Knuth-Morris-Pratt algorithm

The algorithm we present now is an improvement due to Knuth of the Morris-Pratt algorithm, based on avoiding situations which lead to certain letter comparison failures.

	j—i		j−i+p j−1 j	
t:	 BORDER $(x[1i-1])$		Border $(x[1i-1])$ b	
	1	р	i–1 i	
X :	BORDER $(x[1i-1])$		Border $(x[1i-1])$ a	
			1 $\beta_x(i-1) s_x(i)$	
		slided x:	Border $(x[1i-1]) \mid a \mid$	

The observation is that if a = a then the sliding would lead to a comparison failure. So let us enforce that a sliding to compare $x[s_x(i)]$ to t[j] is done if and only if $x[s_x(i)] \neq x[i]$.

If $x[s_x(i)] = x[i]$, what should we do?

Let us note y = x[1...i-1]. We should consider successively Border² $(y) \cdot a$, Border³ $(y) \cdot a$ etc., until we find a k such that Border^k $(y) \cdot a \not \leq x$ or Border^k $(y) = \varepsilon$. Such a border Border^k(y) is called a **maximum disjoint border** of y in x.

If it is non-empty, we slide the word so that we compare $x[s_x^k(i)]$ and t[j].

This disjointedness constraint can be precomputed on the pattern x alone before comparing it to the text t: all we have to do is to change the failure function s_x of the algorithm of Morris and Pratt and provide a new one. The search algorithm itself does not change.

The disjointedness implicitly entails that it is a relative concept: we consider the disjoint border of a *proper prefix* of another word. Thus, the letter with follows the prefix is used as a constraint, i.e., it must not follow the disjoint border.

Let $ya \leq x$. Let us note $\overline{\mathsf{Border}}_x(y)$ the maximum disjoint border of y in x. In this case, the letter a is used to constrain the definition of the disjoint border, as we must have $\overline{\mathsf{Border}}_x(y) \cdot a \not\leq y$.

What if y=x, then? In this case, there is no right-context, like the letter a above, to constrain the maximum disjoint border. In this case, we still can take the maximum border, i.e., $\overline{\mathsf{Border}}_y(y)=\mathsf{Border}(y)$.

More precisely, if the maximum border of y is not followed by a, then it is also the maximum disjoint border we are looking for. In other words:

$$\overline{\mathsf{Border}}_{\mathsf{X}}(y) = \mathsf{Border}(y)$$
 if $ya \leqslant x$ and $\mathsf{Border}(y) \cdot a \not\leqslant y$

If the maximum border of y is followed by a we must take the maximum disjoint border of the maximum border:

$$\overline{\mathsf{Border}}_{\mathsf{X}}(y) = \overline{\mathsf{Border}}_{\mathsf{X}}(\mathsf{Border}(y))$$
 if $ya \leqslant x$ and $\mathsf{Border}(y) \cdot a \leqslant y$

By extension, if x = y, we take the maximum border:

$$\overline{\mathsf{Border}}_y(y) = \mathsf{Border}(y)$$

In summary, assuming $ya \le x$ and $y \ne \varepsilon$

$$\overline{\mathsf{Border}}_y(y) = \mathsf{Border}(y)$$

$$\overline{\mathsf{Border}}_x(y) = \begin{cases} \overline{\mathsf{Border}}_x(\mathsf{Border}(y)) & \text{if } \mathsf{Border}(y) \cdot a \leqslant y \\ \mathsf{Border}(y) & \text{otherwise} \end{cases}$$

By taking the length of each side of the equations,

$$|\overline{\mathsf{BORDER}}_{\chi}(y)| = \begin{cases} |\mathsf{BORDER}(y)| & \text{if } x = y \text{ or } \mathsf{BORDER}(y) \cdot a \not \leq y \\ |\overline{\mathsf{BORDER}}_{\chi}(\mathsf{BORDER}(y))| & \text{otherwise} \end{cases}$$

