EE269
Signal Processing for Machine Learning
Fall 2020-2021

Instructor : Mert Pilanci

Stanford University

Sep 14 2020

Outline

- Introduction
- Administrative
- Applications of SP&ML
- Topics
- Class Project

Administrative

Teaching staff

- Zoom lectures: Mon, Wed 2:30 PM - 3:50 PM
- Instructor: Mert Pilanci
  - Email: pilanci@stanford.edu
  - Office hours: Monday 4-5pm via Zoom (see Canvas for the link)
- CA: Tolga Ergen, ergen@stanford.edu
  - CA office hours: TBA
- Public web page :
  `http://web.stanford.edu/class/ee269/`
- Lecture slides
  `http://web.stanford.edu/class/ee269/slides.html`

Please check Canvas for up-to-date info
Annotated and updated slides will be available at
Canvas/Files For all questions please use Piazza

About EE-269

- Our goal in this course is to help you to:
  - Learn mathematical models for **signals, systems and transformations**.
  - Learn methods that **extract information** from signals.
  - Learn about the **theory** of machine learning relevant to signal processing applications
  - Learn how to implement **algorithms** for processing, manipulating, learning and classifying signals.

Textbooks

- Pattern Recognition and Machine Learning:
  Available online: `https://www.microsoft.com/en-us/research/people/cmbishop/prml-book/`
- Signal Processing for Communications, Prandoni and Vetterli
  Available online:
  `www.sp4comm.org`
- Deep Learning, Goodfellow, Bengio and Courville
  Available online: `https://www.deeplearningbook.org/`

- Additional references (see Canvas)
  Introduction to Applied Linear Algebra – Vectors, Matrices, and Least Squares, Boyd and Vandenberghe
  Available online: `http://vmls-book.stanford.edu`

Prerequisites

- Exposure to signals and systems (EE 102A and EE 102B or equivalent)
- Basic probability (EE 178 or equivalent)
- Basic programming skills (Matlab or Python),
- Familiarity with linear algebra (EE 103 is recommended).

Grading policy

- Homework: 60%, submission via Gradescope.
- Project: 40% (final video presentation and report)
- Extra credit: 5% for Piazza contributions.

Homework

- Assigned homeworks will be bi-weekly.
- The problem sets will also include programming assignments to implement algorithms covered in the class.
- We also support Python and MATLAB.
- Please start on homework early.

Group Study

- Homework:
  - Working in groups is allowed, but each member must submit their own writeup.
  - Write the members of your group on your solutions (Up to four people are allowed).
- Project:
  - You will be asked to form groups of about 2-3 people and choose a topic
  - We'll collect data, and apply SP/ML algorithms to analyze the data, extract information, learn and test models
  - Proposal submission (1 page)
  - Final report and video submission (Nov 20)

For details see Canvas!

Any questions?

Definition of Signal Processing

1. A **signal** is mathematically just a function
2. **Signal processing**:
   - Convert one signal to another
     e.g. filter, de-noise, interpolate
   - Information extraction and interpretation
     e.g. speech recognition, computer vision

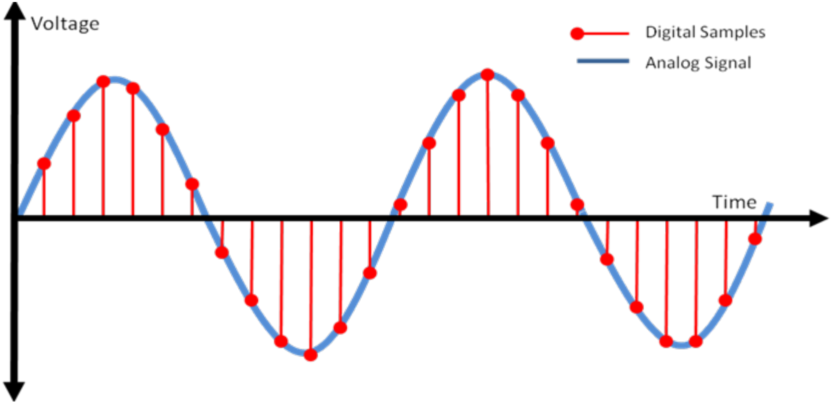
Digital Signal Processing

- *Digitus*: finger (in Latin)
- Discrete samples
- Discrete representation
- Can be samples of a continuous signal $x(t)$

$$x[n] = x(nT)$$

- Can be discrete by nature

Example: Sampling



Earliest examples of a digital signal

Egypt, 25th century BC

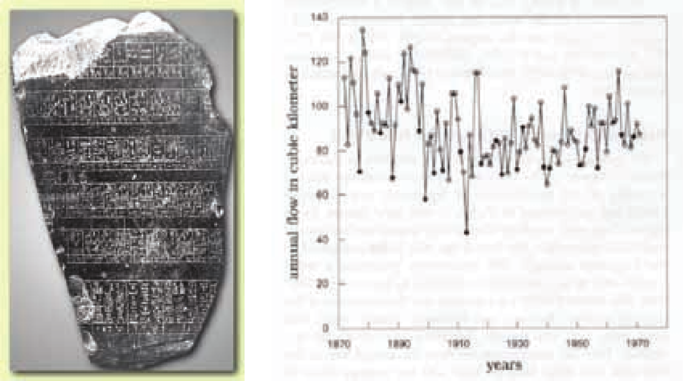


Figure 1.2 Representations of flood data for the river Nile: circa 2500 BC (left) and 2000 AD (right).

