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Gossip Protocols on Distributed Systems

Order without authority

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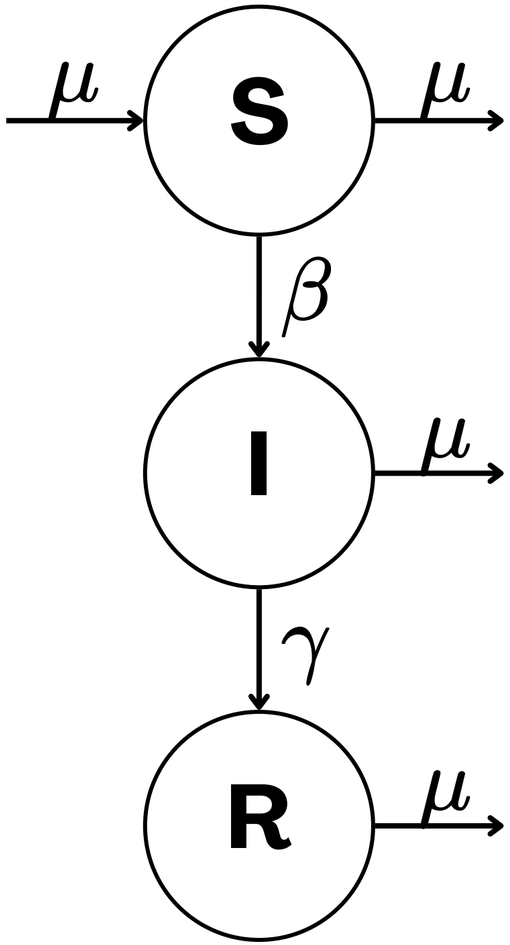
Overview

1. Epidemic & Gossip Models
2. Distributed Systems
3. Gossip Protocols
4. Applications

Why bother?

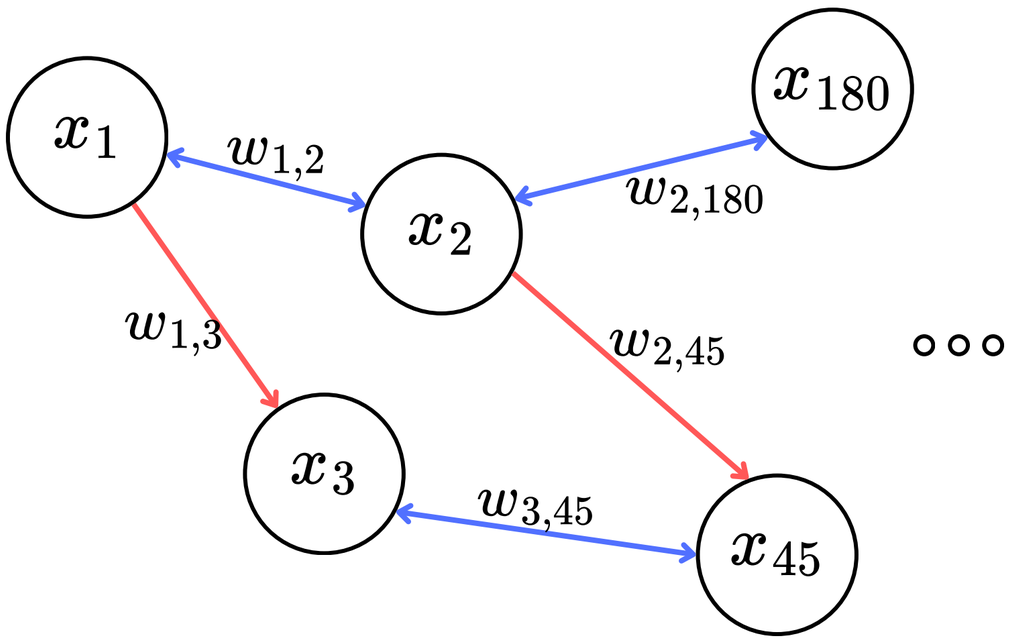
Scalable & Resilient approach where performance matters.

