An Adaptive Algorithm for Efficient Message Diffusion in Unreliable Environments

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Our goal

We want to solve the reliable broadcast problem in large-scale distributed systems, using as few messages as possible

We want our solution to be able to adapt to changes in the system configuration

Outline

- Distributed systems
- Large scale systems
- Reliable broadcast
- Probabilistic approach
- Adaptation & Optimality

Distributed systems

"A distributed system is one that stops you from getting any work done when a machine you've never even heard of crashes."

Leslie Lamport quoted by Sape Müllender in Distributed Systems, 2nd edition. Addison-Wesley, 1993.

- As slow as the slowest
- As weak as the weakest

$\Rightarrow$ In large-scale systems, this is even worse...

Large scale

- Many nodes (processes)

  and/or

- Long-distances (high-latency)

  ⇒ Changes occur frequently

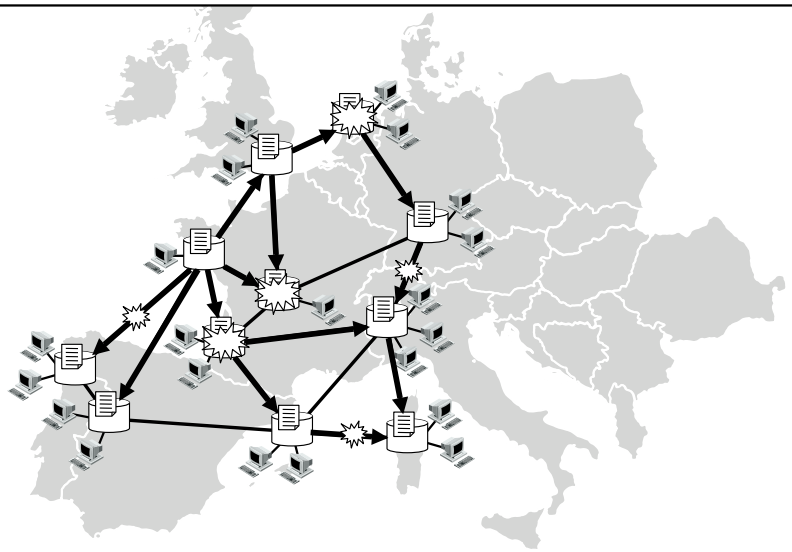
  ⇒ Difficult to act globally

Reliability

- Try to solve typical problems, e.g., consensus, reliable broadcast, atomic commitment, etc., despite the occurrence of failures
- A solution depends on the actual failure model, e.g., crash-stop, crash-recovery, Byzantine, etc.

Gossiping algorithms

Principle: only talk to some of your neighbors



Probabilistic model

Model definition

- The system is defined as a graph $G = (\Pi, \Lambda)$
  $\Pi = \{p_1, p_2, .. p_n\}$ is a set processes (vertices)
  $\Lambda = \{l_1, l_2, .. l_m\} \subseteq \Pi \times \Pi$ is a set of links (edges)
- Processes communicate by message passing
- A failure probability P_i is associated with each process p_i and a message-loss probability L_j is associated with each link l_j. This probabilities set defines a configuration.

Probabilistic reliability

Problem statement

Validity. If a process broadcasts a message m, then it eventually delivers m.

Agreement. If a process delivers a message m, then every process eventually delivers m **with probability K**.

Integrity. For any message m, every process delivers m at most once, and only if m was previously broadcast by some process.

Our goal revisited

- We want to provide a solution the probabilistic reliable broadcast in large-scale systems
- We want our solution to adapt to changes in the unreliability probabilities of processes & links
- We want to measure the effectiveness of our adaptive strategy with respect an algorithm that minimizes the number of messages

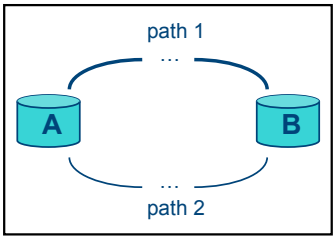
Optimality & adaptation

Optimality. A probabilistic reliable broadcast algorithm O is optimal to some configuration C w.r.t. the number of messages if there is no algorithm X such that processes executing X in C exchange fewer messages than processes executing O in C.

