JICE: Joint Data Compression and Encryption for Wireless Energy Auditing Networks

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Outline

- **Motivation**
- Design of JICE
- Secrecy of JICE
- Experiment

Wireless Energy Auditing

- Buildings account for 40% electricity use
- Wireless appliance submetering

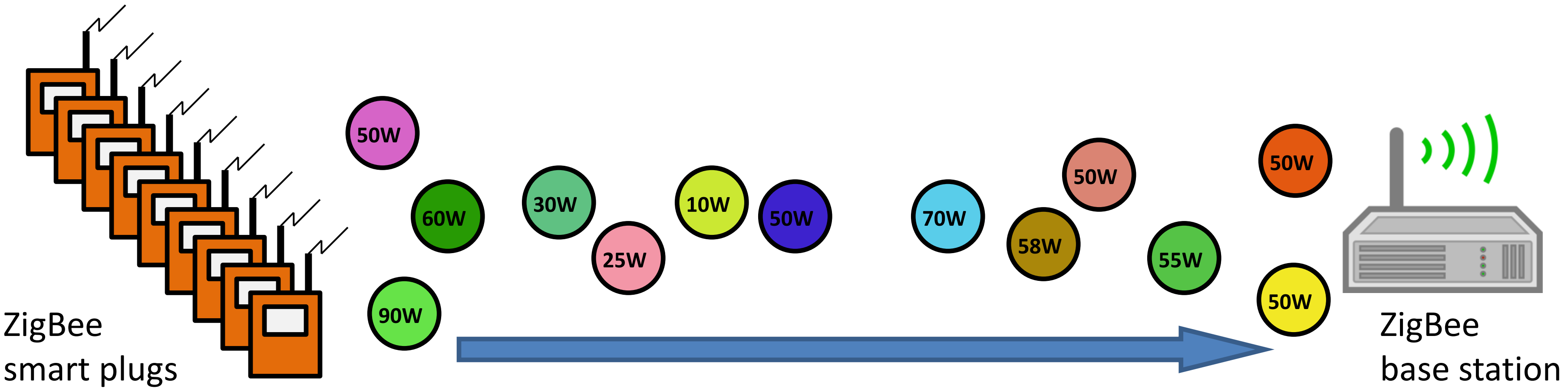
Smart plugs (ZigBee radio)

Wireless Energy Auditing

- Buildings account for 40% electricity use
- Wireless appliance submetering
  - Efficiency analysis
    56% energy wasted in our office[Jung 2013]

Smart plugs (ZigBee radio)

Objectives & Challenges



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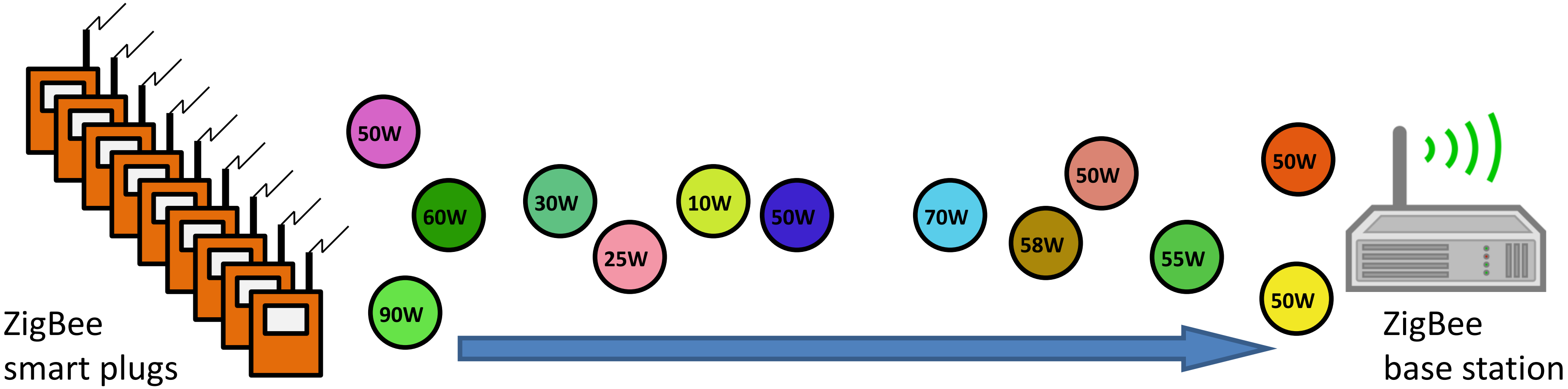

- **Increase coverage (# of meters) and sampling rate**
  - 10% coverage by 455 plugs [Haggerty 2012]
  - Down to 1Hz to support load profiling

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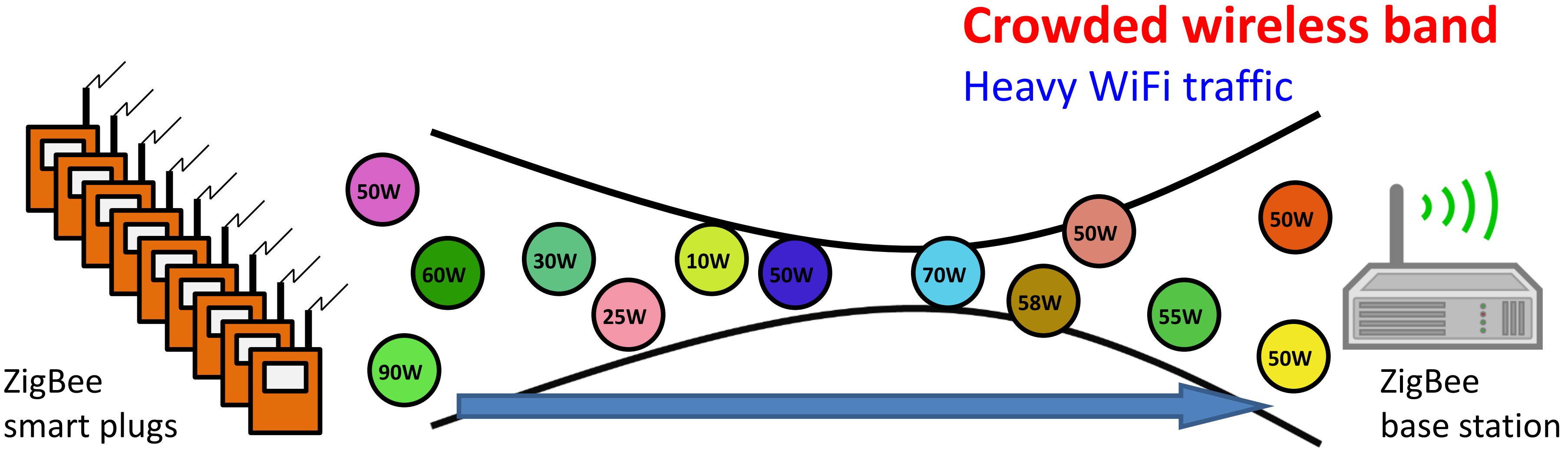

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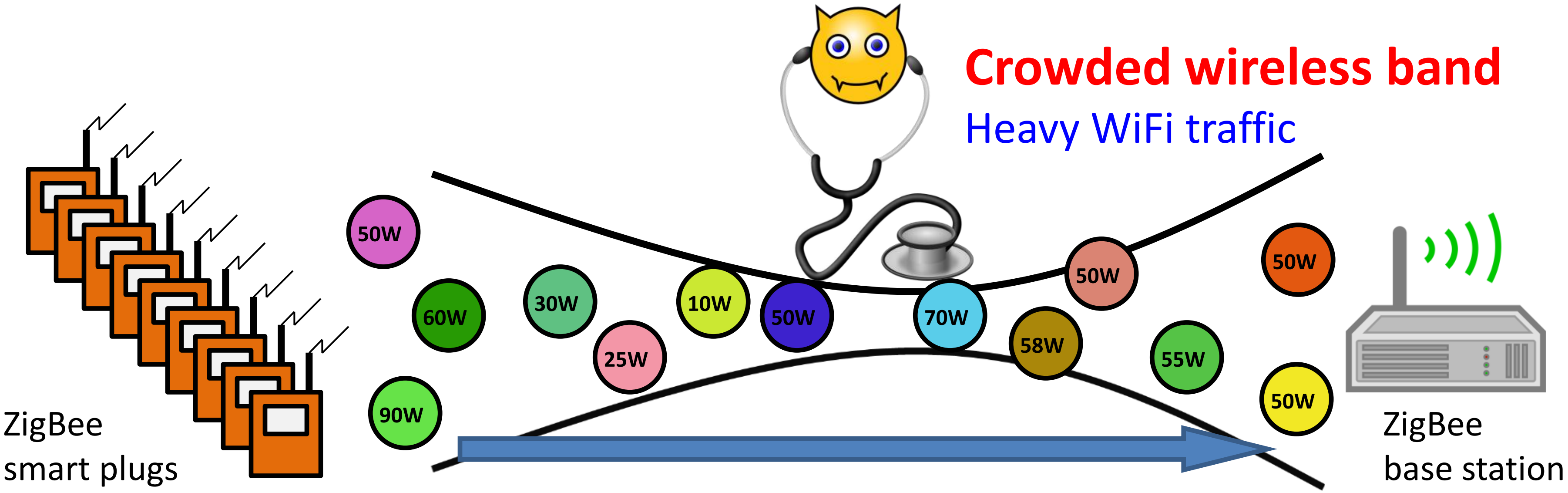

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- **Data secrecy during wireless communication**
  - Threat model: wireless eavesdropping
  - Reveal TV channel [Enev 2011]

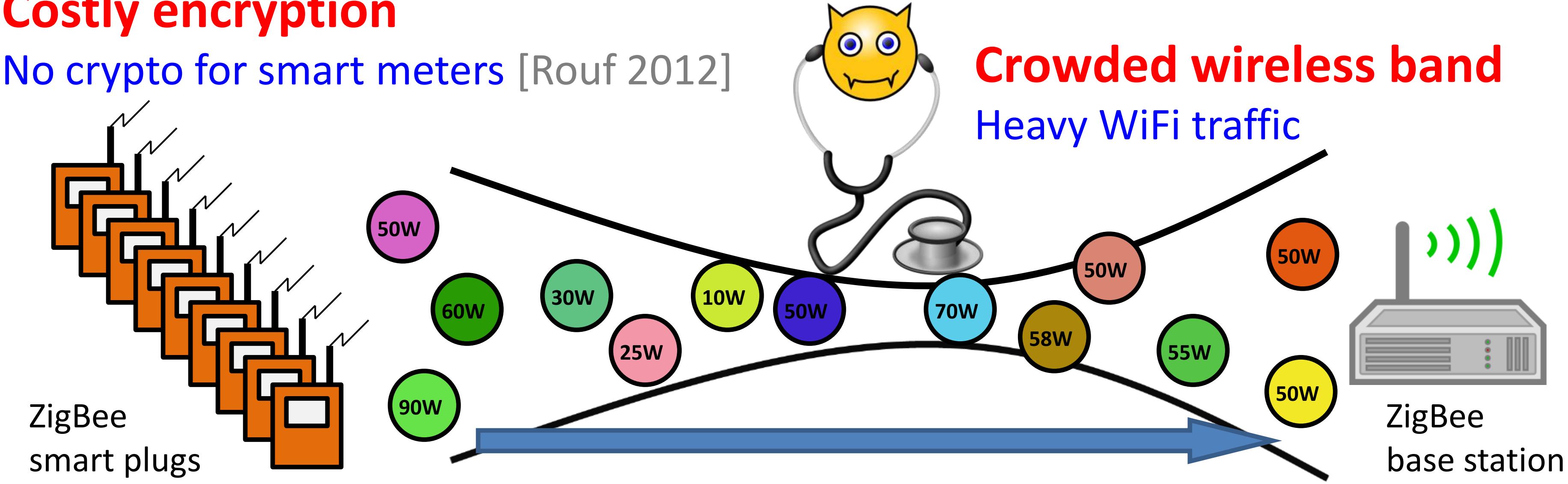
Objectives & Challenges

Costly encryption

No crypto for smart meters [Rouf 2012]

Crowded wireless band

Heavy WiFi traffic



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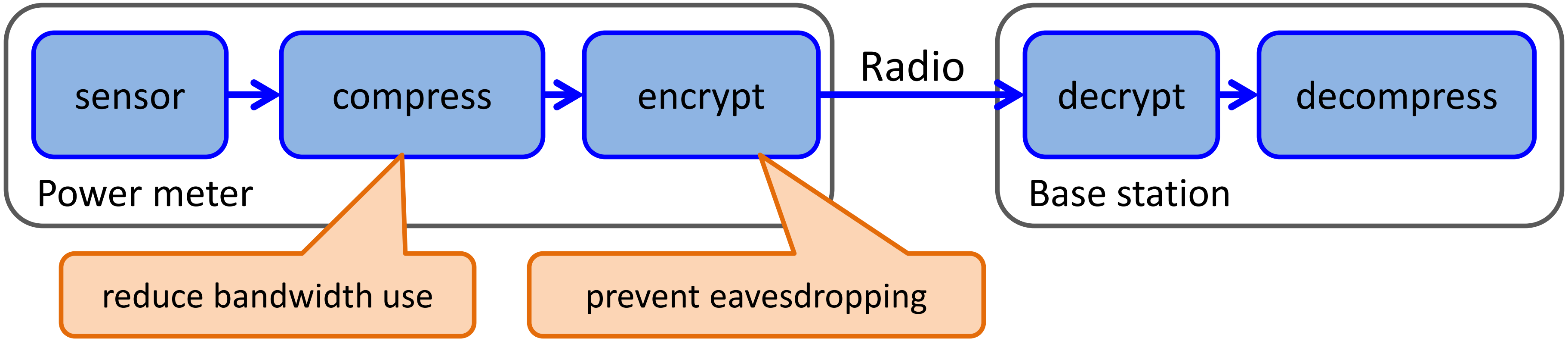
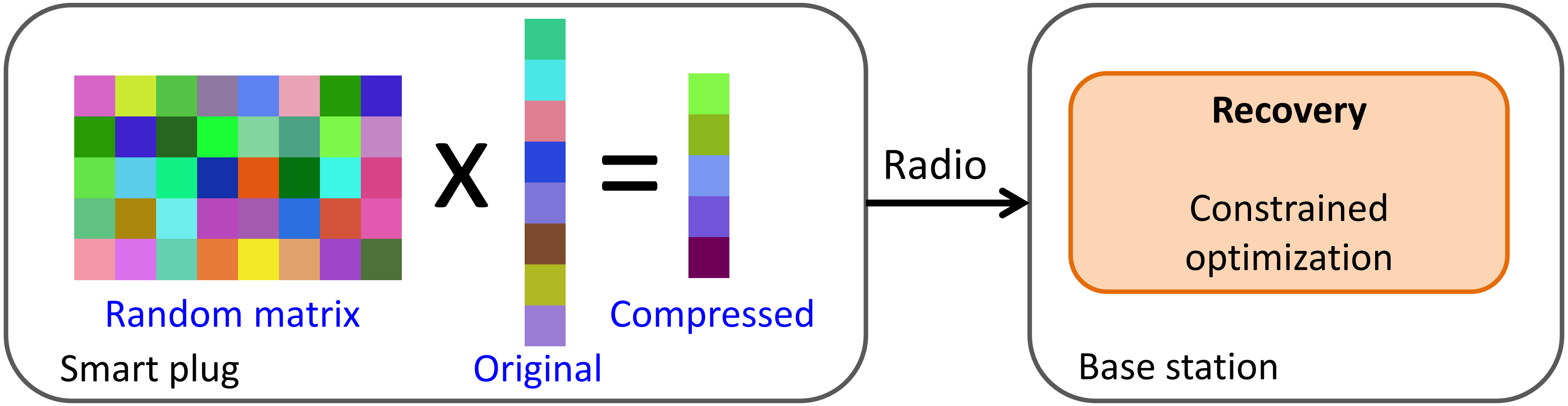
Conventional Scheme (Pipeline)



