How much can we squeeze from an ultrasound signal? And thoughts on AI

Brett Byram & Team

2026

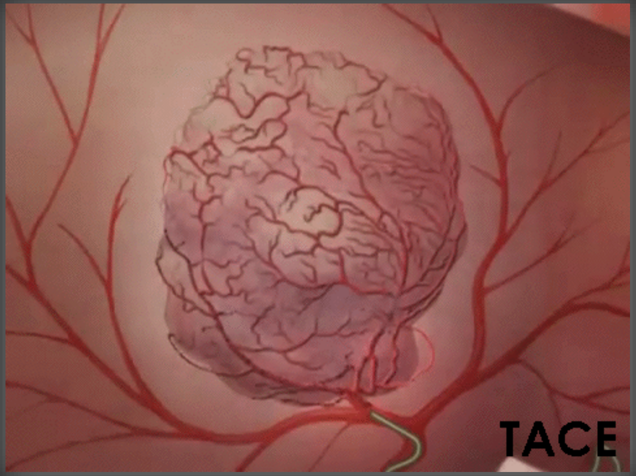
beam
BIOMEDICAL ELASTICITY & ACOUSTIC MEASUREMENT LAB

VISE
VANDERBILT INSTITUTE FOR SURGERY AND ENGINEERING

Vanderbilt LAB FOR Immersive AI Translation

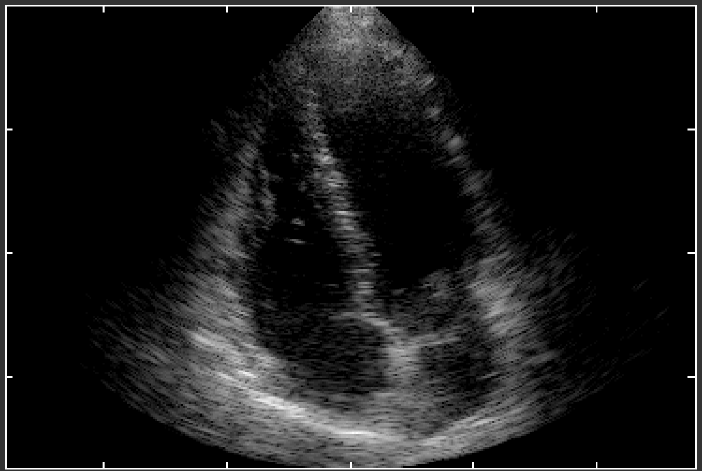
Code Available: https://github.com/VU-BEAM-Lab

Transarterial Chemoembolization Imaging



Left Atrial Appendage Visualization

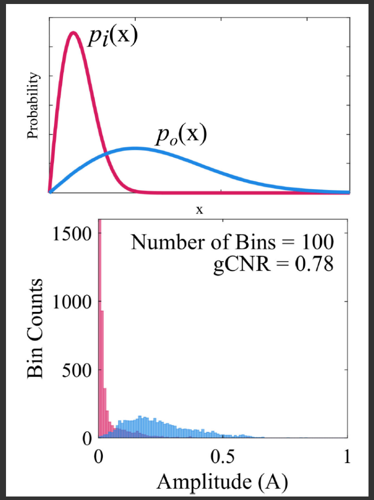
DAS



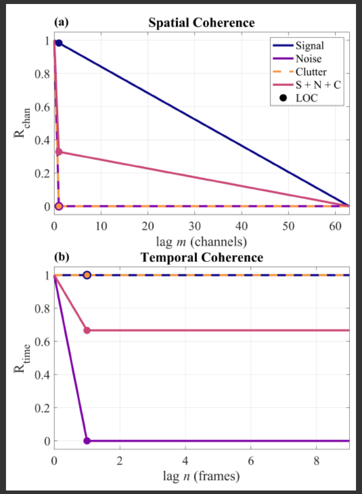
DNN

Image Quality Metrics

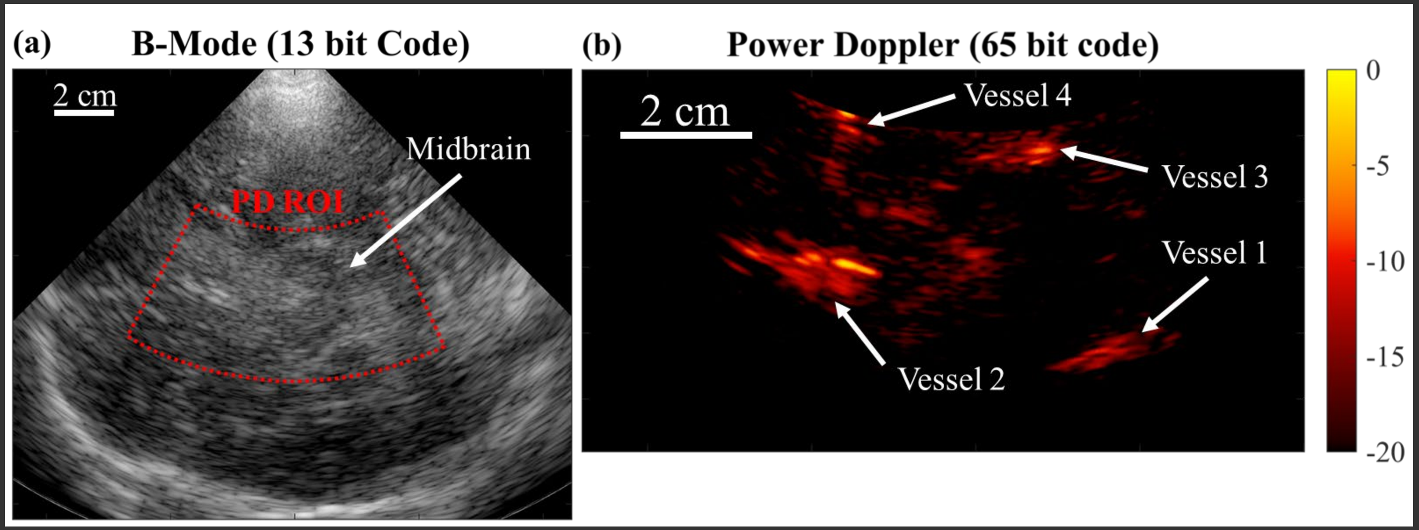
Robust gCNR



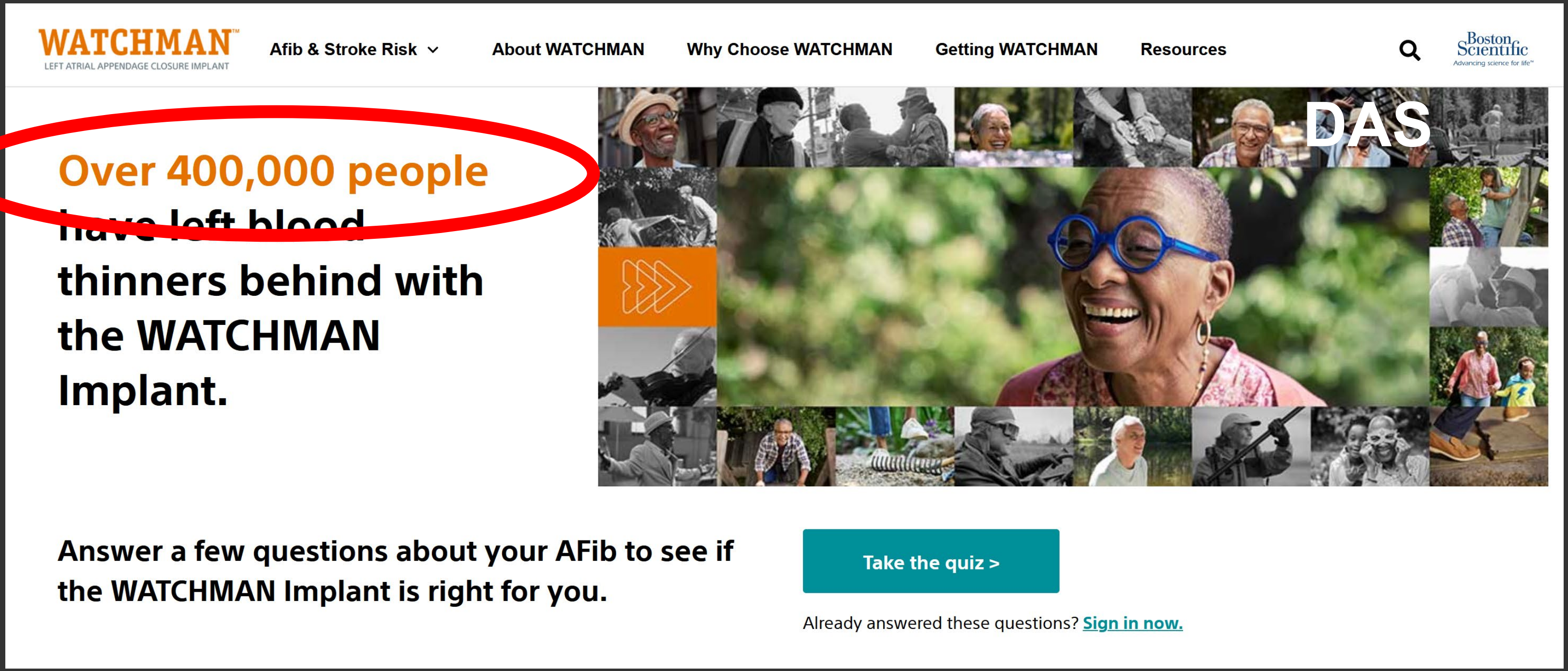
Spatiotemporal Coherence



Transcranial Functional Ultrasound in Adults

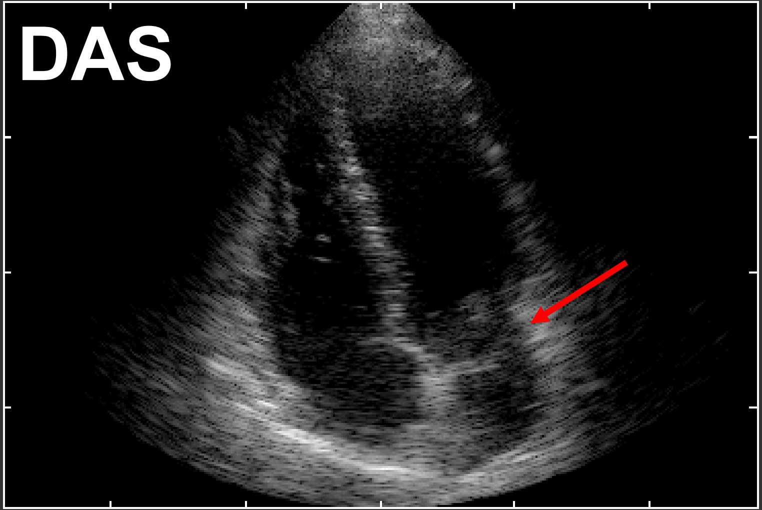


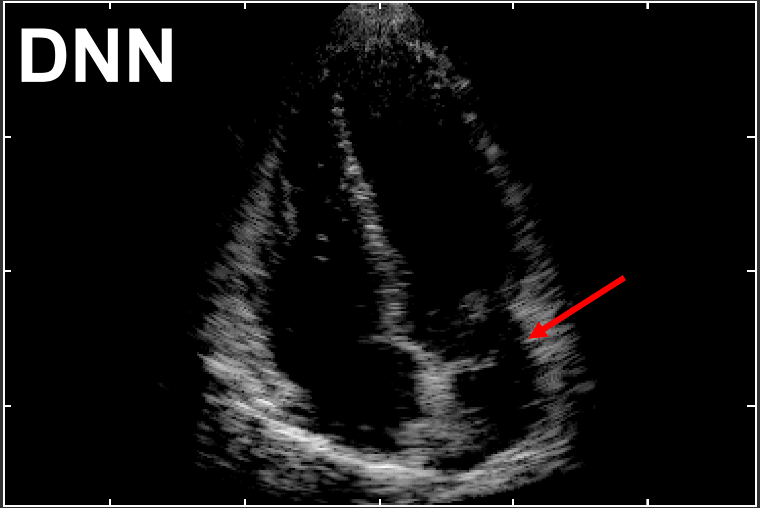
Overview

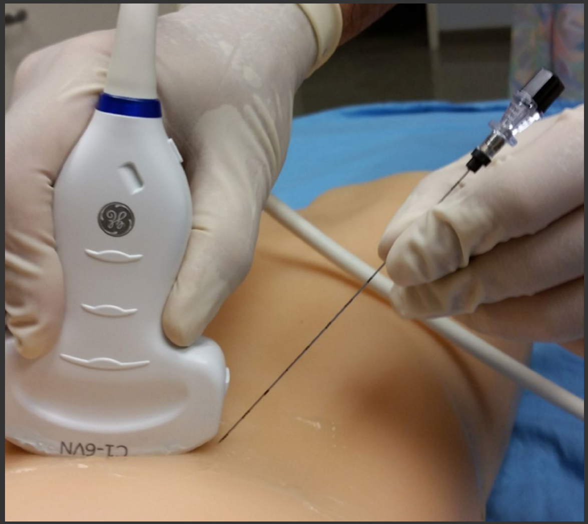


(https://www.watchman.com/en-us/home.html)

Echocardiography







(England et al. JUM, 2018.)

Abdominal Imaging—Especially Biopsy

Watchman FLX

(https://www.bostonscientific.com/.../watchman-flx.html)

Left Atrial Appendage Visualization

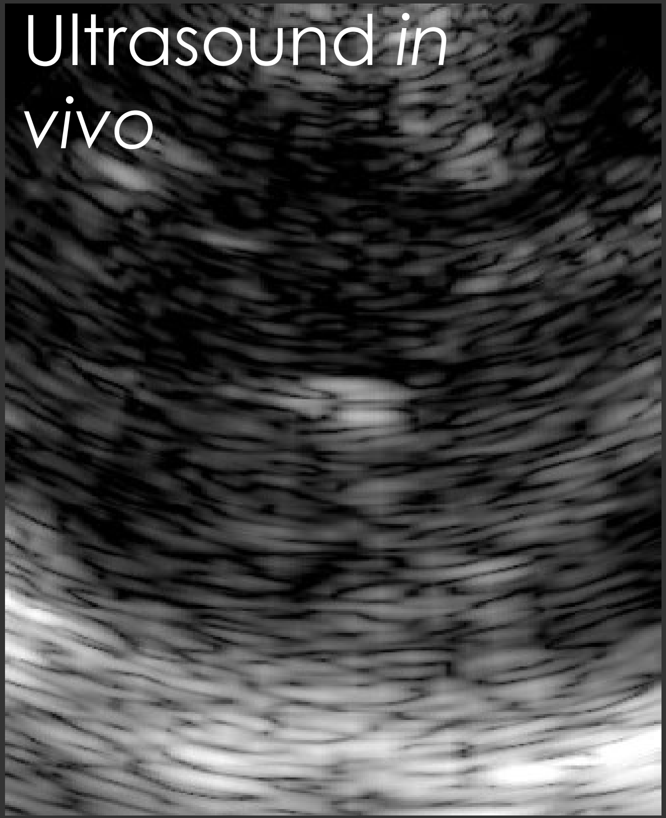
Clinical Failure Rates:

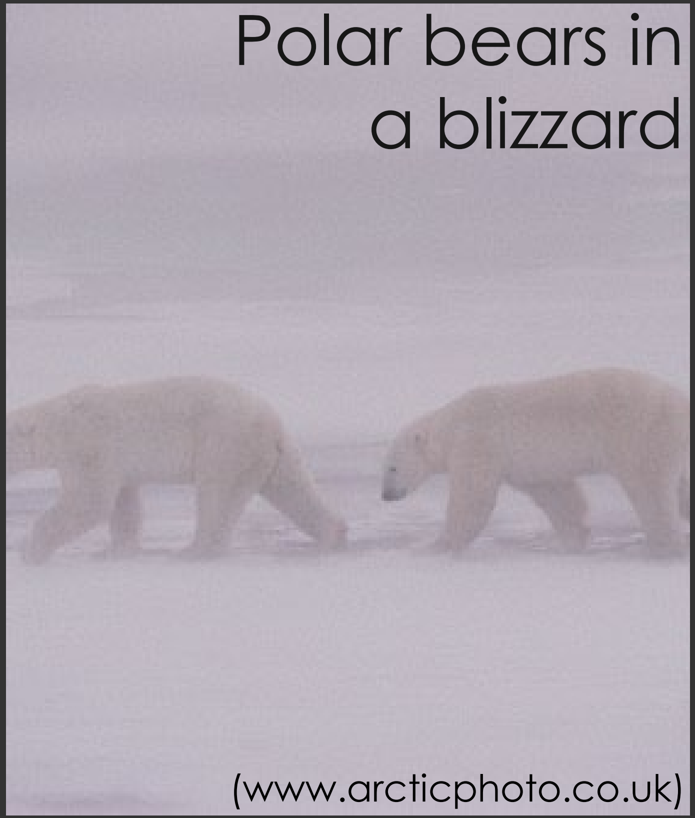
Obstetrics[4-7]	11-64%
Cardiac TTE[1-3]	9-64%
TTE inadequate[8] (Cardiac Imaging)	98.4%

Tumor Detection Example:

Intraoperative US detection -- 98% sensitivity

Transabdominal US detection 40-70%

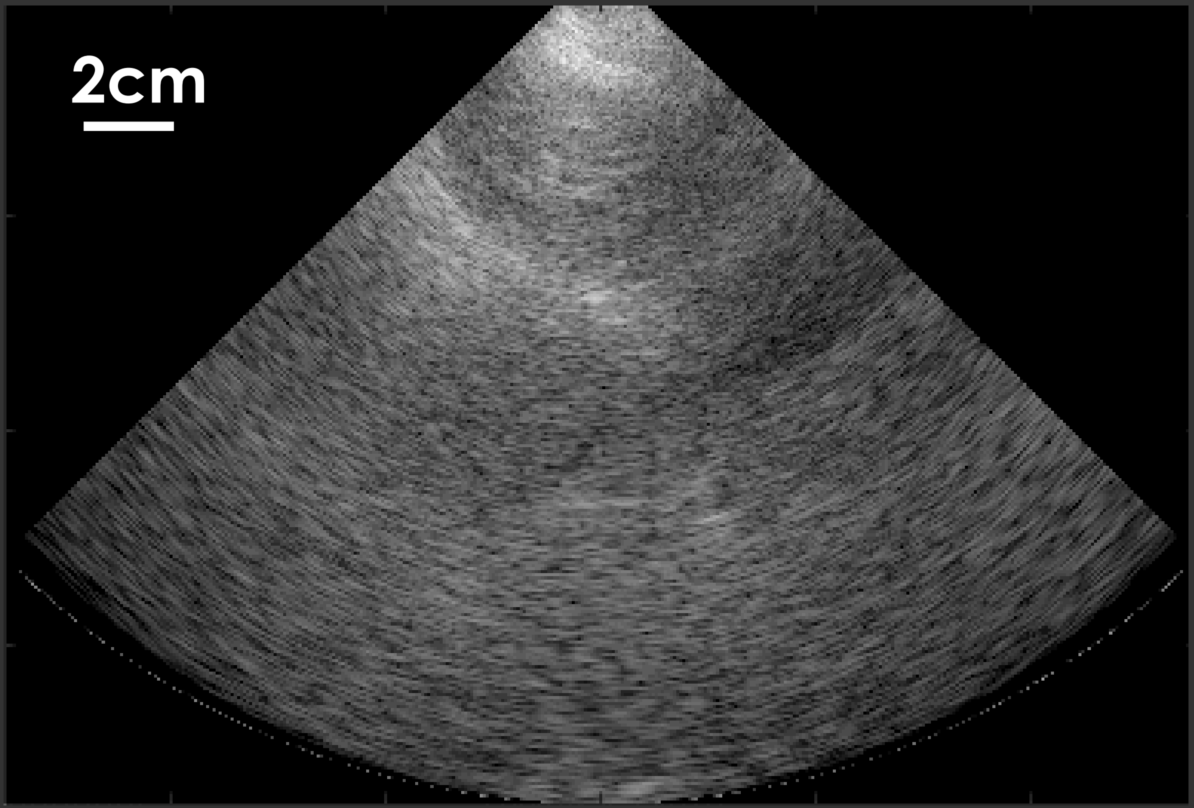




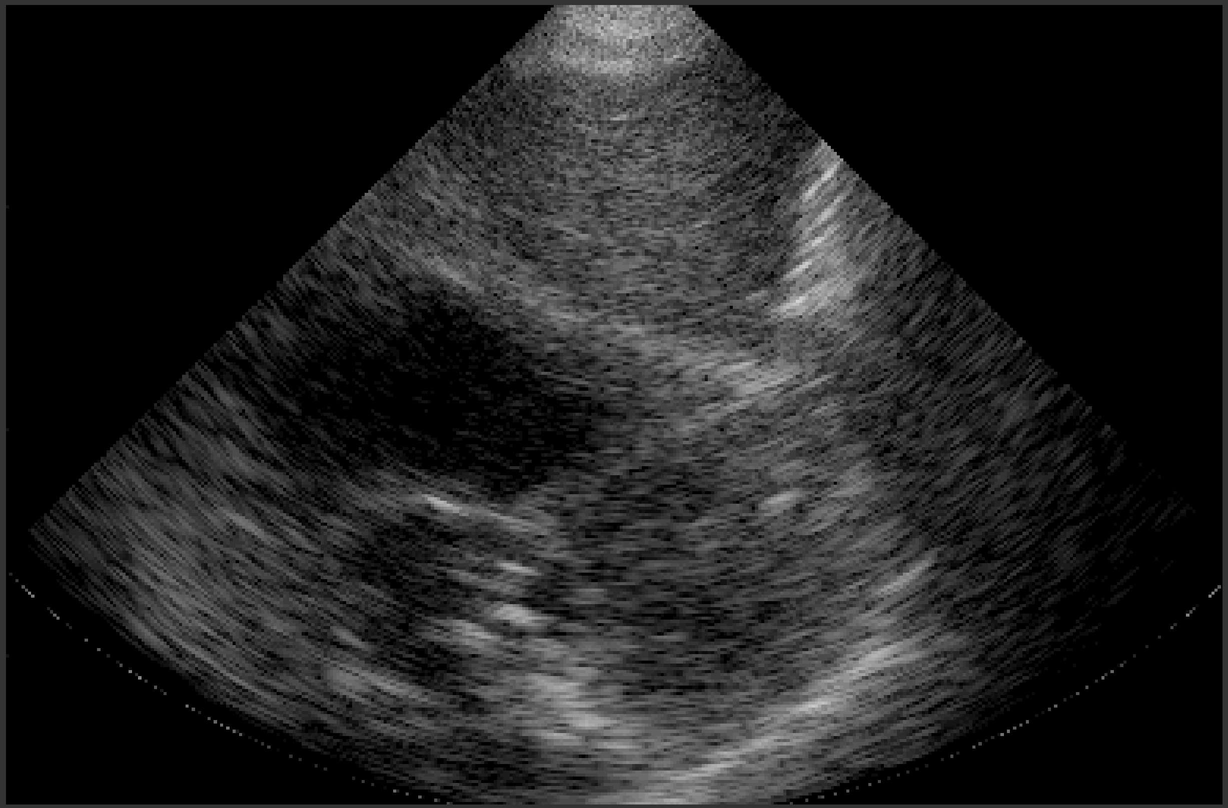
[1] Flynn et al. *Journal of cardiothoracic and vascular anesthesia*, 2010.
[2] Garrett et al. *Annals of vascular surgery*, 2004.
[3] Heidenreich. *Journal of the American College of Cardiology*, 1995.
[4] Hendler et al. *journal of the International Association for the Study of Obesity*, 2004.
[5] Hendler et al. *Journal of ultrasound in medicine,* 2005.
[6] Hendler et al. *American journal of obstetrics and gynecology*, 2004.
[7] Khoury et al. *The journal of maternal-fetal & neonatal medicine,* 2009.
[8] Kurt et al., *Journal of the American College of Cardiology*, 2009.
[9] Ma et al. *JVIR,* 2010.
[10] Olszewski et al. *European journal of echocardiography,* 2007.
[11] Vijayaraghavan et al. *Journal of clinical imaging science*, 2011.

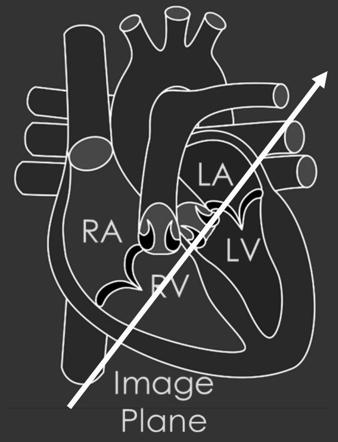
In Normal Patient Populations Ultrasound is Hard!

Patient #1



Patient #2

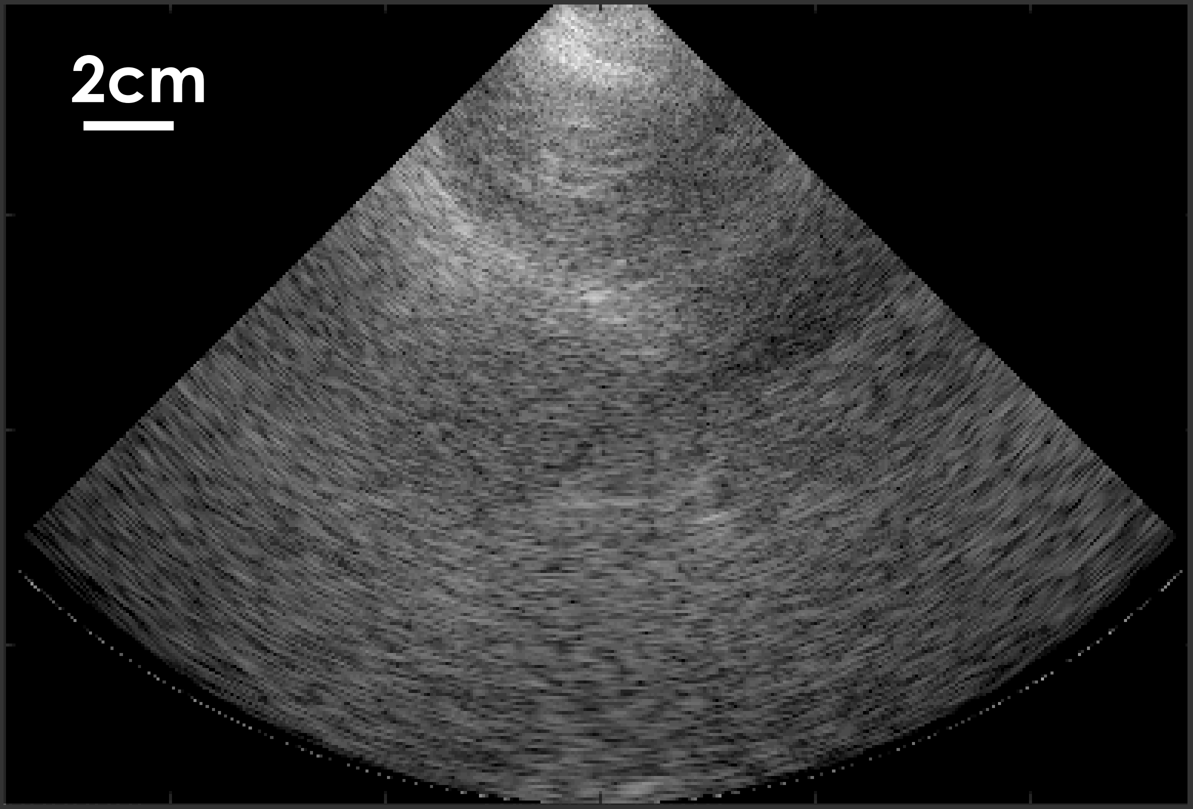




Example Images

Why does ultrasound fail?

Patient #1



~~Why does ultrasound fail?~~

Why do ultrasound exams have such a wide variability in outcome?

- Pressure wave attenuation [1]
- Diffraction-limitations [2,3]
- Multiple scattering or reverberation (sometimes considered distinct) [2, 4, 5],
- Gross sound-speed deviation[6]
- Sound speed and attenuation inhomogeneities [7–13]

[1] Douglas Christensen. *Ultrasonic Bioinstrumentation*. John Wiley and Sons, New York, 1988.

[2] P L Carson and T V Oughton. A modeled study for diagnosis of small anechoic masses with ultrasound. *Radiology*, 122(3):765–71, March 1977.

[3] L. E. Hann, A. M. Bach, L. D. Cramer, D. Siegel, H. H. Yoo, and R. Garcia. Hepatic sonography: comparison of tissue harmonic and standard sonography techniques. *AJR. American journal of roentgenology*, 173(1):201–206, Jul 1999.

[4] S H P Bly, F S Foster, M S Patterson, D R Foster, and J W Hunt. Artifactual Echoes in B-Mode Images due to Multiple Scattering. *Ultrasound Med. Biol.*, 11(1):99–111, 1985.

[5] Gianmarco F Pinton, Gregg E Trahey, and Jeremy J Dahl. Erratum: Sources of image degradation in fundamental and harmonic ultrasound imaging: a nonlinear, full-wave, simulation study. *Ultrasonics, Ferroelectrics and Frequency Control, IEEE Transactions on*, 58(6):1272–83, June 2011.

[6] Martin E Anderson and Gregg E Trahey. The direct estimation of sound speed using pulse-echo ultrasound. *J. Acoust. Soc. Am.*, 104(5):3099–3106, November 1998.

[7] S.W. Smith, G.E. Trahey, and O.T. von Ramm. Phased array ultrasound imaging through planar tissue layers. *Ultrasound Med. Biol.*, 12(3):229 – 243, 1986.

[8] L. M. Hinkelman, D. L. Liu, L. A. Metlay, and R. C. Waag. Measurements of ultrasonic pulse arrival time and energy level variations produced by propagation through abdominal wall. *J. Acoust. Soc. Am.*, 95(1):530–541, Jan 1994.

[9] Makoto Tabei, T Douglas Mast, and Robert C Waag. Simulation of ultrasonic focus aberration and correction through human tissue. *J. Acoust. Soc. Am.*, 113(2):1166–76, 2003.

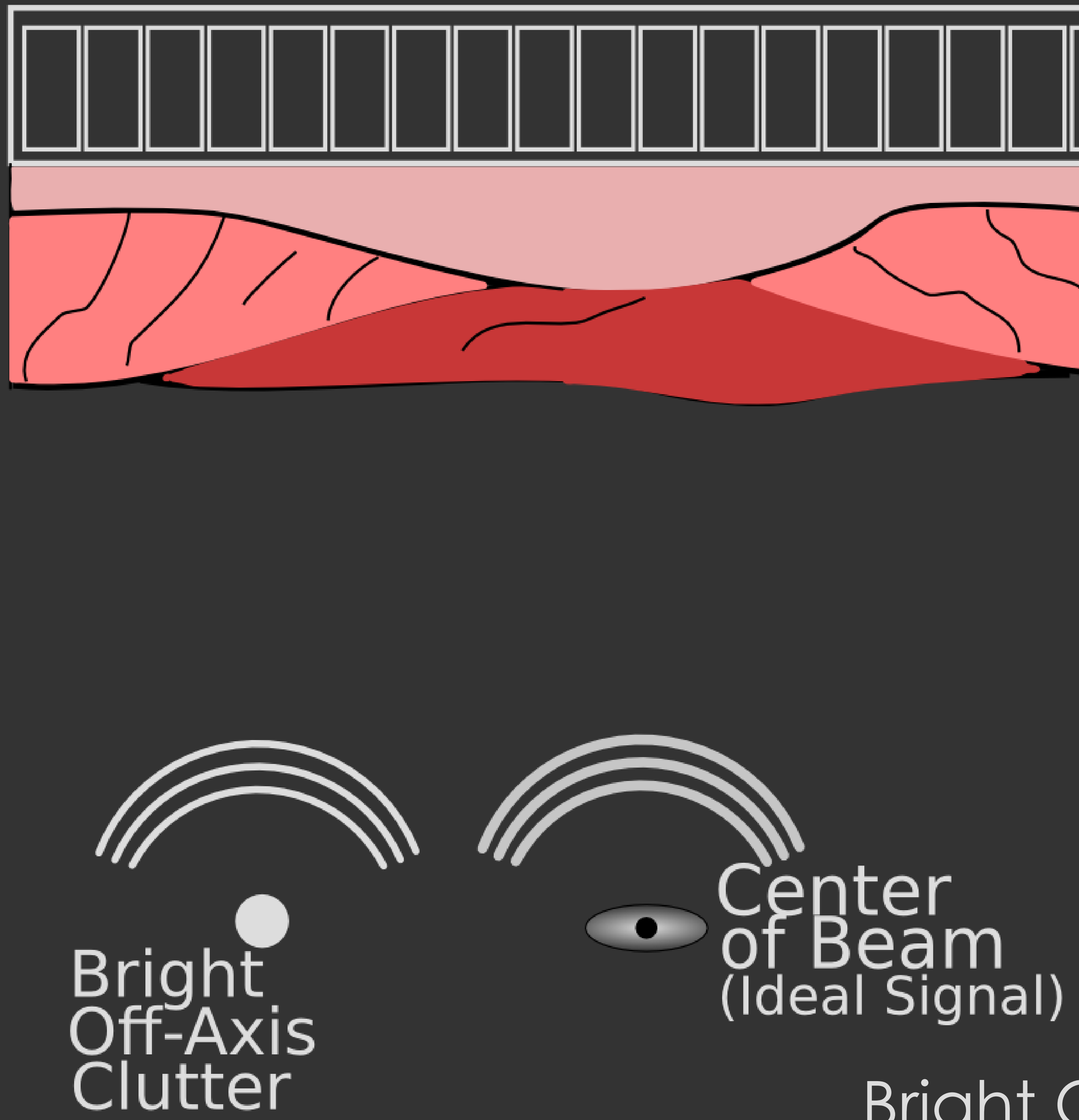
[10] S W Flax and M O'Donnell. Phase-aberration correction using signals from point reflectors and diffuse scatterers: basic principles. *Ultrasonics, Ferroelectrics and Frequency Control, IEEE Transactions on*, 35(6):758–67, January 1988.

[11] Q. Zhu and B. D. Steinberg. Large-transducer measurements of wavefront distortion in the female breast. *Ultrasonic imaging*, 14(3):276–299, Jul 1992.

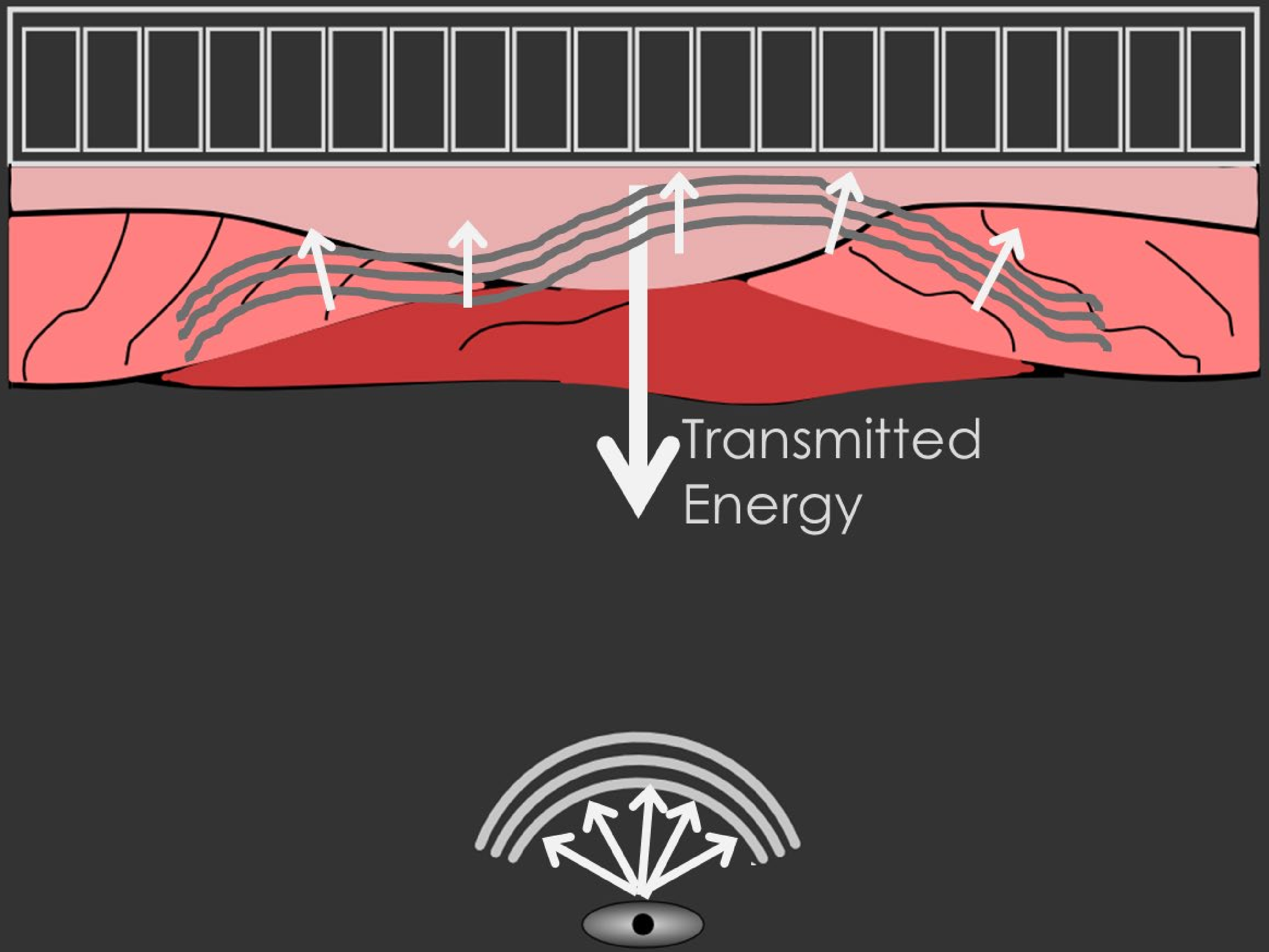
[12] Y. Sumino and R. C. Waag. Measurements of ultrasonic pulse arrival time differences produced by abdominal wall specimens. *J. Acoust. Soc. Am.*, 90(6):2924–2930, Dec 1991.

[13] R.C. Waag, J.P. Astheimer, and Jr. Swartout, G. W. A characterization of wavefront distortion for analysis of ultrasound diffraction measurements made through an inhomogeneous medium. *Sonics and Ultrasonics, IEEE Transactions on*, 32(1):36–48, Jan 1985.

