

Sub-modularity and Antenna Selection in MIMO systems

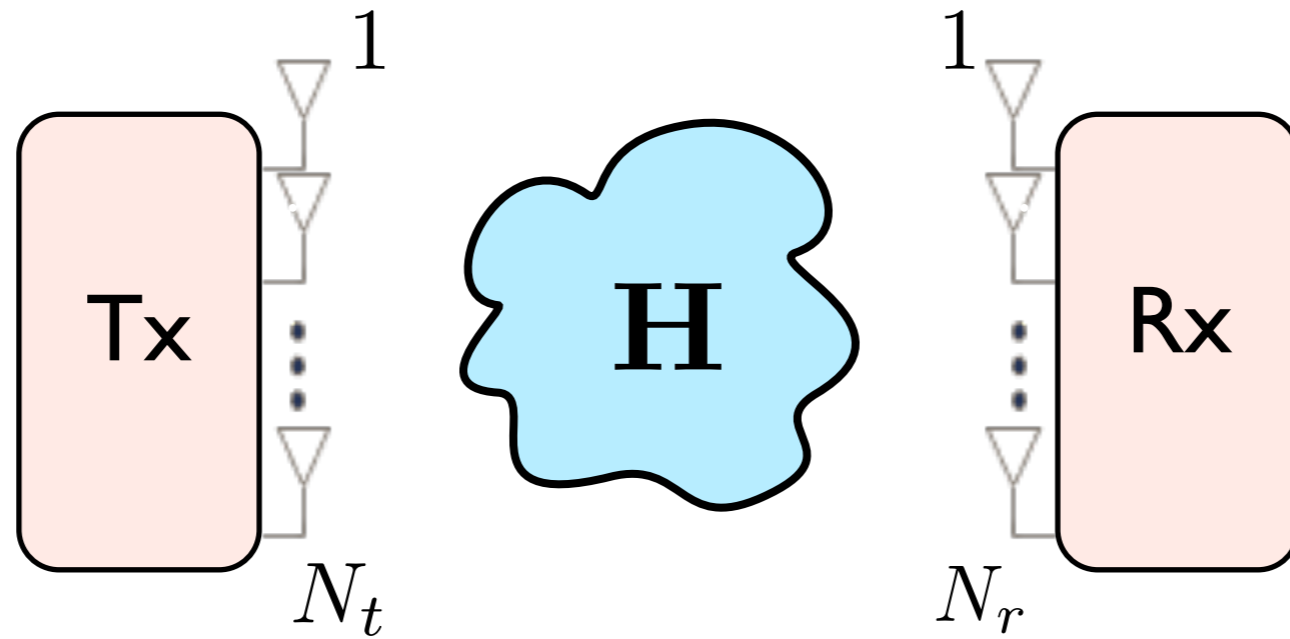
Rahul Vaze



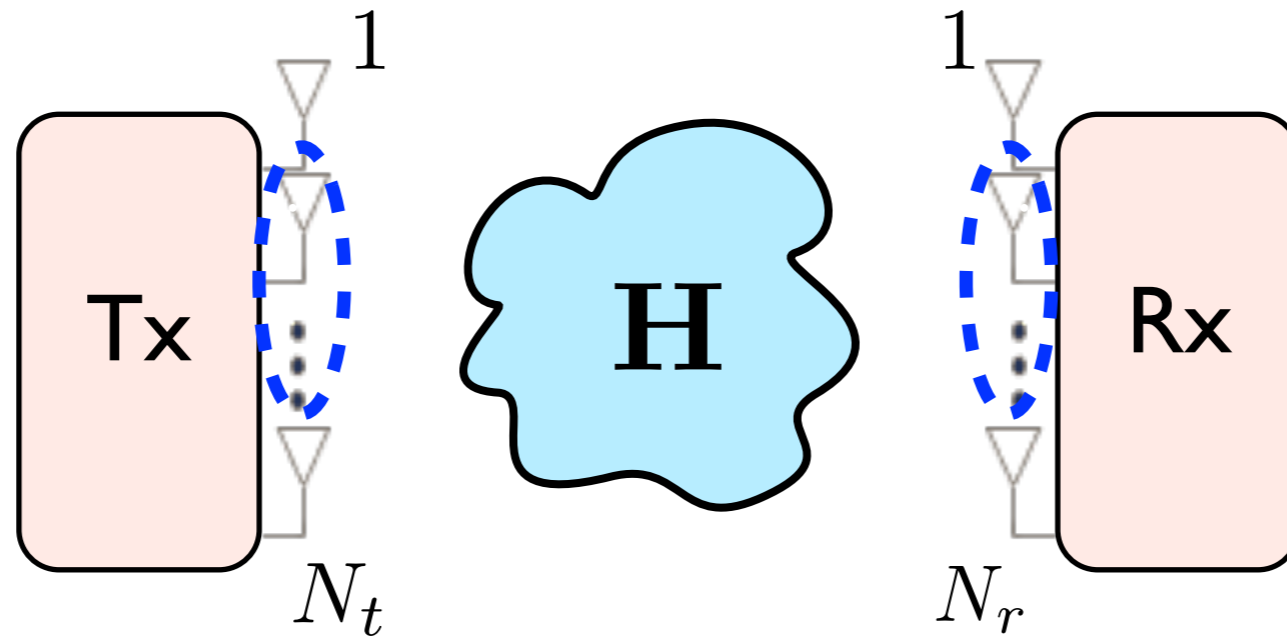
Harish Ganapathy



Point-to-Point MIMO Channel



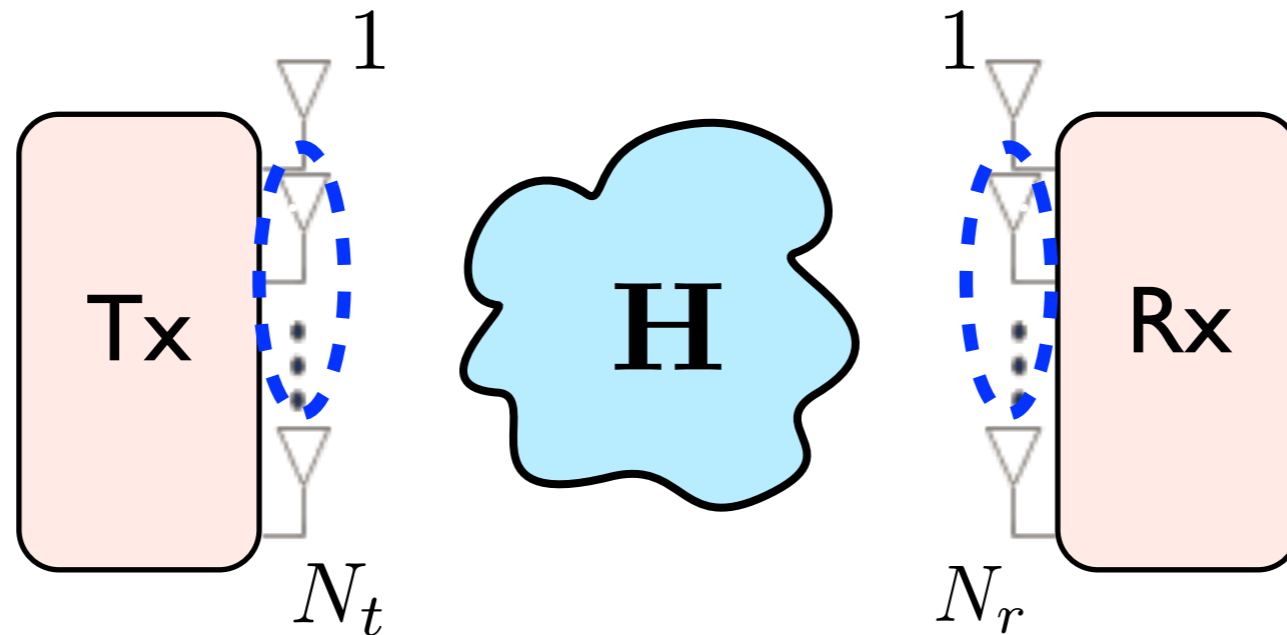
Point-to-Point MIMO Channel



Antenna Selection

- Transmit Side
- Receive Side

Point-to-Point MIMO Channel



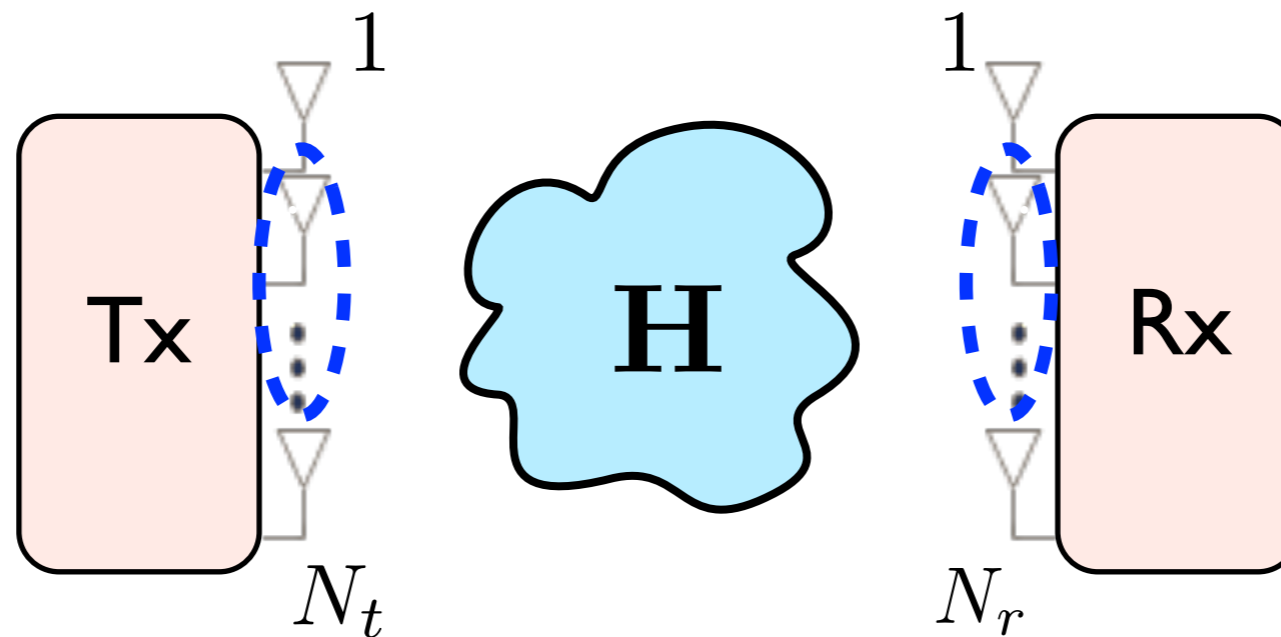
Antenna Selection

- Transmit Side
- Receive Side

Metrics

- Mutual Information
- Reliability

Point-to-Point MIMO Channel



Antenna Selection

- Transmit Side
- Receive Side

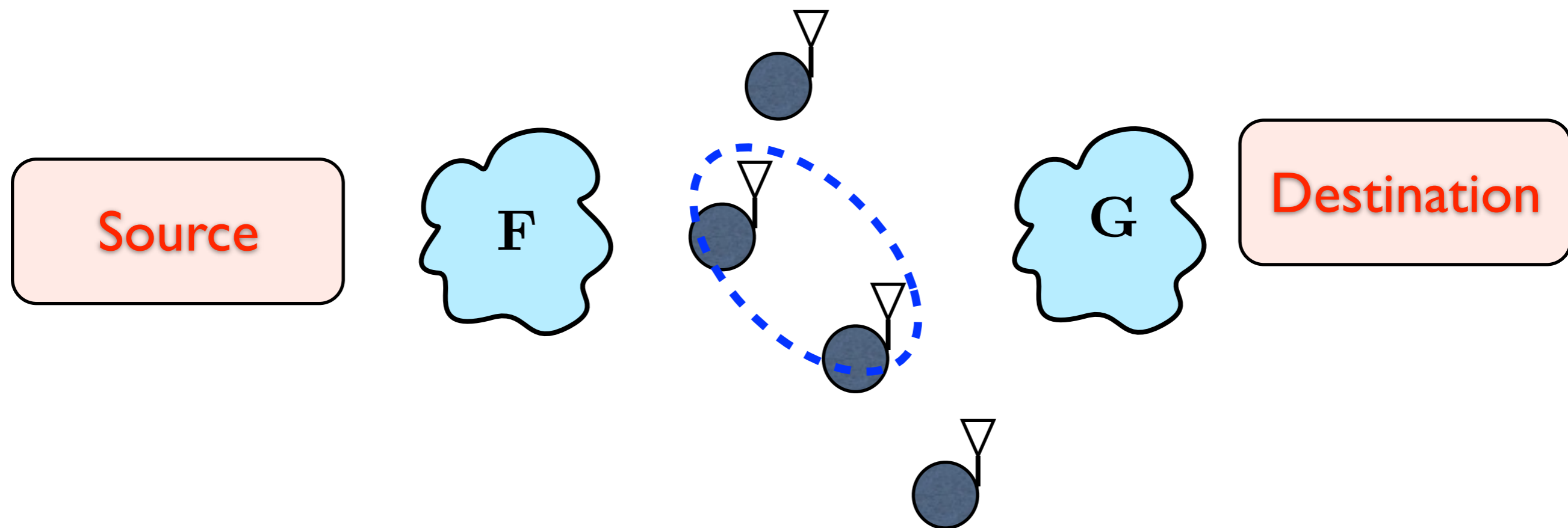
Metrics

- Mutual Information
- Reliability

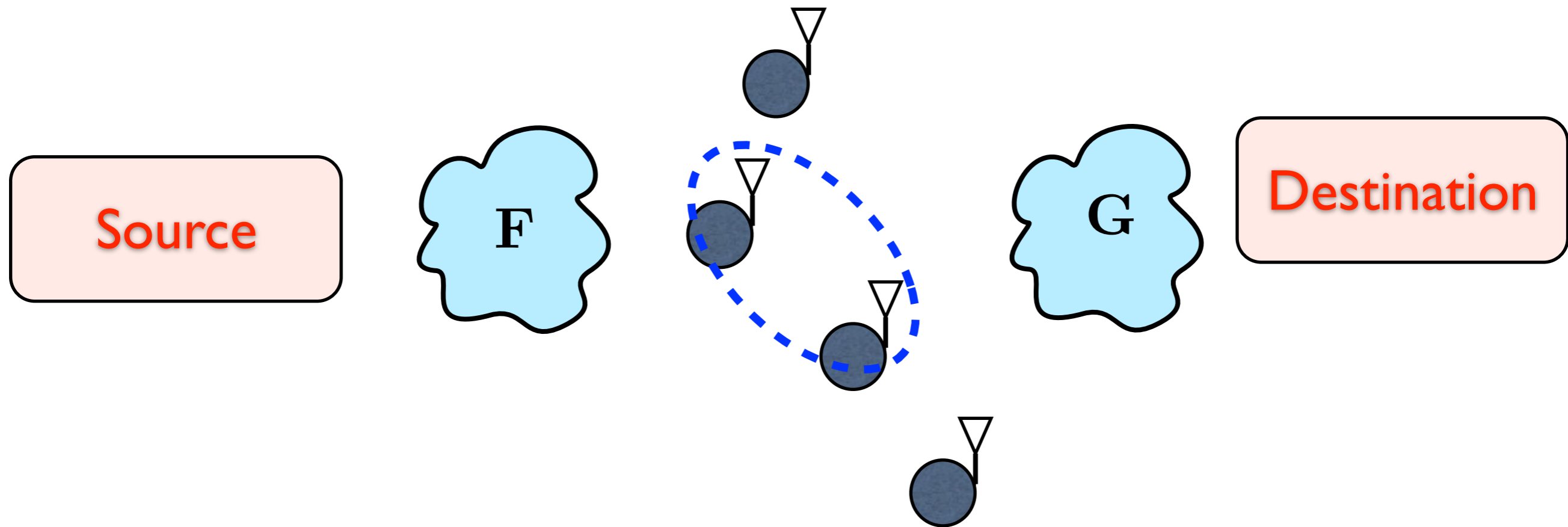
Advantages

- Simplified Circuitry
- Fewer Tx/Rx Chains

Relay Selection



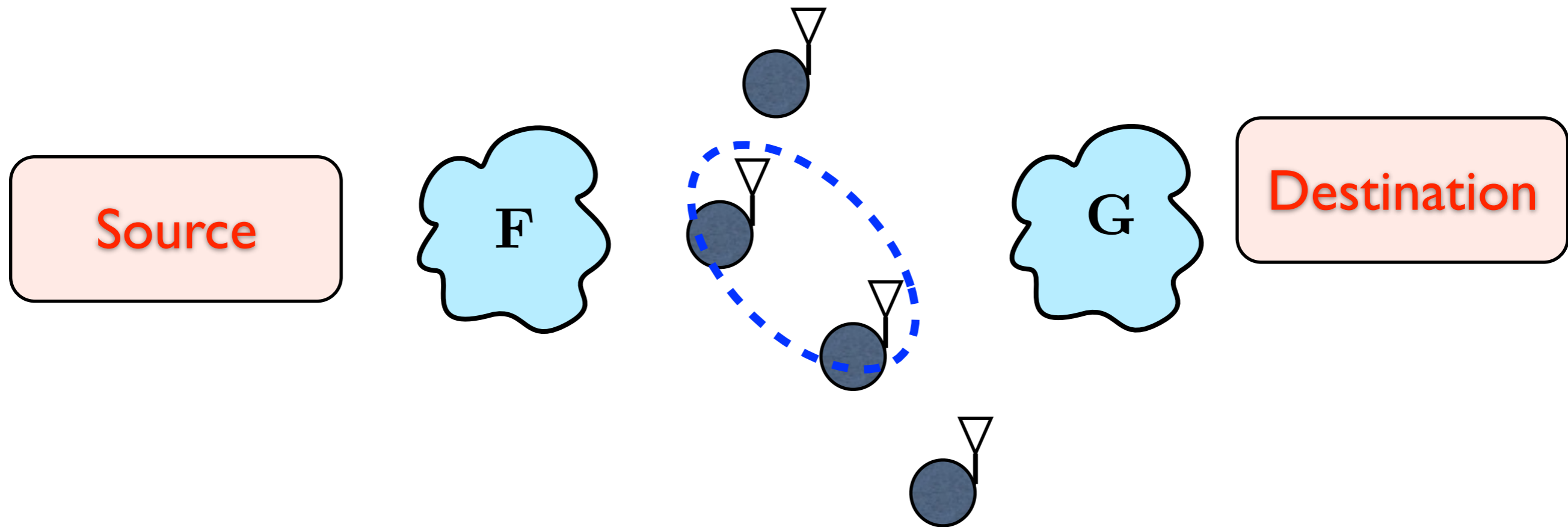
Relay Selection



Protocols

- Amplify-forward
- Decode-forward

Relay Selection



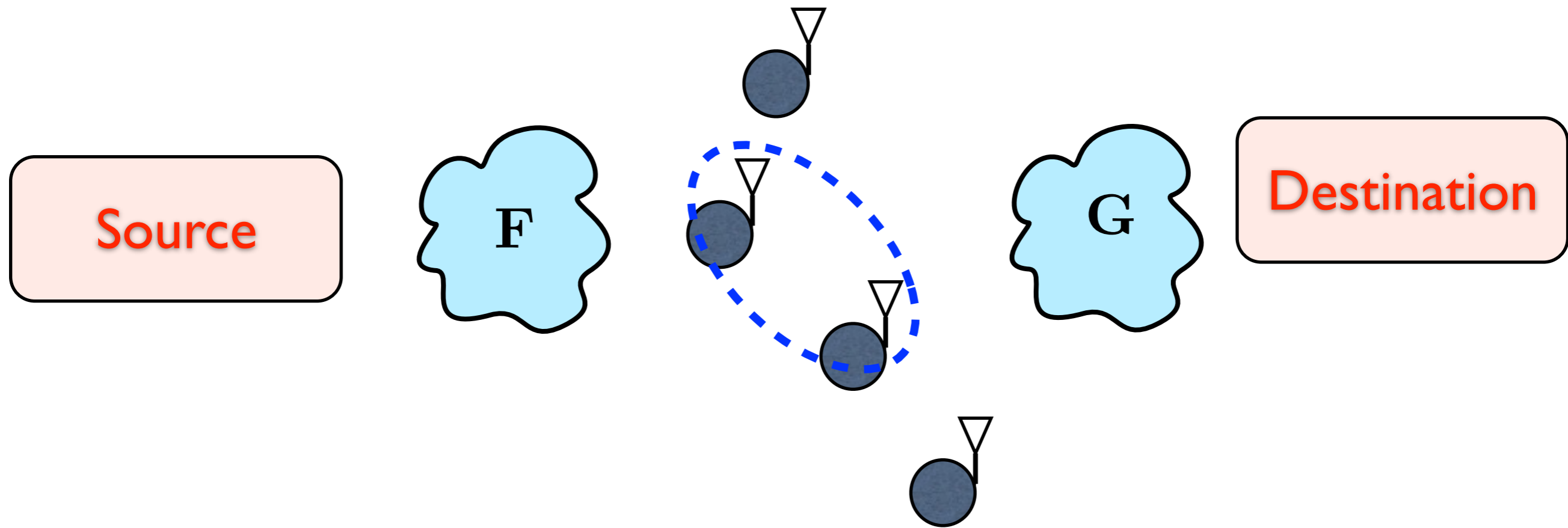
Protocols

- Amplify-forward
- Decode-forward

Metrics

- Mutual Information
- Reliability

Relay Selection



Protocols

- Amplify-forward
- Decode-forward

Metrics

