Part II

Foundations

3 Introduction

Parallel Computing

A parallel computer is a collection of processors usually of the same type, interconnected to allow coordination and exchange of data.

The processors are primarily used to jointly solve a given problem.

Distributed Systems

A set of possibly many different types of processors are distributed over a larger geographic area.

Processors do not work on a single problem.

Some processors may act in a malicous way.

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Cost measures

How do we evaluate sequential algorithms?

- time efficiency
- space utilization
- energy consumption
- programmability
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Asymptotic bounds (e.g., for running time) often give a good indication on the algorithms performance on a wide variety of machines.

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- statements usually only hold for restricted types of parallel machine as parallel computers may have vastly different characteristics (in particular w.r.t. communication)

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Speedup

Suppose a problem P has sequential complexity $T^*(n)$, i.e., there is no algorithm that solves P in time $o(T^*(n))$.

Definition 1

The speedup $S_p(n)$ of a parallel algorithm A that requires time $T_p(n)$ for solving P with p processors is defined as

$$S_p(n) = \frac{T^*(n)}{T_p(n)} \enspace .$$

Clearly, $S_p(n) \leq p$. **Goal:** obtain $S_p(n) \approx p$.

It is common to replace $T^*(n)$ by the time bound of the best **known** sequential algorithm for P!

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Efficiency

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The efficiency of a parallel algorithm A that requires time $T_p(n)$ when using p processors on a problem of size n is

$$E_p(n) = \frac{T_1(n)}{pT_p(n)} \ .$$

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Note that $E_p(n) \leq \frac{T_1(n)}{pT_\infty(n)}$. Hence, the efficiency goes down rapidly if $p \geq T_1(n)/T_\infty(n)$.

Disadvantage: cost-measure does not relate to the optimum sequential algorithm.

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Parallel Models — Requirements

Simplicity
A model should allow to easily analyze various performance measures (speed, communication, memory utilization etc.).

Results should be as hardware-independent as possible.

Implementability
Parallel algorithms developed in a model should be easily implementable on a parallel machine.

Theoretical analysis should carry over and give meaningful performance estimates.

A real satisfactory model does not exist!

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DAG model — computation graph

- nodes represent operations (single instructions or larger blocks)
- edges represent dependencies (precedence constraints)
- closely related to circuits; however there exist many different variants
- branching instructions cannot be modelled
- completely hardware independent
- scheduling is not defined

Often used for automatically parallelizing numerical computations.

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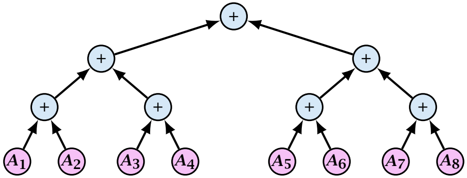
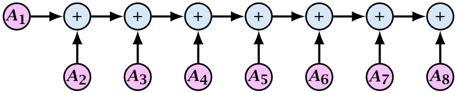
Example: Addition





Here, vertices without incoming edges correspond to input data.

The graph can be viewed as a data flow graph.

DAG model — computation graph

The DAG itself is not a complete algorithm. A scheduling implements the algorithm on a parallel machine, by assigning a time-step t_v and a processor p_v to every node.

Definition 3

A scheduling of a DAG $G = (V, E)$ on p processors is an assignment of pairs (t_v, p_v) to every internal node $v \in V$, s.t.,

- $p_v \in \{1, \dots, p\}$; $t_v \in \{1, \dots, T\}$
- $t_u = t_v \Rightarrow p_u \neq p_v$
- $(u, v) \in E \Rightarrow t_v \geq t_u + 1$

where a non-internal node x (an input node) has $t_x = 0$.
T is the length of the schedule.

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The parallel complexity of a DAG is defined as

$$T_p(n) = \min_{\text{schedule } S} \{T(S)\} \ .$$

$T_1(n)$: #internal nodes in DAG
$T_\infty(n)$: diameter of DAG

Clearly,

$$T_p(n) \geq T_\infty(n)$$
$$T_p(n) \geq T_1(n)/p$$

Lemma 4
A schedule with length $\mathcal{O}(T_1(n)/p + T_\infty(n))$ can be found easily.