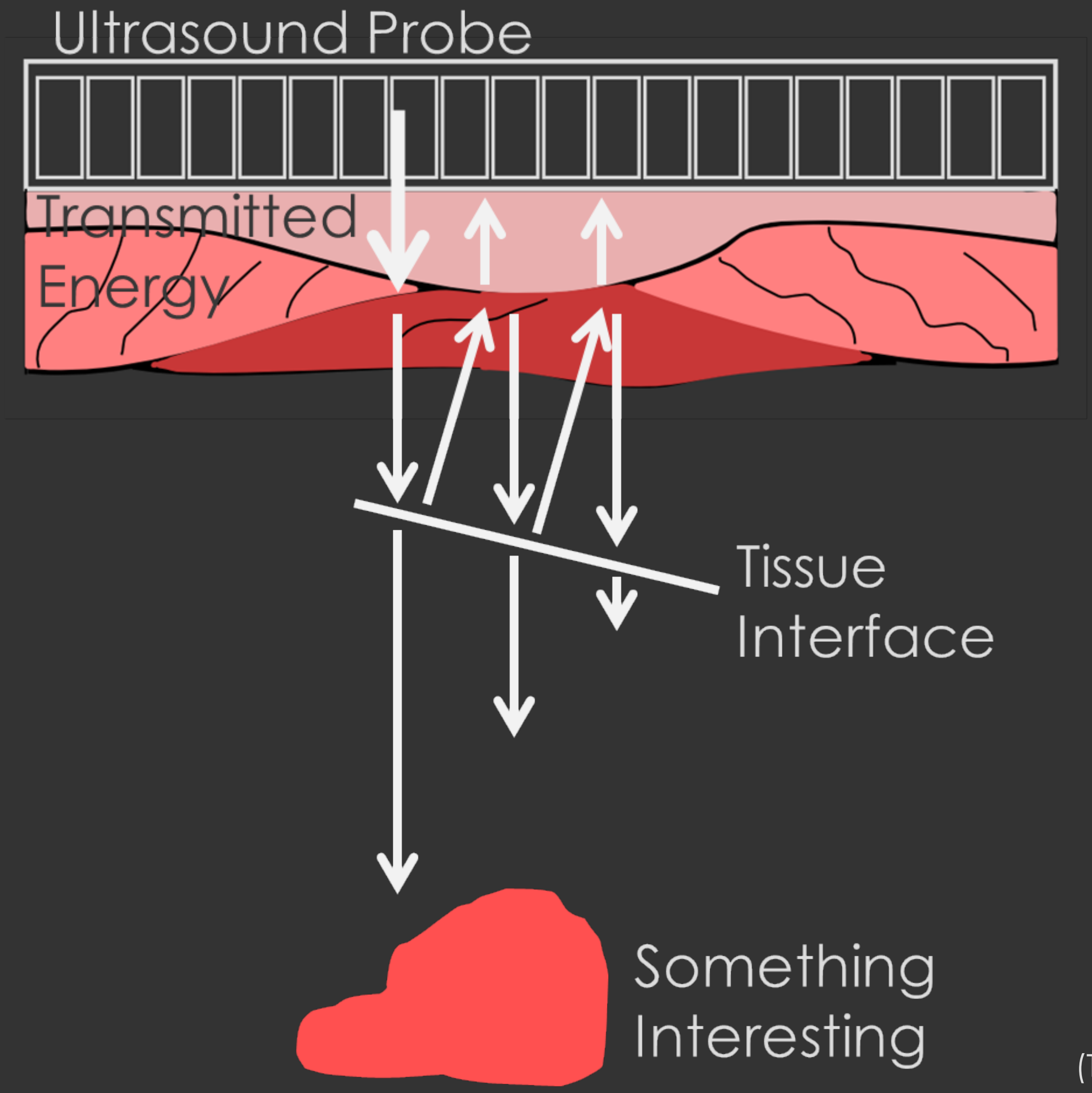
Sources of Image Degradation

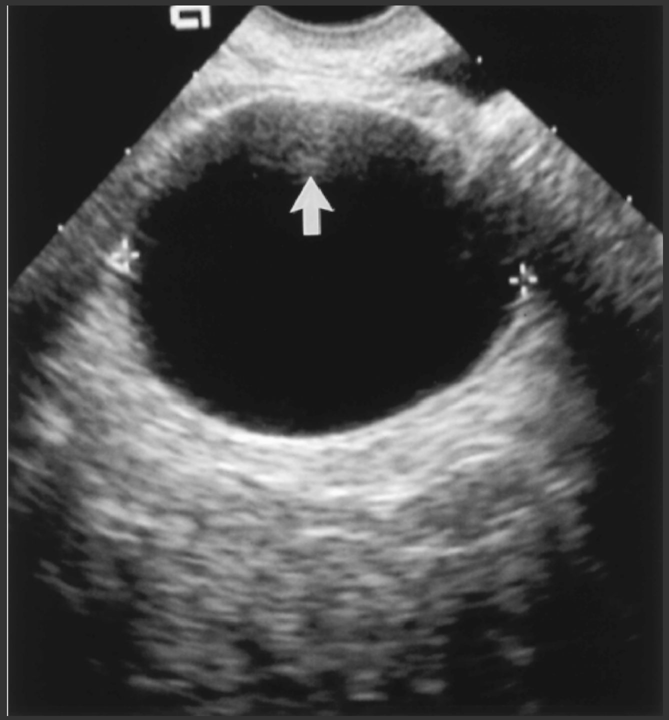


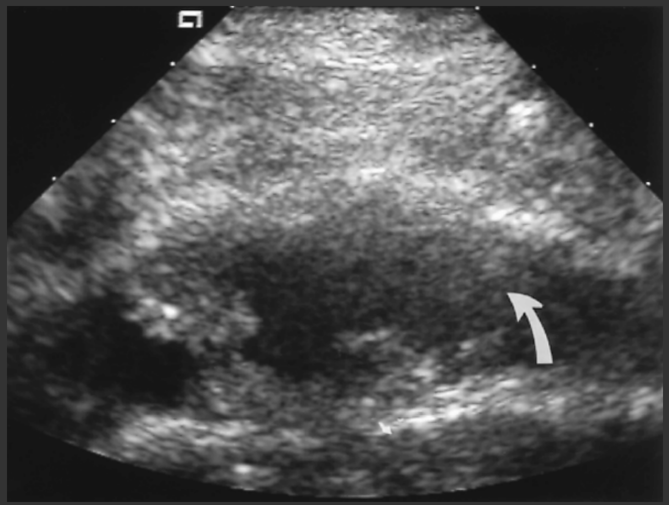
Bright Off-Axis Scattering



Wavefront Distortion (Phase Aberration)







(The Core Curriculum: Ultrasound, 2001)

Reverberation (Multipath Scattering)

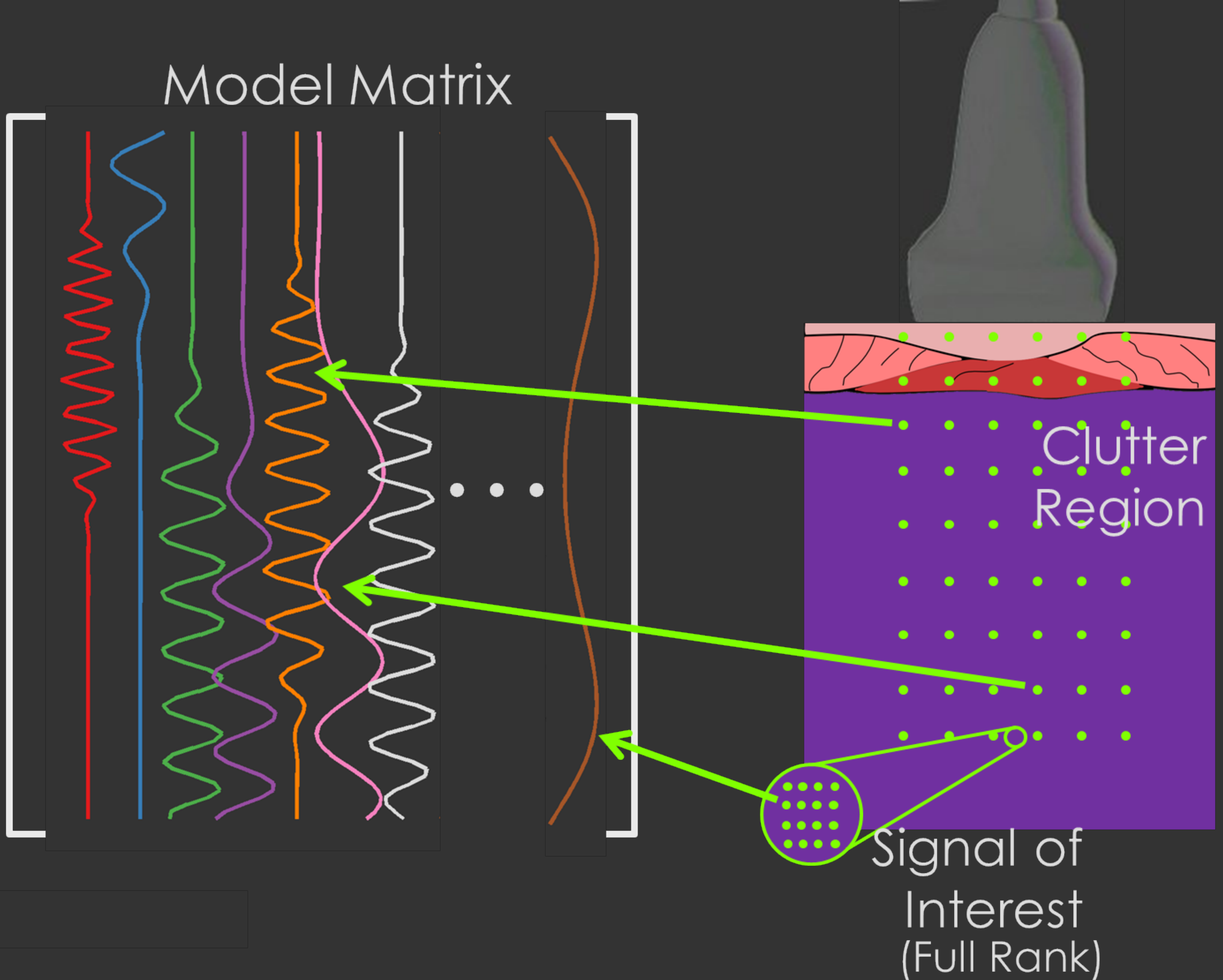
So what can we do?

Aperture Domain Model Image Reconstruction (ADMIRE)

Kaz Dei

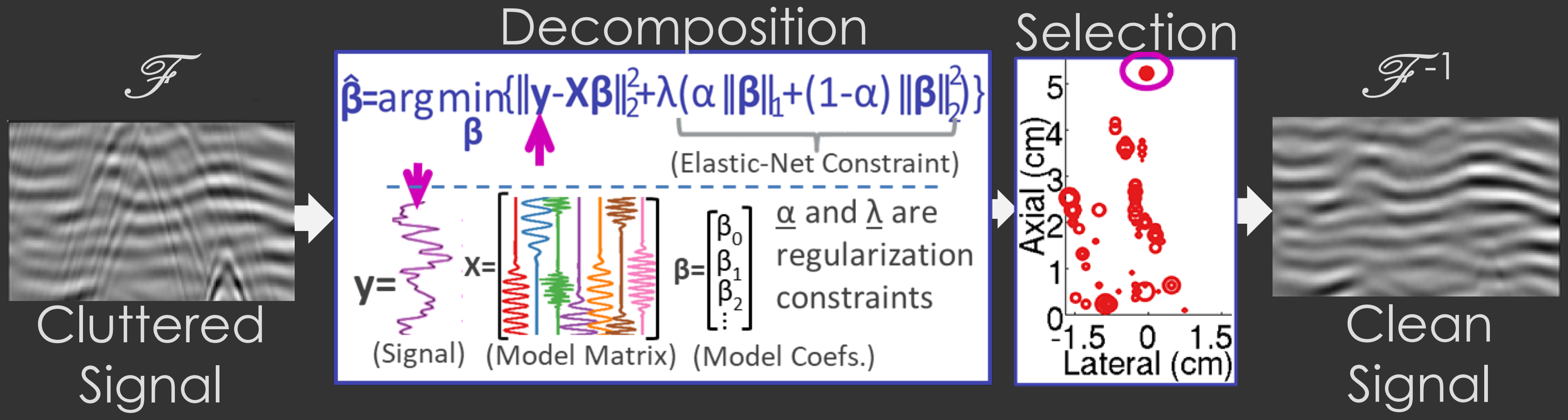
Chris Khan

Siggi Schlunk



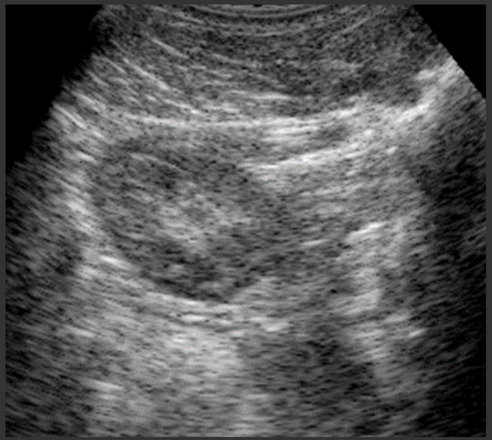
ADMIRE Replacing One Source of Nonlinearity for Another

ADMIRE Algorithm

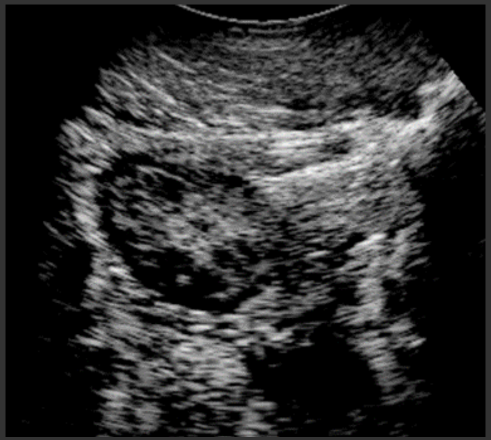


Example

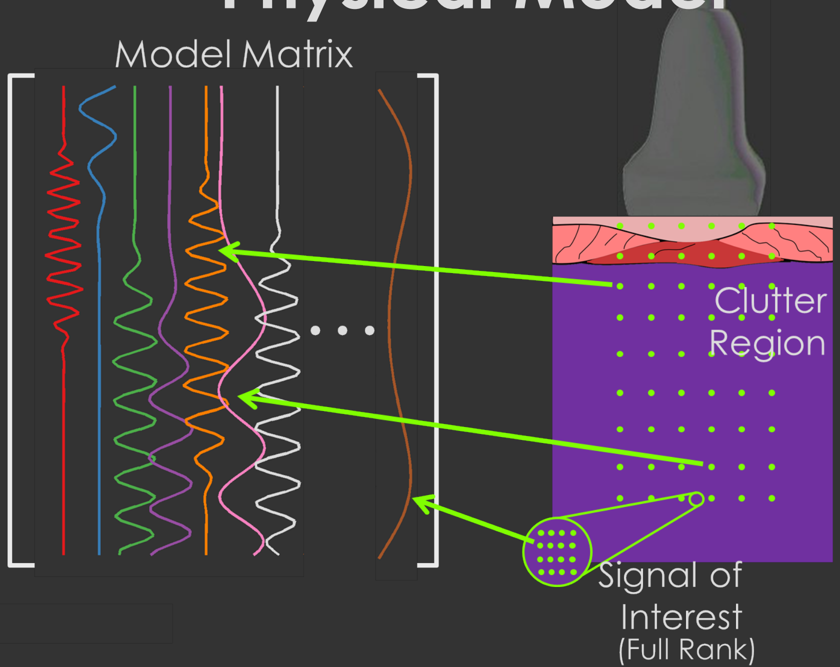
B-Mode



ADMIRE



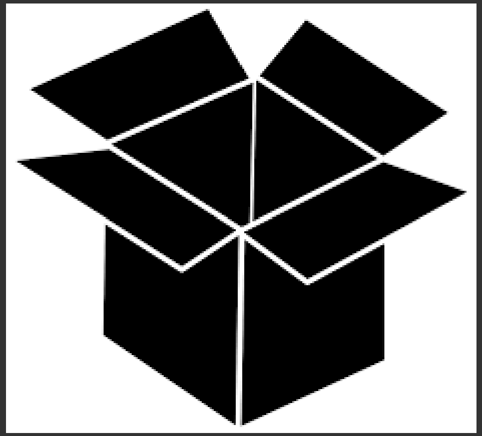
Physical Model



Aperture Domain Model Image Reconstruction (ADMIRE)

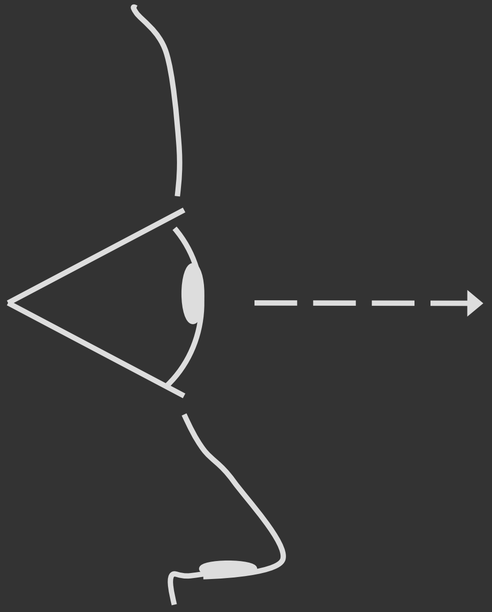
Deep Networks for Beamforming

Motivating Deep Networks from classic ideas that we may feel more comfortable with

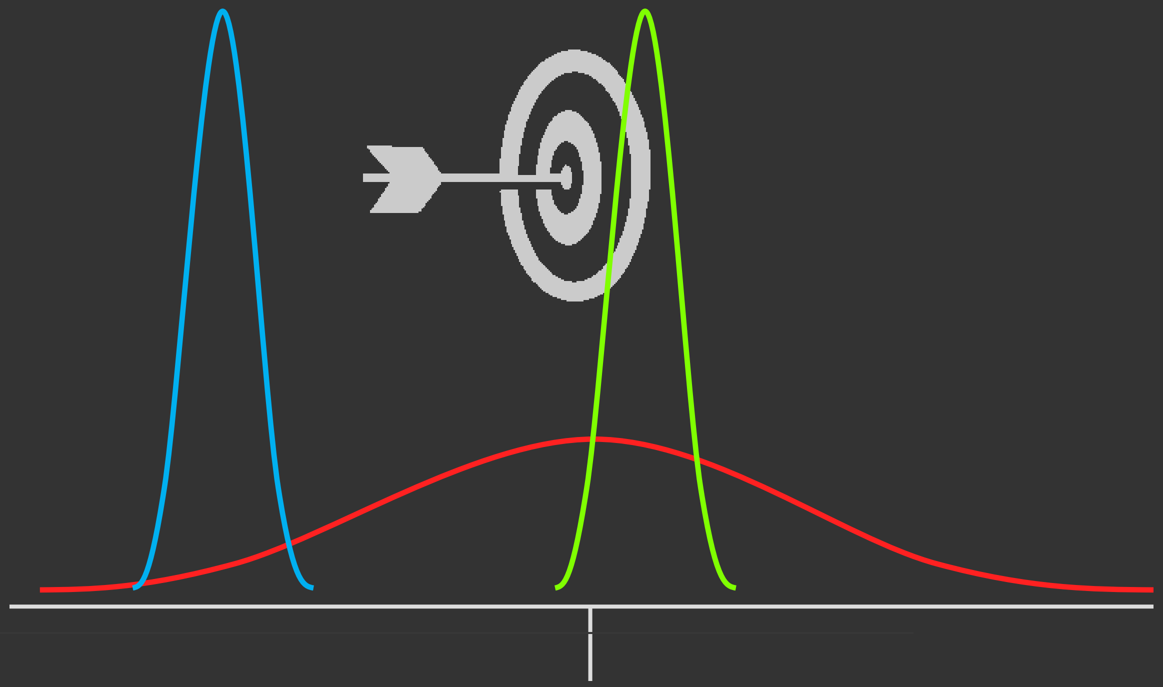


1.) Estimation Theory (*e.g.* statistics)
2.) Curve Fitting (*e.g.* regression)
3.) Logic

Estimation Theory



How far is the target?

