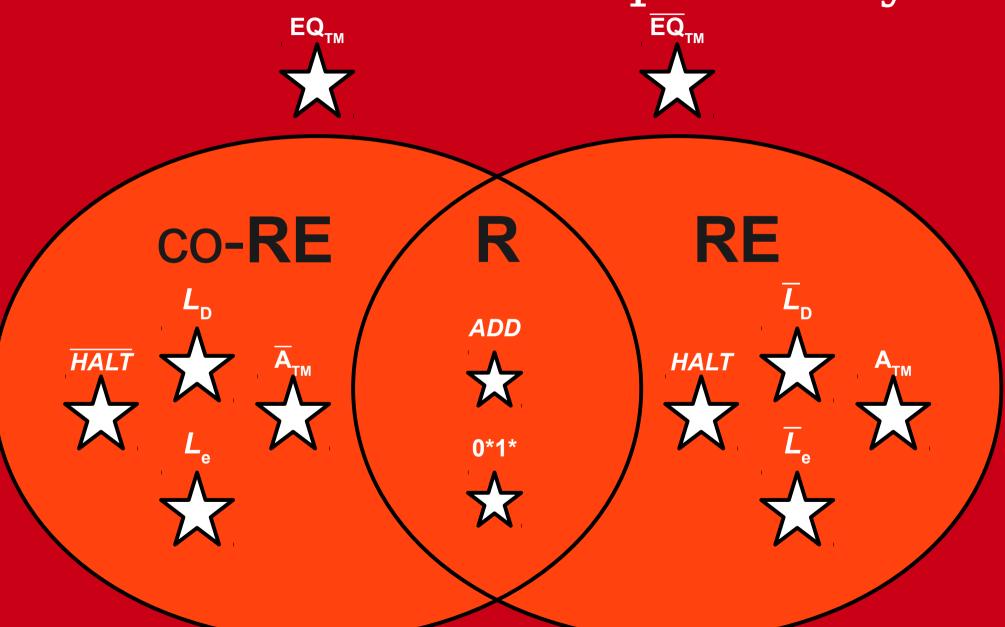
Complexity Theory Part I

Problem Set 7 due right now using a late period

The Limits of Computability



What problems can be solved by a computer?

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

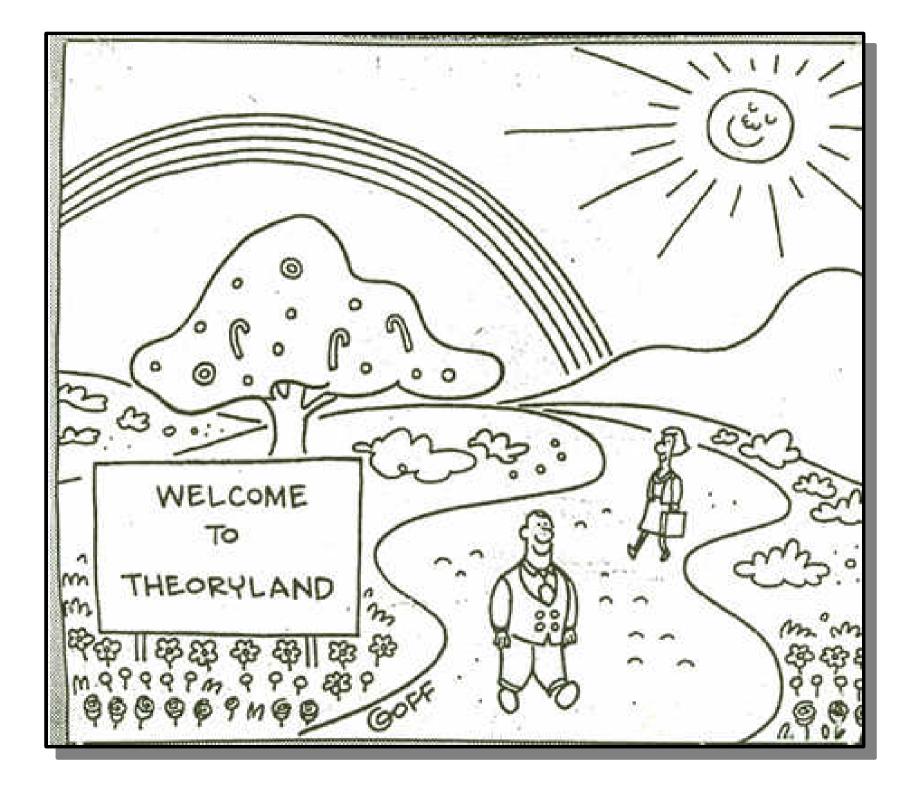
Where We've Been

- 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.

It may be that since one is customarily concerned with existence, [...] finiteness, and so forth, one is not inclined to take seriously the question of the existence of a better-than-finite algorithm.



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It may be that since one is customarily concerned with existence, [...] decidability, and so forth, one is not inclined to take seriously the question of the existence of a better-than-decidable algorithm.

A Decidable Problem

- **Presburger arithmetic** is a logical system for reasoning about arithmetic.
 - $\forall x. \ x + 1 \neq 0$
 - $\forall x. \ \forall y. \ (x + 1 = y + 1 \rightarrow x = y)$
 - $\forall x. \ x + 0 = x$
 - $\forall x. \ \forall y. \ (x + y) + 1 = x + (y + 1)$
 - $\forall x. ((P(0) \land \forall y. (P(y) \rightarrow P(y+1))) \rightarrow \forall x. P(x)$
- 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).

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

$$2^{2^0} = 2$$
 $2^{2^1} = 4$

$$2^{2^0} = 2$$
 $2^{2^1} = 4$
 $2^{2^2} = 16$

$$2^{2^{0}} = 2$$
 $2^{2^{1}} = 4$
 $2^{2^{2}} = 16$
 $2^{2^{3}} = 256$

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

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

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

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

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

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

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

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

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

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

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

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

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

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

The Limits of Decidability

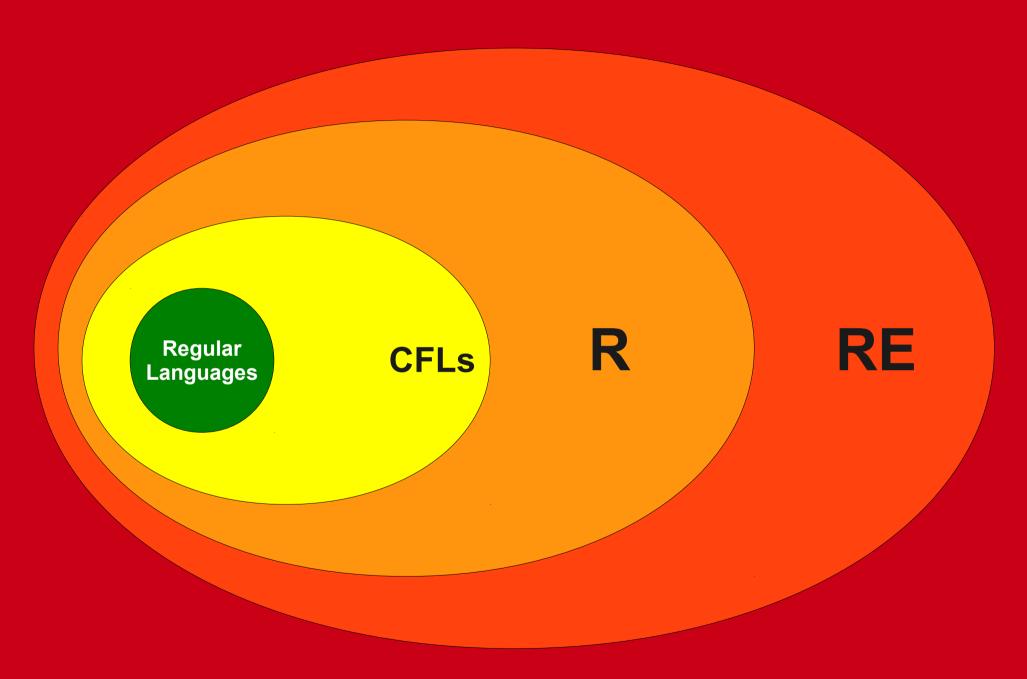
- The fact that a problem is decidable does not mean that it is *feasibly* decidable.
- In computability theory, we ask the question

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

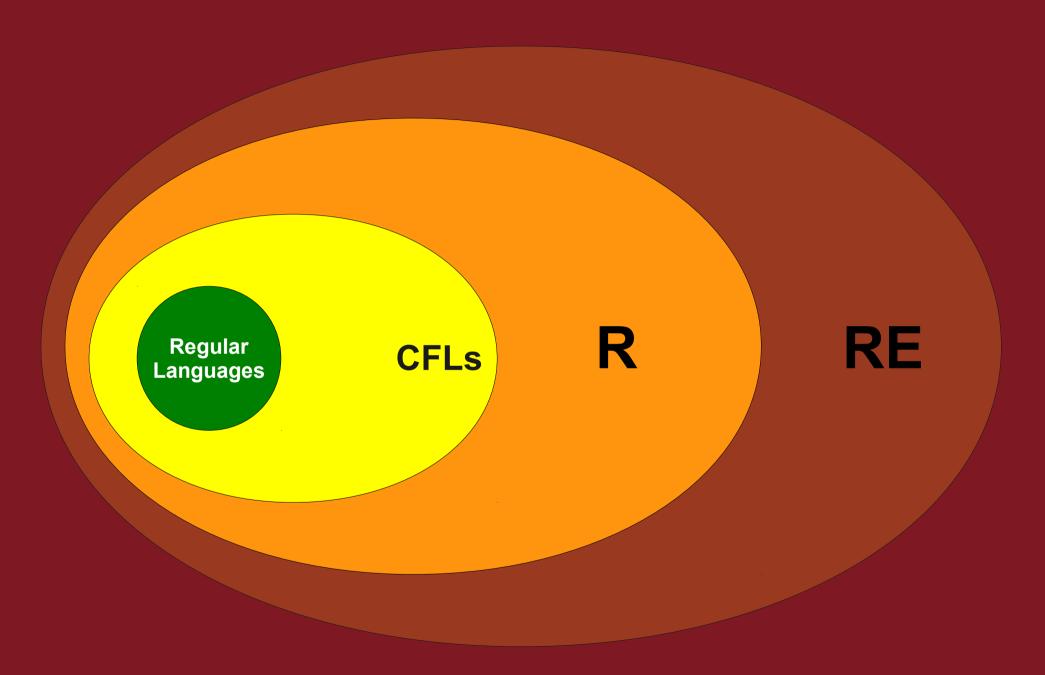
• In complexity theory, we ask the question

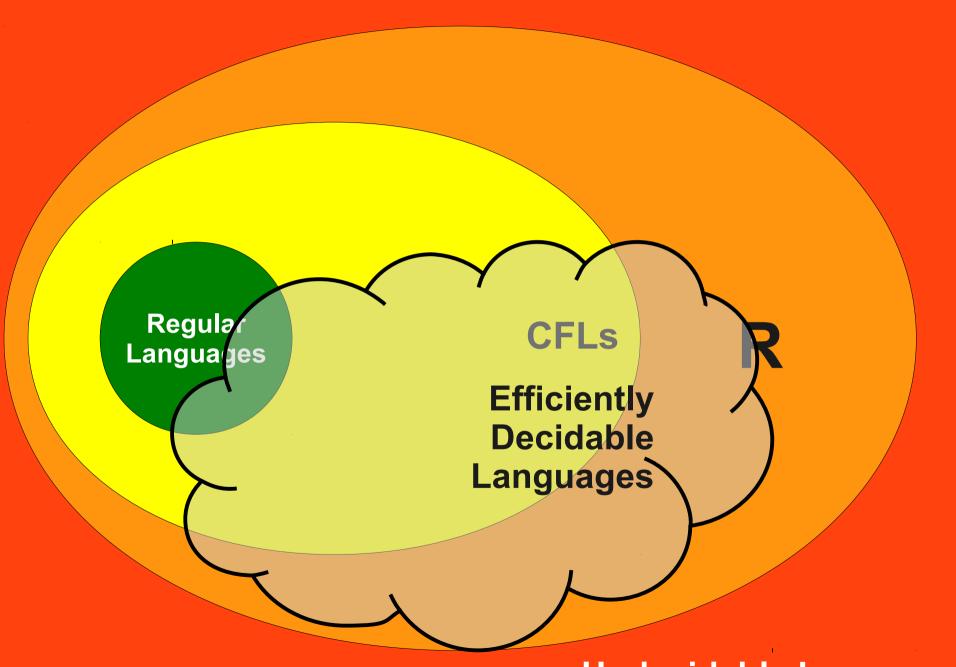
Is it possible to solve problem *L* **efficiently**?

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



All Languages





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*?

Measuring Complexity

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

Measuring Complexity

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- How might we measure the complexity of *D*?

Number of states.

Size of tape alphabet.

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Amount of tape required.

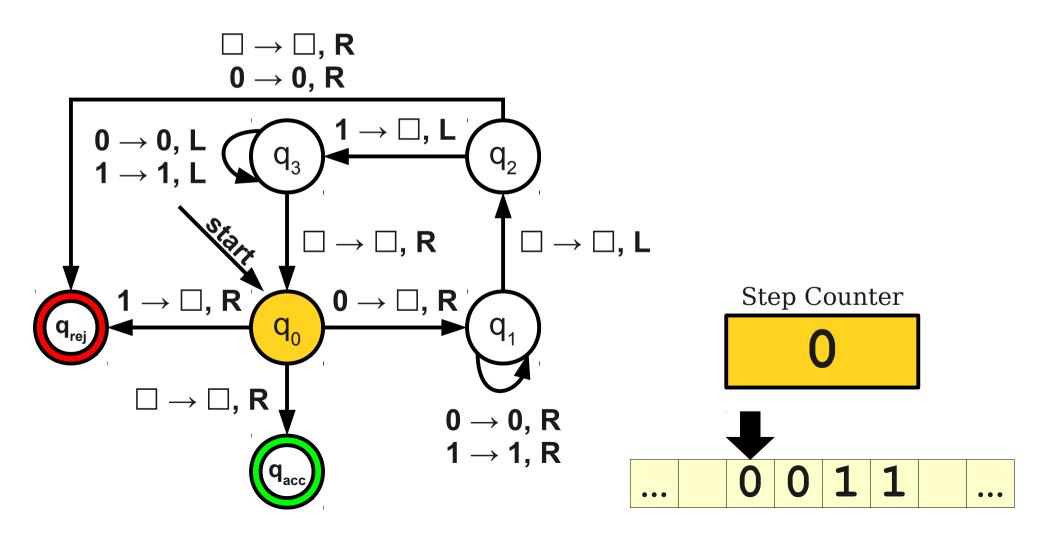
• Number of steps required.

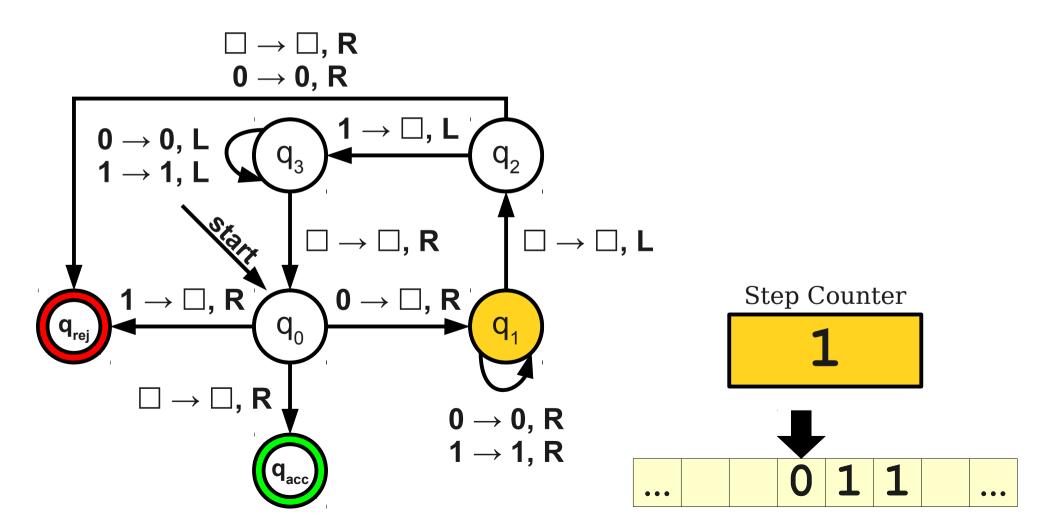
Number of times a given state is entered.

