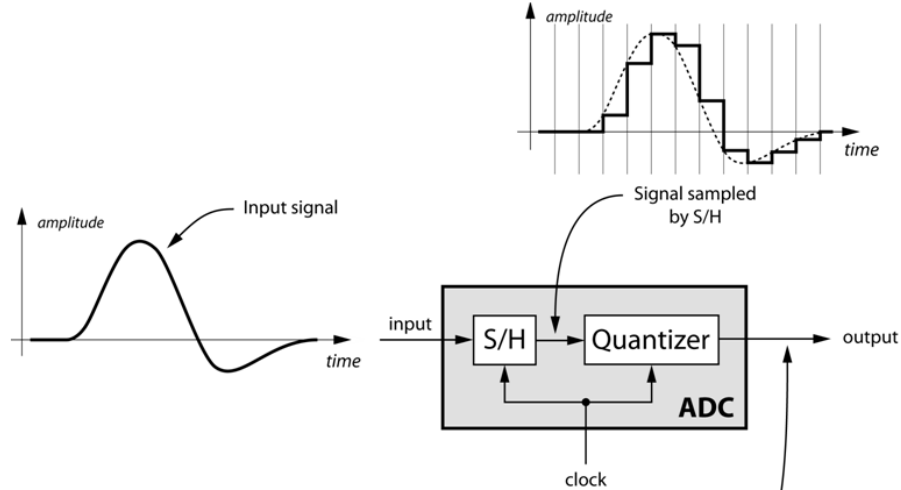
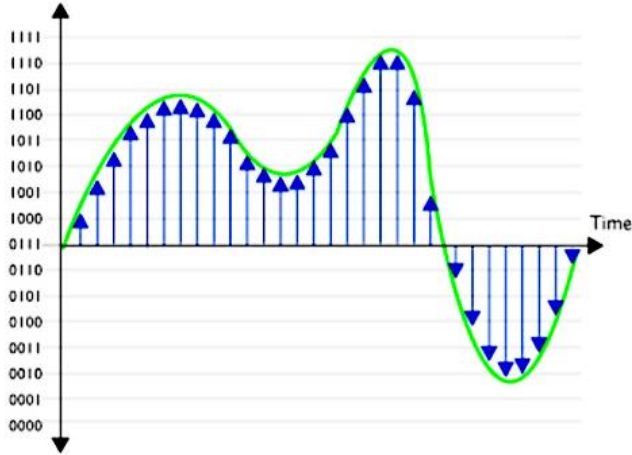


