

Introduction To Haskell Programming

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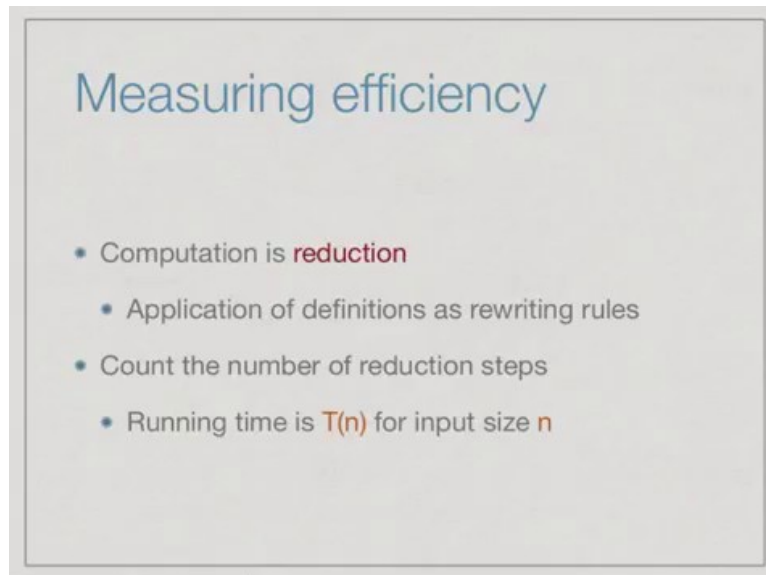
Module # 04

Lecture – 01

Measuring efficiency

Whenever we write a program to solve a given task, we need to know how much resources it requires, how much space and how much time. Here we will focus on how to compute the amount of time required by a Haskell program.

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Measuring efficiency

- Computation is **reduction**
 - Application of definitions as rewriting rules
- Count the number of reduction steps
- Running time is **$T(n)$** for input size **n**

Remember that the notion of computation in Haskell is rewriting or reduction, in other words we take function definitions and when we use them to simplify expressions by replacing the left hand side of a define by its right hand side. In this way we keep applying these, rewriting rules until no further simplification is possible for the given expression. Hence it makes sense to count the number of reduction steps and use this as a measure of the running time for Haskell program.

Now normally, the running time of a program depends on the size of the input, it obviously takes more time to sort a large list than a small list. So, we typically express the running time

as a function of the input size, if the input size is n , let us write T of n is the function which describes the dependence of the time on the input size.

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Example: Complexity of ++

```

[] ++ y = y
(x:xs) ++ y = x:(xs++y)

```

- $[1,2,3] ++ [4,5,6] \Rightarrow$
 $1:([2,3] ++ [4,5,6]) \Rightarrow$
 $1:(2:([3] ++ [4,5,6])) \Rightarrow$
 $1:(2:(3:([] ++ [4,5,6]))) \Rightarrow$
 $1:(2:(3:([4,5,6])))$
- $l1 ++ l2$: use the second rule **length** $l1$ times, first rule once, always

So, let us start with an example, here is the definition of the built in function ++ that combines two lists into a single list, so that function is defined by induction on the first argument. So, if we combine the empty list with the list y , then we just get y itself, if we combine the non empty list with y , then we take the first element of the first list x and move it to be the first element of the inductively combined list $xs++y$.

So, let us execute this on an input such as $[1,2,3] ++ [4,5,6]$. Since, the first list is non empty, the second definition applies and so we now have to append 1 to the result of $[2,3] ++ [4,5,6]$. Once again we apply the second definition, so inside the bracket now we have 2 appended to the list $[3] ++ [4,5,6]$. Once again we apply the second definition. So, we get the list 3 appended to the $[] ++ [4,5,6]$

Now the base case applies, so $[] ++ [4,5,6]$ is just $[4, 5, 6]$. So, we get the final answer which is 1 appended to 2 appended to 3 appended to the list, 4, 5, 6 written as $1: (2: (3: ([4,5,6])))$. So, from this it is clear that when we execute ++ for each element in the first list we have to apply the second rule once. So, the second rule is used length of $l1$ times and finally, when the length of $l1$ becomes zero, we will apply the first rule once and this behavior is independent of the actual values of $l1$ and $l2$. We will always use the second rule length of $l1$ times followed by one application of the first rule.

