

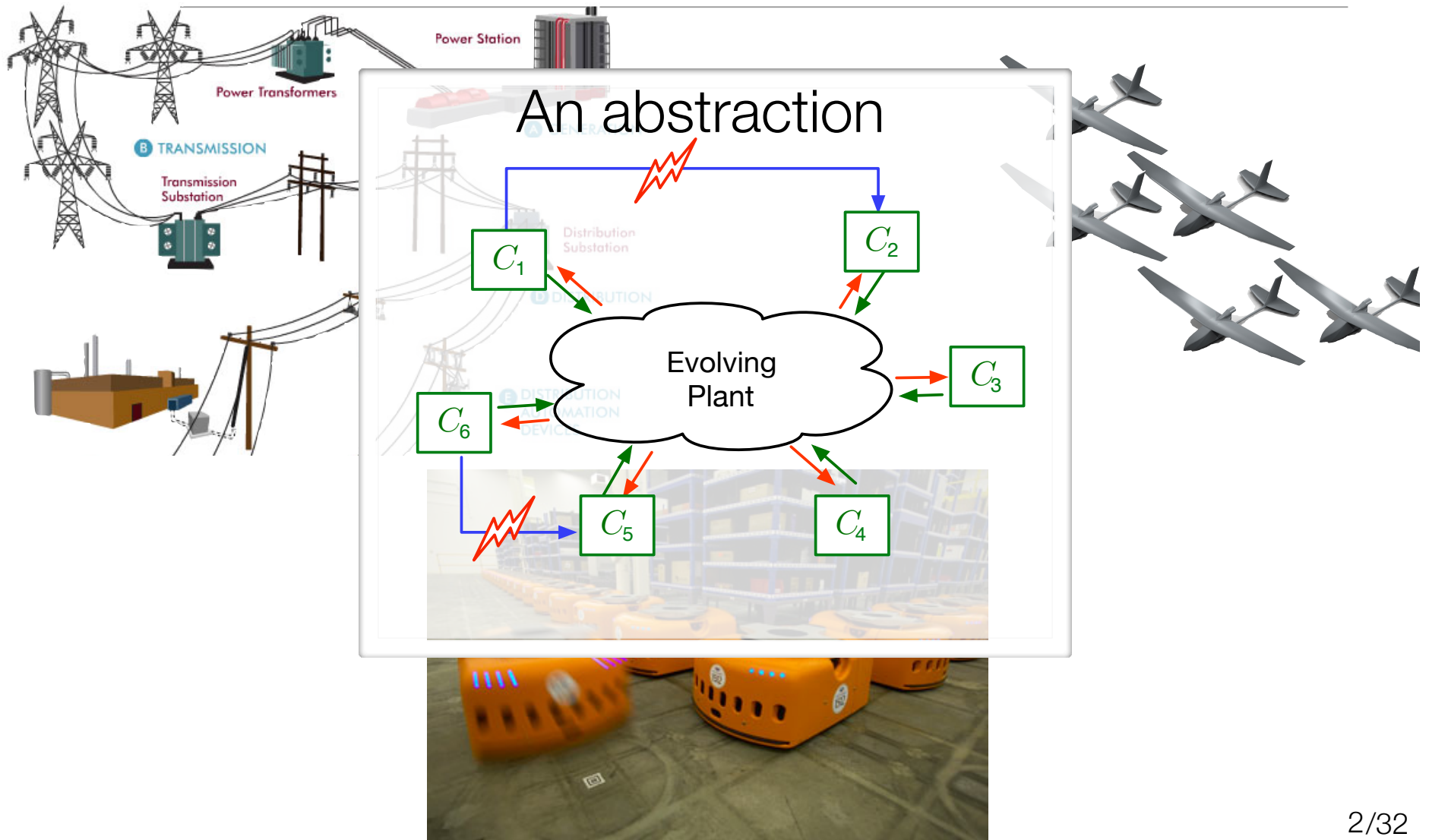
# Implicit Communication for Control

Gireeja Ranade

Works of Pulkit Grover, Anant Sahai, Se Yong Park

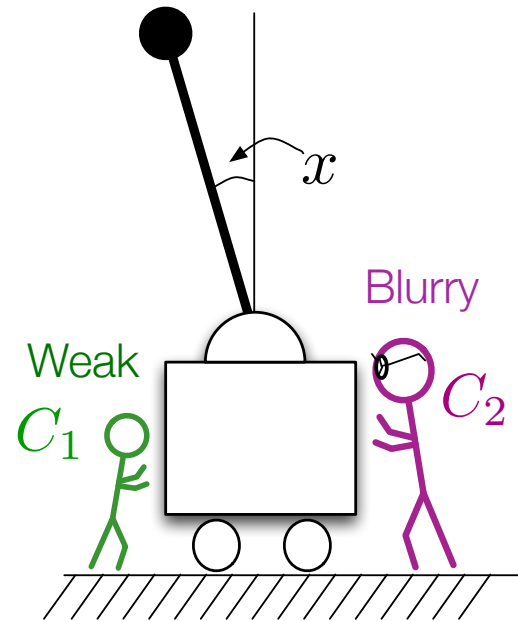
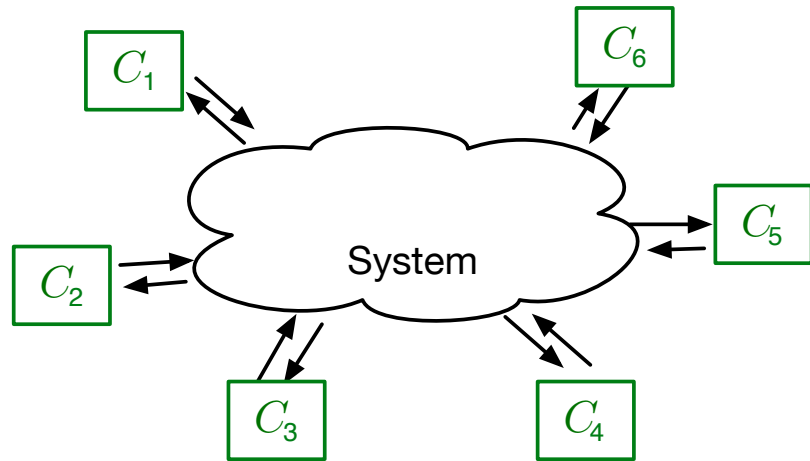
Slides courtesy Pulkit Grover

