Carnegie Mellon University

Ian Lane

18646 – Week 2

Homework 1

Lecture Questions

https://canvas.cmu.edu/courses/21510/quizzes/55580

Outline – Follow on from 2/4

- Landscape of Computing Platforms
- **Hardware Architectures**
  - Multicore vs
  - Instruction le
  - SIMD
  - Simultaneous multithreading
  - **Memory hierarchy**
  - System hierarchy
- How to Write Fast Code?

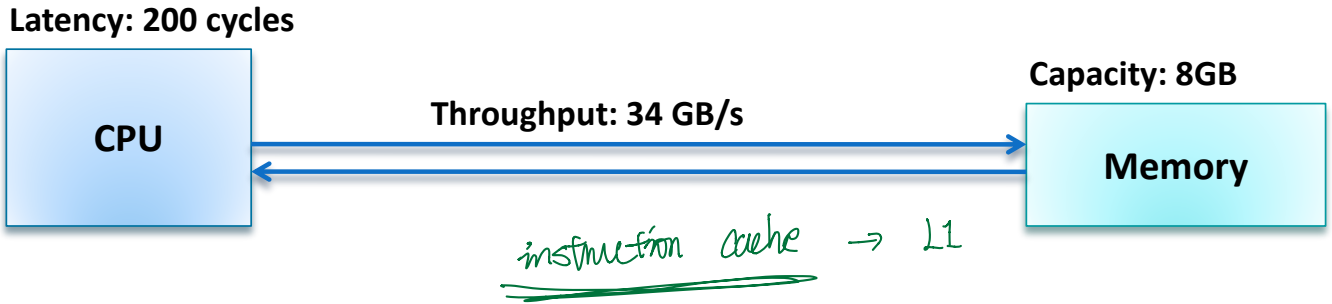
(5) Memory Hierarchy

- **Cache**:
  - A piece of fast memory close to the compute modules in a microprocessor
  - Allows faster access to a limited amount of data
  - Physical properties of wires and transistors determines trade-off between **cache capacity**

Capacity: Size, e.g. number of byt

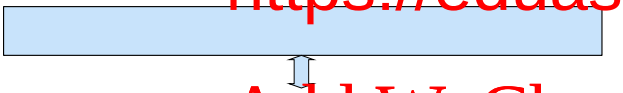
Latency: From start to finish, in u CPU clock cycles

Throughput: Tasks accomplished per unit time, e.g. GB/s



(5) Memory Hierarchy

- **Cache**:
  - A piece of fast memory close to the compute modules in a microprocessor
  - Allows faster access to a limited amount of data
  - Physical properties of wires and transistors determines trade-off between **cache capacity**



ity, (throughput), (latency)

tes, 0.1 GB/s, ~1-10B cycles

6 GB/s, ~100 cycles

16GB, 34.08 GB/s, ~200 cycles

8 MB, 108.8 GB/s, 26-31 cycles

256 KB, 108.8 GB/s, 12 cycles

32 KB Data Cache, 163.2 GB/s, 4-6 cycles

registers

Intel Core2 – 2600k @ 3.4GHz
(viewed from one core)

Working with a Memory Hierarchy

- **Writing fast code → get data from the fastest (closest) level**
- When requesting data from a level in memory hierarchy of limited size, there are two outcomes
  - **Hit**: Data is ava
  - **Miss**: Data is m
- **For fast code → minimize misses, maxi**
- What **application behavior** can a memory hierarchy help with?

locality

Working with a Memory Hierarchy

- **Principle of Locality**
  - The phenomenon of the same value or related storage locations being frequently accessed, usually amenable to performance optimization

- **Temporal Locality**
  - Reuse of specific and/or resources within relatively small time durations

- **Spatial Locality**
  - Use of data elements within relatively close storage locations

When would you get a miss?

- Three types of misses in a memory hierarchy
  - **Compulsory** misses: caused by the first reference
  - **Capacity** misses: due to the finite size of the memory hierarchy
  - **Conflict** misses lly avoidable

Exploiting Benefits of Mem Hierarchy

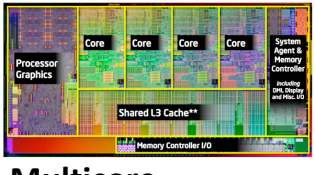
- Motivation:
  - When application exhibit data locality, cache/memory provides faster access to frequently used data
- Advantages:
  - Allows faster a
  - Caches are managed storage: transpare for functional purposes
  - Lower the energy consumption when g ”
- Disadvantages:
  - When using multiple threads share a cache, they will compete for cache space

Outline – Follow on from 2/4

- Landscape of Computing Platforms
- **Hardware Architectures**
  - Multicore vs
  - Instruction le
  - SIMD
  - Simultaneous multithreading
  - Memory hierarchy
  - **System hierarchy**
- How to Write Fast Code?

(6) System Architecture

- A Journey through the opportunities to write ***fast code*** with:
  - Multicore
  - Manycore
  - The Cloud