Modern Examples

- **Audio recording**: an analog pressure wave is sampled and converted to a one-dimensional discrete-time signal.
- **Photos**: the analog scene of light is sampled using a CCD array and stored as a two-dimensional discrete-space signal
- **Text**: messages are represented with collections of characters; each is as- signed a standard 16-bit number and those are stored in sequence.
- **Ratings**: for books (Goodreads), movies (Netflix), vacation rentals (Air bnb) are stored using the integers 0-5

Definition of Machine Learning

- Samuel (1959): Field of study that gives computers the ability to learn without being explicitly programmed.

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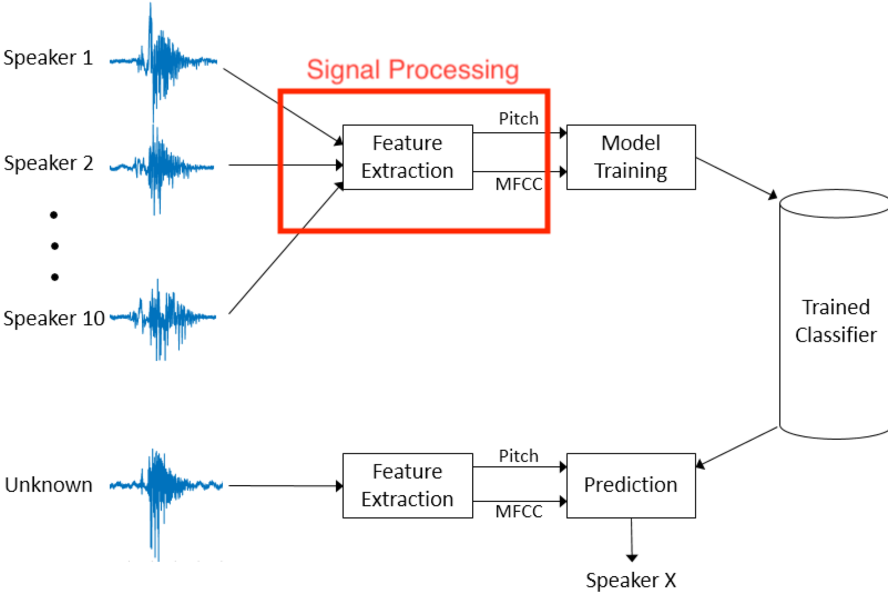
- Kevin Murphy (2012): Algorithms that automatically detect patterns in data use the uncovered patterns to predict future data or other outcomes of interest

SP and ML Example: speaker identification

slide credit: Neuron, Zion-Golumbic et al.

SP and ML Example: speaker identification

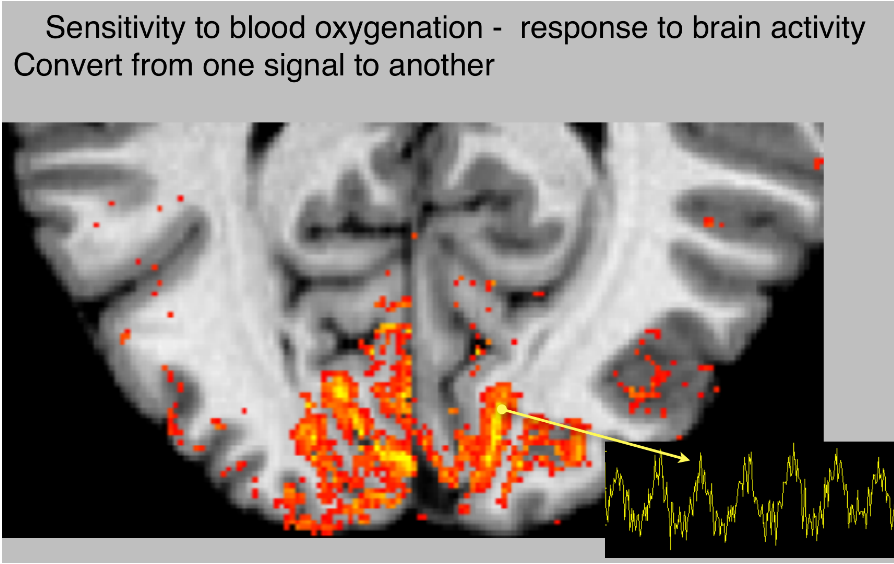


When to apply machine learning

- Humans are unable to explain their expertise
  (e.g. Speech recognition, vision, language)
- Solution changes with time
  (e.g. tracking, noise cancellation, adaptive filtering)
- Solution needs to be adapted to particular cases
  (e.g. biometrics, personalization)