- Inefficient for resource-constrained plugs
  - Computation-intensive compressor and cipher

Compressive Sensing



- Efficient compression
  - Simple matrix multiplication
  - Most computation to recovery side
- Weakly encrypt signal [Rachlin 2008]
  - Shared secret random matrix

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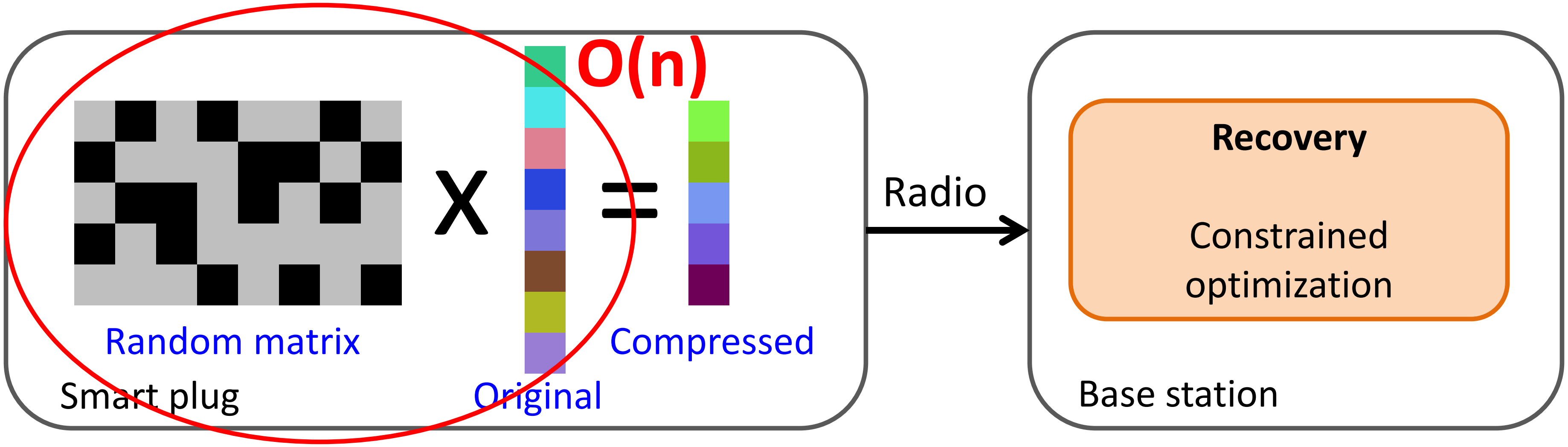

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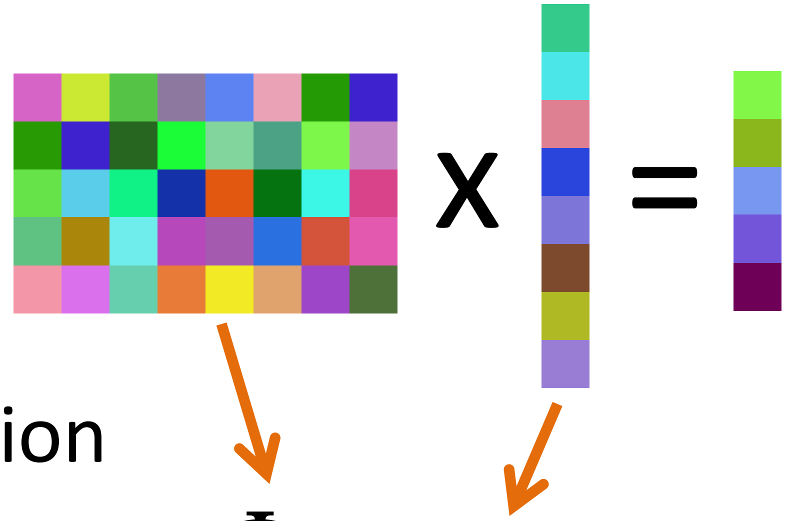
Compressive Sensing Basics



- Compression

$$\boldsymbol{y}_{M\times 1} = \boldsymbol{\Phi}_{M\times N}\,\boldsymbol{x}_{N\times 1} \qquad \boldsymbol{M} < \boldsymbol{N}$$

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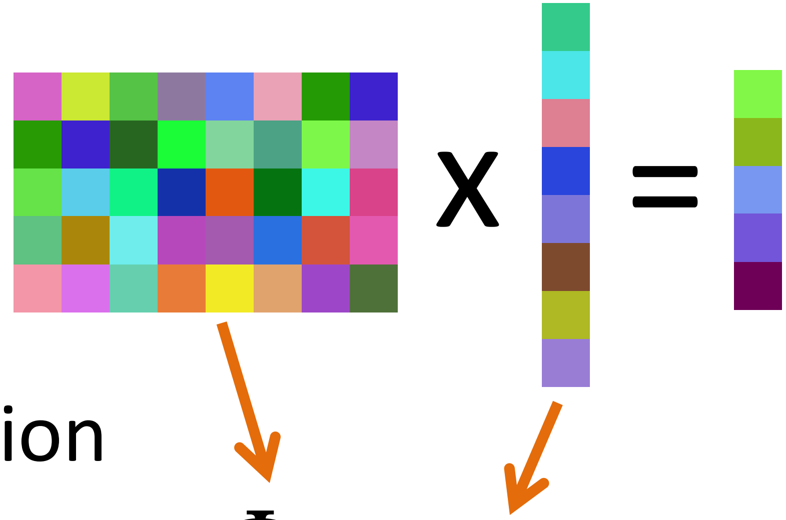

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- Recovery: compute *x* from *y* by

$$x = \Psi_{N\times N} \cdot \arg\min_{z} |z|_1 \quad \text{s.t.} \quad y = \Phi\Psi z$$

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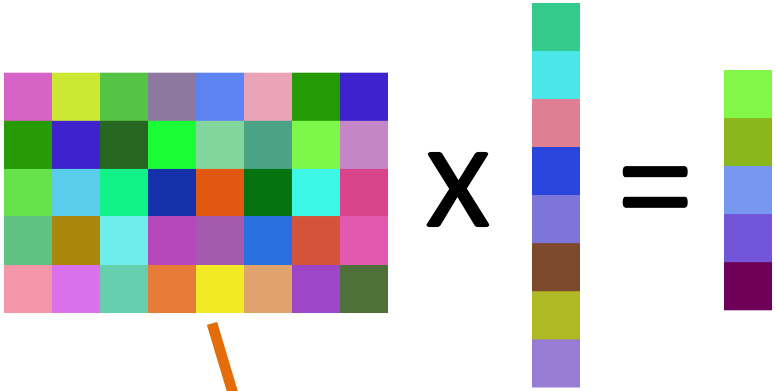

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Representation basis (only used for recovery)

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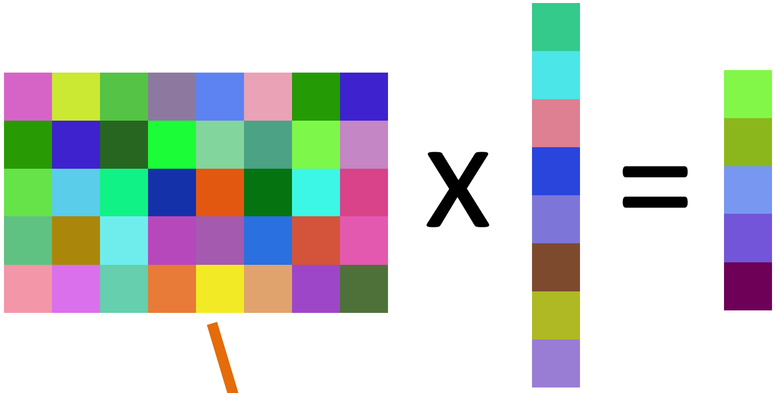

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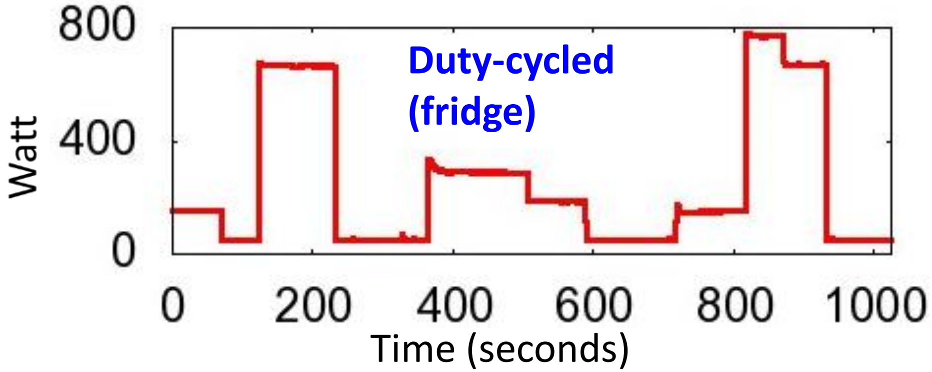
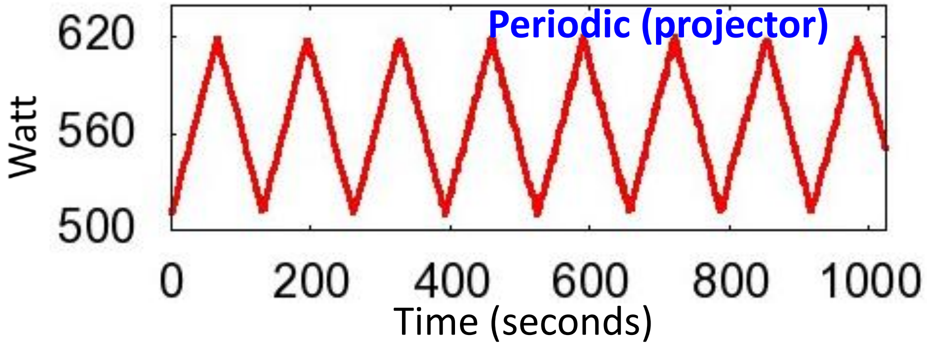
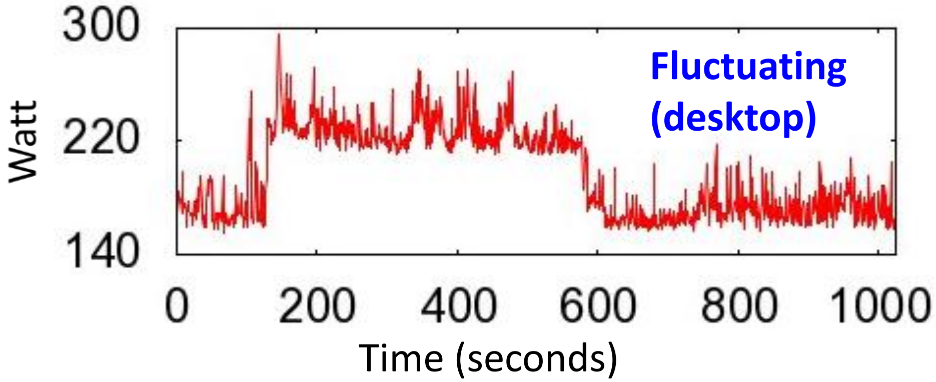
- For better recovery
  - Ψ sparsify *x* ⇨ Ψ^{-1}*x* has many zeros

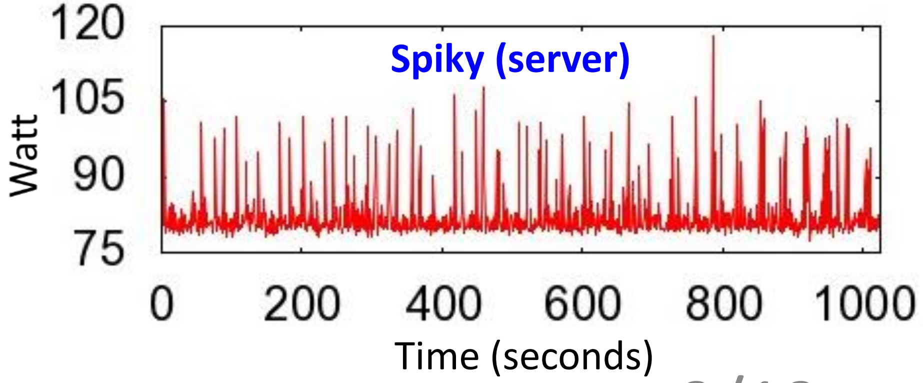
Trace-Driven Design

- Select Φ and Ψ based on traces
  - Data traces from 40 branches for 18 hours
  - Classify power consumption patterns