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Finding an optimal schedule is in general NP-complete.

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Note that the DAG model as defined is a non-uniform model of computation.

In principle, there could be a different DAG for every input size n.

An algorithm (e.g. for a RAM) must work for every input size and must be of finite description length.

Hence, specifying a different DAG for every n has more expressive power.

Also, this is not really a complete model, as the operations allowed in a DAG node are not clearly defined.

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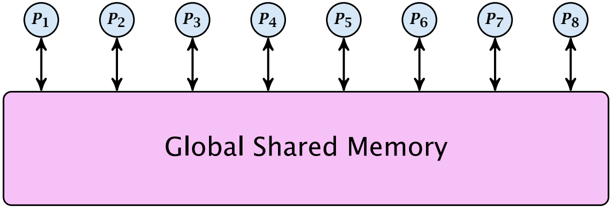

All processors are synchronized.

In every round a processor can:

- read a register from global memory into local memory
- do a local computation à la RAM
- write a local register into global memory

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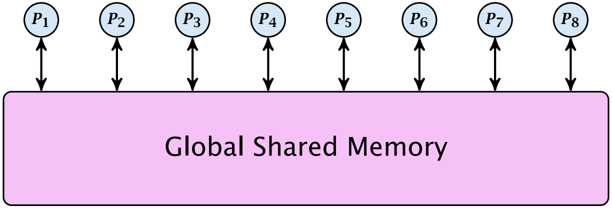

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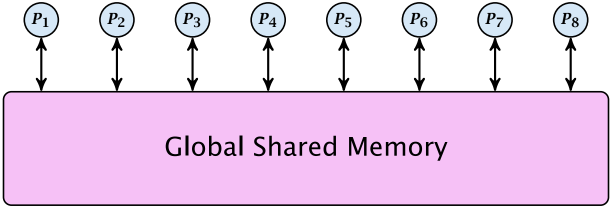

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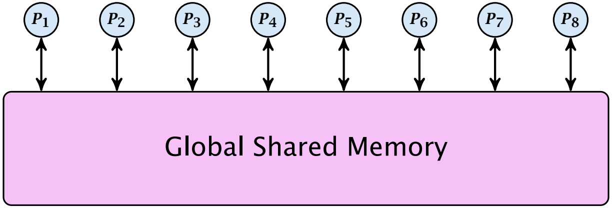

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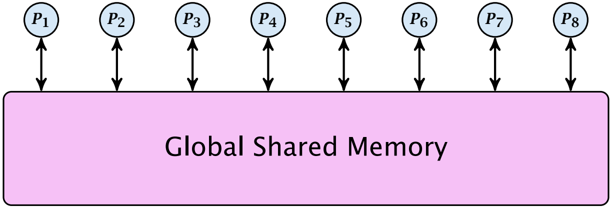

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PRAM Model

Every processor executes the same program.

However, the program has access to two special variables:

- p: total number of processors
- $id \in \{1, \dots, p\}$: the id of the current processor

The following (stupid) program copies the content of the global register $x[1]$ to registers $x[2] \dots x[p]$.