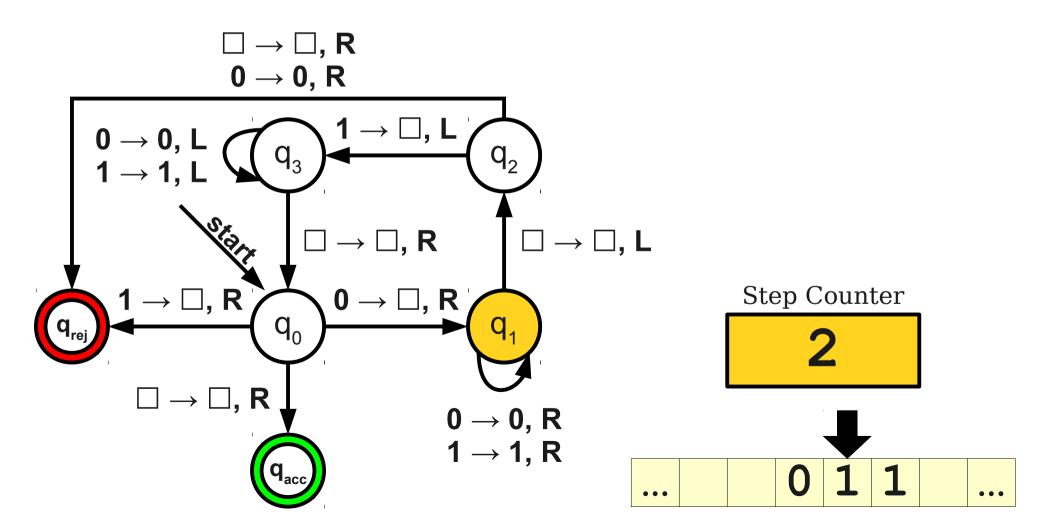
Number of times a given symbol is printed.

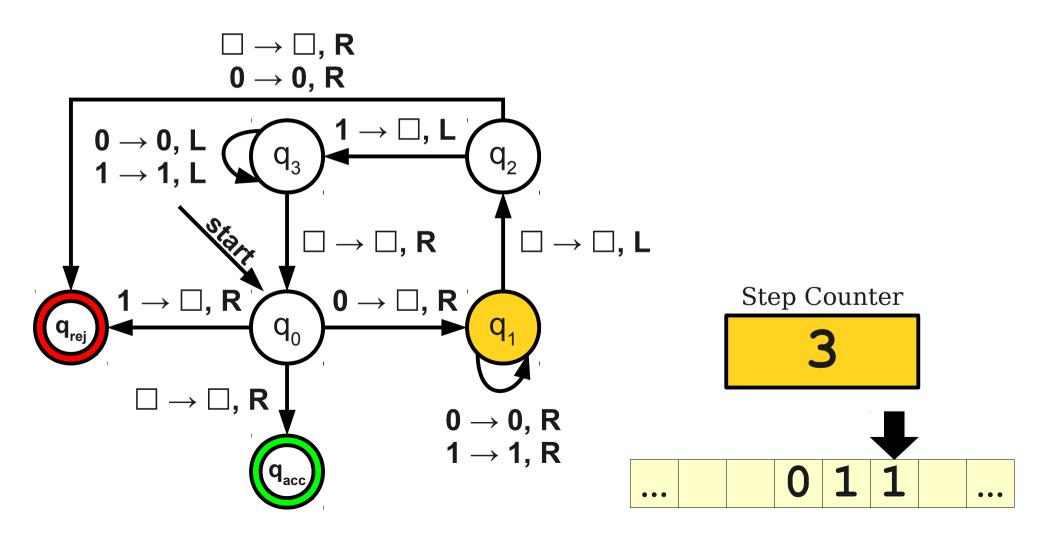
Number of times a given transition is taken.

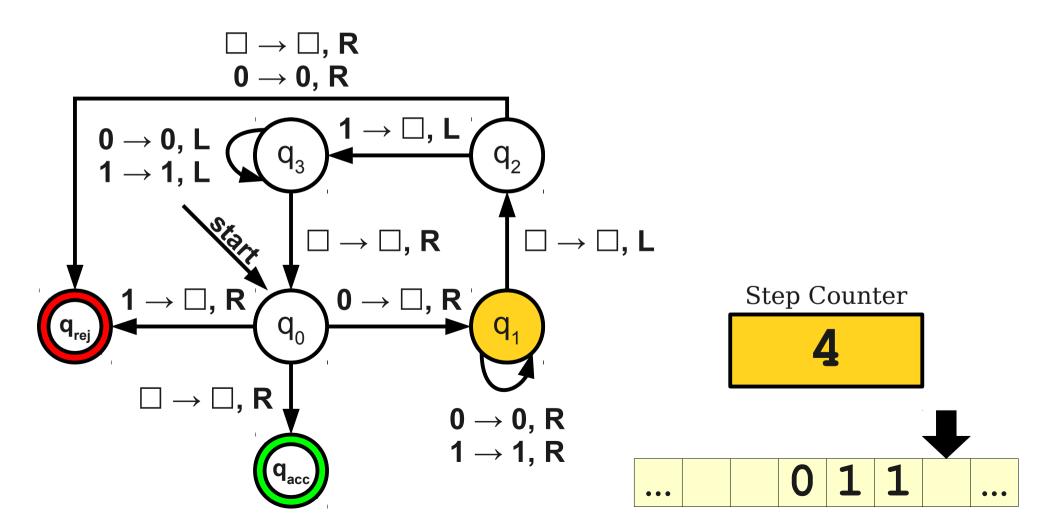
(Plus a whole lot more...)

