02-251: Great Ideas in Computational Biology Metagenomics Phillip Compeau

Introduction to Metagenomics

Fill in the Blank: Over half the cells in your body are: ______.

Introduction to Metagenomics

Fill in the Blank: Over half the cells in your body

are: *bacteria* .

Introduction to Metagenomics

Fill in the Blank: Over half the cells in your body

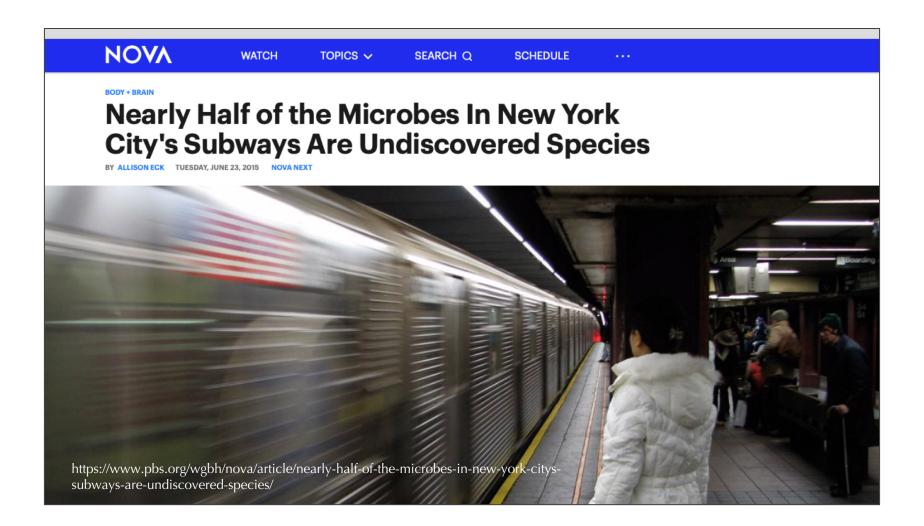
are: <u>bacteria</u>.

Metagenomics: The study of DNA (or RNA) recovered from an environmental sample.





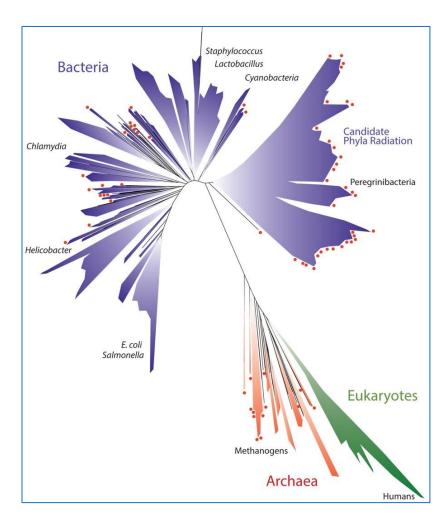
An Example of Metagenomics



"Why Do We Care About Bacteria?"



Darwin's notebook c. 1837



Hug et al., 2016

Courtesy: Nature Biotechnology,

Discovery Magazine

Wait ... How Many Species Are There?

Checkpoint: ...

I'm open to guesses on what you think!

Wait ... How Many Species Are There?

Checkpoint: ...

I'm open to guesses on what you think!

Another can of worms: what is a species?

Introduction

HOW many species are there on Earth? This is a fundamental question in science, but one that remains far from resolved. It is widely agreed that the number of described species (approximately 1.5 million species; Roskov et al. 2014) underestimates actual global richness, but the extent of this underestimation remains unclear. Projections of global biodiversity have ranged from as low as ~2 million species (Costello et al. 2012), up to ~100 million (e.g., Ehrlich and Wilson 1991; May 1992; Lambshead 1993), or even ~1 trillion (Locey and Lennon 2016).

Larsen et al., 2017

Single-cell Sequencing Offers One Way to Analyze an Environmental Sample

Note: Many species cannot be cultured (i.e., separated and grown from a sample).

There do exist **single-cell sequencing** approaches for isolating a cell, amplifying its DNA, and sequencing its genome. But a small sample may contain thousands of species!

