

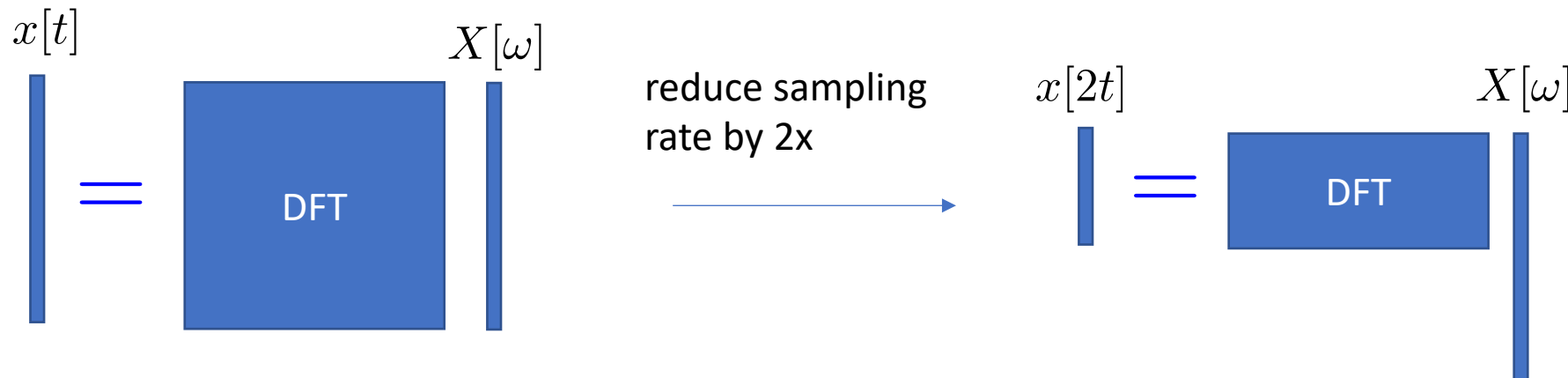
# CS/ECE/ME 532

## Period 18

- Today – Unit 5
  - Sparse solutions to least squares problems
- Today's activity
  - Understanding why L1 gives sparse solutions

Applications:

- breast cancer prediction
- Sub-Nyquist sampling



# Proximal Gradient Descent for Least Squares with L1 regularization

Training a model:

Loss function

$$\min_{\mathbf{w}} \|\mathbf{X}\mathbf{w} - \mathbf{y}\|^2 + \lambda \|\mathbf{w}\|_1$$

No closed form solution.  
Optimization.

L1 gives sparse solutions

## Alternating Gradient Descent with regularization

$$\text{goal: } \min_{\mathbf{w}} \ell(\mathbf{w}) + \lambda r(\mathbf{w})$$

for  $k = 1 \dots$

$$\mathbf{z}^{(k)} = \mathbf{w}^{(k)} - \tau \nabla \ell(\mathbf{w}^{(k)})$$

Gradient Descent

$$\mathbf{w}^{(k+1)} = \arg \min_{\mathbf{w}} \|\mathbf{z}^{(k)} - \mathbf{w}\|_2^2 + \lambda \tau r(\mathbf{w})$$

Regularization Step

stay close to  $\mathbf{z}$ , but regularize

$$\ell(\mathbf{w}) = \|\mathbf{X}\mathbf{w} - \mathbf{y}\|_2^2 \quad r(\mathbf{w}) = \|\mathbf{w}\|_1$$

$$\mathbf{w}^{(k+1)} = \arg \min_{\mathbf{w}} \sum (z_i^{(k)} - w_i)^2 + \lambda \tau |w_i|$$

$$w_i^{(k+1)} = (|z_i| - \lambda \tau / 2)_+ \text{sign}(z_i)$$

soft threshold

