Review:
(1) DNA.
(2) alignment with free software (Clustal omega)
(3) edit distance
(4) LCS
(5) alignment - to maximize total of the column score.

## Last column of an alignment

- Suppose we are to align $\mathrm{S}[1 . . \mathrm{i}]$ and $\mathrm{T}[1 . . \mathrm{j}]$. Consider the last column of the optimal alignment. Three cases can happen:

- In each case, the sub-alignment without the last column is an optimal one (why?)

$$
D[i, j]=D[i-1, j-1]+f(s[i \partial, T[j])
$$



$$
D[i, j]=D[i, j-1]+f(-, T[j 1) .
$$

## Recurrence Relation

- Denote the optimal alignment score of $\mathrm{S}[1 . . \mathrm{i}], \mathrm{T}[1 . . \mathrm{j}]$ by $\mathrm{D}[\mathrm{i}, \mathrm{j}]$. Then $\mathrm{D}[\mathrm{m}, \mathrm{n}]$ is the optimal alignment score.
- Let $f(a, b)$ be the score between two letters $a$ and $b$.
- Consider last column of the alignment.
- Case 1: S[i] v.s. T[j]
- $D[i, j]=D[i-1, j-1]+f(S[i], T[j])$;
- Case 2: S[i] v.s.-
- $D[i, j]=D[i-1, j]+f(S[i],-) ;$
- Case 3: - v.s. T[j]
- D[i,j] = D[i, j-1] + f(-, T[j]);
- Therefore...
$S[1 . . i-1] \quad S[i]$
$T[1 . . j] \quad-$

| $S[1 . . i-1]$ |  |
| :--- | :--- |
| $T[1 . . j-1]$ | $S[i]$ |
| $T[j]$ |  |

$\left.\begin{array}{ll}S[1 . . i-1] \\ T[1 . . j] & S[i]\end{array}\right]$


$$
D[i, j]=\max \left\{\begin{array}{l}
D[i-1, j-1]+f(S[i], T[j]) ; \\
D[i-1, j]+f(S[i],-) ; \\
D[i, j-1]+f(-, T[j]) ;
\end{array}\right.
$$

## Algorithm

$$
\mathrm{D}[0,0]=0 ;
$$

for i from 1 to m

$$
\mathrm{D}[i, 0]=\mathrm{i}^{*} \text { indel; }
$$

for j from 1 to n

$$
\mathrm{D}[0, \mathrm{j}]=\mathrm{j} \text { * indel; }
$$

for i from 1 to m for j from 1 to n

$$
D[i, j]=\max \left\{\begin{array}{l}
D[i-1, j-1]+f(S[i], T[j]) ; \\
D[i-1, j]+f(S[i],-) ; \\
D[i, j-1]+f(-, T[j]) ;
\end{array}\right.
$$

Output $D[m, n]$;

Dynamic Programming Table


Dynamic Programming Table


Getting the actual alignment - backtracking

|  |  | C | A | T | T | G |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 0 |  | -2 | -3 | -4 | -5 |
| A | -1 | -1 | 0 | -1 | -2 | $\rightarrow 3$ |
| T | -2 | -2 | -1 | 1 () | 0 | -1 |
| T | -3 | -3 | -2 | 0 | (2). | 1 |
| G | -4 | -4 | -3 | -1 | 1 | 3 |
| A | -5 | -5 | -3 | -2 | 0 | 2 |

## Complexity

- Time Complexity:
- Filling the table takes $\mathrm{O}(\mathrm{nm})$ time: Each step requires only 3 checks to other points in the matrix.
- How about the backtracking?
- Space Complexity:
- O(nm)


## A Practical Trick




No need to physically record the green arrows. Why?


## Another Trick




If only score is needed, then space complexity can be reduced.

## Score Function

- Now we have the algorithm for any score scheme $f(x, y)$
- Such separation of scoring and algorithm is a good thing. It allows us to optimize the score scheme independent to the algorithm.