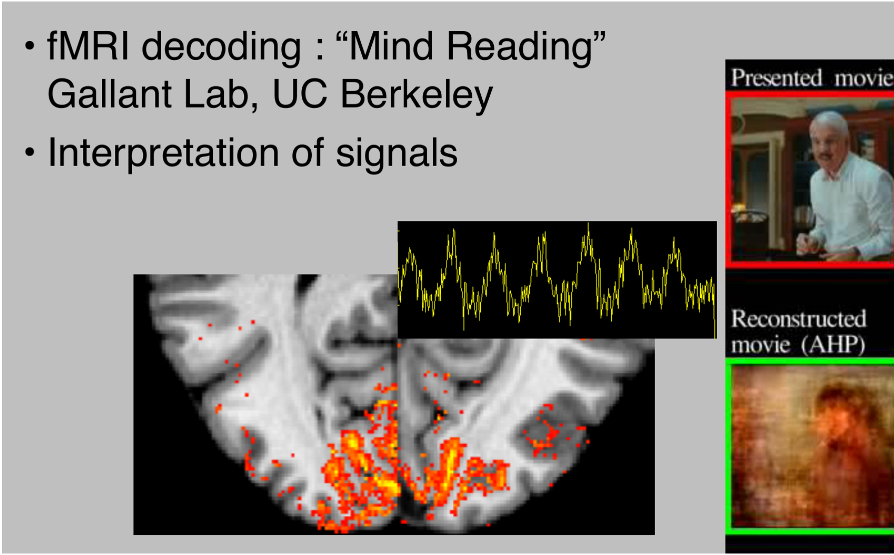
  $\vdots$

Example: functional MRI (1/2)



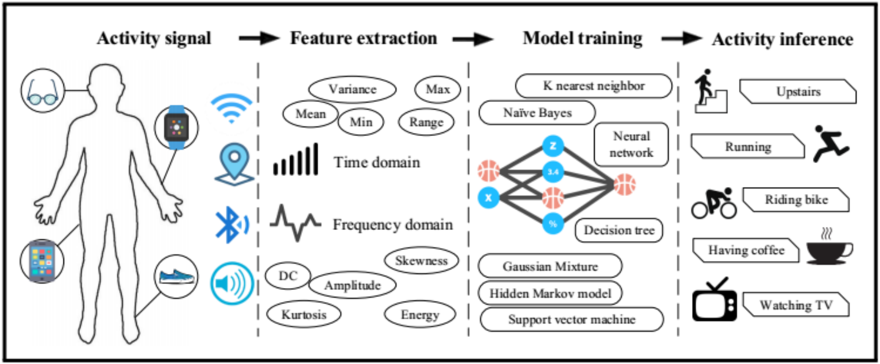
slide credit: Miki Lustig

Example: functional MRI (2/2)



slide credit: Miki Lustig

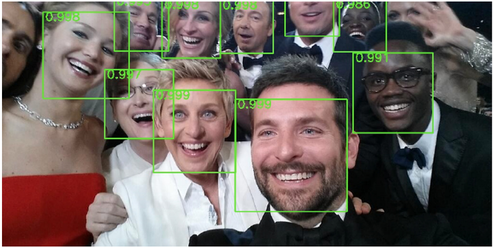
Example: Activity recognition



slide credit: Wisdom D'Almeida

Application: Computer Vision

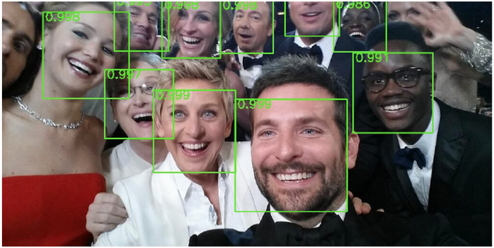
- Face Detection



Viola and Jones face detector (2001)

Application: Computer Vision

- Face Detection



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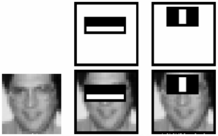
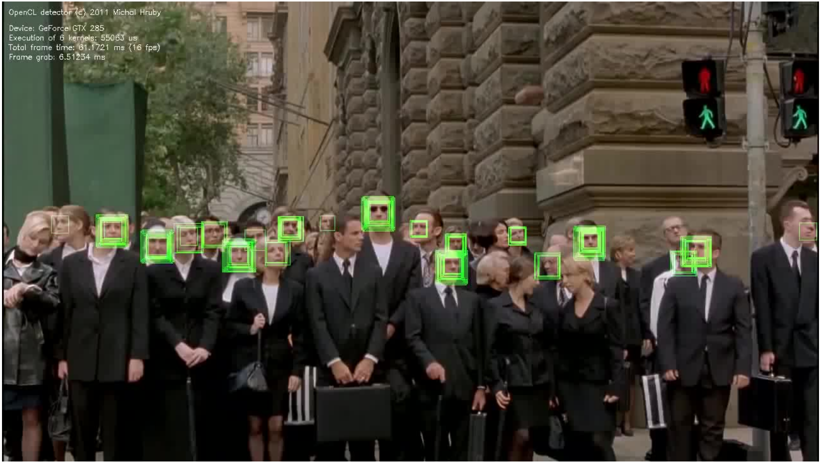


