



# Computational Complexity Theory

## Lecture 3: Reductions; NP-completeness; Cook-Levin theorem

Department of Computer Science,  
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# Recap: Decision Problems

Decision problems  $\leftrightarrow$  Boolean functions  $\leftrightarrow$  Languages

- **Definition.** We say a TM  $M$  decides a language  $L \subseteq \{0,1\}^*$  if  $M$  computes  $f_L$ , where  $f_L(x) = 1$  if and only if  $x \in L$ .

The characteristic function of  $L$ .

# Recap: Complexity Class P

- Let  $T: \mathbb{N} \rightarrow \mathbb{N}$  be some function.
- **Definition:** A language  $L$  is in  $\text{DTIME}(T(n))$  if there's a TM that decides  $L$  in time  $O(T(n))$ .
- **Definition:** Class  $P = \bigcup_{c > 0} \text{DTIME}(n^c)$ .  
  
Deterministic polynomial-time

# Recap: Problems in P

- Cycle detection
- Solvability of a system of linear equations
- Perfect matching
- Planarity testing
- Primality testing

# Recap: Polynomial-time TM

- **Definition.** A TM  $M$  is a *polynomial-time* TM if there's a polynomial function  $q: \mathbb{N} \rightarrow \mathbb{N}$  such that for every input  $x \in \{0,1\}^*$ ,  $M$  halts within  $q(|x|)$  steps.

**Polynomial function.**  $q(n) = O(n^c)$  for some constant  $c$ .

# Recap: Class FP

- What if a problem is not a decision problem? Like the task of adding two integers.
- One way is to focus on the **i-th** bit of the output and make it a decision problem.
- We say that a problem or a function  $f: \{0,1\}^* \rightarrow \{0,1\}^*$  is in **FP** (functional **P**) if there's a polynomial-time TM that computes **f**.

# Complexity Class FP : Examples

- Greatest Common Divisor
- Counting paths in a DAG
- Maximum matching
- Linear Programming
- Factoring Polynomials

# Recap: Class NP

- Solving a problem is generally *harder* than verifying a given solution to the problem.
- Class **NP** captures the set of decision problems whose solutions are efficiently verifiable.

Nondeterministic polynomial-time



# Recap: Class NP

- **Definition.** A language  $L \subseteq \{0,1\}^*$  is in NP if there's a polynomial function  $p: \mathbb{N} \rightarrow \mathbb{N}$  and a polynomial-time TM  $M$  (called the verifier) such that for every  $x$ ,

$$x \in L \iff \exists u \in \{0,1\}^{p(|x|)} \text{ s.t. } M(x, u) = 1$$

$u$  is called a certificate or witness for  $x$  (w.r.t  $L$  and  $M$ ), if  $x \in L$ .

# Recap: Class NP

- **Definition.** A language  $L \subseteq \{0,1\}^*$  is in **NP** if there's a polynomial function  $p: \mathbb{N} \rightarrow \mathbb{N}$  and a polynomial-time TM **M** (called the verifier) such that for every  $x$ ,

$$x \in L \iff \exists u \in \{0,1\}^{p(|x|)} \text{ s.t. } M(x, u) = 1$$

- Class **NP** contains those problems (languages) which have such efficient verifiers.

# Recap: Problems in NP

- Vertex cover
- 0/1 integer programming
- Integer factoring
- Graph isomorphism
- 2-Diophantine solvability

# Recap: Is $P = NP$ ?

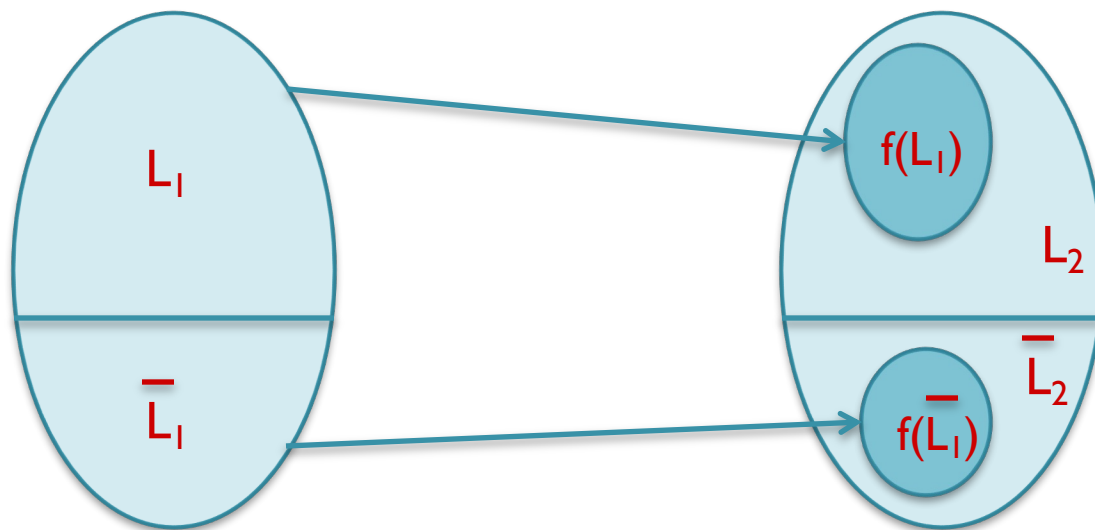
- Obviously,  $P \subseteq NP$ .
- Whether or not  $P = NP$  is an outstanding open question in mathematics and TCS!
- Solving a problem does seem harder than verifying its solution, so most people believe that  $P \neq NP$ .

# Reductions

# Polynomial-time reduction

- **Definition.** We say a language  $L_1 \subseteq \{0,1\}^*$  is polynomial-time (Karp) reducible to a language  $L_2 \subseteq \{0,1\}^*$  if there's a polynomial-time computable function  $f$  s.t.

$$x \in L_1 \iff f(x) \in L_2$$



# Polynomial-time reduction

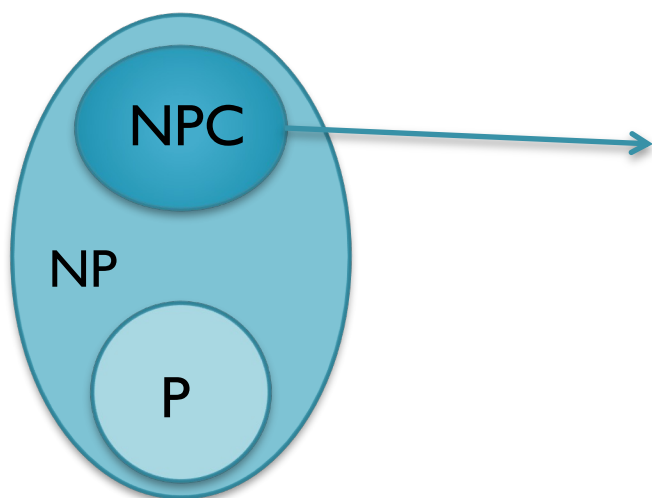
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- **Notation.**  $L_1 \leq_p L_2$
- **Observe.** If  $L_1 \leq_p L_2$  and  $L_2 \leq_p L_3$  then  $L_1 \leq_p L_3$ .  
(*Transitivity*)

# NP-completeness

- **Definition.** A language  $L'$  is *NP-hard* if for every  $L$  in  $NP$ ,  $L \leq_p L'$ . Further,  $L'$  is *NP-complete* if  $L'$  is in  $NP$  and is NP-hard.
- **Observe.** If  $L'$  is NP-hard and  $L'$  is in  $P$  then  $P = NP$ . If  $L'$  is NP-complete then  $L'$  in  $P$  if and only if  $P = NP$ .



Hardest problems inside  $NP$  in the sense that if one NPC problem is in  $P$  then all problems in  $NP$  is in  $P$ .



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- **Observe.** If  $L'$  is *NP-hard* and  $L'$  is in  $P$  then  $P = NP$ . If  $L'$  is *NP-complete* then  $L'$  is in  $P$  if and only if  $P = NP$ .
- **[Homework].** Let  $L_1 \subseteq \{0,1\}^*$  be any language and  $L_2$  be a language in  $NP$ . If  $L_1 \leq_p L_2$  then  $L_1$  is also in  $NP$ .