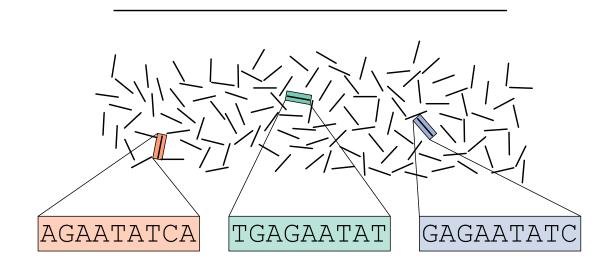
Recall How Sequencing Works

Multiple identical copies of a genome

Shatter the genome into reads

Sequence the reads (Lab)

Assemble the genome using overlapping reads (Computational)



AGAATATCA

GAGAATATC

TGAGAATAT

..TGAGAATATCA...

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Multiple identical copies of a genome

Shatter the genome into reads

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Sequence the reads (Lab)

Checkpoint: How would you solve this problem computationally?

AGAATATCA

Two Approaches for Metagenomics

1. Try to reconcile de Bruijn graph approach to construct multiple graphs and do *n* assemblies (where *n* is unknown in advance).

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2. Use "puzzle on the box" database of all known organisms' genomes and "align" metagenomics reads to these genomes to find which ones (if any) each read may have come from. This process is called **binning** the reads.

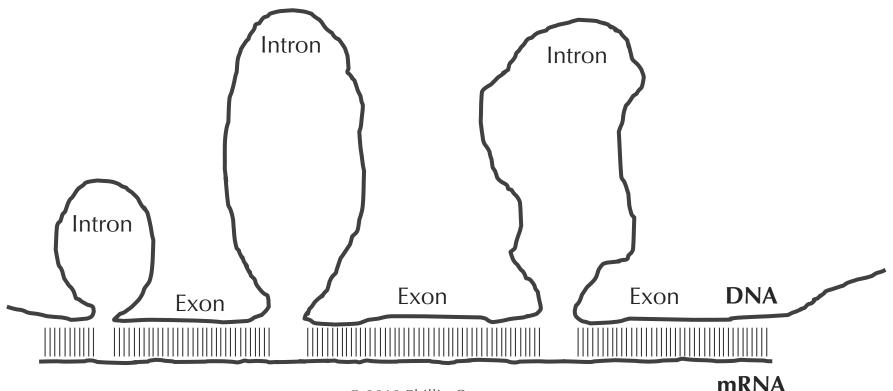
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Prokaryotes (Bacteria and Archaea) Don't Have Introns

Prokaryotes' genes generally don't have introns (i.e., the entire gene is translated into protein).



DNA Has Six "Reading Frames" for Translation into Protein

GluThrPheSerLeuVal***SerIle ***AsnPhePheLeuGlyLeuIleAsn Translated peptides ValTyrGlnAsnPheTrpProPheLeuLys Transcribed RNA GUGAAACUUUUUCCUUGGUUUAAUCAAUAU 5' GTGAAACTTTTTCCTTGGTTTAATCAATAT 3' DNA 3' CACTTTGAAAAAGGAACCAAATTAGTTATA 5' Transcribed RNA CACUUUGAAAAAGGAACCAAAUUAGUUAUA HisPheLysLysArgProLysIleLeuIle PheSerLysGlyGlnAsnLeu***Tyr Translated peptides SerValLysGluLysThr***AspIle

Binning Reads is a Protein Comparison Problem

Moreover, most of the prokaryotic genome is made up of genes.

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Because protein-protein comparisons can be more fruitful, we should compare all six protein translations of each DNA read against a (huge) database consisting of all known prokaryotic proteins.

Why Not Use Sequence Alignment?

Checkpoint: We could perform a local alignment of each protein product of each read against the entire database. What would be its runtime?

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Answer: $O(|Database|^*|Pattern|)$ for each pattern, for a total of $O(|Database|^*|Patterns|)$. Not to mention building the array ...