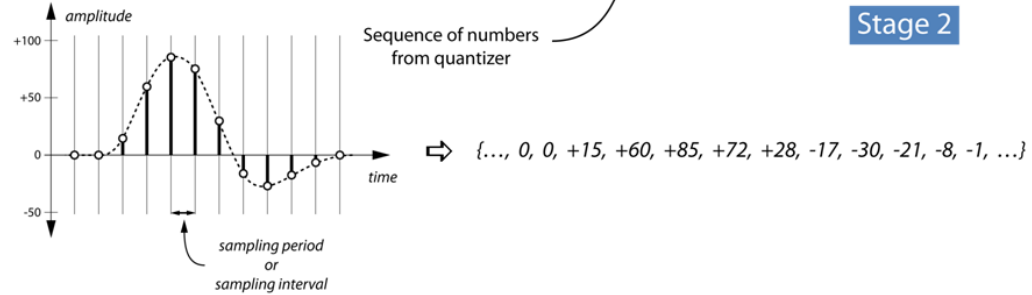
Neural Interfaces

NX-422
Data Compression

Mahsa Shoaran
IEM and Neuro-X Institutes

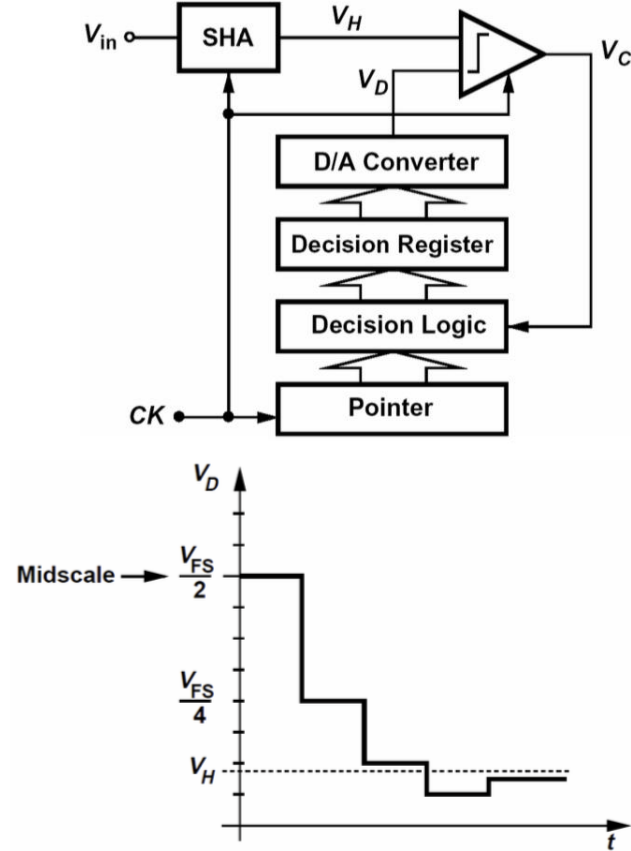
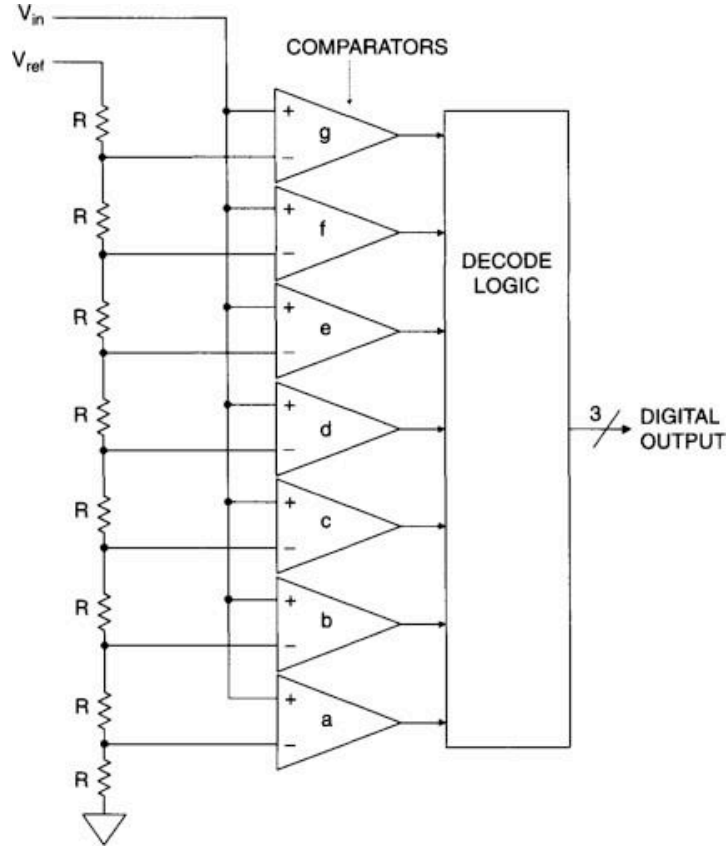