# Decentralized control: “observer-controller” problem



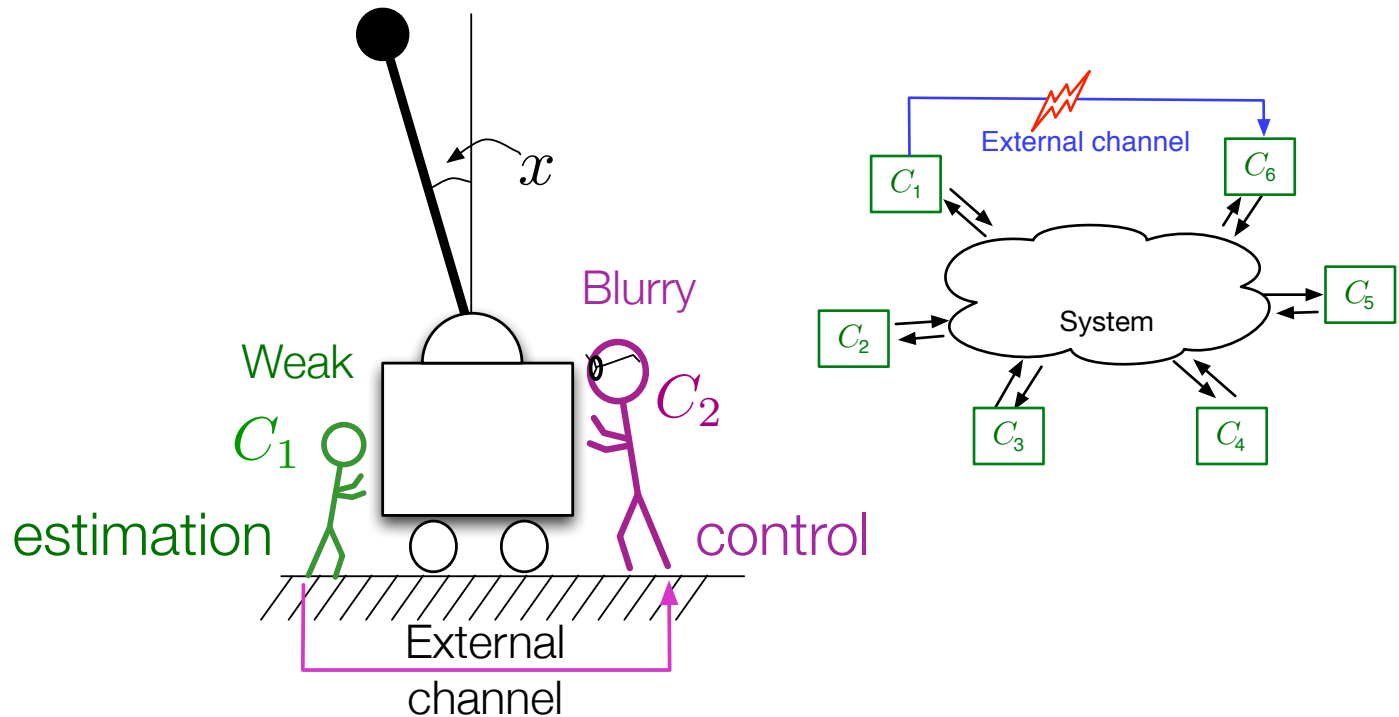
# Decentralized control: a simple example

---



coordination

# Coordination via explicit communication



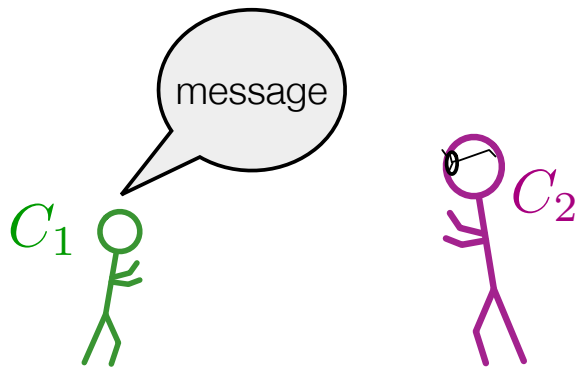
separate estimation and control

point-to-point communication

[Shannon '48]