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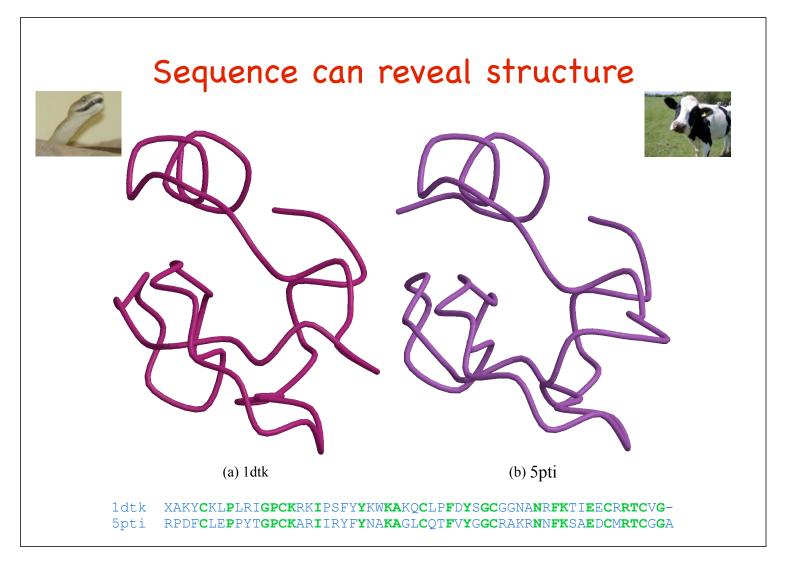
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- 2. Find which seeds match *Text* exactly using BWT (**seed detection**).

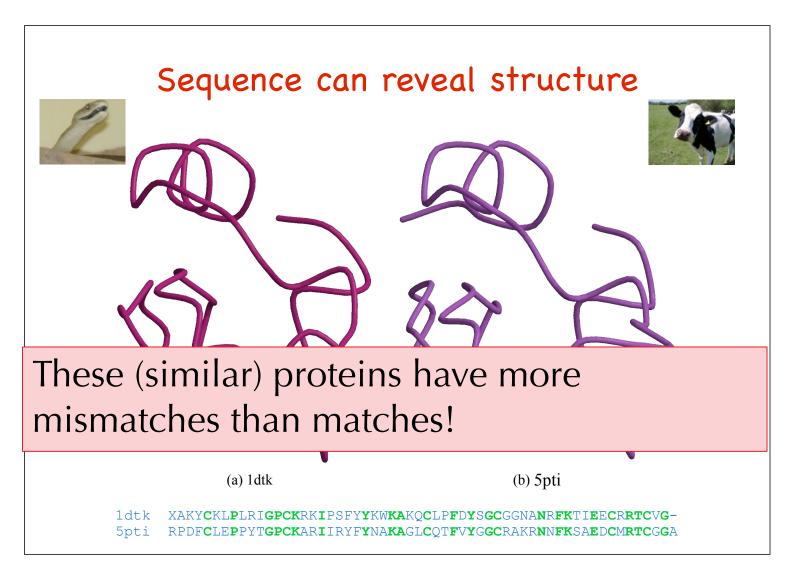
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- 1. Divide *Pattern* into *d*+1 "equal" segments (called **seeds**).
- 2. Find which seeds match *Text* exactly using BWT (**seed detection**).
- Attempt to extend all seeds in both directions to verify whether *Pattern* occurs with at most *d* mismatches (**seed extension**).

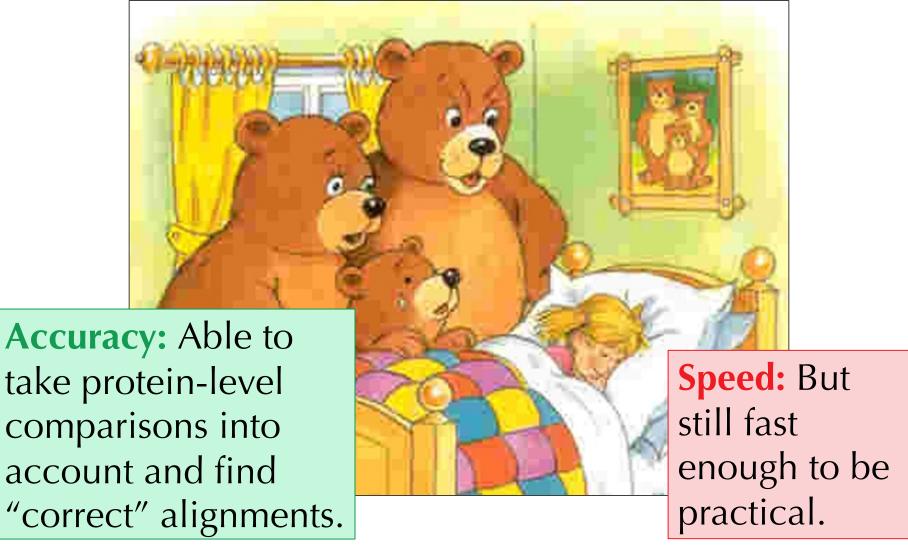
Let's Borrow CK's Slide ...



