

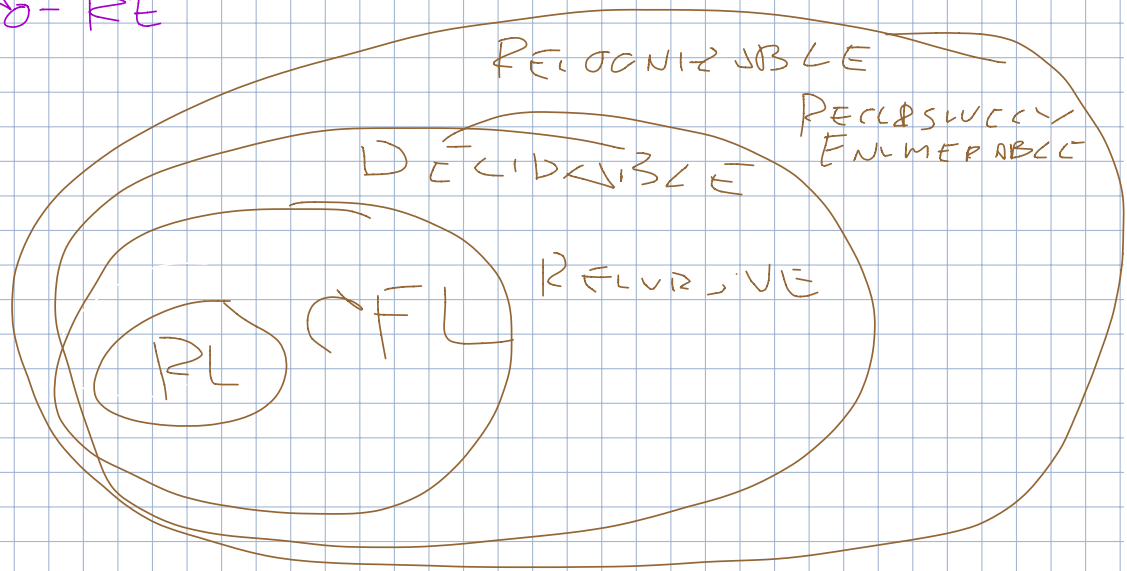
# Mapping Reductions

- A function  $f : \Sigma_1^* \rightarrow \Sigma_2^*$  is called a **mapping reduction** from  $A$  to  $B$  iff
  - For any  $w \in \Sigma_1^*$ ,  $w \in A$  iff  $f(w) \in B$ .
  - $f$  is a computable function.
- Intuitively, a mapping reduction from  $A$  to  $B$  says that a computer can transform any instance of  $A$  into an instance of  $B$  such that the answer to  $B$  is the answer to  $A$ .

# Why Mapping Reducibility Matters

- **Theorem:** If  $B \in \mathbf{R}$  and  $A \leq_M B$ , then  $A \in \mathbf{R}$ .
- **Theorem:** If  $B \in \mathbf{RE}$  and  $A \leq_M B$ , then  $A \in \mathbf{RE}$ .
- **Theorem:** If  $B \in \text{co-}\mathbf{RE}$  and  $A \leq_M B$ , then  $A \in \text{co-}\mathbf{RE}$ .
- *Intuitively:*  $A \leq_M B$  means “A is not harder than B.”

Ch-RE



# Why Mapping Reducibility Matters

- **Theorem:** If  $A \notin \mathbf{R}$  and  $A \leq_M B$ , then  $B \notin \mathbf{R}$ .
- **Theorem:** If  $A \notin \mathbf{RE}$  and  $A \leq_M B$ , then  $B \notin \mathbf{RE}$ .
- **Theorem:** If  $A \notin \text{co-RE}$  and  $A \leq_M B$ , then  $B \notin \text{co-RE}$ .
- *Intuitively:*  $A \leq_M B$  means “ $B$  is at least as hard as  $A$ .”

# Why Mapping Reducibility Matters

If this one is "easy"  
(R, RE, co-RE)...

$$A \leq_M B$$

... then this one is  
"easy" (R, RE,  
co-RE) too.

