

# Lecture 8:

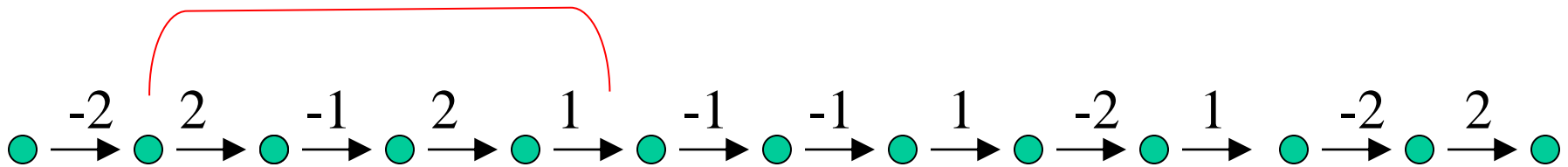
## Weighted linked lists

- Simplifications to general WDAG algorithm
- Sequence graphs & regions of atypical residue composition
- Defining & interpreting scores
- Other applications
  - motif clusters
  - read count data
  - coding sequence

# Weighted Linked Lists (WLLs)

- *WLL* is linked list with weights on each edge
  - simplest kind of WDAG.
- Paths = ‘segments’ or ‘regions’

highest-scoring segment



- Find highest-scoring segments by dynamic programming
  - Much better than “brute force” algorithm!
- Beginning & end of best path determine path uniquely, so
  - traceback is unnecessary
  - single pass through list suffices to find best path.

## *from lecture 7 :*

- To reconstruct best path, need “**traceback**” pointer to immediate predecessor of  $v$  in best path:

$$T(v) = \begin{cases} v & w(v) = 0 \\ \arg \max_{u \in \text{parents}(v)} (w(u) + w((u,v))) & w(v) \neq 0 \end{cases}$$

- in preceding graph,  $T(v)$  is the *parent* on *red edge* coming into  $v$ 
  - if more than one such edge, pick one at random;
  - if no such edge,  $T(v) = v$
- Sometimes useful to record *beginning* of best path:

$$B(v) = \begin{cases} v & w(v) = 0 \\ B(T(v)) & w(v) \neq 0 \end{cases}$$

# Implementing Dynamic Programming in a Computer Program

- Storing entire graph has space complexity =  $O(|V|+|E|)$
- If graph has regular structure, can often “create” and process vertices and edges on the fly, without storing in memory
  - cf. edit graph (to be defined later) for aligning sequences

- ***Highest weight path*** via dynamic programming (no explicit graph):

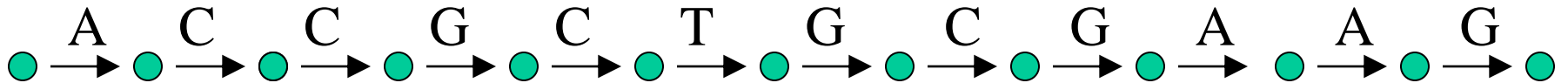
in (pseudo-)pseudocode:

```
cumul = max = 0; start = 1;
for (i = 1; i ≤ N; i++) {
    cumul += s[i];
    if (cumul ≤ 0)
        {cumul = 0; start = i + 1;}
    else if (cumul ≥ max)
        {max = cumul; best_end = i; best_start = start;}
}
if (max ≥ S) print best_start, best_end, max
```

- Correspondence to (implicit) WLL
  - $i$  labels *edges*
  - $\text{cumul} = w(v)$  (where  $v$  is vertex at end of edge  $i$ )
  - $\text{max} = \text{best } w(v)$  so far
  - $\text{best\_end} = i$  corresponding to edge ending at best  $w(v)$  so far
  - $\text{start} = \text{edge following } B(v)$