# Coordination via **implicit** communication?

---



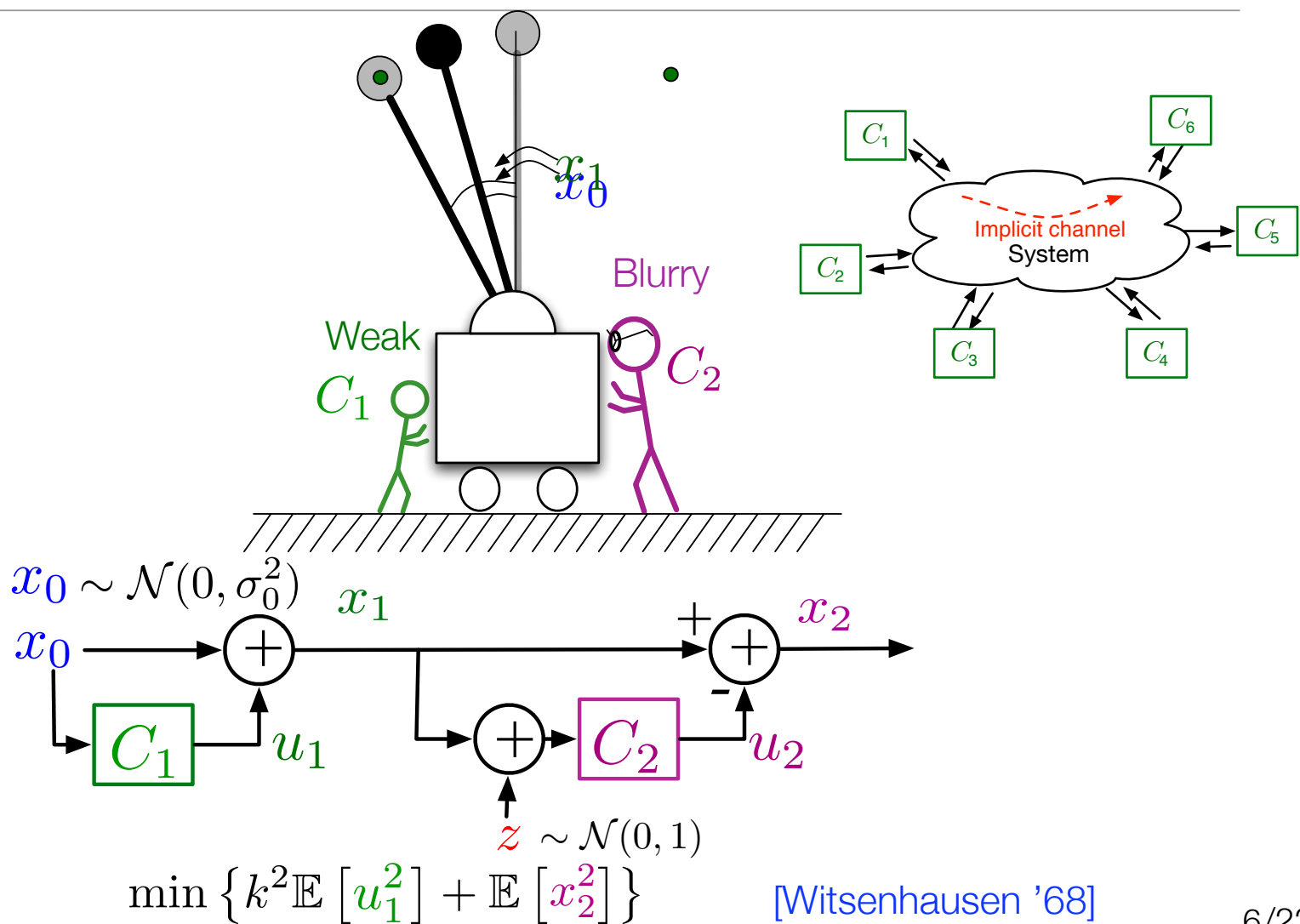
Explicit communication



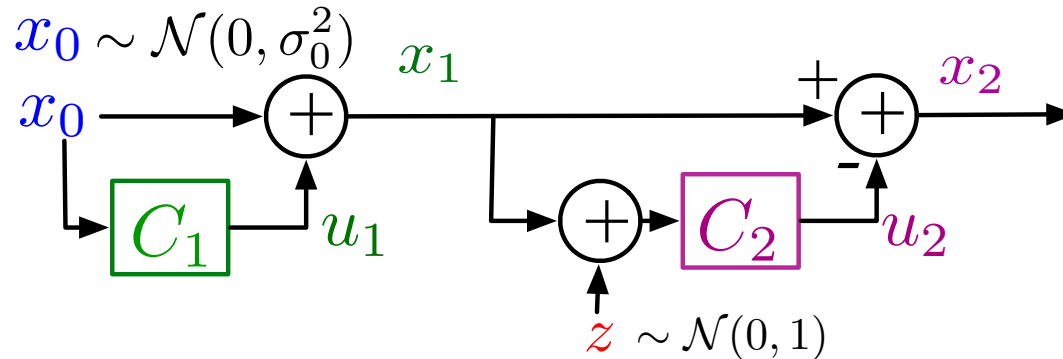
Implicit communication

1. **channel:** the system itself
2. **messages:** endogenously generated

# Implicit communication: an example

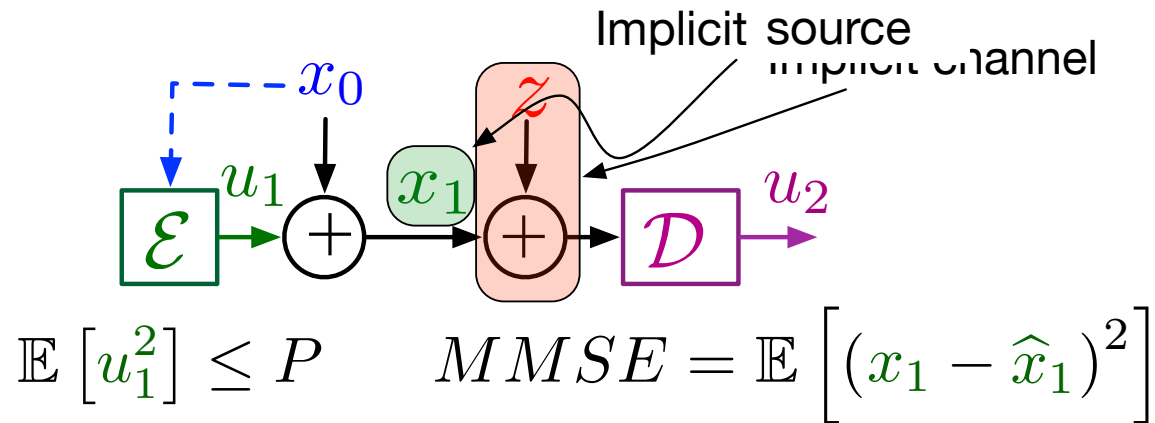


# Toy implicit communication problem: Witsenhausen's counterexample

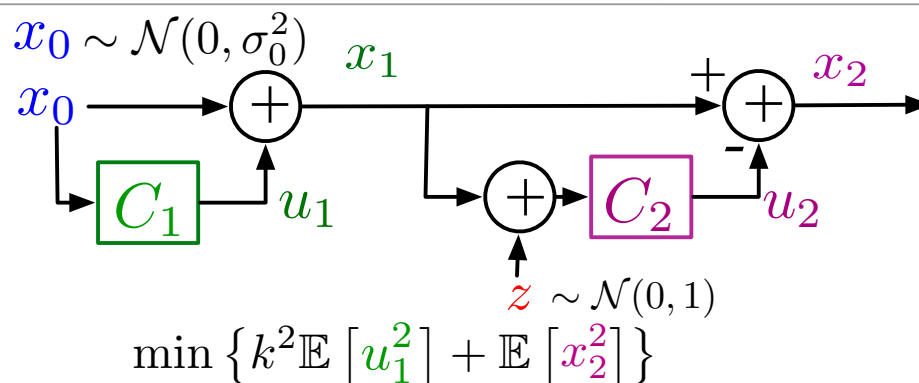


$$\min \{ k^2 \mathbb{E} [u_1^2] + \mathbb{E} [x_2^2] \} \quad [\text{Witsenhausen '68}]$$

Implicit communication interpretation :



# A brief history of Witsenhausen's counterexample



Linear, Quadratic, Gaussian

Nonlinear strategies can outperform linear [Witsenhausen '68]

... by an unbounded factor [Mitter, Sahai '99]

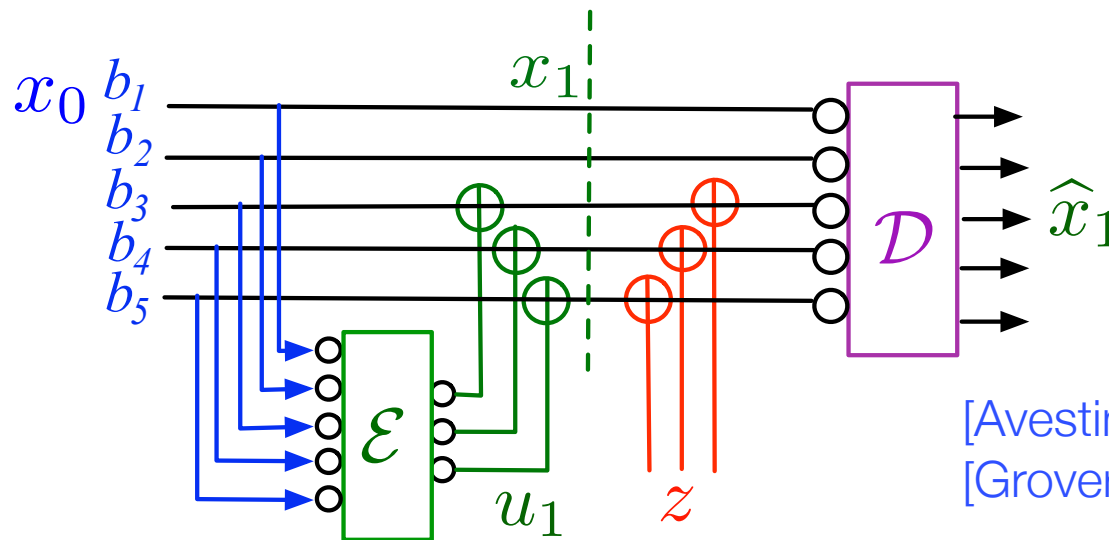
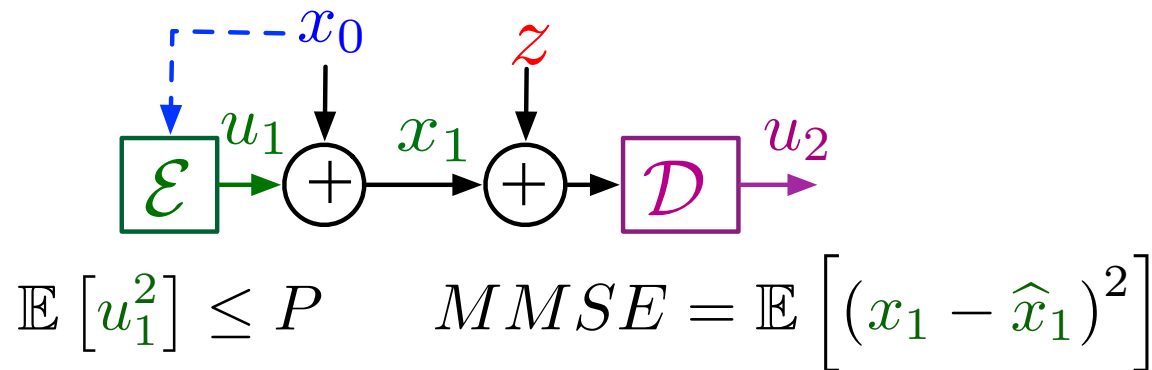
Finding optimal strategy is NP-hard [Papadimitriou, Tsitsiklis '84]