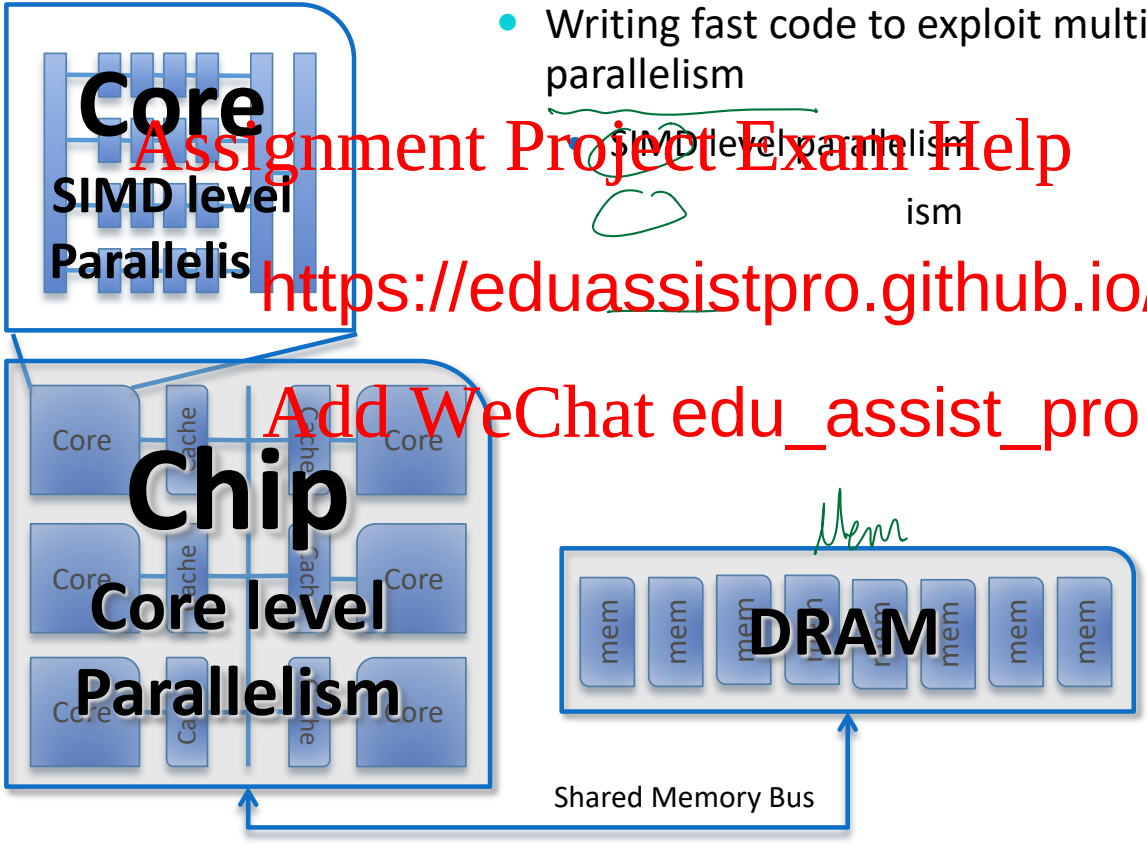


Multicore

Manycore

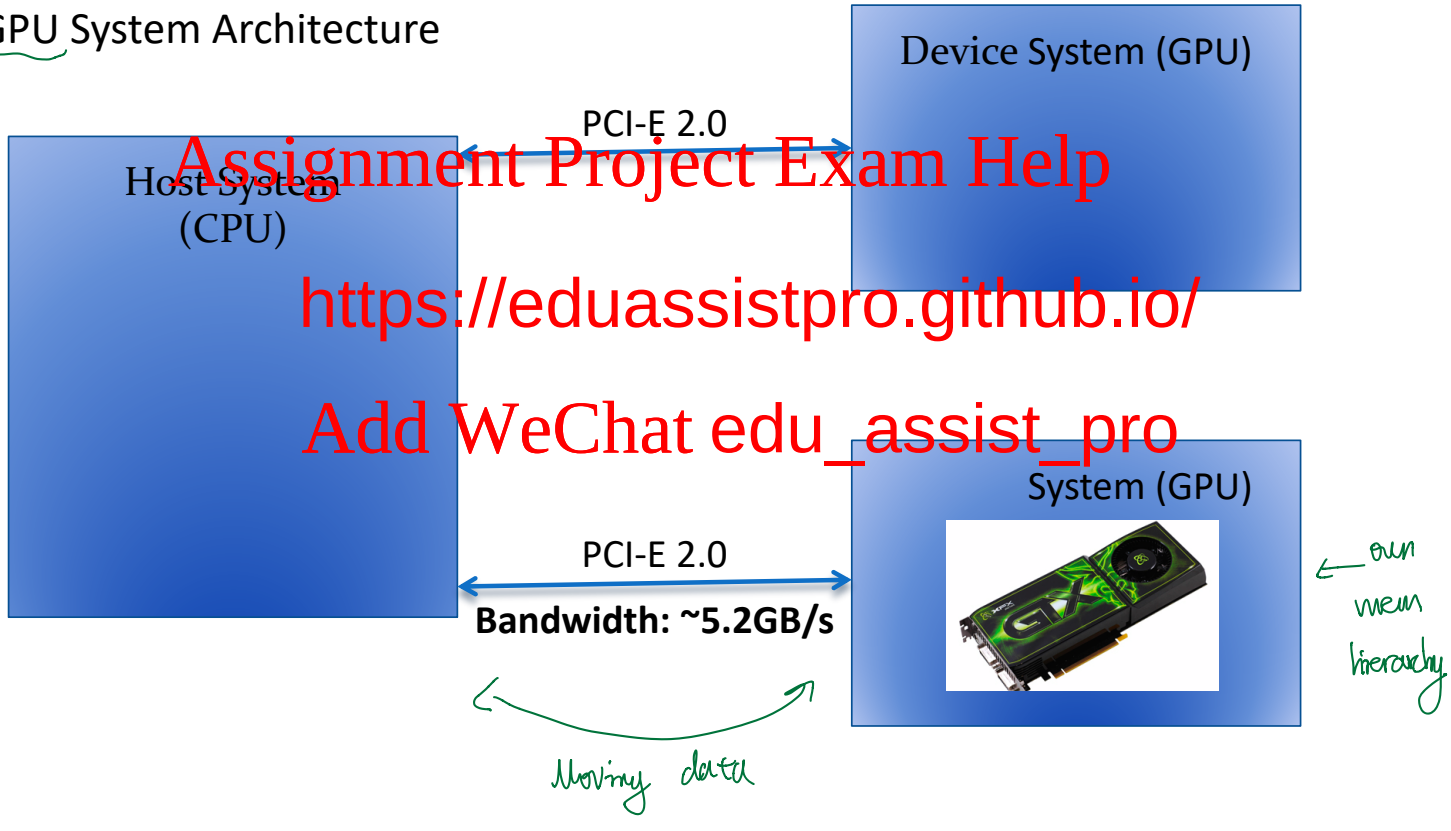
Section 1 - Multicore

- Writing fast code to exploit multicore parallelism
  - SIMD level parallelism
  - ism



