Detecting Deep Fakes With Mice

Machine vs. Biology

“Fake News” Circa 1938

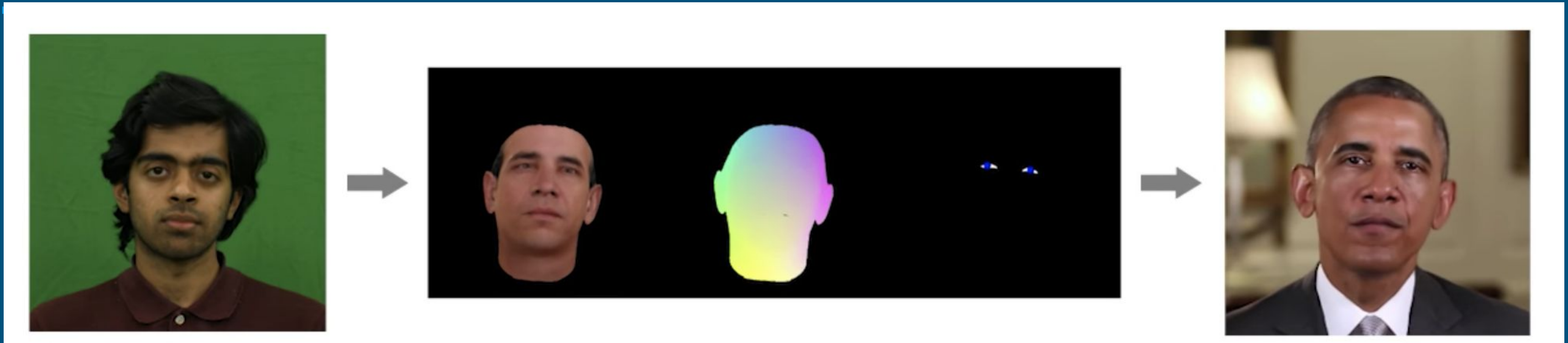
Mars Attacks!, 1938

“War of the Worlds” Hoax

Mercury Theatre, Manhattan

Orson Welles: “Sorry about it!”

2019: AI-Synthesized Media



“Deep Video Portraits,” SIGGRAPH

Face Swap, **Puppet Master**, Lip Sync, Voice Cloning…

ML is crossing the “uncanny valley” faster than CG!

Cybersecurity Threat ?

THE HILL

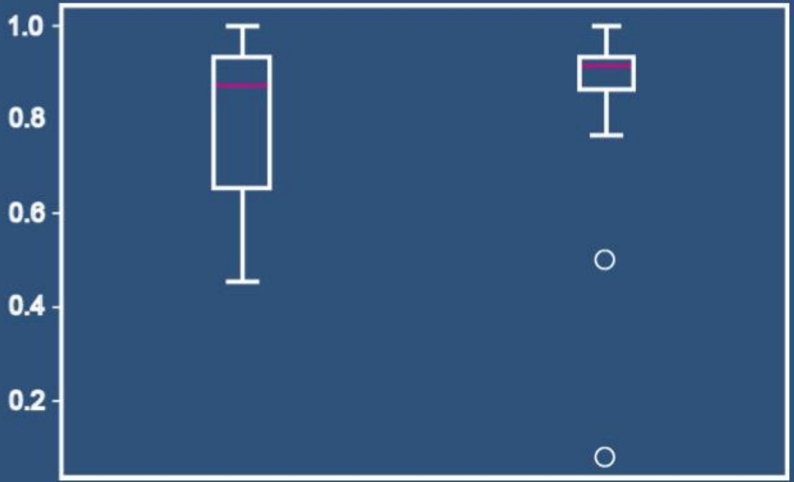
Senators unveil bipartisan bill to target 'deepfake' video threat

“The capability to do all of this is real. It exists now.” - Marco Rubio, Senator

“You don’t need software engineers anymore. You just download it to your PC and run it.” - Chris Bregler, Google

But Who Is Really Fooled ?

Humans
88%



Machines
92%

Fake Speech Study ASVSpoof 2019 DataSet

Machines

Alexander Comerford

Biology

Jonathan Saunders

What is a deep fake?

- Term coined in ~2017
    - Same time as published landmark paper “Generative Adversarial Networks”[6]
- Compound word of “deep learning” and “fake”
- Usually associated with synthesizing images and videos
- Broadly shows the abilities of generative modeling
- The public associates deep fakes with political videos or pornography
- Data about a person -> Puppet of the person

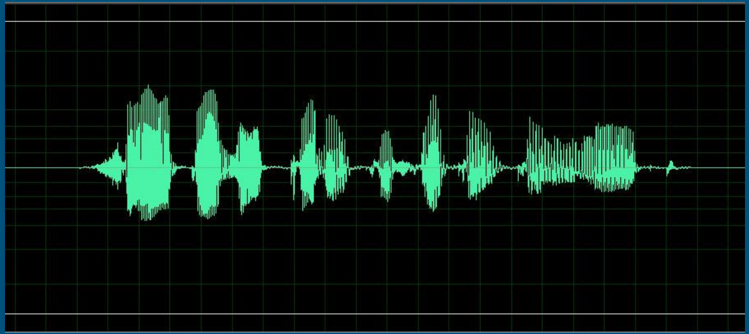
How is a deep fake made?

- Deep fakes are a product of generative modeling and Neural Networks
    - Create a mapping from one data type to another (ex: text to speech)
    - Given data, find a model that generates new but similar samples
    - Unsupervised learning (no data labels, just training data!)
- “Deep” Neural Networks produce the most “fake” samples
- Convincing fakes requires significant resources
    - Fully representative dataset
    - Compute

Good deep fakes are HARD!

- Synthesizing Obama [1]
  - Training:
    - 17 hours of data
    - ~2 weeks on cpu
    - ~2 hours on gpu
    - ? hours of work

general deep fakes are EASY and FUN!



WaveNet [3]

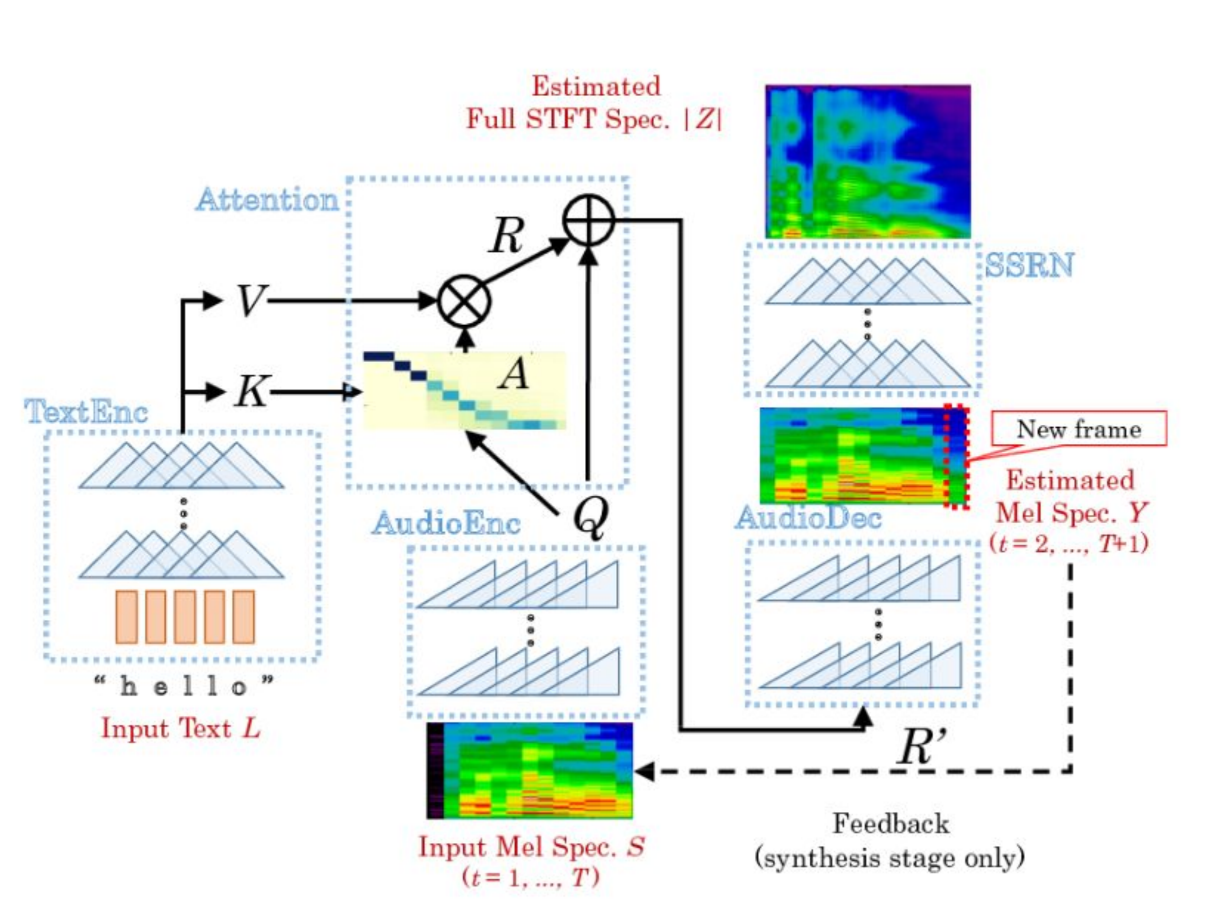
Forensics Face Detection From GANs Using Convolutional Neural Network [2]

History of Text To Speech

"I've been looking forward to black hat all year"

