Dissertation
Towards a Framework for DHT Distributed Computing

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Objective

Our objective is to create a generalized framework for distributed computing using Distributed Hash Tables.

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Or

We want to build a completely decentralized distributed computing framework.

What do I Mean by Distributed Computing?

A system where we can take a task and break it down into multiple parts, where each part is worked upon individually.

Challenges of Distributed Computing

Distributed Computing platforms experience these challenges:

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Distributed Computing platforms experience these challenges:

Scalability As the network grows, more resources are spent on maintaining and organizing the network.

Fault-Tolerance As more machines join the network, there is an increased risk of failure.

Load-Balancing Tasks need to be evenly distributed among all the workers.

Distributed Key/Value Stores

Distributed Hash Tables are mechanisms for storing values associated with certain keys.

- Values, such as filenames, data, or IP/port combinations are associated with keys.
- These keys are generated by taking the hash of the value.
- We can get the value for a certain key by asking any node in the network.

How Does It Work?

- DHTs organize a set of nodes, each identified by an **ID**.
- Nodes are responsible for the keys that are closest to their IDs.
- Nodes maintain a small list of other peers in the network.
  - Typically a size $\log(n)$ subset of all nodes in the network.
- Each node uses a very simple routing algorithm to find a node responsible for any given key.

Current Applications

Applications that use or incorporate DHTs:

- P2P File Sharing applications, such as BitTorrent.
- Distributed File Storage.
- Distributed Machine Learning.
- Name resolution in a large distributed database.

Strengths of DHTs

DHTs are designed for large P2P applications, which means they need to be (and are):

- Scalable
- Fault-Tolerant
- Load-Balancing

DHTs Address the Specified Challenges

The big issues in distributed computing can be solved by the mechanisms provided by Distributed Hash Tables.

Uses For DHT Distributed Computing

The generic framework we are proposing would be ideal for:

- Embarrassingly Parallel Computations
  - Any problem that can be framed using Map and Reduce.
  - Brute force cryptography.
  - Genetic algorithms.
  - Markov chain Monte Carlo methods.
- Use in either a P2P context or a more traditional deployment.

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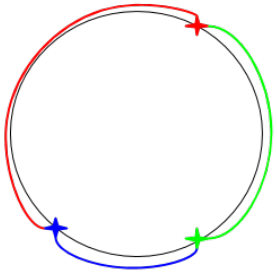
Required Attributes of DHT

- A distance and midpoint function.
- A closeness or ownership definition.
- A Peer management strategy.

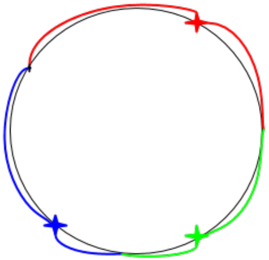
Chord's Closest Metric.

Figure: A Voronoi diagram for a Chord network, using Chord's definition of closest.



Chord Using A Different Closest Metric

Figure: A Voronoi diagram for a Chord network, where closest is defined by the node being the closest in either direction.



Terms and Variables

- Network size is n nodes.
- Keys and IDs are m bit hashes, usually SHA1.
- Peerlists are made up of:

Short Peers	The neighboring nodes that define the network's topology.
Long Peers	Routing shortcuts.

Functions

lookup(*key*)	Finds the node responsible for a given key.
put(*key*, *value*)	Stores *value* at the node responsible for *key*, where $key = hash(value)$.
get(*key*)	Returns the *value* associated with *key*.

Chord

- Ring Topology
- Short Peers: predecessor and successor in the ring.
- Responsible for keys between their predecessor and themselves.
- Long Peers: $\log n$ nodes, where the node at index i in the peerlist is

$$root(r + 2^{i-1} \mod m), 1 < i < m$$

A Chord Network

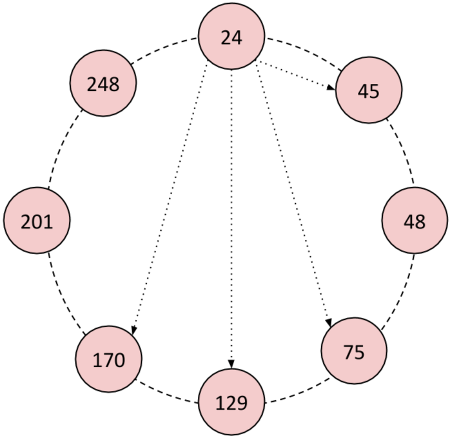


Figure: An 8-node Chord ring where $m = 8$. Node 24's long peers are shown.