Random Matrix Φ

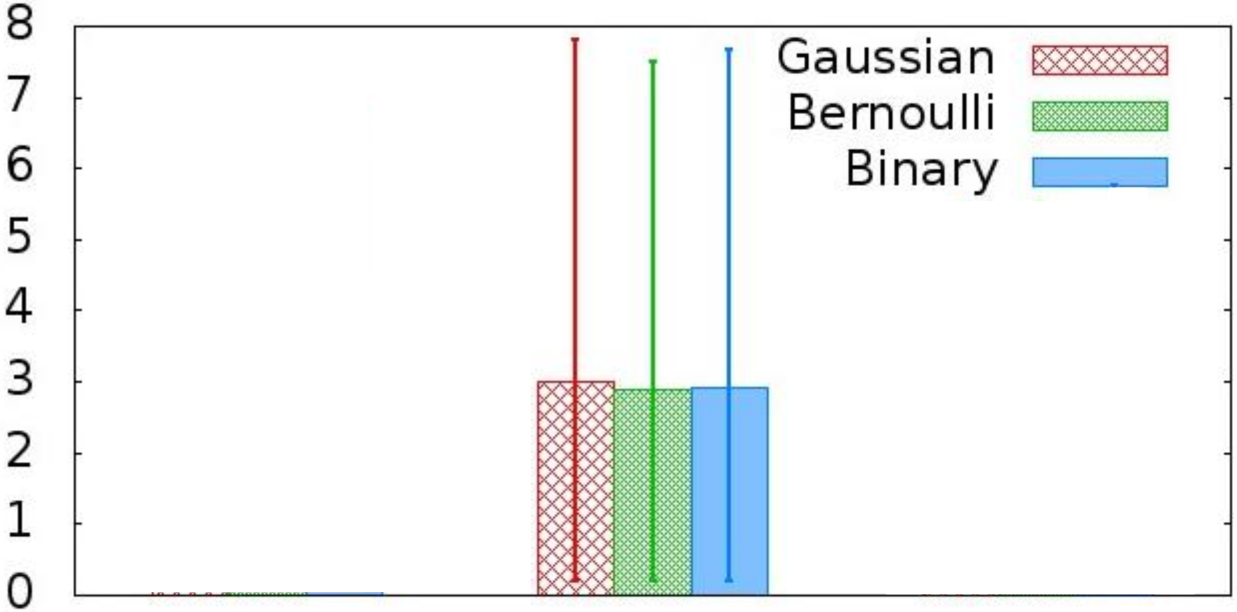
- Gaussian, Bernoulli, Binary

$$\textbf{recovery error} = \frac{\| \tilde{x} - x \|_2}{\| x \|_2}$$

x : **original**

$\tilde{x}$: **recovered**

Recovery error (%)



Representation basis

cosine transform

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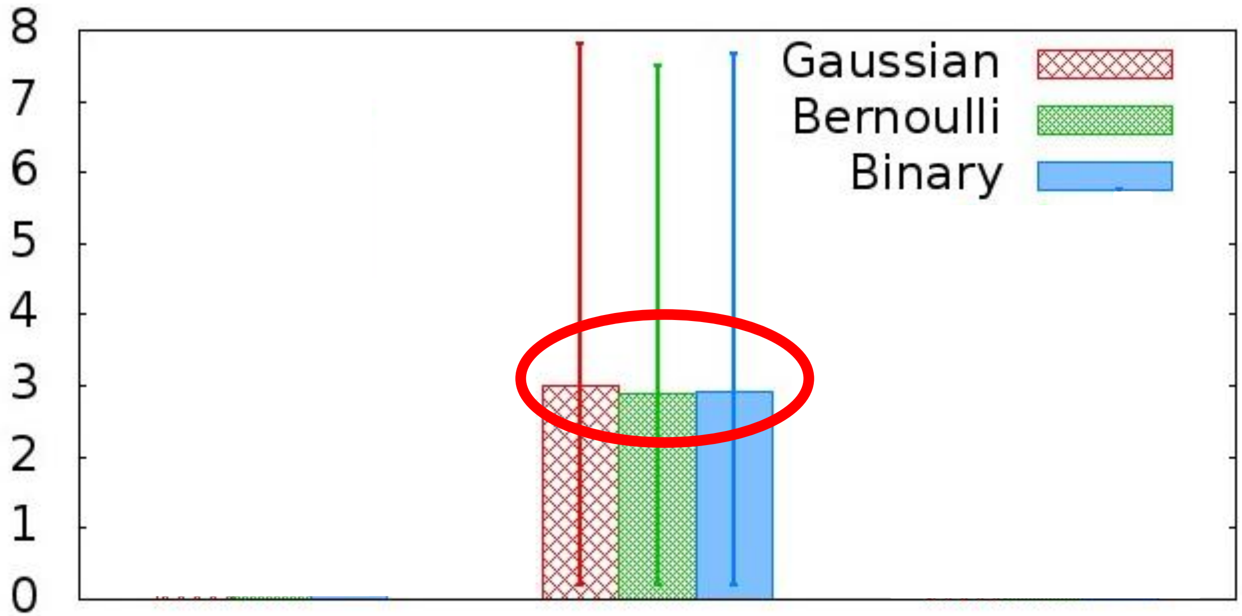

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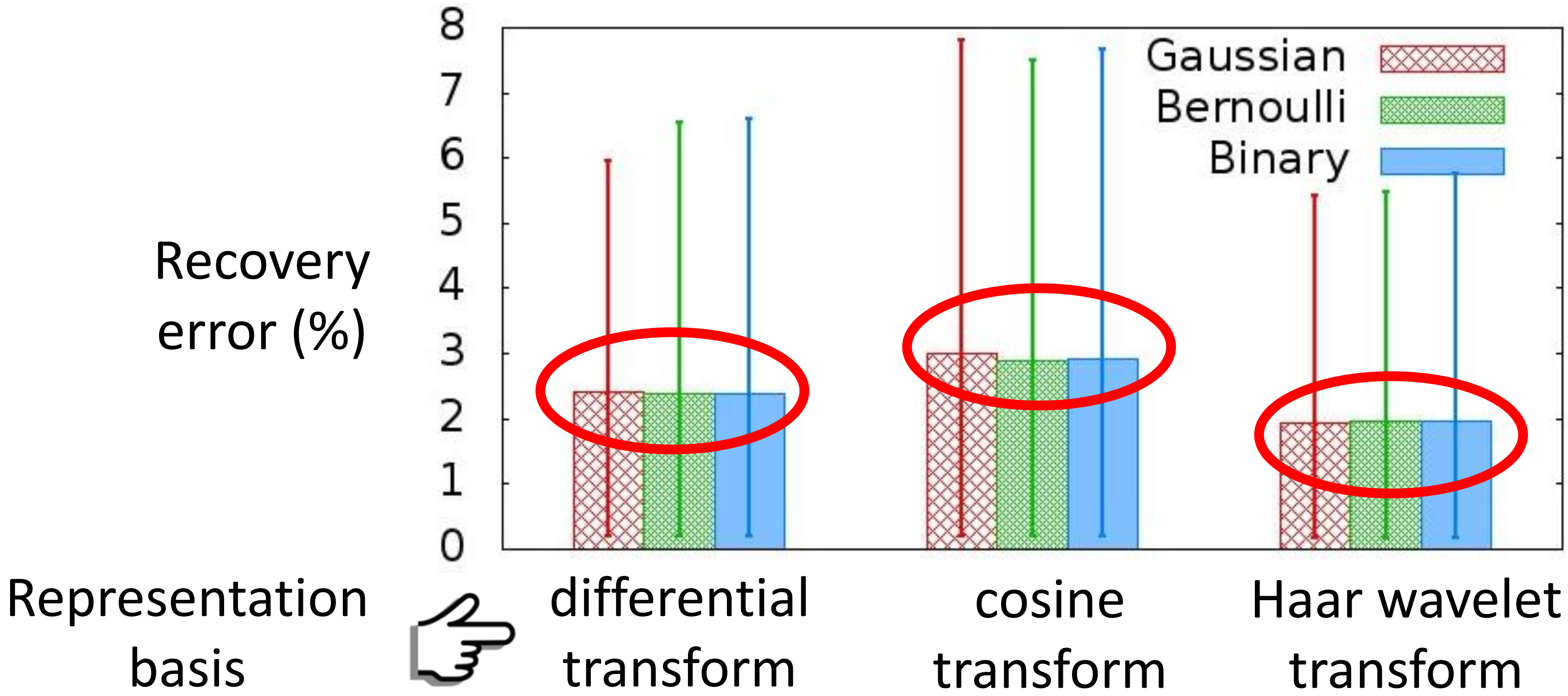

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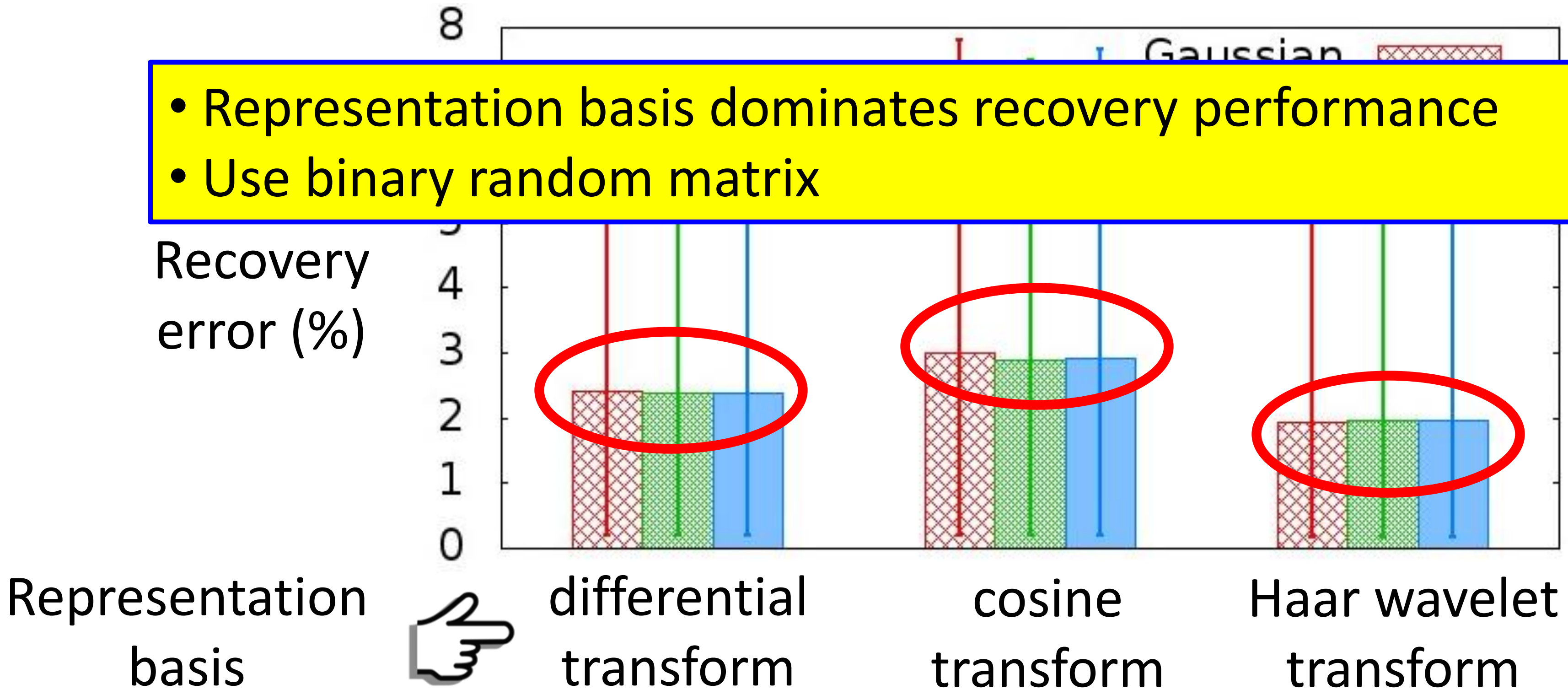
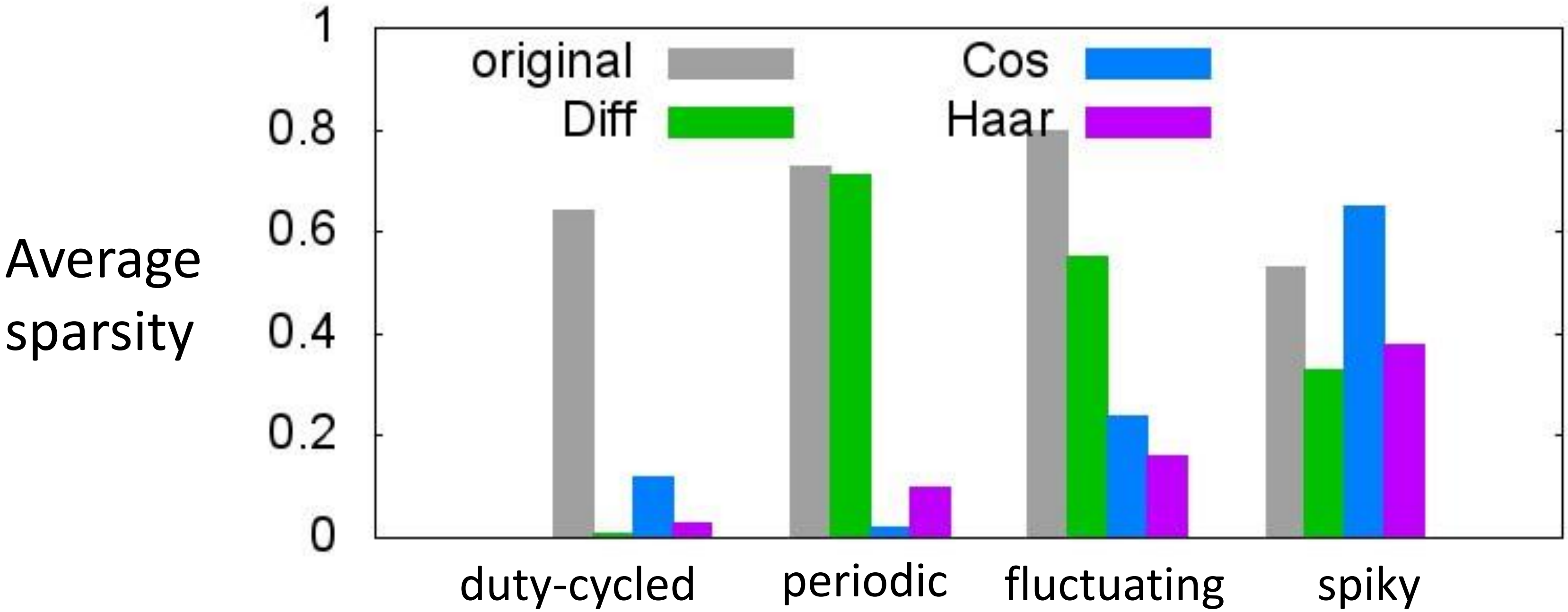


