SequenceAlignment

January 28, 2020

1 Lecture 7: Sequence Alignment

CBIO (CSCI) 4835/6835: Introduction to Computational Biology

1.1 Overview and Objectives

In our last lecture, we covered the basics of molecular biology and the role of sequence analysis. In this lecture, we'll dive deeper into how sequence analysis is performed and the role of algorithms in addressing sequence analysis. By the end of this lecture, you should be able to:

- Define the notion of algorithmic complexity and how it relates to sequence alignment and analysis
- Describe and define the abstract problems of shortest common superstring (SCS) and longest common substring (LCS), and how they specifically relate to sequence analysis
- Recall different methods of scoring sequence alignments and their advantages and drawbacks
- Describe the different distance metrics and methods of scoring sequence alignments
- Explain why local or global sequence alignments are preferred in certain situations

1.2 Part 0: range

This mysterious range function has showed up a few times so far. What does it do?

```
[1]: r = range(10) print(r)
```

range(0, 10)

Not terribly useful output information, to be fair.

```
[2]: r = range(10)
1 = list(r) # cast it as a list
print(1)
```

```
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
```

range(i) generates a list of numbers from 0 (inclusive) to i (exclusive). This is very useful for looping!

```
[3]: for i in range(10):
    print(i, end = " ")
```

```
0 1 2 3 4 5 6 7 8 9
```

You can also provide a *second* argument to range, which specifies a *starting* point for the counting (other than 0). That starting point is still *inclusive*, and the ending point still *exclusive*.

```
[4]: for i in range(5, 10):
    print(i, end = " ")
```

5 6 7 8 9

Finally, you can also provide a *third* argument, which specifies the *interval* between numbers in the output. So far, that interval has been 1: start at 0, to go i, by ones. You can change that "by ones" to whatever you want.

```
[5]: for i in range(5, 10, 2): # read: from 5, to 10, by 2 print(i)
```

5

7

9

You can get really crazy with this third one, if you want: you can go backwards by putting in a negative interval.

```
[6]: for i in range(10, 0, -2): # from 10, to 0, by -2 print(i)
```

10

8

6

4

2

Same rules apply, though: the starting point is *inclusive* (hence why we see a 10), and the ending point is *exclusive* (hence why we *don't* see a 0).

range is particularly useful as a way of looping through a list of items by index.

```
[7]: list_of_interesting_things = [93, 17, 5583, 47, 2359875, 4, 381]
for item in list_of_interesting_things:
    print(item, end = " ")
```

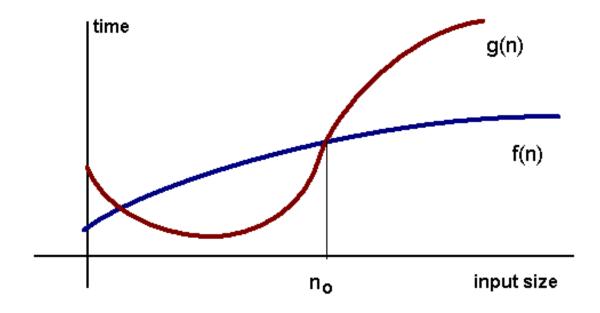
93 17 5583 47 2359875 4 381

This is how we've seen loops so far: the loop variable (here it's item) is a literal item in the list. But what if, in addition to the item, I needed to know where in the list that item was (i.e., the item's list index)?

```
[8]: list_length = len(list_of_interesting_things)
for index in range(list_length): # use range of the list length!
   item = list_of_interesting_things[index] # pull out the item AT that index
   print("Item " + str(item) + " at index " + str(index))
```

```
Item 93 at index 0
Item 17 at index 1
Item 5583 at index 2
Item 47 at index 3
Item 2359875 at index 4
Item 4 at index 5
Item 381 at index 6
```

1.3 Part 1: Complexity



1.3.1 Big "Oh" Notation

From computer science comes this notion: how the runtime of an algorithm changes with respect to its input size.

 $\mathcal{O}(n)$ - the " \mathcal{O} " is short for "order of the function", and the value inside the parentheses is always with respect to n, interpreted to be the variable representing the size of the input data.

