Lecture 6

• Algorithmic complexity

• Directed graphs, DAGs

• DAG structure

• Dynamic programming to find highest weight paths in WDAGs

Algorithmic Complexity

- Basic questions about an algorithm:
	- how long does it take to run?
	- how much space (RAM or disk space) does it require?
- Would like precise function *f*(*N*), e.g.

 $f(N) = .05 N^3 + 50.7 N^2 + 6.03 N$

for

- running time in secs, or
- space in kbytes,
- as function of the size *N* of input data set.
- But
	- tedious to derive &
	- depends on (often uninteresting though important!) hardware $\&$ software implementation details.

• Instead, more customary to give "the" *asymptotic complexity,* i.e. expression *g*(*N*) such that

 $C_1g(N) < f(N) < C_2g(N)$

for some constants C_1 and C_2 , and *N* large enough.

- This is written $O(g(N))$, where notation $O($) means "up to an unspecified multiplicative constant".
	- $-$ e.g. for the $f(N)$ above, the dominating term for large N is .05 *N*³ , so
		- can take $g(N) = N^3$
		- asymptotic complexity = $O(N^3)$.
- Can be misleading, since
	- for small *N* a different term may dominate
		- (e.g. 2^d term in above example much more important for $N <$ 1000)
	- size of constant may be quite important
		- (big difference between .05 and 5,000,000!)
		- e.g. BLAST and Smith-Waterman both *O*(*N*²), but size of constant enormously different
	- but very useful as rough guide to performance.

• Cache misses (non-cache memory accesses) and disk accesses often dominate running time, yet are 'invisible' to complexity analysis (because affect constant factor only)

- Another limitation to complexity analysis:
	- time or space requirement may depend on specific characteristics of input data.
- Usually give "worst case" complexity – applies to the worst data set of a given size,

but

- in biological situations the *average biologically occurring case* is
	- more relevant
	- often much easier than worst case (which may never arise in practice), or even "average case" in some idealized sense.
- Proof that a problem is *NP-hard*
	- (has complexity very likely greater than any polynomial function of *N* and therefore effectively unsolvable for large *N*)
	- can be useful in guiding search for more efficient algorithms
	- *but* can also be misleading, since
		- we need *some* solution anyway, for data sets occurring in practice
		- average *biologically relevant* case may be quite manageable

Directed Graphs

- A *directed graph* is a pair (*V*, *E*) where
	- *V* is a finite set of *vertices*, or *nodes*.
	- *E* is a set of ordered pairs (called *edges*) of vertices in *V*.
- An edge (v_i, v_j) is said to *leave* v_i and to *enter* v_j . $-(v_i \text{ and } v_j \text{ are vertices})$
- *in-degree* of a vertex = # edges entering it;
- *out-degree* = # edges leaving it.

Example:

- $V = \{1, 2, 3, 4, 5, 6\},\$
- $E = \{(1,2), (1,3), (2,4), (4,1), (5,3), (3,1)\}\$
- Vertex 3 has in-degree 2 and out-degree 1.

Paths and Cycles

- A *path* of *length k* in *G from u* to *u'* (vertices) is
	- $-$ a sequence *P* of vertices (v_0, v_1, \ldots, v_k) such that
		- $v_0 = u$,
		- $v_k = u'$, and
		- (v_{i-1}, v_i) is an edge for $i = 1, 2, ..., k$.
- A path can have length 0.
- We write $|P| = k$.
- A *cycle* is a path of length ≥ 1 from a vertex to itself.
- In example at right,
	- (*1,2,4*) is a path,
	- (*1,3,5*) is not, and
	- (*1,2,4,1*) and (*1,3,1*) are cycles.

- Can join
	- $-$ any path $(u, ..., v)$ from u to v , to
	- $-$ any path $(v, ..., w)$ from v to w
	- to get a path (*u*, ... , *v*, ... , *w*) from *u* to *w*.