Stage 1

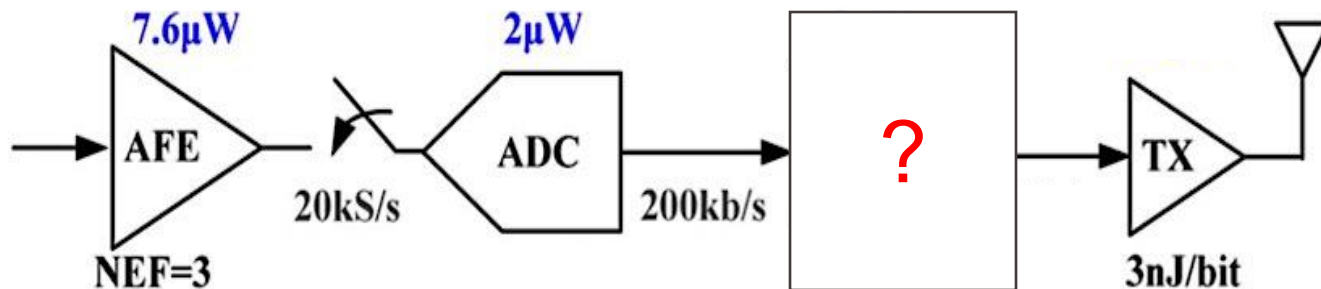


Stage 2

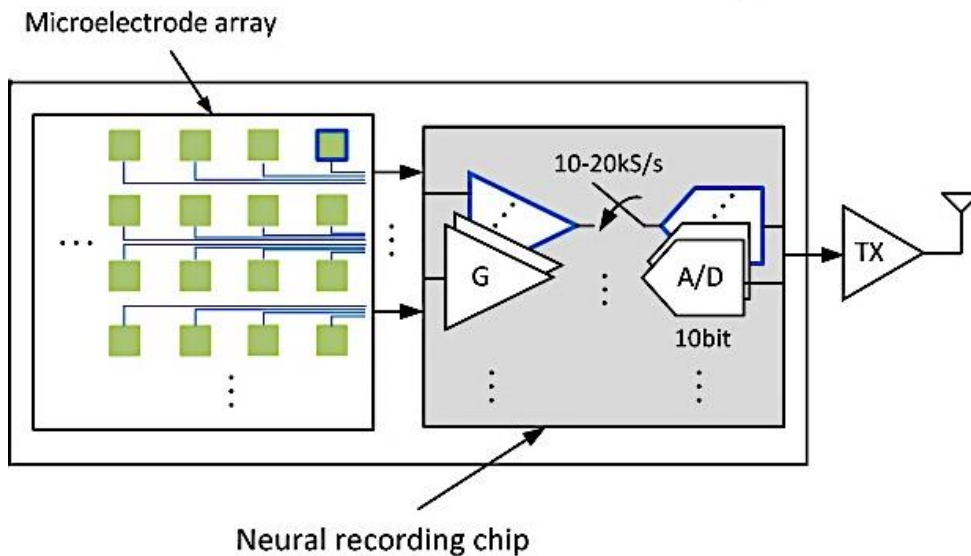
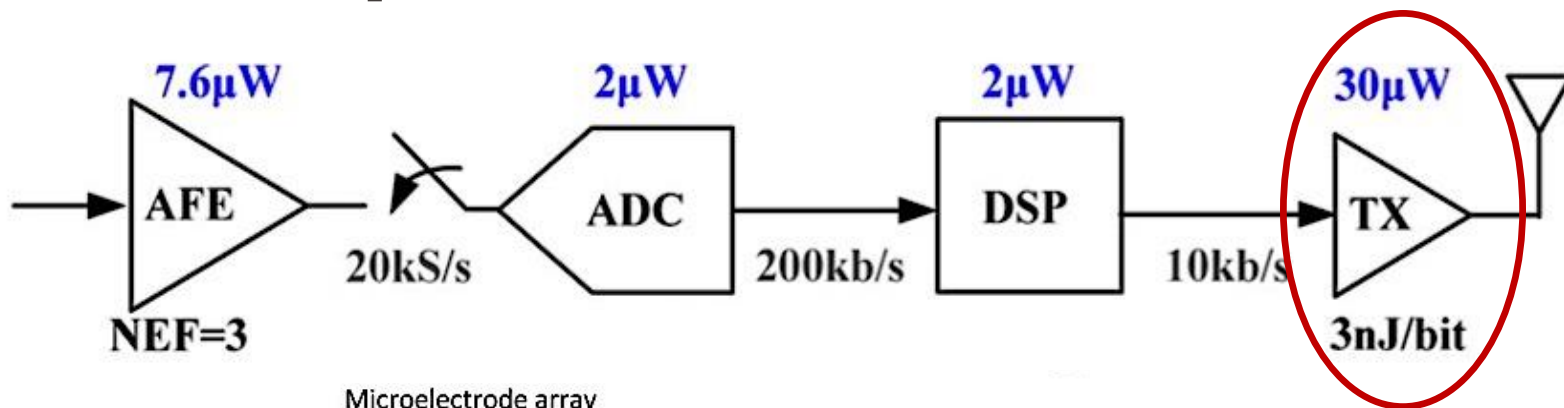
Recap: Flash and SAR ADC