- Representation basis dominates recovery performance
- Use binary random matrix

Representation Basis Ψ

- Differential transform (**Diff**)
- Cosine transform (**Cos**)
- Haar wavelet transform (**Haar**)

$$\text{sparsity} = \frac{\#\ \text{of nonzeros}}{\text{signal length}}$$



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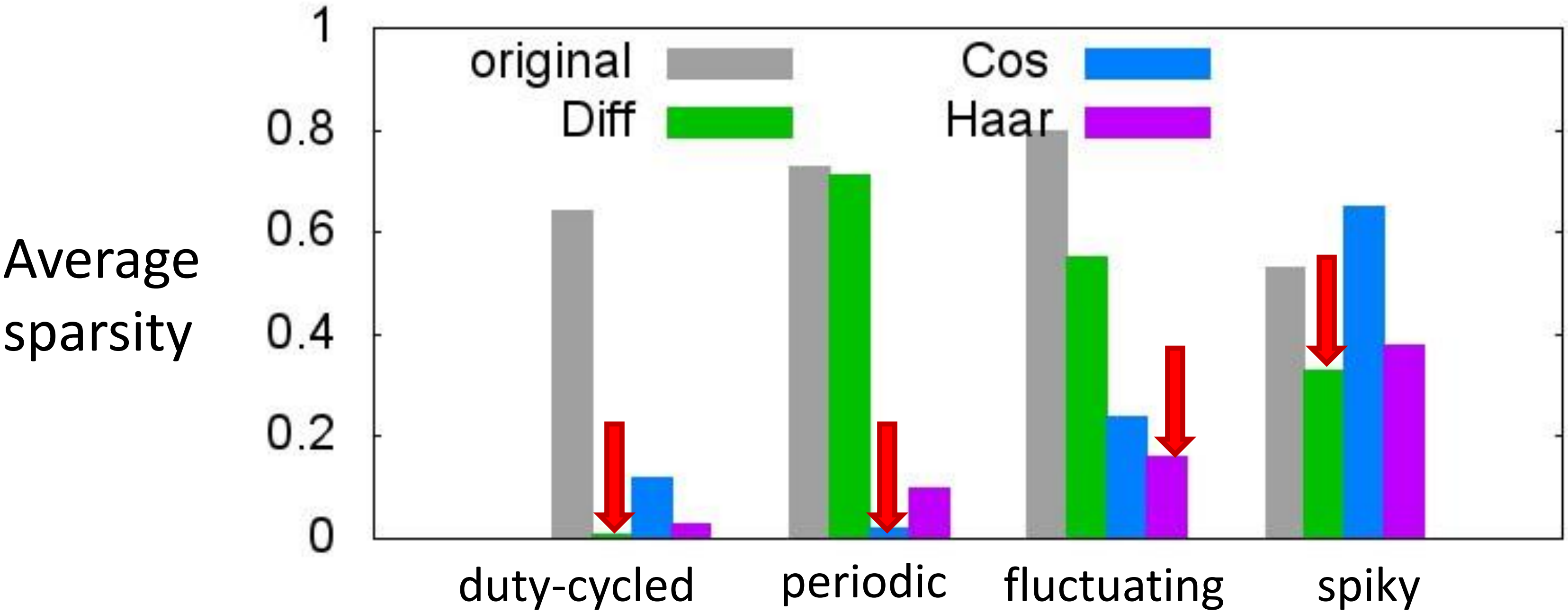

Best choice: Diff Cos Haar Diff

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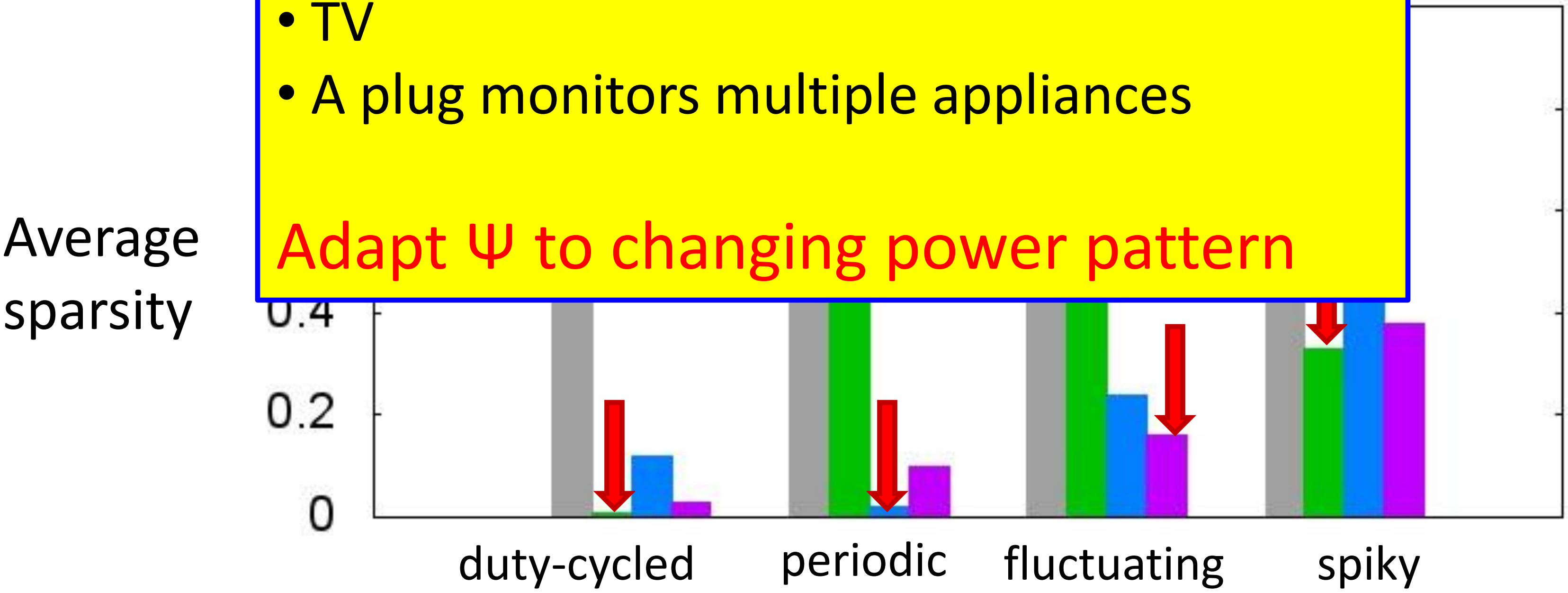
Changing power pattern:

- TV
- A plug monitors multiple appliances

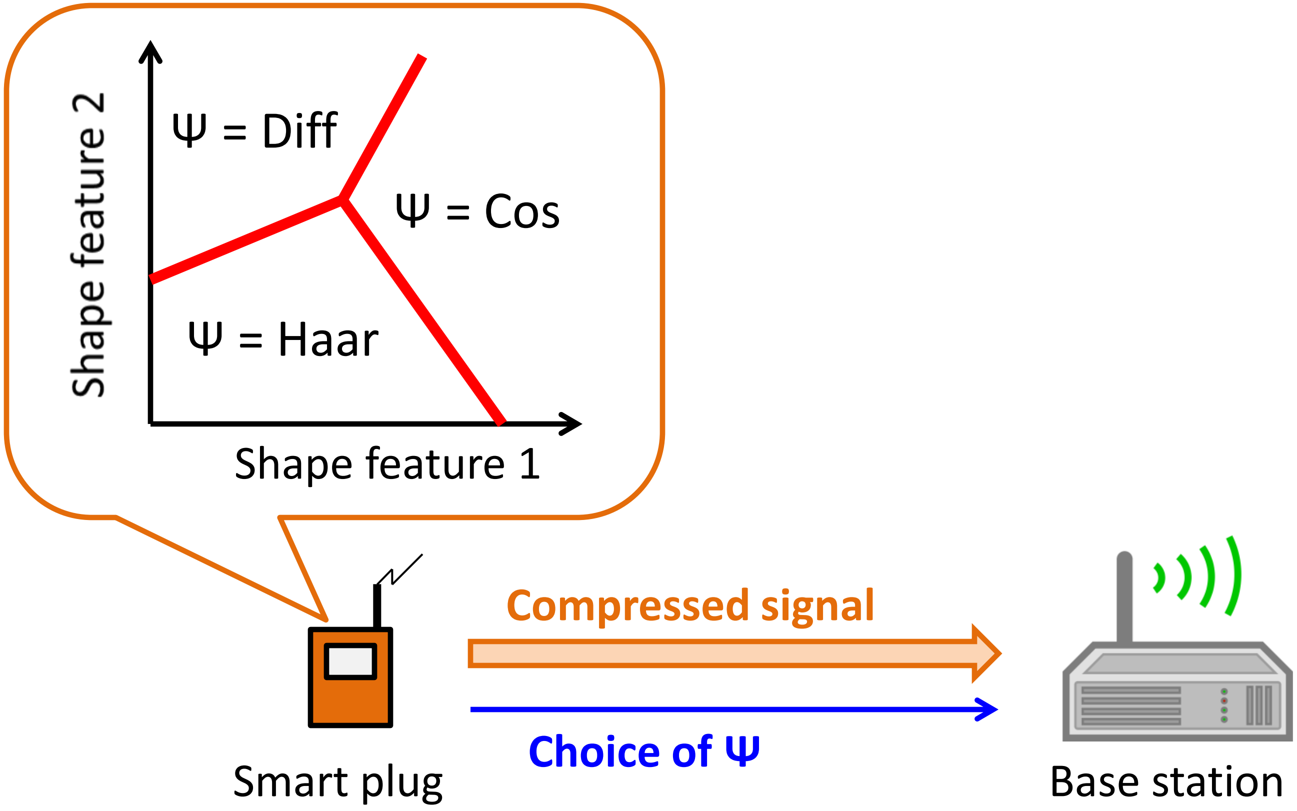
Adapt Ψ to changing power pattern



Best choice: Diff Cos Haar Diff

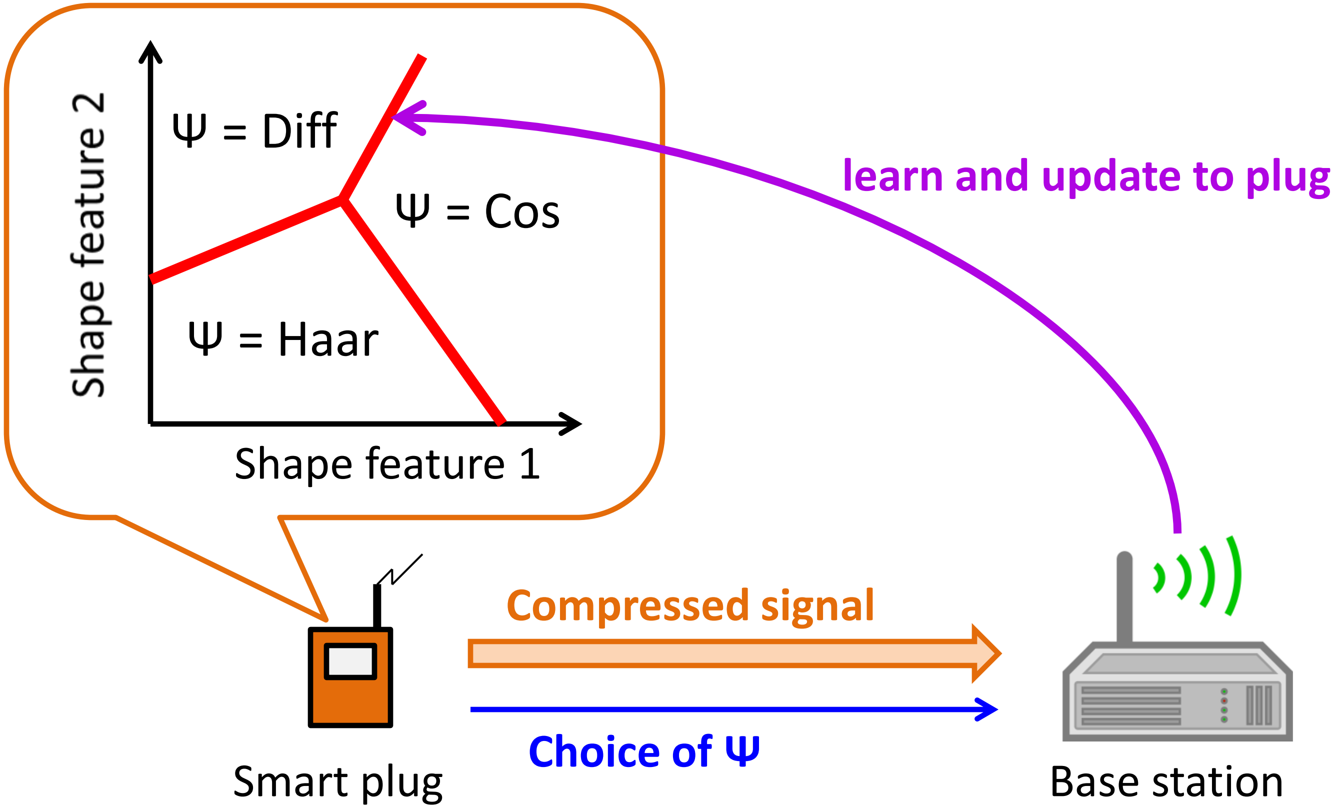
Adaptive Representation Basis

- Machine learning approach
  - Plug selects Ψ based on shape features



Adaptive Representation Basis

- Machine learning approach
  - Plug selects Ψ based on shape features
  - Base station learns decision boundaries



