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Large Scale Data Processing

Lecture 1 – Basic notation, definitions

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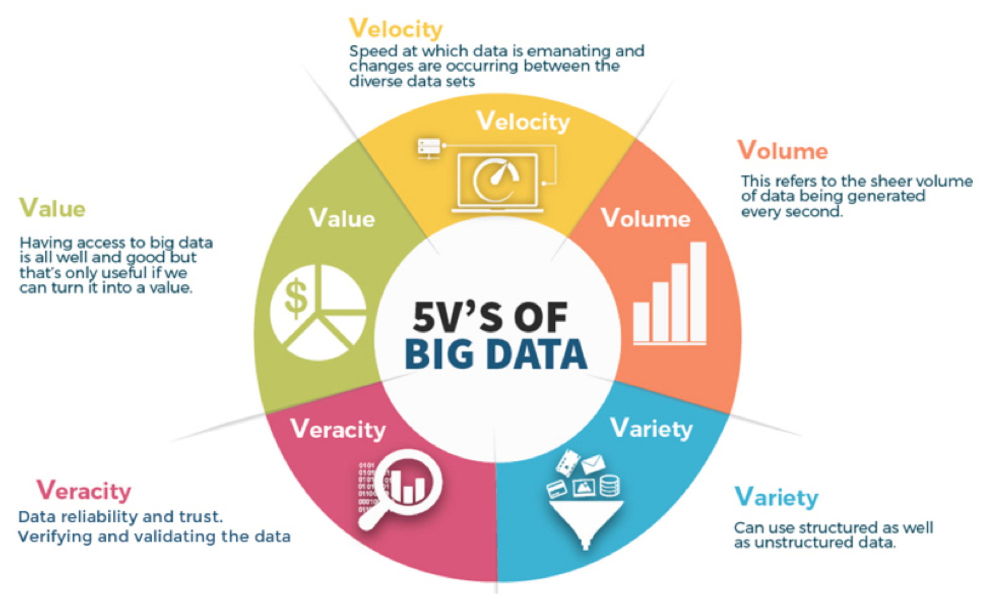
Overview

- Big data – 5Vs
- Types of processing
- Flynn’s taxonomy
- Compilers
- Python - GIL
- Paralellism in ML
- I/O
- POSIX I/O vs HPC
- Synchronous processing
- Asynchronous processing

Overview

Big data – 5Vs


Velocity
Speed at which data is emanating and changes are occurring between the diverse data sets
Volume
This refers to the sheer volume of data being generated every second.
Value
Having access to big data is all well and good but that's only useful if we can turn it into a value.
Veracity
Data reliability and trust.
Verifying and validating the data
Variety
Can use structured as well as unstructured data.
Velocity
Volume
Value
Veracity
Variety
5V'S OF
BIG DATA