Fault Tolerence in Chord

- Local maintenance thread gradually fixes the network topology.
    - Each node “notifies” its successor.
    - The successor replies with a better successor if one exists.
- The long peers are gradually updated by performing a lookup on each entry.

Handling Churn in General

- Short peers, the neighbors, are regularly queried to:
    - See of the node is still alive.
    - See if the neighbor knows about better nodes.
- Long peer failures are replaced by periodic maintenance.

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Introduction

- Build on DGVH and VHash
- Create an abstract model of a DHT based on Voronoi/Delaunay
- Can be used as a bootstrapping network for other distributed systems
- Can emulate the topology of other DHTs

Goals

VHash sprung from two related ideas:

- We wanted a way be able optimize latency by embedding it into the routing overlay.

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    - Distributed algorithms for this problem don't really exist.

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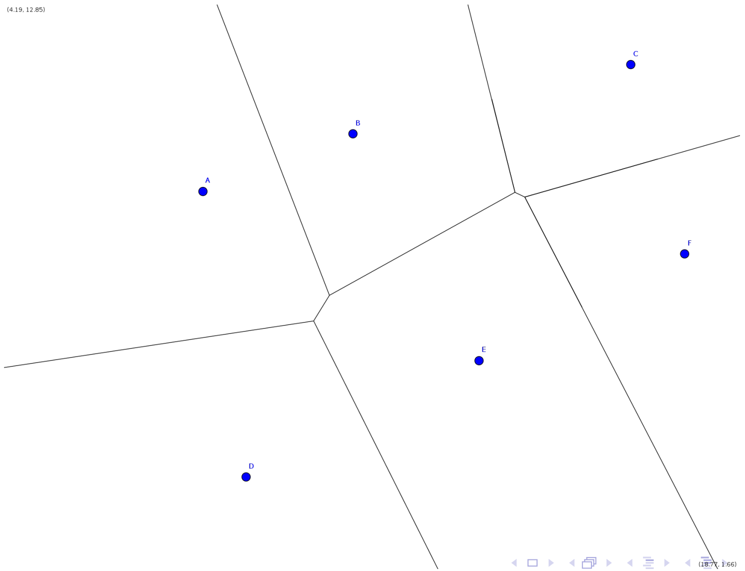
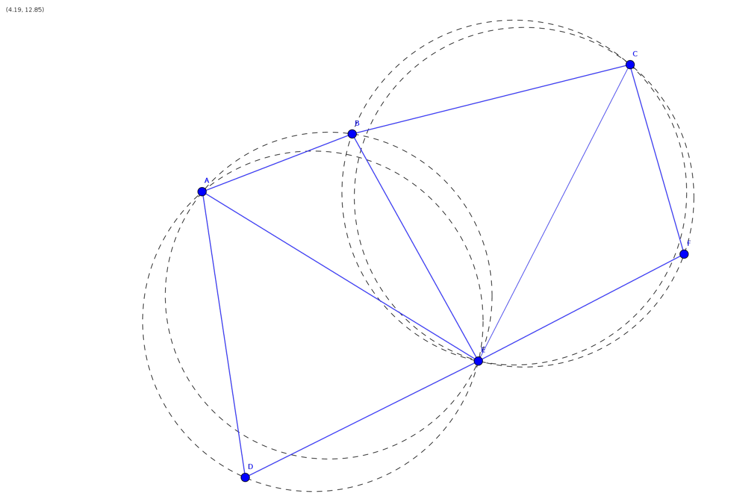
- We wanted a way be able optimize latency by embedding it into the routing overlay.
- We wanted to create a DHT based off of Voronoi tessellations. Unfortunately:
  - Distributed algorithms for this problem don't really exist.
  - Existing approximation algorithms were unsuitable.

Voronoi Tesselation



Delaunay Triangulation



DHT and Voronoi Relationship

- We can view DHTs in terms of Voronoi tessellation and Delaunay triangulation.
  - The set of keys the node is responsible for is its Voronoi region.
  - The nodes neighbors are its Delaunay neighbors.