# Few words on reductions

- As to how we define a reduction from one language to the other (or one function to the other) is usually guided by a question on whether two complexity classes are different or identical.
- For polynomial-time reductions, the question is whether or not  $P$  equals  $NP$ .
- Reductions help us define *complete problems* (the 'hardest' problems in a class) which in turn help us compare the complexity classes under consideration.

# Class NP : Examples

- Vertex cover (NP-complete)
- 0/1 integer programming (NP-complete)
- 3-coloring planar graphs (NP-complete)
- 2-Diophantine solvability (NP-complete)
- Integer factoring (unlikely to be NP-complete)
- Graph isomorphism (Quasi-P) *Babai 2015*

# How to show existence of an NPC problem?

- Let  $L' = \{ (\alpha, x, l^m, l^t) : \text{there exists a } u \in \{0,1\}^m \text{ s.t. } M_\alpha \text{ accepts } (x, u) \text{ in } t \text{ steps} \}$
- **Observation.**  $L'$  is NP-complete.
- The language  $L'$  involves Turing machine in its definition. Next, we'll see an example of an NP-complete problem that is arguably more natural.

# A natural NP-complete problem

- **Definition.** A Boolean formula on variables  $x_1, \dots, x_n$  consists of AND, OR and NOT operations.

e.g.  $\varphi = (x_1 \vee x_2) \wedge (x_3 \vee \neg x_2)$

- **Definition.** A Boolean formula  $\varphi$  is satisfiable if there's a  $\{0,1\}$ -assignment to its variables that makes  $\varphi$  evaluate to 1.

# A natural NP-complete problem

- **Definition.** A Boolean formula is in Conjunctive Normal Form (CNF) if it is an AND of OR of literals.

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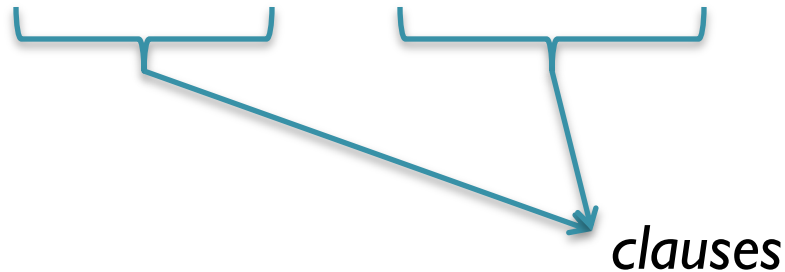


*literals*

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- **Definition.** Let **SAT** be the language consisting of all *satisfiable CNF formulae*.
- **Theorem.** (Cook 1971, Levin 1973) **SAT** is **NP-complete**.

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- **Definition.** Let **SAT** be the language consisting of all *satisfiable CNF formulae*.

- **Theorem.** (Cook 1971, Levin 1973) **SAT** is **NP-complete**.

Easy to see that **SAT** is in **NP**.

Need to show that **SAT** is **NP-hard**.

# Proof of Cook-Levin Theorem

# Cook-Levin theorem: Proof

- **Main idea:** Computation is ***local***; i.e., every step of computation *looks at* and *changes* only constantly many bits; and this step can be implemented by a small CNF formula.

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  - $x \in L \iff \varphi_x \in SAT$
  - Notation:  $|\varphi_x| :=$  size of  $\varphi_x$   
= number of  $\vee$  or  $\wedge$  in  $\varphi_x$

# Cook-Levin theorem: Proof

- Language  $L$  has a poly-time verifier  $M$  such that
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- Idea:** For any fixed  $x$ , we can capture the computation of  $M(x, \dots)$  by a CNF  $\varphi_x$  such that

$$\exists u \in \{0,1\}^{p(|x|)} \text{ s.t. } M(x, u) = 1 \iff \varphi_x \text{ is satisfiable}$$



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- For any fixed  $x$ ,  $M(x, ..)$  is a deterministic TM that takes  $u$  as input and runs in time polynomial in  $|u|$ .

# Cook-Levin theorem: Proof

- **Main Theorem.** Let  $N$  be a deterministic TM that runs in time  $T(n)$  on every input  $u$  of length  $n$ , and outputs  $0/1$ . Then, (think of  $N = M(x, ..)$  for a fixed  $x$ .)

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  1. There's a CNF  $\varphi(u, \text{"auxiliary variables"})$  of size  $\text{poly}(T(n))$  such that for every  $u$ ,  $\varphi(u, \text{"auxiliary variables"})$  is satisfiable as a function of the "auxiliary variables" if and only if  $N(u) = 1$ .
  2.  $\varphi$  is computable in time  $\text{poly}(T(n))$  from  $N, T$  &  $n$ .

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  2.  $\varphi$  is computable in time  $\text{poly}(T(n))$  from  $N, T$  &  $n$ .
- $\varphi(u, \text{"auxiliary variables"})$  is satisfiable as a function of all the variables if and only if  $\exists u$  s.t  $N(u) = 1$ .

# Cook-Levin theorem: Proof

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  2.  $\varphi$  is computable in time  $\text{poly}(T(n))$  from  $N, T$  &  $n$ .
- Cook-Levin theorem follows from above!

# Proof of Main Theorem

# Main theorem: Proof

- Step 1. Let  $N$  be a deterministic TM that runs in time  $T(n)$  on every input  $u$  of length  $n$ , and outputs  $0/1$ . Then,
  1. There's a Boolean circuit  $\psi$  of size  $\text{poly}(T(n))$  such that  $\psi(u) = 1$  if and only if  $N(u) = 1$ .
  2.  $\psi$  is computable in time  $\text{poly}(T(n))$  from  $N, T$  &  $n$ .
- Step 2. “Convert” circuit  $\psi$  to a CNF  $\varphi$  efficiently by introducing auxiliary variables.

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The key insight:  $\psi$  “encodes”  $N$ .
- **Step 2.** “Convert” circuit  $\psi$  to a CNF  $\varphi$  efficiently by introducing auxiliary variables.



# Main theorem: Step I

- Assume (w.l.o.g) that **N** has a single tape and it writes its output on the first cell at the end of computation.

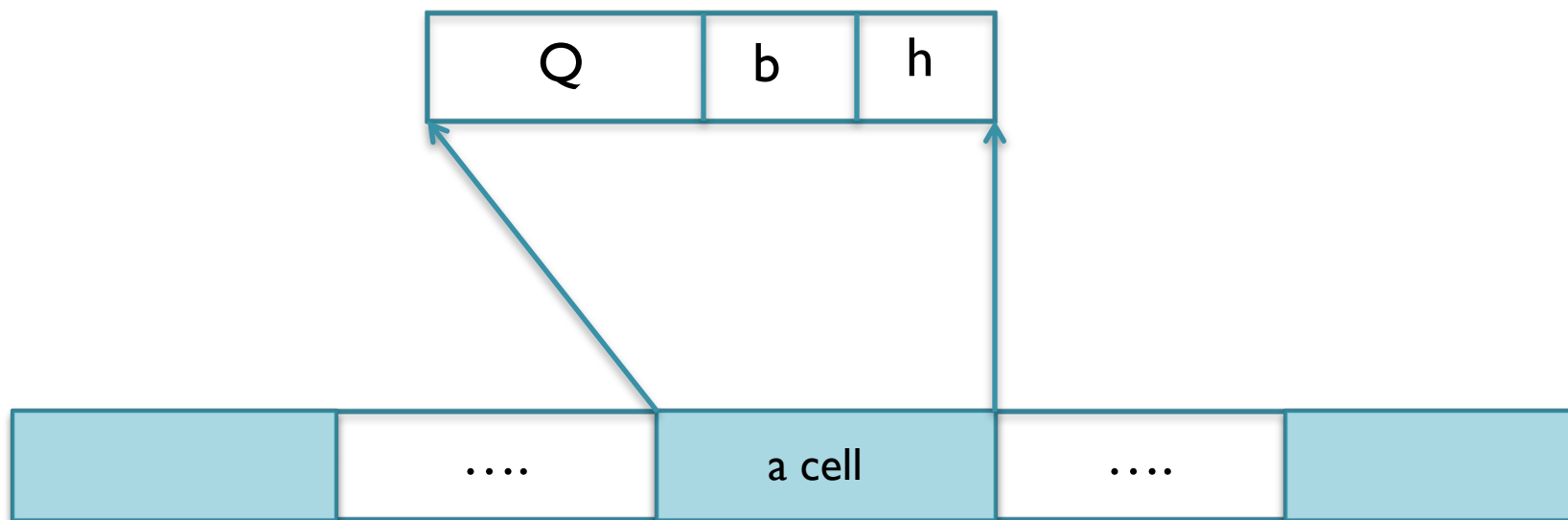
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- A step of computation of **N** consists of
  - Changing the content of the current cell
  - Changing state
  - Changing head position
- Think of a 'compound' tape: Every cell stores the current state, a bit content and head indicator.

