# An Alternative Approach to Alignments

Vineet Joshi, Prateek Tandon, Frank Lin

#### **Project Goal**

To find an alternative, more efficient method to deal with patterns containing long regions of deletions.

#### **Problems Solved**

 Matching cDNA to its genomic loci (matching exons to genomic loci while ignoring introns).

 Detecting sequence deletions in a mutated gene, when compared to a reference genome.

#### Motivation

- In this course, we covered exact pattern matching using suffix trees.
  - We wanted to expand upon what we learned and apply our knowledge to a more biological problem.
- Ukkonen's paper "Approximate String-Matching Over Suffix Trees".
  - Try to use suffix trees to solve this problem.

#### Motivation

- Current methods, using dynamic programming and affine gap penalties, require O(mn) time.
  - We wanted to find a method that has a better average time complexity.
- We wanted to look for a method that doesn't penalize the gaps occurring in the intron regions.
  - To better estimate of the overall alignments.

#### Motivation

 The simple dynamic programming solution for alignments has the drawback that it is explicitly repeated over identical repeated substrings of T.

#### Approach

#### We used a combination of theories from:

- K-difference problem
- Suffix trees (with suffix links)
- Dynamic programming
- Ukkonen's algorithm for K differences

# Overview of Ukkonen's Algorithm

- The number of columns evaluated by the method is ≤ n and proportional to q (where q is the total number of different viable prefixes in T).
- For a small k, q can be considerably smaller than n.

#### Essential entries :

- The approximate string matching problem can be solved using only entries  $D(i, j) \le k$  of D.
- Call each entry  $D(i,j) \le k$  an essential entry.
- Replace the inessential entries of D with ∞ as this will not affect contents of the essential part.
- Ukkonen uses Semi-global alignment, which does not penalize gaps in the beginning.

## Our Implementation

- We start filling in the columns starting with  $t_1$ , using the Ukkonen method involving suffix tree for T, only evaluating for columns that have a unique Q.
- We allow for k-mismatches in the regions that overlap between cDNA and gene.
- We will extend the matching beyond a certain threshold length "L" that is long enough to ensure that the current matches are not occurring by chance alone.

## A Greedy Approach

We define the effective essential entry as

$$D(j,i) \le \left\lceil k * \frac{j}{m} \right\rceil$$

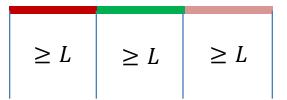
- Assumption: It is not very likely that the sequencing errors/mutations will occur closely but will be spread across uniformly.
- Let  $j_i$  be the highest index in column i that has an "effective essential entry". Similarly, let  $j_{i+1}$  be the highest index in column i+1 that has an "effective essential entry".
- We decide to break with the current matching at column i if  $j_i > j_{i+1}$  and also the matching length "j" in P has exceeded the threshold "L".

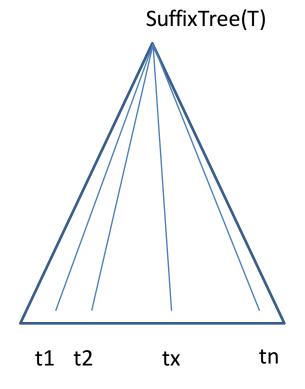
	ti-3	ti-2	ti-1	ti	ti+1	ti+2	ti+3	
р0	0	0	0	0	0	0	0	0
								••
pj-2	2	2	$\infty$	1	1	$\infty$	••	
pj-1	$\infty$	3	2	$\infty$	2	1		
pj	∞	∞	∞	<b>↑</b> 3 <del>←</del>	∞	$\infty$		
pj+1	∞	∞	∞	∞	$\infty$	$\infty$		
pj+2	∞	∞	∞	∞	∞	∞		

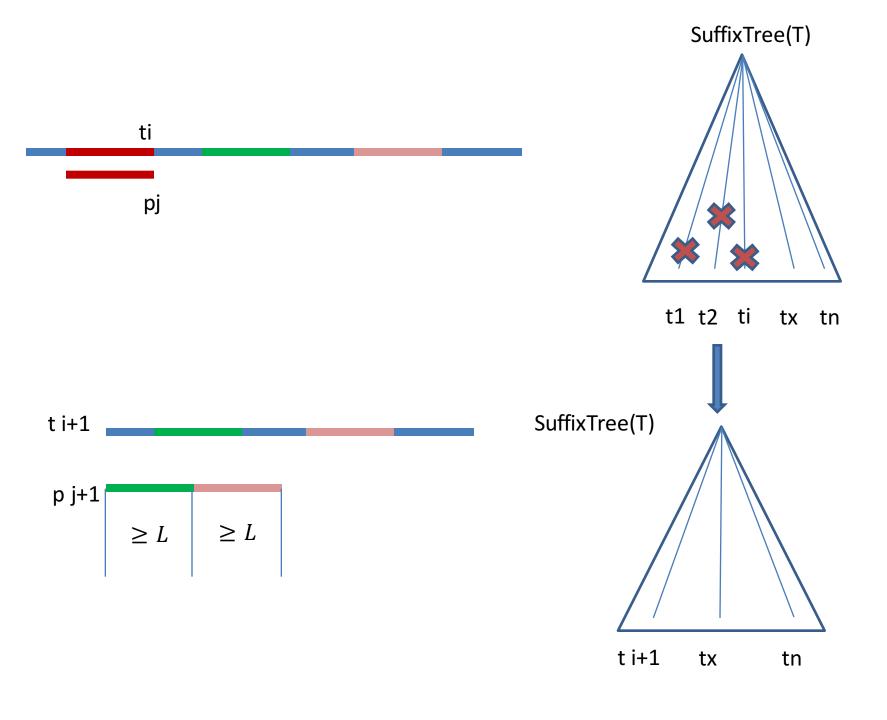
### A Greedy Approach

- We continue matching the remaining P with the remaining T and we will now have shorter columns in our table.
- So this problem becomes an equivalent problem with k' mismatches between text  $T' = t_{i+1}, t_{i+2}, ..., t_n$  and pattern  $P' = p_{j+1}, p_{j+2}, ..., p_m$
- In general, after processing the s<sup>th</sup> exon, we check if the node\_length = (m-j<sub>s-1</sub>) then we copy to the edit distance matrix, else we compute it and store it.
- This can be done relatively easily since we already keep track of the indices at the leaves in Suffix tree (T).