Distributed Greedy Voronoi Heuristic

- Assumption: The majority of Delaunay links cross the corresponding Voronoi edges.
- We can test if the midpoint between two potentially connecting nodes is on the edge of the Voronoi region.
- This intuition fails if the midpoint between two nodes does not fall on their Voronoi edge.

DGVH Heuristic

```
1:  Given node $n$ and its list of $candidates$.
2:  $peers \leftarrow$ empty set that will contain $n$'s one-hop peers
3:  Sort $candidates$ in ascending order by each node's distance to $n$
4:  Remove the first member of $candidates$ and add it to $peers$
5:  for all $c$ in $candidates$ do
6:      if Any node in $peers$ is closer to $c$ than $n$ then
7:          Reject $c$ as a peer
8:      else
9:          Remove $c$ from $candidates$
10:         Add $c$ to $peers$
11:     end if
12: end for
```

DGVH Time Complexity

For k candidates, the cost is:

$$k \cdot \lg(k) + k^2 \text{ distances}$$

However, the expected maximum for k is $\Theta(\frac{\log n}{\log \log n})$, which gives an expected maximum cost of

$$O(\frac{\log^2 n}{\log^2 \log n})$$

or

$$O(\frac{\log^4 n}{\log^4 \log n})$$

Depending on whether we gossip with a single neighbor or all neighbors.

Summary

- DGVH is simple approximation for Delaunay Triangulation that guarantees a fully connected graph.
- Creates a fully connected subset of the Delaunay Triangulation.
- A DHT using DGVH can optimize over a metric such as latency and achieve superior routing speeds as a result.
- We built VHash to test this.
- UrDHT fully implements this and use

What is UrDHT

- Abstract framework for implementing DHTs or various topologies
- Three Components
  - Storage
  - Networking
  - Logic
    - Protocol
    - Space Math

The Protocol

- Consists of
  - Node Information
  - Short peers
  - Long Peers
  - The functions we use
- Replaced `lookup` with `seek`
- Maintenance is gossip based, using functions provided by the Space Math
- Short peer selection is done by DGVH by default
- Once short peers are selected, `handleLongPeers` is called

Space Math

- Defines the DHT topology
- Requires a way to generate short peers and choose long peers

Space Functions

- `idToPoint` takes key, maps it to a point in space
- `distance` outputs the shortest distance between *a* and *b*
- `getDelaunayPeers` which is DGVH
- `getClosest`
- `handleLongPeers`

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DHTs To Implement

We demonstrated how to implement

- Chord / Symphony
- Kademlia
- ZHT

Setup

- Tested four different topologies
  - Chord
  - Kademlia
  - Euclidean
  - Hyperbolic
- We create a 500 node network, adding one node at a time and completing a maintenance cycle.

Data Collected

- Reachability
- The average degree of the network.
- The worst case degree of the network.
- The average number of hops between nodes using greedy routing.
- The diameter of the network.

Chord Degree

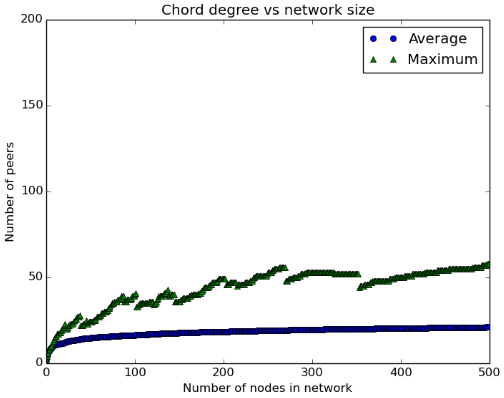

Figure: This is the average and maximum degree of nodes in the Chord network. This Chord network utilized a 120 bit hash and thus degree is bound at 122 (full fingers, predecessor and successor) when the network reaches 2^{120} nodes.

Chord Distance

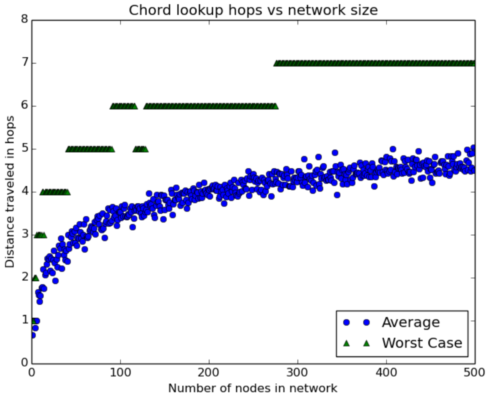

Figure: This is the number hops required for a greedy routed lookup in Chord. The average lookup between two nodes follows the expected logarithmic curve.