Semi-exhaustive search techniques [Baglietto, Parisini, Zoppoli '01]  
 [Lee, Lau, Ho '01]  
 [Lee, Marden, Shamma '09]



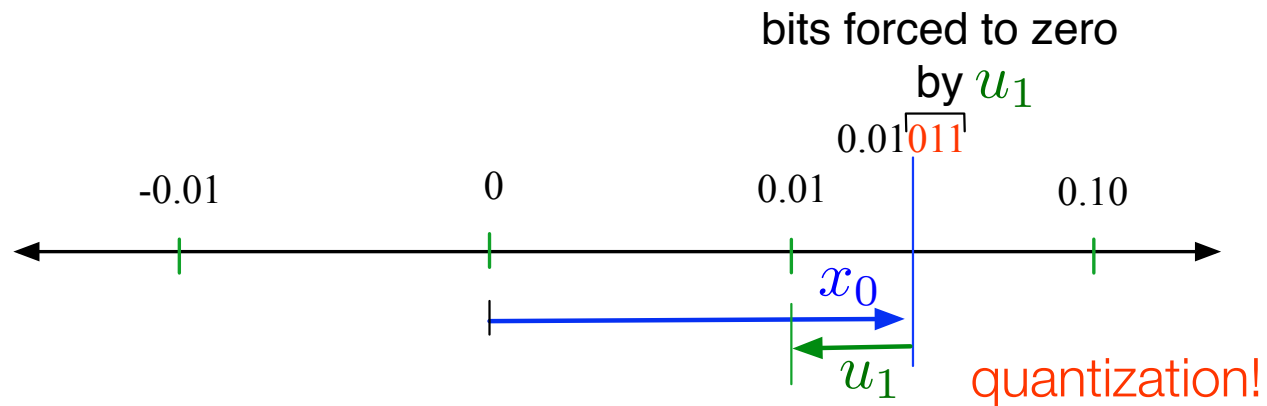
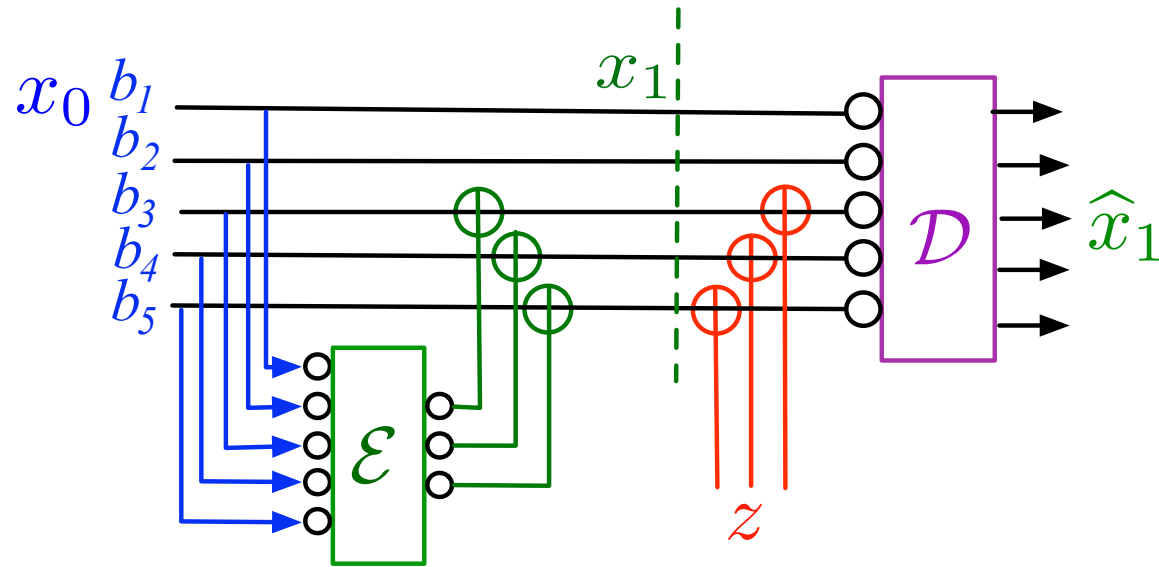
# Understanding Witsenhausen's counterexample: A deterministic abstraction

Implicit communication interpretation :



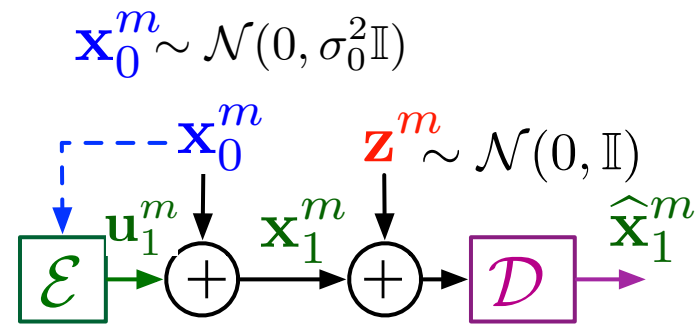
[Avestimehr, Diggavi, Tse '08]  
[Grover, Sahai '09]