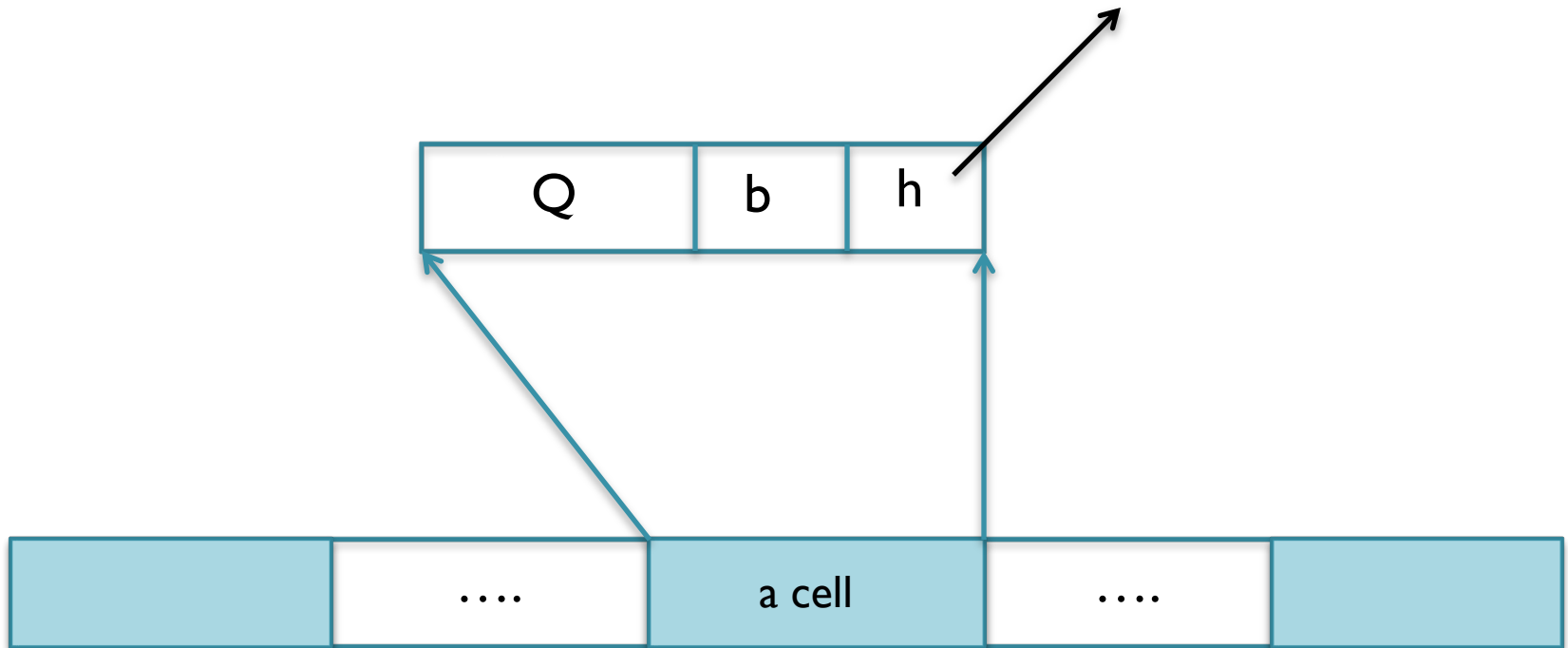
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A compound tape

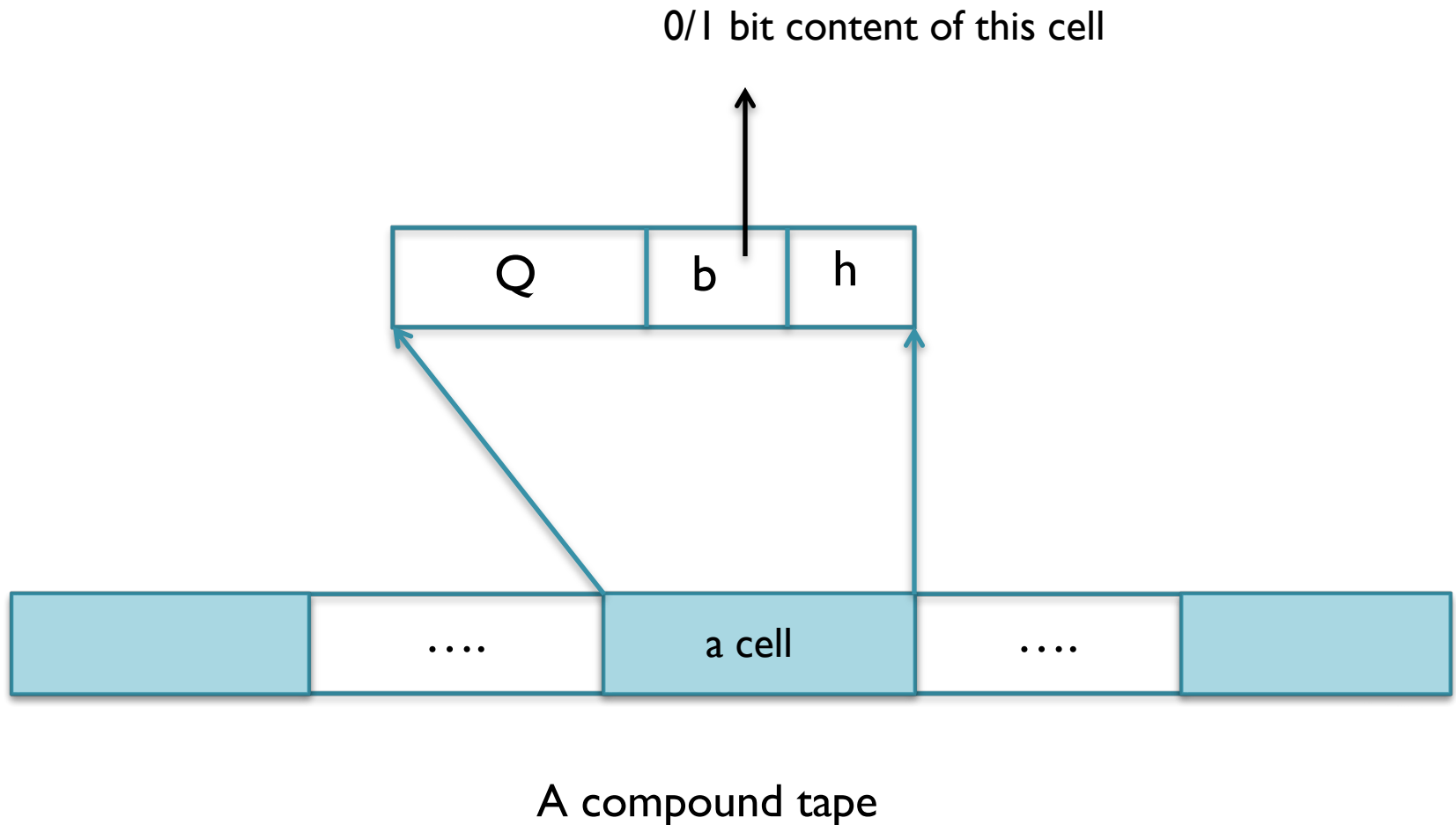
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$h = 1$  if head points to this cell  
 $= 0$  otherwise



