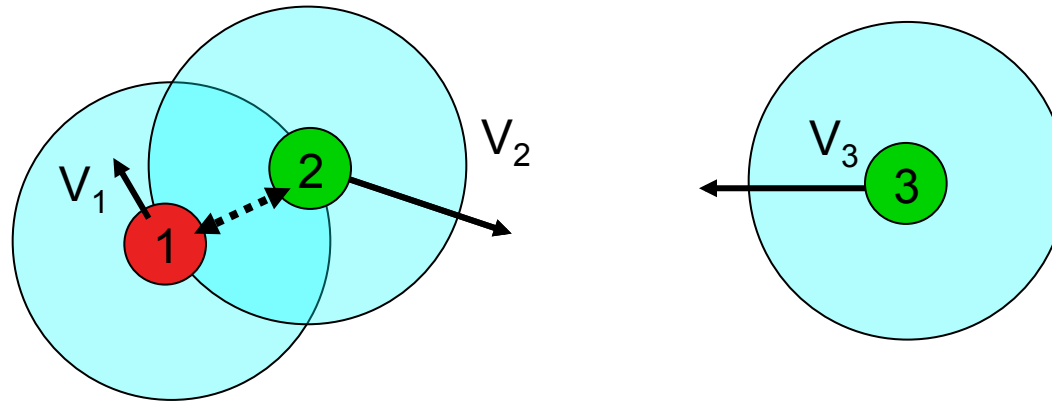




# Optimization in Delay Tolerant Networks

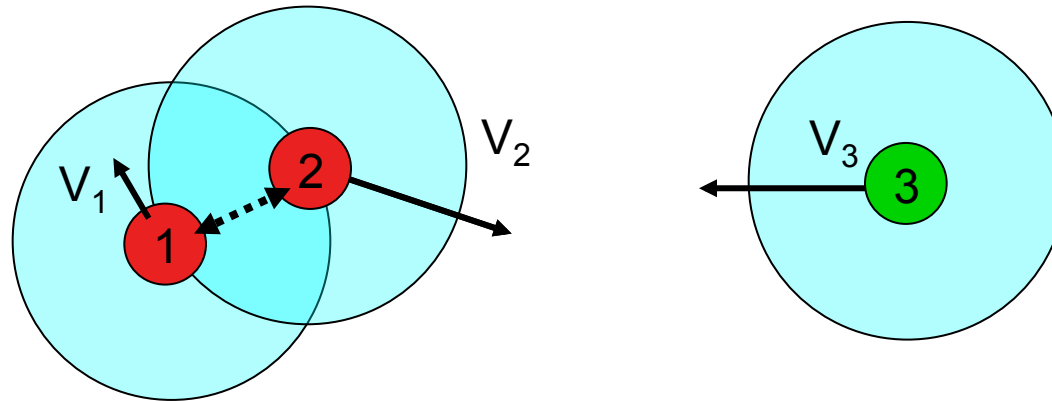
Giovanni Neglia  
EVALUATION SEMINAR

# Delay Tolerant Networks



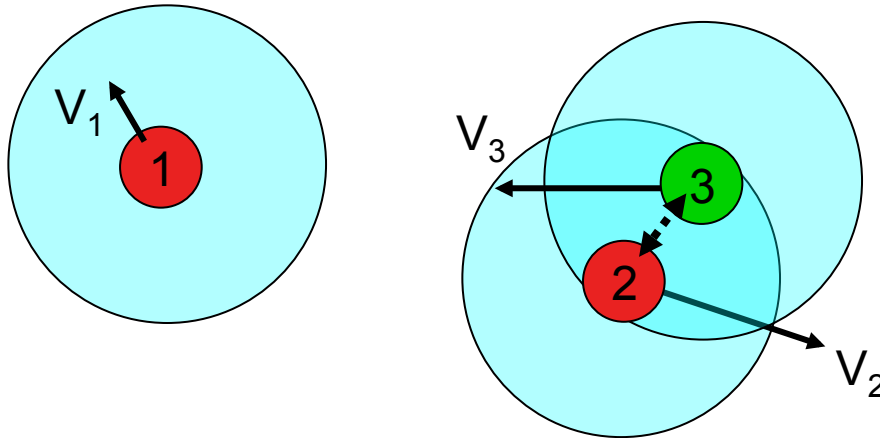
- no path at a given time instant between two nodes
- need to rely on nodes mobility to deliver packets (store, carry and forward)
- incomplete knowledge about future meetings
  - rely on multiple copies