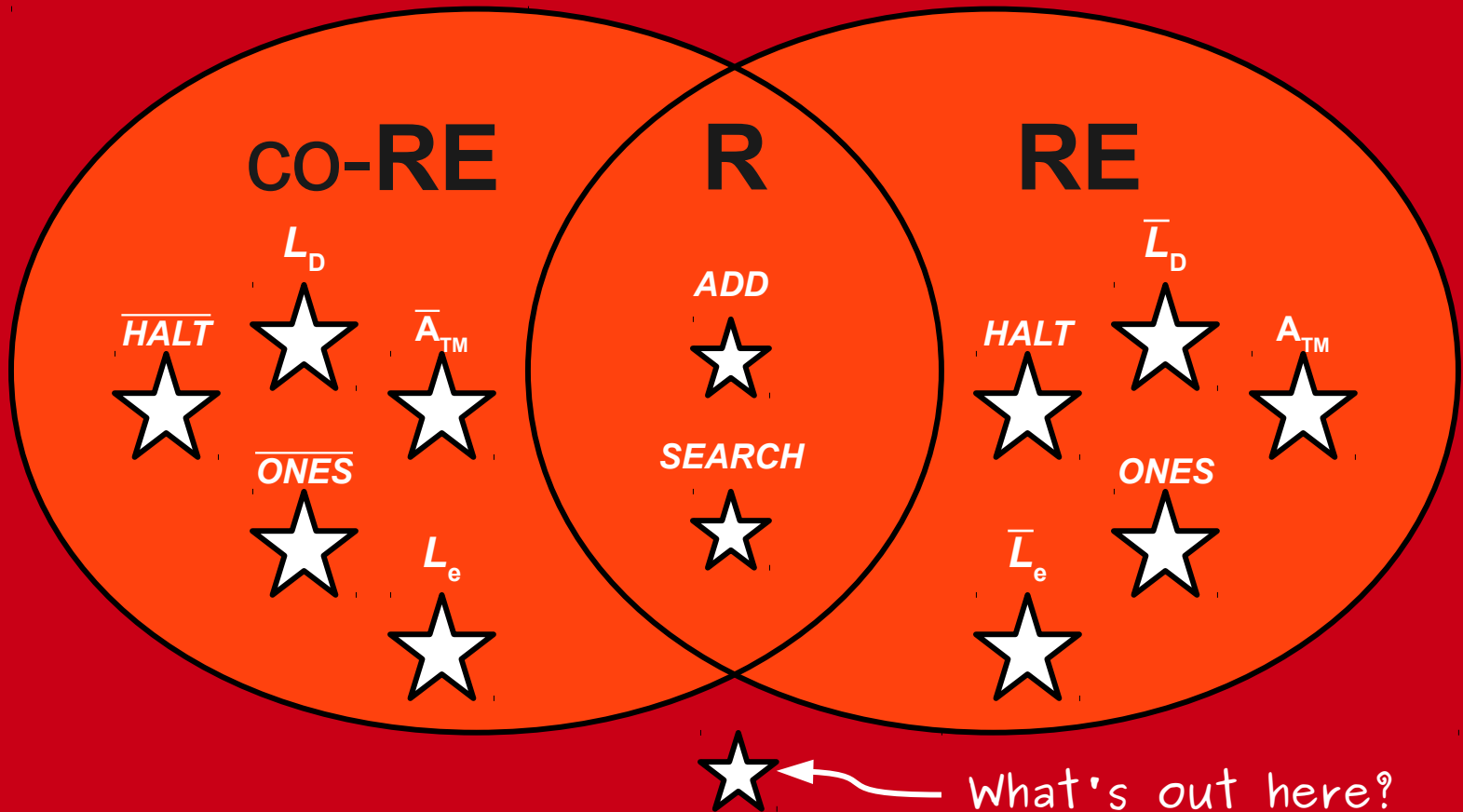
# Why Mapping Reducibility Matters

If this one is "hard"  
(not  $\mathcal{R}$ , not  $\mathcal{RE}$ , or not  
 $\text{co-RE}$ )...

$$A \leq_M B$$

... then this one is  
"hard" (not  $\mathcal{R}$ , not  
 $\mathcal{RE}$ , or not  $\text{co-RE}$ )  
too.

# The Limits of Computability



What problems can be  
solved by a computer?

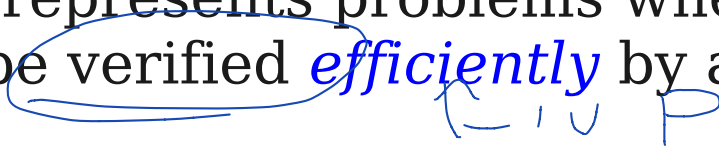


What problems can be  
solved **efficiently** by a computer?