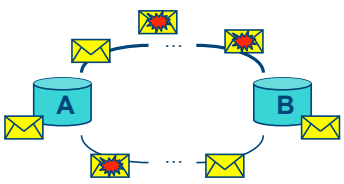
Adaptation. A probabilistic reliable broadcast algorithm A is adaptive to some configuration C if and only if the number of messages exchanged by processes executing A in C in response to a reliable broadcast is **eventually** equal to the number of messages exchanged by processes executing O in C

Optimal algorithm (1)

- Use **adaptive** gossiping, not **random** gossiping (traditional)
- **Example:**
  - Failure probability of path 1 = L
  - Failure probability of path 2 = αL, with α > 1 (path 1 more reliable than 2)
- Probability **K** of reaching B from A

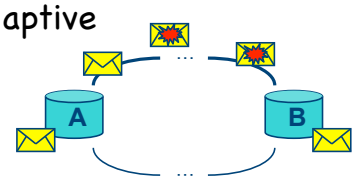


Random



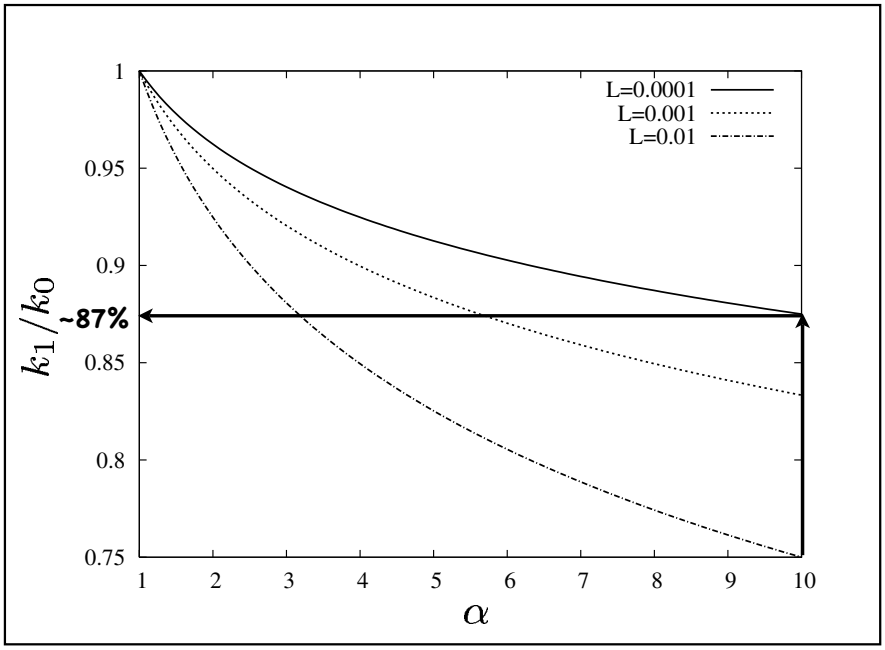
$$K = 1 - L^{k_0/2}(\alpha L)^{k_0/2} = 1 - (\sqrt{\alpha}\, L)^{k_0}$$

