Complexity Theory Space Complexity

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Computational Logic

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Review

Space Complexity

Review: Space Complexity Classes

Recall our earlier definition of space complexities:

Definition 10.1

- Let $f : \mathbb{N} \to \mathbb{R}^+$ be a function.
 - ► DSPACE(f(n)) is the class of all languages \mathcal{L} for which there is an O(f(n))-space bounded Turing machine deciding \mathcal{L} .
 - ▶ NSPACE(f(n)) is the class of all languages \mathcal{L} for which there is an O(f(n))-space bounded nondeterministic Turing machine deciding \mathcal{L} .

Being O(f(n))-space bounded requires a (nondeterministic) TM

- to halt on every input and
- to use $\leq f(|w|)$ tape cells on every computation path.

Space Complexity Classes

Some important space complexity classes:

$$L = LOGSPACE = DSPACE(\log n)$$
 logarithmic space

$$PSPACE = \bigcup_{d \ge 1} DSPACE(n^d)$$
 polynomial space

$$EXPSPACE = \bigcup_{d \ge 1} DSPACE(2^{n^d})$$
 exponential space

 $NL = NLOGSPACE = NSPACE(\log n)$

$$NPSPACE = \bigcup_{d \ge 1} NSPACE(n^d)$$

$$NEXPSPACE = \bigcup_{d \ge 1} NSPACE(2^{n^d})$$

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The Power Of Space

Space seems to be more powerful than time because space can be reused.

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Example 10.2

SAT can be solved in linear space:

Just iterate over all possible truth assignments (each linear in size) and check if one satisfies the formula.

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Example 10.3

TAUTOLOGY can be solved in linear space:

Just iterate over all possible truth assignments (each linear in size) and check if all satisfy the formula.

More generally: $NP \subseteq PSPACE$ and $CONP \subseteq PSPACE$

Linear Compression

Theorem 10.4

- For every function $f : \mathbb{N} \to \mathbb{R}^+$, for all $c \in \mathbb{N}$, and for every f-space bounded (deterministic/nondeterministic) Turing machine \mathcal{M} :
- there is a max{1, $\frac{1}{c}f(n)$ }-space bounded (deterministic/nondeterminsitic) Turing machine \mathcal{M}' that accepts the same language as \mathcal{M} .

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Proof idea.

Similar to (but much simpler than) linear speed-up.

This justifies using *O*-notation for defining space classes.

п

Tape Reduction

Theorem 10.5

- For every function $f : \mathbb{N} \to \mathbb{R}^+$ all $k \ge 1$ and $\mathcal{L} \subseteq \Sigma^*$:
- If \mathcal{L} can be decided by an f-space bounded k-tape Turing-machine,
- it can also be decided by an f-space bounded 1-tape Turing-machine

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Proof idea.

Combine tapes with a similar reduction as for time. Compress space to avoid linear increase.

Recall that we still use a separate read-only input tape to define some space complexities, such as LOGSPACE.

Theorem 10.6 For all functions $f : \mathbb{N} \to \mathbb{R}^+$:

 $DT_{IME}(f) \subseteq DS_{PACE}(f)$ and $NT_{IME}(f) \subseteq NS_{PACE}(f)$

Proof.

Visiting a cell takes at least one time step.

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Theorem 10.7

For all functions $f : \mathbb{N} \to \mathbb{R}^+$ with $f(n) \ge \log n$:

 $\mathsf{DSpace}(f) \subseteq \mathsf{DTime}(2^{O(f)})$ and $\mathsf{NSpace}(f) \subseteq \mathsf{DTime}(2^{O(f)})$

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Proof.

Based on configuration graphs and a bound on the number of possible configurations.

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Number of Possible Configurations

Let $\mathcal{M} := (Q, \Sigma, \Gamma, q_0, \delta, q_{start})$ be a 2-tape Turing machine (1 read-only input tape + 1 work tape)

Recall: A configuration of \mathcal{M} is a quadruple (q, p_1, p_2, x) where

- $q \in Q$ is the current state,
- ▶ $p_i \in \mathbb{N}$ is the head position on tape *i*, and
- $x \in \Gamma^*$ is the tape content.