Real-time face detection



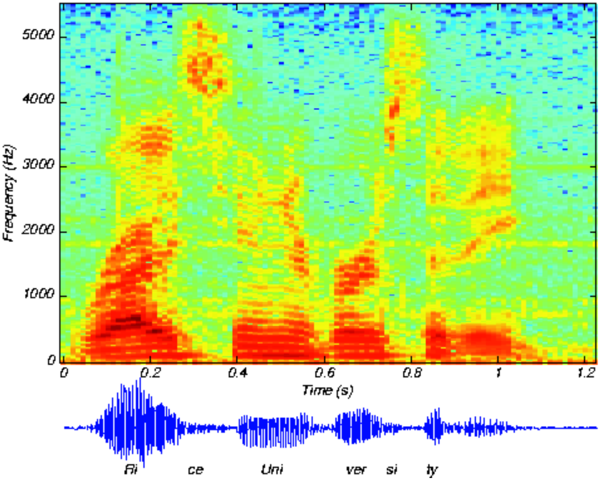
Application: Speech Recognition

- Voice Search (e.g., Google), Speech Transcription

- Text to Speech

Baidu Deep Voice Demo
Google Tacotron

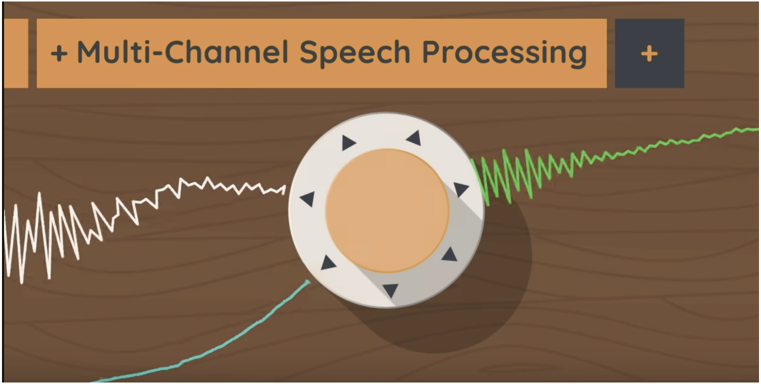
Spectrogram



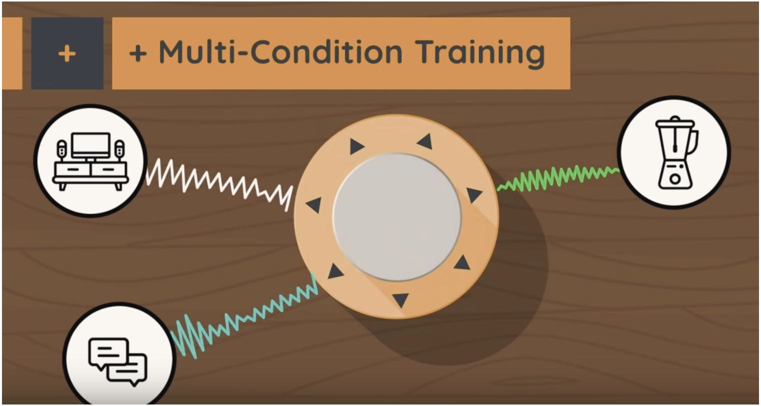
Spectrogram online

Array Signal Processing

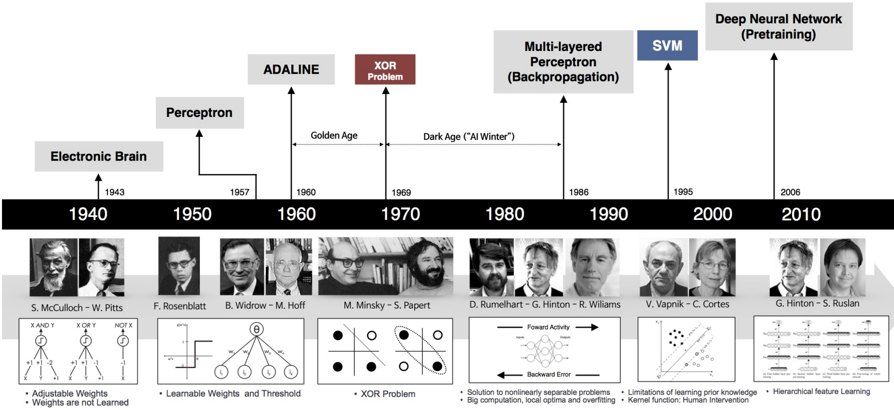
Array Signal Processing



Array Signal Processing

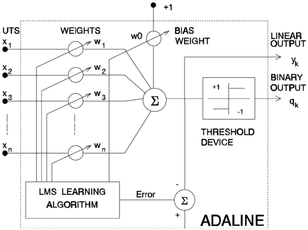


Neural Networks



Adaline: Adaptive Linear Neuron

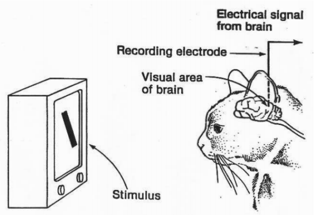
- Bernard Widrow and Ted Hoff (1960)

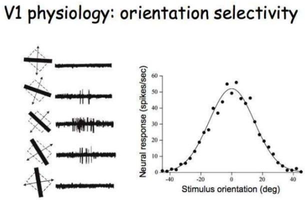


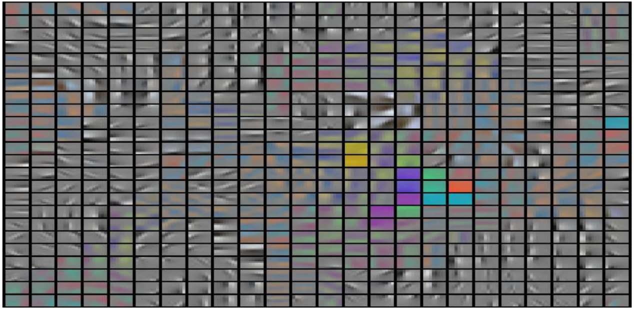
Adaline: Adaptive Linear Neuron (1960)