Let's Borrow CK's Slide ...



We Need a "Just Right" Binning Approach



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Basic local alignment search tool. - NCBI - NIH

https://www.ncbi.nlm.nih.gov/pubmed/2231712 *

by SF Altschul - 1990 - Cited by 75316 - Related articles

J Mol Biol. 1990 Oct 5;215(3):403-10. Basic local alignment search tool. Altschul SF(1), Gish W,

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Key Point: BLAST is a **heuristic**, meaning that it does not promise that it will bin all reads correctly; in other words, it is not solving a computational problem exactly.

Basic local alignment search tool. - NCBI - NIH

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- Input: a database (in this case a protein) and a query (in this case a protein corresponding to one of six reading frame translations of sequencing read). Plus, some parameters (later).
- Output: A collection of high-scoring local alignments of the query against the database (there may be none, or more than are found).

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Gaps are "expensive" computationally (they cause sequence alignment to go from O(n) to $O(n^2)$), so BLAST waits until the last possible moment to incorporate them.

Step 1: Divide A Given Read into k-mers

Note: *k* is one of the additional parameters that we mentioned.

```
CFCDIQL
CFC
FCD
CDI
CDI
DIQ
IQL
```

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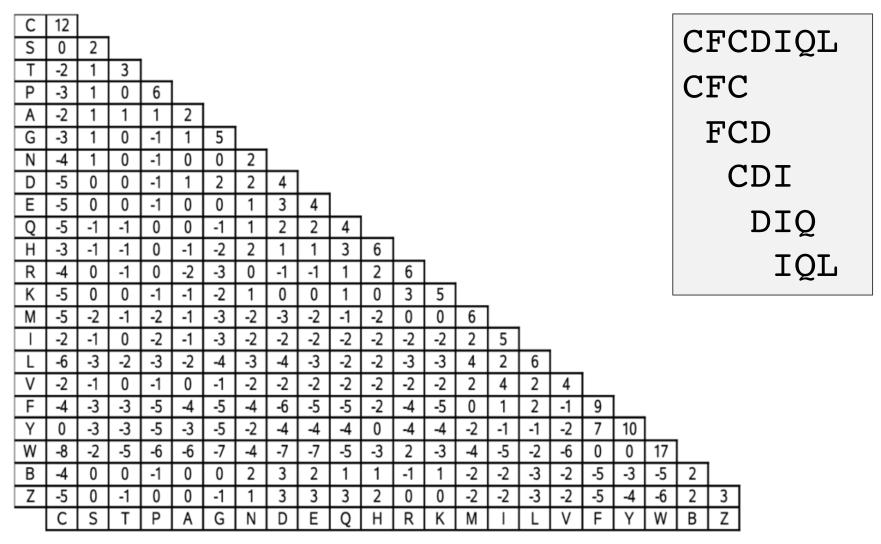
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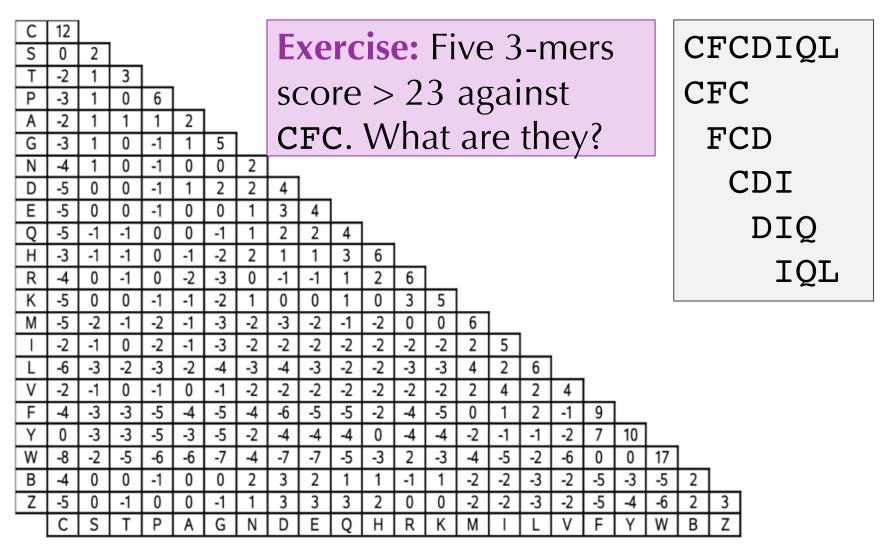
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Checkpoint: What do you think happens to the sensitivity of BLAST as *k* increases/decreases?

