

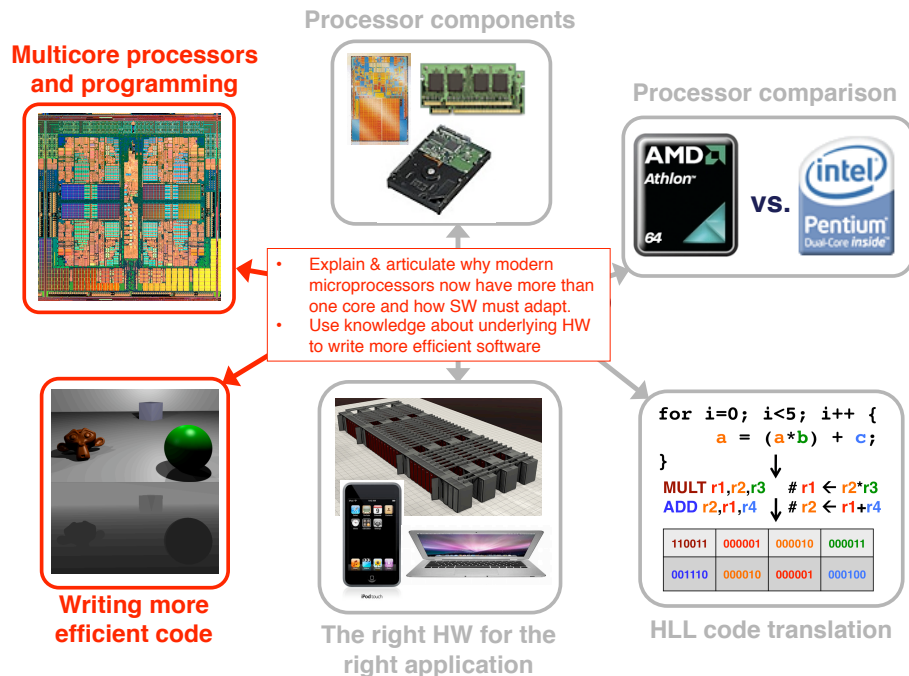
## Lecture 25

### Threads and GPUs

## Suggested Readings

### • Readings

- H&P: Chapter 7 – especially 7.1-7.8
  - (Over next 2 weeks)
- Introduction to Parallel Computing
  - [https://computing.llnl.gov/tutorials/parallel\\_comp/](https://computing.llnl.gov/tutorials/parallel_comp/)
- POSIX Threads Programming
  - <https://computing.llnl.gov/tutorials/pthreads/>
- How GPUs Work
  - [www.cs.virginia.edu/~gfx/papers/pdfs/59\\_HowThingsWork.pdf](http://www.cs.virginia.edu/~gfx/papers/pdfs/59_HowThingsWork.pdf)



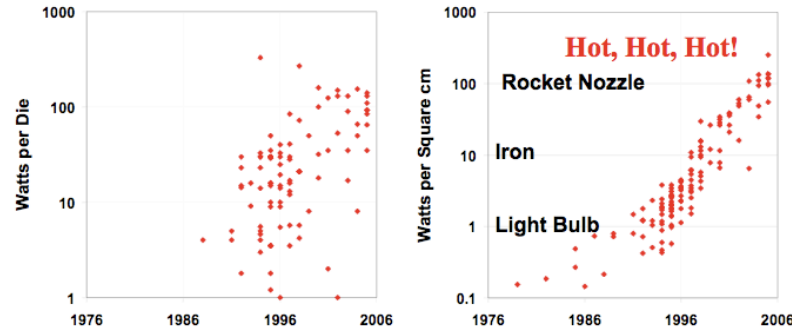
## Recap: L23 – Intro to Parallel Processing

- Types of multi-processors
  - Room-level, on-chip
- Types of machines
  - SISD (uniprocessor, pipelined, superscalar)
  - SIMD (more today)
  - MISD (not really used)
  - MIMD (centralized & distributed shared memory)
- More detail about MIMD
- How parallelization impacts performance
- What can impede performance of parallel machines?
  - Coherency, latency, contention, reliability, languages, algorithms

## Recap: L24 – Parallel Processing on MC

- Simple quantitative examples on how (i) reliability, (ii) communication overhead, and (iii) load balancing impact performance of parallel systems
- Technology drive to multi-core computing