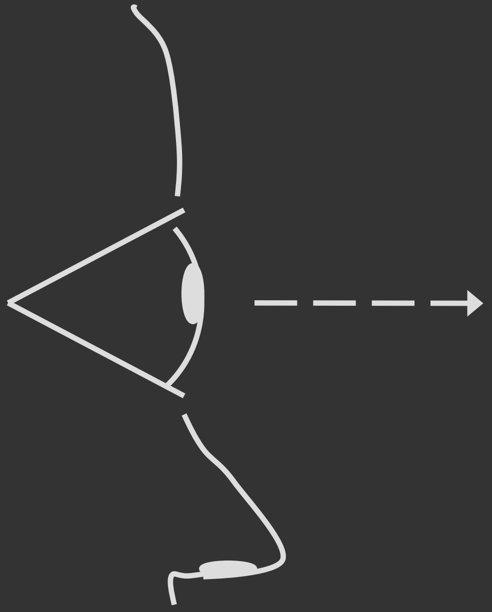


$$\text{bias} = \mathrm{E}\left[\tau_0 - \hat{\tau}_0\right]$$

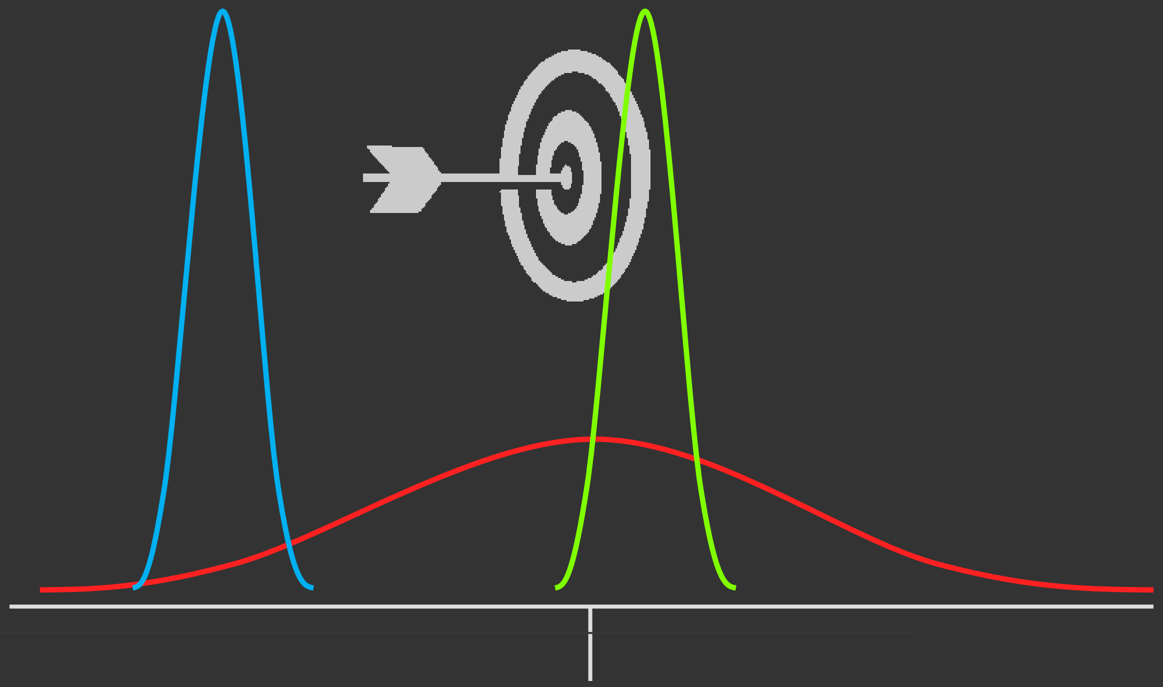
$$\text{variance} = \mathrm{E}\left[(\tau_0 - \hat{\tau}_0)^2\right] - \text{bias}^2$$

$$\text{mean square error} = \mathrm{E}\left[(\tau_0 - \hat{\tau}_0)^2\right] = \text{variance} + \text{bias}^2$$

Biased Estimation



How far is the target?



$$\text{bias} = \mathrm{E}\left[\tau_0 - \hat{\tau}_0\right]$$

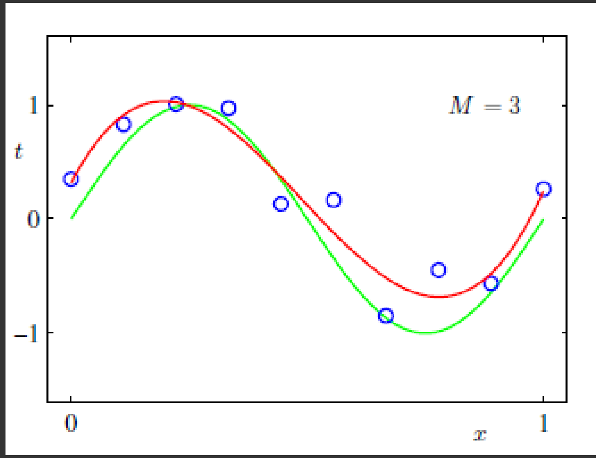
$$\text{variance} = \mathrm{E}\left[\left(\tau_0 - \hat{\tau}_0\right)^2\right] - \text{bias}^2$$

$$\text{mean square error} = \mathrm{E}\left[\left(\tau_0 - \hat{\tau}_0\right)^2\right] = \text{variance} + \text{bias}^2$$

$$Var(x) = \frac{1}{N-1}\sum_{n=0}^{N-1}\left(x_n - \bar{x}\right)^2$$

Biased Estimation

Curve Fitting

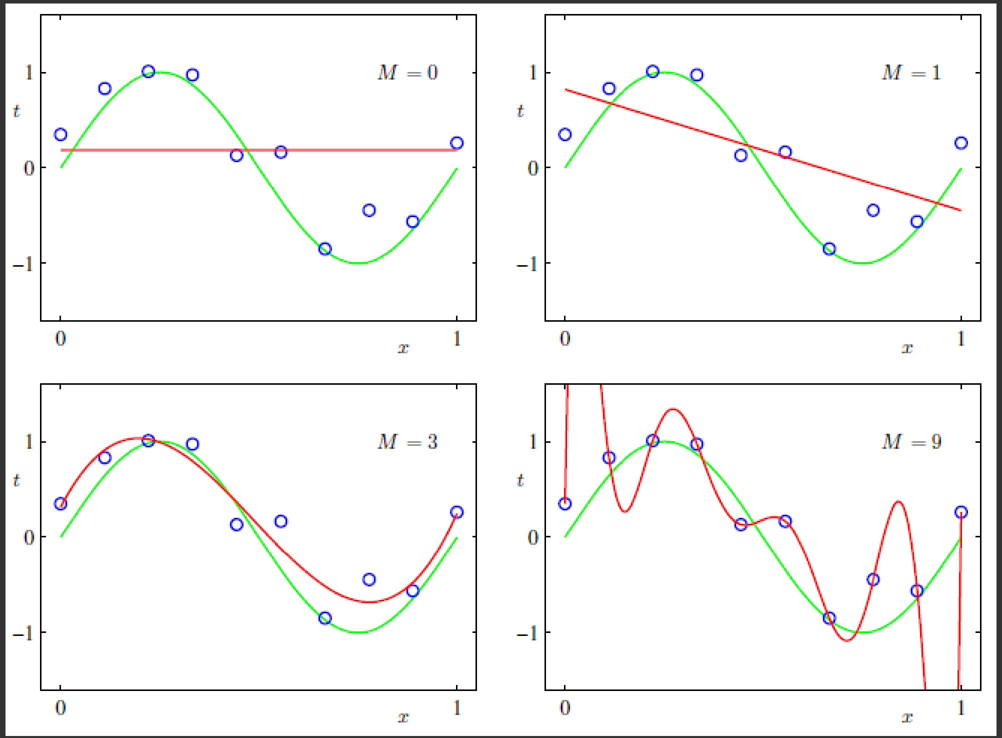


Choose bases:

- Sinusoids (e.g. Fourier Transforms)
- Polynomials
- Bessel functions
- Custom functions (e.g. ADMIRE[1])

[1]B. Byram et al., "A model and regularization scheme for ultrasonic beamforming clutter reduction," in *IEEE UFFC*, vol. 62, no. 11, pp. 1913-1927, 2015

Common Problems:

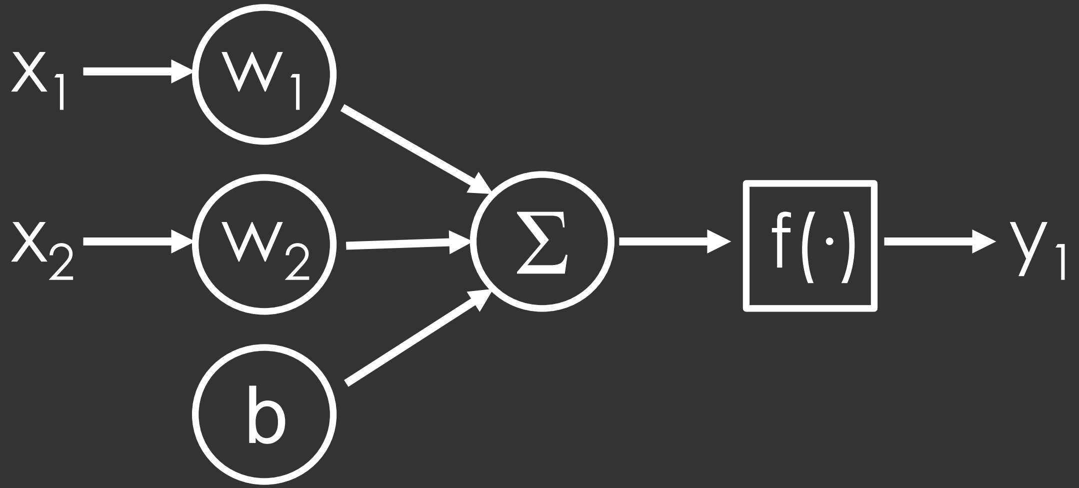


Many classic strategies to overcome these problems
—regularization
—acquire more data
—choose different bases
—etc.

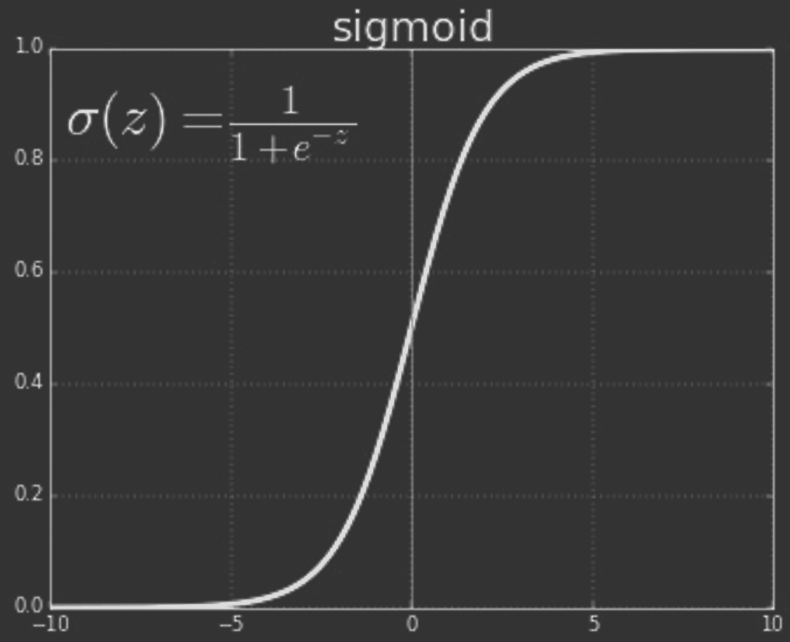
Demonstration of DNNs as curve fitting: http://neuralnetworksanddeeplearning.com/chap4.html