DAGs

- A *directed acyclic graph* (DAG) is a directed graph with no cycles.
- In a DAG, for distinct nodes v_i and v_j , we say
	- $-v_i$ is a *parent* of v_j , and v_j is a *child* of v_i , if
		- there is an edge (v_i, v_j)
	- $-v_i$ is an *ancestor* of v_j , and v_j is a *descendant* of v_i , if
		- there is a path from v_i to v_j
- In a DAG the length of a path cannot exceed |*V*| *-* 1,
	- (where $|V|$ = total # vertices in graph)

because

- $-$ in a path of length $\geq |V|$,
	- at least one vertex *v* would have to appear twice in the path;
- but then there would be a path from *v* to *v*, i.e. a cycle.

Structure of DAGs

- Define the *depth* of a node *v* in *V* as: – the length of the longest path ending at *v*; by above, the depth is well-defined and $\leq |V|$ - 1.
- *Every descendant w of a node v has higher depth than v*: If
	- $(u, ..., v)$ is path of length $n = \text{depth}(v)$ ending at v , and

$$
-(v, ..., w)
$$
 is path from v to w,

then $(u, ..., v, ..., w)$ is a path of length $> n$ ending at *w*, so depth $(w) > n$.

- *Every node v of positive depth has a parent of depth exactly one less*:
	- $-$ Let $(u, ..., v', v)$ be path of length $n =$ depth (v) ending at v .
	- Then *v'* is a parent of *v*.
	- $-$ Since $(u, ..., v')$ has length $n-1$, depth $(v') \geq n-1$.
	- Since also depth(*v'*) < *n* (because *v* is a descendant of *v'*), depth(ν) is exactly $n-1$.
- *The nodes on any path are of increasing depth*.

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Important special cases:

- A (*rooted*) *tree* is a DAG which
	- has unique depth 0 node (the *root*), *and*
	- every other node has in-degree 1
		- (i.e. has a unique parent, of depth one less than that of the node).
- A *binary tree* is a tree in which
	- every node has out-degree at most 2.
- A *linked list* is a tree in which
	- every node has out-degree at most 1
	- or equivalently, a DAG in which \exists at most one node of each depth

binary tree

linked list

Remarks on Depth Structure

- For *dynamic programming* algorithm
	- $-$ we need an order v_1 , v_2 , ..., v_n for the vertices
		- (not a path!)

in which parents appear before children.

– From the above, *depth order*

• (in which depth 0 nodes are listed first, then depth 1 nodes, etc.) is such an order.

- In general there are many other such orders.
- We haven't given constructive procedure for finding the depths of all vertices.
	- For an arbitrary DAG, can be done in $O(|V| + |E|)$ time;
	- we omit algorithm, since for DAGs related to sequence analysis, the depth structure is obvious.

Weighted Directed Graphs

- A *weighted directed graph* is
	- a directed graph (*V*, *E*) together with
	- a function *w* from *E* to the real numbers,
		- i.e. with a numerical *weight w*(*e*) (which may be positive, negative, or 0) associated to each edge *e*.
	- A weighted DAG is called a WDAG.
- The (*sum*) *weight of a path* is defined to be the sum of the weights on the edges of the path.
- Similarly, the *product weight of a path* is the product of the edge weights
	- usually only consider this when all weights are non-negative.
- weight of a path P is written $w(P)$
- For a path of length 0 (i.e. consisting of a single vertex):
	- the sum weight is θ
	- the product weight is 1

Highest Weight Paths on WDAGs

- *Problem:* find a path with the highest possible weight.
- *Solution*:
	- "Brute force" approach
		- i.e. simply enumerating all possible paths and comparing their weights
		- is usually impractical (too many paths!)
	- Instead, use the method of *dynamic programming* ('The Fundamental Algorithm of Computational Biology').
- Let $P_n = (v_0, v_1, \ldots, v_n)$ be a path of highest weight.
- Then for each $k < n$, the sub-path $P_k = (v_0, v_1, \ldots, v_k)$ must have highest weight of all paths ending at *v^k* , because
	- $-$ *if* $Q = (u_0, u_1, \ldots, v_k)$ were another path ending at v_k and having higher weight than P_k ,
	- *then* the path $(Q, v_{k+1}, ..., v_n)$ would have weight $w((Q, v_{k+1}, ..., v_n)) = w(Q) + w((v_k, ..., v_n))$ $> w(P_k) + w((v_k, ..., v_n)) = w(P_n),$

contradicting assumption that *Pn* has highest weight.

