NP and Completeness

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Where Are We?

We have a whole collection of complexity classes based on
- time bounds,
- space bounds,
- determinism vs. nondeterminism

While there are some separation results (based on diagonalization) it is in general exceedingly difficult to distinguish between various low complexity classes.
The most famous case being \( P \) versus \( NP \).

Reductions, Again

In the absence of a separation result, a reasonable attempt is to consider a natural "difficulty order" on a class, and identify maximal elements.

This is strictly analogous to our old notion of reduction \( \preceq \) in classical computability theory. Ideally we want a natural decision problem \( C \) that is \( NP \)-complete:
- \( C \) is in \( NP \), and
- for all \( A \in NP \), \( A \preceq C \).

Technically, we want \( \preceq \) to be a preorder (reflexive and transitive).

Polynomial Time Turing Reductions

Perhaps the most obvious attempt would be to use Turing reductions, but with the additional constraint that the Turing machine must have polynomial running time. This is called a polynomial time Turing reduction.

Notation: \( A \leq^p B \).

Note that this actually makes sense for any kind of problem, not just decision problems. Also, it really captures nicely the idea that problem \( A \) is easier than \( B \) since we could use a fast algorithm for \( B \) to construct a fast algorithm for \( A \).

Just to be clear: in a computation with oracle \( B \) we only charge for the steps taken by the ordinary part of the Turing machine, the solutions provided by the oracle do not count towards the time complexity.

Example 1

Proposition
The decision version of Vertex Cover is polynomial time Turing reducible to the function version.

This is not hard:
- On input \( G \) and \( k \) hand over \( G \) to the oracle.
- Get back a minimal vertex cover \( C \).
- Check whether \( |C| \leq k \).

This is clearly linear time in the size of the input – recall that we charge nothing for the work of the oracle.

Example 2

Proposition
The function version of Vertex Cover is polynomial time Turing reducible to the decision version.

This requires some work. Let \( n \) be the number of vertices in \( G \), say, \( V = \{v_1, \ldots, v_n\} \).

- First, do a binary search to find the size \( k_0 \) of a minimal cover, using the oracle for the decision problem.
- Then find the least vertex \( v \) such that \( G - v \) has a cover of size \( k - 1 \).
  - Place \( v \) into \( C \) and remove it from \( G \).
- Recurse.

This is no longer linear but still polynomial time.

Exercise
Determine the exact running time of this oracle algorithm.
The last argument is fairly typical: many function and search problems can be rephrased as decision problems without losing much: they are polynomial time Turing reducible to the decision version.

Hence for difficult problems we can focus on the decision version and still get a good idea what the complexity of the more natural function/search version is.

BTW: I could not figure out how to reduce the function version of the Pebbling Problem to the decision version. Excellent extra credit project.

So let’s focus on decision problems from now on.

Proposition
Polynomial time Turing reducibility is a preorder.

For transitivity, this works since polynomials are closed under substitution. Hence we can from equivalence classes as usual, the polynomial time Turing degrees. We won’t pursue this idea here.

Proposition
$B \in \mathbb{P}$ and $A \leq_p B$ implies $A \in \mathbb{P}$.

Here we can simply replace the oracle by a real polynomial algorithm.

As before in classical recursion theory, we can consider weaker reductions instead. In this case, many-one reducibility turns out to be the right notion.

Let $A$ and $B$ be two decision problems, with Yes-instances $Y_A$ and $Y_B$, respectively.

Definition
$A$ is polynomial time reducible to $B$ if there is a polynomial time computable function $f$ such that $x \in Y_A \iff f(x) \in Y_B$.

Notation: $A \leq^p_m B$.

This may seem obvious, but note that it does not work for other classes (e.g., exponential time computable reductions).

Incidentally, it does work for linear time computable reductions.

Proposition
Polynomial time reducibility is a preorder.

Proof.
Reflexivity is trivial. For transitivity, consider a polynomial time reduction $f$ from $A$ to $B$ and $g$ from $B$ to $C$.

Obviously $h(x) = g(f(x))$ is a reduction from $A$ to $C$.

