

and Technology

### Large Scale Data Processing Lecture 1 - Basic notation, definitions

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## Overview

Big data – 5Vs

Types of processing

Flynn's taxonomy

Compilers

Python - GIL



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Flynn's taxonomy

Compile

hon - G



### Big data - 5Vs



### Big data - 5Vs

- Volume enormous volumes of data,
- Velocity data flows in time from multiple sources and with varying speed,
- Value data can be hard to obtain,
- Veracity (wiarygodność) biases, noise and abnormality in data,
- Variety many sources and types of data both structured and unstructured,

#### Sometimes this definition is extended to 7Vs:

- ▶ Validity if data correct and accurate for the intended use,
- Volatility how long is data valid and how long should it be stored,

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Python - Gl



- Sequential processing
- Distributed processing
- Parallel processing
- Concurrent processing



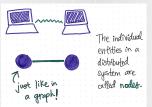
### Sequential processing

- processing that occurs in the order that it is received
- processor inevitably executes the same program



### Distributed processing

- more than one computer (or processor) run an application
- memory is distributed!
- includes parallel processing in which a single computer uses more than one CPU to execute programs



- nodes run operations, that decomposes original large problem
- operations within a node are fast; communication between nodes is slow
- nodes operates on their own clocks



### Parallel processing

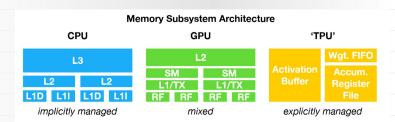
- Programs use parallel hardwares to execute computation more quickly
- Possible hardware:
  - multi-core processors
  - symmetric multiprocessors
  - graphics processing unit (GPU)
  - field-programmable gate arrays (FPGAs)
  - computer clusters
- Parallel programming requires to think about:
  - How does code divide original huge problem into smaller sub-problems?
  - ▶ Which is the optimal use of parallel hardware?



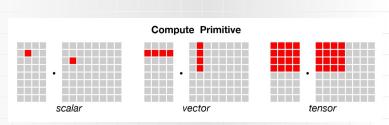
#### CPU vs GPU vs TPU

#### Types of processing

► Memory Subsystem Architecture



Compute Primitive





### CPU vs GPU vs TPU

- Dimension of data:
  - ► CPU: 1 X 1 data unit
  - GPU: 1 X N data unit
  - ► TPU: N X N data unit
- Performance
  - CPU can handle tens of operation per cycle
  - GPU can handle tens of thousands of operation per cycle
  - ► TPU can handle upto 128000 operations per cycle
- Purpose
  - CPU designed to solve every computational problem in a general fashion; cache and memory optimal for any general programming problem
  - GPU designed to accelerate the rendering of graphics
  - ► TPU designed to accelerate deep learning tasks developed with TensorFlow

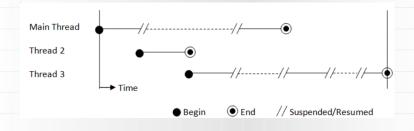


### Concurrent processing

- concurrency is when multiple sequences of operations are run in overlapping periods of time
- task A and task B both need to happen independently of each other, and A starts running, and then B starts before A is finished
- address limits of resources
- taxonomy:
  - multitasking
  - multiprocessing
  - preemption: preemptive, cooperative

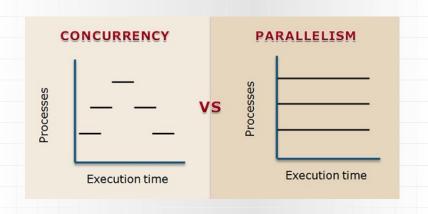


### Concurrency example





### Concurrent vs parallel





## Overview

a – 5Vs

processing

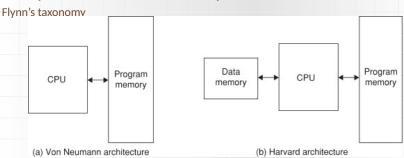
Flynn's taxonomy

Compiler

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### Computer architecture recap



	Architecture	
Criterion	(a)	(b)
Memory/Bus	one	two
Complexity	simple	complicated
Single instruction	two clock cycles	one clock cycle
Performance	low	high (pipelining)
Cost	cheap	high



### Data and Instruction streams

Flynn's taxonomy

In Flynn's taxonomy we use following criteria to define system architectures:

