- Using the time/frequency domain

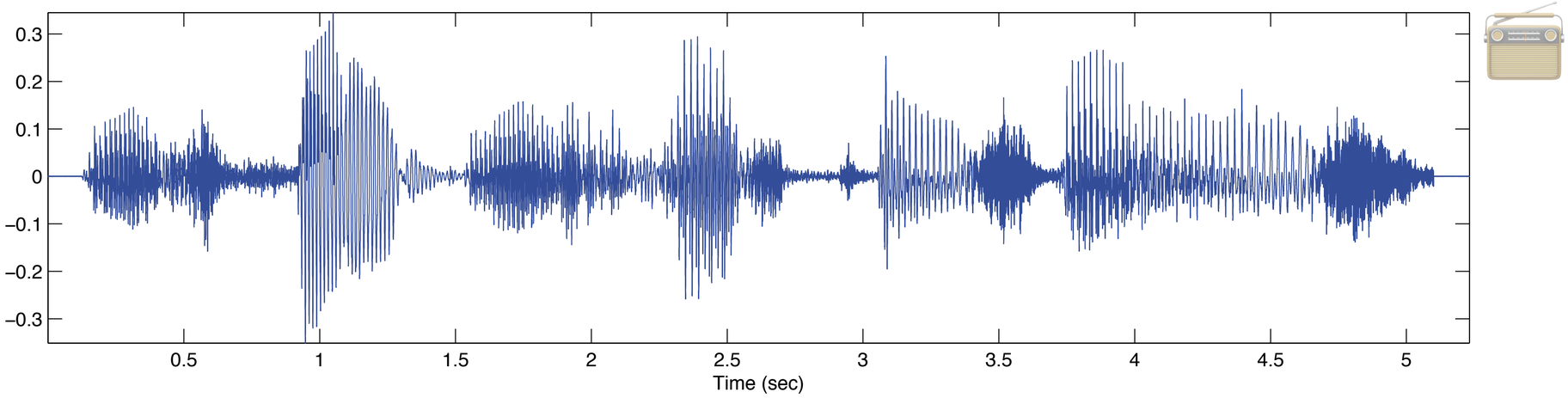
  - Take successive DFTs
  - Keep their magnitude
  - Stack them in time
  - Now you can compare sounds!



