

Notes on Parallel Computing

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Here it has been assumed that as a prerequisite, the reader has a basic understanding of C programming language and familiarity with Basics of Computer Architecture.

1 Introduction

Moore's Law states

The number of transistors in a dense integrated circuit doubles approximately every two years.
(1)

This law has been true for the past 50 years. This has led to the increase in the number of cores in a processor.

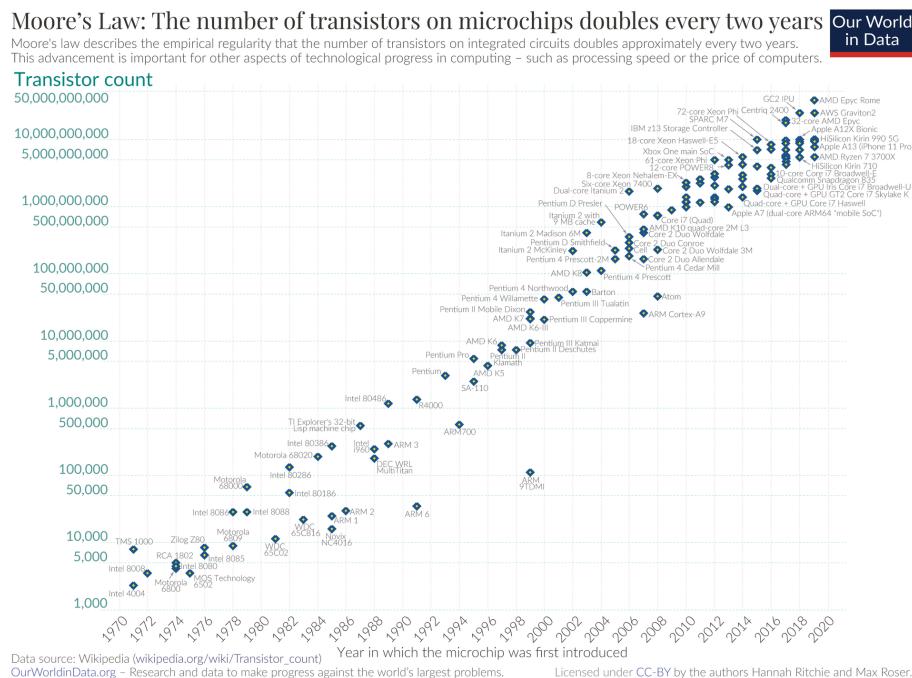


Figure 1: Moore's Law Graph

But computing power is saturating. The power consumption is increasing and the heat dissipation is becoming a problem. Moore's Law is not sustainable. The solution to this problem is parallel computing. Parallel Computing is the use of multiple

processors to perform a computation. It is a form of computation in which many calculations are carried out simultaneously, operating on the principle that large problems can often be divided into smaller ones, which are then solved concurrently. It leads to Faster execution times from days or months to hours or seconds. Example: Climate Modelling, Bioinformatics, Computational Fluid Dynamics, etc. The large amount of data can be processed in parallel. Example: Google, Facebook, process billions of requests per day. Parallelism cannot be achieved in all problems. It is not always possible to divide the problem into smaller problems. But it is more natural for certain kinds of problems. Example: Climate Modelling.

Because of the Computer Architecture trends the CPU Speeds have saturated and thus slow memory bandwidth is the bottleneck. Parallelism helps in data transfer Overlap.

2 Classification of Architectures - Flynn's Taxonomy

Flynn's Taxonomy is a classification of computer architectures based on the number of instruction streams and data streams.

- SISD - Single Instruction, Single Data (Serial Computers)
- SIMD - Single Instruction, Multiple Data
- MISD - Multiple Instruction, Single Data
- MIMD - Multiple Instruction, Multiple Data

2.1 SIMD - Single Instruction Multiple Data

It uses vector processors and processor array. In this, a single instruction is executed on multiple data elements simultaneously.

- Vector Processors - They are capable of executing a single instruction on multiple data elements simultaneously.
 - Processor Array - It is a collection of processors that work in parallel on different data elements.
-

For example, CM-2, Cray-90, Intel Xeon Phi, Intel -vector instructions (1028 bytes), etc.

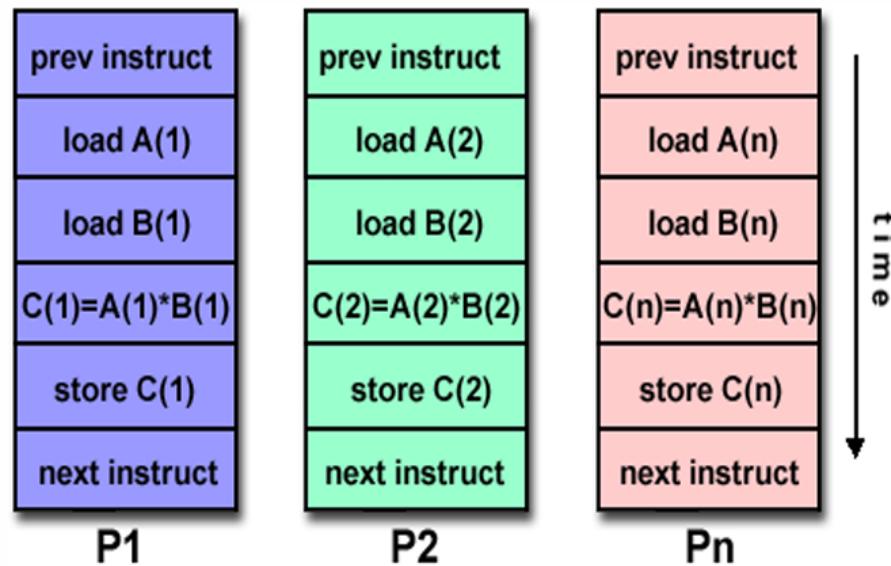


Figure 2: SIMD Architecture

[Link to Parallel Computing Tutorial](#) This link provided by LLNL provides a good tutorial on parallel computing for more information. Consider the figure 2. Say two vectors A and B are given of size n (i.e. n elements). The operation is to perform a element-wise multiplication between the two given vectors. We are given n processors (from P₁,...,P_n) Then, in case of SIMD architecture we will pass say ith element of the vector to the ith processor i.e. the first processor will get the first element of the vector, the second processor will get the second element of the vector and so on. Then the processor will simultaneously with time start executing the same instruction on the data element that it has been given. So as shown in the figure 2, all the processors will simultaneously load the data element i.e. ith processor will load the ith element of the vector A. P₁ will load A(1), P₂ will load A(2) and so on P_n will load A(n). Then they will simultaneously execute the next instruction to load the data element of the vector B. Thus, the ith processor will load the ith element of the vector B i.e. P₁ will load B(1), P₂ will load B(2) and so on P_n will load B(n). Then, once the data has been loaded, the processors will simultaneously execute the next instruction to multiply the data elements that they have loaded.

Thus, P1 will multiply A(1) and B(1), P2 will multiply A(2) and B(2) and so on Pn will multiply A(n) and B(n). Then, the processors will simultaneously execute the next instruction to store the element in the result vector C. The ith processor will store the result in the ith element of the vector C. Thus, P1 will store the result in C(1), P2 will store the result in C(2) and so on Pn will store the result in C(n). Thus, the SIMD architecture is used to perform the element-wise multiplication of two vectors in parallel. This is how the SIMD Architecture works.

2.2 MISD - Multiple Instruction Single Data

This is not very common. It is used in fault-tolerant systems. In this, multiple instructions are executed on the same data. Some of the examples are:

- Fault-tolerant systems
- Redundant systems
- N-modular redundancy
- Cryptography - Multiple algorithms to crack same data

2.3 MIMD - Multiple Instruction Multiple Data

In this, multiple instructions are executed on multiple data elements. It is the most common architecture. Some of the examples are IBM SP, most supercomputers, cluster, Computational grids, etc.. At a given time step different processors can execute different instructions on different data elements.

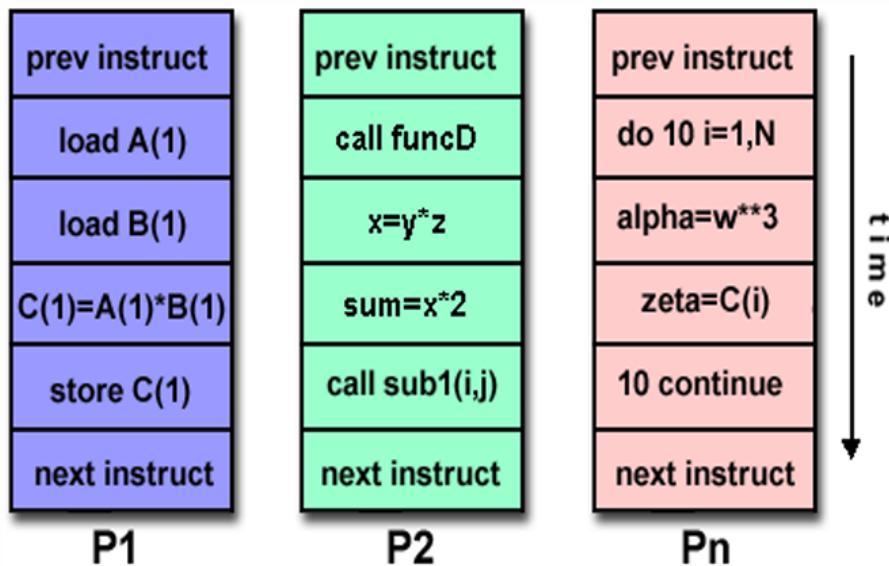


Figure 3: MIMD Architecture

As shown in figure 3, each of the processor P_1, P_2, \dots, P_n can execute different instructions on different data elements simultaneously in time. P_1 is doing element wise multiplication, P_2 is running a completely different instruction simultaneously on completely different data elements and so on. Thus, MIMD architecture is used to perform different instructions on different data elements in parallel. This is how the MIMD Architecture works.

3 Classification based on Memory

- Shared Memory
- Distributed Memory

3.1 Shared Memory

In this, all the processors share the same memory. It requires special computer architecture for memory management (explained later). It is easier to program.

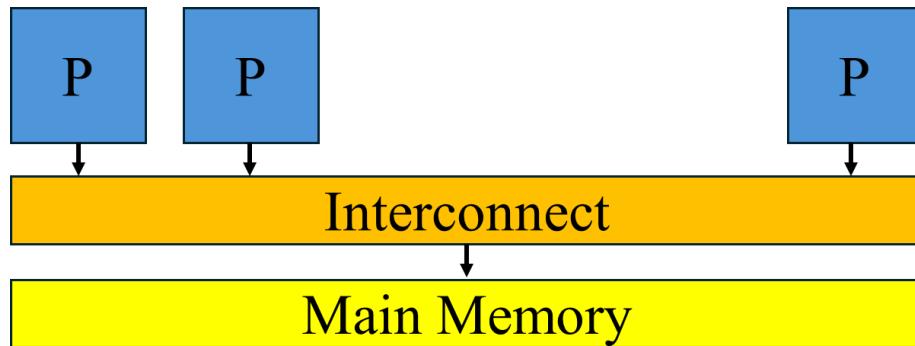


Figure 4: Shared Memory Architecture

As shown in figure 4, in this the n processors share the same physical address space i.e. say the address is 0x7FFF5FBFFD98 then, whenever a processor accesses the address 0x7FFF5FBFFD98 then it refers to the same physical address location in the memory for all the processors P₁, P₂, ..., P_n i.e. thus address 0x7FFF5FBFFD98 is at the same physical location for all the processors. Thus, any of the processor can access the address 0x7FFF5FBFFD98 or the address 0x7FFF5FBFFD98 refers to the same physical location for all the processors. This is called sharing the same physical address space. It will be cleared further when you will see Distributed Memory Architecture. It will be explained in detail later how the shared memory is managed in the computer architecture and thus will clear the doubts about how the shared memory is managed. This leads to certain problems in Read and Write and Maintaining Cache Coherence (explained later) Thus, any communication between the processors can be done thorough this shared memory. There are two types of shared memory:

- Uniform Memory Access (UMA) - All processors have equal access time to all memory locations.
- Non-Uniform Memory Access (NUMA) - Access time depends on the location of the memory.

In general, the time taken by the processor to access a memory location depends on the distance between the processor and the memory location.

3.1.1 Uniform Memory Access (UMA)

In this, all the processors have equal access time to all memory locations. It is easier to program.

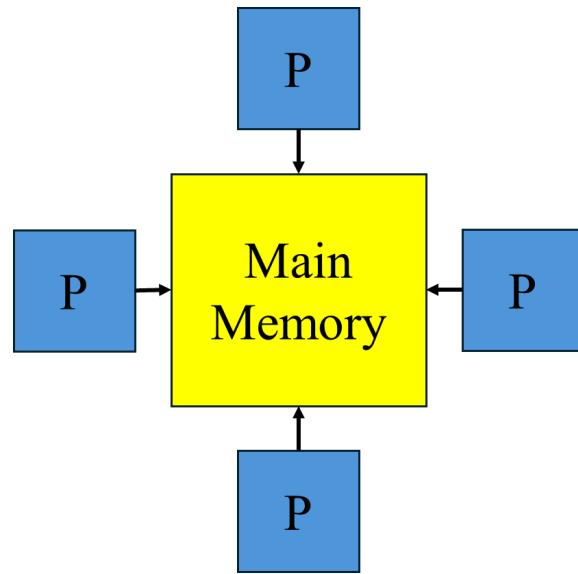


Figure 5: Uniform Memory Access Architecture

As shown in figure 5, all the processors have equal access time to all the memory locations i.e. the time taken by the processor to access a memory location is same for all the processors. All can be thought of as being at the same distance from the memory location. Thus, all the processors have equal access time to all the memory locations.

3.1.2 Non-Uniform Memory Access (NUMA)

In this, the access time depends on the location of the memory. It is difficult to program.

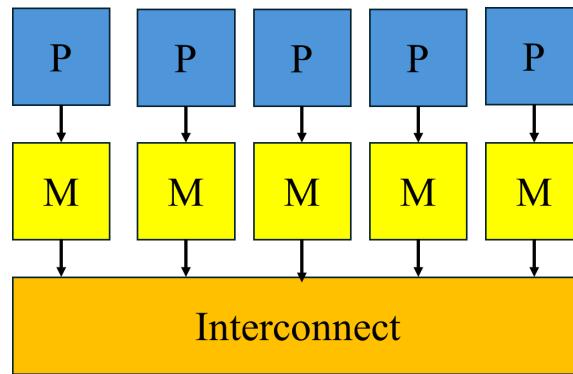


Figure 6: Non-Uniform Memory Access Architecture

As shown in figure 6, each processor might have some portion of shared physical address space that is physically close to it and therefore accessible to it in less time. Thus, the time taken by the processor to access a memory location depends on the location of the memory.

3.2 Distributed Memory Architecture

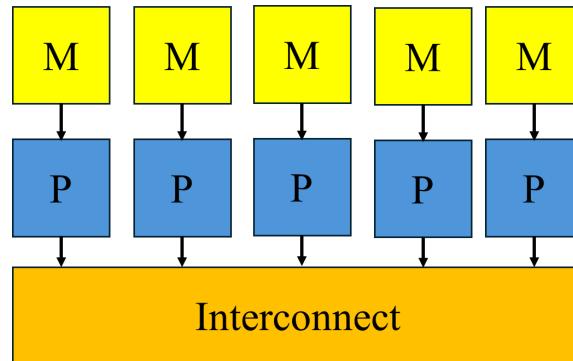


Figure 7: Distributed Memory Architecture

As shown in figure 7, If two processors access the same memory address say 0x7FFF5FBFFD98 then they will get different data since the physical address space is not shared. Thus, the address 0x7FFF5FBFFD98 refers to different physical locations for different processors. The only way to access data between processor is by sending and receiving data i.e. message passing. This is generally preferred when we wish to use very large number of cores. It is difficult to program.

3.3 Shared Memory Architectures: Cache Coherence

Now consider the figure 4. As shown in the figure the processors are connected to the Main Memory via Interconnect. Note that even in case of shared memory architecture individual processors have their own caches. Now suppose there is a variable X in the Main Memory and the value of X is 5. Now suppose the processor P1 tries to access the variable X, it will be a Cache miss and hence the value of X will be loaded into the cache of the processor P1. Now suppose the processor P2 tries to access the variable X, it will be a Cache miss and hence the value of X will be loaded into the cache of the processor P2. Now suppose the processor P1 changes the value of X to 10, it will be a Cache hit and hence the value of X will be updated in the cache of the processor P1. Now suppose the processor P2 tries to access the variable X, it will be a Cache hit and hence the value of X used will be the stale value 5. This is called Cache Coherence Problem. The value of X is not consistent across the caches of the processors. There are two ways to solve this problem:

- Write Update Protocol - Propagate Cache lines to other processors on every write to a processor as well as Global memory. Write operation in write update takes longer time because it has to send the data to all the processors. In Read operation, write update is better as the update data is there in local caches of the processor, hence its a faster read.
- Write Invalidate Protocol - Whenever one of the Processor updates the data it sends a signal to other processor to invalidate the data in the cache. Thus, next time if the processor requires that data it will be a cache miss and the data loads from the main memory. Each processor gets the latest data from the main memory. In update protocol, the write updates are faster as it is required to send only an invalidate signal to the processors. In write invalidate protocol, read operation will be a cache miss: thus requires fetching data from memory.

In write update protocol, if the data is present in another processor it will get updated regardless of whether that data is going to be used on not by that processor. This does not happen in write invalidate protocol. Thus, more traffic in write update protocol. This is why most of the systems use write invalidate protocol. NOTE: The specific steps of protocols vary from implementation to implementation.

3.3.1 State Transition Diagram

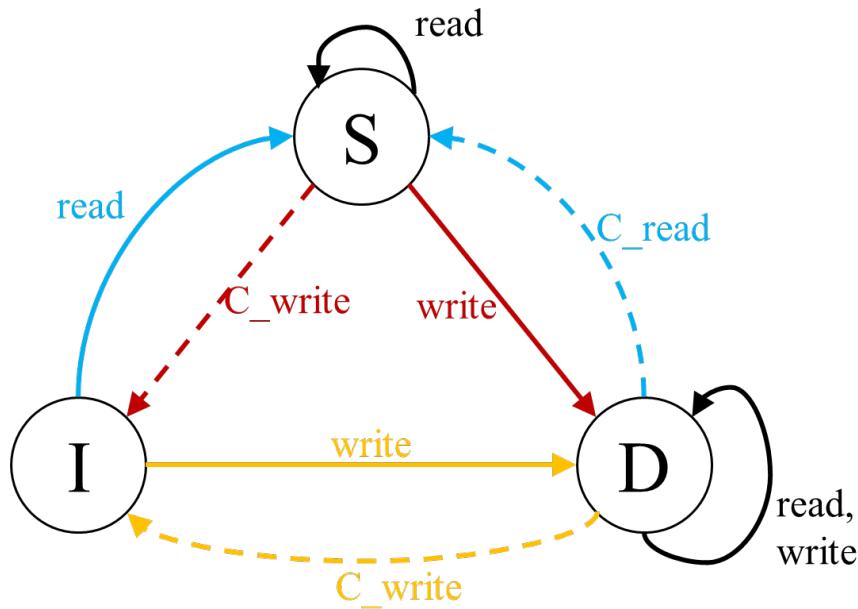


Figure 8: State Transition Diagram for invalidate protocol

A cache line can be in either of the three states - Shared (S) - a variable shared by 2 caches, Invalid (I) - another Processor has updated the data, Dirty (D) - the data has been updated by the processor. In the figure shown in 8, the state transition diagram for the invalidate protocol is shown. The solid lines indicate the Primary action and the dashed lines indicate the Cache coherence protocol action.

