#### On Utilization of Contributory Storage in Desktop Grids



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## Contributory Storage: Cheap Storage using Shared Resources

- Distributed setup with many participants
- Nodes contribute storage space for sharing
- Create a uniform global storage space
- Typically supports decentralized store/lookup
- Many systems build upon this idea
  - PAST, CFS, OceanStore, Kosha, LOCKSS,...



# Goal: Use of Contributory Storage in Scientific Computing

- Advantages:
  - Provides economical storage with large capacity
  - Supports parallel access to distributed resources
- Challenges:
  - Limited individual file sizes
  - Unreliable and transient participants
  - $\rightarrow$  Simple replication or file splitting is likely not to work

## Need for techniques to use shared storage in scientific computing



### Our Contribution: PeerStripe Reliable Shared Storage

- Utilizes storage contributed by peer nodes
- Adapts data striping to support large files
- Employs error coding for fault tolerance
- Leverages multicast for efficient replication
- Supports easy integration with applications

#### Outline

- Preamble
- End to our Means
- Evaluation Study
- Conclusion



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- Problem
  - Motivation
- Our Contributions
- Core Technologies



### Core Technologies: Structured Peer-to-Peer Networks

- Implement Distributed Hash Table abstraction
- Facilitate decentralized operation
- Provide self-organization of participants
- Systems based on these networks provide:
  - Mobility and location transparency
  - Load-balancing
- We use Free Pastry substrate from Rice University and Microsoft



## Core Technologies: Increasing Data Availability

- Erasure codes
  - Provide redundancy against failures
  - Incur less space overhead than replication
  - Advanced codes can withstand multiple failures
- Multicast communication protocol
  - Supports simultaneous messaging to many nodes
  - Can be leveraged for efficient replication



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- Software Architecture
- Splitting a file
- Redundancy with multicast
- Error coding
- Interfacing with applications



#### PeerStripe Software Tasks

#### 1. Storing large files

- Split file into different size chunks
- Use DHT's to store chunks

#### 2. Error coding chunks

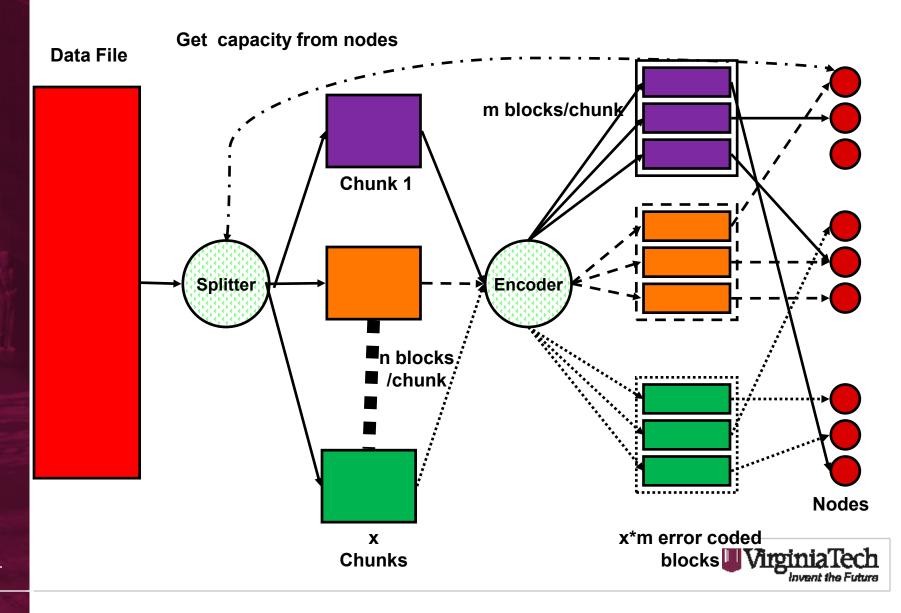
• Use online code to provide redundancy

#### 3. Chunk replication

- Replicate commonly used chunks
- 4. Interface with applications
  - Provide API's for applications to use