Algorithm 1 copy

```
1: if $id = 1$ then $round \leftarrow 1$
2: while $round \le p$ and $id = round$ do
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PRAM Model

Every processor executes the same program.

However, the program has access to two special variables:

- p: total number of processors
- $id \in \{1, \dots, p\}$: the id of the current processor

The following (stupid) program copies the content of the global register $x[1]$ to registers $x[2] \dots x[p]$.

Algorithm 1 copy

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- processors can effectively execute different code because of branching according to *id*
- however, not arbitrarily; still uniform model of computation

Often it is easier to explicitly define which parts of a program are executed in parallel:

Algorithm 2 sum

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// computes sum of $x[1] \ldots x[p]$
// red part is executed only by processor 1
$r \leftarrow 1$
while $2^r \leq p$ do
        for $id \bmod 2^r = 1$ pardo
        // only executed by processors whose $id$ matches
                $x[id] = x[id] + x[id + 2^{r-1}]$
        $r \leftarrow r + 1$
return $x[1]$
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Different Types of PRAMs

Simultaneous Access to Shared Memory:

- EREW PRAM:
  simultaneous access is not allowed
- CREW PRAM:
  concurrent read accesses to the same location are allowed; write accesses have to be exclusive
- CRCW PRAM:
  concurrent read and write accesses allowed
  - commom CRCW PRAM
    all processors writing to $x[i]$ must write same value
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    values may be different; an arbitrary processor succeeds
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The above is an EREW PRAM algorithm.

On a CREW PRAM we could replace Line 4 by
for $1 \le id \le p$ **pardo**

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PRAM Model — remarks

- similar to a RAM we either need to restrict the size of values that can be stored in registers, or we need to have a non-uniform cost model for doing a register manipulation (cost for manipulating $x[i]$ is proportional to the bit-length of the largest number that is ever being stored in $x[i]$)
  - in this lecture: uniform cost model but we are not exploiting the model
- global shared memory is very unrealistic in practise as uniform access to all memory locations does not exist
- global synchronziation is very unrealistic; in real parallel machines a global synchronization is very costly
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Network of Workstations — NOWs

- interconnection network represented by a graph $G = (V, E)$
- each $v \in V$ represents a processor
- an edge $\{u, v\} \in E$ represents a two-way communication link between processors u and v
- network is asynchronous
- all coordination/communiation has to be done by explicit message passing

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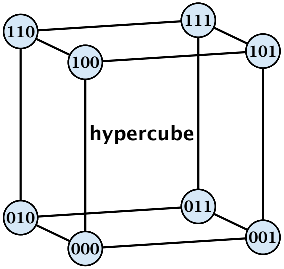
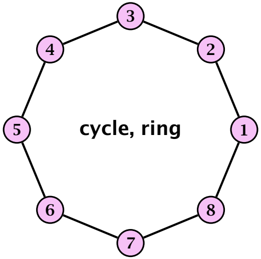
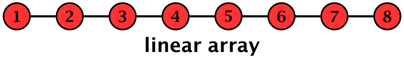
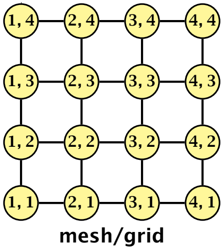
Typical Topologies









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Computing the sum on a d-dimensional hypercube. Note that $x[0] \ldots x[2^d - 1]$ are stored at the individual nodes.

Processors are numbered consecutively starting from 0

Algorithm 4 sum

```
// computes sum of $x[0] \ldots x[2^d - 1]$
$r \leftarrow 1$
while $2^r \le 2^d$ do // $p = 2^d$
    if $id \bmod 2^r = 0$ then
        $temp \leftarrow$ receive$(id + 2^{r-1})$
        $x[id] = x[id] + temp$
    if $id \bmod 2^r = 2^{r-1}$ then
        send$(x[id], id - 2^{r-1})$
    $r \leftarrow r + 1$
if $id = 0$ then return $x[id]$
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Remarks

- One has to ensure that at any point in time there is at most one active communication along a link
- There also exist synchronized versions of the model, where in every round each link can be used once for communication
- In particular the asynchronous model is quite realistic
- Difficult to develop and analyze algorithms as a lot of low level communication has to be dealt with
- Results only hold for one specific topology and cannot be generalized easily

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Performance of PRAM algorithms

Suppose that we can solve an instance of a problem with size n with $P(n)$ processors and time $T(n)$.

We call $C(n) = T(n) \cdot P(n)$ the time-processor product or the cost of the algorithm.

The following statements are equivalent

- $P(n)$ processors and time $\mathcal{O}(T(n))$
- $\mathcal{O}(C(n))$ cost and time $\mathcal{O}(T(n))$
- $\mathcal{O}(C(n)/p)$ time for any number $p \leq P(n)$ processors
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Suppose we have a PRAM algorithm that takes time $T(n)$ and work $W(n)$, where work is the total number of operations.

We can nearly always obtain a PRAM algorithm that uses time at most

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parallel steps on p processors.