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,

Overview

Types of processing

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

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Sequential processing

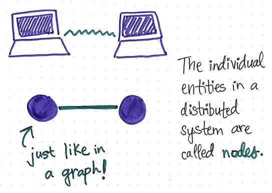
Types of processing

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

Distributed processing

Types of 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

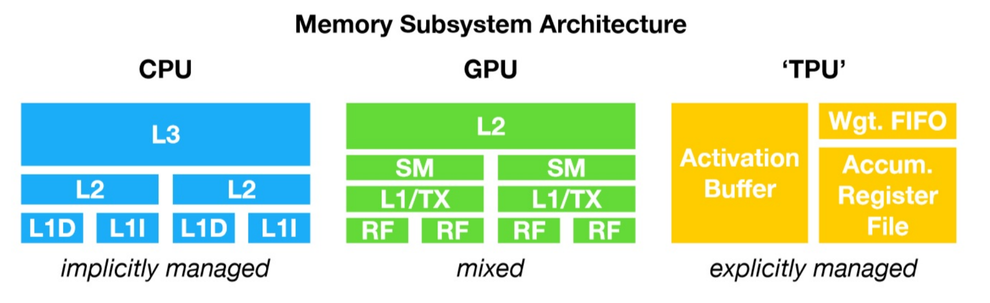
Types of processing

- 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

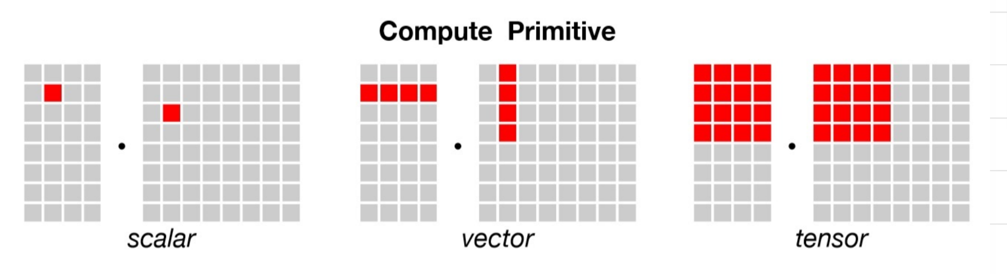
- Memory Subsystem Architecture



CPU vs GPU vs TPU

Types of processing

- Compute Primitive



CPU vs GPU vs TPU

Types of processing

- 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

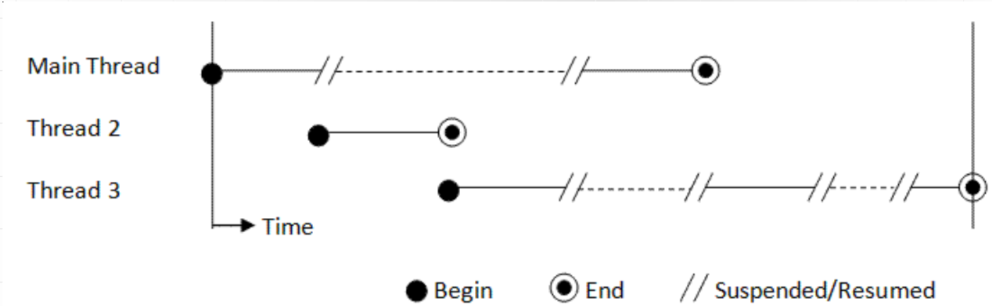
Concurrent processing

Types of 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

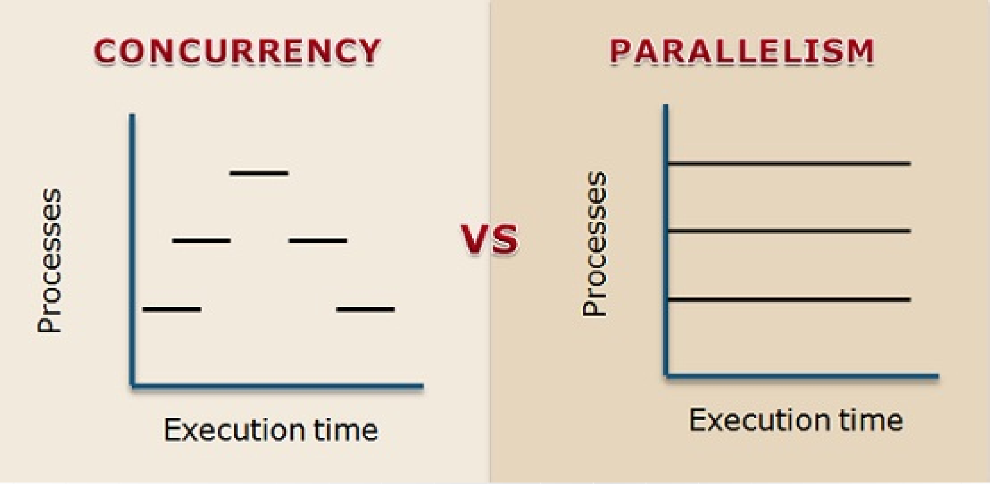
Concurrency example

Types of processing



Concurrent vs parallel

Types of processing



Overview

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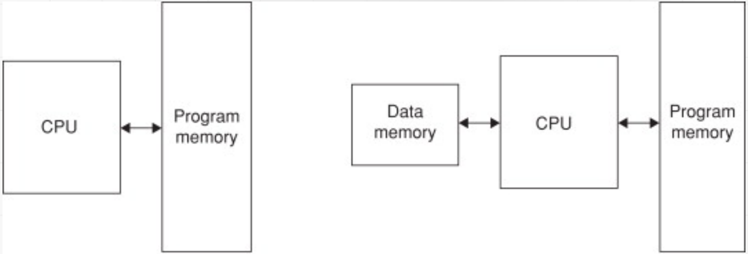
Computer architecture recap