Logic

x_1	x_2	x_1 and x_2
T	T	T
T	F	F
F	T	F
F	F	F

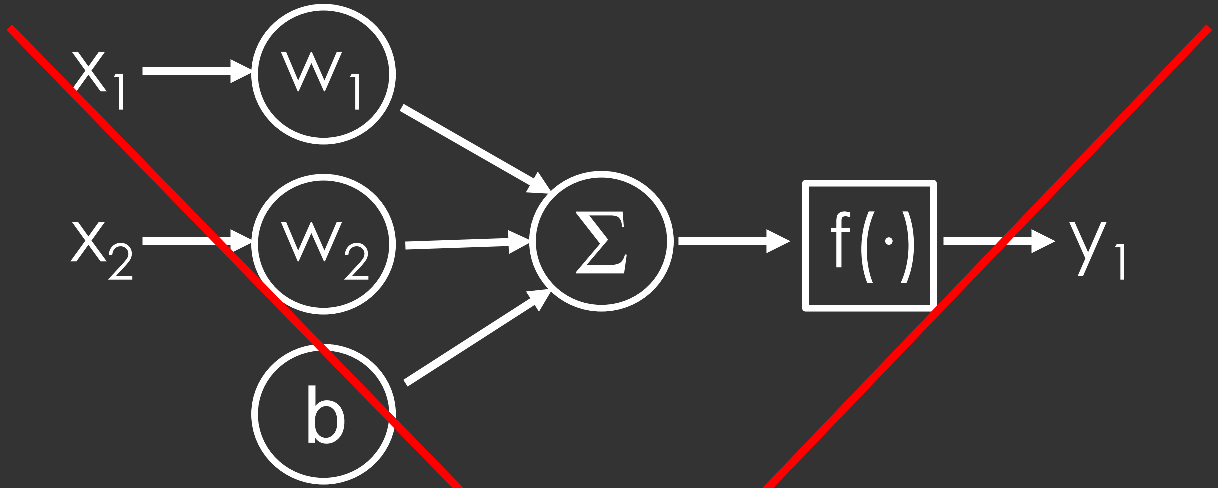


$$y_1 = f(x_1 * w_1 + x_2 * w_2 + b)$$

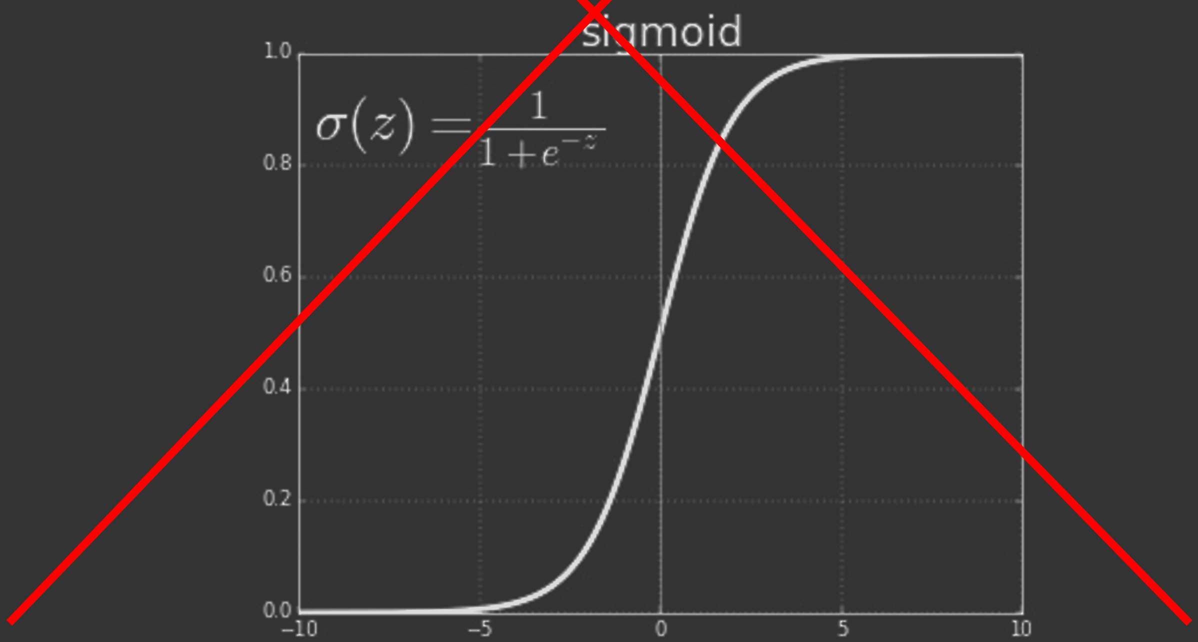


Logic/Deductive Reasoning

x_1	x_2	x_1 xor x_2
T	T	F
T	F	T
F	T	T
F	F	F

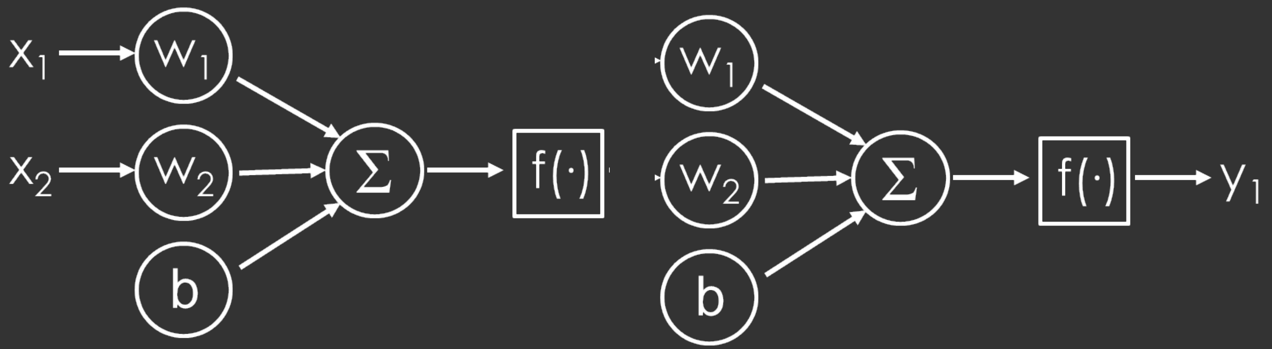


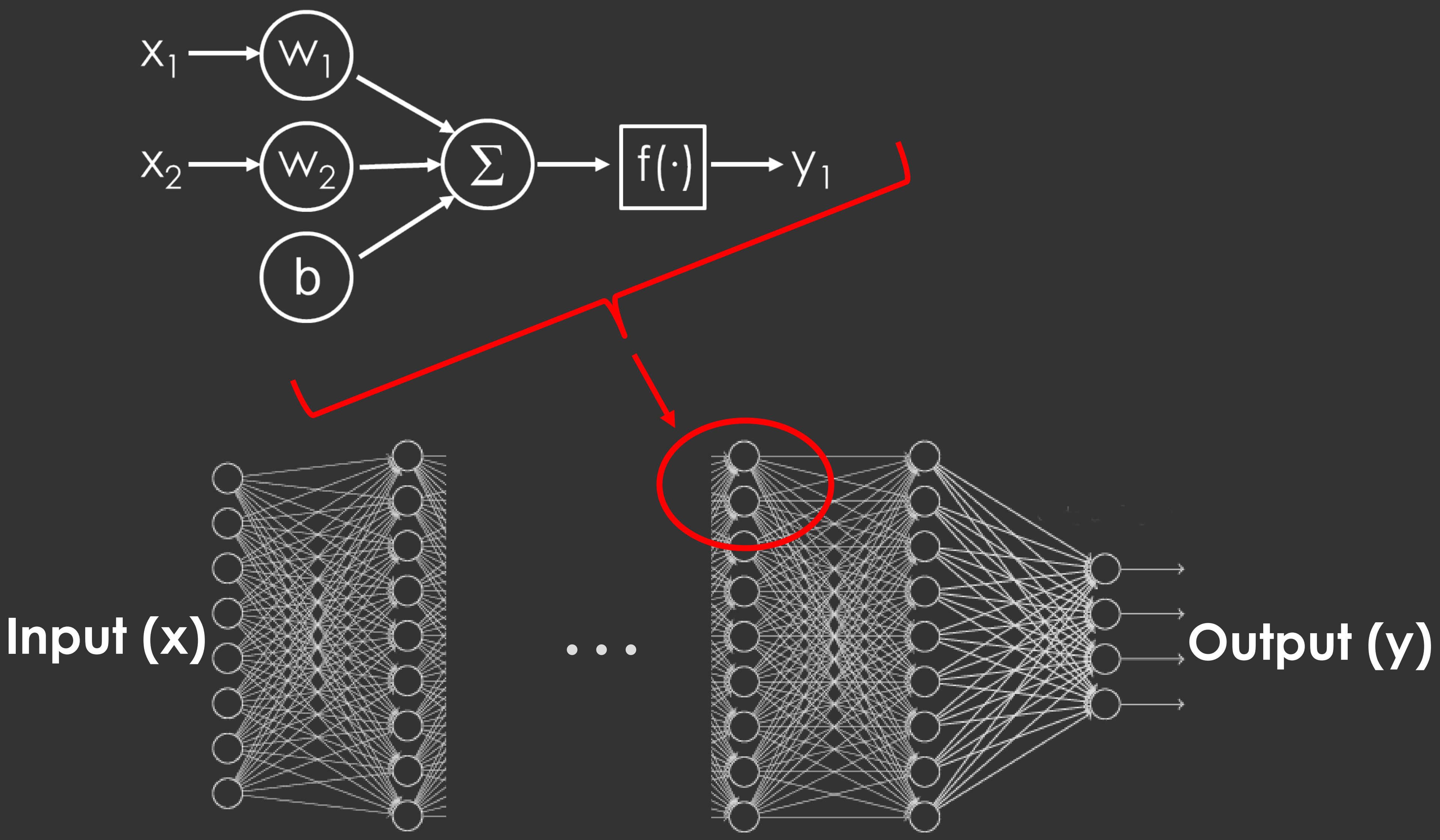
$$y_1 = f(x_1 * w_1 + x_2 * w_2 + b)$$



Logic/Deductive Reasoning

x_1	x_2	x_1 xor x_2
T	T	F
T	F	T
F	T	T
F	F	F





$p_1=f(W_1\,x+b_1)$ . . . $y=f(W_n\,p_{n-1}+b_n)$

Deep Neural Network

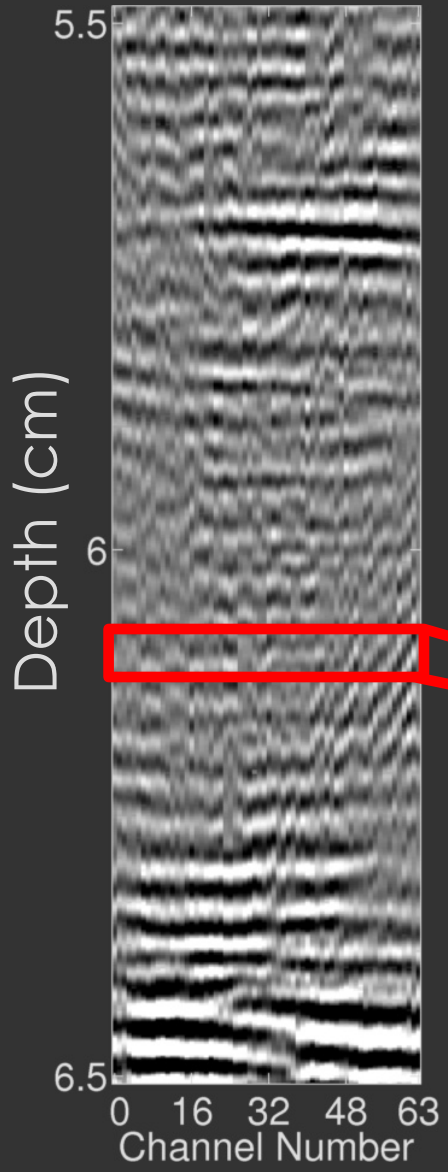
Deep Network Beamforming—our flavor

Adam Luchies

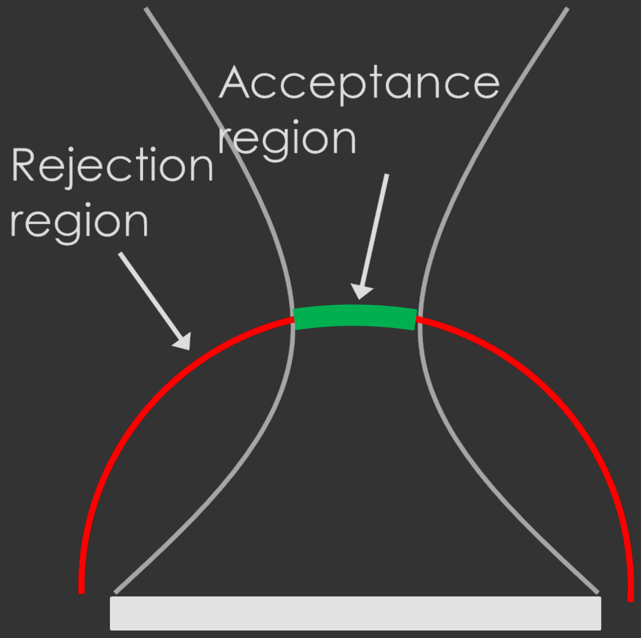
Jaime Tierney

Ying-Chun (Preston) Pan

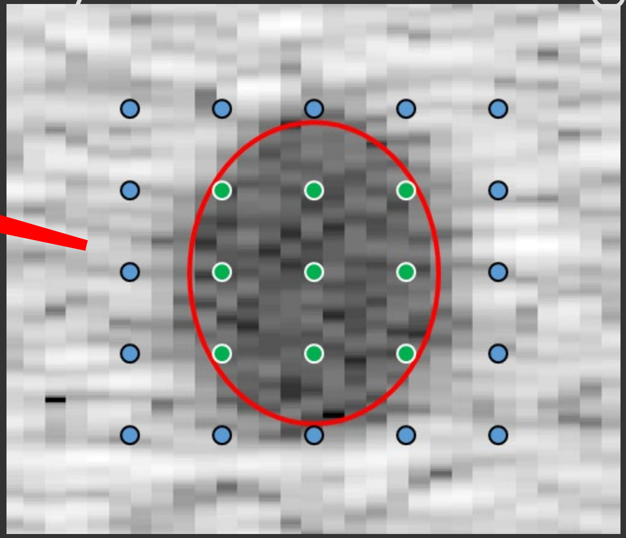
For ultrasound beamforming there are no curated data sets.