1.3.2 Limits

Big-oh notation is a representation of limits, and most often we are interested in "worst-case" runtime. Let's start with the example from the last lecture.

```
[9]: a = [1, 2, 3, 4, 5]
for element in a:
    print(element)
1
2
3
4
5
```

How many steps, or iterations, does this loop require to run?

Alright, back to complexity:

```
[10]: a = range(100)
for element in a:
    print(element, end = " ")
```

0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95 96 97 98 99

How many iterations does this loop require?

For iterating once over any list using a single for loop, how many iterations does this require?

Algorithms which take n iterations to run, where n is the number of elements in our data set, are referred to as running in $\mathcal{O}(n)$ time.

This is roughly interpreted to mean that, for *n* data points, *n* processing steps are required.

Important to note: we never actually specify *how much time* a single processing step is. It could be a femtosecond, or an hour. Ultimately, it doesn't matter. What does matter when something is $\mathcal{O}(n)$ is that, if we add one more data point (n+1), then however long a single processing step is, the algorithm should take only that much longer to run.

How about this code? What is its big-oh?

```
[11]: a = range(100)
b = range(1, 101)
for i in a:
    print(a[i] * b[i], end = " ")
```

0 2 6 12 20 30 42 56 72 90 110 132 156 182 210 240 272 306 342 380 420 462 506 552 600 650 702 756 812 870 930 992 1056 1122 1190 1260 1332 1406 1482 1560 1640 1722 1806 1892 1980 2070 2162 2256 2352 2450 2550 2652 2756 2862 2970 3080 3192

```
3306 3422 3540 3660 3782 3906 4032 4160 4290 4422 4556 4692 4830 4970 5112 5256 5402 5550 5700 5852 6006 6162 6320 6480 6642 6806 6972 7140 7310 7482 7656 7832 8010 8190 8372 8556 8742 8930 9120 9312 9506 9702 9900
```

Still $\mathcal{O}(n)$. The important part is not (directly) the number of lists, but rather how we operate on them: again, we're using **only 1** for **loop**, so our runtime is directly proportional to how long the lists are.

How about this code?

```
[12]: a = range(100)
x = []
for i in a:
     x.append(i ** 2)

for j in a:
     x.append(j ** 2)
```

Trick question! One loop, as we've seen, is $\mathcal{O}(n)$. Now we've written a second loop that is also $\mathcal{O}(n)$, so literally speaking the runtime is $2 * \mathcal{O}(n)$, but what happens to the 2 in the limit as $n \to \infty$?

The 2 is insignificant, so the overall big-oh for this code is still $\mathcal{O}(n)$.

How about this code?

```
[13]: a = range(100)
for element_i in a:
    for element_j in a:
        print(element_i * element_j, end = " ")
```