Idea:

- $W_i(n)$ denotes operations in parallel step i, $1 \le i \le T(n)$
- simulate each step in $\lceil W_i(n)/p \rceil$ parallel steps
- then we have

$$\sum_i \lceil W_i(n)/p \rceil \le \sum_i \left(\lfloor W_i(n)/p \rfloor + 1 \right) \le \lfloor W(n)/p \rfloor + T(n)$$

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$$\sum_i \lceil W_i(n)/p \rceil \leq \sum_i \left(\lfloor W_i(n)/p \rfloor + 1\right) \leq \lfloor W(n)/p \rfloor + T(n)$$

Performance of PRAM algorithms

Suppose we have a PRAM algorithm that takes time $T(n)$ and work $W(n)$, where work is the total number of operations.

We can nearly always obtain a PRAM algorithm that uses time at most

$$\lfloor W(n)/p \rfloor + T(n)$$

parallel steps on p processors.

Idea:

- $W_i(n)$ denotes operations in parallel step i, $1 \le i \le T(n)$
- simulate each step in $\lceil W_i(n)/p \rceil$ parallel steps
- then we have

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Why nearly always?

We need to assign processors to operations.

- every processor p_i needs to know whether it should be active
- in case it is active it needs to know which operations to perform

design algorithms for an arbitrary number of processors; keep total time and work low

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for $p = \mathcal{O}(T^*(n)/T(n))$.

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Algorithm for computing the sum has work $W(n) = \mathcal{O}(n)$. optimal

$T(n) = \mathcal{O}(\log n)$. Hence, we achieve an optimal speedup for $p = \mathcal{O}(n/\log n)$.

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Communication Cost

When we differentiate between local and global memory we can analyze communication cost.

We define the communication cost of a PRAM algorithm as the worst-case traffic between the local memory of a processor and the global shared memory.

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Algorithm 5 MatrixMult(A, B, n)

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1: Input: $n \times n$ matrix $A$ and $B$; $n = 2^k$
2: Output: $C = AB$
3: for $1 \le i, j, \ell \le n$ pardo
4:     $X[i, j, \ell] \leftarrow A[i, \ell] \cdot B[\ell, j]$
5: for $r \leftarrow 1$ to $\log n$
6:     for $1 \le i, j \le n$; $\ell \bmod 2^r = 1$ pardo
7:         $X[i, j, \ell] \leftarrow X[i, j, \ell] + X[i, j, \ell + 2^{r-1}]$
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What happens if we have n processors?

Phase 1

p_i computes $X[i,j,\ell] = A[i,\ell] \cdot B[\ell,j]$ for all $1 \le j,\ell \le n$

n^2 time; n^2 communication for every processor

Phase 2 (round r)

p_i updates $X[i,j,\ell]$ for all $1 \le j \le n; 1 \le \ell \bmod 2^r = 1$

$\mathcal{O}(n \cdot n/2^r)$ time; no communication

Phase 3

p_i writes i-th row into $C[i,j]$'s.

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Alternative Algorithm

Split matrix into blocks of size $n^{2/3} \times n^{2/3}$.

$$\underbrace{\begin{pmatrix} A_{1,1} & A_{1,2} & A_{1,3} & A_{1,4} \\ A_{2,1} & A_{2,2} & A_{2,3} & A_{2,4} \\ A_{3,1} & A_{3,2} & A_{3,3} & A_{3,4} \\ A_{4,1} & A_{4,2} & A_{4,3} & A_{4,4} \end{pmatrix}}_{A} \cdot \underbrace{\begin{pmatrix} B_{1,1} & B_{1,2} & B_{1,3} & B_{1,4} \\ B_{2,1} & B_{2,2} & B_{2,3} & B_{2,4} \\ B_{3,1} & B_{3,2} & B_{3,3} & B_{3,4} \\ B_{4,1} & B_{4,2} & B_{4,3} & B_{4,4} \end{pmatrix}}_{B} = \underbrace{\begin{pmatrix} C_{1,1} & C_{1,2} & C_{1,3} & C_{1,4} \\ C_{2,1} & C_{2,2} & C_{2,3} & C_{2,4} \\ C_{3,1} & C_{3,2} & C_{3,3} & C_{3,4} \\ C_{4,1} & C_{4,2} & C_{4,3} & C_{4,4} \end{pmatrix}}_{C}$$