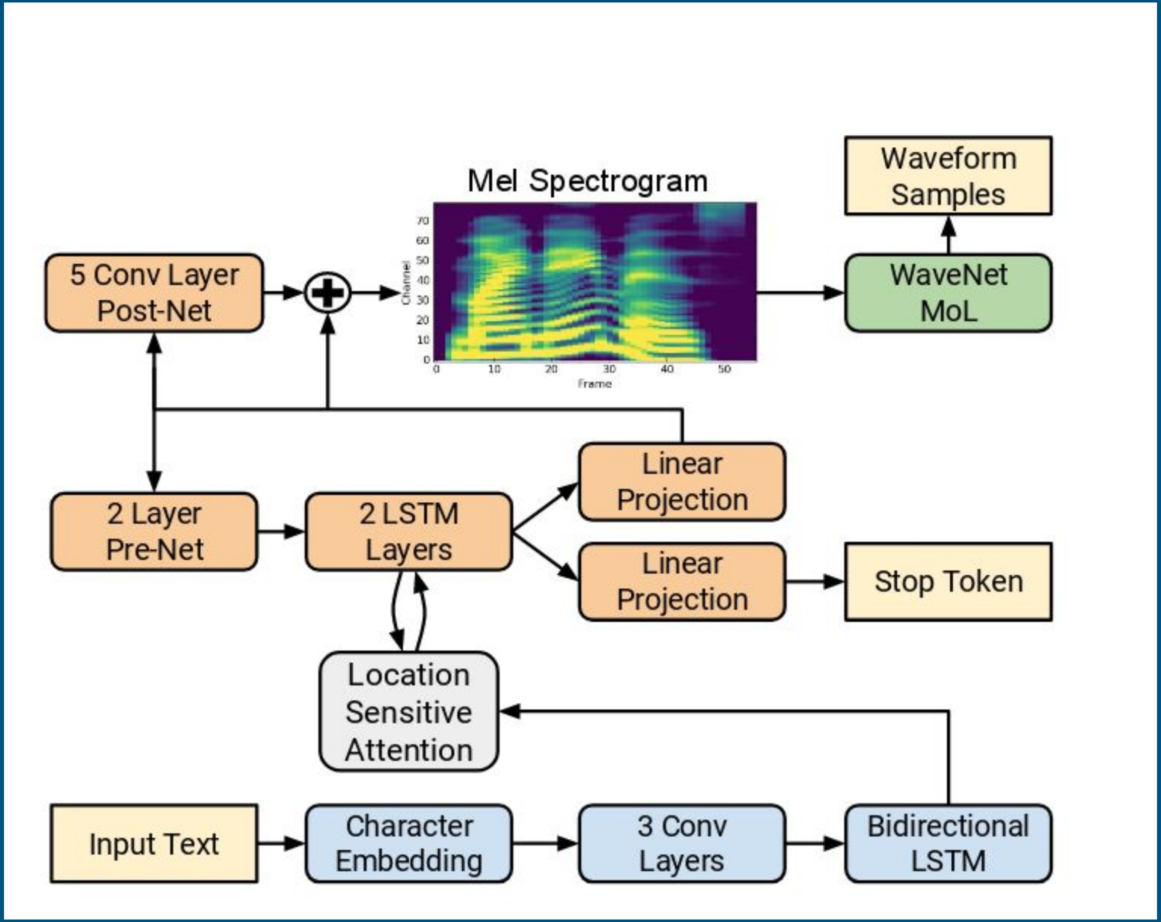
DC-TTS

https://github.com/Kyubyong/dc_tts



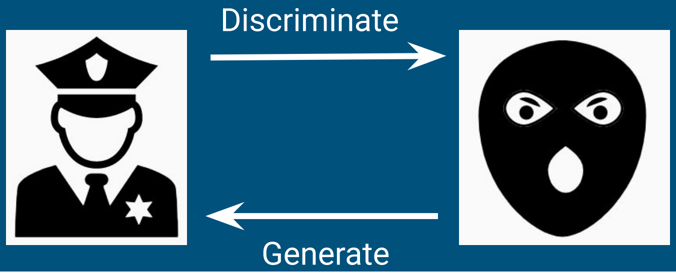
Tacotron2

https://github.com/NVIDIA/tacotron2



Taking advantage of GAN[6] discriminators

- GANs are Generative Models
- Generative and Discriminative component
  - Creates samples (Audio, Images, Videos)
  - Classifies samples as “real” or “fake”
- Components train by playing a “game” to trick the other
- We want a powerful discriminator
- Train WaveGAN on asv-spoof data
  - Epochs: 5k
  - Parameter combinations: 300



$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

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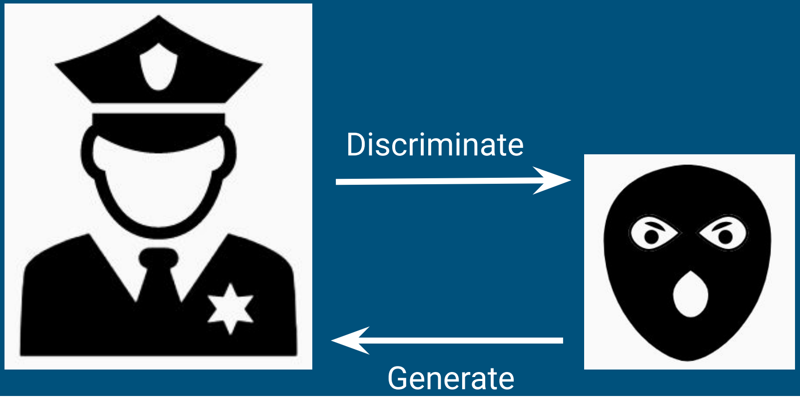

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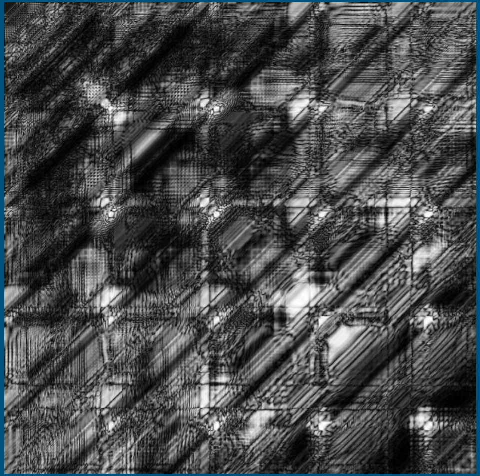
Approach 1: GAN[6] discriminators

- Discriminator is not powerful enough to generalize
- Future directions
  - Train discriminator on non generator samples
  - Richer features
  - Train discriminator separately after convergence

Approach 2: Bispectral Analysis

- Use the bispectrum of the raw audio as the evaluating feature[8]
- Bicoherence (normalized bispectrum) of a signal represents higher-order correlations in the Fourier domain

"There are different cultures in different departments"



Approach 2: Bispectral Analysis

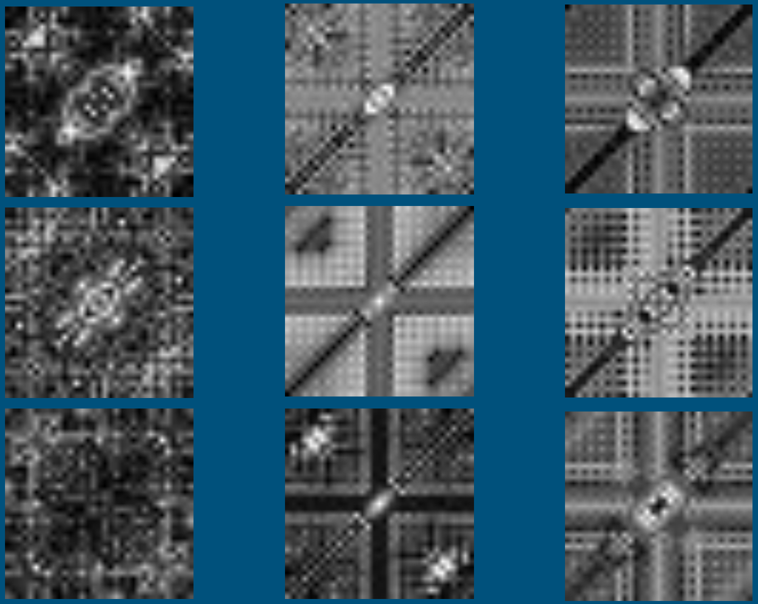
- The averaged bicoherent magnitude across segments of a waveform produces a signature

DC-TTS | Tacotron2 | Human

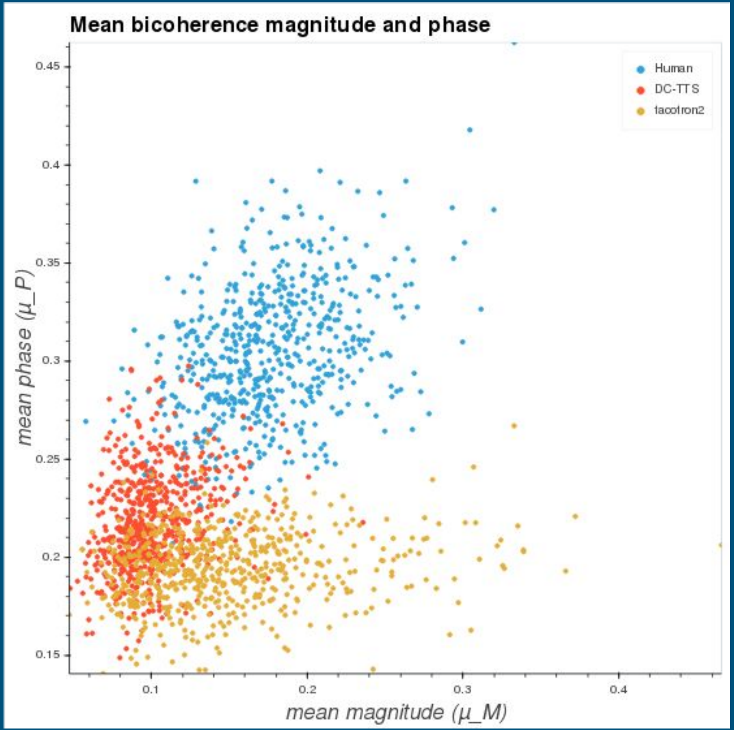
“There are different cultures in different departments.”

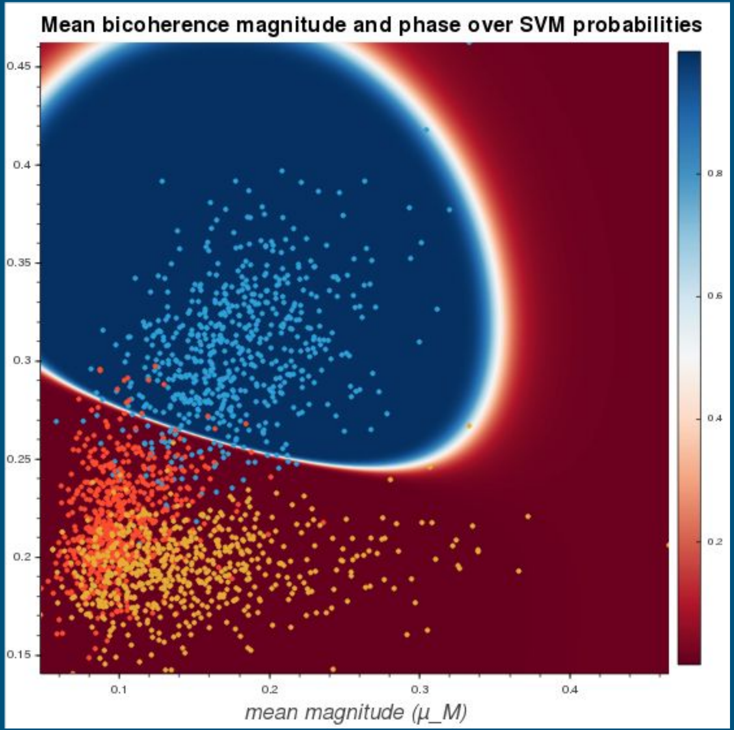
“Don’t you think it was a fine performance.”

“Where do we go from here.”



Approach 2: Bispectral Analysis





Accuracy:	0.95
Precision:	0.95
Recall:	0.94
Samples:	1800

* Samples from LJ speech dataset

References

[1] Suwajanakorn, Supasorn, et al. “Synthesizing Obama.” *ACM Transactions on Graphics*, vol. 36, no. 4, 2017, pp. 1–13., doi:10.1145/3072959.3073640.
[2] Do Nhu, Tai & Na, In & Kim, S.H.. (2018). Forensics Face Detection From GANs Using Convolutional Neural Network.
[3] Aaron van den Oord, Sander Dieleman, Heiga Zen, Karen Simonyan, Oriol Vinyals, Alex Graves, Nal Kalchbrenner, Andrew Senior, Koray Kavukcuoglu, “WaveNet: A Generative Model for Raw Audio” arXiv:1609.03499 [cs], Sep. 2016.
[4] Chris Donahue, Julian McAuley, Miller Puckette, “Adversarial Audio Synthesis" arXiv:1802.04208v3 [cs] Feb. 2019
[5] Shan Yang, Lei Xie, Xiao Chen, Xiao Lou, Xuan Zhu, Dongyan Huang, Haizhou Li, “Statistical Parametric Speech Using Generative Adversarial Networks Under A Multi-Task Learning Framework” arXiv:1707.01670v2 [cs] Jul. 2017
[6] Generative Adversarial Networks “Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, Yoshua Bengio” 1406.2661 [cs] Jun. 2014
[7] Marc Schröder. Interpolating Expessions in Unit Selection. In *Proc. 2nd ACII*, Lisbon, Portugal, 2007
[8] Albadawy, Ehab & Lyu, Siwei & Farid, Hany. (2019). Detecting AI-Synthesized Speech Using Bispectral Analysis.
[9] Caroline Chan, Shiry Ginosar, Tinghui Zhou, and Alexei A Efros. Everybody dance now. arXiv:1808.07371 2018

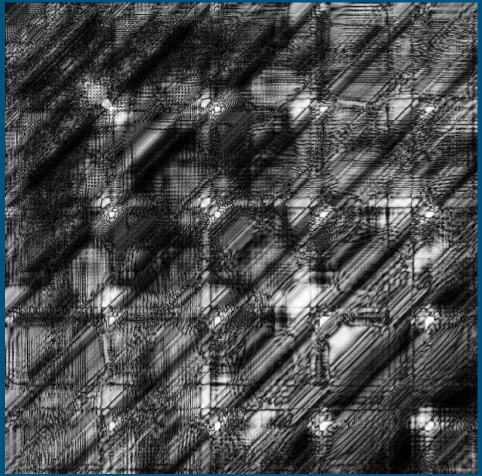
Detecting Deep Fakes: Insights from Biological Neural Nets

Jonathan Saunders, University of Oregon

What kind of deepfake detection do we want?