Shape Feature & Decision Table

$$\text{shape feature vector} = \begin{bmatrix} \text{\# of zero crossings} \\ \text{\# of sharp changes} \\ \text{standard deviation} \end{bmatrix}$$

# of zero crossings > Δ_1 ?	N	N	N	N	Y	Y	Y	Y
# of sharp changes > Δ_2 ?	N	N	Y	Y	N	N	Y	Y
Standard deviation > Δ_3 ?	N	Y	N	Y	N	Y	N	Y
Choice of basis	**ADT**	**ADT**	**HWT**	**DCT**	**HWT**	**HWT**	**ADT**	**DCT**

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- Trained at base station
  - Minimize recovery error

Outline

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- **Secrecy of JICE**
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Statistics Leak and Perturbation

- Φ is unknown to attacker
  - “Provide a computational guarantee of secrecy” [Rachlin 2008]
- **Leak ℓ_2-norm, mean and variance**

Zero mean: appliance is off
High mean: appliance is on

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$$\tilde{x} = x + n$$

$$n = \Psi \cdot [k, 0, 0, \cdots, 0]^T$$

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- **Statistics depend on *k***

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- **Leak ℓ$_2$-norm, mean and variance**

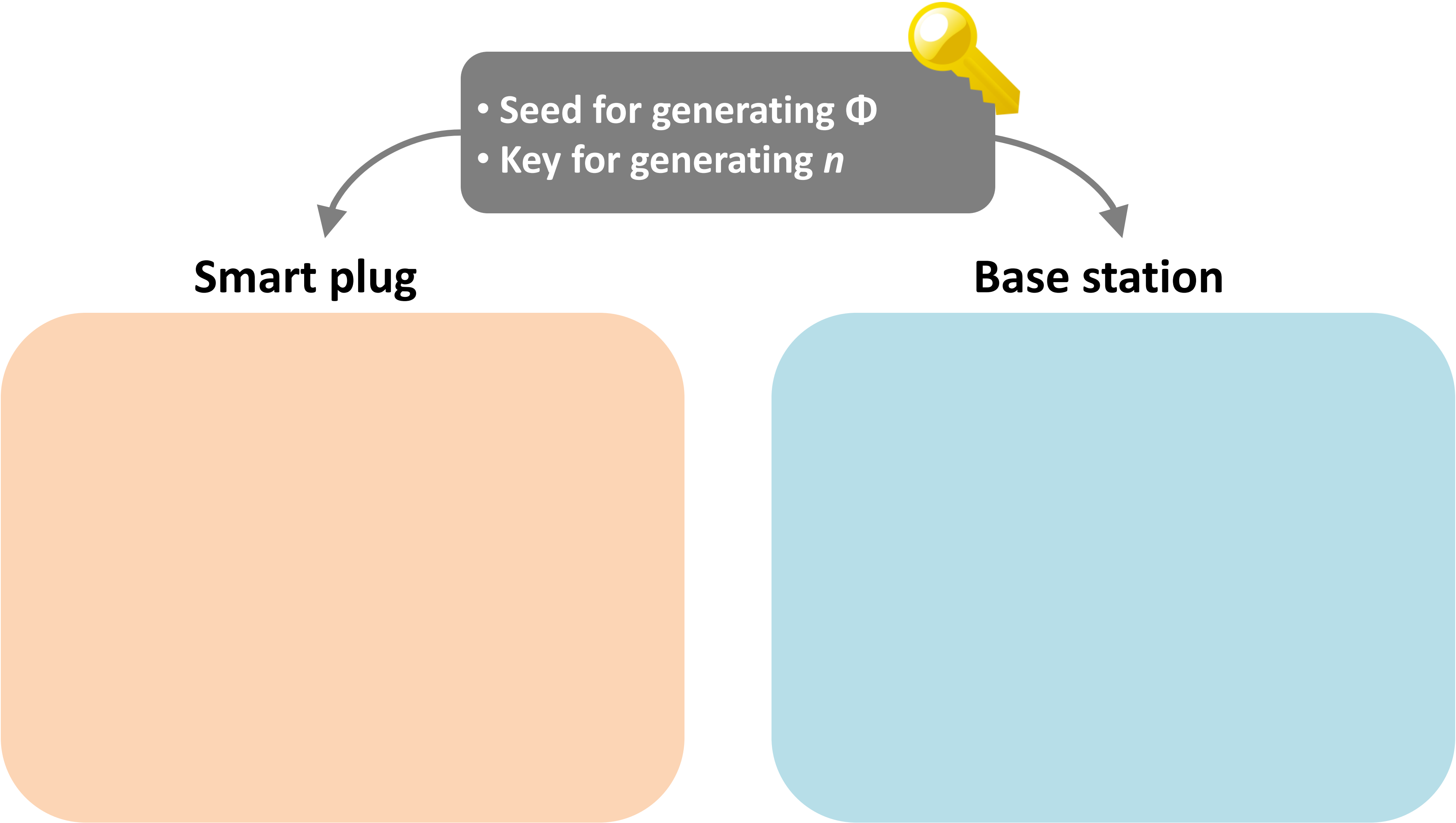
$$\tilde{x} = x + n$$

$$\boxed{n = \Psi \cdot [k, 0, 0, \cdots, 0]^T}$$

Very sparse in transform domain

- ***Statistics depend on k***
- Little (no) change to sparsity
  - Little impact on recovery

Recap of JICE



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- Key for generating *n*

Smart plug

Base station

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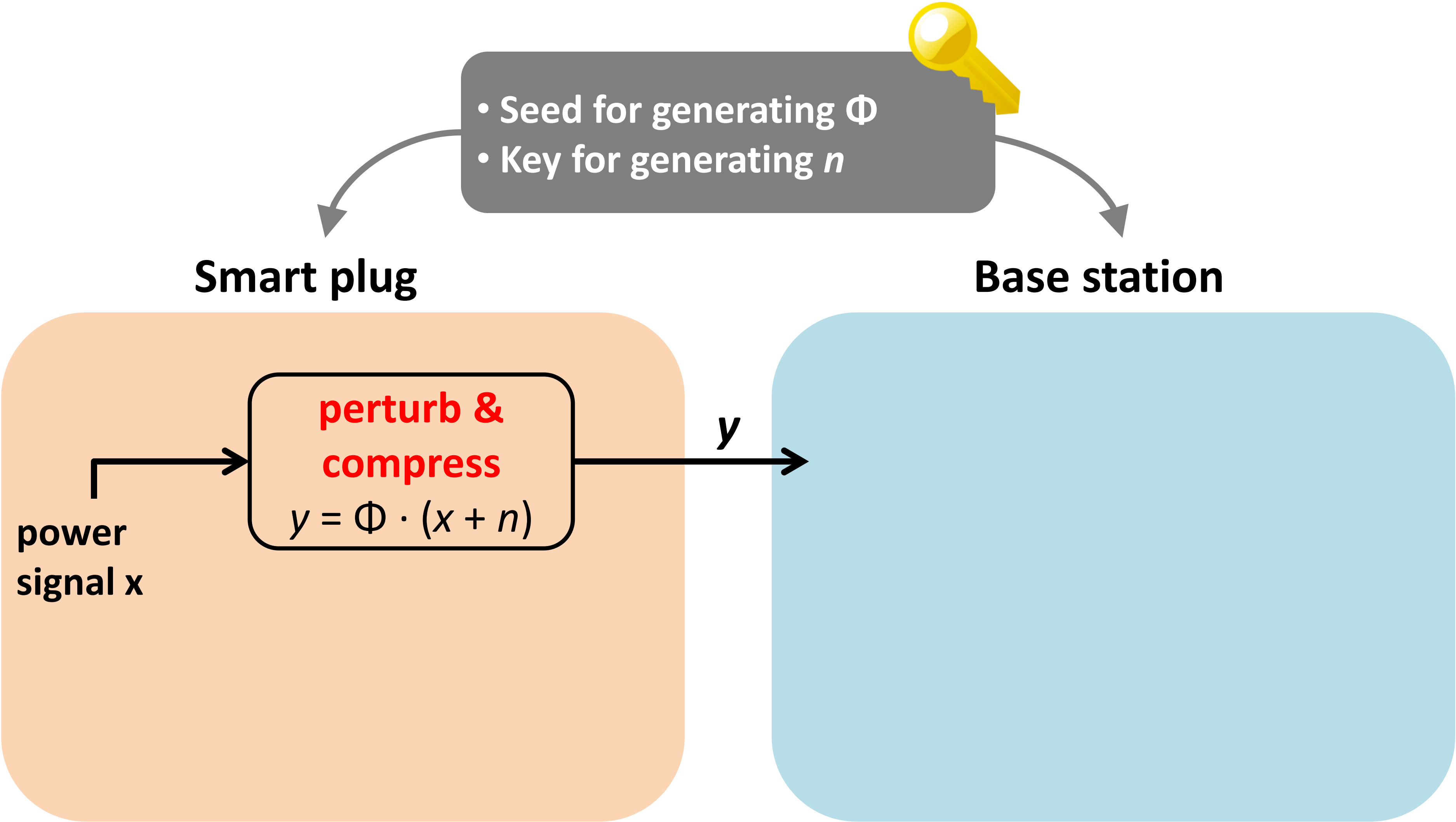

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Base station

perturb & compress

$y = \Phi \cdot (x + n)$

power signal x

y

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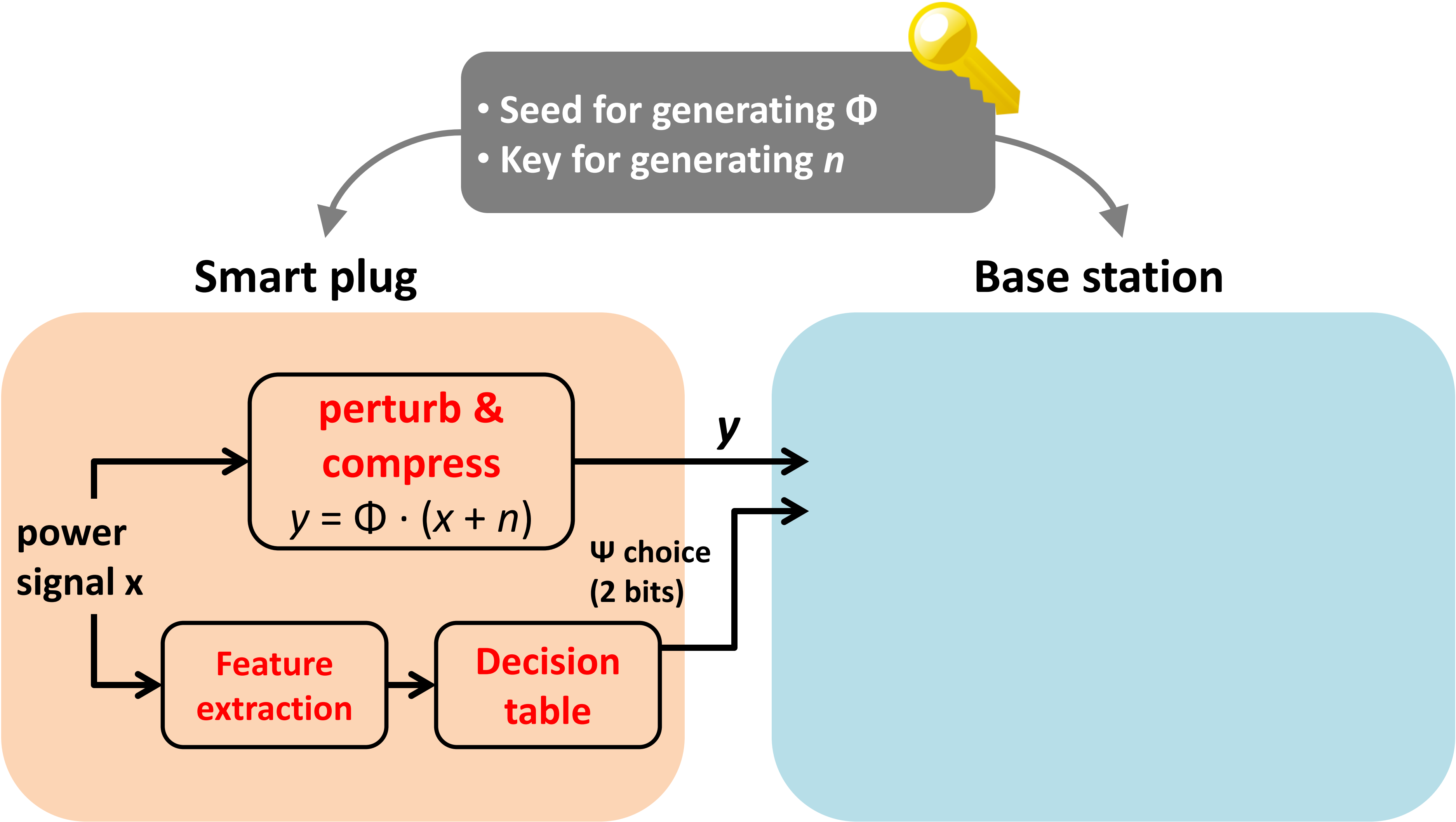

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Feature extraction

Decision table

Ψ choice (2 bits)