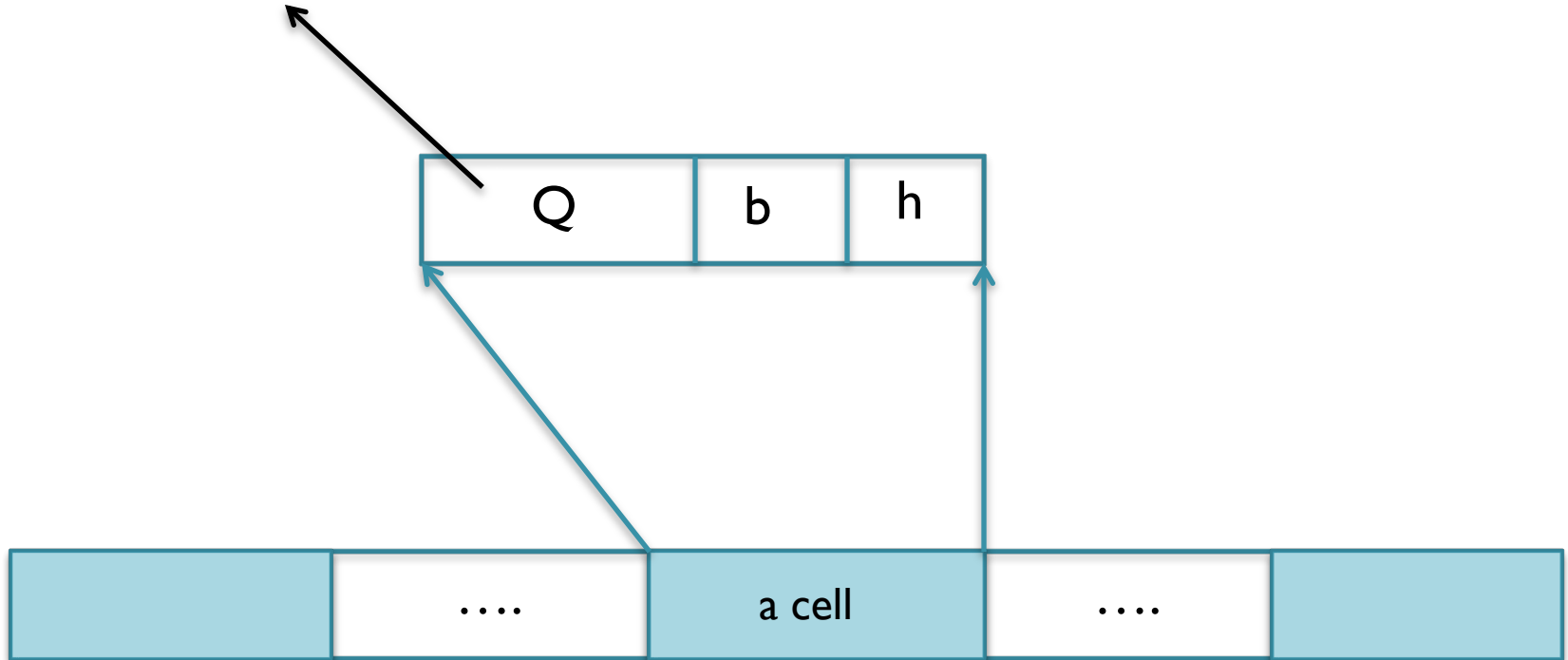
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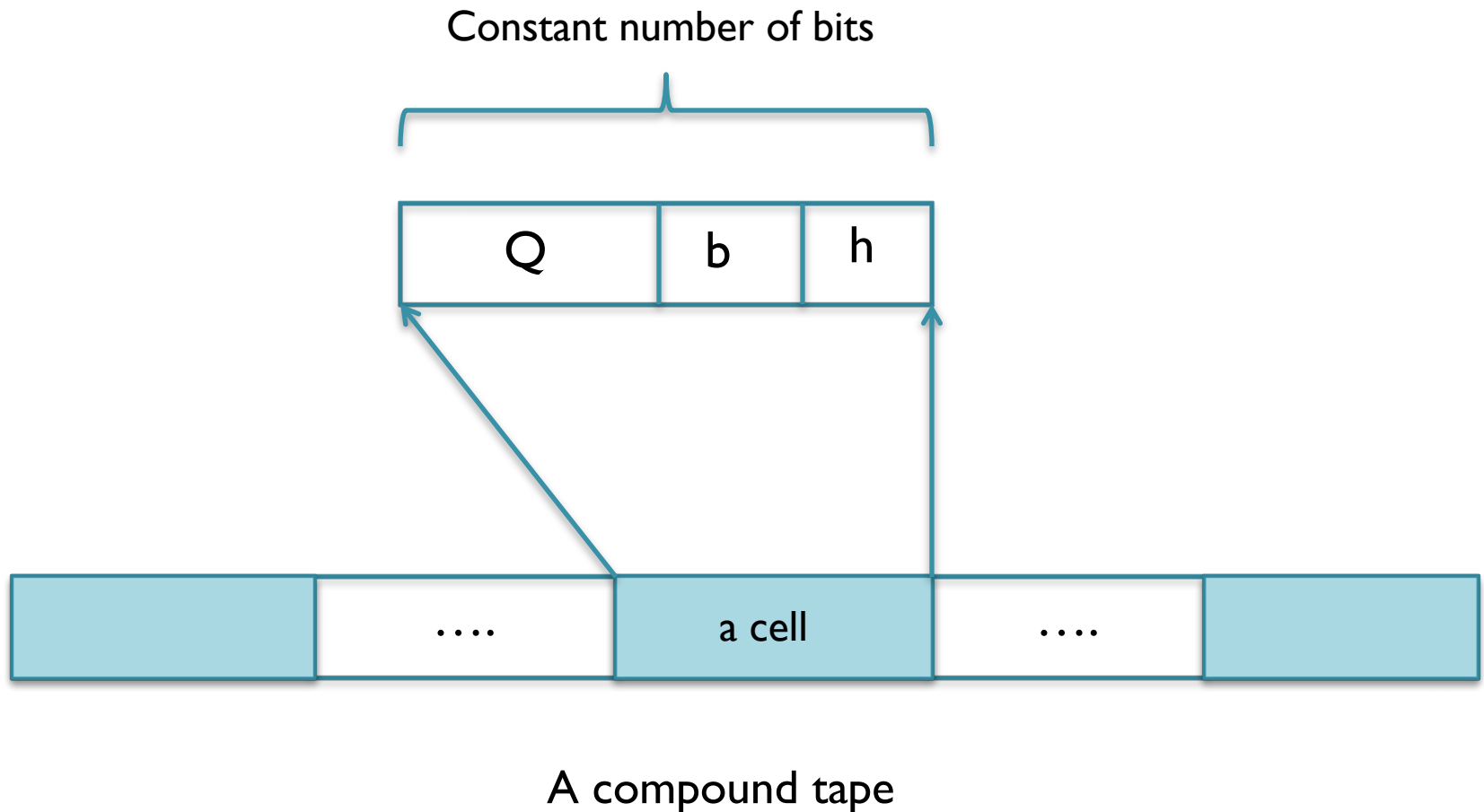
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Current state when  $h = 1$