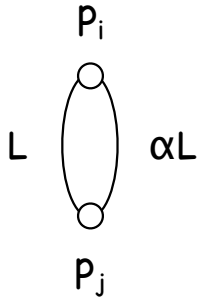
Adaptive



$$K = 1 - L^{k_1}$$

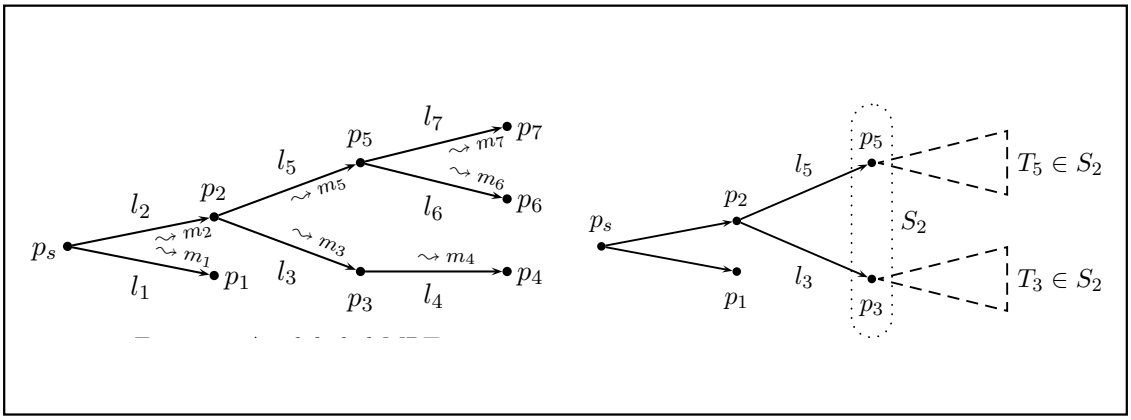
Optimal algorithm (2)





Maximum reliability tree

The maximum reliability tree is a spanning tree containing the most reliable path in G connecting all processes in Π



The reach function

Given a tree T_i and a vector $\vec{m}_i$, the reach function computes the probability that all processes in T_i are reached by at least one message

$$reach(T_i, \vec{m}_i) = \begin{cases} 1 & \text{if } T_i = \perp \\ \prod_{T_j \in S_i} (1 - [1 - (1 - P_i) \times (1 - L_j) \times (1 - P_j)]^{\vec{m}_i[j]}) \times reach(T_j, \vec{m}_j) & \text{otherwise} \end{cases}$$

$$reach(T_i, \vec{m}_i) = \prod_{j=1}^{n-1} 1 - [1 - (1 - P_{pred(j)}) \times (1 - L_j) \times (1 - P_j)]^{\vec{m}_i[j]}$$

Optimization problem

With $\lambda_j = 1 - (1 - P_{pred(j)}) \times (1 - L_j) \times (1 - P_j)$, we end up with the following optimization problem:

$$\begin{aligned} \textit{minimize} \quad & c(\vec{m}) = \sum_{j=1}^{|\vec{m}|} m[j] \\ \textit{subject to} \quad & r(\vec{m}) = \prod_{j=1}^{|\vec{m}|} 1 - \lambda_j^{m[j]} \geq K \end{aligned}$$

The optimize function

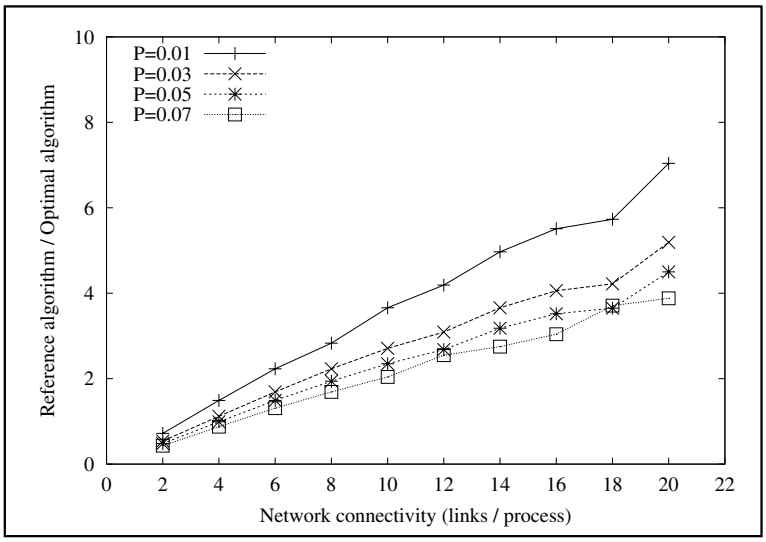
We use a greedy algorithm, since our optimization problem is itself greedy

function $optimize(mrt, K)$
  $\vec{m} \leftarrow (1, 1, 1, \cdots, 1)$
  while $r(\vec{m}) < K$ **do**
    let $\vec{u}_j$ be such that $\frac{r(\vec{m}+\vec{u}_j)}{r(\vec{m})}$ is maximum
    $\vec{m} \leftarrow \vec{m} + \vec{u}_j$
  return $\vec{m}$

