Optimizing near duplicate detection for peer-to-peer networks

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Introduction

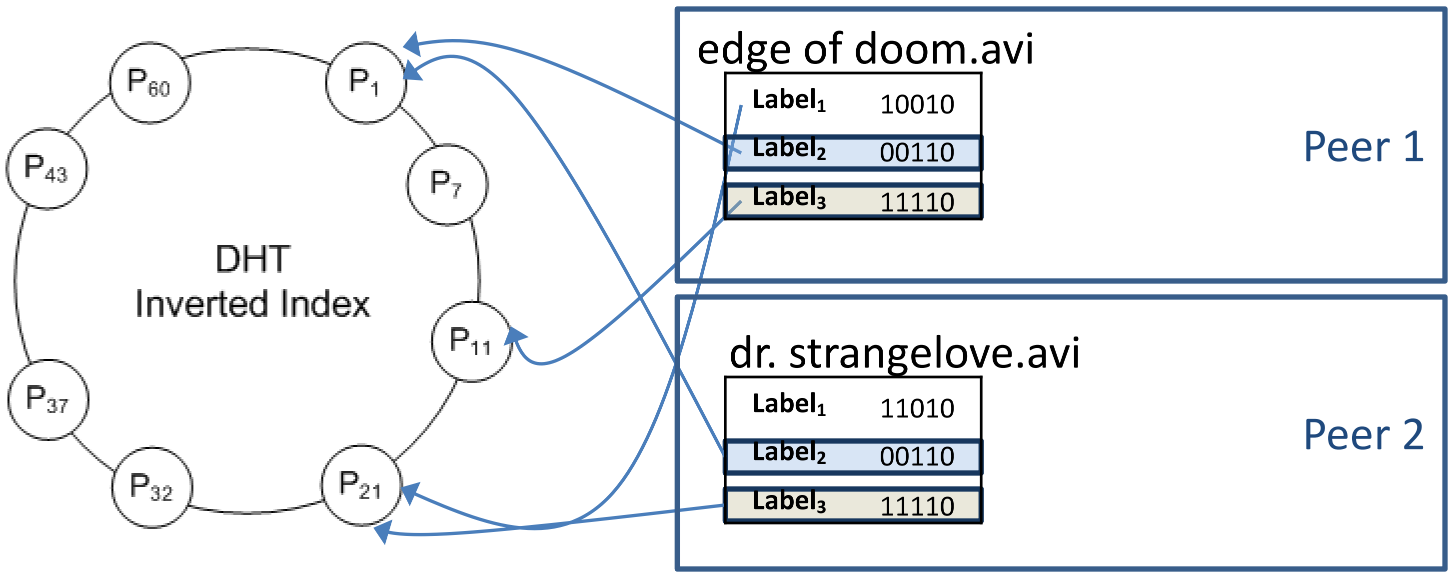
- Near duplicate on the **content level*:***
  - near duplicates: resources with minor differences
  - videos with different advertisements, text with last-update-time
  - audio/video of different quality
  - different performance of the same song
- Why near duplicate detection for P2P?
  - Multimedia
    - finding alternative sources to parallelize the download
    - finding media of different resolutions/qualities
    - detecting copies of copyrighted multimedia
    - ignore minor differences, e.g., advertisements
  - Text
    - different versions of the same text
    - ignore insignificant changes, e.g., last-update-time
    - detect copyrighted text
- *Common property:*
  - *One can decide a priori on the minimum similarity for considering two files as near duplicates*
  - *Desired detection probability*

Locality Sensitive Hashing for NDD

- Use Locality Sensitive Hashing (LSH) for building an inverted index of files/resources
  - Resources R_1, R_2, R_3, …
  - $R_i \approx R_j$ when $sim(R_i , R_j) > minSim$
  - $LSH(R_i) \rightarrow$ Labels $\{label_1, label_2, \dots, label_l\}$
  - For example, $LSH(R_i) \rightarrow \{10010, 01011, 11011\}$
  - If $sim(R_i , R_j) > minSim \rightarrow R_i$ and R_j share a label w.h.p.,
  - If $sim(R_i , R_j) < minSim \rightarrow R_i$ and R_j do not share a label w.h.p.