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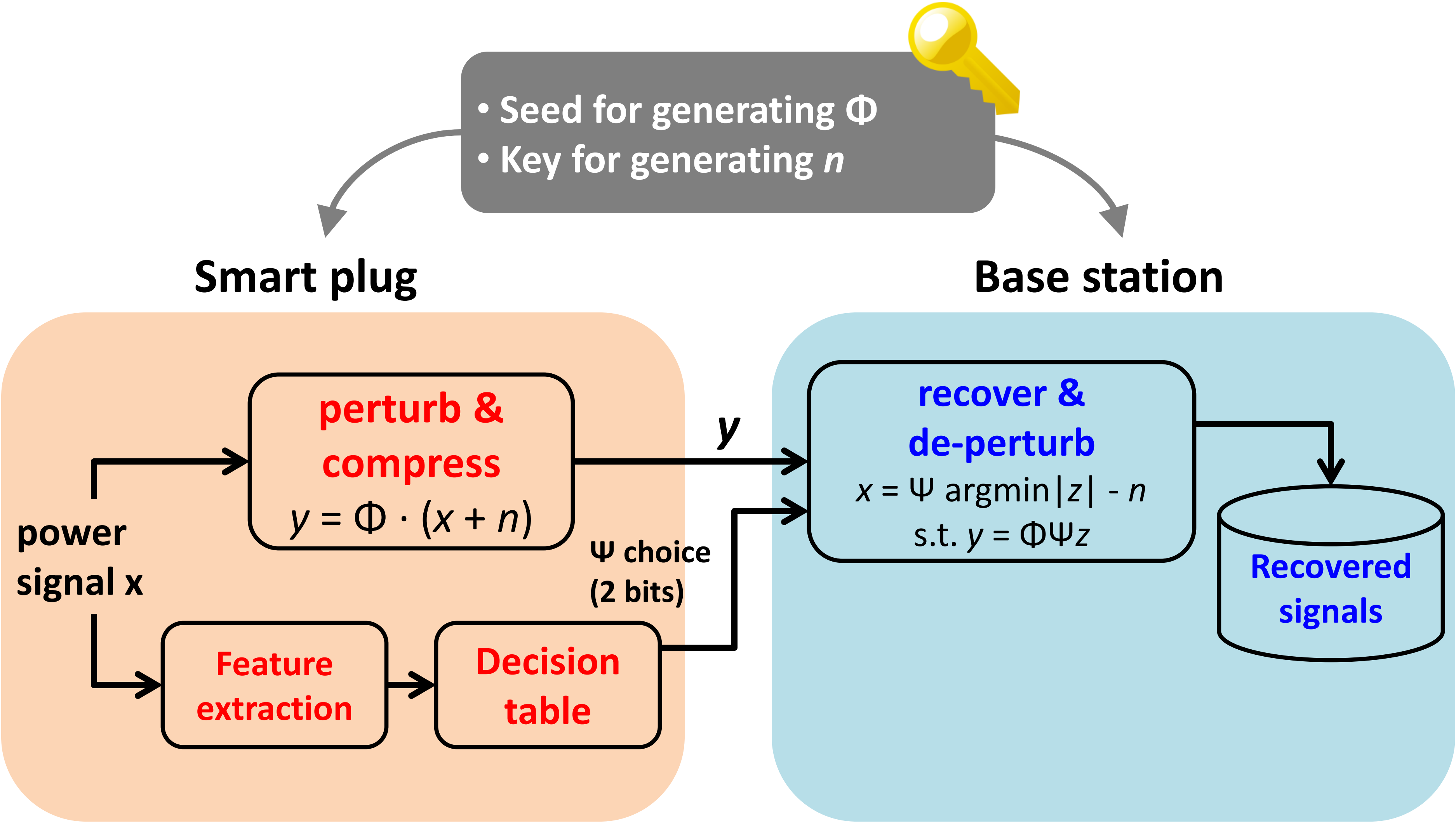

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Recovered signals

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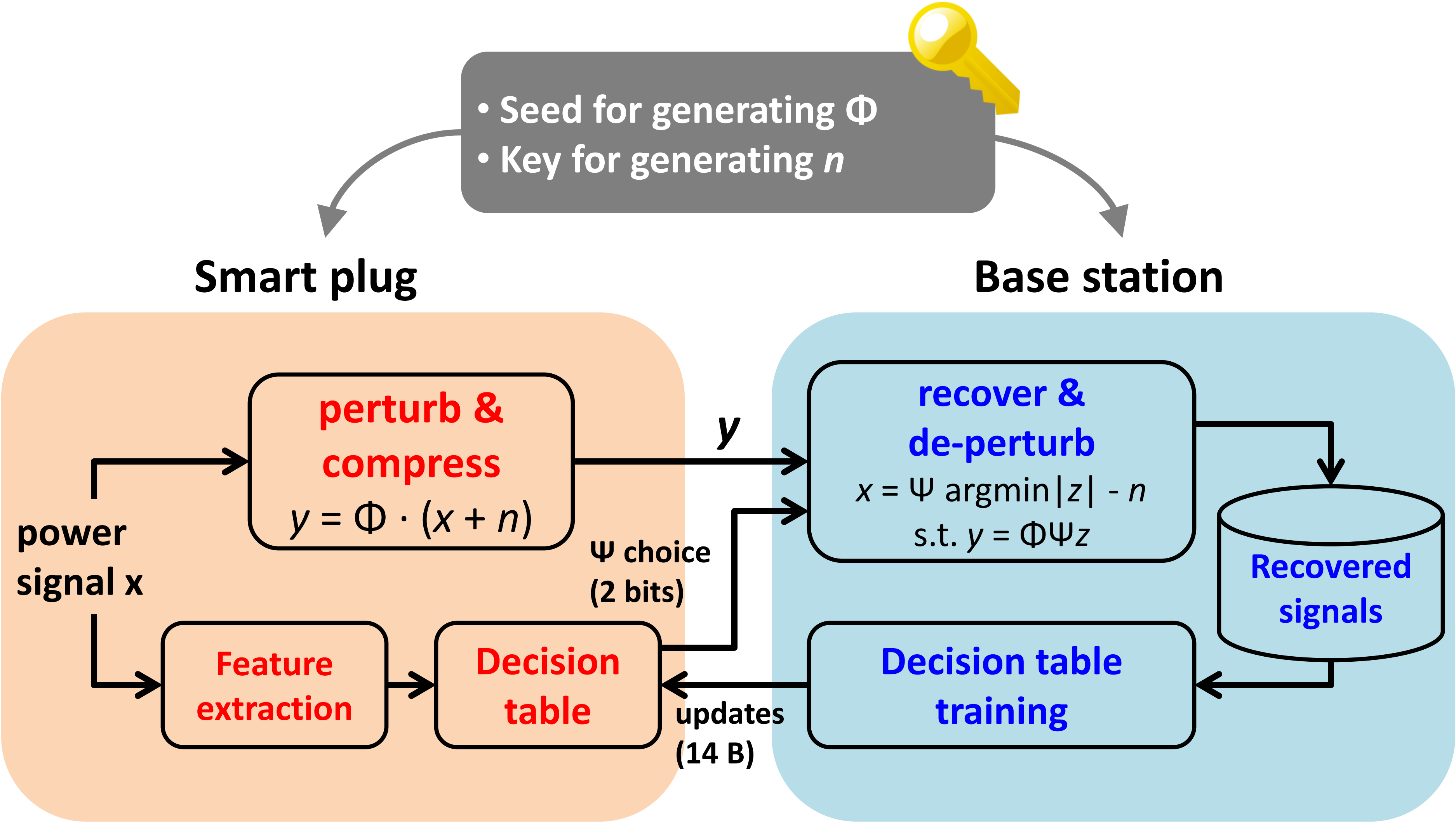

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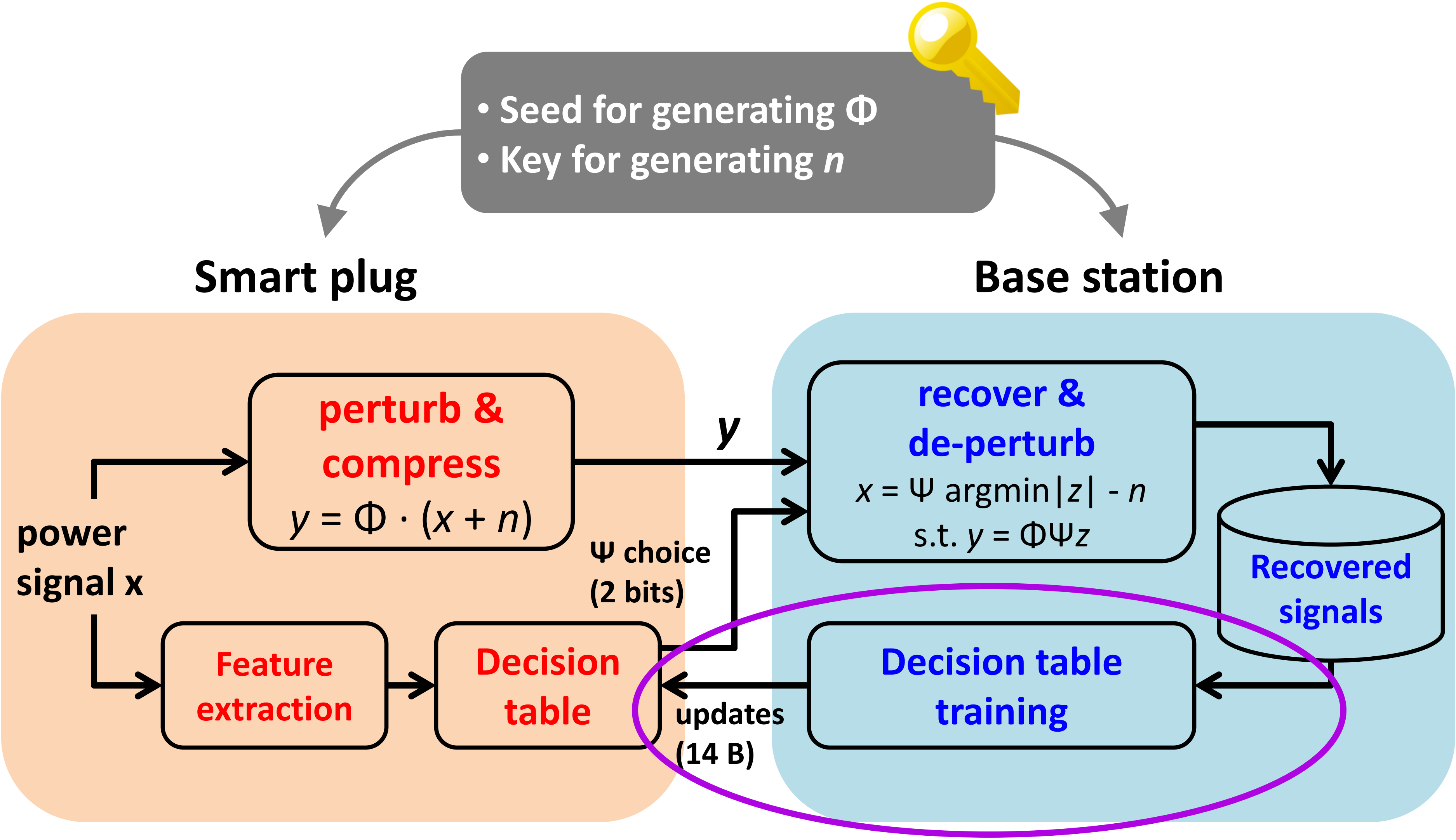

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updates (14 B)

Decision table training

executed every a few hours

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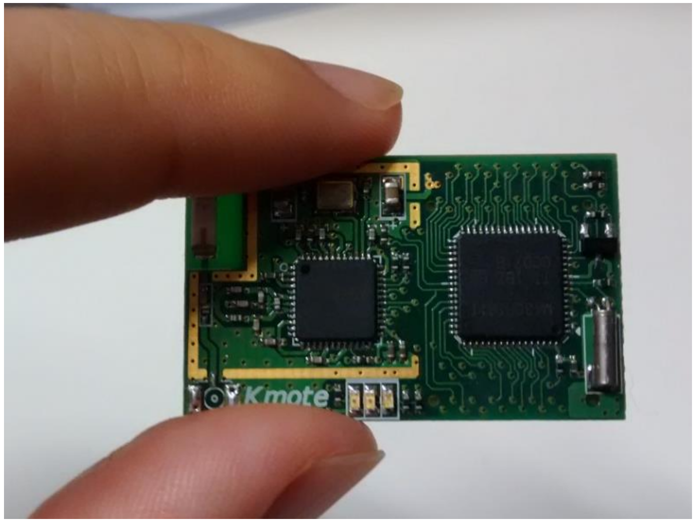
- **Experiment**

Implementation

Warning
The maximum allowable current is 16A.
Do not shock and heating.
Decomposition can cause electric shock.
Power Meter
sonnonet

Smart plug
[Sonnonet]



Kmote

- Smart plug
  - Kmote (8MHz MCU, 10KB RAM, ZigBee, TinyOS)

- Baselines
  - **Pipeline**: Lossy compressor [Liu 2013] + AES
  - **Downsampling**
  - **Lossless pipeline**: SLZW + AES

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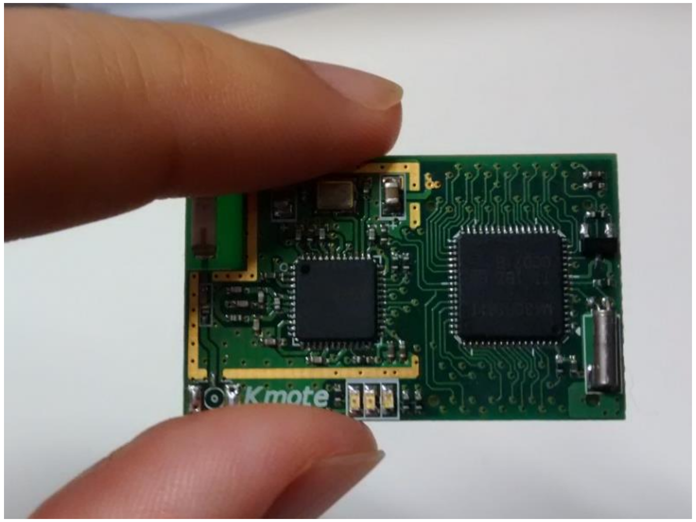