Why the clock flattening? **POWER!!!!**



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## Threads First

- Outline of Threads discussion:
  - What's a thread?
    - How many people have heard of / used threads before?
  - Coupling to architecture
  - Example: scheduling threads
    - Assume different architectural models
  - Programming models
  - Why intimate knowledge about HW is important

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## Today: L25 – Threads and GPUs

- All issues covered in L23 & L24 apply to “on-chip” computing systems as well as “room level” computing systems
- That said, 2 models that lend themselves well to on-chip parallelism deserve special discussion:
  - Threads
  - GPU-based computing

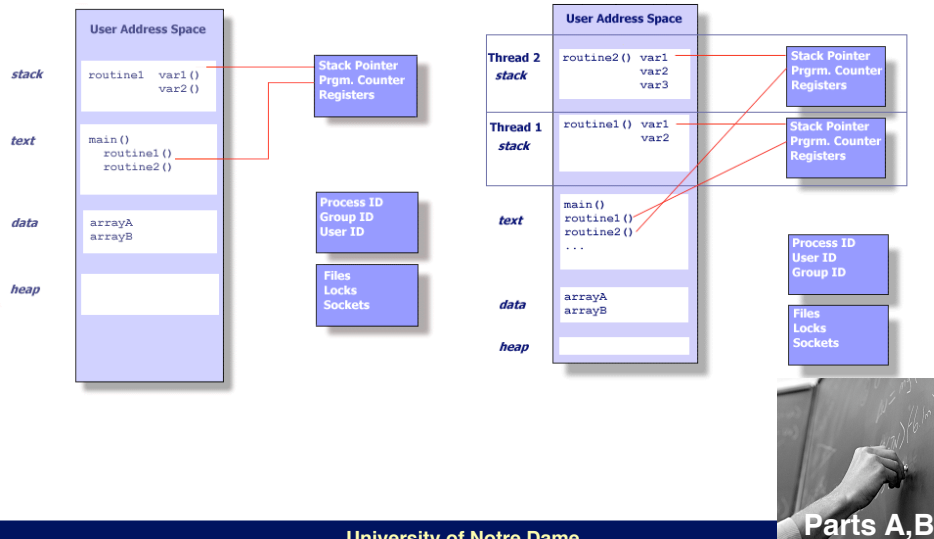
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## Processes vs. Threads

- |   |  |
|---|--|
| <ul style="list-style-type: none"> <li>• Process           <ul style="list-style-type: none"> <li>– Created by OS</li> <li>– Much “overhead”               <ul style="list-style-type: none"> <li>• Process ID</li> <li>• Process group ID</li> <li>• User ID</li> <li>• Working directory</li> <li>• Program instructions</li> <li>• Registers</li> <li>• Stack space</li> <li>• Heap</li> <li>• File descriptors</li> <li>• Shared libraries</li> <li>• Shared memory</li> <li>• Semaphores, pipes, etc.</li> </ul> </li> </ul> </li> </ul> | <ul style="list-style-type: none"> <li>• Thread           <ul style="list-style-type: none"> <li>– Can exist within process</li> <li>– Shares process resources</li> <li>– Duplicate bare essentials to execute code on chip               <ul style="list-style-type: none"> <li>• Program counter</li> <li>• Stack pointer</li> <li>• Registers</li> <li>• Scheduling priority</li> <li>• Set of pending, blocked signals</li> <li>• Thread specific data</li> </ul> </li> </ul> </li> </ul> |
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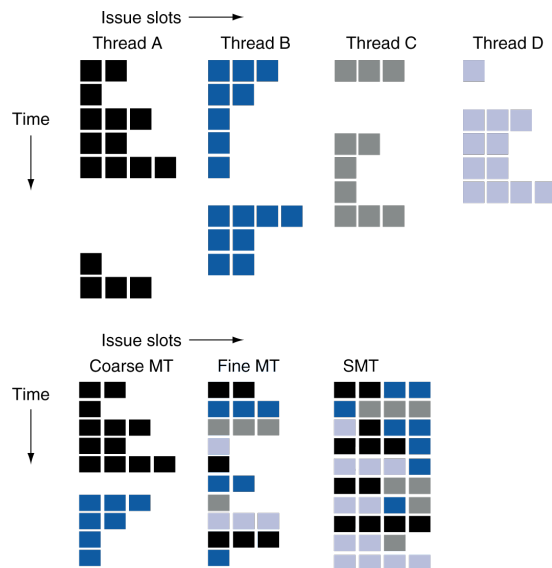
# Processes vs. Threads



