



# Out of Core Simplification

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# Models are getting bigger

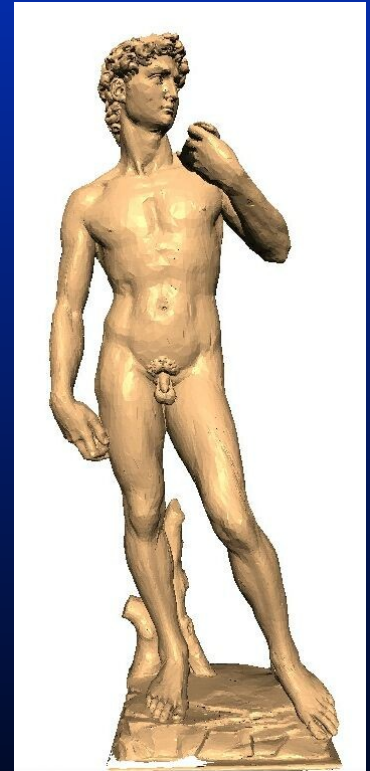
Models now ride Moore's Law

*Major source: 3D scanning*

*Example: Digital Michelangelo*

*Sizes currently in the 300 millions*

*Well beyond most core memories*





# Can't we do "big"?

Maybe, but not "massive"

*That is, models not fitting in core*

*Previous limit less than 10 million faces*

What's the problem with out of core?

