Single-component privacy guarantees in Helper Data Systems and Sparse Coding with Ambiguation

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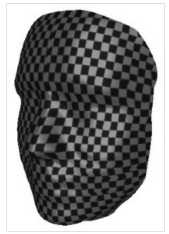
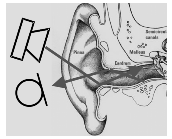
Outline

- Biometric privacy
- Attacker model & use case
- Two main approaches
  - Helper Data Systems
  - Sparse Coding with Ambiguation
- Single-component privacy
  - motivation
  - results

Biometric privacy

Not "secret". Why protect stored biometric data?





- Function creep
- Privacy
  - medical conditions
  - database crossmatching
  - tracking
- Security of biometric authentication
  - fake biometrics
  - sensor spoofing
- Framing
  - synthesized fingerprints/DNA at crime scene

Attacker model & use case

Use case: Biometric authentication

- biometric only.
  - no typed PINs
  - no prover device

Attacker model:

- no access to biometric during enrolment / verification
- full access to enrolled data
  - insider
  - hacker
- full access to encryption keys
- there is no special secure hardware

Problem: How to store biometric enrolment data?

Approach #1: Helper Data System + hash

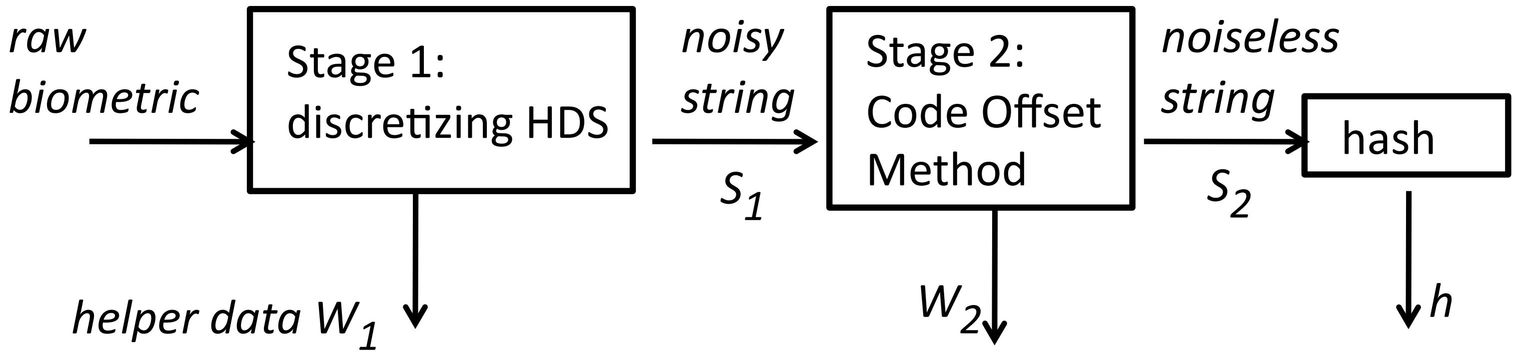
Store **hash** of biometric data ← *just like passwords!*

- needs error correction
- adversary sees redundancy data

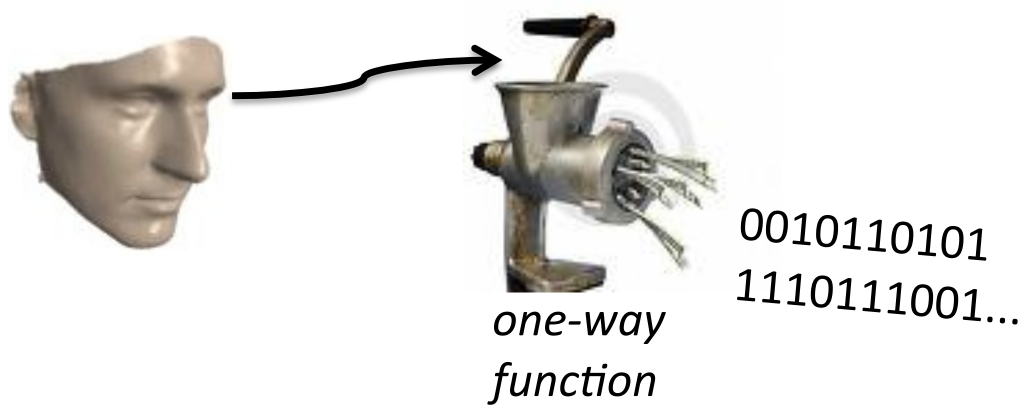
Two-stage secure error correction

1. "Zero Leakage" disretizing HDS
2. Code Offset Method

*"**Helper Data System**"*
(secure sketch, fuzzy extractor)