Now consider the figure 8. Suppose the cache line is in the shared state S i.e. the data is shared by at least two caches (i.e. in different processors). Then if it is read by either of the processors, it will remain in the shared state S indicated by the solid black line.

If it is written by one of the the processor, it will go to the dirty state D from shared state S for the processor that writes the data as shown by the solid red line from S to D, and because of the cache coherence protocol action, it will go to the invalid state I for the other processor as shown by dashed the red line in the figure 8 from S to I.

If the cache line is in the dirty state D i.e. the data has been updated by the processor, then if it is read/write by the processor, it will remain in the dirty state D as

shown by solid black line in the figure 8 from D to D.

If the cache line is in the invalid state I i.e. the data has been updated by another processor, then, if it is read by the processor, it will be a cache miss and hence the data will be loaded from the main memory and the cache line will go to the shared state S as shown by the solid blue line in the figure 8 going from I to S. Because of this read, the cache coherence protocol action will be to go from the Dirty state D to the shared state S for the other processor as shown by the dashed blue line in the figure 8 from D to S.

If the cache line is in the invalid state I i.e. the data has been updated by another processor, then, if it is written by the processor, it will go to the dirty state D as shown by the solid yellow line in the figure 8 from I to D. Thus, as a result the processor will send an invalidate signal to all the processors as part of the cache coherence protocol, the cache line which was in Dirty state D for the other processor will thus become invalid. Thus, the dirty state D will go to Invalid state I for the other processor as shown in figure 8 by a dashed yellow line from D to I.

3.4 Implementation of Cache Coherence Protocols

3.4.1 Snooping Protocol

It is generally used for Bus based architectures. Only one operation can be done at a time. All the memory operations are propagated over the bus and snooped. The idea is that each processor has a specialised cache controller which always snoops onto the bus. Thus, any write operation in any of the cache is publicly broadcasted onto the bus and thus is known by all the other cache controllers of the processors hearing on the bus. Thus, any information related to the cache line present in their cache is invalidated. But this has a problem that only one operation can be done at a time thus, it is slow and not scalable. It requires specialised cache controllers for each processor which increases the cost of architecture. All the data write/read are costly because all the processors are continuously writing on bus and other processors are snooping on the bus. To overcome this problem, the directory based protocol is used.

3.4.2 Directory Based Protocol

It is generally used for Network based architectures. It is scalable and faster. It is used in large scale systems. In the snooping protocol all the other processors even which do not have that data are also snooping on the bus and are listening

even though they are not concerned with data. Hence, a mechanism is required where the invalidate signals are sent only to certain processors. This is done by maintaining a directory for each cache line which contains the information about which processors have the data. Thus, the invalidate signals are sent only to the processors which have the data. Thus, instead of broadcasting memory operations to all the processors, cache coherence operations are propagated only to the relevant processors. A centralised directory maintains states of all the cache lines and the processors which have the data. Consider it has M cache lines and P processors, thus a matrix of $M \times P$ is maintained where each row represents a cache line and each column represents a processor. The data about which processor contains that cache line is maintained by presence bits (1 and 0s) in the matrix. wherever the presence bit is 1, it means that the processor has the data and wherever the presence bit is 0, it means that the processor does not have the data. Thus, any invalidate signal will be sent only to the processor with presence bit as 1. The directory also maintains who is the current owner of the cache line. Note that this is called a *Full Bit Vector Scheme* where the number of presence bits is of the $\mathcal{O}(M \times P)$. Huge number of cache lines/processors requires huge amount of memory for storing directory and less memory for storing the actual data. Thus, requires lots of swaps to memory thus, losing the advantage of parallelism. Ideally, at all times only some of the cache lines will be of interest to only some of the processors. Thus, the matrix $M \times P$ is sparse. Thus, a *Sparse Bit Vector Scheme* is used where the number of presence bits is of the $\mathcal{O}(M + P)$. Here the number of cache lines (m) is much lesser than the total number of cache lines(M) ($M \ll m$) and the number of processors (p) is much less than the total number of Processors (P). ($p \ll P$). Thus, a limited number of cache lines and processors are of interest at any given time.

3.5 False Sharing

A cache is made up of multiple cache lines. All the cache coherence protocols, such as write invalidate, write update deal with the granularity of cache lines and not at the scale of individual variables. Thus, if a variable is in one of the cache lines of caches of two processors and if one of the processors updates some other variable belonging to the same cache line, then even though the variable in the other processor was not updated, since the entire cache line is invalidated, the variable in the other processor will be invalidated. This is called False Sharing.

Let us understand this with an example, Consider modern day caches, a modern day cache lines are of 64 bytes in size. Now consider the data to be stored be of double type which takes 16 bytes. Thus, we can store 4 double type variables in a cache

line. Now consider two processors P1 and P2. Suppose a cache line is shared by the processors P1 and P2. Now, say P1 updates the first variable out of the four variables stored in that cache line. Now consider a situation where P2 does not ever required to read or write the first variable but it requires to read or write the second variable. But, since P1 updates the first variable of the cache line and as the cache coherence protocols deal with granularity of cache lines and not of the individual variables, this will lead to the entire cache line being invalidated for the processor P2. Thus, even though the processor P1 deals only with the first variable and P2 deals with only the second variable, the entire cache line will be invalidated for P2. This is called False Sharing. This leads to unnecessary cache misses and thus, the performance of the system is degraded. Thus, even though these two processors are accessing different variables of the same cache line i.e. it is not true sharing, since processor P1 deals only with the first variable and processor P2 deals with only the second variable, but still any updating to either of the variable will lead to invalidating the entire cache line for the other processor. Thus, it is called False sharing. It unnecessarily introduces cache coherence protocols even though the processors are not sharing the same variable or the same element.

4 Interconnection networks for a Parallel Computer

Interconnection networks for a parallel computer provide mechanisms for data transfer between processing nodes or between processor and memory modules. A black-box view of interconnection network consists of n inputs and m outputs. Interconnections networks are build using links and switches. **Links** are set of wires or fibres for carrying information. They limit the speed of propagation because of capacitive coupling, attenuation of signal strength which are a function of length of link. **Switch:** A switch maps input ports to output ports. Degree of a switch is the total number of ports on a switch. It supports internal buffering when output ports are busy and allows Routing (to alleviate congestion on Network) and multicast (same output on multiple ports). There are two type of networks:

- Static/Direct Networks - It is point to point communication links among the processing nodes Example: Hypercube, Mesh, Torus, etc.
- Dynamic/Indirect Networks - They are connected by switches linking processing nodes and memory banks. Example: Crossbar, Omega, etc.

The classification is as shown in figure 9. The diagram on the left shows a Static Network and the diagram on the right shows Indirect Network.

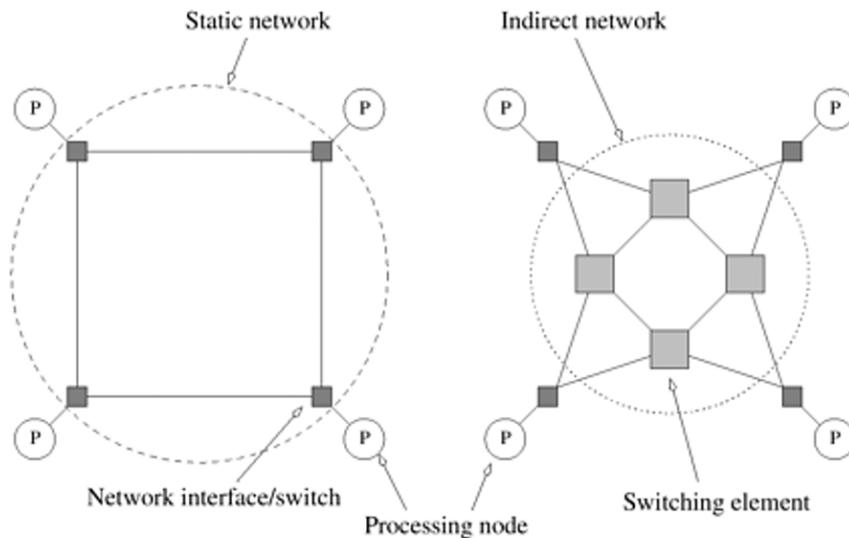


Figure 9: Classification of Interconnection Network

4.1 Network Topology

Network topology is evaluated broadly in terms of cost and scalability with performance.

4.1.1 Bus-based networks

It is a shared medium that is common to all node. They are scalable in cost but unscalable in terms of performance. The cost of the network is thus proportional to the number of nodes p , thus scales as $\mathcal{O}(p)$. The distance between any two nodes in the network is constant $\mathcal{O}(1)$. Since they broadcast information among nodes, there is a little overhead associated with broadcast compared to point to point message transfer. The bounded bandwidth places limitation on the overall performance of the network. Example: Intel Pentium and Sun Enterprise servers. The demands for bandwidth can be reduced by cache for each node i.e. Private data, thus, only remote data is to be accessed through the bus. This is as shown in figure 10.

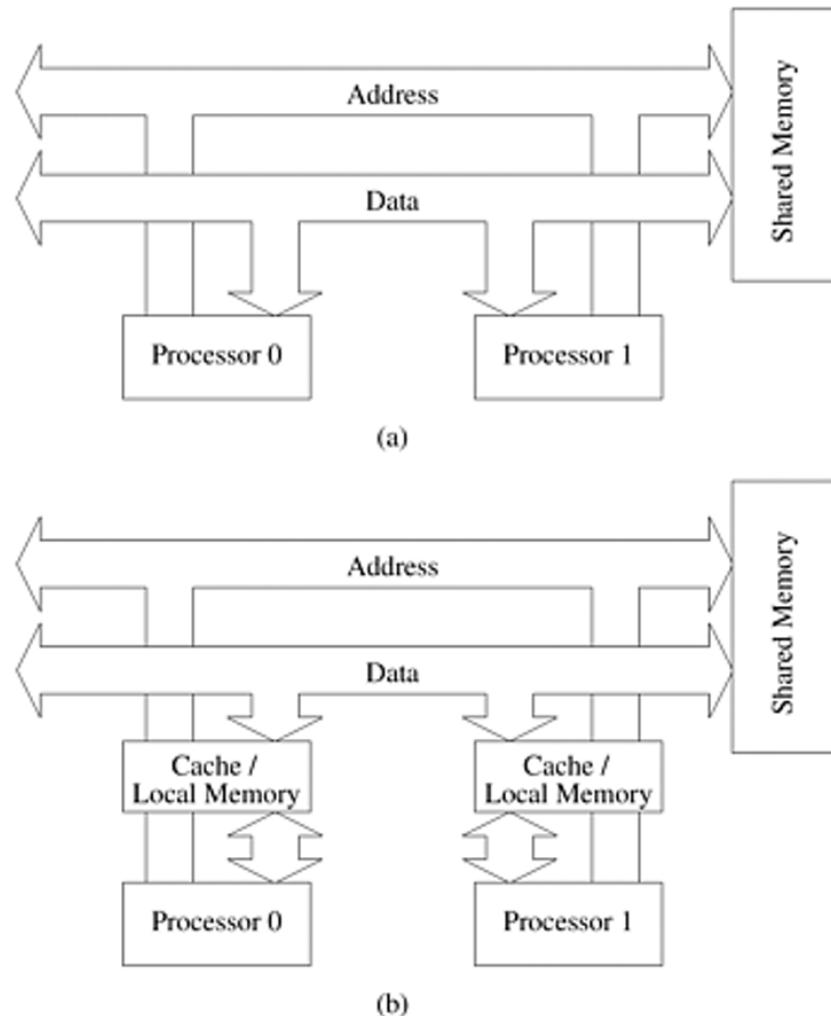


Figure 10: Bus-based Network

The figure at the top shows a bus-based interconnects with no local caches. The figure at the bottom shows a bus-based interconnects with local memory/caches.

4.1.2 Cross-bar Networks

Consider the figure 11. It connects p processors to b memory banks. It is a non-blocking network i.e. the connection of a processing node to a memory bank does not block the connection of any other processing nodes to other memory banks.

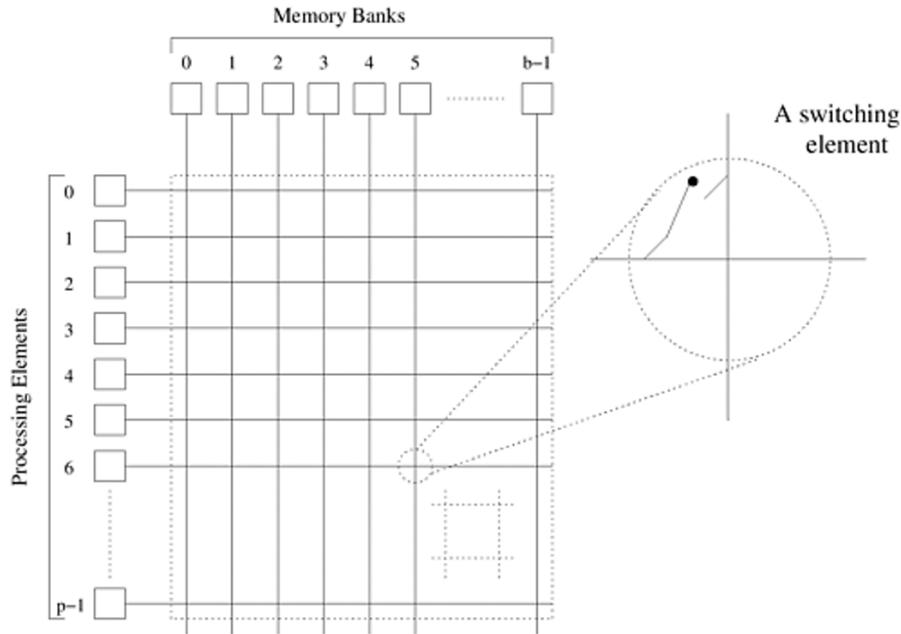


Figure 11: Cross-bar Network

The total number of switching nodes is $\Theta(pb)$. Generally, $b > p$ so that all the processors can access some memory bank. Thus as p is increased, the complexity of switching network grows as $\Omega(p^2)$. Thus, as number of processing nodes becomes large, switch complexity is difficult to realize at high data rates. Thus, Cross bar networks are not scalable in terms of cost but are scalable in terms of performance.

4.1.3 Multistage Network

Consider the figure 12. It lies between crossbar and bus network topology. It is more scalable than bus in terms of performance and more scalable than cross bar in terms of cost.

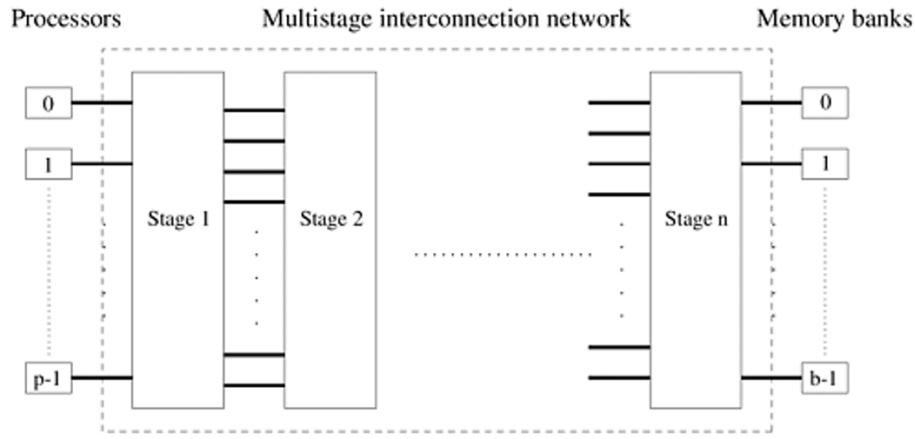


Figure 12: Multistage Network

Omega Network is a type of multistage network with p number of inputs (p processing node), p number of outputs (p memory banks) and $\log(p)$ number of stages each consisting of $p/2$ switches. At any consecutive intermediate stage, a link exists between input i and output j according to the following interconnection pattern:

$$j = \begin{cases} 2i & 0 \leq i \leq p/2 - 1 \\ 2i + 1 - p & p/2 \leq i \leq p - 1 \end{cases} \quad (2)$$

This is called a perfect shuffle i.e. left rotation on binary representation of i to obtain j . In order to understand, consider the example shown in the figure 13. The figure shows a perfect shuffle interconnection for eight inputs and outputs.

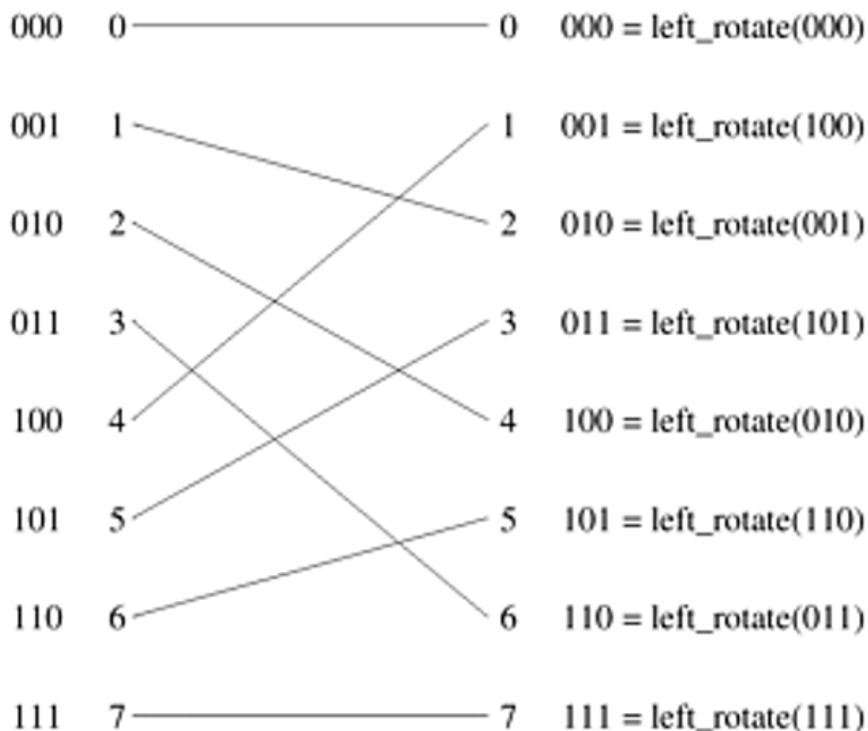


Figure 13: A perfect shuffle interconnection for eight inputs and outputs

Starting from the first input 000. It should be connected to the output obtained on left rotating the input i.e. 000. Thus, as can be clearly seen in the figure it is connected to 000. Similarly, the second input 001 should be connected to the output obtained on left rotating the input i.e. 010. Thus, as can be clearly seen in the figure it is connected to 010. Similarly, the third input 010 should be connected to the output obtained on left rotating the input i.e. 100. It can be seen that there is a connection for 010 to 100 and so on for all the inputs till 111 whose left rotation will be 111 and hence a connection between 111 to 111. Switching nodes can be in either of the two configurations pass through or cross-over as shown in the figure



Figure 14: Pass-through and Cross-over configuration of Switching Nodes

In figure 14 the figure on the left shows pass-through configuration of a switching node in which the inputs are sent straight to outputs and the figure on the right shows cross-over configuration of a switching node in which the inputs are crossed over and sent out.