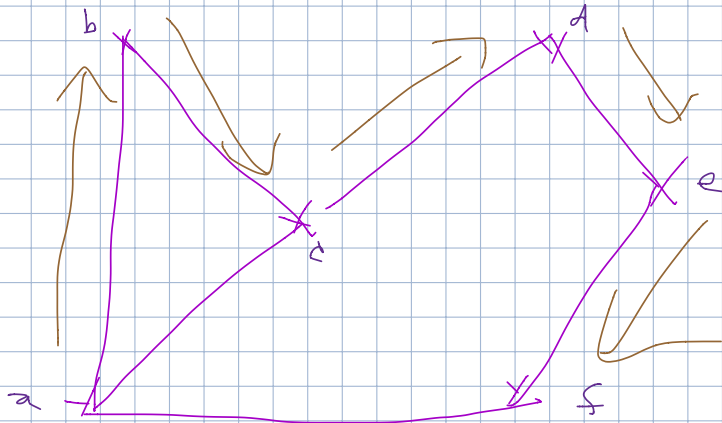
# Where We've Been

- The class **R** represents problems that can be solved by a computer.
- The class **RE** represents problems where “yes” answers can be verified by a computer.
- The class co-**RE** represents problems where “no” answers can be verified by a computer.
- The mapping reduction can be used to find connections between problems.

# Where We're Going

- The class **P** represents problems that can be solved *efficiently* by a computer.
- The class **NP** represents problems where “yes” answers can be verified *efficiently* by a computer. 
- The class co-**NP** represents problems where “no” answers can be verified *efficiently* by a computer.
- The *polynomial-time* mapping reduction can be used to find connections between problems.

# The Traveling Salesman Problem - NP



$a \rightarrow b \rightarrow c \rightarrow d \rightarrow e \rightarrow f$

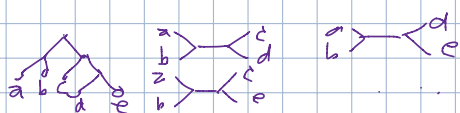
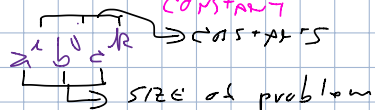
$P \Rightarrow$  Polynomial Time Solvable

$n \rightarrow$  Size of problem (e.g. # cities)

$n^k \rightarrow k$  fixed

$$n^2 \in [c]$$

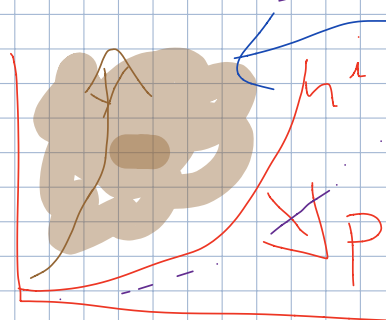
constant



$$n^4 \rightarrow n^3 \rightarrow n^{2.3}$$

$$n^{1.521} \rightarrow n^{1.384}$$

BINARY SEARCH  $\rightarrow O(\log n)$



NP

$\hookrightarrow$  Non-Deterministic Polynomial

# A Decidable Problem

- **Presburger arithmetic** is a logical system for reasoning about arithmetic.
  - $\forall x. x + 1 \neq 0$
  - $\forall x. \forall y. (x + 1 = y + 1 \rightarrow x = y)$
  - $\forall x. x + 0 = x$
  - $\forall x. \forall y. (x + y) + 1 = x + (y + 1)$
  - $\forall x. ((P(0) \wedge \forall y. (P(y) \rightarrow P(y + 1))) \rightarrow \forall x. P(x))$
- Given a statement, it is decidable whether that statement can be proven from the laws of Presburger arithmetic.
- Any Turing machine that decides whether a statement in Presburger arithmetic is true or false has to move the tape head at least  $2^{2^{cn}}$  times on some inputs of length  $n$  (for some fixed constant  $c$ ).