Let $\gamma_x(i)$ be the length of the disjoint maximum border of $x[1 \dots i]$:

$$\gamma_X(i) = |\overline{\mathsf{Border}}_X(x[1...i])| \qquad 1 \leqslant i \leqslant |x|$$

or, equivalently,

$$\gamma_{x}(|y|) = |\overline{\mathsf{Border}}_{x}(y)| \qquad y \leqslant x$$

Therefore

$$\gamma_{\scriptscriptstyle X}(|y|) = \begin{cases} \beta_{\scriptscriptstyle X}(|y|) & \text{if } x = y \text{ or } \mathsf{Border}(y) \cdot a \not < y \\ \gamma_{\scriptscriptstyle X}(|\mathsf{Border}(y)|) & \text{otherwise} \end{cases}$$

that is to say

$$\gamma_{x}(|y|) = \begin{cases} \beta_{x}(|y|) & \text{if } x = y \text{ or Border}(y) \cdot a \nleq y \\ \gamma_{x}(\beta_{x}(|y|)) & \text{otherwise} \end{cases}$$

If |y| = i, we can write instead

$$\gamma_{x}(i) = \begin{cases} \beta_{x}(i) & \text{if } x = y \text{ or Border}(y) \cdot a \leq y \\ \gamma_{x}(\beta_{x}(i)) & \text{otherwise} \end{cases}$$

The condition can also be rewritten in terms of β_x and i, just as we did with the Morris-Pratt algorithm, pages 35 and 19. Let |y| = i, then

BORDER
$$(y) \cdot a \not < y \iff x[\beta_x(i) + 1] \neq x[i + 1]$$

 $x = y \iff |x| = i$

So, finally, for $1 \le i \le |x|$,

$$\gamma_{x}(i) = \begin{cases} \beta_{x}(i) & \text{if } i = |x| \text{ or } x[\beta_{x}(i) + 1] \neq x[i + 1] \\ \gamma_{x}(\beta_{x}(i)) & \text{otherwise} \end{cases}$$

which allows us to naturally extends γ_x on 0: $\gamma_x(0) = \beta_x(0) = -1$.

Before going further, let us check by hand the following values of $\gamma_{\chi}(i)$ and compare them to $\beta_{\chi}(i)$: we must always have $\gamma_{\chi}(i) \leqslant \beta_{\chi}(i)$, since we plan an optimisation.

X									С		
i	0	1	2	3	4	5	6	7	8	9	10
$\beta_{x}(i)$	-1	0	0	0	1	2	1	2	3	4	0
$\beta_{x}(i)$ $\gamma_{x}(i)$	-1	0	0	-1	0	2	0	0	-1	4	0

One difference between β_X and γ_X is that, in the worst case, there is always an empty maximum border ε , i.e., $\beta_X(i)=0$, whereas there may be no maximum disjoint border at all, i.e., $\gamma_X(i)=-1$. For instance, the prefix abc of x has an empty maximum border, i.e., $\beta_X(3)=0$, but has no maximum disjoint border, i.e., $\gamma_X(3)=-1$, since x[1]=x[4].

This definition of γ_x relies on β_x , more precisely, the computation of $\gamma_x(i)$ requires $\beta_x^p(i)$, i.e., values $\beta_x(j)$ with j < i, since

$$\beta_{x}(0) = -1$$
 $\beta_{x}(i) = 1 + \beta_{x}^{k}(i-1)$ $1 \le i$

where k is the smallest non-zero integer such that

• either $1 + \beta_x^k(i-1) = 0$ or $x[1 + \beta_x^k(i-1)] = x[i]$ or, equivalently,

$$\mathsf{Border}(ya) = \begin{cases} \mathsf{Border}^k(y) \cdot a & \mathsf{if Border}^k(y) \cdot a \leq y \\ \varepsilon & \mathsf{if Border}^{k-1}(y) = \varepsilon \end{cases}$$

where k is the smallest non-zero integer such that $\mathsf{Border}^k(y) \cdot a \leqslant y$ or $\mathsf{Border}^{k-1}(y) = \varepsilon$.