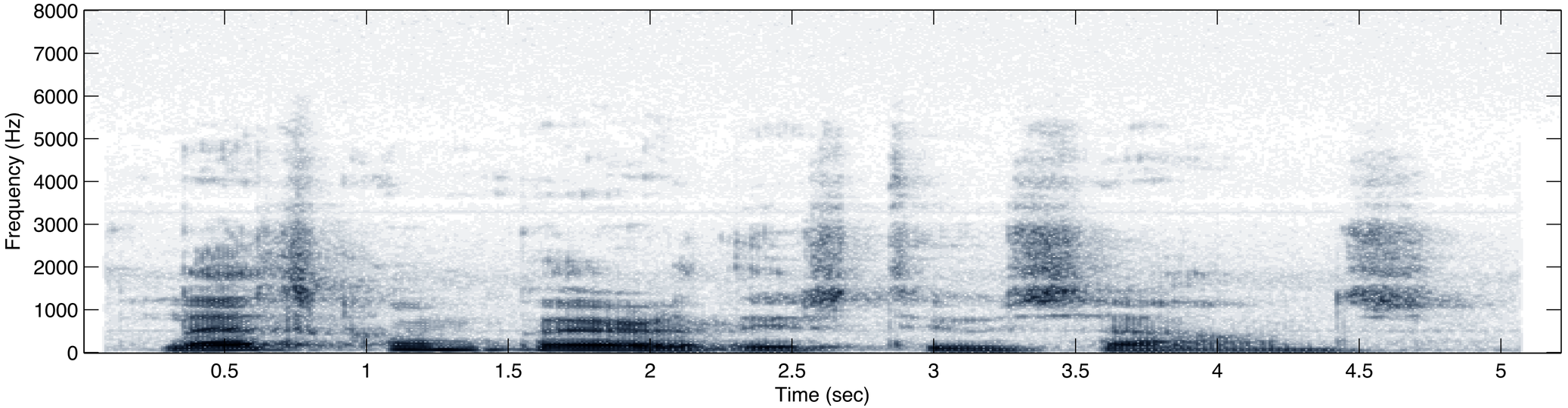


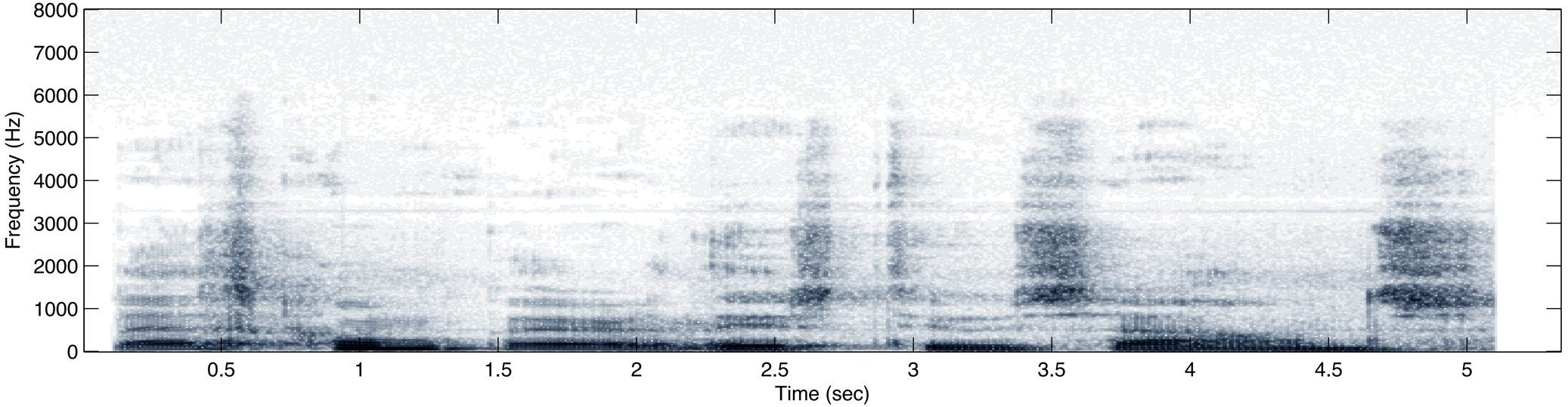
Example input





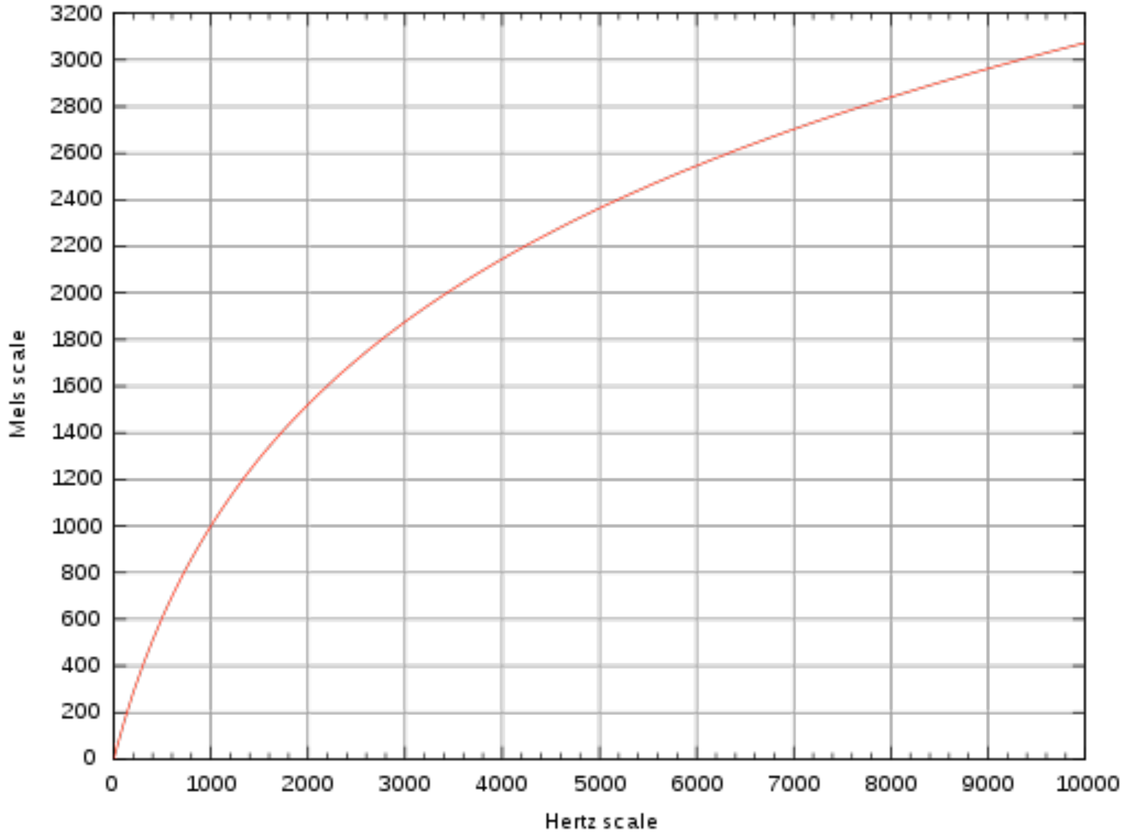
Example features



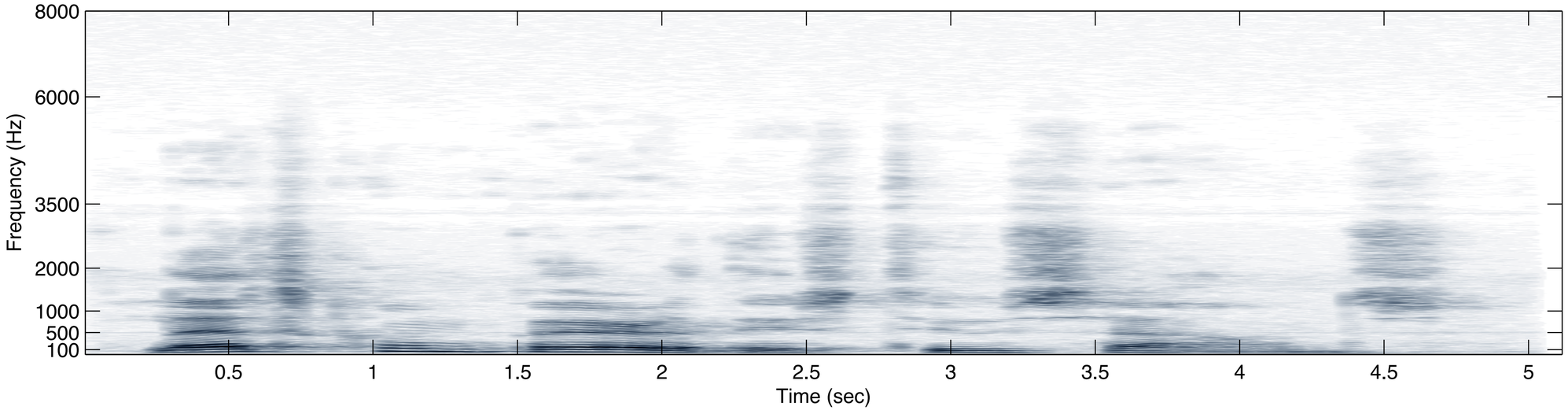


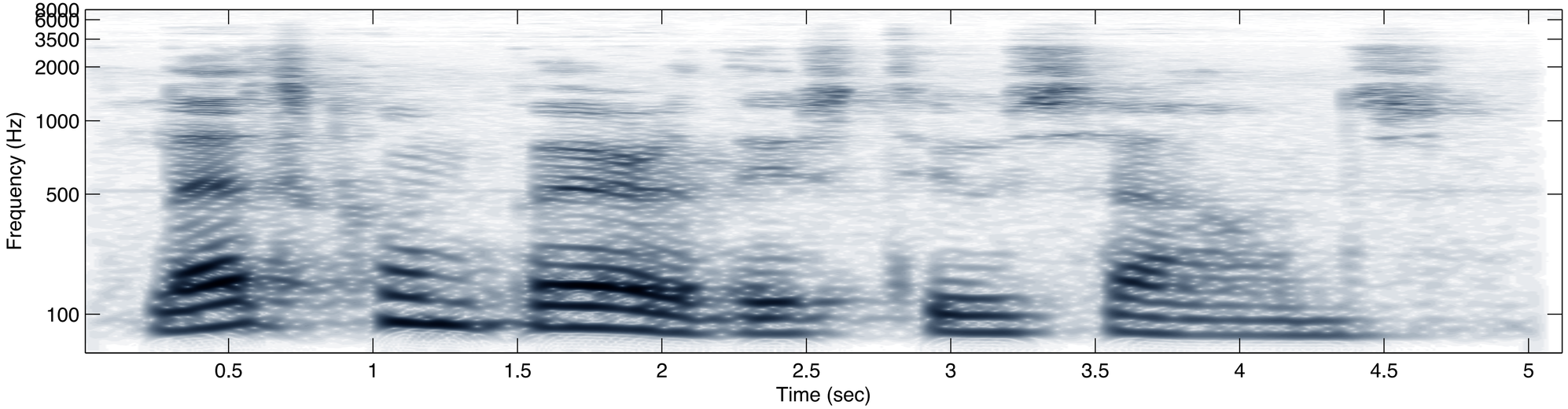
A lesson from pitch perception

- Frequencies are not “linear”
  - Perceived scale is called *mel scale*
- Use that spacing instead
  - i.e. warp the frequency axis



Warped spectra





A lesson from loudness perception

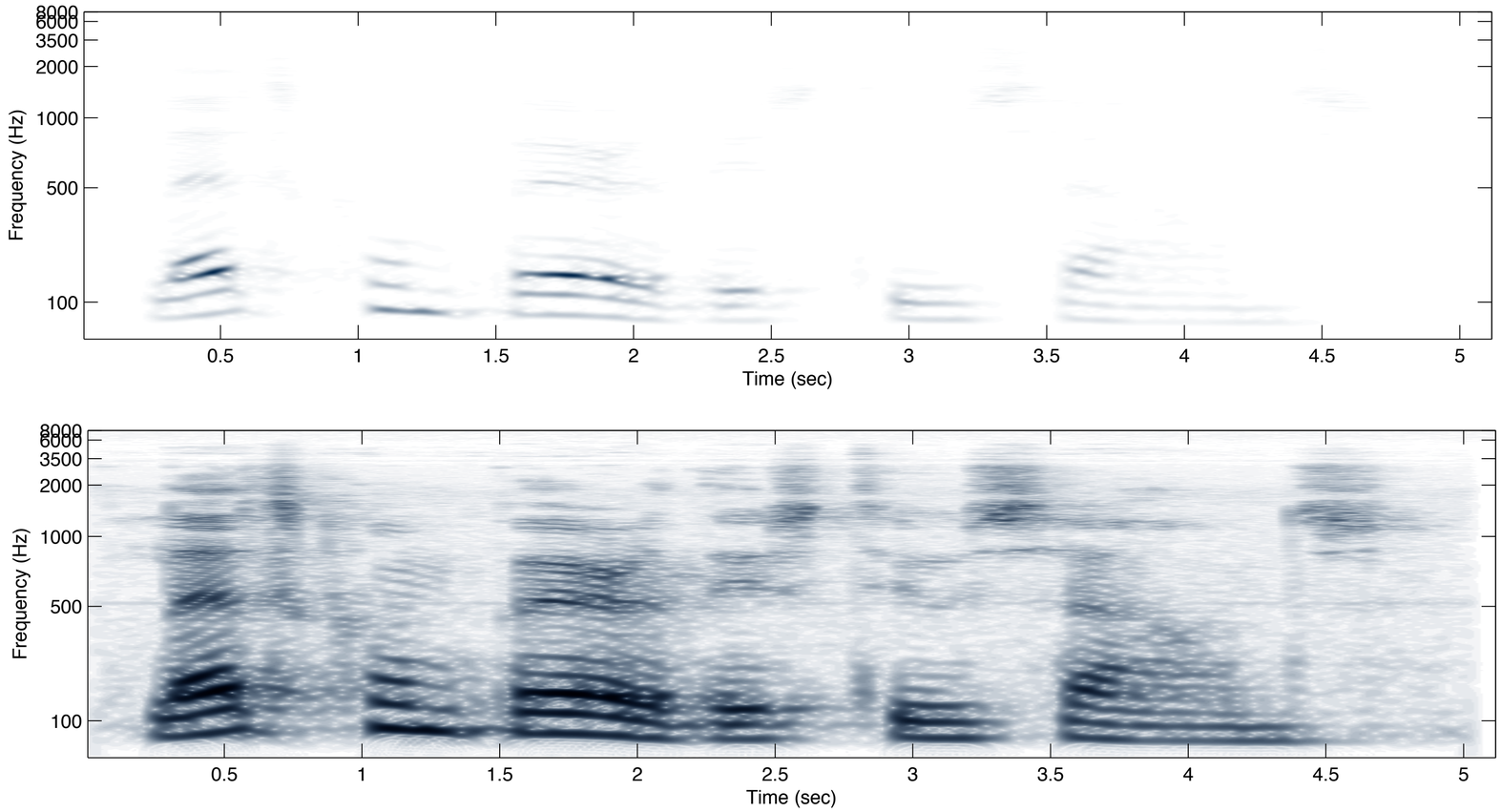
- We don’t perceive loudness linearly either
- How much louder is the second utterance?