Locality Sensitive Hashing over a DHT

- LSH-based inverted index
  - LSH(R_i) → Labels {$label_1$, $label_2$, …, $label_l$}



  - Indexing: DHT.put($label_x$, R_i), for $1<=x<=l$, for all resources
  - Querying for near duplicates of query R_i : DHT.get(R_i. $label_x$), for $1<=x<=l$ → union is **potential** near duplicates
  - Possible false positives

Locality Sensitive Hashing

- LSH-based inverted index
  - LSH(R_i) → Labels {$label_1$, $label_2$, …, $label_l$}

edge of doom.avi

$Label_1$	10010
$Label_2$	00110
$Label_3$	11110

$l=3$

$k=5$

dr. strangelove.avi

$Label_1$	11010
$Label_2$	00110
$Label_3$	11110

- Existing works: inverted index over DHT using the labels as keys [LSHForest, Haghani09]
- Crucial parameters
  - ↑ l → false positives↑, network cost↑, detection probability↑
  - ↑ k → false positives↓, network cost↓, detection probability↓
- Focus of our work:
  - *find the optimal combination of l, k that provides the desired detection probability for the given network → minimize network cost and make the algorithm more efficient and scalable*

POND: Peer-to-peer Optimized Near duplicate Detection

- Coordinator
  1. Collect network statistics
  2. Compute optimal parameters
  3. Propagate optimal parameters to network

- All peers:
  1. Re-compute labels for all resources
  2. Re-index labels to DHT

- Periodic repetition to compensate for churn

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Collecting network statistics

- Coordinator collects network statistics
  - Network size [Ganesh07]
  - Number of resources per peer
  - Probability distribution function (PDF) for all pairwise similarities in the corpus
- Sampling of a small number of neighbors
  - Pairwise similarities: peers transmit only the media representations (a few kbytes per peer)
  - PDF: represented as equi-width histogram

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Computing the optimal parameters (I)

- Coordinator computes optimal configuration
- Input parameters:
  - minimum similarity minSim, detection probability pr_{min}
- Required statistics:
  - average #queries, number of peers N
- Cost (to minimize)
  - Maintenance: indexing the resources in the DHT
  - Query:
    - querying the DHT for the labels
    - cost for retrieving the false positives
    - cost for retrieving the true near duplicates
- Constraint
  - Detection probability >= pr_{min}

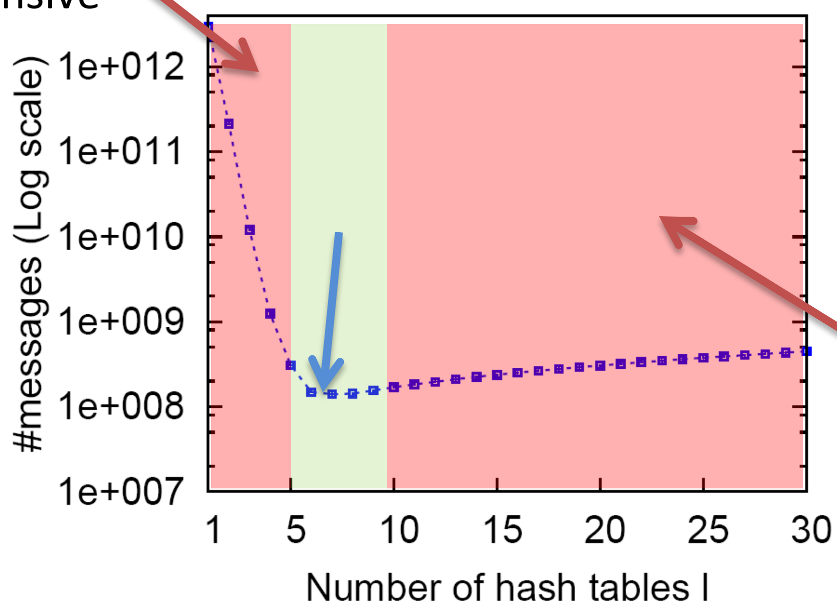
Computing the optimal parameters (II)

Probabilities

- Reduce false positive probability: ↑*k* , ↓*l*
- Increase detection probability: ↓ *k* , ↑*l*
- Optimal combination (proof in the paper)

$$k_0 = \frac{\log\left(1-(1-pr_{min})^{1/l}\right)}{\log\left(0.5-\frac{1}{2\cdot minSim}\right)+\log(minSim)}$$

Querying too expensive



Cost function convex → convex optimization to identify the combination with minimum cost

Maintenance too expensive

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Propagating the optimal parameters

- Propagating the optimal parameters
  - Dissemination over DHT [El-Ansary03]
  - Cost: O(N) messages, O(log(N)) time
- Each peer
  - Computes the updated labels of all its resources
  - Indexes them in the DHT: O(log(N)) per resource

