Fast Algorithms for Improved Transcriptome Analysis I: Transcriptomic Mapping

Rob Patro



COMputational **Bl**ology and **N**etwork **E**volution

website: https://combine-lab.github.io/

We're interested in a wide range of comp. bio problems:

- Biological network evolution
- Chromatin structure & epigenetic regulation
- Data representation & storage:
 - Dynamic text indexing
 - short-read compression
- Computational transcriptomics
 - Efficient read mapping
 - Transcript-level expression inference
 - transcriptome assembly & analysis



COMputational **Bl**ology and **N**etwork **E**volution

website: https://combine-lab.github.io/

We're interested in a wide range of comp. bio problems:

- Biological network evolution
- Chromatin structure & epigenetic regulation
- Data representation & storage:
 - Dynamic text indexing
 - short-read compression
- Computational transcriptomics (this and the next lecture)
 - Efficient read mapping
 - Transcript-level expression inference
 - transcriptome assembly & analysis

Zeng & Mortazavi, Nature Immunology 2012 Select cell population Quality control Extract total RNA RIN AAAAA mRNA Small RNA Size-select by Poly(A) select PAGE or by kit 'ribosome minus' Recovered RNA amount measurement Small RNA mRNA Ligate RNA adapter Fragment Agilent bioanalyzer Convert to cDNA = cDNA Construct library Agilent bioanalyzer Sequence Quantitation New transcript Variant mining discovery Map reads onto the genome Calculate RPKM SNP editing 2 RPKM 1 RPKM 1 RPKM

Uses of RNA-Seq are manifold

Whole transcriptome analysis

- Quantification & differential expression
- Novel txp discovery
 - reference-based
 - de novo
- Variant detection
 - Genomic SNPs
 - RNA editing

- What is dynamic & changing over time (as disease progresses)?
- What is tissue specific (in fetal development but not after)?
- What is condition specific (under stress conditions vs. not)?

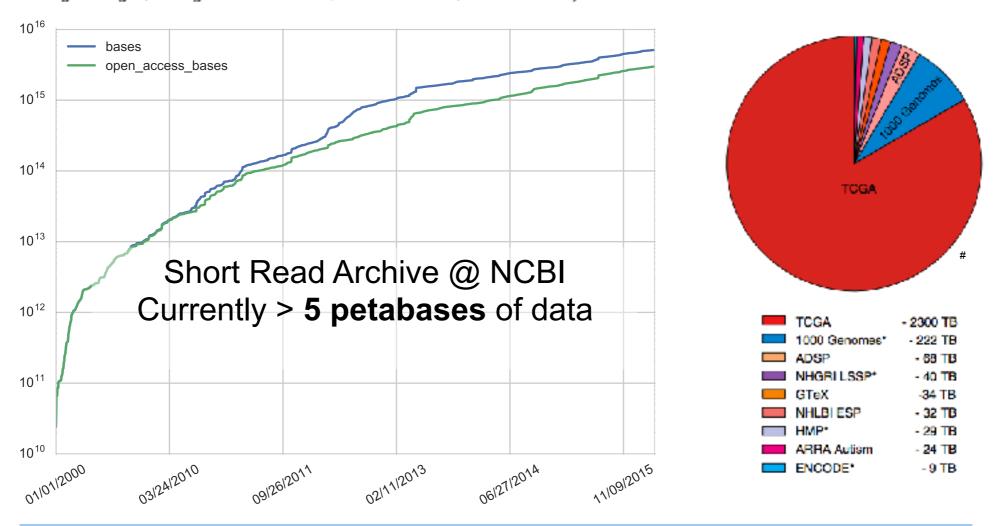
Why do we still need faster analysis?

OPINION Open Access



The real cost of sequencing: scaling computation to keep pace with data generation

Paul Muir^{1,2,3}, Shantao Li⁴, Shaoke Lou^{4,5}, Daifeng Wang^{4,5}, Daniel J Spakowicz^{4,5}, Leonidas Salichos^{4,5}, Jing Zhang^{4,5}, George M. Weinstock⁶, Farren Isaacs^{1,2}, Joel Rozowsky^{4,5} and Mark Gerstein^{4,5,7}*



In addition to new data, re-analysis of existing experiments often desired: In light of new annotations, discoveries, and methodological advancements.