Two words, how much louder is the second one?

- Representation of magnitude shouldn’t be linear

Linear scale to log scale

- I've been cheating and showing logarithmic energy already
  - It's hard to really see the data in linear scale



Sound recap

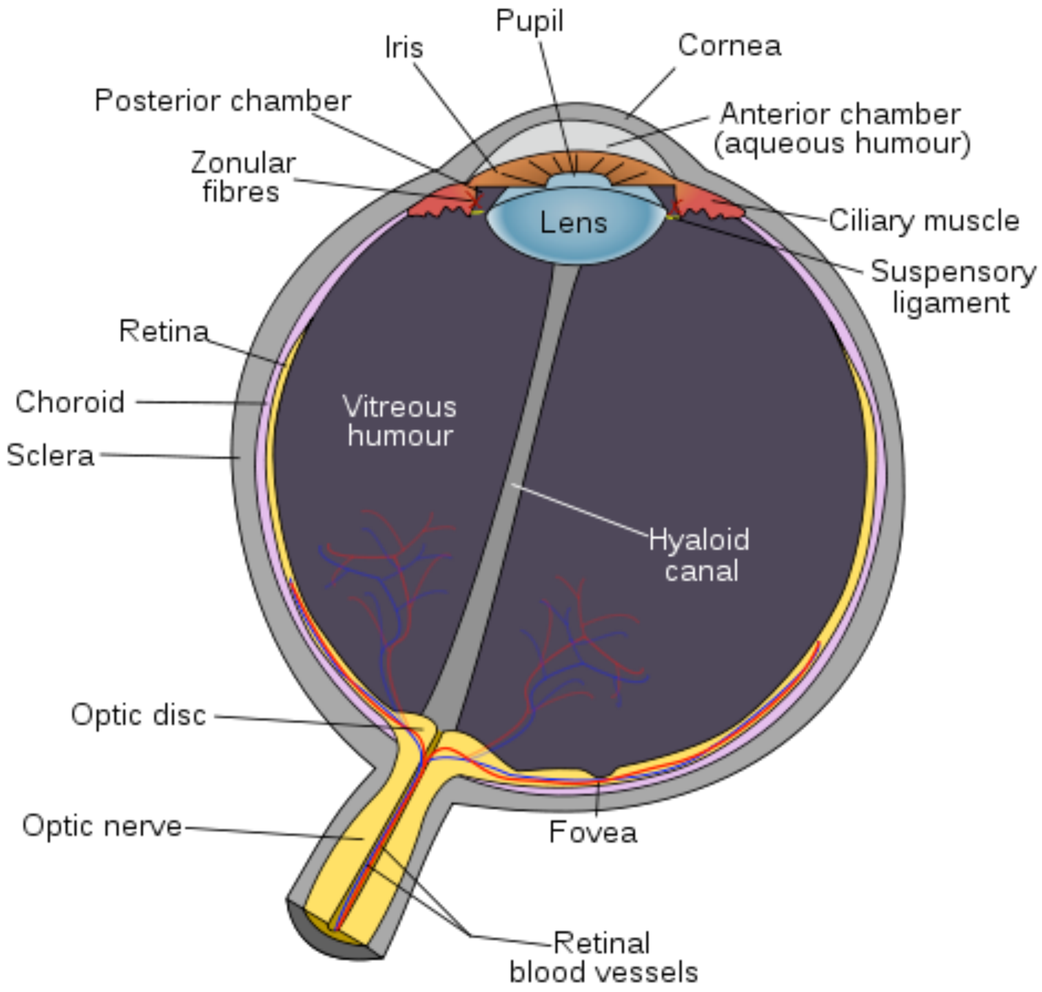
- Go to time/frequency domain
  - We do so in the cochlea
- Frequencies are not linear
  - We perceive them in another scale
- Amplitude is not linear either
  - Use log scale instead
- Resulting features are the backbone of all speech tech!
  - Further tweaks exist (more later)

Seeing

- Images and videos
  - Typical 2/3D signals
- Bit of physiology and psychology
- Using these to represent images

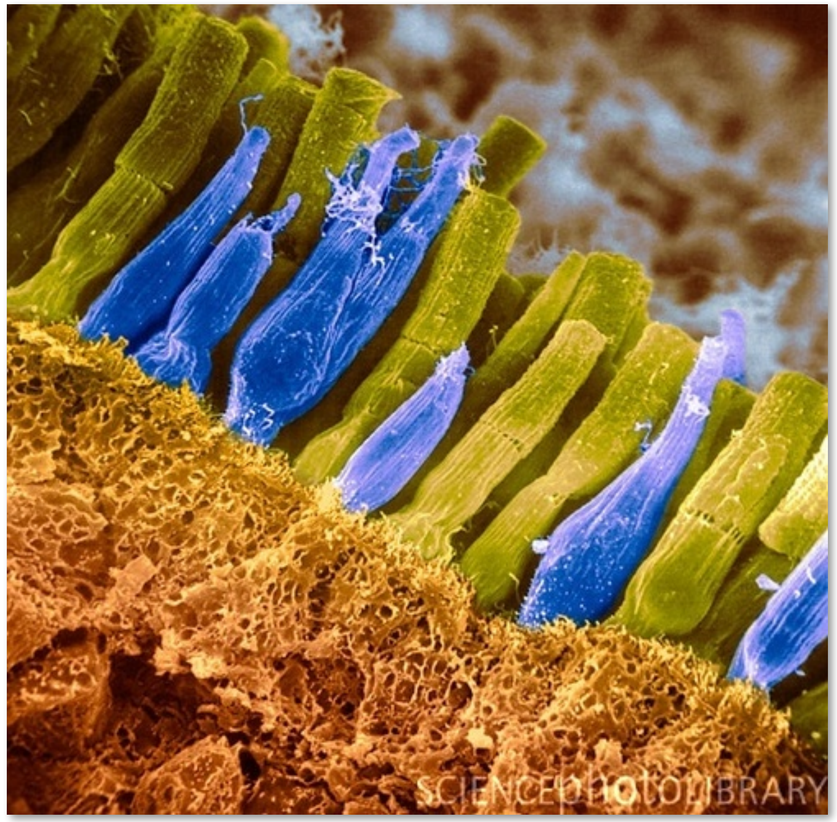
The hardware

- The human eye
  - Lens in the front
  - Retina in the back
- The lens projects an incoming image on the retina
- Retina translates to neural code