$h$ is still polynomial time computable since polynomials are closed under substitution.

This may seem obvious, but note that it does not work for other classes (e.g., exponential time computable reductions).

Incidentally, it does work for linear time computable reductions.

Lemma
1. If $B$ is in $\mathbb{P}$ and $A \leq^p_m B$ then $A$ is also in $\mathbb{P}$.
2. If $B$ is in $\mathbb{NP}$ and $A \leq^p_m B$ then $A$ is also in $\mathbb{NP}$.

Proof.
(1) Replace the oracle $B$ by a polynomial time algorithm.

(2) Combine the transducer for the reduction and the nondeterministic acceptor for $B$: produces a nondeterministic polynomial time acceptor for $A$.
Hardness and Completeness

Definition
B is NP-hard if for all A in NP: A ≤p B.

B is NP-complete if B is in NP and is also NP-hard.

The existence of NP-hard sets is trivial, but existence of NP-complete sets is far from obvious. Also note

Proposition
If B in NP-complete and B is in P then P = NP.

If indeed P ≠ NP as expected, then no NP-complete problem can have a polynomial time algorithm. This is the weak lower bound result that we are after.

Constructing an NP-complete Problem

How do we get our hands on an NP-complete problem?

It is tempting to try to scale down the Halting set.

So we want to use the universal machine \( U_{nd} \) that can simulate machines in the enumeration \( \{ N_e \} \) of nondeterministic, polynomial time Turing machines just mentioned. A first shot would be to define

\[ K = \{ e \# x \# 1^{t+|x|} \mid x \text{ accepted by } N_e \} \]

It is easy to see that \( K \) is NP-hard, but there is no reason why it should be in NP; simulation of \( N_e \) is not a task that can be handled within a fixed polynomial time bound (\( U_{nd} \) itself is not polynomial time).

So a simple head-on universality argument fails here.

Universal Machines

We can construct an enumeration \( \{ M_e \} \) of all polynomial time Turing machines: just run a clock and stop the machine after \( n^2 + c \) steps if it has not halted already.

But then there is a universal, deterministic machine \( U_d \) that simulates \( M_e \) with only a polynomial slowdown. More precisely, \( U_d \) on input \( e \# x \) simulates \( M_e \) on \( x \) in running time \( q(n^2 + c) \) where \( q \) is some polynomial (even low degree).

Of course, \( U_d \) itself is not a polynomial time machine, the running time increases for different choices of \( e \).

Likewise, there is a universal, nondeterministic machine \( U_{nd} \) that simulates nondeterministic polynomial time machines \( N_e \) with only a polynomial slowdown in the same sense as above. Again, \( U_{nd} \) itself is not polynomial time.

So, one has to be a bit careful where the polynomial time bounds should go.

An Ugly Set

We can fix the problem by padding the input so that we can compensate for the running time of \( N_e \).

\[
K = \{ e \# x \# 1^{t} \mid x \text{ accepted by } N_e \text{ in } t = |x|^2 + |x| \text{ steps } \}
\]

Proposition
\( K \) is in NP.

Proof.
To see this note that the slowdown by \( U_{nd} \) is polynomial, say, the simulation takes \( q(n^2 + c) \) steps.

But then \( U_{nd} \) can test, in time polynomial in \( |e\#x\#1^t| = |x| + t + c \), whether \( N_e \) indeed accepts \( x \).

Hardness

Proposition
\( K \) is NP-hard.

Proof.
Consider \( A = L(N_e) \in \text{NP} \) arbitrary. Then the function

\[ x \mapsto e \# x \# 1^{t+|x|} \]

is polynomial time computable and shows that \( A \leq_p K \).

Hence, \( K \) is indeed NP-complete.

It Works, But . . .

So we have the desired existence theorem.

Theorem
There is an NP-complete language.

Alas, this result is perfectly useless when it comes to our list of NP problems: they bear no resemblance whatsoever to \( K \).

We have a foothold in the world of NP-completeness, but to show that one of these natural problems is NP-complete we would have to find a reduction from \( K \) to, say, Pebbling or Vertex Cover.