Kademlia Degree

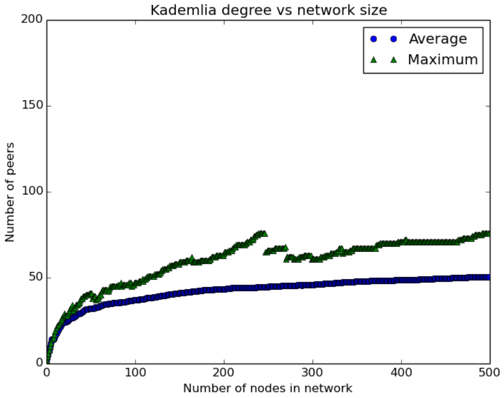

Figure: This is the average and maximum degree of nodes in the Kademlia network as new nodes are added. Both the maximum degree and average degree are $O(\log n)$.

Kademlia Distance

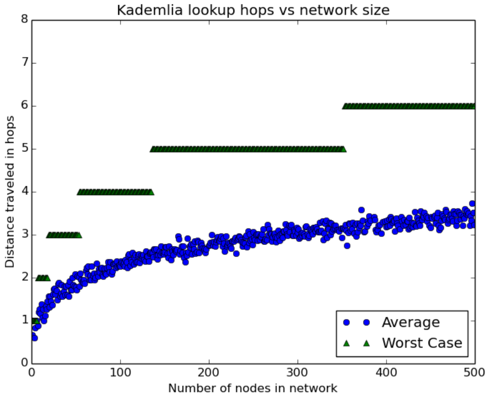

Figure: Much like Chord, the average degree follows a distinct logarithmic curve, reaching an average distance of approximately three hops when there are 500 nodes in the network.

Euclidean Degree

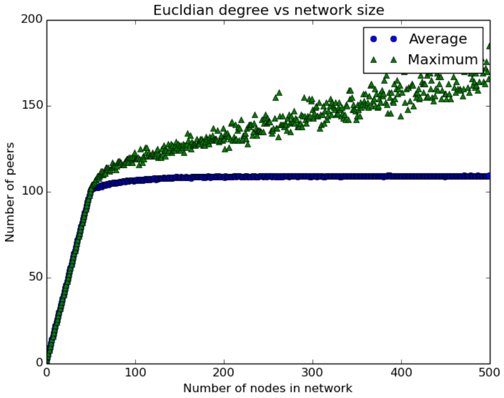

Figure: Because the long peers increase linearly to the maximum value (49), degree initially rises quickly and then grows more slowly as the number of long peers ceases to grow and the size short peers increases with network size.

Euclidean Distance

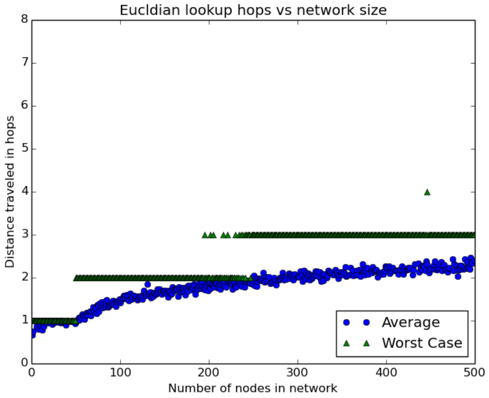

Figure: The inter-node distance stays constant at 1 until long peers are filled, then rises at the rate of a randomly connected network due to the distribution of long peers selected

Hyperbolic Degree

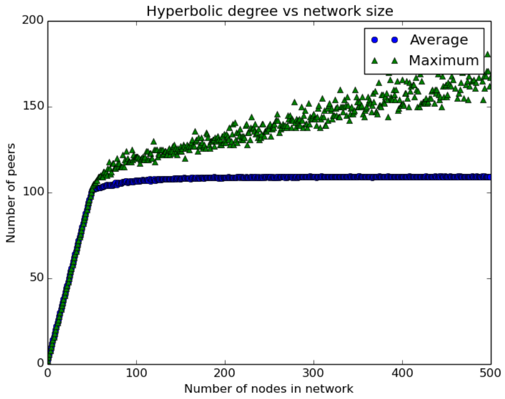

Figure: The Hyperbolic network uses the same long and short peer strategies to the Euclidean network, and thus shows similar results.