Let $w \in \Sigma^*$ be an input to \mathcal{M} and n := |w|. Then also $p_1 \le n$.

If \mathcal{M} is f(n)-space bounded we can assume $p_2 \leq f(n)$ and $|x| \leq f(n)$

Hence, there are at most

 $|Q| \cdot n \cdot f(n) \cdot |\Gamma|^{f(n)} = n \cdot 2^{O(f(n))} = 2^{O(f(n))}$

different configurations on inputs of length *n* (the last equality requires $f(n) \ge \log n$).

Configuration Graphs

The possible computations of a TM \mathcal{M} (on input *w*) form a directed graph:

- Vertices: configurations that \mathcal{M} can reach (on input w)
- Edges: there is an edge from C_1 to C_2 if $C_1 \vdash_M C_2$ (C_2 reachable from C_1 in a single step)
- This yields the configuration graph
 - Could be infinite in general.
 - For f(n)-space bounded 2-tape TMs, there can be at most 2^{O(f(n))} vertices and 2 ⋅ (2^{O(f(n))})² = 2^{O(f(n))} edges

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A computation of \mathcal{M} on input *w* corresponds to a path in the configuration graph from the start configuration to a stop configuration.

Hence, to test if \mathcal{M} accepts input w,

- construct the configuration graph and
- find a path from the start to an accepting stop configuration.

Complexity Theory

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Proof.

Visiting a cell takes at least one time step.

Theorem 10.7

For all functions $f : \mathbb{N} \to \mathbb{R}^+$ with $f(n) \ge \log n$:

 $\mathsf{DSpace}(f) \subseteq \mathsf{DTime}(2^{O(f)})$ and $\mathsf{NSpace}(f) \subseteq \mathsf{DTime}(2^{O(f)})$

Proof.

Build the configuration graph (time $2^{O(f(n))}$) and find a path from the start to an accepting stop configuration (time $2^{O(f(n))}$).

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Basic Space/Time Relationships

Applying the results of the previous slides, we get the following relations:

 $L \subseteq NL \subseteq P \subseteq NP \subseteq PSPACE \subseteq NPSPACE \subseteq ExpTime \subseteq NExpTime$

We also noted $P \subseteq \text{coNP} \subseteq PS_{PACE}$.

Open questions:

- What is the relationship between space classes and their co-classes?
- What is the relationship between deterministic and non-deterministic space classes?

Nondeterminism in Space

Most experts think that nondeterministic TMs can solve strictly more problems when given the same amount of time than a deterministic TM: Most believe that $P \subsetneq NP$

How about nondeterminism in space-bounded TMs?

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How about nondeterminism in space-bounded TMs?

Theorem 10.8 (Savitch's Theorem, 1970) For any function $f : \mathbb{N} \to \mathbb{R}^+$ with $f(n) \ge \log n$:

 $\mathrm{NSPACE}(f(n)) \subseteq \mathrm{DSPACE}(f^2(n)).$



That is: nondeterminism adds almost no power to space-bounded TMs!

Consequences of Savitch's Theorem

Savitch's Theorem: For any function $f : \mathbb{N} \to \mathbb{R}^+$ with $f(n) \ge \log n$:

 $\mathrm{NSPACe}(f(n)) \subseteq \mathrm{DSPACe}(f^2(n)).$

Corollary 10.9

PSPACE = NPSPACE.

Proof.

 $PSPACE \subseteq NPSPACE$ is clear. The converse follows since the square of a polynomial is still a polynomial.

Similarly for "bigger" classes, e.g., ExpSpace = NExpSpace.

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Corollary 10.10

 $\mathrm{NL} \subseteq \mathrm{DSPACe}(O(\log^2 n)).$

Note that $\log^2(n) \notin O(\log n)$, so we do not obtain NL = L from this.