Convolutional Neural Networks

Selectivity and Topographic maps in V1

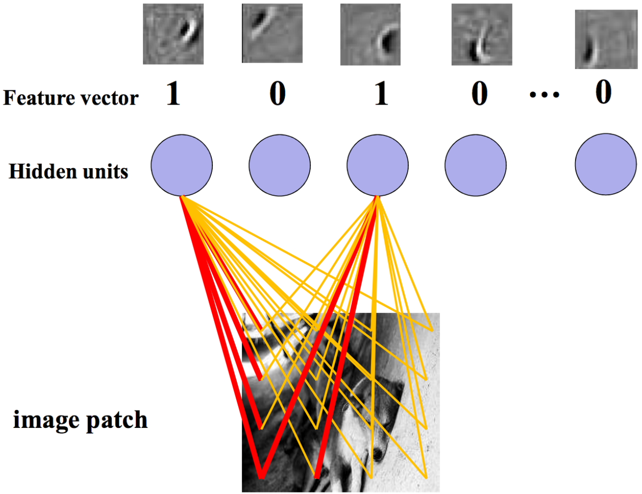






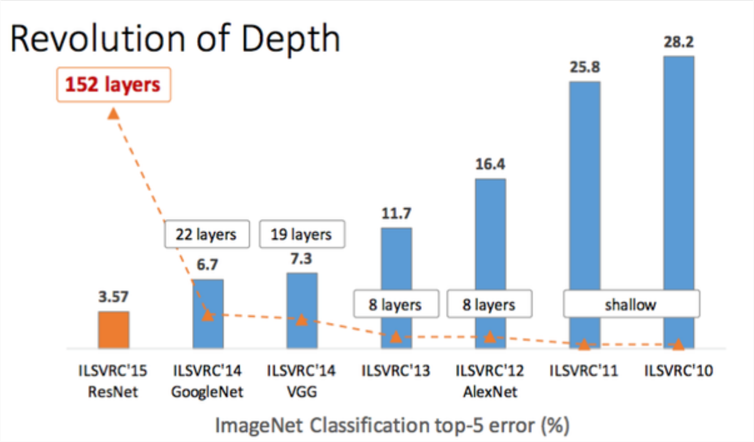
Hubel and Wiesel, 1968

Convolutional Neural Networks

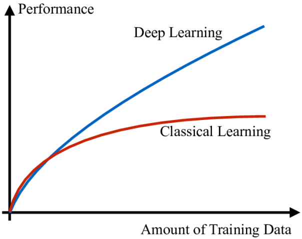


- Fukushima (1980), LeCun (1989)

Revolution of Depth: Deep Learning

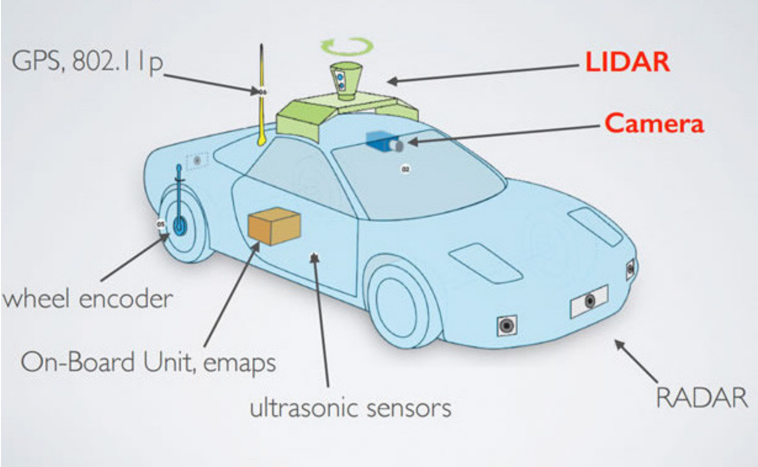


Classical Learning vs Deep Learning



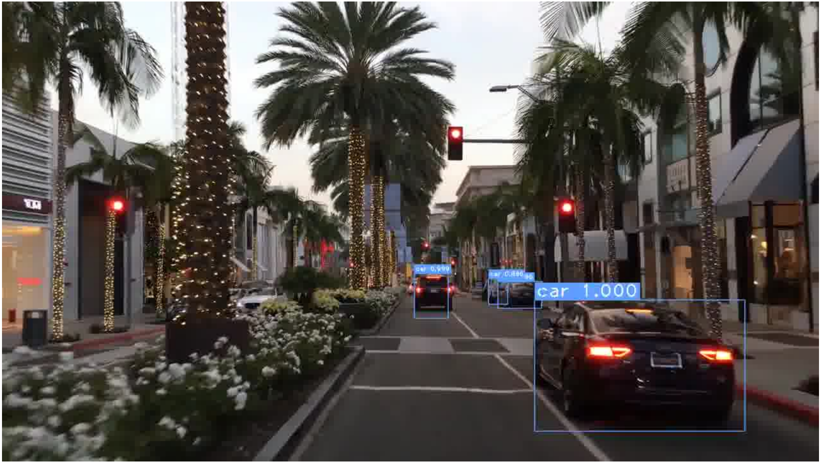
- Classical learning algorithms often require feature engineering
- No need for feature engineering in deep learning: features are learned through optimization
- Deep learning scales much better with more data than classical learning algorithms
- Deep learning have achieved accuracies that are far beyond that of classical learning methods in speech processing, natural language processing, computer vision, and reinforcement learning