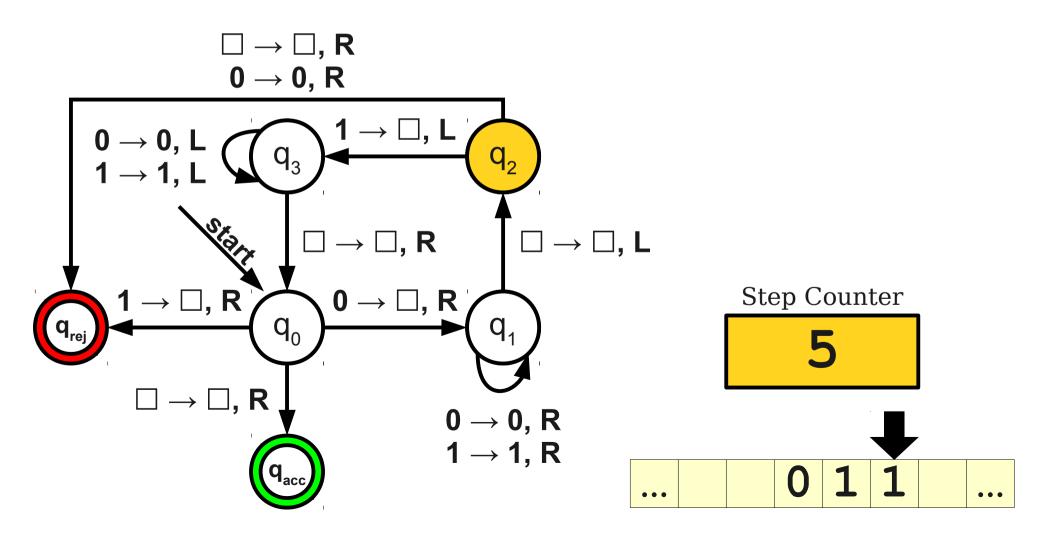


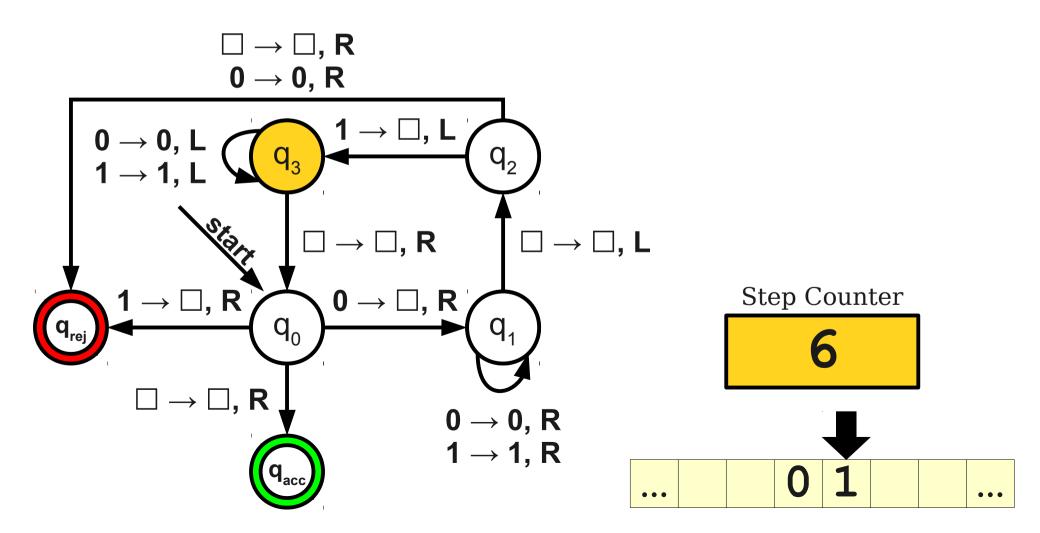


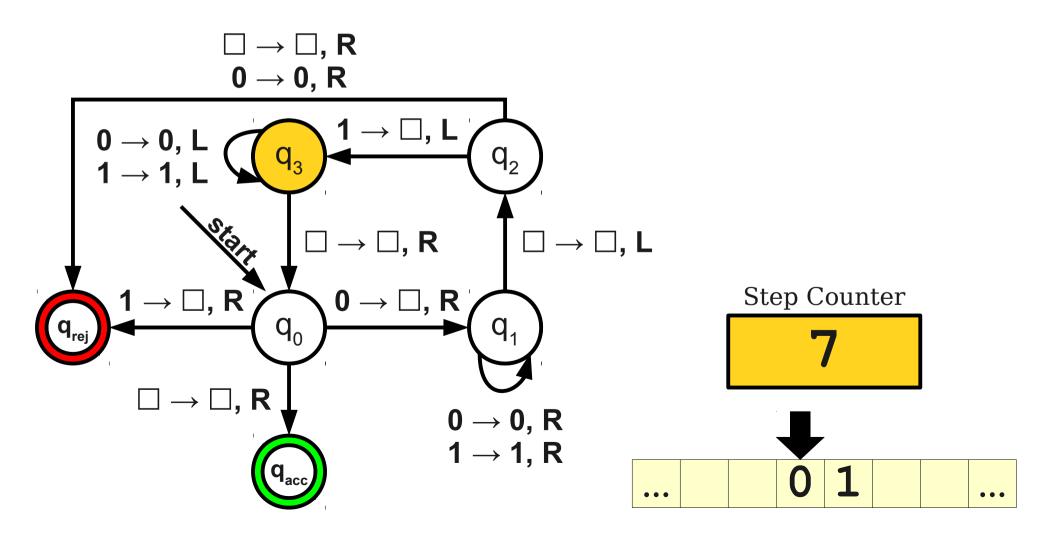


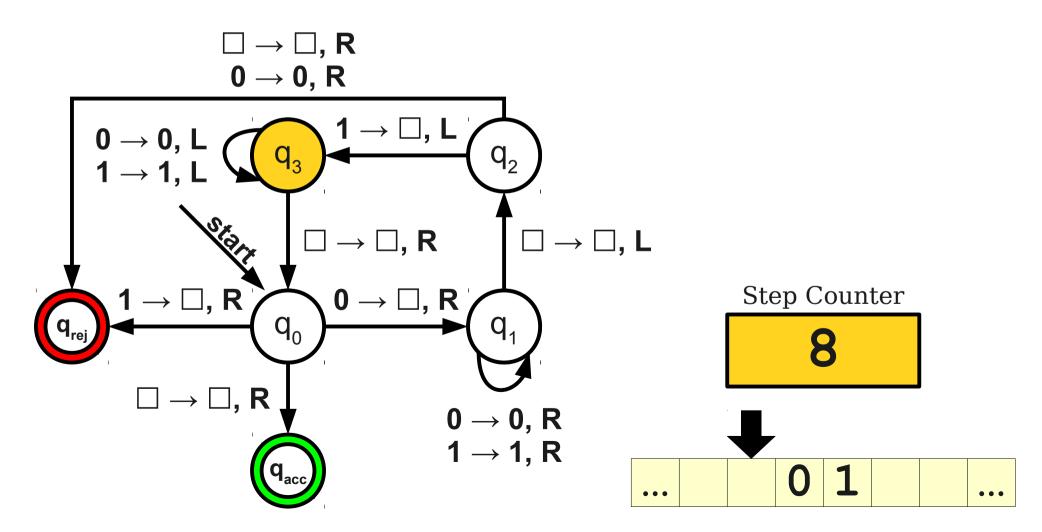


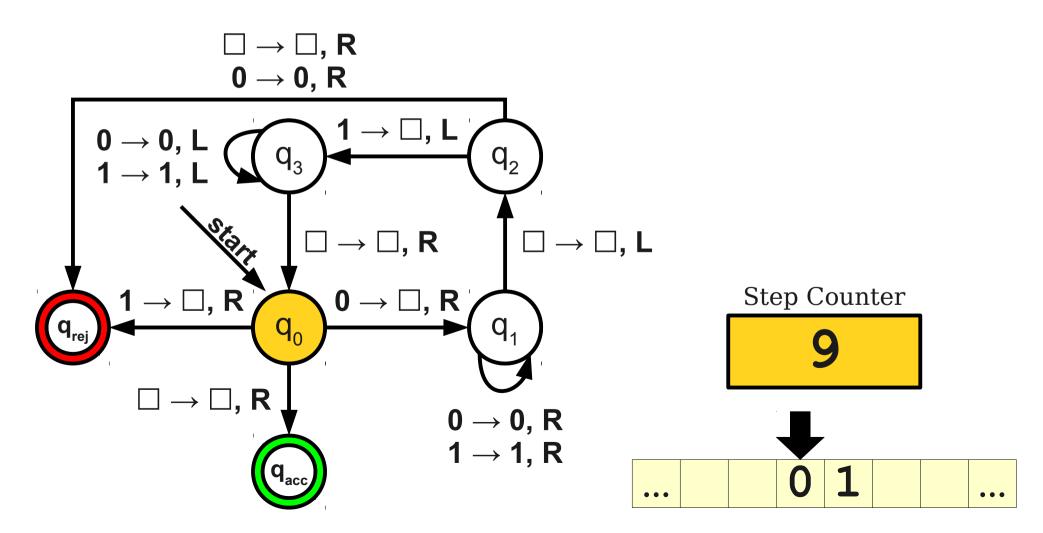


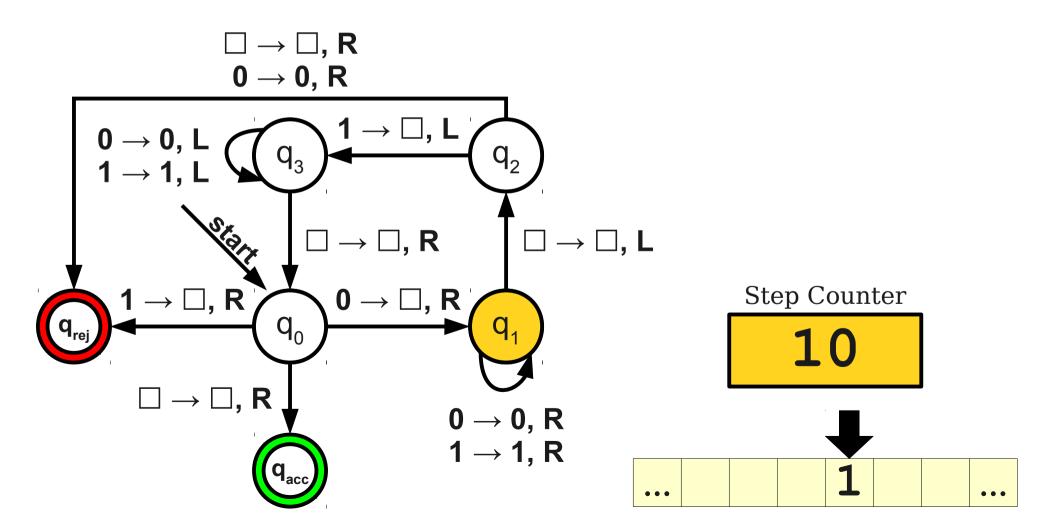


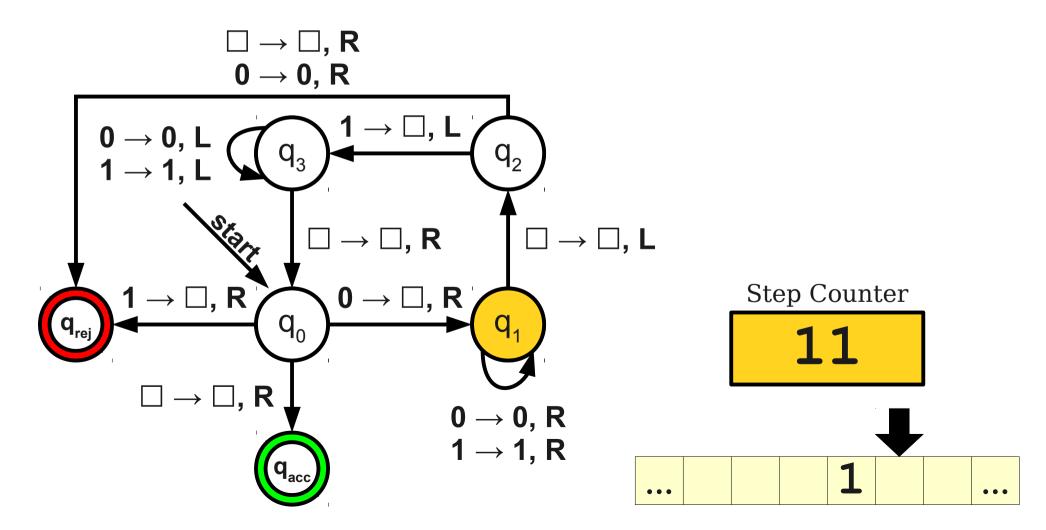


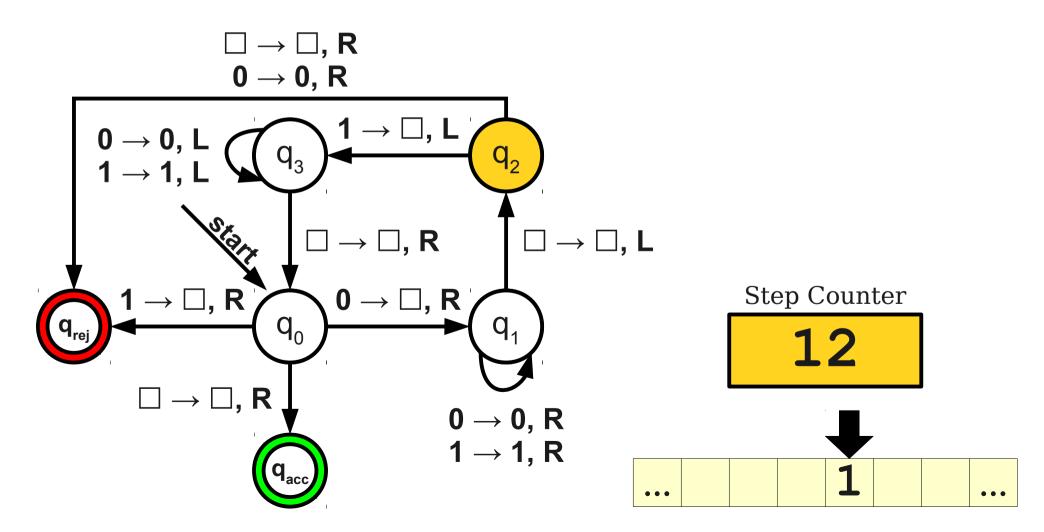


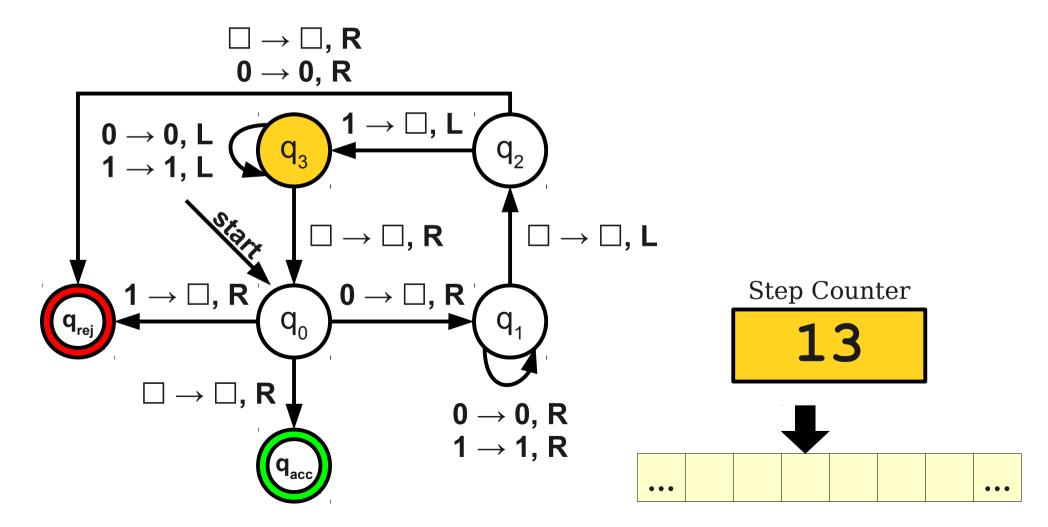


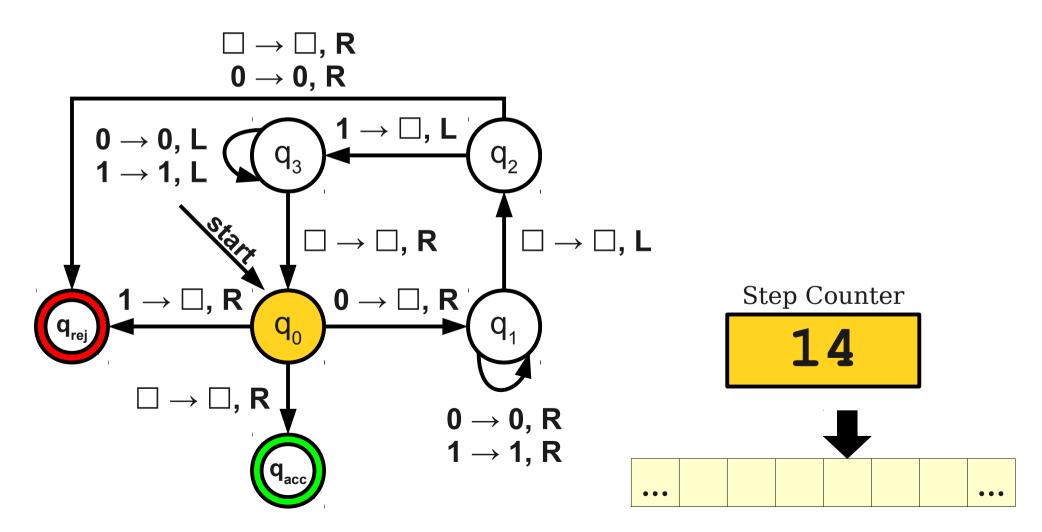


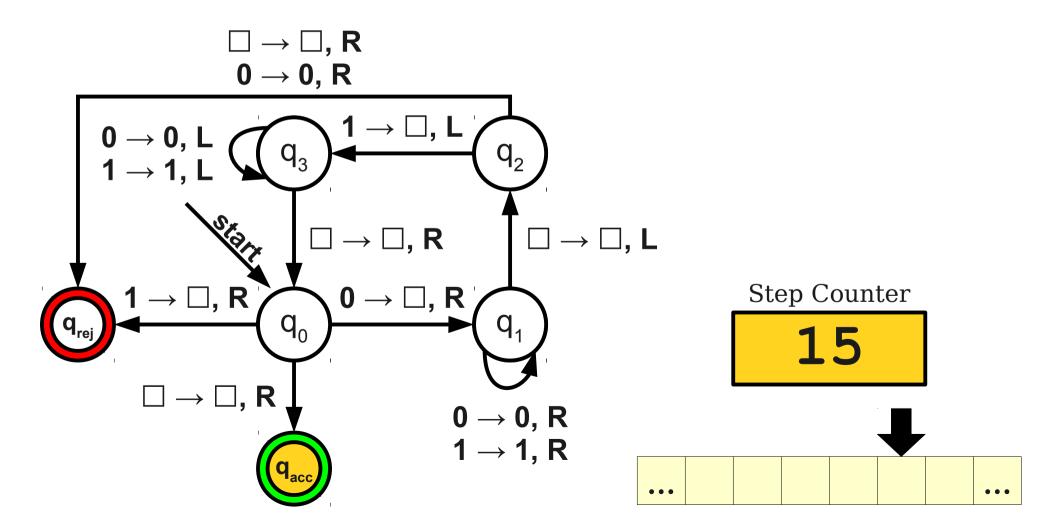


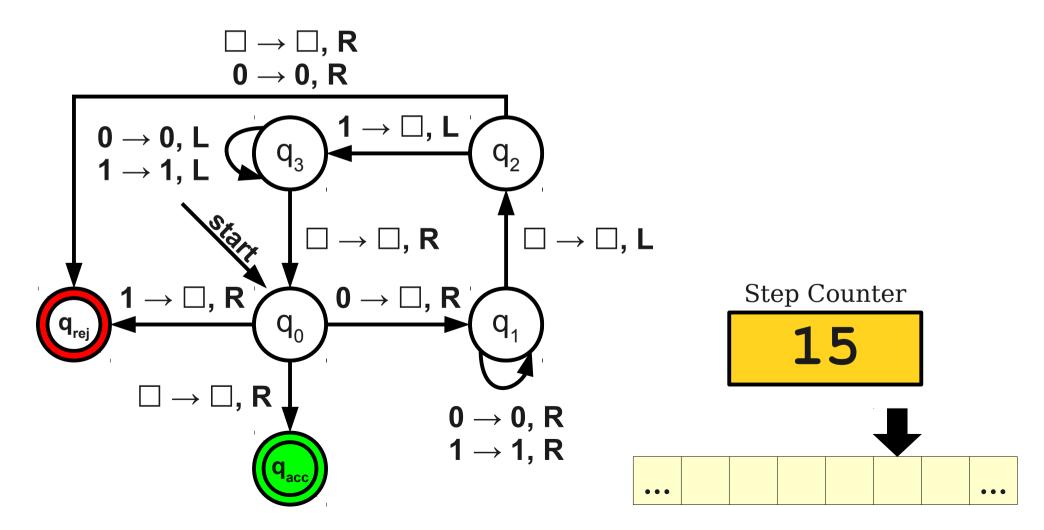


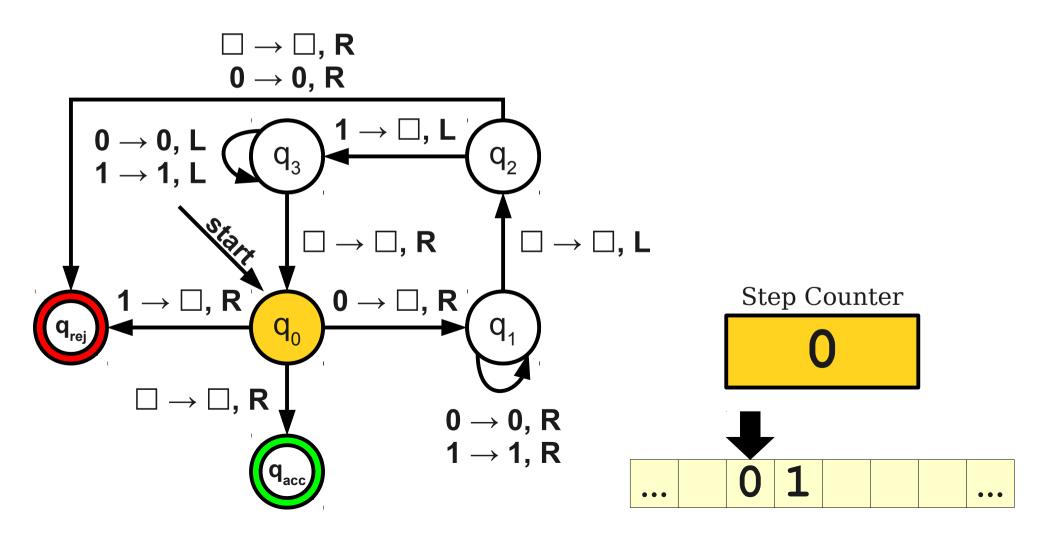


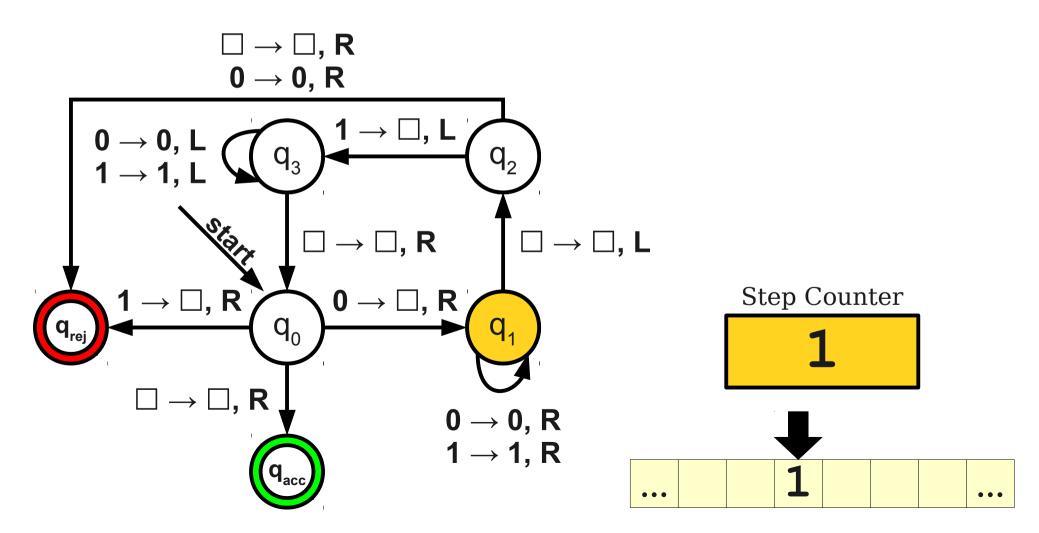


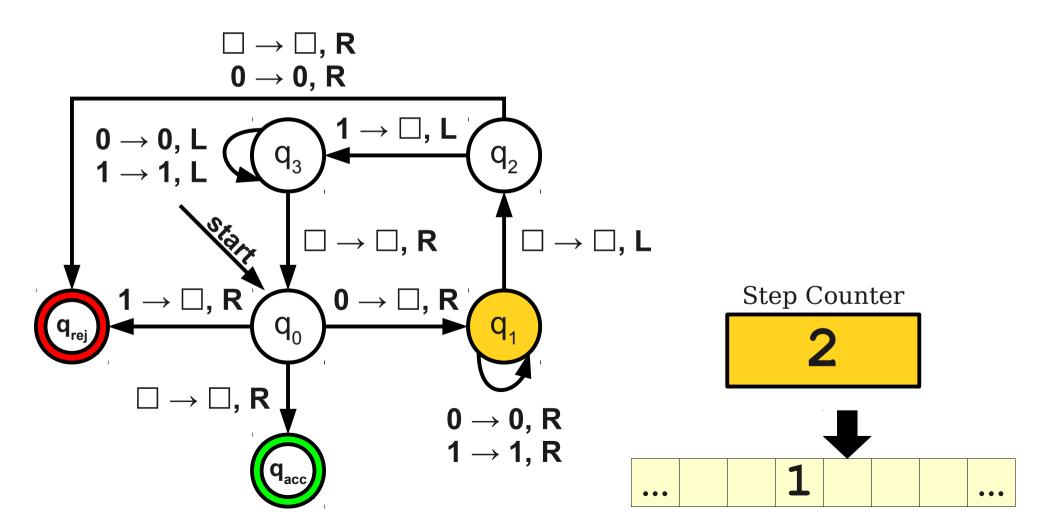


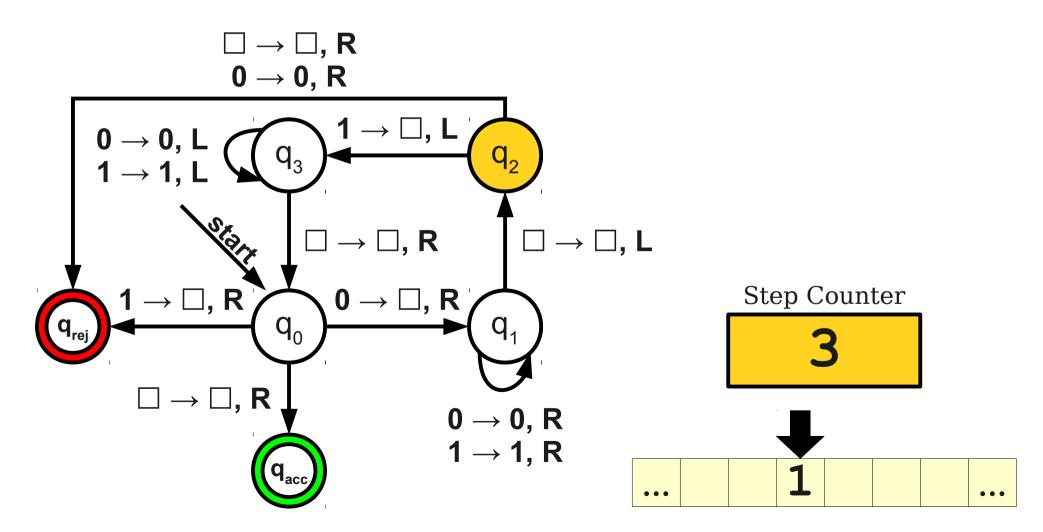


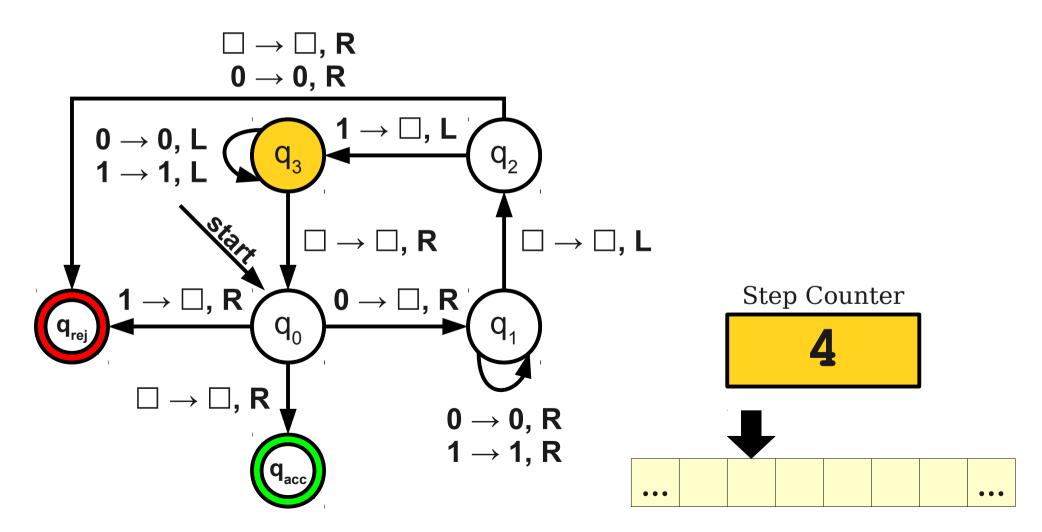


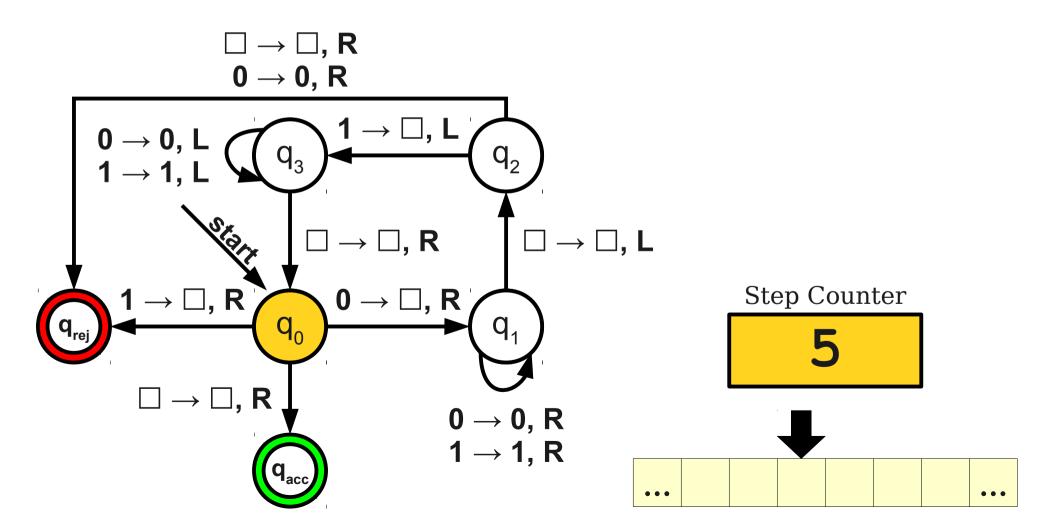


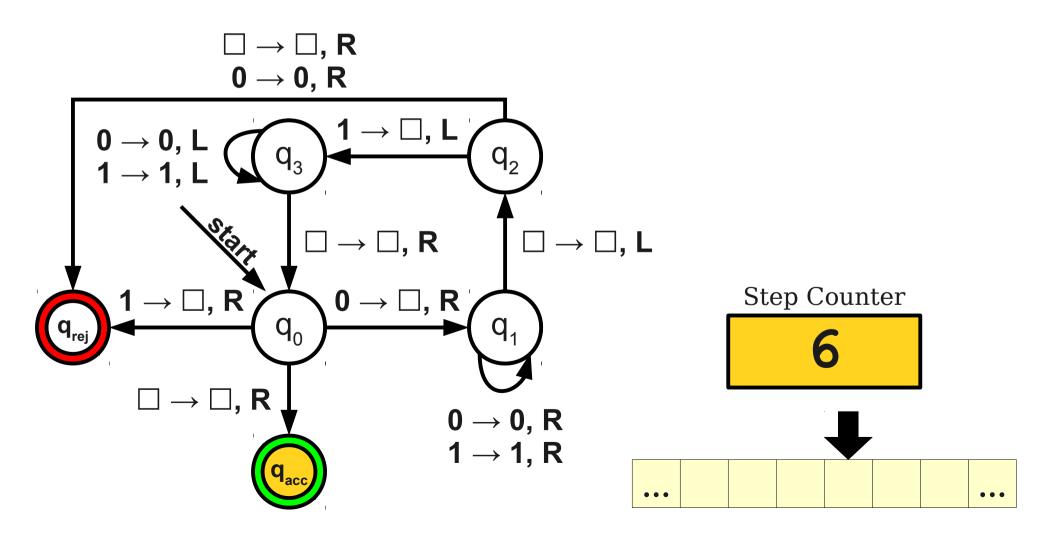


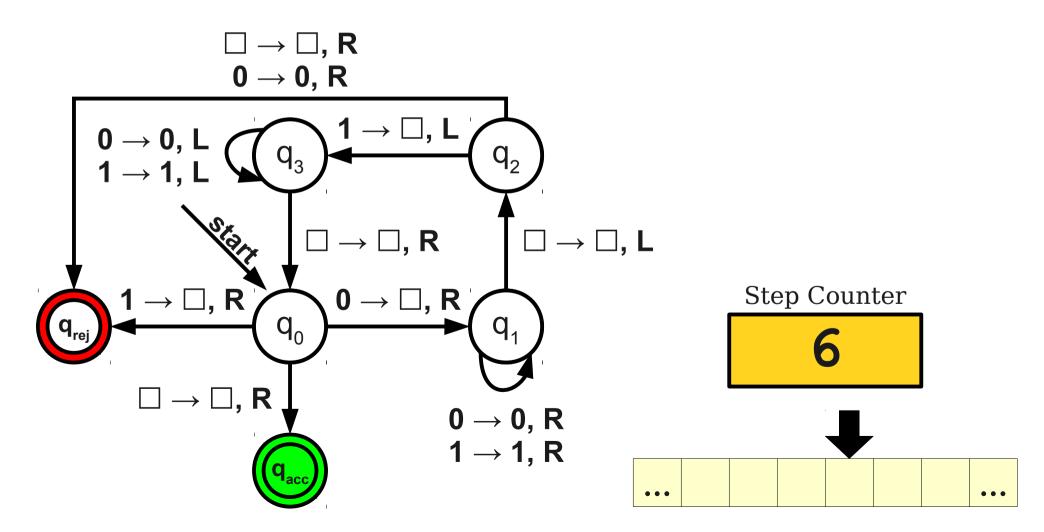


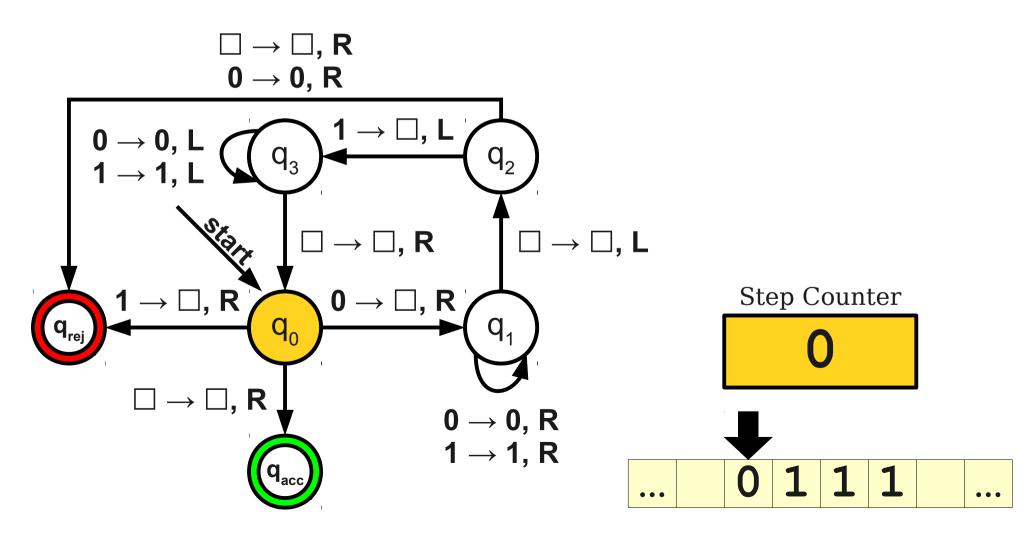


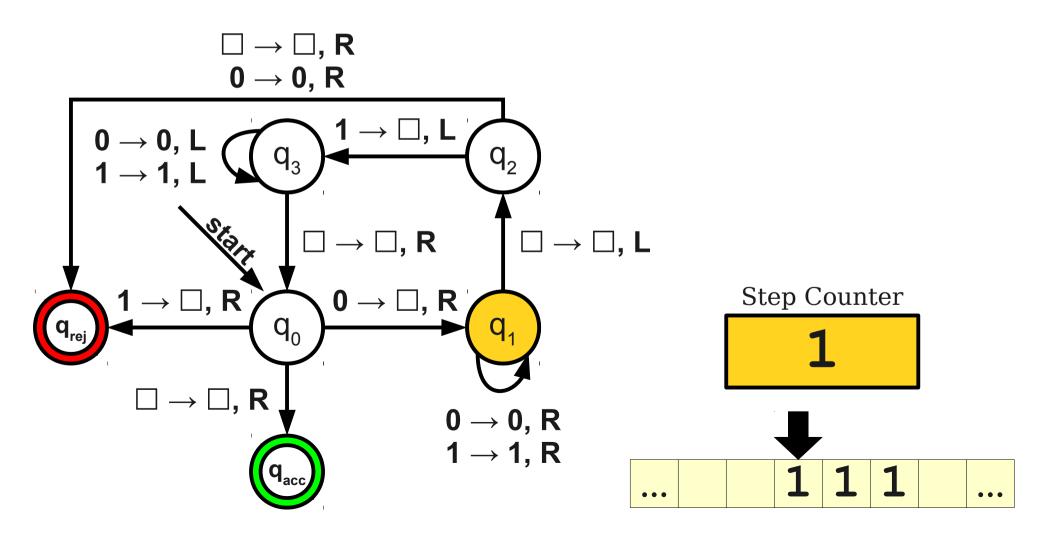


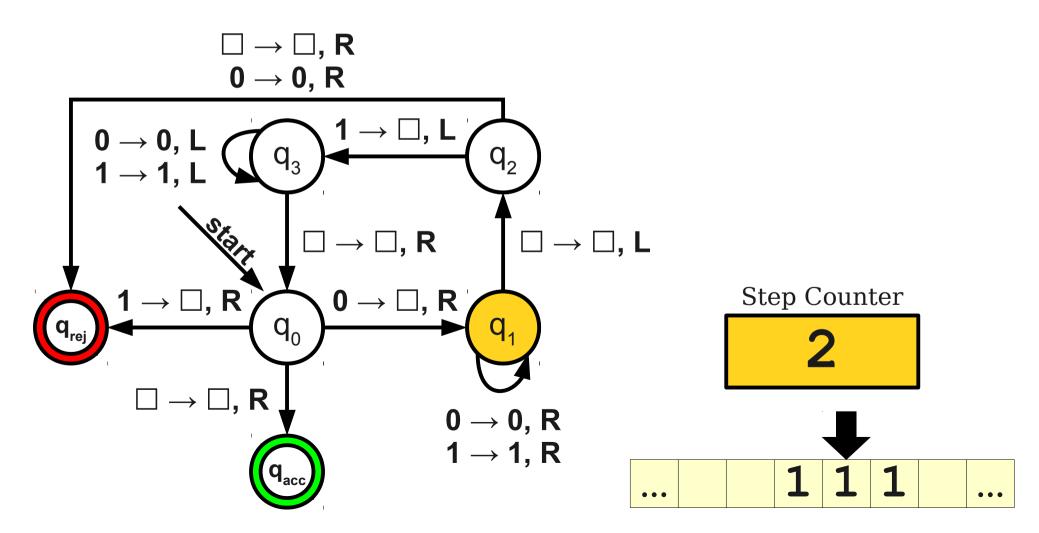


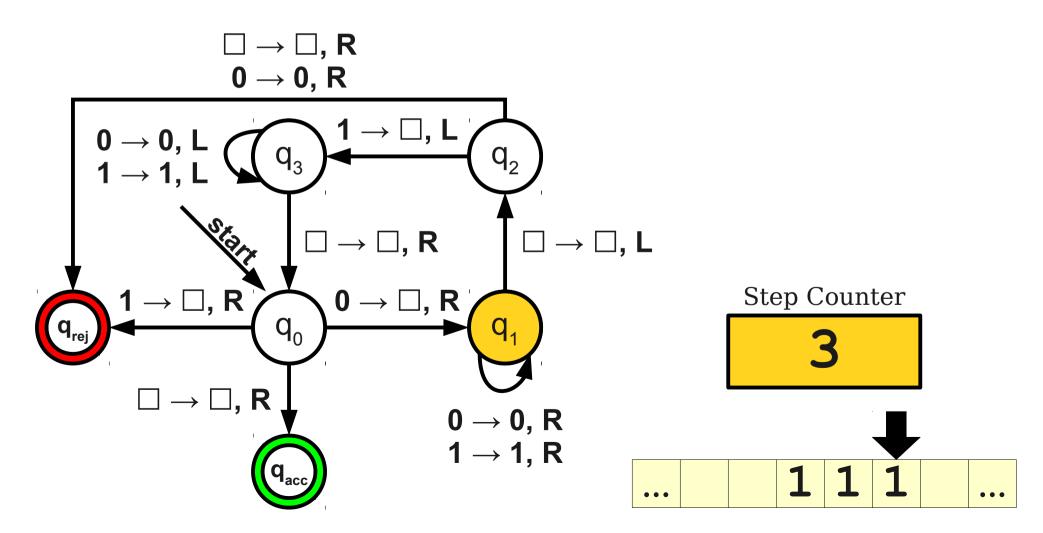


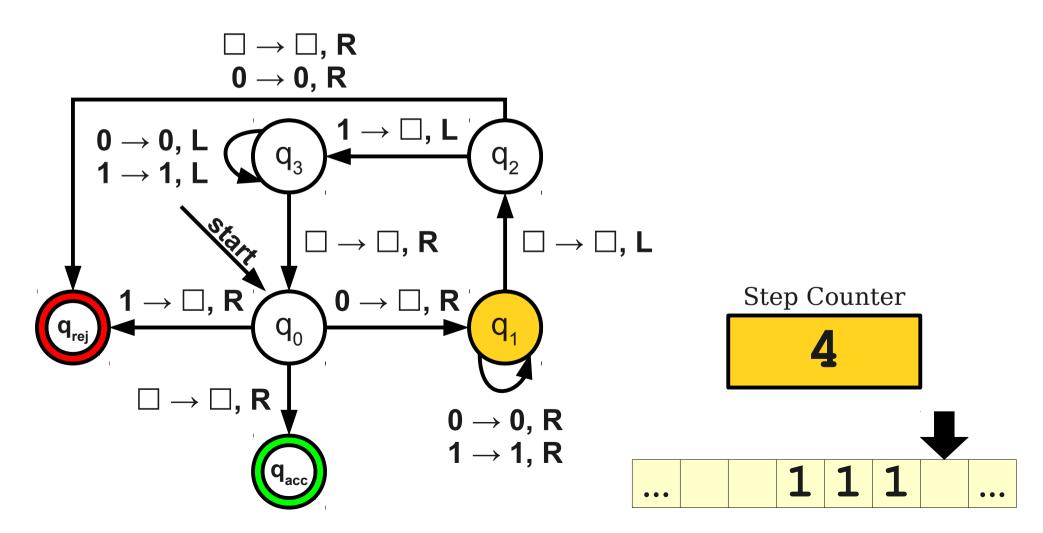


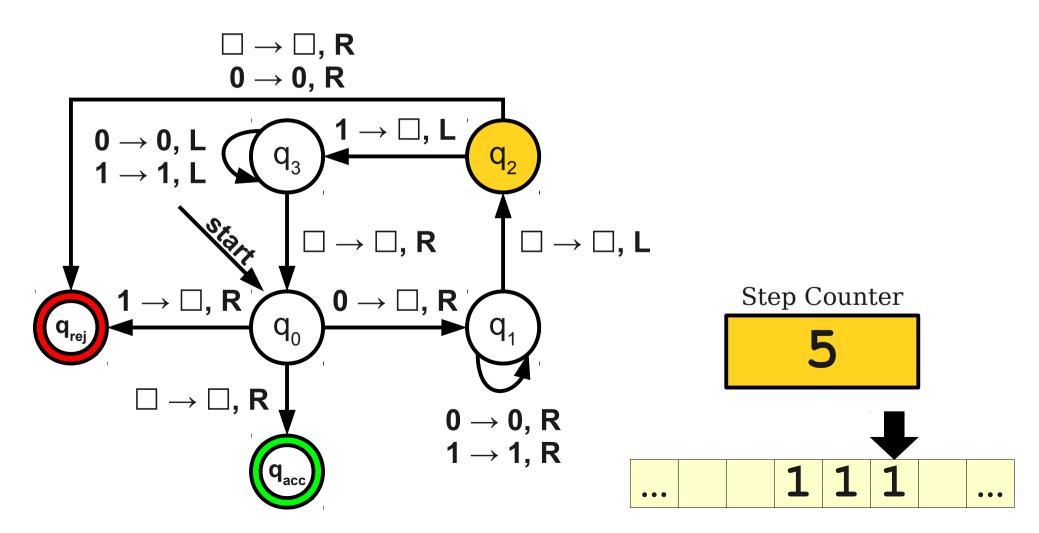


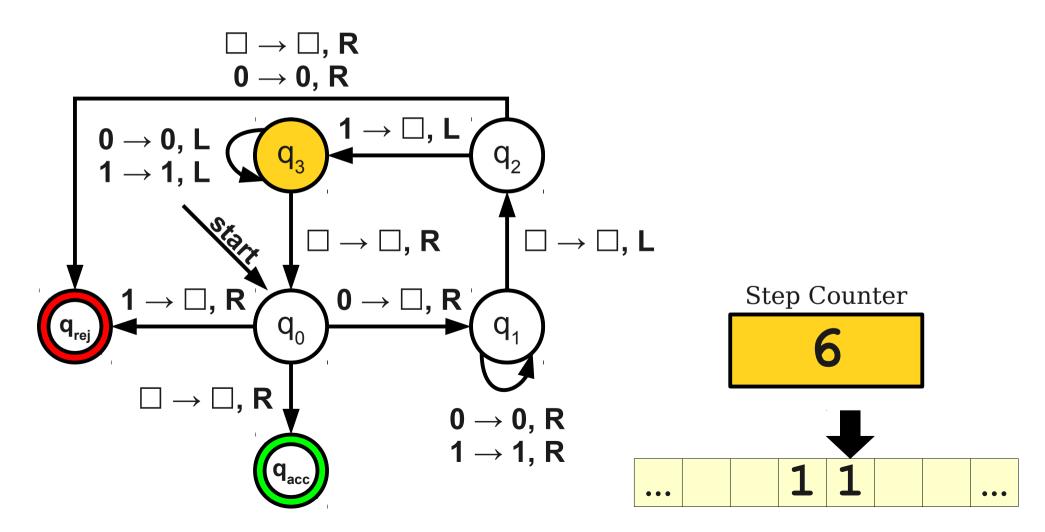


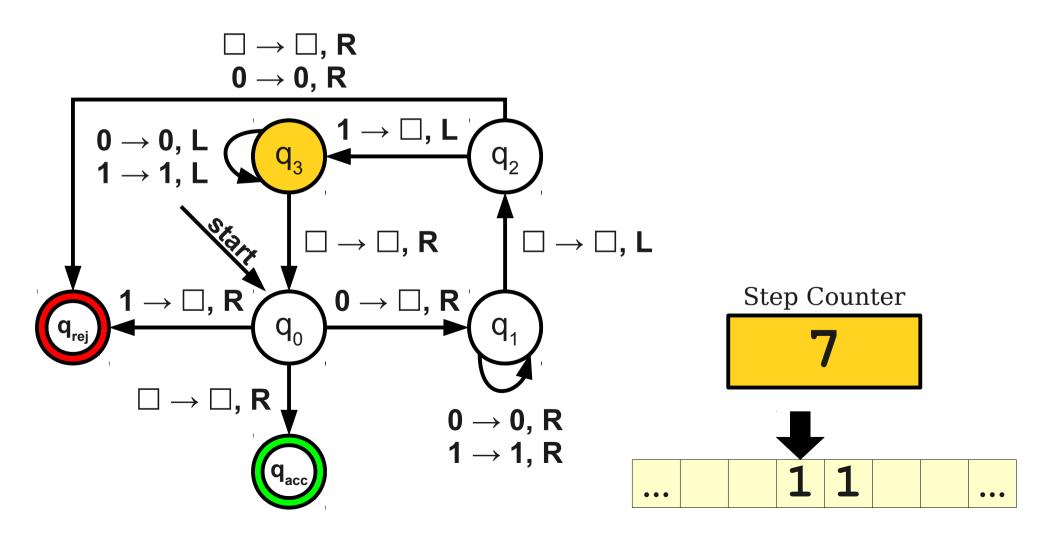


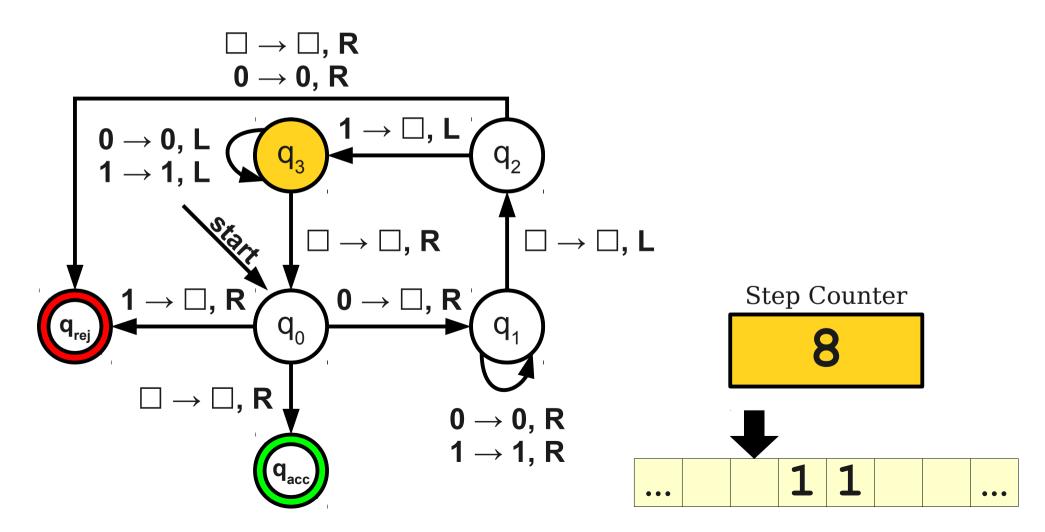


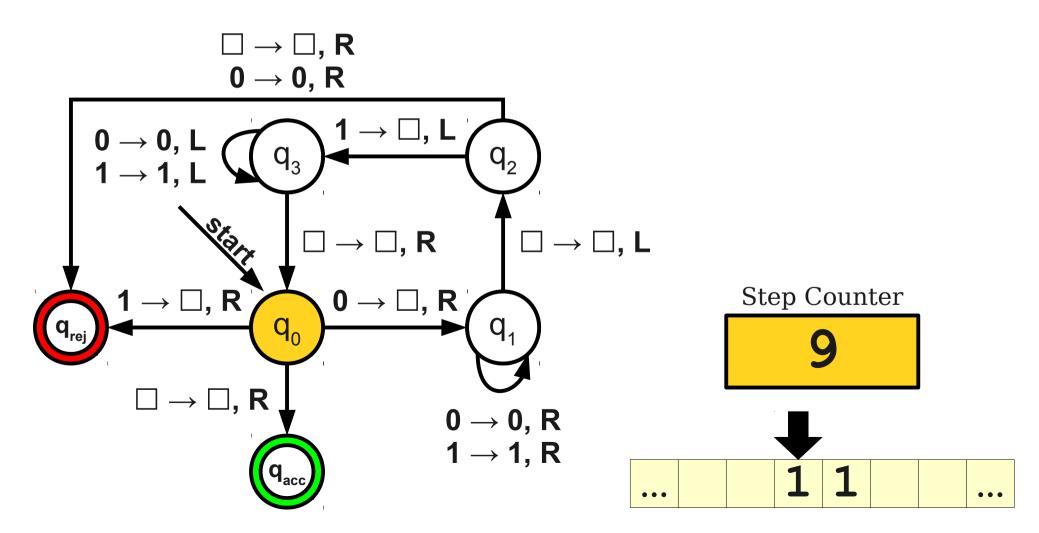


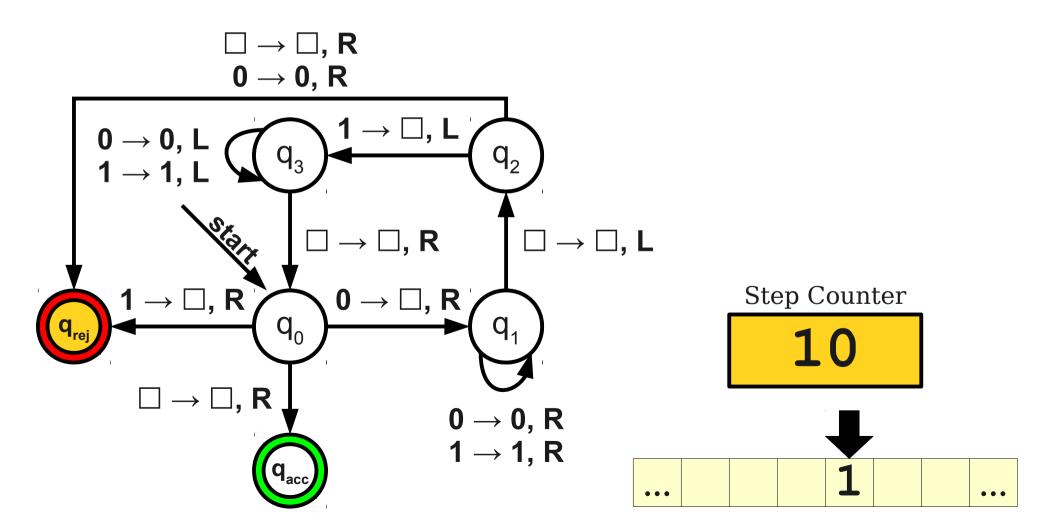


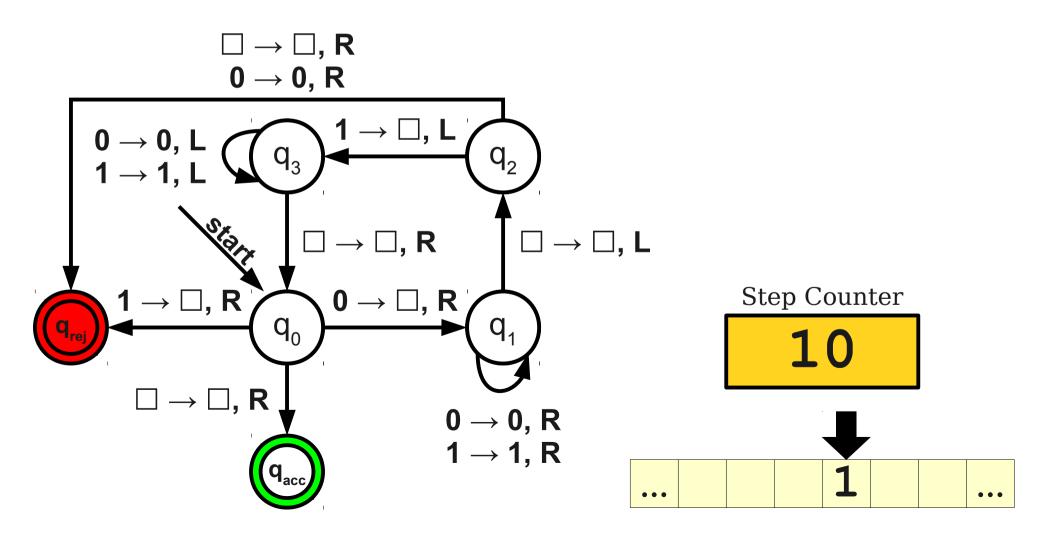












- The number of steps a TM takes on some input is sensitive to
 - The structure of that input.
 - The length of the input.
- How can we come up with a consistent measure of a machine's runtime?

- The **time complexity** of a TM *M* is a function denoting the *worst-case* number of steps *M* takes on any input of length *n*.