# For Reference

- Assume  $c = 1$ .

$$2^{2^0} = 2$$

$$2^{2^1} = 4$$

$$2^{2^2} = 16$$

$$2^{2^3} = 256$$

$$2^{2^4} = 65536$$

$$2^{2^5} = 18446744073709551616$$

$$2^{2^6} = 340282366920938463463374607431768211456$$

# The Limits of Decidability

- The fact that a problem is decidable does not mean that it is *feasibly* decidable.
- In **computability theory**, we ask the question

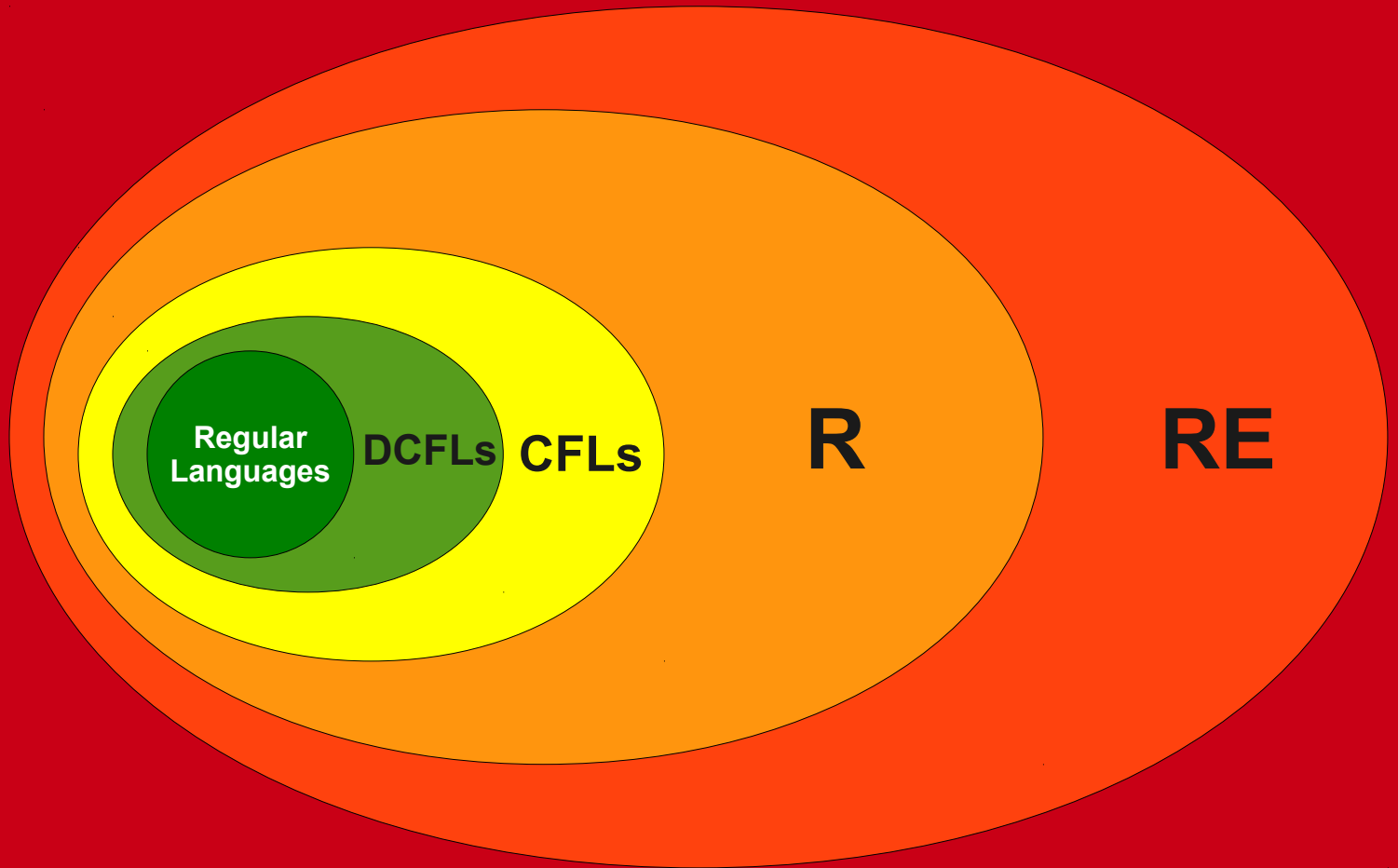
Is it **possible** to solve problem  $L$ ?