Example: Self-driving cars



slide credit: Jonathan Petit

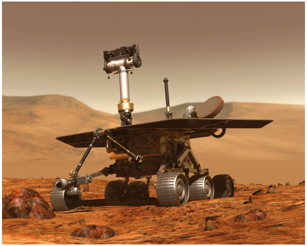
Example: Self-driving cars



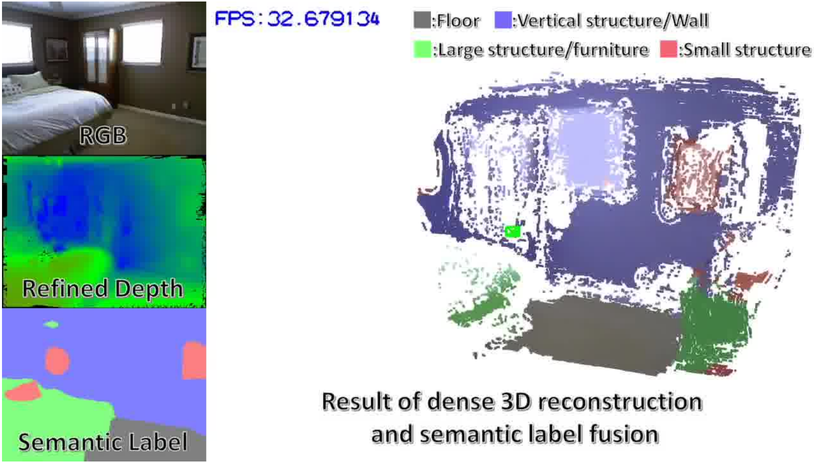
Application: Robotics

- Helicopter control

- Robot perception and navigation

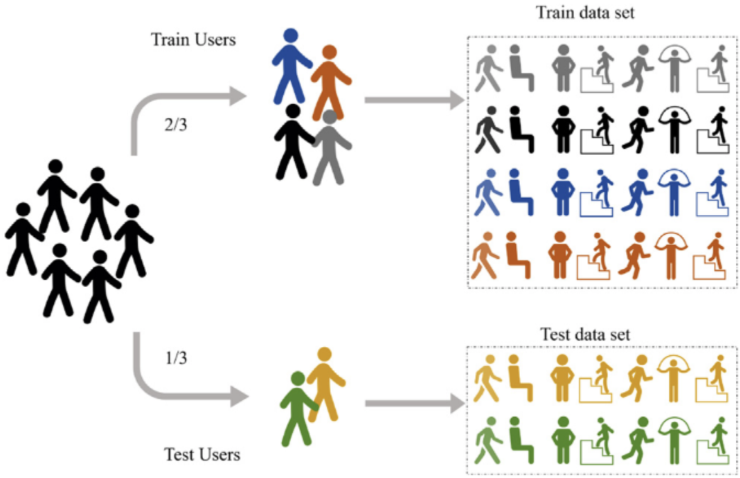


Application: Self-navigating drones



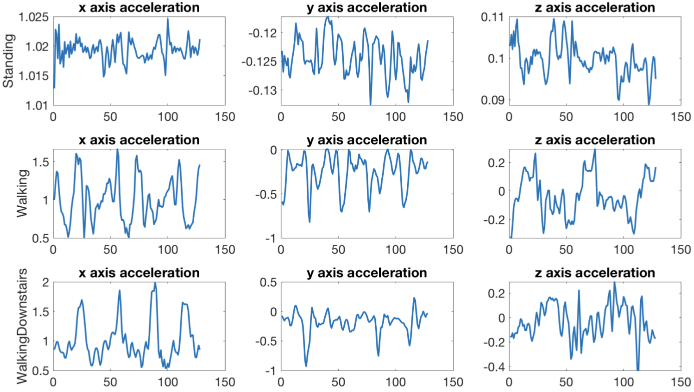
Classical learning vs deep learning in signal processing

- Example: Activity recognition with wearable sensors



Human Activity Recognition

- Human Activity Recognition Using Smartphones Dataset (Reyes-Ortiz et al, 2012)
- Time domain training signals $x_1[n], x_2[n], \ldots x_m[n]$



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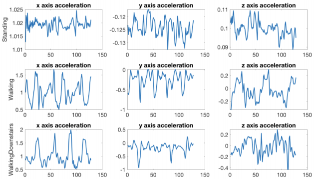
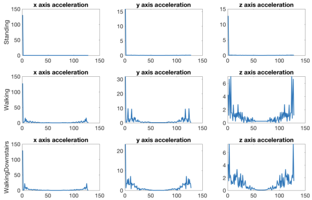