# Strategies for the deterministic abstraction



# Asymptotically infinite-length extension of Witsenhausen's counterexample

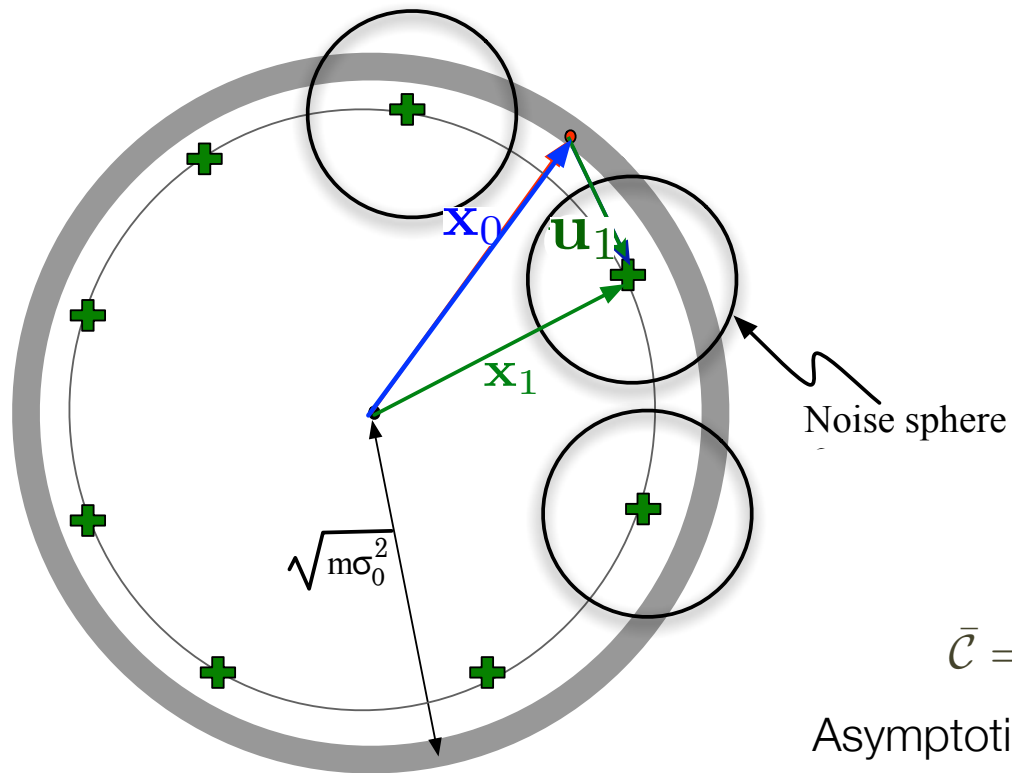
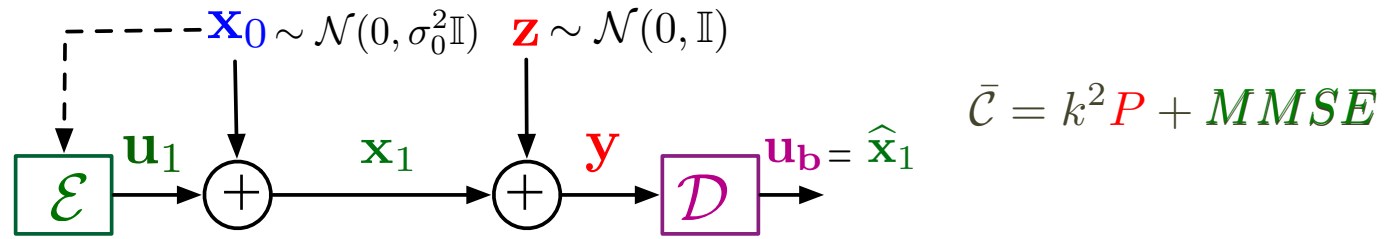
---



$$\min_m \left\{ \frac{k^2}{m} \mathbb{E}[\|u_1^m\|^2] + \frac{1}{m} \mathbb{E}[\|x_{1:1}^m - \hat{x}_{11}^m\|^2] \right\}$$