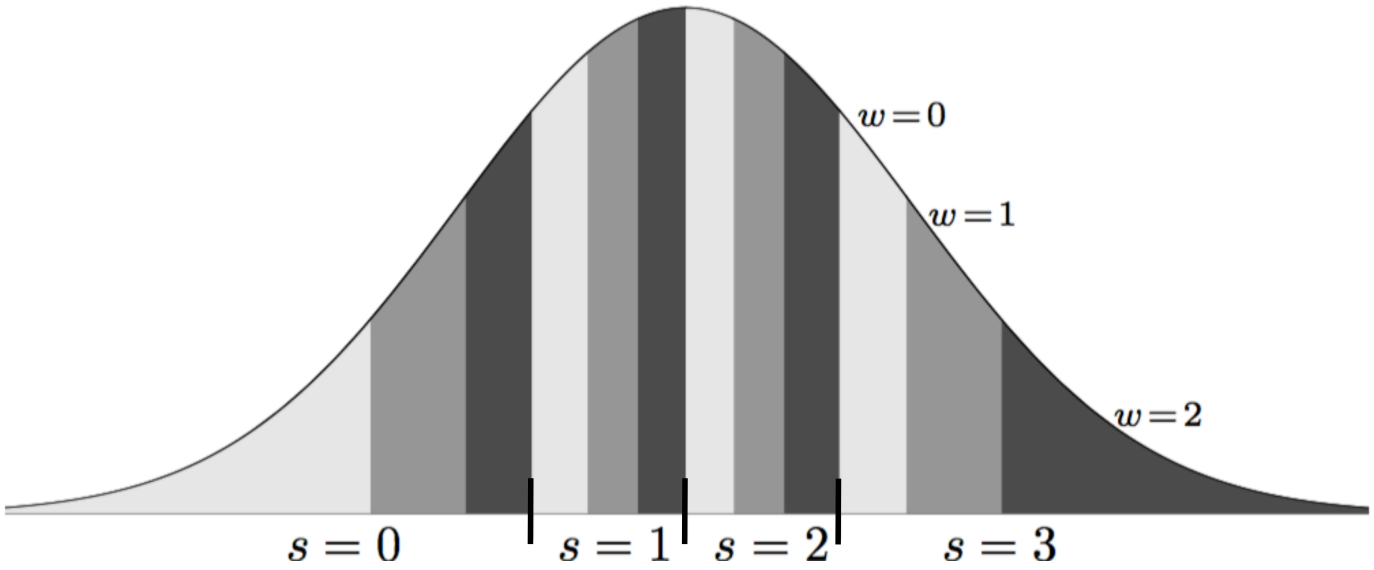
Store enrolment data: (ID, W_1, W_2, h). The W_j should not leak about S_j.


one-way
function
0010110101
1110111001...

Zero-Leakage discretizing HDS

[de Groot et al. 2012]
[Stanko et al. 2017]

- split data into 1D features (real numbers)
- apply stage1 HDS to each dimension separately



Helper Data w = "least signifcant digits"