Good luck on that.
The Key Problems

- Reductions
- Cook-Levin
- LOOP Programs
- Program Equivalence

Cook-Levin Theorem

Of course, there might be some other, clever, structural approach to satisfiability testing. That seems unlikely in light of the following result.

Theorem (Cook-Levin 1971/1973)
The Satisfiability Problem is NP-complete.

Membership in NP is easy using the standard guess-and-verify approach. But hardness takes work: we have to express the computation of a Turing machine as a Boolean formula.

Note that the following proof should be read just once. Then throw it away and reconstruct your own proof.

Proof Idea

Let \( A \) be an arbitrary set (of yes-instances) in NP.
There is a deterministic polynomial time Turing machine \( M \) such that \( M \) accepts \((x, w)\) iff \( x \in A \) where \( w \) is some witness of length polynomial in \( n = |x| \).

The idea is to construct a (rather large) Boolean formula \( \Phi \) such that

\[ \Phi(x) \text{ is satisfiable} \iff M \text{ accepts } (x, w) \text{ for some } w. \]

While the formula is fairly long, it has a clear structure and it can easily be constructed in time polynomial in \( n \).
It has lots of variables that express information about states, head position and tape inscriptions: the satisfying truth assignment translates directly into an accepting computation of \( M \).

Coding Time

First off, let \( N = p(n) \) be the running time of the machine.
If we have a list of Boolean variables \( X_0, X_1, \ldots, X_N \) and a truth assignment \( \sigma \) we can think of \( \sigma(X_t) \) as the value of variable \( X_t \) at time \( t \).
We can use logic to pin down the value of \( X_{t+1} \) in terms of \( X_t \) (and other variables):

\[ \bigwedge_{i < N} X_{i+1} \iff \psi(X_t, \ldots) \]

Coding Numbers

If we need to code a number \( r \) in a certain range, say \( 1 \leq r \leq m \), we can simply use variables \( X(1), X(2), \ldots, X(m) \)
plus a stipulation that exactly one of them is true under \( \sigma \):

\[ \text{EO}_m(X(1), X(2), \ldots, X(m)) \]

Here

\[ \text{EO}_k(x_1, \ldots, x_k) = (x_1 \lor x_2 \ldots \lor x_k) \land \bigwedge_{1 \leq i < j \leq k} \neg(x_i \land x_j). \]

Note that the size of \( \text{EO}_k \) is \( O(k^2) \).
Combining these two ideas we can set up polynomially many Boolean variables states:
\[ S_i(p), \ 0 \leq t \leq N, \ 1 \leq p \leq m. \]
head position:
\[ H_i(t), \ 0 \leq i, t \leq N. \]
tape inscription:
\[ C_i(t), \ 0 \leq i, t \leq N. \]
that express, for each time \( 0 \leq t \leq N \), which state the machine is in, where the head is, and what’s on the tape.

For simplicity, we assume here that the only tape symbols are 0 and 1, it is not too hard to deal with the general situation.

Initially the input is on the first part of the tape:
\[ H_0(0) \land S_0(q_0) \land C_0(1) = x_1 \land C_0(2) = x_2 \land \ldots \land C_0(n) = x_n \]
and at the end we accept:
\[ S_N(q_f) \]
Note that \( C_0(n+1), \ldots, C_0(N) \) is not fixed and can be set arbitrarily by \( \sigma \).

It is not too hard to see that the whole formula \( \Phi_x \) in the end has size polynomial in \( n \).

Now suppose \( \Phi_x \) is satisfied by truth assignment \( \sigma \).
Then \( M \) accepts the original tape inscription \( (x, w) \) where \( x \) is the real input and \( w \) is the bits chosen freely by \( \sigma \).

Since \( \Phi_x \) forces the values of all the variables to correspond to a computation of \( M \) on input \( (x, w) \) we have the desired witness and \( x \) must be a Yes-instance.

Conversely, every witness plus corresponding accepting computation can be translated into a satisfying truth assignment \( \sigma \).

That’s it. \( \square \)

The hardness of Satisfiability holds up even when the formulae in question are rather restricted.