hope : can use laws of large numbers to simplify

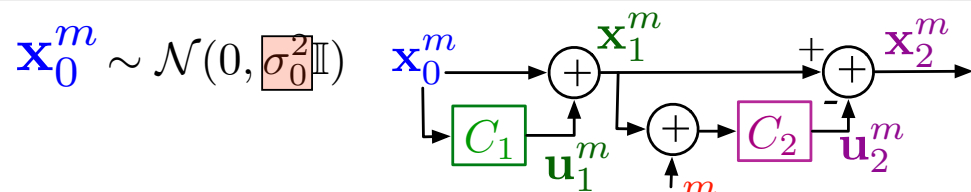
# A strategy : vector quantization



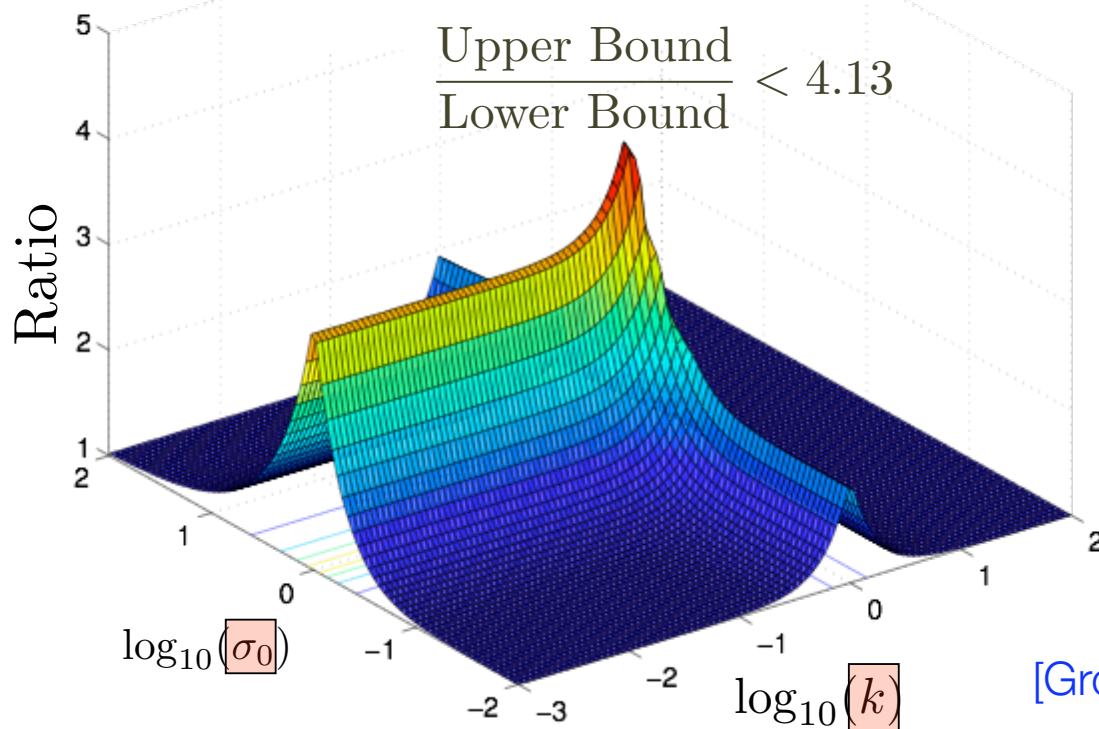
$$\bar{C} = k^2 P + MMSE$$

$$\text{Asymptotic upper bound : } \bar{C} = k^2 + 0$$

# Ratio of upper and lower bounds



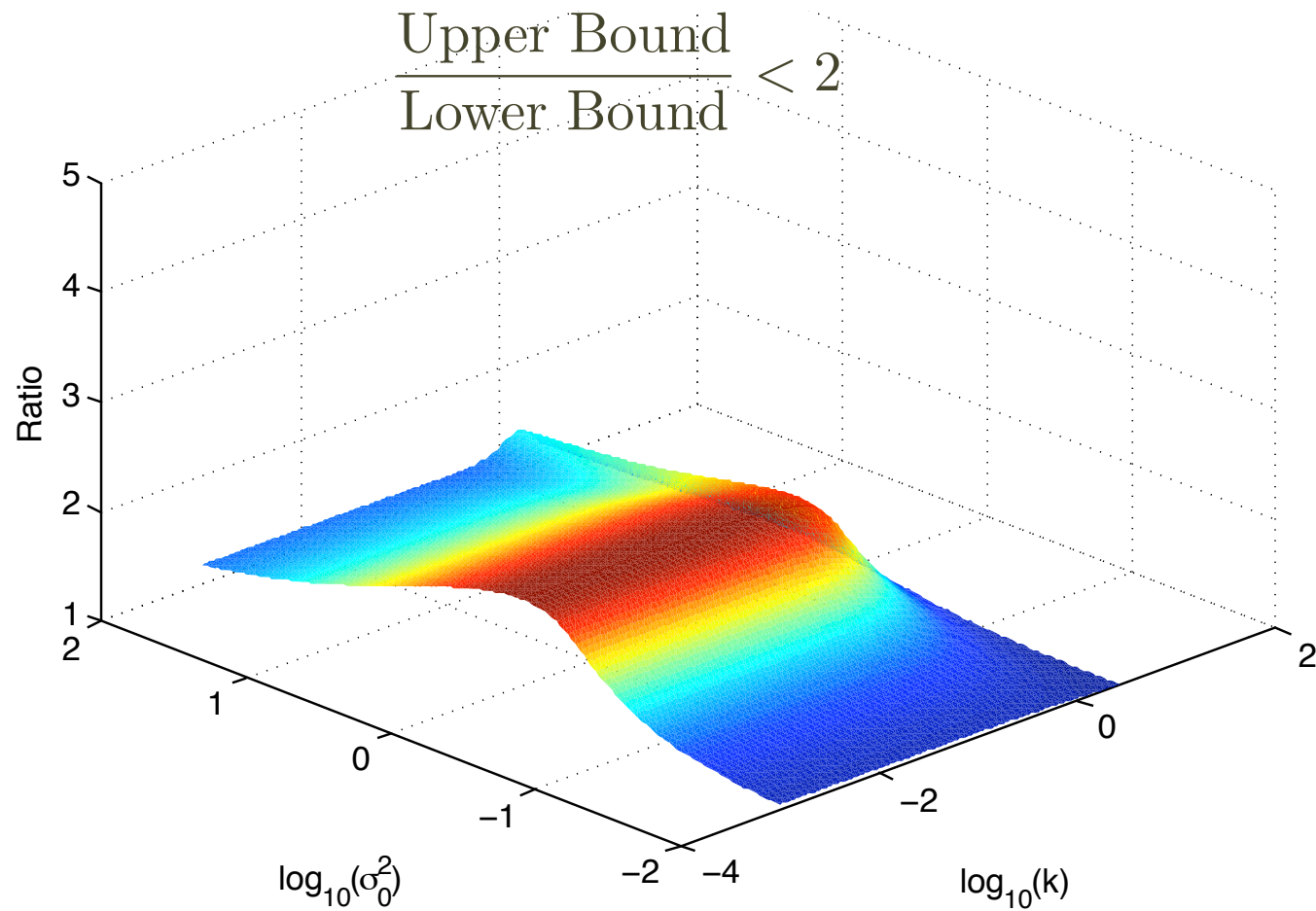
$$\min \left\{ \frac{k^2}{m} \mathbb{E} [\|\mathbf{u}_1^m\|^2] + \frac{1}{m} \mathbb{E} [\|\mathbf{x}_1^m - \hat{\mathbf{x}}_1^m\|^2] \right\}$$



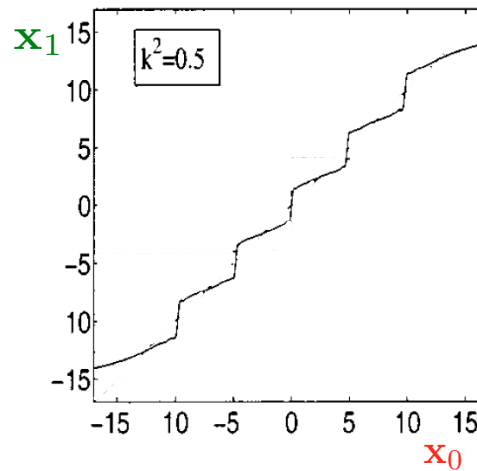
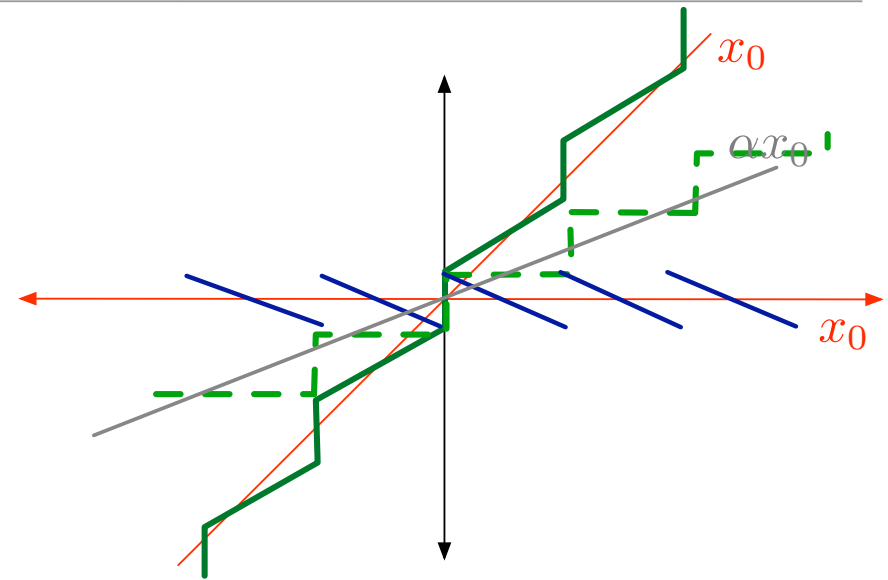
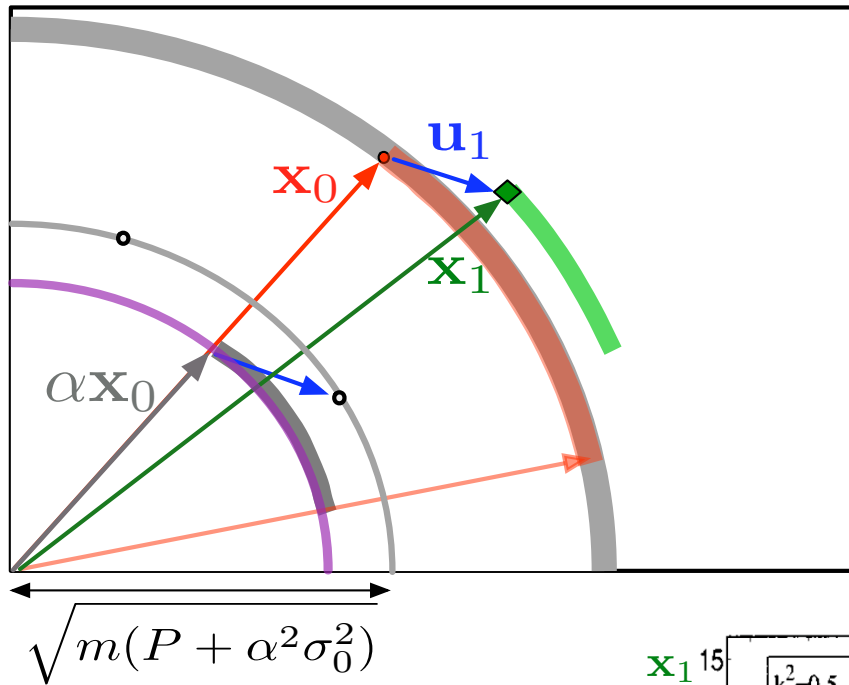
[Grover, Sahai '08]