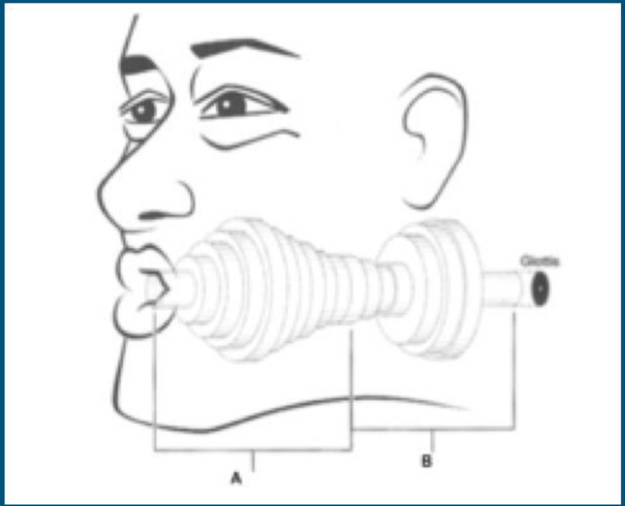
Generation Algorithm Dependent

- Throw data at it
- Always vulnerable to new algorithm
  - Eg. Phase-based detection defeated if complex spectra used in generation



Generation Algorithm Independent

- Requires phonetics & neuroscience
- General solution



ned2 look closer in2 this slimy clarinet

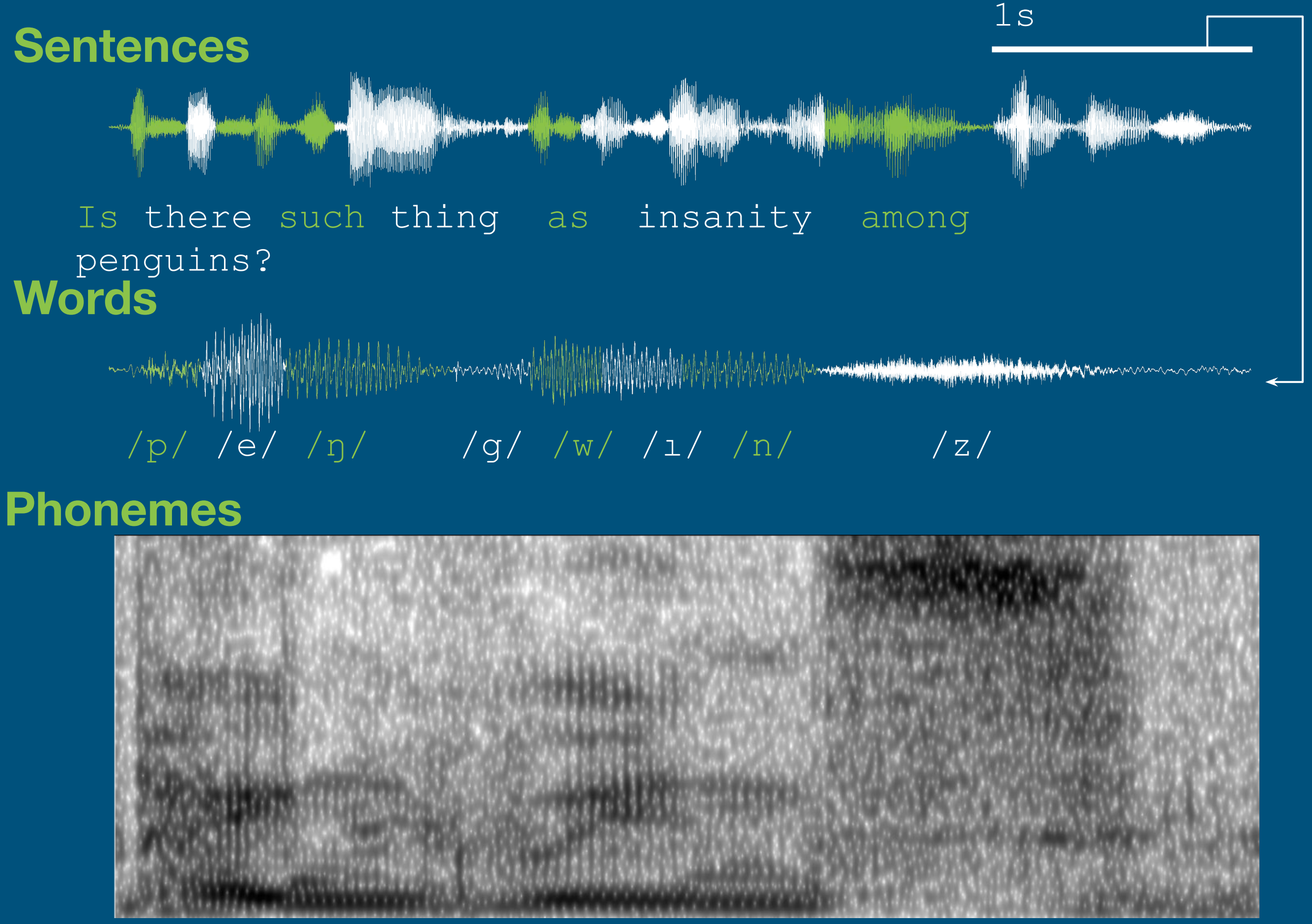
Listening to people talk is hard

Speech is...

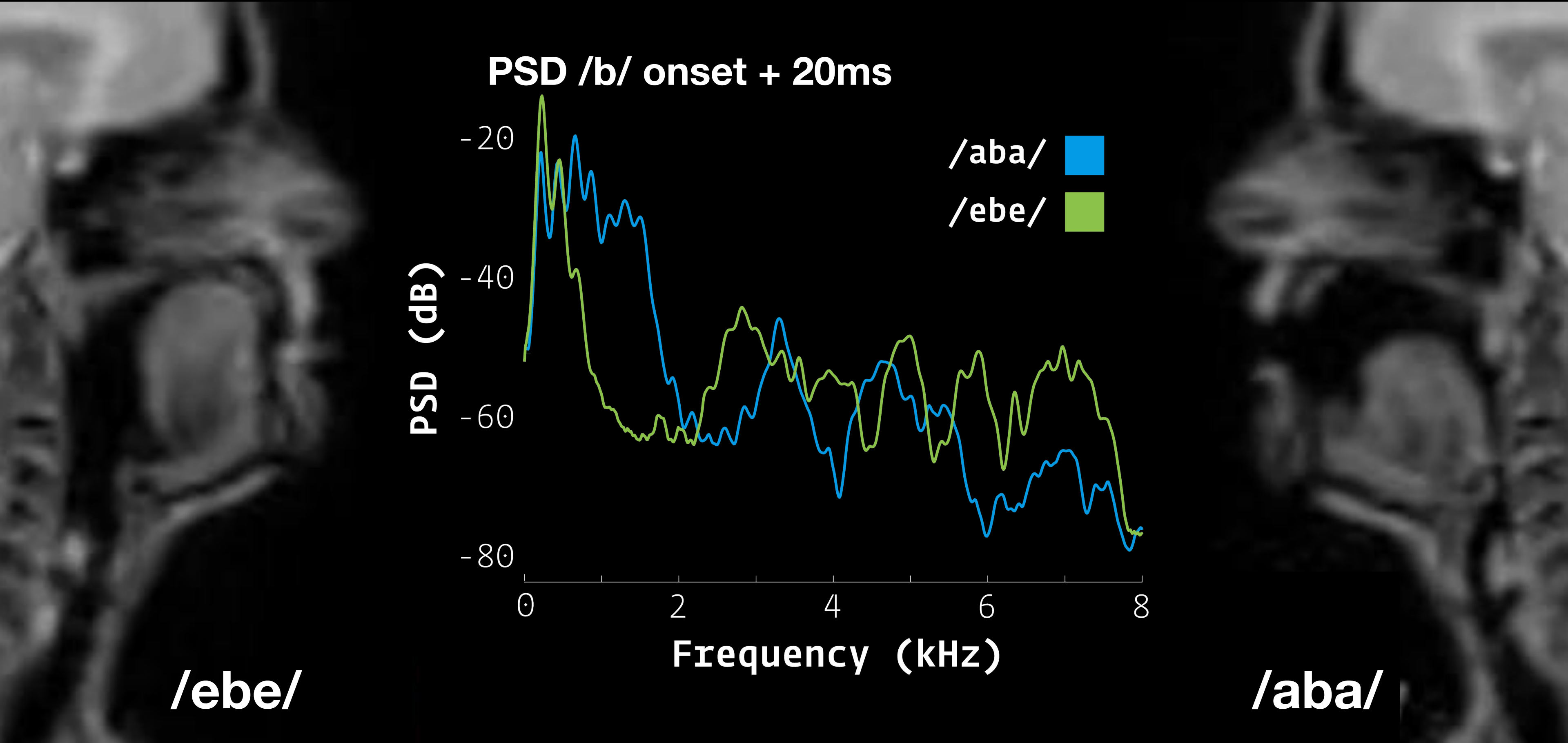
- Hierarchical
- ***Fast:***
  - 10-30 phonemes/s

To detect phonemes, have to normalize...

- Voice Timbre
- Rate
- Prosody
- Accent



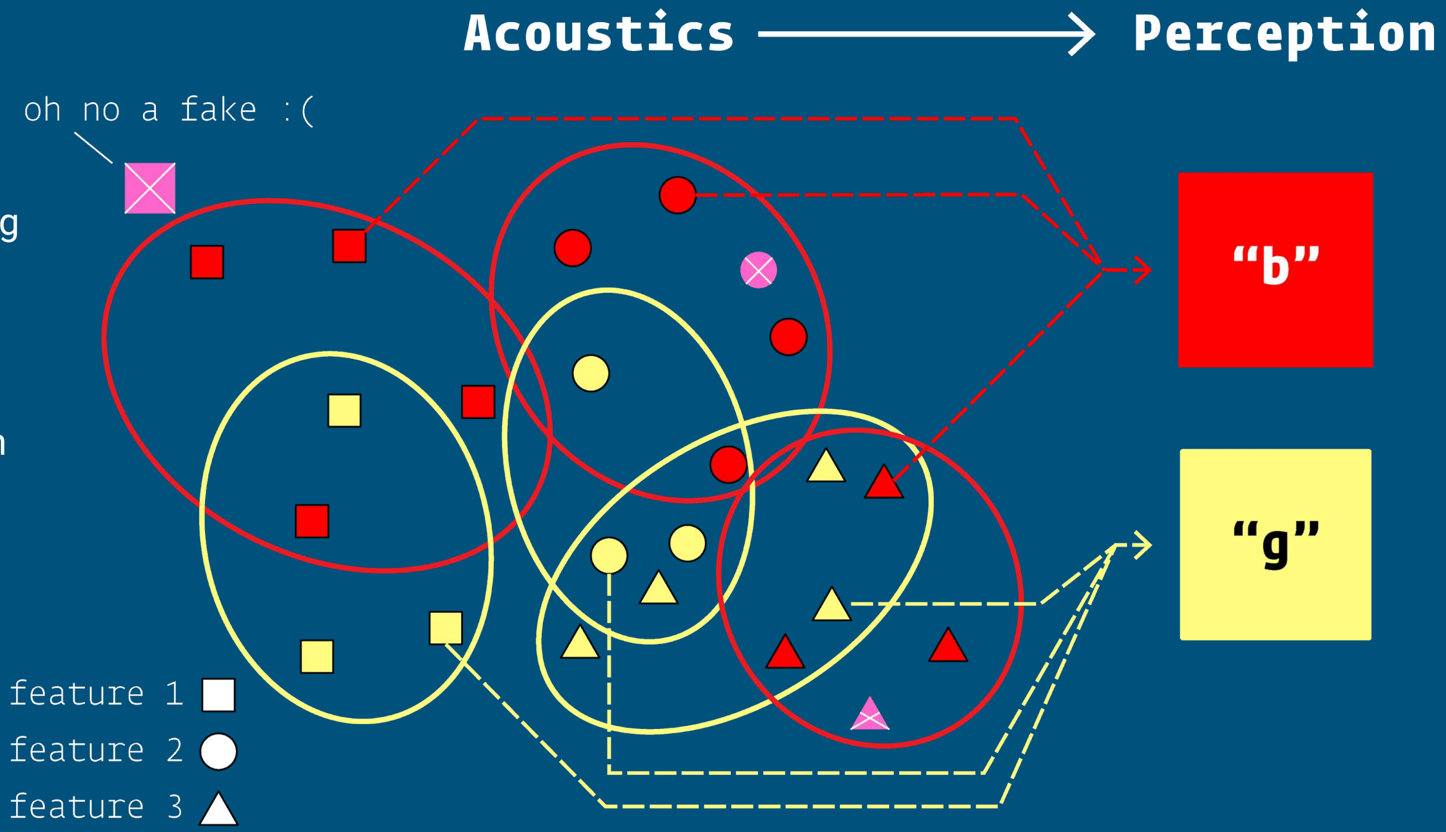
Coarticulation: No unique acoustic structure for phonemes



