

# (Deterministic) Communication amid Uncertainty

**Madhu Sudan**

Microsoft, New England

Based on joint works with:

- (1) Adam Kalai (MSR), Sanjeev Khanna (U.Penn), Brendan Juba (Harvard)  
and (2) Elad Haramaty (Technion)

# Classical Communication

- The Shannon setting
  - Alice gets  $m \in [N]$  chosen from distribution  $P$
  - Sends some compression  $y = E(m)$  to Bob.
  - Bob computes  $\hat{m} = D(y)$ 
    - (with knowledge of  $Q = P$ ).
  - Hope  $m = \hat{m}$ .
- Classical Uncertainty:  $y \approx E(m)$
- Today's talk: Bob knows  $Q \approx P$ .

# Outline

- Part 1: Motivation
- Part 2: Formalism
- Part 3: Randomized Solution
- Part 4: Issues with Randomized Solution
- Part 5: Deterministic Issues.

# Motivation: Human Communication

- Human communication vs. Designed communication:
  - Human comm. dictated by languages, grammars ...
    - Grammar: Rules, often violated.
    - Dictionary:  $\exists$  multiple meanings to word.
    - Redundant: But  $\neq$  error-correcting code.
- Theory for human communication?
  - Information theory?
  - Linguistics? (Universal grammars etc.)?

# Behavioral aspects of natural communication

- (Vast) Implicit context.
- Sender sends increasingly long messages to receiver till receiver “gets” (the meaning of) the message.
  - Where do the options come from?
  - Comes from language/dictionary – but how/why?
- Sender may use feedback from receiver if available; or estimates receiver’s knowledge if not.
  - How does estimation influence message.

## Model:

- Reason to choose short messages: Compression.
  - Channel is still a scarce resource; still want to use optimally.
- Reason to choose long messages (when short ones are available): Reducing ambiguity.
  - Sender unsure of receiver's prior (context).
  - Sender wishes to ensure receiver gets the message, no matter what its prior (within reason).

## Back to Problem

- Design encoding/decoding schemes ( $E/D$ ) so that
  - Sender has distribution  $P$  on  $[N]$
  - Receiver has distribution  $Q$  on  $[N]$
  - Sender gets  $m \in [N]$
  - Sends  $E(P, m)$  to receiver.
  - Receiver receives  $y = E(P, m)$
  - Decodes to  $\hat{m} = D(Q, y)$
- Want:  $m = \hat{m}$  (provided  $P, Q$  close),
  - While minimizing  $\mathbb{E}_{m \leftarrow P} |E(P, m)|$

# Contrast with some previous models

- Universal compression?
  - Doesn't apply:  $P, Q$  are not finitely specified.
  - Don't have a sequence of samples from  $P$ ; just one!
- K-L divergence?
  - Measures inefficiency of compressing for  $Q$  if real distribution is  $P$ .
  - But assumes encoding/decoding according to same distribution  $Q$ .
- Semantic Communication:
  - Uncertainty of sender/receiver; but no special goal.



## Closeness of distributions:

- $P$  is  $\Delta$ -close to  $Q$  if for all  $m \in [N]$ ,  
$$|\log P(m) - \log Q(m)| \leq \Delta$$
- $P$   $\Delta$ -close to  $Q \quad \Rightarrow \quad D(P||Q), D(Q||P) \leq \Delta$   
(symmetrized, “worst-case” KL-divergence)

# Dictionary = Shared Randomness?

- Modelling the dictionary: What should it be?
- Simplifying assumption – it is shared randomness, so ...
- Assume sender and receiver have some shared randomness  $R$  and  $P, Q, m$  are independent of  $R$ .
  - $y = E(P, m, R)$
  - $\hat{m} = D(Q, y, R)$
- Want  $\forall m, \Pr_R[\hat{m} = m] \geq 1 - \epsilon$

# Solution (variant of Arith. Coding)

- Use  $R$  to define sequences
  - $R_1 [1], R_1 [2], R_1 [3], \dots$
  - $R_2 [1], R_2 [2], R_2 [3], \dots$
  - ...
  - $R_N [1], R_N [2], R_N [3], \dots$
- $E_\Delta(P, m, R) = R_m[1 \dots L]$ , where  $L$  chosen s.t.  $\forall z \neq m$ 
  - Either  $R_z[1 \dots L] \neq R_m[1 \dots L]$
  - Or  $\log P(z) < \log P(m) - 2\Delta$
- $D_\Delta(Q, y, R) = \hat{m}$  s.t.  $\hat{m}$  max.  $Q(\hat{m})$  among  $\hat{m} \in \{z | R_z[1 \dots L] = y\}$