Now, the number of switches required in each stage is $p/2$ as a switching element takes two inputs and return two outputs. Thus, since there are p inputs, $p/2$ switches are required in each stage. Thus, the total number of switches required is $\log(p) * p/2 = \Theta(p \log(p))$. Recall, that the number of switches required in complete cross bar network scaled as $\Theta(p^2)$ and the number of switching nodes in case of a bus-based network scaled as $\Theta(p)$. Thus, $\Theta(p) < \Theta(p \log p) < \Theta(p^2)$. This, proves that the multistage network is more scalable than the cross bar network in terms of cost and more scalable than the bus network in terms of performance.

Omega Network

Consider the complete omega network as shown in the figure 15. We now understand the routing scheme of the omega network.

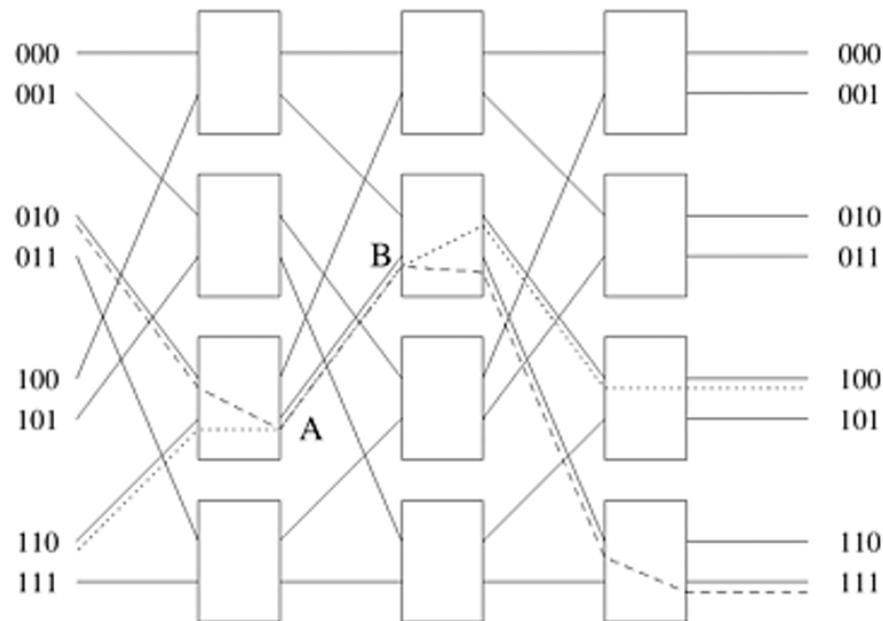


Figure 15: Omega Network

Let s be the binary representation of processors that need to write some data to bank t . Now the bits are written in the binary representation. The most significant bit is the left most bit and the least significant bit is the right most bit. Now the routing scheme works as follows, at the first switching node, if the most significant bits of s and t are the same, then the data is routed in pass-through mode. If bits are different than the data is routed through cross-over mode. At the second switching node, if the second most significant bits of s and t are the same, then the data is routed in pass-through mode. If bits are different than the data is routed through cross-over mode. This is done for all the bits of s and t , by repeating over next switching stage using the next most significant bit. In this way, it uses all $\log p$ bits in the binary representation of s and t .

For example, consider a message to be passed from 010 to 111. As shown in the figure 15 by dashed lines. As the message reaches the first switching elements because the most significant bits of 010 and 111 are different the message is routed through cross-over mode. As the message reaches the second switching elements because the second most significant bits of 010 and 111 are the same it is routed through pass-through mode. As the message reaches the third switching elements because the third most significant bits of 010 and 111 are different the message is routed through cross-over mode. Thus, the message is passed from 010 to 111.

Consider another example, consider a message to be passed from 110 to 100. As shown in the figure 15 by solid lines. As the message reaches the first switching elements because the most significant bits of 110 and 100 are the same the message is routed through pass-through mode. As the message reaches the second switching elements because the second most significant bits of 110 and 100 are different it is routed through cross-over mode. As the message reaches the third switching elements because the third most significant bits of 110 and 100 are the same the message is routed through pass-through mode. Thus, the message is passed from 110 to 100.

Now consider the case where both of the messages in the above examples were to be passed from 010 to 100 and 110 to 111 simultaneously. As shown in the figure 15 by solid and dashed lines. In the case when the processor two and six are communicating simultaneously then one may disallow access to another memory bank the another processor. This is because they have a common link in the routing scheme shown by AB in the figure 15. This property is called **blocking networks**.

4.1.4 Completely Connected Networks

In this, each node has a direct communication link to every other node in the network. A node can send a message to another node in a single step, since a communication link exists between them. It is a static counter part of crossbar switching networks as the connection between any input/output pair does not block communication between any other pair. For example, a completely connected network of eight nodes is as shown in the figure 16.

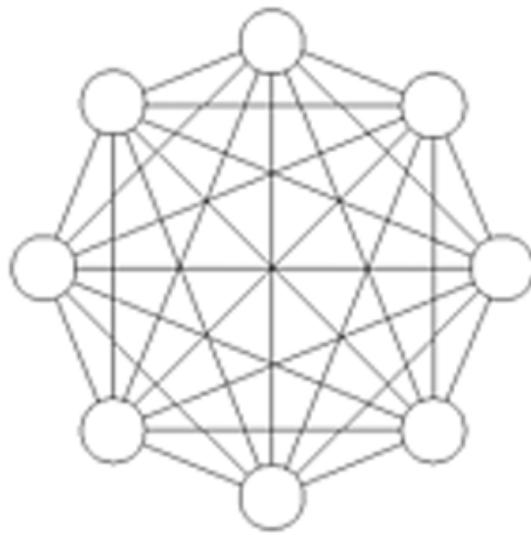


Figure 16: Completely Connected Network

4.1.5 Star Connected Network/Star Topology

In this, all the nodes are connected to a central node. The central node acts as a switch to connect the nodes.

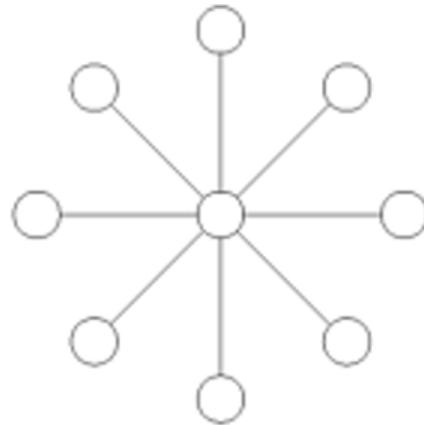


Figure 17: Star Connected Network

As shown in the figure 17. Every other processor has a communication link connecting it to this processor. It is thus similar to a shared bus. Here, the central

processor thus acts as a bottleneck.

4.1.6 Linear Arrays, Meshes and k-d Meshes

Linear arrays are as shown in figure 18. It is a one-dimensional array of processing nodes. Each node is connected to its immediate neighbours.



Figure 18: Linear Array

As shown in the figure 18 there are two possible cases, the left figure shows a linear array with no wraparound links. It is a static network in which each node (except the two nodes at the ends) has two neighbors, one each to its left and right. The right figure shows a linear array with wraparound links also called a 1D torus. The wraparound links connect the last node to the first node and the first node to the last node. The ring has a wraparound connection between the extremities of linear array. Each node has two neighbors in this case.

2D Mesh

It is a linear array extended to 2D as shown in the figure 19

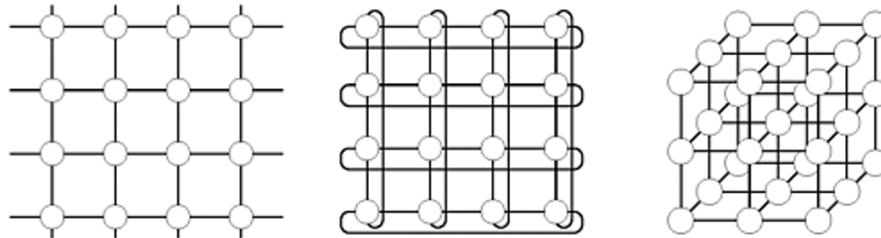


Figure 19: Mesh

It has \sqrt{p} nodes in each direction. As shown in the figure there are three possible cases for a 2D mesh. The leftmost figure shows a 2D mesh with no wraparound links. In this each (i,j) node is connected to $(i+1,j), (i,j+1), (i-1,j), (i,j-1)$. It can be laid out in 2D space. A variety of regulatory structure computations map naturally to 2D. 2D mesh were often used as interconnects in parallel machines.

The middle figure shows a 2D mesh with wraparound links. It is also called a 2D Tori.

The rightmost figure is a 3D Cube with no wraparound which is a generalization of

2D mesh to 3D. In this, each node is connected to six other nodes, two along each of the three dimensions. 3D simulations can be mapped naturally to 3D.

General Class of k-d meshes

It is a class of topologies with d dimensions and k nodes along each dimension. Thus, in total k^d nodes. A 1D linear arrays is a special case of a k -d mesh with $d=1$. A 2D mesh is a special case of a k -d mesh with $d=2$. A hypercube has two nodes along each dimensions and has $\log_2 p$ dimensions. It is thus, written as 2-log mesh. A d -dimensional hypercube is constructed by connection two ($d-1$) dimensional hypercube as shown in the figure 20.

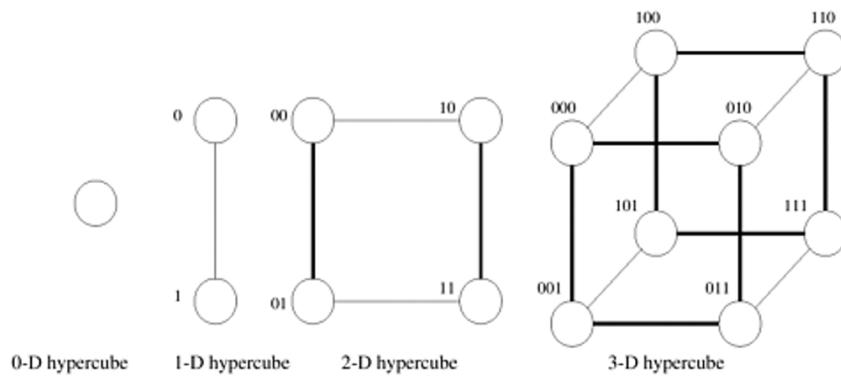


Figure 20: Hypercube

The hypercubes follow a numbering scheme which is useful later on for writing many parallel algorithms. Number the nodes then place the two $d-1$ dimensional ($p/2$ nodes) hypercubes side by side. Prefix one with 0 and the other with 1. **Property: The minimum distance between two nodes is given by the number of bits that are different in two labels.** For example, 0110 and 0101 are different in two bits. the third and fourth place bits. Thus, the minimum distance between them is two link apart. This property can be used for deriving parallel algorithms for hypercube architecture. A 4D hypercube with 16nodes is as shown in the figure 21

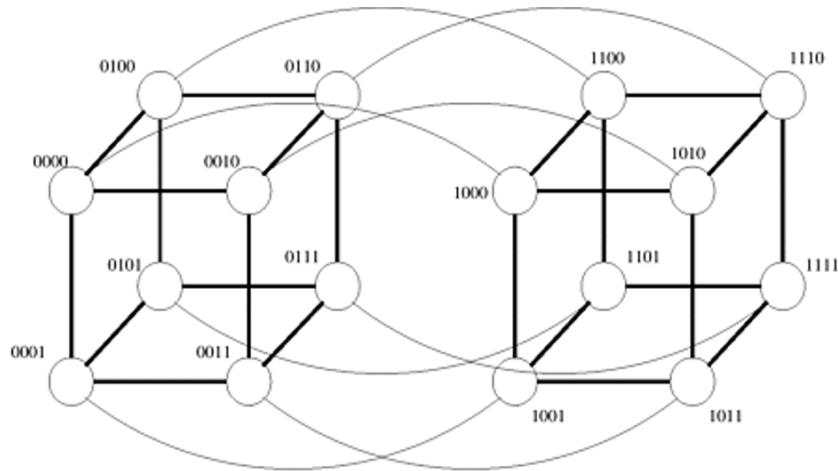


Figure 21: 4D Hypercube

4.1.7 Tree Based Networks

It is a hierarchical network. It is a tree with a root node and each node has a parent and children as shown in the figure 22.

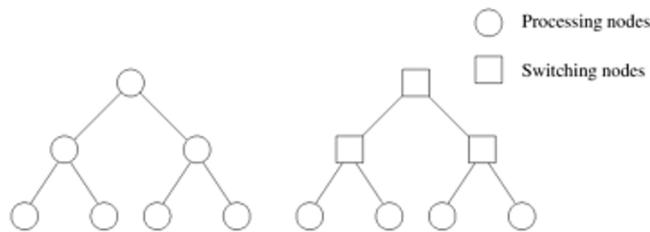


Figure 22: Tree Based Network

Note that there is only one path between any pair of nodes. IN the figure 22, the left figure shows a Static Tree Network where each processing element is at each node of the tree. The right figure shows a Dynamic Tree Network where the nodes at intermediate level are switching nodes, and the leaf nodes are processing elements.

Routing: Source sends the message up the tree until it reaches the node at the root of the smallest sub tree containing both the source and destination nodes. Then the message is routed down the tree towards the destination node. At higher levels of tree, example, nodes in left sub tree of a node communicate with nodes in right tree, root node must handle all the messages. This leads to communication bottleneck.

It is solved by dynamic tree called Fat Tree as shown in figure 23 by increasing the number of connection links and switching nodes close to the root.

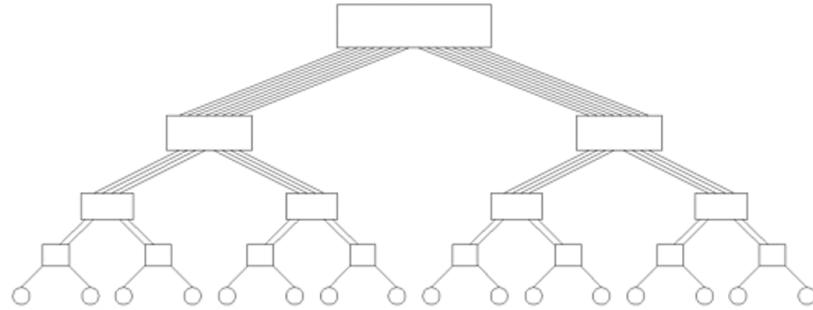


Figure 23: Fat Tree with 16 Processing Nodes

The processors are arranged in leaves and all the other nodes correspond to switches. Note that here the property that the number of links from a node to a children is equal to the number of links from the node to its parent. Thus, the edges become fatter as we traverse up. Now any pair of processors can communicate without contention : non-blocking network. It has a constant bisection bandwidth networks as the number of links crossing the bisection is constant. As shown in the example figure 23 a two level fat tree has a diameter of four.

4.2 Evaluating Static Networks

The performance of a static network is evaluated in terms of cost, performance and scalability.

4.2.1 Diameter

The diameter of a network is the maximum distance between any two processing nodes in the network. The distance between any two processing nodes is defined as the shortest path (in terms of number of links) between them. For example, the diameter of a completely connected network is 1 and of the star-connected network is two. The diameter of a ring network is $\lfloor p/2 \rfloor$. The diameter of a 2D mesh without wraparound connection is $2(\sqrt{p} - 1)$. The diameter of a 2D mesh with wraparound connection is $2\lfloor \sqrt{p}/2 \rfloor$. The diameter of a complete binary tree is $2 \log(\frac{p+1}{2})$ because two communicating nodes may be in separate subtrees of the root node and a message might have to travel all the way to the root and then down the other subtree.

4.2.2 Connectivity

The connectivity of a network is a measure of the multiplicity of paths between any two processing nodes. A network with high connectivity is desirable since it lowers latency of communication resources.

Arc Connectivity of the network: The minimum no. of arcs that must be removed from the network to break it into two disconnected network. For example, Arc connectivity of Linear array, tree star connected networks is 1. For rings, 2D meshes without wraparound is 2. It is 4 for 2D meshes with wraparound. It is d for d -dimensional hyper cubes.

4.2.3 Bisection Width and Bisection Bandwidth

Bisection Width: The bisection width of a network is defined as the minimum no. of communication links that must be removed to partition into two equal halves. For example, bisection width of ring=2. Bisection width of 2D p node mesh without wraparound = \sqrt{p} . For a 2D mesh with wraparound bisection width = $2\sqrt{p}$. Bisection width of a hypercube, by deconstructing the connection we get from $2(d - 1)$ dimensional hypercube to 1d dimensions hypercube. Hence, $p/2$ nodes to be cut to separate into two subcubes.

Channel Width: No. of bits that can be communicated simultaneously over a link connecting two nodes. Channel width = no. of physical wires in each communication link. **Channel rate:** The peak rate at which a single physical wire can deliver bits is called the channel rate.

Channel bandwidth: Peak rate at which data can be communicated between the ends of a communication link. Thus,

$$\text{Channel bandwidth} = \text{Channel Width} \times \text{Channel rate} \quad (3)$$

Bisection bandwidth: The minimum volume of communication allowed between any two halves of the network.

$$\text{Bisection bandwidth/Cross section bandwidth} = \text{Bisection Width} \times \text{Channel width} \quad (4)$$

It is also a measure of cost as it provides a lower bound on areas in 2D packing and volume in 3D. Say bisection width = w , lower bound on area in 2D packaging gives $\Theta(w^2)$ and for volume in 3D packaging is $\Theta(w^{3/2})$. According to it, the hypercubes and completely connected networks are more expensive.

4.2.4 Cost

Number of communication links or number of wires required by the network. For example, linear array = $p-1$ links to connect p nodes. For, d -dimensional wraparound mesh = dp links. For a hypercube, $\frac{p \log p}{2}$ links.

All of this has been summarise in the following table 1.