- Mutual Information
- Reliability

Implementation

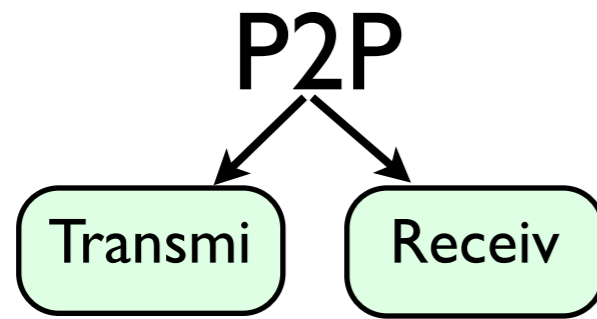
- Centralized
- Distributed

Prior Work

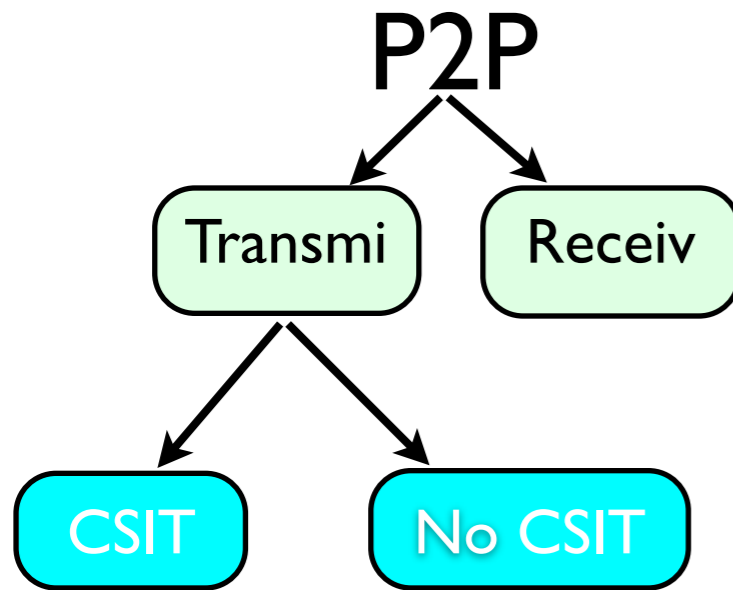
Prior Work

P2P

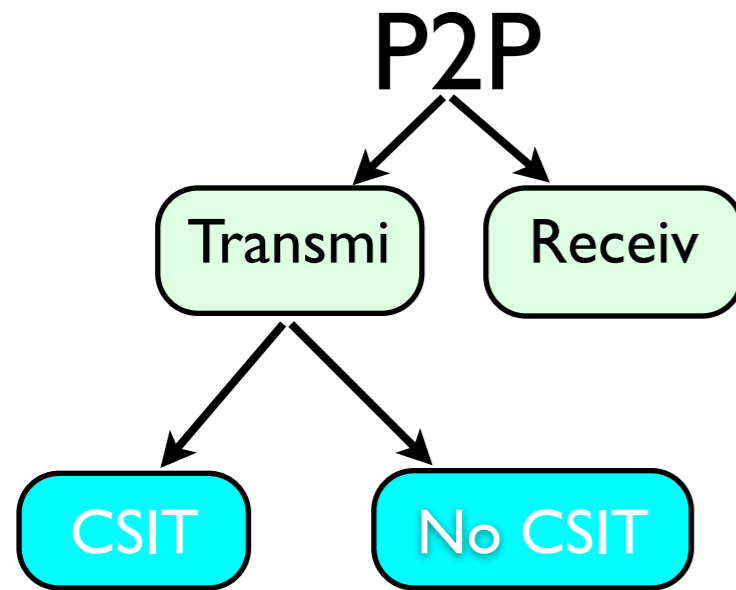
Prior Work



Prior Work

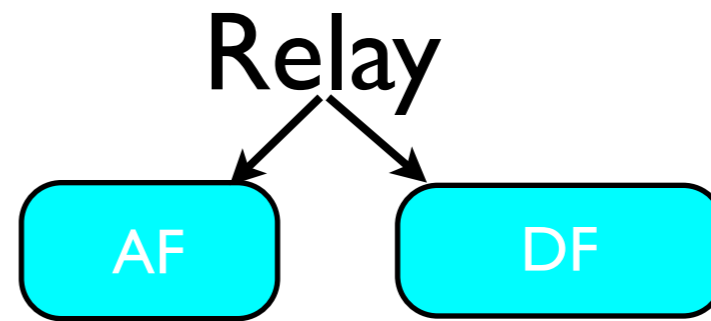
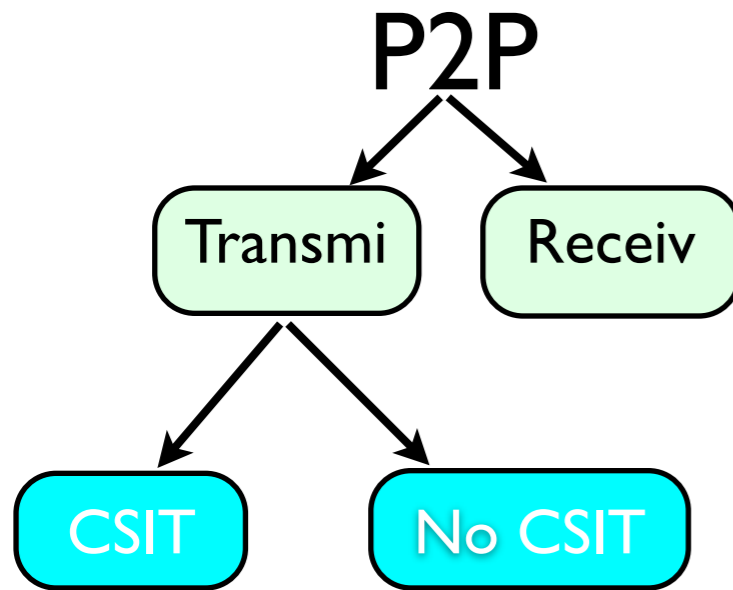


Prior Work

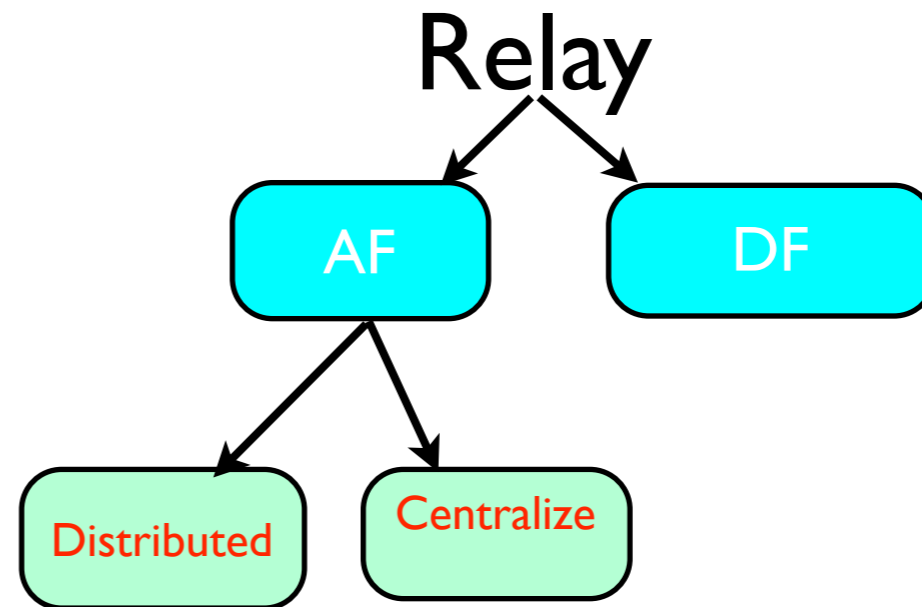
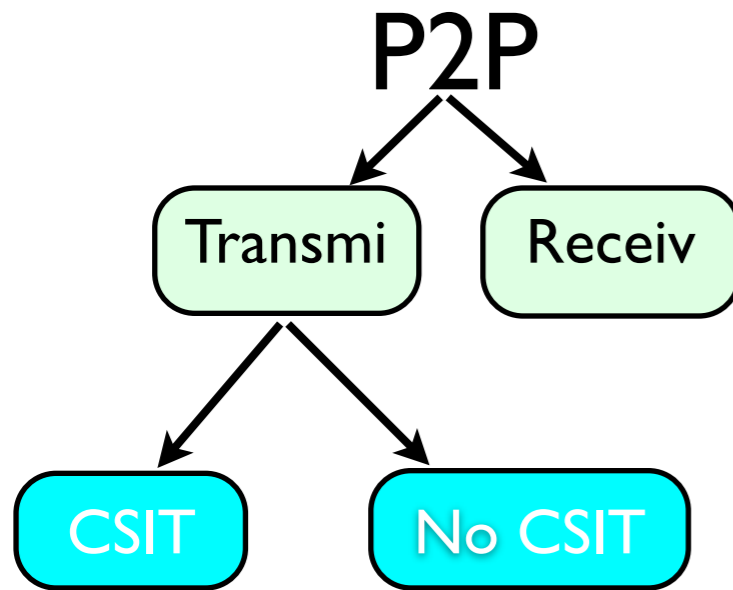


Relay

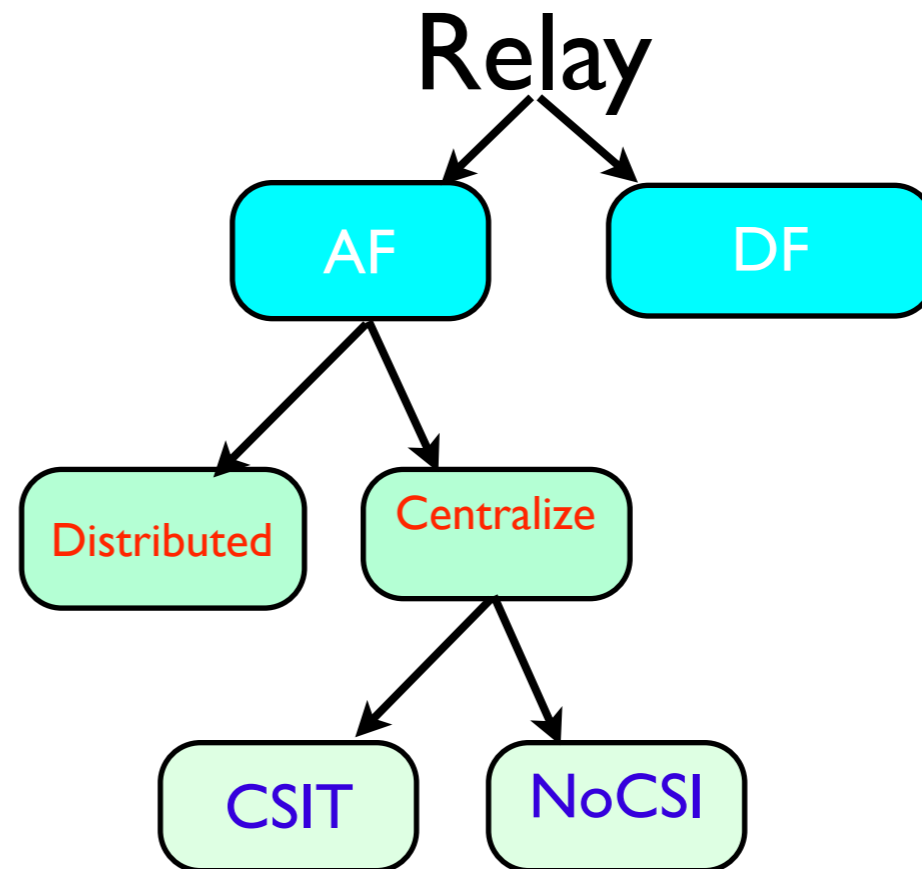
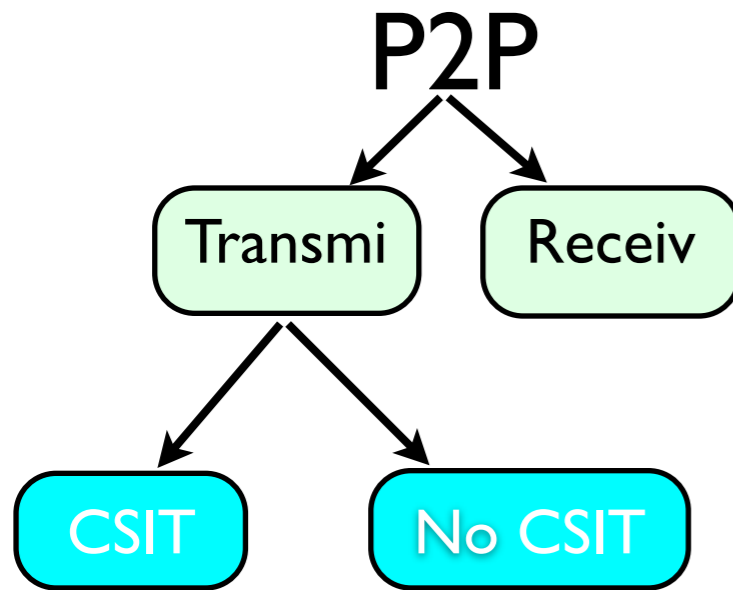
Prior Work



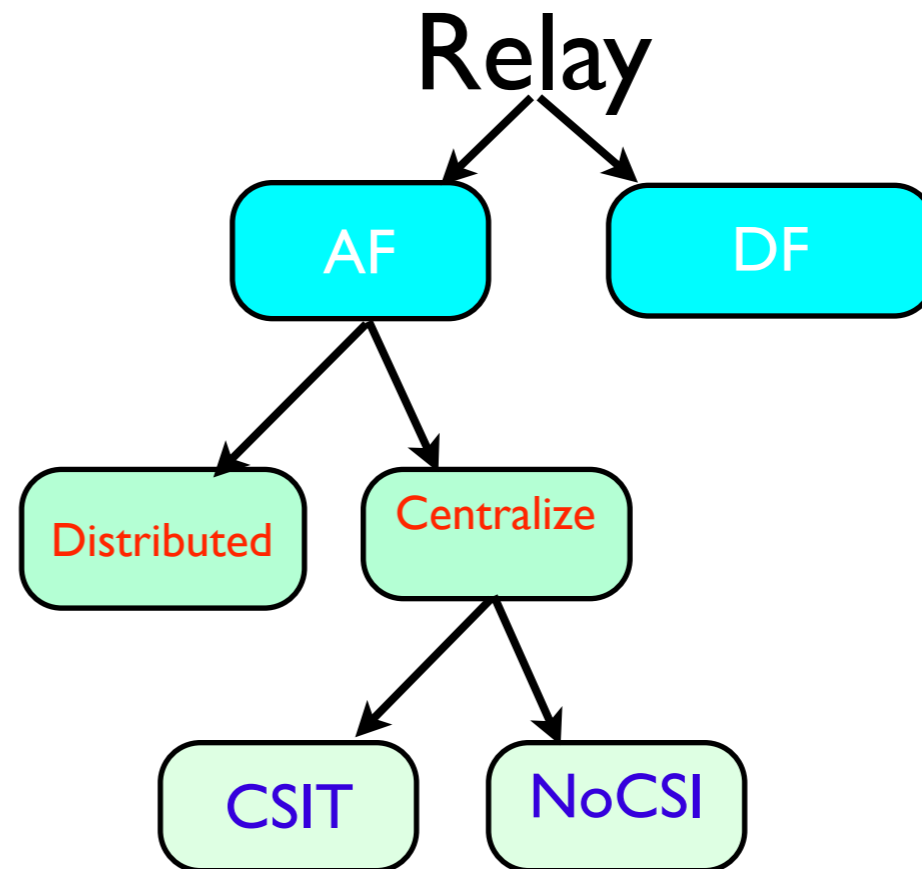
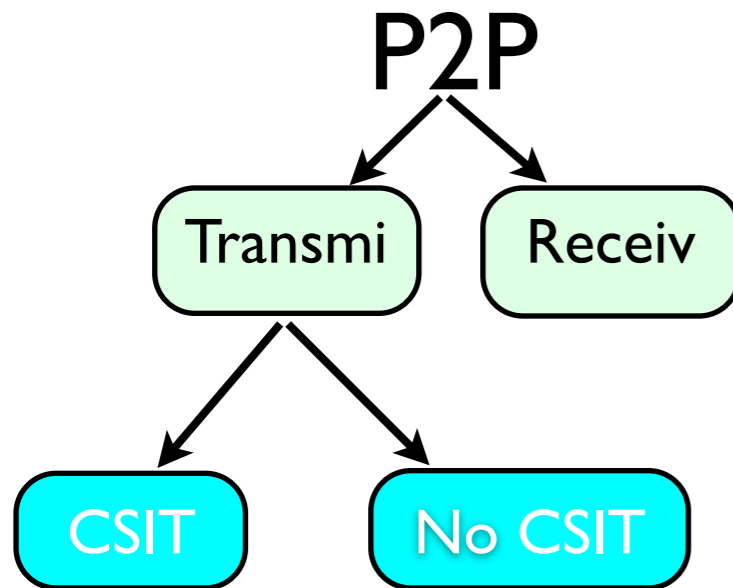
Prior Work



Prior Work



Prior Work



Lot of work assuming Genie-Aided Antenna Selection
No provably good simple algorithm for Antenna Selection

Implementation

- **Most analytical work assumes brute-force**
(exponential complexity)

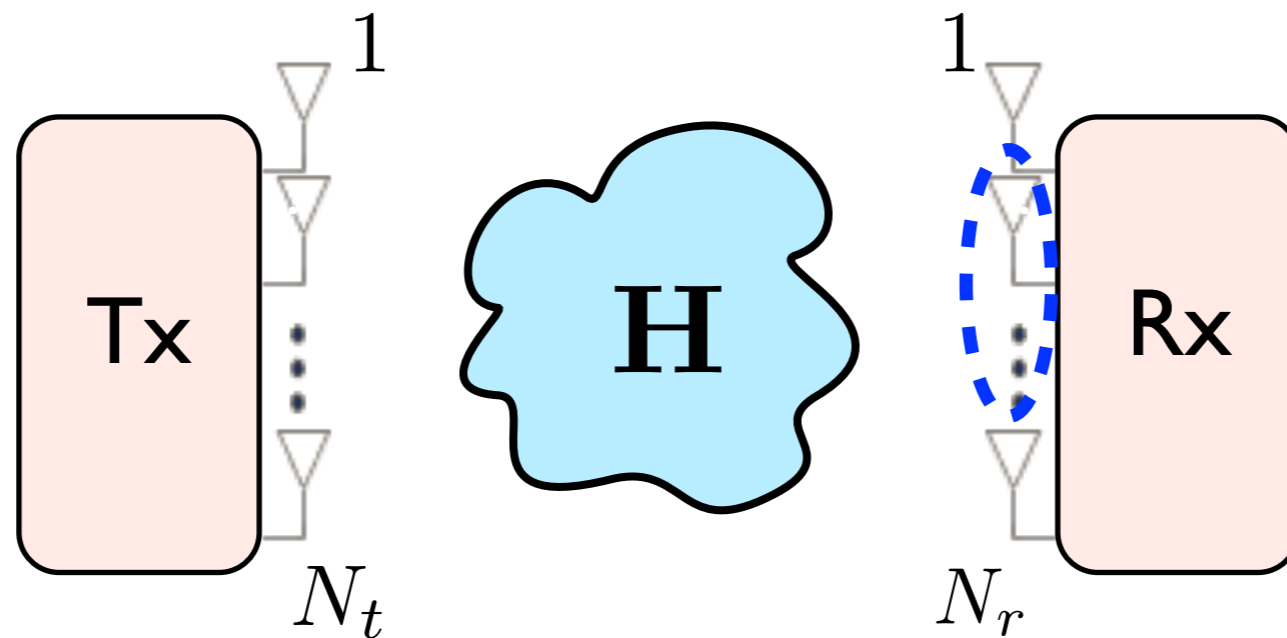
Implementation

- Most analytical work assumes brute-force (exponential complexity)
 - If subset size is L then number of computations $\binom{N_t}{L}$
Prohibitive for large antennas, e.g. Massive MIMO