# Example







# A Greedy Approach

 We stop if all of pattern P is matched to some location in T and report all such matches.

 Otherwise, we report all the partial matches if P doesn't match completely by the time we go over the entire text T.

### Runtime Analysis

- The basic Ukkonen method runs in time O(mq + n)
- This method will take time

$$O(mq + n) + O(m'q' + n') + O(m''q'' + n'') + \cdots$$
  
  $\leq l * O(mq + n)$ , where  $l$  is the number of exons in the cDNA.

Also,

$$q \le \min\left(n, \frac{12}{5}(m+1)^{k+1}(|\Sigma|+1)^k\right)$$
$$q \le O(\min\left(n, m^{k+1}|\Sigma|^k\right))$$

Therefore, this method will have a runtime of

$$\leq O(l * m * \min(n, m^{k+1} |\Sigma|^k) + n)$$

• This will have a worst case running time of O(lmn) but will have an average case runtime which will be always be better than O(lmn).

# Further Runtime Improvements

- Ukkonen suggests the use of more complicated data structures to get rid of the dependency on n.
  - Possibly dictionaries and stacks
  - Possibly balanced search trees

• For example, the runtime can be reduced to O(mq \* logq + output size)

• Which would also reduce our runtime to l \* O(mq \* logq + output size)

#### Plausible?

- Average length of exons is around 150 bp
- We set a threshold "L" of  ${f 100}\ {m bp}$
- Size of Human genome  $\sim 3 \times 10^9 \ bp$
- Therefore, the probability of seeing 100 bp length aligning by chance is  $\sim \frac{3\times10^9}{4^{100}}$

~ 1.8669046e-51

#### Plausible?

- On average, there are 8.8 exons and 7.8 introns per gene
  - In Silico Biol. 2004;4(4):387-93.
- Distributions of exons and introns in the human genome.
  - Sakharkar MK, Chow VT, Kangueane P.
- Average intron length is > 1 kb and
- Average exon length is only 150 bp
  - http://people.ibest.uidaho.edu/~bree/courses/17\_EB R\_ME\_genome.pdf

#### Pros and Cons of Our Implementation

#### **Pros**

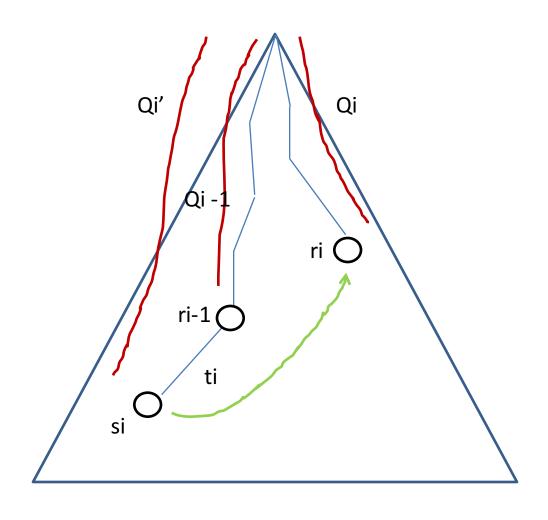
- Average time complexity < O(mn)</li>
- Overall less space required
- Can align cDNA to genomic loci

#### Cons

- Current implementation can not give multiple matches (only first best match)
- Might not be efficient for very small exon lengths
  - Possibly change "L"
- Further improvements needed

Questions?

- Length L(i, j) of the shortest substring of T ending at  $t_j$  whose edit distance from  $P_i$  equals P(i, j)
- Each such column D(\*, i) together with column L (\*, i) will be stored with state  $r_i = g(root, Q_i)$  as  $d(r_i) = D(*, i)$  and  $l(r_i) = L(*, i)$
- $r_i = g(root, Q_i)$  and  $s_i = g(r_{i-1}, t_i) = g(root, {Q_i}')$
- Theorm :  $Q_i$  is always a suffix of  ${Q_i}'$
- The traversal goes through states  $r_0, s_1, ..., r_1, s_2, ..., r_2, ..., r_{n-1}, s_n, ..., r_n$



- Consider the sub-path from  $r_{j-1}$  to  $r_j$ . The go to transition  $g(r_{j-1}, t_j) = s_j$  is taken first.
- After that there are two cases...
- Case 1: If  $s_j$  has already been visited during the traversal, then follow the suffix transition path until the first state r is encountered such that d(r) and l(r) have non-empty values. Then  $r_i = r$ .

#### Case 2:

- If  $s_j$  has not been visited yet, then evaluate a pair (d, l) of columns as
- $(d,l) = dp(d(r_{j-1}), l(r_{j-1}), t_j)$
- This gives (d, l) = (D(\*, j), L(\*, j))
- Where  $|Q_i|$  is the maximum entry in column l
- The algorithm then follows the suffix link path from  $s_j$  to the state r whose depth (distance from root) is  $|Q_i|$ .
- Then  $r_j = r$  and the algorithm saves columns (d, l) as  $d(\mathbf{r_j}) = d$  and  $l(\mathbf{r_j}) = l$