- In **complexity theory**, we ask the question

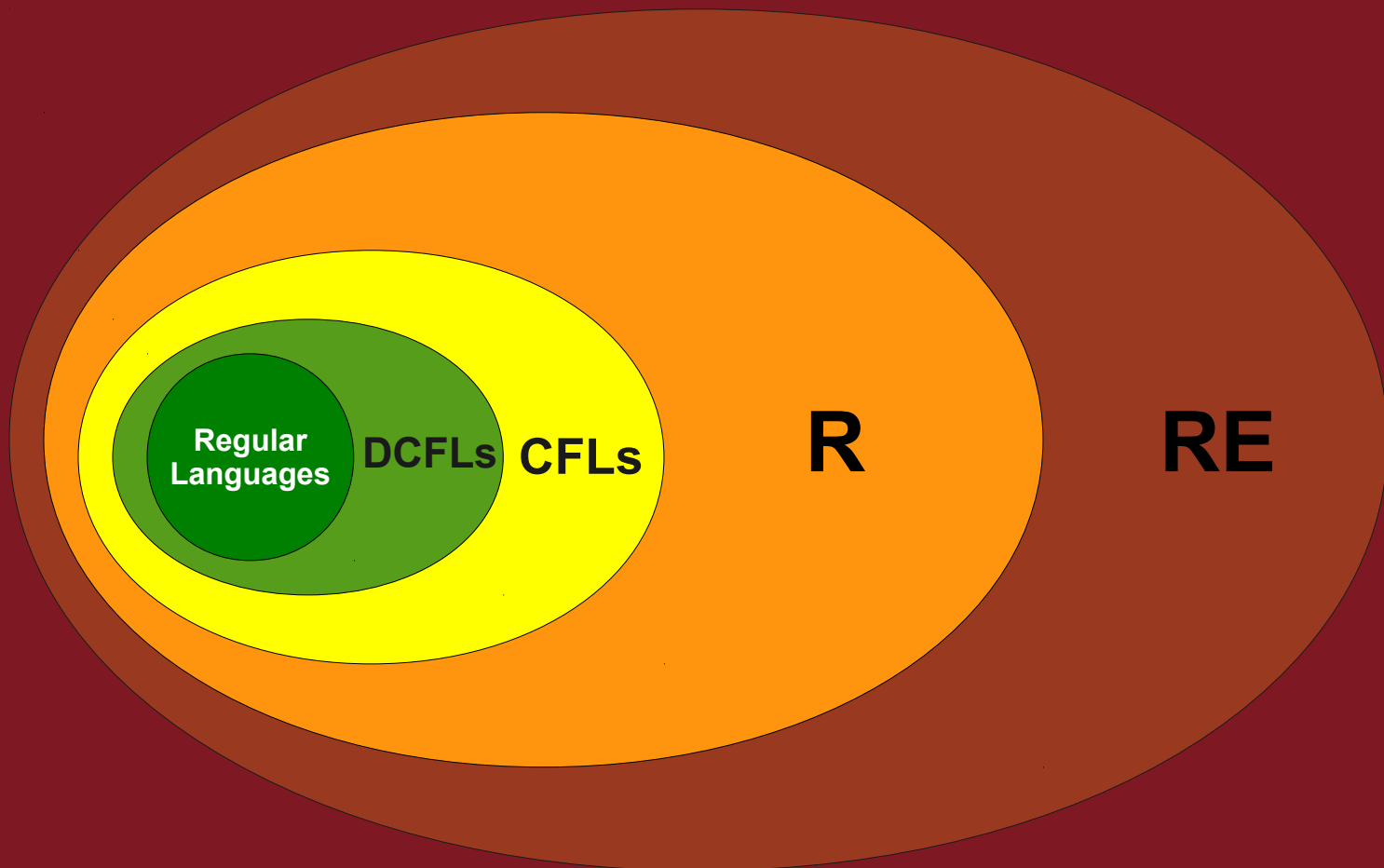
Is it possible to solve problem  $L$  **efficiently**?

- In the remainder of this course, we will explore this question in more detail.