**Definition**

A **literal** is a variable or negated variable. A formula is in **conjunctive normal form (CNF)** if it is a conjunction of disjunctions of literals: \( \Phi_1 \land \Phi_2 \land \ldots \land \Phi_n \) where \( \Phi_i = z_{i,1} \lor z_{i,2} \lor \ldots \lor z_{i,k(i)}, \ z_{i,j} \) a literal.

It is in \( k \)-CNF if \( k(i) = 3 \) for all \( i \).

**Theorem**

The Satisfiability Problem is **NP-complete for formulae in 3-CNF**.

The last result can be used to establish the NP-hardness of many problems such as Vertex Cover.

It now suffices to find a polynomial time computable function
\[ f : 3\text{-CNF} \rightarrow \text{Graphs} \times \text{Integers} \]
such that \( \varphi \) in 3-CNF is satisfiable iff for \( f(\varphi) = (G,k) \) the graph \( G \) has a vertex cover of size \( k \).

This is much, much easier than having to deal with general formulae.
Satisfiability is a tremendously important practical problem, but if this were the only relevant NP-complete problem the whole notion would still be somewhat academic.

But as Dick Karp realized after reading Cook’s paper, there are dozens (actually: thousands) of combinatorial problems that all turn out to be NP-complete. So none of them will admit a polynomial time solution unless \( P = NP \).

The proof method is interesting: some problems are proven hard by direct reduction from SAT, then these are used to show other problems are hard, and so on... By transitivity one could, in principle, produce a direct reduction from SAT, but in reality these direct reductions are often very hard to find.

### Vertex Cover

**Theorem**

Vertex Cover is \( NP \)-complete.

**Proof.**

Suppose we have a 3-CNF formula \( \Phi = \Phi_1 \land \Phi_2 \land \ldots \land \Phi_m \) where \( \Phi_i = z_{i,1} \lor z_{i,2} \lor z_{i,3} \).

The Boolean variables are \( x_1, \ldots, x_n \).

We start with a graph \( G' \) on \( 2n + 3m \) vertices.

- Vertices: \( x_i, \pi_i \) for \( i = 1, \ldots, n \) and \( u_{i,1}, u_{i,2}, u_{i,3} \) for \( i = 1, \ldots, m \).
- Edges: one edge between \( x_i \) and \( \pi_i \), and three edges that turn \( u_{i,1}, u_{i,2}, u_{i,3} \) into a triangle.

**Proof, cont’d.**

It is easy to see that every vertex cover of \( G' \) must have at least \( n + 2m \) vertices (one for each \( x \)-edge, and two for each triangle).

And such covers exist, lots of them: you can pick at random one of \( x_i \) or \( \pi_i \), and exactly two of \( u_{i,1}, u_{i,2}, u_{i,3} \).

So far we have only used \( n \) and \( m \), but not the formula itself.

Let \( G \) be the graph obtained by adding \( 3m \) more edges to \( G' \):

- connect \( u_{i,j} \) to \( x_s \) if \( z_{i,j} = x_s \) and connect \( u_{i,j} \) to \( \pi_s \) if \( z_{i,j} = \neg x_s \).

Lastly, set the bound to \( k = n + 2m \).

**Claim**

\( G \) has a cover of size \( k = n + 2m \) iff the formula is satisfiable.

To see this, note that any cover \( C \) defines an assignment \( \sigma \):

\[
\sigma(x_i) = \begin{cases} 
1 & \text{if } x_i \in C; \\
0 & \text{otherwise}.
\end{cases}
\]

Then \( \sigma \) satisfies the formula.

Conversely, every satisfying assignment translates into a cover.

\( \square \)

### Important Points

For this construction to work we need two crucial ingredients:

- The graph \( G \) and the bound \( k \) can be computed from \( \Phi \) in polynomial time.
- \( G \) has a vertex cover of size \( k \) if, and only if, \( \Phi \) is satisfiable.

Many other completeness proofs look very similar: it is trivial to see that the problem is in \( NP \), and it requires work (sometimes a lot of it) to produce hardness.
We have defined primitive recursive functions in an algebraic manner; here is the analogous programming language.