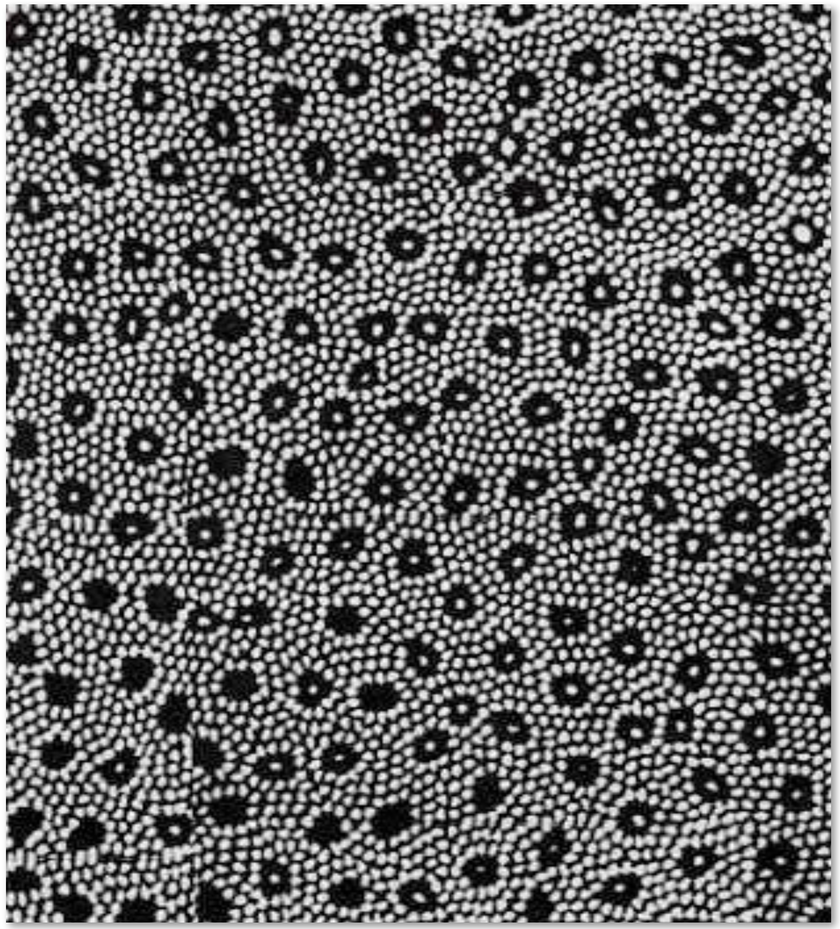
The retina

- Think of it as the equivalent to the cochlea
  - Does a preliminary feature coding
- Photoreceptor cells
  - Mostly rods and cones
- Acts like a film



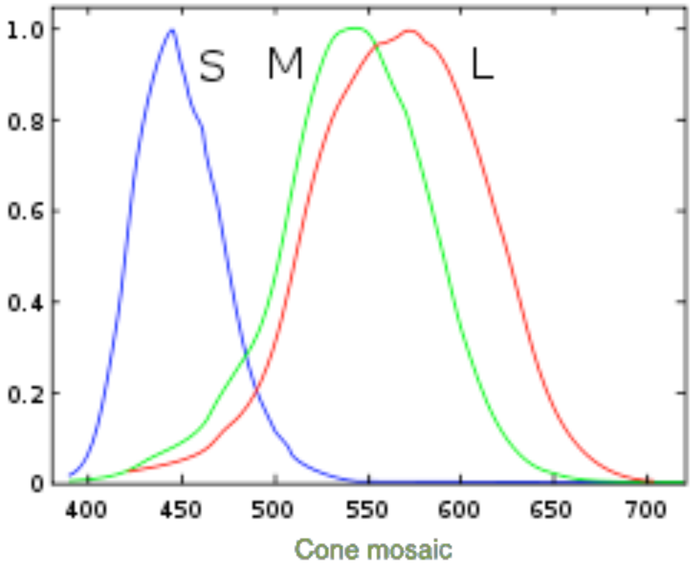
Rods and cones

- Neurons that convert light to electricity
  - “Phototransduction”
- Cones
  - Detect color, need lots of light
  - ~8 million of them
  - Mostly in the center of the retina
- Rods
  - Not much color, work with minimal light
  - Located all around the retina
  - Many more than cones, ~120 million

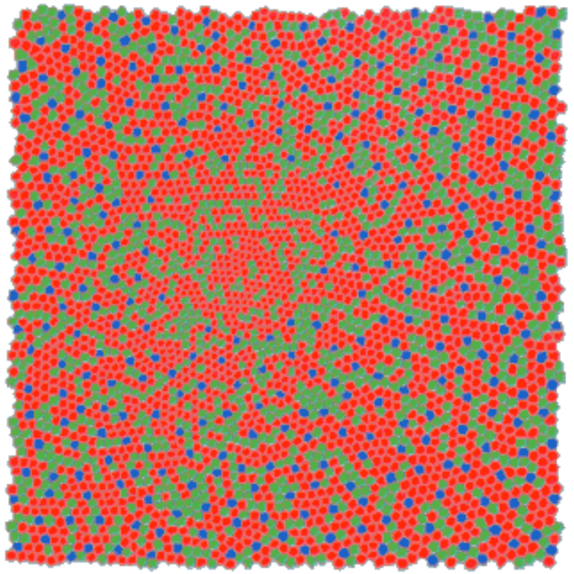


Cones and color

- Three kinds of cones
  - Short/Blue
    - React to short wavelengths
    - Very few (S/(M+L) = .01)
  - Medium/Green
    - React to medium wavelengths
  - Long/Red
    - React to long wavelengths
    - More of them (L/M = 1.5)