Epidemic & Gossip Models



$$\begin{cases} \dot{S} &= \mu(1-S) - \beta I S \\ \dot{I} &= \beta I S - (\mu+\gamma) I \\ \dot{R} &= \gamma I - \mu R \end{cases}$$

Distributed Systems



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$x_i = \{\text{id}, \text{value}, \text{timestamp}\}$

Why: Ensure scalability, reliablity, privacy

Examples:

1. Blockchain
2. BitTorrent
3. Cloud Infrastructures(Amazon S3)

Gossip Protocols

What: Rules for sharing **information** $f(\text{value}_i)$

How:

1. **Decentralized** communication
2. Exchanges are **synchronized**
3. **No perfect** communication
4. **Concurrent** information

Gossip Protocols ~ Anti-Entropy

- **SI** Model-inspired
- **Continuous** updates
- **Robust**
- Convergence: $\mathcal{O}(\log n)$

A. Push Style

```
on timeout do
  Q ← random(P)
  send PUSH(P.value, P.time) to Q
  set timeout Δ

on receive PUSH(v, t) do
  if P.time < t then
    P.value ← v
    P.time ← t
```

Gossip Protocols ~ Anti-Entropy

B. Pull Style

```
on timeout do
  Q ← random(P)
  send PULL(P, P.time) to Q
  set timeout Δ

on receive PULL(Q, t) do
  if P.time > t then
    send REPLY(P.value, P.time) to Q

on receive REPLY(v, t) do
  if P.time < t then
    P.value ← v
    P.time ← t
```

C. Push-Pull Style

```
on timeout do
  Q ← random(P)
  send PUSHPULL(P,P.value, P.time) to Q
  set timeout Δ

on receive PUSHPULL(Q, v, t) do
  if P.time < t then
    P.value ← v
    P.time ← t
  else
    send REPLY(P, P.value, P.time) to Q

on receive REPLY(Q, v, t) do
  if P.time < t then
    P.value ← v
    P.time ← t
```

Gossip Protocols ~ Rumor-Mongering Approach

- **SIR** model-inspired
- **Rare** updates
- More **efficient**
- Usually **Push-style**
- Convergence: $\mathcal{O}(\log n)$

Stop Rule:

- **When**
  - ***Blind***: Evaluation at **each turn**
  - ***Feedback***: Evaluation after a **notice**
- **How**
  - ***Counter***: Stop **after k** evaluations
  - ***Coin***: Stop with **probability 1/k**

Distributed Aggregation of the Mean

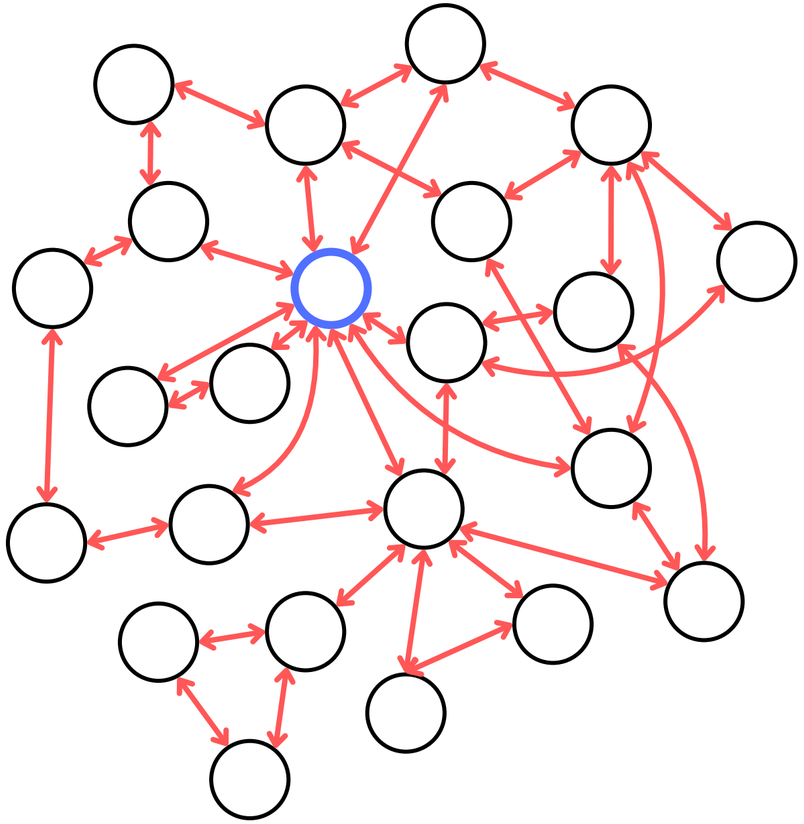
```
on timeout do
  Q ← random(getPeers(P))
  P.state ← P.value
  send PUSHPULL(P,P.state) to Q
  set timeout Δ

on receive PUSHPULL(Q, s) do
  send REPLY(P, P.state) to Q
  P.state ← (P.state + s) / 2

on receive REPLY(Q, v) do
  P.state ← (P.state + v) / 2
```