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Example: elem

```
elem :: Int -> [Int] -> Bool
elem i [] = False
elem i (x:xs)
  | (i==x) = True
  | otherwise = elem i xs
```

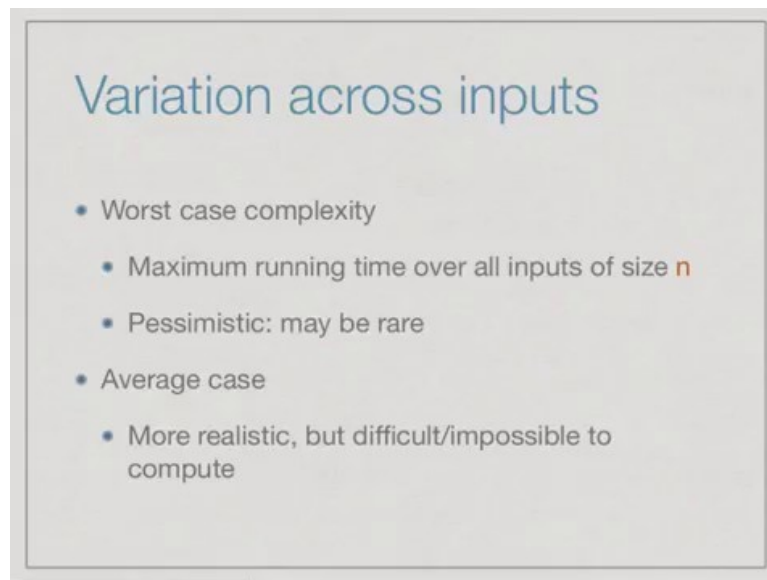
- elem 3 [4,7,8,9] \Rightarrow elem 3 [7,8,9] \Rightarrow elem 3 [8,9] \Rightarrow elem 3 [9] \Rightarrow elem 3 [] \Rightarrow False
- elem 3 [3,7,8,9] \Rightarrow True
- Complexity depends on input size **and** value

On the other hand, let us look at this function elem, which stands for element of. It checks if a given integer belongs to a list of integers. So, the base case says that the element i never belongs to the empty list and otherwise, we check whether it is the first element of the non empty list, if so we return True, if it is not so, we continue to search for the element in the rest of the xs. Now, if we apply the element function to a list which does not contain the value, then the second clause gets executed as many times as the length of the input until we reach the empty list and gets false.

So, we start with elem 3 of [4, 7, 8, 9] then in turn we strip off the 4, the 7, the 8, the 9 until we get to elem 3 of the empty list and then say False. On the other hand if we are lucky, we might find the element right away. For instance, if the first element of this list was not a 4, but a 3, then in one step we would find that the first element matches the pattern we are looking for and we would return True. So, in general the actual execution times of function on an input depends both on the input size and the actual value of the input.

When we executed ++, we saw that the value of the input did not play any role, we would always execute the command, the second definition as many times as the length of the first list and then execute the first definition once. But, in most functions depending on what we passed to the function the execution may take time less or more time.

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So, to account for variation across the values of the inputs, the standard idea is to look at the worst possible input, this is called the worst case complexity. Now, this basically takes the maximum running time over all inputs of size n and defines this to be the worst case complexity of the function, this is perhaps a bit pessimistic, because the worst case might occur very rarely. But, on the other hand this is the only concrete case that we can typically analyze.

It would often be nice if we could actually make some kind of statistical average and compute the average case. But, in many cases it is difficult to define a standard distribution of probability across all inputs and compute a meaningful average. So, though the average case complexity is a more realistic measure of how long the function takes, it is either difficult or impossible to compute in general. So, we must unfortunately settle for the worst case complexity.

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Asymptotic complexity

- Interested in $T(n)$ in terms of orders of magnitude
- $f(n) = O(g(n))$ if there is a constant k such that $f(n) \leq k g(n)$ for all $n > 0$
- $an^2 + bn + c = O(n^2)$ for all a, b, c
(take $k = a+b+c$ if $a, b, c > 0$)

$3n^2 + 5n + 2 \leq 10n^2, n > 0$

The other feature that is usually used when analyzing algorithms is to use what is called asymptotic complexity. So, we are interested in how $T(n)$ grows as a function of n , but we are interested only in orders of magnitude, we are not really interested in exact details of the constants involved. So, the standard way to express this is to use this so called Big O notation. So, big O notation says that $f(n)$ is no bigger than $g(n)$, in other words $f(n)$ is dominated by some constant times $g(n)$ for every $n > 0$.

As an example, suppose we have the concrete function $f(n)$ as the quadratic $an^2 + bn + c$. We claim that this is actually Big O of n^2 . For instance, supposing we take a concrete value such as $3n^2 + 5n + 2$ then we could take $3+5+2$ and say that this is always $\leq 10n^2$ for all $n > 0$. So, if a and b and c are all positive then we can just add up the coefficients to come up with this value k .