Lawson EJ, et al. (2015) *Seeing Speech*

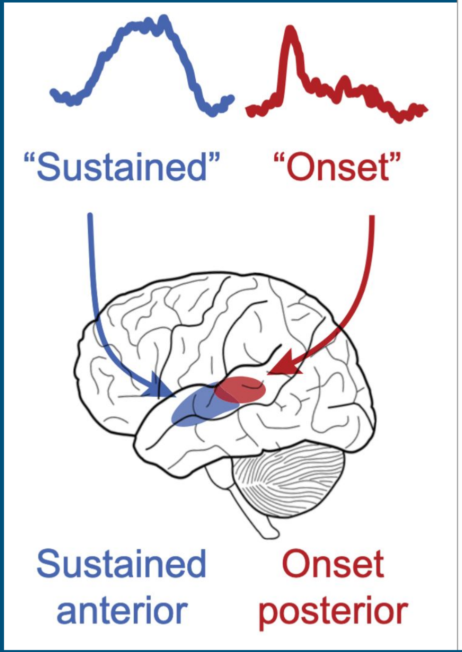
The Auditory System: designed to be gullible

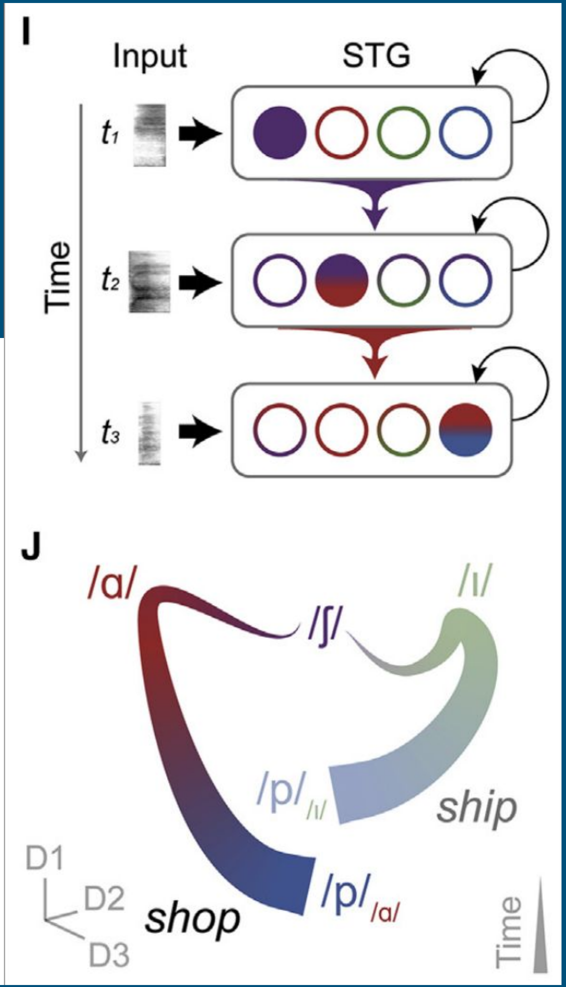
- Complex, overlapping feature space
- Collapse redundant/irrelevant acoustic information
- Bad fakes fool the auditory system



How does the brain do it?

- Phrase onsets signalled by posterior auditory cortex
- Recurrent anterior cortical networks compare past to present





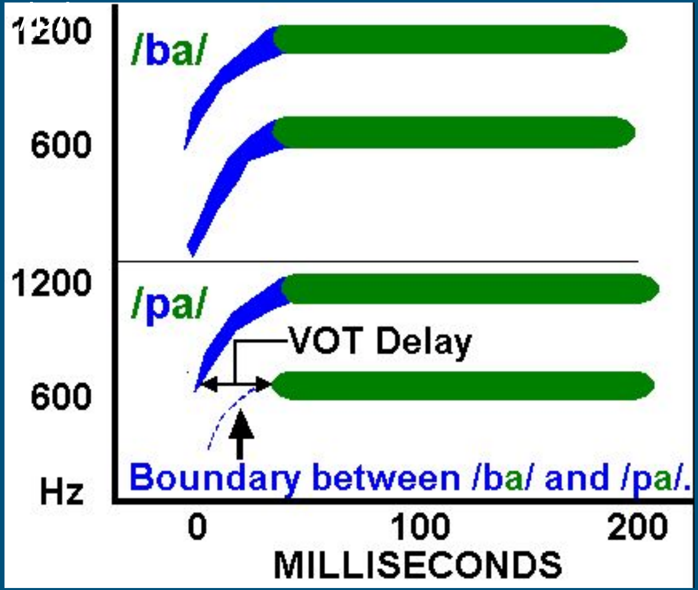
The rest is all theory :(

Hamilton LS, Edwards E, Chang EF (2018) *Curr.Bio.* 28:1860-1871
Yi HG, Leonard MK, Chang EF (2019) *Neuron* 102(6):1096-1110

Can’t crack the speech circuit in humans

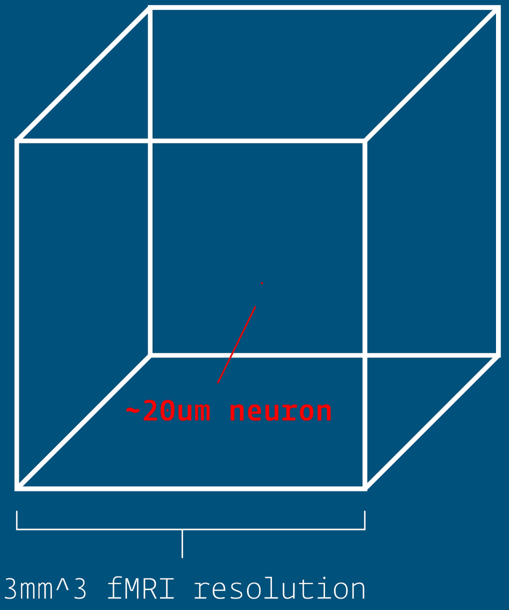
Speech is too fast

~20ms of sound distinguishes /b/ from



Neurons are too small

~630k neurons in an fMRI voxel



http://www.indiana.edu/~p1013447/dictionary/vot.htm

Can't study phonetic processing in humans?

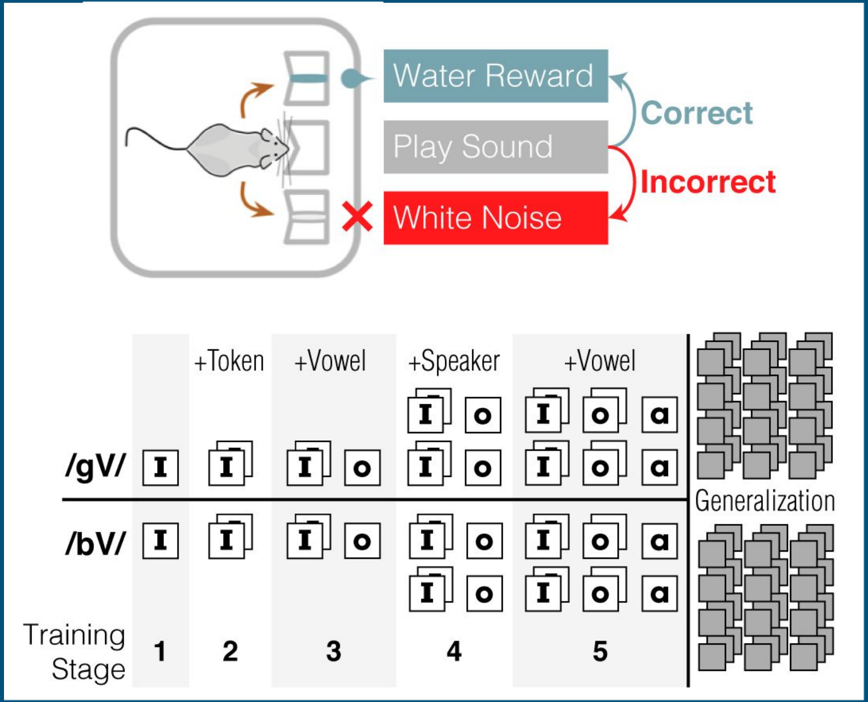
Teach mice English (phonemes)

To discriminate /bV/ vs. /gV/ consonant-vowel pairs...

1. Center poke to play sound
2. Go left if /g/, right if /b/
3. Get that water or face the consequences

5 training stages add speakers + vowels

Onto a generalization stage w/ 180 recordings

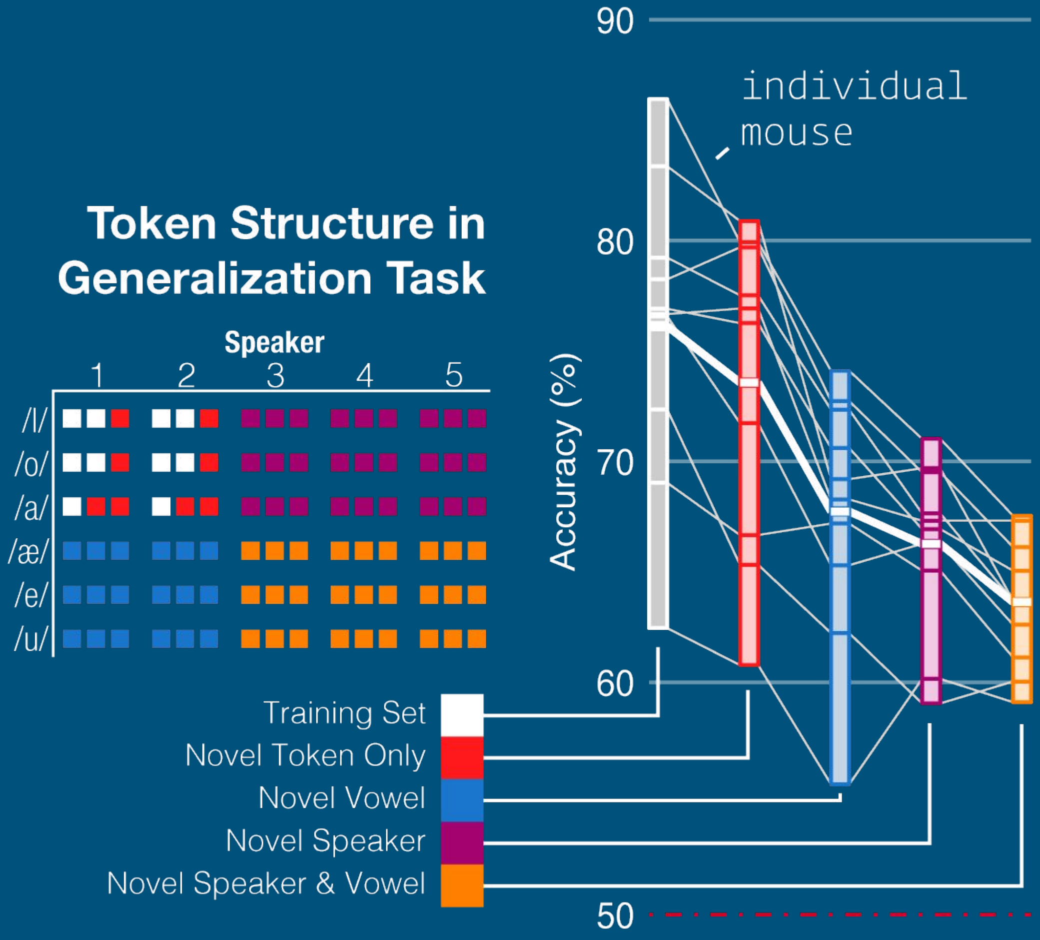


Saunders JL, Wehr M (2019) *J. Acoust. Soc. Am* 145:1168

PSA: We are releasing the next hot shit in behavior hardware/software this summer: **git.io/rpilot**