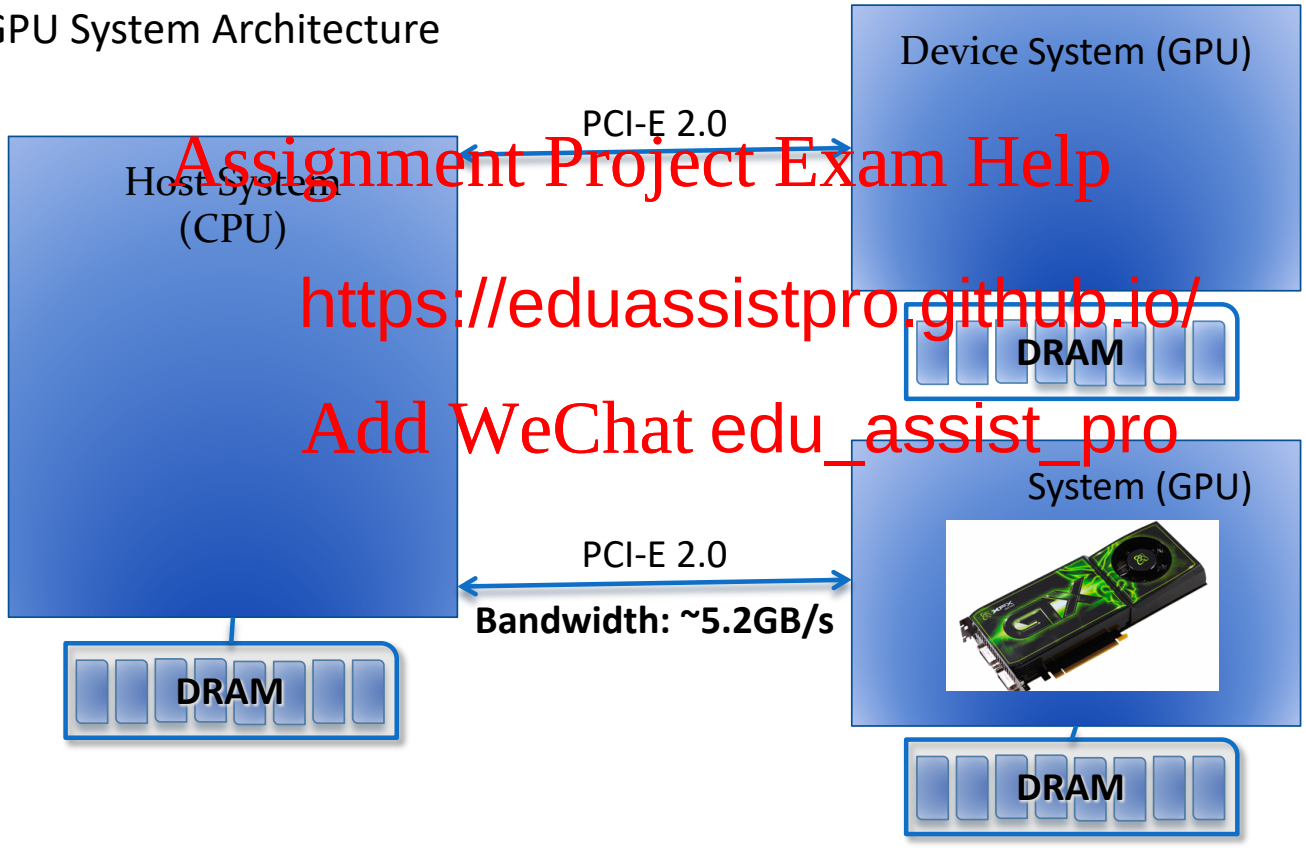
Section 2 - Manycore

- GPU System Architecture

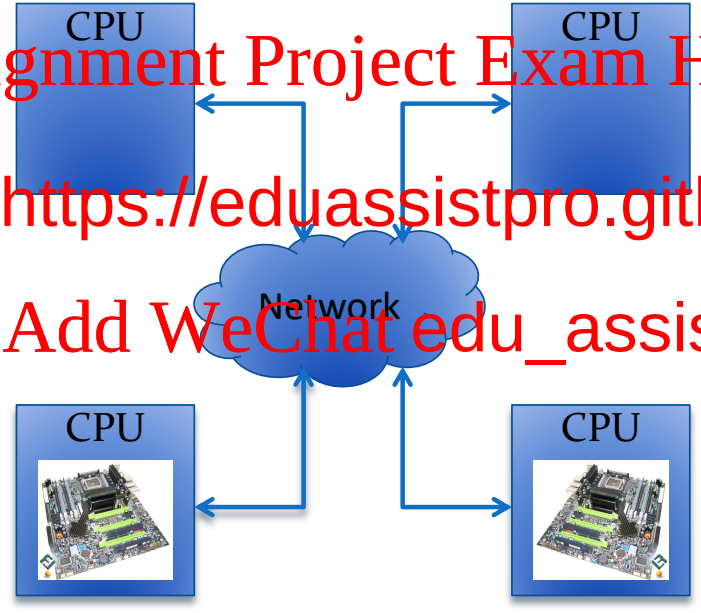


Section 2 - Manycore

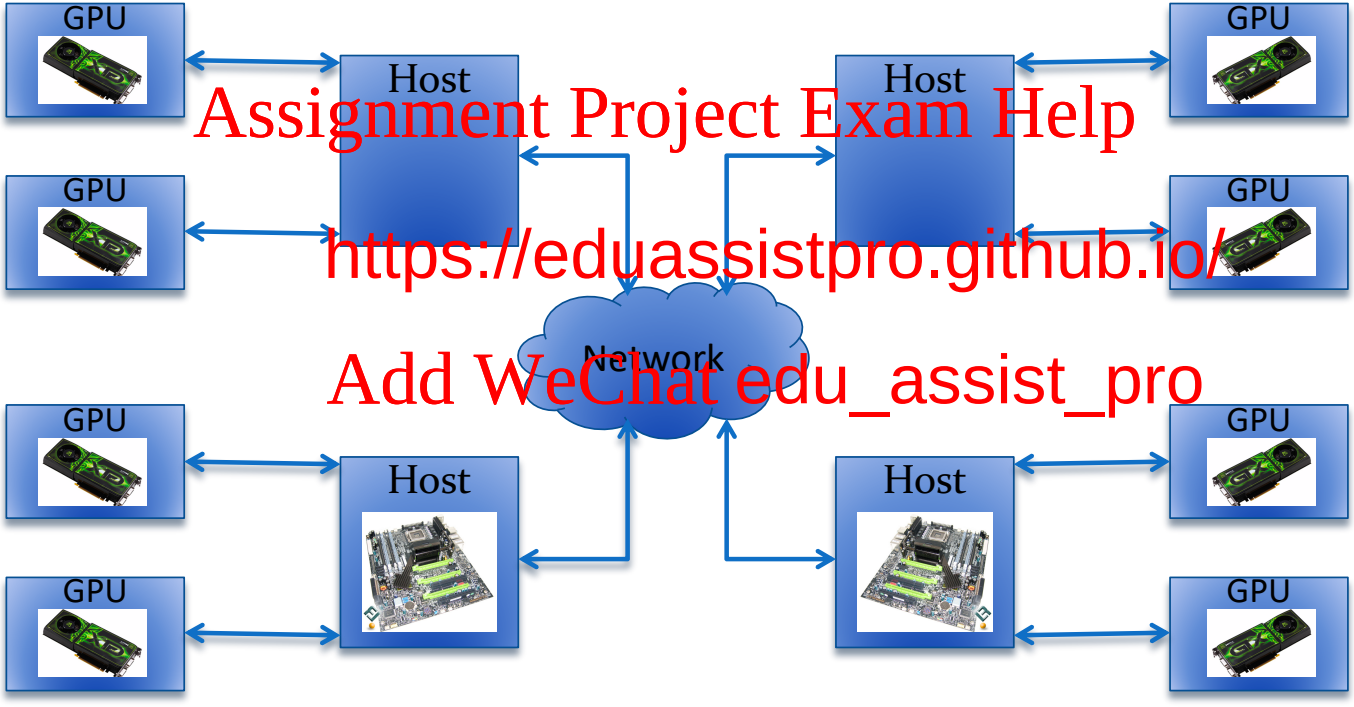
- GPU System Architecture



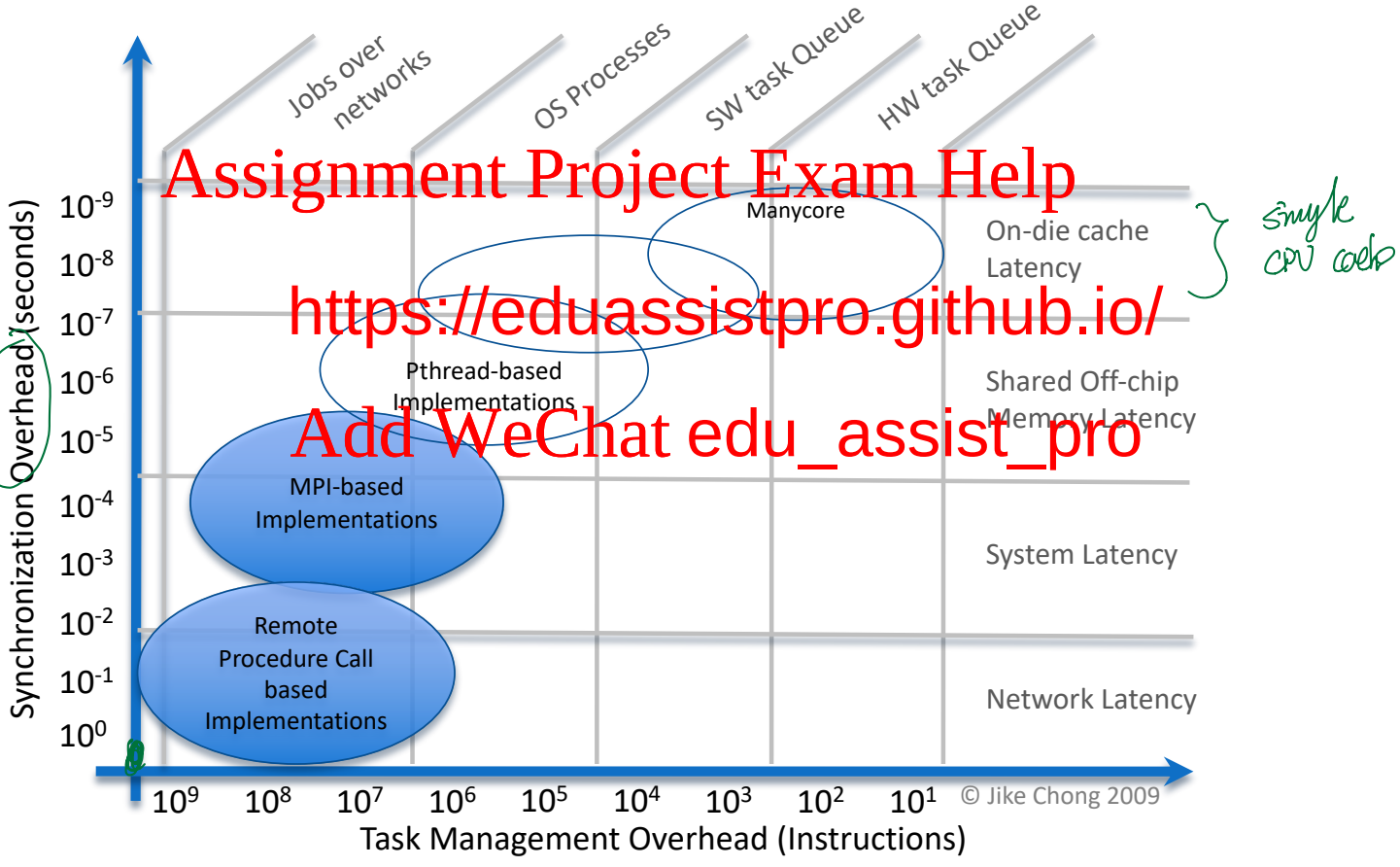
Section 3 – The Cloud



Section 3 – The Cloud



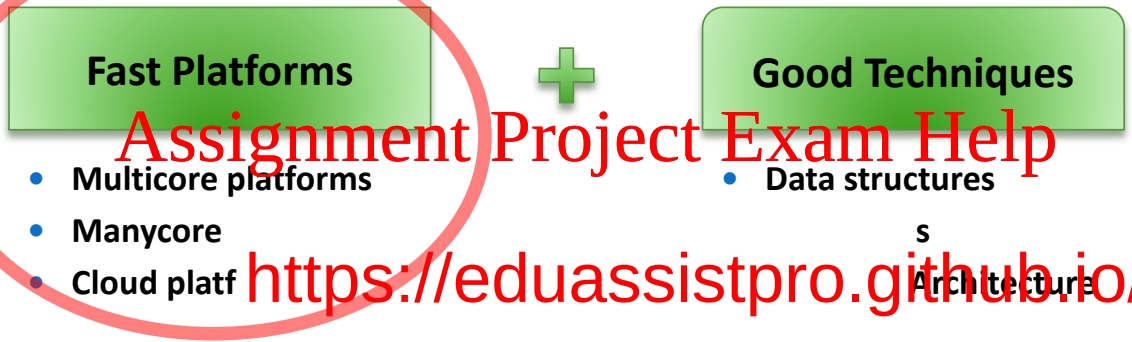
A Game of Granularity



Outline

- Landscape of Computing Platforms
- Hardware Architectures
  - Multicore vs
  - Instruction le
  - SIMD
  - Simultaneous multithreading
  - Memory hierarchy
  - System hierarchy
- **How to Write Fast Code?**

How to Write Fast Code?



- We focus on the fast hardware in this l
- Combines with **good techniques** to produce fast code…

  …in order to solve a problem or improve an outcome

How to Write Fast Code?

- Recognizing levels of concurrenc tion