3-Nearest Neighbors, ℓ_2-norm distance on $x[n]$. **Accuracy** : 0.77



3-Nearest Neighbors, ℓ_2-norm distance on $|X[k]|$. **Accuracy** : 0.85

Human Activity Recognition

- 3-Nearest Neighbors, ℓ_2-norm distance on $x[n]$.
  accuracy : 77%
- 3-Nearest Neighbors, ℓ_2-norm distance on $|X[k]|$.
  accuracy : 85%
- 1D Convolutional Net (4 layers)
  accuracy : 91%
- Wavelet Transform Features (entropy, zero crossing, simple statistics) + linear classifier
  accuracy : 95%

Topics

- Vector spaces and Hilbert spaces

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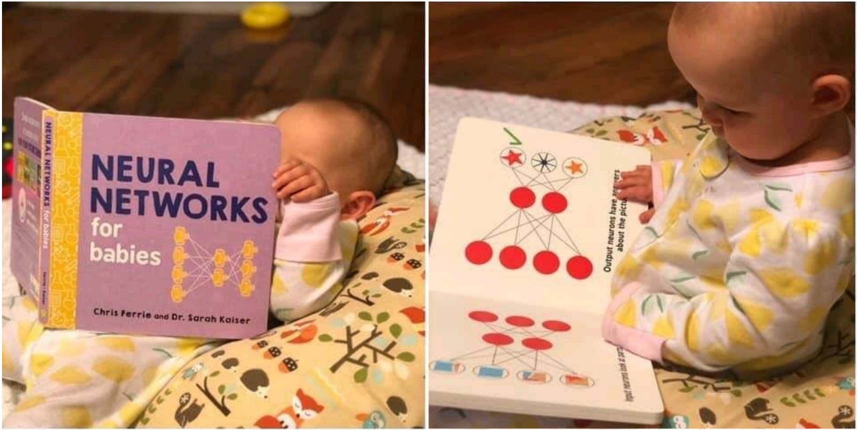
- Neural Networks
- Adaptive Filters
- Convolutional Networks and Deep Learning

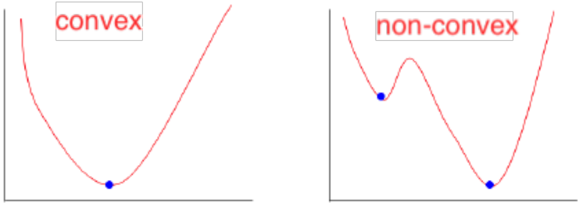
Some interesting questions we will explore

- **How to find optimal signal representations for machine learning?**
- **How to find optimal signal classifiers?**
- **Is feature engineering necessary?**
- **Can neural networks automatically find good features?**
- **Can we replace domain knowledge with neural networks and data?**
- **When does a deep neural network perform better than a classical model?**
- **How can we understand what neural network models are learning?**

How neural networks work?



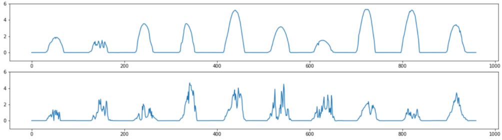
How neural networks work?



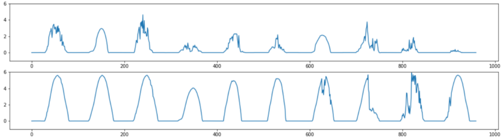
- Traditional machine learning models such as Least-Squares, Support Vector Machines etc.
- Neural network training problems are **non-convex**
  - challenging to train
  - hard to interpret
- Neural networks can be formulated as convex optimization models in higher dimensions!

Sample projects from previous years

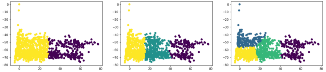
Photovoltaic power pattern clustering



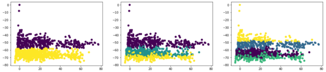
(a) Two class clustering of Raw Feature data



(b) Two class clustering of Raw Wavelet data



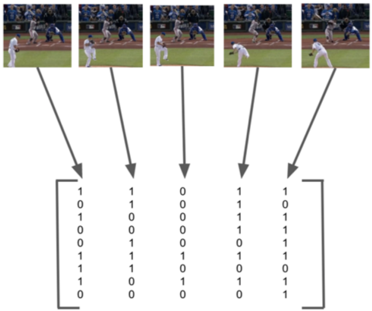
(a) Clustering performed directly on data (left plot indicates unexpected clustering)



(b) Clustering performed data projected onto Principal Components 2 through 9 (left plot aligns with expected clustering)

Sample projects from previous years

Tracking objects in video recordings



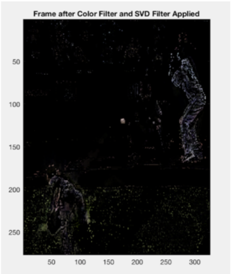
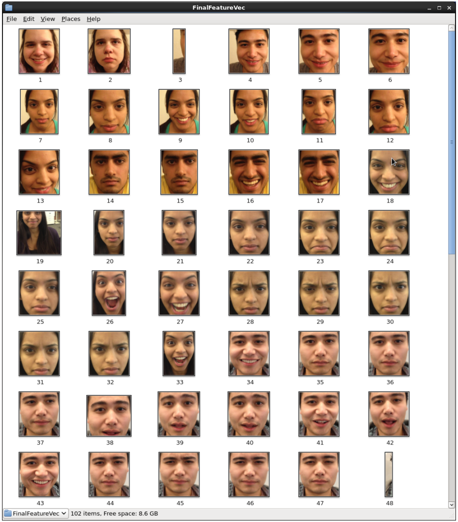