You can check that if any of the coefficients is negative you can just drop it. So, you can just add up this sum of the positive coefficients and that should work. So, usually it turns out to be a simple problem which is you just take the highest power.

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Asymptotic complexity

- Interested in $T(n)$ in terms of orders of magnitude
- $f(n) = O(g(n))$ if there is a constant k such that $f(n) \leq k g(n)$ for all $n > 0$
 - $an^2 + bn + c = O(n^2)$ for all a, b, c
(take $k = a+b+c$ if $a, b, c > 0$)
- Ignore constant factors, lower order terms
- $O(n), O(n \log n), O(n^k), O(2^n), \dots$
polynomial exponential

So, usually we ignore the constant factor, so we ignore constants like a , b and c and we take then among the terms that contributes to the complexity the highest power and we say that this function is $O(n^2)$. So, given this we typically express the complexity of the function terms of functions like $n \log n$ or n^k for some k . So, these are the so called polynomial functions or we have exponential and so on. So, this is the typical notation that we will use to describe the complexity of our functions.

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Asymptotic complexity ...

- Complexity of `++` is $O(n)$, where n is the length of the first list
- Complexity of `elem` is $O(n)$
 - Worst case!

So, in this notation we saw that the complexity of ++ is $O(n)$, when n is the length of the first list, the length of the second list is immaterial. Therefore, it really is irrelevant as for as the input goes. On the other hand, for the function elem we again got a linear dependence $O(n)$, but this is not true for all inputs, we saw that it could actually terminate in one step if the first element matches the length element we are looking for. So, this is really a case where we are applying this worst case definition in order to determine the complexity of the function.

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Complexity of reverse

```

myreverse :: [a] -> [a]
myreverse [] = []
myreverse (x:xs) = (myreverse xs) ++ [x]

```

$n-1$ $+1$

- Analyze directly (like ++), or write a recurrence for $T(n)$
- $T(0) = 1$ ✓
 $T(n) = T(n-1) + n$

So, let us try and analyze the complexity of function that we wrote earlier. So, this is our inductive definition of reverse, we said that we can reverse the empty list by just returning the empty list. On the other hand, if we have a non empty list then we pick the tail of the list, reverse it inductively and then append the first element afterwards. Now, unfortunately this append we know depends on the length of the tail.

So, we could try to analyze this directly or we could use the fact that we know something about ++ to write what is called a recurrence. Recurrence expresses $T(n)$ in terms of smaller values of T . So, in this case if we have an empty list, if the list length is 0, so here this input size is the length of the list to be reversed. So, if the length is 0 then clearly we can reverse it in one step. Now, if the length is not zero then we have to first reverse the tail.

So, this means that in order to reverse the length of list of length n we have to first reverse the list of length $n-1$ and then what we saw in our first analysis was that this function ++ will take time proportional to $n-1$ iterations of the second definition plus 1 iteration of the first

definition and therefore, it will take n steps. So, this gives us the behavior of the time complexity of reverse in a recursive form.

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Complexity of reverse

```
myreverse :: [a] -> [a]
myreverse [] = []
myreverse (x:xs) = (myreverse xs) ++ [x]
```

- Analyze directly (like ++), or write a recurrence for $T(n)$
 - $T(0) = 1$
 $T(n) = T(n-1) + n$
- Solve by expanding the recurrence

So, how do we solve this kind of thing to get an expression for $T(n)$, well the easiest way is just to expand the recurrence.

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Complexity of reverse ...

- $T(n)$
 - $= T(n-1) + n$
 - $= (T(n-2) + n-1) + n$
 - $= (T(n-3) + n-2) + n-1 + n$
 - ...
 - $= T(0) + 1 + 2 + \dots + n$
 - $= 1 + 1 + 2 + \dots + n$
 - $= 1 + n(n+1)/2$
 - $= O(n^2)$