17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95 96 97 98 99 0 2 4 6 8 10 12 14 16 18 20 22 24 26 28 30 32 34 36 38 40 42 44 46 48 50 52 54 56 58 60 62 64 66 68 70 72 74 76 78 80 82 84 86 88 90 92 94 96 98 100 102 104 106 108 110 112 114 116 118 120 122 124 126 128 130 132 134 136 138 140 142 144 146 148 150 152 154 156 158 160 162 164 166 168 170 172 174 176 178 180 182 184 186 188 190 192 194 196 198 0 3 6 9 12 15 18 21 24 27 30 33 36 39 42 45 48 51 54 57 60 63 66 69 72 75 78 81 84 87 90 93 96 99 102 105 108 111 114 117 120 123 126 129 132 135 138 141 144 147 150 153 156 159 162 165 168 171 174 177 180 183 186 189 192 195 198 201 204 207 210 213 216 219 222 225 228 231 234 237 240 243 246 249 252 255 258 261 264 267 270 273 276 279 282 285 288 291 294 297 0 4 8 12 16 20 24 28 32 36 40 44 48 52 56 60 64 68 72 76 80 84 88 92 96 100 104 108 112 116 120 124 128 132 136 140 144 148 152 156 160 164 168 172 176 180 184 188 192 196 200 204 208 212 216 220 224 228 232 236 240 244 248 252 256 260 264 268 272 276 280 284 288 292 296 300 304 308 312 316 320 324 328 332 336 340 344 348

```
7410 7505 7600 7695 7790 7885 7980 8075 8170 8265 8360 8455 8550 8645 8740 8835
8930 9025 9120 9215 9310 9405 0 96 192 288 384 480 576 672 768 864 960 1056 1152
1248 1344 1440 1536 1632 1728 1824 1920 2016 2112 2208 2304 2400 2496 2592 2688
2784 2880 2976 3072 3168 3264 3360 3456 3552 3648 3744 3840 3936 4032 4128 4224
4320 4416 4512 4608 4704 4800 4896 4992 5088 5184 5280 5376 5472 5568 5664 5760
5856 5952 6048 6144 6240 6336 6432 6528 6624 6720 6816 6912 7008 7104 7200 7296
7392 7488 7584 7680 7776 7872 7968 8064 8160 8256 8352 8448 8544 8640 8736 8832
8928 9024 9120 9216 9312 9408 9504 0 97 194 291 388 485 582 679 776 873 970 1067
1164 1261 1358 1455 1552 1649 1746 1843 1940 2037 2134 2231 2328 2425 2522 2619
2716 2813 2910 3007 3104 3201 3298 3395 3492 3589 3686 3783 3880 3977 4074 4171
4268 4365 4462 4559 4656 4753 4850 4947 5044 5141 5238 5335 5432 5529 5626 5723
5820 5917 6014 6111 6208 6305 6402 6499 6596 6693 6790 6887 6984 7081 7178 7275
7372 7469 7566 7663 7760 7857 7954 8051 8148 8245 8342 8439 8536 8633 8730 8827
8924 9021 9118 9215 9312 9409 9506 9603 0 98 196 294 392 490 588 686 784 882 980
1078 1176 1274 1372 1470 1568 1666 1764 1862 1960 2058 2156 2254 2352 2450 2548
2646 2744 2842 2940 3038 3136 3234 3332 3430 3528 3626 3724 3822 3920 4018 4116
4214 4312 4410 4508 4606 4704 4802 4900 4998 5096 5194 5292 5390 5488 5586 5684
5782 5880 5978 6076 6174 6272 6370 6468 6566 6664 6762 6860 6958 7056 7154 7252
7350 7448 7546 7644 7742 7840 7938 8036 8134 8232 8330 8428 8526 8624 8722 8820
8918 9016 9114 9212 9310 9408 9506 9604 9702 0 99 198 297 396 495 594 693 792
891 990 1089 1188 1287 1386 1485 1584 1683 1782 1881 1980 2079 2178 2277 2376
2475 2574 2673 2772 2871 2970 3069 3168 3267 3366 3465 3564 3663 3762 3861 3960
4059 4158 4257 4356 4455 4554 4653 4752 4851 4950 5049 5148 5247 5346 5445 5544
5643 5742 5841 5940 6039 6138 6237 6336 6435 6534 6633 6732 6831 6930 7029 7128
7227 7326 7425 7524 7623 7722 7821 7920 8019 8118 8217 8316 8415 8514 8613 8712
8811 8910 9009 9108 9207 9306 9405 9504 9603 9702 9801
```

Nested for loops are brutal—the inner loop runs in its entirety for every single iteration of the outer loop. In the limit, for a list of length n, there are $\mathcal{O}(n^2)$ iterations.

One more tricky one:

```
[14]: xeno = 100
while xeno > 1:
    xeno /= 2
    print(xeno, end = " ")
```

50.0 25.0 12.5 6.25 3.125 1.5625 0.78125

Maybe another example from the same complexity class:

```
[15]: xeno = 100000
while xeno > 1:
    xeno /= 10
    print(xeno, end = " ")
```

10000.0 1000.0 100.0 10.0 1.0

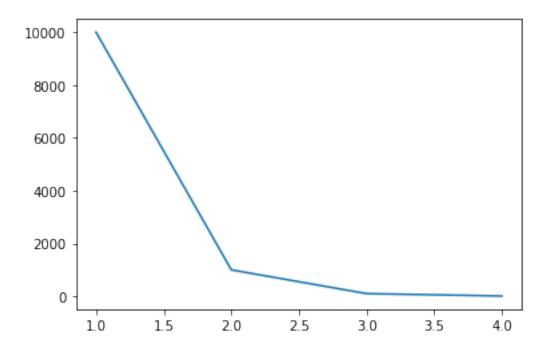
What does this "look" like?

```
[16]: # I'm just plotting the iteration number against the value of "xeno".

%matplotlib inline
import matplotlib.pyplot as plt

x = []
y = []
xeno = 10000
i = 1
while xeno > 1:
    x.append(i)
    y.append(xeno)
    xeno /= 10
    i += 1
plt.plot(x, y)
```