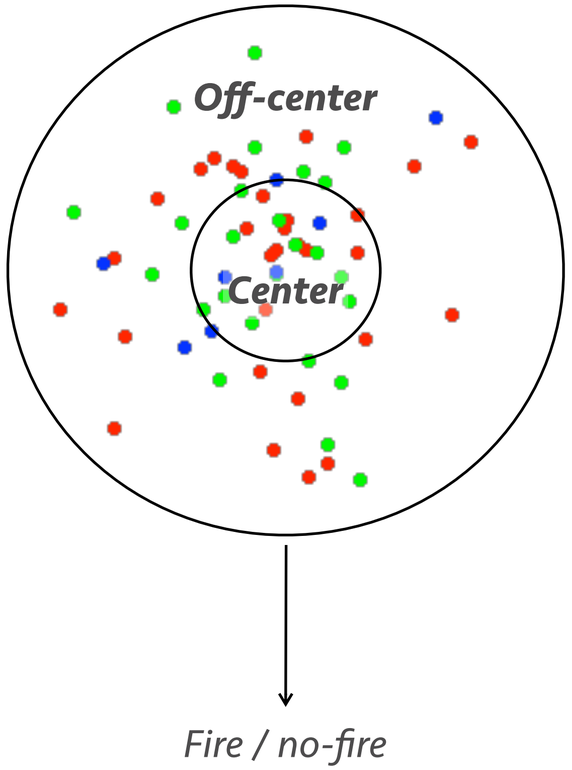


Cone mosaic



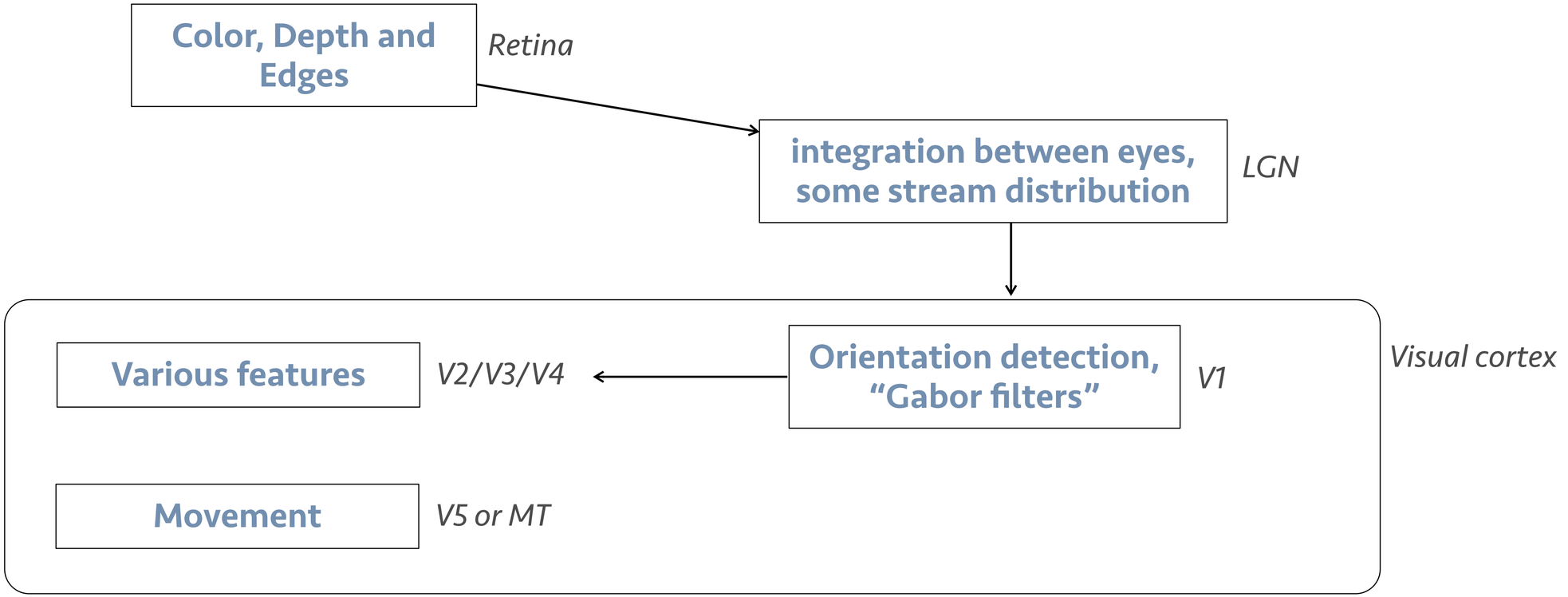
Receptive fields

- For each cone/rod bunch there's a decision
  - Fire a neural signal, or not?
- This is governed by a "receptive field"
  - On-center cells fire when light in center
  - Off-center cells fire when light off-center
    - Both don't fire much when light is uniform
- This favors "informative firing"
  - Essentially capturing edges



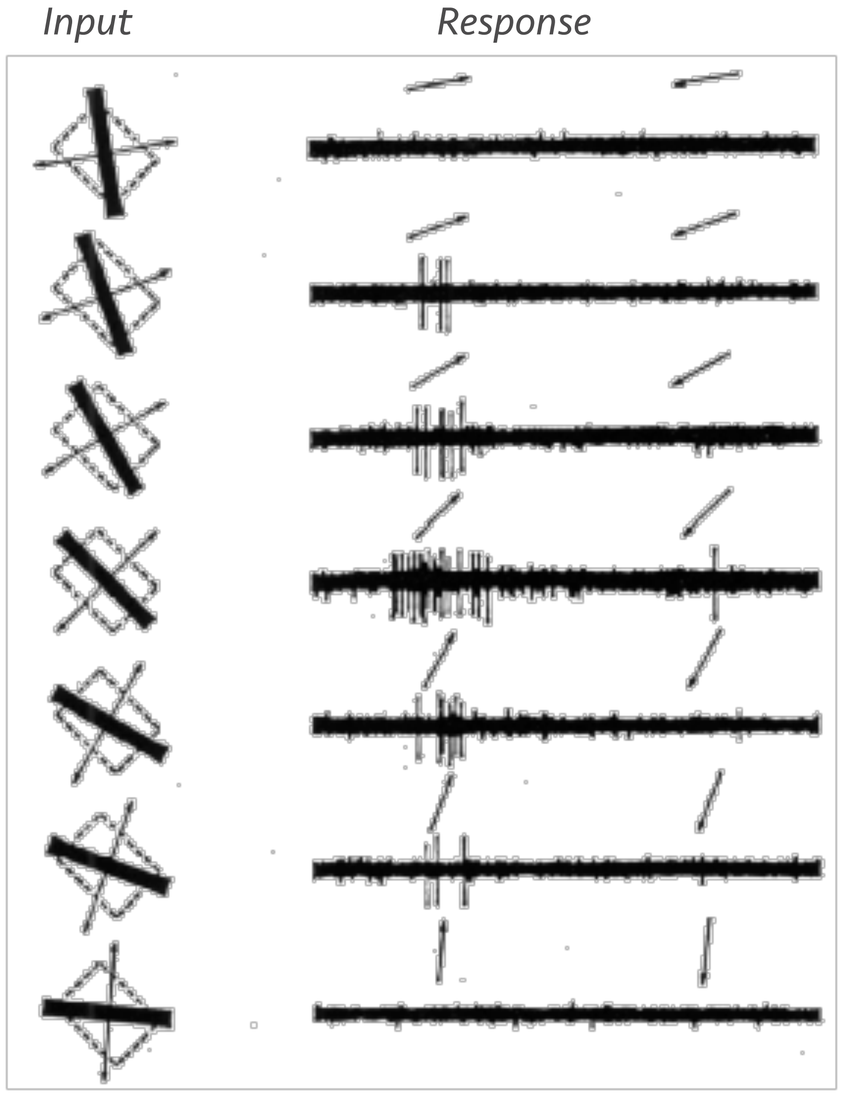
Going up the brain (super simplified version)

- Neural pathway



The V1

- Collection of cells that respond to orientations
- Different groups fire for different orientations
- “Recognition of orientation patterns”

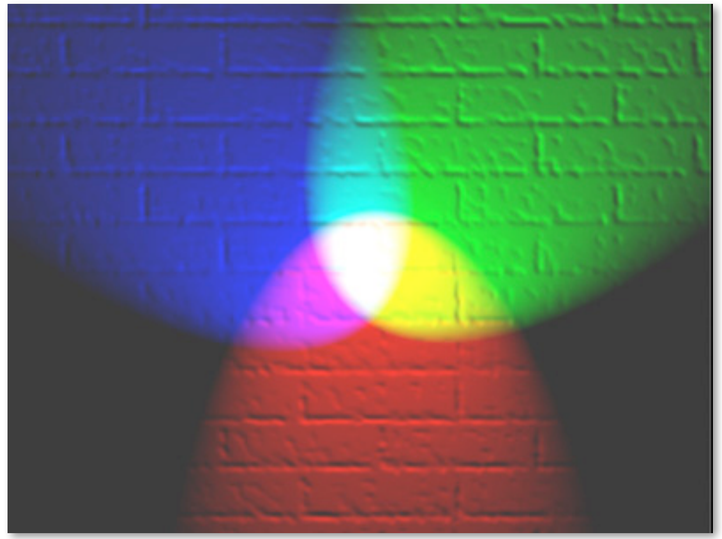


So why do we care about all that?

- Learn from the master!
  - We can see better than machines
  - We are a pretty good source of inspiration
- Remember who you cater to
  - Your vision algorithms will be evaluated by human eyes
  - They need to “speak the same language”

A lesson from the cones

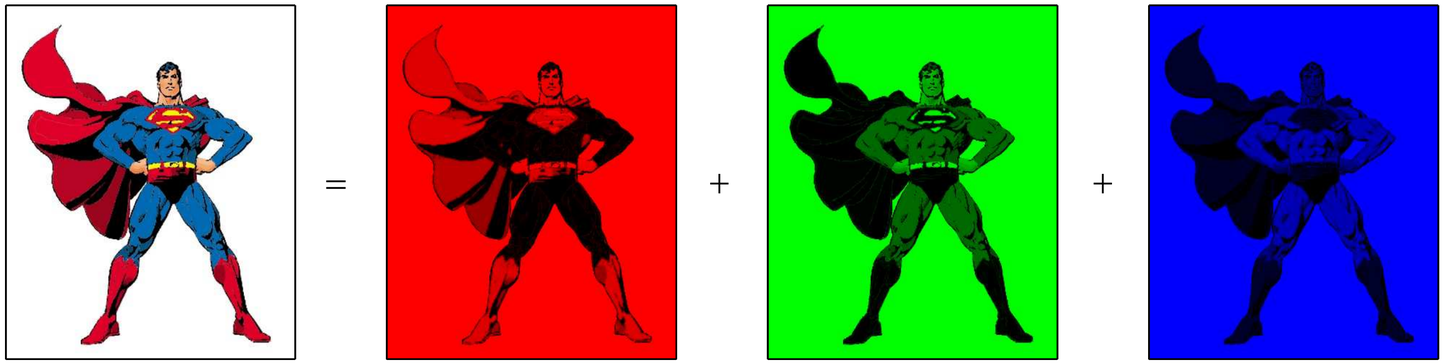
- The colors to use are Red/Green/Blue
  - Superimposing them can create other colors