# Delay Tolerant Networks



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# Resources vs Performance Trade-off

- More copies ( $C$ )  $\Rightarrow$  smaller delivery time ( $T_d$ )
  - Different ways to curb the infection
    - Gossip, K-hop, Spray&Wait
- Optimization problems:
  - Determine policy parameters/routing in order to
    - minimize  $E[T_d + \gamma C]$
    - minimize  $E[T_d]$  given that  $C \leq C_{\max}$
    - maximize  $P(T_d < T_{\max})$  given that  $C \leq C_{\max}$
  - ...for different routing schemes

# Contributions:

## Centralized Approaches

The controller knows infection state/topology

- Markov Decision Processes => threshold policies
  - minimize  $E[T_d + \gamma C]$ , [Chants06]
  - minimize  $E[T_d]$  given  $E[C] \leq C_{\max}$ , (with E. Altman)
    - [Infocom09] controller learns policy at runtime (stochastic approximation)
- Cast as a stochastic shortest path problem
  - maximize  $P(T_d < T_{\max})$ , Frank's problem
    - Efficient heuristic for an urban bus network [IEEETVT12]

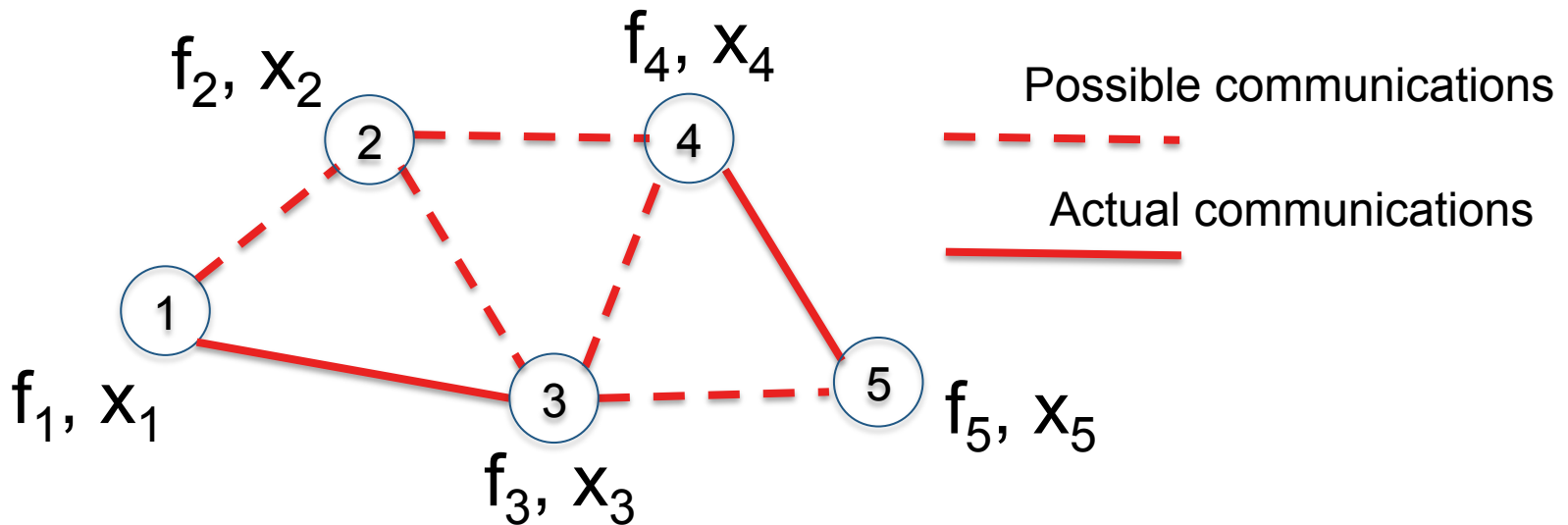
# Contributions:

## Decentralized Approaches

Goal: nodes learn their optimal policy under partial information

- Explore the solution space at runtime with genetic algorithm-like techniques (with S. Alouf)
  - EU-project BIONETS (BIOlogically-inspired autonomic NETworks and Services)  
[ElsevierComNet10]
- Use distributed (sub-)gradient techniques

# Distributed Subgradients Methods

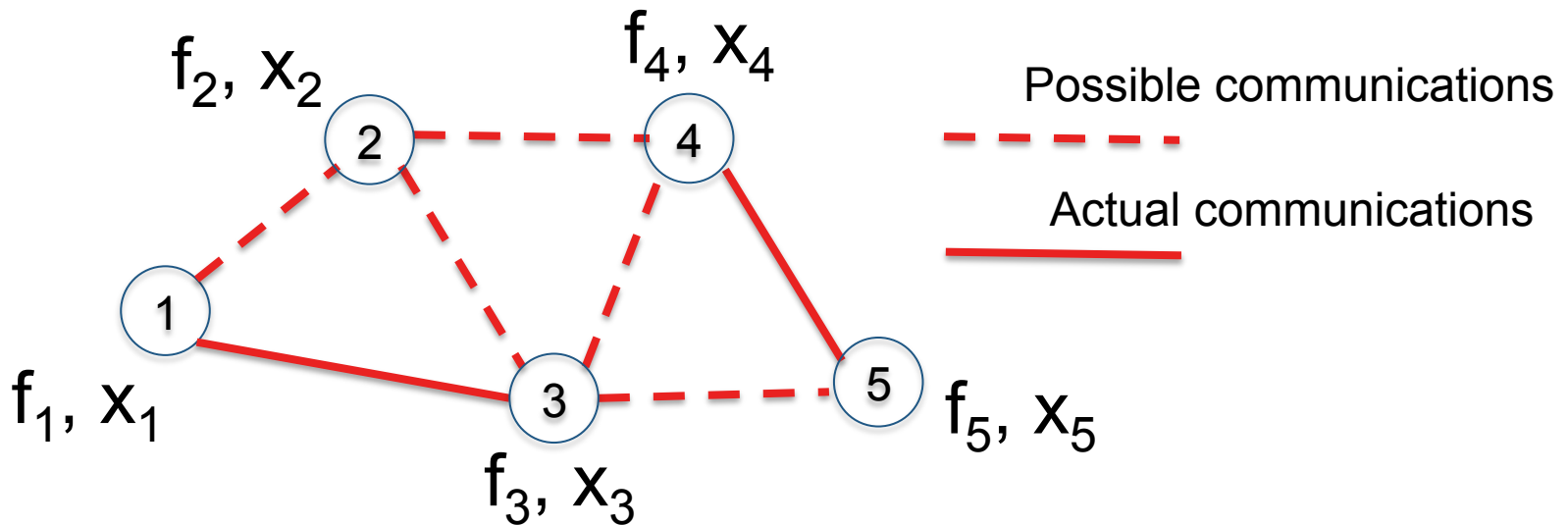


The goal:

- $\operatorname{argmin}_{\mathbf{x}} F(\mathbf{x}) = \sum_{i=1}^N f_i(\mathbf{x})$ ,  $f_i$  convex
- each node knows only  $f_i$  and can communicate with its neighbours