Network	Diameter	Bisection Width	Arc connectivity	Cost
Completely connected	1	$p^2/4$	$p-1$	$\frac{p(p-1)}{2}$
Star	2	1	1	$p-1$
Ring	$\lfloor p/2 \rfloor$	2	2	$p-1$
Complete Binary Tree	$2 \log(\frac{p+1}{2})$	1	1	$p-1$
Linear Array	$p-1$	1	1	$p-1$
2D mesh (no wraparound)	$2(\sqrt{p} - 1)$	\sqrt{p}	2	$2\sqrt{p}(\sqrt{p} - 1)$
2D mesh (wraparound)	$2\lfloor \sqrt{p}/2 \rfloor$	$2\sqrt{p}$	4	$2p$
Hypercube	$\log p$	$\frac{p}{2}$	$\log p$	$\frac{p \log p}{2}$
Wraparound k-array d cube	$d\lfloor k/2 \rfloor$	$2k^{d-1}$	$2d$	dp

Table 1: Summary of Static Networks

5 Graphical Processing Units

A CPU has at max of 32 Cores and 8 threads per core. It is good for serial processing. Thus, they are called Multi-core architectures. But for parallel processing, we need more cores. Thus, we need to use GPUs. GPUs have 1000s of cores and are good for parallel processing. Thus, are called Many-Core Architectures. GPUs consist of a large number of light-weight cores which are not as powerful as CPU Cores. In the early, days before 2014 NVIDIA GPUs were used for gaming and video applications for graphical displays. These can be done in stages with each stage consisting of independent computations like reading pixels, shading, etc. which can be done in highly parallel manner. Reading of one pixel is independent of reading of other pixel. Processing/rendering of pixels can happen simultaneously. Higher no. of cores of GPU helps in processing in real time. Thus, GPU many-core architectures consisting of light-weight cores as they can perform only simple computations and not very heavy computations are used. Typically GPU and CPU coexists in a heterogeneous setting. GPUs do not exist in standalone setting. A program runs on a CPU(coarse-grain parallelism) and CPU offloads some of the computations to the GPU for light-weight computations (fine-grain parallelism). NVIDIA's GPU architectures consists of CUDA (Compute Unified Device Architecture) which is a parallel computing platform and application programming interface (API) model created by NVIDIA. CUDA programming model is based on C/C++ and is used to program NVIDIA GPUs. It is used to write parallel programs that run on the GPU.

GPUs were initially used for gaming (possible to divide up monitor pixels to process things in parallel). They are also efficient in Matrix calculations.

5.1 GPU Architecture



Figure 24: GPU Architecture

A GPU Architecture is shown in figure 24. The GPU Architecture consists of five main components:

- TPC - Texture Processing Clusters
- SMX - Streaming Multiprocessors
- SP - Single Precision (GPU Core)
- DRAM - Device RAM (GPU RAM)
- ROP - Render Output Unit

GPU cores are called Streaming Multiprocessors (SMX). SP cores are called Single Precision (GPU Core). Coarse level parallelism tasks execute on SMx which gives fine level parallel tasks to execute on SP. Thus, promotes coarse and fine level parallelism. For example, the latest NVIDIA Architecture Kepler consists of 15 SMX with each of 192 SP cores = 2880 SP cores in total. The speed of each of the processors is 745 MHz which is much less than that of a CPU. GPUs follow SIMD (Single Instruction Multiple Threads) model. NVIDIA GPU has L2 cache, common memory and individual caches. Each SMX has its own 32 bit registers for storing the context of GPU threads. Consider the figure 25 of one SMX, the GPU has 65536 registers,

192 SP cores - Single Precision Cores for single precision calculations, 64 DP cores - Double Precision Cores for double precision calculations, 32 Special Function Units (SFUs) - for certain special function, 32 load/store units for loading data from overall GPU memory to shared memory within each SMX, 16 Texture filtering units, Shared Memory of size 6 KB. CUDA gives the programmer freedom to use some of it as shared memory and some of it as L1 cache. Shared memory is controlled by the programmer and L1 cache is taken care by architecture.

Computations are organised as blocks. Blocks are given to SMX. A block consists of many threads and threads are given to SP cores.

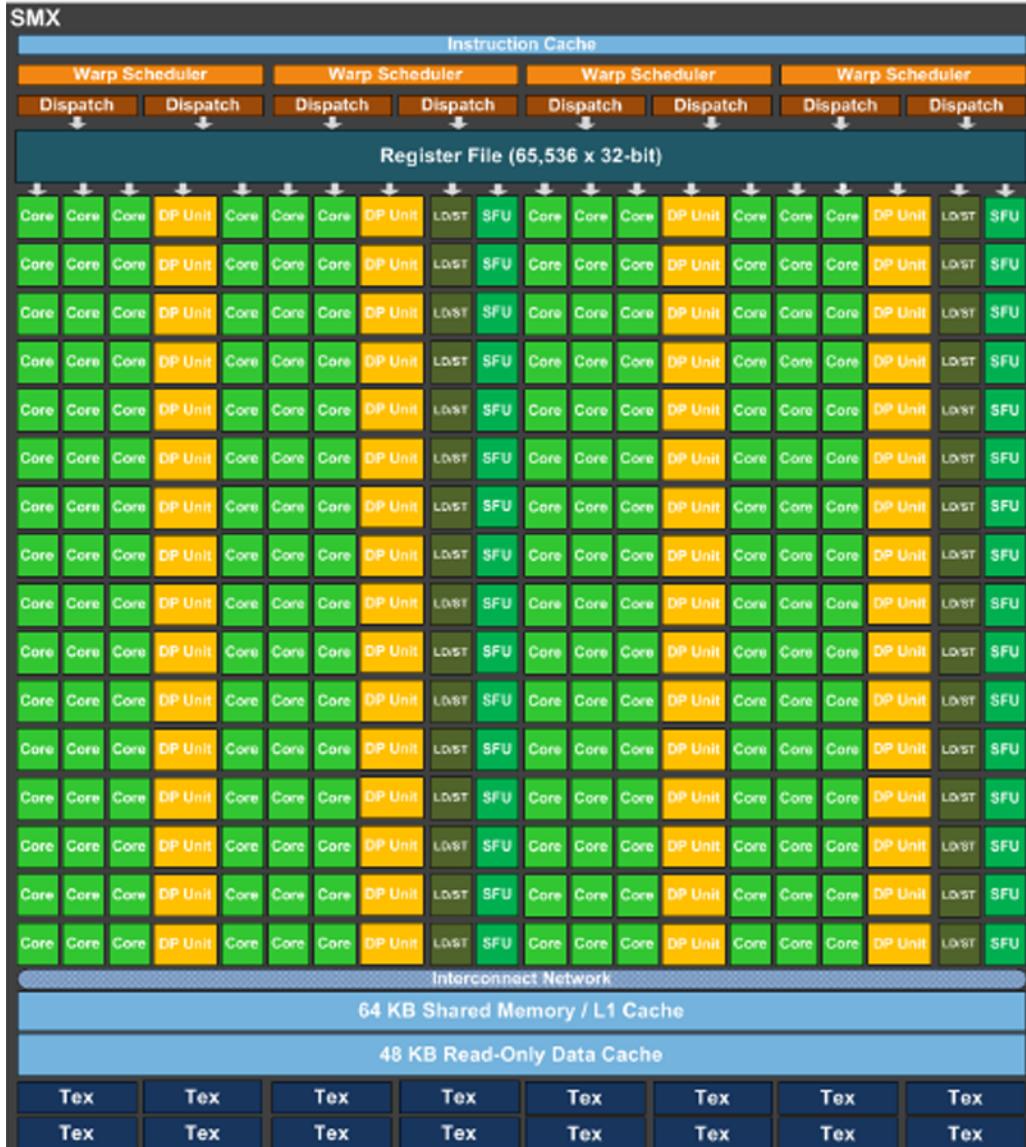


Figure 25: SMX Architecture

5.2 CUDA Memory Spaces

Consider the figure 26 of CUDA Memory Spaces. CPU pushes the relevant data to Global memory to be executed on GPU. It spawns GPU kernels/function which are executed on SMX. Each thread in SMX loads data from global memory/device

memory to shared memory.

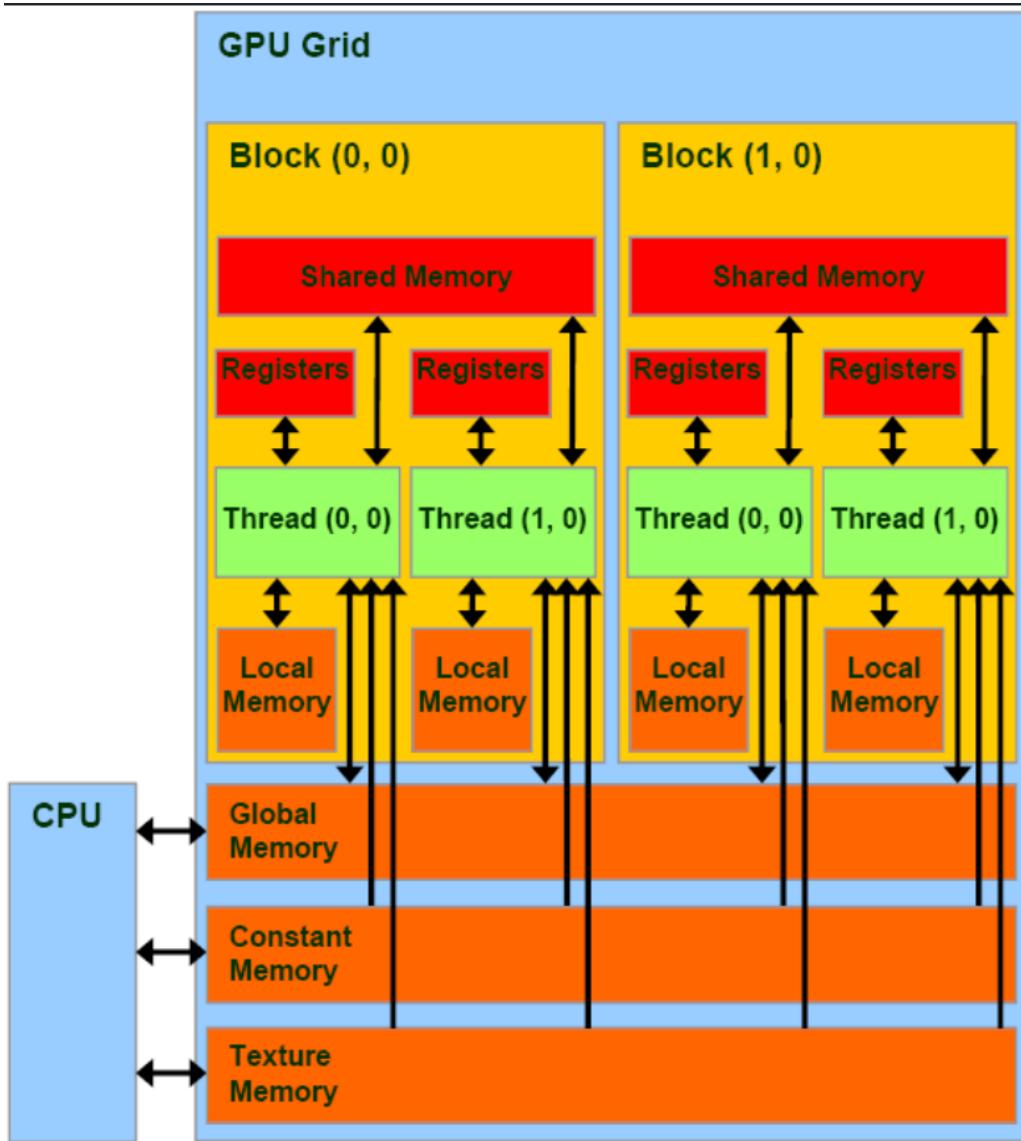


Figure 26: CUDA Memory Spaces

The memory spaces in CUDA are:

- Global Memory - It is the main memory of the GPU. It is accessible for read-/write by all the threads in all the SMXs. It can also be accessed by host -

CPU. for Kepler K40 it is around 12 GB. It has a latency of around 200-400 clock cycle (300 ns)

- Constant Memory - It is read only memory. It is used to store constants that are used by all the threads in all the blocks.
- Texture Memory - It can be accessed by all threads. It is used to store textures, used for texture mapping. It is used to improve performance of reads that exhibit spatial locality among the threads.
- Shared Memory - Each SMX has its own individual memory. It is the memory shared by all the threads in a block executing in a SMX. It is faster than global memory. Shared memory has a latency of 20-30 clock cycles (5 ns). The threads can read/write to this memory.
- Local Memory - It is the memory local to each thread, used to store temporary variables. Each thread has read/write access to this memory.
- Registers - They are present in each SMX. It is the memory local to each thread. It is used to store the context of the thread. Kepler K40 has 64K registers in each SMX.

The host can read/write global, constant and texture memory. GPUs prefer to access data from shared memory than device memory because of latency.

Difference between CPU and GPU Threads: There are a few differences between CPU and GPU threads regarding context switching. Context switching is much faster in GPUs because state of thread (thread block) stored in shared memory and threads stays till execution completion. Unlike in CPUs where in case of context switch memory related to that thread gets dumped to main memory or disk. Thus, loading the data for the thread next requires loading data from main memory or disk which is slow. Thus, context switching is faster in GPUs as there is no need to bring in any data as it already is loaded in the shared memory. Also, in case of GPUs the cache is explicitly managed by the programmer. The programmer will have to explicitly bring the frequently accessed data from the device to the shared memory. Unlike in CPUs where the cache is managed by the hardware.

6 Parallelization Principles

Parallel programs incur overheads which are not present in sequential programs. They are:

- Communication Overhead - Time taken to communicate between processors.
- Synchronization Overhead - Time taken to synchronize between processors.
- Idling Overhead - Time taken by a processor to wait for other processors.

A good parallel program tries to minimise these overheads.

6.1 Evaluation of Parallel Programs

The performance of a parallel program is evaluated using the following metrics:

- Execution Time (T_p) - Time taken by the parallel program to execute.
- Speedup (S) - It is the ratio of time taken by the *best* sequential program to the time taken by the parallel program.

$$S(p, n) = \frac{T(1, n)}{T(p, n)}$$

where, $T(1, n)$ is the time taken by the best sequential program and $T(p, n)$ is the time taken by the parallel program with p processors. Here, n indicates the data size. If we employ p processors we generally expect the speedup of p i.e. the time taken for execution in parallel to be reduced by p times. But, usually, $S(p, n) < p$. This is because of the overheads in parallel programs. The overheads are as discussed due to communication, synchronization and idling.

In some cases we may even get $S(p, n) > p$. This is called Super linear Speedup. A large data in sequential program may not fit in cache, thus there will be a lot of cache misses. But in parallel program, the data is distributed among the processors and thus the data fits in the cache and there are less cache misses. Thus, decomposing the problem to p processor then each will require a small part of the data and thus the entire data could fit into caches of all the individual processors and thus there will be less cache misses and thus the Speedup for that parallel program will be more than p . This is called Super linear Speedup when the speedup is more than p (expected speedup).

- Efficiency - Now generally, we expect the speed up to be of p times. But, speedup alone does not tell the full picture since the same speedup can be achieved by using different number of processors (Say a speedup of 3 can be achieved by using 3 processors or by using 100 processors). Thus, we normalize the speedup by the number of processors to get efficiency. Efficiency is the ratio of speedup to the number of processors. It gives the idea of how efficiently our program uses the processors. A low efficiency implies that the overheads are not handled properly and thus are dominating the execution time.

$$E(p, n) = \frac{S(p, n)}{p}$$

Generally, Efficiency is less than 1 but sometimes it can be more than 1 because of the super linear speedup.

- Scalability - It is the ability of the program to maintain efficiency as the number of processors increases. This is important because we want to be able to use more processors to solve larger problems. If the efficiency decreases as the number of processors increases then the program is not scalable. Thus, the analysis of how the program behaves with increasing the number of processors p or increasing the problem size n is called scalability analysis. Scalability thus tell limitations of the program and how well the program scales in relation to number of processors and problem size.

Ideally, we would like the Speedup to be linear i.e. Speedup should increase linearly with increase in the number of processors. But, in reality, the speedup is sub-linear. Similarly, we would like the efficiency to remain constant with

increase in the number of processors but, in practical it decreases with increase in the number of processors. This can be explained by Amdahl's Law.

Amdahl's Law: The performance improvement to be gained from using some faster mode of executing is limited by the fraction of the time the faster mode can be used. For the context of parallel programming, it states that the speedup of a program is limited by the fraction of the program that cannot be parallelized. Thus, overall speedup is given in terms of fractions of computation time with and without enhancement. Consider a sequential program which takes t_s time, which has f_s part of the program which cannot be parallelized and let f_p be the part of the program that can be parallelized. Thus, in an ideal case the time taken by the parallel program will be addition of $f_s t_s$ i.e. time taken by the fraction of the sequential program and $\frac{f_p t_s}{p}$ time taken by the parallelized part of the program. Hence, the total time taken by the parallel program is $f_s t_s + \frac{f_p t_s}{p}$. Thus, speedup is given by the ratio of the time taken by the sequential program to the time taken by parallel program. It is given by:

$$S(p) = \frac{t_s}{f_s t_s + \frac{f_p t_s}{p}} = \frac{1}{f_s + \frac{f_p}{p}}$$

where, f_s is the fraction of the program that cannot be parallelized i.e. serial and f_p is the fraction of the program that can be parallelized. Thus, the speedup is limited by the fraction of the program that cannot be parallelized. This is because not all the operations can be parallelized and some operations are dependent on the previous operations.

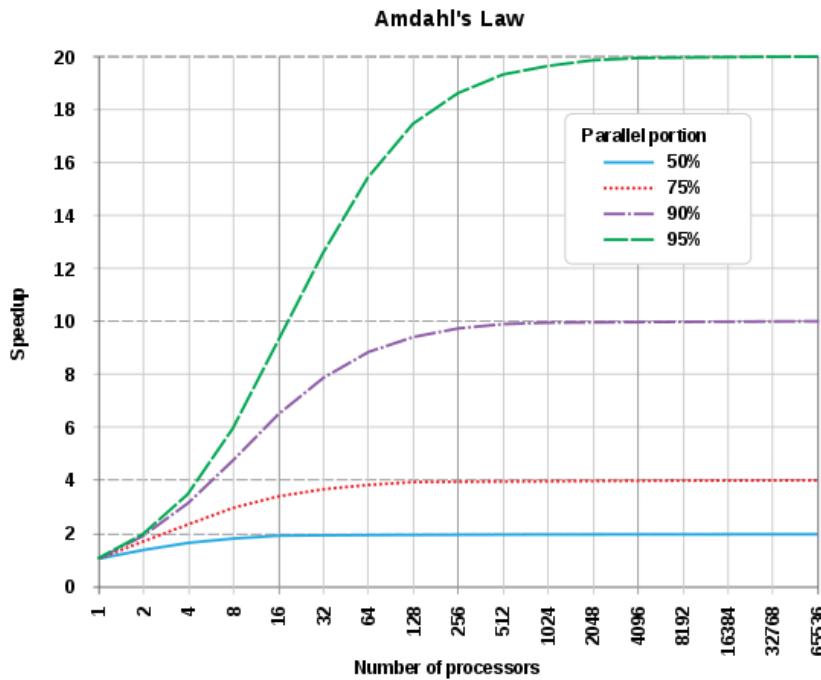


Figure 27: Amdahl's Law

It can be seen in the figure 27 that even for highly parallelizable programs ($f_p = 0.95$) the speedup curve starts to flatten out as the number of processors increases. Thus, it explains that the speedup curves starts flattening out as the number of processors increases.

The Amdahl's Law assumes that the problem size is fixed even on increasing the number of processors, thus the fractions f_s and f_p remain constant. But, in reality, the problem size increases with the number of processors. Thus, Gustafson's Law was proposed to address this issue.

Gustafson's Law: Increase the problem size proportionally so as to keep the overall time constant. Here the proportional increase means that the order of computations should increase proportionally to keep the overall time constant and not that the the problem size should be increased linearly with the number of processors.

