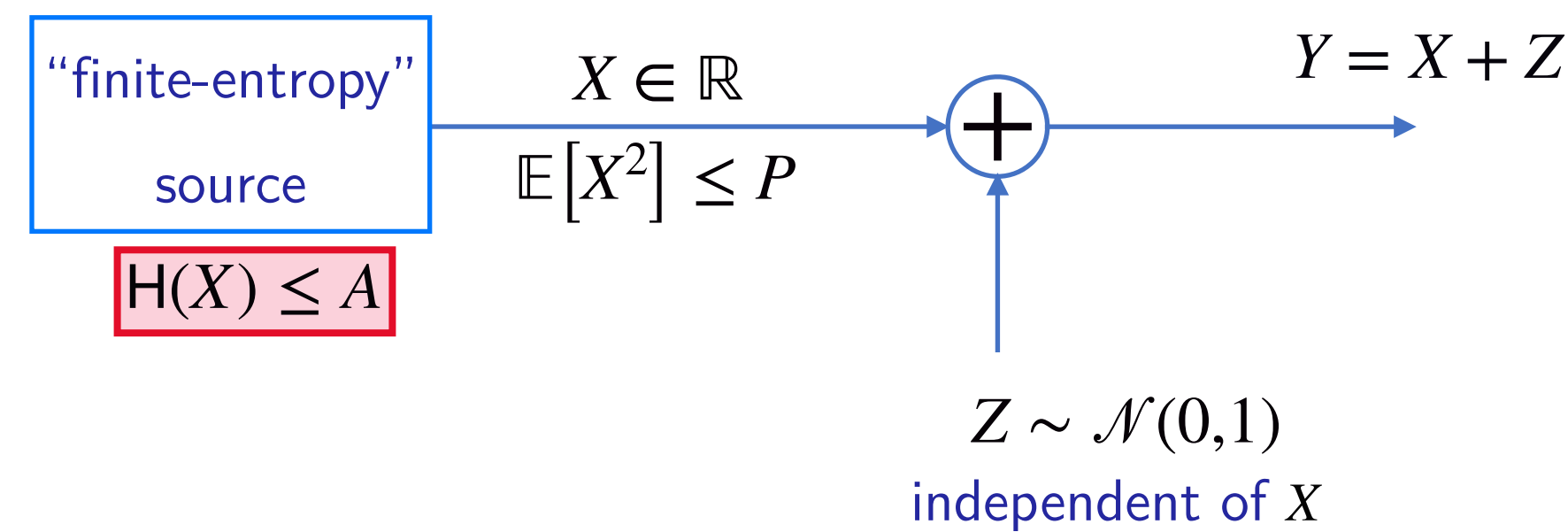


# Additive Gaussian Channels with an Input-Entropy Constraint

a.k.a. a reason to study discrete distributions on continuous alphabets

Adway Girish [EPFL], Emre Telatar [EPFL], Shlomo Shamai [Technion]



$$C_H(A, P) = \sup_{P_X: \begin{matrix} E[X^2] \leq P, \\ H(X) \leq A \end{matrix}} I(X; Y)$$

