FALL 2019 : ELEC 7970-001: Statistical Signal Processing with Sparsity
T Th 9:30 am – 10:45 pm Broun 306

Instructor: Prof. J.K. Tugnait 313 Broun, 4-1846, tugnajk@auburn.edu
Office Hours: MW 11:00am – 11:50 am; 3:00 – 4:00 pm;
e-mail for appointment at other times.

Prerequisites: ELEC 7410 or equivalent or Consent of the Instructor.

Course Material:

- R. Baranuik, M.A. Davenport, M.F. Duarte and C. hegde, "An Introduction to Compressive Sensing," 2011.
  Online `http://legacy.cnx.org/content/col11133/1.5/`
- S. Theodoridis, Y. Kopsinis, & K. Slavakis, "Sparsity-Aware Learning and Compressed Sensing: An Overview," Chapter 23 in: S. Theodoridis & R. Chellappa (eds), *Academic Press Library in Signal Processing. Vol. 1, Signal Processing Theory and Machine Learning*, pp. 1271-1377, 2014.
  Online (free) arXiv:1211.5231 [cs.IT] `https://arxiv.org/abs/1211.5231`
- T. Hastie, R. Tibshirani, & M. Wainwright, *Statistical learning with Sparsity: The Lasso and Generalizations*, CRC Press, 2015.
  Online (free) `https://web.stanford.edu/~hastie/StatLearnSparsity/index.html`
- \+ selected tutorial/journal articles.

Grading Basis (tentative):

Homework:	40 %
Take-home Midterm:	30 %
Project :	30 %

Two interrelated topics will be covered in this course; see the course announcement (next page).

Tentative Coverage:

1. **Compressed Sensing:** Parts of Chapters 2-5 of R. Baranuik, M.A. Davenport, M.F. Duarte and C. hegde, "An Introduction to Compressive Sensing," 2011.
2. **Sparse Signal/Parameter Recovery:** Parts of Chapters 2-5 and 10 of T. Hastie, R. Tibshirani, & M. Wainwright, *Statistical learning with Sparsity: The Lasso and Generalizations*, CRC Press, 2015.

COURSE ANNOUNCEMENT

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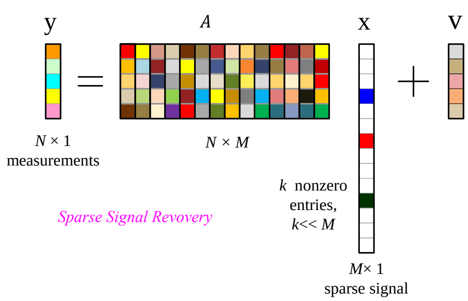
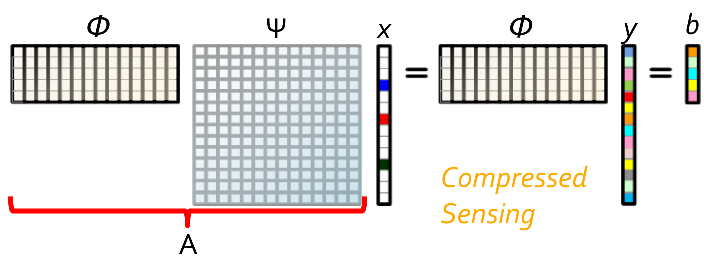
- $+$ selected tutorial magazine/journal articles.

Two interrelated topics will be covered in this course:

1. **Sparse Signal/Parameter Recovery:** Solving an under-determined system of equations when vector of unknowns is sparse (only a few nonzero elements).
   Given noisy measurements $\mathbf{y}_{N\times 1} = \mathbf{A}_{N\times M}\mathbf{x} + \mathbf{v}$ of desired signal $\mathbf{x}_{M\times 1}$ in noise $\mathbf{v}$ where $N \ll M$, recover $\mathbf{x}$ when number of nonzero entries k in $\mathbf{x}$ satisfy $k \ll M$





2. **Compressed Sensing (CS):** Digital Camera example: Acquire full N-sample signal $\mathbf{y}$. Compute complete set of transform coefficients via square transform matrix $\mathbf{\Psi}^\top$ as $\mathbf{x} = \mathbf{\Psi}^\top\mathbf{y}$. Suppose signal is k-sparse (enough to know k largest elements of $\mathbf{x}$). Then k largest coefficients are located and the $N-k$ smallest coefficients are discarded; and the k values and locations of the largest coefficients are encoded. Image is reconstructed via $\mathbf{y} = \mathbf{\Psi}\mathbf{x}$ since $\mathbf{\Psi}\mathbf{\Psi}^\top = \mathbf{I}$. This sample-then-compress framework is inefficient.

   In compressed sensing, the acquisition and compression steps are fused into one. Using a $k \times N$ sensing matrix $\mathbf{\Phi}$, acquire k-sample $\mathbf{b} = \mathbf{\Phi}\mathbf{y} = \mathbf{A}\mathbf{x}$ where $\mathbf{A} = \mathbf{\Phi}\mathbf{\Psi}$.

   Recovering sparse $\mathbf{x}$ from $\mathbf{b}$ is a sparse signal recovery problem. Design of $\mathbf{\Phi}$ is the main issue in CS. Image is reconstructed via $\mathbf{y} = \mathbf{\Psi}\mathbf{x}$.

   `http://www.eng.auburn.edu/~tugnait/candes_review`
   `http://www.eng.auburn.edu/~tugnait/rice_note`