The effective exploitation of his powers of abstraction must be regarded as one of the most vital activities of a competent programmer.

## "

## Transition vs. Transversion



- Transition happens more frequently $2 / 3$ of SNPs are transitions.
- In other words, transition is easier and therefore should be less penalized.
E.g.:

```
AAAGCAAA
AAAT-AAA
AAAGCAAA AAA-TAAA
```

- This can be easily achieved by changing score scheme $f(a, b)$.


## Alignment v.s. LCS vs. Edit Distance

- By a properly defined score scheme, alignment can represent LCS and Edit distance, respectively.
- match =
- mismatch =
- indel =


## How to Build a Score Function

- First, know what you want.
- Purpose 1: the optimal alignment reveals the true evolutionary history.
- Purpose 2: high score indicates homology (derived from same ancestor).
- We want purpose 1 if possible, but purpose 2 is also useful.

```
ATGCA-TTTATTCCGAGG
||| | || ||| || ||
ATGTACTT-ATTACGTGG
```


## Philosophy of a Score Function

- For purpose 1, right away: we might be wrong.
- That is, the alignment that has highest score may not be the one that actually matches evolutionary history.
- So you should never trust that an alignment must be right. It just optimizes the score.
- Should we give up purpose 1 at all?


## Philosophy of A Score Function

- For purpose 1, the optimal alignment may be approximately correct under certain conditions in practice.
- As long as we know the limitation, we can still use it.
- For example, for the following alignment, it is "very likely" the alignment is approximately equal to the evolutionary history.
-ACGTATTACCGG-TTACCG
-|||n ||||||| |||||
-ACGGATTACCGGATTACCG
- Limitation we keep in mind: when score is low, alignment itself is not too useful.


## Gaps

AGATTITTTTC
AGA--ITTTC
$g(3)$

$3 * 8(1)$

- The left seems "simpler" than the right.
- Indeed, during evolution, indels are relatively rare. However, insertion or deletion a segment of $k$ consecutive bases is much easier than $k$ scattered indels.
- But our current scoring method (adding up column scores) cannot distinguish the two.
- Currently, a gap of length $k$ costs $k^{*}$ indel. Thus, this is called the linear gap penalty.


## Arbitrary gap penalty

- Consecutive insertions or deletions are called a gap. Suppose the gap penalty of a length k gap is $\mathrm{g}(\mathrm{k})$ instead of the simple $\mathrm{c}^{*} \mathrm{k}$.
- Assume $g(x)+g(y)<=g(x+y)$. (Otherwise does not serve the purpose of grouping indels.)
- Can the old DP still work?

$D[i, j]=D[i-k, j]+g(k)$
$g(k)-g(k-1)$


## Arbitrary Gap Penalty

- Old algorithm does not work anymore because we do not know the contribution of the last column to the gap penalty in the last two cases.
- The length of the gap is needed.


## Alignment Algorithm for Arbitrary Gap Penalty

- We still use $D[i, j]$ to denote the optimal alignment score of $S[1 . . i]$ and $T[1 . . j]$.
- We change cases 2 and 3 to include the last gap (not the last column).
- $D[i, j]=$ max of the following three cases:



|  |  |
| :--- | ---: |
| $S[1 . . i-1]$ | $S[i]$ |
| $T[1 . . j-1]$ | $T[j]$ |

(1)

(2)
recurrence rebation : O(m+n)
$O(m \times n \times(m+n)))$


## Time Complexity

- Cubic time complexity.
lecture
2022.01 .13 stopped here
- In bioinformatics, very often we face the choice between:
- Reality: How close it approximates the real biology
- Simplicity: How easy it can be computed
- Now let's simplify the $\mathrm{g}(\mathrm{k})$ a little. We basically want a function that grows slower than linear.
- $g(k)=a+b * k$
- $a=$ gap open penalty
- b = gap extension penalty
- This is called affine gap penalty, in contrast to linear gap penalty.