- Effective mapping of concurrency in an application with parallelism of a platform

→ **Fast code**

Concurrency Opportunity Recognition

- **The Application Developer**
- **Applicatio**
- **The Proble**

Distinction: Concurrency vs. Parallelism

Concurrency	Parallelism
The property of an **application** that…	The property of a **platform** that…
…allows for tasks to **hav**	o **have the potential** to be…
…**executed simultaneo**	aneously
The **application architecture** in which…	Th re in which…
…**more than one task** is active and able to…	can be active and…
…**make progress** at one time	…**make progress** at same time
We **expose concurrency** in our applications.	We **exploit parallelism** in our platforms.

The Application Developer

- Writing fast code is a process coherent with

"general problem solving behavior"

Newell and Simon, Human Problem Solving (1972), pp. 72-73

- The process of pr

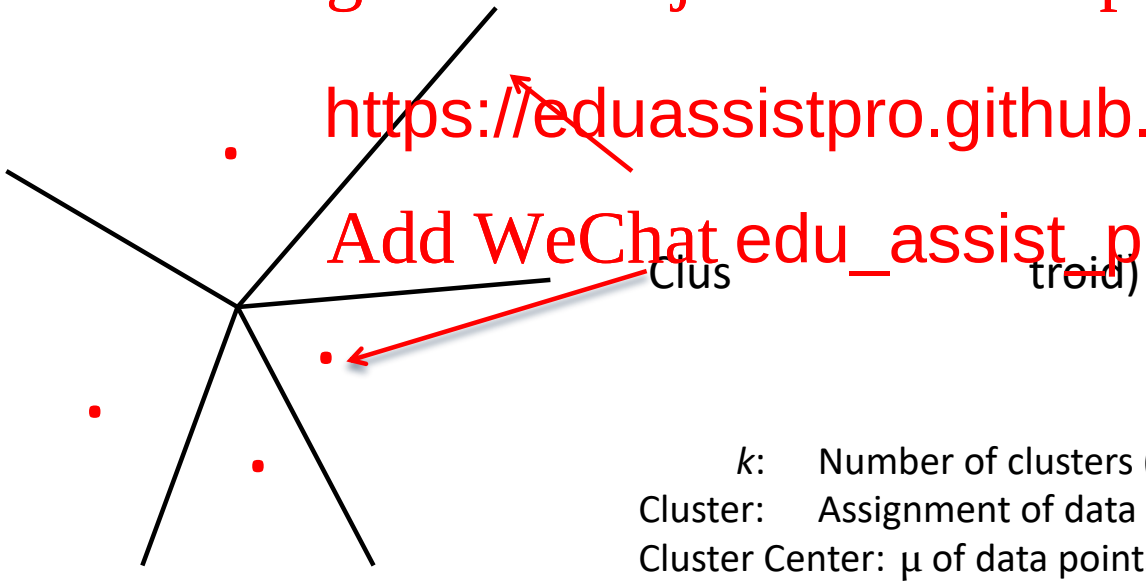
1. Understand the **current state**
2. Observe the **internal representation**
3. **Search** among alternatives
4. Select from a set of **choices**

k-means Problem

- Find *k* cluster centers that minimize the distance from each data point to a cluster center
- Important algorithm in machine learning:
  - Statistical dat
  - Vector quanti
- NP-hard for arbitrary input
- ***k*-means algorithm** frequently finds at solutions quickly
- Issues:
  - Worst case running time is super-polynomial
  - Approximation can be arbitrarily bad

k-means Problem

- Find *k* cluster centers that minimize the distance from each data point to a cluster center



k: Number of clusters (defined a-priori)
Cluster: Assignment of data points to a class
Cluster Center: μ of data points in a cluster