  - Each color pixel is thus represented by three values $\{r,g,b\}$
    - We saw that already when using tensors to represent color images

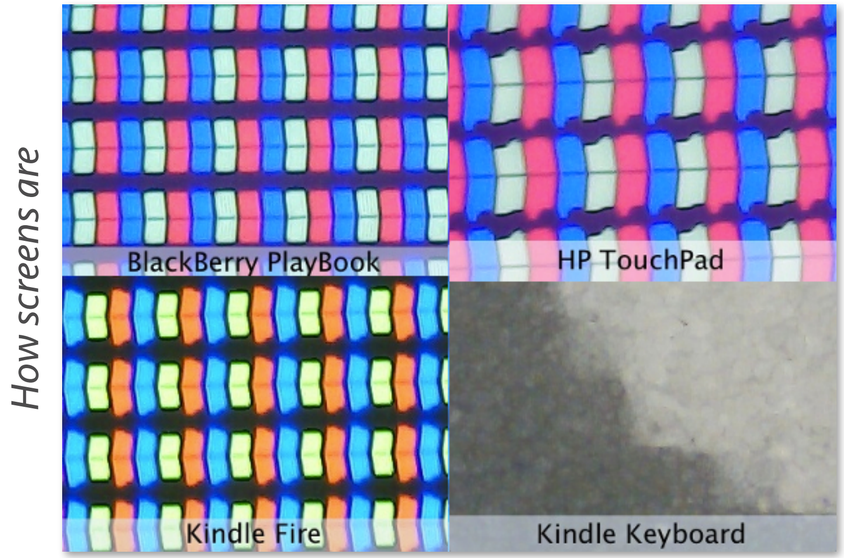
RGB representation

- A perceptually useful representation for color
  - Think of it as a basis set
    - Additive representation
  - Your color screen uses it!



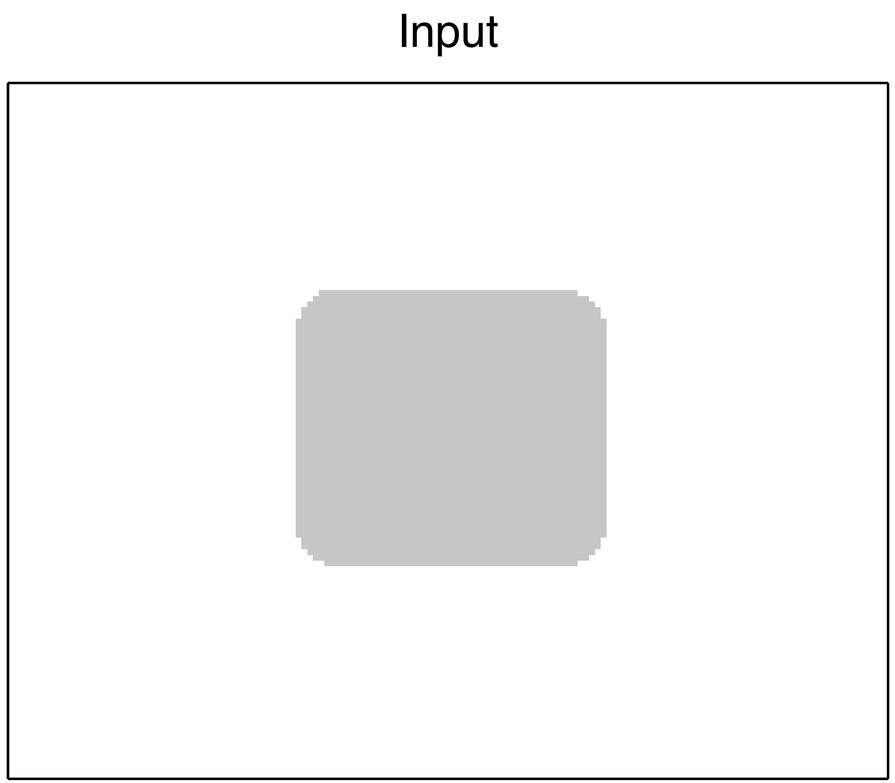
- An alternative is CMYK
  - Cyan/Magenta/Yellow/Black
    - A subtractive representation

- Various other schemes



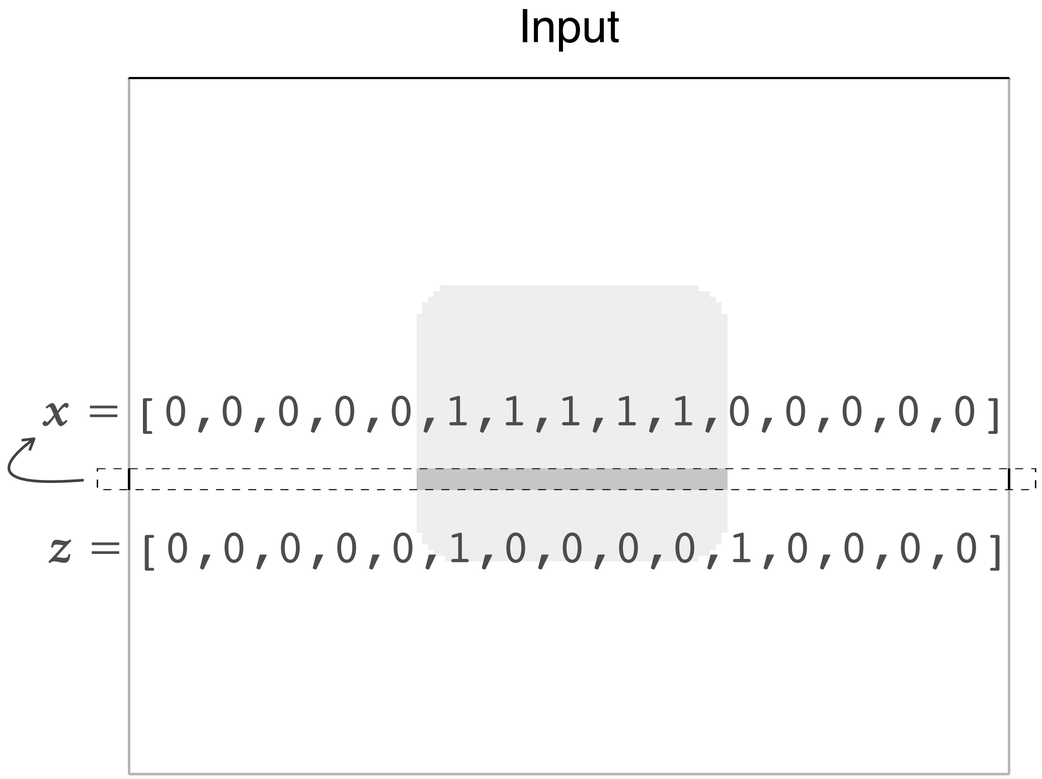
A lesson from receptive fields

- It’s the visual changes that convey information



How do we detect the middle part?

- Let's focus on one row only
  - Can we somehow "measure change"?



Simple logic:

```
if x[i] != x[i-1] then:
    change = True
 else:
    change = False
```

An alternative continuous "change" measure:

$$z[i] = \left|\left| x[i] - x[i-1] \right|\right|$$

Using a convolution:

$$z = \left|\left| [1,-1] * x \right|\right|$$

How about on two dimensions?