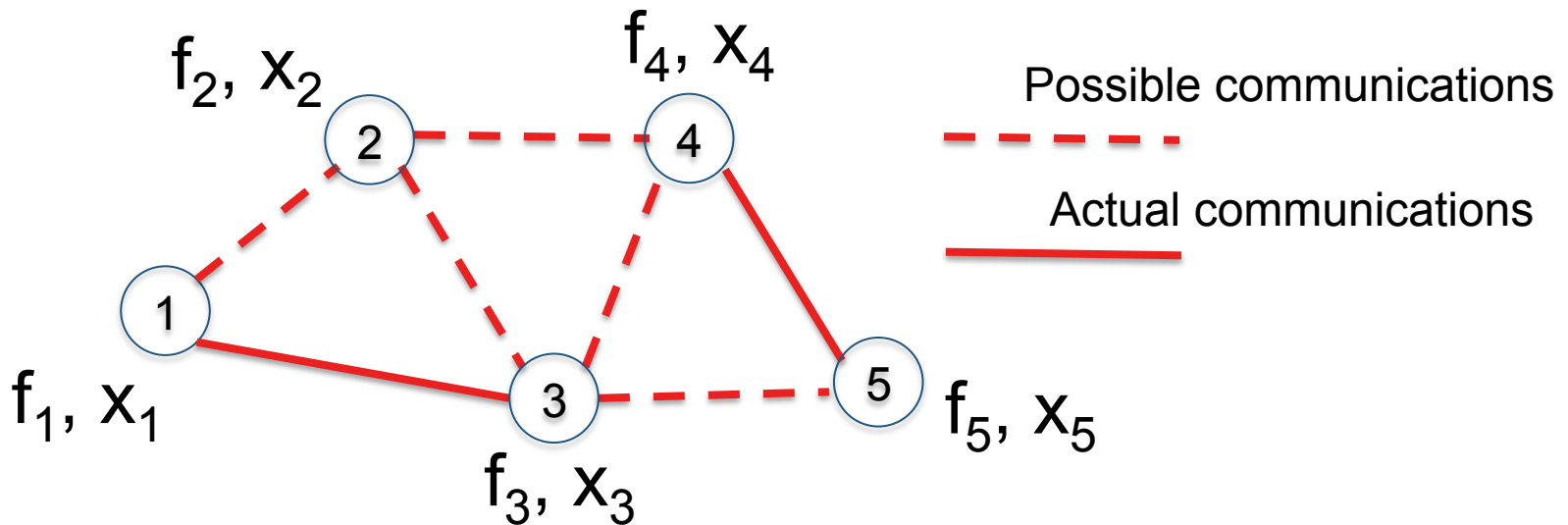


# Distributed Subgradients Methods



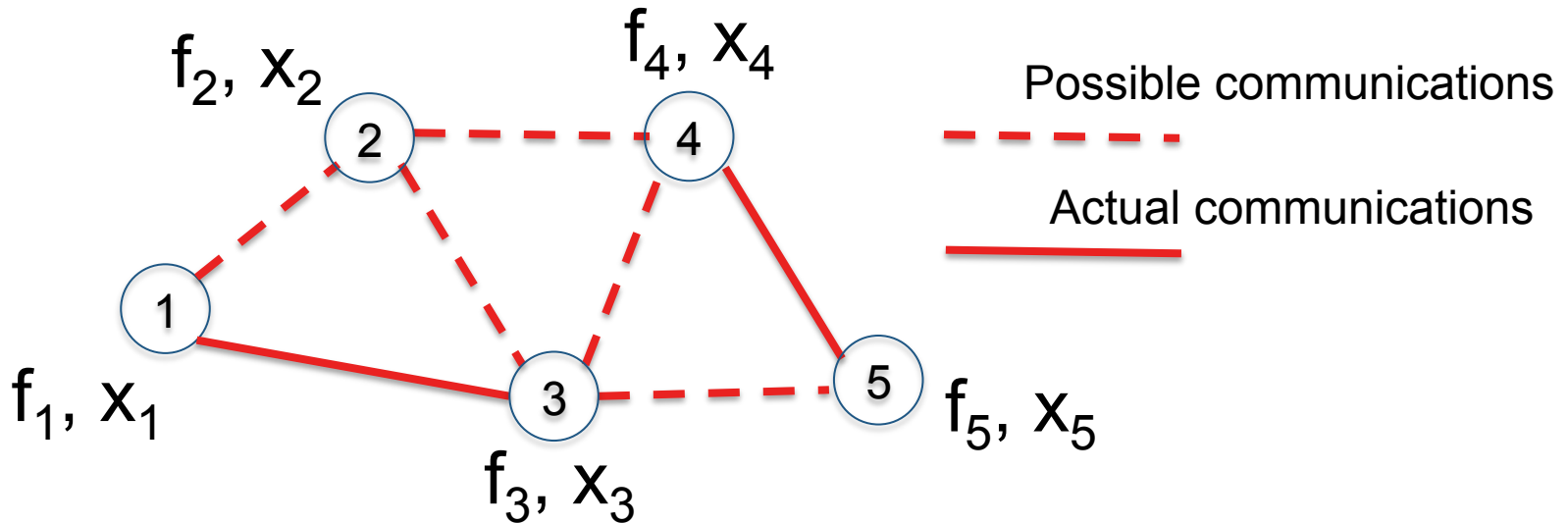
$$\blacksquare \quad \hat{\mathbf{x}}^{(i)}(k+1) = \sum_{j \in N_i}^N w_{ij} \hat{\mathbf{x}}^{(j)}(k) + \gamma(k) \nabla f_i(\hat{\mathbf{x}}^{(i)}(k))$$