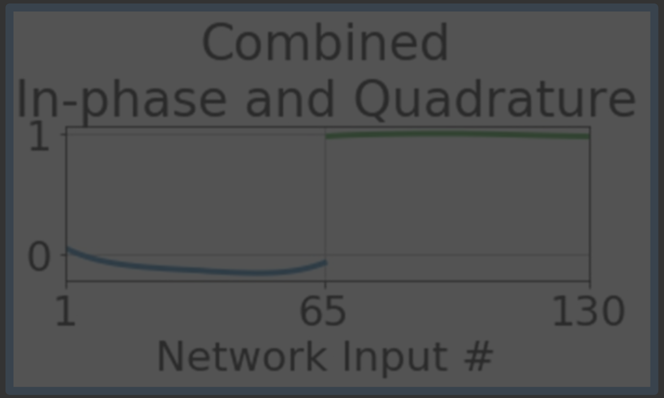
Single Scatterer Training

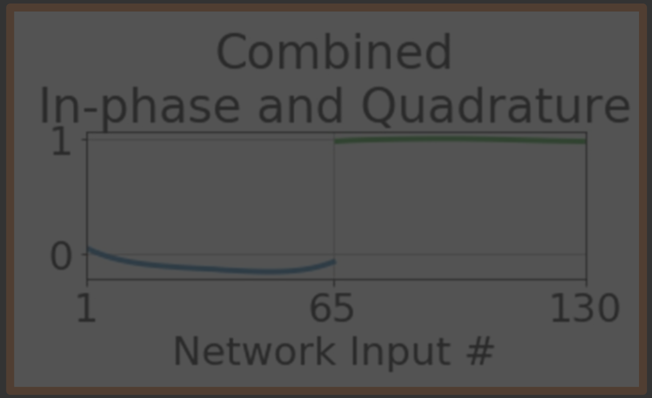


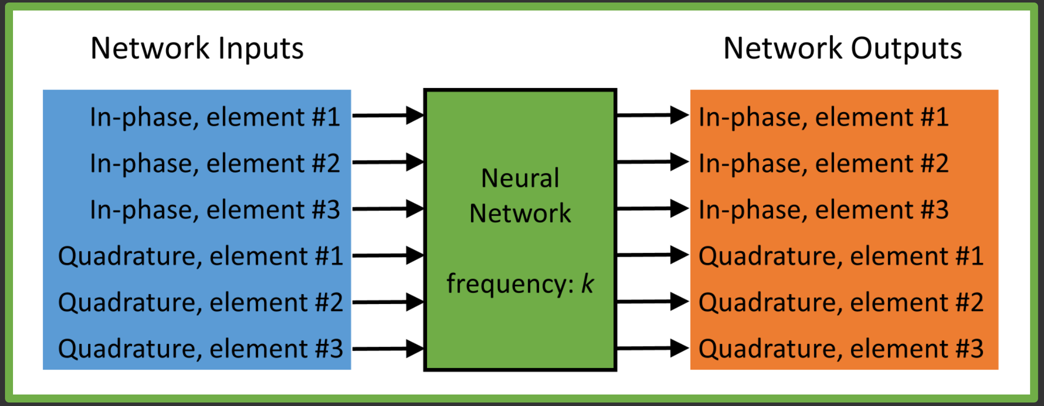
Many Scatterer Training

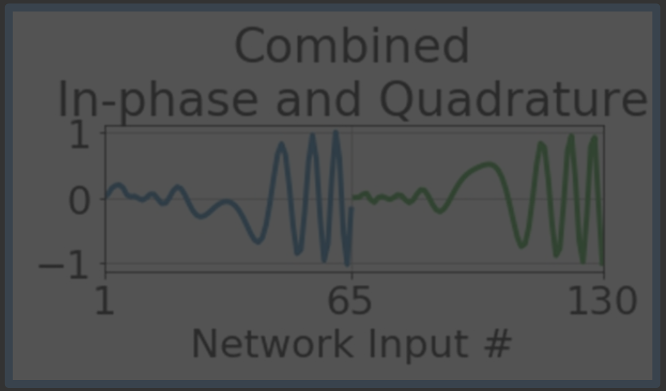


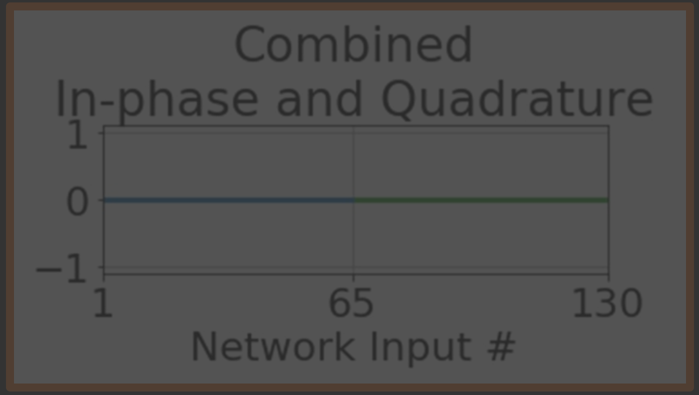
Deep Network Training with Sims



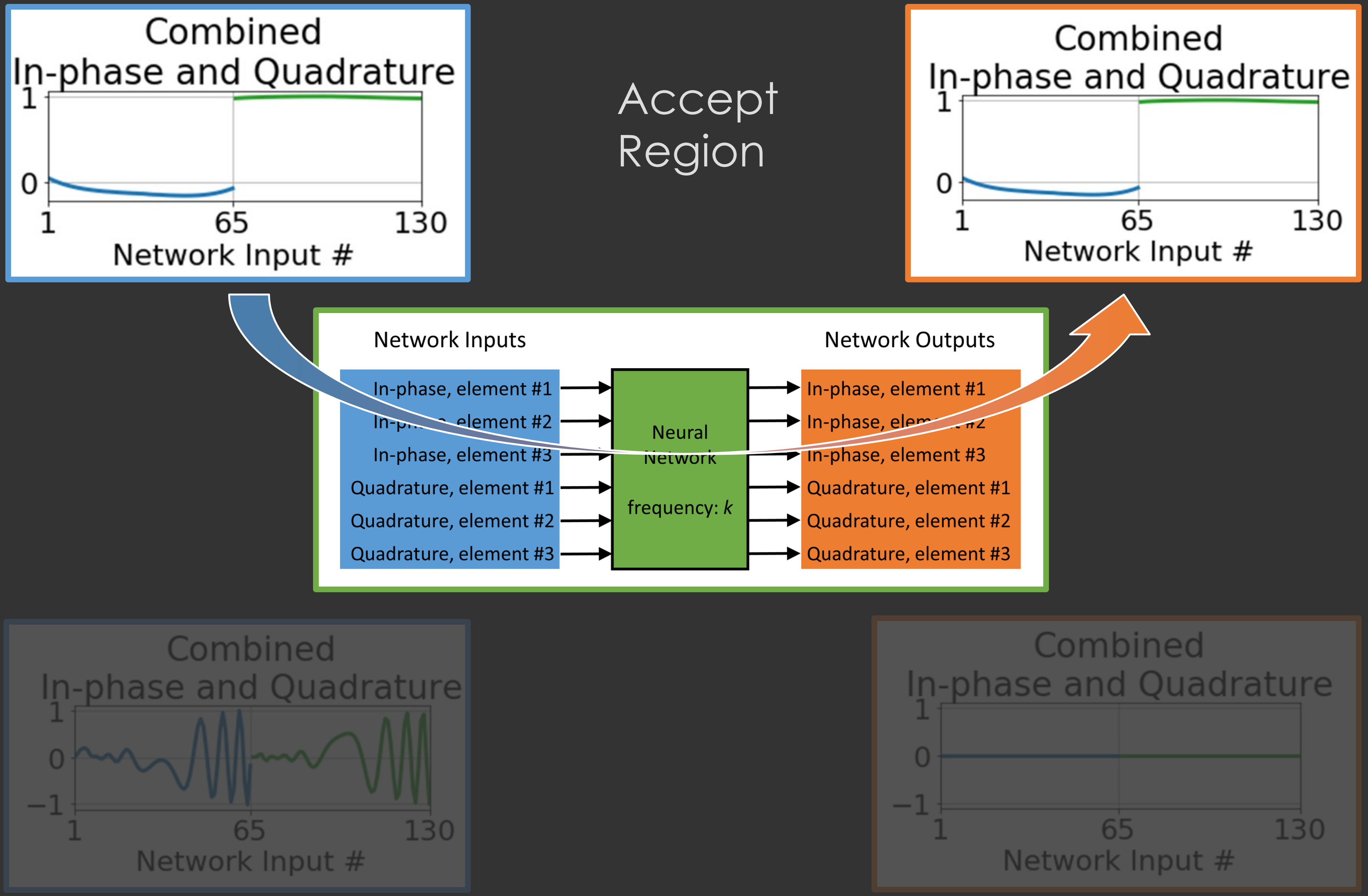




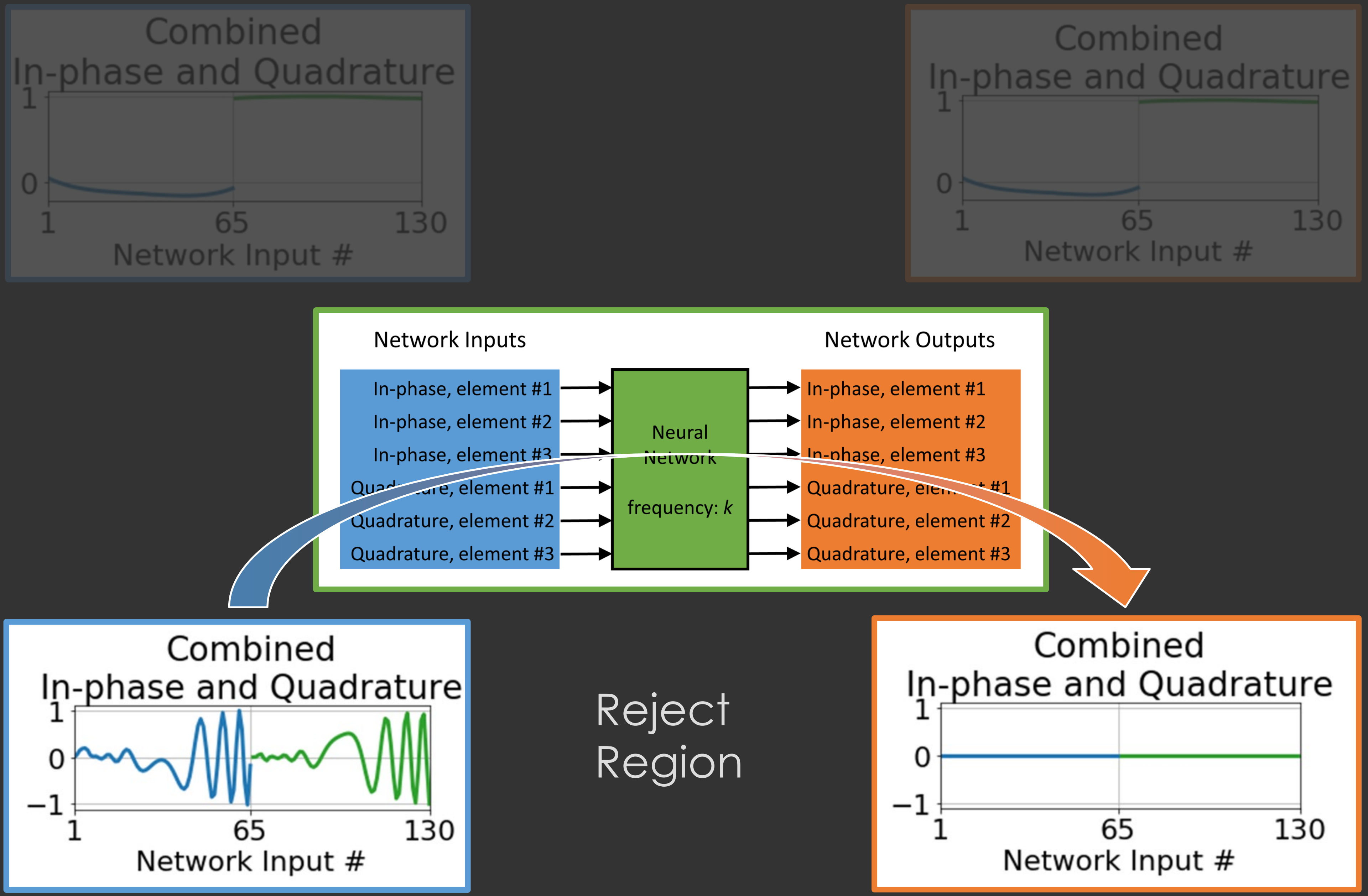




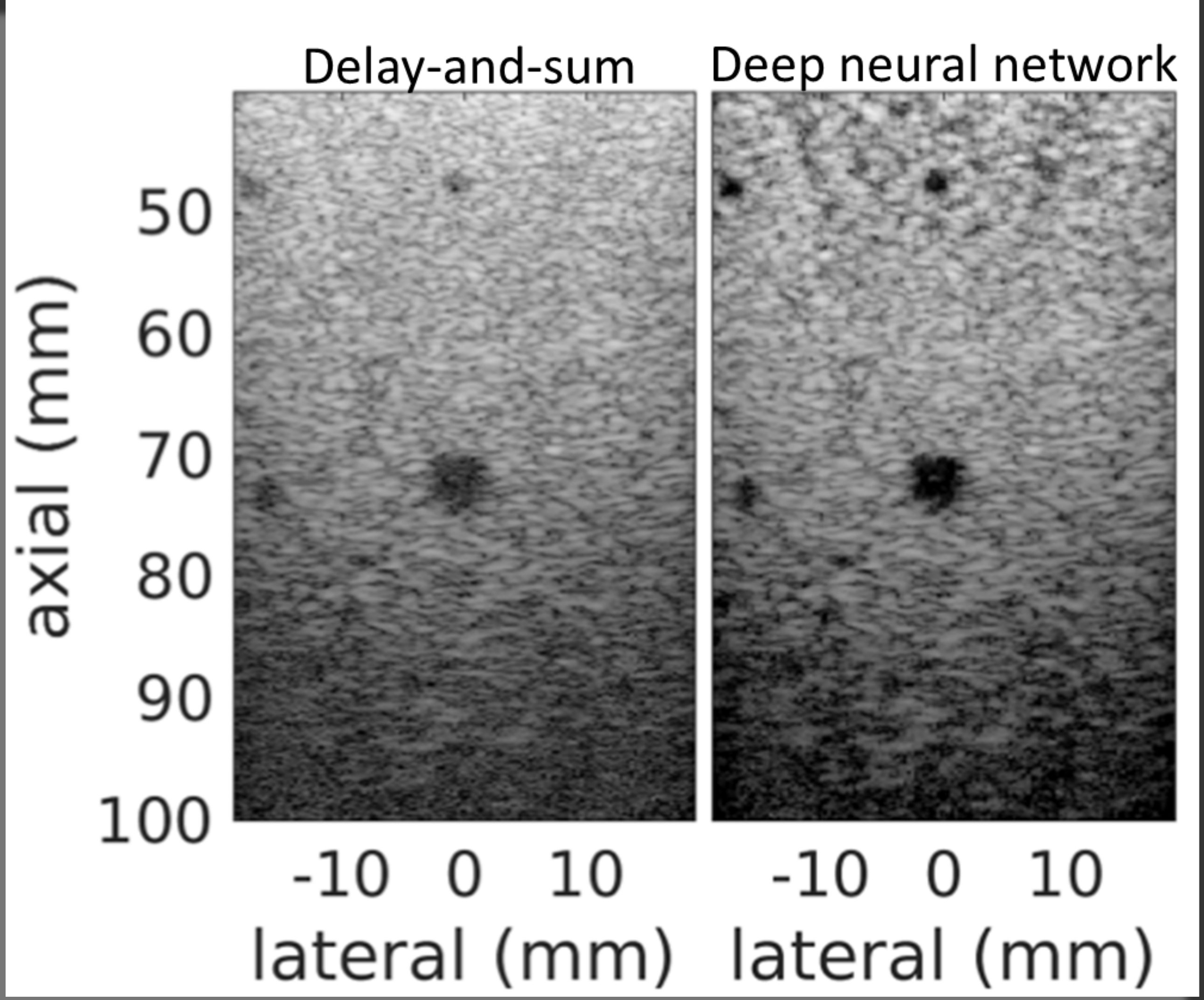
Neural Network Architecture



Neural Network Architecture



Neural Network Architecture

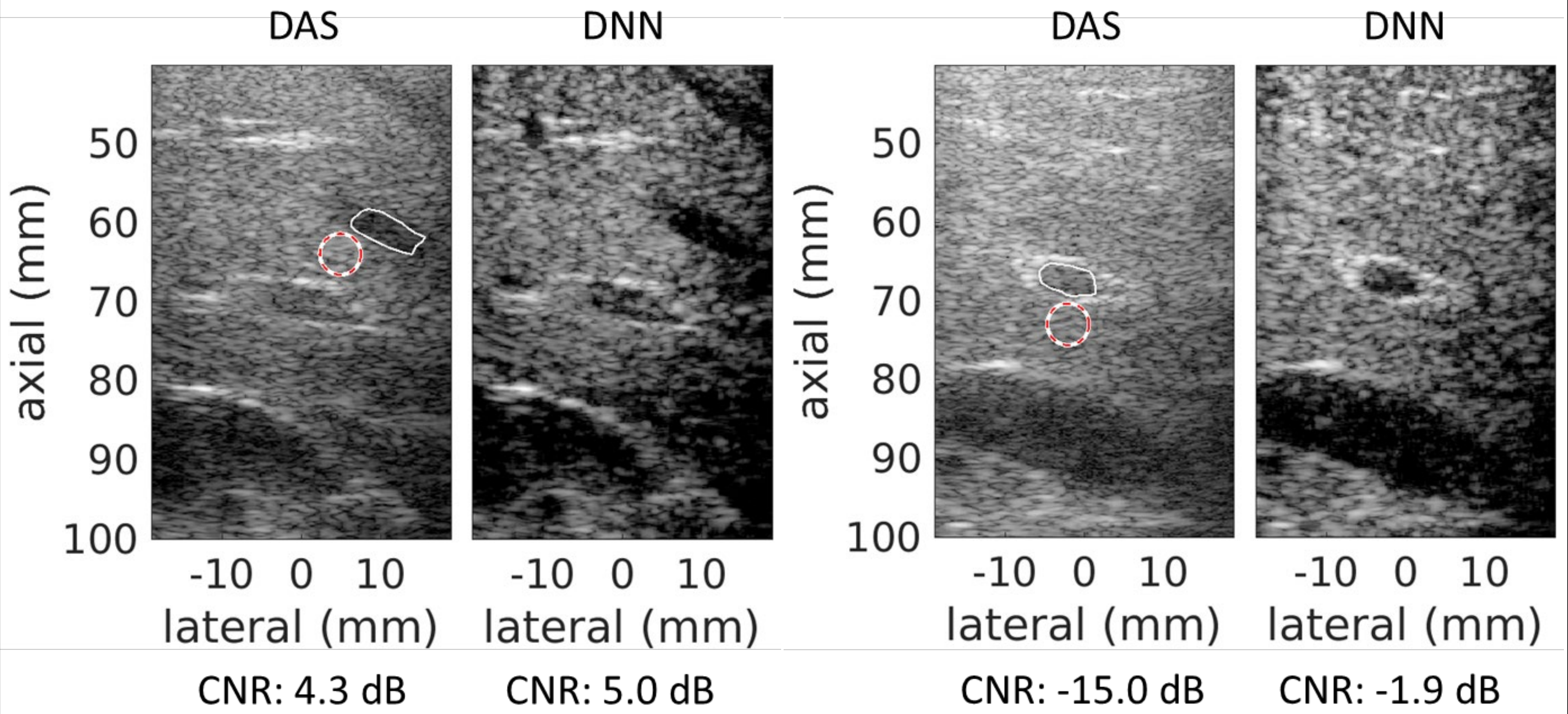


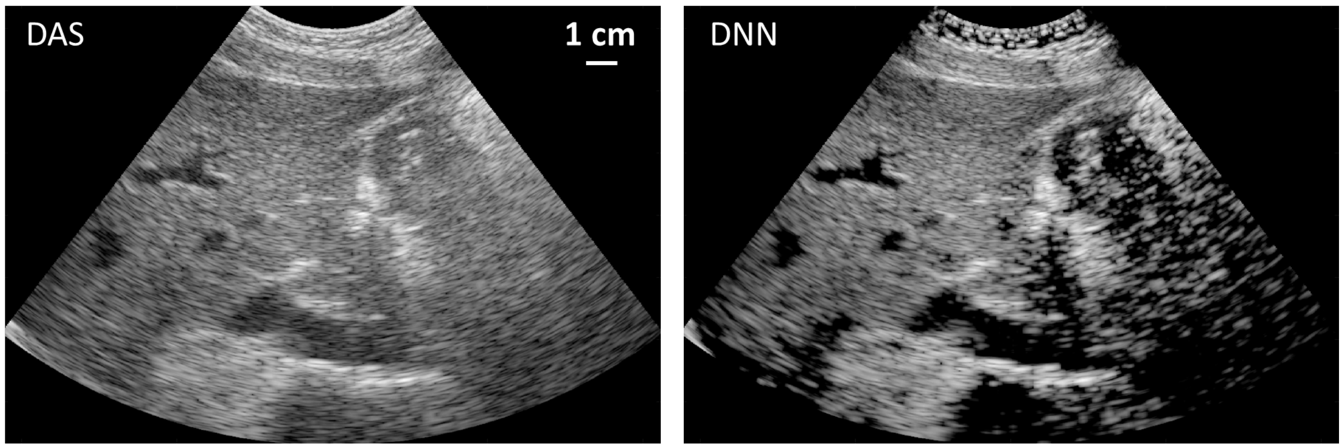
	CR (dB)	CNR (dB)	SNRs
DAS	16.4±0.7	4.2±0.4	1.94±0.07
DNN	25.1±1.0	5.3±0.3	1.97±0.07
	N = 5		

Train with simulations

Generalize to phantoms

Physical Phantom



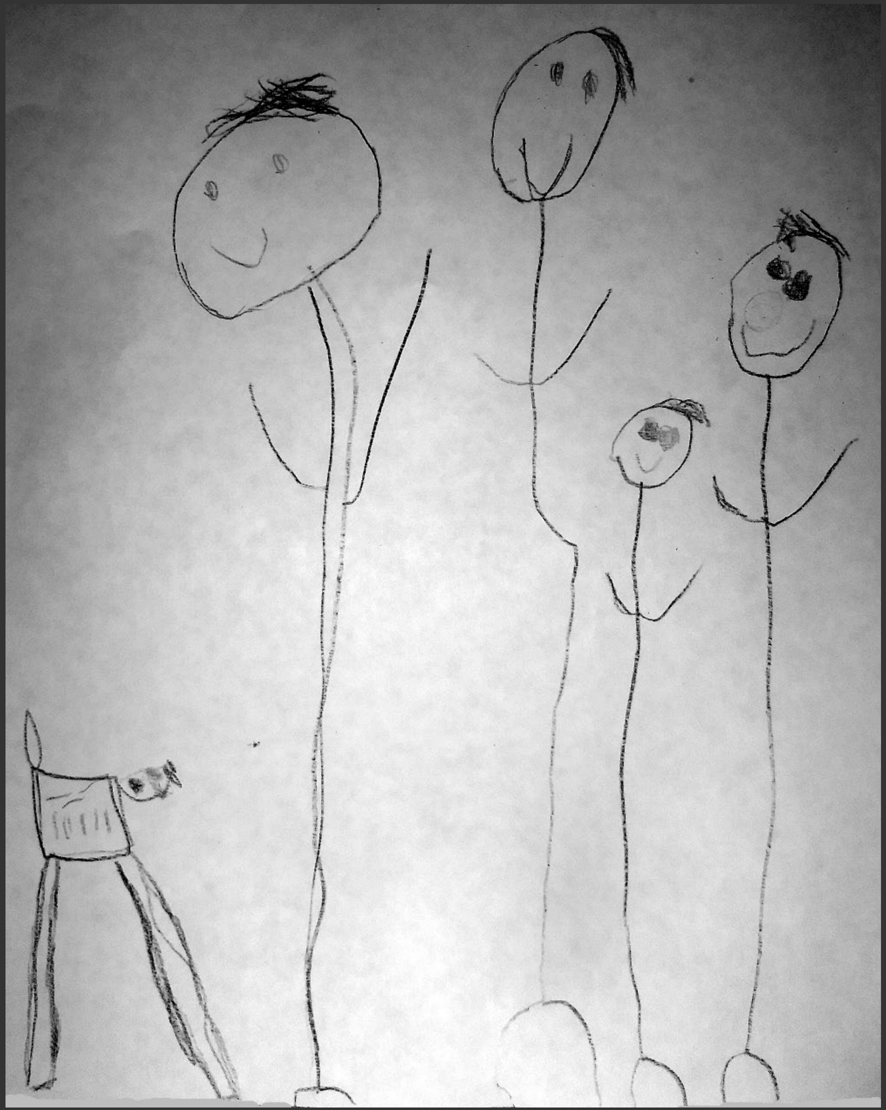


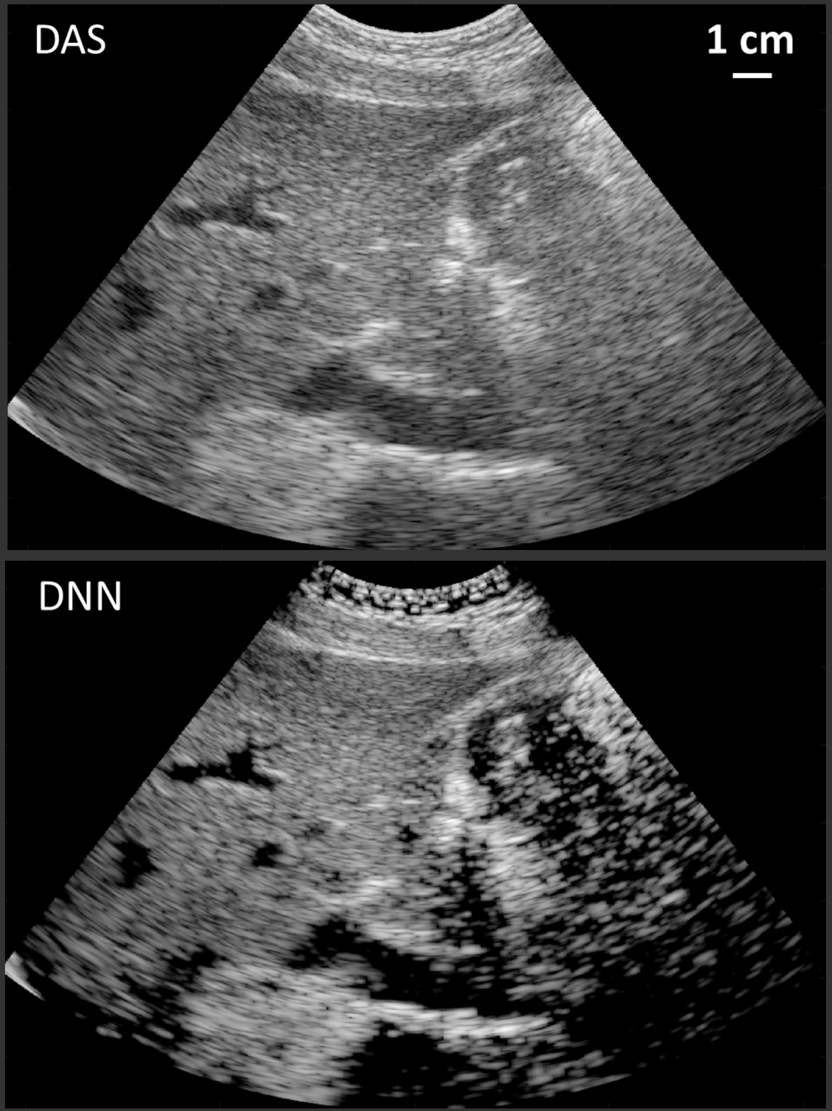
Train with simulations

Generalizes in vivo

In vivo imaging

Are we just creating caricatures?



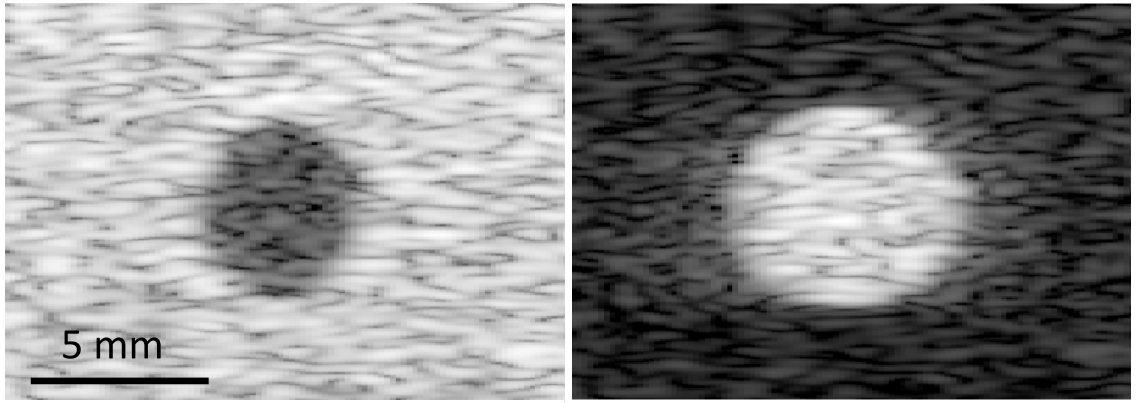


If we’re careful, then we can train DNN (nonlinear) beamformers that provide more information than linear beamformers

Similar trends with ADMIRE
using some modest changes

Delay-and-Sum (DAS)

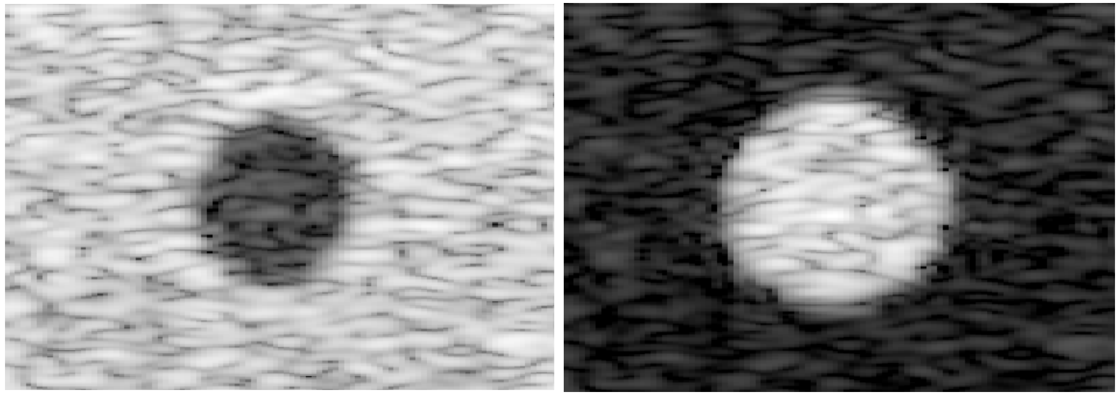
Intrinsic CR: -30 dB | Intrinsic CR: 40 dB



Measured CR: -26 dB | Measured CR: 37 dB

DNN Beamforming

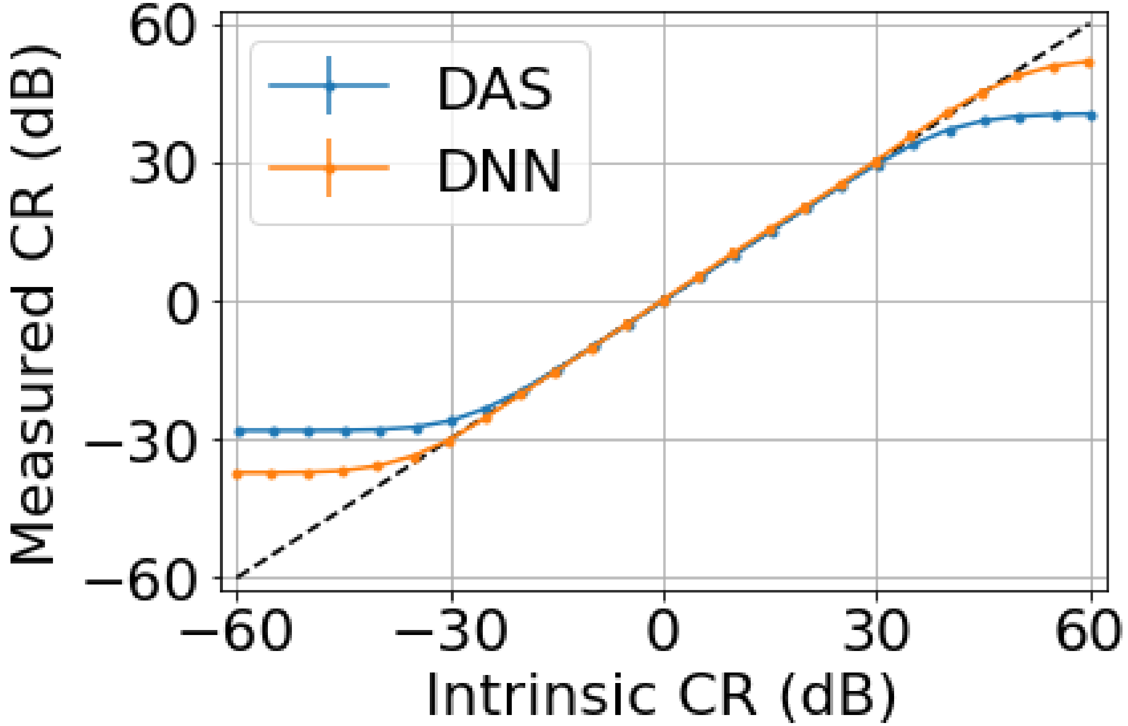
Intrinsic CR: -30 dB | Intrinsic CR: 40 dB



Measured CR: -30 dB | Measured CR: 40 dB

Images shown with 60 dB dynamic range.