- We need three filters:
  - One for horizontal changes

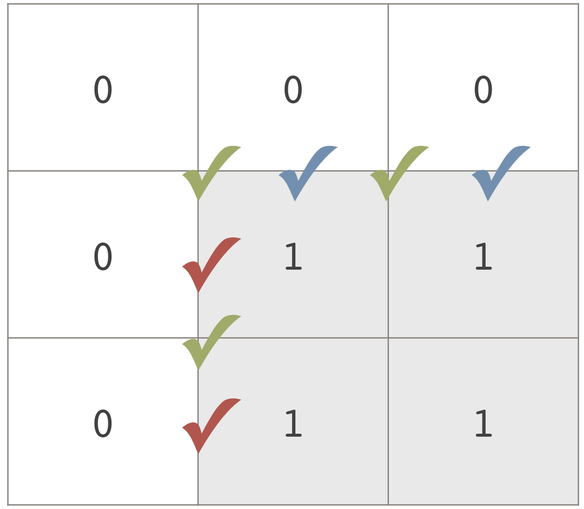
$$f_h = [+1, -1]$$

  - One for vertical changes

$$f_v = \begin{bmatrix} -1 \\ +1 \end{bmatrix}$$

  - One for diagonal changes

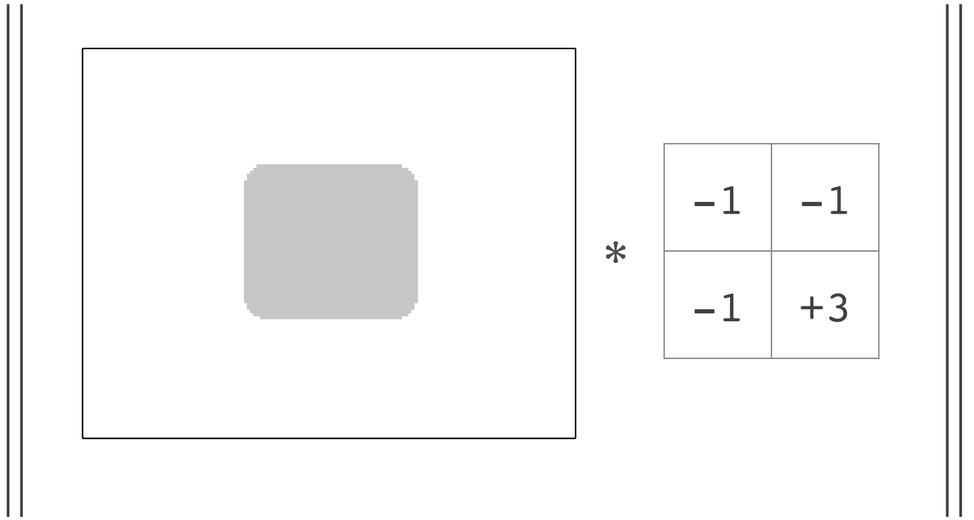
$$f_d = \begin{bmatrix} -1 & 0 \\ 0 & +1 \end{bmatrix}$$



Combining everything in one operation

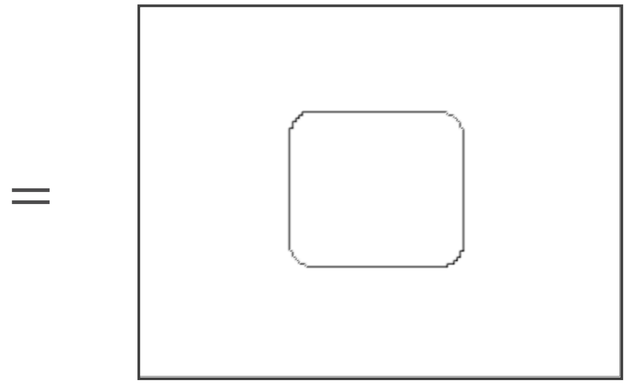
- Convolutions are linear:

$$
\begin{aligned}
& f_h * x + f_v * x + f_d * x \\
&= (f_h + f_v + f_d) * x \\
&= \begin{bmatrix} -1 & -1 \\ -1 & +3 \end{bmatrix} * x
\end{aligned}
$$



- Change detector is now:

$$z = \left\| f * x \right\|$$



Edge detection

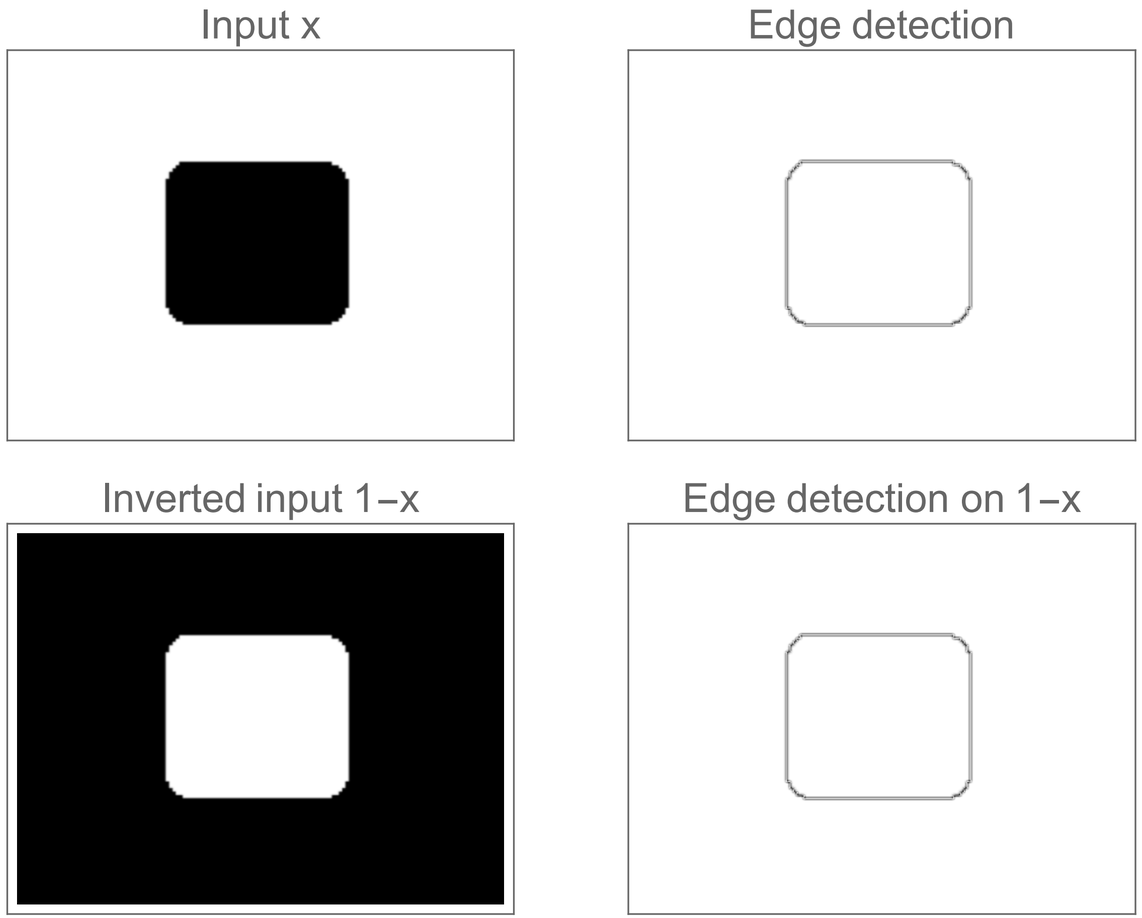
- Construct a filter like retinal receptive fields

$$f = \begin{bmatrix} -\frac{1}{8} & -\frac{1}{8} & -\frac{1}{8} \\ -\frac{1}{8} & 1 & -\frac{1}{8} \\ -\frac{1}{8} & -\frac{1}{8} & -\frac{1}{8} \end{bmatrix}$$

- Convolve images with it to produce a representation that peaks at edges
  - Ignores other parts (like constant values)