Again variables range over \(\mathbb{N}\), and we have a single constant 0. The programs are described informally as follows:

- initialize: \(x = 0\)
- assignments: \(x = y\)
- increment: \(x++\)
- sequential composition: \(P; Q\)
- control: do \(x : P\) od

Note that there are no arithmetic operations, no conditionals, no subroutines, ...

The Loops

The semantics are clear except for the loop construct:

```
   do x : P od
```

This is intended to mean:

```
   Execute P exactly n times where n is the value of x before the loop is entered.
```

In other words, if \(P\) changes the value of \(x\) the number of executions will still be the same. We could get the same effect by not allowing \(x\) to appear in \(P\).

It follows that all loop programs terminate, regardless of the input.

Note that this would not be true for while-loops. As we will see, while-loops are significantly more powerful than our do-loops.

Here are some typical examples for the use of loops.

**LOOP Addition**

Addition is easy to implement addition in a LOOP program:

```
1 // add : x, y --> z
2   z = x;
3   do y :
4       z++;
5   od
```

Here is multiplication:

```
1 // mult : x, y --> z
2   z = 0;
3   do x :
4       do y :
5           z++;
6       od
7   od
```

**LOOP Predecessor**

How about the predecessor function? In some frameworks (like the \(\lambda\)-calculus) this is the first real challenge.

```
1 // pred : x --> z
2   z = 0;
3   v = 0;
4   do x :
5       z = v;
6       v++;
7   od
```

**LOOP Sign and Conditionals**

The sign function \(\text{sign}(x) = \min(x,1)\) can also be implemented by abusing the loop construct as a Boolean test.

```
1 // sign : x --> z
2   z = 0;
3   v = 0;
4   v++;
5   do x :
6       z = v;
7   od
```

Now we can build conditionals.

```
1 // if( x > 0 ) P;
2   z = sign(x);
3   do z :
4       P;
5   od
```

**LOOP is PR**

Theorem

The loop-computable functions are precisely the primitive recursive functions.

Proof.

The only difficult part in the argument is to show that

- loop-computable functions are closed under primitive recursion, and
- application of a loop operation preserves primitive recursiveness.

For simplicity assume that there is only one parameter \(y\). Suppose \(P : y \to z\) and \(Q : x, u, y \to z\) are two loop programs computing \(g : \mathbb{N} \to \mathbb{N}\) and \(h : \mathbb{N}^3 \to \mathbb{N}\).

We show that \(f = \text{Prec}[g, h] : \mathbb{N}^2 \to \mathbb{N}\) is loop-computable by constructing a loop program for \(f\) directly.
Here is a program $P_f$ for $f$. Variable $s$ is new.

// $P_f$: $x, y \rightarrow z$

\begin{verbatim}
  s = x;
x = 0;
P; // $y \rightarrow z$
do s:
  u = z;
  Q; // $x, u, y \rightarrow z$
x++;
od
\end{verbatim}

It is a good exercise to determine the semantics $[P_f]$ in detail.

For the opposite direction consider a loop program $P$ with variables $x_1, x_2, ..., x_k$ and semantics $f = [P]: \mathbb{N}^k \rightarrow \mathbb{N}^k$.

We may assume by induction that $f = (f_1, \ldots, f_k)$ is primitive recursive in the sense that each of the $f_i$ is so p.r. Now consider program $Q$:

\begin{verbatim}
do x: P od
\end{verbatim}

For simplicity, assume $x = x_1$. Define the vector valued function $F(0, x) = x$.

\[ F(n+1, x) = [P](F(n, x)) \]

Using sequence numbers we can show that all the component functions of $F$ are primitive recursive. But then $[Q](x) = F(x_1, x)$.

There is a natural way to distinguish between loop programs of different complexity: we can count the nesting depth of the loops in the program.

**Definition**

Let $\text{Loop}(k)$ be the class of loop programs that have nesting depth at most $k$.

Level 0 is not very interesting: it is easy to see that any scalar function that is $\text{Loop}(0)$-computable is an affine function of the form

\[ f(x) = c \cdot x + d \]

where $c$ and $d$ are both constant, $c \in \{0, 1\}$.