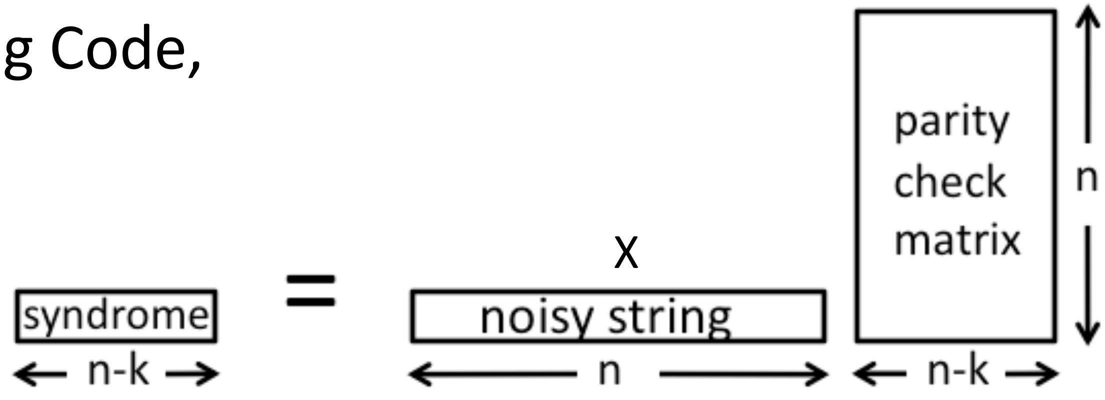
- in **quantile form**
- does not leak about Most Significant Digits (s)

Reconstruction: go to nearest interval that has correct index *w*

The Code Offset Method

[Bennett et al. 1991]
[Juels+Wattenberg 1999]
[Dodis et al. 2008]

Use linear Error-Correcting Code,
with syndrome decoder.
Message length k;
codeword length n;
syndrome length n-k.



Enrollment: **W = Syn X** *"least significant digits" !*

Reconstruction: $\hat{\mathbf{X}}$ **= X' ⊕ SynDec(W⊕Syn X')**

yields error pattern

Syn(x⊕x')

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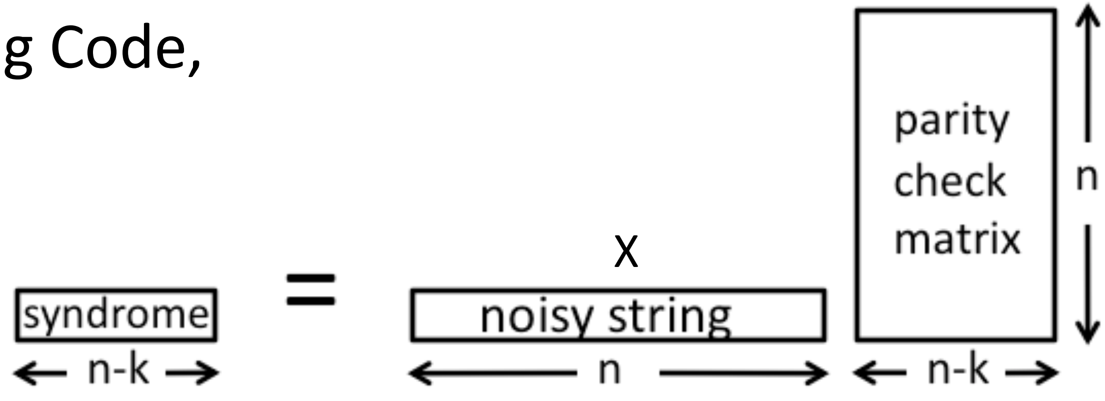