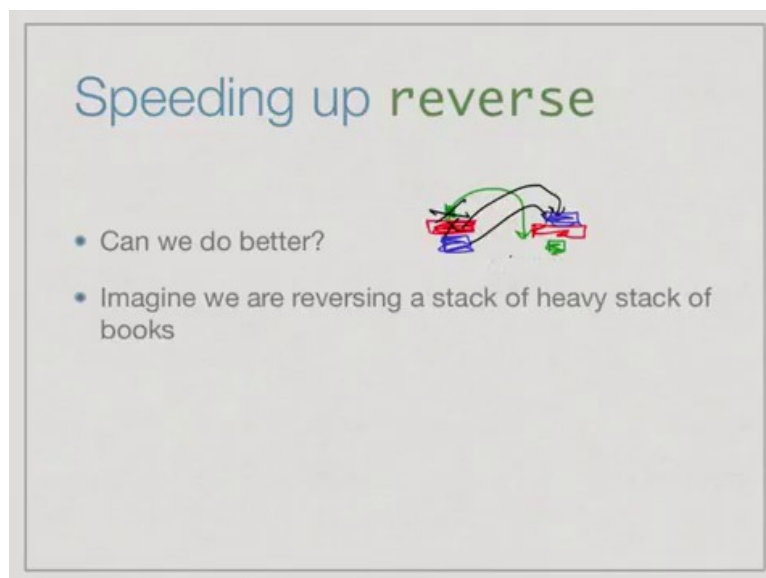
$T(0) = 1$
 $T(n) = T(n-1) + n$

So, here is our recurrence now. It says $T(0)$ is 1 and $T(n)$ is $T(n-1) + n$. So, now, we start with $T(n)$ and using the second item of the recurrence we expand it as $T(n-1) + n$. Now, in turn we

can apply the same definition to $T(n-1)$ and get it as $T(n-2) + n-1$. So, this is just an expansion of this recurrence, where n is substituted uniformly by $n-1$. In this way we keep expanding.

And so we are building up this term over here $n-2 + n-1 + n$ and we have what remains, eventually we come down to the point where $n-n$ which is 0 comes to us and we have on the right if you check this will be $n-(n-1)$ so 1, 2, 3 and all that. So, this is the summation of $i=1$ to n and this is well known is $n*(n+1)/2$ and hence going by our earlier way of calculating the Big O the highest terms of this is $n^2/2 + n/2$. So, the highest term is n^2 and if we ignore all constants this turns out to be order n^2 . In other words we are actually spending n^2 time in order to reverse the list of n elements which seems rather inefficient.

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The slide is titled "Speeding up reverse" in a blue and green font. It contains two bullet points and a diagram. The diagram shows two stacks of books. The left stack has a red book at the bottom and a blue book on top. The right stack has a green book at the bottom and a red book on top. Arrows indicate the movement of books from the left stack to the right stack: a green arrow from the red book, a blue arrow from the blue book, and a red arrow from the green book.

- Can we do better?
- Imagine we are reversing a stack of heavy stack of books

So, how do we improve on this? So, the idea is that we do not reverse the list in place as we are trying to do, but build up a second list. So, imagine that we have a stack of books, so maybe we have a red book and blue book then a green book ((Refer Time: 12:06)). So, now, what we do is we move this book to a new stack. So, we now have a green book here and we have move green book here, then we move the red book onto this and now we have a red book here and no red book. Finally, we move the blue book to new stack, now we have a blue book on top and now notice that this second stack is the reverse of the first stack.

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Speeding up reverse

- Can we do better?
- Imagine we are reversing a stack of heavy stack of books
- Transfer to a new stack, top to bottom
- New stack is in reverse order!

So, in other words we transfer to the new stack from top to bottom, and the new stack is the old stack in reverse order. So, we can use this idea to write a more efficient version of reverse.

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Speeding up reverse ...

```
transfer :: [a] -> [a] -> [a]
transfer [] l = l
transfer (x:xs) l = transfer xs (x:l)
```

- Input size for transfer l1 l2 is length l1
- Recurrence
$$T(0) = 1$$
$$T(n) = T(n-1) + 1$$
- Expanding: $T(n) = 1 + 1 + \dots + 1 = O(n)$
 $n+1$

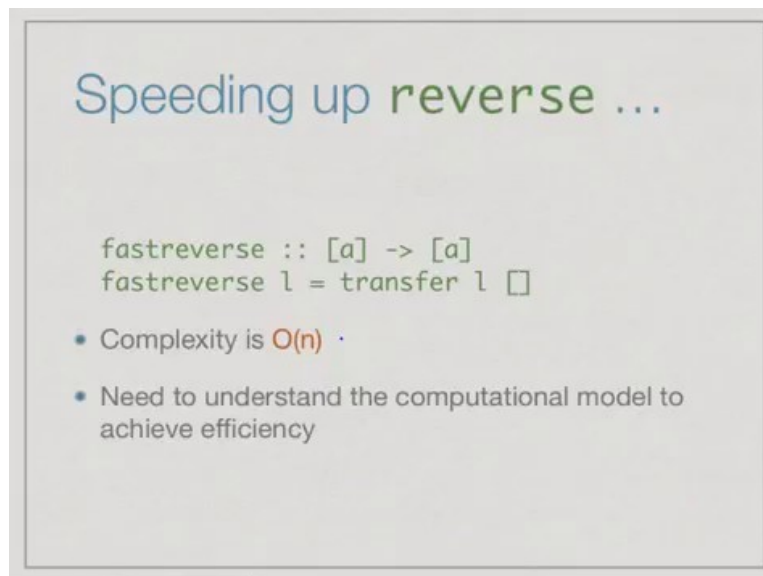
So, here is the idea of moving a list from one side to another side and reverse. So, what we do is we transfer the contents of our first list to the second list. So, the first list is empty then there is nothing to transfer and just leave the second list as it is, if the first list is non empty then this x is the book on top of the stack, so we move it to the top of the second stack. So, if

we want to transfer $x:xs$ to l then we keep the xs in the first stack and move this x from the first stack to the second stack.