[16]: [<matplotlib.lines.Line2D at 0x7fb2d2f32510>]



In the first one, on each iteration, we're dividing the remaining space by 2, halving again and again and again.

In the second one, on each iteration, we're dividing the space by 10.

 $O(\log n)$. We use the default (base 10) because, in the limit, constants don't matter.

1.4 Part 2: SCS and LCS

Recall from the last lecture what SCS (shortest common superstring) was:

• The shortest common superstring, given sequences *X* and *Y*, is the shortest possible sequence that contains all the sequences *X* and *Y*.

For example, let's say we have X = ABACBDCAB and Y = BDCABA. What would be the shortest common superstring?

Here is one alignment: BDCABA (second string) and ABACBDCAB (first string). The ABA is where the two strings overlap. The full alignment, BDCABACBDCAB, has a length of 12.

Can we do better?

ABACBDCAB and BDCABA, which gives a full alignment of ABACBDCABA, which has a length of only 10. So this alignment would be the SCS.

(When do we need to use SCS?)

1.4.1 Longest Common Substring (LCS)

In a related, but different, problem: longest common substring asks:

• Given sequences *X* and *Y*, the longest common substring is the constituent of the sequences *X* and *Y* that is as long as possible.

Let's go back to our sequences from before: X = ABACBDCAB and Y = BDCABA. What would be the longest common substring?

The easiest substrings are the single characters A, B, C, and D, which both *X* and *Y* have. But these are short: only length 1 for all. Can we do better?

ABACBDCAB and BDCABA, so the longest common substring is BDCAB.

(When do we need LCS?)

1.4.2 Rudimentary Sequence Alignment

Given two DNA sequences *v* and *w*:

v: ATATATAT

w: TATATATA

How would you suggest aligning these sequences to determine their similarity?

Before we try to align them, we need some objective measure of what a "good" alignment is!

1.5 Part 3: Distance Metrics

Hopefully, everyone has heard of *Euclidean distance*: this is the usual "distance" formula you use when trying to find out how far apart two points are in 2D space.

How is it computed?

For two points in 2D space, a and b, their Euclidean distance $d_e(a, b)$ is defined as:

$$d_e(a,b) = \sqrt{(a_x - b_x)^2 + (a_y - b_y)^2}$$

So if a = (1,2) and b = (5,3), then:

$$d_e(a,b) = \sqrt{(1-5)^2 + (2-3)^2} = \sqrt{(-4)^2 + (-1)^2} = \sqrt{16+1} = 4.1231$$

How can we measure distance between two sequences?

There is a metric called **Hamming Distance**, which counts number of differing corresponding elements in two strings.

We'll represent the Hamming distance between two strings v and w as $d_H(v, w)$.

v: ATATATAT

w: TATATATA

 $d_H(v, w) = 8$

That seems reasonable. But, given how similar the two sequences are (after all, the LCS of these two is 7 characters), what if we shifted one of the sequences over by one space?

v: ATATATAT-

w: -TATATATA

Now, what's $d_H(v, w)$?

$$d_H(v, w) = 2$$

The only elements of the two strings that don't overlap are the first and last; they match perfectly otherwise!

1.5.1 Edit distance

Hamming distance is useful, but it neglects the possibility of insertions and deletions in DNA (what is the only thing it counts?). So we need something more robust.

The *edit distance* between two strings is the *minimum number of elementary operations* (insertions, deletions, or substitutions / mutations) required to transform one string into the other.

Hamming distance: i^{th} letter of v with i^{th} letter of w (how hard is this to do?)

Edit distance: i^{th} letter of v with j^{th} letter of w (how hard is this to do?)