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Query execution

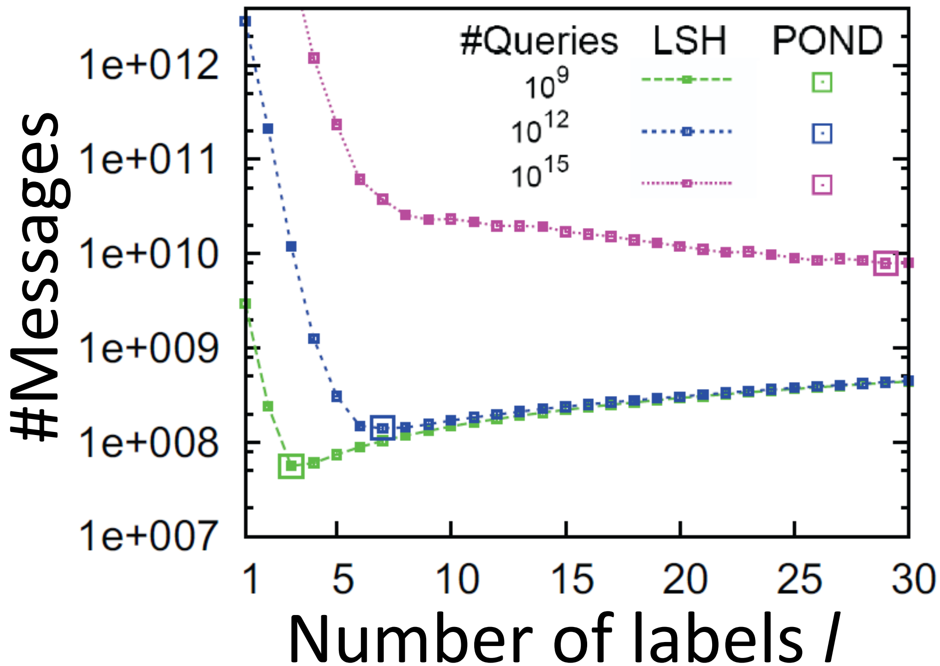
- Finding all near duplicates of a resource R_q
  - Compute the labels of the resource, according to *l* and *k*
  - Lookup all labels at DHT → potential near duplicates
  - For each potential near duplicate
    - Send a *compact representation* of R_q to the peer (a few Kbytes)
    - Retrieve the file only if it is a near duplicate
    - Large multimedia files are never transmitted over the network

Evaluation

- Datasets:
  - Reuters RCV1: 802 thousands documents, ~1 Gbyte
  - 22455 videos (TubeKit [Shah08]), 144 Gbytes
  - 22455 audios (82 Gbytes)
- Compare with non-optimized LSH
  - Network Cost
  - Retrieval effectiveness – Recall

Comparison with non-optimized alg.

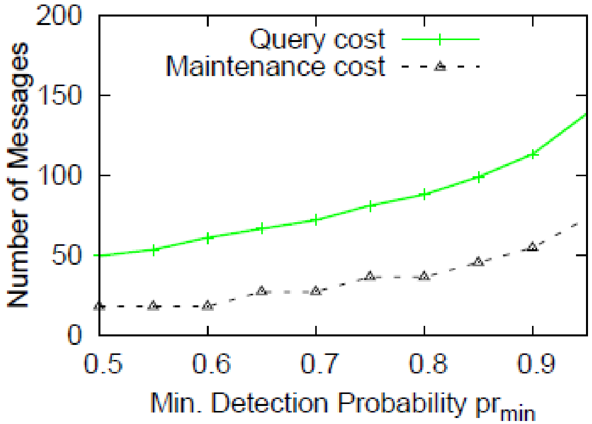
- RCV1, pr_{min}=0.8, minSim=0.9, 100000 peers
- Vary #queries per republishing period



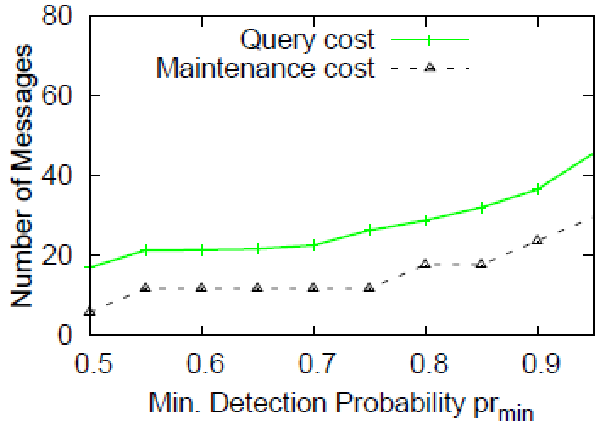
- POND derives configuration with ***minimal*** cost
- Same probabilistic guarantees and recall with non-optimized LSH