Therefore, let us find another definition of Border(ya) which relies on Border(y) but **not** on Border(y) with $2 \le q$. This can be achieved by considering again the figure

$$y \cdot a$$
: Border $(y) \mid b \mid$ Border $(y) \mid a \mid$

Indeed, if a=b then $\mathsf{Border}(ya)=\mathsf{Border}(y)$. Else, $a\neq b$, and thus the maximum border can be found among the *disjoint* borders of $\mathsf{Border}(y)$, otherwise $\mathsf{Border}(ya)=\varepsilon$.

$$\mathsf{Border}(ya) = \begin{cases} \overline{\mathsf{Border}}_{\mathsf{X}}^q(\mathsf{Border}(y)) \cdot a & \mathsf{if } \overline{\mathsf{Border}}_{\mathsf{X}}^q(\mathsf{Border}(y)) \cdot a \leqslant y \\ \varepsilon & \mathsf{if } y = \varepsilon \mathsf{ or } \overline{\mathsf{Border}}_{\mathsf{X}}^{q-1}(\mathsf{Border}(y)) = \varepsilon \end{cases}$$

where $ya \leqslant x$ and q is the smallest integer such that $\overline{\mathsf{Border}}_x^q(\mathsf{Border}(y)) \cdot a \leqslant y$ or $\overline{\mathsf{Border}}_x^{q-1}(\mathsf{Border}(y)) = \varepsilon$.

By taking the lengths and letting $0 \le i \le |x| - 1$ and |y| = i,

$$\beta_{x}(0) = -1$$

$$\beta_{x}(i+1) = \begin{cases} \gamma_{x}^{q}(\beta_{x}(i)) + 1 & \text{if } x[\gamma_{x}^{q}(\beta_{x}(i)) + 1] = x[i+1] \\ 0 & \text{if } i = 0 \text{ or } \gamma_{x}^{q-1}(\beta_{x}(i)) = 0 \end{cases}$$

where q is the smallest integer such that

- either $x[\gamma_{x}^{q}(\beta_{x}(i)) + 1] = x[i + 1]$
- or $\gamma_X^{q-1}(\beta_X(i)) = 0$

Since $\gamma_x(i) = -1$ if and only if i = 0, we have

$$\gamma_x^{q-1}(\beta_x(i)) = 0 \Longleftrightarrow \gamma_x(\gamma_x^{q-1}(\beta_x(i))) = \gamma_x(0) \Longleftrightarrow \gamma_x^q(\beta_x(i)) = -1$$
$$\Longleftrightarrow \gamma_x^q(\beta_x(i)) + 1 = 0$$

Therefore we can simplify the new definition of β_x as

$$eta_X(0) = -1$$
 $eta_X(1) = 0$
 $eta_X(i+1) = \gamma_X^q(eta_X(i)) + 1$
 $1 \le i \le |X| - 1$

where q is the smallest integer such that

- either $x[\gamma_{x}^{q}(\beta_{x}(i)) + 1] = x[i + 1]$
- or $\gamma_{X}^{q}(\beta_{X}(i)) + 1 = 0$

Knuth-Morris-Pratt/Maximum disjoint borders/Imperative

```
G_{AMMA}(x)
  1 \gamma_x[0] \leftarrow -1; offset \leftarrow -1
                                                                                                   \triangleright offset = \beta_{\nu}(0)
 2 for i \leftarrow 1 to |x| - 1
 3
                do repeat
 4
                                   offset \leftarrow \gamma_x[offset]
 5
                         until offset = -1 or x[offset + 1] = x[i]
                      offset \leftarrow offset +1 \triangleright offset = \gamma_{\nu}^{q}(\beta_{\nu}(i-1)) + 1 = \beta_{\nu}(i)
 6
                      if i = |x| or x[offset + 1] = x[i + 1]
 8
                         then \gamma_x[i] \leftarrow offset
                                                                                                      \triangleright \gamma_{\mathbf{v}}(i) = \beta_{\mathbf{v}}(i)
                                                                                              \triangleright \gamma_{\vee}(i) = \gamma_{\vee}(\beta_{\vee}(i))
 9
                         else \gamma_x[i] \leftarrow \gamma_x[offset]
10
        Gamma \leftarrow \gamma_{x}
```

With the algorithm of Morris and Pratt, it was convenient to use a failure function $s(i) = 1 + \beta(i-1)$. Similarly, we need here another failure function, noted r, such that $r(i) = 1 + \gamma(i-1)$, for $1 \le i$.