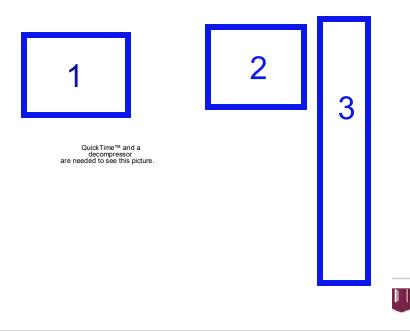


#### Part 1: Splitting Files into Chunks



#### Part 2: Error Coding Chunks

- Each chunk is separately error coded
  - 1. A chunk is split into equal n size blocks
  - 2. The blocks are error coded into m encoded blocks
  - 3. Encoded blocks are inserted into the DHT



## **Investigation of Error Codes**

#### Error codes tested and used:

- XOR code: Protect against single failures
- Online code: Protect against multiple failures

#### + Good redundancy with small space overhead

- Recovery may consume resources



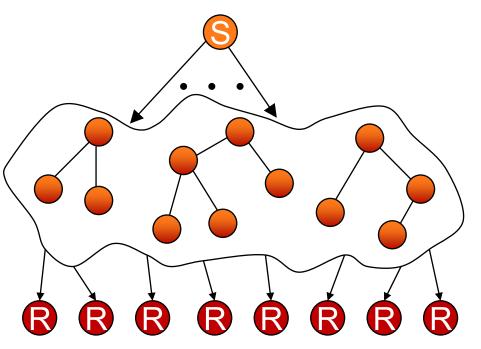
### Part 3: Multicast-based Replication

- Leverage multicast for efficient and fast data dissemination to multiple destinations
- Faster recovery at the cost of space
- Challenge: Creation of a multicast-tree from source to replica destinations



#### Creating a Multicast Tree

- Use greedy approach
  - Start from the source S
  - Using locality-aware DHT select random nodes close to S as first tier
  - Repeat selecting at each tier till replica location R is reached
- Employ standard multicast protocols, e.g.
  Bullet to push data from S to R





# Part 4: Interfacing with Applications

- Modify applications to use direct calls to the PeerStripe API
  - Works well for new applications
- Link applications with an interposing library to redirect I/O
  - Transparent integration with existing applications



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- Simulation
- Real world
  - PlanetLab
  - Condor



#### **Evaluation: Overview**

#### 1. Simulation study:

- Successful File Stores
- Number and size of chunks created
- System utilization (in terms of storage capacity)
- File availability with error coding
- Error code performance
- Effects of participant churn
- 2. Design verification on PlanetLab
- 3. Integration with Condor desktop grid

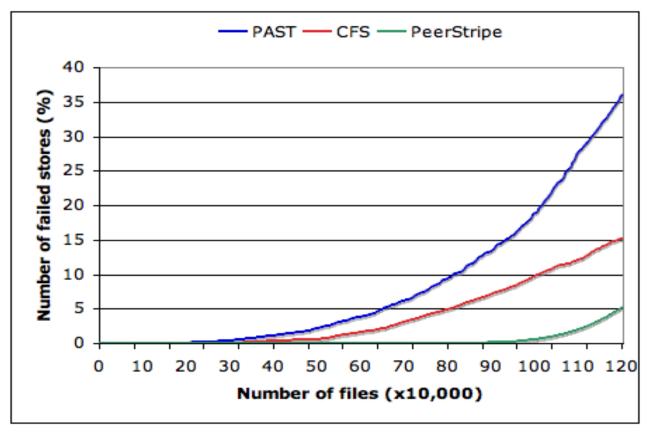


#### Simulation Study Setup

- 10,000-node directly connected network
- Assigned node capacities with mean 45 GB and variance 10 GB
- File system trace of 1.2M files totaling 278.7 TB
- Compare with PAST and CFS storage systems