Proving Savitch's Theorem

Simulating nondeterminism with more space:

- Use configuration graph of nondeterministic space-bounded TM
- Check if an accepting configuration can be reached
- Store only one computation path at a time (depth-first search)

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Things we can do:

- Store one configuration:
 - one configuration requires $\log n + O(f(n))$ space
 - if $f(n) \ge \log n$, then this is O(f(n)) space
- Store log n configurations (remember we have log² n space)
- Iterate over all configurations (one by one)

Proving Savitch's Theorem: Key Idea

To find out if we can reach an accepting configuration, we solve a slighly more general question:

YIELDABILITY

Input: TM configurations C_1 and C_2 , integer *k Problem:* Can TM get from C_1 to C_2 in at most *k* steps?

Approach: check if there is an intermediate configuration C' such that

- (1) C_1 can reach C' in k/2 steps and
- (2) C' can reach C_2 in k/2 steps
- \rightsquigarrow Deterministic: we can try all C' (iteration)
- \rightsquigarrow Space-efficient: we can reuse the same space for both steps

An Algorithm for Yieldability

```
Q1 CANYIELD(C_1, C_2, k) {
     if k = 1:
02
        return (C_1 = C_2) or (C_1 \vdash_M C_2)
03
     else if k > 1:
04
        for each configuration C of \mathcal{M} for input size n:
05
06
          if CANYIELD(C_1, C, k/2) and
07
             CANYIELD(C, C_2, k/2):
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            return true
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     // eventually, if no success:
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```

• We only call CANYIELD only with k a power of 2, so $k/2 \in \mathbb{N}$

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- During iteration (line 05), we store one C in O(f(n))
- Calls in lines 06 and 07 can reuse the same space
- Maximum depth of recursive call stack: log₂ k

Overall space usage: $O(f(n) \cdot \log k)$

Simulating Nondeterministic Space-Bounded TMs

Input: TM \mathcal{M} that runs in NSPACE(f(n)); input word w of length n Algorithm:

- ► Modify *M* to have a unique accepting configuration *C*_{accept} when accepting, erase tape and move head to the very left
- Select *d* such that $2^{df(n)} \ge |Q| \cdot n \cdot f(n) \cdot |\Gamma|^{f(n)}$
- Return CanYIELD($C_{\text{start}}, C_{\text{accept}}, k$) with $k = 2^{df(n)}$

Space requirements: CANYIELD runs in

$$O(f(n) \cdot \log k) = O(f(n) \cdot \log 2^{df(n)}) = O(f(n) \cdot df(n)) = O(f^2(n))$$

"Select *d* such that $2^{df(n)} \ge |Q| \cdot n \cdot f(n) \cdot |\Gamma|^{f(n)}$ "

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- f(n) was not part of the input!
- Even if we knew *f*, it might not be easy to compute!

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How does the algorithm actually do this?

- f(n) was not part of the input!
- Even if we knew f, it might not be easy to compute!

Solution: replace f(n) by a parameter ℓ and probe its value

- (1) Start with $\ell = 1$
- (2) Check if \mathcal{M} can reach any configuration with more than ℓ tape cells (iterate over all configurations of size $\ell + 1$; use CANYIELD on each)
- (3) If yes, increase ℓ by 1; goto (2)
- (4) Run algorithm as before, with f(n) replaced by ℓ

Therefore: we don't need to know *f* at all. This finishes the proof.

Relationships of Space and Time

Summing up, we get the following relations:

 $L \subseteq NL \subseteq P \subseteq NP \subseteq PSPACE = NPSPACE \subseteq ExpTime \subseteq NExpTime$

We also noted $P \subseteq \text{coNP} \subseteq PSPACE$.

Open questions:

- Is Savitch's Theorem tight?
- Are there any interesting problems in these space classes?
- ► We have PSPACE = NPSPACE = CONPSPACE. But what about L, NL, and CONL?

 \sim the first: nobody knows; the others: see upcoming lectures