 - By convention, n denotes the length of the input.
 - Assume we're only dealing with deciders, so there's no need to handle looping TMs.
- 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.

A Slight Problem

- Consider the following TM over $\Sigma = \{0, 1\}$ for the language $BALANCE = \{ w \in \Sigma^* \mid w \}$ has the same number of 0s and 1s 3:
 - M = "On input w:
 - Scan across the tape until a o 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?

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 At most is found.
- If none are found, accept.
- If one is found, continue scanning until a matching 1 or 0 is found.
- If none are found, reject.
- Otherwise, cross off that symbol and repeat."

At most *n* steps.

At most 1 step.

At most *n* more steps.

At most 1 step

At most *n* steps to get back to the start of the tape.

At most 3n + 2 steps.

 \times At most n/2 loops.

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

At most n/2 loops

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. That tells us how *scalable* our algorithm will be.
- 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.

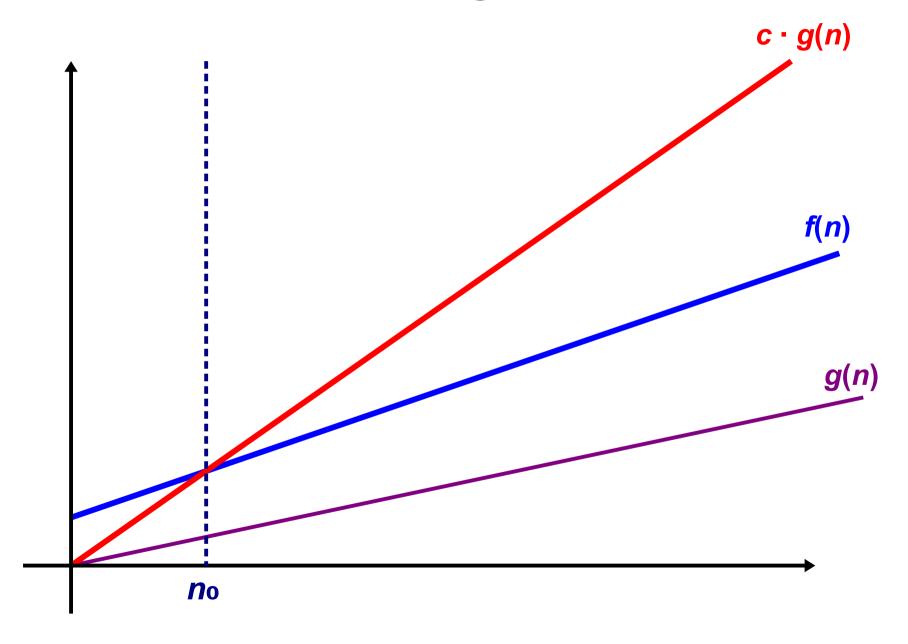
Big-O Notation

- Ignore *everything* except the dominant growth term, including constant factors.
- Examples:
 - 4n + 4 = O(n)
 - 137n + 271 = O(n)
 - $n^2 + 3n + 4 = O(n^2)$
 - $2^n + n^3 = O(2^n)$
 - 137 = 0(1)
 - $n^2 \log n + \log^5 n = O(n^2 \log n)$

Big-O Notation, Formally

- Formally speaking, let $f, g : \mathbb{N} \to \mathbb{N}$.
- We say f(n) = O(g(n)) iff
 - There are constants n_0 , c such that $\forall n \in \mathbb{N}$. $(n \ge n_0 \to f(n) \le c \cdot g(n))$