A compound tape

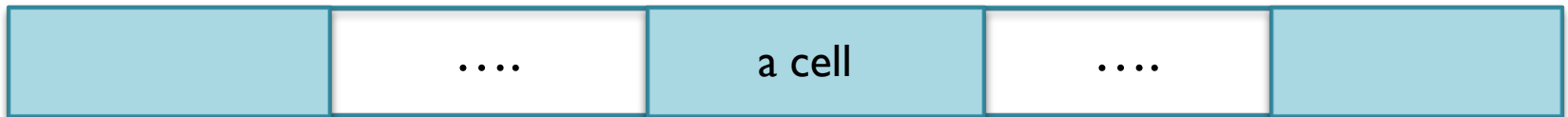
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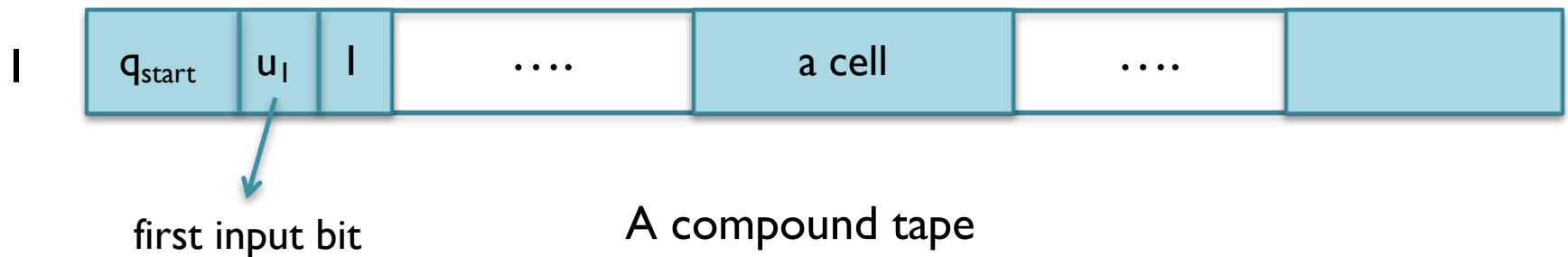
# Main theorem: Step I

- Computation of **N** on inputs of length **n** can be completely described by a sequence of **T(n)** compound tapes, the **i-th** of which captures a *'snapshot'* of **N's** computation at the **i-th** step.

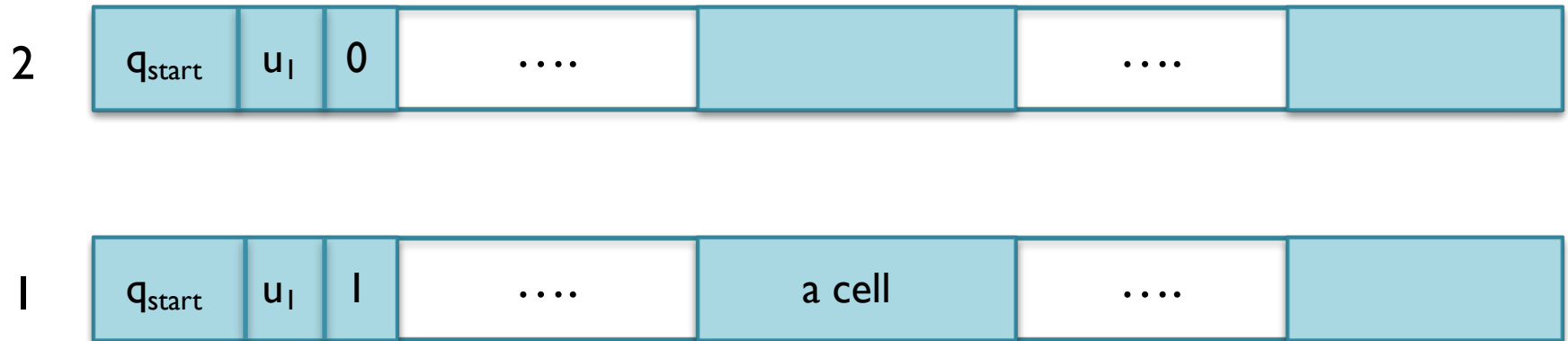


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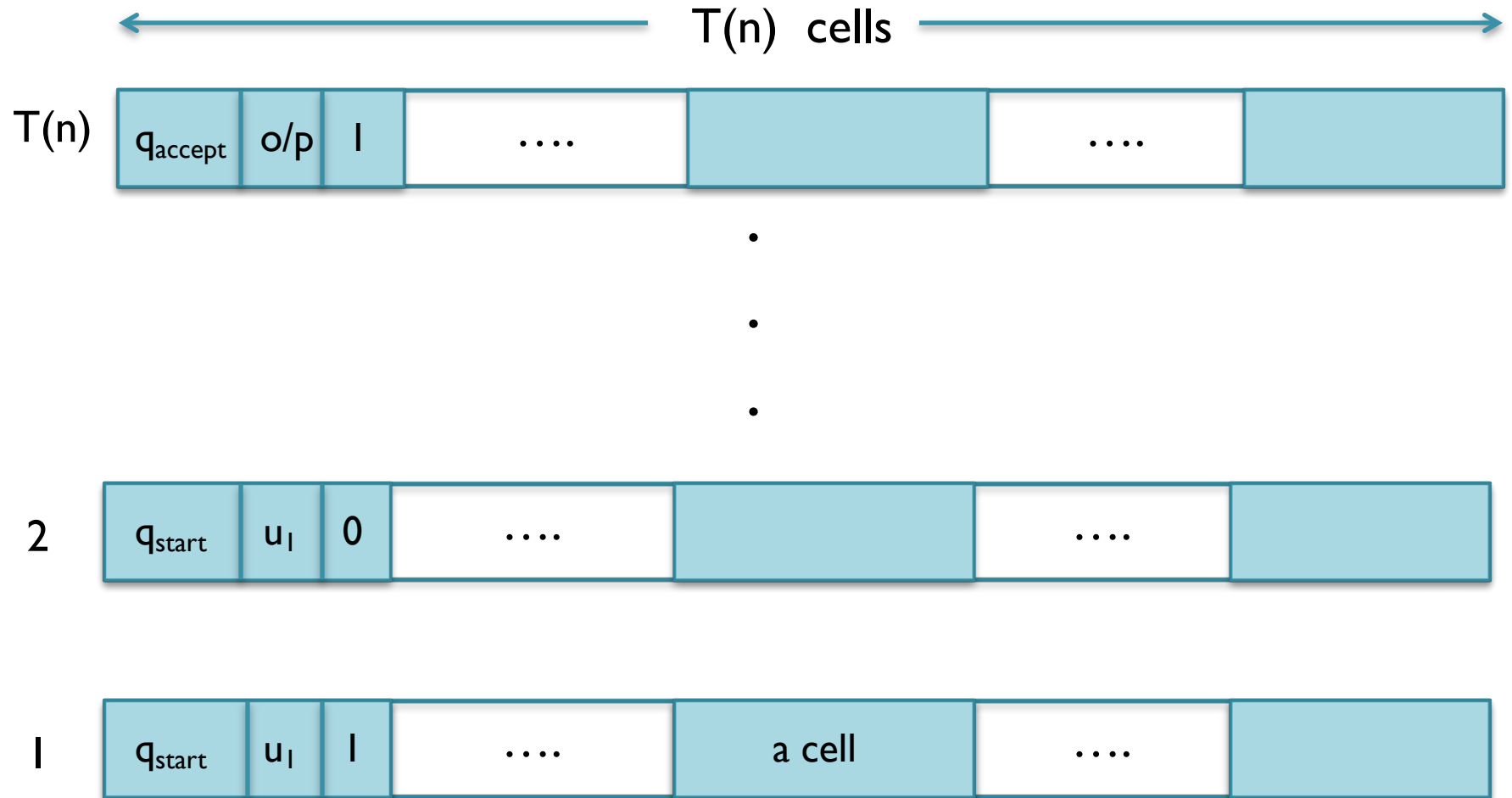