. . . with dirty-paper coding strategy

---



# Conjectured optimal strategy: Dirty-paper coding



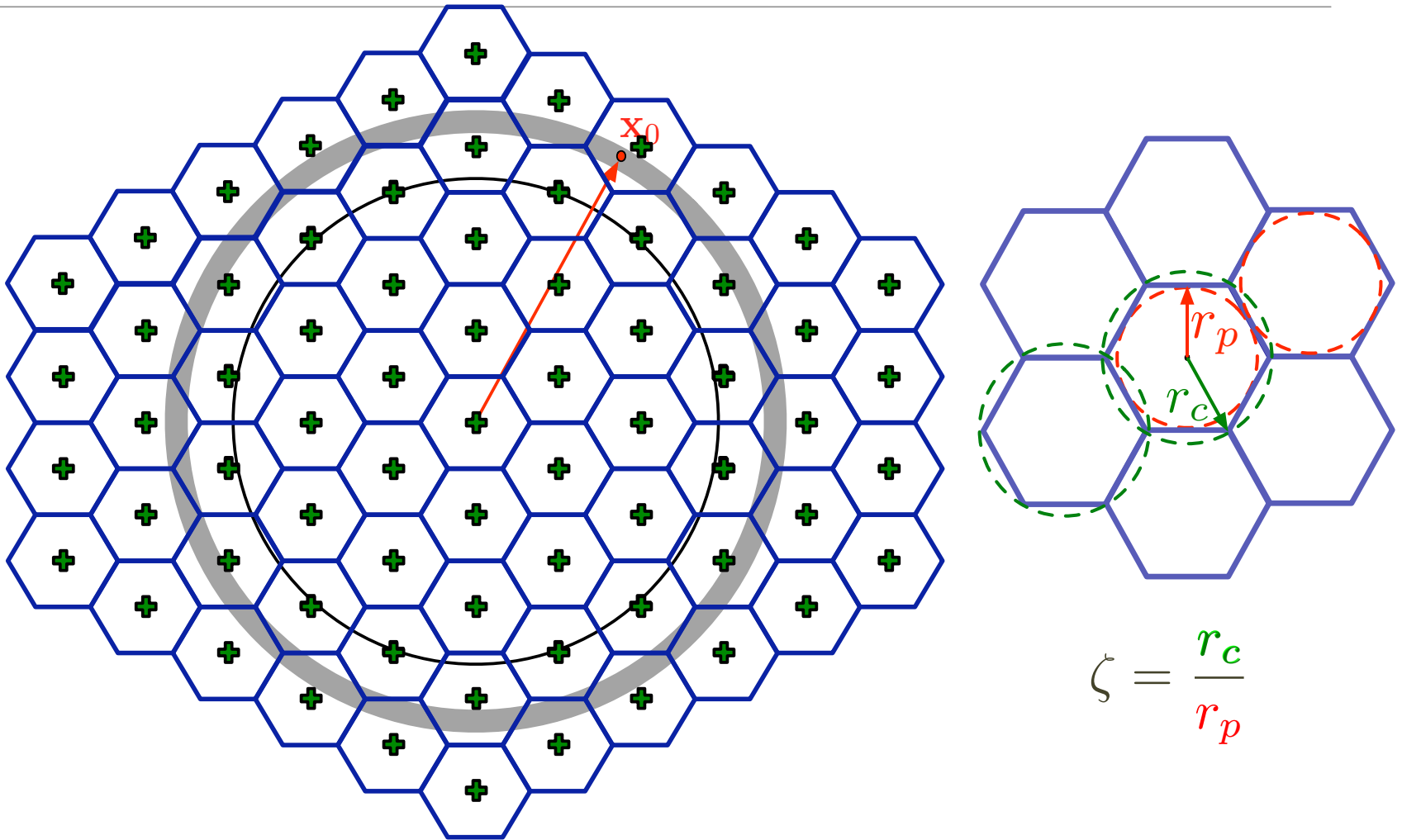
[Baglietto, Parisini, Zoppoli '01]  
[Lee, Lau and Ho '01]

---

# Finite-vector lengths



# Quantization upper bounds



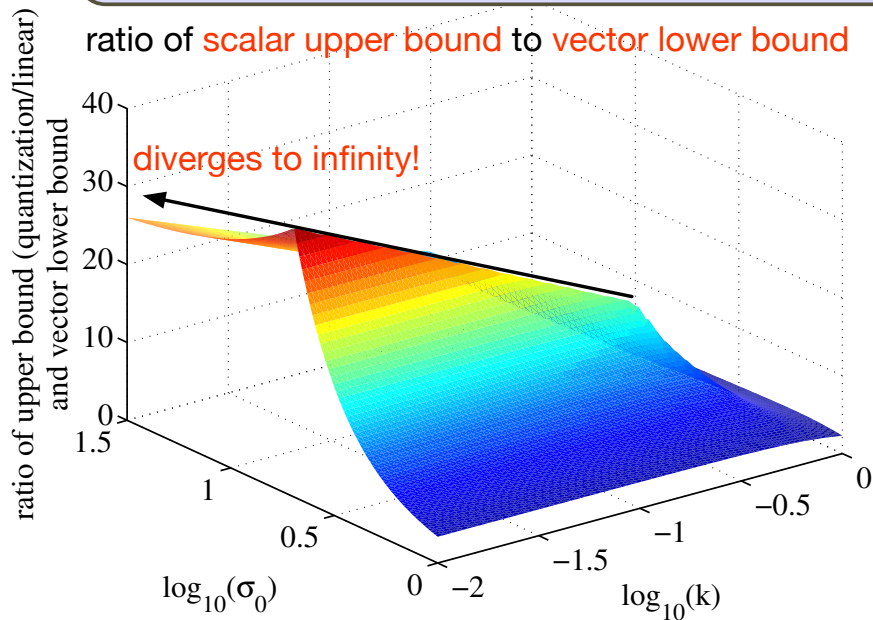
# Lower bound

Use old lower bound

**Theorem** [Grover, Sahai '08]

$$\bar{C}_{\min} \geq \inf_{P \geq 0} k^2 P + \left( \left( \sqrt{\kappa(P)} - \sqrt{P} \right)^+ \right)^2$$

$$\kappa(P) = \frac{\sigma_0^2}{(\sigma_0 + \sqrt{P})^2 + 1}$$



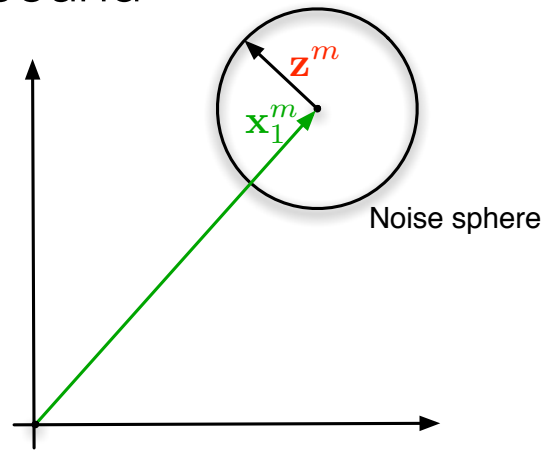
Need tighter lower bounds  
for tiny blocklengths

[Shannon '59][Shannon, Gallager, Berlekamp '67]  
[Blahut '74][Pinsker '67][Sahai '06][Sahai, Grover  
'07][Polyanskiy, Poor, Verdu '08]

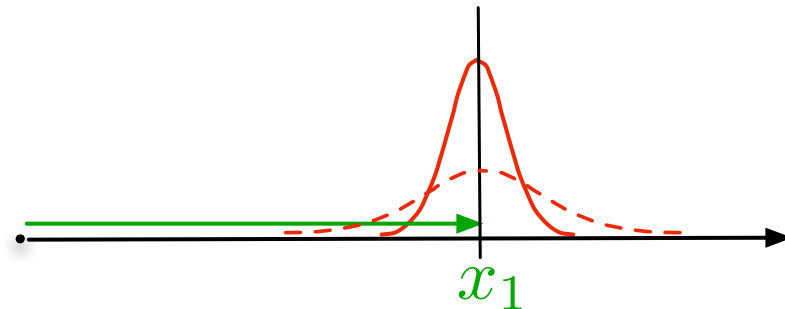
Need bounds that work in a  
distortion setting!

