Global Network Positioning: A New Approach to Network Distance Prediction

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New Challenges

• Large-scale distributed services and applications
  – Napster, Gnutella, End System Multicast, etc
• Large number of configuration choices
• \( K \) participants \( \Rightarrow O(K^2) \) e2e paths to consider
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Role of Network Distance Prediction

- On-demand network measurement can be highly accurate, but
  - Not scalable
  - Slow
- Network distance
  - Round-trip propagation and transmission delay
  - Relatively stable
- Network distance can be predicted accurately without on-demand measurement
  - Fast and scalable first-order performance optimization
  - Refine as needed
Applying Network Distance

- Napster, Gnutella
  - Use directly in peer-selection
  - Quickly weed out 95% of likely bad choices
- End System Multicast
  - Quickly build a good quality initial distribution tree
  - Refine with run-time measurements

- Key: network distance prediction mechanism must be scalable, accurate, and fast
State of the Art: IDMaps [Francis et al ‘99]

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**IDMaps Benefits**

- Significantly reduce measurement traffic compared to \((\# \text{ end hosts})^2\) measurements
- End hosts can be simplistic
Challenging Issues

• Scalability
  – Topology data widely disseminated to HOPS servers
  – Requires more HOPS servers to scale with more client queries

• Prediction speed/scalability
  – Communication overhead is $O(K^2)$ for distances among $K$ hosts

• Prediction accuracy
  – How accurate is the “Tracers/end hosts” topology model when the number of Tracers is small?

• Deployment
  – Tracers/HOPS servers are sophisticated; probing end hosts may be viewed as intrusive
Global Network Positioning (GNP)

- Model the Internet as a geometric space (e.g. 3-D Euclidean)
- Characterize the position of any end host with coordinates
- Use computed distances to predict actual distances

- Reduce distances to coordinates
Landmark Operations

Internet
Landmark Operations

- Small number of distributed hosts called Landmarks measure inter-Landmark distances
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- Compute Landmark coordinates by minimizing the overall discrepancy between measured distances and computed distances
  - Cast as a generic multi-dimensional global minimization problem
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Landmark Operations

- Landmark coordinates are disseminated to ordinary end hosts
  - A frame of reference
  - e.g. (2-D, \((L_1,x_1,y_1)\), \((L_2,x_2,y_2)\), \((L_3,x_3,y_3)\))
Ordinary Host Operations

Internet

L₁
L₂
L₃

(x₁, y₁)
(x₂, y₂)
(x₃, y₃)

x
y
Ordinary Host Operations

- Each ordinary host measures its distances to the Landmarks, Landmarks just reflect pings
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GNP Advantages Over IDMaps

• High scalability and high speed
  – End host centric architecture, eliminates server bottleneck
  – Coordinates reduce $O(K^2)$ communication overhead to $O(K^*D)$
  – Coordinates easily exchanged, predictions are locally and quickly computable by end hosts

• Enable new applications
  – Structured nature of coordinates can be exploited

• Simple deployment
  – Landmarks are simple, non-intrusive (compatible with firewalls)
Evaluation Methodology

- 19 Probes we control
  - 12 in North America, 5 in East Asia, 2 in Europe
- Select IP addresses called Targets we do not control

- Probes measure
  - Inter-Probe distances
  - Probe-to-Target distances
  - Each distance is the minimum RTT of 220 pings
Evaluation Methodology (Cont’d)

• Choose a subset of well-distributed Probes to be Landmarks, and use the rest for evaluation
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Computing Coordinates

- Multi-dimensional global minimization problem
  - Will discuss the objective function later
- Simplex Downhill algorithm [Nelder & Mead ‘65]
  - Simple and robust, few iterations required
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Data Sets

Global Set
• 19 Probes
• 869 Targets uniformly chosen from the IP address space
  – biased towards always-on and globally connected nodes
• 44 Countries
  – 467 in USA, 127 in Europe, 84 in East Asia, 39 in Canada,
    ..., 1 in Fiji, 65 unknown