# Multi-threading

- **Idea:**
  - Performing multiple threads of execution in parallel
    - Replicate registers, PC, etc.
  - Fast switching between threads
- **Flavors:**
  - **Fine-grain multithreading**
    - Switch threads after each cycle
    - Interleave instruction execution
    - If one thread stalls, others are executed
  - **Coarse-grain multithreading**
    - Only switch on long stall (e.g., L2-cache miss)
    - Simplifies hardware, but doesn't hide short stalls
      - (e.g., data hazards)
  - **SMT (Simultaneous Multi-Threading)**
    - Especially relevant for superscalar

# Coarse MT vs. Fine MT vs. SMT



# Mixed Models:

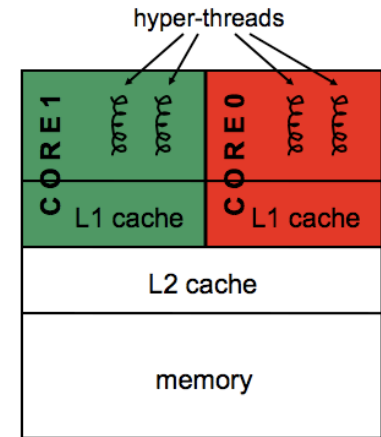
- Threaded systems and multi-threaded programs are not specific to multi-core chips.
  - In other words, could imagine a multi-threaded uni-processor too...
- However, could have an N-core chip where:
  - ... N threads of a single process are run on N cores
  - ... N processes run on N cores – and each core splits time between M threads

# Comparison: multi-core vs SMT

- Multi-core:
  - Since there are several cores, each is smaller and not as powerful (but also easier to design and manufacture)
  - However, great with thread-level parallelism
- SMT
  - Can have one large and fast superscalar core
  - Great performance on a single thread
  - Mostly still only exploits instruction-level parallelism

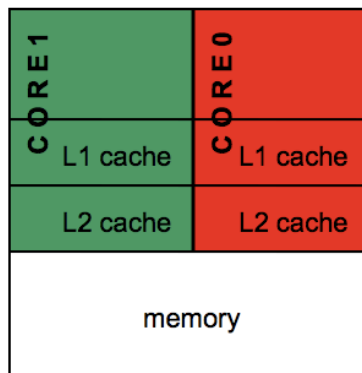
# Or can do both...

- Dual-core Intel Xeon processors
- Each core is hyper-threaded
- Private L1 caches
- Shared L2 caches



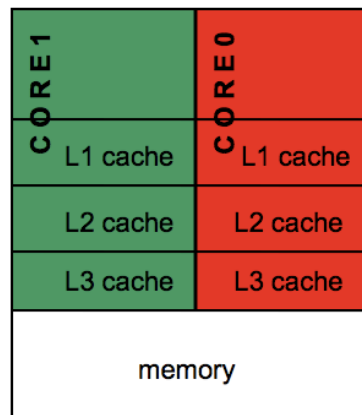
# Real life examples...