Hamming distance is easy, but gives us the wrong answers. Edit distance gives us much better answers, but it's hard to compute: **how do we know which** *i* **to pair with which** *j***?**

What's the edit distance for v = TGCATAT and w = ATCCGAT?

One solution:

- 1. TGCATAT (delete last T)
- 2. TGCATA (delete last A)

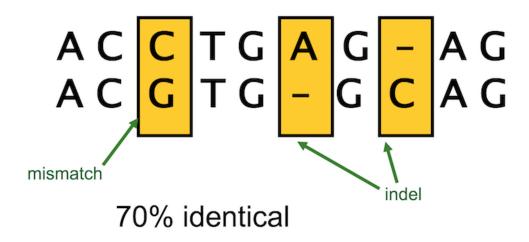
- 3. ATGCAT (insert A at front)
- 4. ATCCAT (mutate G to C)
- 5. ATCCGAT (insert G before last A)

ATCCGAT == ATCCGAT, done in 5 steps!

Can it be done in 4 steps?

(...mmmaybe-but that's for next week!)

1.6 Part 4: Global vs Local Alignment



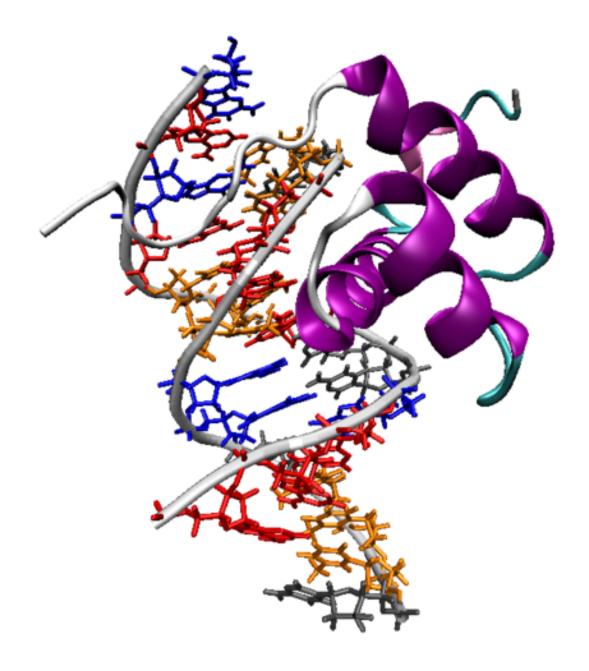
indel is a portmanteau of "insertion" and "deletion", so we don't need to worry about which strand we're actually referring to.

What is the edit distance here?

1.6.1 Highly conserved subsequences

Things get hairier when we consider that two genes in different species may be similar over **short**, **conserved regions** and dissimilar over remaining regions.

Homeobox regions have a short region called the *homeodomain* that is highly conserved among species–responsible for regulation of patterns of anatomical development in animals, fungi, and plants.



- A global alignment would not find the homeodomain because it would try to align the *entire* sequence.
- Therefore, we search for an alignment which has a low edit score *locally*, meaning we have to search aligned substrings of the two sequences.

Here's an example global alignment that minimizes edit distance over the entirety of these two sequences:

Here's an example local alignment that may have an *overall larger edit distance*, but it finds the highly conserved substring:

"BUT!", you protest.

"If the local alignment has a higher edit score, how do we find it at all?"

We've already seen that we need to consider three separate possibilities when aligning sequences:

- 1. Insertions / Deletions (characters added or removed)
- 2. Mutations / Substitutions (characters modified)
- 3. Matches (characters align)

With Hamming distance, two characters were either the same or they weren't (options 1 and 2 above were a single criterion).

With edit distance, we separated #1 and #2 above into their own categories, but they are still weighted the same (1 insertion = 1 mutation = 1 edit)

Are all insertions / deletions created equal? How about all substitutions?

1.6.2 Scoring Matrices

Say we want to align the sequences:

 $v = \mathtt{AGTCA}$

w = CGTTGG

But instead of using a standard edit distance as before, I give you the following *scoring matrix*:

	Α	G	Т	С	_
Α	1	-0.8	-0.2	-2.3	-0.6
G	-0.8	1	-1.1	-0.7	-1.5
Т	-0.2	-1.1	1	-0.5	-0.9
С	-2.3	-0.7	-0.5	1	-1
_	-0.6	-1.5	-0.9	-1	n/a

This matrix gives the specific edit penalties for particular substitutions / insertions / deletions.