- Intuitively, when n gets "sufficiently large" (i.e. greater than n_0), f(n) is bounded from above by some constant multiple (specifically, c) of g(n).

$$f(n) = O(g(n))$$



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)O(n) steps loops O(1) steps O(n) steps O(n) steps O(n) loops

 $O(n^2)$ steps

A Quick Note

- Time complexity depends on the model of computation.
 - A computer can binary search over a sorted array in time $O(\log n)$.
 - A TM has to spend at least *n* time doing this, since it has no random access.
- For now, assume that the slowdown going from a computer to a TM or vice-versa is not "too bad."

The Story So Far

- We now have a definition of the runtime of a TM.
- We can use big-O notation to measure the relative growth rates of different runtimes.
- **Big question:** How do we define efficiency?

Time-Out For Announcements!

Problem Set 6 Graded

All Problem Set 6's have been graded.
 Late submissions will be returned at the end of lecture today.

A Question from Last Time

"Aren't there some cases where we can know a TM is infinite looping? Couldn't we modify the U_{TM} so it keeps a record of IDs and then if it sees the same one twice know it was in a loop? This doesn't guarantee to find all loops, but would it be useful?"

Back to CS103!

What is an efficient algorithm?

Searching Finite Spaces

- Many decidable problems can be solved by searching over a large but finite space of possible options.
- Searching this space might take a staggeringly long time, but only finite time.
- From a decidability perspective, this is totally fine.
- From a complexity perspective, this is totally unacceptable.