**Exercise**

Give a detailed proof of the last claim.

The following program computes the remainder for modulus 2.

// $\text{mod2} : x \rightarrow u$

\begin{verbatim}
  u = 0;
v = 1;
do x :
  t = u; // swap u and v
  u = v;
v = t;
od
\end{verbatim}

**Exercise**

Show that $x \mod m$ is $\text{Loop}(1)$-computable for every fixed modulus $m$.

The following program computes the integer quotient $x/2$.

// $\text{div2} : x \rightarrow u$

\begin{verbatim}
  u = 0;
v = 0;
do x :
  u++;
  t = u; // swap u and v
  u = v;
v = t;
od
\end{verbatim}

**Exercise**

Show that $x \div m$ is $\text{Loop}(1)$-computable for ever fixed modulus $m$. 

Rudimentary Functions

As it turns out, there is a well-known class of number-theoretic functions \( \mathbb{N}^n \rightarrow \mathbb{N} \) that looks very similar to Loop 1 programs.

Definition

A function is (Kalmar) rudimentary if it belongs to the clone generated from constants 0, 1, addition, predecessor, division and remainder with fixed modulus, and an if-then function.

By an if-then function we mean the following:

\[
W(x, y) = \begin{cases} 
  y & \text{if } x > 0, \\
  0 & \text{otherwise.}
\end{cases}
\]

This is similar to classical the question-mark operator in the C programming language (the third argument is fixed to 0 in this case): \( x \, ? \, y : 0 \).

Example: Division by 2

Rudimentary is Loop 1

Theorem

A function is Loop(1)-computable if, and only if, it is rudimentary.

Proof.

We have just verified that rudimentary programs are Loop(1)-computable. The other direction is more difficult: every Loop(1) program is already rudimentary.

Prove that Loop(1) is Rudimentary.

Theorem

A function is Loop(1)-computable if, and only if, it is rudimentary.

Proof.

We have just verified that rudimentary programs are Loop(1)-computable. The other direction is more difficult: every Loop(1) program is already rudimentary. For the proof, consider a single loop \( Q \):

\[
d x : P \text{ od}
\]

Suppose the variables are \( x \) where \( x = x_1 \), as before. The loop body \( P \) is Loop(0), so the effect of executing it \( P \) is an affine function on each of the variables:

\[
x'_i = c_i \cdot x_{p(i)} + d_i
\]

where \( c_i \in \{0, 1\} \) and \( d_i \geq 0 \) constant.

Example: Division by 2

Variables are \( \{z, x, u, v, t\} \) where \( z \) is clamped at 0.

1. \( u = z; \ v = z; \)
2. \( \text{do } x:\)
3. \( u++; \)
4. \( t = u; \ u = v; \ v = t; \)
5. \( \text{od} \)

The dependency graph for the loop body looks like so:

```
1 ➔ 2 ➔ 3 ➔ 4 ➔ 5
```

The edge labels indicate the increment factor \( d_i \), and we pretend that there are instructions \( z = z \) and \( x = x \).

Dependency is Unicyclic

Note that the indegree of every node in \( G \) is at most 1. Hence the strongly connected components of \( G \) are just cycles, and all these components are isolated from each other.

But then the values of the registers on a cycle at time \( t \) (after \( t \) executions of the loop) are of the form

\[
x = \begin{cases} 
  a_0 & \text{if } t = 0, \\
  a \cdot (t \div l) + \sum_{i < t \mod l} a_i & \text{otherwise.}
\end{cases}
\]

where \( l \) is the length of the cycle, and the \( a_i \) are the labels, \( a \) being the sum of all these labels.

Hence the final value of a variable after execution of \( P \) is a rudimentary function of the initial values. Since rudimentary functions are closed under composition, the whole Loop(1) program can only compute a rudimentary function.
### Equivalence of Programs

We define equivalence of programs in terms of the function computed by the respective programs, a purely extensional characterization.

**Definition**

Two programs $P$ and $Q$ are equivalent if they compute the same function $\mathbb{N}^n \to \mathbb{N}$.