# Performance

- Obviously decoding always correct.
- Easy exercise:
  - $\text{Exp}_m [E(P, m)] = H(P) + 2 \Delta$ 
    - $(H(P) \equiv \sum_m P(m) \log_2 \frac{1}{P(m)} \text{ "binary entropy"})$
- Limits:
  - No scheme can achieve  $(1 - \epsilon) \cdot [H(P) + \Delta]$
  - Can reduce randomness needed.

# Implications

- Reflects the tension between ambiguity resolution and compression.
  - Larger the  $\Delta$  ((estimated) gap in context), larger the encoding length.
- Coding scheme reflects the nature of human process (extend messages till they feel unambiguous).
- The “shared randomness” is a convenient starting point for discussion
  - Dictionaries do have more structure.
  - But have plenty of entropy too.
  - Still ... should try to do without it.

# Deterministic Compression?

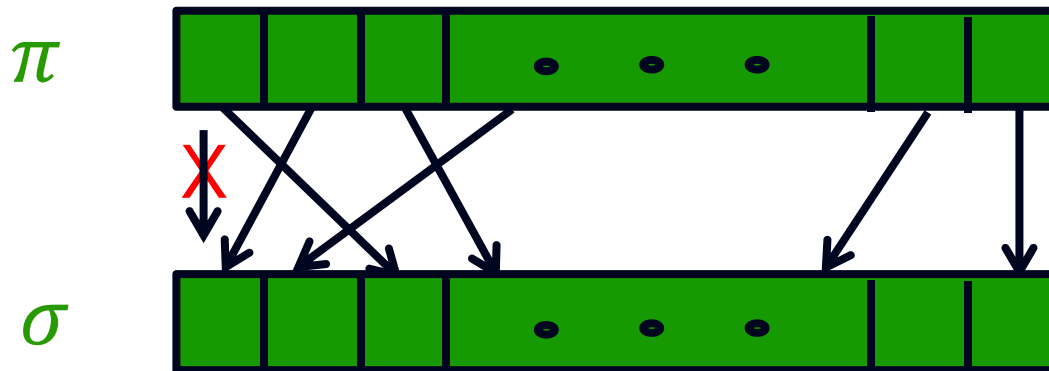
- Randomness fundamental to solution.
  - Needs  $R$  independent of  $P, Q$  to work.
- Can there be a deterministic solution?
  - Technically: Hard to come up with single scheme that compresses consistently for all  $(P, Q)$ .
  - Conceptually: Nicer to know “dictionary” and context can be interdependent.

## Challenging special case

- Alice has permutation  $\pi$  on  $[N]$ 
  - i.e.,  $\pi$  1-1 function mapping  $[N] \rightarrow [N]$
- Bob has permutation  $\sigma$
- Know both are close:
  - $\forall m \in [N], |\pi^{-1}(m) - \sigma^{-1}(m)| \leq \ell$  (say  $\ell = 2$ )
- Alice and Bob know  $i$  (say  $i = 1$ ).
  - Alice wishes to communicate  $m = \pi(i)$  to Bob.
- Can we do this with few bits?
  - Say  $O(1)$  bits if  $i = 1, \ell = 2$ .

# Model as a graph coloring problem

- Consider family of graphs  $U_{N,\ell}$ :
  - Vertices = permutations on  $[N]$
  - Edges = close permutations with distinct messages. (two potential Alices).



- Central question: What is  $\chi(U_{N,\ell})$ ?