4 3 11 9 7 13 5 6 1 12 2 8 0 10

4 3 11 9 7 13 5 6 1 12 2 8 0 10

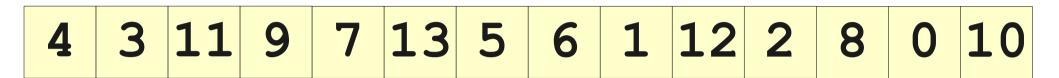
Goal: Find the length of the longest increasing subsequence of this sequence.

 4
 3
 11
 9
 7
 13
 5
 6
 1
 12
 2
 8
 0
 10

Goal: Find the length of the longest increasing subsequence of this sequence.

4 3 11 9 7 13 5 6 1 12 2 8 0 10

Goal: Find the length of the longest increasing subsequence of this sequence.





























Longest so far: 4



Longest so far: 4



Longest so far: 4

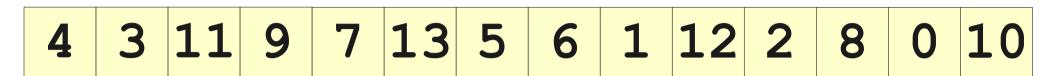




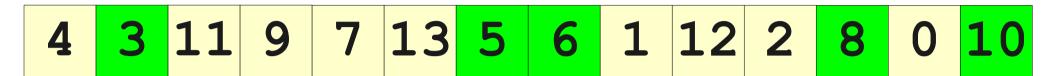
Longest so far: 4



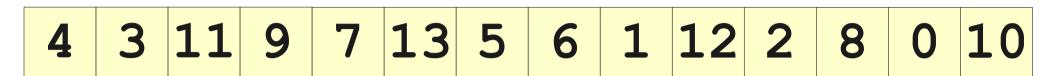




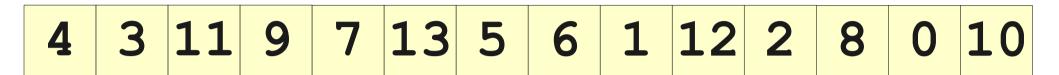
Longest so far: 4 11



Longest so far: 4 11



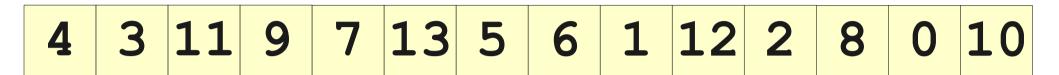
Longest so far: 4 11



Longest so far:



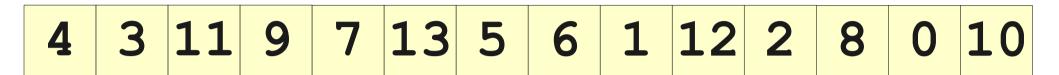
How many different subsequences are there in a sequence of *n* elements?



Longest so far:



How many different subsequences are there in a sequence of n elements? 2^n

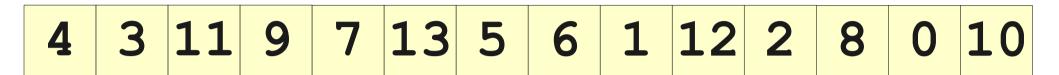


Longest so far:

4 11

How many different subsequences are there in a sequence of n elements? 2^n

How long does it take to check each subsequence?

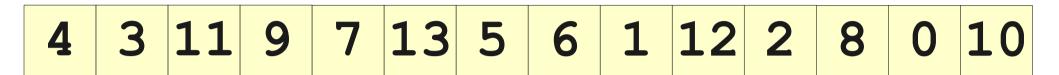


Longest so far:

4 11

How many different subsequences are there in a sequence of n elements? 2^n

How long does it take to check each subsequence? O(n) time.



Longest so far:

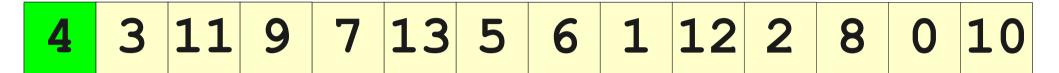
4 11

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How long does it take to check each subsequence? O(n) time.

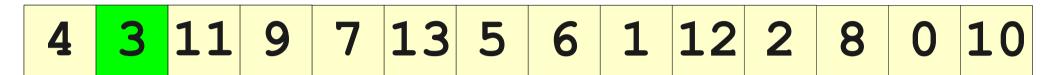
Runtime is around $O(n \cdot 2^n)$.

4 3 11 9 7 13 5 6 1 12 2 8 0 10

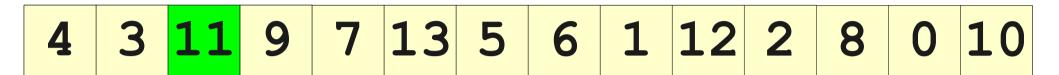


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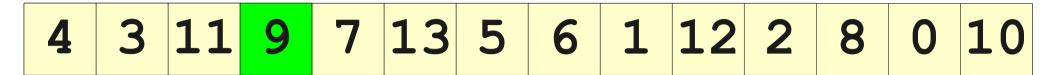
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4 3 11 9 7 13 5 6 1 12 2 8 0 10



1 1 2



1 1 2

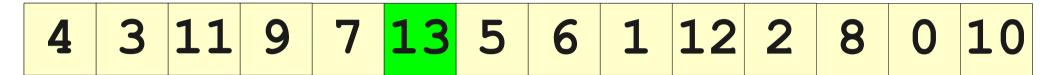


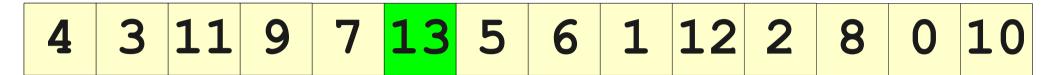
1 1 2 2



1 1 2 2









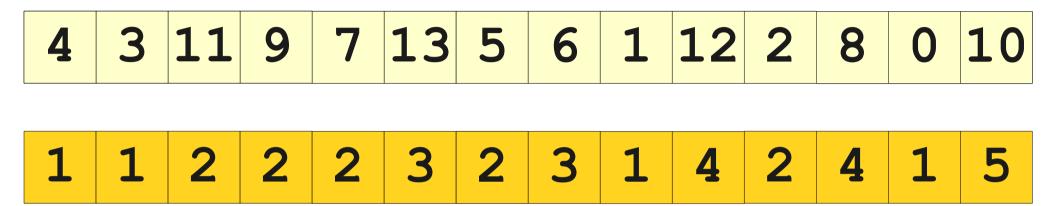


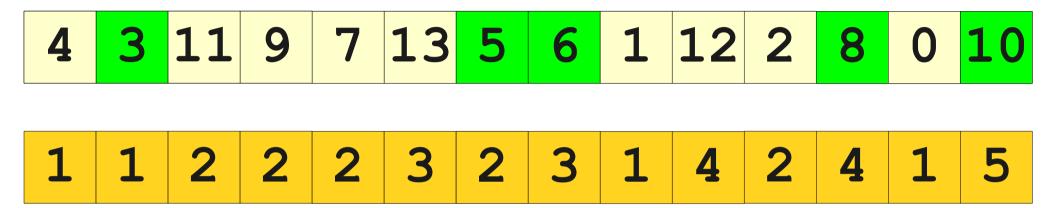
1 1 2 2 2 3 2

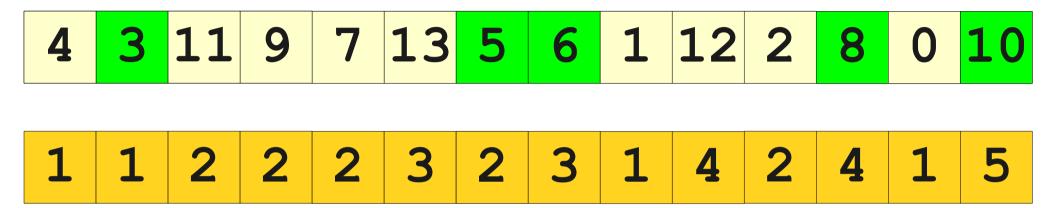


1 1 2 2 2 3 2

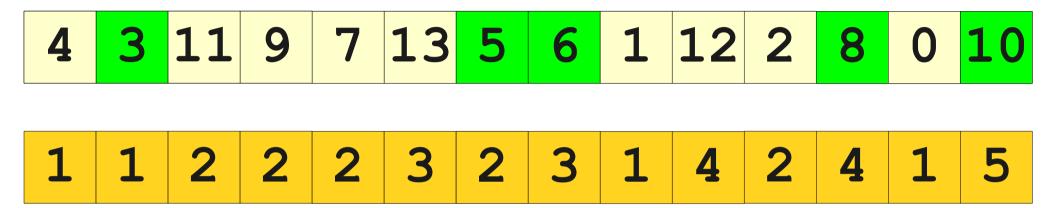




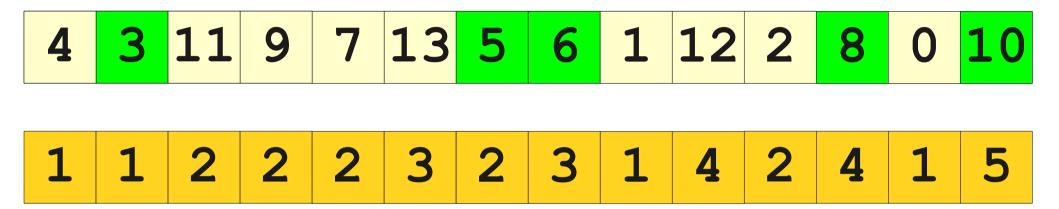




How many elements of the sequence do we have to look at when considering the *k*th element of the sequence?

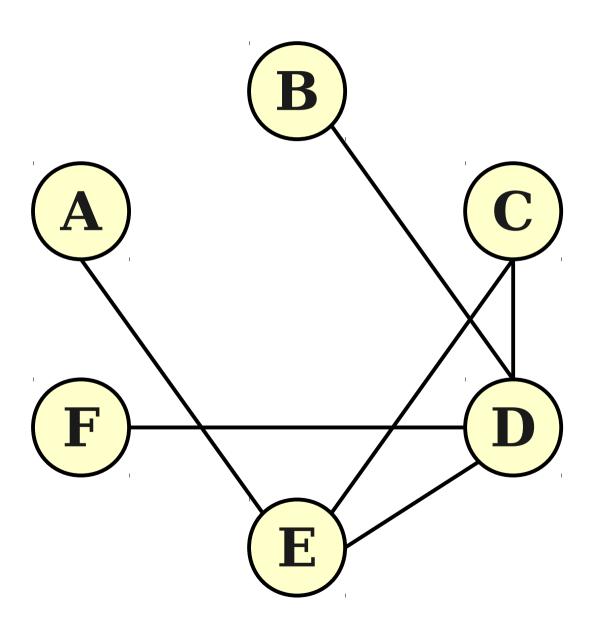


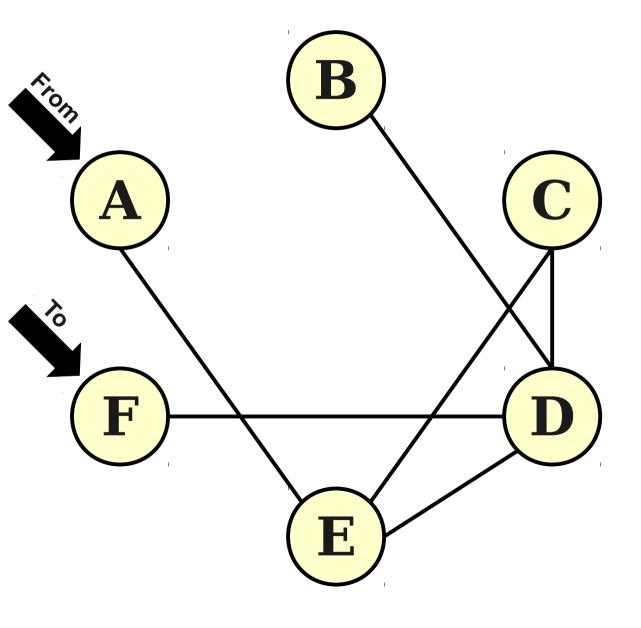
How many elements of the sequence do we have to look at when considering the *k*th element of the sequence? *k* - 1

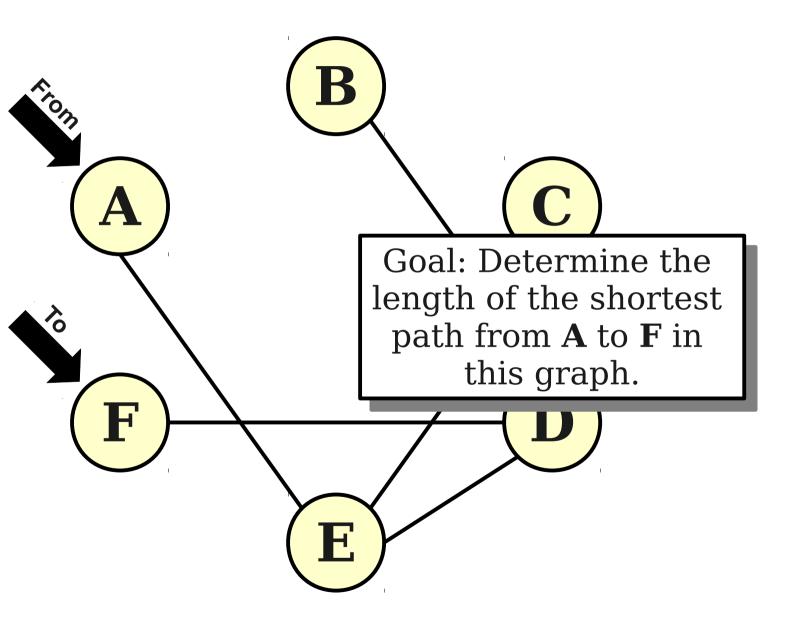


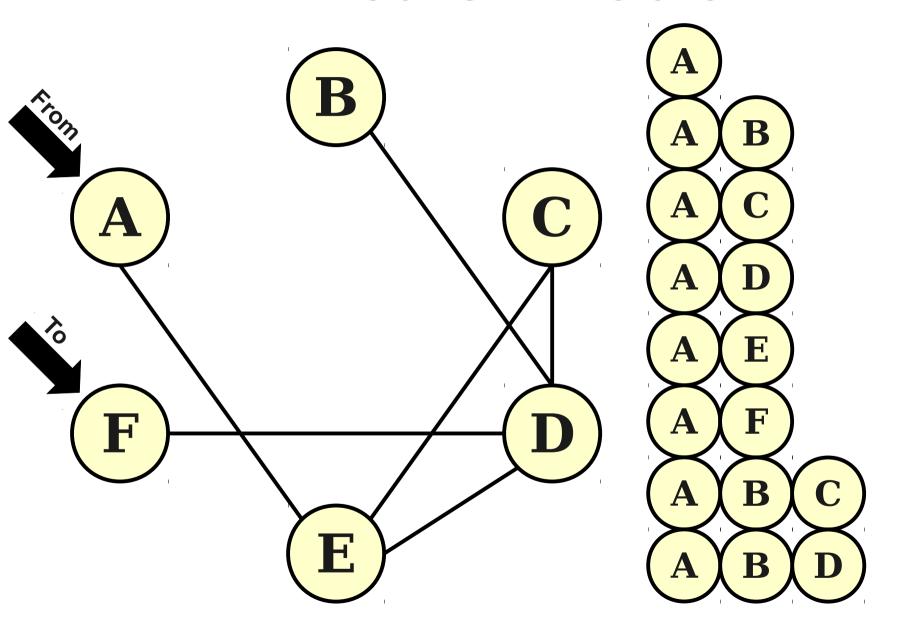
How many elements of the sequence do we have to look at when considering the *k*th element of the sequence? *k* - 1

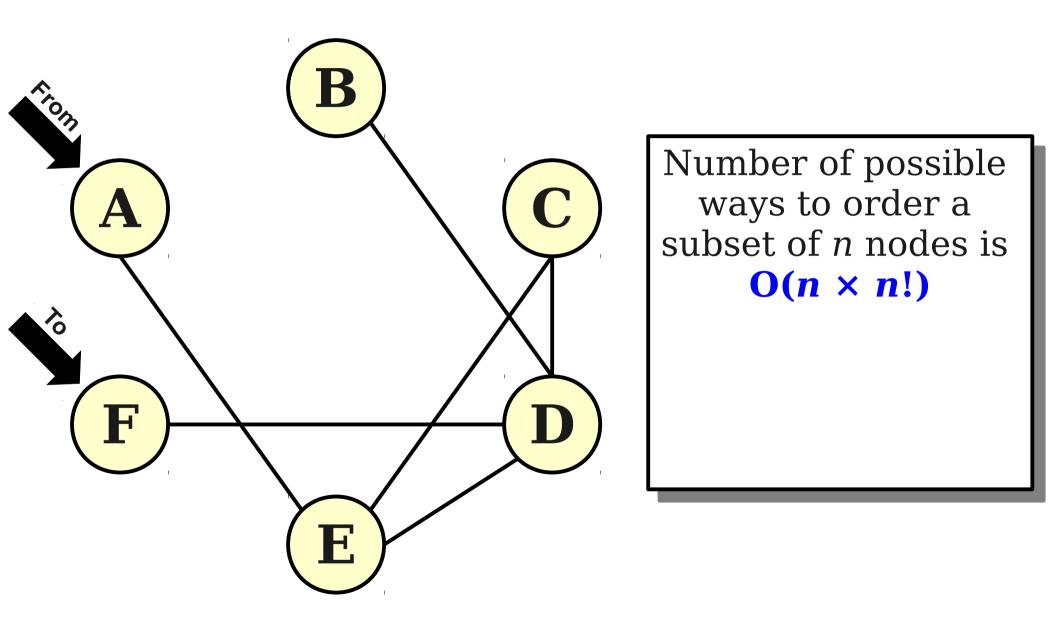
Total runtime is
$$1 + 2 + ... + (n - 1) = \mathbf{O}(n^2)$$