So, now, it is clear that this function does not depend on the second list that is passed. So, this is the bit like $++$. So, the input size is actually the length of $l1$ and it is clear that we have a recurrence of this form which says that if I have an empty list, then I do it in one step as a first argument, if I have a non empty list then it takes me one step to produce an instance of transfer of size $n-1$.

So, $T(n)$ is $T(n-1) + 1$ and now using our expansion if we expand this n times we come down to $T(0)$. So, we get $1+1+1+\dots$ $n+1$ times and $n+1$ is just order of n , in other words as we clearly know from the way we describe the process manually transferring a list in reverse from one stack to another stack takes times proportional to the length of the list.

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Speeding up reverse ...

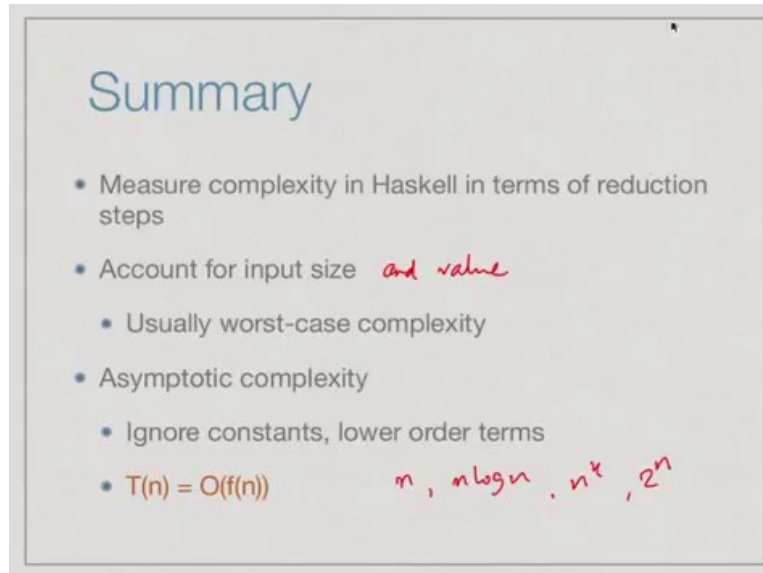
```
fastreverse :: [a] -> [a]
fastreverse l = transfer l []
```

- Complexity is $O(n)$.
- Need to understand the computational model to achieve efficiency

And now we are done, because we can just start with an empty second stack as we said before and transfer everything from the first stack to the second stack. So, we have a `fastreverse` which is written in terms of this linear function `transfer` and `fastreverse` of l is just transfer the contents of l to the empty stack. The complexity of this function is linear, so notice that we had to take a look at how lists are treated in Haskell and how computation works in order to come up with the slightly non obvious definition of `reverse`, which matches the intuitive complexity that we have for the function. So, this shows that you cannot blindly

apply the techniques from one programming language to another without understanding the computation model, if you want to achieve the efficiency that you like.

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Summary

- Measure complexity in Haskell in terms of reduction steps
- Account for input size *and value*
 - Usually worst-case complexity
- Asymptotic complexity
 - Ignore constants, lower order terms
- $T(n) = O(f(n))$ *$n, n \log n, n^k, 2^n$*

To summarize, we measure the complexity of a Haskell function in terms of the number of reduction steps we take to arrive at the answer. So, reduction consists of applying a definition in a function and rewriting the left hand side by the right hand side. Now, when we compute the function we have to account for the input size, but also for the input value, we saw the function elem could return quickly or take a long time depending on whether not the value we are looking for belongs to the list.

So, to account for the input size and the value, we usually use worst case complexity, because the desirable goal of computing average case complexity is very hard. And finally, we said that we will use traditional algorithmic ideas and express the efficiency in terms of asymptotic complexity. So, we will ignore the constants, ignore lower order terms and write $T(n)$ in terms of Big O of $f(n)$, where $f(n)$ will typically be a function like n or $n \log n$ or n^k or 2^n .