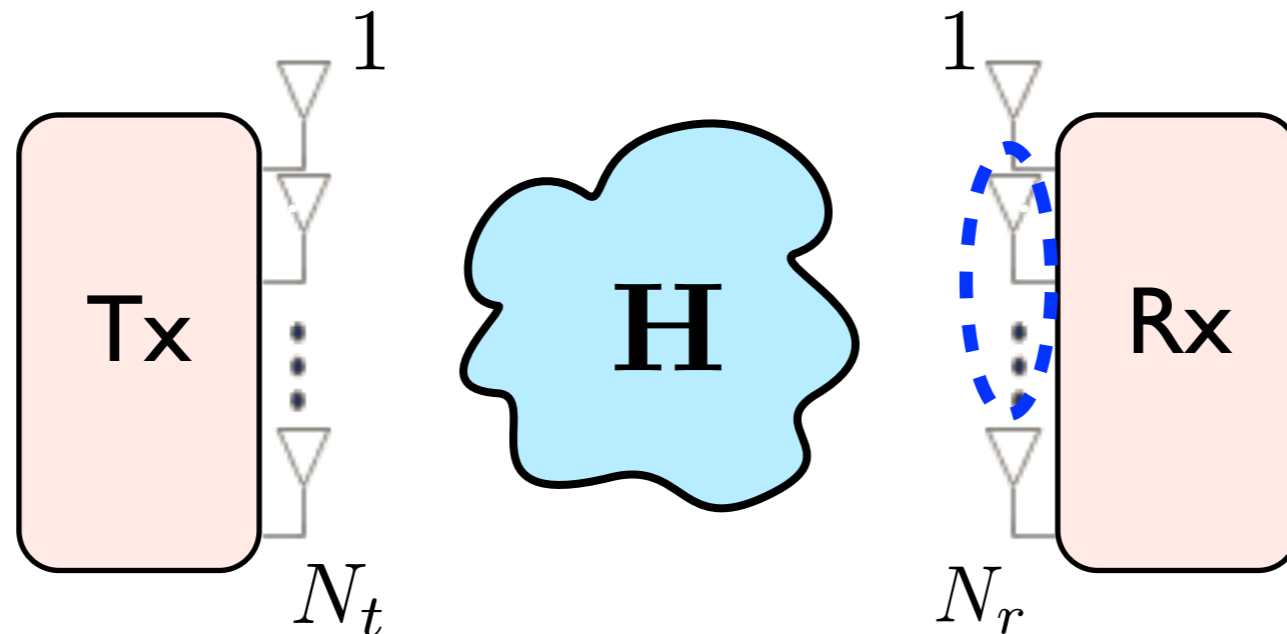
Implementation

- Most analytical work assumes brute-force (exponential complexity)
 - If subset size is L then number of computations $\binom{N_t}{L}$
Prohibitive for large antennas, e.g. Massive MIMO
- Lots of greedy/heuristic algorithms
 - No theoretical guarantees

Objective for Point-to-Point MIMO Channel



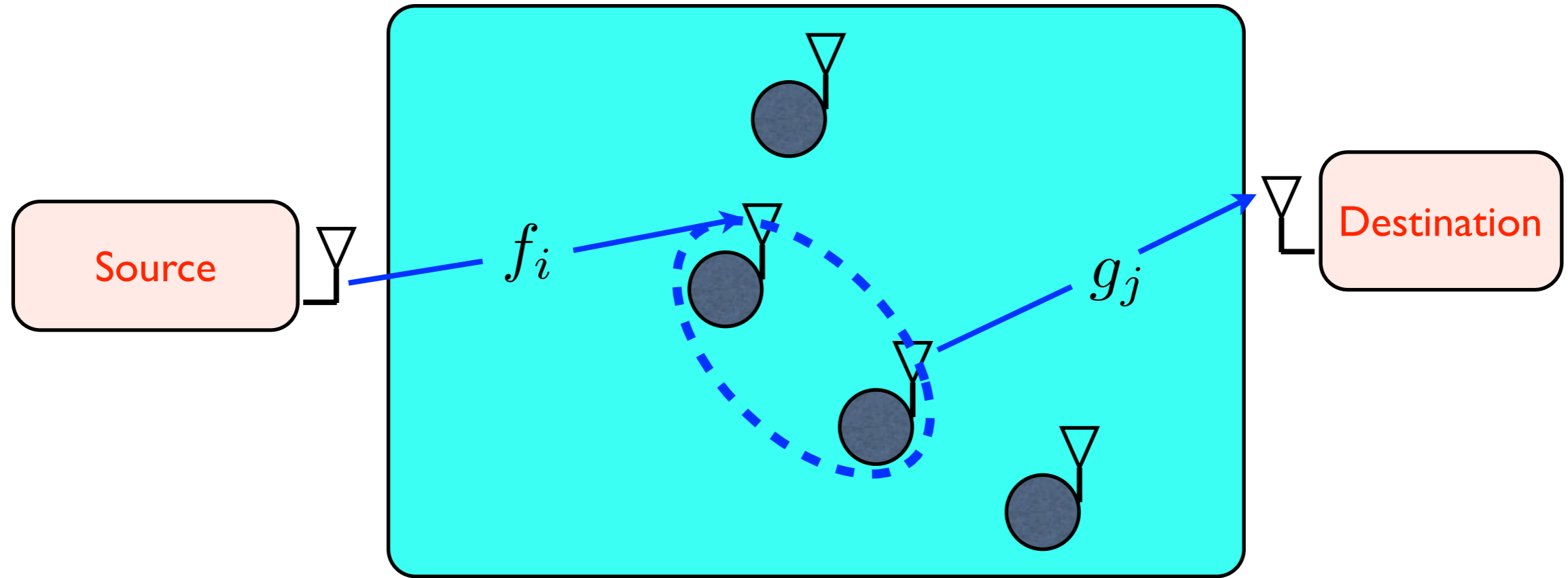
Objective for Point-to-Point MIMO Channel



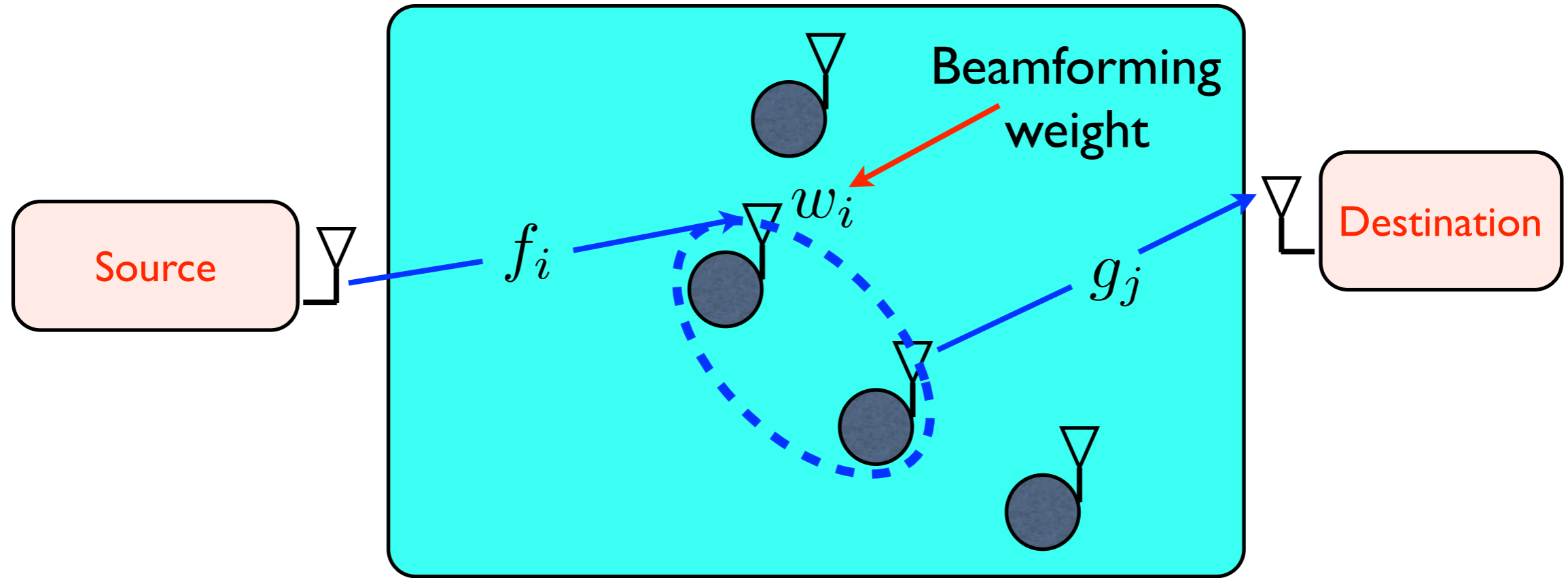
Find the size L **receive** antenna subset that maximizes the mutual information

$$\max_{\mathcal{R}_L \subset \{1, 2, \dots, N_r\}, |\mathcal{R}_L| = L} \log \det \left(\mathbf{I} + \frac{P}{N_t} \mathbf{H}_{\mathcal{R}_L} \mathbf{H}_{\mathcal{R}_L}^\dagger \right)$$

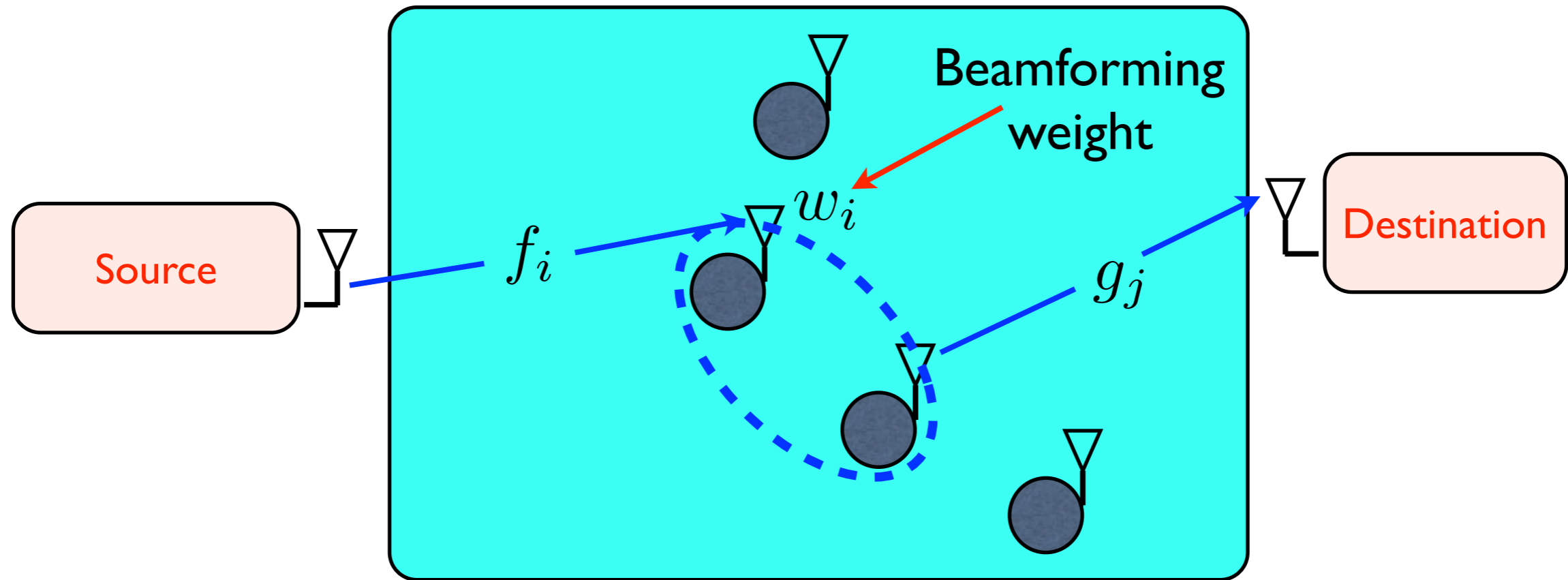
Objective for Relay Selection



Objective for Relay Selection



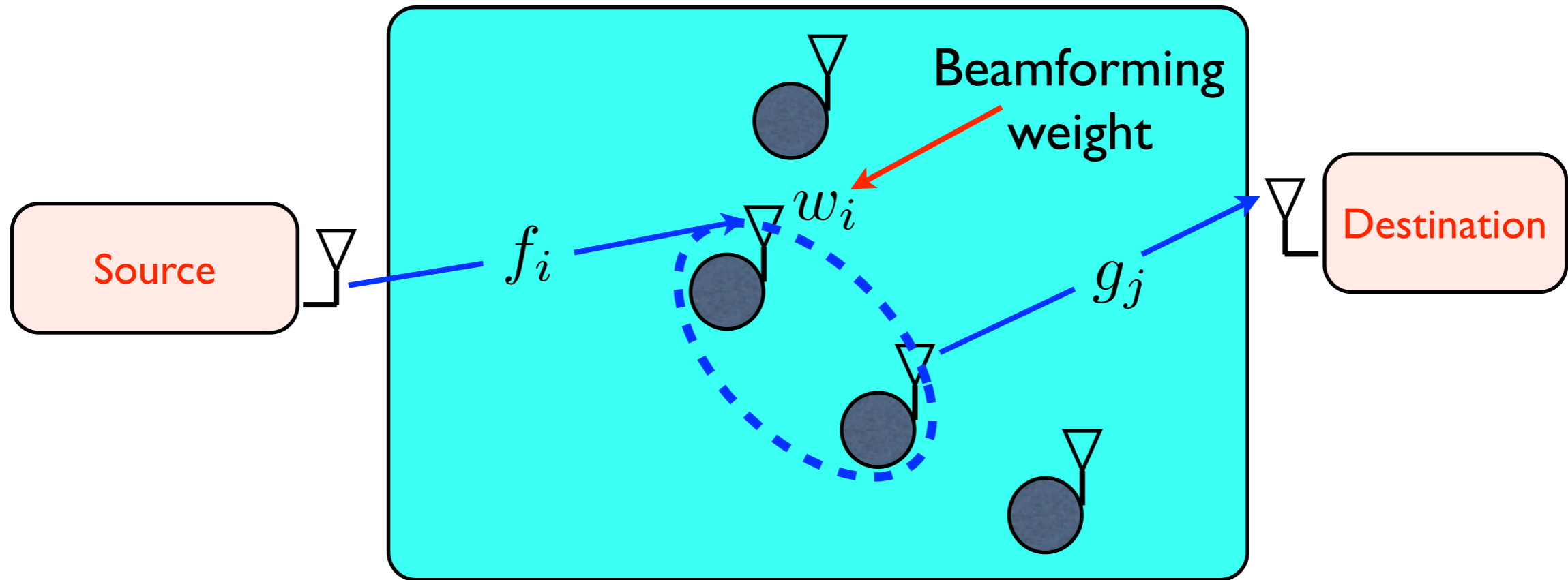
Objective for Relay Selection



Find the size L **relay antennas** subset that maximizes the mutual information

$$\max_{\mathcal{T}_L \subseteq \{1, 2, \dots, N\}} \max_{\mathbf{w}} \log \left(1 + \frac{\mathbf{w}^\dagger \Delta \Delta^\dagger \mathbf{w}}{\mathbf{w}^\dagger (\Sigma \Sigma^\dagger + \mathbf{I}) \mathbf{w}} \right)$$

Objective for Relay Selection



Find the size L **relay antennas** subset that maximizes the mutual information

$$\max_{\mathcal{T}_L \subseteq \{1, 2, \dots, N\}} \max_{\mathbf{w}} \log \left(1 + \frac{\mathbf{w}^\dagger \Delta \Delta^\dagger \mathbf{w}}{\mathbf{w}^\dagger (\Sigma \Sigma^\dagger + \mathbf{I}) \mathbf{w}} \right)$$

$$\Delta = \left[\frac{g_{t_1} f_{t_1}}{\gamma_{t_1}}, \dots, \frac{g_{t_L} f_{t_L}}{\gamma_{t_L}} \right]^T,$$

$$\mathbf{w} = [w_{t_1}, \dots, w_{t_L}]^T,$$

Our Contribution

Our Contribution

P2P

Greedy Algorithm with linear complexity achieves at least $(1 - 1/e)$ fraction of the optimal solution

Our Contribution

P2P

Greedy Algorithm with linear complexity achieves at least $(1 - 1/e)$ fraction of the optimal solution

Implication: Genie-aided analysis holds

Our Contribution

P2P

Greedy Algorithm with linear complexity achieves at least $(1 - 1/e)$ fraction of the optimal solution

Implication: Genie-aided analysis holds

Relay

Greedy Algorithm with linear complexity achieves the optimal solution

Some Preliminaries

Some Preliminaries

Let $f : 2^U \rightarrow \mathbb{R}$

Some Preliminaries

Let $f : 2^U \rightarrow \mathbb{R}$

Then f is called *monotone* if $f(S \cup \{a\}) \geq f(S)$. $S \subset U$, $a \in U$

Some Preliminaries

Let $f : 2^U \rightarrow \mathbb{R}$

Then f is called *monotone* if $f(S \cup \{a\}) \geq f(S)$. $S \subset U$, $a \in U$

Then f is called *sub-modular* if

Some Preliminaries

Let $f : 2^U \rightarrow \mathbb{R}$

Then f is called *monotone* if $f(S \cup \{a\}) \geq f(S)$. $S \subset U$, $a \in U$

Then f is called *sub-modular* if

$$f(S \cup \{a\}) - f(S) \geq f(T \cup \{a\}) - f(T), \quad S \subseteq T.$$

Some Preliminaries

Let $f : 2^U \rightarrow \mathbb{R}$

Then f is called *monotone* if $f(S \cup \{a\}) \geq f(S)$. $S \subset U$, $a \in U$

Then f is called *sub-modular* if

$$f(S \cup \{a\}) - f(S) \geq f(T \cup \{a\}) - f(T), \quad S \subseteq T.$$

Diminishing Returns Property: Value of adding an element to smaller set is more than that of the bigger set

Some Preliminaries

Let $f : 2^U \rightarrow \mathbb{R}$

Then f is called *monotone* if $f(S \cup \{a\}) \geq f(S)$. $S \subset U$, $a \in U$

Then f is called *sub-modular* if

$$f(S \cup \{a\}) - f(S) \geq f(T \cup \{a\}) - f(T), \quad S \subseteq T.$$

Diminishing Returns Property: Value of adding an element to smaller set is more than that of the bigger set

Then f is called *modular* if

Some Preliminaries

Let $f : 2^U \rightarrow \mathbb{R}$

Then f is called *monotone* if $f(S \cup \{a\}) \geq f(S)$. $S \subset U$, $a \in U$

Then f is called *sub-modular* if

$$f(S \cup \{a\}) - f(S) \geq f(T \cup \{a\}) - f(T), \quad S \subseteq T.$$

Diminishing Returns Property: Value of adding an element to smaller set is more than that of the bigger set

Then f is called *modular* if

$$f(S \cup \{a\}) - f(S) = f(T \cup \{a\}) - f(T), \quad S \subseteq T.$$

Some Preliminaries

Let $f : 2^U \rightarrow \mathbb{R}$

Then f is called *monotone* if $f(S \cup \{a\}) \geq f(S)$. $S \subset U$, $a \in U$

Then f is called *sub-modular* if

$$f(S \cup \{a\}) - f(S) \geq f(T \cup \{a\}) - f(T), \quad S \subseteq T.$$

Diminishing Returns Property: Value of adding an element to smaller set is more than that of the bigger set

Then f is called *modular* if

$$f(S \cup \{a\}) - f(S) = f(T \cup \{a\}) - f(T), \quad S \subseteq T.$$

Non-Diminishing Returns Property: Value of adding an element to smaller set is equal to the bigger set

Why Sub-Modular Functions ?