**All Languages**



Regular  
Languages

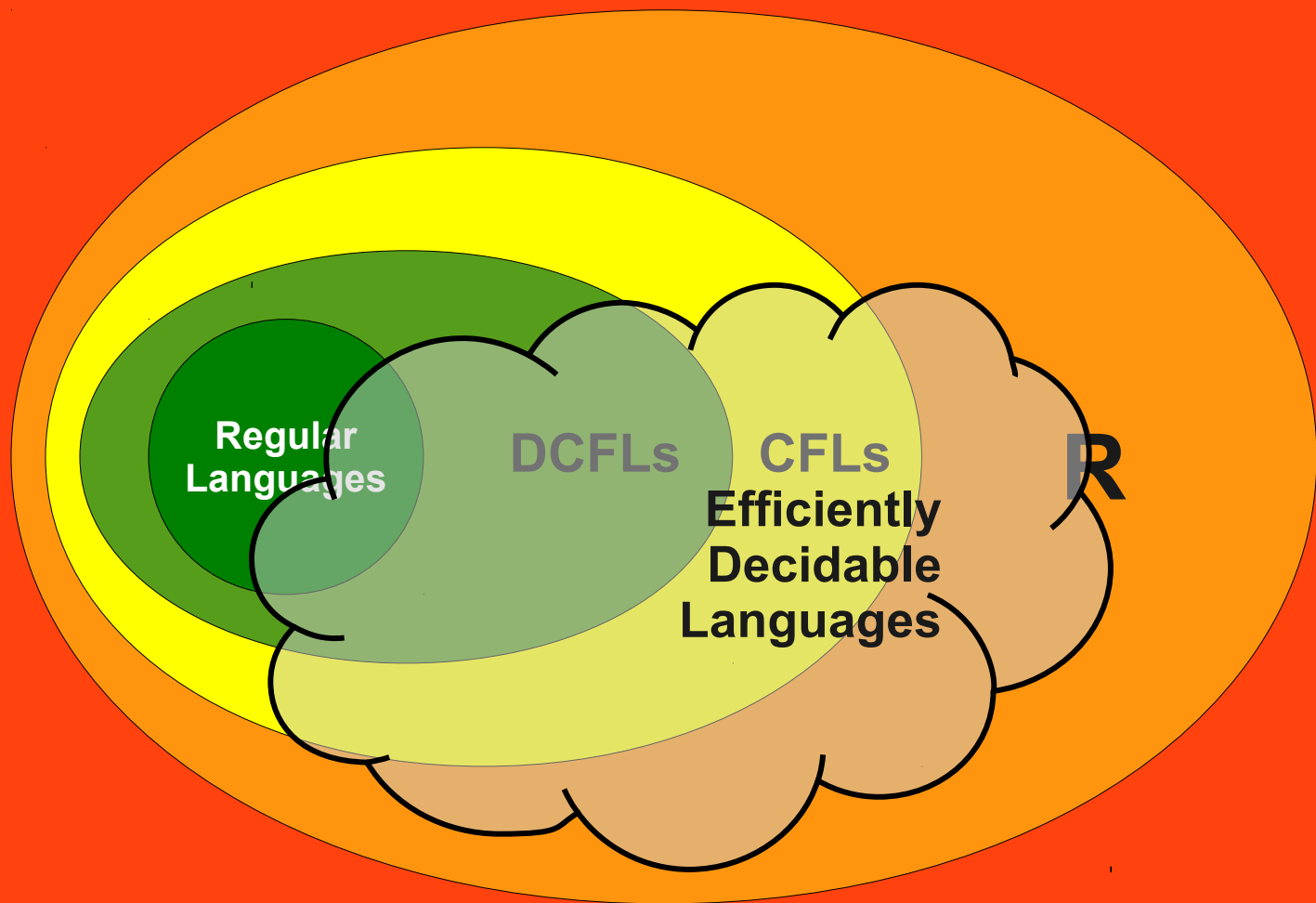
DCFLs

CFLs

R

RE

All Languages



**Undecidable Languages**

# The Setup

- In order to study computability, we needed to answer these questions:
  - What is “computation?”
  - What is a “problem?”
  - What does it mean to “solve” a problem?
- To study complexity, we need to answer these questions:
  - What does “complexity” even mean?
  - What is an “efficient” solution to a problem?

# Measuring Complexity

- Suppose that we have a decider  $D$  for some language  $L$ .
- How might we measure the complexity of  $D$ ?

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  - Number of states.
  - Size of tape alphabet.
  - Size of input alphabet.
  - Amount of tape required.
  - Number of steps required.
  - Number of times a given state is entered.
  - Number of times a given symbol is printed.
  - Number of times a given transition is taken.
  - (Plus a whole lot more...)