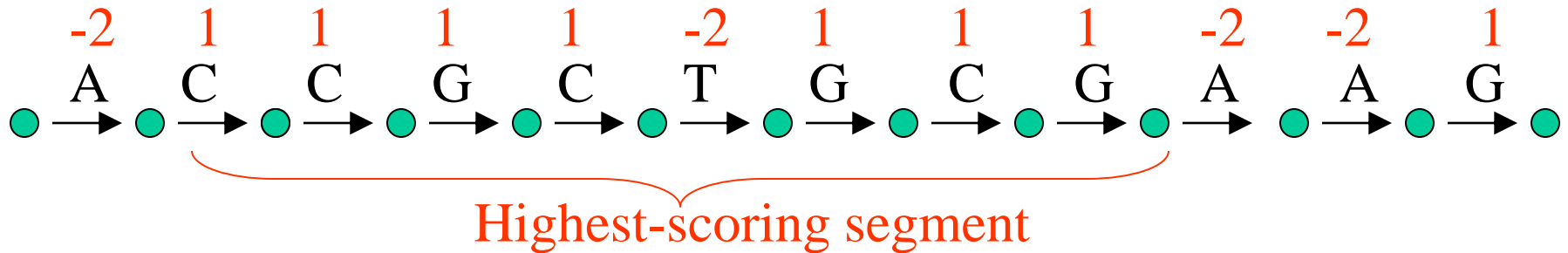
# Applications to Sequences

- A *sequence graph* of a sequence is linked list whose edges are labelled by sequence residues (in order):
- e.g. graph for sequence ACCGCTGCGAAG is:



# Weighted Sequence Graphs

- If attach weight to each residue, sequence graph becomes a WLL.



- Useful for identifying sequence regions ('target regions') with atypical composition:



- In DNA:
  - GC-rich regions in AT-rich thermophile genomes
    - generally correspond to RNA genes (Rob Klein & Sean Eddy)
  - *horizontally transferred* regions
  - isochores (mammalian DNA)
- In proteins:
  - hydrophobic regions
    - transmembrane segments
  - hydrophilic regions
    - loops, intrinsically disordered regions
  - acidic or basic regions

# ‘Optimal’ scores

- *Assume* sequence consists of
  - *target regions* with residue freqs  $t_r$
  - *background regions* with residue freqs  $b_r$
  - *independence assumption* applies in both
- *Then* ‘best’ scoring system to detect the target regions uses LLRs:
$$s(r) = \log_a(t_r / b_r)$$
- if residue freqs are unknown, can usually estimate iteratively

# Karlin / Altschul approximation

- for  $s(r) = \log_a(t_r / b_r)$ , expected # segments of score  $\geq S$  in (random) backgd seq of length  $N$   
 $\approx NK a^{-S}$
- for some constant  $K$  (not depending on  $S$ )
- Note that  $a^{-S} = a^{-LLR} = 1 / LR$   
so (apart from  $K$ ) this is essentially the observation in lecture 6:

(from lecture 6)

## Average likelihood ratios

- *average LR* (for sites)  $\approx$  *average spacing* between occurrences of ‘site-like’ sequences *in background*
- So e.g. for 3’ splice sites
  - if the average *LR* is 1000, then one expects ‘splice-site-like’ sequences to occur on average once per kb *in background sequence*
  - ***N.B.*** This says nothing about the frequency of *actual* splice sites! (which could be greater or smaller than 1 per kb), and so doesn’t by itself provide the probability that an *apparent* splice site is an *actual* site.

# Example: Finding 60% G+C regions in 40% G+C genomes

- Score system (LLR) :
  - $s(C) = s(G) = \log_{10} (.3 / .2) = .176$
  - $s(A) = s(T) = \log_{10} (.2 / .3) = -.176$
- Avg score (per position) in hiGC region:  
 $.3 .176 + .3 .176 + .2 (-.176) + .2(-.176) = .0352$
- 100-base hiGC region:  
Score  $\sim 3.52$ ; occurs once per  $\sim 10^{3.52} \approx 3.3$  kb in backgd
- 300-base hiGC region:  
Score  $\sim 10.5$ ; occurs once per  $\sim 10^{10.5} \approx 36$  Gb

- So:
  - 300-base hiGC regions are unexpected in background
    - (likely have biological ‘significance’)
  - but 100-base such regions are frequent
- Caveats to preceding:
  - Applies to a specific assumed hiGC composition
  - we ignored K
    - Can get more precise results by simulation