Advocating for analysis-efficient computing

- Compute *only* the information required for your analysis; ask what information you *need* to solve your problem, not what output current tools are generating
- Often the efficiency of the analysis is related to the size of the (processed)
 data's representation
- Not all analyses require such efficient solutions, should concentrate on problems where this is actually needed.

I'll provide some (hopefully) compelling examples:

- RapMap: Read alignment → quasi-mapping (get "core" info much faster)
- Salmon: Fast, state-of-the-art quantification using quasi-mapping, dual-phase inference & fragment eq. classes
- RapClust: Fast, accurate de novo assembly clustering using quasimapping & fragment eq. classes

We believe these ideas are **general**, and can be applied to many problems

Advocating for analysis-efficient computing

- Compute *only* the information required for your analysis; ask what information you *need* to solve your problem, not what output current tools are generating
- Often the efficiency of the analysis is related to the size of the (processed)
 data's representation
- Not all analyses require such efficient solutions, should concentrate on problems where this is actually needed.

I'll provide some (hopefully) compelling examples:

Boiler (by your very own Pritt & Langmead) is also a beautiful example of this idea.

When we have a particular analysis in mind — transcript identification & quantification — we can compress data much more aggressively & effectively.

We believe these ideas are **general**, and can be applied to many problems



Given an RNA-seq read, where *might* it come from?

Two main "regimes"

Align to transcriptome

Align reads directly to txps

No "split" alignments — transcripts contain spliced exons directly.

Typically *a lot* of multi-mapping (80-90% of reads may map to multiple places)

Does not require target genome

Can be used in *de novo* context (i.e. after *de novo* assembly)

Align to genome

Align reads to target genome

Reads spanning exons will be "split" (gaps up to 10s of kb)

Typically little multi-mapping (most reads have single genomic locus of origin)

Requires target genome

Can be used to find new transcripts

Given an RNA-seq read, where does it come from?

Two main "regimes"

Align to transcriptome

Main computational challenge comes from ubiquitous multi-mapping.

Bowtie

Bowtie 2

BWA

STAR

HISAT (1&2)

Align to genome

Main computational challenge comes from spliced alignments.

Top Hat

STAR

HISAT (1&2)

Map Splice

Subread Aligner

. . .

. . .

Given an RNA-seq read, where does it come from?

Two main "regimes"

Align to transcriptome

Main computational challenge comes from ubiquitous multi-mapping.

We'll focus on this "regime" today.

Bowtie

Bowtie 2

BWA

STAR

Align to genome

Main computational challenge comes from spliced alignments.

Top Hat

STAR

HISAT (1&2)

Map Splice

Subread Aligner

Problem 1: RNA-Seq Read Alignment Mapping

What if we don't *need* alignment?

Claim: Some (but not all) of the analyses we're interested in performing may not actually require the read alignment

How much more efficient may a solution be if we only care about **where** and not exactly **how** a read corresponds to the reference?

Validation: For a very common analysis, RNA-seq-based quantification and differential expression testing, we can replace alignment with mapping with virtually **no loss in accuracy.**

Alignment is *fast* . . . but not always as fast as our data is *big*

A single *sample* may contain 10s of millions of reads

An *experiment* may consist of many samples e.g. conditions, time course samples, etc.

Condition A	Condition B	Condition C	Condition D	Condition E
Replicate 1				
Replicate 2				
Replicate 3				
Replicate 4				

A single experiment may easily consist of 100s of millions of reads.