Effect of desired detection probability:: Network cost

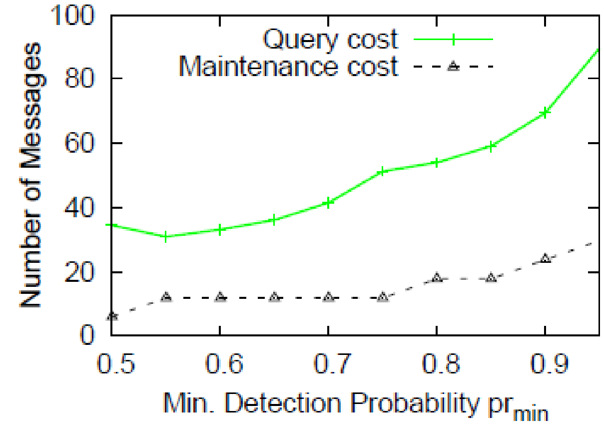
RCV1 (100k peers)



Videos(1000 peers)



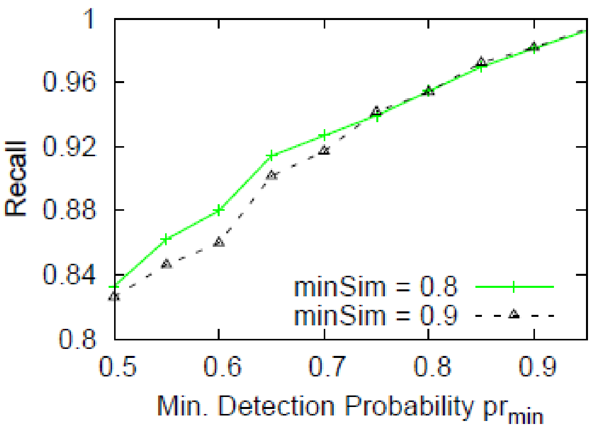
Audio(1000 peers)



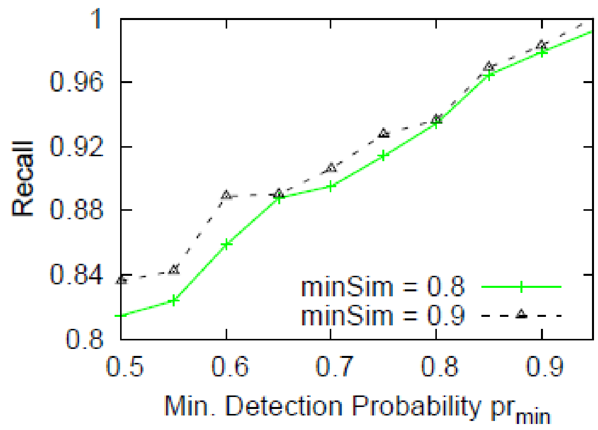
- Maintenance cost per resource/query cost per query
- Cost can be controlled using pr_{min}
- Manageable for large collections, e.g., for indexing 100 videos with pr_{min}=0.9, only ~2000 small messages required
- All messages are equi-sized and below 1Kbyte → transfer volume proportional to #messages

Effect of desired detection probability:: Recall

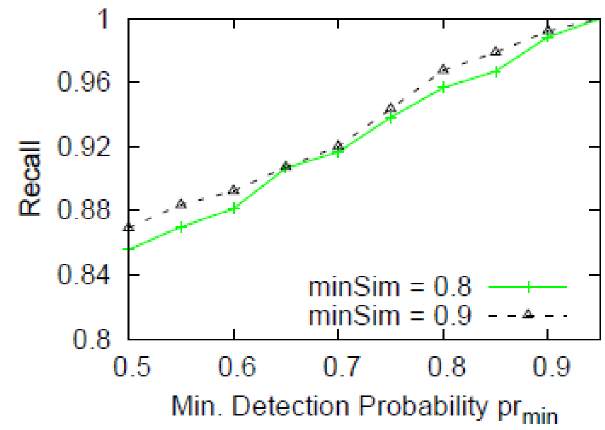
RCV1 (100k peers)



Videos(1000 peers)



Audio(1000 peers)