Flynn's taxonomy



(a) Von Neumann architecture (b) Harvard architecture

Criterion	Architecture (a)	Architecture (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

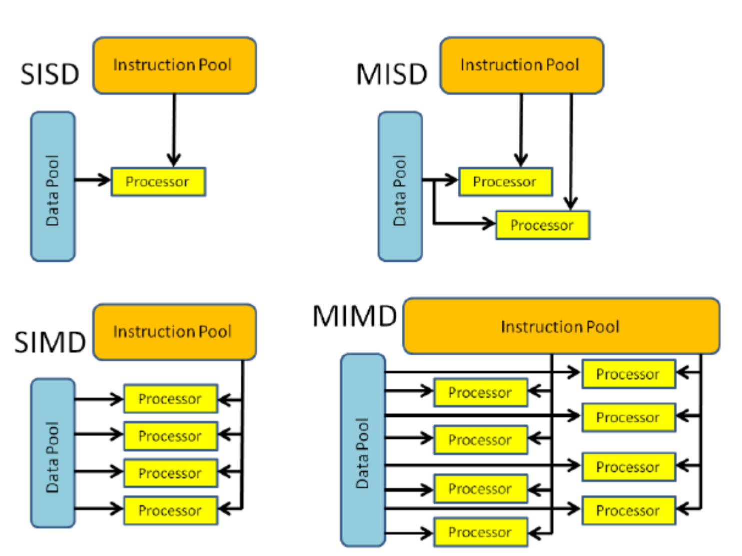
In Flynn’s taxonomy we use following criteria to define system architectures:

- 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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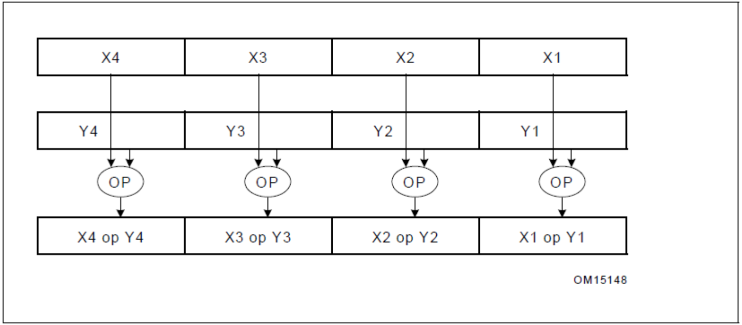
Compilation process, optimizations