Quasi-mapping: A stand-in for alignment

Concept:

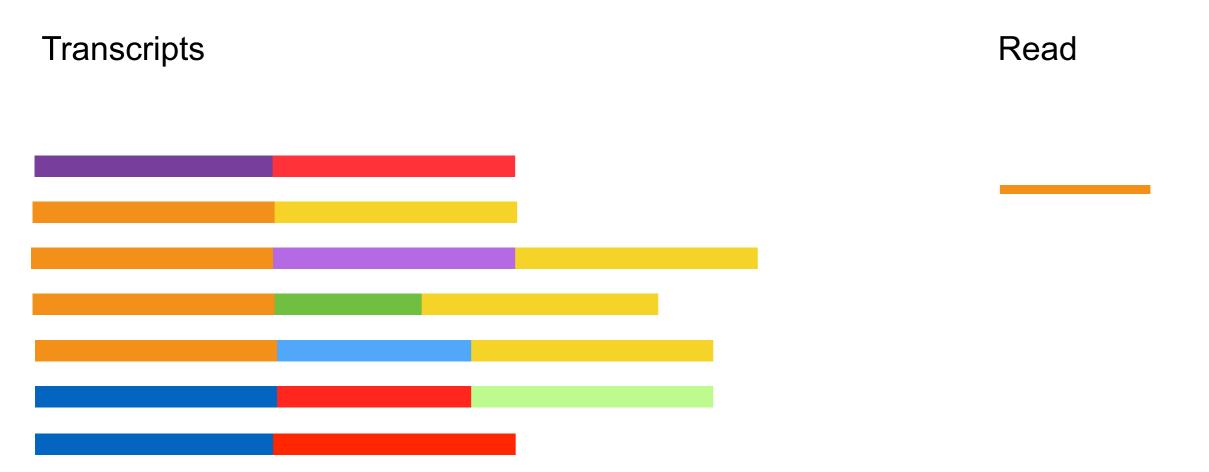
For a given fragment, a quasi-mapping specifies the *target* where a fragment "matches well", and the *position*, and *orientation* of the fragment w.r.t the target, but *not details of the alignment*.

Algorithm:

Relies on a suffix array to compute the *Maximum Mappable Prefix* (MMP) and *Next Informative Position* (NIP) when mapping a read.

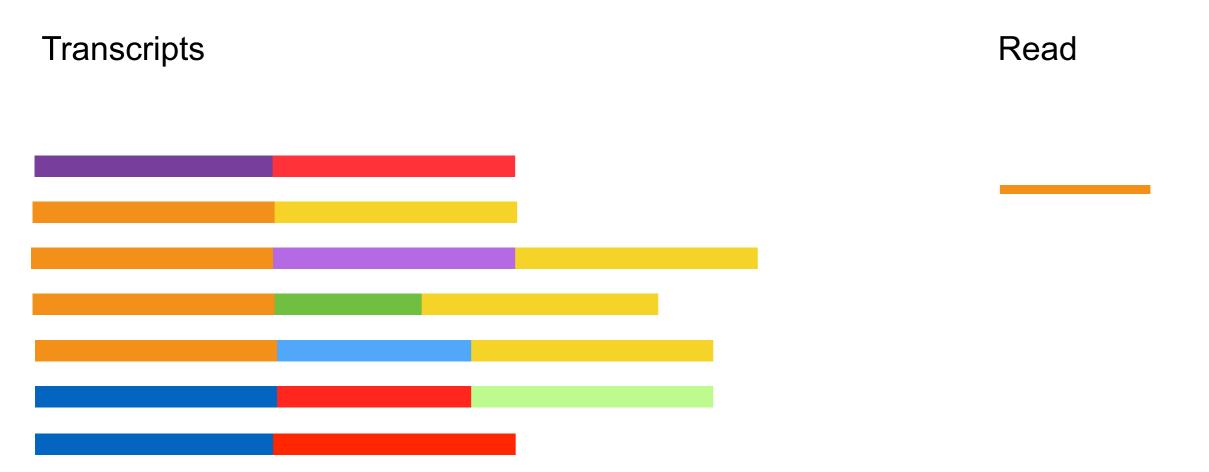
Given a carefully-designed algorithm, quasi-mapping information can be obtained *very* quickly.