- Push-Pull style
- At each round:
  - **Average** of the states: **constant**
  - **Variance** of the states: **shrinks**
- **Overapproximation** in case of concurrent messages
- Performance depends on ***getPeers()***

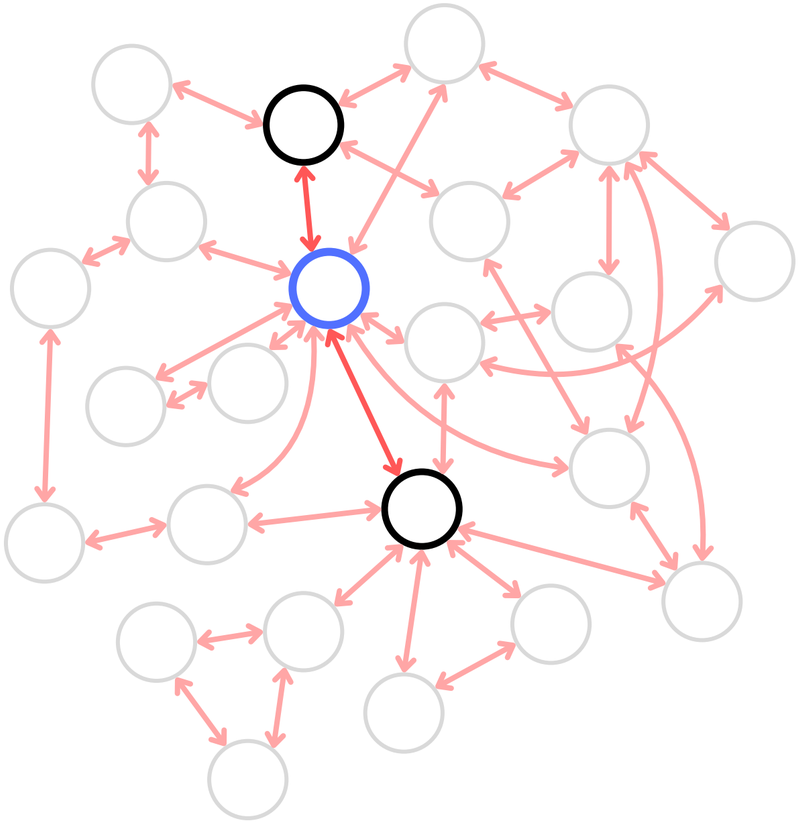
Peer Sampling problem: NewsCast



- Churning:
  - Nodes **enter** and **leave** the network

- **NewsCast**:
  - Use a **Peer View** of size ***k***
  - Peer View contains **descriptors**: *{P, P.timestamp}*
  - Message: *{P.peerView* U *P.descriptor}*

Peer Sampling problem: NewsCast



k = 2

- Churning:
  - Nodes **enter** and **leave** the network

- **NewsCast**:
  - Use a **Peer View** of size ***k***
  - Peer View contains **descriptors**: *{P, P.timestamp}*
  - Message: *{P.peerView U P.descriptor}*

```
on receive MESSAGE(Q.peerView) do
  P.peerView ← extractNewest(P.peerView U Q.peerView, k)
```

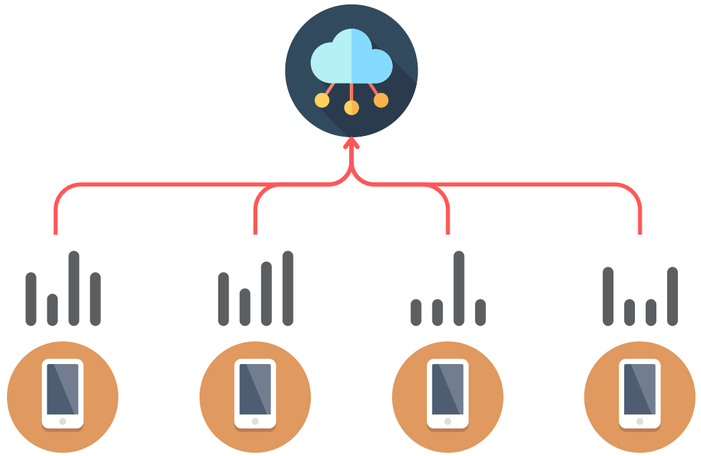
Gossip Learning

- Distributed Learning approach
  - Build ML models from **distributed data**
  - Each node trains **its model** from **its data**