Greedy Method : *At each step add an element that maximizes the incremental gain.*

Why Sub-Modular Functions ?

Greedy Method : *At each step add an element that maximizes the incremental gain.*

Theorem (Nemhauser et. al. 1978): *If f is **monotone** and **sub-modular**, then the greedy method achieves at least $(1 - 1/e)$ fraction of the optimal solution.*

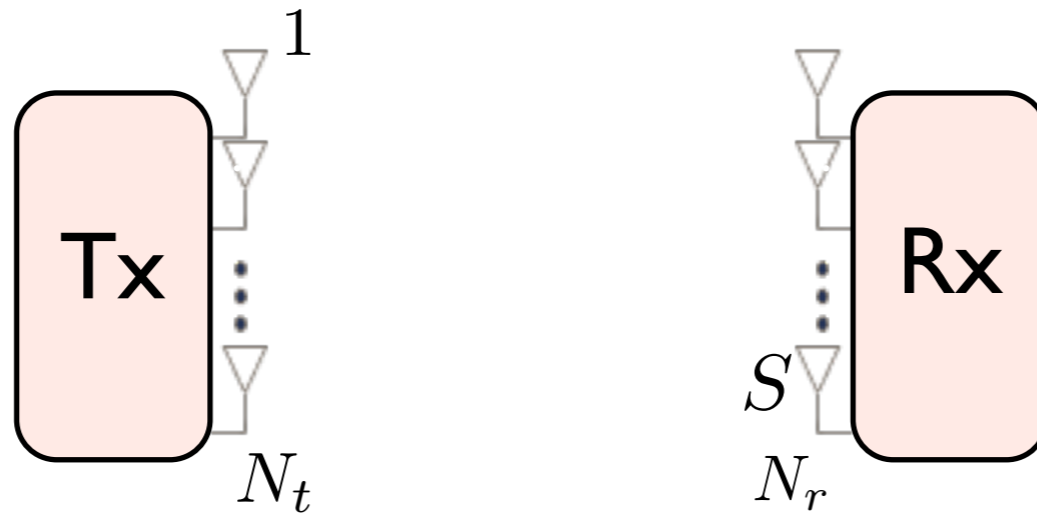
Why Sub-Modular Functions ?

Greedy Method : At each step add an element that maximizes the incremental gain.

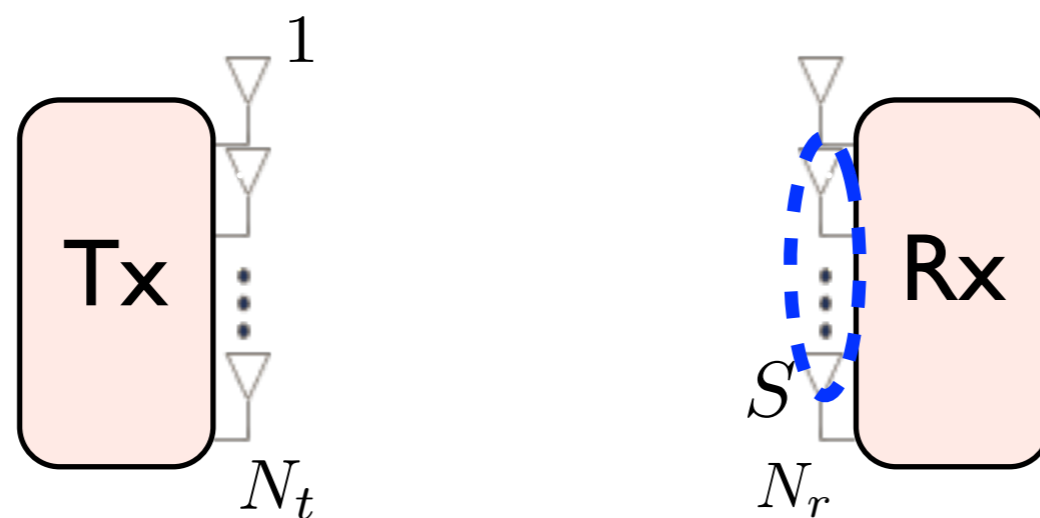
Theorem (Nemhauser et. al. 1978): If f is **monotone** and **sub-modular**, then the greedy method achieves at least $(1 - 1/e)$ fraction of the optimal solution.

Theorem (Rado 1968, Edmonds 1971): If f is **monotone** and **modular**, then the greedy method achieves the optimal solution.

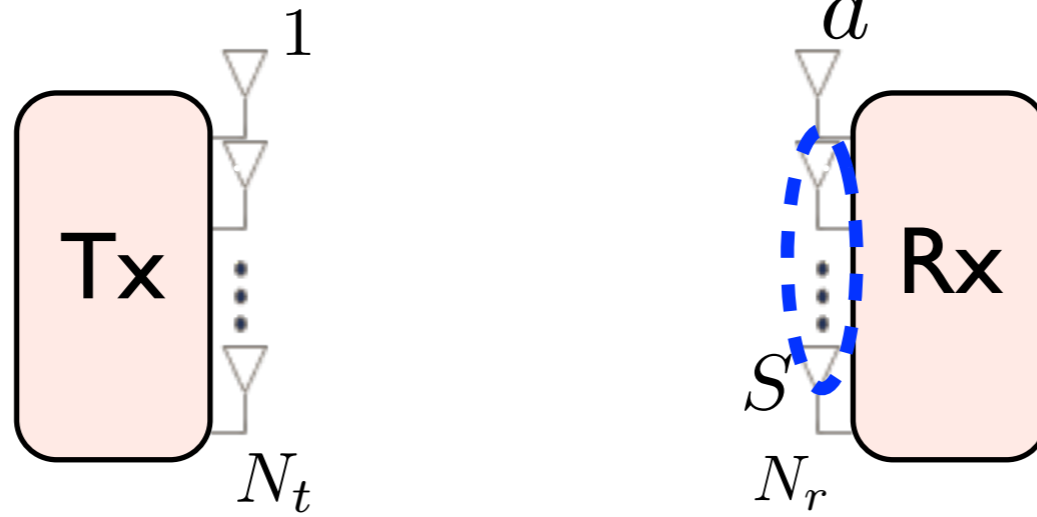
Receive Antenna Selection is Sub-Modular



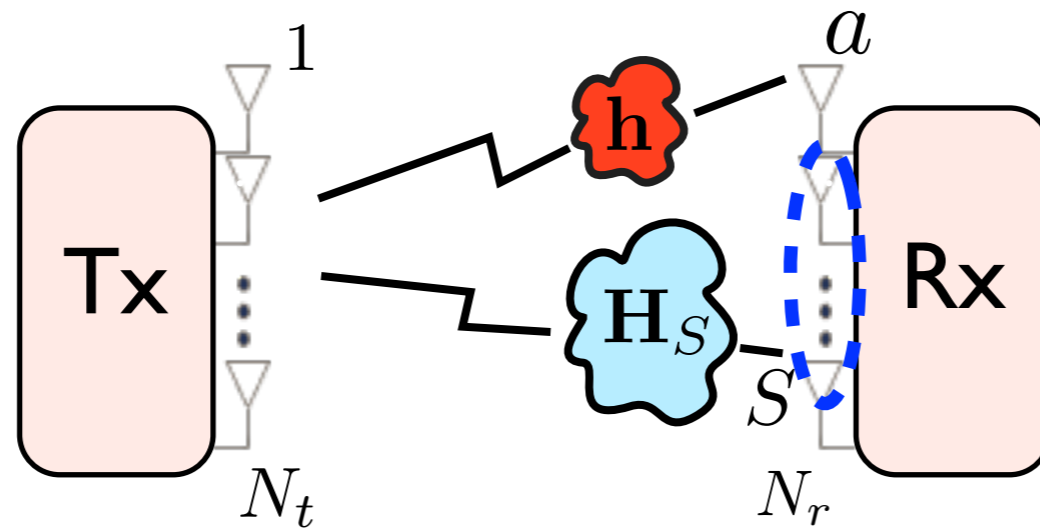
Receive Antenna Selection is Sub-Modular



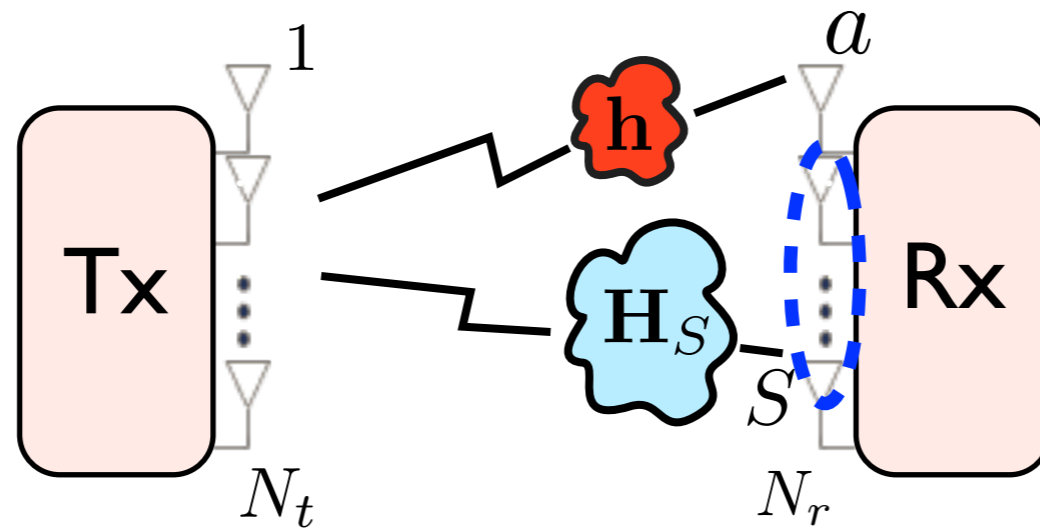
Receive Antenna Selection is Sub-Modular



Receive Antenna Selection is Sub-Modular

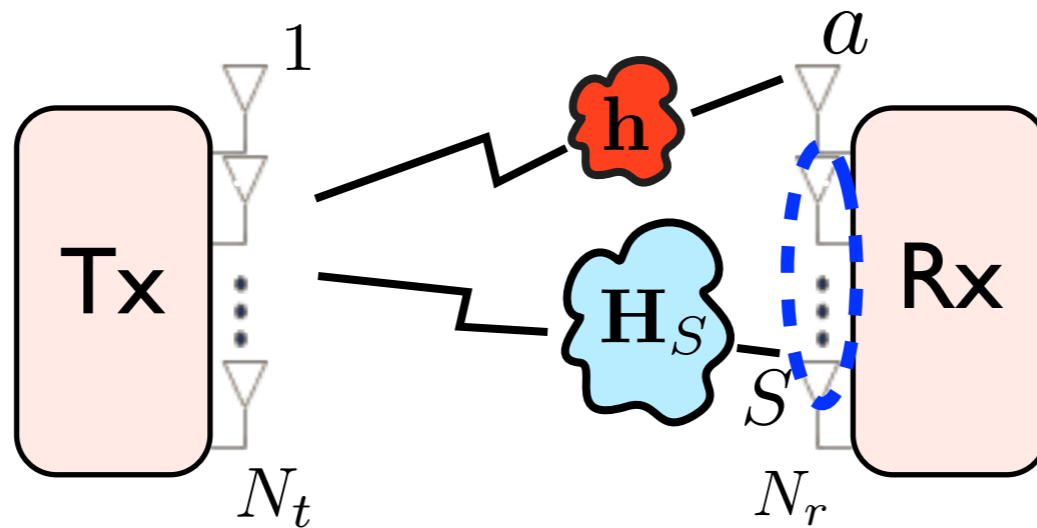


Receive Antenna Selection is Sub-Modular



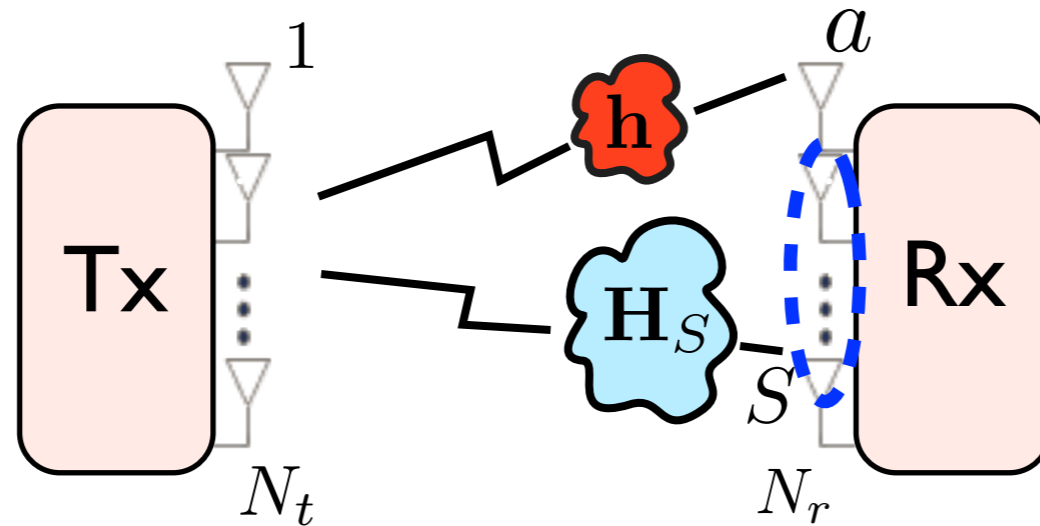
$$f(S \cup \{a\}) - f(S) = \log \det \left(\mathbf{I}_{|S|+1} + \frac{P}{N_t} \begin{bmatrix} \mathbf{H}_S \\ \mathbf{h} \end{bmatrix} [\mathbf{H}_S^\dagger \quad \mathbf{h}^\dagger] \right) - \log \det \left(\mathbf{I}_{|S|} + \frac{P}{N_t} \mathbf{H}_S \mathbf{H}_S^\dagger \right),$$

Receive Antenna Selection is Sub-Modular



$$\begin{aligned}
 f(S \cup \{a\}) - f(S) &= \log \det \left(\mathbf{I}_{|S|+1} + \frac{P}{N_t} \begin{bmatrix} \mathbf{H}_S \\ \mathbf{h} \end{bmatrix} [\mathbf{H}_S^\dagger \quad \mathbf{h}^\dagger] \right) - \log \det \left(\mathbf{I}_{|S|} + \frac{P}{N_t} \mathbf{H}_S \mathbf{H}_S^\dagger \right), \\
 &= \log \det \left(\mathbf{I}_{N_t} + \frac{P}{N_t} [\mathbf{H}_S^\dagger \quad \mathbf{h}^\dagger] \begin{bmatrix} \mathbf{H}_S \\ \mathbf{h} \end{bmatrix} \right) - \log \det \left(\mathbf{I}_{N_t} + \frac{P}{N_t} \mathbf{H}_S^\dagger \mathbf{H}_S \right)
 \end{aligned}$$

Receive Antenna Selection is Sub-Modular

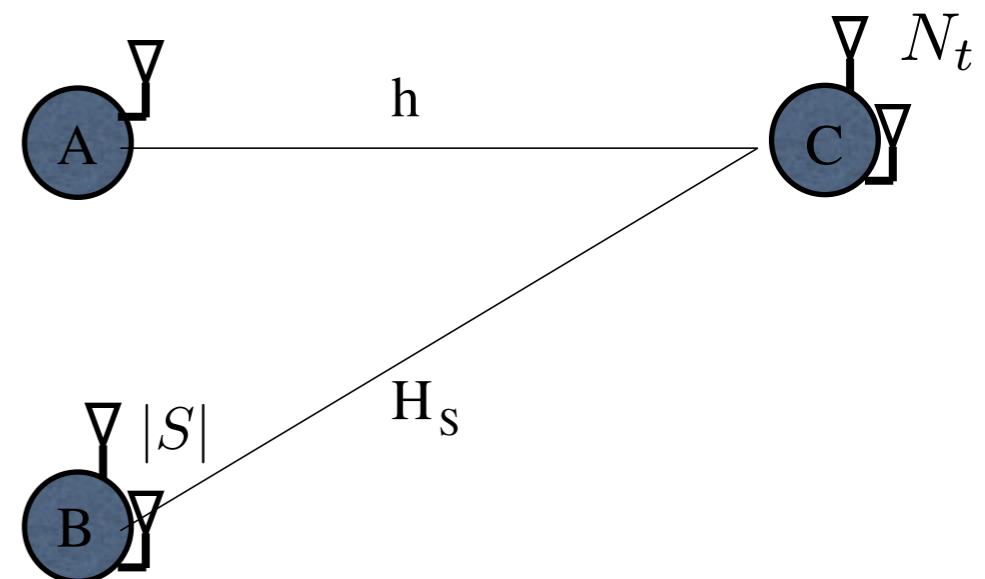


$$f(S \cup \{a\}) - f(S) = \log \det \left(\mathbf{I}_{|S|+1} + \frac{P}{N_t} \begin{bmatrix} \mathbf{H}_S \\ \mathbf{h} \end{bmatrix} [\mathbf{H}_S^\dagger \quad \mathbf{h}^\dagger] \right) - \log \det \left(\mathbf{I}_{|S|} + \frac{P}{N_t} \mathbf{H}_S \mathbf{H}_S^\dagger \right),$$