Related Problems and Algorithms

- ***k*-means++**: Maximize scattering on initial cluster centers
- **KD-trees**: Fast *k*-means - Pre-compute distance between data points
- ***x*-means**: *k*-means with efficient estimation of the number of classes

- Gaussian Mixture
  - Probabilistic as
  - Multivariate Gaussian distributions inste

- Expectation Maximization algorithms (E
  - Find maximum likelihood estimates of parameters in a statistical model, where the model depends on unobserved latent variables.
- Expectation Maximization Algorithms for Conditional Likelihoods
  - Estimate parameters in a statistical model to optimize conditional likelihood (where the objective function is a rational function)

k-means Algorithm (“*Lloyd’s algorithm*”)

- Given an initial set of *k* means $\mathbf{m}_1^{(1)},\ldots,\mathbf{m}_k^{(1)}$
- **Expectation Step:** Assign each observation to the cluster with the closest mean
- **Maximization Step:** Calculate the new centroid of the observations in the cluster.

$$\mathbf{m}_i^{(t+1)} = \frac{1}{|S_i^{(t)}|} \sum_{\mathbf{x}_j \in S_i^{(t)}} \mathbf{x}_j$$

- Iterate until convergence or stopping criteria met

The Algorithm

Example:

k=5

Distance metric=euclidean

Dimensions=2

1. Randomly select cluster Centers
2. Assign closest Center to each data point
3. Update Centers based on assignments from (2)
4. Re-iterate steps 2-3 until convergence or stopping criteria met

The Algorithm

Example:

k=5

Distance metric=euclidean

Dimensions=2

1. Randomly select cluster Centers
2. Assign closest Center to each data point
3. Update Centers based on assignments from (2)
4. Re-iterate steps 2-3 until convergence or stopping criteria met

The Algorithm

Example:

k=5

Distance metric=euclidean

Dimensions=2

1. Randomly select cluster Centers
2. Assign each data point to closest Center
3. Update Centers based on assignments from (2)
4. Re-iterate steps 2-3 until convergence or stopping criteria met

The Algorithm

Example:

k=5

Distance metric=euclidean

Dimensions=2

1. Randomly select cluster Centers
2. Assign closest Center to each data point
3. Update Centers based on assignments from (2)
4. Re-iterate steps 2-3 until convergence or stopping criteria met

The Algorithm

Example:

k=5

Distance metric=euclidean

Dimensions=2

1. Randomly select cluster Centers
2. Assign closest Center to each data point
3. Update Centers based on assignments from (2)
4. Re-iterate steps 2-3 until convergence or stopping criteria met

The Phases

1. **Initialization:** Randomly select *k* cluster centers
   - Select *k* samples from data as initial centers [Forgy Partition]
2. **Expectation:** Assign each data point go closest center
   - Compare e r center (*k*)
   - Distance M nsions)
3. **Maximization:** Update centers nments
   - For each cluster (*k*) compute m ns) from data points assigned to that cluster
4. **Evaluate:** Re-iterate steps 2-3 until convergence or stopping criteria met
   - Percentage of data points re-assigned
   - Number of iterations (2-3)

A Fast Implementation of *k*-means

- Following the process of problem solving with *k*-means:
  1. Understand the **current state**
     - Running on a platform
     - Using a spec
     - Achieving a
     - Meeting a specific criteria/requireme
  2. Observe the **internal representation**
  3. **Search** among alternatives
  4. Select from a set of **choices**

Assumption:
Starting from a functionally correct reference implementation

n:
rve the *current state* and
n requirements
to solve a problem

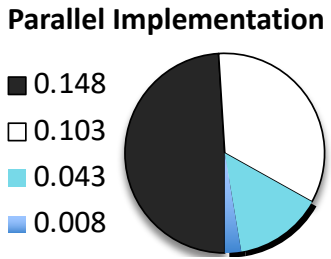
Understanding the Current State

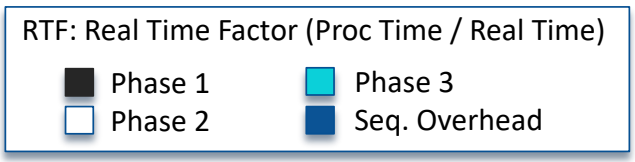
- **Running on a platform**
  - *Platform:* *Linux + GCC on x86 multicore processor*
- **Using a specific set of resources (given X)**
  - *Computation:*
  - *Data:* *3D RAM*
  - *Synchronization:* *on-chip shared-memor*
- **Achieving a specific performance**
  - *As measured in Mini-Project 1*
- **Meeting a specific criteria/requirement**
  - *Matrix-Multiply*
  - *k-means*

What to Measure for Performance?

- **Performance Analysis: Roofline Model**

- A few simple techniques:
  - Observe the ph
  - Characterize th
  - Reason about why a piece of code is slow
  - Identify performance bottlenecks





Current state: *k*-means algorithm

- 4 Phases (Initialization, Expectation, Maximization, Evaluate)
  - Majority of time spent on Expectation and Maximization phases
- Entire data set can fit in memory on a single machine
- Number of sampl ry significantly
- Evaluation for any number of clusters (
- Example Data Sets:
  - *ionosphere_scale*: 351 Samples, 34 Dimensions
  - *svmguide*: 7089 Samples, 4 Dimensions
  - *cod-rna*: 59535 Samples, 8 Dimensions
  - *ljcnn1*: 191681 Samples, 22 Dimensions