#### Number of Successful File Stores



- 7.0x improvement over PAST
- 2.9x improvement over CFS

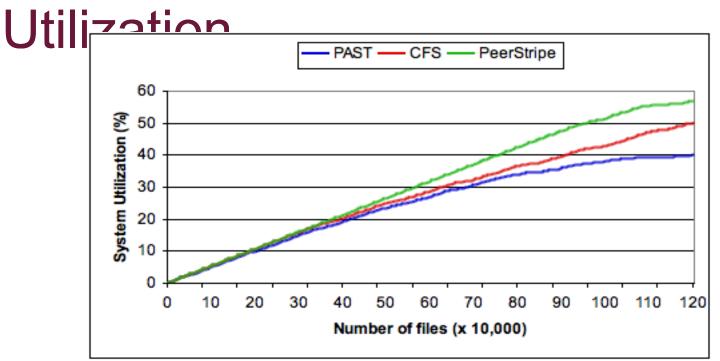


#### Number and Size of Chunks

- CFS: 61.25 chunks with stdev of 13.8
  - Fixed chunk size of 4 MB
- PeerStripe: 3.72 chunks with stdev of 3.1
  - Average chunk size 81.28 MB with stdev 19.9 MB
- → Fewer chunks in PeerStripe allows
  - Fewer expensive p2p lookups
  - Performance similar to PAST



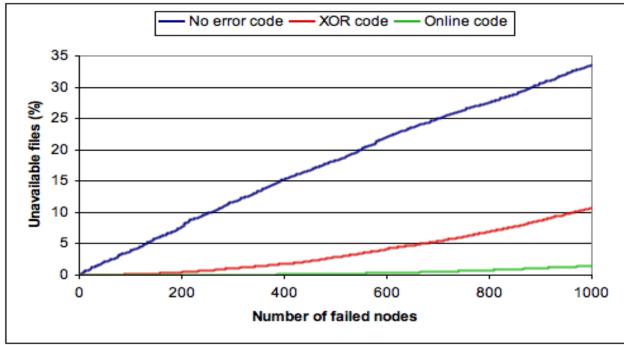
## **Overall System Capacity**



- PeerStripe: 20.19% better than PAST
- PeerStripe: 7.18% better than CFS
- PeerStripe can utilize the available storage capacity more efficiently even at higher utilization



### Error Coding: File Availability



- XOR code 23% less failures
- Online code 32% less failures
- Online code provides excellent fault tolerance against node failures



### **Error Coding Performance**

• Compare XOR (1:1) and Online code with NULL code

Erasure code	Encoded size		Encoding time	
	Size(MB)	Overhead	Time	Overhead
Null	4	0%	11	0%
XOR	6	50%	79	618%
Online	4.12	3%	264	2300%

- XOR factor of 3.3 times faster than online codes
- Online code slower than XOR,
  - Decoding can start as soon as a block becomes available and can be overlapped with retrieval of other blocks
- The efficiency of online code overshadows its overhead



#### Effects of Participant Churn

• Failed up to 20% of total nodes

Nodes failed	Data lost	Data regenerated		
(percentage of total)	Total (GB)	Total (GB)	Average (GB)	Sd (GB)
10 percent	0	28044.35	28.04	79.85
20 percent	142.18	58625.78	29.31	80.02

- 29.3 GB of data was regenerated per node failure
- Total of 58,625.8 GB regenerated
- 142.2 GB data was lost which is small compared to the 278.7 TB of total data
- The data recreated per failure is small: 0.01%



#### Verification on PlanetLab

- 40 different distributed sites
- Number of failed stores reduced by 330% w.r.t. PAST 105% w.r.t. CFS
- Storage utilization: CFS 52%, PAST - 47%, PeerStripe - 63%
- Online codes provided 98.6% availability through four node failures



#### Interfacing with Condor

- Utilize a 32-node Condor pool
- CFS and PeerStripe worked for smaller files
- DHT lookups introduced an overhead few for PeerStripe
- Overhead for PeerStripe is small

QuickTime™ and a decompressor are needed to see this picture.



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#### Conclusion

- P2p-based storage can be extended with erasure coding and striping to provide robust, scalable, and reliable distributed storage for scientific computing.
- PeerStripe achieves better utilization of collective capacity of nodes with good performance
- Error coding is effective in providing fault tolerance and data availability
- Multicast can be used for replica maintenance
- Use of interposing library allows easy integration with new and existing applications



#### Questions?

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