Dependence on  $A$ ,  
fix  $P = 1$ ,  $C_H(A) = C_H(A, 1)$

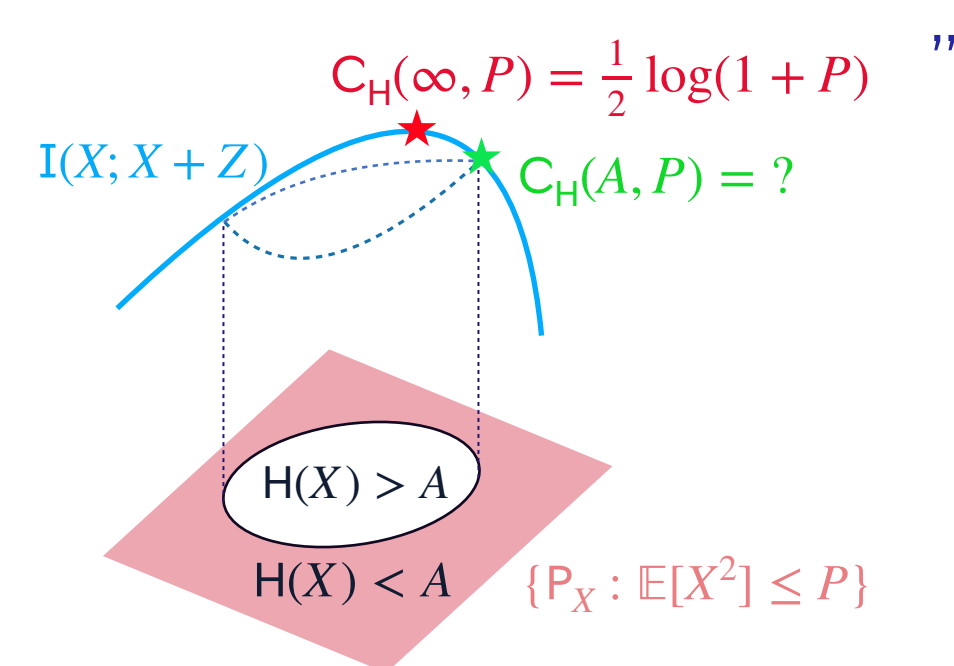
Dependence on  $P$

## Motivation

Capacity-achieving distributions for continuous alphabet channels are sometimes surprisingly discrete (e.g., amplitude-constrained Gaussian channel [1], fading channel [2]);  
what happens if they are forced to be discrete?