Generalization Performance

- Mice learn generalizable consonant categories
- Performance decreases with dissimilarity to training set
- Generalization deficit similar across mice



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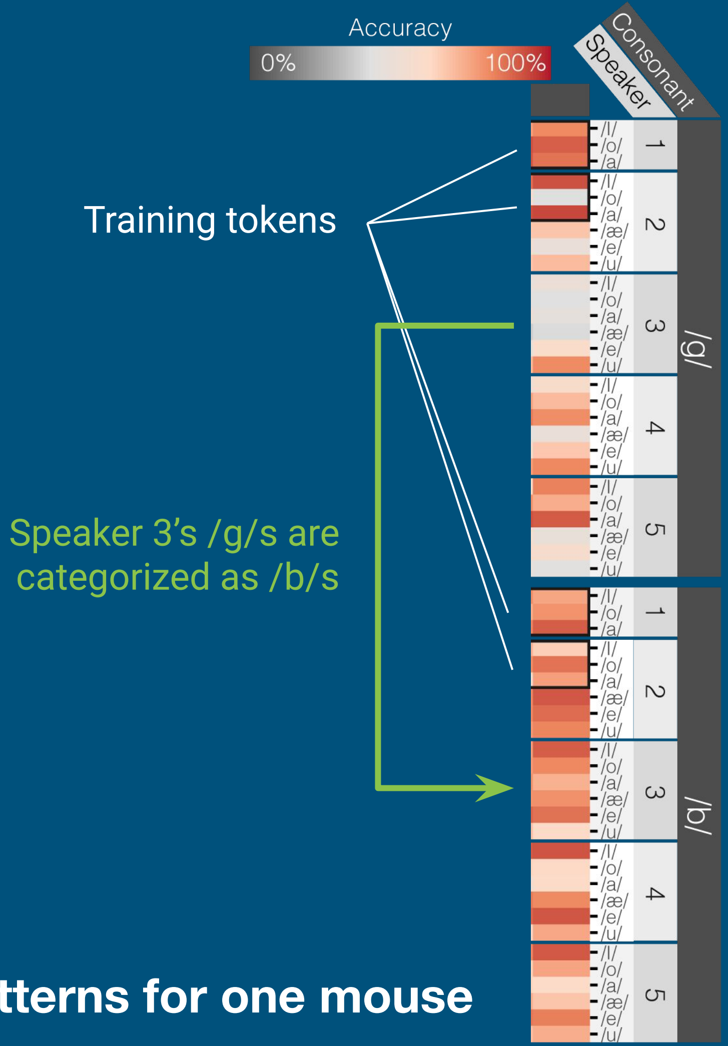
Nonuniform Error Patterns

- Each mouse has a complex discrimination boundary



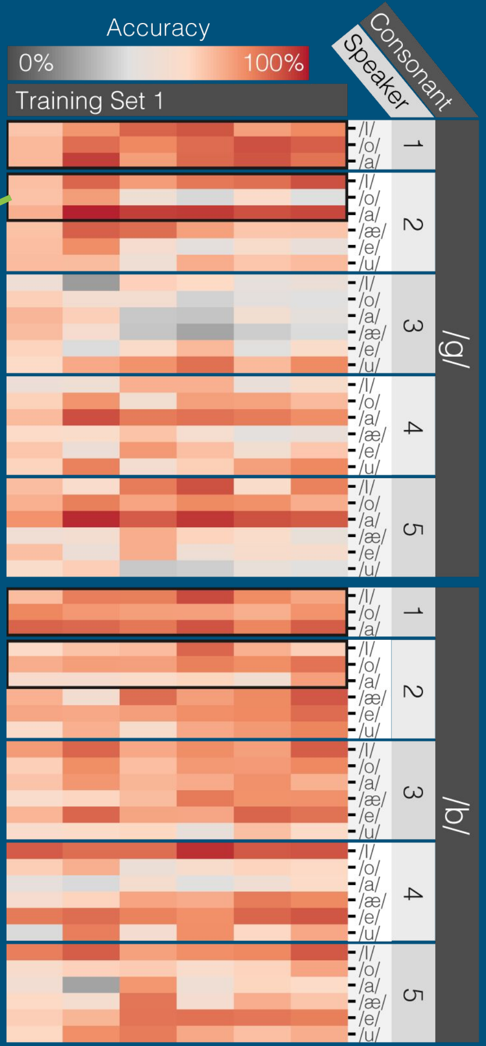
Error Patterns for one mouse

Saunders JL, Wehr M (2019) *J. Acoust. Soc. Am* 145:1168

Nonuniform Error Patterns

- Each mouse has a complex discrimination boundary
- But general patterns are preserved across mice

A hard token in the training set



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Nonuniform Error Patterns

- Each mouse has a complex discrimination boundary
- But general patterns are preserved across mice

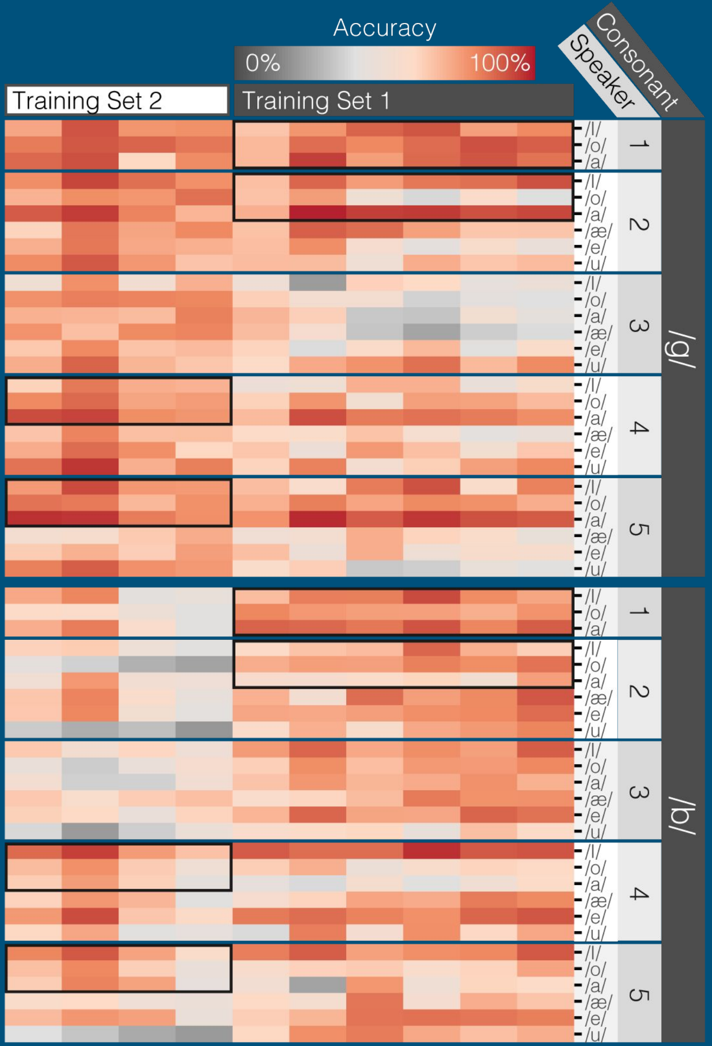
When we trained on a different set of tokens…

- Wholly different error pattern
- Biases are mostly from training, not stimuli

Mice learn a complex acoustic representation of consonants

Group 2 training tokens

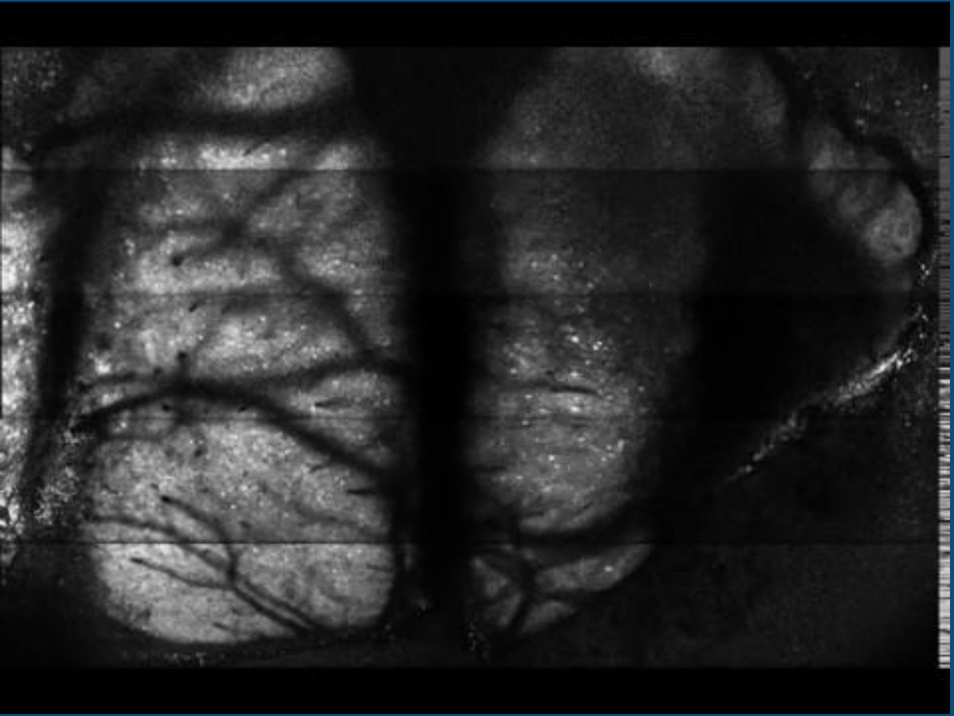
Global bias towards /g/



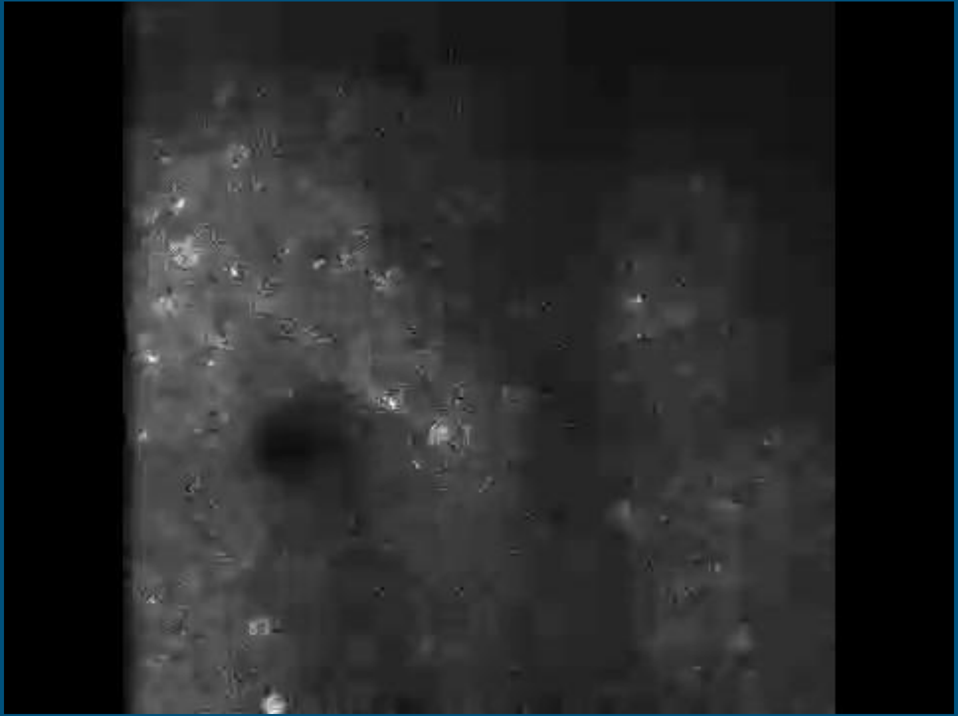
Saunders JL, Wehr M (2019) *J. Acoust. Soc. Am* 145:1168

This Fall: record entire surface of auditory cortex during learning & testing

Example data from Evan Vickers, UOregon, pers. comm.