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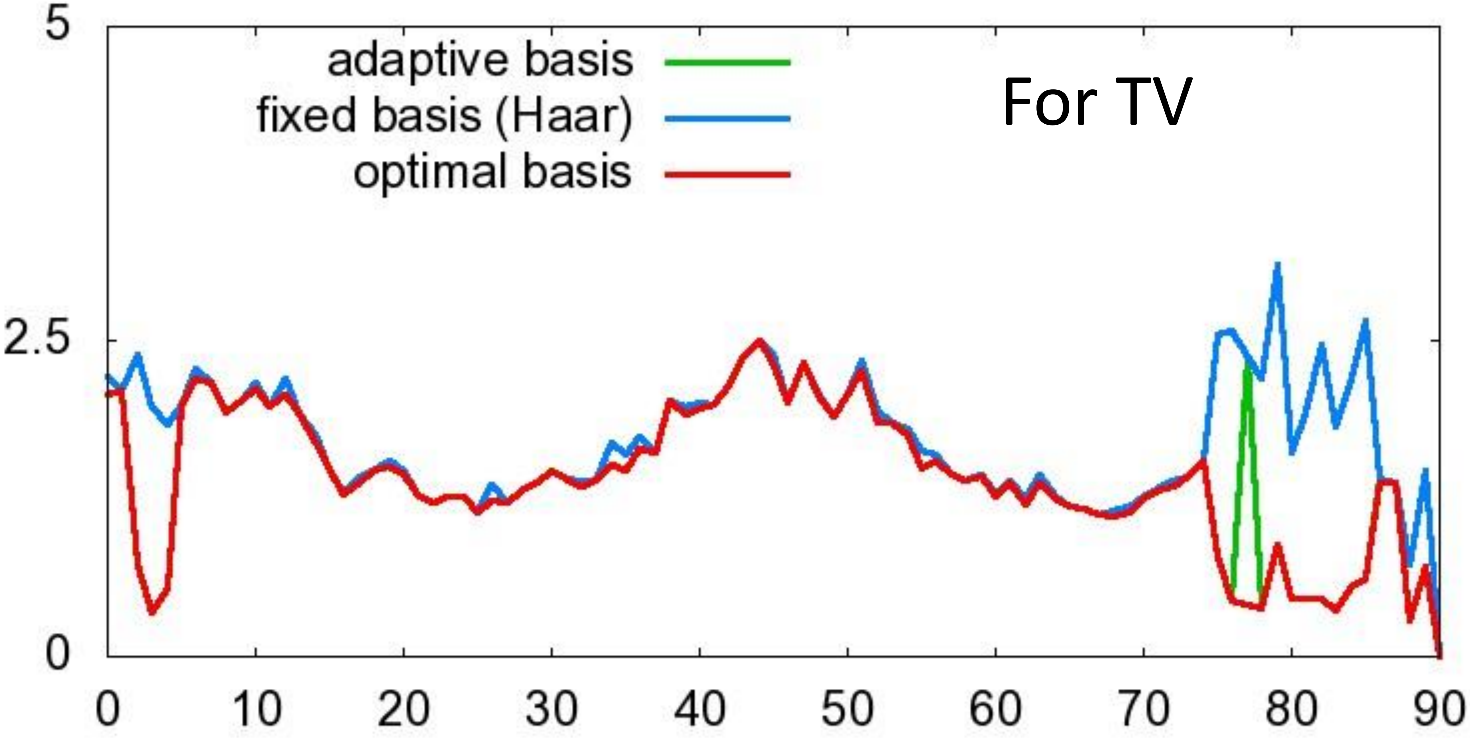
Same compression ratio with JICE

  - **Pipeline**: Lossy compressor [Liu 2013] + AES
  - **Downsampling**
  - **Lossless pipeline**: SLZW + AES

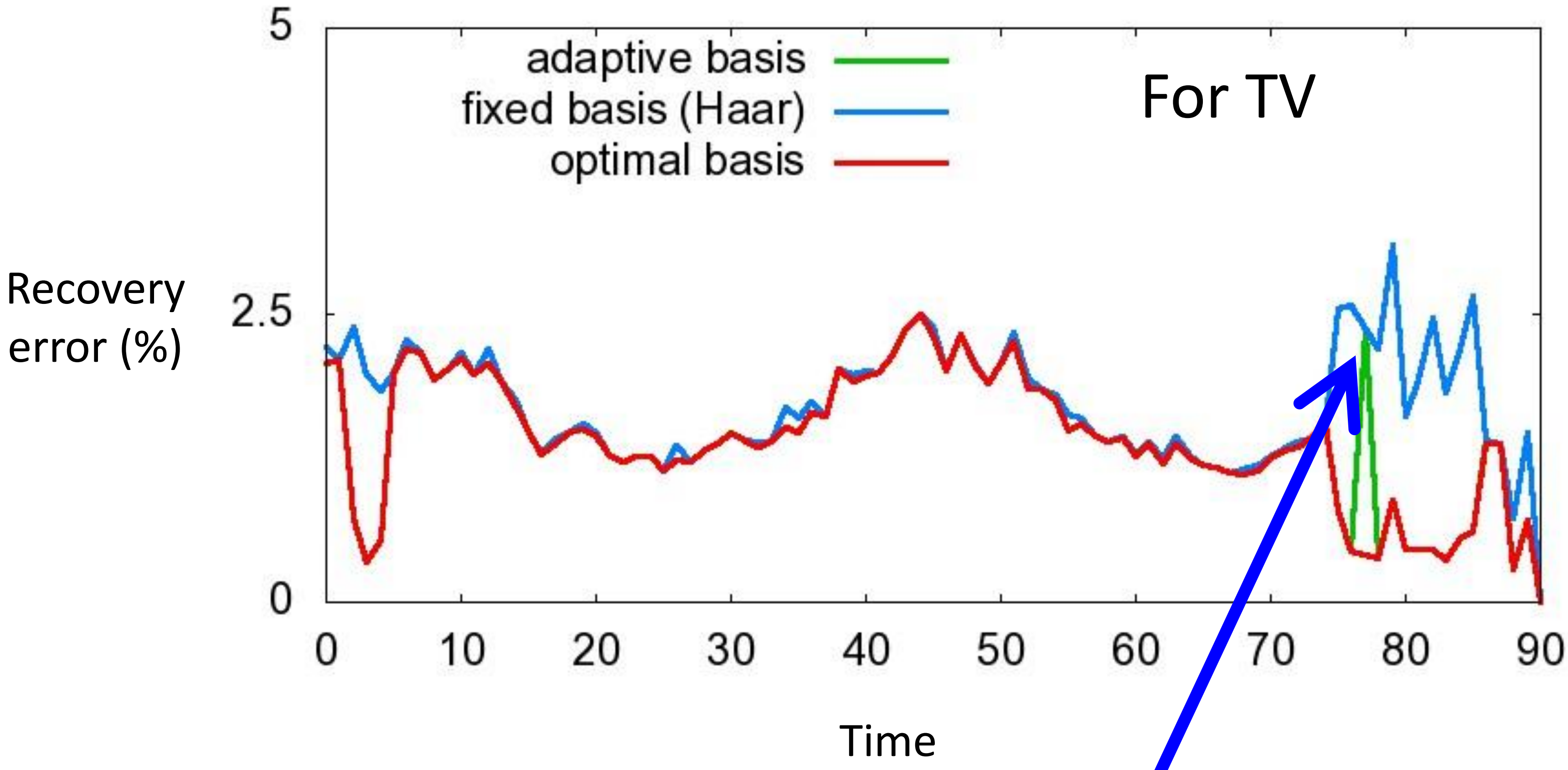
Adaptive Basis vs. Fixed Basis

Recovery error (%)



Time

Adaptive Basis vs. Fixed Basis



JICE achieves best performance with one exception

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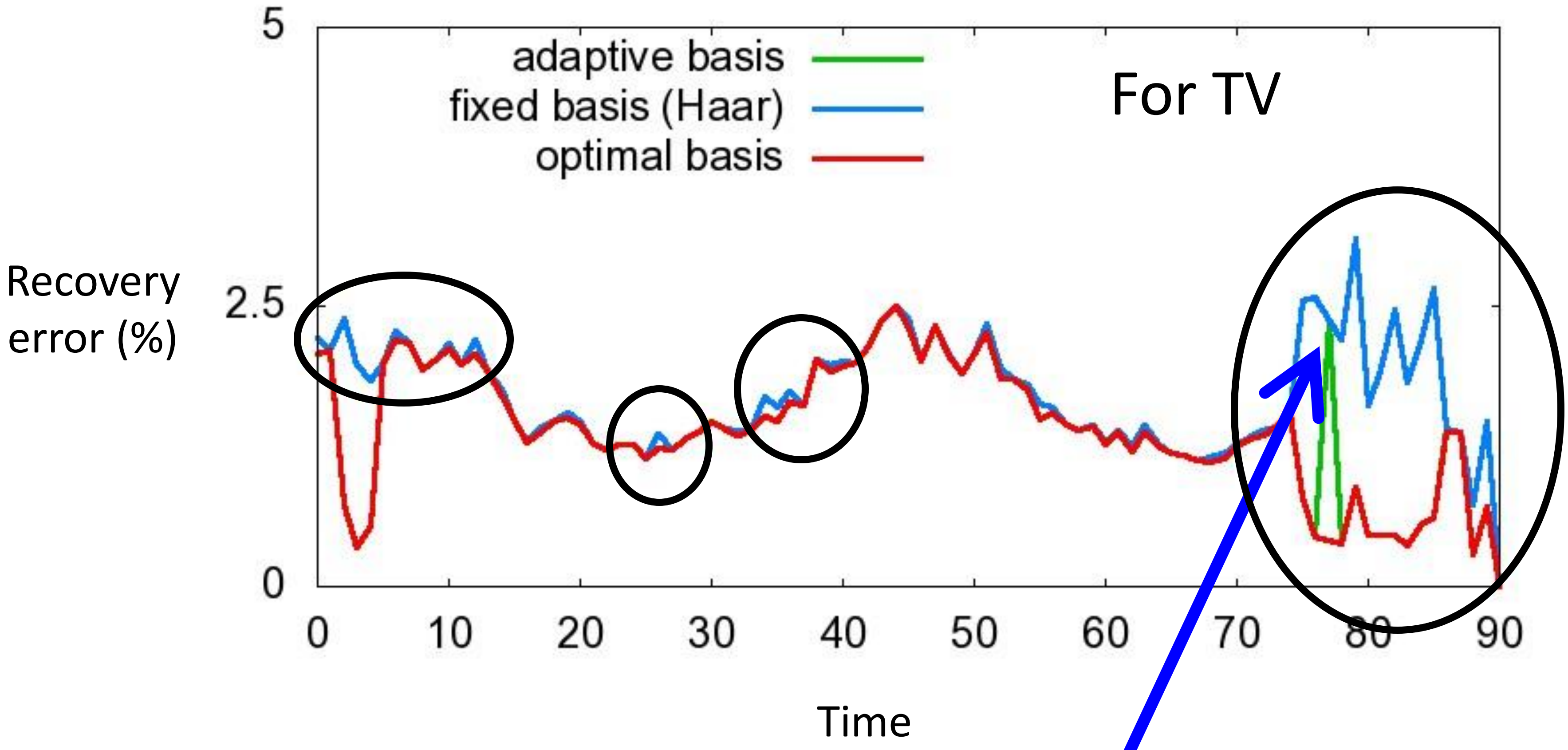

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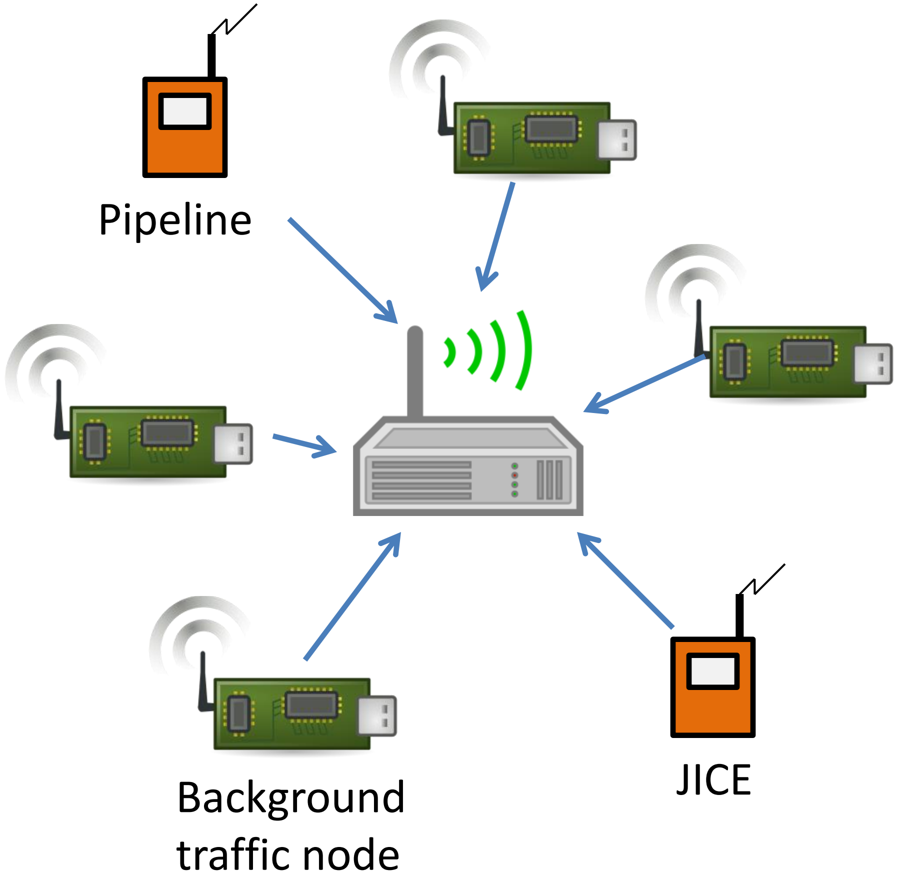
Data Fidelity and Scalability