Strong Scaling: The scaling keeping the problem size constant (Amdahl's law) is called strong scaling.

Weak Scaling: The scaling due to increasing the problem size (Gustafson's

Law) is called weak scaling.

- Isoefficiency - Generally, efficiency decreases with increasing number of processors P and increases with increasing problem size N. Isoefficiency is the ability of the program to maintain efficiency as the number of processors increases and the problem size increases. For example, consider the formula for parallel Gaussian elimination in LAPACK package for solving Linear Algebra.

$$T_{par}(N, P) = \frac{2}{3} \frac{N^3}{P} t_f + \frac{(3 + 1/4 \log_2 P) N^2}{\sqrt{P}} t_v + (6 + \log_2 P) N t_m$$

$$T_{seq}(N) = \frac{2}{3} N^3 t_f$$

$$E = \frac{T_{seq}(N)}{P T_{par}(N, P)} = (1 + \frac{3 \sqrt{P} (3 + 1/4 \log_2 P)}{N} \frac{t_v}{t_f} + \frac{3 P (6 + \log_2 P)}{N^2} \frac{t_m}{t_f})^{-1}$$

where, t_f is the time taken for a floating point operation, t_v is the time taken for a vector operation and t_m is the time taken for a memory operation. Thus, we can see that from the dominant term in the efficiency equation that as P is increased, N should be increased by $\mathcal{O}(\sqrt{P})$ to keep the efficiency constant. Now in Gaussian Elimination function the amount of computations to be carried out is $\mathcal{O}(N^3)$, thus the isoefficiency function is $\mathcal{O}(P\sqrt{P})$. The isoefficiency function is the ability of the program to maintain efficiency as the number of processors increases and the problem size increases. Thus upon increasing the problem size it is the number of processors that should be increased to keep the efficiency constant. Thus, the lesser the number of processors to increase with a large increase in the problem size the better the program isoefficiency. Thus, the isoefficiency should be as small as possible. Smaller isoefficiency functions imply higher scalability. Consider two parallel programs with isoefficiency functions $W1 = \mathcal{O}(P)$ and $W2 = \mathcal{O}(\sqrt{P})$. Then the second algorithm is considered to be more scalable since only small amount of processors need to be added. Similarly, an algorithm with an isoefficiency function of $\mathcal{O}(P)$ is highly scalable while an algorithm with quadratic or exponential isoefficiency function is poorly scalable.

7 Parallel Programming Classification and Steps

7.1 Parallel Program Models

Classification based on the way the program and Data is written and executed:

- Single Program Multiple Data (SPMD): We write a single program and run it on multiple processors. Each processor runs the same program but on different data using processor ids to execute certain parts of data. It is the most common model used in parallel programming.
- Multiple Program Multiple Data (MPMD): Different processors run different programs on different data. It is used in distributed memory systems. For example, used in climate modelling. It is not a very popular model.

7.2 Programming Paradigms

Classification based on the way the parallel program uses shared memory model or message passing:

- Shared memory Model - If there is a common global memory to access certain data. For example - Threads, OpenMP, CUDA
- message Passing model - If there is no global memory and the processes explicitly send data whenever required. For example, MPI (Message Passing Interface)

7.3 Parallelizing a Program

There is no general rule as it all depends on the application. Given a sequential program/algorithm, how to go about producing a parallel version. There are four steps to parallelize a program are:

- Decomposition - Identifying parallel tasks with large extent of possible concurrent activity; splitting the problem into tasks that can be executed in parallel.
 - Assignment - Assign the tasks to the processors and grouping the tasks into processes with best load balancing. i.e. amount of work performed by each of the processes must be equal. This is not necessarily done in Decomposition task. It specifies how to group tasks together for a process in order to have balance workload, reduce communication and management cost. This is done by
-

structured approaches such as code inspection (parallel loops) or understanding of application. Sometimes the grouping is done statically and sometimes dynamically (i.e. the grouping is done at runtime) based on the load.

Both decomposition and assignment steps are usually independent of architecture or programming model, but cost and complexity of using primitives may affect decisions.

- **Orchestration** - It is the process of managing the execution of the parallel program. It involves managing the synchronization and communication between the processes.
- **Mapping** - Mapping the processes to the processors. It is the process of mapping the processes to the processors. It is done in such a way that the processes are mapped to the processors in such a way that the communication overhead is minimized.

7.4 Data Parallelism and Data Decomposition

Data Parallelism: Given data is divided across the processing entities. **Owner computes own:** Thus, each process own and computes a portion of the data, it decides which data to communicate between other processes. This is called owner computes rule. The data is divided into chunks and each chunk is assigned to a process. This is called data parallelism where the data is divided across the processing entities and thus the parallelism is dictated by the data.

Domain Decomposition: Multi-dimensional domain in simulations divided into subdomains equal to processing entities is called domain decomposition. The given P processes are arranged in multi-dimensions forming a process grids. Consider the figure 28.

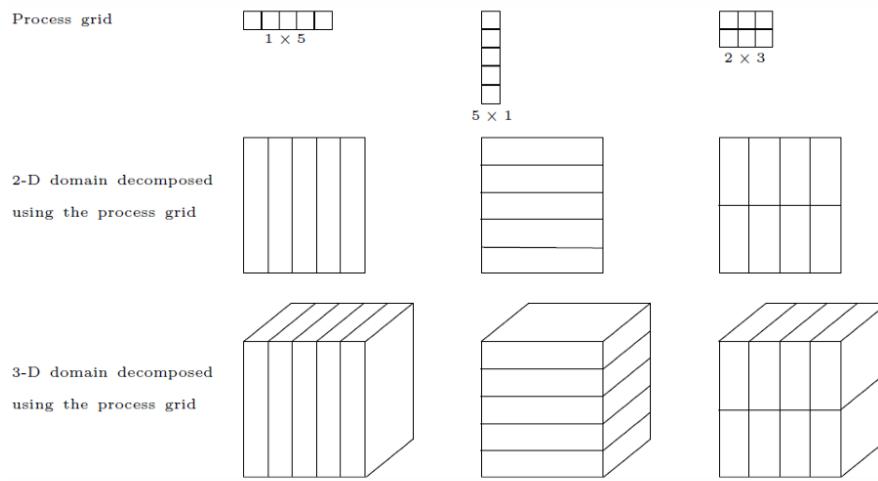


Figure 28: Domain Decomposition

It shows that if the process grid is arranged as a 1×5 grid than the 2D domain can be decomposed using the process grid as shown and the domain is divided into 5 equal parts. Each process is assigned a part of the domain. The domain decomposition is done in such a way that the communication between the processes is minimized. Similarly, same concept can be applied for a 3D domain as well as shown in the figure 28 shows many such ways for decomposing the domain (data) based on different arrangements of process grids. For a given process grid we decompose the domain so as to map the domain onto process grid such that the communication between the processes is minimized.

7.5 Data Distributions

For dividing the data in a dimension using the processes in a dimension, data distribution schemes are followed. Common data distributions are:

- Block Distribution - The data is divided into blocks and each block is assigned to a process. It is the simplest form of data distribution. It is used when the data is uniformly distributed.
- Cyclic Distribution - The data is distributed in a cyclic manner. It is used when the data is not uniformly distributed.
- Block-Cyclic Distribution - It is a combination of block and cyclic distribution. It is used when the data is not uniformly distributed.

For example, consider the figure 29.

b_1	\leftrightarrow	b_2
0	1	2
3	4	5
0	1	2
3	4	5
0	1	2
3	4	5
0	1	2
3	4	5

Figure 29: Data Distribution

Here, it can be seen that the process grid is arranged as a 2×3 grid and the blocks of data are distributed in a cyclic manner.

7.6 Task Parallelism

We decompose into tasks that can be executed in parallel. It is used when the data is not uniformly distributed. The independent tasks are identified and mapped to different processors. The tasks are grouped by a process called mapping. Here, we are trying to achieve two objectives - balance the groups and minimize inter-group dependencies. This is represented as a Task graph. For example, consider the task dependency graph shown in figure 30.

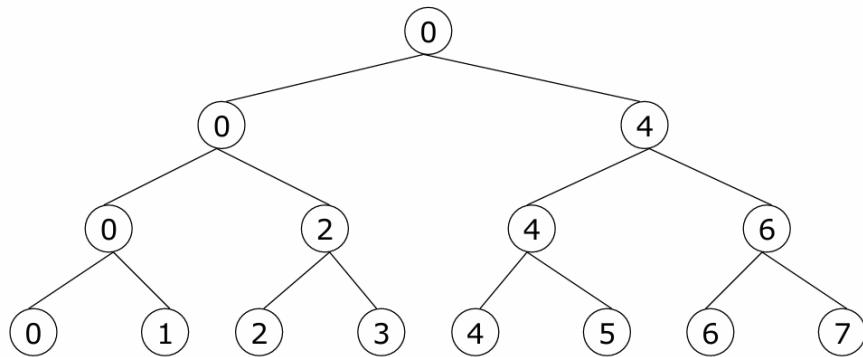


Figure 30: Task Dependency Graph

Each node shown represents a task. In general a task can be a statement or a block of statements in a program. Suppose, independent tasks follow a tree like parallelism as shown in figure 30. The 8 tasks at the bottom are independent and then they are merged to form 4 tasks and then 2 tasks and then 1 task. Suppose we wish to map this tasks to 8 processors. So, we can map the 8 tasks to 8 processors. Then to merge the tasks we assign it to one of the processor as shown in figure 30, this allows as one of the processor already has the data and the other processor can directly access the data from the processor which has the data. Thus, the communication overhead is minimized and similarly for the other tasks. In general, assigning a task graph to processors is an NP complete problem. Thus, we use heuristics to assign the tasks to the processors.

7.7 Orchestration

It is the process of managing the execution of the parallel program. It involves managing the synchronization and communication between the processes.

7.7.1 Maximizing data locality:

It is the process of maximizing data locality in a processor and avoid unnecessary communication. Thus, it is about **minimizing the volume of data exchange**. (like not communicating intermediate results) or **Minimizing the frequency of interactions - packing**. For example, say to compute parallel dot products. Say we have two vectors A and B and we wish to find dot product between two. It requires multiplying the corresponding elements of the two vectors and then summing

them up. Thus, we can do the multiplication part in parallel across various processes or various threads. Now the communication part can be done in two ways - either we can communicate the intermediate results to the master processor and then sum them up or we can sum them up in the individual processors and then communicate the final result to the master processor. The second approach is better as it minimizes the volume of data exchange. Thus, the orchestration is about minimizing the volume of data exchange and **minimizing the frequency of interactions**. Thus, structuring the communication in such a way that the communication overhead is minimized. Point to point communication between two processors involves latency and bandwidth. The latency is the time taken to establish the connection between the two processors and the bandwidth (measured in MB/s) is the rate at which the data can be communicated between the two processors. By minimizing the frequency of interactions we can minimize the overall delay i.e. latency. For example, consider that a processor is required to send 10 arrays to another processor, then in order to minimize the frequency of interactions we can pack all the 10 arrays into one packet and send it to the other processor. In sending 10 arrays together to another processor we require to establish connection only once, thus the delay because of latency occurs only once but in case if we send it as 10 different arrays, we would be required to establish communication between the processors each time which would mean delay due to latency each time. Thus, Packing will minimize the frequency of interactions and thus the overall delay. This idea is called **packing**. Note that in this case the volume of data remains the same in both the cases but the frequency of interactions is minimized in the second case.

7.7.2 Minimizing contention and hotspots:

(Avoiding communication bottlenecks) Do not use the same communication pattern with the other processes in all the processes. For a given communication pattern, following a certain order will incur a communication bottleneck while following a different order will not incur a communication bottleneck and this can affect the performance. For example, consider a situation where every process communicates data with every other process. This is as shown in table 2.

Process	A	B	B	D	E
A	-	2	3	4	5
B	1	-	3	4	5
C	1	2	-	4	5
D	1	2	3	-	5
E	1	2	3	4	-

Table 2: Communication Pattern

In the table 2, the communication takes place according to the rule that for each of the processor at time= t , it communicates with t if $(t \neq id)$. Thus, starting from time $t = 0$, for Processor A ($id = 0$), it won't communicate to anyone else since its $t = id$, for processor B ($id = 1$), at time $t = 0$ it will communicate (since $t \neq id$) with Processor A. Similarly for processor C, at time $t = 0$, it will communicate (since $t \neq id$) with processor A and so on for Processors D and E, at time $t = 0$ they will communicate with Processor A. Similarly, at $t = 1$, Processor A will communicate with Processor B, for processor B, it will not communicate since $(t = id)$, for Processor C it will communicate with Processor B at time $t = 1$ and so on for other processors. This is followed for all the processors at all the time steps. Now see that at some timestep t all the processors will communicate to processor with $id = t$. This will result in communication bottleneck, although it looks like the processors are communicating in parallel, but at some timestep t all the processors will communicate to the same processor and thus the communication bottleneck will occur. Even at the hardware level because of the switches and common network links, it can receive only one package at a time. Now as the number of processes increase say to a 1000, then at some time step t all 999 processes will try and communicate with one of the process at some time step t . Thus leading to communication bottleneck. The solution is to come up with an algorithm where each process follows a different order in which it communicate with the processes so that at no time step all of them end up communicating with the same processor. This is called **minimizing contention and hotspots** which refers to avoiding use of the same communication pattern with the other processes in all the processes.

7.7.3 Overlapping computations with interactions

One of the solutions is **Overlapping computations with interactions**. The idea is to split communication into phases into two parts: one part in which the computations depend on the communicated data (type 1) and second is computations that do not depends on communicated data (type 2). While communicating for type 1 per-

form computations for type 2. This can be done especially on the receiver side which do not depend on the communicated data and thus can perform the computation. In other words, the computations are being overlapped with the communications.

7.7.4 Replicating data or computations

Balancing the extra computation or storage cost with the gain due to less communication. For example, consider two processes 0 and 1. 0 computes a matrix A by doing an outer product of two vectors (say a and b) and then distributed this matrix A to process 1. Then processes computes with their own part of the matrix. Instead of his approach, we can replicate the vectors a and b to process 1 and then process 1 can compute the matrix A by itself. This will reduce the communication overhead since it will be a lightweight communication compared to sending a part of the Matrix A. But, this will increase the computation overhead since the process 1 will have to compute the matrix A by itself. Now after both of them compute the matrix A, they can work on their respective parts of the matrix. Depending on the vector sizes instead of computing half of the matrix which could be very huge in size, we are communicating only the vectors thereby reducing the communications. This is called **Replicating data or computations** as we are replicating the data and computations to reduce the communication overhead. Here, both of the processes end up replicating the data and computations by computing the matrix A to reduce the communication overhead. Ultimately, it all depends on the computation cost and communication cost and the trade-off between them.

7.8 Mapping

Mapping the processes to the processors. Which process runs on which particular processor.

- **Network topology and communication pattern:** It can depend on network topology and communication pattern of processes. The aspect of mapping the communication pattern to the network topology in an intelligent way plays an important role in the performance of the parallel program. For example, consider a 2D mesh network topology. The processes are arranged in a 2D grid and the communication pattern is such that each process communicates with its neighbours. Then we would like to do a natural mapping i.e. map the processes to the processors in such a way that the processes which communicate with each other are mapped to the processors which are close to each other.
-

This will reduce the communication overhead as the communication between the processes will be faster.

- **Heterogeneous systems:** On processor speeds in case of heterogeneous systems (different processors have different speeds). In case of homogeneous systems all the processors have same speed and communication cost is same. In case of heterogeneous systems the communication cost as well as processor speed is different for different processors and thus the mapping can depend on the communication cost. For example, consider a system with 2 processors A and B. Processor A is faster than processor B. Now, if the communication cost between processor A and B is less than the computation cost of processor B then it is better to map the process which communicates with processor B to processor A. This is because the communication cost is less than the computation cost of processor B. Thus, we wish to map the processes to processors in such a way that heavy compute tasks are mapped to faster processors and light compute tasks are mapped to slower processors.

All data and task parallel strategies generally follow static mapping i.e. at the beginning of the program the mapping is done and it remains constant throughout the program. But, in some cases dynamic mapping is done i.e. the mapping is done at runtime. For example, consider a situation where the load on the processors is not uniform and the load on the processors keeps changing. In such cases, dynamic mapping is done where the mapping is done at runtime based on the load on the processors by the master processor. The idea here is that a process/global memory can hold a set of tasks. The master processors distributed some tasks to all the processes. Once a processor completes its tasks, it asks the coordinator process for more tasks. This is referred to as self-scheduling or work stealing, where the processes are scheduled dynamically based on the load on the processors. Here we don't fix the tasks onto the processors but let the processes decide dynamically which tasks to take up. Thus, even in case of heterogeneous processors, the processes working on a high speed processor can finish tasks quickly and will then steal more work from the slower processors. This is called work stealing.

To summarise the various steps they are as shown in the table 3

Step	Architecture-Dependent?	Description
Decomposition	Mostly no	Identifying parallel tasks with large extent of possible concurrent activity but not too much
Assignment	Mostly no	Balance workload; reduce communication volume; Assigning the tasks to the processors
Orchestration	Yes	Reduce non inherent communication via data locality; reduce communication and synchronization cost as seen by the processor; reduce serialization at shared resources; schedule tasks to satisfy dependencies early; Managing the execution of the parallel program
Mapping	Yes	Put related processes on the same processor if necessary; exploit network topology; Mapping the processes to the processors

Table 3: Summary of Steps

As shown in the table 3, the decomposition and assignment steps try to identify independent tasks and balance the workload. Once these tasks are fixed and the communication patters are fixed, the orchestration step tries to minimize the communication overhead and the mapping step tries to map the processes to the processors in such a way that the communication overhead is minimized. The Orchestration and Mapping steps are architecture dependent as they depend on the network topology and the communication pattern of the processes. The first two steps Decomposition and Assignment are mostly independent of the architecture and are done at the programming level.

7.9 Example

Given a 2d array of float values, repeatedly average each elements with immediate neighbours until the difference between two iterations is less than some tolerance value. Consider a 2d domain with some grid points, we start with some initial values at this grid point and we keep updating the values over time. For example, it could be solving a heat equation where the heat spreads over a plate, thus the grid points represent temperature at different points on the plate and thus averaging the value

reduces the temperature at that point. So we are looking at how the values of these temperatures evolve over time.

```

1 do{
2     diff=0.0
3     for (i=0; i<n; i++)
4         for (j=0; j<n; j++){
5             temp=A[i][j];
6             A[i][j]=average(neighbours);
7             diff+=abs(A[i][j]-temp);
8         }
9 }while (diff>tolerance);

```

Listing 1: Parallel Program for Averaging

Consider the figure 31 which shows the grid points and the neighbours of the grid points.