Dorsal surface,
4.5mm x 3mm, 0.3Hz(10x)

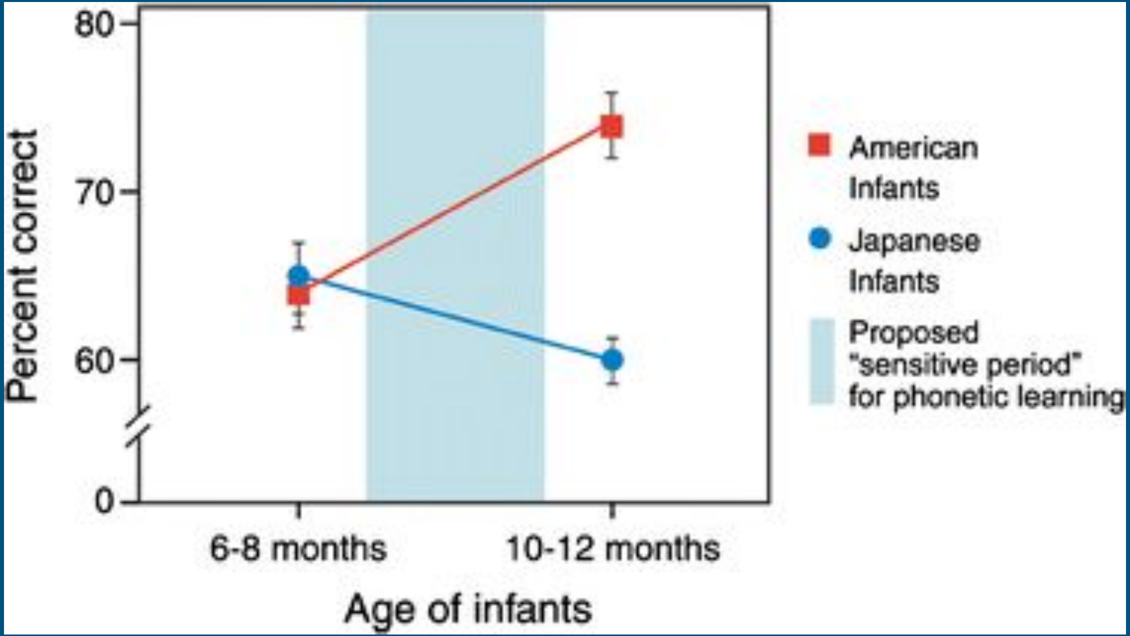


Primary Auditory Cortex,
230um depth, 500um^2 area, 7Hz(5x)

Now: Are category representations plastic?

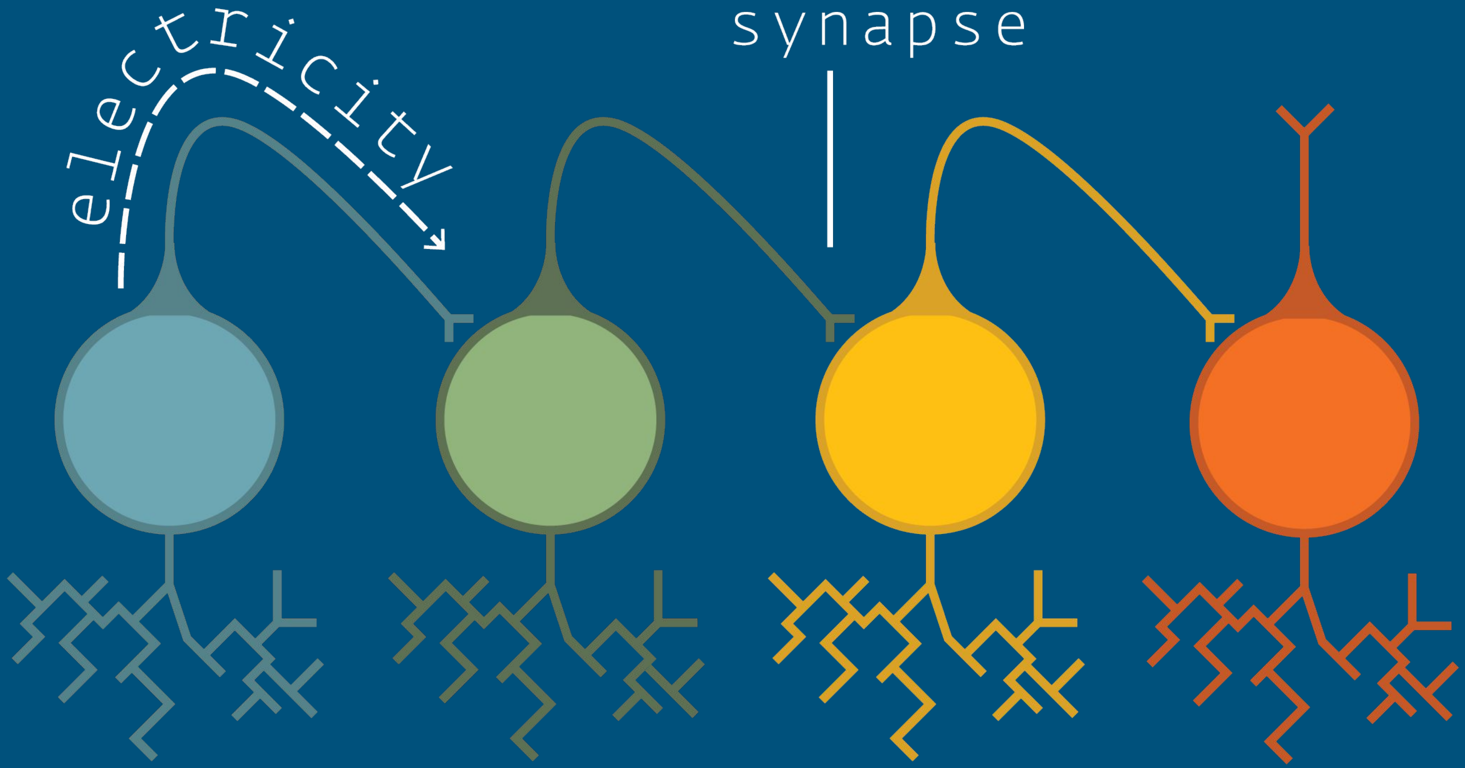
- Some of our mice failed to learn, but why?
- Humans can't hear some phonetic contrasts that aren't in their language