Hyperbolic Distance

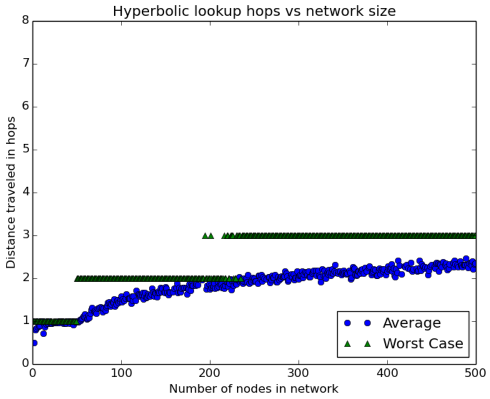

Figure: Like the Euclidean Geometry, our Poincarè disc based topology has much shorter maximum and average distances.

Conclusion

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Introduction

- In this project, we set out to confirm the results of ChordReduce
- Objectives:
  - Confirm that high levels of churn can help a DHT based computing environment.
  - Develop better strategies than randomness

Distribution in Networks of Different Sizes

Table: The median distribution of tasks (or files) among nodes. We can see the standard deviation is fairly close to the expected mean workload ($\frac{tasks}{nodes}$). Each row is the average of 100 trials. Experiments show there is practically little deviation in the median load of the network.

Nodes	Tasks	Median Workload	σ
1000	100000	69.410	137.27
1000	500000	346.570	499.169
1000	1000000	692.300	996.982
5000	100000	13.810	20.477
5000	500000	69.280	100.344
5000	1000000	138.360	200.564
10000	100000	7.000	10.492
10000	500000	34.550	50.366
10000	1000000	69.180	100.319

Distribution of Work in A DHT

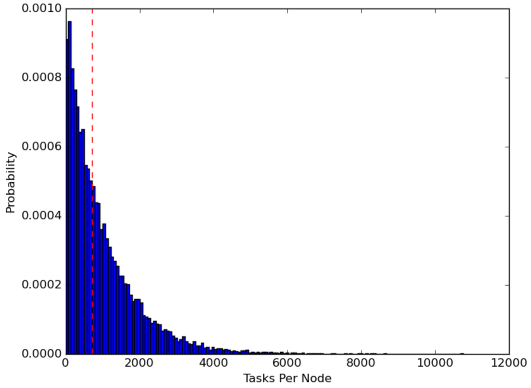

Figure: The probability distribution of workload in a DHT with 1000 nodes and 1,000,000 tasks or files. The vertical dashed line designates the median.

Distribution of Work in Chord

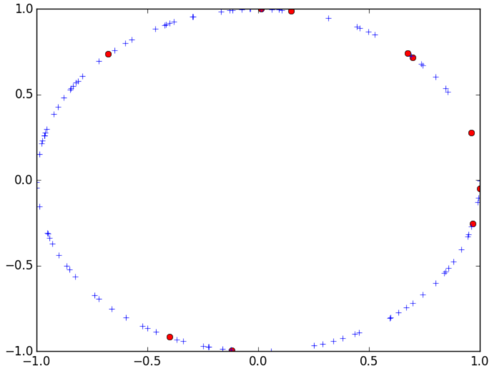

Figure: A visual example of data and nodes in a Chord DHT with 10 nodes (represented by red circles) and 100 tasks (blue pluses).

Terms and Assumptions

- Time is measured in ticks.
- A tick is enough time to perform aggressive, reactive maintenance[1]
- Jobs are measured in tasks; each task can correspond to a file or a piece of a file

[1] This has been implemented and tested.

Variables

- Strategy
- Homogeneity
- Work Measurement
- Number of Nodes
- Number of Tasks
- Churn Rate
- Max Sybils or Node Strength
- Sybil Threshold
- Number of Successors

Output

- Ideal Runtime
- Runtime
- Runtime Factor
- Task Distribution

Strategy

- The network load-balances using churn
- `churnRate` chance per tick for each node to leave network
- Pool of potentially joining joins at the same rate

Runtime

Table: Runtime factor of networks of varying sizes and number of tasks, each using the Churn strategy to load-balance. Each result is the average of 100 trials. The networks are homogeneous and each node consumes one task per tick. A runtime of 1 is the ideal and target.