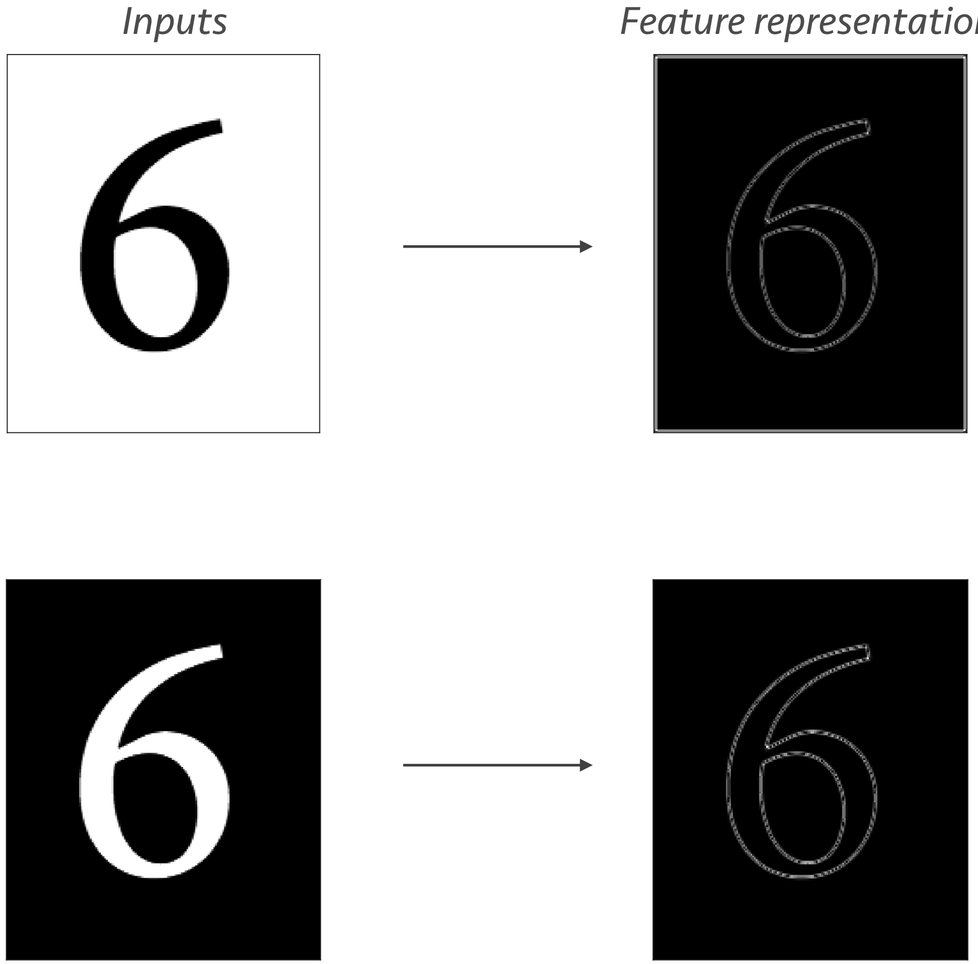
Edge detection examples

- Reduces input to relevant information only



Why is this important?

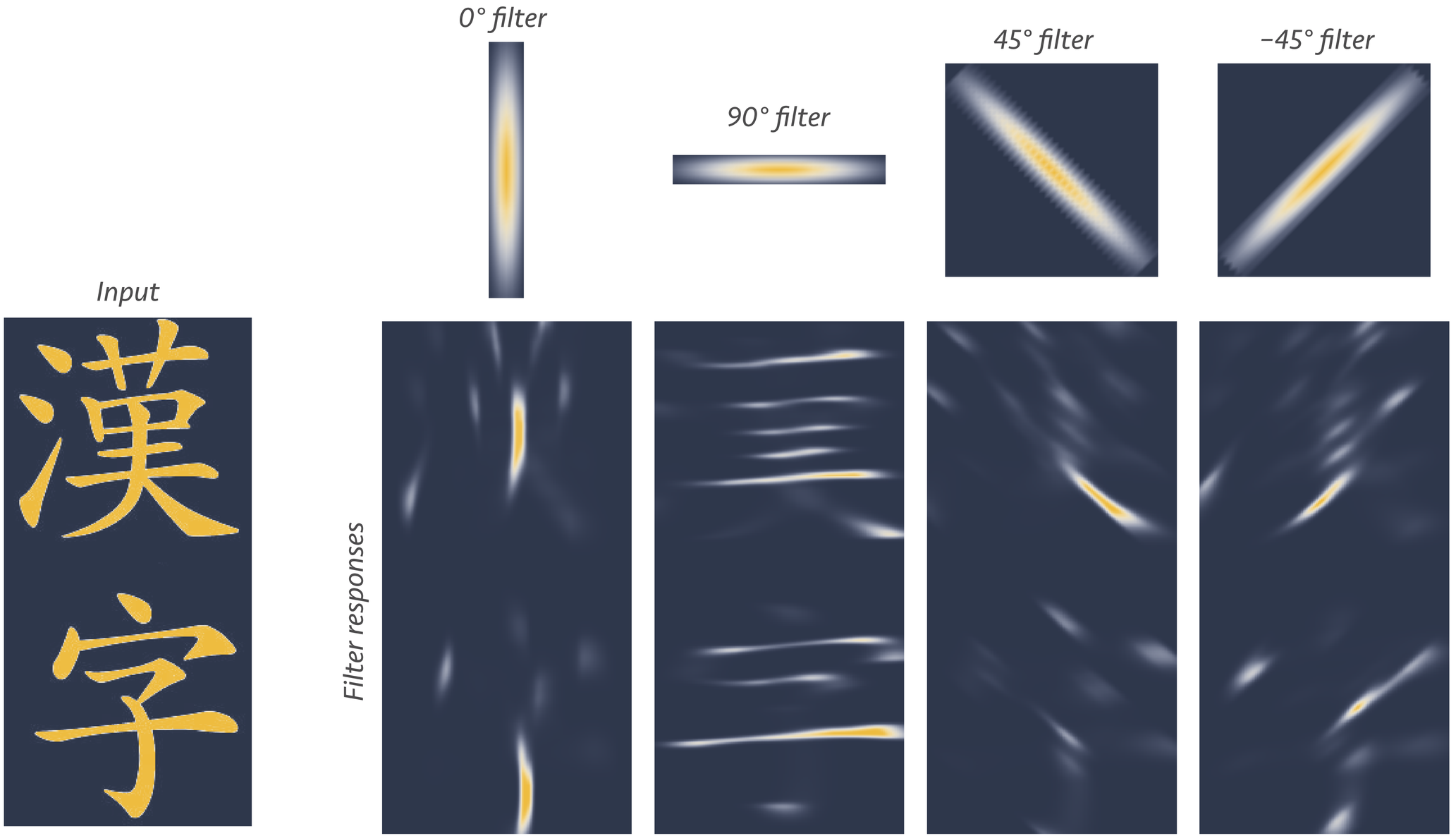
- We often care only about the shapes, e.g. text



A lesson from the V1

- More edge detection
  - Describe image using multiple orientations
- Gabor transform
  - Convolve with filters of varying angles
- Feature representation is the presence of each orientation at each point

Mimicking the V1 with filters



Extending this idea

- We think of images as collections of:
  - Lines/edges, blobs, corners, ridges, …
- We can make filters for each type
  - Rich computer vision literature on the subject
    - Interesting neuroscience as well, e.g. the Halle Berry neuron
- We'll be encountering such features later on when we'll operate on images

Scale space

- Detail is optional
  - We may want it, or we may not
    - e.g. squinting
- Images are often looked at varying “scales”
  - Remove detailed/fine information and focus at coarse elements

Recap

- Features are needed to represent data
  - We can't just take norms to express distance
- Selection of features caters to our needs
  - Our senses are an "optimal" feature selector
  - What can we learn from it?
- Know what you want to look for
  - Different features work best in different cases

Ok, but what about …

- Non-sensory signals?
  - Mechanical readings, biomedical signals, finance, …
- How do we get features for these?
  - We need to see the bigger picture in the features we used in this lecture
- Next lecture:
  - Adaptive feature selection
  - How to use math to derive perceptual features, and learn to “perceive” new modalities

Pointers to more info

- Auditory perception and audio features
  - Wikipedia
    - http://en.wikipedia.org/wiki/Auditory_system
    - http://en.wikipedia.org/wiki/Psychoacoustics
  - Textbook section 7.5
- Visual perception and visual features
  - Wikipedia:
    - http://en.wikipedia.org/wiki/Visual_perception
    - http://en.wikipedia.org/wiki/Feature_detection_(computer_vision)

And one more thing …

- Problem Set 1 is out
  - Already posted on piazza

- Due September 18th (11:59:59.99 PM CST)
  - See your TAs sooner rather than later

Problem set rules

- We will only accept typeset PDFs!
  - Handwritten/scanned submissions will not be graded!
- Don’t cheat!
  - Work on your own, avoid peeking at past solutions (we can tell)
  - It’s fine to discuss solution approaches with classmates
    - but finalize things by yourself