# Can use *non-residue-based* scores to find:

- Regions enriched in particular sequence *motifs*:
  - CpG islands in mammalian genomes
    - positive weight (e.g. +17) to the first C of each CpG, and
    - negative weight (e.g. -1) to every other base

(This approach was used in *Nature* human genome paper).
  - Regions rich in (known) transcription-factor motifs
  - Optimal scores are LLRs, but now based on ‘symbol frequencies’ (where symbol = presence/absence of motif)

# CpG Islands

- Regions in mammalian genomes where CpGs are *not* significantly underrepresented
  - likely not methylated in the germ line
- Found at 5' ends of ~60% of protein-coding genes (& in some RNA genes);
  - frequently extends into first exon & even coding sequence
- More likely to be associated with “housekeeping” genes (expressed in all or most cells),
  - less frequently with tissue-specific genes
- May play regulatory role (methylation of island can shut down gene)
- Substantial length variation: 75% are less than 850bp, but longest (in human) is 37kb



- Regions targeted by *next-gen read experiments*  
(symbols = *read start counts*)
  - CNVs (Homework 6)
  - Hypersensitive sites
  - CHIP-seq
- Conserved regions in *sequence alignments*  
(symbols = *alignment columns*)

- Coding sequences (symbols = *successive trinucleotides within a reading frame*)
  - Target freqs: codon freqs in known coding seq
  - Background: trinuc freqs in background

Phe	171 UUU	} AAA 0	Ser	147 UCU	} AGA 10	Tyr	124 UAU	} AUA 1	Cys	99 UGU	} ACA 0
	203 UUC			GAA 14			172 UCC			GGA 0	
Leu	73 UUA	— UAA 8	Ser	118 UCA	— UGA 5	stop	— 0 UAA	— UUA 0	stop	— 0 UGA	— UCA 0
	125 UUG	— CAA 6		45 UCG	— CGA 4	stop	— 0 UAG	— CUA 0	Trp	— 122 UGG	— CCA 7

Leu	127 CUU	} AAG 13	Pro	175 CCU	} AGG 11	His	104 CAU	} AUG 0	Arg	47 CGU	} ACG 9	
	187 CUC			GAG 0			197 CCC			GGG 0		147 CAC
	69 CUA	— UAG 2		170 CCA	— UGG 10		Gln	121 CAA		— UUG 11	63 CGA	— UCG 7
	392 CUG	— CAG 6		69 CCG	— CGG 4			343 CAG		— CUG 21	115 CGG	— CCG 5

Ile	165 AUU	} AAU 13	Thr	131 ACU	} AGU 8	Asn	174 AAU	} AUU 1	Ser	121 AGU	} ACU 0
	218 AUC			GAU 1			192 ACC			GGU 0	
Met	71 AUA	— UAU 5	Thr	150 ACA	— UGU 10	Lys	248 AAA	— UUU 16	Arg	113 AGA	— UCU 5
	221 AUG	— CAU 17		63 ACG	— CGU 7		331 AAG	— CUU 22		110 AGG	— CCU 4

Val	111 GUU	} AAC 20	Ala	185 GCU	} AGC 25	Asp	230 GAU	} AUC 0	Gly	112 GGU	} ACC 0	
	146 GUC			GAC 0			282 GCC			GGC 0		262 GAC
	72 GUA	— UAC 5		160 GCA	— UGC 10		Glu	301 GAA		— UUC 14	168 GGA	— UCC 5
	288 GUG	— CAC 19		74 GCG	— CGC 5			404 GAG		— CUC 8	160 GGG	— CCC 8

# Coding sequences in prokaryotes

- Starting model:
  - codon freqs 1 / 61
  - background freqs 1 / 64 (equal freq assumption)
  - score per codon:  $\log_{10}(64 / 61) = .021$
  - times 300 codons (typical gene len): 6.25
  - $10^{6.25} = 1.8 \text{ Mb}$
  - Requirement for starting ATG – factor of 64
  - Can detect typical genes without any amino acid or codon bias info!
- Get better freqs from these predictions; iterate