Optimal algorithm

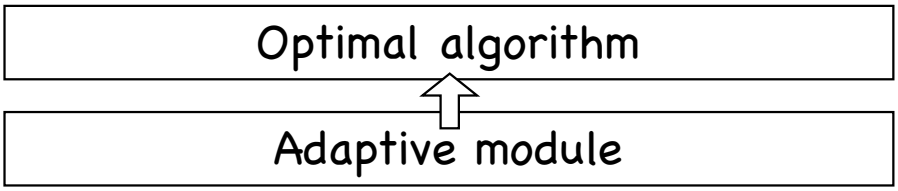
```
1:  To execute broadcast(m) do
2:      mrt_k ← mrt_k(G, C)
3:      propagate(m, mrt_k, p_k)
4:      deliver(m)

5:  when receive (m, mrt_j) for the first time
6:      propagate(m, mrt_j, p_k)
7:      deliver(m)

8:  function propagate(m, mrt_j, p_k)
9:      m_j ← optimize(mrt_j, K)
10:     for all subtree T_i ∈ S_{j,k} do
11:         repeat m_j[i] times
12:             send (m, mrt_j) to p_i
```

Performance of the optimal algorithm



From optimal to adaptive

- Our algorithm is proven to be optimal when it has exact knowledge of the system configuration
- By replacing such (unrealistic) exact knowledge with a module that approximates the changing configurations, we get an adaptive algorithm
- As soon as the approximation module converged towards the actual system configuration, we are again optimal



Adaptive algorithm

```
1:  INITIALIZATION:
2:    for all p_i ∈ Π do
3:      initializeReliability(C_k[p_i])
4:      C_k[p_i].d ← ∞
5:      C_k[p_i].seq ← 0
6:      C_k[p_i].suspected ← 0
7:      Δ_k[p_i] ← δ
8:    C_k[p_k].d ← 0

9:    Λ_k ← {l_{k,i} | p_i ∈ neighbors(p_k)}
10:   for all l_i ∈ Λ_k do
11:     initializeReliability(C_k[l_i])
12:     C_k[l_i].d ← 0

13: TO UPDATE (Λ_k, C_k):

14:   every Δ_k[p_k] do :
15:     C_k[p_k].seq ← C_k[p_k].seq + 1
16:     for all p_i ∈ neighbors(p_k) do
17:       send (Λ_k, C_k) to p_i

18:   when received (Λ_j, C_j) from p_j do                {Event 1}
19:     adjust ← C_k[p_j].suspected −
                          (C_j[p_j].seq − C_k[p_j].seq)
20:     C_k[p_j].suspected ← 0
21:     if adjust > 0 then
22:       increaseReliability(C_k[l_{k,j}], adjust)
23:       if adjust > 1 then Δ_k[p_j] ← Δ_k[p_j] + δ
24:     if adjust < 0 then
25:       decreaseReliability(C_k[l_{k,j}], |adjust|)
26:     for all p_i ∈ Π do
27:       selectBestEstimate(C_k[p_i], C_j[p_i])
28:     for all l_i ∈ (Λ_k ∩ Λ_j) do
29:       selectBestEstimate(C_k[l_i], C_j[l_i])
30:     for all l_i ∈ Λ_j − (Λ_k ∩ Λ_j) do
31:       C_k[l_i] ← C_j[l_i]
32:       C_k[l_i].d ← C_k[l_i].d + 1
33:     Λ_k ← Λ_k ∪ Λ_j
                                                          {Event 2}
34:   when not[updated C_k[p_j], p_j ≠ p_k, in the last Δ_k[p_j]] do
35:     C_k[p_j].d ← C_k[p_j].d + 1
36:     if p_j ∈ neighbors(p_k) then
37:       C_k[p_j].suspected ← C_k[p_j].suspected + 1
38:       decreaseReliability(C_k[p_j], 1)
39:       decreaseReliability(C_k[l_{k,j}], 1)

40:   every Δ_tick do                                     {Event 3}
41:     increaseReliability(C_k[p_k], 1)
                                                          {Event 4}
42:   when recovering from a crash lasting n × Δ_tick do
43:     decreaseReliability(C_k[p_k], n)
```

```
1:  Initialization
2:    U ← 100                  {precision of probabilistic intervals}

3:  function initializeReliability(estimate)
4:    with estimate do
5:      for all u = 1..U do
6:        P_{F|B}[u] ← (2u−1)/(2U)          {probabilistic intervals}
7:        P_B[u] ← 1/U                      {with equal initial beliefs}

8:  function decreaseReliability(estimate, factor)
9:    with estimate repeat factor times
10:     for all u = 1..U do
11:       P_B[u] ← P_B[u]×P_{F|B}[u] / Σ_{v=1}^{U} P_B[v]×P_{F|B}[v]

12: function increaseReliability(estimate, factor)
13:   with estimate repeat factor times
14:     for all u = 1..U do
15:       P_B[u] ← P_B[u]×(1−P_{F|B}[u]) / Σ_{v=1}^{U} P_B[v]×(1−P_{F|B}[v])
```