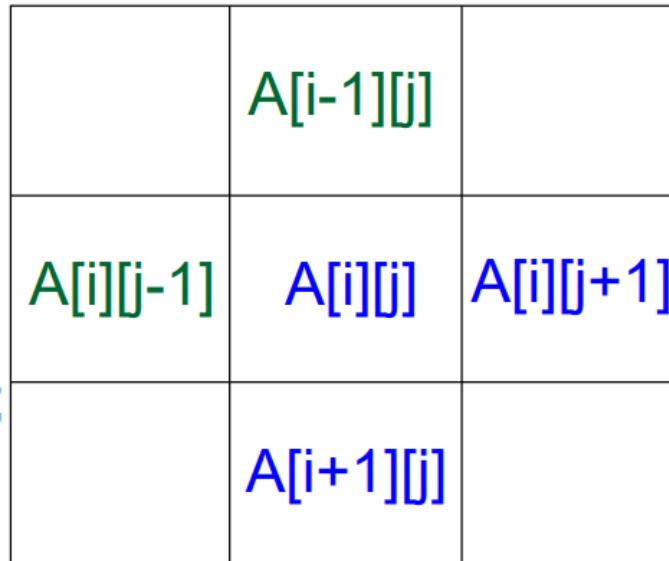


Figure 31: Grid Points

In this we go over all the values of the grid points and update the value of the grid point by averaging the values of the neighbours. We keep doing this until the difference of global variable diff between the two iterations is less than some tolerance value. There are two methods to solve this problem: one is Jacobi method where we take the values of the neighbour from the previous time step and the other is Gauss-Seidel method where we take the values of the neighbour from the current time step

whenever available (for the lower index values we use the latest values and for the higher index values we use the previous values). Suppose we want to parallelize the program. For the purpose of parallelizing the program we wish to decompose the problem into tasks that can be executed in parallel.

1. One way is to consider each element in parallel. A parallel process or a parallel thread for each of the element i.e. concurrent task for each element update: which would require a max concurrency of n^2 tasks (for $n \times n$ elements in the grid). Practically, this is not feasible as the number of tasks is very large and the overhead of creating and managing the tasks is very high. This many parallel number of threads is not practically possible, as for larger values of n the number of threads required will be n^2 , thus many threads would have to be mapped to the same processors and would require a lot of context switching between threads and context switching between the processes which can thus affect the performance.
 2. Another way is to consider tasks for elements in anti-diagonal. Note that values in a particular diagonal depends on the values from the previous diagonal but not among the elements in that diagonal. Now we consider a particular diagonal, for some element in the diagonal for using the Gauss-Siedel method we require the values of the neighbours from the previous diagonal at latest time step and the value from the next diagonal at previous time step. This works out, since we are computing diagonal by diagonal starting from the left top corner and moving towards the right bottom corner. Thus, the values of the neighbours are available from the previous diagonal at the latest time step and the next diagonal at the previous time step. Also note that the values of the elements in the diagonal are independent of each other and thus can be computed in parallel. Thus, we can consider the tasks for the elements in the anti-diagonal and compute the values of the elements in the anti-diagonal in parallel. This way we can reduce the number of tasks to $2n - 1$ tasks (for $n \times n$ elements in the grid). This is a better approach than the previous approach as the number of tasks is reduced and the tasks are independent of each other and can be computed in parallel. Note that for the diagonals which are at the ends, will have small number of elements, thus the parallelism will also be very small. This also will have a synchronization cost because the processes assigned to a particular diagonal cannot start executing until the earlier diagonals have finished executing. Thus, the parallelism will be limited by the number of elements in the diagonal and the synchronization cost.
 3. What we follow is block distribution of the data. Consider the figure 32 which
-

shows the block distribution of the data.

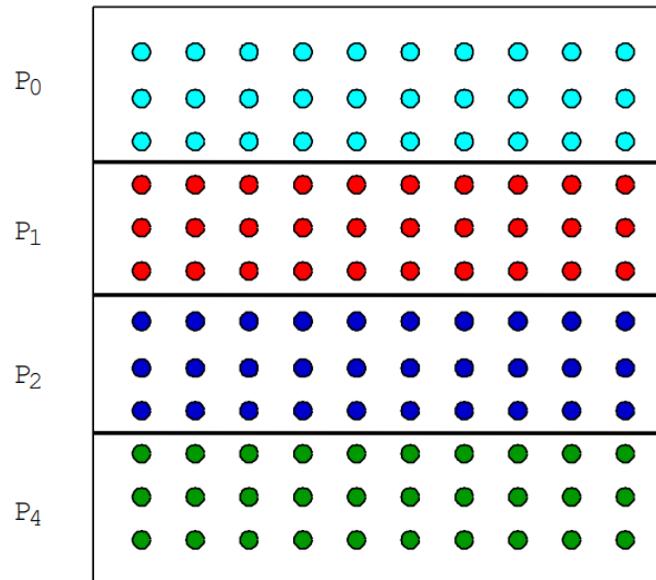


Figure 32: Block Distribution

In this we have divided the 2d grid across the rows. First set of rows is assigned to P0, the second set of rows assigned to P1 and so on. Each processor will be responsible for updating the values of the elements in the rows assigned to it. Now for orchestration step, we try to find out what are the synchronization and communication requirements and we try to ensure correctness and minimize communication and synchronization calls. It depends on the programming/-model architecture - shared memory model/message passing model.

Shared address space/Shared memory model

Now we consider Shared Address space (SAS) version of the above program as shown in lstlisting 2.

```

1 int n, nprocs; /* matri: (n+2 x n+2) elements */
2 float **A, diff=0;
3 LockDec(lock_diff);
4 BarrierDec(barrier1);
5 main()
6 begin
7     read(n); /*read input parameter: matrix size*/
8     Read(nprocs);

```

```

9     A = malloc(a 2-d array of (n+2) x (n+2) doubles);
10    Create(nprocs-1,Solve, A);
11    initialize(A); /*initialize the matrix A somehow*/
12    Solve(A);
13    Wait_for_End (nprocs-1);
14 end main

```

Listing 2: Shared Address Space Version

Note that here we are using $n + 2$ processors in order to take care of the boundary processors. Here, the array A will be shared and the main process creates the different processes and then it is solved. Let us now look at the psuedo code for the Solve function.

```

1 procedure Solve(A) /* solve the equation system*/
2     float **A;
3 begin
4     int i, j, pid, done =0;
5     float temp;
6     mybegin = 1 +(n/nprocs)*pid;
7     myend =mybegin+(n/nprocs);
8     while(!done) do /* outermost loop over sweeps*/
9         diff=0; /*initialize difference to 0*/
10        Barriers(barrier1, nprocs);
11        for (i=mybeg to myend) do /*sweep for all points of grid*/
12            for (j=1 to n) do
13                temp=A[i,j]; /*save old value of element*/
14                A[i,j]=0.2*(A[i,j]+A[i,j-1]+A[i-1,j]+A[i,j+1]+A[i+1,
15                j]); /* compute average*/
16                diff+=abs(A[i,j]-temp);
17            end for
18        end for
19        if(diff/(n*n) < TOL) then done =1;
20    end while
21 end procedure

```

Listing 3: Solve Function

Now this particular function is going to be executed by all the processes. But depending on the process id different processes will end up processing different parts of the grid. Thus, it uses Single Program Multiple Data Model. It uses the same single program but executed by different processes on different data. The $mybegin = 1 + (n/nprocs) * pid$ and $myend = mybegin + (n/nprocs)$ are the starting and ending points of the grid that the process is responsible for and thus it is calculated based on the process id for each of the processor. Now all the processes enter the while loop. Here, we have a global variable diff and matrix A which is shared by

all the processes. At the beginning of the loop all the processes synchronize as shown in the code by Barriers. Each of the processes then execute the statement 11. Although they will be executing the same statement but the beginning and the ending row will differ depending on the process id, thus different processes will be executing this code for different sets of rows. Now, the processes will be updating the values of the elements in the grid and then calculating the difference between the new value and the old value. After taking the average note that they update the value of diff, but since diff is a global variable it gets updated by all the processes which is then later on compared with tolerance to determine the end of the loop. This was just an overview of the program. For understanding the benefits of computing in parallel, we need to understand the importance of parallel statements like barrier. A barrier is a function call that achieves synchronization calls between the processes. When a particular process calls a barrier, it keeps waiting in the barrier call until all the other processes have reached the barrier call. Thus, the barrier call ensures that all the processes have reached the barrier call before any of the processes can proceed further. This is important in the above program as we need to ensure that all the processes have completed the computation of the elements in the grid before we can proceed to the next iteration. This avoids the situation where some of the processes have completed the computation and some of the processes have not completed the computation and thus the processes which have completed the computation will be waiting for the other processes to complete the computation instead of moving with the computation so as to avoid the use of stale values which are still not updated by the other processors.

The matrix A is a global variable and is thus shared by all the processes. But during execution note that the processes are updating the values of the elements in the matrix A. Thus, in case when the elements at the boundary of two processors are updated, it may lead to a problem since it may happen that the processor may not yet have updated some of the values at the boundary but when the other processor updates the element under its control it may use the updated value of the element in some cases and stale value of the element in some cases. Thus, the updates of the elements at the boundary of the processors should be done in a synchronized way. This can be achieved in Case of Jacobi method by maintaining a temporary array which is local to each processor, that stores values for the current time step based on the values stored in the global matrix (which contains values at the previous time step). Once all the processes have reached the end of the iteration which can be found using a barrier call. Then the temporary matrix will be copied to the global matrix and the next iteration will start. This way the updates of the elements at the boundary of the processors will be synchronized in case of Jacobi method. Here, we are ignoring this case for the sake of simplicity and are assuming that this problem is somehow handled internally.

Then we have a waitforend followed by solving matrix A in the code in 2. The waitforend is for the main process waiting for all the processes to finish which can be done by making all the process send a synchronization message to the first process which is an All to one communication. Note that diff variable is a global variable thus is a shared variable which is read and written to by all processes. Thus, it may result in garbage values since all the processes try to simultaneously read and change a shared variable. This is because of the race conditions because of context switching at the assembly level language which may result in garbage values. The solution to this is to use locks. A lock is a mechanism that allows only one process to access the shared variable at a time. Thus, when a process is accessing the shared variable, it locks the shared variable and then accesses the shared variable and then unlocks the shared variable. This way only one process can access the shared variable at a time. In computer science, a lock or mutex (from mutual exclusion) is a synchronization primitive. A lock is designed to enforce a mutual exclusion concurrency control policy. This means that only one thread at a time may acquire the lock and all other threads attempting to acquire the lock are blocked until the thread that acquired the lock releases it. In other words, in order to protect the shared variables by means

of this locking mechanisms of mutex locks (mutual exclusion locks) where only that process which holds the lock will go ahead and execute these statements and it is only when the process releases this lock that the other processes can go ahead and execute the statements. This is called mutual exclusion because the processes are mutually excluding each other and one process gets exclusive access to that part of the code which is called a critical section. Note that this is also happening with the matrix A which is also a global variable and thus a shared variable. Thus, especially at the boundary values of the processors, where the values may be updated and read simultaneously, it is important to use locks to protect those boundary values when you are using shared arrays.

Another way to resolve these is by using temporary matrices which are local to each processor and then copying the values of the temporary matrix to the global matrix after all the processes have completed the computation. This way the updates of the elements at the boundary of the processors will be synchronized. This is called double buffering.

Note that in the case we are using locking mechanisms, which are very costly and need to be used sparingly, since each time after the processes updates the value, for updating the value in the diff variable, the processes are waiting for the lock to be released by the other process and then only they can proceed further. Note that this happens for each of the grid point updates. This can lead to a lot of waiting time and thus the performance of the program can be affected. So then the question arises, how to reduce the waiting time and the contention for the lock. Note that diff is needed only for calculating the final global value and to find out whether the convergence condition is achieved or not. Hence, instead of each process updating this global diff variable on every update of the grid point, we can have a local diff variable for each process which is updated by each process and then at the end of the iteration the local diff variables of all the processes are added to get the global diff variable. This way the contention for the lock is reduced and the waiting time is reduced since it is only at the time when all the local variables are added to the global diff variable that the lock is required. This is called reduction operation. Thus, we have reduced the locking overhead from $\mathcal{O}(n^2)$ for each grid point update to $\mathcal{O}(p)$ where p is the number of processes. This is a significant improvement in the performance of the program.

Now the updated solve psuedo code is as shown in the listing 4.

```
1 procedure Solve(A) /* solve the equation system*/
2     float **A;
3 begin
4     int i, j, pid, done =0;
5     float mydiff, temp;
```

```

6      mybegin = 1 +(n/nprocs)*pid;
7      myend =mybegin+(n/nprocs);
8      while(!done) do /* outermost loop over sweeps*/
9          mydiff=diff=0; /*initialize difference to 0*/
10         Barriers(barrier1, nprocs);
11         for (i=mybeg to myend) do /*sweep for all points of grid*/
12             for (j=1 to n) do
13                 temp=A[i,j]; /*save old value of element*/
14                 A[i,j]=0.2*(A[i,j]+A[i,j-1]+A[i-1,j]+A[i,j+1]+A[i+1,
15 j]); /* compute average*/
16                 mydiff+=abs(A[i,j]-temp);
17             end for
18         end for
19         lock(diff-lock);
20         diff +=mydiff;
21         unlock(diff-lock)
22         barrier(barrier1,nprocs);
23         if(diff/(n*n) < TOL) then done =1; /* checking the
24 terminating condition*/
25         Barrier(barrier1,nprocs);
26     end while
27 end procedure

```

Listing 4: Updated Solve Function

Note that now in the pseudo code a new local variable mydiff has been introduced for each of the processes which is updated by each of the processes and then at the end of the iteration the local mydiff variables of all the processes are added to get the global diff variable using the locking mechanism as shown in the code 4. See that the statement lock(diff-lock) and unlock(diff-lock) are used to lock and unlock (or releasing the lock) the global diff variable respectively This way the contention for the lock is reduced and the waiting time is reduced since it is only at the time when all the local variables are added to the global diff variable that the lock is required. Also note that the barrier call is used to synchronize the processes at the end of the iteration. This is important as we need to ensure that all the processes have completed the computation of the elements in the grid and added their value from mydiff is added to global diff before checking the terminating condition in order to proceed to the next iteration.

Now there is another barrier call after we check the terminating condition. This is because in case if the terminating condition is not met then one of the process may start executing for the next iteration and see that in the beginning of the iteration set diff=0. Thus, while the other processes are still checking the terminating condition, they may encounter diff=0 in the terminating condition which is wrong. Thus, we

add another barrier for letting all the processes check the terminating condition with the correct diff value and once all the processes are done, then proceed to the next iteration.

Then, the done=1 condition at the convergence point is updated redundantly by all the processes. Note that the code that does the update is identical to the sequential program.

This is also one of the advantages of a shared memory program over a message passing program. In a shared memory program, the code that is written is identical to the sequential program and the parallelism is achieved by adding the parallel constructs like locks and barriers. Thus, the code is easier to write and debug as compared to a message passing program where the code is completely different from the sequential program and the parallelism is achieved by sending messages between the processes.

Message Passing Version

Here we cannot assume A to be a global shared array which all the processes can access. Because there is no concept of shared variable in message passing model. Each process will have to maintain its part of the matrix. The only way to receive values update by some other processor is by using the explicit message passing between these two processes. Thus, we need to send the data to the processes.

We do a domain decomposition to decompose the 2D domain into different processes and each process follows the owner compute rule. Here we have more communication and on top of that we will be maintaining local data structures because there is no concept of global data structures. Here, we use something called as ghost rows. This can be understood as follows. Consider the figure 33.

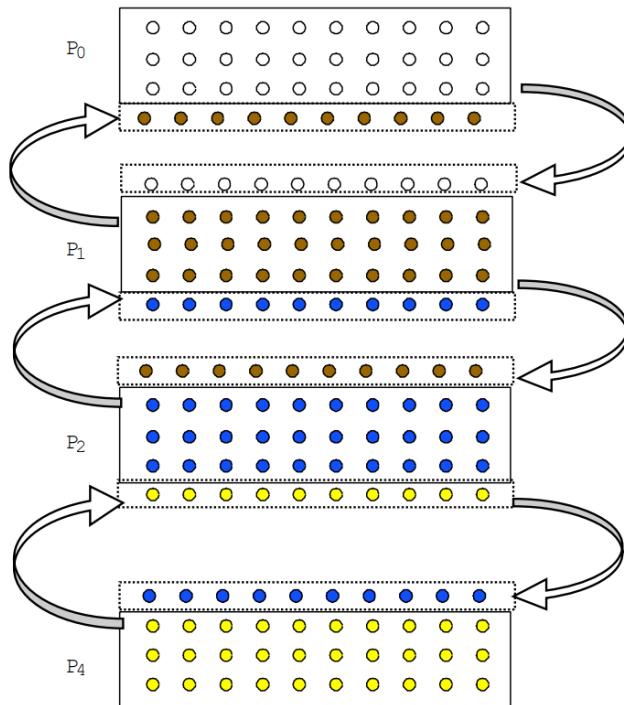


Figure 33: Ghost Rows

Here, we have divided the 2D grid into 4 processes as done in the previous case of shared memory model. Each process is responsible for updating the values of the elements in the rows assigned to it. Here Each process will have its local array because there is no concept of shared array in order to maintain these elements. In addition each process has an additional ghost row as shown in the figure 33. These rows are to accommodate the boundary rows coming from other processes. For example, as shown in the figure 33, the process 0 has a ghost row at the bottom which will accommodate the boundary row from process 1. Similarly, the process 1 has a ghost row at the top to accommodate boundary row from process 0 and at the bottom which will accommodate the boundary row from process 2 and so on. The ghost row values will be used for updating the local values and they will not be updated by the processes themselves. The ghost row values will be used just to update the local values of the processes and they will be updated by the processes which own them. Thus, the name ghost rows. They are also called as halo rows or halo regions or ghost zone regions. Then each process can imply do sequential computation.