Note that this is a weaker notion than having the same semantics, $[P] = [Q]$. For example, there is no reason why equivalent programs should use the same internal variables.

More importantly, the two programs can be based on two different ways of computing the function in question. Clearly, this type of equivalence is very hard to detect.

### Entscheidungsproblem

For each class $C$ of programs such as rudimentary, elementary, Loop($k$), primitive recursive we now have a decision problem:

**Problem:** Program Equivalence for $C$

**Instance:** Two programs $P$ and $Q$ in class $C$.

**Question:** Are $P$ and $Q$ equivalent?

This is the problem one would like to solve when one verifies the correctness of program transformations: $Q$ is obtained from $P$ by applying a transformation, and we want to make sure that the meaning of $P$ has not changed.

### Inequivalence

Alas, for technical reasons it is often better to consider Inequivalence: Is there some input on which the two programs yield different output?

One reason for this twist is that Inequivalence of programs is semi-decidable, even if we have no constraints on the class $C$ (actually, we have to insist on total functions rather than partial ones as in the case of arbitrary computable functions). For Inequivalence one can conduct a brute-force search over all possible inputs to find an $x$ such that

$$P(x) \neq Q(x).$$

This may appear rather nonsensical, but in lower complexity classes the distinction between Equivalence and Inequivalence becomes quite important. Of course, as far as decidability is concerned, there is no difference between Equivalence and Inequivalence.

### Loop 0

**Proposition**

Inequivalence for Loop(0) programs is decidable in polynomial time.

**Proof.**

Given the program $P$, we can easily compute an index $i$ and constants $c \in \{0, 1\}, d \geq 0$ such that $P$ computes

$$x \mapsto c \cdot x_i + d$$

But then equivalence and hence inequivalence are trivial to check: index and constants have to be the same for both programs.

**Exercise**

Devise a fast algorithm to test Equivalence of Loop(0) programs.

### Loop 2 and Up

**Lemma**

Inequivalence for Loop(2) programs is undecidable.

**Proof.**

Given a multivariate integer polynomial $p(x)$ one can easily build a program $P$ that computes

$$\text{signbar}(p(x)) \in \{0, 1\}$$

$P$ is naturally level 2 since all the arithmetic can be handled there.

Let $Q$ be the trivial program that computes the constant 0 function. Then Inequivalence for $P$ and $Q$ comes down solving a Diophantine equation, which problem is undecidable by Matiyasevich’s theorem.

### Loop 1

That leaves Inequivalence for level 1 open: can we check if two rudimentary functions disagree on some input?

One might suspect that Inequivalence of rudimentary functions is indeed decidable since these functions are in some sense periodic or piecewise affine.

But the details bear some careful explanation: level 2 is not far away, and there Inequivalence is already undecidable.

As it turns out, Inequivalence for Loop(1) program is decidable, but is already NP-hard, so there is likely no fast algorithm for checking equivalence of such programs.
Describing Rudimentary Functions

**Definition**

Define an equivalence relation \( \equiv_{\beta,\mu} \) on \( \mathbb{N}^n \) as follows: \( x \) and \( y \) are equivalent if

- \( x_i < \beta \lor y_i < \beta \) implies \( x_i = y_i \), and
- \( x_i \geq \beta \land y_i \geq \beta \) implies \( x_i = y_i (\text{mod } \mu) \).

Each equivalence class of \( \equiv_{\beta,\mu} \) is either a singleton or infinite.

The number of equivalence classes is \((\beta + \mu)^n\); each component of the vector is either completely fixed (if it is less than \( \beta \)) or fixed modulo \( \mu \).

A simple case arises when \( \beta = 0 \): then we are simply subdividing \( \mathbb{N}^n \) into hypercubes of size \( \mu^n \).