# Large-deviation technique to tighten the lower bound

Lower bound



reality



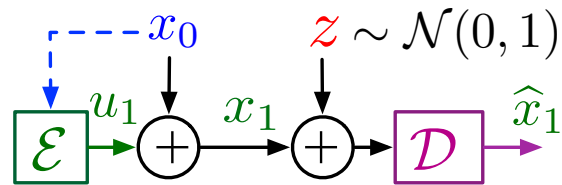
Noise can behave **atypically!**

**Atypical** noise behaviors are **typical** under a **different distribution**

$$\bar{C}_{\min} \geq \inf_{P \geq 0} k^2 P + \left( \left( \sqrt{\kappa(P)} - \sqrt{P} \right)^+ \right)^2$$

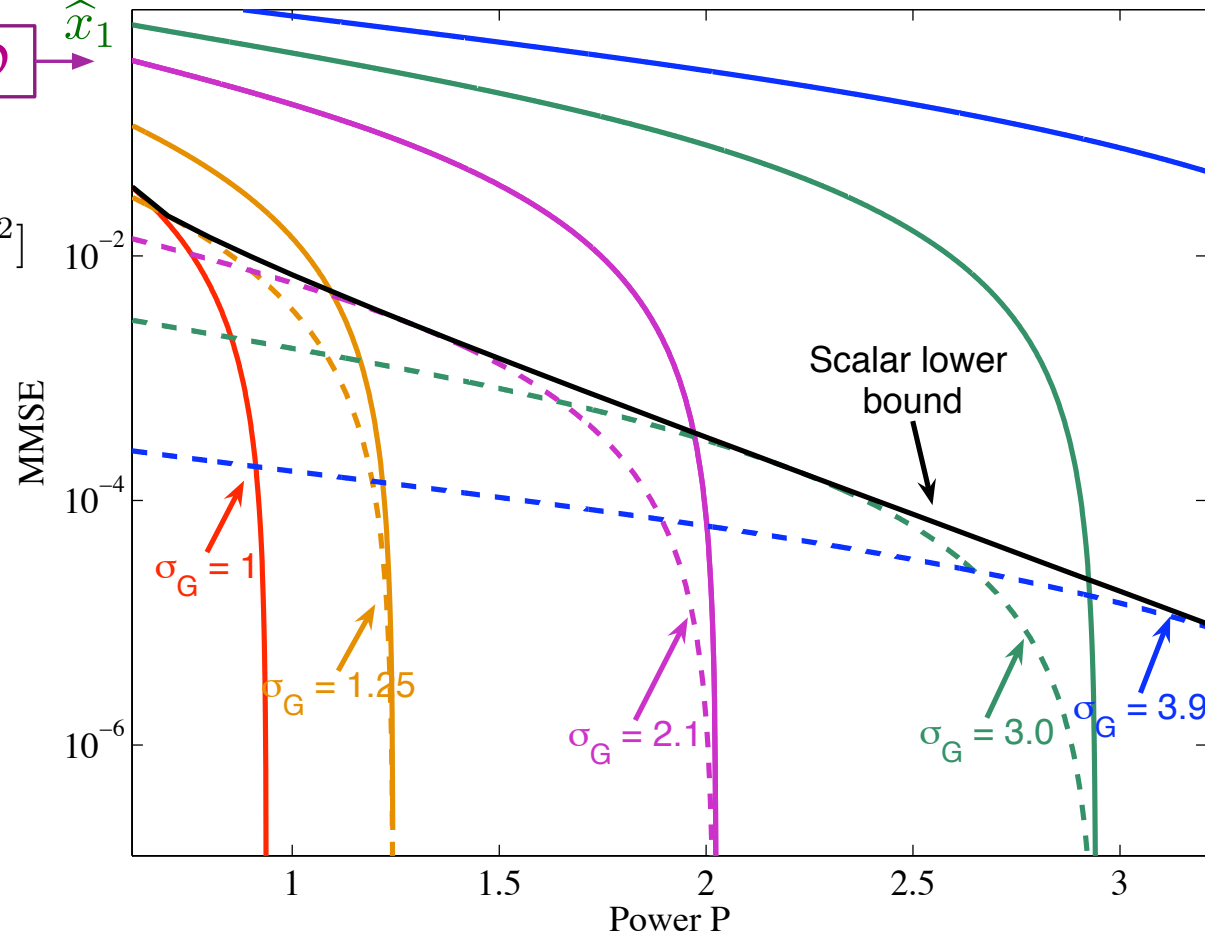
$$\kappa(P) = \frac{\sigma_0^2 \sigma_G^2}{(\sigma_0 + \sqrt{P})^2 + \sigma_G^2}$$

# “Sphere-packing” extension of lower bound



$$P = \mathbb{E}[u_1^2]$$

$$MMSE = \mathbb{E}[(x_1 - \hat{x}_1)^2]$$



# Summary

---

Implicit communication promises substantial gains

. . . can be understood using information theory

Deterministic abstractions yield useful insights

Large-deviation techniques are needed to obtain finite-length results

# The finite-length lower bound

---

For  $\sigma_G^2 \geq 1$  and  $L > 0$

$$\bar{J}_{\min}(m, k^2, \sigma_0^2) \geq \inf_{P \geq 0} k^2 P + \eta(P, \sigma_0^2, \sigma_G^2, L),$$

$$\eta(P, \sigma_0^2, \sigma_G^2, L) = \frac{\sigma_G^m}{c_m(L)} \exp\left(-\frac{mL^2(\sigma_G^2 - 1)}{2}\right) \left( \left( \sqrt{\kappa_2(P, \sigma_0^2, \sigma_G^2, L)} - \sqrt{P} \right)^+ \right)^2,$$

$$\kappa_2(P, \sigma_0^2, \sigma_G^2, L) := \frac{\sigma_0^2 \sigma_G^2}{\frac{2}{c_m^m(L)} e^{1-d_m(L)} ((\sigma_0 + \sqrt{P})^2 + d_m(L) \sigma_G^2)}$$

$$c_m(L) := \frac{1}{\Pr(\|\mathbf{Z}^m\|^2 \leq mL^2)} = (1 - \psi(m, L\sqrt{m}))^{-1}$$

$$d_m(L) := \frac{\Pr(\|\mathbf{Z}^{m+2}\|^2 \leq mL^2)}{\Pr(\|\mathbf{Z}^m\|^2 \leq mL^2)} = \frac{1 - \psi(m+2, L\sqrt{m})}{1 - \psi(m, L\sqrt{m})}$$