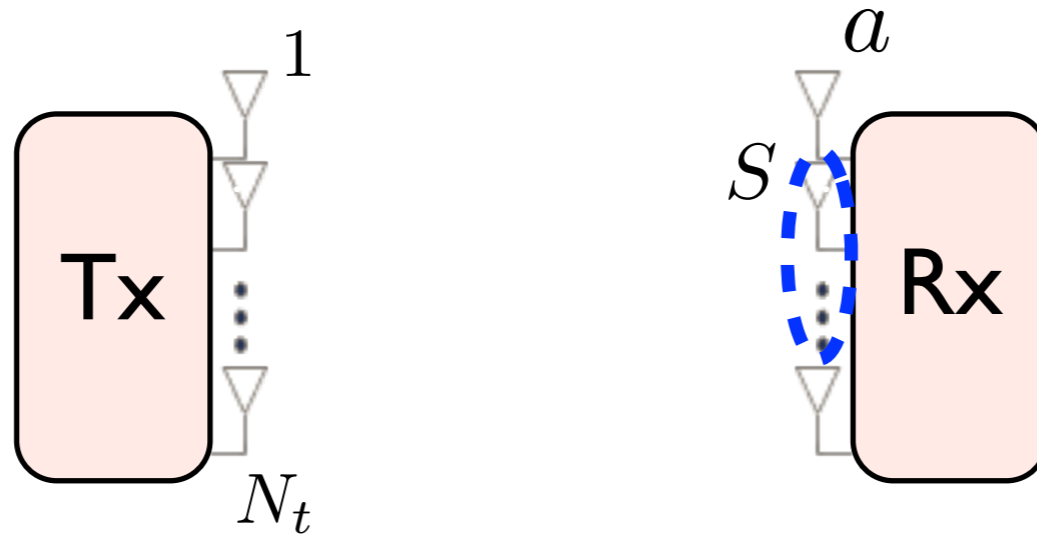
$$= \log \det \left(\mathbf{I}_{N_t} + \frac{P}{N_t} [\mathbf{H}_S^\dagger \quad \mathbf{h}^\dagger] \begin{bmatrix} \mathbf{H}_S \\ \mathbf{h} \end{bmatrix} \right) - \log \det \left(\mathbf{I}_{N_t} + \frac{P}{N_t} \mathbf{H}_S^\dagger \mathbf{H}_S \right)$$

$$f(S \cup \{a\}) - f(S)$$

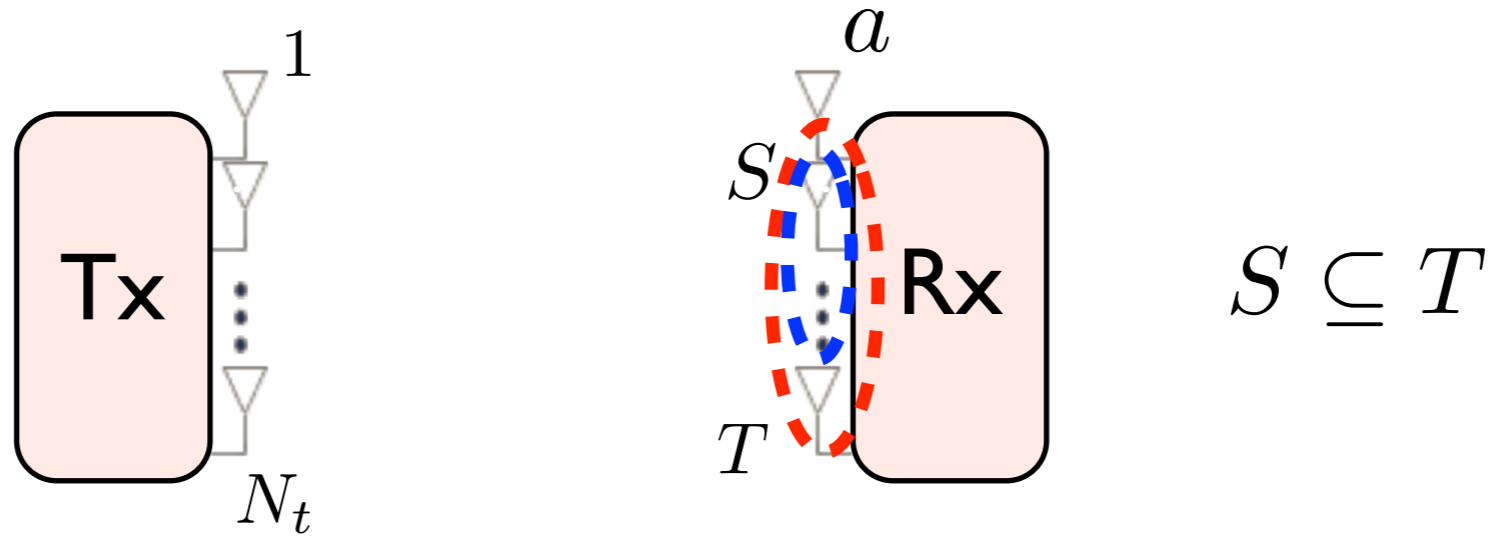
Mutual Information
between **A** and **C** with
Gaussian Signalling



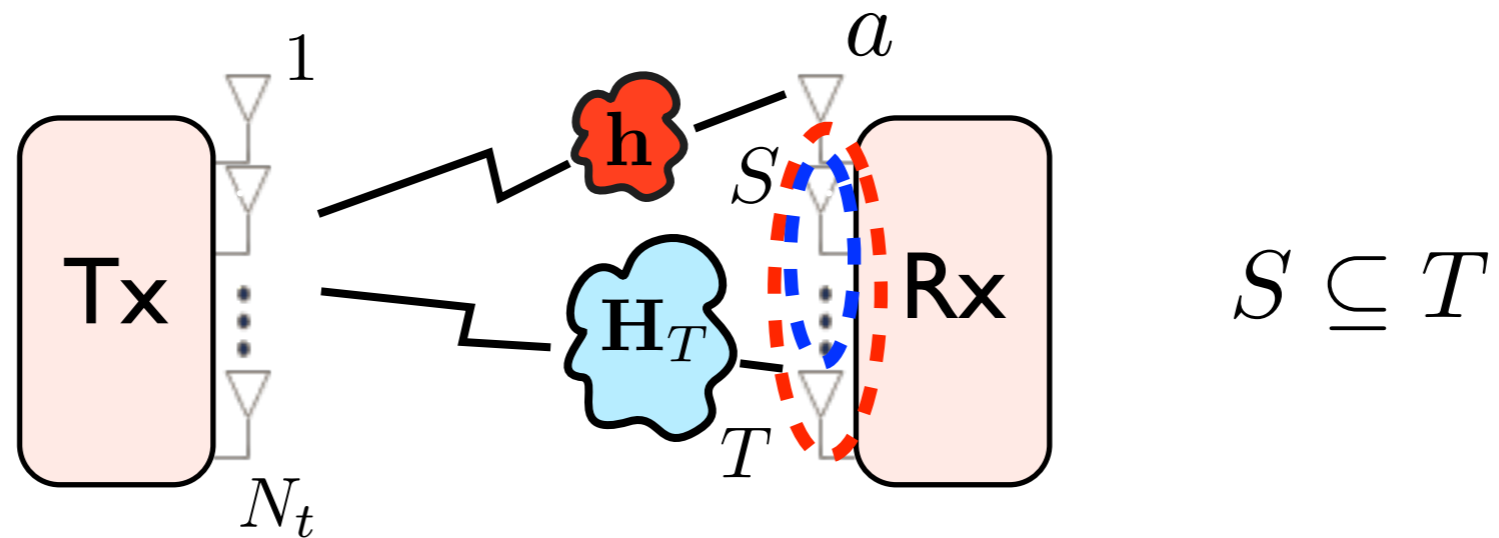
Receive Antenna Selection is Sub-Modular



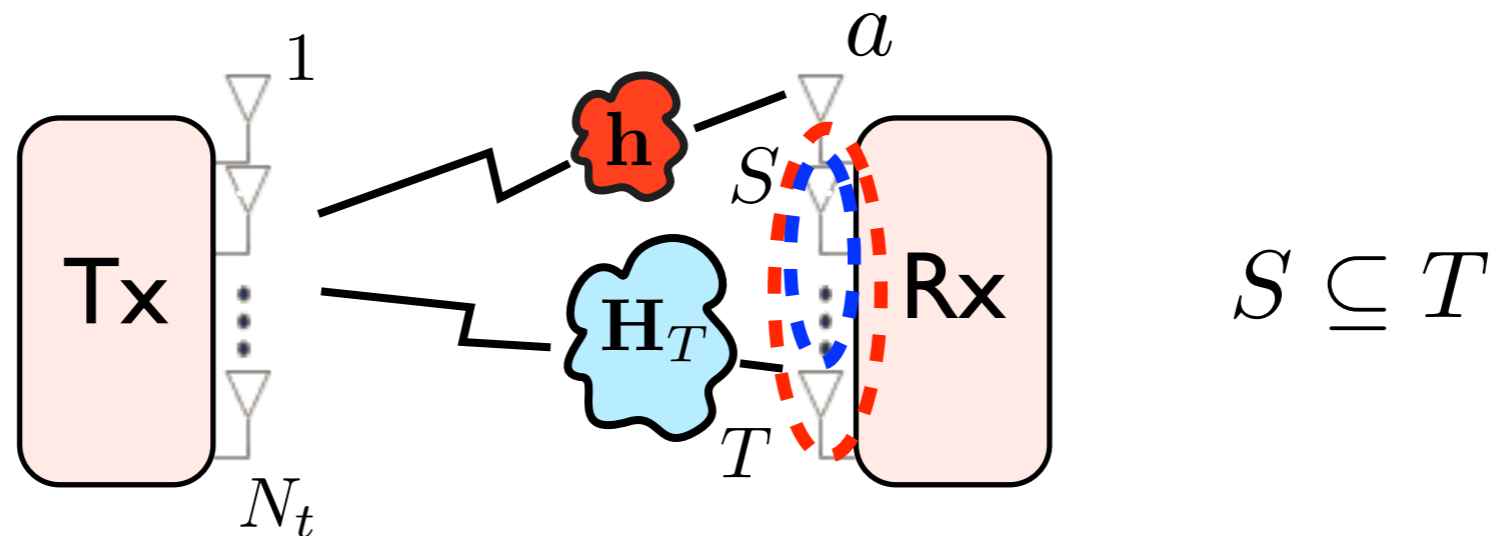
Receive Antenna Selection is Sub-Modular



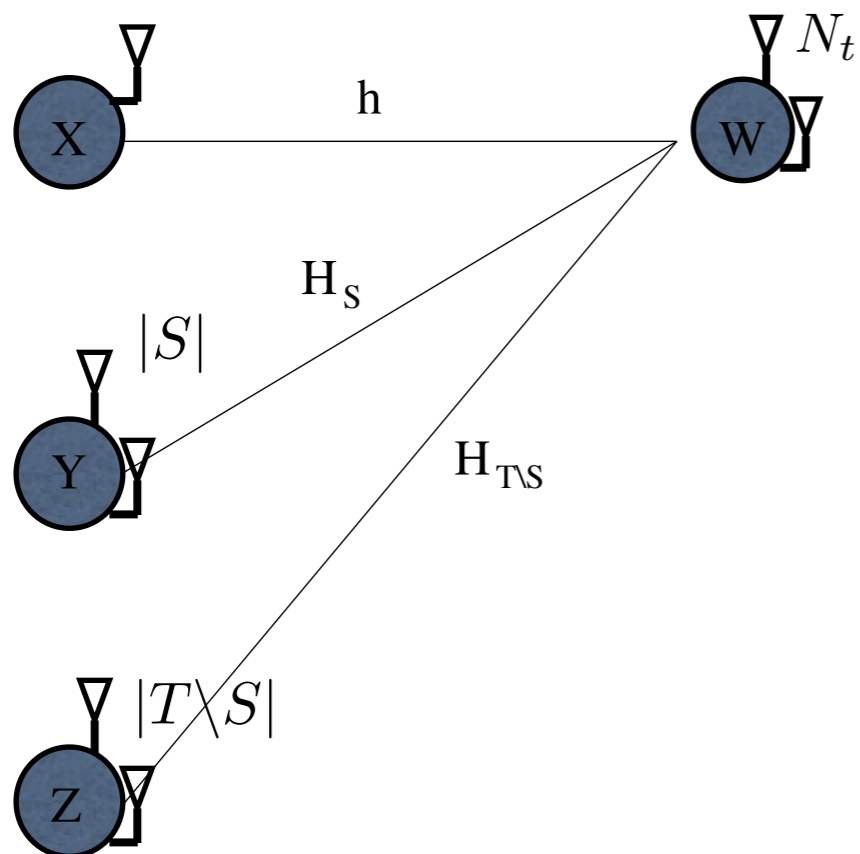
Receive Antenna Selection is Sub-Modular



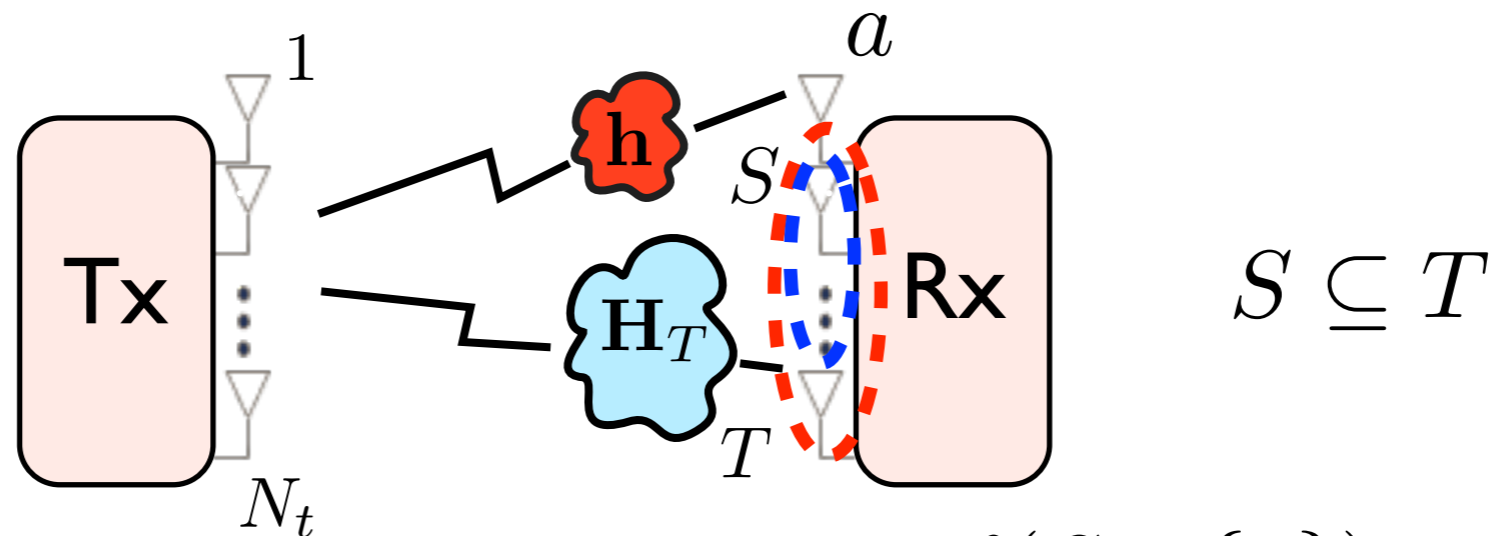
Receive Antenna Selection is Sub-Modular



$f(T \cup \{a\}) - f(T)$
 is Mutual Information
 between **X** and **W**

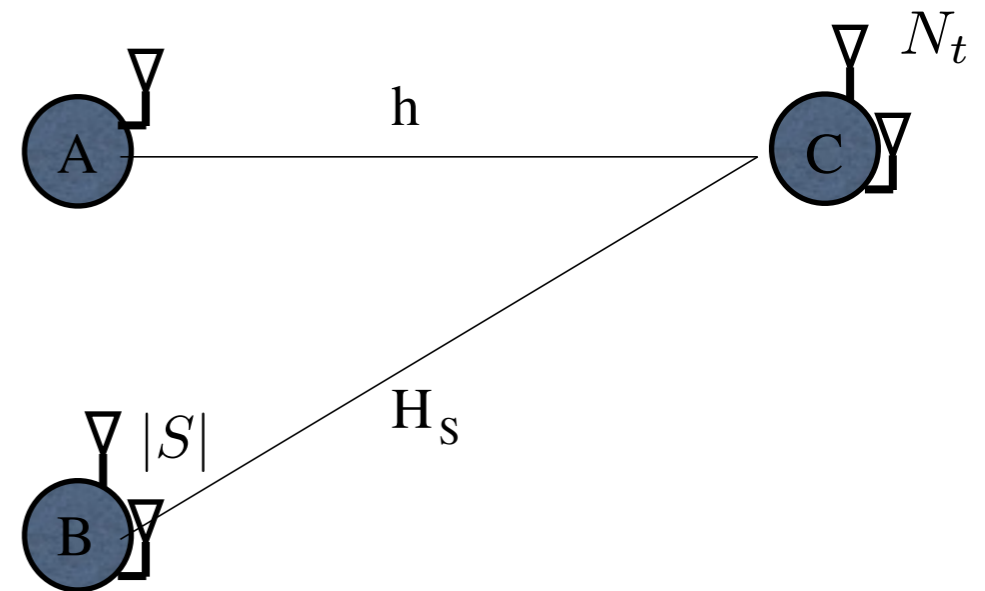
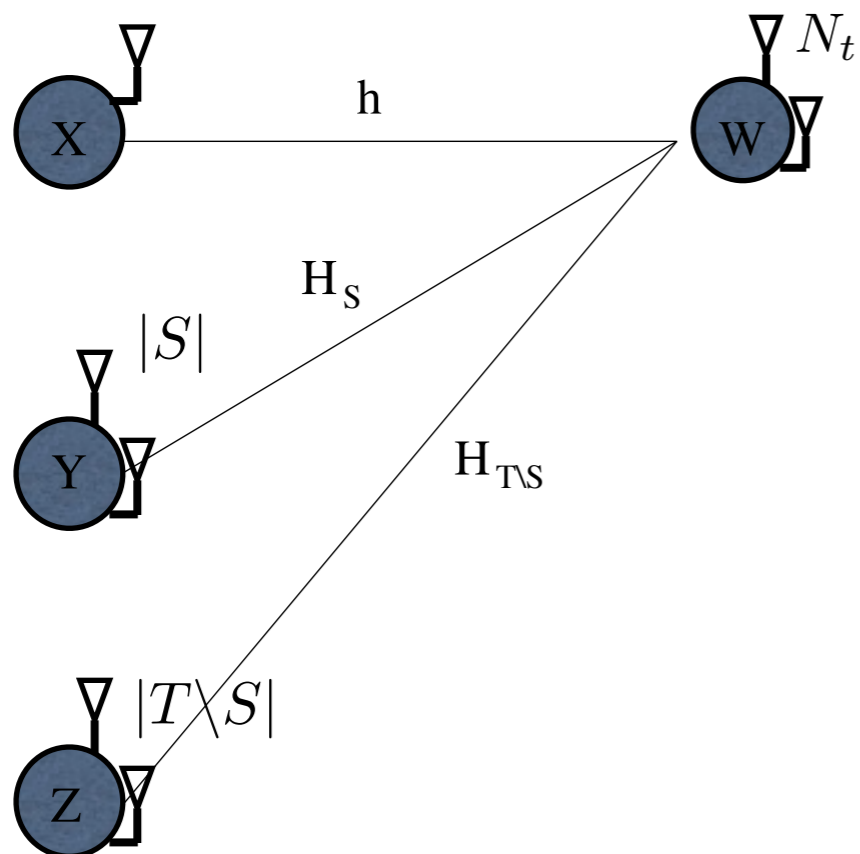


Receive Antenna Selection is Sub-Modular

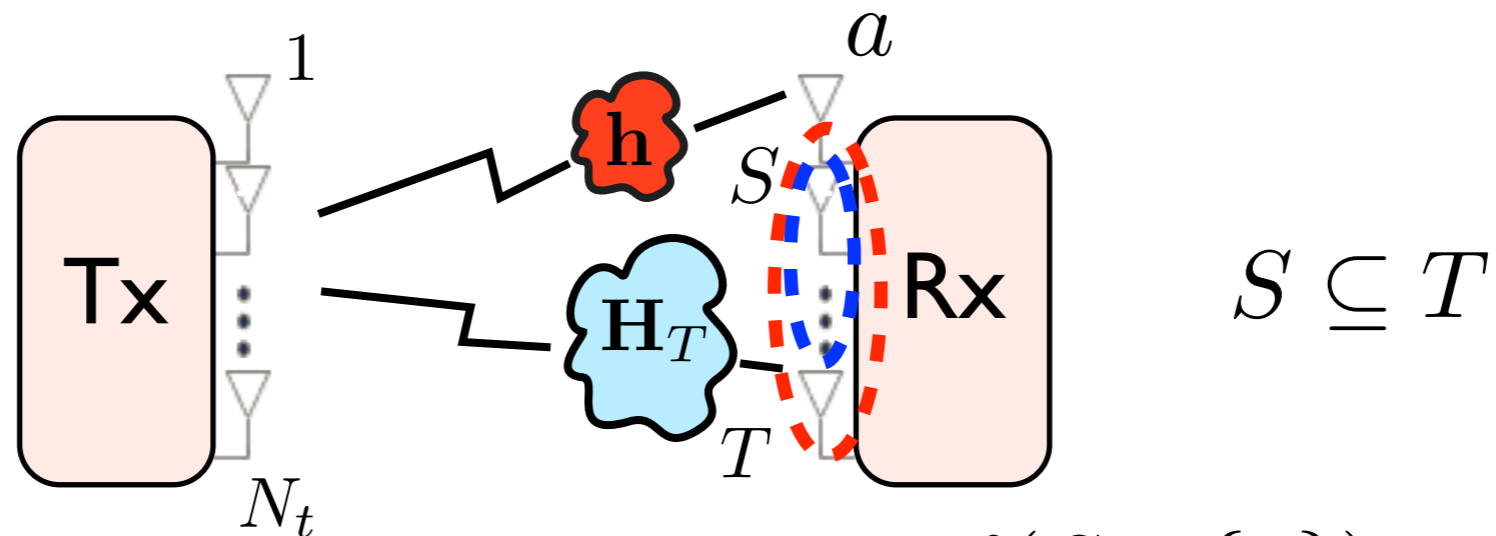


$f(T \cup \{a\}) - f(T)$
 is Mutual Information
 between **X** and **W**

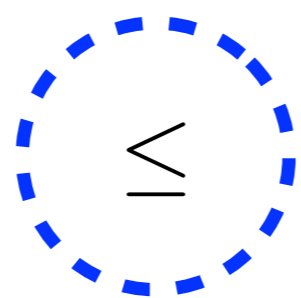
$f(S \cup \{a\}) - f(S)$
 Mutual Information
 between **A** and **C**