Enrollment: **$W = \text{Syn } X$** *"least significant digits" !*

Reconstruction: **$\hat{X} = X' \oplus \text{SynDec}(W \oplus \text{Syn } X')$**

yields error pattern

$\text{Syn}(x \oplus x')$

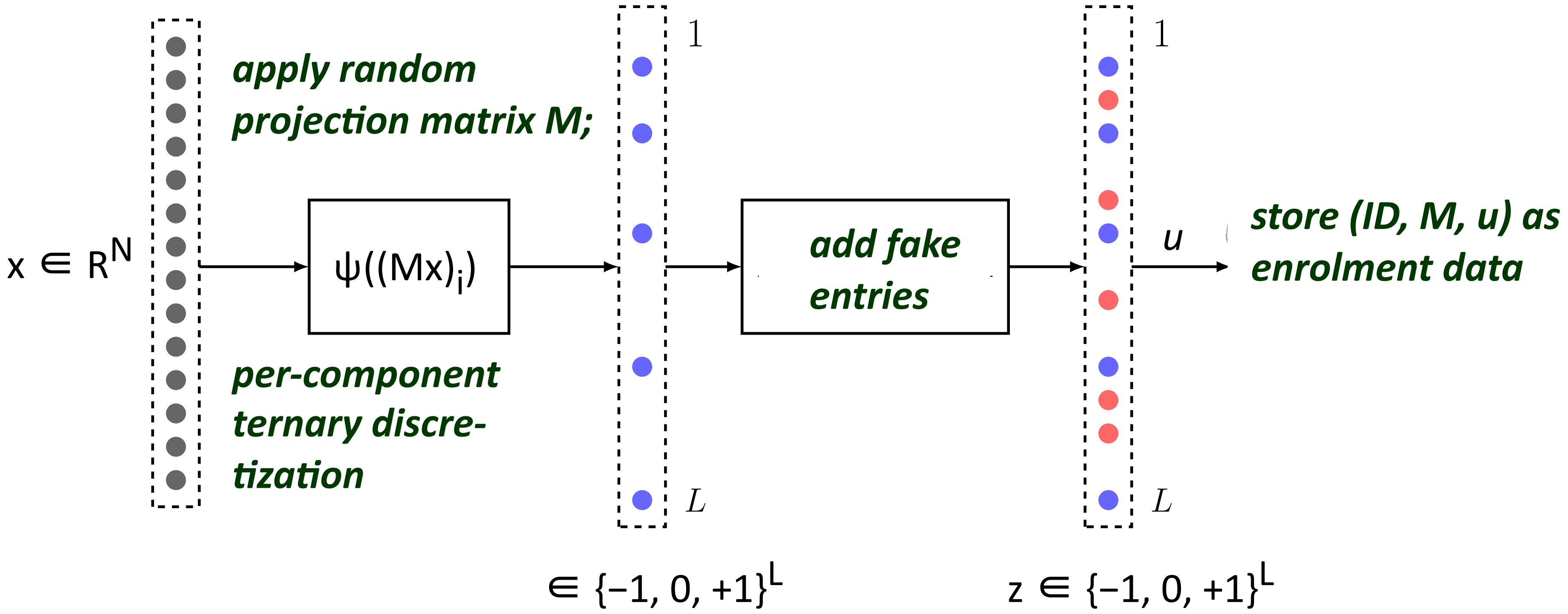
The Spammed Code Offset Method [Skoric + de Vreede 2014]

- hide w in lots of fake helper data

Approach #2: Sparse Coding [Razeghi et al. 2017]

Sparse Coding with Ambiguation

- sort of Locality Sensitive Hash, but with artificial noise
- no error-correcting code



Verification of vector y: inner product $u \cdot \psi(My)$ should be large enough

Privacy

	Helper Data Approach	***Sparse Coding approach***
Philosophy	Reveal least significant part of X • noisy anyway • does not represent X, but noise	Reveal location of reliable parts • use *polarisation* effect of random projections • add fake entries for privacy
Advantages	• compact • well controlled privacy	No ECC
Disadvantages	• input must have high entropy • error-correcting code	• reveals signs of reliable parts • enrolment data not compact (?)

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CAVEAT

We are ignoring other approaches!

- homomorphic crypto ← *slow; needs trusted party*
- Locality Sensitive Hashing ← *privacy unclear*
- ....

Single-component privacy guarantees

Biometric feature vector $X \in R^N$

Motivation

- What if one biometric feature X_i reveals a medical condition?

We investigate two aspects of such leakage

- sign of X_i
- $|X_i|$ > threshold?