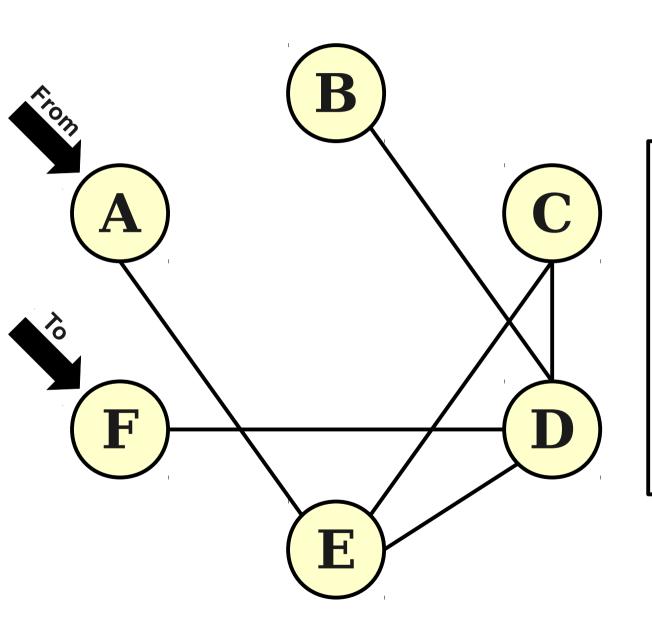






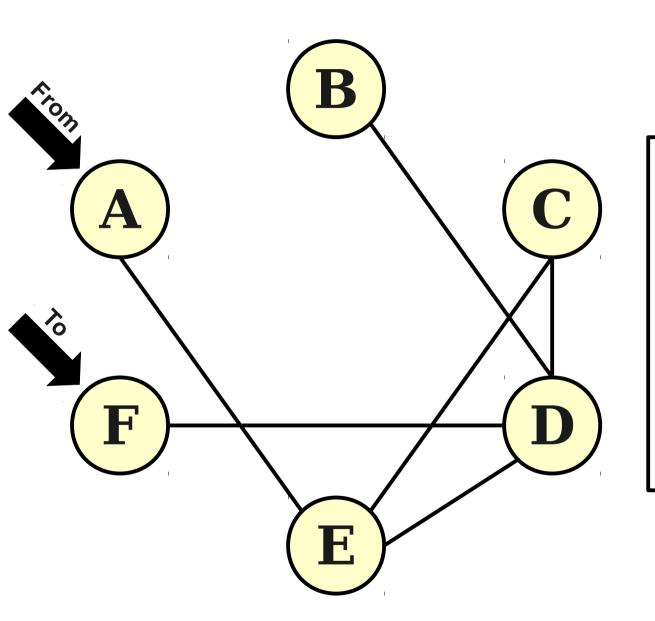






Number of possible ways to order a subset of n nodes is $O(n \times n!)$

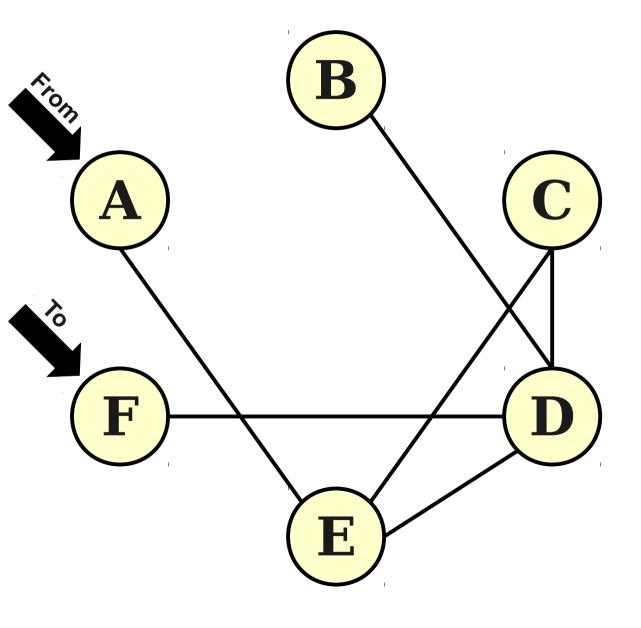
Time to check a path is O(n).

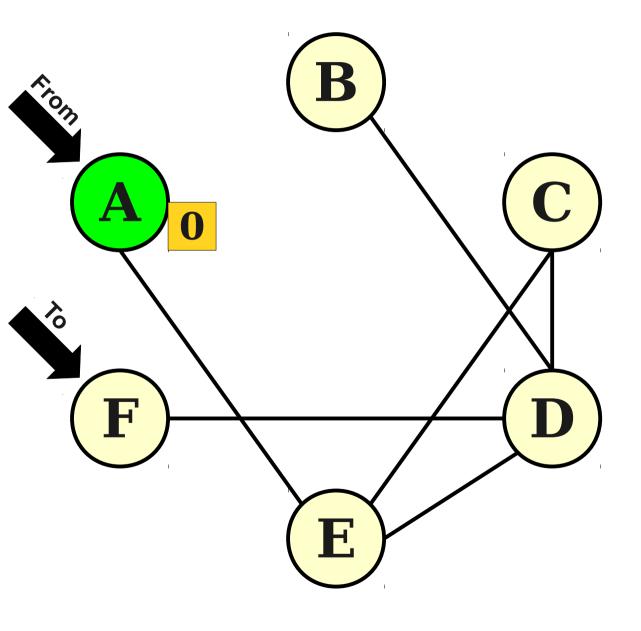


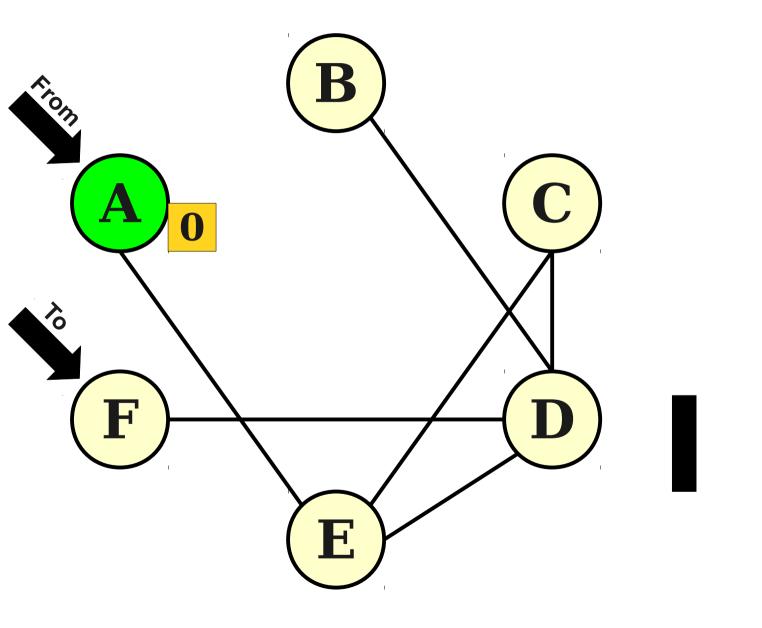
Number of possible ways to order a subset of n nodes is $O(n \times n!)$

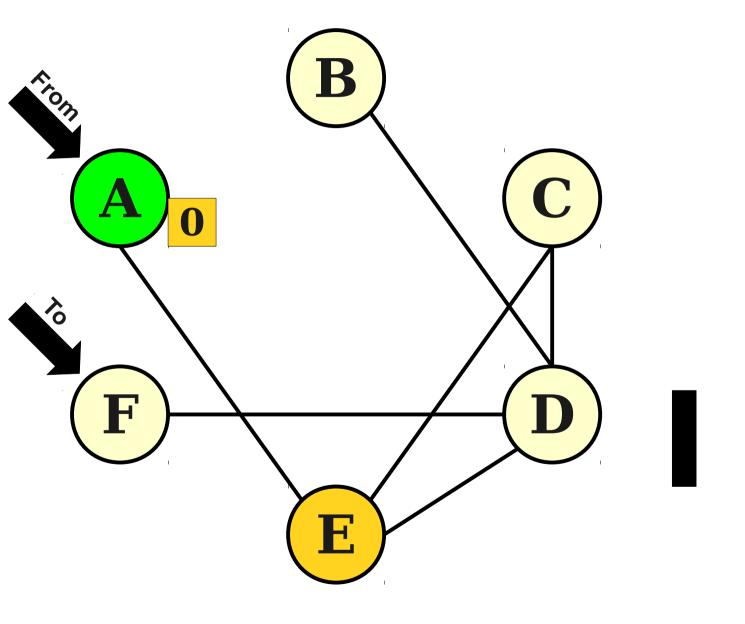
Time to check a path is O(n).