- 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

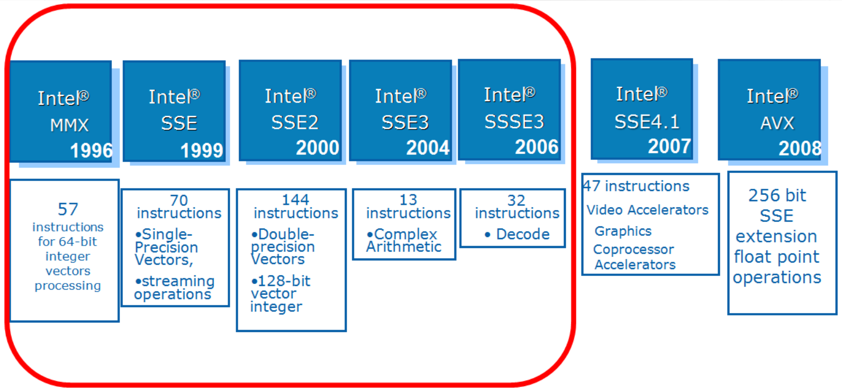
Compilers

- 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



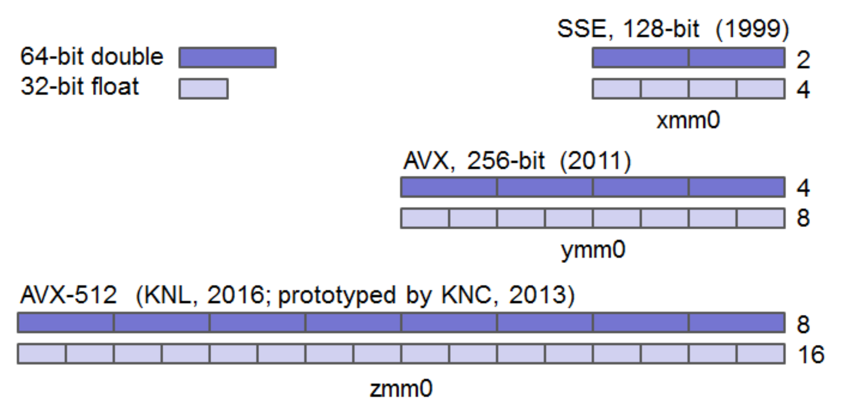
Vector registers

Compilers



Vector registers

Compilers



Overview

Python - GIL

```python
import time


def countdown(n):
    while n > 0:
        n -= 1


def main():
    n = 50000000

    st = time.time()
    countdown(n)
    end = time.time()

    print('Processing took:', end - st, '(s)')


if __name__ == '__main__':
    main()
```

It takes about **3.09 seconds**

Python - GIL

```python
from threading import Thread
import time


def countdown(n):
    while n > 0:
        n -= 1


def main():
    n = 50000000

    t1 = Thread(target=countdown, args=(n//2,))
    t2 = Thread(target=countdown, args=(n//2,))

    st = time.time()
    t1.start(); t2.start()
    t1.join(); t2.join()
    end = time.time()

    print('Processing took:', end - st, '(s)')


if __name__ == '__main__':
    main()
```

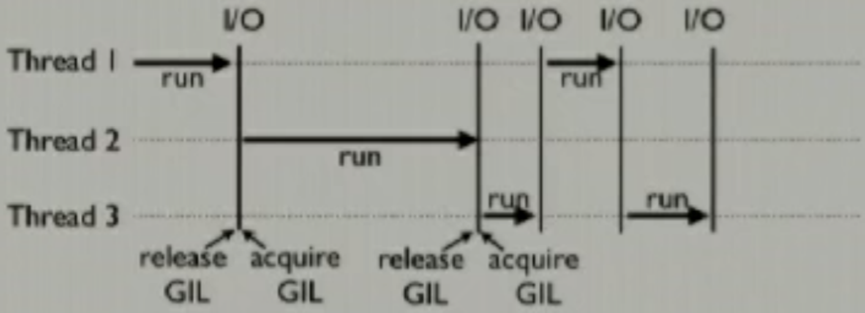
It takes about **5.37 seconds**!

Python - GIL

- 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.),

Python - GIL

- 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.)

Python - GIL

- 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

Overview

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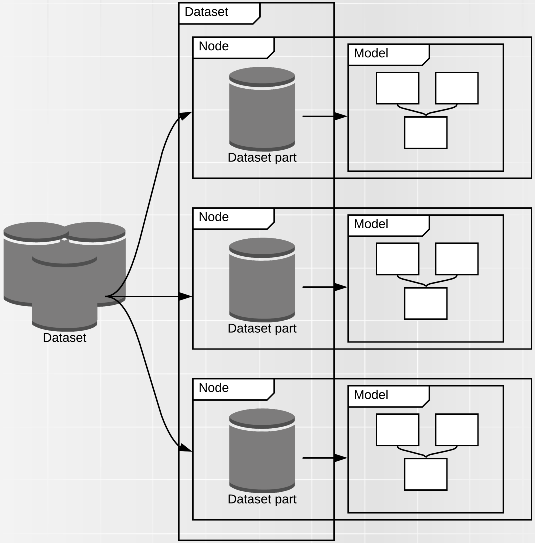
Data Parallelism

Paralellism in ML

- same model on each distributed node
- split data among nodes
- repeat
  - train
  - synchronize

Data Parallelism

Paralellism in ML



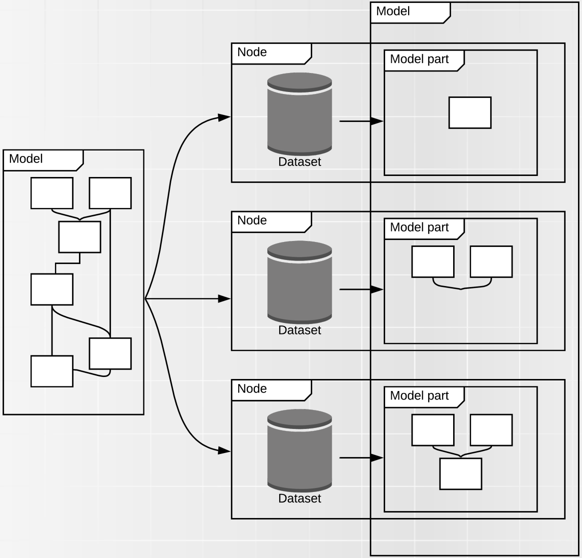
Task Parallelism

Paralellism in ML

- parts of model on each distributed node
- same data on each node, or get results of previous part of model