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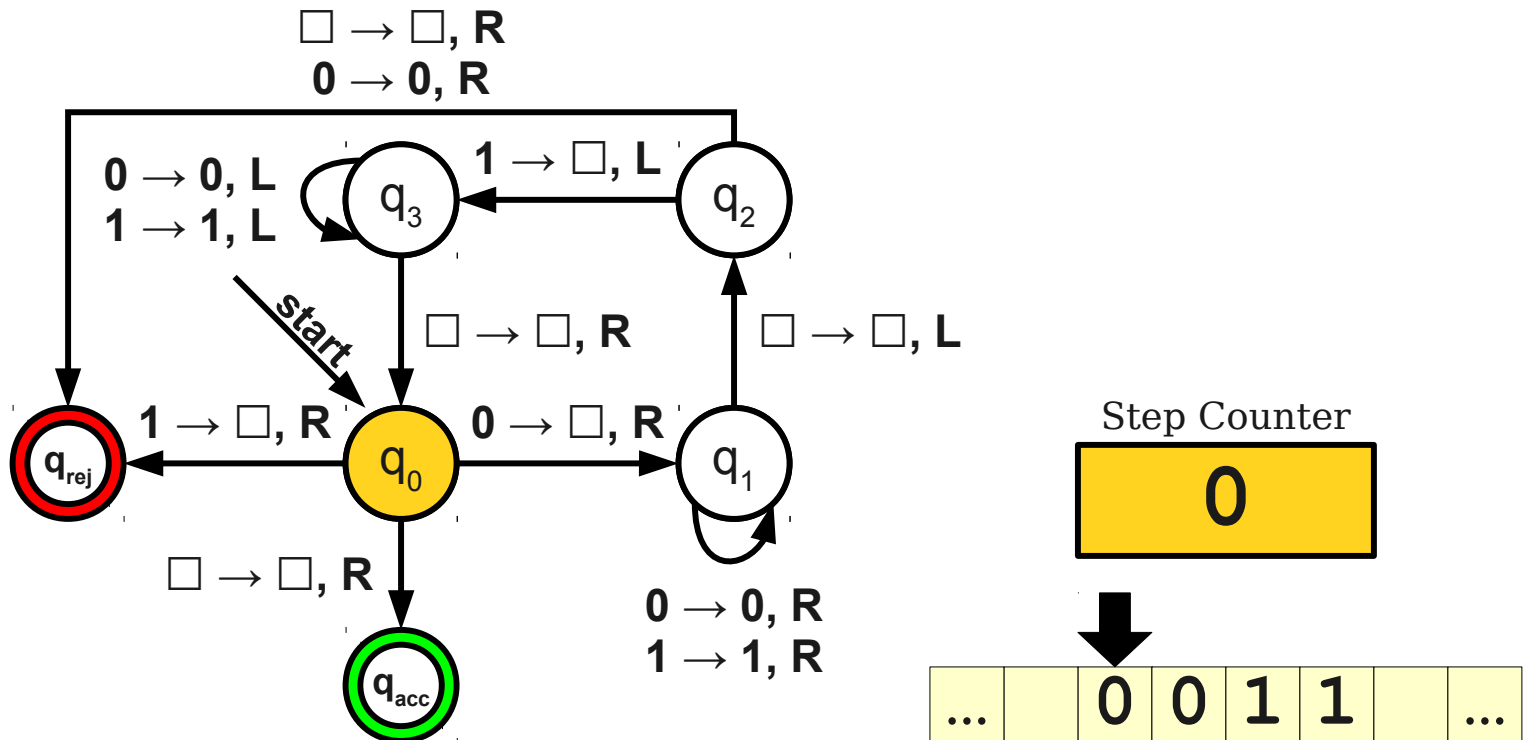
Number of times a given symbol is printed.

Number of times a given transition is taken.

(Plus a whole lot more...)

# Time Complexity

- A **step** of a Turing machine is one event where the TM takes a transition.





# Time Complexity

- The number of steps a TM takes on some input is sensitive to
  - The structure of that input.
  - The length of the input.
- How can we come up with a consistent measure of a machine's runtime?

# Time Complexity

- The **time complexity** of a TM  $M$  is a function (typically denoted  $f(n)$ ) that measures the *worst-case* number of steps  $M$  takes on any input of length  $n$ .
  - By convention,  $n$  denotes the length of the input.
  - If  $M$  loops on some input of length  $k$ , then  $f(k) = \infty$ .
- The previous TM has a time complexity that is (roughly) proportional to  $n^2 / 2$ .
  - Difficult and utterly unrewarding exercise: compute the *exact* time complexity of the previous TM.

$O(n^2/2)$   
 $\rightarrow O(n^2)$

# A Slight Problem

- Consider the following TM over  $\Sigma = \{0, 1\}$  for the language  $BALANCE = \{ w \in \Sigma^* \mid w \text{ has the same number of 0s and 1s} \}$ :
  - $M =$  “On input  $w$ :
    - Scan across the tape until a 0 or 1 is found.
    - If none are found, accept.
    - If one is found, continue scanning until a matching 1 or 0 is found.
    - If none is found, reject.
    - Otherwise, cross off that symbol and repeat.”
- What is the time complexity of  $M$ ?