- Probabilistic guarantees always satisfied
- Recall:cost tradeoff fine-tuned with pr_{min}
- Recall insensitive to minSim: algorithm adapts the parameters to satisfy pr_{min}

Conclusions

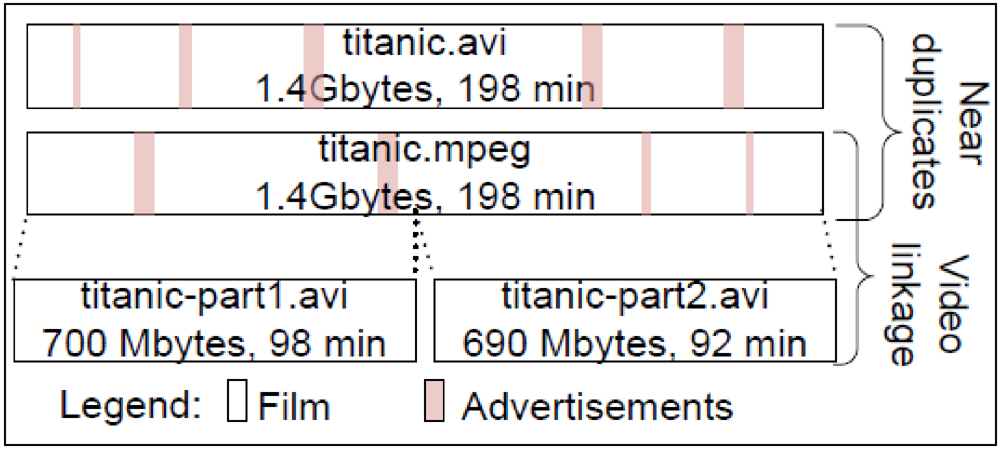
- Target: Determine the *l* and *k* values that minimize the network cost and satisfy the probabilistic guarantees
- Performance improvements easily reaches an order of magnitude
- Additional information in the paper
  - Compact representations for text, audio, video
  - Video linkage, with extensive evaluation
- Future work
  - Repeat analysis using different network configurations [LSHForest05, Haghani09]
  - Effect of similarity function
  - Possible extension to other application scenarios, such as tag recommendation and annotation sharing

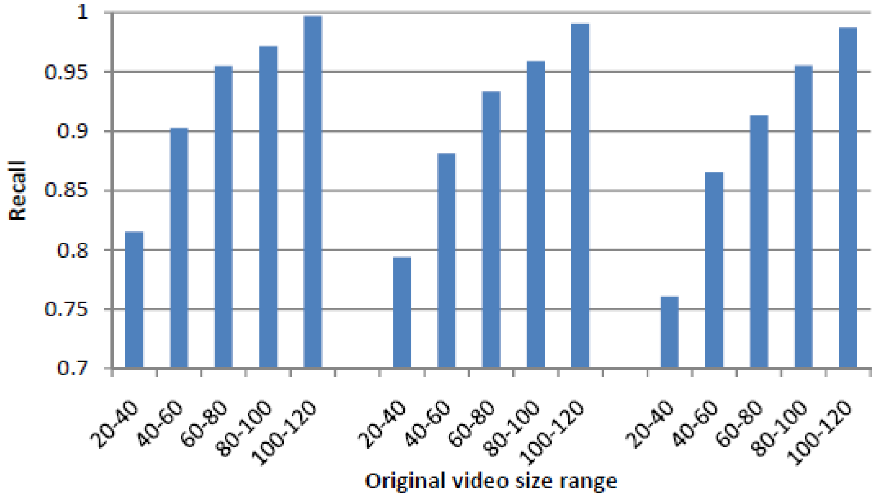
Thank you

Questions?