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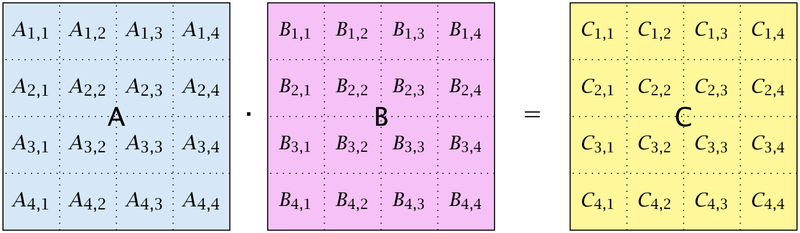
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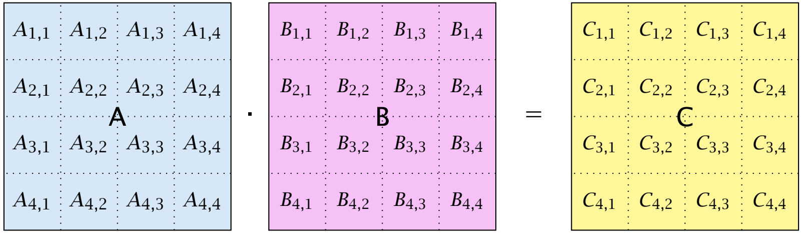

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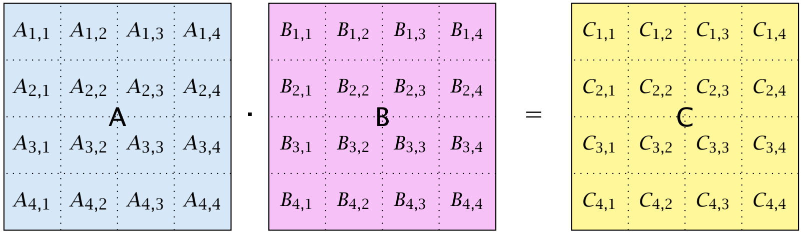
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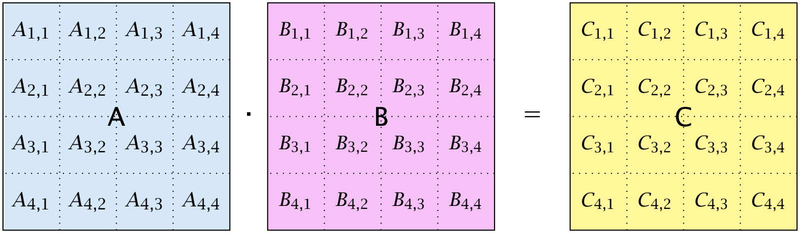
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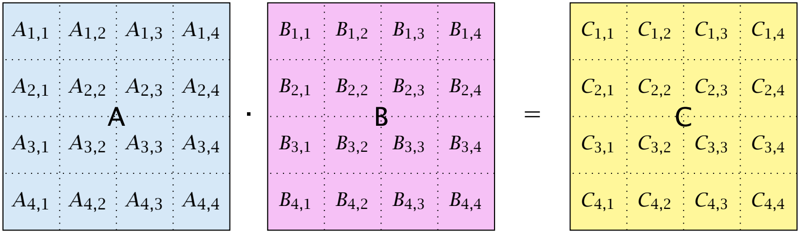
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Note that $C_{i,j} = \sum_\ell A_{i,\ell} B_{\ell,j}$.

Now we have the same problem as before but $n' = n^{1/3}$ and a single multiplication costs time $\mathcal{O}((n^{2/3})^3) = \mathcal{O}(n^2)$. An addition costs $n^{4/3}$.

work for multiplications: $\mathcal{O}(n^2 \cdot (n')^3) = \mathcal{O}(n^3)$
work for additions: $\mathcal{O}(n^{4/3} \cdot (n')^3) = \mathcal{O}(n^3)$
time: $\mathcal{O}(n^2) + \log n' \cdot \mathcal{O}(n^{4/3}) = \mathcal{O}(n^2)$

Alternative Algorithm

The communication cost is only $\mathcal{O}(n^{4/3}\log n')$ as a processor in the original problem touches at most $\log n$ entries of the matrix.

Each entry has size $\mathcal{O}(n^{4/3})$.

The algorithm exhibits less parallelism but still has optimum work/runtime for just n processors.

much, much better in practise

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