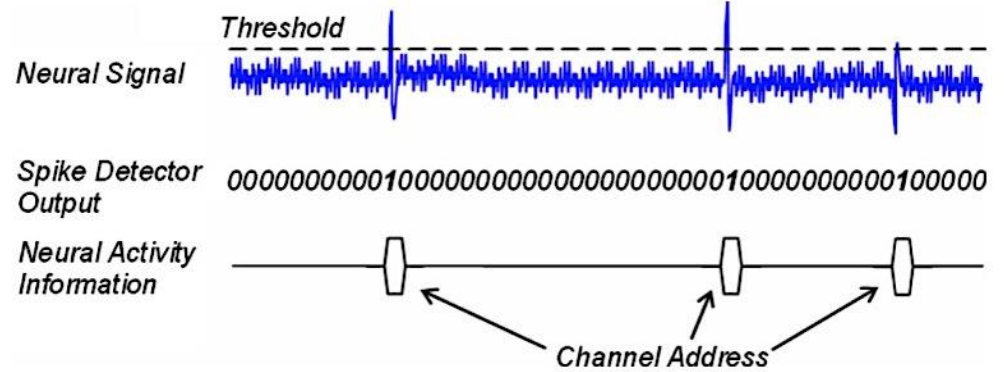
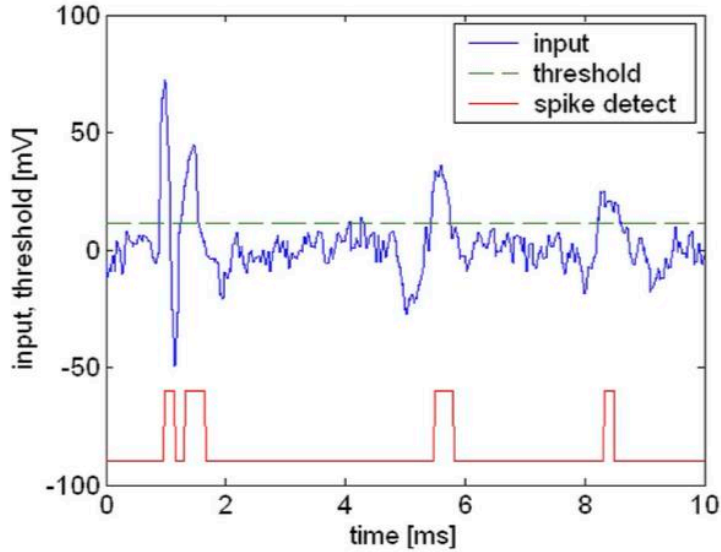
- The typical circuit blocks used in sensors for medical monitoring and their associated energy cost and power consumption



Data Compression

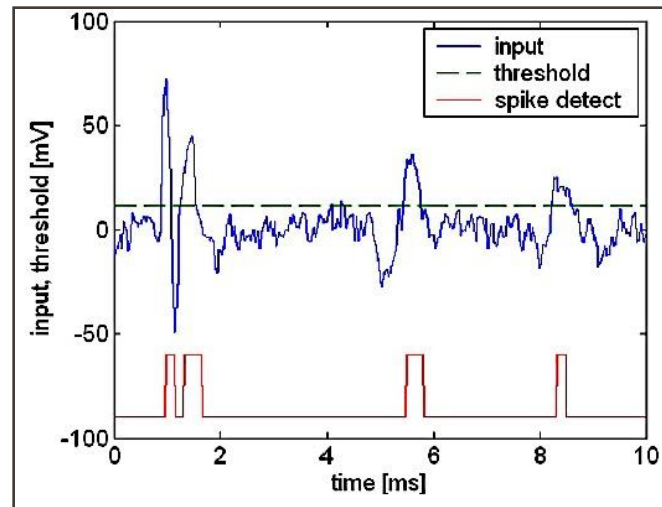


■ Spike Detection



■ Spike Detection

- High compression ratio (CR)
- × Losing the raw waveform
- × Unreliable in long-time



- Compressive Sensing (CS):
 - CS relies on the signal of interest being sparse in some basis, Ψ .
 - Many biological signals of interest are sparse e.g. EEG, ECG, etc.

Foundation: *Shannon/Nyquist sampling theorem*



“if you sample densely enough (at the Nyquist rate), you can perfectly reconstruct the original analog data”

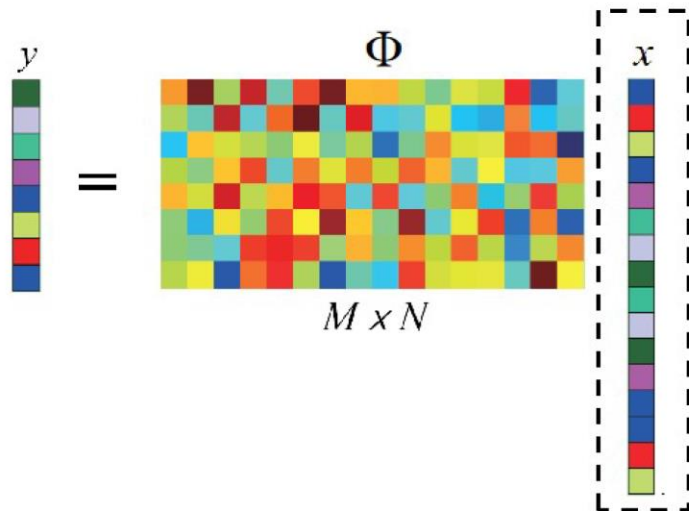


Signal Type	Sampling Rate	Frequency of Events
Extracellular APs	30 kHz	10 – 150 /s