A Fast Implementation of *k*-means

- Following the process of problem solving with *k*-means:
  1. Understand the **current state**
  2. Observe the **internal representation**
     - Application
       - Identified
     - Implementation concerns
       - Task considerations
       - Data representations
       - Concurrency opportunities
  3. **Search** among alternatives
  4. Select from a set of **choices**

Example Code (Initialize)

kmeans/seq_kmeans.c
lines: 116-119

```
....
    /* pick first numClusters elements of objects[] as initial cluster centers*/
    for (i=0; i<numClusters; i++)
        for (j=0; j<numCoords; j++)
            clu
....

__inline static float euclid_dist_2(int numdims, float                    2)
{
  int i;
  float ans=0.0;
  for (i=0; i<numdims; i++)
    ans += (coord1[i]-coord2[i]) * (coord1[i]-coord2[i]);
  return(ans);
}
```


Define distance metric (Euclidian)

kmeans/seq_kmeans.c
lines: 51-63

Example Code (Initialize)

kmeans/seq_kmeans.c
lines: 116-119

....

Active Data Structures

objects: N x D

clusters: k x D

...ers*/

__inline static float euclid_dist_2(int numdims, float 2)

{

Active Data Structures

coord1: 1 x D

coord2: 1 x D

ans: 1

}

Define distance metric (Euclidian)

kmeans/seq_kmeans.c
lines: 51-63

Possible concurrencies:
D (sum reduction) ← euclid_dist_2()

Example Code (Expectation)

kmeans/seq_kmeans.c
lines: 136-147

```
....
    delta = 0.0;
    for (i=0; i<numObjs; i++) {
      /* find the array index of nestest cluster center */
      index = find_near                                    [i], clusters);

          ...

      /* if membership changes, increase delta by 1 */
      if (membership[i] != index) delta += 1.0;

      /* assign the membership to object i */
      membership[i] = index;
...
```


Evaluate distance to each cluster centroid and select closest

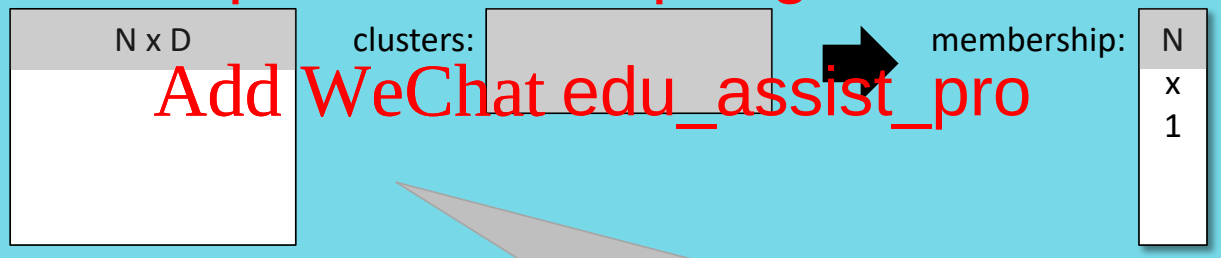
Example Code (Expectation)

kmeans/seq_kmeans.c
lines: 136-147

```
....
    delta = 0.0;
    for (i=0; i<numObjs; i++) {
      /* find the array index of nestest cluster center */
      index = find_near                                    [i], clusters);

      membership[i] = index;
...
```


Active Data Structur



Possible Concurrencies:

N (independent)
D (sum reduction) ← euclid_dist_2()
k (min reduction)

Example Code (Maximization)

kmeans/seq_kmeans.c
lines: 148-162

```
....
    /* update new cluster centers : sum of objects located within */
        newClusterSize[index]++;
        for (j=0; j<numCoords; j++)
            newClusters[ind
    }

    /* average the sum and replace old cluster cente                    */
    for (i=0; i<numClusters; i++) {
        for (j=0; j<numCoords; j++) {
            if (newClusterSize[i] > 0)
                clusters[i][j] = newClusters[i][j] / newClusterSize[i];
            newClusters[i][j] = 0.0;   /* set back to 0 */
        }
        newClusterSize[i] = 0;       /* set back to 0 */
    }
...
```

prepare for next iteration

Example Code (Maximization)

kmeans/seq_kmeans.c
lines: 148-162

```
....
    /* update new cluster centers : sum of objects located within */
        newClusterSize[index]++;
        for (j=0; j<numCoords; j++)
          newClusters[ind
Active Data Structur
    objects:                N x D                membership                ters:                k x D
        }
        newClusterSize[i] = 0;       /* set bac
    }
...
```


Possible Concurrencies:
D (independent)
N (Histogram computation into k bins

The phases - concurrency

1. **Initialization:** Randomly select *k* cluster centers
2. **Expectation:** Assign closest center to each data point
   - *N* (independent)
   - *k* (min re
   - *D* (sum re
3. **Maximization:** Update centers nments
   - *D* (independent)
   - *N* (Histogram computation into k bins)
4. **Evaluate:** Re-iterate steps 2-3 until convergence

A Fast Implementation of *k*-means

- Following the process of problem solving with *k*-means:
  1. Understand the **current state**
  2. Observe the **internal representation**
  3. **Search** amon
  4. Select from a