It also allows us to codify our understanding of biology and biochemistry into how we define a "good" alignment. For instance, this penalizes matching A with G more heavily than C matched with T.

Here is a sample alignment using this scoring matrix:

Score:
$$-0.6 - 1 + 1 + 1 - 0.5 - 1.5 - 0.8 = -2.4$$

1.6.3 Making a scoring matrix

Scoring matrices are created based on biological evidence.

Some mutations, especially in amino acid sequences, may have little (if any!) effect on the protein's function. Using scoring matrices, we can directly quantify that understanding.

- Polar to polar mutations (aspartate -> glutamate)
- Nonpolar to nonpolar mutations (alanine -> valine)
- Similarly behaving residues (leucine -> isoleucine)

1.6.4 Standard scoring matrices

For nucleotide sequences, there aren't really "standard" scoring matrices, since DNA is less conserved overall and less effective to compare coding regions.

There are, however, some common amino acid scoring matrices. We'll discuss two:

- 1. PAM (Point Accepted Mutation)
- 2. BLOSUM (**Blo**cks **Substitution Matrix**)

1.6.5 PAM

PAM is a more theoretical model of amino acid substitutions.

It is always associated with a number, e.g. 1 PAM, written as PAM_1 . This means the given PAM_1 scoring matrix is built to reflect a **1% average change in all amino acid positions** of the polypeptide, according to evolution.

Some important notes: - This is an *average*. Even with PAM_{100} , not every residue will have changed (some are more conserved than others) - Some residues may have mutated several times! - Some residues may have mutated back to their original state! - Some residues may not have changed at all

 PAM_{250} is a widely used scoring matrix.

	Ala	Arg	Asn	Asp	Cys	Gln	Glu	Gly	His	Ile	Leu	Lys	
	A	R	N	D	С	Q	E	G	Н	I	L	K	
Ala A	13	6	9	9	5	8	9	12	6	8	6	7	
Arg R	3	17	4	3	2	5	3	2	6	3	2	9	
Asn N	4	4	6	7	2	5	6	4	6	3	2	5	
Asp D	5	4	8	11	1	7	10	5	6	3	2	5	
Cys C	2	1	1	1	52	1	1	2	2	2	1	1	
Gln Q	3	5	5	6	1	10	7	3	7	2	3	5	
Trp W	0	2	0	0	0	0	0	0	1	0	1	0	
Tyr Y	1	1	2	1	3	1	1	1	3	2	2	1	
Val V	7	4	4	4	4	4	4	4	5	4	15	10	

Mutating A to A is clearly the most preferable (highest score in that row of 13 points), but after 250 evolutions, a mutation from A to G also seems very favorable (12 points).

1.6.6 BLOSUM

Unlike PAM, scores in BLOSUM are derived from direct empirical observations of the frequencies of substitutions in blocks of local alignments in related proteins. They both, however, often obtain identical alignment scores.

Like PAM, BLOSUM also has a number associated with it, this time to represent the observed substitution rate between two proteins sharing some amount of similarity.

BLOSUM₆₂ is a common scoring matrix, representing substitution rates in proteins sharing no more than 62% identity.

	С	S	Т	Р	 F	Υ	W
С	9	-1	-1	3	 -2	-2	-2
S	-1	4	1	-1	 -2	-2	-3
Т	-1	1	4	1	 -2	-2	-3
Р	3	-1	1	7	 -4	-3	-4
F	-2	-2	-2	-4	 6	3	1
Υ	-2	-2	-2	-3	 3	7	2
W	-2	-3	-3	-4	 1	2	11

1.7 Next week

We'll look at how to use these matrices to determine the best alignments of sequences!

1.8 Administrivia

• You should everything you need now for Assignment 2. Any questions so far? Due next week!

1.9 Additional Resources

- 1. Jones, Neil C. and Pevzner, Pavel A. *An Introduction to Bioinformatics Algorithms*, Chapter 6. 2004. ISBN-13: 978-0262101066
- 2. Based heavily on the modified slides of Dr. Phillip Compeau.