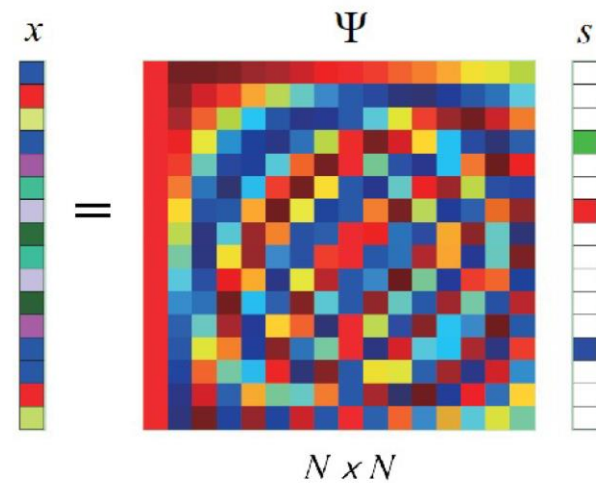
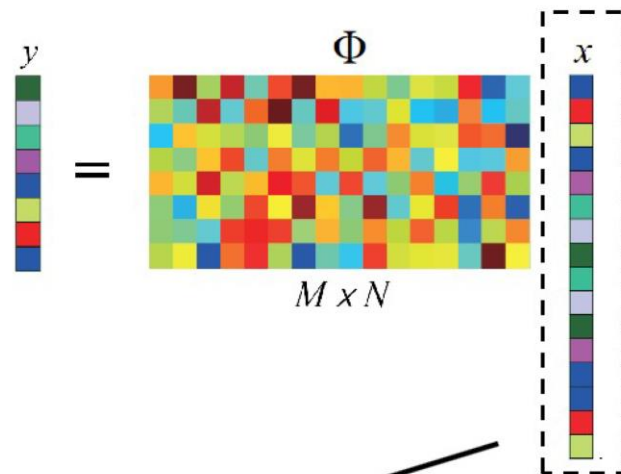
What we want:

- Compression: minimize data, but retain the information
- Low cost: must be less than transmission savings
- Generality: we don't want to customize every sensor design

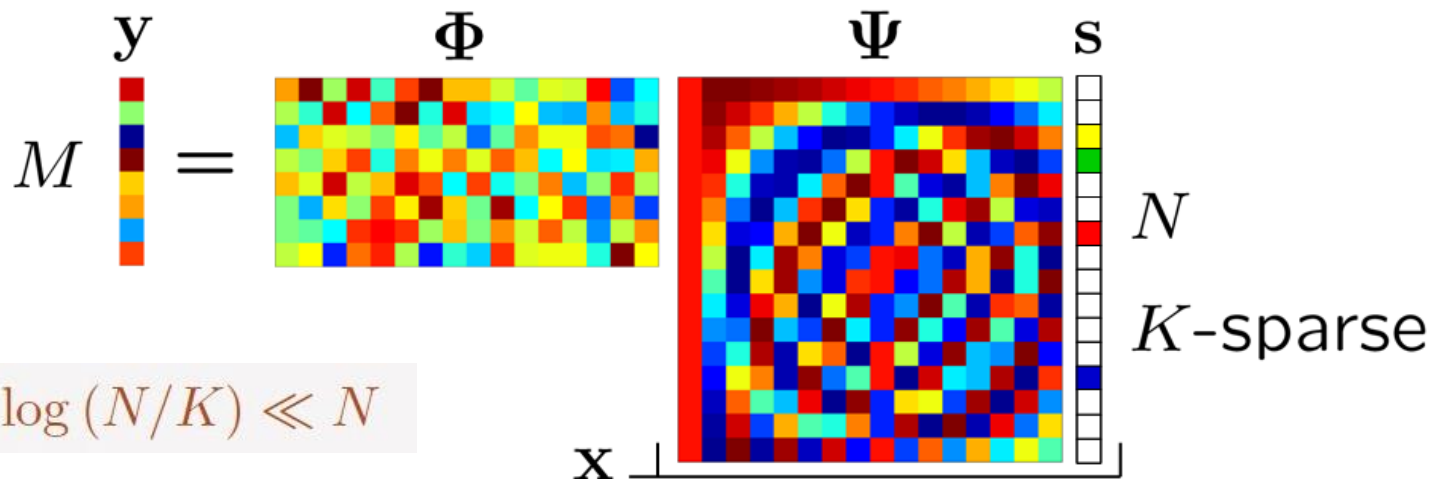
- In 2006, **Candès and Donoho** proved that given a signal's sparsity, it may be reconstructed with even fewer samples than the sampling theorem requires
- A compressive sensing system samples a high-dimensional signal with significantly smaller number of measurements than sampled at the Nyquist rate, given that the signal is **sparse in a basis**