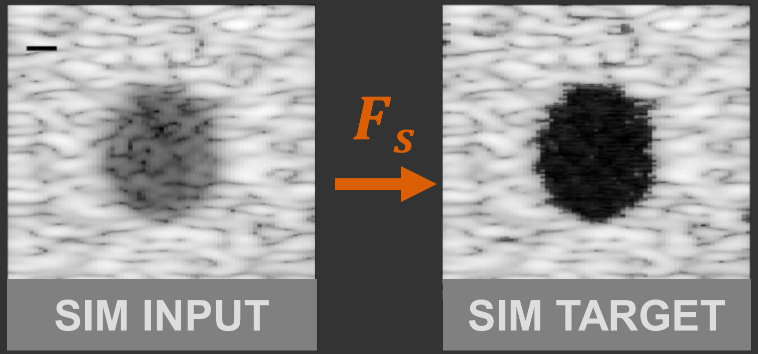
Training with **Hypo**echoic Cysts (No Reverberation)



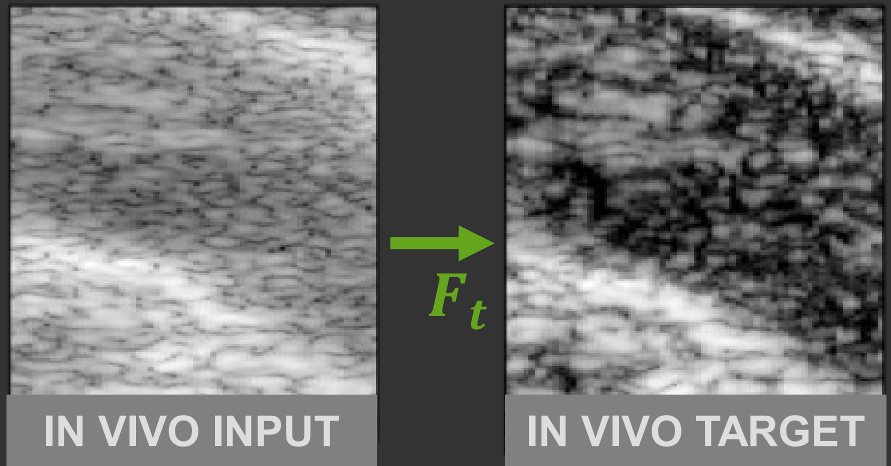
	DAS	**DNN**
CRDR	55 dB	80 dB

DNN Domain Adaptation

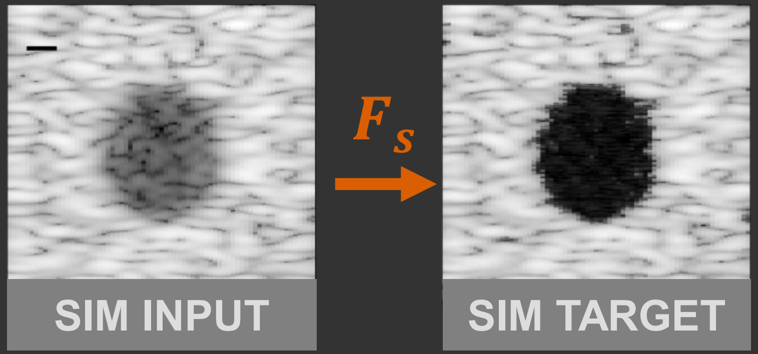
We trained deep networks with simulated data…



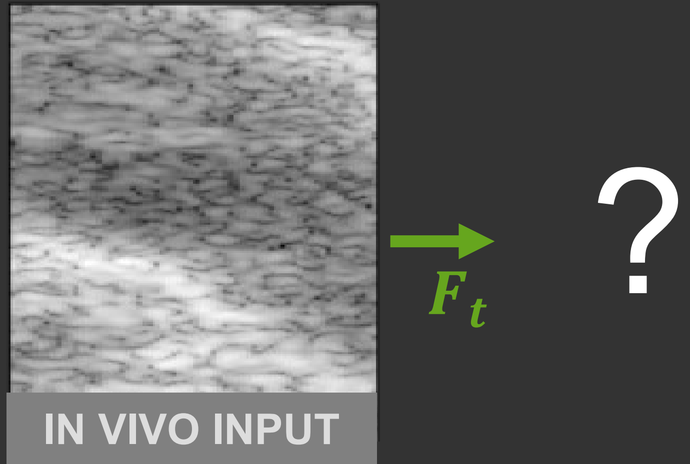
Wouldn't we rather train with actual *in vivo* data?



We trained deep networks with simulated data…

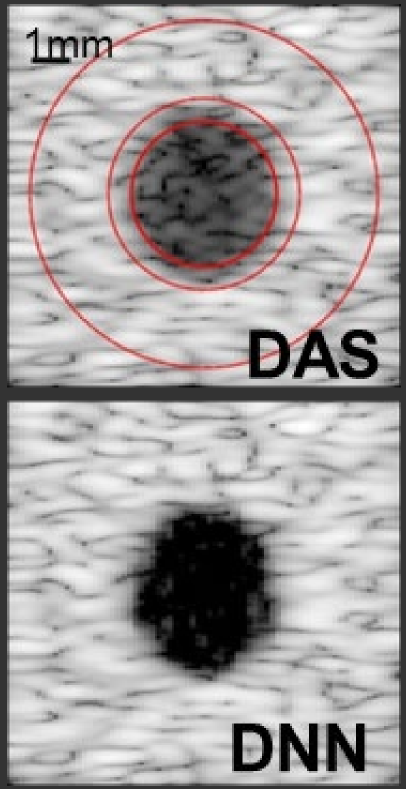


Wouldn't we rather train with actual *in vivo* data?



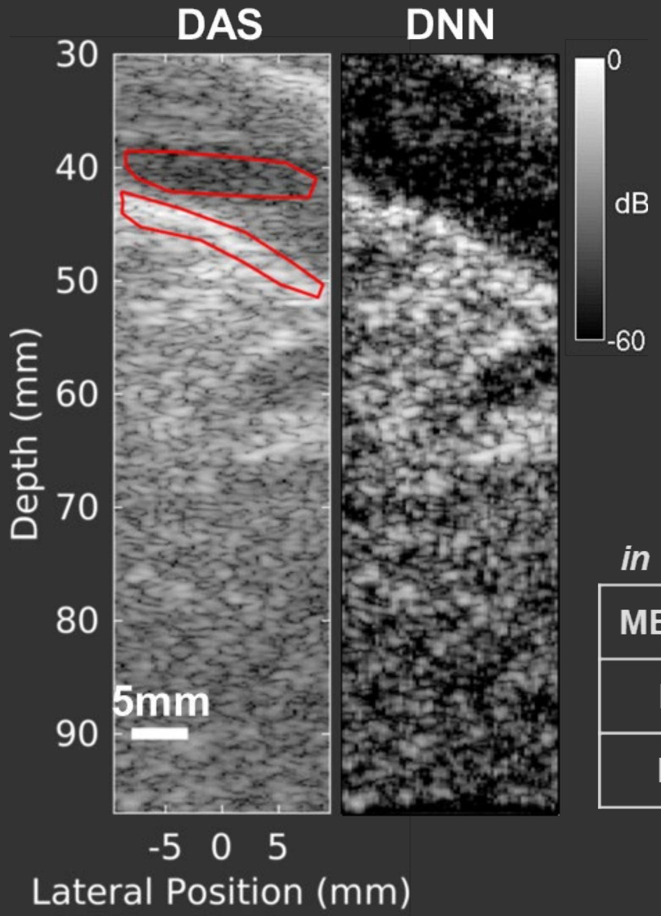
Train with sims

Applies to sims



Simulation (N=21)

METHOD	CNR (dB)	CR (dB)
DAS	5.06 (±0.21)	28.0 (±0.81)
DNN	5.93 (±0.23)	39.6 (±1.47)

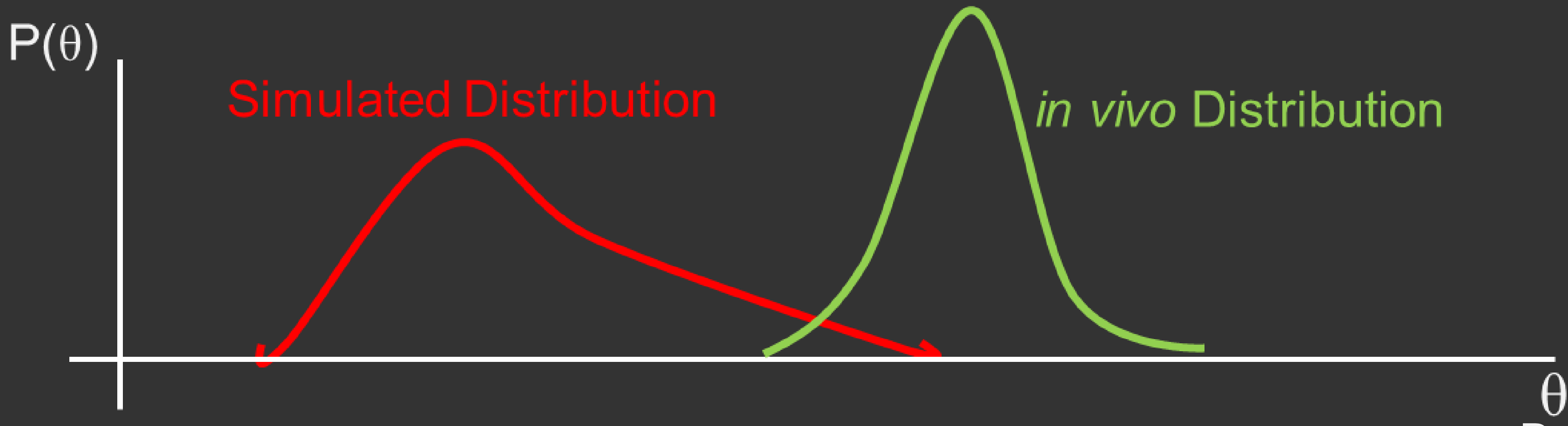


Train with simulations

Generalizes in vivo

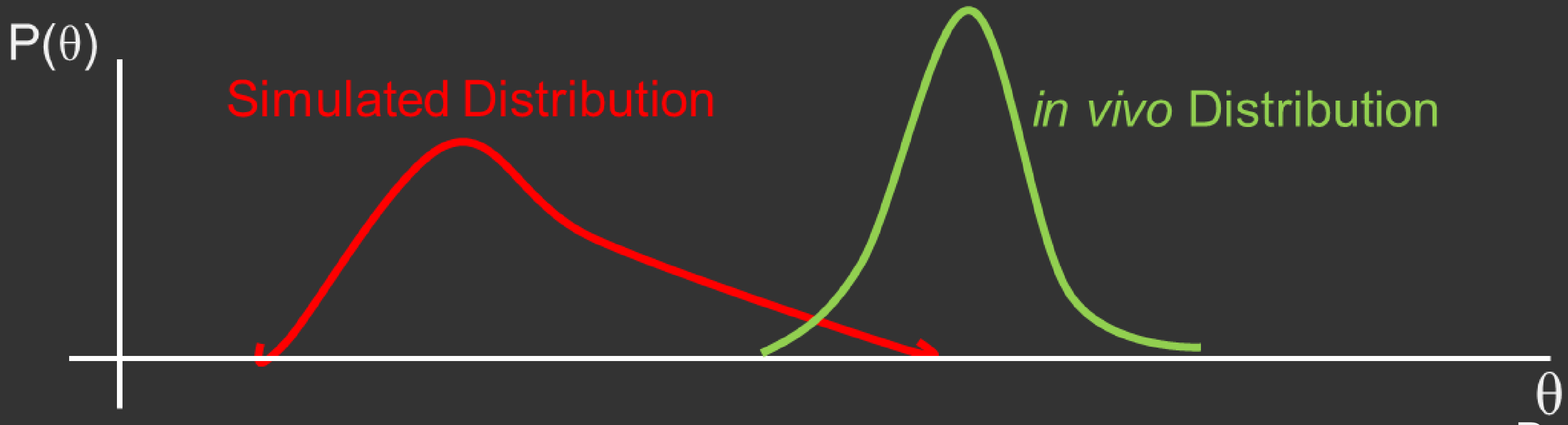
***in vivo* (N=9)**

METHOD	CNR (dB)	CR (dB)
DAS	1.70 (±1.39)	14.2 (±6.03)
DNN	-0.39 (±2.00)	23.3 (±7.30)



Domain Shift Problem

What causes the domain mismatch?



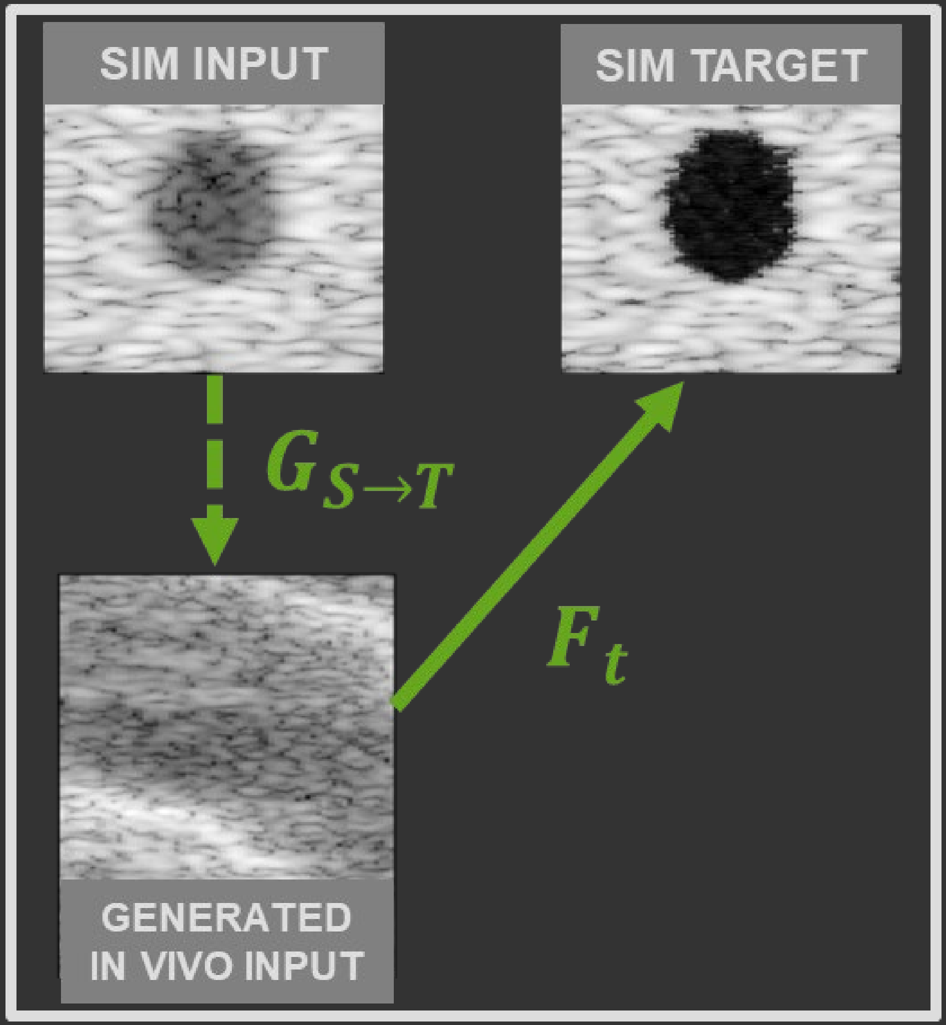
Cycle-Consistent Adverserial Domain Adaptation (CyCADA)

$$L_F = \mathbb{E}_{x_S \sim X_S}[\|F_t(G_{S\to T}(x_S)) - y_S\|_l]$$

$$L = L_{GAN} + \lambda_F L_F$$

[15]Hoffman, Judy, et al. "Cycada: Cycle-consistent adversarial domain adaptation." International conference on machine learning. PMLR, 2018.

Assumption: Domain shift only exists for the inputs.