# Distributed Subgradients Methods



$$\blacksquare \quad \hat{\mathbf{x}}^{(i)}(k+1) = \underbrace{\sum_{j \in N_i}^N w_{ij} \hat{\mathbf{x}}^{(j)}(k)}_{\text{Consensus}} + \underbrace{\gamma(k) \nabla f_i(\hat{\mathbf{x}}^{(i)}(k))}_{\text{Gradient}}$$

# Distributed Subgradients Methods



- $$\hat{\mathbf{x}}^{(i)}(k+1) = \sum_{j \in N_i}^N w_{ij} \hat{\mathbf{x}}^{(j)}(k) + \gamma(k) \nabla f_i(\hat{\mathbf{x}}^{(i)}(k))$$
- For dynamic networks w/ intercommunication times
  - Deterministic upper bounded
  - Independent ON/OFF

# Our Research Directions

What is missing for application in DTNs?

- Link dynamics originated from nodes' mobility
  - Shown that convergence holds when contacts derive from a generic Markovian process [Infocom11]

- Asynchronous operation

- $$\hat{\mathbf{x}}^{(i)}(k+1) = \sum_{j \in N_i}^N w_{ij} \hat{\mathbf{x}}^{(j)}(k) + \gamma_i(k) \nabla f_i(\hat{\mathbf{x}}^{(i)}(k))$$
- ongoing

- Convergence speedup

# Our Research Directions

Convergence speed (w/ K. Avrachenkov)

- $\hat{\mathbf{x}}^{(i)}(k+1) = \sum_{j \in N_i}^N w_{ij} \hat{\mathbf{x}}^{(j)}(k) + \gamma_i(k) \nabla f_i(\hat{\mathbf{x}}^{(i)}(k))$ 
  - two components: consensus and gradient
- How to set the weights in a **distributed way**?
  - maximize the spectral gap of weight matrix  $W$
  - our proposal: minimize  $\text{tr}(W^{2n})$ 
    - [submitted CDC]

# Our Research Directions

- How to set the weights in a **distributed way**?
  - maximize the spectral gap of weight matrix  $W$ 
    - spectral gap =  $1 - \max\{|\lambda_i|, i=2, \dots, N\}$
  - our proposal: minimize  $\text{trace}(W^{2n})$ 
    - $\text{trace}(W^{2n}) = 1 + \sum_{i>1} \lambda_i^{2n}$
    - Distributed algorithm
    - Tradeoff

approx. quality vs communication via  $n$

# Thank you



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