Compressive Sensing



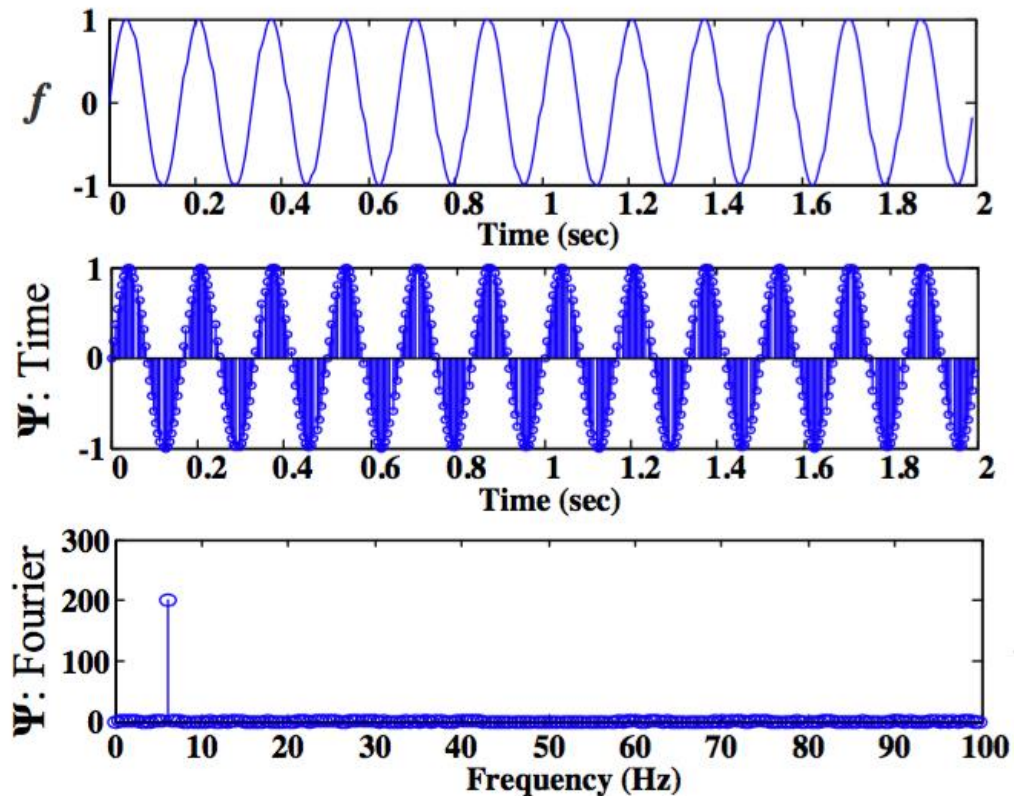
- Low cost, generality

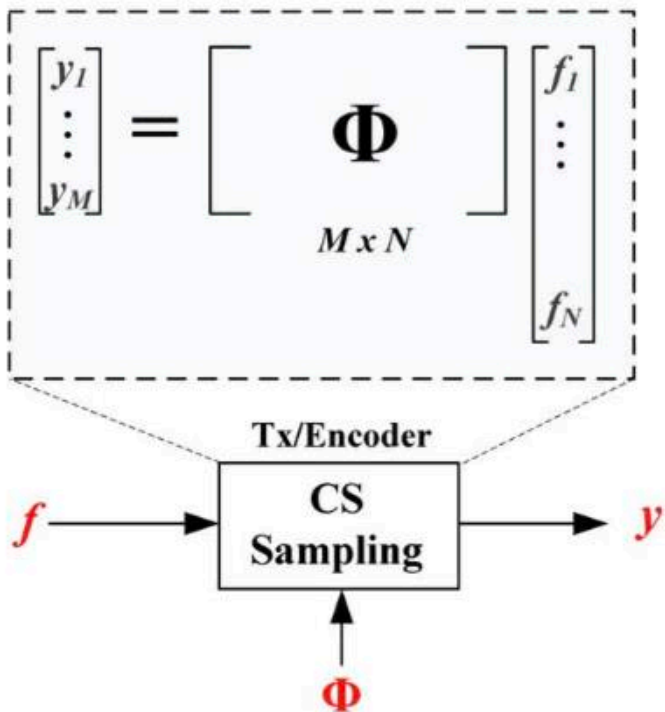