CyCADA Domain Adaptation

$$L_F = \mathbb{E}_{x_s \sim X_S}[\|F_t(G_{S\to T}(x_s)) - y_s\|_l]$$

Our Domain Adaptation

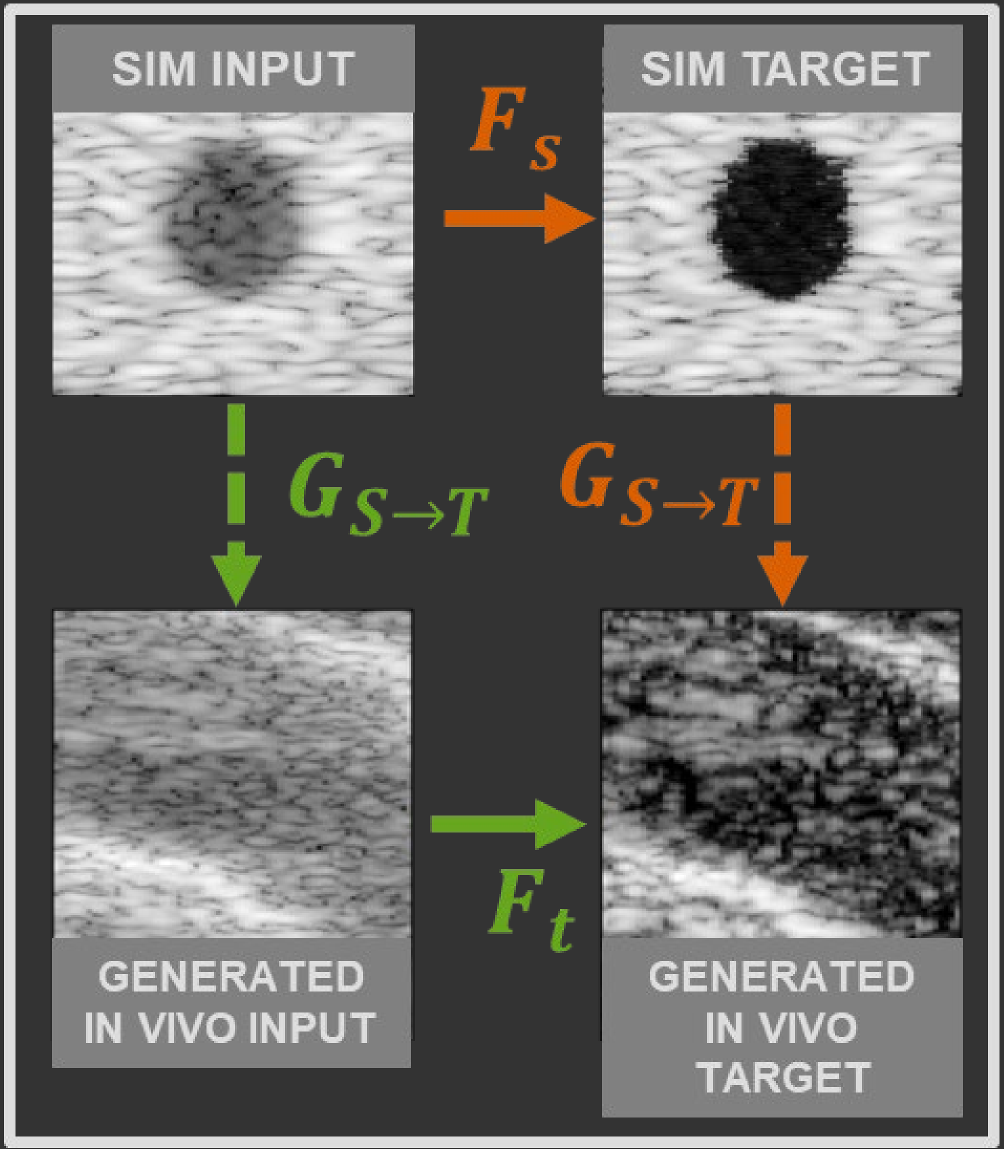
$$L_{F_{T1}} = \mathbb{E}_{x_s \sim X_S}[\|F_t(G_{S\to T}(x_s)) - G_{S\to T}(y_s)\|_l]$$

Input AND output adaptation

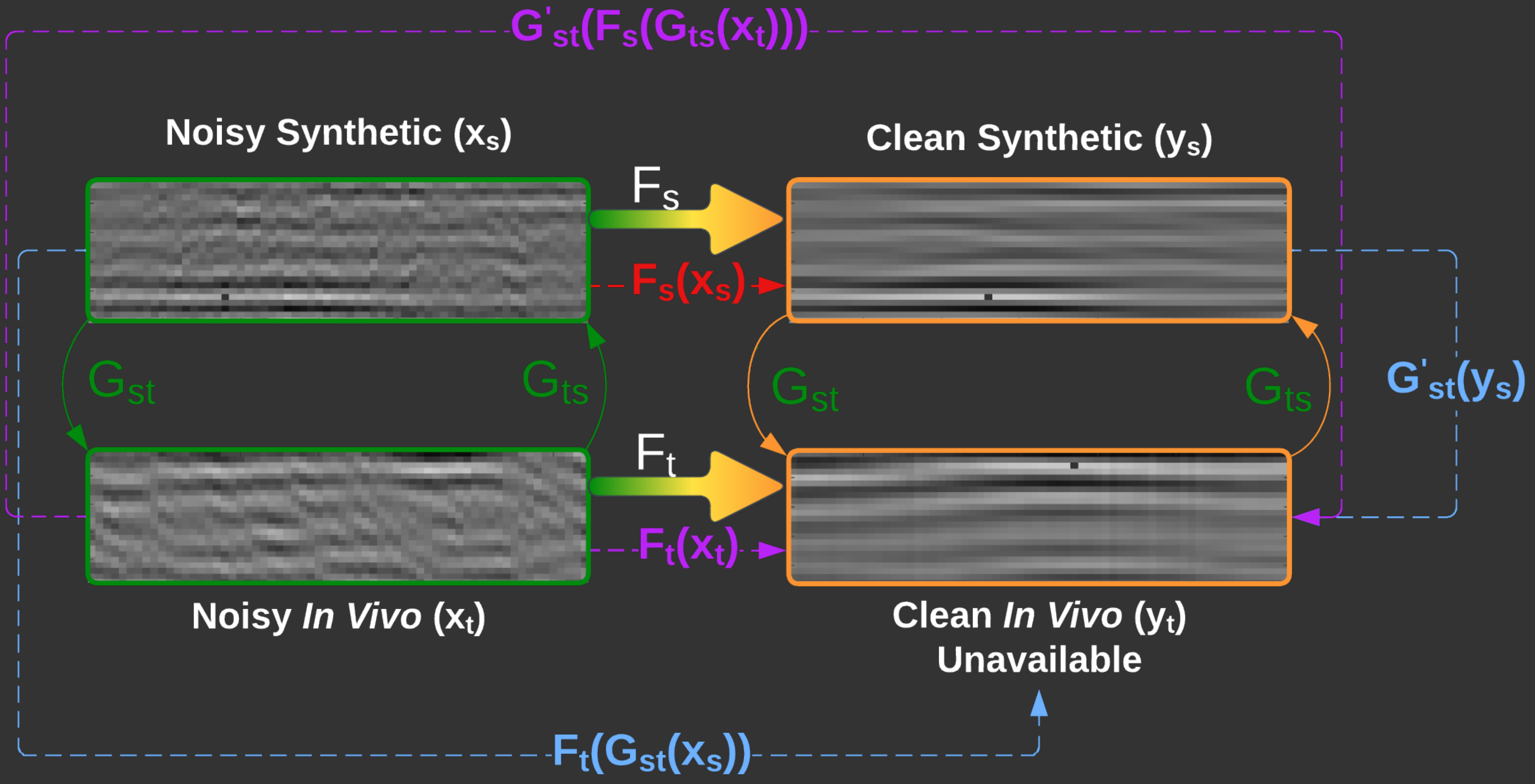
Add Augmented Feature Mapping

F_t is not exactly F_s

(Simulated Beamformer) (in vivo Beamformer)



Solution: Domain Adaptation



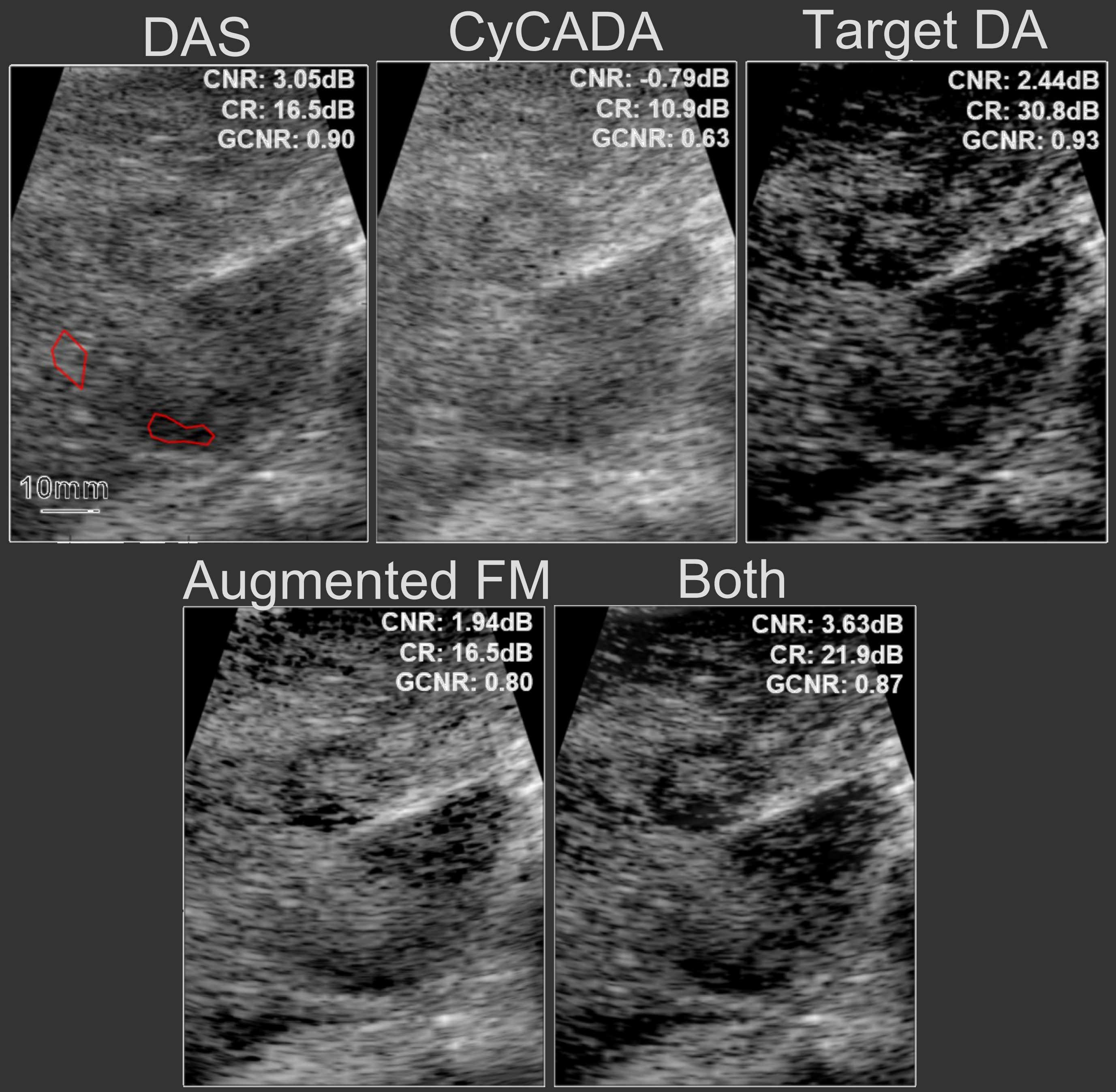
Regressor losses:

Synthetic regressor (F_s) loss: $||F_s(x_s) - y_s||_1$

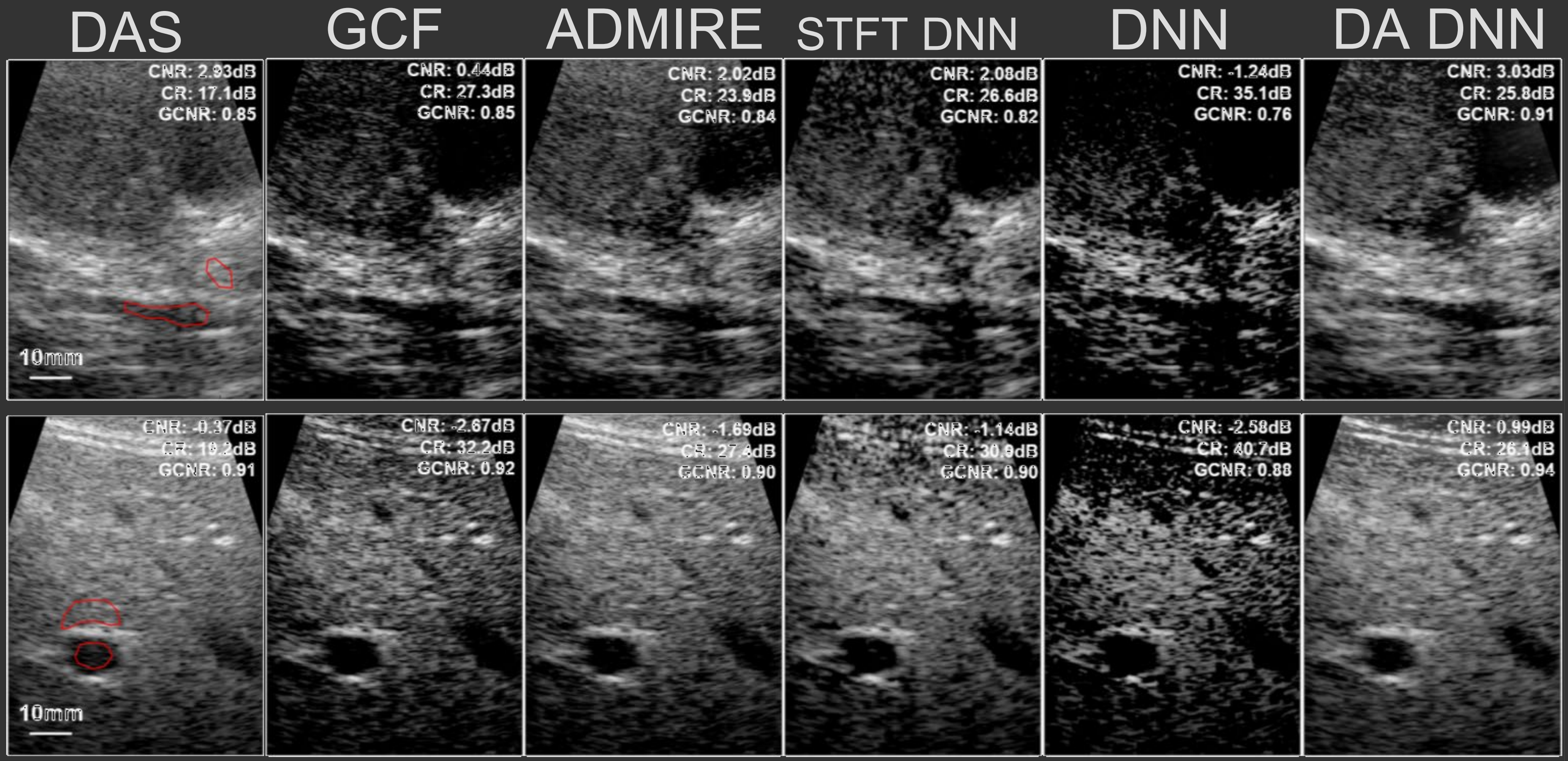
Invivo regressor (F_t) loss 1: $||F_t(G_{st}(x_s)) - G'_{st}(y_s)||_1$

Invivo regressor loss 2: $||F_t(x_t) - G'_{st}(F_s(G_{ts}(x_t)))||_1$

Cycle-GAN Domain Adaptation with Augmented Feature Mapping



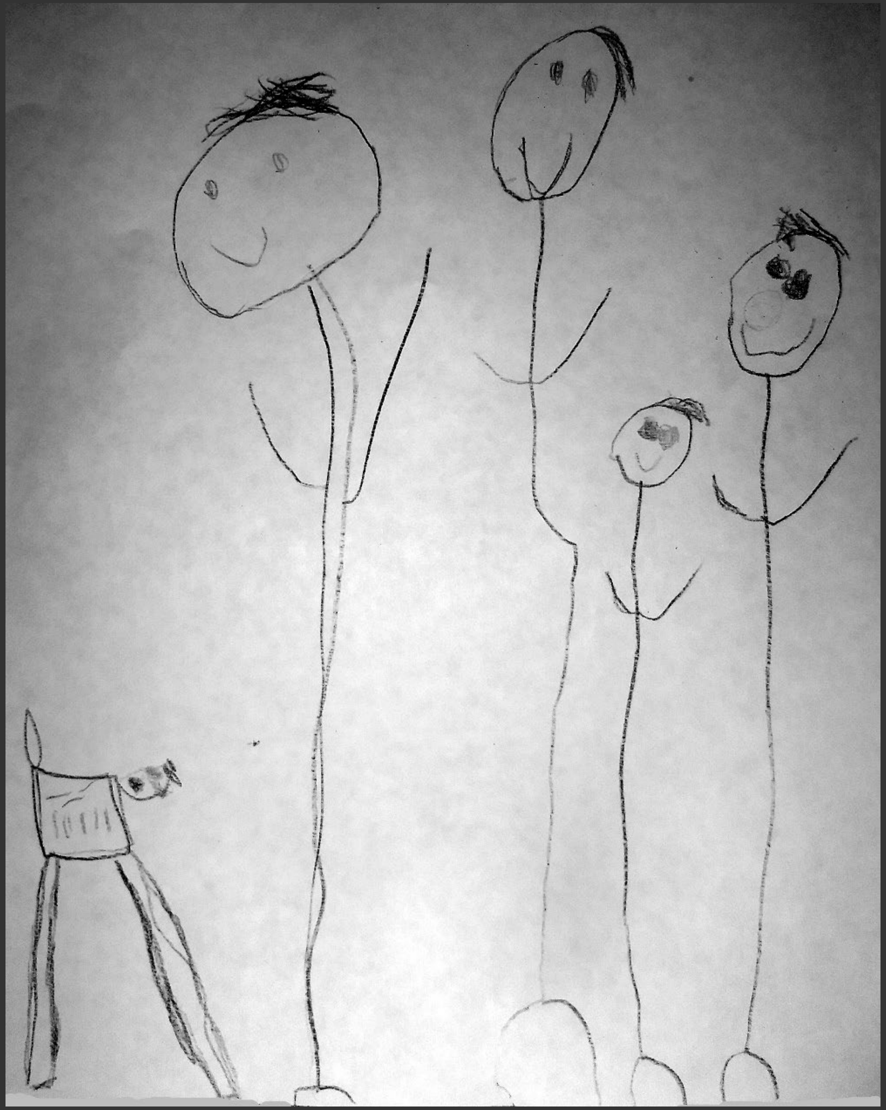
Unlabeled Training Scheme



Method	CNR (dB)	CR (dB)	GCNR
DAS	1.94 (±1.63)	14.5 (±3.94)	0.78 (±0.13)
GCF	0.42 (±1.45)	25.8 (±5.40)	0.82 (±0.08)
ADMIRE	1.56 (±1.58)	21.8 (±5.43)	0.82 (±0.10)
STFT DNN	1.95 (±1.61)	24.0 (±5.77)	0.84 (±0.09)
DNN	-0.09 (±2.37)	35.3 (±7.49)	0.82 (±0.08)
DA DNN	3.11 (±1.05)	22.0 (±4.81)	0.88 (±0.07)

DA-DNN Compared to Other Beamformers

Still creating caricatures but we're capturing more expansive representations



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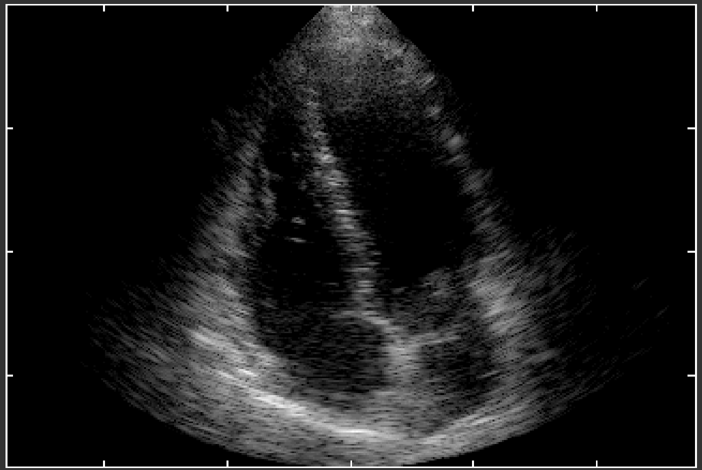
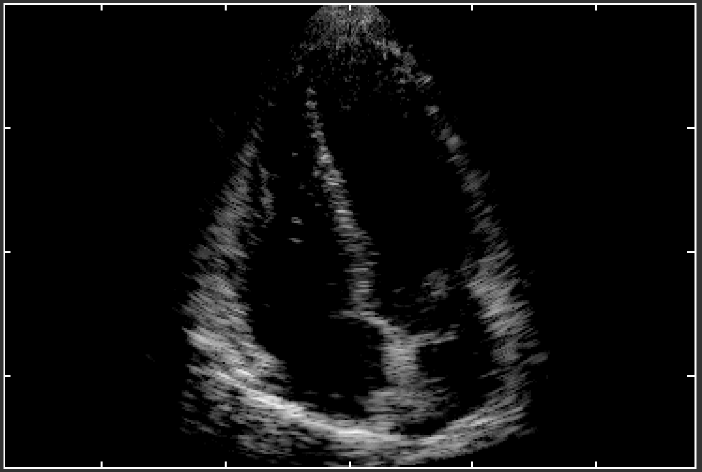
DAS



DNN



Code Available: https://github.com/VU-BEAM-Lab