Consider the following scenario:



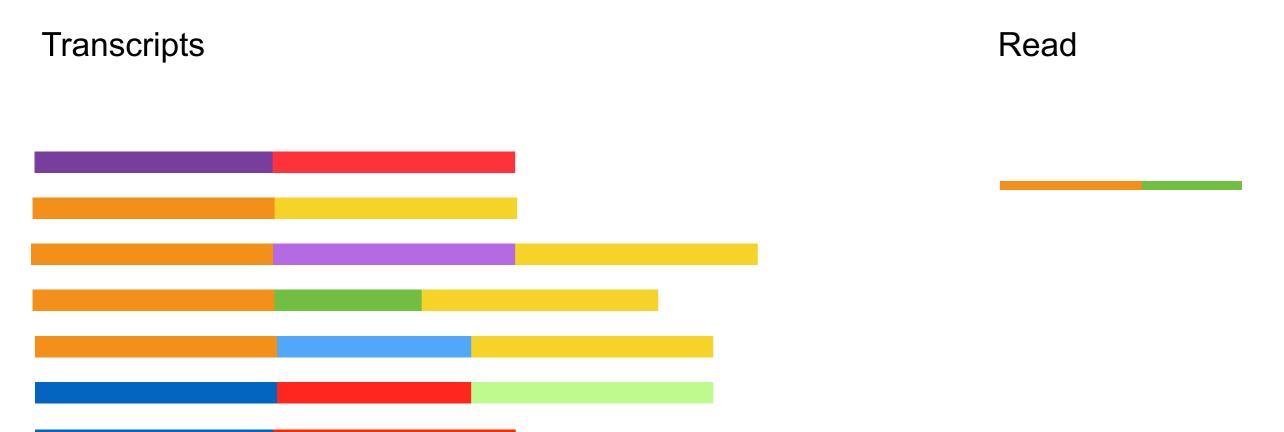
Consider the following scenario:

Say that colors represent exonic sequence. Intuitively, from where does the read originate?

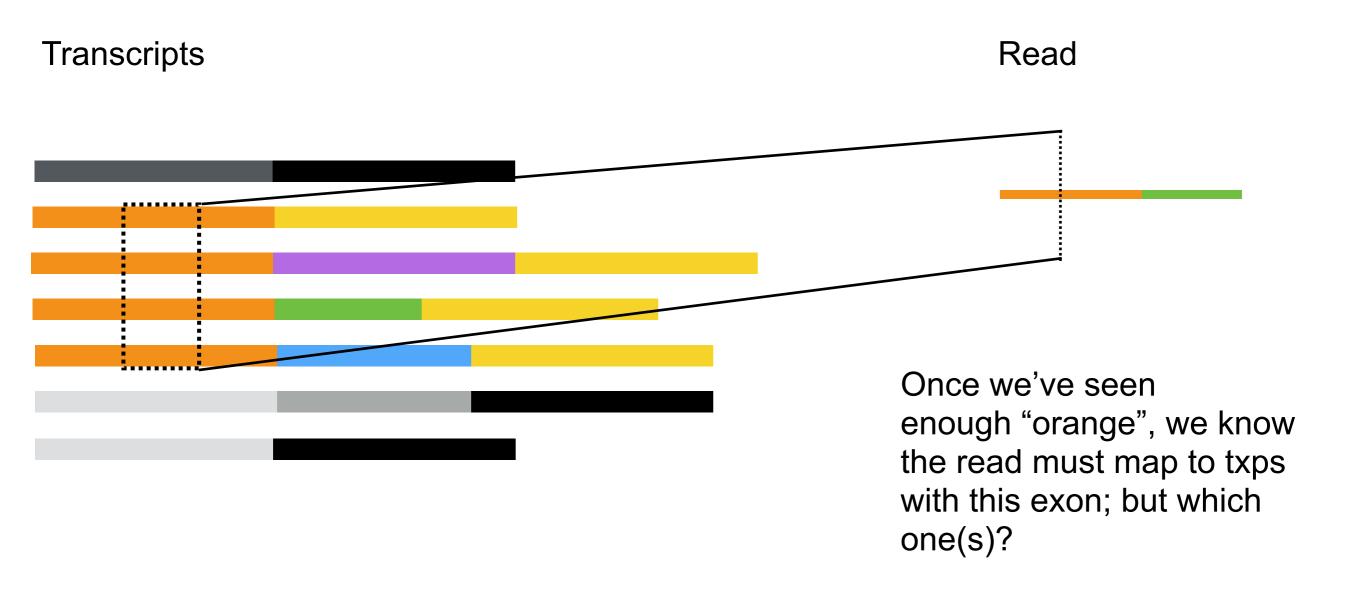


Consider the following scenario:

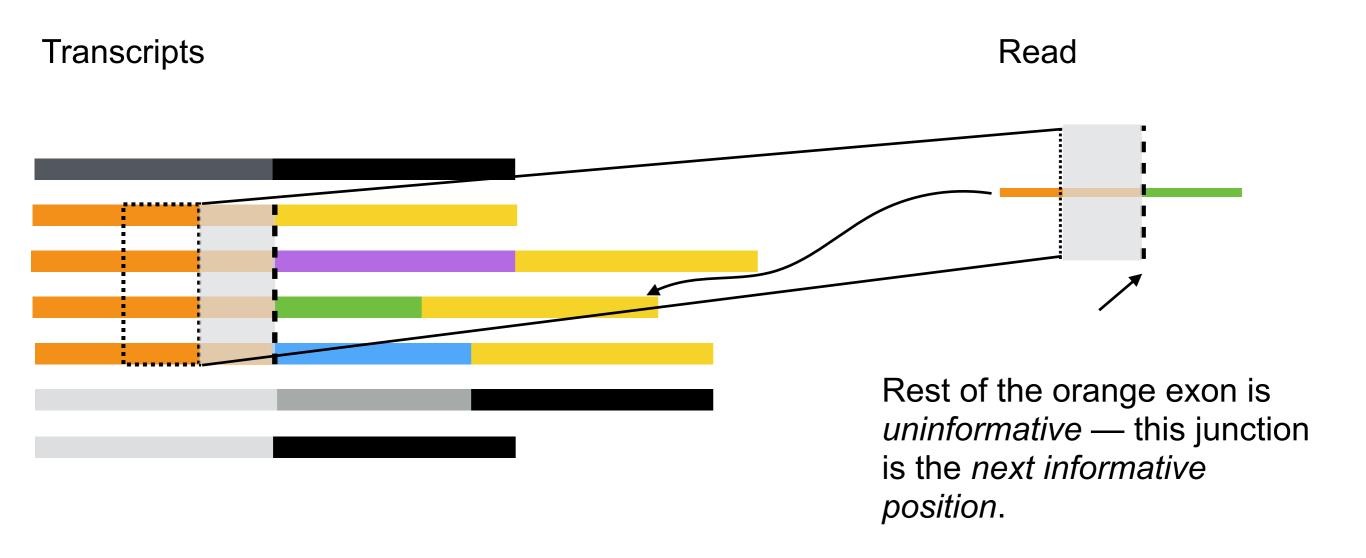
Say that colors represent exonic sequence. Intuitively, from where does the read originate? What about *this* read?



Consider the following scenario:

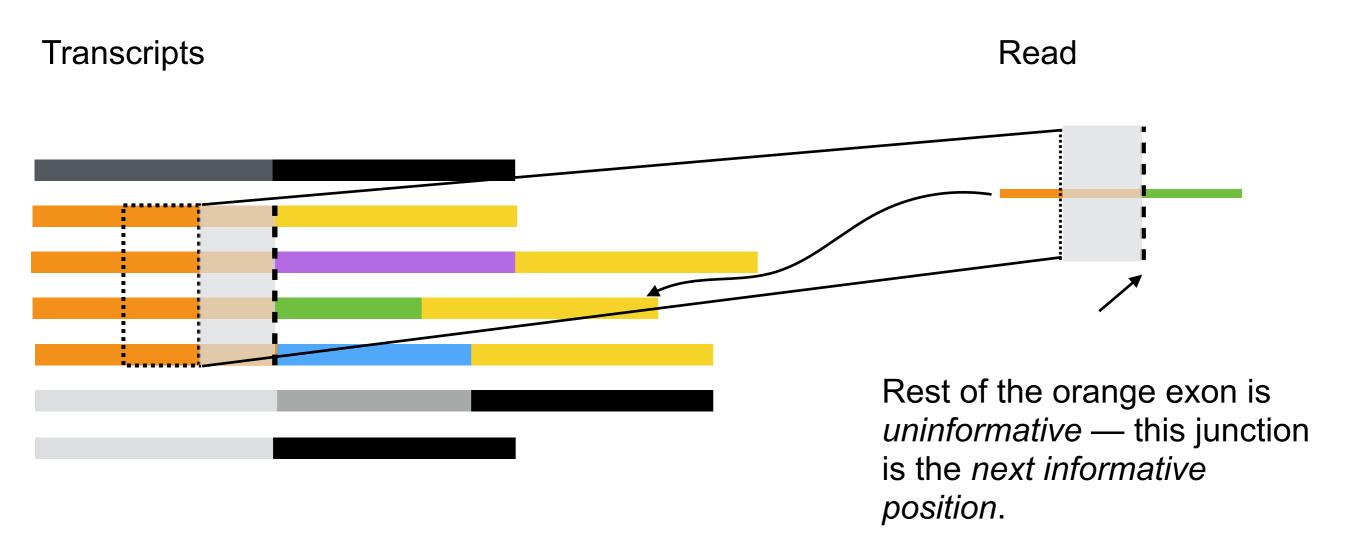


Consider the following scenario:

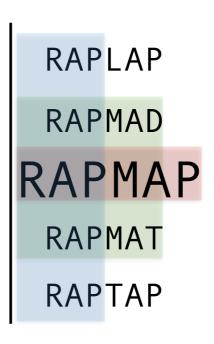


Consider the following scenario:

Is there some *general/formal* way to always find the next informative position (NIP) when mapping a read?



RapMap: A Rapid, Sensitive and Accurate Tool for Mapping RNA-seq Reads to Transcriptomes



GitHub repository: https://github.com/COMBINE-lab/RapMap

Preprint: http://biorxiv.org/content/early/2016/01/16/029652

(appeared @ ISMB 16)

RapMap Index

Generalized suffix array on transcriptome (\$ character separating transcripts)

Hash from k-mers to SA intervals (for speed) (can be dense or minimum perfect hash)

Very fast bit-vector rank — rank9*— allow constant time access to transcript start positions in generalized suffix array

Benefits of this indexing structure

The suffix array allows us to encode / find the NIPs *dynamically* (and guided by the length of matching context)

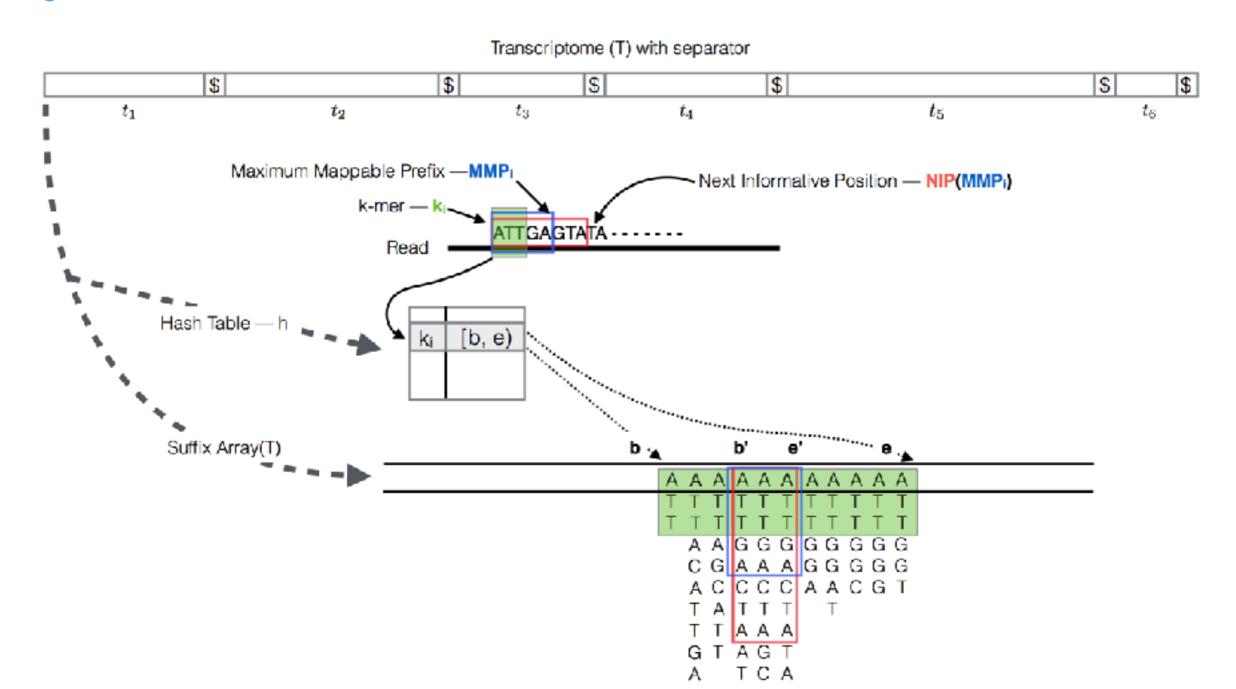
Allows us to efficiently deal with intervals of exact matches (efficient).