Abilene Set
• 10 Probes are on Abilene
• 127 Targets that are Abilene connected web servers
Performance Metrics

- **Directional relative error**
  - Symmetrically measure over and under predictions

\[
\frac{\text{predicted} - \text{measured}}{\min(\text{measured}, \text{predicted})}
\]

- **Relative error** = abs(Directional relative error)

- **Rank accuracy**
  - % of correct prediction when choosing some number of shortest paths
GNP vs IDMaps (Global)
GNP vs IDMaps (Global)

![Graph showing directional relative error vs measured path distances. The graph compares GNP with 15 landmarks in 7D to IDMaps with 15 tracers.]

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Why the Difference?

- IDMaps tends to heavily over-predict short distances
- Consider (measured ≤ 50ms)
  - 22% of all paths in evaluation
  - IDMaps on average over-predicts by 150%
  - GNP on average over-predicts by 30%
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GNP vs IDMaps (Abilene)

Cumulative Probability vs Relative Error

- GNP, 9 Landmarks, 8D
- IDMaps, 9 Tracers
GNP vs IDMaps (Abilene)
GNP vs IDMaps (Abilene)
Basic Questions

- How to measure model error?
- How to select Landmarks?
- How does prediction accuracy change with the number of Landmarks?
- What is geometric model to use?
- How can we further improve GNP?
Measuring Model Error

\[
error = \sum (f (d_{ij}, \hat{d}_{ij}))
\]

- \(d_{ij}\) is measured distance
- \(\hat{d}_{ij}\) is computed distance
- \(f (d_{ij}, \hat{d}_{ij})\) is an error measuring function
Error Function

- Squared error

\[ f(d_{ij}, \hat{d}_{ij}) = (d_{ij} - \hat{d}_{ij})^2 \]

- May not be good because one unit of error for short distances carry the same weight as one unit of error for long distances
More Error Functions

- Normalized error

\[
f(d_{ij}, \hat{d}_{ij}) = \left( \frac{d_{ij} - \hat{d}_{ij}}{d_{ij}} \right)^2
\]

- Logarithmic transformation

\[
f(d_{ij}, \hat{d}_{ij}) = \left( \log(d_{ij}) - \log(\hat{d}_{ij}) \right)^2
\]
## Comparing Error Functions

<table>
<thead>
<tr>
<th></th>
<th>6 Landmarks</th>
<th>15 Landmarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Squared Error</td>
<td>1.03</td>
<td>0.74</td>
</tr>
<tr>
<td>Normalized Error</td>
<td>0.74</td>
<td>0.50</td>
</tr>
<tr>
<td>Logarithmic</td>
<td>0.75</td>
<td>0.51</td>
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<tr>
<td>Transformation</td>
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</table>
Selecting N Landmarks

- Intuition: Landmarks should be well separated
- Method 1: Clustering
  - start with 19 clusters, one probe per cluster
  - iteratively merge the two closest clusters until there are N clusters
  - choose the center of each cluster as the Landmarks
- Method 2: Find “N-Medians”
  - choose the combination of N Probes that minimizes the total distance from each not chosen Probe to its nearest chosen Probe
- Method 3: Maximum separation
  - choose the combination of N Probes that maximizes the total inter-Probe distances
K-Fold Validation

- Want more than just one set of \( N \) Landmarks to reduce noise
- Select \( N+1 \) Landmarks based on a criterion
- Eliminate one Landmark to get \( N \) Landmarks
- i.e., \( N+1 \) different sets of \( N \) Landmarks that are close to the selection criterion
## Comparing Landmark Selection Criteria

(6 Landmarks)

<table>
<thead>
<tr>
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<th>Clustering</th>
<th>N-Medians</th>
<th>Max sep.</th>
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<tbody>
<tr>
<td>GNP</td>
<td>0.74</td>
<td>0.78</td>
<td>1.04</td>
</tr>
<tr>
<td>IDMaps</td>
<td>1.39</td>
<td>1.43</td>
<td>5.57</td>
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## Comparing Landmark Selection Criteria
(9 Landmarks)