Churn Rate	10^3 nodes, 10^5 tasks	10^3 nodes, 10^6 tasks	100 nodes, 10^4 tasks	100 nodes, 10^5 tasks	100 nodes, 10^6 tasks
0	7.476	7.467	5.043	5.022	5.016
0.0001	7.122	5.732	4.934	4.362	3.077
0.001	6.047	3.674	4.391	3.019	1.863
0.01	3.721	2.104	3.076	1.873	1.309

Churn vs Runtime factor

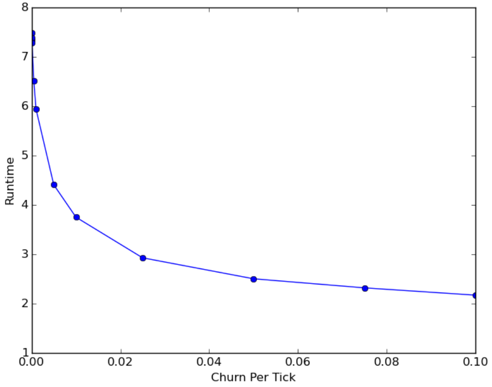

Figure: This graph shows the effect churn has on runtime in a distributed computation. Runtime is measured as how many times slower the computation runs than an ideal computation, where each node receives an equal number of tasks. The lower the runtime factor, the closer it is

Churn vs Average Work Per Tick

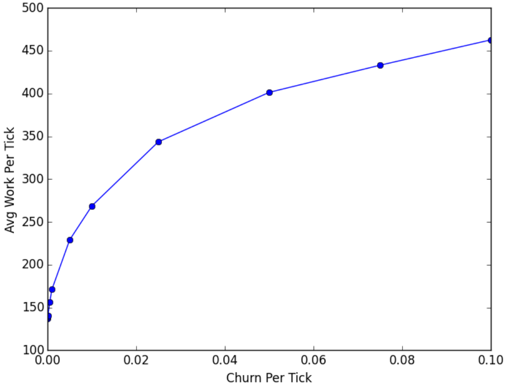

Figure: With more and more churn in the network, new nodes have a higher chance of joining the network and acquiring work from overloaded nodes. This results in more average work being done each tick, as there are less nodes simply idling.

Base Work Distribution

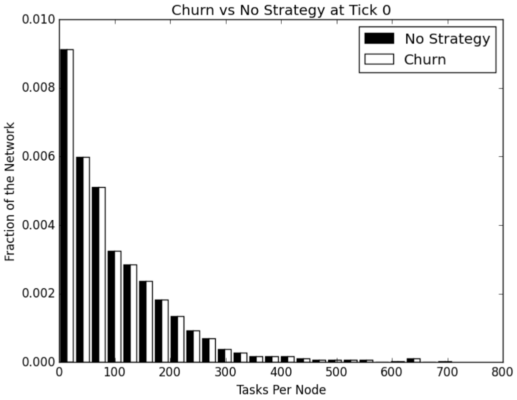

Figure: The initial distribution of the workload in both networks. As both networks start with same initial configuration, the distribution is currently identical. This greatly resembles the distribution we saw in Figure 12.

Churn Distribution after 35 Ticks

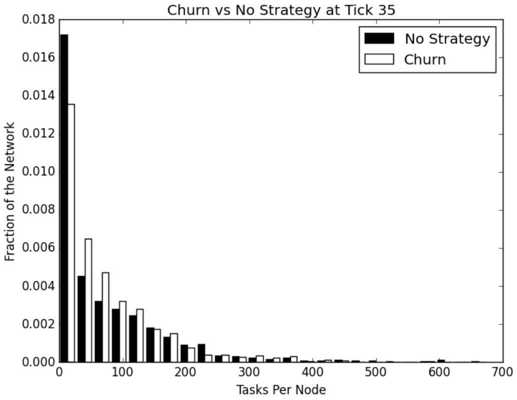

Figure: After 35 ticks, the effects of churn on the workload distribution become more pronounced. More nodes have consumed all their tasks and are simply idling, but significantly less in the network using churn.

Remarks

- Diminishing returns
- Maintenance costs can get excessive
- We don't actually have to kill nodes, most of the speedup is from joining.