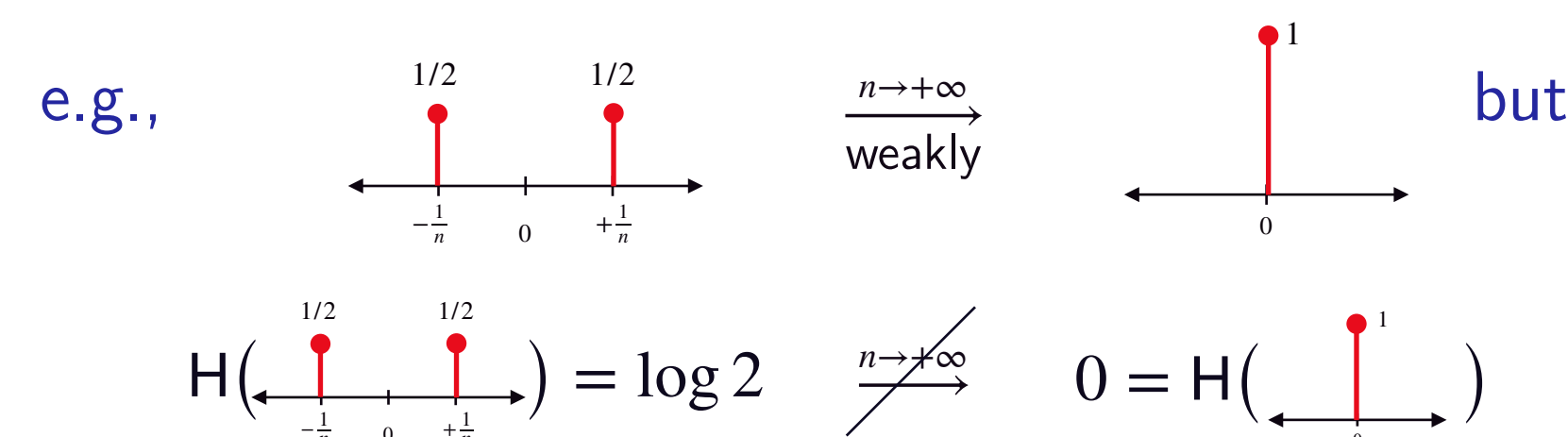
## Difficulties

1. Non-convex optimization problem



2. Discrete distributions over continuous alphabets?

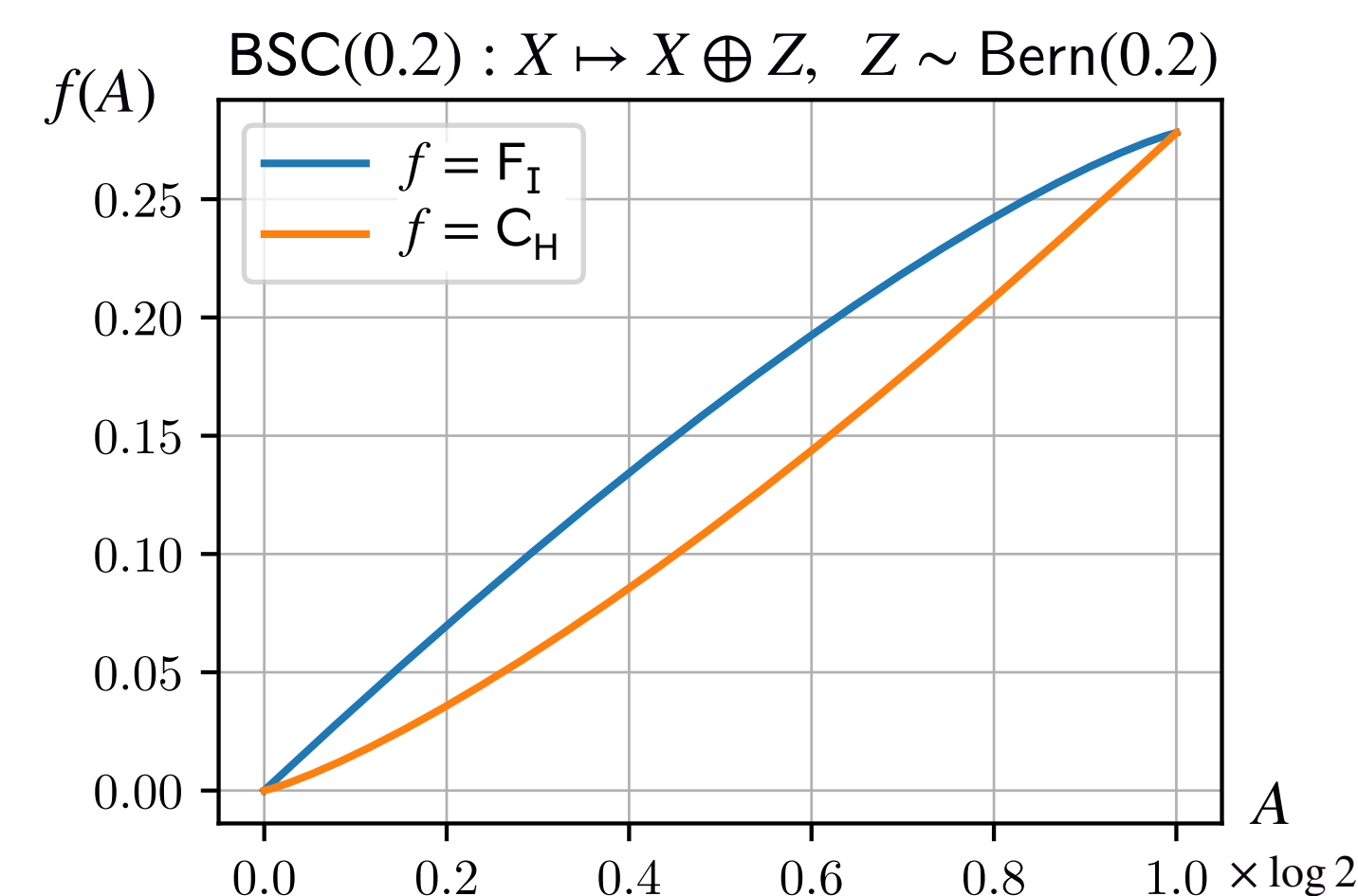
3.  $H$  is not continuous w.r.t. usual topologies on distributions,



## Connections to SDPI and $F_I$ -curves [3]

$$F_I(A) = \sup_{P_{XW}: \begin{matrix} E[X^2] \leq 1, \\ I(X; W) \leq A \end{matrix}} I(W; Y)$$

$F_I(A) \geq C_H(A)$  for general channels, usually strict, e.g.,



But for such power-constrained Gaussian channels, it is known that  $W = X$  is optimal (in  $F_I$  as above) asymptotically as  $A \rightarrow 0^+, \infty$ , with the correct rate [3]!

## References

- [1] Smith, J.G., 1971. The information capacity of amplitude-and variance-constrained scalar Gaussian channels. *Information and control*, 18(3), pp.203-219.
- [2] Abou-Faycal, I.C., Trott, M.D. and Shamai, S., 2001. The capacity of discrete-time memoryless Rayleigh-fading channels. *IEEE transactions on Information Theory*, 47(4), pp.1290-1301.
- [3] du Pin Calmon, F., Polyanskiy, Y. and Wu, Y., 2017. Strong data processing inequalities for input-constrained additive noise channels. *IEEE Transactions on Information Theory*, 64(3), pp.1879-1892.

## Add cardinality constraint

$$C_H^n(A, P) = \sup_{P_X: \begin{matrix} E[X^2] \leq P, H(X) \leq A, \\ |\text{supp}(P_X)| = n \end{matrix}} I(X; Y)$$

Then  $P_X \equiv \{(p_i, x_i)\}_{i=1}^n$ ,  $p_i > 0$ ,  $x_i$  distinct

→ Constrained optimization over  $\mathbb{R}^{2n}$

KKT conditions **necessary** for optimality:

there exist  $\lambda_1, \lambda_2 \geq 0$  such that

1.  $E \left[ Z \log \frac{1}{f_Y(x_i + Z; P_X)} \right] = 2\lambda_2 x_i$
2.  $E \left[ \log \frac{1}{f_Y(x_i + Z; P_X)} \right] = C_H^n(A, P) + \lambda_2 (x_i^2 - P) + \lambda_1 \left( \log \frac{1}{p_i} - A \right)$  (difficult)

Initial conjecture: two-point distribution is optimal for small  $P$ : **False!**