Figure 2.7 - Frame after SVD filter applied

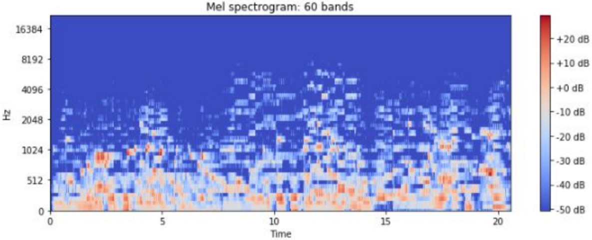
Sample projects from previous years

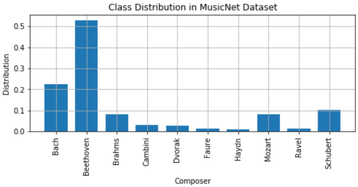
Emotion detection from faces

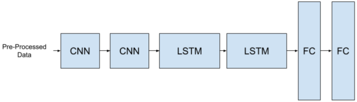


Sample projects from previous years

Composer classification for classical Music







Sample projects from previous years

Predicting Epileptic Seizures from EEG data

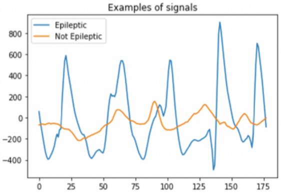


Figure 1. Original image of eye with border

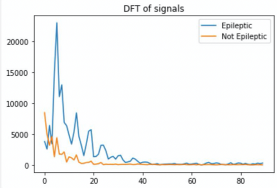


Figure 2. DFT comparison between epileptic and non-epileptic signals

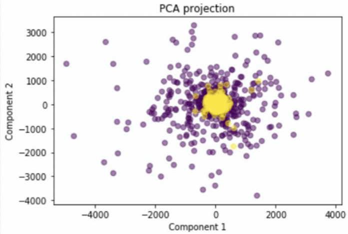
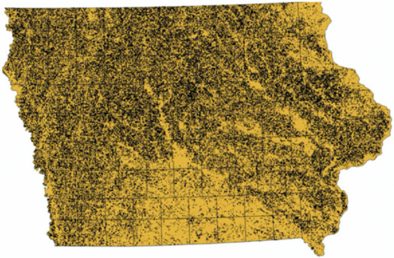


Figure 3. Projection of points onto top 2 principal components

Tracking Crop Planting Dates Using Satellite Images



Example MODIS band resampled and masked to leave only corn pixels

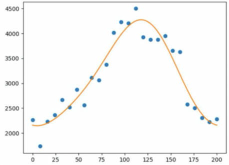


Figure 2: Estimated phenology curve for red wavelength (MODIS SR band
using two sine terms, two cosine terms, and a constant

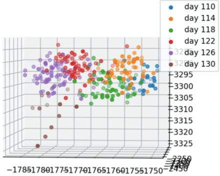


Figure 3: Planting dates binned in four day intervals, projected onto the first three FLD basis vectors

Sample projects from previous years

Audio Direction of Arrival Estimation

Figure 1: Rode NT4 stereo microphone cardioid capsule geometry.

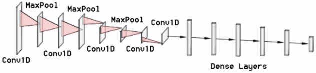


Figure 6: Visualization of the final CNN architecture.

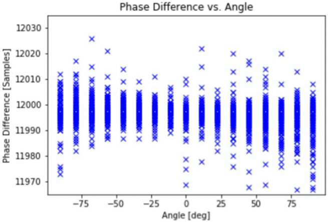


Figure 3: Interchannel phase difference for recorded data as a function of angle.

Sample projects from previous years

Flight State Estimation of Unmanned Aerial Vehicles

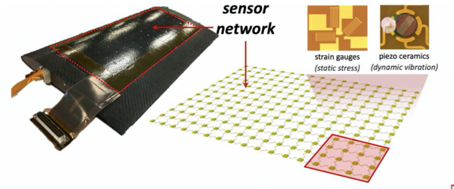


Fig. 1. A composite UAV wing outfitted with a bio-inspired stretchable sensor network consisting of distributed micro-sensors.

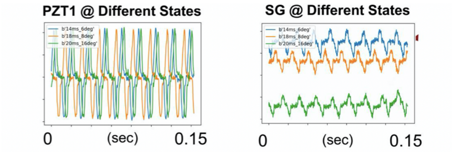
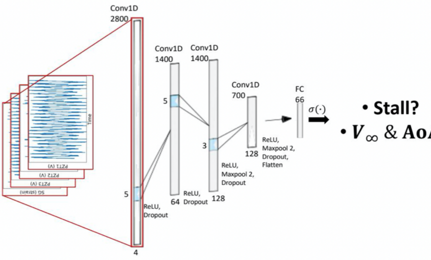


Fig. 4. Sample 0.15 seconds data of data collected at different states (left: data collected by PZT 1 senors, right: data collected by strain gauge)



Questions?