## Designs with private L2 caches



Both L1 and L2 are private

Examples: AMD Opteron, AMD Athlon, Intel Pentium D



A design with L3 caches

Example: Intel Itanium 2

# Writing threaded programs for supporting HW



## Impact of modern processing principles (Lots of “state”)

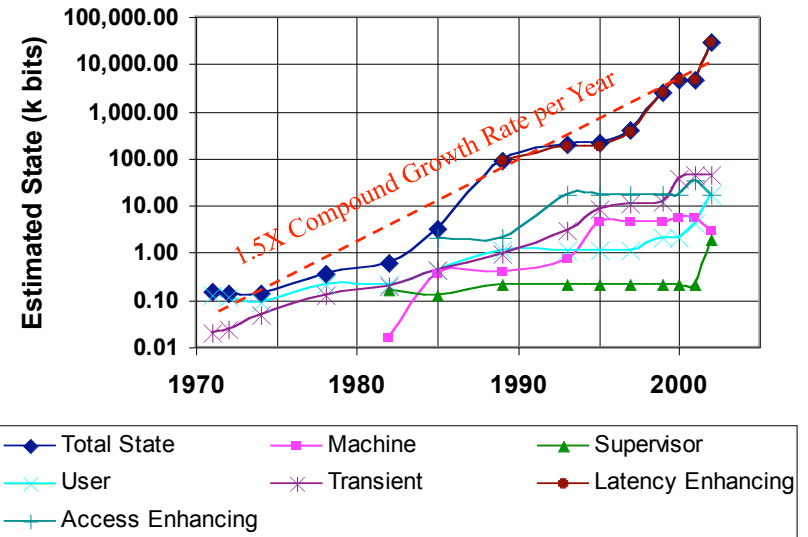
- **User:**
  - state used for application execution
- **Supervisor:**
  - state used to manage user state
- **Machine:**
  - state that configures the system
- **Transient:**
  - state used during instruction execution
- **Access-Enhancing:**
  - state used to simplify translation of other state names
- **Latency-Enhancing:**
  - state used to reduce latency to other state values

## GPU discussion points

- **Motivation for GPUs:**
- **Necessary processing**
- **Example problem:**
  - Generic CPU pipeline
  - GPU-based vs. Uni-processor Z-buffer problem
- **What does a GPU architecture look like?**
  - Explain in context of SIMD
- **Applicability to other computing problems**



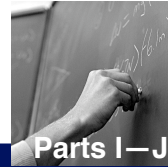
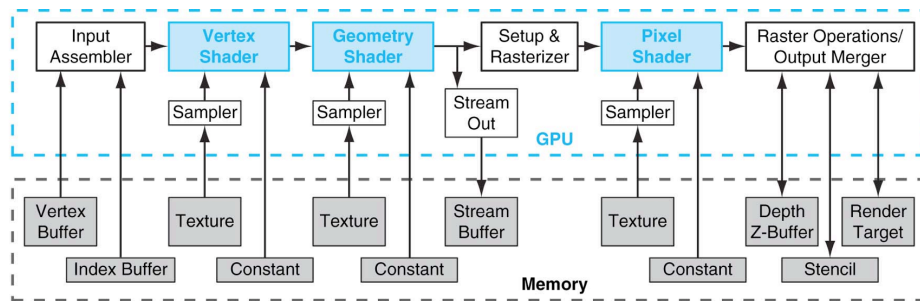
## Impact of modern processing principles (Total State vs. Time)



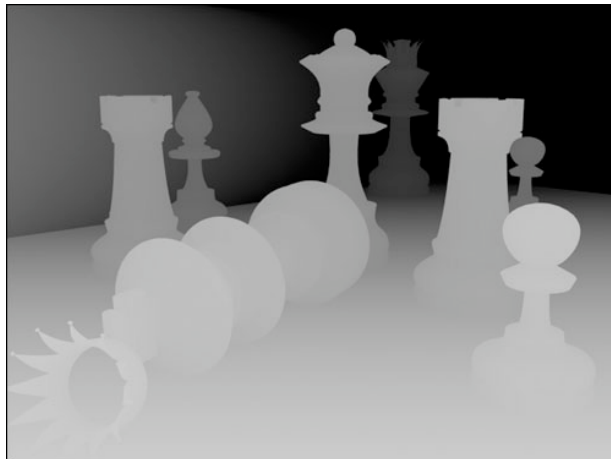
## How is a frame rendered?

- **Helpful to consider how the 2 standard graphics APIs – OpenGL and Direct 3D – work.**
  - These APIs define a logical graphics pipeline that is mapped onto GPU hardware and processors – along with programming models and languages for the programmable stages
  - *In other words, API takes primitives like points, lines and polygons, and converts them into pixels*
- **How does the graphics pipeline do this?**
  - First, important to note that “pipeline” does not mean the 5 stage pipeline we talked about earlier
  - Pipeline describes sequence of steps to prepare image/scene for rendering