- Alternative to **federated learning**

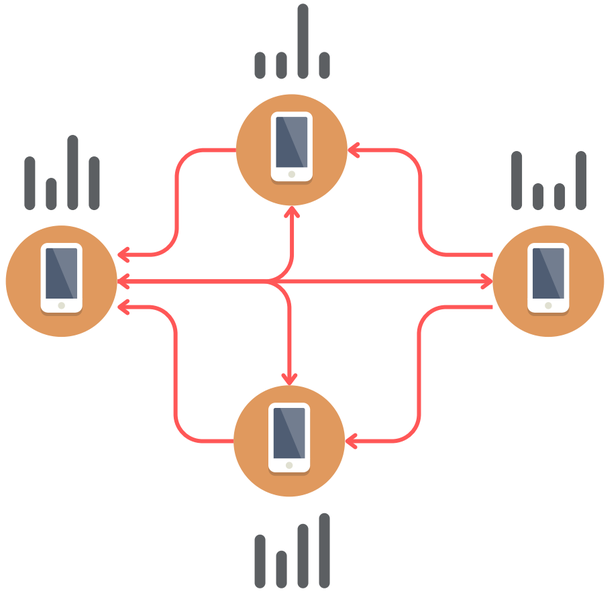
- Ok for **Supervised** Learning
- Use of **Stochastic Gradient Descend**

- Messages: *{P.modelWeights, P.timestamp}*



Federated Learning approach

Gossip Learning approach



Gossip Learning

```
initialize
  P.currentModel ← initModel()
  P.lastModel ← P.currentModel
  set eta, X, y as learingRate, P.data, P.labels

on timeout do
  Q ← random(getPeer(P))
  send MESSAGE(P.currentModel) to Q
  set timeout Δ

on receive MESSAGE(Q.model) do
  P.currentModel ← update(merge(P.lastmodel,
Q.model))

  P.lastModel ← Q.model
```

```
on update(model) do
 weights, timestamp ← model
 eta ← 1 / (learningRate * timestamp)

 weights ← (1 - eta * learningRate) * weights +
eta SGD(weights, P.data, P.labels)

 return (weights, timestamp + 1)

on merge(model1, model2) do
  weights1, timestamp1 ← model1
  weights2, timestamp2 ← model2

  newWeights ← (weights1 * timestamp1 + weights2
* timestamp2) / (timestamp1 + timestamp2)

  newTimestamp ← timestamp1 + timestamp2

  return (newWeights, newTimestamp)
```

Bibliography

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Thanks

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Distributed Aggregation of the Mean

Concurrent messages:

```
on timeout do
  Q ← random(getPeers(P))
  P.state ← P.value
  send PUSHPULL(P,P.state) to Q
  set timeout Δ

on receive PUSHPULL(Q, s) do
  d ← P.state - (P.state + s)/2
  send REPLY(P, d) to Q
  P.state ← P.state - d

on receive REPLY(Q, d) do
  P.state ← P.state + d
```

Distributed Aggregation of the Mean

Convergence

- Goal: $\mathbb{E}[\sigma^2(t+1)] = \rho\sigma^2(t) = \frac{1}{2\sqrt{e}}\sigma^2(t)$
- Assumptions: $\forall i, \mathbb{E}[x_i] = 0 \quad \wedge \quad \mathbb{V}[x_i] < \infty \quad \wedge \quad \forall i \neq j,\ \mathrm{corr}(x_i, x_j) = 0$
  getPeer() random "enough"
- Result 1: $\mathbb{E}[\sigma^2(t+1)] \approx \mathbb{E}[2^{-\mathbf{x}}]\mathbb{E}[\sigma^2(t)]$
- Idea 2: getPeer() creates a random permutation of the nodes,
  and pairs each of them to another one, picked at random.
- Result 2: $\mathbb{P}[x = x_j] = \mathbb{P}[x' = x_j - 1] = \frac{1}{(j-1)!}e^{-1} \qquad x' \sim \mathrm{Pois}(\lambda = 1)$