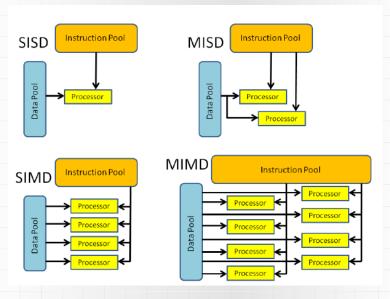
- number of instructions stream(s) single or multiple,
- number of data stream(s) single or multiple,

Hence we get following acronyms: (S/M) I (S/M) D



### Architectures

Flynn's taxonomy





# Examples

Flynn's taxonomy

- ➤ SISD sequential computer; von Neumann architecture; many PCs before 2010 and mainframes
- ► SIMD GPU; modern CPUs with vectorization
- ► MISD systolic computer; fault-tolerant systems
- MIMD cluster, where each processor is programmed separately; Intel Xeon Phi; multi-core superscalar processors; distributed systems



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Compilers

Dython C



## Compilation process, optimizations

#### Compilers

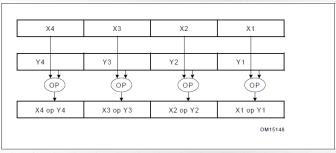
- we won't get into the details of the compilation process,
- programming languages:
  - interpreted (e.g., Python, JavaScript),
  - compiled (e.g., C, C++, Rust),
  - mixed (e.g., Java Bytecode+JVM, Python in some cases),
- interpreted PLs are in general slower than compiled ones (however there is JIT),
- this is caused by heavy optimizations, which are applied in the compilation process, e.g.:
  - ► removal of unused code if the compiler detects that some variable, function etc. is declared, but is never used, then all instructions concerning that variable are removed (can be problematic in some cases like embedded systems; see: volatile in C/C++)
  - unrolling loops into vector operations ...



### Vectorization

#### Compilers

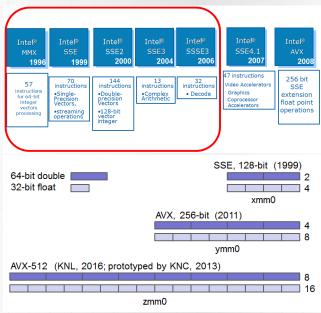
- ▶ 32/64-bit CPUs use general purpose registers with a capacity of 32/64 bits each,
- however there are some special registers with a size equal to the multiple of the architecture size (multiples of 32/64 bits),
- operations on these registers take one CPU cycle,
- hence we can speed up computations





### **Vector registers**

Compilers





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a - 5Vs

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Compile

Python - GIL

```
import time
 1
 2
 3
    def countdown(n):
        while n > 0:
 5
           n -= 1
 6
 7
 8
    def main():
 9
        n = 50000000
10
11
        st = time.time()
12
      countdown(n)
13
        end = time.time()
14
15
        print('Processing took:', end - st, '(s)')
16
17
18
    if __name__ == '__main__':
19
        main()
20
```

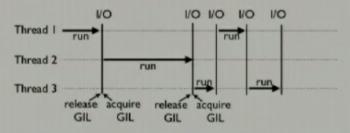
It takes about 3.09 seconds

```
from threading import Thread
 2
    import time
 3
4
    def countdown(n):
5
6
         while n > 0:
             n = 1
8
9
    def main():
10
         n = 50000000
11
12
13
        t1 = Thread(target=countdown, args=(n//2,))
         t2 = Thread(target=countdown, args=(n//2,))
14
15
        st = time.time()
16
17
        t1.start(); t2.start()
         t1.join(); t2.join()
18
         end = time.time()
19
20
         print('Processing took:', end - st, '(s)')
21
22
23
24
    if __name__ == '__main__':
         main()
25
```

It takes about 5.37 seconds!

- the main reason for that is the Global Interpreter Lock,
- from Python 3.2 there were some improvements,
- ► GIL ensures that only one thread in the interpreter runs at a given time,
- why? needed for implementation simplification (memory managements, calls to external C functions etc.),

With the GIL, you get cooperative multitasking



- · When a thread is running, it holds the GIL
- GIL released on I/O (read, write, send, recv, etc.)

- the problem occurs especially for CPU bound threads (very little I/O),
- additionally there is no smart thread scheduling algorithm,
- this could lead to a situation where only one thread is running all the time and the others wait,
- together with a special check mechanism in the Python interpreter implementation this can cause extreme slowdown of running times



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