Strategy

- Nodes with loads $\leq$ `sybilThreshold` create Sybils
- This check occurs every 5 ticks before work is performed
- These Sybils are randomly placed
- Act as a virtual node so the same node essentially exists in multiple locations
- Sybils are removed if the node that created it has no work

Effects of Network Size

- A homogeneous, 1000 node/100,000 task network, never have an average runtime factor greater than 1.7
- Minimum was 1.36.
- In the same network with 1,000,000 tasks, these runtimes were 1.25 and 1.12 respectively.
- On average, the 1,000,000 task network had a runtime factor 0.82 less than the 100,000 task network.

Random Injection vs No Strategy After 35 ticks

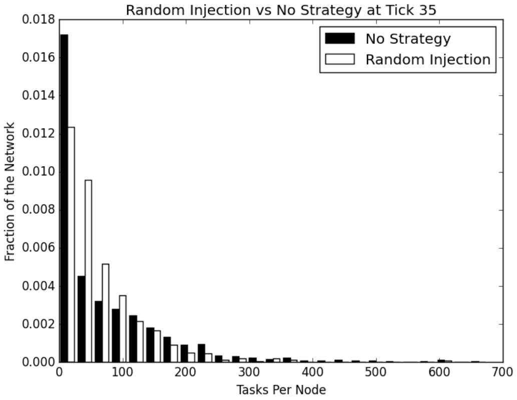

Figure: The networks after 35 ticks. The network using random injection has significantly less underutilized nodes and substantially more notes with some or lots of work.

Random Injection in a Heterogeneous Network

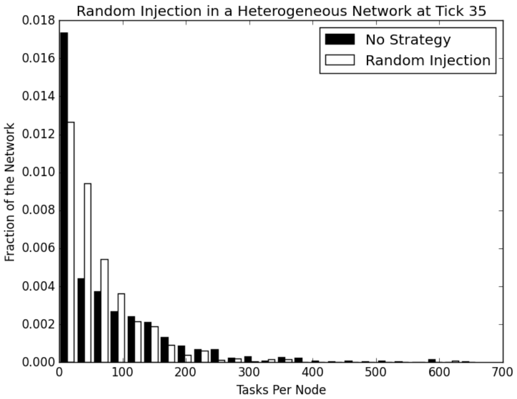

Figure: The workload distribution of heterogenous networks after 35 ticks.

Random Injection VS Churn

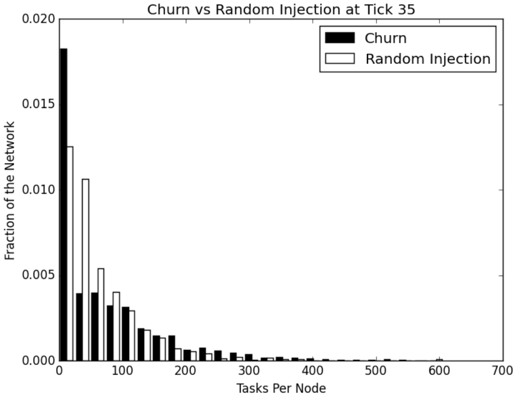

Figure: The networks after 35 ticks. The network using random injection load-balances significantly better than the network using Churn.

Impacts of Variables

- `sybilThreshold` would lower the runtime factor.
- Churn had no significant effect
- `Maxsybils` (node strength) had no effect in homogeneous networks

Remarks

- Best runtime factor
- Could still incur high maintenance costs, especially with nodes being deleted as soon as they are made

Strategy

- Rather than creating Sybils randomly, nodes create one in their successors
- Finding node id uses mashes
- Estimates which successor has most work.
- Tested estimation against smart method.

Base Runtime

- The base runtime in a 1000 node/100,000 task homogeneous network was 5.033
- 2.4 lower than no strategy
- Base runtime in a heterogeneous runtime was worse
- `numSuccessors` improves the runtime factor (0.3 for base network)
- Other variables had no significant effect.