*Requires slow disk access*

*So must minimize disk access*

*Most simplification algs don't*



# Out of core strategies

For good out of core performance, use

*Locality (reducing working set)*

*Reuse (minimizing swapping)*

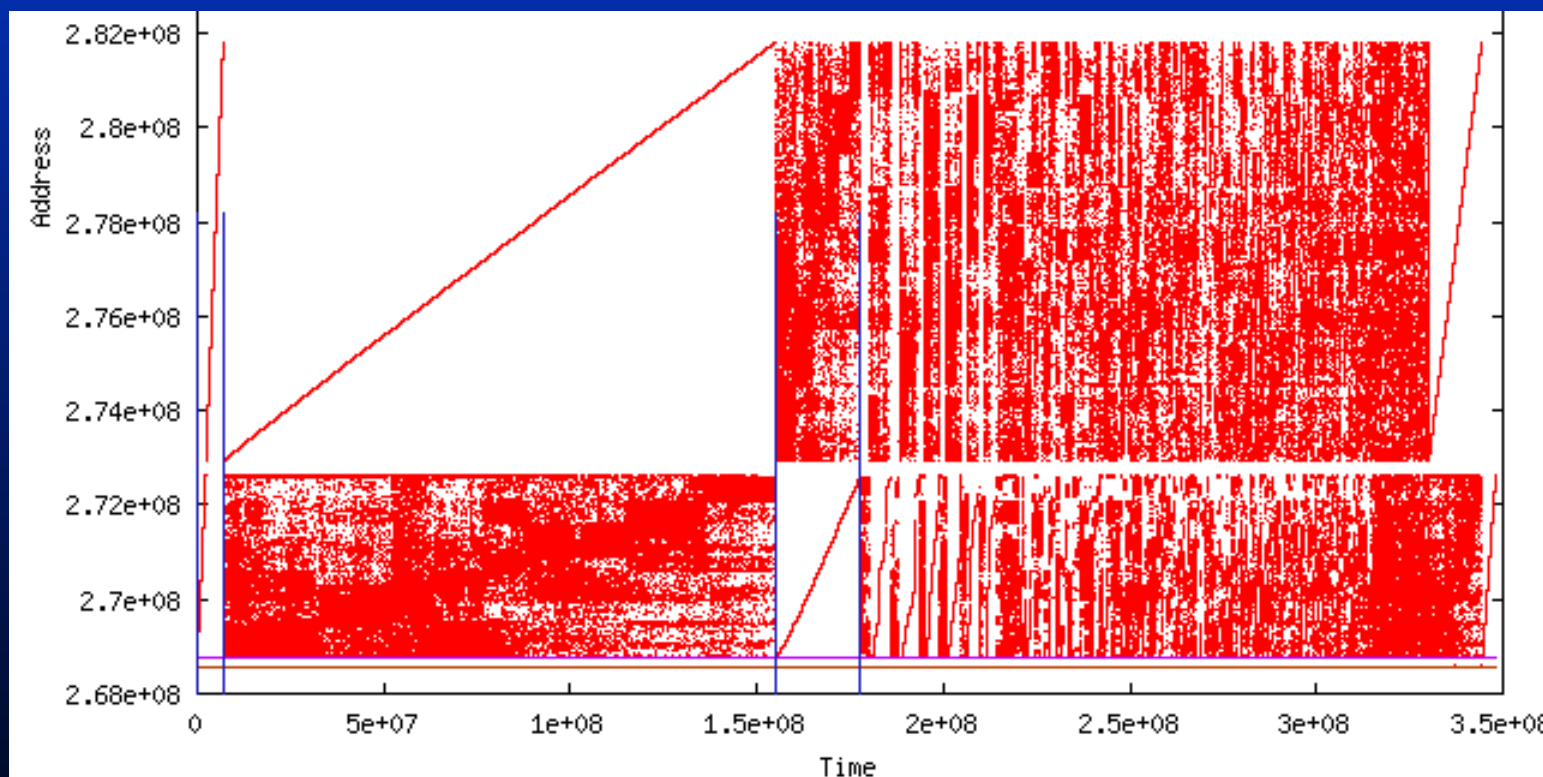
Most existing algorithms poor at both

*Locality not guaranteed in model formats*

*Most algorithms are greedy -- poor reuse*



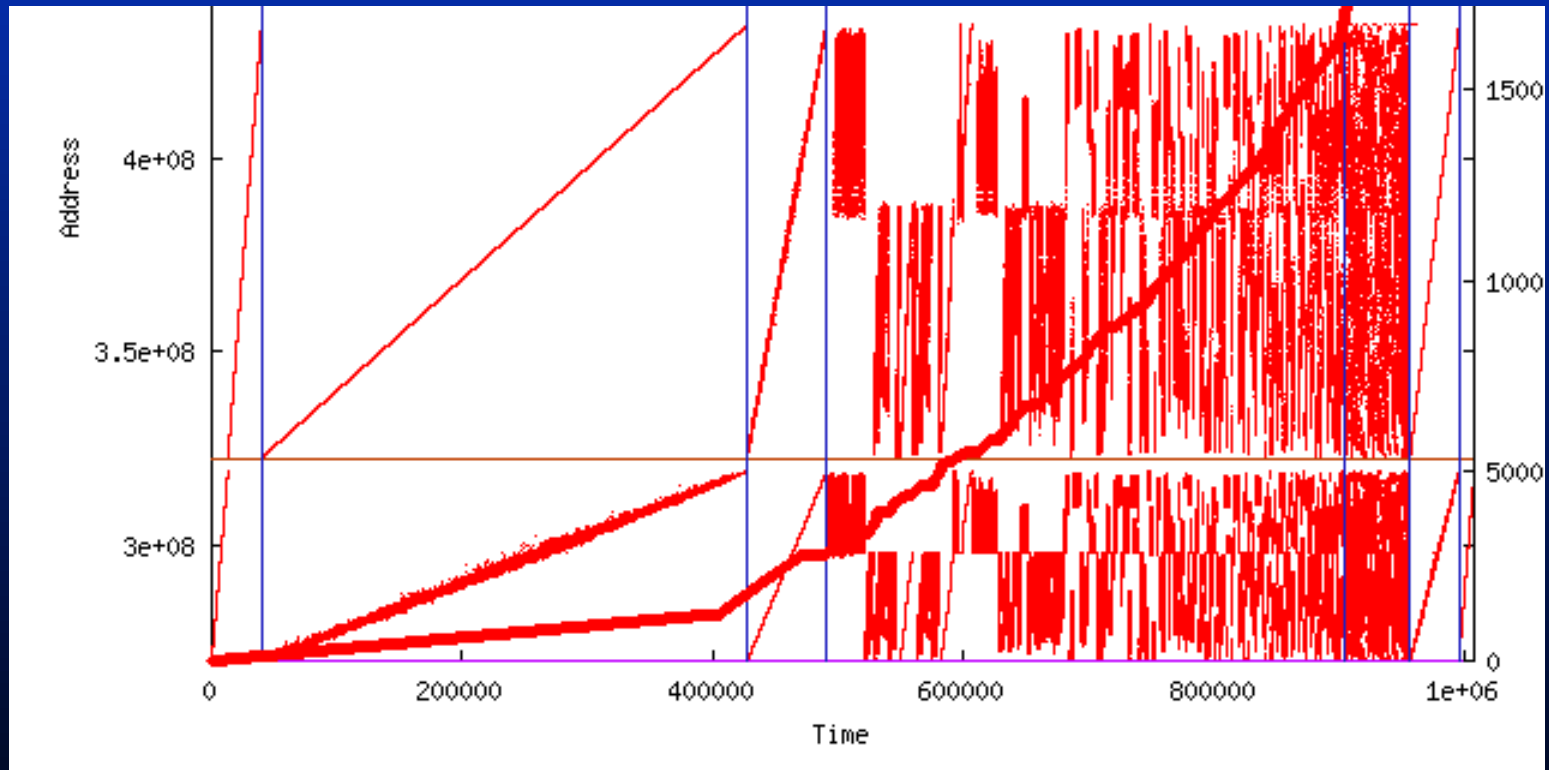
# Demo: *bunny* vs. *dragon*



RSimp on bunny



# Demo: *bunny* vs. *dragon*



RSimp on dragon



# Solutions: *Lindstrom*

Modification of Rossignac & Borrel

Adds locality by deref'ing to create “soup”