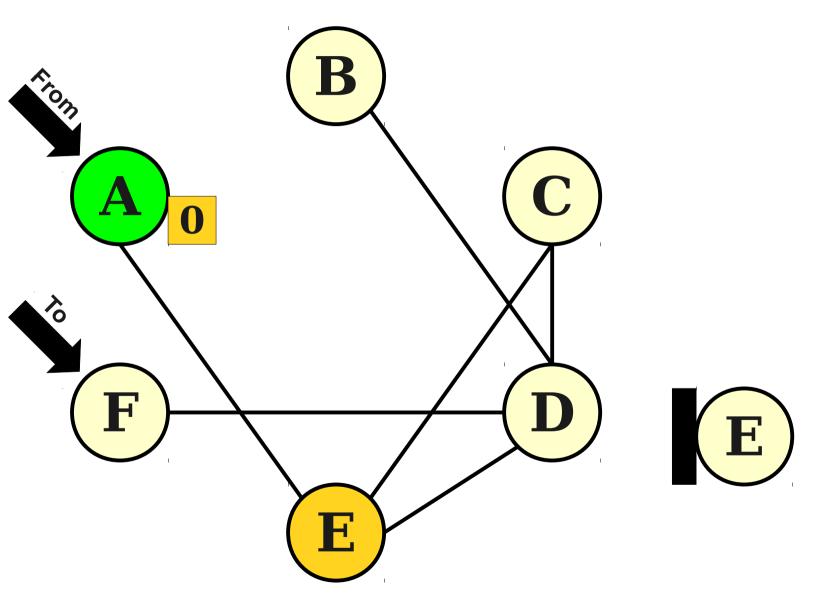
Runtime: $O(n^2 \cdot n!)$

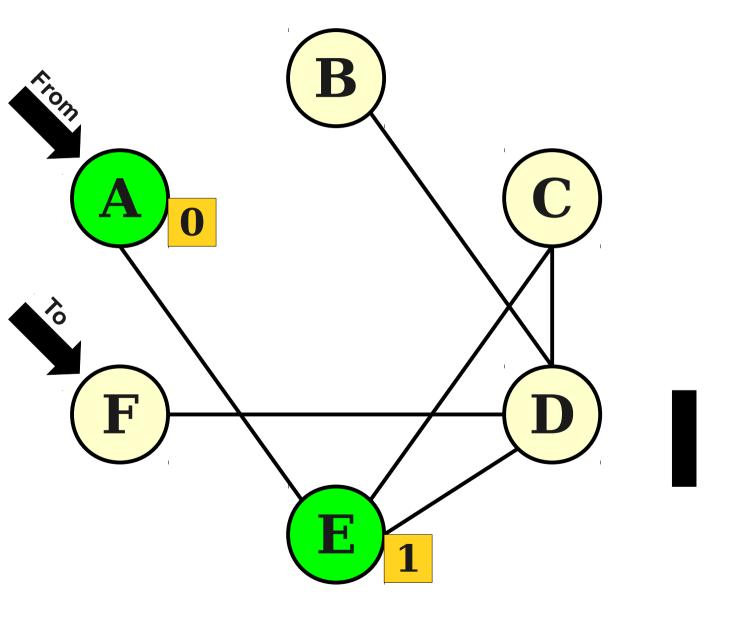


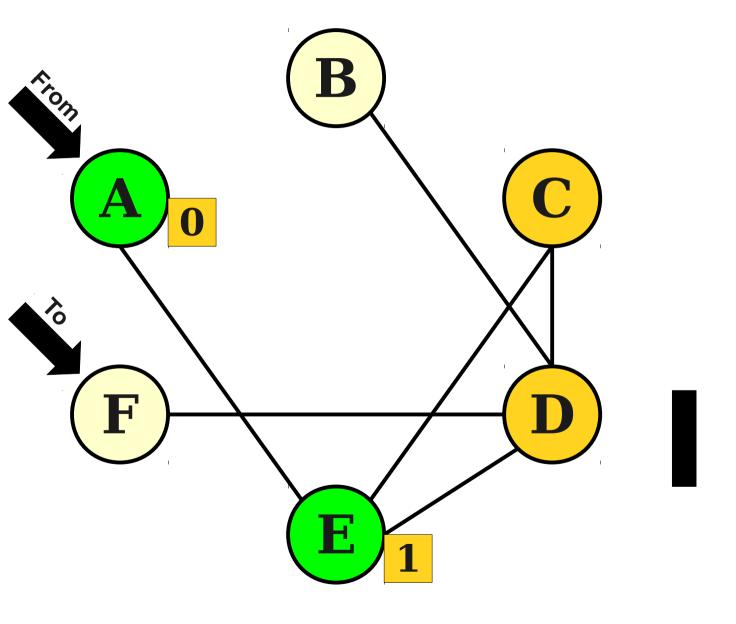


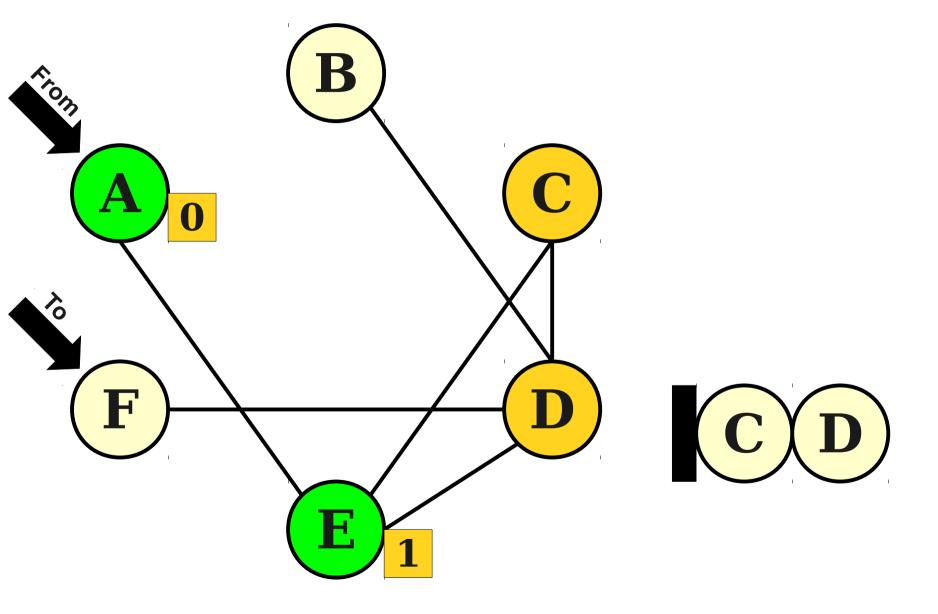


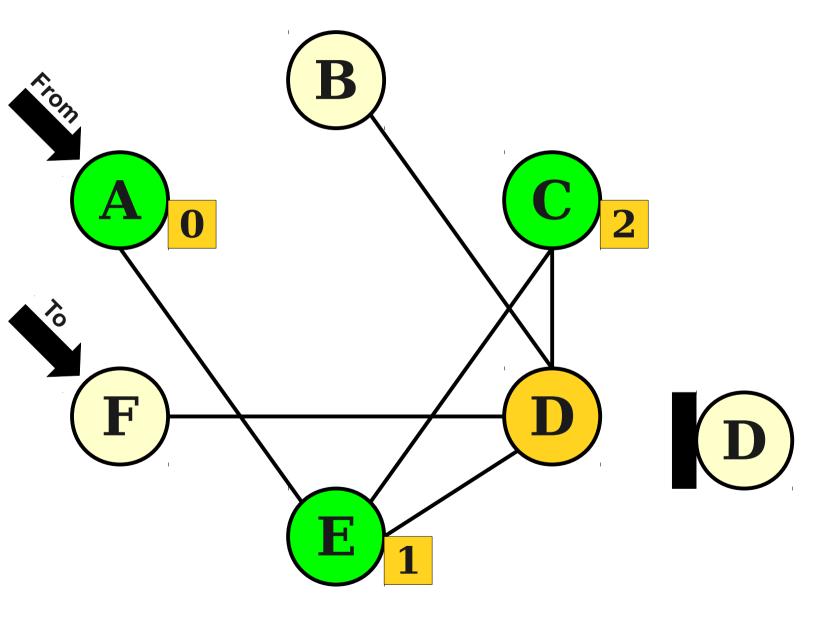


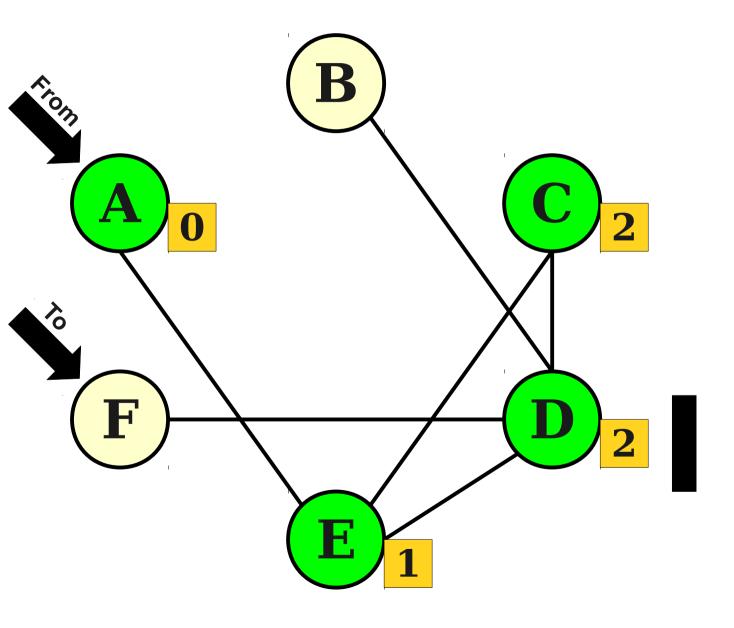


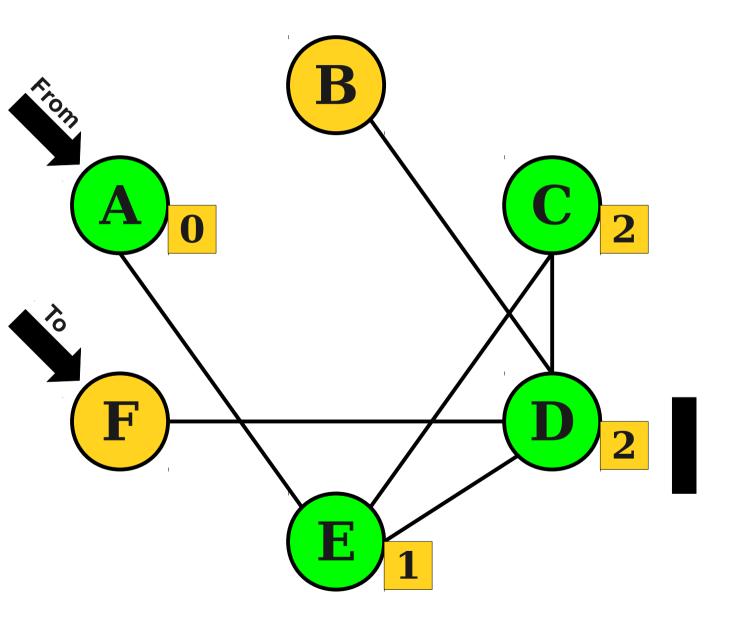


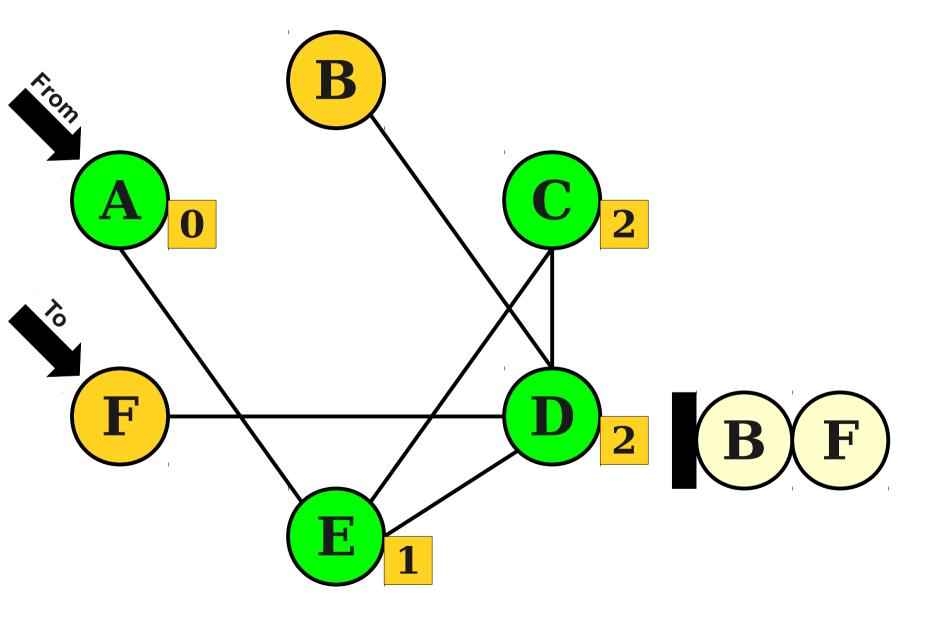


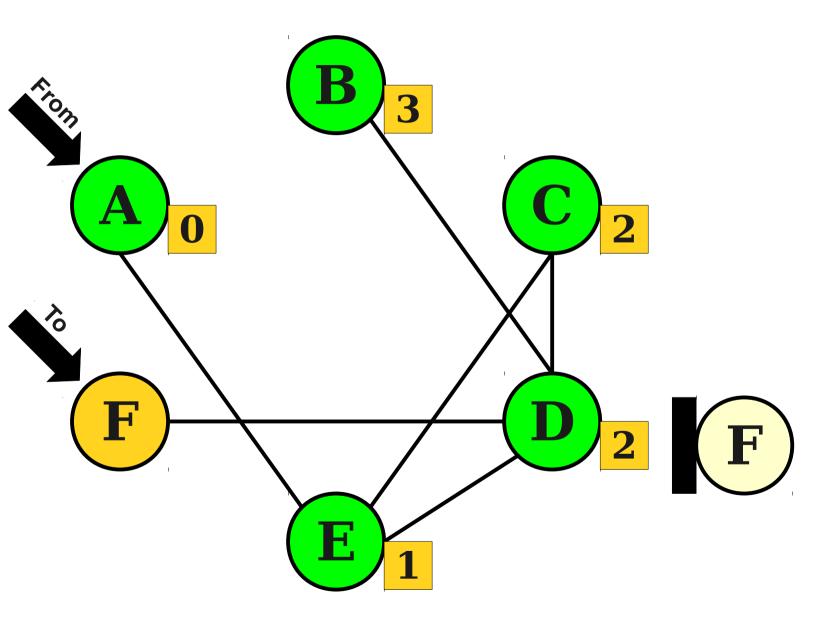


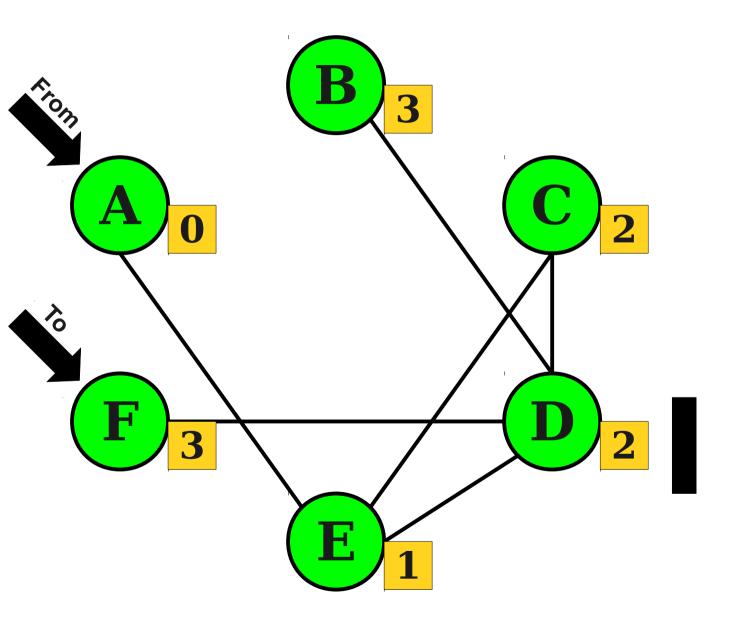


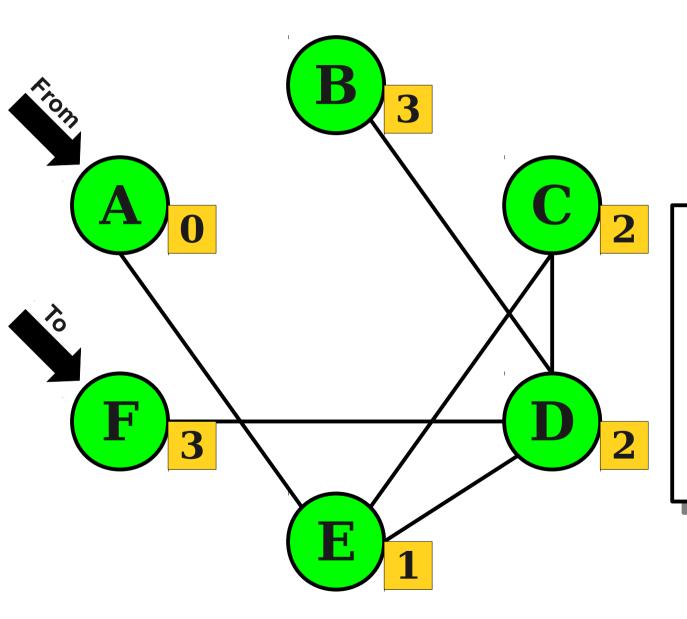












With a precise analysis, runtime is O(n + m), where n is the number of nodes and m is the number of edges.

For Comparison

- Longest increasing
 Shortest path subsequence:
 - Naive: $O(n \cdot 2^n)$
 - Fast: $O(n^2)$

- problem:
 - Naive: $O(n^2 \cdot n!)$
 - Fast: O(n + m), where *n* is the number of nodes and m the number of edges. (Take CS161 for details!)

Defining Efficiency

- When dealing with problems that search for the "best" object of some sort, there are often at least exponentially many possible options.
- Brute-force solutions tend to take at least exponential time to complete.
- Clever algorithms often run in time O(n), or $O(n^2)$, or $O(n^3)$, etc.

Polynomials and Exponentials

- A TM runs in **polynomial time** iff its runtime is some polynomial in *n*.
 - That is, time $O(n^k)$ for some constant k.
- Polynomial functions "scale well."
 - Small changes to the size of the input do not typically induce enormous changes to the overall runtime.
- Exponential functions scale terribly.
 - Small changes to the size of the input induce huge changes in the overall runtime.

The Cobham-Edmonds Thesis

A language L can be **decided efficiently** iff there is a TM that decides it in polynomial time.

Equivalently, L can be decided efficiently iff it can be decided in time $O(n^k)$ for some $k \in \mathbb{N}$.

Like the Church-Turing thesis, this is **not** a theorem!

It's an assumption about the nature of efficient computation, and it is somewhat controversial.

The Cobham-Edmonds Thesis

- Efficient runtimes:
 - 4n + 13
 - $n^3 2n^2 + 4n$
 - n log log n
- "Efficient" runtimes:
 - n^{1,000,000,000,000}
 - 10⁵⁰⁰

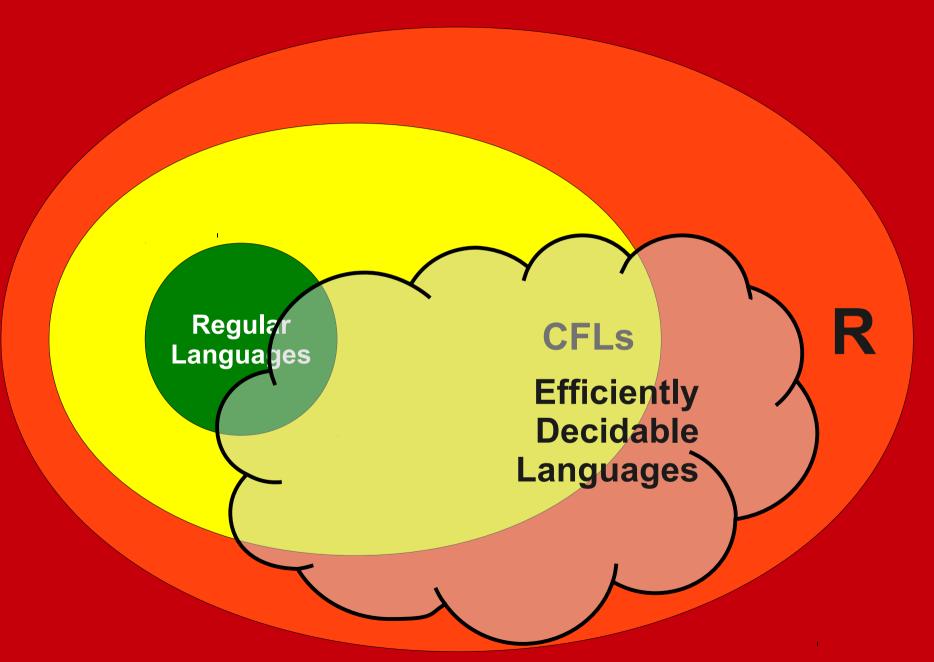
- Inefficient runtimes:
 - 2ⁿ
 - n!
 - *n*ⁿ
- "Inefficient" runtimes:
 - $n^{0.0001 \log n}$
 - 1.00000001^n

The Complexity Class **P**

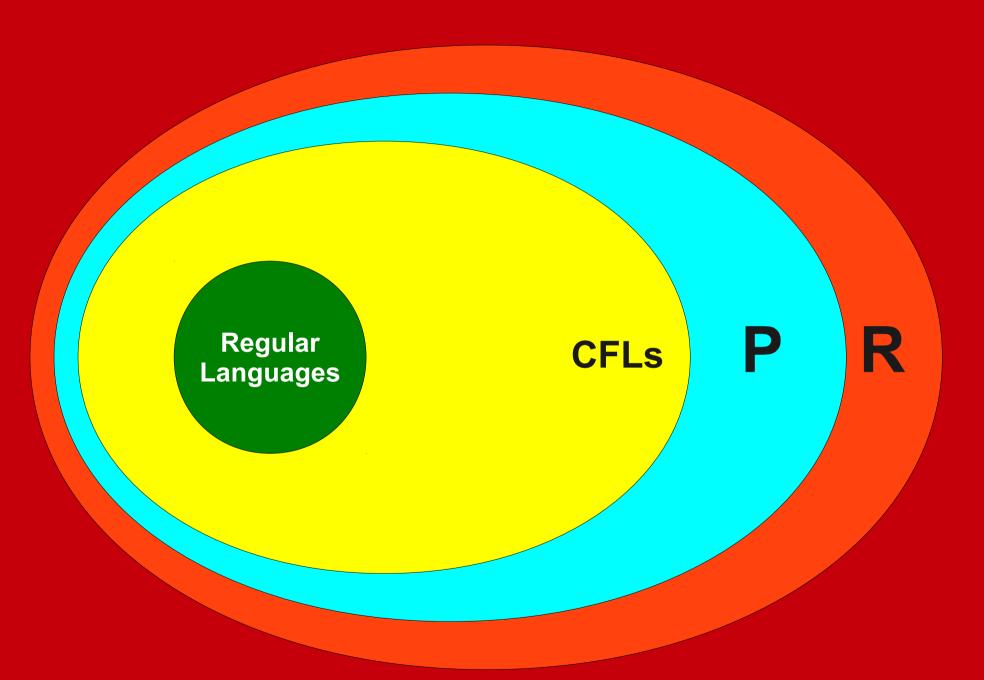
- The **complexity class P** (for **p**olynomial time) contains all problems that can be solved in polynomial time.
- Formally:
 - $\mathbf{P} = \{ L \mid \text{There is a polynomial-time decider for } L \}$
- Assuming the Cobham-Edmonds thesis, a language is in P iff it can be decided efficiently.

Examples of Problems in **P**

- All regular languages are in **P**.
 - All have linear-time TMs.
- All CFLs are in **P**.
 - Requires a more nuanced argument (the *CYK algorithm* or *Earley's algorithm*.)
- Many other problems are in P.
 - More on that in a second.



Undecidable Languages



Undecidable Languages