Results for HDS: first stage

Under the assumption of even prob.distribution of X_i

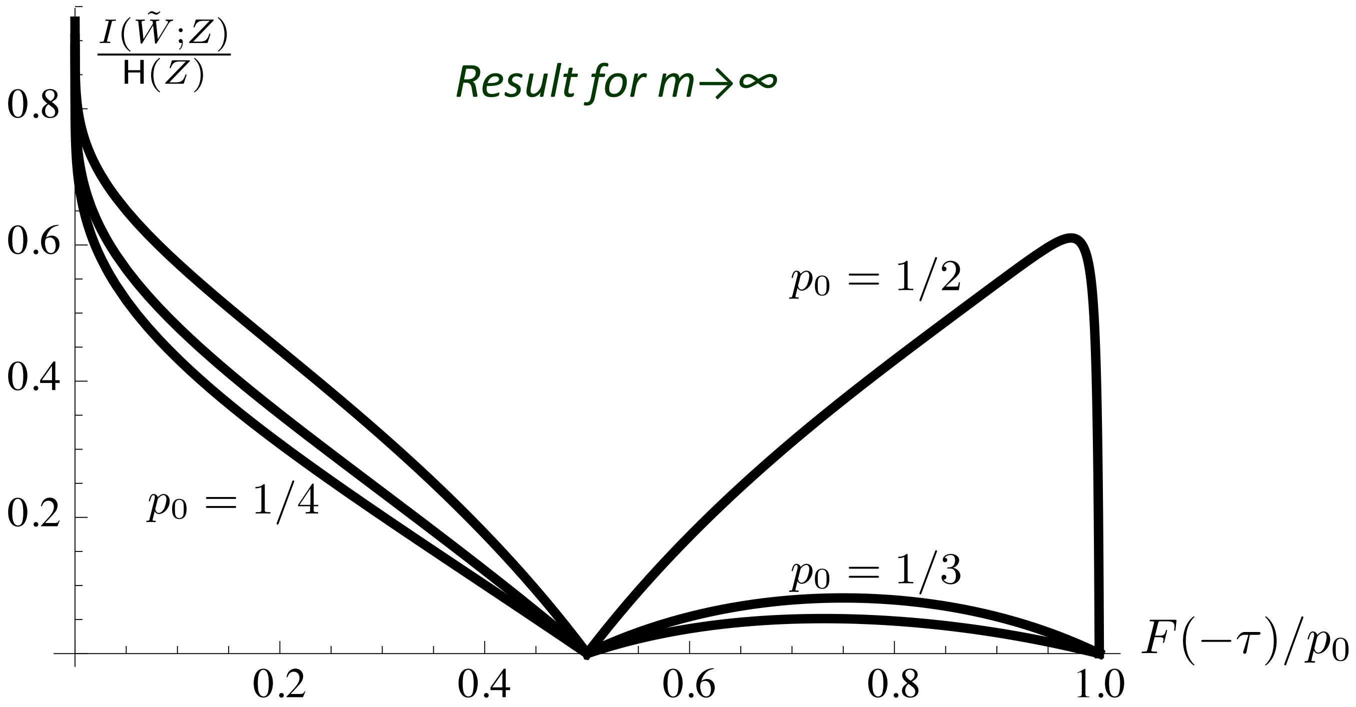
Leakage about sign(X_i)

- none, if #quant.intervals is even
- (some leakage if odd)

m = #helper data values
p_0 = Prob[S=0]

Leakage about binary variable Z = [|X_i| > τ]

- *assuming large threshold* τ: **no leakage at m=2**
- nonzero at m>2



Results for HDS: 2nd stage

Sign of X_i becomes bit value

- input for 2nd stage
- Does the Code Offset Method leak this bit?