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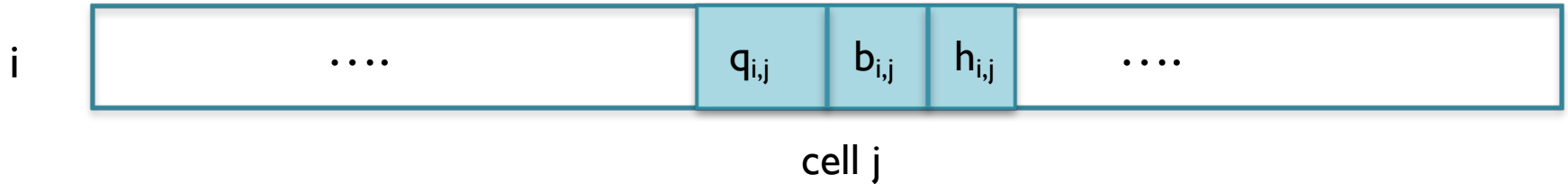
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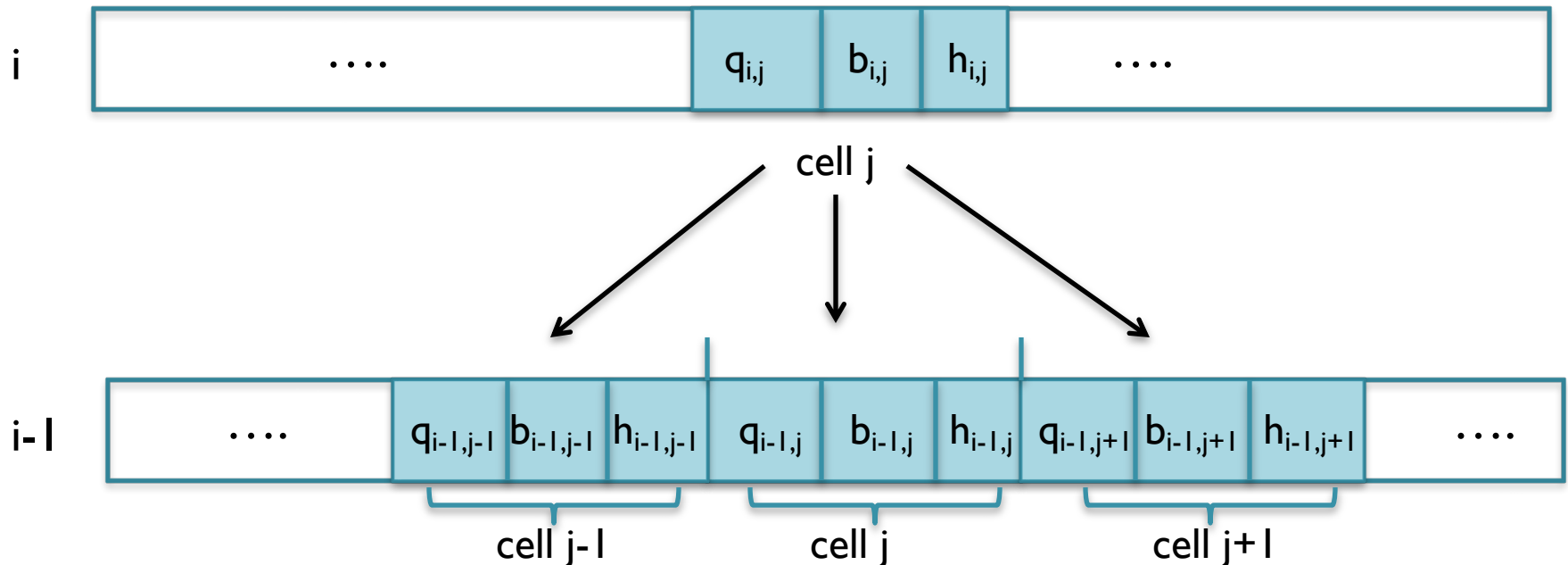
# Main theorem: Step 1

- $h_{i,j} = 1$  iff head points to cell  $j$  at  $i$ -th step
- $b_{i,j}$  = bit content of cell  $j$  at  $i$ -th step
- $q_{i,j}$  = a sequence of  $\log |Q|$  bits which contains the current state info if  $h_{i,j} = 1$ ; otherwise we don't care



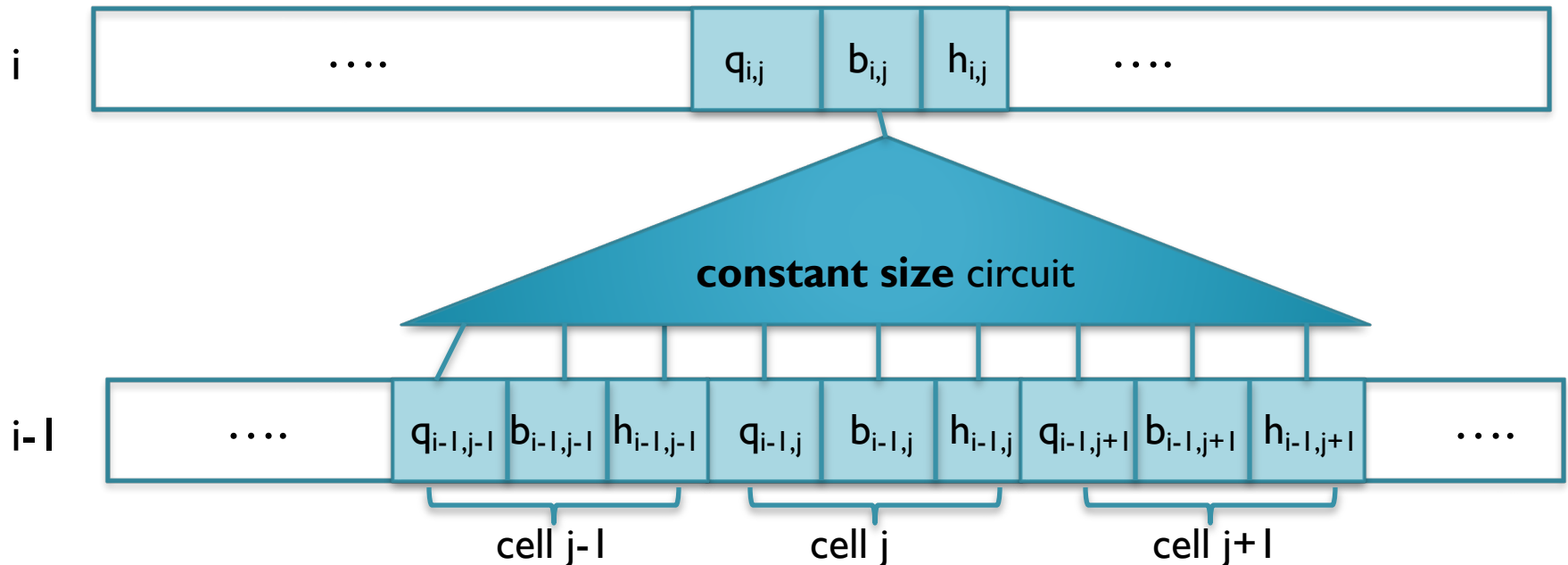
# Main theorem: Step I

- **Locality of computation:** The bits in  $h_{i,j}$ ,  $b_{i,j}$  and  $q_{i,j}$  depend only on the bits in
  - $h_{i-1,j-1}$ ,  $b_{i-1,j-1}$ ,  $q_{i-1,j-1}$ ,
  - $h_{i-1,j}$ ,  $b_{i-1,j}$ ,  $q_{i-1,j}$ ,
  - $h_{i-1,j+1}$ ,  $b_{i-1,j+1}$ ,  $q_{i-1,j+1}$