Subpaths of a highest-weight path can't be improved:

- So generalize the problem as follows:
- find, for *each* vertex *v*, the highest weight of all paths ending at v – call this $w(v)$
- Can find *w*(*v*) in single pass through *V*, as follows:
	- process the *v* in depth order (*or any order in which parents precede children*)
	- $-$ if *v* has no parents, $w(v) = 0$ (the only path ending at *v* is (*v*)).
	- for any other *v*, except for the path (*v*) (which has weight 0), any path ending at *v* is of form $(v_0, v_1, \ldots, v_k, u, v)$. Then
	- *u* is a parent of *v*, so *w*(*u*) has already been computed, and $w((v_0, v_1, \ldots, v_k, u, v)) \leq w(u) + w((u, v))$ with equality for an appropriate choice of *vⁱ* .
	- Therefore we may compute $w(v)$ as

$$
w(v) = \max(0, \max_{u \in parents(v)} (w(u) + w((u,v))))
$$

Example

$w(v)$ – depth 0 nodes

$w(v)$ – depth 1 nodes

$w(v)$ – depth 2 nodes

$w(v)$ – depth 3 nodes

$w(v)$ – depth 4 nodes

• 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:

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

• Then highest weight of any path in graph is

 $\max_{v \in V} (w(v))$

- updated as each node is visited
	- indicated by $\vert \quad \vert$ in preceding graph –

and so doesn't require additional pass through vertices

- if $u = \argmax_{v \in V} (w(v))$, can reconstruct highest weight path by tracing back from *u*, using *T*:
	- path ends at *u*;
	- immediate predecessor of *u* is *T*(*u*);
	- $-$ predecessor of $T(u)$ is $T(T(u))$; etc.
	- $-$ stop when $T(v) = v$.
- In preceding example, highest weight is 6 and $u = v_{11}$

Dynamic programming on WDAGs

Complexity of Dynamic Programming

- Time to find a best path is $O(|E|+|V|)$:
	- in initial pass, visit each node, and each edge into that node: *O*(*|E|+*|*V*|)
	- in traceback, visit subset of nodes, and unique edge from each node: *O*(|*V*|)
	- (Complexity to find *all* highest weight paths can be higher)
	- For very large graphs, even $O(|E|+|V|)$ may be unacceptable!
- Space requirements:
	- If only want *weight* of best path, and beginning and end, then
		- don't need *T*(*v*), and
		- $-$ only need retain $w(v)$ and $B(v)$ until have processed all children of *v* (or when best path found so far ends at *v*).

Space depends on graph structure, but usually $<< O(|V|)$.

- $-$ If want path itself, must store $T(v) \forall v$
	- $-$ space $= O(|V|)$
	- \exists algorithms (for some graphs) to reduce this, but may take more time.

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

Same dynamic programming approach can be used to find:

- 1. Highest product weight path (if weights are \geq 0)
- 2. Highest weight path that
	- *starts* in particular subset *V'* of vertices,
		- don't consider paths that start outside *V'* :
		- i.e. when computing $w(v)$, don't consider trivial path unless $v \in V'$
	- and/or *ends* in particular subset *V''*
		- only scan for the maximum $w(v)$ over V'
- 3. Sum of product weights of all paths ending at particular vertex
	- *sum* over all edges coming into *v*, instead of *maximizing*
	- this useful for probability calculations
- Will use the above variants later!