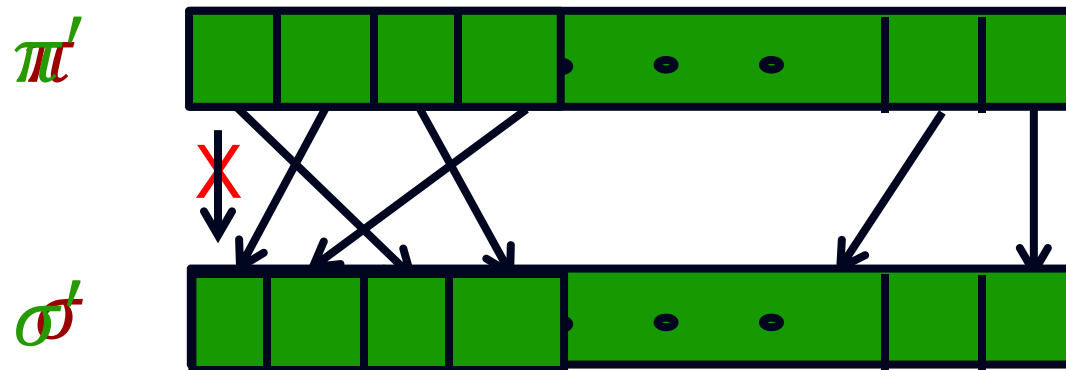


# Main Results [w. Elad Haramaty]

- Claim: Compression length for toy problem  
$$\in [\log \chi(U_{N,\ell}), \log \chi(U_{N,2\ell})]$$
- Thm 1:  $\chi(U_{N,\ell}) \leq \ell^{O(\ell \log^* N)}$ 
  - $\log^{(i)} N \equiv \log \log \dots N$  ( $i$  times)
  - $\log^* N \equiv \min \{i \mid \log^{(i)} N \leq 1\}$ .
- Thm 2:  $\exists$  uncertain comm. schemes with
  1.  $\text{Exp}_m[|E(P, m)|] \leq O(H(P) + \Delta + \log \log N)$   
(0-error).
  1.  $\text{Exp}_m[|E(P, m)|] \leq \ell^{O(\epsilon^{-1}(H(P) + \Delta + \log^* N))}$  ( $\epsilon$ -error).
- Rest of the talk: Graph coloring

# Restricted Uncertainty Graphs

- Will look at  $U_{N,\ell,k}$ 
  - Vertices: restrictions of permutations to first  $k$  coordinates.
  - Edges:  $\pi' \leftrightarrow \sigma'$   
 $\Leftrightarrow \exists \pi$  extending  $\pi'$  and  $\sigma$  extending  $\sigma'$  with  $\pi \leftrightarrow \sigma$



# Homomorphisms

- $G$  homomorphic to  $H$  ( $G \rightarrow H$ ) if
  - $\exists \phi: V(G) \rightarrow V(H)$  s.t.  $u \leftrightarrow_G v \Rightarrow \phi(u) \leftrightarrow_H \phi(v)$
- Homomorphisms?
  - $G$  is  $k$ -colorable  $\Leftrightarrow G \rightarrow K_k$
  - $G \rightarrow H$  and  $H \rightarrow L \Rightarrow G \rightarrow L$
- Homomorphisms and Uncertainty graphs.
  - $U_{N,\ell} = U_{N,\ell,N} \rightarrow U_{N,\ell,N-1} \rightarrow \cdots \rightarrow U_{N,\ell,\ell+1}$
- Suffices to upper bound  $\chi(U_{N,\ell,k})$

## Chromatic number of $U_{N,\ell,\ell+1}$

- For  $f: [N] \rightarrow [2\ell]$ , Let
$$I_f = \{ \pi \mid f(\pi_1) = 1, f(\pi_i) \neq 1, \forall i \in [2\ell] - \{1\} \}$$
- Claim:  $\forall f, I_f$  is an independent set of  $U_{N,\ell,\ell+1}$
- Claim:  $\forall \pi, \Pr_f [ \pi \in I_f ] \geq \frac{1}{4\ell}$
- Corollary:  $\chi(U_{N,\ell,\ell+1}) \leq O(\ell^2 \log N)$