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<tr>
<td>GNP</td>
<td>0.68</td>
<td>0.7</td>
<td>0.83</td>
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<tr>
<td>IDMaps</td>
<td>1.16</td>
<td>1.09</td>
<td>1.74</td>
</tr>
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</table>
## Landmark Placement Sensitivity

<table>
<thead>
<tr>
<th></th>
<th>Max</th>
<th>Min</th>
<th>Mean</th>
<th>Std Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>GNP</td>
<td>0.94</td>
<td>0.64</td>
<td>0.74</td>
<td>0.069</td>
</tr>
<tr>
<td>IDMaps</td>
<td>1.84</td>
<td>1.0</td>
<td>1.29</td>
<td>0.23</td>
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Number of Landmarks/Tracers

Cumulative Probability

Relative Error

GNP, 15 Landmarks, 7D
GNP, 12 Landmarks, 7D
GNP, 9 Landmarks, 5D
GNP, 6 Landmarks, 5D
IDMaps, 15 Tracers
IDMaps, 12 Tracers
IDMaps, 9 Tracers
IDMaps, 6 Tracers
What Geometric Model to Use?

- Spherical surface, cylindrical surface
  - No better than 2-D Euclidean space
- Euclidean space of varying dimensions
Euclidean Dimensionality

Cumulative Probability vs. Relative Error

- 15 Landmarks, 9D
- 15 Landmarks, 8D
- 15 Landmarks, 7D
- 15 Landmarks, 6D
- 15 Landmarks, 5D
- 15 Landmarks, 4D
- 15 Landmarks, 3D
- 15 Landmarks, 2D
Why Additional Dimensions Help?

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2-dimensional model
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2-dimensional model

3-dimensional model
Reducing Measurement Overhead

- Hypothesis: End hosts do not need to measure distances to all Landmarks to compute accurate coordinates.
Reducing Measurement Overhead

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![Diagram showing end hosts and landmarks](image)
Reducing Measurement Overhead

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Reducing Measurement Overhead

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![Diagram showing end host T and various landmarks P1, P2, P3, P4, P5, P6, with coordinates (x', y')](image-url)
Using 9 of 15 Landmarks in 8 Dimensions
Using 9 of 15 Landmarks in 8 Dimensions
Triangular Inequality Violations
Removing Triangular Inequality Violations

• Remove Target (t) from data if
  – t in \{a, b, c\}
  – \frac{(a,c)}{((a,b)+(b,c))} > \text{threshold}

• Try two thresholds
  – 2.0; 647 of 869 Targets remain
  – 1.5; 392 of 869 Targets remain
  – Note: at 1.1, only 19 of 869 Targets remain!!!
Removing Triangular Inequality Violations

![Graph showing cumulative probability against relative error. The graph has a red line labeled "Original data." ]
Removing Triangular Inequality Violations

![Graph showing cumulative probability against relative error]

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Removing Triangular Inequality Violations

Cumulative Probability vs. Relative Error

- Original data
- > 2.0 removed
- > 1.5 removed
Removing Triangular Inequality Violations

Cumulative Probability vs. Relative Error

- Original data
- > 2.0 removed
- > 1.5 removed
- Random removal

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Why Not Use Geographical Distance?
Summary

- Network distance prediction is key to performance optimization in large-scale distributed systems
- GNP is scalable
  - End hosts carry out computations
  - $O(K*D)$ communication overhead due to coordinates
- GNP is fast
  - Distance predictions are fast local computations
- GNP is accurate
  - Discover relative positions of end hosts
Future Work

• Understand the capabilities and limitations of GNP
• Can we learn about the underlying topology from GNP?
• Is GNP resilient to network topology changes?
• Can we reduce the number of measured paths while not affecting accuracy?
• Design better algorithms for Landmark selection
• Design more accurate models of the Internet
• Apply GNP to overlay network routing problems
• Apply GNP to geographic location problems