/ra/-/la/ discrimination

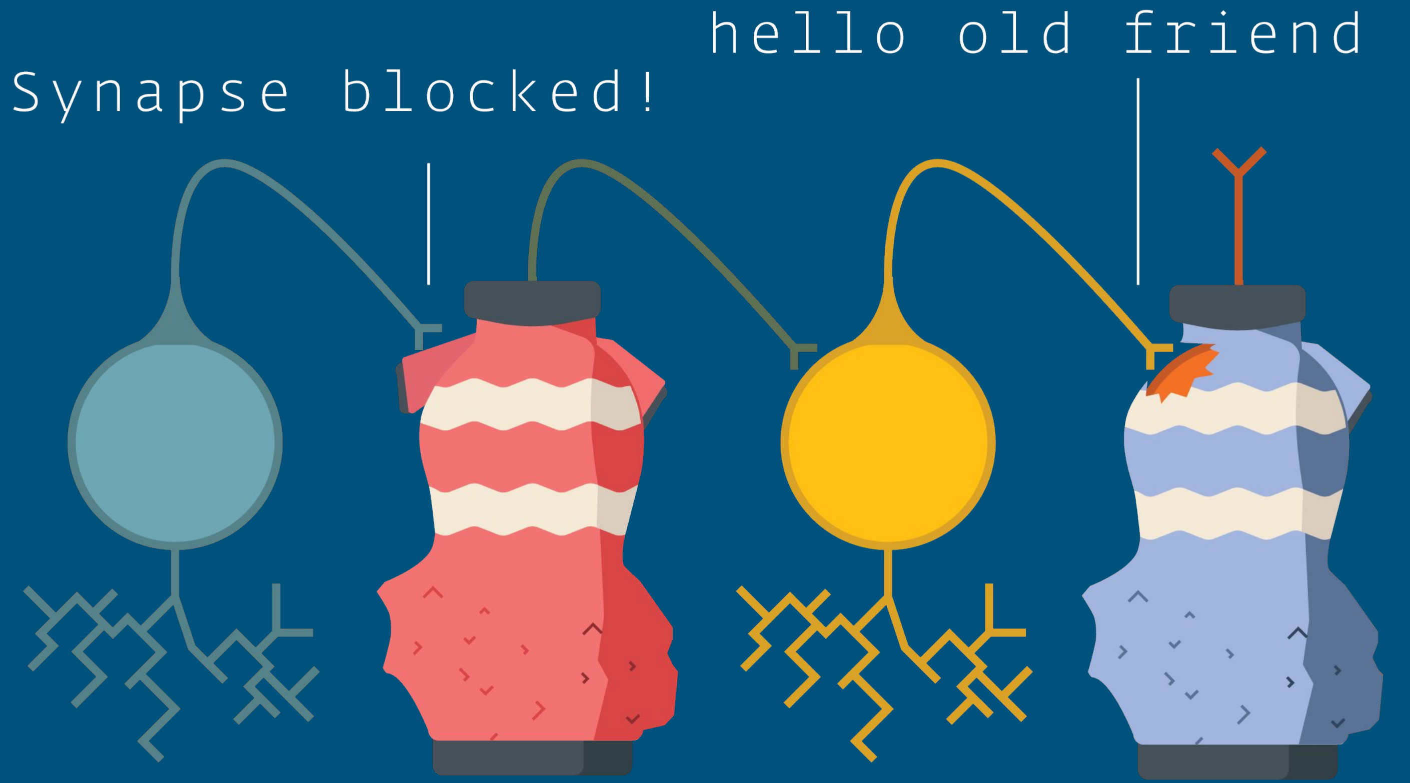


Kuhl, P. K., et al. (2006). *Dev. Sci. 9(2)*

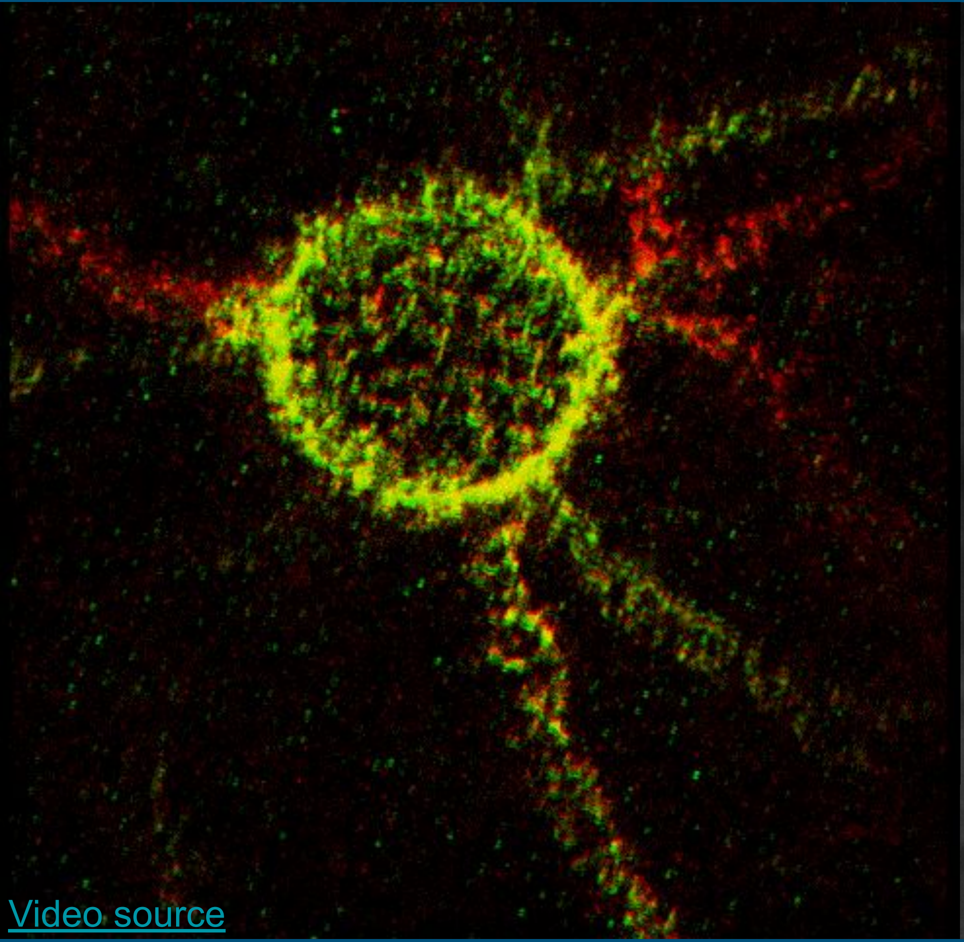
Information is stored in the synapses...



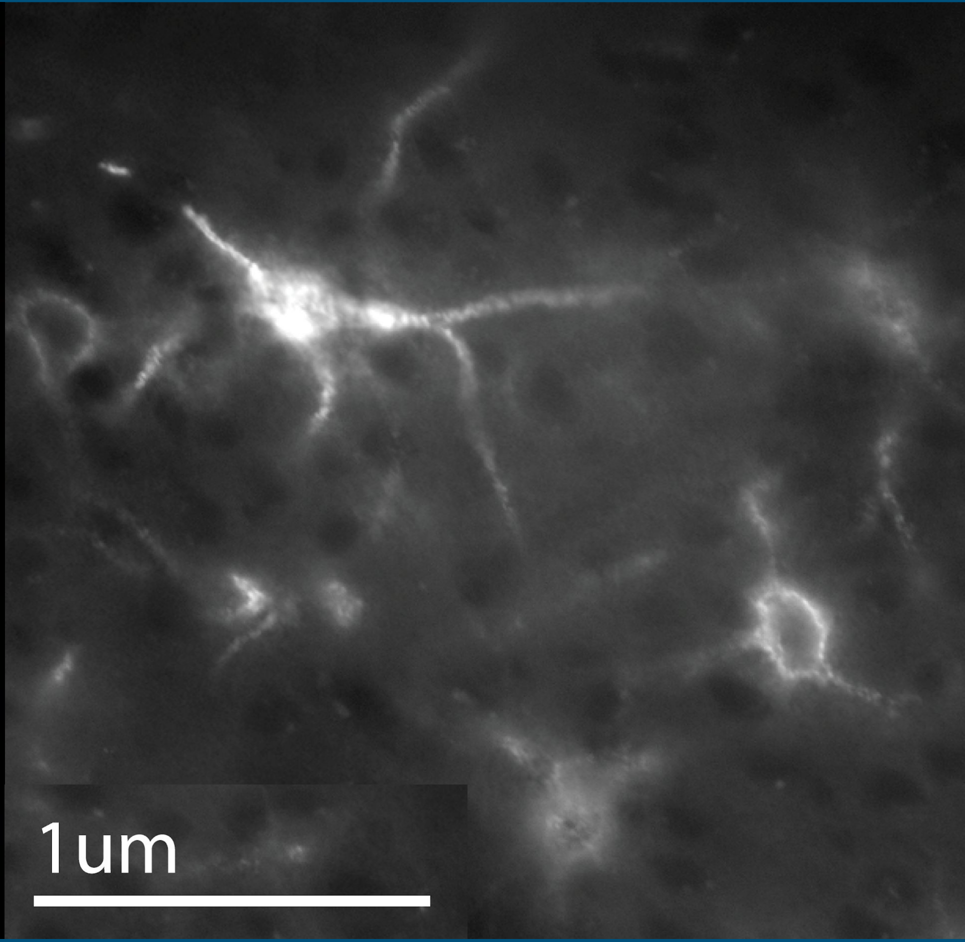
Synaptic patterns are stabilized by extracellular proteins - perineuronal nets



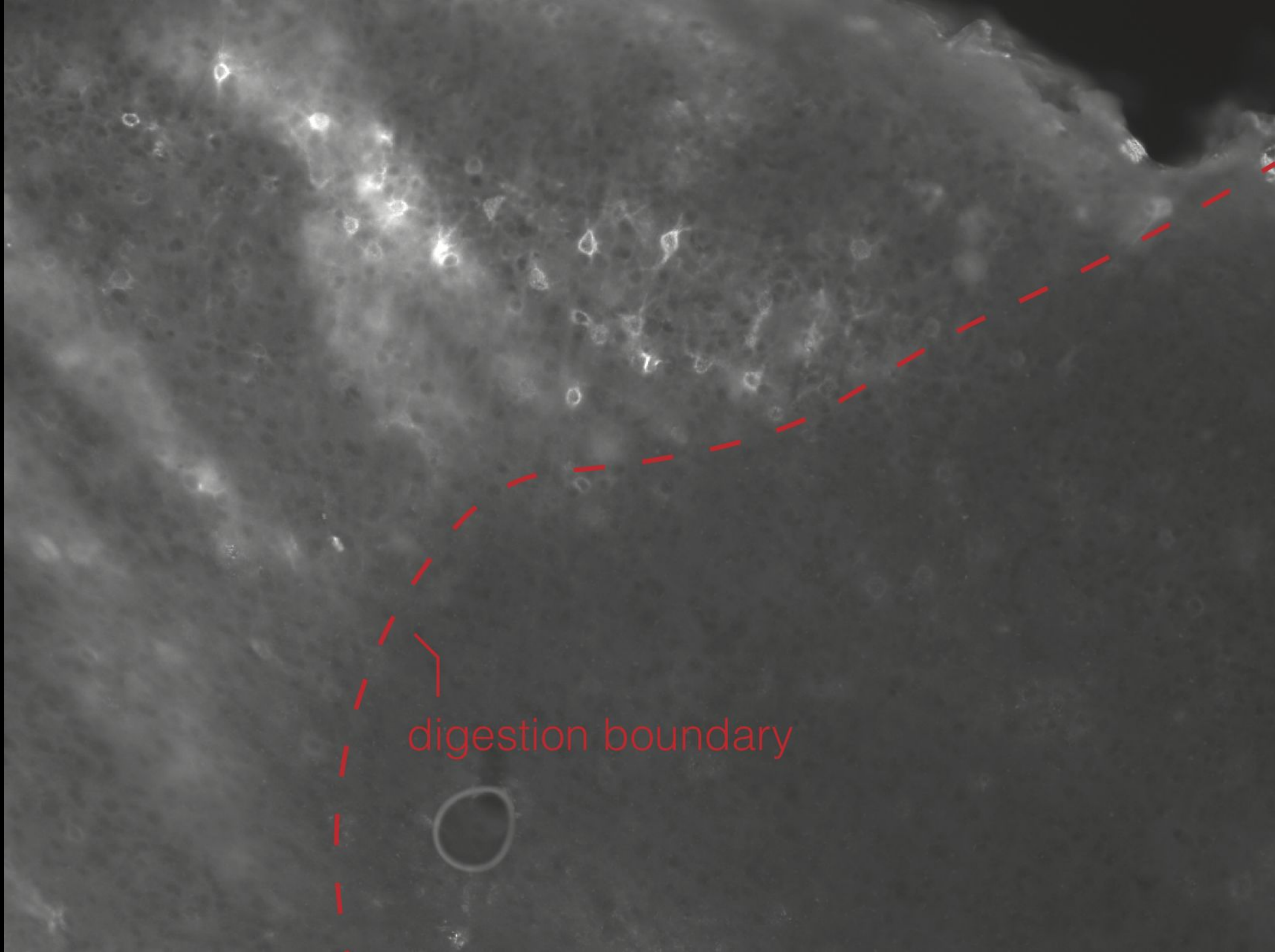
A subset of neurons wear perineuronal nets



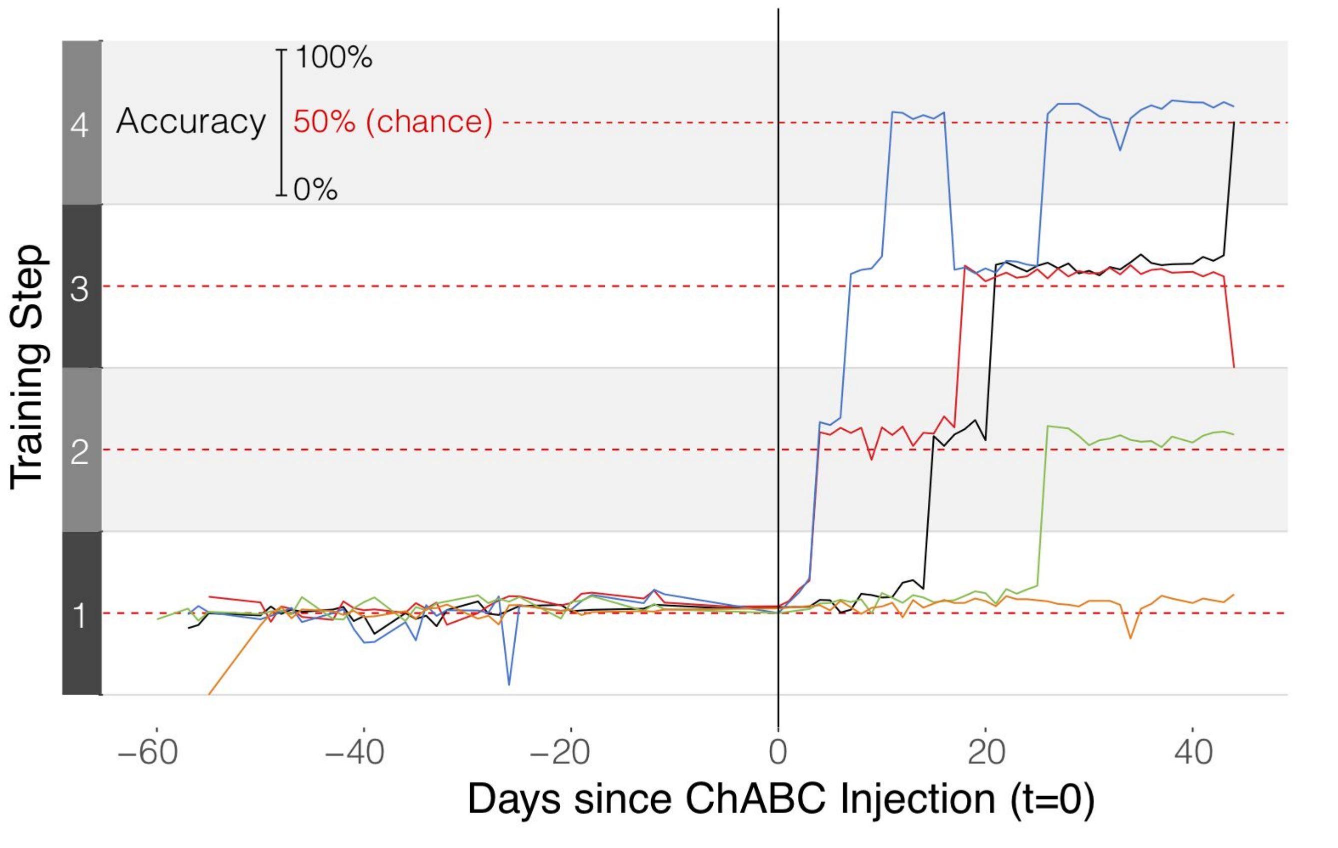
[Video source]



What if we destroy them and let them grow back?