Evaluation of video linkage

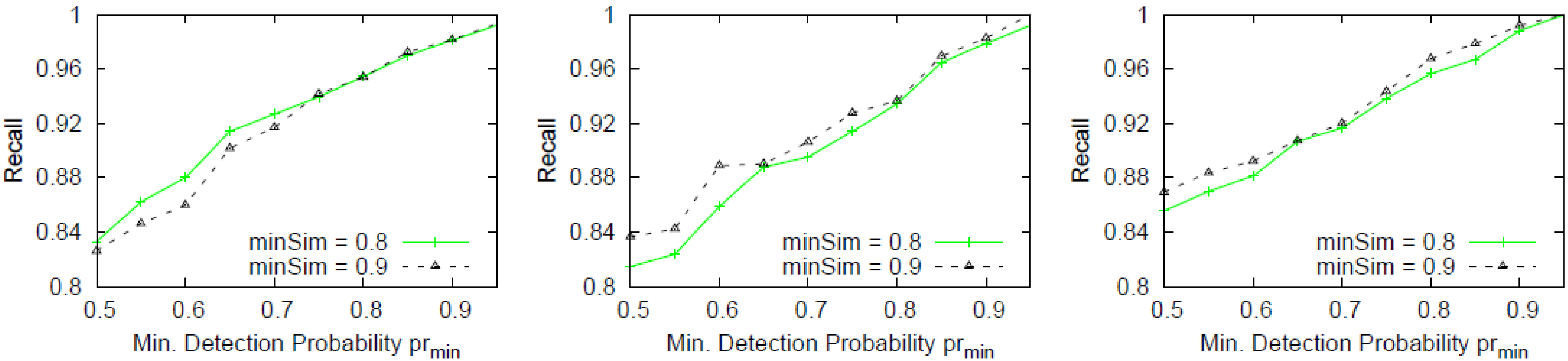
- Video linkage:
  - Experimental evaluation:
    - Split video to X parts (X={2,3,4})
    - pr_{min}=0.9, minSim=0.9
    - Use any one of the parts as a query, and try to detect the original file
    - Cost: At most 110 messages, for the largest videos



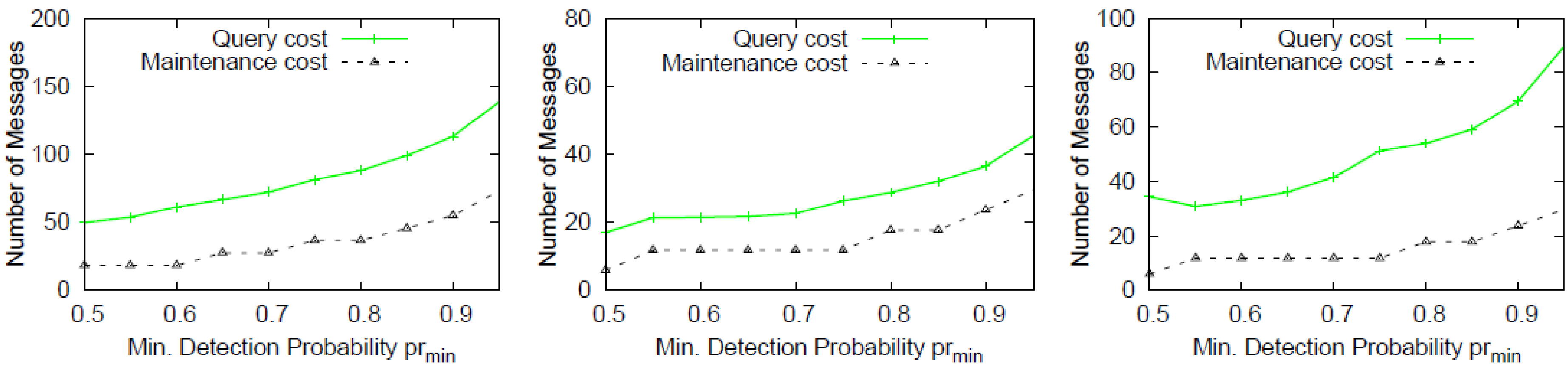


Effect of desired detection probability

- Recall:



- Cost:



Related work

Existing work on NDD

- P2P MACSIS [Yang03]
  - NDD for audio files
  - Based on gossiping
- Optimizing LSH for centralized systems [Dong08]
  - Focuses on computational cost
- LSH with p-stable distributions [Haghani09]
- LSH Forest [LSHForest05]
  - Repeating the analysis of POND for these network configurations

Further details (I)

- Extensions presented in the paper
  - Compact representations for text, audio, video
    - Independent of binary encoding and resolution
    - |representation(R_i)| only a few Kbytes, even for videos
    - DHT.put(R_i. $label_x$, representation(R_i))
    - Instead of exchanging the resources, peers exchange representations

Further details (II)

- Extensions presented in the paper
  - Video linkage
    - For practical reasons, users may break large videos e.g., titanic.avi → titanic-part1.avi and titanic-part2.avi
    - Use keyframes to *conceptually* split each video to smaller segments
    - Expected number of segments configurable
    - Each video segment is handled individually, w.r.t. indexing and query execution
    - Discovering one segment sufficient for full linkage
    - Experimental evaluation