*Done w/ little thrashing in linear time*

Hashes vertices on each input face

*Add normal to quadric in each vertex hash entry*

*Retain face if 3 vertices hash differently*

Output retained faces, quadric mins



# Solutions: *Lindstrom*

## Advantages

*Extremely fast: single linear pass on “soup”*

*56 million faces in several minutes*

*Can handle 100s millions of faces*

## Disadvantages

*Poor accuracy: a non-adaptive algorithm*

*Not sensitive to topology*





# Solutions: *Lindstrom*



(2K faces)

(20K faces)

(200K faces)



# Solutions: *Shaffer & Garland*

Addition to Lindstrom's approach

First, apply Lindstrom's algorithm

*Resulting model fits in core memory*

Then, adaptively simplify

*Using refining algorithm similar to  $RS_{imp}$*

*(We discuss  $RS_{imp}$  shortly)*



# Solutions: *Shaffer & Garland*

## Advantages

*Improved mean accuracy about 35%*

## Disadvantages

*Somewhat slower*

*Not sensitive to topology*

*Introduces spurious topological joins*

*Limited output size*



# Solutions: *Shaffer & Garland*



(2K faces)

(20K faces)

(200K faces)



# Solutions: VMRSimp

Modification of RSimp by Brodsky & Watson

RSimp refined toward desired output size by

*Define a poor 8 patch (vertex) approximation*

*Repeat*

*Choose patch with most normal variation*

*Split patch according to normal variation*

*Until desired number vertices reached*



# Solutions: VMRSimp

Modification makes simplification a sort

*Each patch a range on input array*

*Splitting patch means sorting into subranges*

Thus locality is built and refined

*Allows reliance on virtual memory*

*Added modification allows quality/reuse tradeoff*

56M faces in 32 bit address space



# Solutions: VMRSimp

## Advantages

*Mean accuracy improves additional 30%*

*Maximum error reduced 2-5 times*

*Topological sensitivity (boundaries, joins)*

*Very large output sizes (10M+) possible*

## Disadvantages

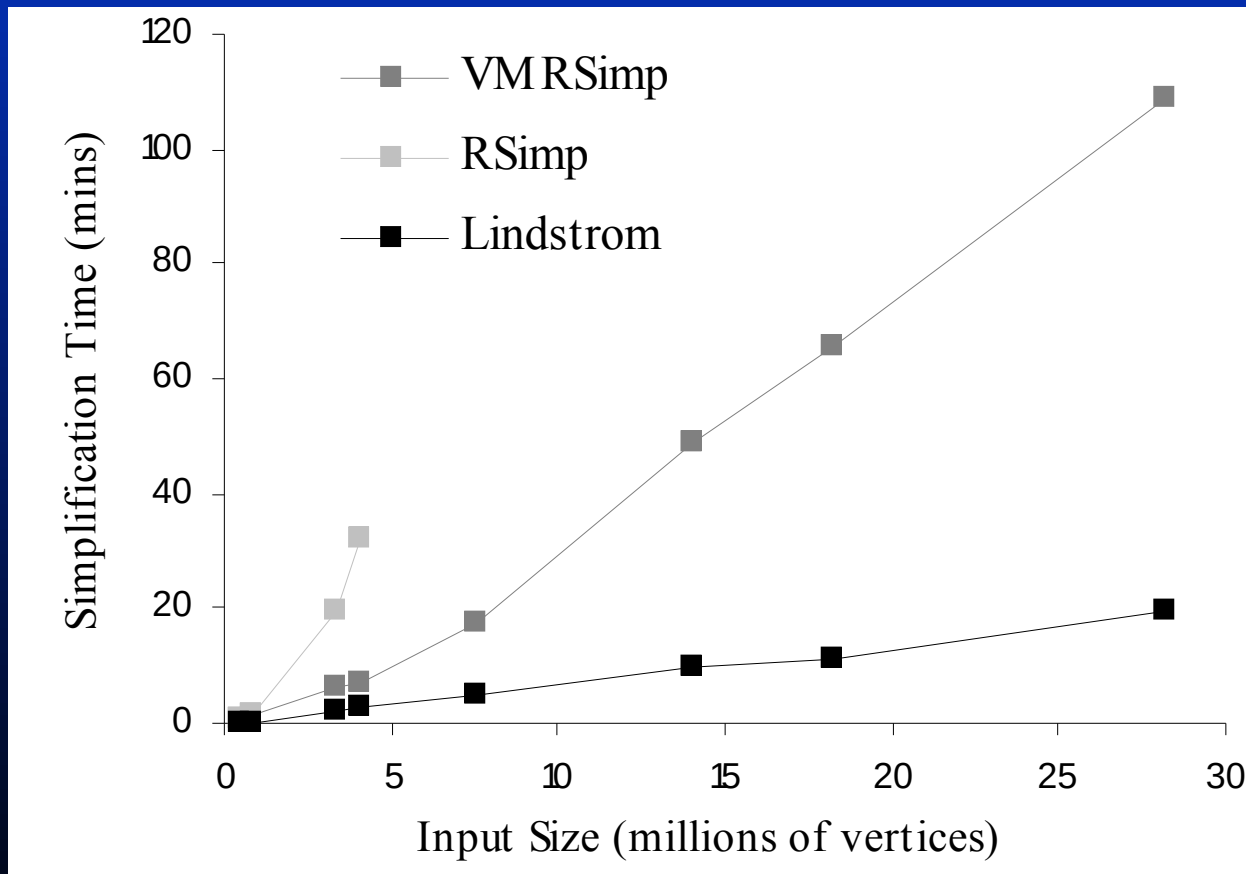
*About twice as slow as Shaffer & Garland*