**Example**

Consider the function

\[
  f(x, y) = x + x \mod 2 + y \div 2 + 1
\]

For \( \beta = 0, \mu = 2 \) we get the following classes:

\[
\begin{array}{cccccccc}
0 & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 \\
\hline
x & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\
7 & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\
6 & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\
5 & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\
4 & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\
3 & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\
2 & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\
1 & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\
0 & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\
\end{array}
\]

**Theorem**

For each rudimentary function \( f : \mathbb{N}^n \to \mathbb{N} \) there are constants \( \beta \) and \( \mu \) such the restriction of \( f \) to the equivalence classes of \( \equiv_{\beta,\mu} \) is an affine function:

\[
  f(x) = \sum_i c_i \cdot x_i + c.
\]

**Proof**

Use induction on the buildup of \( f \). Here are the important cases.

- \( f_1 + f_2 \quad \beta = \max(\beta_1, \beta_2) \quad \mu = \mu_1 \mu_2 \)
- \( f_1 \cdot 1 \quad \beta = \beta_1 + \mu_1 \quad \mu = \mu_1 \)
- \( W(f_1, f_2) \quad \beta = \max(\beta_1, \beta_2) + \mu_2 \quad \mu = \mu_1 \mu_2 \)
- \( f_1 \div c \quad \beta = \beta_1 \quad \mu = c \mu_1 \)
- \( f_1 \mod c \quad \beta = \beta_1 \quad \mu = c \mu_1 \)

\( \square \)

Simple Example

Suppose \( g(x) \) is affine on the classes of \( \equiv_{0,\mu} \).

So there is a family of \( \mu \) many affine functions \( G_i \) such that

\[
  g(x) = G_{x \mod \mu}(x)
\]

Set \( f(x) = g(x) \mod c \). Then

\[
  f(x) = G_{x \mod \mu}(x) \mod c = G_{x \mod \mu}(x \mod c) \mod c
\]

and we have to distinguish at most \( c \mu \) classes for \( f \).

A Basis Set

One can push things a bit further and show that if a rudimentary function \( f \) is piecewise affine with respect to \( \equiv_{\beta,\mu} \) then \( f \) is completely determined by its values on the basis set

\[
  S = \{ x \mid x_i \leq \beta + 2\mu \}.
\]

In other words, if \( g \) is another rudimentary function with parameters \( \beta \) and \( \mu \) and we have

\[
  \forall x \in S (f(x) = g(x))
\]

then the two functions already agree everywhere.
Note that $\equiv_{\beta',\mu'}$ refines $\equiv_{\beta,\mu}$ whenever $\beta' \geq \beta$ and $\mu' = c\mu$.

Hence we can always choose the same parameters for any two functions.

**Theorem**

Let $f_1$ and $f_2$ be two rudimentary functions with common parameters $\beta$ and $\mu$. Then the two functions are equivalent iff they agree on
\[
\{ x \mid x_i \leq \beta + 2\mu \}.
\]

**Inequivalence**

Theorem

Inequivalence for Loop(1) is NP-complete

Proof.

For membership, we can easily compute the common parameters $\beta$ and $\mu$ from the programs.

We can then guess the witness in the test set
\[
S = \{ x \mid x_i \leq \beta + 2\mu \}.
\]
and verify that the two programs indeed differ on this input by running the corresponding computations.

Except for guessing the witness, all of this can be handled in in deterministic polynomial time. But the witnesses are short, so the whole procedure is in NP.

**Hardness**

For hardness we show how to reduce 3SAT to Inequivalence.

Suppose we have Boolean variables $x_1, x_2, \ldots, x_n$ and clauses $C_1, C_2, \ldots, C_m$.

Now consider a clause $C_i$, say, $C_i = x \lor y \lor z$. We compute the truth value $c_i \in \{0,1\}$ of $C_i$ as follows:

\[
\begin{align*}
  z &= 0; \\
  &\text{if } (x == 1) \quad z = 1; \\
  &\text{if } (y == 0) \quad z = 1; \\
  &\text{if } (z == 1) \quad z = 1;
\end{align*}
\]

Lastly, we compute $\min(c_1, \ldots, c_m)$, the truth value of the whole formula.

The corresponding program is easily Loop(1) (it operates solely on Boolean values and does not begin to exploit the possibilities of arithmetic) and inequivalent to 0 iff the formula is satisfiable.