Neighbor Injection after 35 Ticks

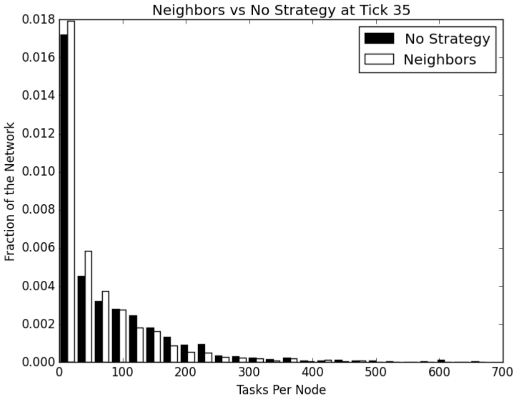

Figure: Despite have more idling nodes, we see that the nodes using the neighbor injection strategy have acquired smaller workloads and have effectively shifted part of the histogram left.

Smart Neighbor Injection after 35 Ticks

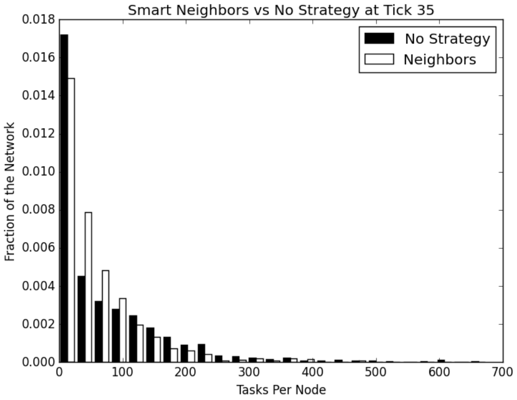

Figure: After 35 ticks, we see the network using the smart neighbor injection strategy has significantly less nodes with little or no work, more nodes with smaller amounts of work, and less nodes with large amounts of tasks.

Remarks

- Smart method improved runtime factor by 1.2 on average
- Smart would require querying, “dumb” estimation still would provide improvement
- Less churn of joining nodes

Strategy

- Nodes with too much work ask for help
- Predecessor with smallest workload and below `sybilThreshold` creates a Sybil
- Reactive vs Proactive

Invitation at 35 Ticks

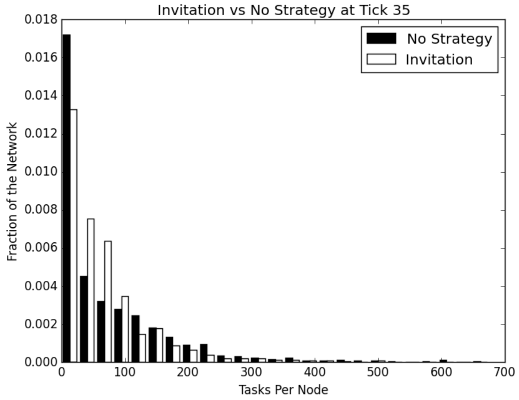

Figure: At 35 ticks, we can see the network using the invitation strategy perform markedly better than the network using no strategy. The highest load is around 500 tasks in the network using invitation, compared to approximately 650 tasks in the network using no strategy.

Invitation vs Smart Neighbors at Tick 35

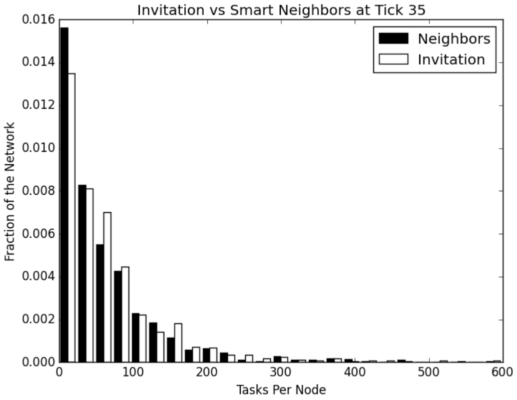

Figure: After 35 ticks, differences between the two strategies have emerged. The network using the invitation strategy has significantly less nodes with a small work load and many more with large work loads.

Remarks

- Impact of Invitation was closely tied to the number of nodes in the network.
    - 100 node/ 100,000 task network (1000 tasks per node), the base average runtime factor was 3.749.
    - 1000 node/ 100,000 task network had a base average runtime of 5.673.
- Performed poorer in heterogeneous networks, but better than base on average (6.097 vs 7.5).
- Better than smart neighbors and uses less bandwidth.

Summary

- Reactive vs Proactive
- Heterogeneity was best handled by Churn or Random Injection.
- Random injection was best overall
- Load balanced did not mean faster since node strength was not taken into account.

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Conclusion

- Load Balancing