Also  
SPACE

# A Loss of Precision

- When considering *computability*, using high-level TM descriptions is perfectly fine.
- When considering *complexity*, high-level TM descriptions make it nearly impossible to precisely reason about the actual time complexity.
- What are we to do about this?

# The Best We Can

$M =$  “On input  $w$ :

- Scan across the tape until a 0 or 1 is found. **At most  $n$  steps.**
- If none are found, accept. **At most 1 step.**
- If one is found, continue scanning until a matching 1 or 0 is found. **At most  $n$  more steps.**
- If none are found, reject. **At most 1 step**
- Otherwise, cross off that symbol and repeat.” **At most  $n$  steps to get back to the start of the tape.**

**At most  $n/2$  loops**

+

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**At most  $3n + 2$  steps.**

×

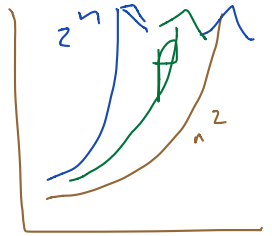
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**At most  $n/2$  loops.**

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**At most  $3n^2 / 2 + n$  steps.**

# An Easier Approach



- In complexity theory, we rarely need an exact value for a TM's time complexity.
- Usually, we are curious with the long-term growth rate of the time complexity.
- For example, if the time complexity is  $3n + 5$ , then doubling the length of the string roughly doubles the worst-case runtime.
- If the time complexity is  $2^n + n^2$ , since  $2^n$  grows much more quickly than  $n^2$ , for large values of  $n$ , increasing the size of the input by 1 doubles the worst-case running time.

# Big-O Notation

- Ignore *everything* except the dominant growth term, including constant factors.
- Examples:
  - $4n + 4 = \mathbf{O(n)}$
  - $137n + 271 = \mathbf{O(n)}$
  - $n^2 + 3n + 4 = \mathbf{O(n^2)}$
  - $2^n + n^3 = \mathbf{O(2^n)}$
  - $137 = \mathbf{O(1)}$
  - $n^2 \log n + \log^5 n = \mathbf{O(n^2 \log n)}$

# Big-O Notation, Formally

- Let  $f : \mathbb{N} \rightarrow \mathbb{N}$  and  $g : \mathbb{N} \rightarrow \mathbb{N}$ .
- Then  $f(n) = O(g(n))$  iff there exist constants  $c \in \mathbb{R}$  and  $n_0 \in \mathbb{N}$  such that

$$\text{For any } n \geq n_0, f(n) \leq cg(n)$$

- Intuitively, as  $n$  gets “large” (greater than  $n_0$ ),  $f(n)$  is bounded from above by some multiple (determined by  $c$ ) of  $g(n)$ .



# Properties of Big-O Notation

- **Theorem:** If  $f_1(n) = O(g_1(n))$  and  $f_2(n) = O(g_2(n))$ , then  $f_1(n) + f_2(n) = O(g_1(n) + g_2(n))$ .
  - Intuitively: If you run two programs one after another, the big-O of the result is the big-O of the sum of the two runtimes.
- **Theorem:** If  $f_1(n) = O(g_1(n))$  and  $f_2(n) = O(g_2(n))$ , then  $f_1(n)f_2(n) = O(g_1(n)g_2(n))$ .
  - Intuitively: If you run one program some number of times, the big-O of the result is the big-O of the program times the big-O of the number of iterations.
- This makes it substantially easier to analyze time complexity, though we do lose some precision.

# Life is Easier with Big-O

$M$  = “On input  $w$ :

- Scan across the tape until a 0 or 1 is found.
- If none are found, accept.
- If one is found, continue scanning until a matching 1 or 0 is found.
- If none is found, reject.
- Otherwise, cross off that symbol and repeat.”

$O(n)$  steps

$O(1)$  steps

$O(n)$  steps

$O(1)$  steps

+  $O(n)$  steps

---

$O(n)$  steps

×  $O(n)$  loops

---

$O(n^2)$  steps

$O(n)$   
loops

# Next Time

- **P**
  - What problems can be decided efficiently?
- **Polynomial-Time Reductions**
  - Constructing efficient algorithms.
- **NP**
  - What can we *verify* quickly?