Task Parallelism

Paralellism in ML



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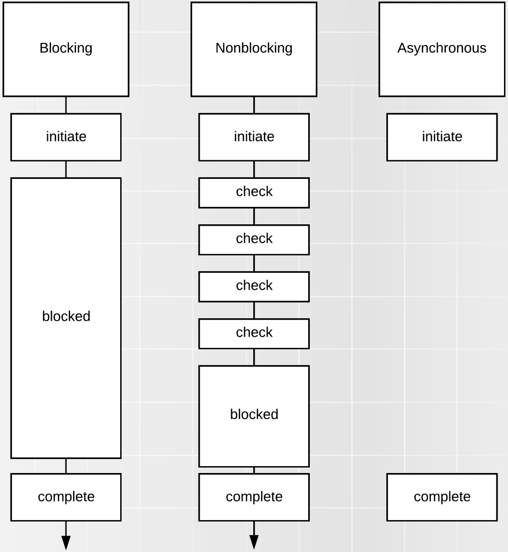
I/O

- blocking
- nonblocking
- asynchronous

I/O


Blocking
initiate
blocked
complete
Nonblocking
initiate
check
check
check
check
blocked
complete
Asynchronous
initiate
complete

Overview

POSIX I/O vs HPC

- POSIX is state-full, OS track all file descriptors
- POSIX gives a lot of unneeded metadata
- POSIX has strong consistency - after write, you can read it

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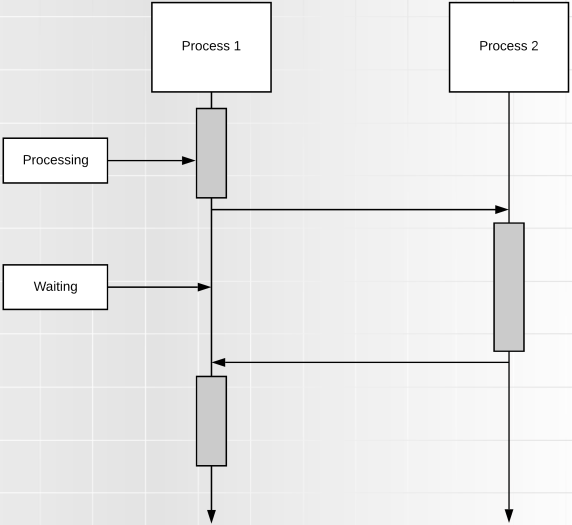
POSIX I/O vs HPC

- HPC applications ensures that two process do not write to same file part
- in HPC, consistency is reduced to smaller subset than whole cluster
- noatime

Overview

Synchronous processing

- make request
- wait for response
- continue processing



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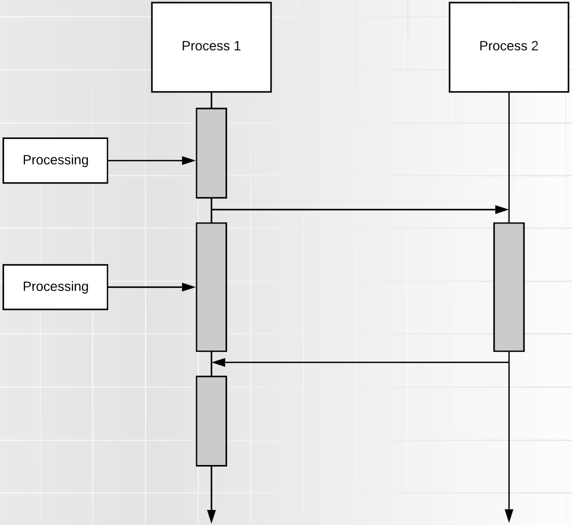
Asynchronous processing

- make request
- continue processing
- request result arrives, do anything with it
- continue processing



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