Bayesian inference (1)

$$P_{B|F}[u] = \frac{P_{F|B}[u] \times P_B[u]}{\sum_{v=1}^{U} P_{F|B}[v] \times P_B[v]}$$

Bayesian inference (2)

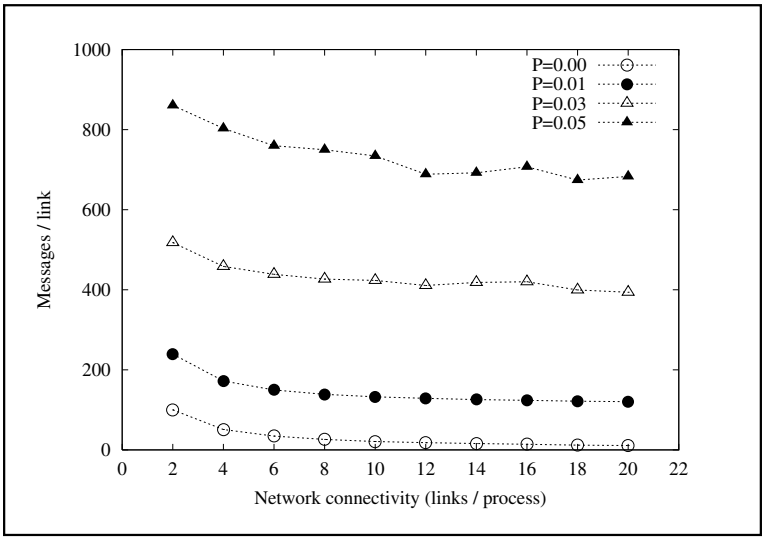
u	$C_k[p_i].P_{F\|B}[u]$	$C_k[p_i].P_B[u]$
1	[0.0 , 0.2)	0.2
2	[0.2 , 0.4)	0.2
3	[0.4 , 0.6)	0.2
4	[0.6 , 0.8)	0.2
5	[0.8 , 1.0]	0.2

(a) Initial configuration

u	$C_k[p_i].P_{F\|B}[u]$	$C_k[p_i].P_B[u]$
1	[0.0 , 0.2)	0.04
2	[0.2 , 0.4)	0.12
3	[0.4 , 0.6)	0.20
4	[0.6 , 0.8)	0.28
5	[0.8 , 1.0]	0.36

(b) After a failure suspicion

Adaptation convergence



Question?