Now consider the following Generating processes code for the message passing version as shown in listing 5.

```

1 int n, nprocs; /* matrix: (n+2 x n+2) elements */
2 float **myA;
3 main()
4 begin
5     read(n); /*read input parameter: matrix size*/
6     realead(nprocs);
7     A = malloc(a 2-d array of (n+2) x (n+2) doubles);
8     Create(nprocs-1,Solve, A);
9     initialize(A); /*initialize the matrix A somehow*/
10    Solve(A);
11    Wait_for_End (nprocs-1);
12 end main

```

Listing 5: Message Passing Version - Generating Processes

Now consider the following Solve function for the message passing version as shown in listing 6 which contains Array allocation and ghost row copying.

```

1 procedure Solve(A) /* solve the equation system*/
2     float **A;
3 begin
4     int i, j, pid, done =0;
5     float mydiff, temp;
6     myend=(n/nprocs);
7     myA=malloc (array of (n/nprocs) x (n) floats);
8     while(!done) do /* outermost loop over sweeps*/
9         mydiff=0; /*initialize local difference to 0*/
10        if (pid!=0) then
11            SEND(&myA[1,0],n*sizeof(float),(pid-1),row);
12        if (pid!=nprocs-1) then
13            SEND(&myA[myend,0],n*sizeof(float),(pid+1),row);
14        if (pid!=0) then
15            RECEIVE (&myA[0,0],n*sizeof(float),(pid-1),rpw);
16        if(pid!=nprocs-1) then
17            RECIEVE(&myA[myend+1,0],n*sizepf(float),(pid-1),row);
18        for (i=1 to myend) do /*sweep for all points of grid*/
19            for (j=1 to n) do
20                temp=A[i,j]; /*save old value of element*/
21                A[i,j]=0.2*(A[i,j]+A[i,j-1]+A[i-1,j]+A[i,j+1]+A[i+1,
j]); /* compute average*/
22                mydiff+=abs(A[i,j]-temp);
23            end for
24        end for
25        if(pid!=0) then
26            SEND(mydiff ,sizeof(float),0,DIFF);

```

```

27         RECIEVE(done , sizeof(int) ,0 , DONE);
28     else
29         for k=1 to nproces-1 do
30             RECEIVE(tempdiff , sizeof(float) ,k , DIFF);
31             mydiff+=tempdiff;
32         end for
33         if (mydiff/(n*n)<TOL) then done =1;
34         for k = 1 to nprocs-1 do
35             SEND(done , sizeof(int) ,k , DONE);
36         end for
37     end while
38 end procedure

```

Listing 6: MPI - Solve Function

In the code 6, the myA is the local array for each of the processes which is used to store the local values of the elements in the grid for the domain allocated to it (some subset or rows and all columns). These can be done in many ways: one is to make each of the processes read from a file and the other is to make one of the process can initialize the entire matrix and then distribute it to the various processes. For the sake of simplicity, let us assume that the processes are somehow able to initialize the matrix. Inside the while loop, each of the process maintains a local diff value (no concept of shared/global memory since it is a message passing model nothing is shared). Then, at the beginning of the iteration each processes send their boundary data to the neighbouring processes and the neighbouring processes receive this boundary data and store into the ghost rows of their local array. This is done using the SEND and RECEIVE functions as can be seen in the code. The conditions written here are because the process 0 does not have a process before it and the last process does not have a process after it so they do not need to send or receive the boundary data to any processes before and after and need to send and receive data only to the processes that they share a boundary with. Here pid is the processid which does from 0 to nprocs-1. Thus, based on the process id the send and recieve blocks will change and based on these decisions the processes will change the corresponding send and receive statements. For example from the code we can see that a process with pid not 0 sends its top row to a lower rank process and a process with pid not equal to nprocs-1 sends its bottom row to a higher rank process. Then we have the corresponding receive statement for the same. This way the boundary data is exchanged between the processes and the ghost rows are updated with the boundary data. Then the processes update the values of the elements in the grid and then calculate the local diff value as done in the sequential code.

This time the diff value is not a global variable but a local variable for each of the

processes. Then, the processes send their local diff values to the process 0 which is the master process. The process 0 receives the local diff values from all the processes and then adds them to get the global diff value. Then, the process 0 checks the terminating condition and if the terminating condition is met then it sends the done signal to all the processes and the processes terminate. This is the message passing version explained in a nutshell using a Psuedocode.

7.10 Notes on Message Passing Version

- In a shared memory model although there is no explicit communication, when a process writes the variable and the other process reads it you can take it as some kind of communication. But the communication is receiving process initiated i.e. when the receiving process receives the data is the communication completed whereas in message passing version a process explicitly sends to another process thus it is sender initiated.
- The synchronization in case of Message passing version is implicit. It is not explicitly done using barriers as in the case of Shared memory model but the synchronization happens using these communications (denoted by SEND and RECEIVE calls in the program). This arises the question whether a deadlock situation can arise due to communications in case for MPI? It may happen in the case when all the processes are waiting for the other process to send something and none of the processes are sending anything. This is called a deadlock situation. Say all the processes execute a RECEIVE statement and until this operation is completed they cannot move on to the next statement to SEND. This will lead to a deadlock situation since all the processes are stuck at RECEIVE statement to receive data but none of the processes are sending anything. This can also be though in other way that consider that all the processes execute SEND statement and it is such that the processes will move on to the next statement only after it has been received by some other processes. Then in these cases a deadlock situation will happen since all the SEND operations of all the processes will be waiting for each other to execute their RECEIVE statement which will not happen because those processes are also waiting for other processes to consume the message. Thus, all the processes will be at the SEND stage waiting for each other. This can be avoided by using non-blocking communication calls. Such a communication is called synchronized communication where we want that a process return from SEND only if the other process begins to receives the message, thus called synchronized communications since the processes are synchronizing. We can

try and break the deadlock by one process sending the data and the other process receiving the data.

- The communication is done at one in whole rows at the beginning of the iteration, not grid-point by grid-point. Instead of sending rows in each grid point the entire row is sent in one shot.
- Note the communication pattern when the mydiff variable is sent from all the processes to the master process and the master process forms the global value using all this local values. This kind of communication pattern is called All to One communication and is called reduction. This is very common operation in parallel programming where all the processes send their local values to the master process and the master process combines all these local values to form the global value. Thus, many parallel programming libraries support automatic functions for reduction. Finally, the master process sends the done signal to all the processes which is called One to All communication which is also called a Broadcast operation where one of the process broadcasts a message to all the other processes. Thus, we can use the following code by replacing the SEND and RECEIVE operations to broadcast and reduction operations.

```
1  /*communicate local diff values and determine if done, using
   reduction and broadcast*/
2  REDUCE(0,mydiff,sizeof(float),ADD);
3  if(pid==0) then
4      if (mydiff/(n*n)<TOL)then
5          done =1;
6      endif
7      BROADCAST(0,done,sizeof(int),DONE);
8
```

Note that the reduce operation is called to combine the diff at the process 0 using ADD operation to reduce. The ADD operation is used to add the diff values of all the processes to get the global diff value. There are even other various operators which can be applied to the reduce operation like MAX, MIN, etc. Then the master process checks the terminating condition. The BROADCAST operation is used to broadcast the done signal to all the processes. Thus, it can be simplified using the reduction and broadcast operations.

7.11 Send and Receive Alternatives

Recall that in the message passing version we used the SEND and RECEIVE operations to send and receive the data between the processes. Now it may happen that

the send operation i.e. the process will wait until the data is sent (the receiver starts executing its receive and starts getting the message from the sender process) and the receive operation is also i.e. the process will wait until the data is received (the sender starts executing its send and starts sending the message to the receiver process). This can be avoided by using asynchronous operations. Many MPI libraries support Asynchronous communications sends and receives where a process does not have to wait for the other process to start executing i.e. in asynchronous send a process that sends the data does not have to wait until another process starts receiving the data and similarly, in case of asynchronous receive, a process does not have to wait for the other process to start sending the data. Asynchronous operations can be categorised into blocking asynchronous and nonblocking asynchronous operations for receive/send. This will be seen in detail in MPI.

7.12 Summary

- Shared Address Space: Shared and private data are explicitly separate. Communication is implicit in access patterns and synchronization takes place via atomic operations like locks and barriers on shared data. Synchronization is thus explicit and distinct from data communication.
- Message Passing: There is no concept of shared memory and all the data structures are local data. Data is distributed among local address spaces. Here, the communication is explicit and synchronization (at least for the above example) is implicit i.e. no explicit barrier but there are message passing versions where you can explicit synchronization as well.
- Note that the decomposition and Assignment were similar in both Shared Address Space model and Message passing model, where the difference was in orchestration and mapping. Consider the following table for summary table 4.

	Shared Address Space	Message Passing
Explicit in global structure?	Yes	No
Communication	Implicit	Explicit
Synchronization	Explicit	Implicit
Explicit replication of border rows?	No	Yes

Table 4: Summary

8 Shared Memory Parallelism - OpenMP

8.1 Introduction

Recall the word, processes, used in case of shared memory address space models. Here, the processes are referred to as threads. Threads are lightweight processes which share the same address space. Individual threads need to use barriers and lock to protect the variables. The program also needs to mention certain variables as shared and certain variables as local. Thus, threads can access the same data structures and variables. The programming library that is used for shared memory parallelism is OpenMP (a portable programming model). OpenMP is a set of compiler directives, library routines, and environment variables that can be used to specify high-level parallelism in Fortran and C/C++ programs. What are compiler directives? Within your code you can add certain statements which are guidelines to the compiler to do certain special things. For example, there are certain levels of optimization O1, O2,... one can direct the compiler to optimize certain section of code to a certain level of code using these compiler directives. In case of OpenMP compiler directives are given related to shared memory parallelism. Compiler directives are also called pragmas in OpenMP.

It is very easy to program using OpenMP to convert the sequential program by writing the sequential code and then using the OpenMP directives and execute using OpenMP flags to achieve parallelism. First version of OpenMP came in 1997 with the latest version 4.5 in 2015.

8.2 Fork-Join Model

OpenMP uses a fork-join model. The main program is called the master thread and the master thread forks a team of threads whenever it encounters parallel construct. The team of threads then execute the parallel region and then the threads join back to the master thread. This is as shown in the figure 34.

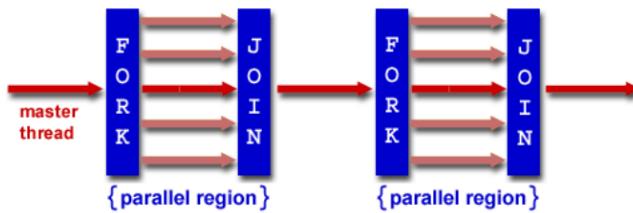


Figure 34: Fork-Join Model

The program begins as a single thread called master thread. Then when it encounters parallel construct, it forks/spawns a team of threads. The statements are then executed in parallel for the parallel region. At the end of the parallel region the team of threads synchronize and terminate and join back to the master thread.

This is one of the good things about OpenMP has selective parallelism i.e. only certain sections of the code are executed in parallel based on the requirement. Thereby we are adhering to Amhadal's Law which says that not all parts of the code can be parallelized and only certain parts of the code can be parallelized. Thus we are not spawning all of the program in parallel and only those where we require parallelism.

OpenMP consists of:

- Work-sharing constructs: specifies how region should be parallelised and distributed among threads.
- Synchronization constructs: for providing synchronization between threads.
- Data environment constructs: for specifying which data is shared and which is private.
- Library calls, environment variables: special function calls and set environment variables. (set env command before executing your code).

A construct is a directive combined with the region where the directive applies. Above shown are the three constructs OpenMP supports. OpenMP support loop-level parallelism to parallelize mainly for/do loops. If there are no dependencies between the iterations of the for loops then we can distribute this iterations to the processes where some process executes some set of iterations and the other process executes the other set of iterations. This is called loop-level parallelism. It gives the user a control over the fine-grained parallelism i.e.what regions to be parallelised.

Hence, we call this as fine-level parallelism. It follows Amdahl's law which says that only certain parts of the sequential code can be parallelized which is what is seen in this case. Note that in this we can also change the phases of parallelism meaning that based on the requirement we can change the number of threads that are executing the parallel region. Regions which can be more parallelized, one can have more number of threads. This is called dynamic parallelism. In addition OpenMP also supports coarse-level parallelism i.e. parallelism where executing completely two different sections of code in parallel in addition to fine-level parallelism. In the recent versions of OpenMP it also support executions on accelerators (GPUs), SIMD vectorizations (automatically updates a vector in parallel units) and task-core affinity. The task-core affinity refers to the fact that the tasks can be explicitly mapped to a particular core. This can be helpful when we want to keep data which is highly related closer in order to save time.

8.3 Parallel Construct

omp parallel is the parallel construct in OpenMP. It is used to create a team of threads. The syntax is as follows:

```
1 #pragma omp parallel
2 {
3     /*parallel region*/
4 }
```

The parallel construct is followed by a block of code which is executed by all the threads in the team. The block of code is called the parallel region. So when a compiler encounters the pragma omp parallel construct it creates a team of threads and the subsequent region inside the block is then executed in parallel. Before the encounter with the omp parallel the compiler will execute the code in the sequential manner on a master thread. This is thus achieved by the parallel directive along with the block of code to be executed in parallel enclosed in curly braces which will be executed in parallel by a number of threads is called parallel construct.

How many number of threads? There are various ways to specify it, one can set an environment variable from command line set env omp numthreads=number of threads. Another way is to use the omp set numthreads(number of threads) function in the code. We can also specify the number of threads in clauses. The following clauses can be used:

- if (condition): will execute in parallel if the condition is true.
 - num_threads (n): will execute in parallel using n threads.
-

- default (shared — none): specifies the default data scope for variables within a parallel region. Should the variables be shared or private among the threads.
- private (list): specifies a list of variables that are private to each thread.
- firstprivate(list): specifies a list of variables that are private to each thread and are initialized with the value of the variable outside the parallel region.
- shared(list): specifies a list of variables that are shared among all the threads.
- copyin(list): specifies a list of variables that are shared among all the threads and are initialized with the value of the variable outside the parallel region.
- reduction(operator:list): specifies a list of variables that are private to each threads and which undergo changes by different threads. Then at the end of this parallel region all of these private variables are combined using the operator specified to give a value.
- proc bind (master — close — spread): specifies the binding of the threads to the cores. How you want the task to be distributed to the cores. To the same core as the master thread or close to the master thread or spread.

Consider the code as shown in the listing below which return the number of threads used in the parallel region. So say n threads were used then it would return n, n times each time when executed by one of the thread.

```
1 #include <omp.h>
2 int main()
3 {
4     int nthreads;
5     #pragma omp parallel
6     {
7         nthreads = omp_get_num_threads();
8         printf("Number of threads = %d\n", nthreads);
9     }
10    return 0;
11 }
```

I encourage you to run these codes by simply copying and pasting it into your IDE and then execute them to see the results.

Consider another Hello World code as shown in the listing below.

```
1 #include <omp.h>
2 int main()
3 {
```

```
4     int nthreads,tid;
5     #pragma omp parallel private(nthreads,tid){
6         printf("Hello World\n");
7     }
8     return 0;
9 }
```

So some number of threads will be spawned and you will see the Hello World printed by each of the threads.

8.4 Work sharing construct

The work sharing construct is used to distribute the work among the threads. using the parallel construct we have spawned multiple threads. Now to specify how to distribute the work among the threads we use work sharing construct. There are three types of work sharing constructs - loops, sections, single.

8.4.1 for-loop

It is used for a for-loop or a do loop using pragma omp for (clause) as in the case of parallel construct. The following clauses can be used :

- private (list)
- firstprivate(list)
- lastprivate(list): here the value of the variable in the list is equal to the value that is set by the last thread.
- linear(list):
- reduction(operator:list)
- schedule([modifier[,modifier]:]kind[,chunksize]): To distribute the iterations among the threads, schedule clause specifies how we schedule the iterations of the loop among the different threads.
- collapse(n): Useful for nested level parallelism. Say two for loops are nested and we want to parallelize both of them then we can use the collapse clause. In general only one of the for loop collapses but using collapse clause we can parallelise both of them by collapsing both the for loops. Say first for loop executes for 3 iterations and the second for loop executes for two iterations,

Then using collapse we can consider them as a total of six iterations in parallel across the threads. If we don't use the collapse clause only the outermost three iterations will be distributed among the threads.

- ordered(n): In some cases we want threads to execute in order i.e. we want the threads managed by the first thread to be executed first and then the second thread and so on.
- nowait: To tell the threads not to wait for each other at the end of for loop. By default all the threads will be waiting for each other for all the threads to finish executing the for loop.

For construct is the most commonly used and th most important construct in OpenMP. Note that we are assuming that the iterations can be independently executed and simultaneously in parallel by the threads. This works as long as the iterations are not dependent on each other whereas in the case when the iterations are dependent on each other say we are using a value in the loop which is dependent on the value resulted in previous loop, in those cases the programmer should not use for construct.

Schedule clause: The assignment of iterations to threads depend on the schedule clause. There are five schedule clauses.

1. schedule(static,chunk size): In this the total number of iterations of the for loop will divided by this chunk size to obtain chunks and these chunks are distributed to the threads in a round-robin manner. For example, say 20 iterations of for loop and say chink size is 2 then $20/2 = 10$ chunks are formed which each consisting of two iterations (first chunk consists of first two iterations and so on) and say we have only four threads then these chunks are distributed among these four threads in a round-robin manner. First chunk to first thread, second chunk to second thread, third chunk to third thread, fourth chunk to fourth thread and back from fifth chunk to first thread and so on.
2. schedule(dynamic, chunksize): It is the same as above but here the chunks can be distributed dynamically, based on OpenMP runtime system libraries own policy to distribute these chunks to the threads that are ready to execute in a dynamic fashion.
3. schedule(runtime): Here we give complete freedom to the OpenMP library to distribute the iterations based on the availability of thread.

Consider the following for-loop example code 7.

```

1 #include<omp.h>
2 #define CHUNKSIZE 100
3 #define N 1000
4 main(){
5     int i,chunk;
6     float a[N],b[N],c[N];
7     /*some initializations*/
8     for (i=0;i<N;i++)
9         a[i]=b[i]=i*1.0;
10
11     chunk=CHUNKSIZE;
12     #pragma omp parallel shared(a,b,c,chunk) private(i) {
13         #pragma omp for schedule(dynamic,chunk) nowait
14         for(i=0;i<N;i++)
15         {
16             c[i]=a[i]+b[i];
17         }/*end of parallel section*/
18     }
19 }
```

Listing 7: for-Example: Addition of two Arrays

Here we are adding two arrays a and b to form a third array c . Note that we can perform this addition completely independent of each other and hence a good opportunity for using parallelism. First for parallelization we need to spawn the threads for which we used `#pragma omp parallel shared(a,b,c,chunk) private(i)`. Here a,b,c are shared among all the threads (since they could be very large arrays) and $chunk$ is also a shared variable and iterator i is private variable to each thread because each thread is going to have its own set of iterations, and those set of iterations should be managed by a private iterator i to avoid any conflicts between which iterations to perform among the threads. Then we use the `for` construct to parallelize the `for` loop with a dynamic schedule clause and `nowait` for threads to not wait after finishing their iterations. Note we can also combine the two pragma into one line in the code as `#pragma omp parallel for shared(a,b,c,chunk) private(i) schedule(dynamic,chunk) nowait`.

8.4.2 Coarse Level parallelism - Sections and Tasks

In addition to fine-level parallelism as shown with the `for` loop example, OpenMP also supports coarse-level parallelism. When we talk about given a set of iterations to a thread that is a fine-level parallelism regarding the iterations of the `for` loop. but now suppose that we wish to execute two different functions containing many such `for` loops in parallel then it requires a coarse-level parallelism, we can use the

sections construct. Consider the following code showing use of sections construct as shown in the listing 8.

```
1 #pragma omp parallel sections <\clause-list\>
2 {
3     #pragma omp section
4         structure-block i
5     #pragma omp section
6         structure-block j
7     ...
8 }
```

Listing 8: Sections Construct

Now suppose the structure blocks consists of functions and we wish to execute them in parallel, then as shown, we first enclose the entire in pragma omp sections and then the small parts which we wish to execute in parallel to be in pragma omp parallel section. Then the first section will be executed by one thread and the second section will be executed by another thread and so on.