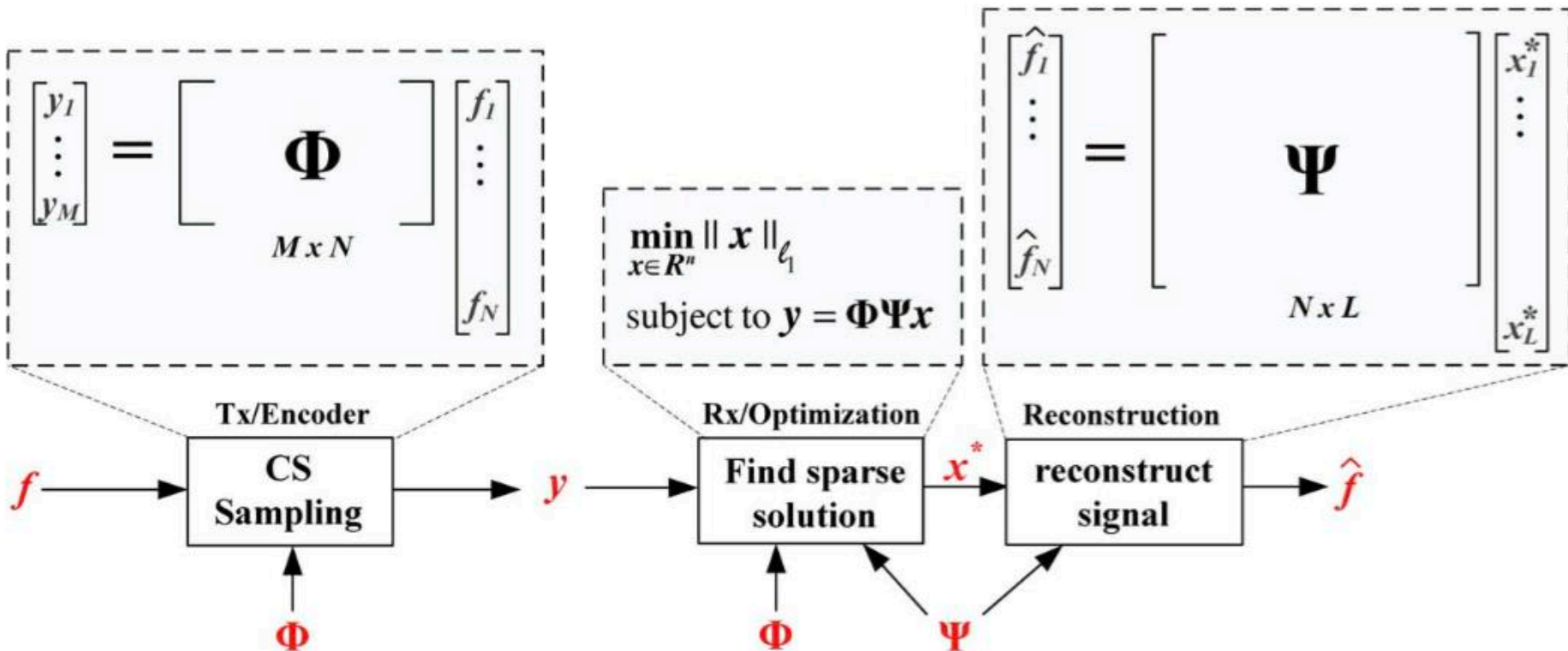
$$M \geq cK \log(N/K) \ll N$$

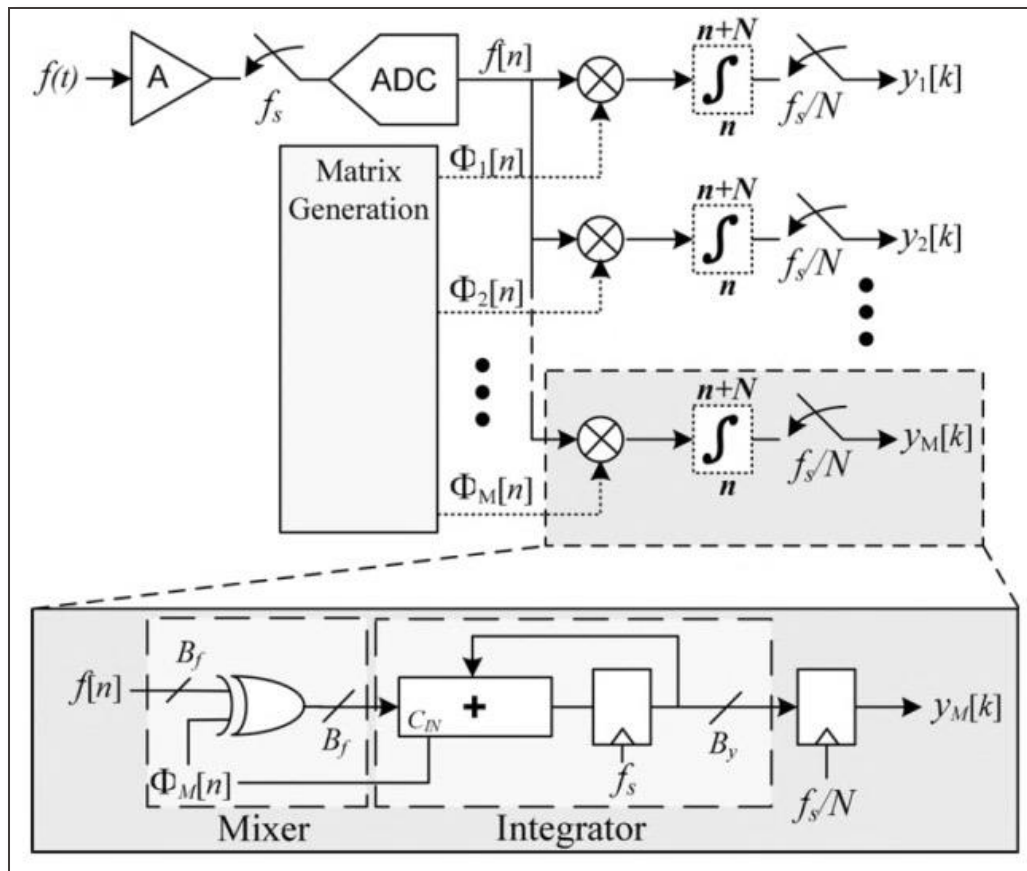
- Random measurement matrix (random 0, 1)