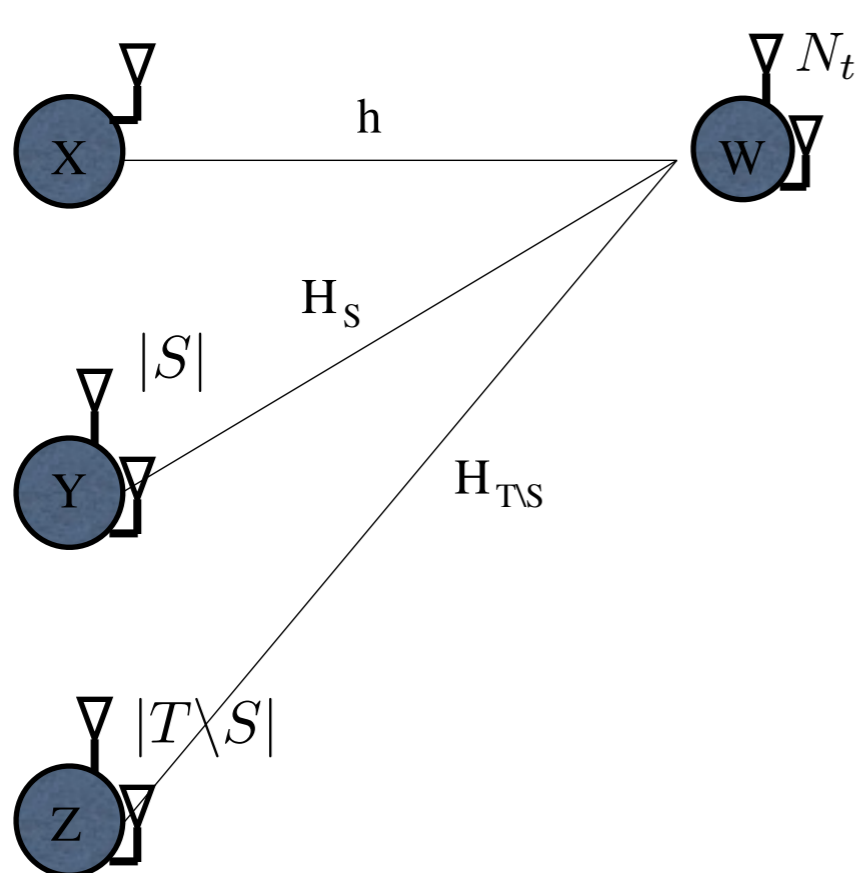
Receive Antenna Selection is Sub-Modular



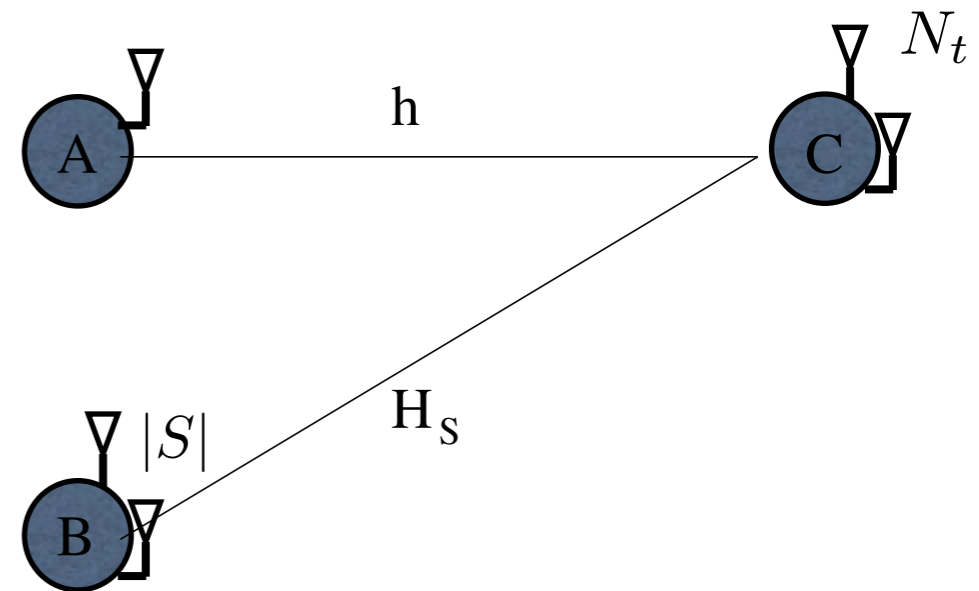
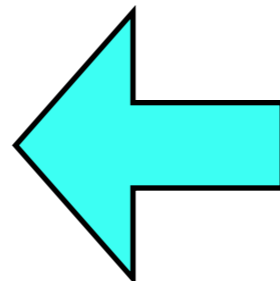
$f(T \cup \{a\}) - f(T)$
is Mutual Information
between **X** and **W**



$f(S \cup \{a\}) - f(S)$
Mutual Information
between **A** and **C**



Physically
Degraded



Result

Result

Greedy Algorithm :

Result

Greedy Algorithm :

Start with $\mathcal{R}_L = \Phi$

Result

Greedy Algorithm :

Start with $\mathcal{R}_L = \Phi$

At step i , $\mathcal{R}_L = \mathcal{R}_L \cup \{i^*\}$, **Choose the best among the rest**

$$i^* = \arg \max_{i \in \{1, 2, \dots, N_r\}, i \notin \mathcal{R}_L} \log \det \left(\mathbf{I} + \frac{P}{N_t} \mathbf{H}_{\mathcal{R}_L \cup \{i\}} \mathbf{H}_{\mathcal{R}_L \cup \{i\}}^\dagger \right),$$

Result

Greedy Algorithm :

Start with $\mathcal{R}_L = \Phi$

At step i , $\mathcal{R}_L = \mathcal{R}_L \cup \{i^*\}$, **Choose the best among the rest**

$$i^* = \arg \max_{i \in \{1, 2, \dots, N_r\}, i \notin \mathcal{R}_L} \log \det \left(\mathbf{I} + \frac{P}{N_t} \mathbf{H}_{\mathcal{R}_L \cup \{i\}} \mathbf{H}_{\mathcal{R}_L \cup \{i\}}^\dagger \right),$$

Repeat until $|\mathcal{R}_L| = L$.

Result

Greedy Algorithm :

Start with $\mathcal{R}_L = \Phi$

At step i , $\mathcal{R}_L = \mathcal{R}_L \cup \{i^*\}$, **Choose the best among the rest**

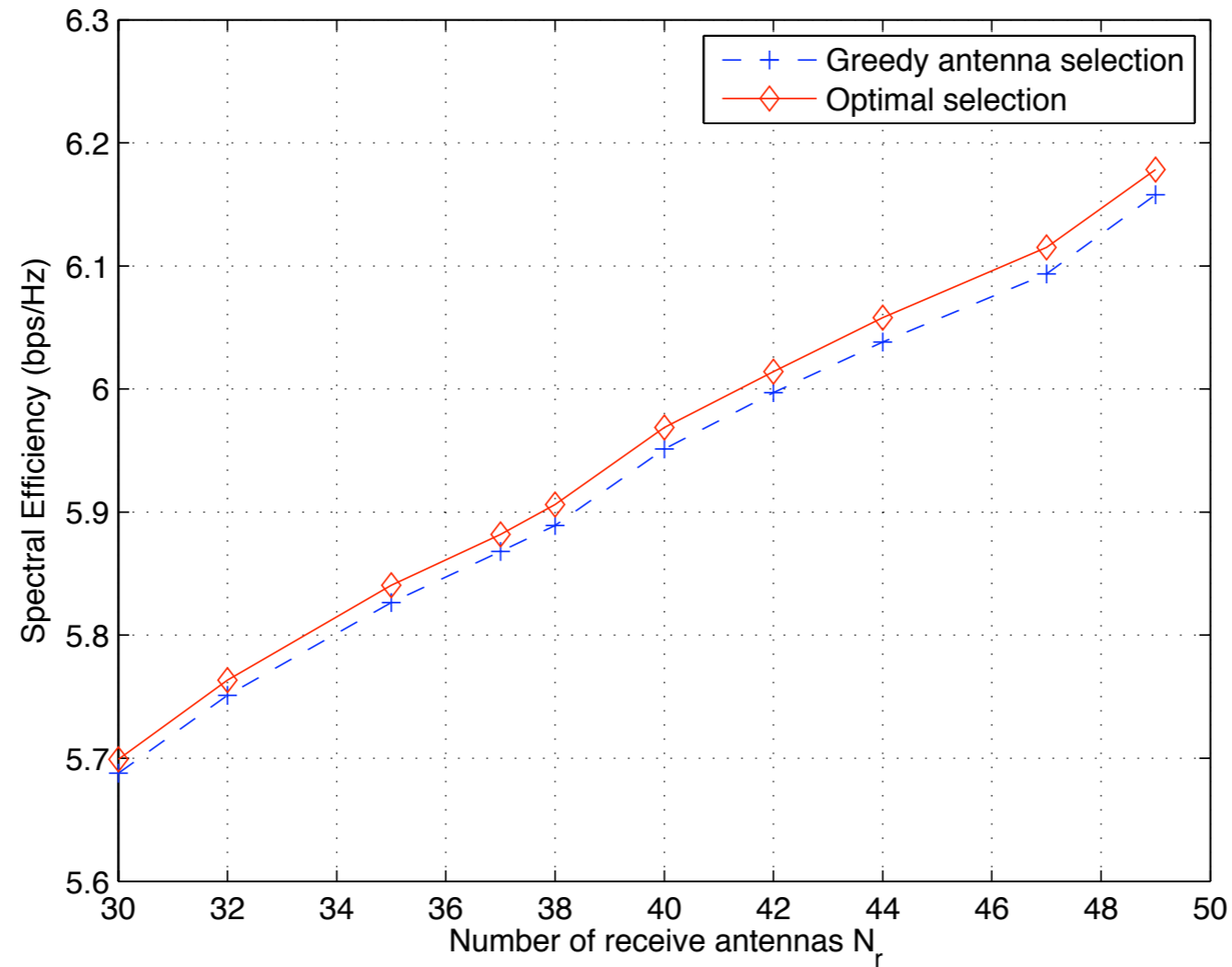
$$i^* = \arg \max_{i \in \{1, 2, \dots, N_r\}, i \notin \mathcal{R}_L} \log \det \left(\mathbf{I} + \frac{P}{N_t} \mathbf{H}_{\mathcal{R}_L \cup \{i\}} \mathbf{H}_{\mathcal{R}_L \cup \{i\}}^\dagger \right),$$

Repeat until $|\mathcal{R}_L| = L$.

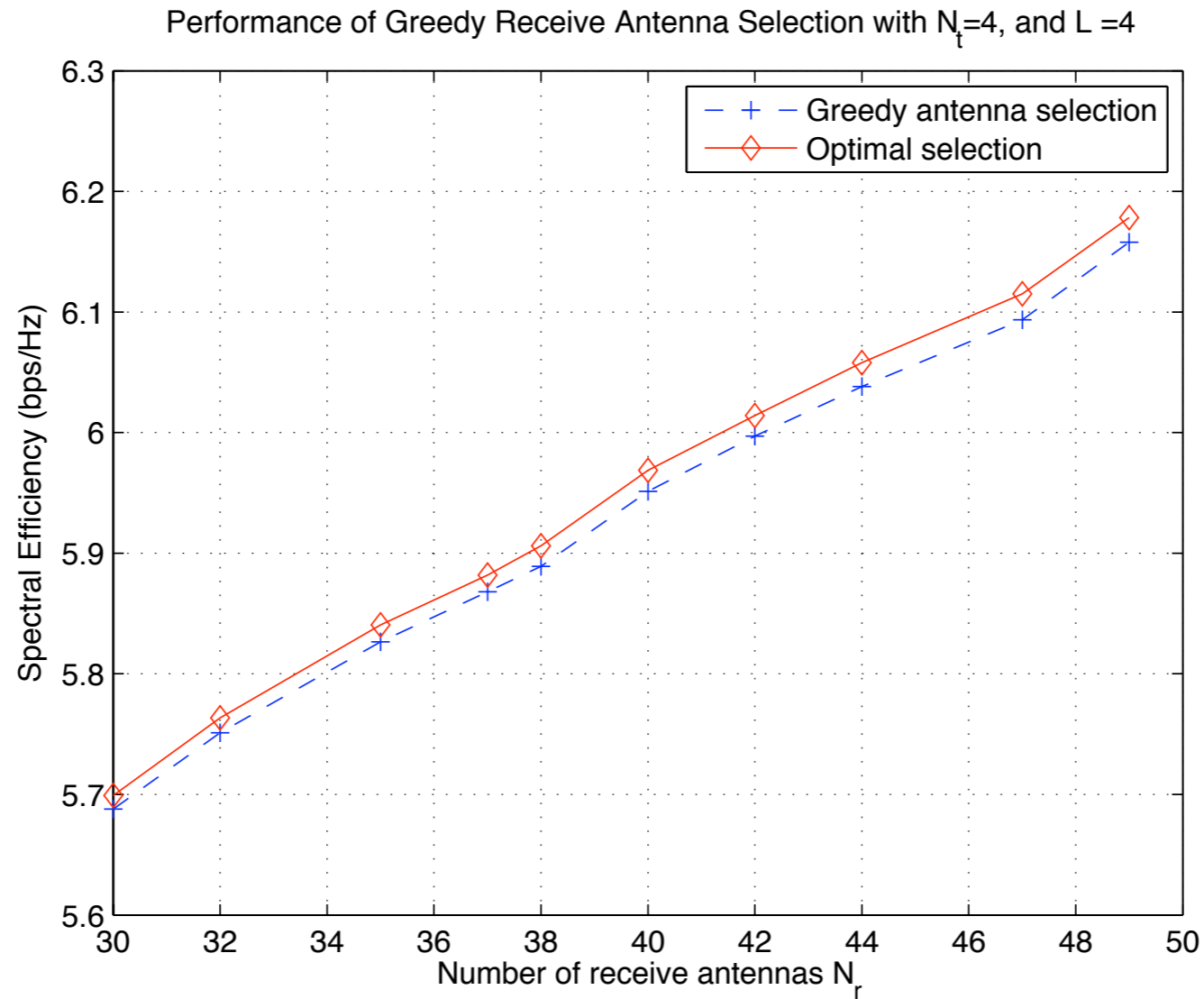
Theorem: *Greedy Algorithm for receive antenna selection with linear complexity achieves at least $(1 - 1/e)$ fraction of the optimal solution.*