OpenMP also supports dynamically spawning tasks. Suppose you have a parallel region and you wish to execute a few set of statements (a task) i.e. we are dynamically creating a task. This generally occurs in large simulations where depending on the requirement one might need to create a task dynamically. This is done using the task construct. This task will be automatically assigned to one of the threads. This is another coarse-level parallelism that OpenMP supports. Tasks is more dynamic construct where your code might be creating tasks dynamically and you want to assign them to the threads dynamically. Task will be assigned to one of the threads you have spawned by OpenMP. You can also use a depend clause which allows us to create dependencies between the tasks by specifying certain variable_list. Suppose a tasks uses some variable x and executes its program and now we wish to use that variable for another task such that the second task depends on the first task. Then we can use the depend clause to specify that variable and thus to have the second task depends on the first task. This is done using the depend clause. Thus, it creates dependencies between variables and thus, second task begins execution only after the first task has finished execution. Thus, it creates the dependencies between the tasks. Now you can dynamically create task graphs where nodes in the graphs represent the tasks and the edges between the nodes represent the dependencies between the tasks. This is a very powerful construct in OpenMP. Thus, with the tasks construct OpenMP can follow its own scheduling mechanism to assign the tasks to the threads such that the dependencies are maintained. This is as shown in the listing 9.

```
1 #pragma omp parallel <\clause-list\>
```

```
2 {
3     ...
4     #pragma omp task \<clause-list\>
5     ...
6     #pragma omp task depend(dependence type: variable\_list)
7 }
```

Listing 9: Tasks Construct

8.5 Synchronization Directives

Having distribute work among the threads there is always a chance of threads accessing some common variables. Hence, you need to synchronize the threads and protect certain variables using locking mechanisms. OpenMP supports this using the following synchronization directives: Note that all of this are already enclosed in a parallel region/parallel construct.

- **pragma omp master:** This is used to specify that the block of code following this directive is executed by the master thread only. This is generally useful for print statements where you want only one thread to print the output. Say to print the value of a variable.
- **pragma omp critical:** This is used to specify that the block of code following this directive is executed by only one thread at a time. Say you are updating a variable and we do not want multiple threads to update the variable at the same time else it might result in garbage values. Then we can use the critical directive to protect the variable by enclosing that statement in this directive and only one thread can update the variable at a time.
- **pragma omp barrier:** This is used to specify that the threads wait at this point until all the threads have reached this point.
- **pragma omp atomic:** This is used to specify that the operation statement (expression) following this directive is executed atomically i.e. only one thread can execute this operation at a time.
- **pragma omp ordered:** This is used to specify that the block of code following this directive is executed in the order of the thread number. Say we want the first thread to execute those statements first and then the second thread to execute those statements and so on. This is useful when we want to maintain the order of the threads executing the statements.Say for example an array is

distributed among threads and then we wish to print the entire array. Then we would like to print the array in the order of the threads i.e. the first set of elements residing in the first thread to print and then the second and so on.

- pragma omp flush: This is used to specify that the threads flush their private data to the shared memory. This is used to ensure that the shared memory is updated with the latest values of the private data. For example, say a thread has updated a variable and we want to ensure that the shared memory is updated with the latest value of the variable. Now there is no guarantee that the variable can be updated immediately to the shared array and be visible to the other threads. There may be a time lapse before it gets written to the shared array and before its visible to the other threads. Because the operating system maintains its own buffers where it may store the variables. Instead, if we wish to immediately flushed out so that it is visible to the other threads, then we can use the flush directive. Flush directive is used when we wish to see consistent view of memory among the threads. Using flush directive, Thread-visible variables (global variables, shared variables etc..) are written to memory. If a variable list is used, only variables in the list are flushed. Consider the following code as shown in the listing 10.

```
1 int sync(NUMBER_OF_THREADS);
2 float work[NUMBER_OF_THREADS];
3 #pragma omp parallel private(iam,neighbor) shared (work, sync)
4 {
5 iam = omp_get_thread_num();
6 sync[iam]=0;
7 #pragma omp barrier
8
9 /*Do computation into my portion of work array*/
10 work[iam]=compute(iam);
11
12 /* Announce that I am done with my work
   * The first flush ensures that my work is
   * made visible before sync.
   * The second flush ensures that sync is made visible.
13 */
14 #pragma omp flush(work)
15 sync[iam]=1;
16 #pragma omp flush(sync)
17
18 /* Wait for neighbor*/
19 neighbor = (iam>0?iam : omp_get_num_threads())-1;
20 while(sync[neighbor]==0){
```

```
24     #pragma omp flush(sync)
25 }
26 /* Read neighbor's values of work array*/
27 ...=work[neighbor];
28 }
```

Listing 10: Flush Directive

Here in the example, a thread writes its respective value to its respective array elements and at the same time neighboring thread tries to read the values that are written by this particular thread. Since, the neighboring threads are trying to read the values that are written by the threads, we need to ensure that the values are written to the shared memory before they are read by the neighboring threads. This is done using the flush directive. The first flush directive ensures that the values are written to the shared memory before they are read by the neighboring threads. The second flush directive ensures that the sync array is made visible to the neighboring threads. The above shown SPMD code is executed by all the threads. From the perspective of a thread the iam variables denotes its thread id, the neighbor represents the neighboring thread id. The work and sync are the variables that are shared among the threads. The work array is the main array where the threads write their respective values (and also being read by the other threads) and the sync array is used to signal the other threads to say that this thread has finished writing to the work array so that the other thread can read those values. In order to ensure that the values are written to the shared memory before they are read by the neighboring threads, the sync variable has to be flushed out. Note that we can get the thread id as shown in the code using `omp_get_thread_num`. So at the beginning of the code each thread will get its thread id and then set the `sync[id]=0` and then barrier is used to ensure that all the threads have reached this point. Each thread then does some computation and at the end of the computation stores its result to its corresponding work element. Now it requires to announce that it is done with its work so that the neighboring thread can make use of that value. This is done using flush statement so that the changes in work array is visible and then it changes the value of sync array to 1 to signal the other threads that is is done. Then another flush statement so that the changes in sync are visible. Then the neighboring threads will find out its thread id based on their own thread id and will actively look whether the neighboring variables are updated or not. If not then it will keep on checking until the neighboring thread has updated the value (because of the while loop), it keeps flushing the sync variable. Once the sync variable is updated then it reads the value of the

work array of the neighboring thread.

8.6 Data Scope Attribute Clauses

OpenMP supports many clauses supporting data scope. Data scopes is explicitly specified by data scope attribute clauses.

1. private: A separate variable will be created fore each of the thread and it is initialized to the default value to which any programming language initializes it to(generally garbage values by default in C/C++).
2. firstprivate: If you want a private variable for a thread to be initialized with value of the variable that existed before entering the parallel clause i.e. value in the master thread, it is to be declared as firstprivate. In this, separate private copies will be created for each thread and the value will be initialized to that of a variable in the master thread before entering the parallel region.
3. lastprivate: When you exit a parallel region the value that will be assigned to the variable will be the one that is assigned by the thread that executed at last. In a parallel region, multiple threads will be executing, the value of this private variable will be the one assigned by the thread that executes at last to the variable in the master thread.
4. shared: Declaring the list of variables to be shared among the threads.
5. default: To set the default behavior of the variables in the parallel region. Most variables are shared by default.
6. reduction: If you wish to combine all the private variables in all the threads and reduce it using some operator (say like addition) to get the final value of the reduction to be assigned to a variable in the master thread after exiting the parallel region.
7. copyin: Copyin acts similar to private.
8. copyprivate: It is used to assign thread private variables and if you wish to assign some variables as thread private and initialize them, then we use copyprivate. More will be seen later.

Sometimes while declaring a large multidimensional arrays as private leads to overhead because now each thread would have to create this large multidimensional arrays. Moreover, declaring them as firstprivate will incur even further overhead as each thread now also requires it to initialize the threads which results in overheads.

8.6.1 threadprivate

They are global variable-list where private copies are maintained for each thread (just like private variables) but the variable values will exist across different parallel regions. Say for example say a variable x is declared as threadprivate, then separate copy of x will be maintained for each of the threads. Say now at the end of the first parallel region the value of the variable x in the first thread is say 5. Now in the next parallel region if we declare the variable x as private then the value of 5 will be lost and x will be initialized to some other initial value in the first thread. This would happen if we had not declared the variable x as threadprivate. But since we have declared the variable as threadprivate, the value 5 will exist across multiple parallel regions in the first thread. So for doing this, we declare a variable using a special directive threadprivate instead of private. Consider the following code 11.

```
1 #include<omp.h>
2 int alpha[10], beta[10], i;
3 #pragma omp threadprivate(alpha)
4 main(){
5     /* explicitly turn off dynamic threads*/
6     omp_set_dynamic(0);
7     /*First parallel region*/
8     #pragma omp parallel private(i,beta)
9     for(i=0;i<10;i++) alpha[i]=beta[i]=i;
10    /*Second parallel region*/
11    #pragma omp parallel
12    printf("alpha[3]=%d and beta=%d\n",alpha[3],beta[3]);
13 }
```

Listing 11: threadprivate Directive

Note that we have declared alpha as threadprivate variable. In the first parallel region we have declared i and beta as private variables to each thread. Then in the first parallel region we are assigning value to alpha and beta arrays equal to their array index i (alpha is threadprivate and beta is private). Then in the second region when we print the value of alpha[3] we will get a value of 3 since alpha has been declared as a threadprivate variable and hence will maintain its value across different parallel regions. But when we print beta[3] we will get some garbage value (or may be some initial value if initialized in the second parallel region). This is because we have declared beta as private and not threadprivate. So for beta its scope exists only inside that parallel region whereas for alpha its scope exists across different parallel regions. Hence, if we want the scope of a variable to span across different parallel regions we have to declare them as threadprivate. Note that here the parallelism should be the same for using threadprivate i.e. say if you have spawned 4 threads

in the first parallel region then you must spawn only 4 threads in the next parallel region. Thus, we have used set_dynamic(0) to turn off the dynamic parallelism. If we leave it to OpenMP then it may spawn different number of threads in different parallel regions.

8.6.2 default-example

Consider the following example code for better understanding of concepts of private, shared and default 12.

```
1 int x, y, z[1000];
2 #pragma omp threadprivate(x)
3
4 void fun(int a){
5     const int c = 1;
6     int i = 0;
7
8     #pragma omp parallel default(none) private(a) shared(z)
9     {
10         int j = omp_get_num_thread();
11         //O.K. - j is declared within parallel region
12         a = z[j];
13         x=c;
14         z[1]=y;
15     }
16 }
```

Listing 12: default-Example

Here we have declared variables x, y and array z as global variables. In this code we have declared x as threadprivate variable. We have a function fun in which we have declared a const it c and int i. Then in the clauses while entering the parallel region we have declared default as none which means that we do not want any of the variables to be shared by default. Then we have declared variable a as private to each of the thread and array z as shared among the threads. Inside the parallel region we have declared a variable j, this works since we have declared j locally to each of the threads. Then we do a=z[j], this works since a is listed as private and z is listed as shared. then we do x=c, this should also work since we have declared x as threadprivate and c is const-qualified type. Then we do z[i]=y, this will not work since although z is a shared variable, but variables i and y are not known inside the parallel region since by default we have set none thus, variables won't be shared inside the parallel region. Also, see that we have not declared anything about the variables y and i so they don't exist inside the parallel region (as default is set

to none, if the default had been set to shared then the variables would have been shared and thus statement would have worked), thus compiler will flag this as error as cannot reference i or y here.

8.7 Library Routines (API)

In addition to the above seen Directive and clauses, OpenMP also supports certain functions like:

- Querying function (number of threads etc)
- General purpose locking routines
- Setting Execution environment (dynamic threads, nested parallelism etc.)

Example of some of the functions are as follows:

- `OMP_SET_NUM_THREADS(num_threads)`: To set the number of threads you wish to spawn in the corresponding parallel region.
 - `OMP_GET_NUM_THREADS()`: To find the number of threads used in the parallel region.
 - `OMP_GET_MAX_THREADS()`: To query the maximum number of available threads you can get for a parallel region.
 - `OMP_GET_THREAD_NUM()`: To get the thread id of a thread inside the parallel region.
 - `OMP_GET_NUM_PROCS()`: To get the number of processors on which OpenMP is executing on.
 - `OMP_IN_PARALLEL()`: To query whether you are in a parallel region.
 - `OMP_SET_DYNAMIC(dynamic_threads)`: Set the number of threads to be spawned dynamically (chosen by OpenMP) or a certain value (say maximum) inside the parallel region.
 - `OMP_GET_DYNAMIC`:
 - `OMP_SET_NESTED(nested)`: To run on or off nested parallelism in OpenMP
 - `OMP_SET_NESTED()`
-

- `omp_init_lock(omp_lock_t *lock)`: To initialize a lock
- `omp_init_nest_lock(omp_nest_lock_t *lock)`
- `omp_destroy_lock(omp_lock_t *lock)`: To free the lock
- `omp_destroy_nest_lock(omp_nest_lock_t *lock)`
- `omp_set_lock(omp_lock_t *lock)`: For acquiring a lock
- `omp_set_nest_lock(omp_nest_lock_t *lock)`
- `omp_unset_lock(omp_lock_t *lock)`: For releasing the lock
- `omp_unset_nest_lock(omp_nest_lock_t *lock)`
- `omp_test_lock(omp_lock_t *lock)`: To see if the lock is available or not
- `omp_test_nest_lock(omp_nest_lock_t *lock)`
- `omp_get_wtime()`: To get the time taken in the parallel region by subtracting the time at the start and at the end of the parallel region.
- `omp_get_wtick()`
- `omp_get_thread_num()`: Number of threads being used
- `omp_get_num_proc()`: Number of processors you are currently using

8.8 Locks

OpenMP supports both simple locks and nestable locks. For a simple lock, if the thread acquires the lock once then it cannot acquire that lock once again i.e. you cannot use the `set_lock` function twice for locking on the same variable by the same thread. Thus, we cannot use a `nest` statement for locking simple locks. This will be a deadlock situation since the thread that once who has acquired lock on it and now putting a lock again means it will be waiting for it to be released but since it was the one to acquire it it will be waiting forever to acquire it once again since the lock will never be released. A lock can be released only by the thread that acquires it. So till the thread does not release the lock it cannot acquire it once again. So acquiring the lock twice in a row will lead to a deadlock situation.

In some cases, it may be desired to use a nested lock. For example in case of some Linear Algebra libraries using OpenMP functions and there are say multiple

routes from the main function to enter into those functions. Say there are multiple ways of accessing those functions. then it is desired to protect each of the functions and thus use nested locks.

Simple locks are not locked if they are already in a locked state. nestable locks can be locked multiple times by the same thread. Simple locks are available if they are locked. Nestable locks are available if they are unlocked or owned by a calling thread i.e. it uses a counter to count the number of locks on it by different threads and they will be released based on the same manner they were locked by different threads in their calling manner, thus they need to be released by all other calling threads for a thread that wishes to use it.

Consider the following code to show the importance of nested locks 13.

```

1 #include <omp.h>
2 typedef struct {int a,b; omp_nest_lock_t lck;} pair;
3
4 void incr_a(pair *p, int a)
5 {
6     // Called only from incr_pair, no need to lock.
7     p->a +=a;
8 }
9 void incr_b(pair *p, int b)
10 {
11     //Called both from incr_pair and elsewhere,
12     //so need a nestable lock.
13
14     omp_set_nest_lock(&p->lck);
15     p->b+=b;
16     omp_unset_nest_lock(&p->lck);
17 }
```

Listing 13: Nested lock-Example

In the above code we have declared a structure which has two integer variables a and b and a lock. pair is a variable of struct type. There are two function declared as incr_a and incr_b. Consider that incr_a is called only from incr_pair so there is no need for lock. Now consider the function incr_b which is say called from both incr_pair and elsewhere, thus we need a nestable lock in order to avoid simultaneous updation (or else may lead to garbage values). Thus we have used set and unset lock around it.

Now consider the following continuation of the code as shown in 14.

```

1 void incr_pair(pair *p, int a, int b)
2 {
3     omp_set_nest_lock(&p->lck);
```

```

4     incr_a(p,a);
5     incr_b(p,b);
6     omp_unset_nest_lock(&p->lck);
7 }
8 void f(pair *p)
9 {
10 extern int work1(), work2(), work3();
11 #pragma omp parallel sections
12 {
13     #pragma omp section
14         incr_pair(p,work1(),work2());
15     #pragma omp section
16         incr_b(p,work3());
17 }
18 }
```

Listing 14: Nest lock-Example2

In this example note that we are using parallel sections for calling the functions incr_pair and incr_b, and each of those functions act on p. Now note that incr_a is called only from incr_pair and thus there is no need for lock, but note that incr_b is called from incr_pair as well as directly from incr_b. Thus, it requires a nested lock for locking the value of p while performing the operation and then releasing the lock, which is done by incr_pair and incr_b using set and unset lock functions.

8.9 Example 1: Jacobi Solver

This is an example of previously explained grid solver, except for the fact that here we are parallelizing across the iterations and not across the rows. Consider the following code as shown in 15

```

1 #include<omp.h>
2 int main(int argc, char**argv){
3 ...
4 int rows,cols;
5 int* grid;
6 int chunk_size, threads=16;
7 ...
8     /*Allocate and initialize the grid */
9     grid=malloc (sizeof(int*)*N*N);
10    for(i=0;i<N;i++){
11        for(j=0;j<N;j++){
12            grid[i*cols+j]=...;
13        }
14    }
```

```

15     chunk_size=N/threads;
16     #pragma omp parallel for num_threads(16) private(i,j) shared(
17     rows,cols,grid) schedule(static,chunk_size) collapse(2)
18     for(i=1;i<rows-1;i++){
19         for(j=1;j<cols-1;j++){
20             grid[i*N+j]=1/4*(grid[i*N+j-1]+grid[i*N+j+1]+grid[(i-1)*
21             N+j]+grid[(i+1)*N+j]);
22         }
23     }

```

Listing 15: jacobi-solver

So as can be seen in the code we have first initialized and then we have used a schedule in parallelizing the code. For that we have declared the `chunk_size=N/num_threads` which is the total number of rows/columns divided by the number of threads=16. So in the next statement where we start parallel region using `pragma omp parallel for` indicates that we are using 16 threads, the iterators `i` and `j` have been declared as private. The number of rows, columns and grids are shared variables i.e. shared among threads. Then we are using static in the schedule clause so the total number of iterations will be given based on `chunk_size` to each of the threads in a round robin manner. Note that we are also using `collapse(2)` which means that it will collapse the two for loops i.e. the total number of iterations will be considered as `rows*cols` and these many iterations will be distributed among all the threads based on the `chunk_size`. In this if we had not used `collapse` then only the first for loop i.e. the iterations for the rows would have been distributed among the threads and now each thread would have to take care of all the iterations for the columns.

8.10 BFS

8.10.1 Version 1 (Nested Parallelism)

Consider the following example code 16

```

1 ...
2     level[0] = s;
3     curLevel = 0;
4     dist[s]=0; dist[v!=s]=-1;
5
6     while(level[curLevel]!=NULL){
7         #pragma omp parallel for ...
8             for(i=0;i<length(level[curLevel]); i++){
9                 v=level[curLevel][i];

```

```
10         neigh=neighbors(v);
11
12     # pragma omp parallel for ...
13     for(j=0;j<length(neigh);j++) {
14         w=neigh[j];
15         if(dist[w] == 1){
16             level[curLevel +1]= union(level[curLevel+1],w);
17             dist[w]
18         }
19     }
20 }
21 }
```

Listing 16: BFS-Example

Here we are at first assigning only the source so the 0th level has only the source vertex s. The current level =0, and distance of the source vertex from the source vertex is set 0 and the distance of other vertex from the source vertex is set to -1. We are suppose to find the distance of the other vertices from the source vertex. Inside the while loop we first set the e

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