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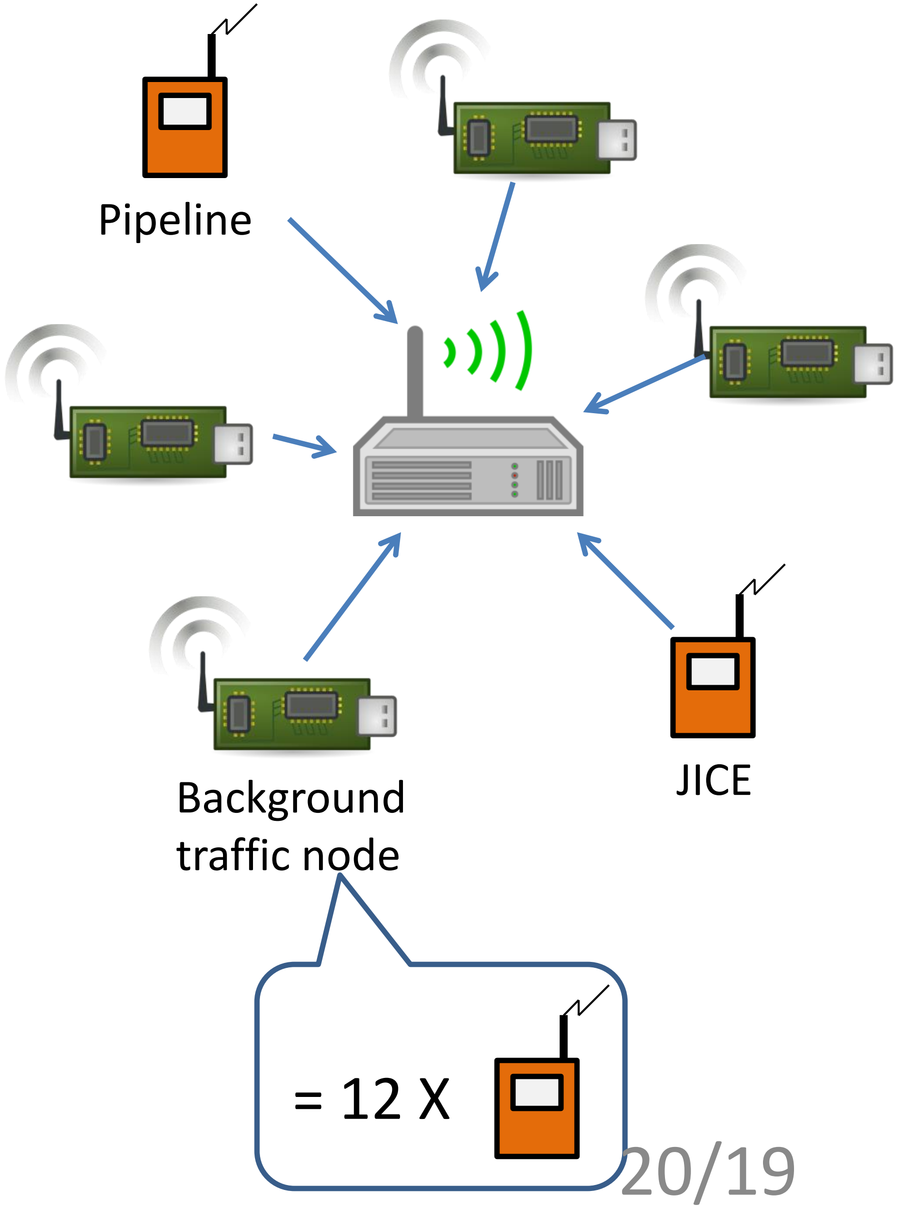

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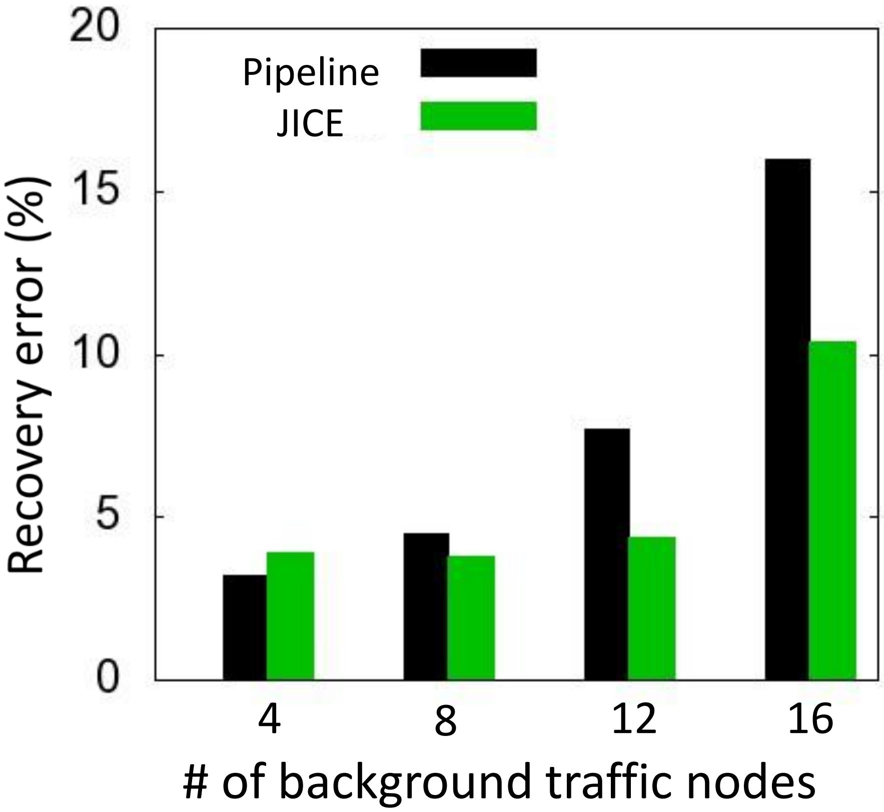
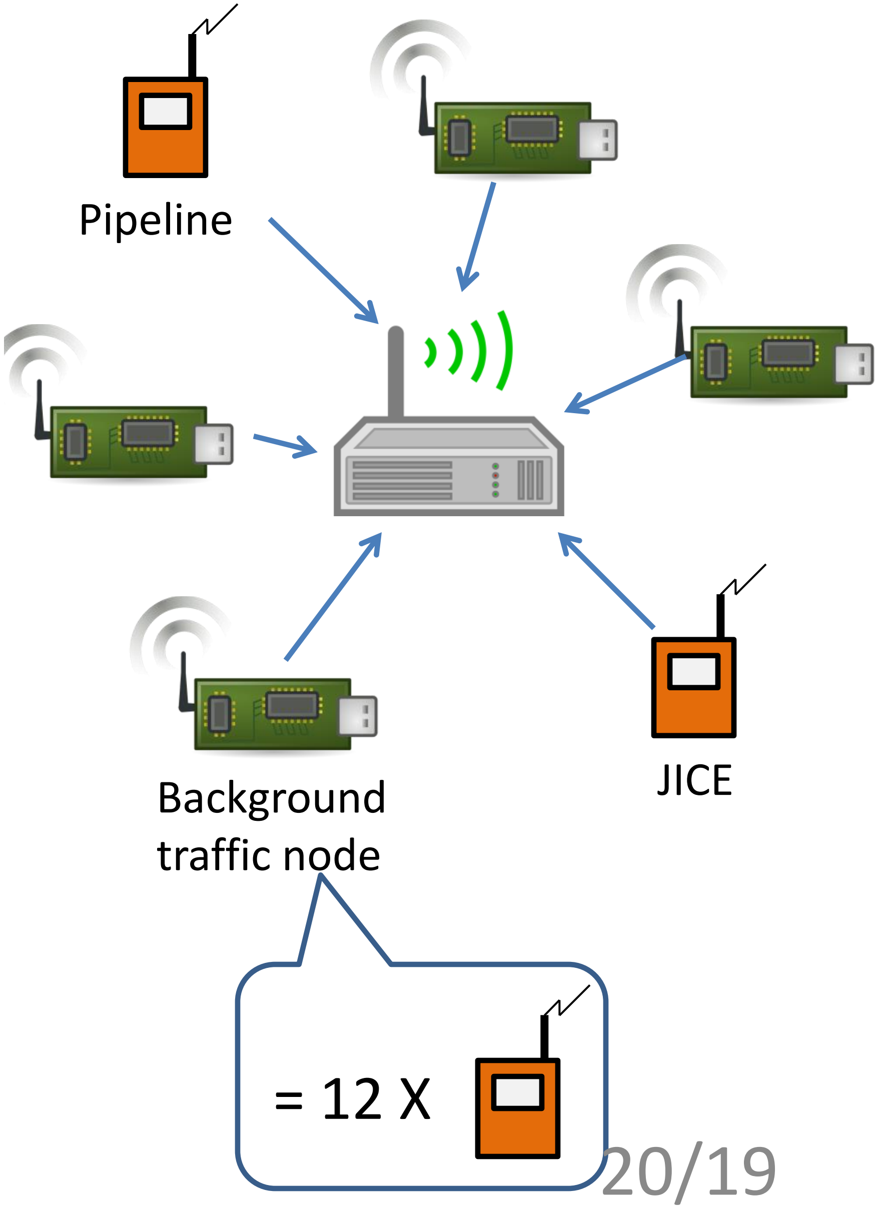
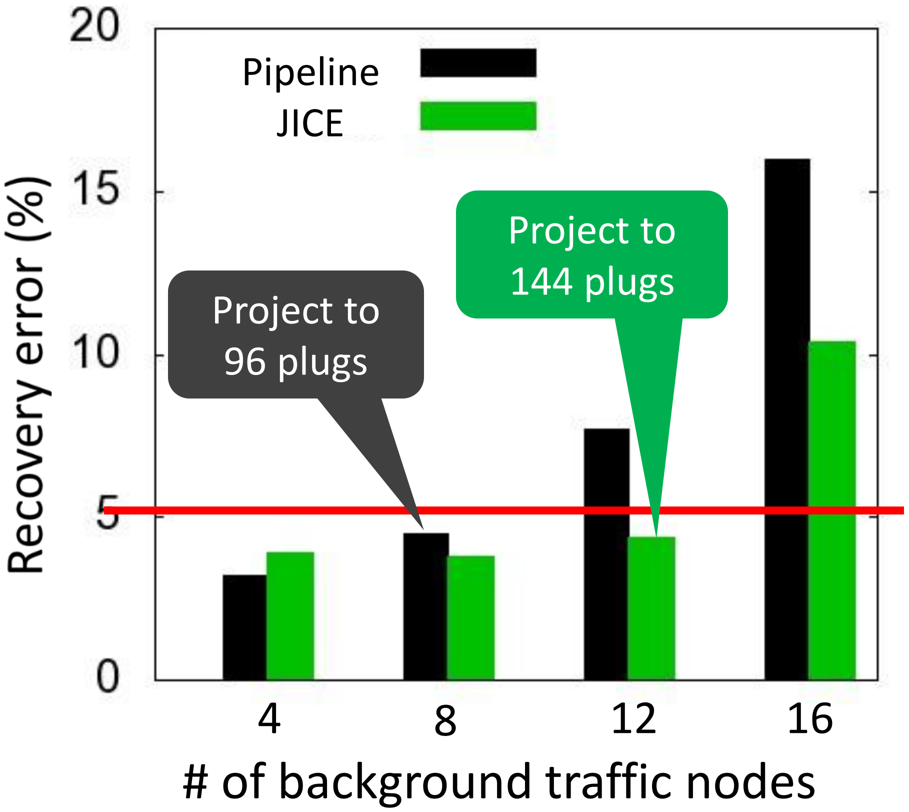
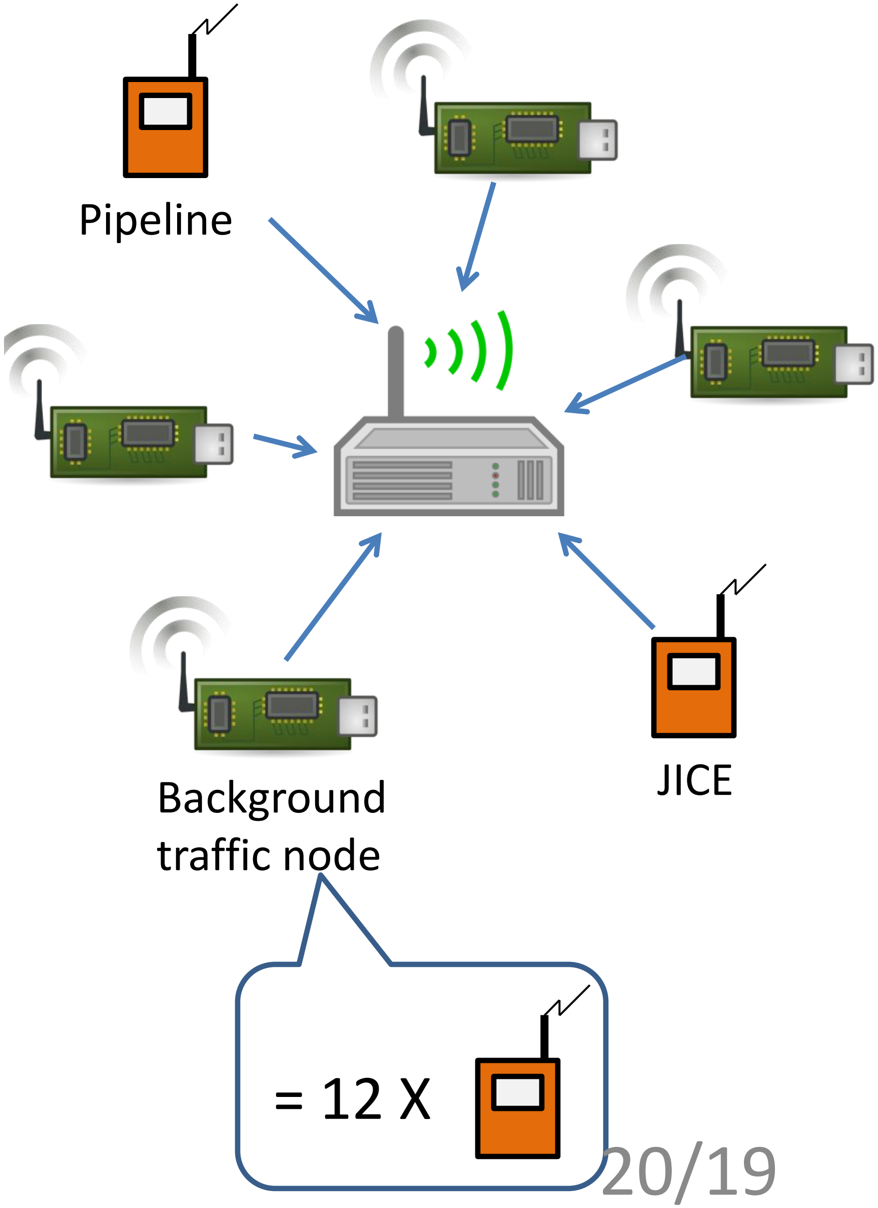




Data Fidelity and Scalability





JICE supports 50% more plugs

Conclusion & Future work

- JICE
  - Supports more nodes for same data fidelity
  - Better data secrecy than pure compressive sensing
  - Adaptive to changing power pattern
- Future work
  - Other applications