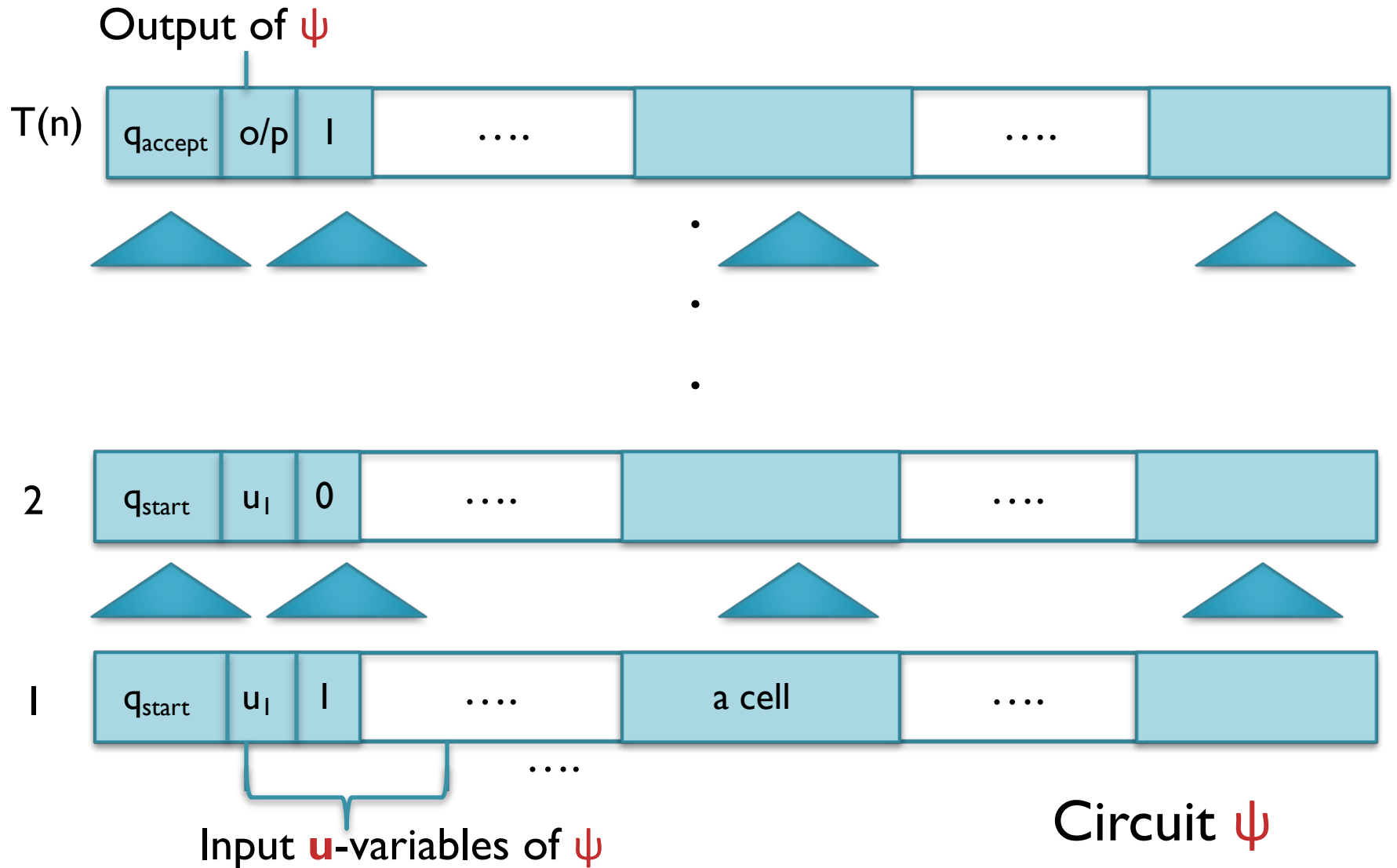


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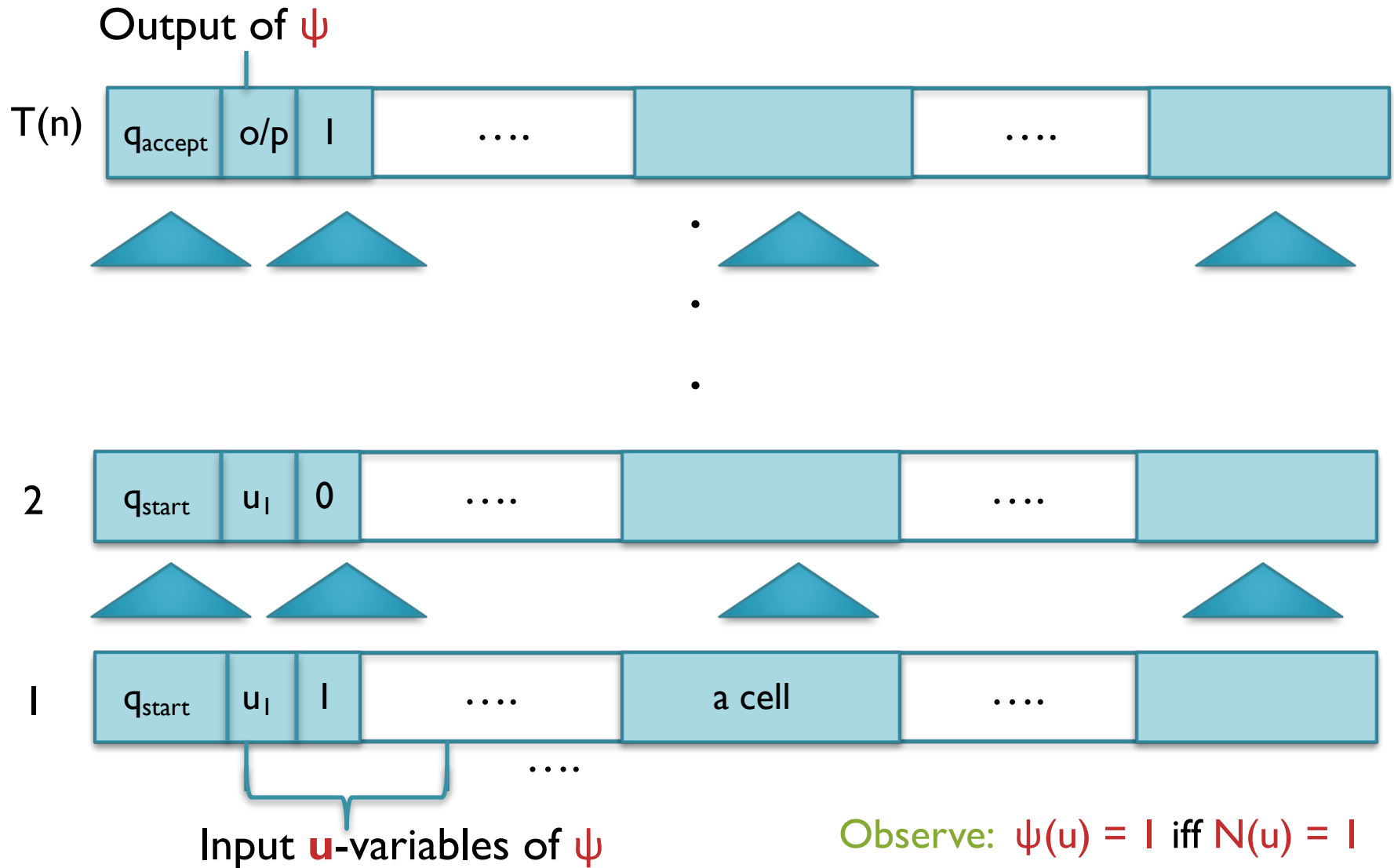


# Main theorem: Step I





# Main theorem: Step I



# Recall Steps 1 and 2

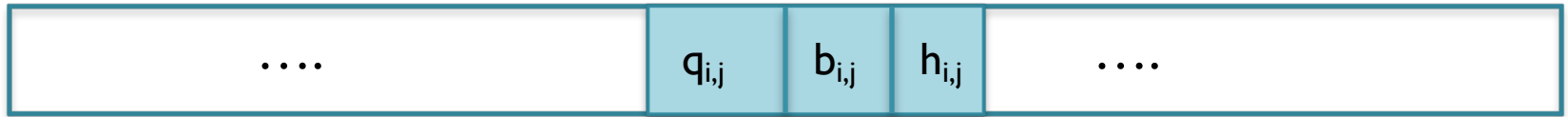
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- **Step 2.** “Convert” circuit  $\psi$  to a CNF  $\varphi$  efficiently by introducing auxiliary variables.