## How is a frame rendered? (Direct3D pipeline)

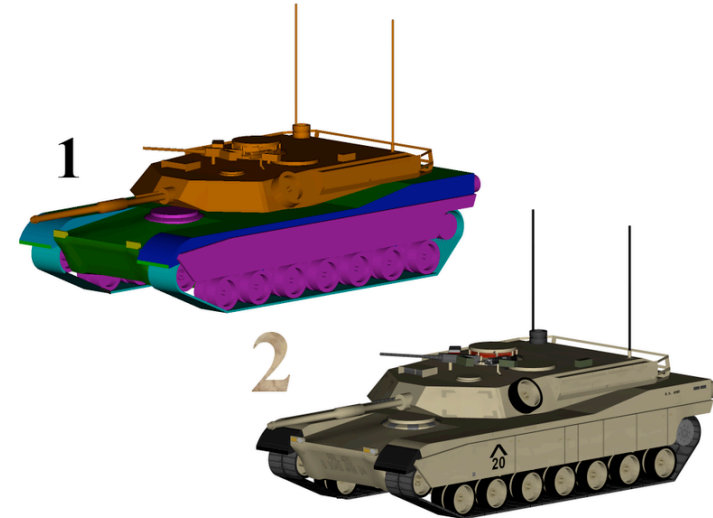


## Example: Z-buffer



<http://blog.yoz.sk/examples/pixelBenderDisplacement/zbuffer1Map.jpg>

## Example: Textures



<http://en.wikipedia.org/wiki/File:Texturedm1a2.png>

## GPUs

- GPU = Graphics Processing Unit
  - Efficient at manipulating computer graphics
  - Graphics accelerator uses custom HW that makes mathematical operations for graphics operations fast/efficient
    - Why SIMD? Do same thing to each pixel
- API language compilers target industry standard intermediate languages instead of machine instructions
  - GPU driver software generates optimized GPU-specific machine instructions

## GPUs

- Also, SW support for GPU programming:
  - NVIDIA has graphics cards that support API extension to C – CUDA (“Computer Unified Device Architecture”)
    - Allows specialized functions from a normal C program to run on GPU’s stream processors
    - Allows C programs that can benefit from integrated GPU(s) to use where appropriate, but also leverage conventional CPU


## Modern GPU

- Often part of a *heterogeneous* system
  - GPUs don’t do all things CPU does
  - Good at some specific things
    - i.e. matrix-vector operations
- GPU HW:
  - No multi-level caches
  - Hide memory latency with threads
    - To process all pixel data
  - GPU main memory oriented toward bandwidth

## GPUs for other problems

- More recently:
  - GPUs found to be more efficient than general purpose CPUs for many complex algorithms
    - Often things with massive amount of vector ops
  - Example:
    - ATI, NVIDIA team with Stanford to do GPU-based computation for protein folding
    - Found to offer up to 40 X improvement over more conventional approach

## GPU Example

<p><b>Power Efficient Supercomputing</b></p> <p>William Dally Bell Professor of Engineering, Stanford University Chief Scientist and Sr. VP of Research, NVIDIA</p> 	<p>High-Performance Computing is Power Limited</p> <ul style="list-style-type: none"> <li>• What can be put on a chip is limited by power, not area.</li> <li>• Cost of energy to run a cluster equals purchase cost in less than 18 months.</li> <li>• Cost of provisioning a machine room with adequate power is typically many times cost of cluster.</li> <li>• What matters now is <math>\mu</math>FLOP</li> </ul>	<p>GPU Computing</p> <ul style="list-style-type: none"> <li>• GPUs are already much of the way to being efficient supercomputer nodes           <ul style="list-style-type: none"> <li>– Simple control</li> <li>– Explicit control of storage hierarchy</li> <li>– Large fraction of energy goes to FLOPs</li> </ul> </li> <li>• Future GPUs will close the gap           <ul style="list-style-type: none"> <li>– More efficient instruction and data supply</li> <li>– Agile memory</li> <li>– Seamless integration into larger machines</li> </ul> </li> <li>• 5GFLOPS/W and beyond – soon</li> </ul>
<p>High performance computing is <i>power limited</i>.</p>	<p>Power-Efficient Supercomputing: Goal</p> <ul style="list-style-type: none"> <li>• 200pJ/FLOP (5GFLOPS/W) sustained</li> <li>• 25% of energy in FPU</li> </ul>	