In order to finish, we need to give the algorithm for the failure function r.

We could then keep Beta and create a separate function KMP-Fall simply by sticking to the above definition:

$$\mathsf{KMP}\text{-}\mathsf{Fail}(\gamma_X,i) \\ \mathsf{1} \quad \mathsf{KMP}\text{-}\mathsf{Fail} \leftarrow \mathsf{1} + \gamma_X[i-1] \\ \qquad \qquad \rhd r_X[i] \leftarrow \mathsf{1} + \gamma_X[i-1]$$

But this is not efficient: it would be better to precompute and store all the values of KMP-Fall in an array.

Let us recall the definition of γ_x . Let $1 \le i \le |x|$ and

$$\begin{split} \gamma_x(0) &= -1 \\ \gamma_x(i) &= \begin{cases} \beta_x(i) & \text{if } i = |x| \text{ or } x[\beta_x(i)+1] \neq x[i+1] \\ \gamma_x(\beta_x(i)) & \text{otherwise} \end{cases} \end{split}$$

Then, for $1 \le i \le |x| - 1$

$$r_{\chi}(1) = 1 + \gamma_{\chi}(0) = 0$$

$$r_{\chi}(1+i) = 1 + \gamma_{\chi}(i) = \begin{cases} 1 + \beta_{\chi}(i) & \text{if } x[\beta_{\chi}(i) + 1] \neq x[i+1] \\ 1 + \gamma_{\chi}(\beta_{\chi}(i)) & \text{otherwise} \end{cases}$$

This can be slightly simplified into

$$r_{x}(1) = 0$$

$$r_{x}(1+i) = \begin{cases} r_{x}(1+\beta_{x}(i)) & \text{if } x[1+\beta_{x}(i)] = x[1+i] \\ 1+\beta_{x}(i) & \text{otherwise} \end{cases}$$

where for $1 \le i \le |x| - 1$.

Now, we need to express β_x in terms of r_x instead of γ_x .

First, let us prove by induction on $0 \le p$ that

$$r_x^p(1+i) = 1 + \gamma_x^p(i)$$
 $0 \le i \le |x| - 1$

Because

$$r_x^0(1+i) = 1 + \gamma_x^0(i) \iff 1+i = 1+i$$

and, assuming it is true up to p, we have

$$r_X^{p+1}(1+i) = r_X(r_X^p(1+i)) = r_X(1+\gamma_X^p(i)) = 1+\gamma_X(\gamma_X^p(i)) = 1+\gamma_X^{p+1}(i)$$

which is the property at rank p + 1.

So, the definition of β_x

$$\beta_x(0) = -1 \qquad \beta_x(1) = 0 \qquad \beta_x(1+i) = 1 + \gamma_x^q(\beta_x(i)) \qquad 1 \leqslant i \leqslant |x| - 1$$

where q is the smallest integer such that either

$$x[\gamma_x^q(1+\beta_x(i))] = x[1+i]$$
 or $1+\gamma_x^q(\beta_x(i)) = 0$, is equivalent to

$$\beta_{x}(0) = -1$$
 $\beta_{x}(1) = 0$ $\beta_{x}(1+i) = r_{x}^{q}(1+\beta_{x}(i))$ $1 \le i \le |x|-1$

where q is the smallest integer such that

- either $x[r_x^q(1 + \beta_x(i))] = x[1 + i]$
- or $r_x^q(1 + \beta_x(i)) = 0$

Or, by changing i + 1 into i,

$$\beta_x(0) = -1$$
 $\beta_x(1) = 0$ $\beta_x(i) = r_x^q(1 + \beta_x(i-1))$ $2 \le i \le |x|$