Step 2: For Each *k*-mer *x*, what other *k*-mers score well against it?





High Scoring *k***-mers Problem:**

- **Input:** an amino acid *k*-mer *x*, a scoring matrix *Score*, and a threshold value *T*.
- Output: All amino acid k-mers y such that $Score(x_1, y_1) + Score(x_2, y_2) + ... + Score(x_k, y_k)$ is > T.

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Note: The k-mers produced are the k-mers that we should look for in the database that match well against x – so we're back to exact pattern matching!

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Checkpoint: Note that *Score* and *T* add more parameters to BLAST. What effect do you think increasing/decreasing *T* has on sensitivity?

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Exercise: Can you find an efficient algorithm solving this problem?

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- Output: All amino acid k-mers y such that $Score(x_1, y_1) + Score(x_2, y_2) + ... + Score(x_k, y_k)$ is > T.

Note: Once we solve this problem, we organize all the resulting k-mers into a trie.

In summary, each read produces a collection of *k*-mers, and each *k*-mer produces a trie of high-scoring *k*-mers.

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In summary, each read produces a collection of *k*-mers, and each *k*-mer produces a trie of high-scoring *k*-mers.

We then "slide" these tries across the database, looking for exact matches. Any exact matches become our **seeds**.

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(Recall from read mapping slides how pattern matching works with the trie.)

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Aho-Corasick algorithm for trie pattern matching (recitation) is O(|Database| + |Tries| + m); m = # of matches found, |Tries| = # letters in all tries.

Database ...CICDVQ...

Query CDI

CFCDIQL
CFC
FCD
CDI
CDI
DIQ
IQL

Note: Just because a *k*-mer has a good score doesn't mean that it can't be *extended* into a longer match with the read.

Database ...CICDVQ...

Query CFCDIQ

CFCDIQL
CFC
FCD
FCD
CDI
CDI
DIQ
IQL

Note: Just because a *k*-mer has a good score doesn't mean that it can't be *extended* into a longer match with the read.

Database ...CICDVQ...

Query CFCDIQ

CFCDIQL
CFC
FCD
CDI
CDI
DIQ
IQL

We extend each seed as far to the left and right as we can until the score w/r/t the database stops increasing. The result is a pair of substrings of the query and database called a maximal segment pair.

Database ...CICDVQ...

Query CFCDIQ

CFCDIQL
CFC
CFC
FCD
CDI
CDI
DIQ
IQL

(Think of MSPs as high-scoring local alignments of query against database without gaps.)

Database ...CICDVQ...

Query CFCDIQ

CFCDIQL
CFC
FCD
FCD
DIQ
IQL

Checkpoint: Recall ... what does "maximal" mean mathematically?

Database ...CICDVQ...

Query CFCDIQ

CFCDIQL
CFC
CFC
FCD
CDI
CDI
DIQ
IQL

Answer: A "local" maximum. In other words, the same query may correspond to many MSPs (or zero MSPs) throughout the database.

Step 5: Trim Maximal Segment Pairs

Yet another threshold parameter *S* is now used; we throw away any MSPs whose score (with respect to the scoring matrix) is < *S*.

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Checkpoint: Does increasing *S* increase or decrease the sensitivity of BLAST?

Checkpoint: Say we have one MSP of length 12 with score 56 and another MSP of length 9 with score 45. Which one is better?