## Better upper bounds:

- Say  $\phi: G \rightarrow H$

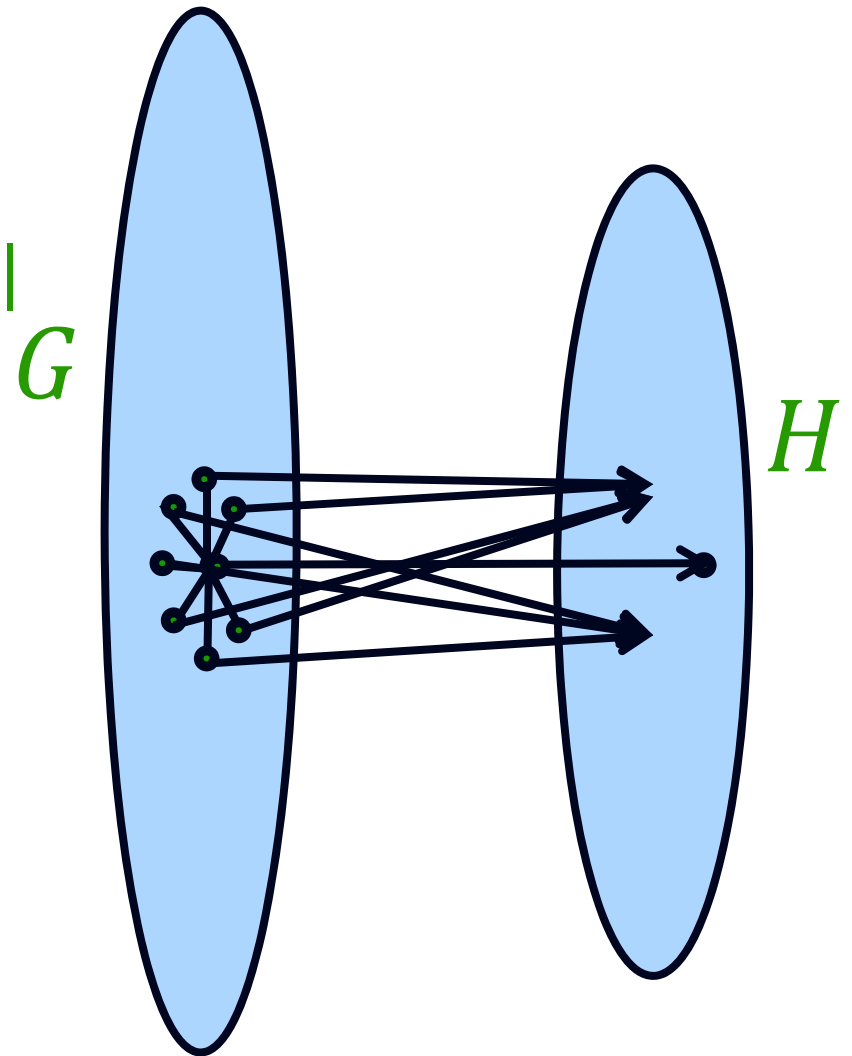
- $d_\phi(u) \equiv |\{ \phi(v) \mid v \leftrightarrow_G u \}|$   
 $d_\phi \equiv \max_u \{d_\phi(u)\}$

- Lemma:

$$\chi(G) \leq O(d_\phi^2 \log \chi(H))$$

- For  $\phi_k: U_{N,\ell,k} \rightarrow U_{N,\ell,k-\ell}$

$$d_{\phi_k} = \ell^{O(k)}$$



## Better upper bounds:

- $d_\phi \equiv \max_u |\{\phi(v) | v \leftrightarrow_G u\}|$
- Lemma:  $\chi(G) \leq O(d_\phi^2 \log \chi(H))$
- For  $\phi_k: U_{N,\ell,k} \rightarrow U_{N,\ell,k-\ell}$ ,  $d_{\phi_k} \leq \ell^{O(k)}$
- Corollary:  $\chi(U_{N,\ell,k}) \leq \ell^{O(k)} \log^{\binom{k}{\ell}} N$
- Aside: Can show:  $\chi(U_{N,\ell,k}) \geq \log^{\Omega(\frac{k}{\ell})} N$ 
  - Implies can't expect simple derandomization of the randomized compression scheme.

# Future work?

- Open Questions:
  - Is  $\chi(U_{N,\ell}) = o_\ell(1)$ ?
  - Can we compress arbitrary distributions to  $O(H(P) + \Delta)$ ?  $O(H(P) + \Delta + \log^* N)$ ? or even  $O(H(P) + \Delta + \log \log \log N)$ ?
- On conceptual side:
  - Better mathematical understanding of forces on language.
    - Information-theoretic
    - Computational
    - Evolutionary

**Thank You**