where q is the smallest integer such that

- either $x[r_x^q(1+\beta_x(i-1))] = x[i]$
- or $r_x^q(1+\beta_x(i-1))=0$

Knuth-Morris-Pratt/Better failure function/Imperative

```
KMP-Fail(x)
       r_x[1] \leftarrow 0; offset \leftarrow 0
                                                                                 \triangleright offset = 1 + \beta_{\downarrow}(1 - 1)
       for i \leftarrow 1 to |x| - 1
 3
               do repeat
 4
                                 offset \leftarrow r_x[offset]
 5
                        until offset = 0 or x[offset] = x[i]
 6
                     offset \leftarrow offset + 1
                                                                                        \triangleright offset = 1 + \beta_{\star}(i)
                                                                    \triangleright offset = 1 + r_{\nu}^{q}(1 + \beta_{\nu}(i - 1))
 8
                     if x[offset] = x[1+i]
 9
                        then r_x[i] \leftarrow r_x[offset]
                                                                                    \triangleright r_{\vee}(i) = r_{\vee}(1 + \beta_{\vee}(i))
                        else r_x[i] \leftarrow offset
10
                                                                                          \triangleright r_{\vee}(i) = 1 + \beta_{\vee}(i)
11
       KMP-Fail \leftarrow r_x
```

Knuth-Morris-Pratt/The code

The Knuth-Morris-Pratt algorithm is exactly the Morris-Pratt algorithm, except that we use a better failure function r instead of s:

```
KMP(x, t)
   r \leftarrow \mathsf{KMP}\text{-}\mathsf{Fail}(x)
2 i \leftarrow 1; i \leftarrow 1
3
     while i \leq |x| and j \leq |t|
           do if i = 0 or x[i] = t[j]
4
5
                    then i \leftarrow i + 1; j \leftarrow j + 1
6
                   else i \leftarrow r[i]
    if |x| < i
8
        then ...
                                     \triangleright Occurrence of x in t at position j - |x|.
9
        else ...
                                                                     No occurrences.
```

Knuth-Morris-Pratt/The code (cont)

If we allow arguments to be functions, we can elegantly factorise the two text search algorithms into one:

```
Search(x, t, f)
    i \leftarrow 1; i \leftarrow 1
    while i \leq |x| and j \leq |t|
3
          do if i = 0 or x[i] = t[j]
                  then i \leftarrow i + 1; j \leftarrow j + 1
4
5
                  else i \leftarrow f[i]
6
    if |x| < i
        then ...
                                   \triangleright Occurrence of x in t at position j-m.
8
        else ...
                                                               No occurrences.
```

Knuth-Morris-Pratt/The code (cont)

Then

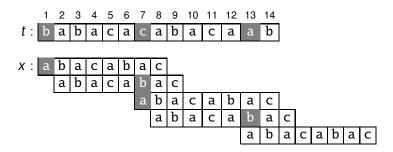
$$\mathsf{MP}(x,t) = \mathsf{Search}(x,t,\mathsf{MP-Fail})$$

 $\mathsf{KMP}(x,t) = \mathsf{Search}(x,t,\mathsf{KMP-Fail})$

Example. Consider the following table for the search of the word x = abacabac in the text t = babacacabacaab.

j	1	2	3	4	5	6	7	8	9	10	11	12	13	14
	b	a	b	a	С	a	С	a	b	a	С	a	a	14 b
														2
	0						1						1	
							0							

Knuth-Morris-Pratt/Example



Comparison of Morris-Pratt and Knuth-Morris-Pratts

For example, here is the table comparing the values of the two failure functions for the same pattern:

X	a	b	a	С	a	b	a	С
i	1	2	3	4	5	6	7	8
$s_x(i)$	0	1	1	2	1	2	3	4
$ \begin{array}{c} x \\ i \\ s_x(i) \\ r_x(i) \end{array} $	0	1	0	2	0	1	0	2