Simulation Result

Performance of Greedy Receive Antenna Selection with $N_t=4$, and $L=4$

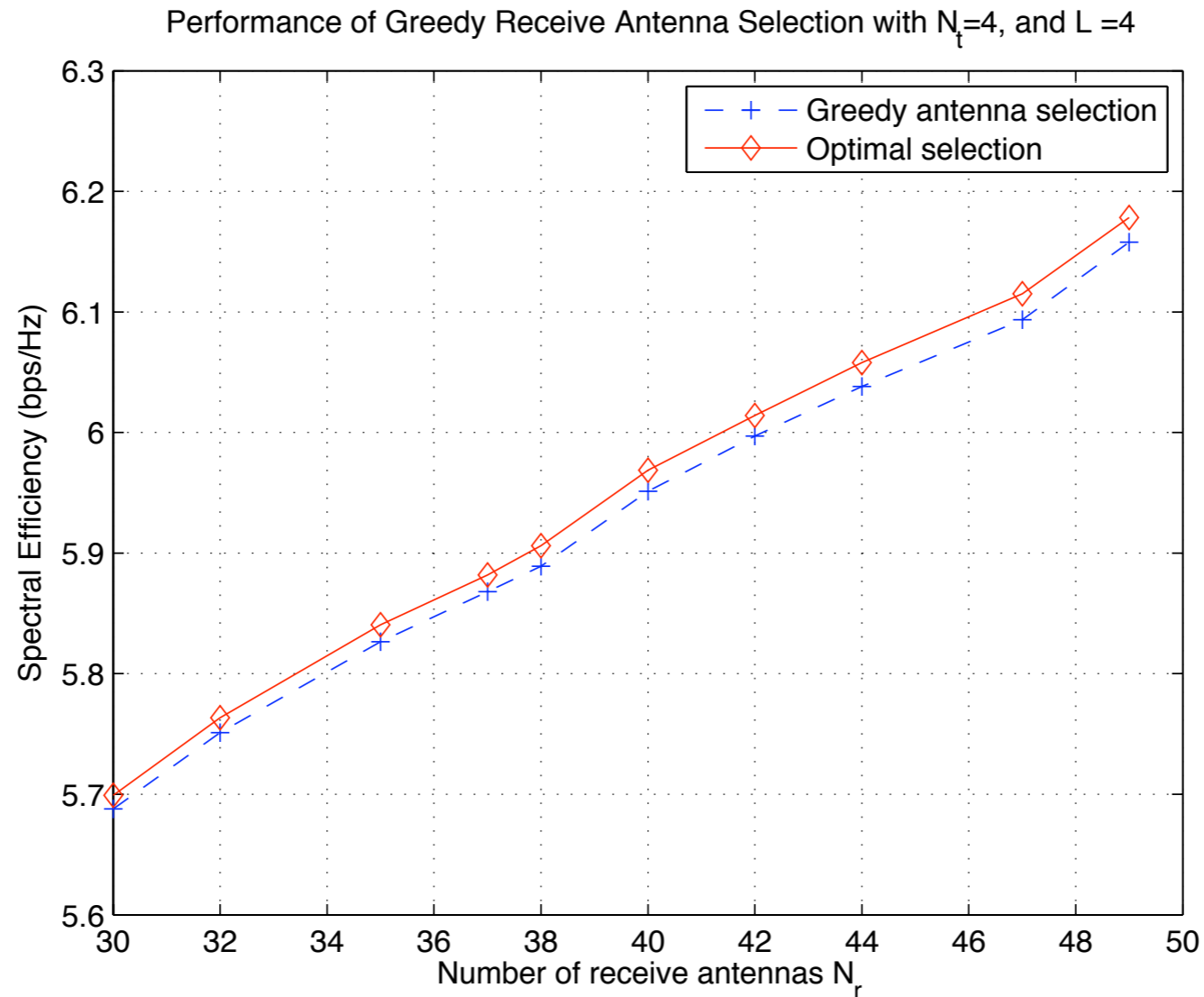


Simulation Result



Massive MIMO

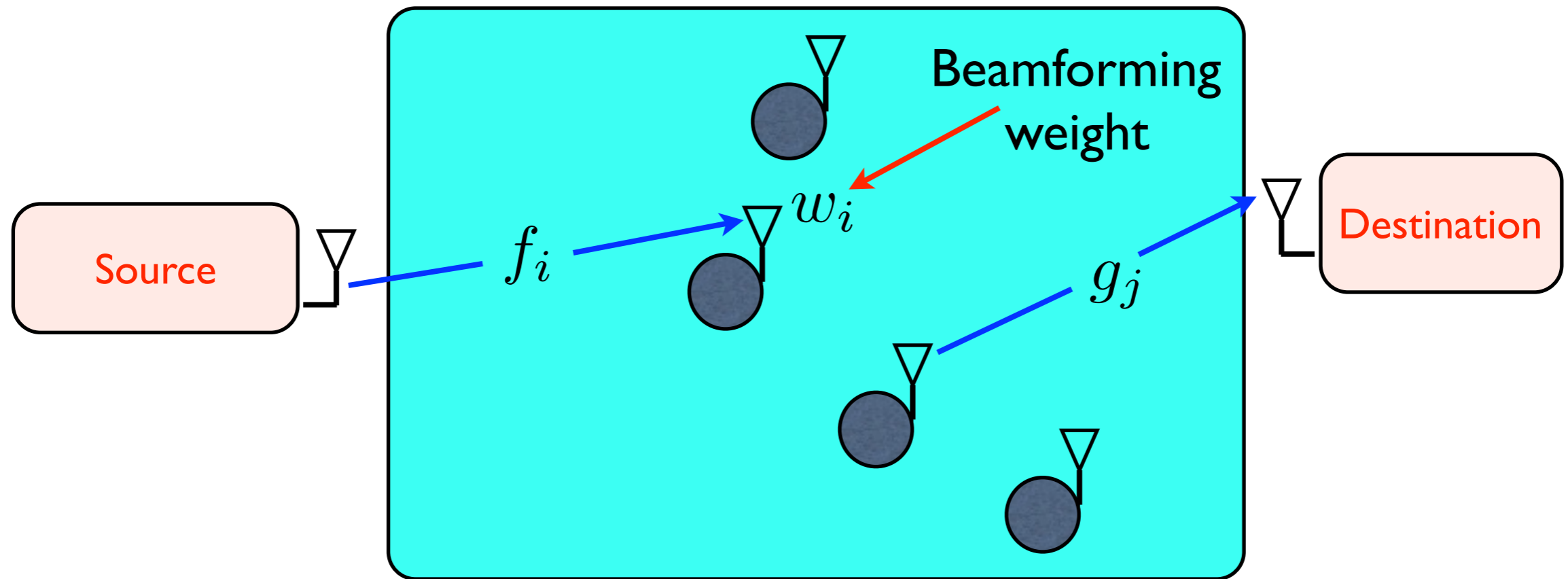
Simulation Result



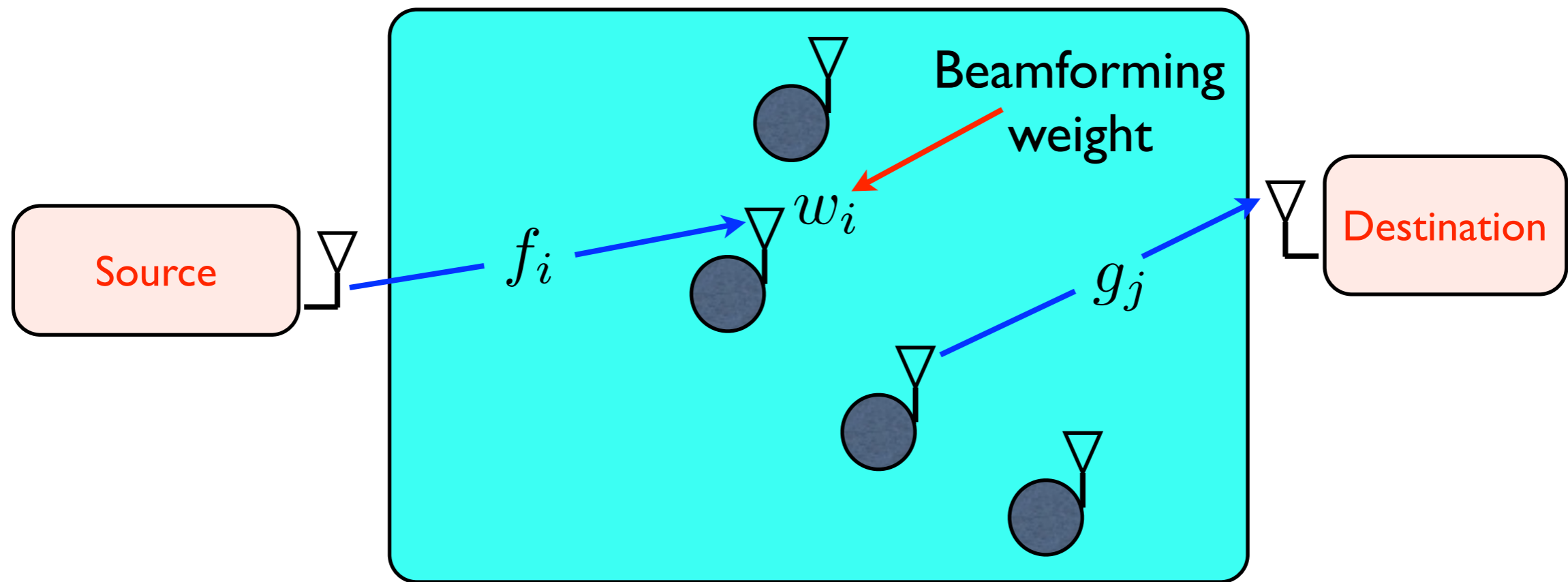
Massive MIMO

Performance Better than promised

Relay Selection



Relay Selection



Find the L **relay antennas** subset that maximizes the mutual information

$$\max_{\mathcal{T}_L \subseteq \{1, 2, \dots, N\}} \max_{\mathbf{w}} \log \left(1 + \frac{\mathbf{w}^\dagger \Delta \Delta^\dagger \mathbf{w}}{\mathbf{w}^\dagger (\Sigma \Sigma^\dagger + \mathbf{I}) \mathbf{w}} \right)$$

Relay Antenna Selection is Modular

Relay Antenna Selection is Modular

$$\max_{\mathcal{T}_L \subseteq \{1,2,\dots,N\}} \max_{\mathbf{w}} \log \left(1 + \frac{\mathbf{w}^\dagger \Delta \Delta^\dagger \mathbf{w}}{\mathbf{w}^\dagger (\Sigma \Sigma^\dagger + \mathbf{I}) \mathbf{w}} \right)$$

$$\Delta = \left[\frac{g_{t_1} f_{t_1}}{\gamma_{t_1}}, \dots, \frac{g_{t_L} f_{t_L}}{\gamma_{t_L}} \right]^T,$$

$$\mathbf{w} = [w_{t_1}, \dots, w_{t_L}]^T,$$

$$\Sigma = \begin{bmatrix} \frac{g_{t_1}}{\gamma_{t_1}} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \frac{g_{t_L}}{\gamma_{t_L}} \end{bmatrix}$$

Relay Antenna Selection is Modular

$$\max_{\mathcal{T}_L \subseteq \{1,2,\dots,N\}} \max_{\mathbf{w}} \log \left(1 + \frac{\mathbf{w}^\dagger \Delta \Delta^\dagger \mathbf{w}}{\mathbf{w}^\dagger (\Sigma \Sigma^\dagger + \mathbf{I}) \mathbf{w}} \right)$$

$$\max_{\mathbf{x}} \frac{\mathbf{x}^T \mathbf{A} \mathbf{x}}{\mathbf{x}^T \mathbf{B} \mathbf{x}}$$

$$\Delta = \left[\frac{g_{t_1} f_{t_1}}{\gamma_{t_1}}, \dots, \frac{g_{t_L} f_{t_L}}{\gamma_{t_L}} \right]^T,$$

$$\mathbf{w} = [w_{t_1}, \dots, w_{t_L}]^T,$$

$$\Sigma = \begin{bmatrix} \frac{g_{t_1}}{\gamma_{t_1}} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \frac{g_{t_L}}{\gamma_{t_L}} \end{bmatrix}$$

Relay Antenna Selection is Modular

$$\max_{\mathcal{T}_L \subseteq \{1,2,\dots,N\}} \max_{\mathbf{w}} \log \left(1 + \frac{\mathbf{w}^\dagger \Delta \Delta^\dagger \mathbf{w}}{\mathbf{w}^\dagger (\Sigma \Sigma^\dagger + \mathbf{I}) \mathbf{w}} \right)$$

$$\Delta = \left[\frac{g_{t_1} f_{t_1}}{\gamma_{t_1}}, \dots, \frac{g_{t_L} f_{t_L}}{\gamma_{t_L}} \right]^T,$$

$$\mathbf{w} = [w_{t_1}, \dots, w_{t_L}]^T,$$

$$\max_{\mathbf{x}} \frac{\mathbf{x}^T \mathbf{A} \mathbf{x}}{\mathbf{x}^T \mathbf{B} \mathbf{x}}$$

$$\Sigma = \begin{bmatrix} \frac{g_{t_1}}{\gamma_{t_1}} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \frac{g_{t_L}}{\gamma_{t_L}} \end{bmatrix}$$

Rayleigh-Ritz Theorem

$$\max_{\mathcal{T}_L \subseteq \{1,2,\dots,N\}} \sum_{i \in \mathcal{T}_L} \frac{|g_i|^2 |f_i|^2}{|f_i|^2 + |g_i|^2 + 1}$$

Relay Antenna Selection is Modular

$$\max_{\mathcal{T}_L \subseteq \{1,2,\dots,N\}} \max_{\mathbf{w}} \log \left(1 + \frac{\mathbf{w}^\dagger \Delta \Delta^\dagger \mathbf{w}}{\mathbf{w}^\dagger (\Sigma \Sigma^\dagger + \mathbf{I}) \mathbf{w}} \right)$$

$$\Delta = \left[\frac{g_{t_1} f_{t_1}}{\gamma_{t_1}}, \dots, \frac{g_{t_L} f_{t_L}}{\gamma_{t_L}} \right]^T,$$

$$\mathbf{w} = [w_{t_1}, \dots, w_{t_L}]^T,$$

$$\max_{\mathbf{x}} \frac{\mathbf{x}^T \mathbf{A} \mathbf{x}}{\mathbf{x}^T \mathbf{B} \mathbf{x}}$$

$$\Sigma = \begin{bmatrix} \frac{g_{t_1}}{\gamma_{t_1}} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \frac{g_{t_L}}{\gamma_{t_L}} \end{bmatrix}$$

Rayleigh-Ritz Theorem

$$\max_{\mathcal{T}_L \subseteq \{1,2,\dots,N\}} \sum_{i \in \mathcal{T}_L} \frac{|g_i|^2 |f_i|^2}{|f_i|^2 + |g_i|^2 + 1}$$

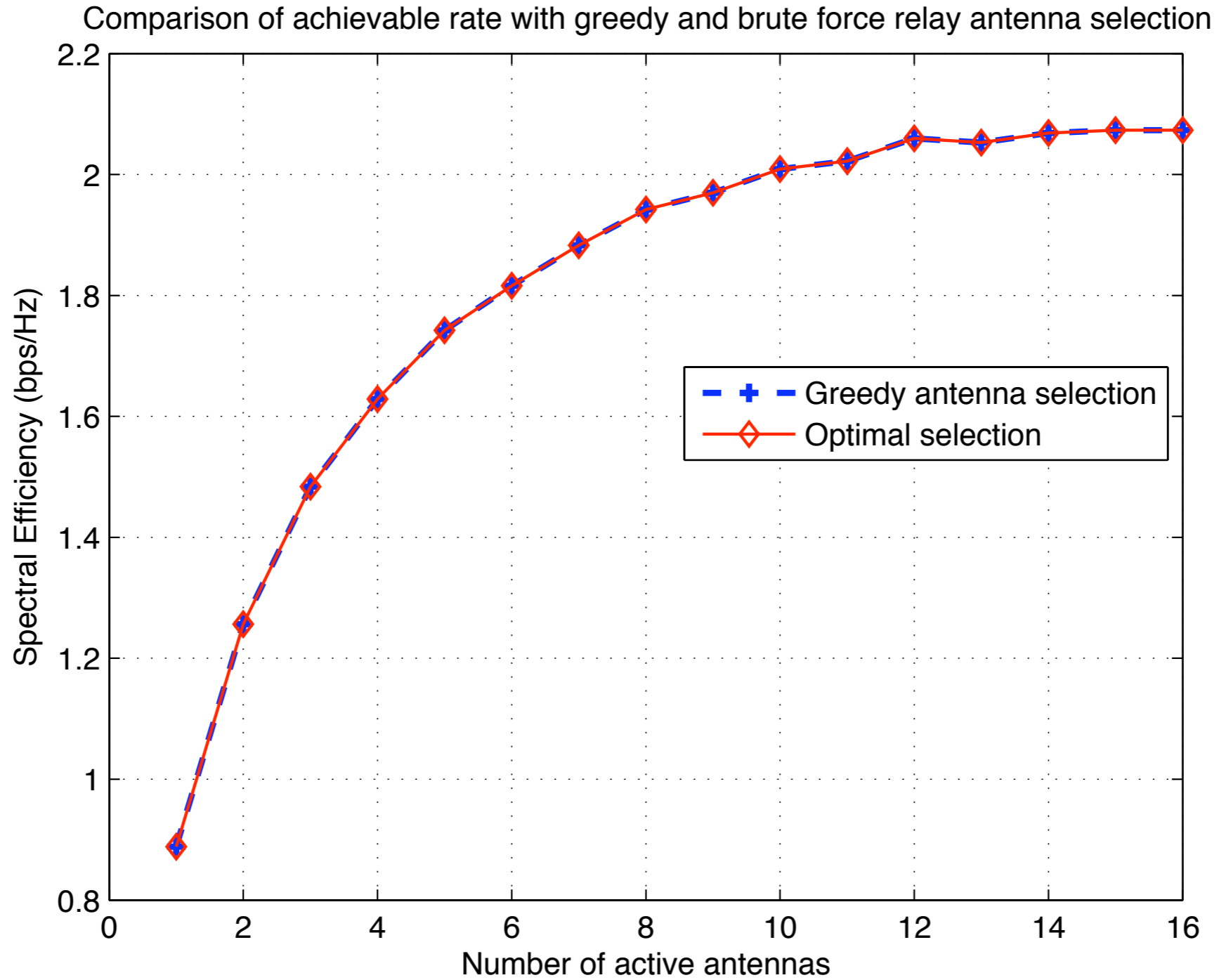
Relay Selection Problem is **Modular**

Result

Result

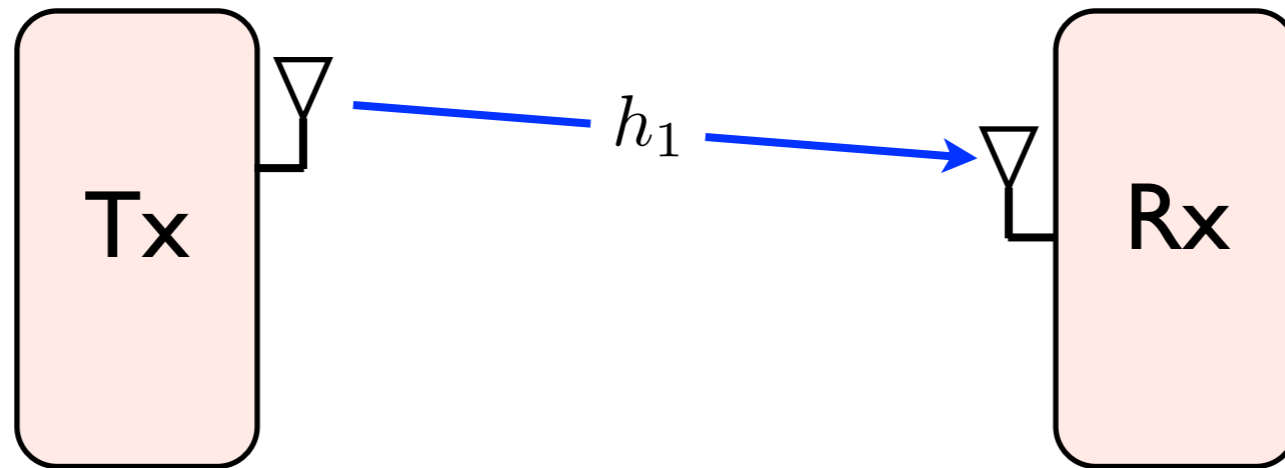
Theorem: *Greedy Algorithm for relay antenna selection with linear complexity achieves the optimal solution.*