*Can reach 32 bit address space limits*





# Solutions: VMRSimp



1 GHz PIII  
RH Linux 7.1  
1 GB Mem

*Accuracy control improves times 25%*





# Solutions: VMRSimp

Output Tris	Lindstrom		Schaffer and Garland		VMRSimp	
	<i>mean</i>	<i>max</i>	<i>mean</i>	<i>max</i>	<i>mean</i>	<i>max</i>
<b>1K</b>	0.4549	26.10	0.4821	25.91	0.3450	14.89
<b>10K</b>	0.0986	24.35	0.0946	24.43	0.0598	12.80
<b>100K</b>	0.0266	24.47	0.0164	24.17	0.0119	10.45

*Metro error as % of model bounding box*



# Solutions: VMRSimp



(2K faces)



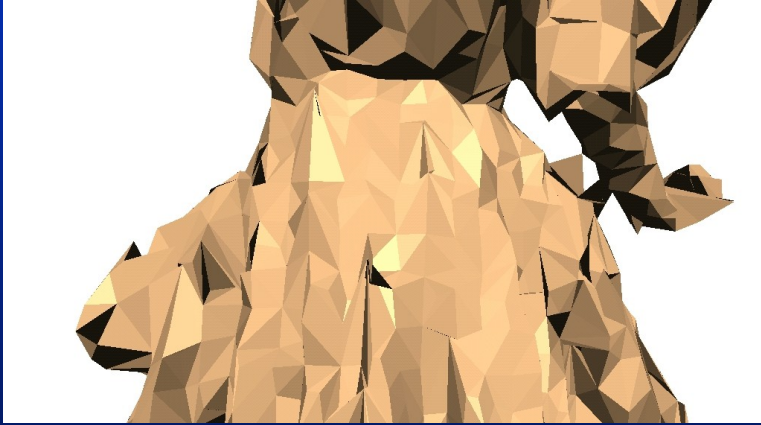
(20K faces)



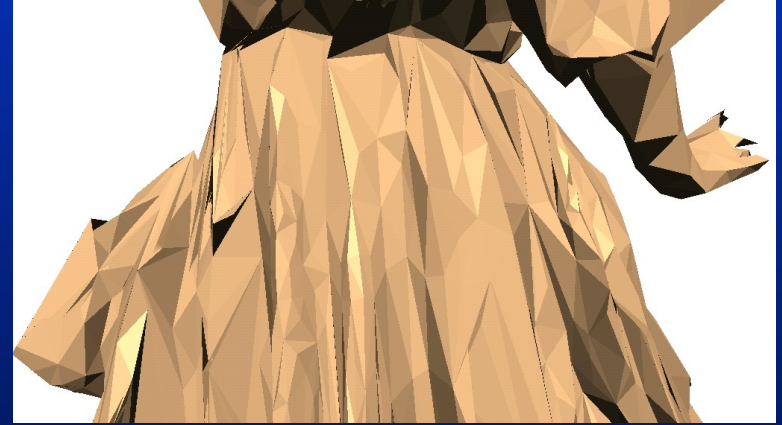
(200K faces)



# Solutions: *comparison*



Lindstrom



VMRSimp



Shaffer & Garland