# Main theorem: Step 2

- Think of  $h_{i,j}$ ,  $b_{i,j}$  and the bits of  $q_{i,j}$  as formal Boolean variables.

auxiliary variables

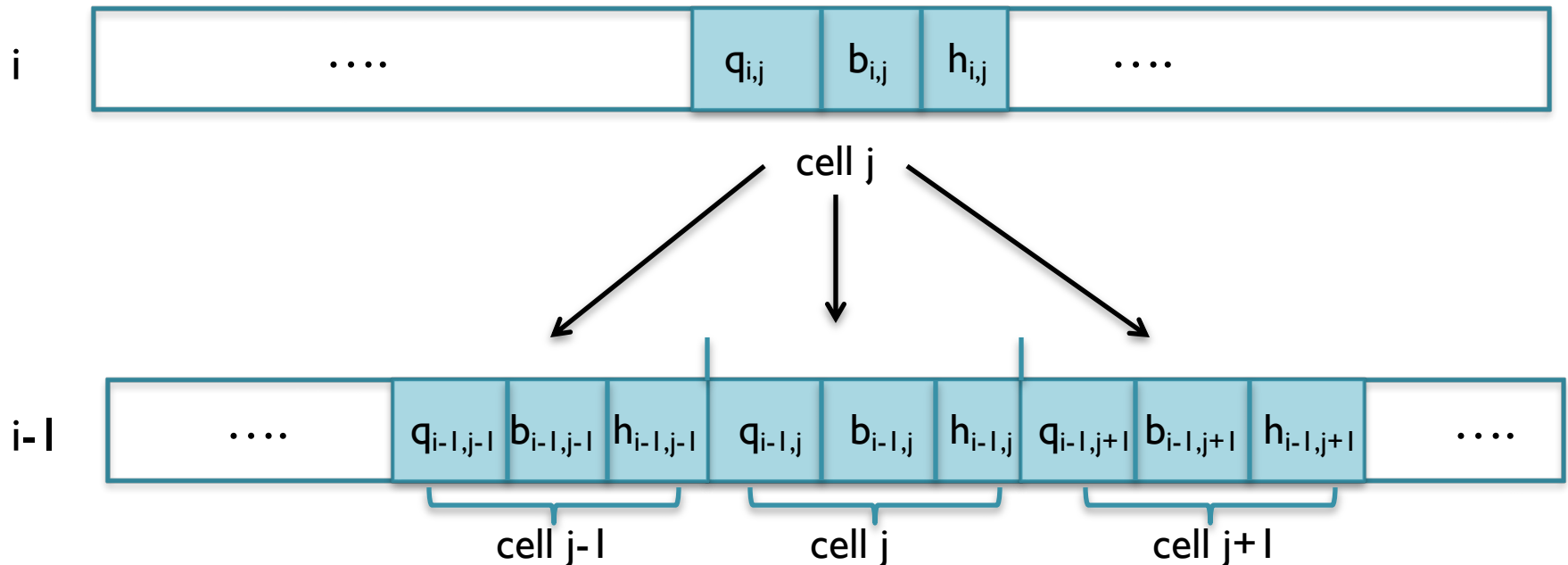
i



cell j

# Main theorem: Step 2

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  - $h_{i-1,j}$ ,  $b_{i-1,j}$ ,  $q_{i-1,j}$ , and
  - $h_{i-1,j+1}$ ,  $b_{i-1,j+1}$ ,  $q_{i-1,j+1}$



# Main theorem: Step 2

- Hence,

$$b_{ij} = B_{ij}(h_{i-1,j-1}, b_{i-1,j-1}, q_{i-1,j-1}, h_{i-1,j}, b_{i-1,j}, q_{i-1,j}, h_{i-1,j+1}, b_{i-1,j+1}, q_{i-1,j+1})$$

= a fixed function of the arguments depending only on  $N$ 's transition function  $\delta$ .

- The above equality can be captured by a constant size CNF  $\Psi_{ij}$ . Also,  $\Psi_{ij}$  is easily computable from  $\delta$ .

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$$x = y \text{ iff } (x \wedge y) \vee (\neg x \wedge \neg y) = 1.$$

# Main theorem: Step 2


- Similarly,

$$h_{ij} = H_{ij}(h_{i-1,j-1}, b_{i-1,j-1}, q_{i-1,j-1}, h_{i-1,j}, b_{i-1,j}, q_{i-1,j}, h_{i-1,j+1}, b_{i-1,j+1}, q_{i-1,j+1})$$

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- The above equality can be captured by a constant size CNF  $\Phi_{ij}$ . Also,  $\Phi_{ij}$  is easily computable from  $\delta$ .

# Main theorem: Step 2

- Similarly,  k-th bit of  $q_{ij}$  where  $1 \leq k \leq \log |Q|$   
 $q_{ijk} = C_{ijk}(h_{i-1,j-1}, b_{i-1,j-1}, q_{i-1,j-1}, h_{i-1,j}, b_{i-1,j}, q_{i-1,j}, h_{i-1,j+1}, b_{i-1,j+1}, q_{i-1,j+1})$   
= a fixed function of the arguments depending only on  $N$ 's transition function  $\delta$ .
- The above equality can be captured by a constant size CNF  $\theta_{ijk}$ . Also,  $\theta_{ijk}$  is easily computable from  $\delta$ .



# Main theorem: Step 2

- Let  $\lambda$  be the conjunction of  $\Psi_{ij}$ ,  $\Phi_{ij}$  and  $\theta_{ijk}$  for all  $i, j, k$ .
  - $i \in [1, T(n)]$ ,
  - $j \in [1, T(n)]$ , and
  - $k \in [1, \log |Q|]$
- $\lambda$  is a CNF in the  $u$ -variables and the auxiliary variables  $h_{i,j}$ ,  $b_{i,j}$  and  $q_{i,j,k}$  for all  $i, j, k$ .  $|\lambda|$  is  $O(T(n)^2)$ .

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- Define  $\varphi = \lambda \wedge b_{T(n), 1}$ .

# Main theorem: Step 2

- **Observe:** An assignment to  $u$  and the auxiliary variables satisfies  $\lambda$  if and only if it “captures” the computation of  $N$  on the assigned input  $u$  for  $T(n)$  steps.

# Main theorem: Step 2

- **Observe:** An assignment to  $u$  and the auxiliary variables satisfies  $\lambda$  if and only if it “captures” the computation of  $N$  on the assigned input  $u$  for  $T(n)$  steps.
- Hence, an assignment to  $u$  and the auxiliary variables satisfies  $\varphi$  if and only if  $N(u) = I$ , i.e., for every  $u$ ,

$$\varphi(u, \text{“auxiliary variables”}) \in \text{SAT} \iff N(u) = I.$$

# Recall the Main Theorem

- **Main Theorem.** Let  $N$  be a deterministic TM that runs in time  $T(n)$  on every input  $u$  of length  $n$ , and outputs  $0/1$ . Then,
  1. There's a CNF  $\varphi(u, \text{"auxiliary variables"})$  of size  $\text{poly}(T(n))$  such that for every  $u$ ,  $\varphi(u, \text{"auxiliary variables"})$  is satisfiable as a function of the "auxiliary variables" if and only if  $N(u) = 1$ .
  2.  $\varphi$  is computable in time  $\text{poly}(T(n))$  from  $N, T$  &  $n$ .
- $\varphi(u, \text{"auxiliary variables"})$  is satisfiable as a function of all the variables if and only if  $\exists u$  s.t  $N(u) = 1$ .

# Main theorem: Comments

- $\varphi$  is a CNF of size  $O(T(n)^2)$  and is also computable from  $N, T$  and  $n$  in  $O(T(n)^2)$  time.
- **Remark 1.** With some more effort, size  $\varphi$  can be brought down to  $O(T(n) \cdot \log T(n))$ .
- **Remark 2.** The reduction from  $x$  to  $\varphi_x$  is not just a poly-time reduction, it is actually a log-space reduction (we'll define this later).

# Main theorem: Comments

- $\varphi$  is a function of  $u$  and some “auxiliary variables” (the  $b_{ij}$ ,  $h_{ij}$  and  $q_{ijk}$  variables).
- Observe that once  $u$  is fixed the values of the “auxiliary variables” are also determined in any satisfying assignment for  $\varphi$ .
- Each clause of  $\varphi$  has only constantly many literals!

# 3SAT is NP-complete

- **Definition.** A CNF is called a **k-CNF** if every clause has at most **k** literals.

e.g. a 2-CNF  $\varphi = (x_1 \vee x_2) \wedge (x_3 \vee \neg x_2)$

- **Definition.** **k-SAT** is the language consisting of all *satisfiable k-CNFs*.



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- **Definition.** **k-SAT** is the language consisting of all *satisfiable k-CNFs*.

- **Theorem.** **3-SAT** is **NP-complete**.

*Proof sketch:*  $(x_1 \vee x_2 \vee x_3 \vee \neg x_4)$  is satisfiable iff  $(x_1 \vee x_2 \vee z) \wedge (x_3 \vee \neg x_4 \vee \neg z)$  is satisfiable.

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- **Definition.** **k-SAT** is the language consisting of all *satisfiable k-CNFs*.
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