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Answer: The way to answer this question is to not say "which is better" but to say "which would be less likely in a random environment?"

p-value: The probability that an event we observe would have occurred in a random reconstruction of whatever we are working with. (This is a very bad statistical definition.)

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In this case, the p-value we want to compute is the probability Pr(s >= Q) that we would observe an MSP of score s at least some threshold Q in a random database.

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In this case, the p-value we want to compute is the probability Pr(s >= Q) that we would observe an MSP of score s at least some threshold Q in a random database.

(Constructing the database and computing this p-value would take two lectures of statistics.)

p-value: The probability that an event we observe would have occurred in a random reconstruction of whatever we are working with. (This is a very bad statistical definition.)

Checkpoint: Are we hoping for MSPs with lower p-values or higher p-values?

Step 7: Combine Nearby MSPs

Database ... XXAAAAAAXXXCCCCCXX...

Query

ZZAAAAAZZZZCCCCCZZ

MSP1 MSP2

Step 7: Combine Nearby MSPs

Database ... XXAAAAAAAXXXCCCCCXX...

Query ZZAAAAAAZZZCCCCCZZ

Combined MSP

We will merge two nearby MSPs into one MSP if their combined p-value is still significant (i.e., below yet another threshold parameter).

Step 8: Align Step in BLAST

We *still* haven't added any gaps to our alignments, but we have trimmed away everything but MSP regions that we know are very interesting.

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We now can perform a (Smith-Waterman) alignment of every MSP we found and report the resulting alignment (with p-value).

In practice, BLAST returns an **E-value**: the expected number of hits of comparable score in a random database.

```
Score = 224 bits (113), Expect = 6e-56
Identities = 161/161 (100*), Gaps = 0/161 (0*)
Strand=Plus/Plus

Query 213 GACTGTGCAATACTTAGAGAACCTATAGCATCTTCTCATTCCCATGTGGAACAGGATGCC 272

Sbjet 1205 GACTGTGCAATACTTAGAGAACCTATAGCATCTTCTCATTCCCATGTGGAACAGGATGCC 1264

Query 273 CACATACTGTCTAATTAATAAATTTTCCAttttttttCAAACAAGTATGAATCTAGTTGG 332

Sbjet 1265 CACATACTGTCTAATTAATAAATTTTCCATTTTTTTTCAAACAAGTATGAATCTAGTTGG 1324

Query 333 TIGATGCCttttttttCCATGACATAATAAAGTATTTCTTT 373

Sbjot 1325 TIGATGCCttttttttCCATGACATAATAAAGTATTTCTTT 1365
```

Note: Very small p-values are approximately equal to their corresponding E-values.

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Sbjet 1265 CACATACTGTCTAATTAATAAATTTTCCATTTTTTTTCAAACAAGTATGAATCTAGTTGG 1324

Query 333 TIGATGCCttttttttCCATGACATAATAAAGTATTTCTTT 373

Sbjot 1325 TIGATGCCttttttttCCATGACATAATAAAGTATTTCTTT 1365
```

Checkpoint: We report all E-values below some threshold; it is just one more parameter affecting sensitivity.

Be Careful with P-Values!





Overview of Metagenomics Process

- 1. Find six reading frames of every read.
- 2. Apply BLAST to resulting query database to produce alignments.
- 3. Use alignments to quantify certainty that a metagenome came from different species (the correct term is "organizational taxonomic unit").

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Checkpoint: We haven't discussed #3 ... how might we do it?

Why We Need Fast Heuristics Like BLAST for "Big Data"

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Short answer: computers are getting faster, but we're also sequencing more organisms, so the database we're consulting is growing too. (This is a common phenomenon across fields.)

Say the runtime of an old and new algorithm are $T_{\rm old}$ and $T_{\rm new}$, respectively. The speedup provided by $T_{\rm new}$ is the ratio $T_{\rm old}$ / $T_{\rm new}$.

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Key Point 1: A slight improvement to algorithm runtime can compound for larger datasets.

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Exercise: Say T_{old} is n^2 and T_{new} is 16*n*lg(n). What is the speedup for an arbitrary n? What happens for $n = 2^5$, 2^{10} , 2^{20} , and 2^{40} ?

Key Point 2: Optimizing read aligners is still an active area of research for this reason!