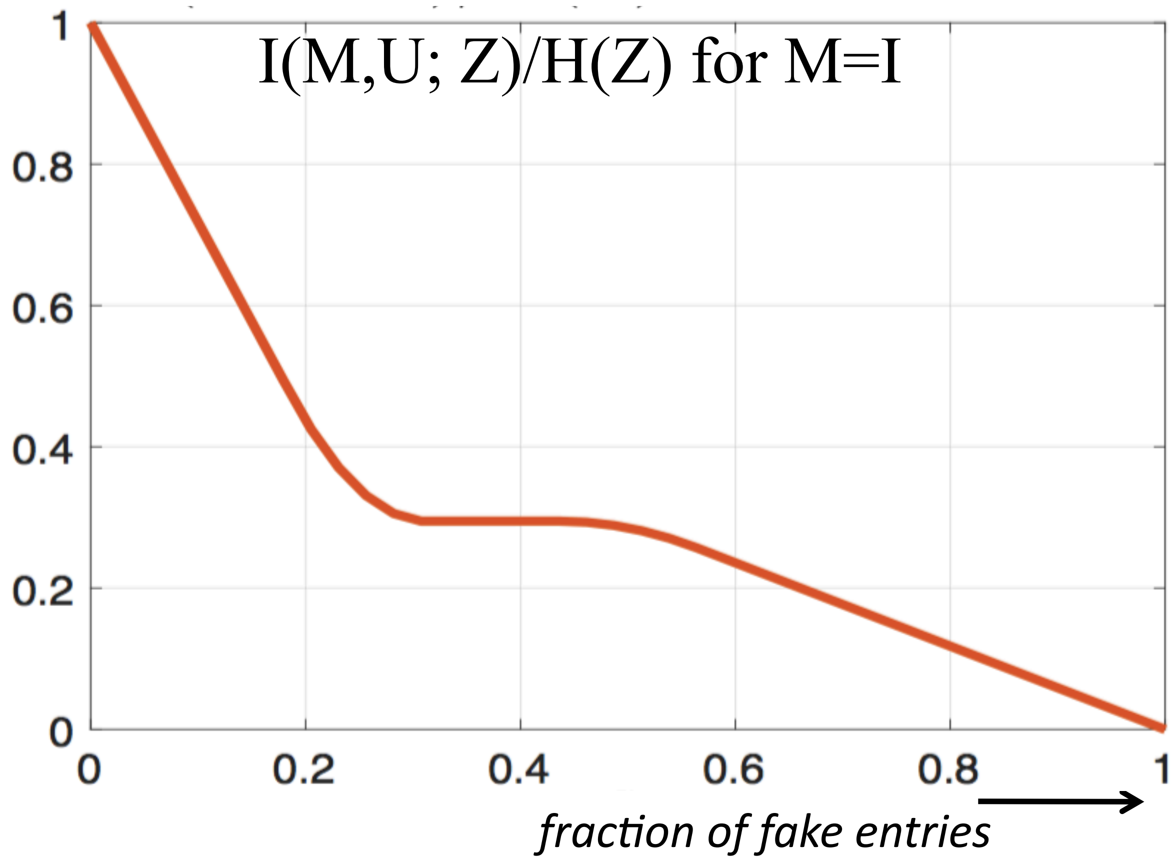
Answer: **the leakage is exponentially small**.

Total leakage about COM input $\approx (N-k)[1-h\left(\frac{1}{2}-\frac{1}{2}(1-2\varepsilon)^r\right)]$

ε = bit error rate
r = row weight of the code

Results for Sparse Coding with Ambiguation

- Very little leakage about **magnitude** of X_i



- **Sign** of X_i:
  Work in progress.
  Adversary's reconstruction prob. of whole X is small.

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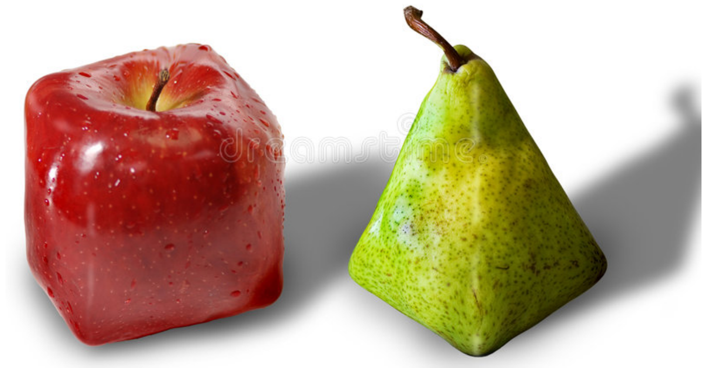

Apples and pears are different, but both taste good!

- Helper Data approach (1st stage):
  - choose even #quant.intervals
  - one-bit helper data works best
- Sparse Coding approach:
  - minimal leakage about single-component magnitude
  - low overall reconstruction probability