- Recovery: a convex minimization problem

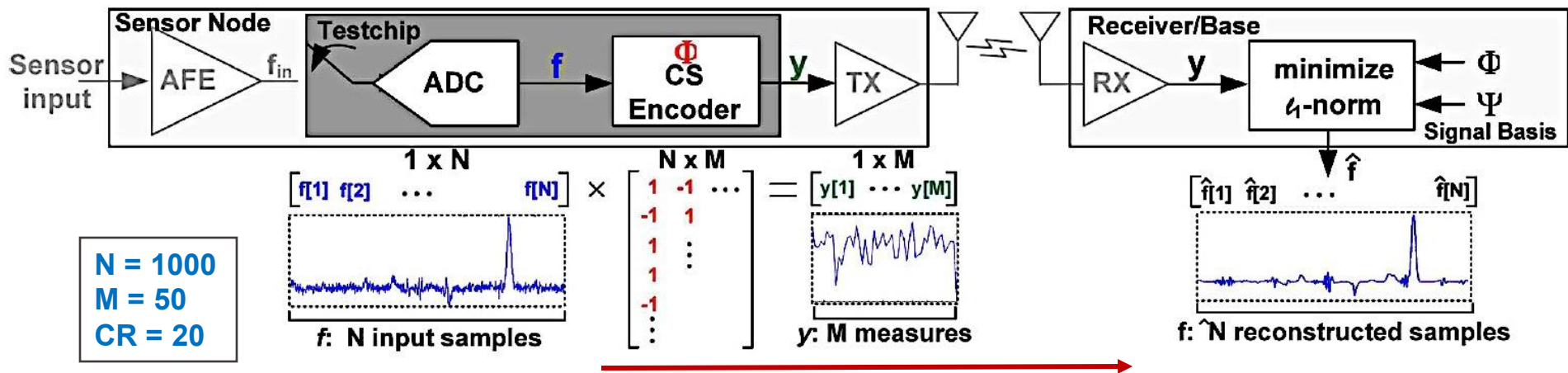
- Sinusoid example:











Compressive Sensing: Digital