Simulation Result

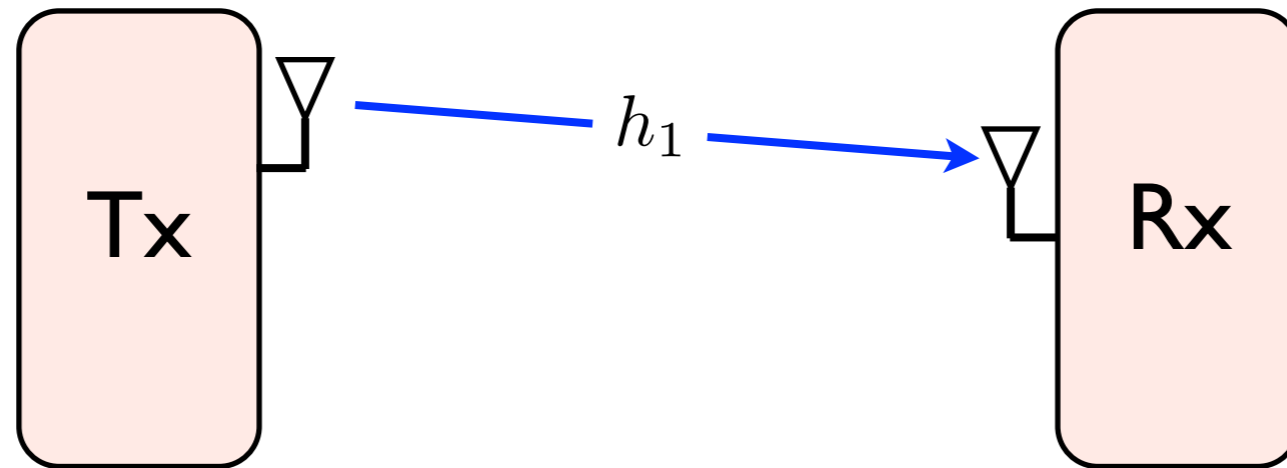


Some Counter-Examples

Transmit Antenna Selection

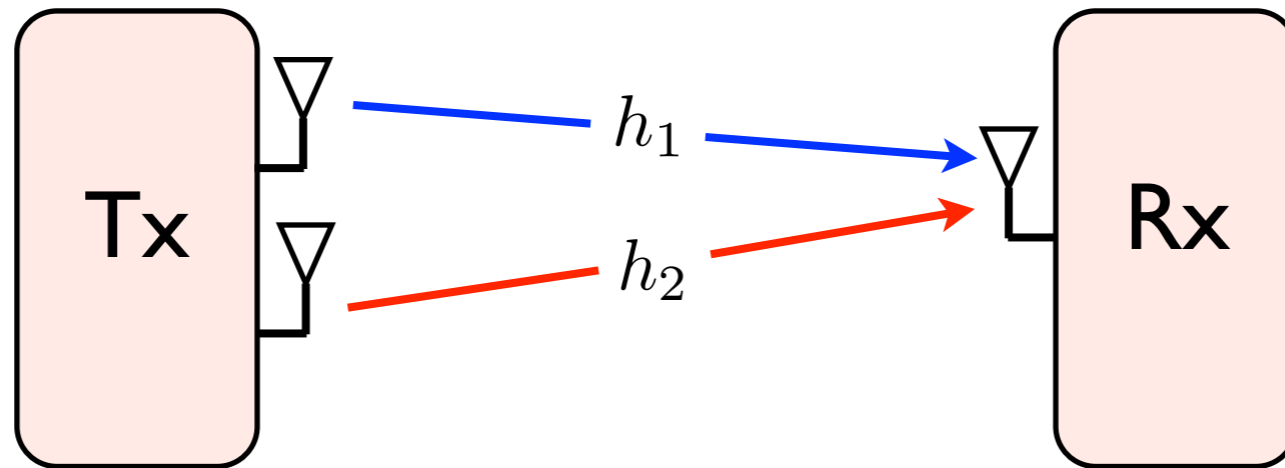


Transmit Antenna Selection



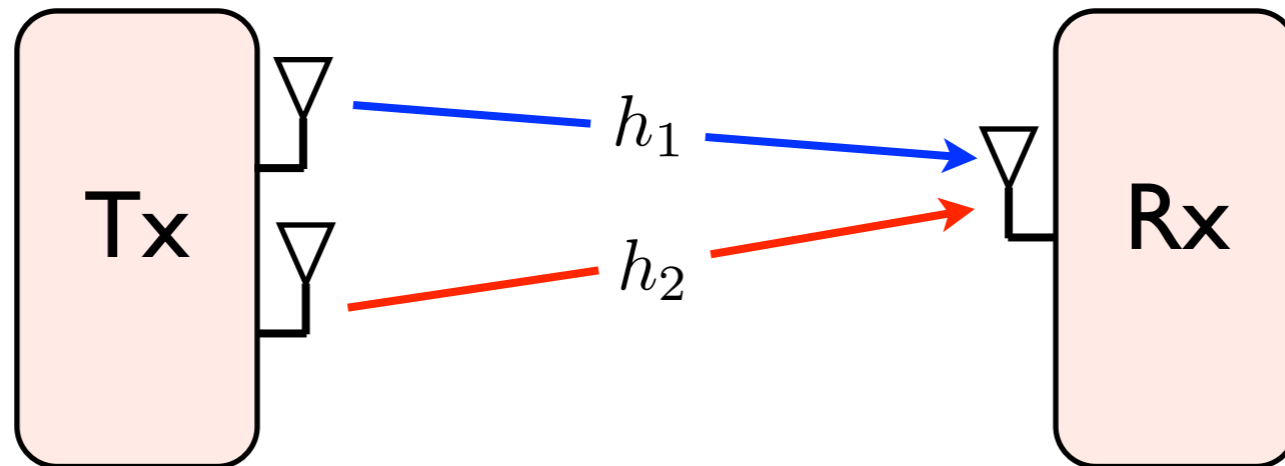
$$C_{\{1\}} = \log(1 + P|h_1|^2)$$

Transmit Antenna Selection



$$C_{\{1\}} = \log(1 + P|h_1|^2)$$

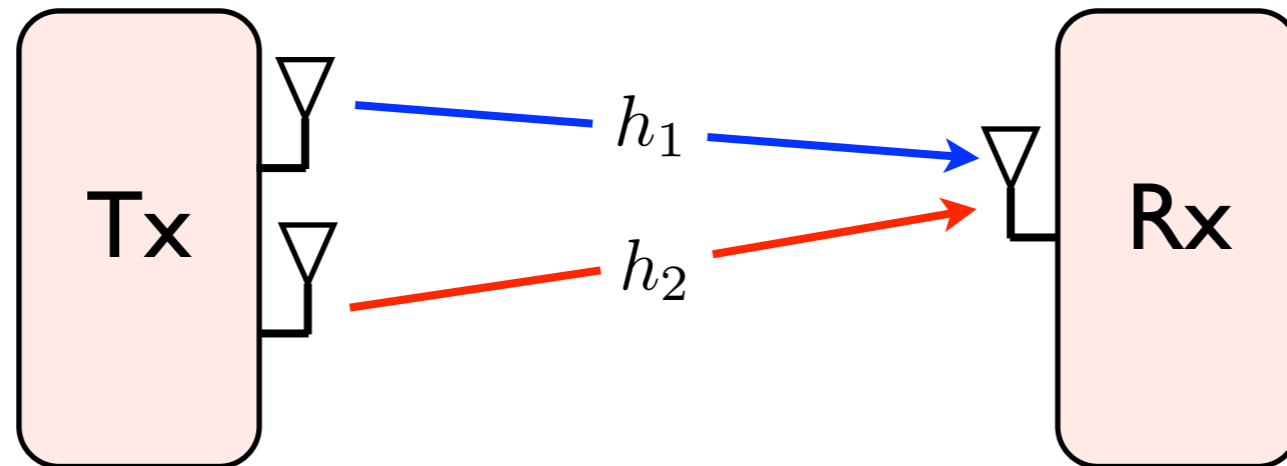
Transmit Antenna Selection



$$C_{\{1\}} = \log(1 + P|h_1|^2)$$

$$C_{\{1,2\}} = \log\left(1 + \frac{P}{2}(|h_1|^2 + |h_2|^2)\right)$$

Transmit Antenna Selection

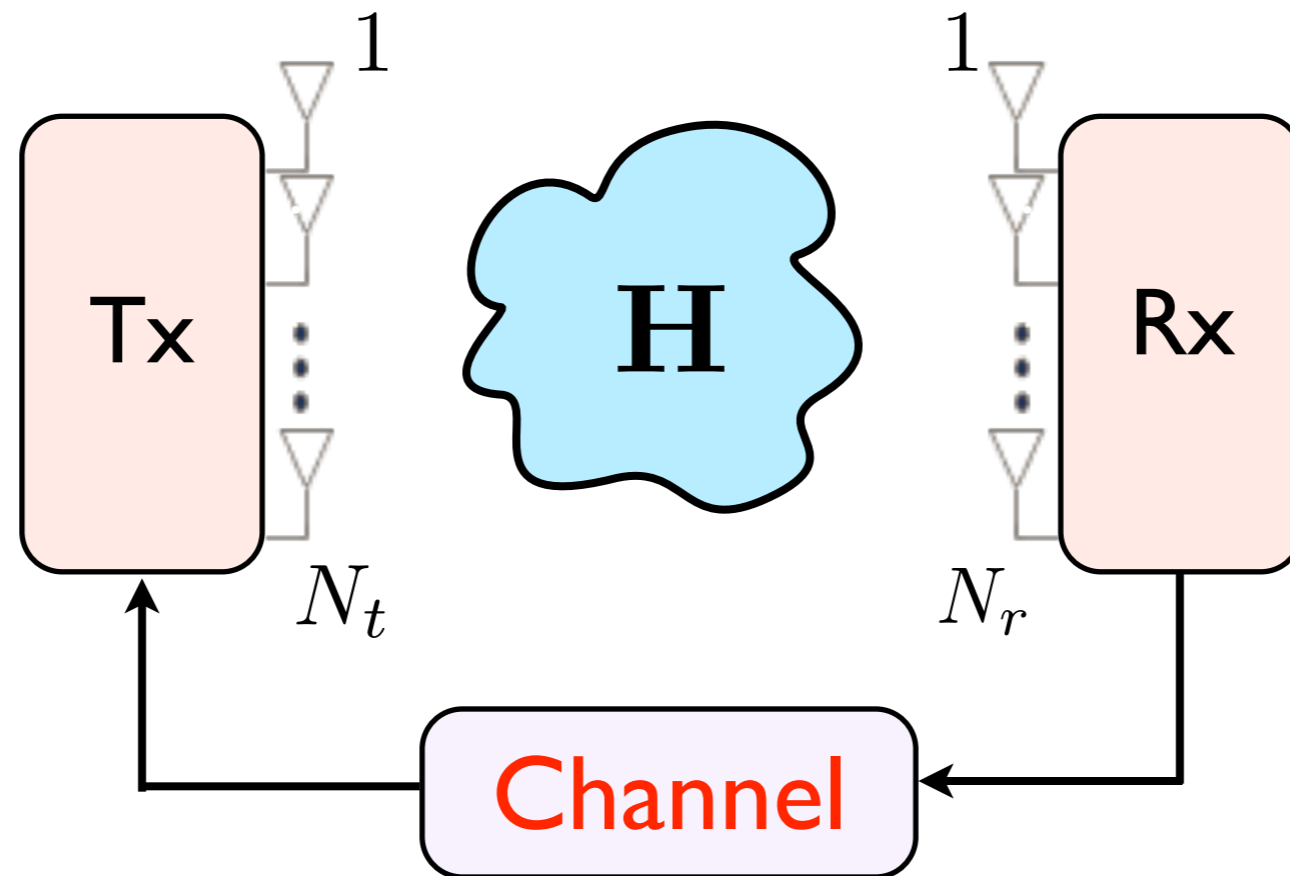


$$C_{\{1\}} = \log(1 + P|h_1|^2)$$

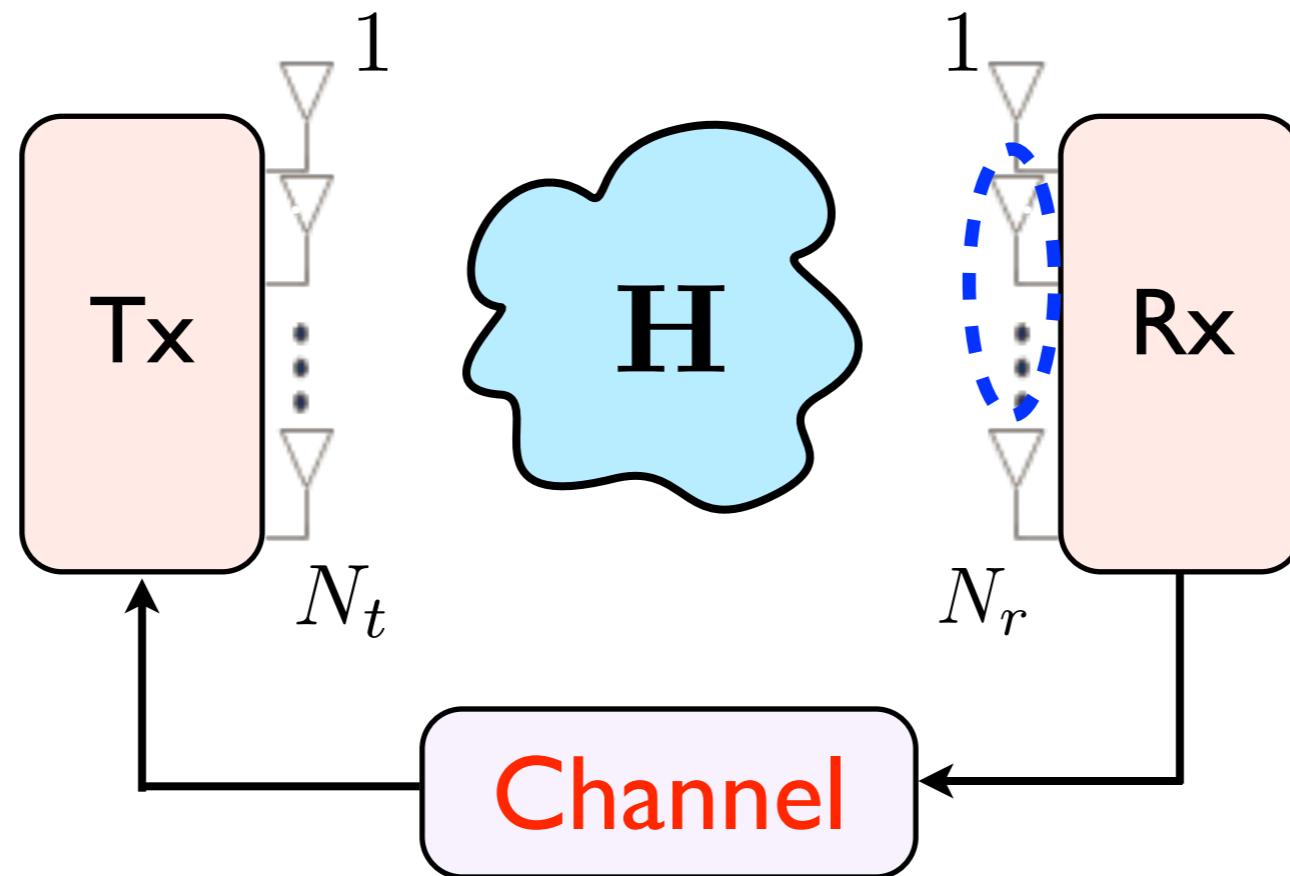
$$C_{\{1,2\}} = \log\left(1 + \frac{P}{2}(|h_1|^2 + |h_2|^2)\right)$$

Transmit Antenna Selection is **NOT** Monotone

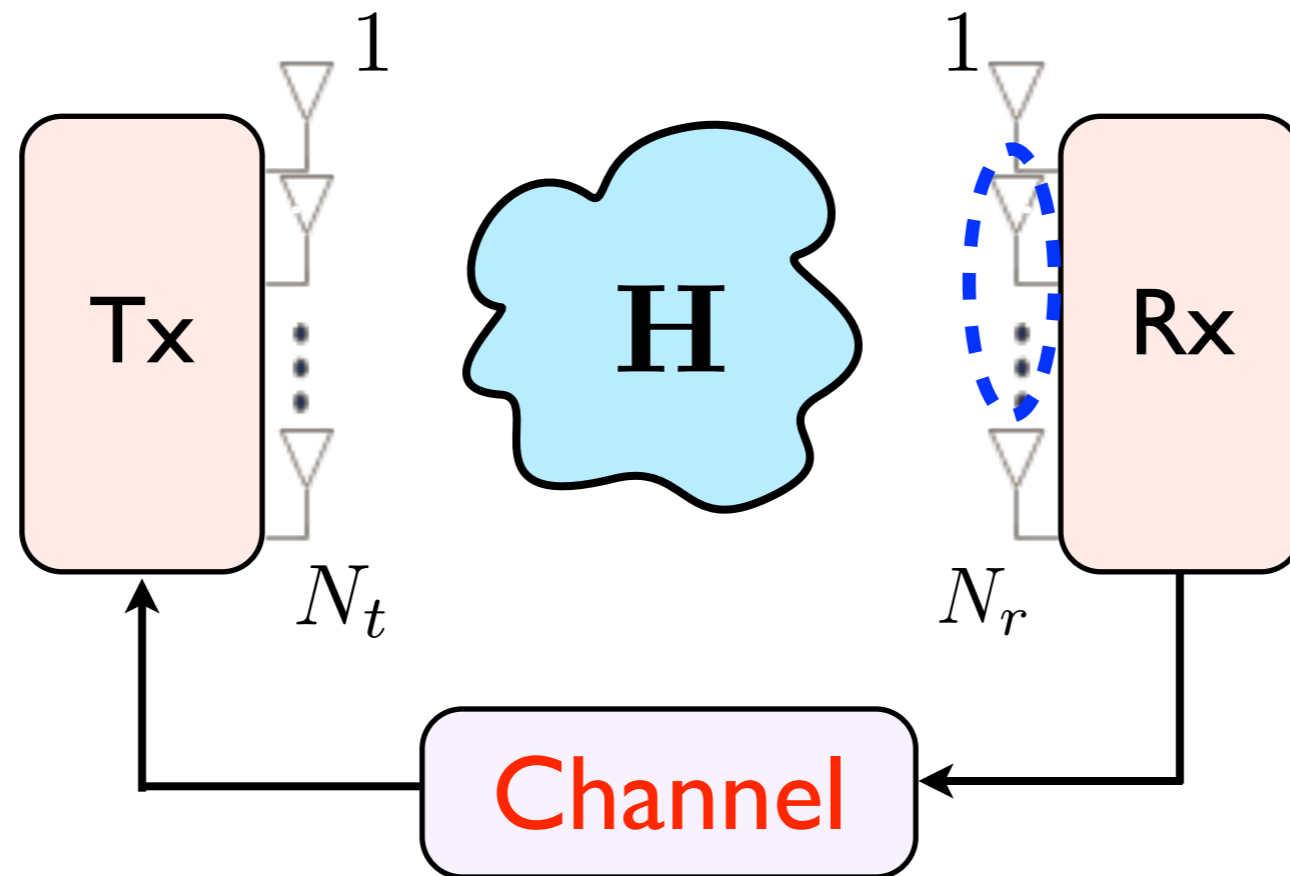
Receive Antenna Selection with CSIT



Receive Antenna Selection with CSIT

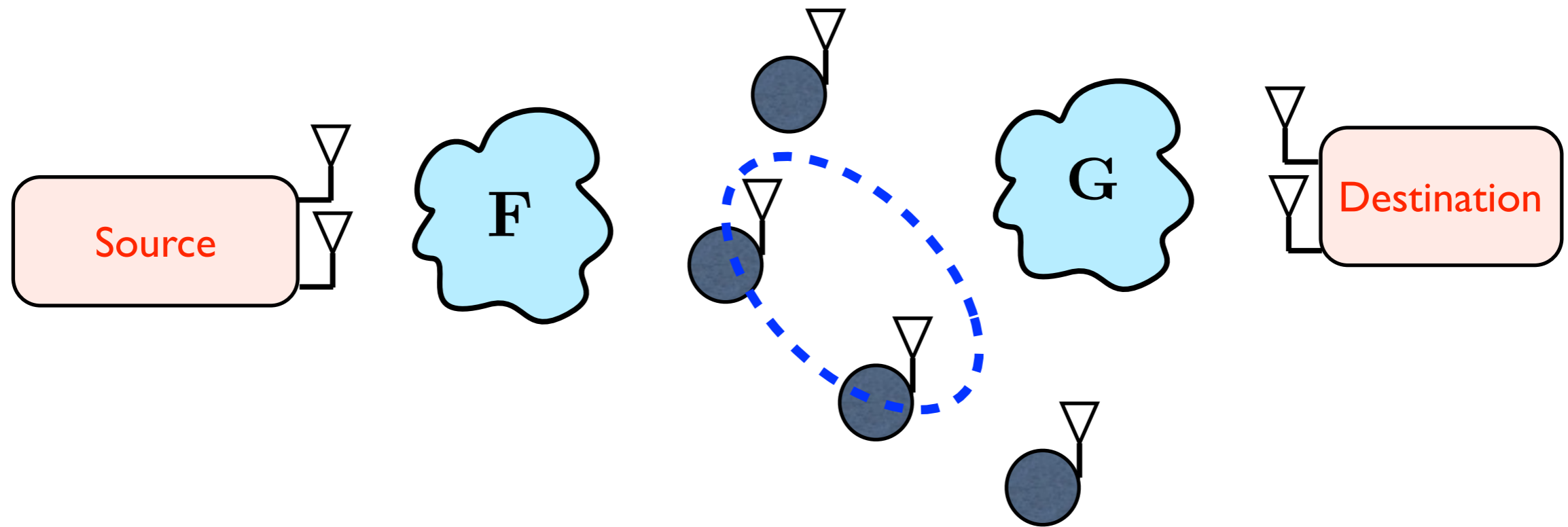


Receive Antenna Selection with CSIT

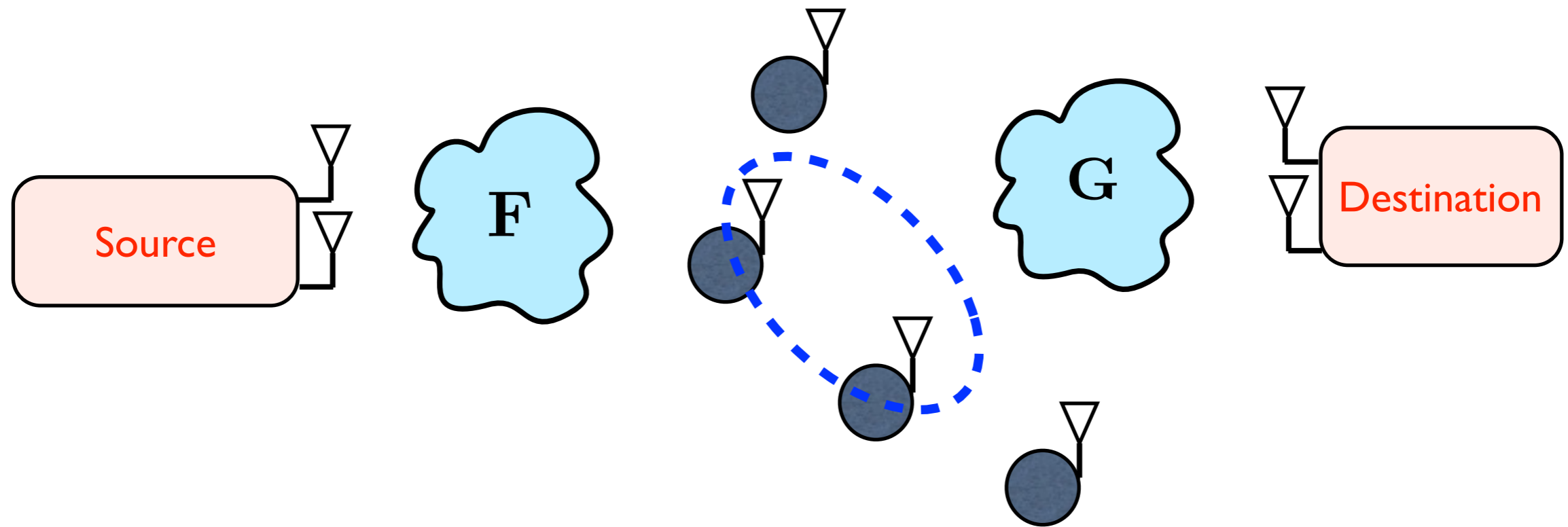


With Waterfilling Receive Antenna Selection is Monotone
but **NOT** Sub-modular

Relay Antenna Selection with MIMO Source-Destination



Relay Antenna Selection with MIMO Source-Destination



With MIMO S-D Relay Antenna Selection is **NOT** Sub-modular

Conclusions

- Theoretical Bounds on Greedy Algorithms
- Relay case - Greedy is Optimal
- Most other antenna selection problems are not sub-modular