Search Among Alternatives

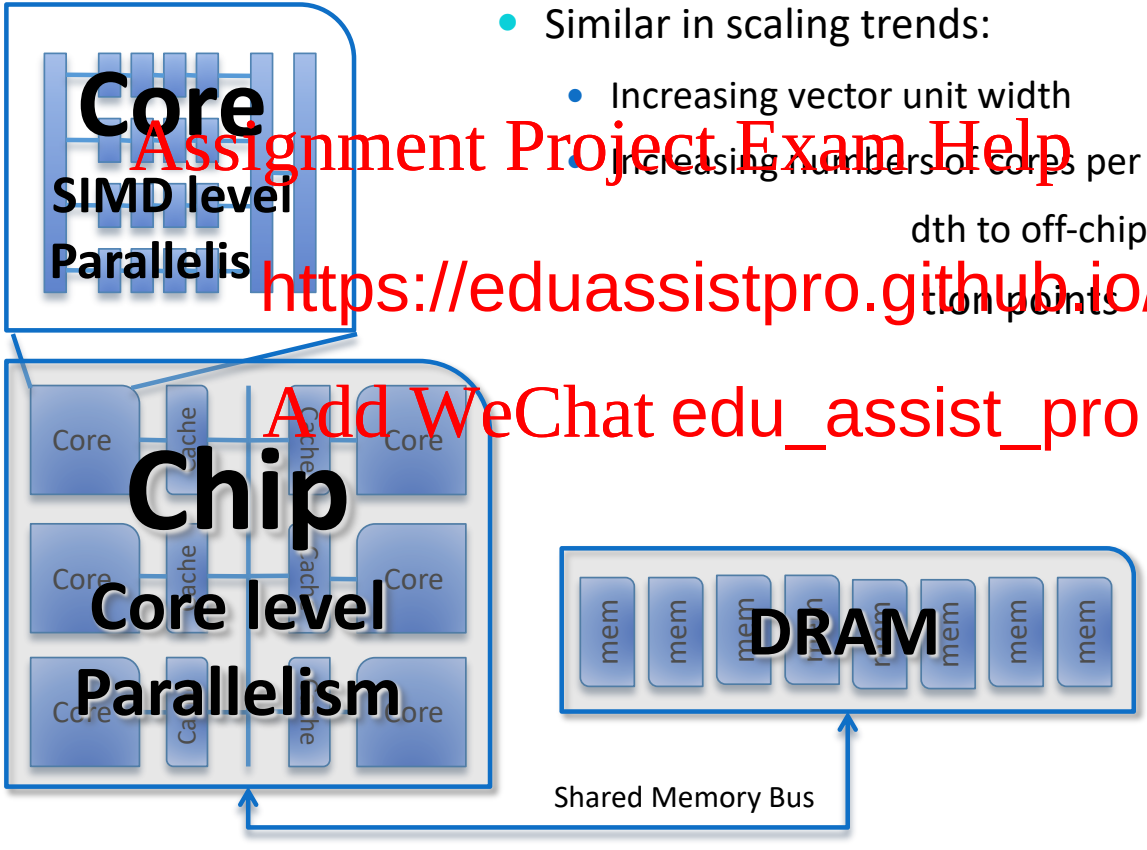
- Given the observed internal representations and the concurrency opportunities…

- What are the implementation **alternatives**?
  - Different mapp **rm parallelism**

- The **search** process
  - More complex than one **application con** **atform parallelism**

  - May want to sequentialize some operations:
    - Some parallel operations are as **"work-efficient"** as sequential operations
    - Reduction – sequential: O(N), Parallel: O(N logN)
  - One level of concurrency could map to multiple levels of parallelism

Multicore and Manycore Parallelism



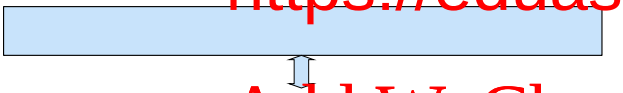
- Similar in scaling trends:
  - Increasing vector unit width
  - Increasing numbers of cores per die

dth to off-chip memory

tion points

Memory Hierarchy

- **Cache**:
  - A piece of fast memory close to the compute modules in a microprocessor
  - Allows faster access to a limited amount of data
  - Physical properties of wires and transistors determines trade-off between **cache capacity**



ity, (throughput), (latency)

tes, 0.1 GB/s, ~1-10B cycles

6 GB/s, ~1M cycles

16GB, 34.08 GB/s, ~200 cycles

8 MB, 108.8 GB/s, 26-31 cycles

256 KB, 108.8 GB/s, 12 cycles

32 KB Data Cache, 163.2 GB/s, 4-6 cycles

Intel Core2 – 2600k @ 3.4GHz
(viewed from one core)

Mapping Concurrency to Parallelism

- How does it map to the platform?
  - SIMD level parallelism
  - Core level parallelism
- How does it map
  - What data is re
  - What are the synchronization points in t
- Expectation & Maximization Phases
  - SIMD & core-level parallelism across data-points (N)
    - Update membership for each data point sequentially
      - Compute distance to each cluster center and select index with min. distance
    - Histogram computation (summation / assignment count for new clusters)
  - Other possible concurrency mappings?

A Fast Implementation of *k*-means

- Following the process of problem solving with *k*-means:
  1. Understand the **current state**
  2. Observe the **internal representation**
  3. **Search** amon
  4. Select from a
     - Does solution met required criteria
     - How to evaluate a mapping?
       - Efficiency: Runs quickly, makes good use of computational resources
       - Simplicity: Easy to understand code is easier to develop, debug, verify and modify
       - Portability: Should run on widest range of parallel computers
       - Scalability: Should be effective on a wide range of processing elements
     - Other considerations: Practicality, Hardware, Engineering cost

Evaluate Choice

- Expectation & Maximization Phases
  - SIMD & core-level parallelism across data-points (N)
    - Update membership for each data point sequentially
    - Histogram computation (summation / assignment count for new clusters)

  → OpenMP

- How we can evaluate the choice and m
  - Efficiency
  - Simplicity / Maintainability
  - Portability
  - Scalability

How to write fast code

- **Expose** concurrencies in applications and algorithms
  - 2/9 - "Concurrency Opportunity Recognition"
  - Mini-Projects (1-3) & Term Project
- **Exploit** parallelis
  - 2/4 - "Advanced Pat
  - Mini-Projects (1-3) & Term Project
- **Explore** mapping between concurrency
  - The rest of the semester….
  - Abstractions to support mapping of concurrencies to parallelisms
    - OpenMP [**Section 1**]
    - CUDA [**Section 2**]
    - Map-Reduce [**Section 3**]

How to Write Fast Code?

- Recognizing levels of concurrenc tion
- Effective mapping of concurrency in an application with parallelism of a platform

→ **Fast code**