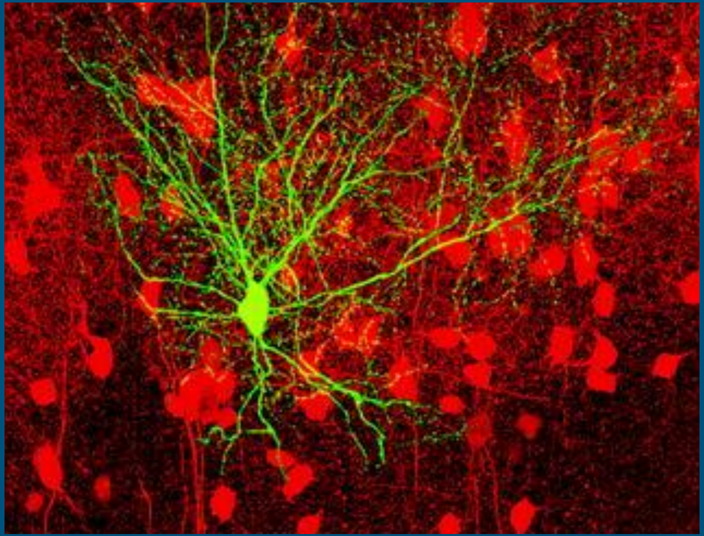
PNN Digestion reopens speech learning

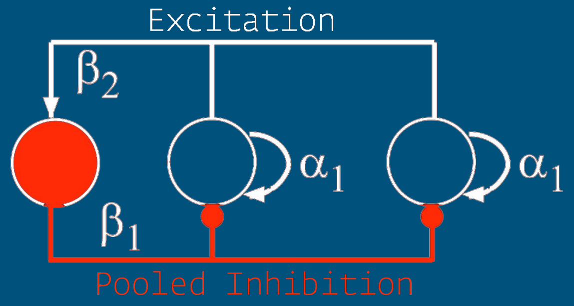


*warning, unpublished pilot experiment, replication in progress

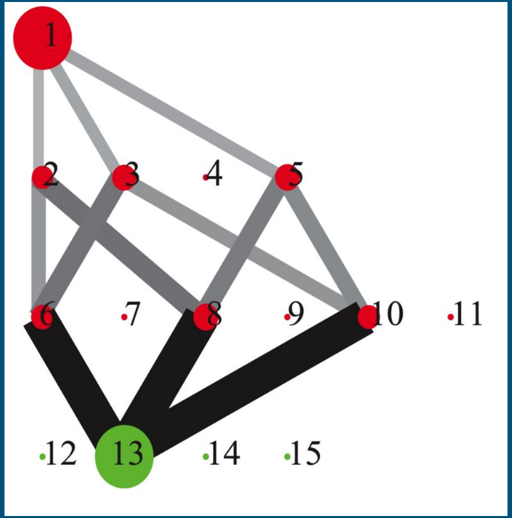
ANNs Need Inhibition

- PNNs are worn by neurons with strong local inhibition
- Local Inhibitory neurons
  - Integrate recent past to steer recurrent computation
  - Store long-term auditory percepts (?)





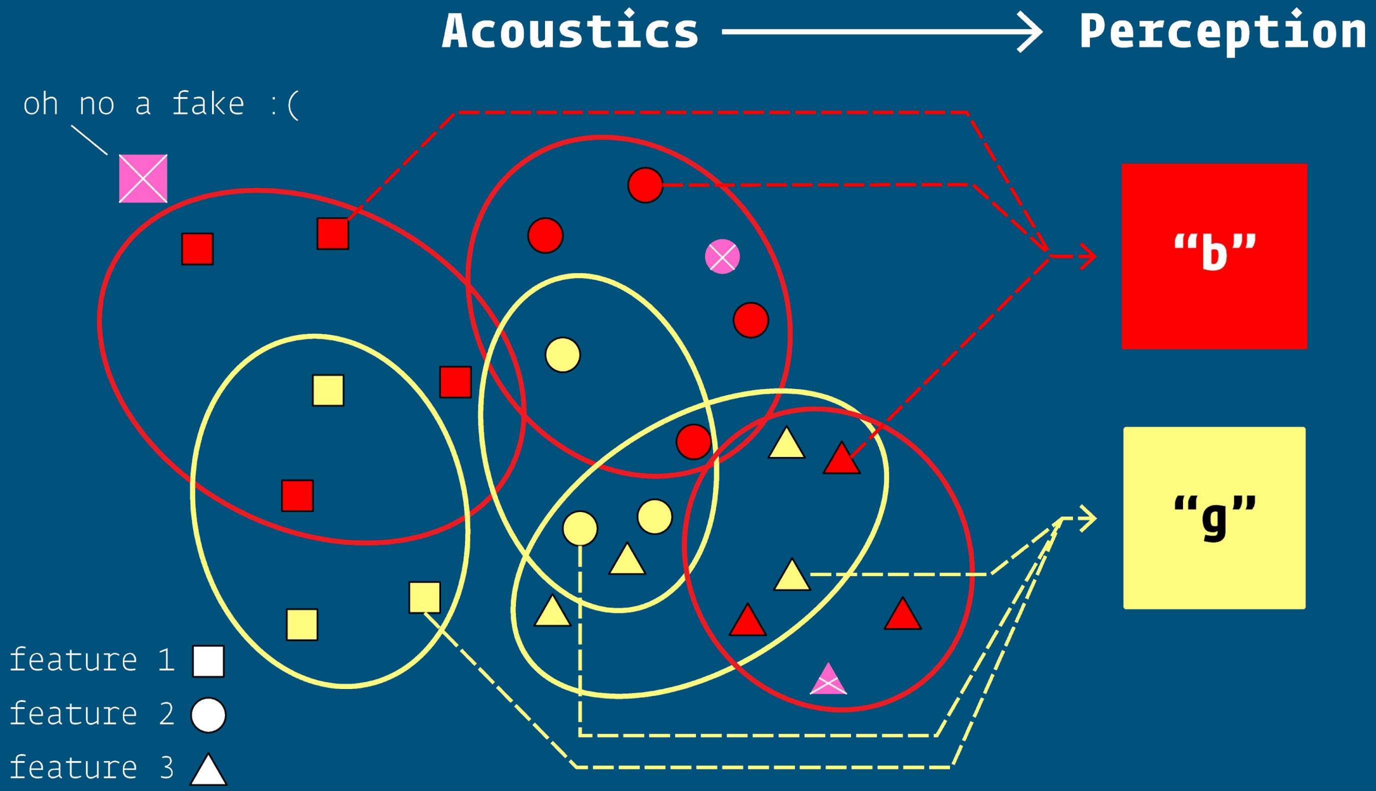
Inhibition 'forbids' some state transitions to steer computation



Staiger JF, et al (2009) *Brain Structure and Function* 214:1
Rutishauser U, et al (2015) *PLOS Comp. Biol.* 11(1): e1004039

Detecting deep fakes like the brain?

Training mice to detect fakes could inform better detection algorithms



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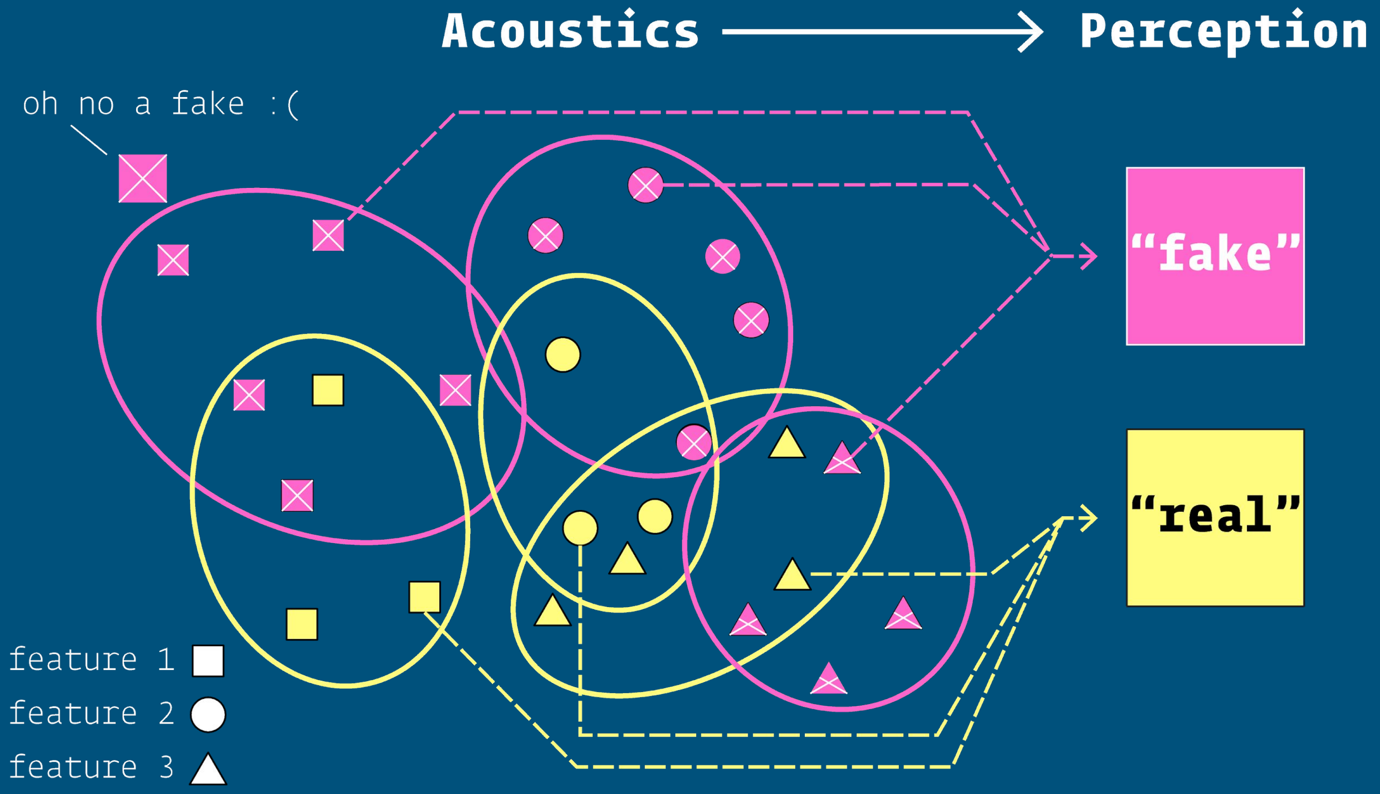

Thank you, BlackHat !

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George Williams, GSI Technology

- Twitter: @cgeorgewilliams

Alex Comerford, Data Scientist

- Github: @cmrfrd

Participate in our Deep Fake Study at: **https://blackhat.deepfakequiz.com**