Length of context changes dynamically with quality of data (errors).

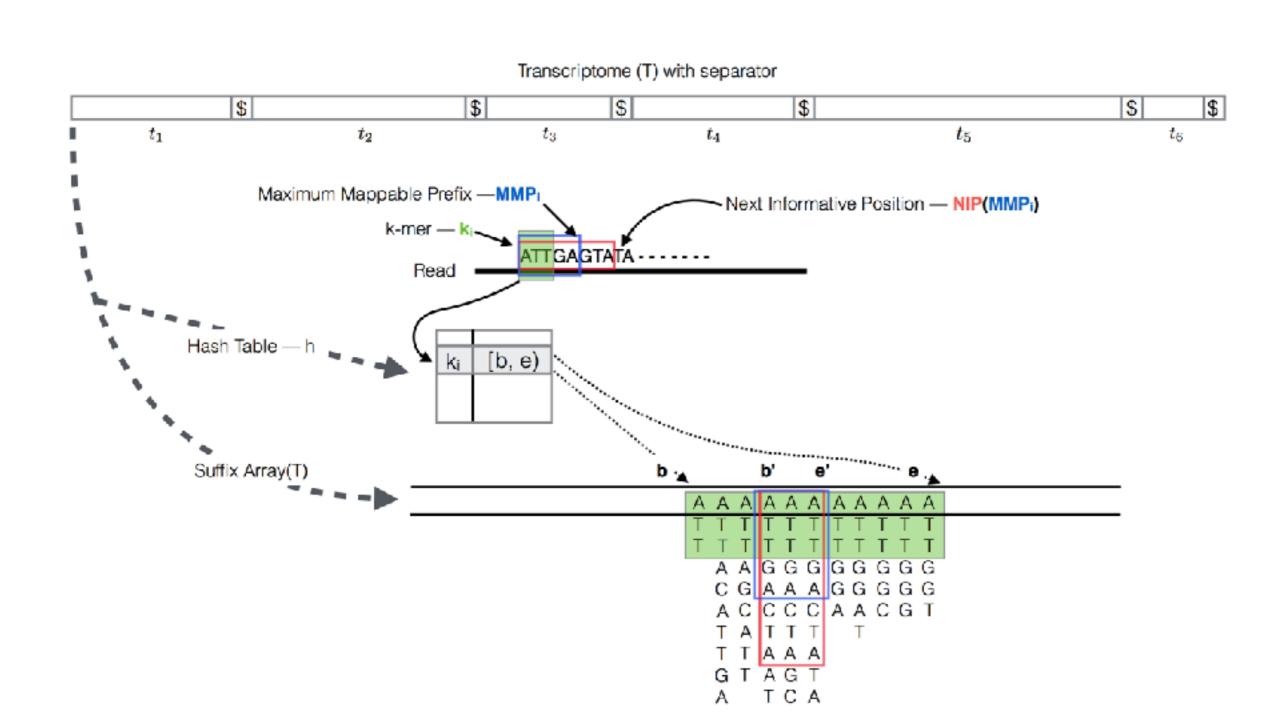
Moving from mapping to full alignment becomes very efficient (ongoing work).

Move from left to right along read, until we find a k-mer with non-empty SA interval.

Compute Maximum Mappable Prefix (MMP) starting with this k-mer — logarithmic in k-mers SA interval

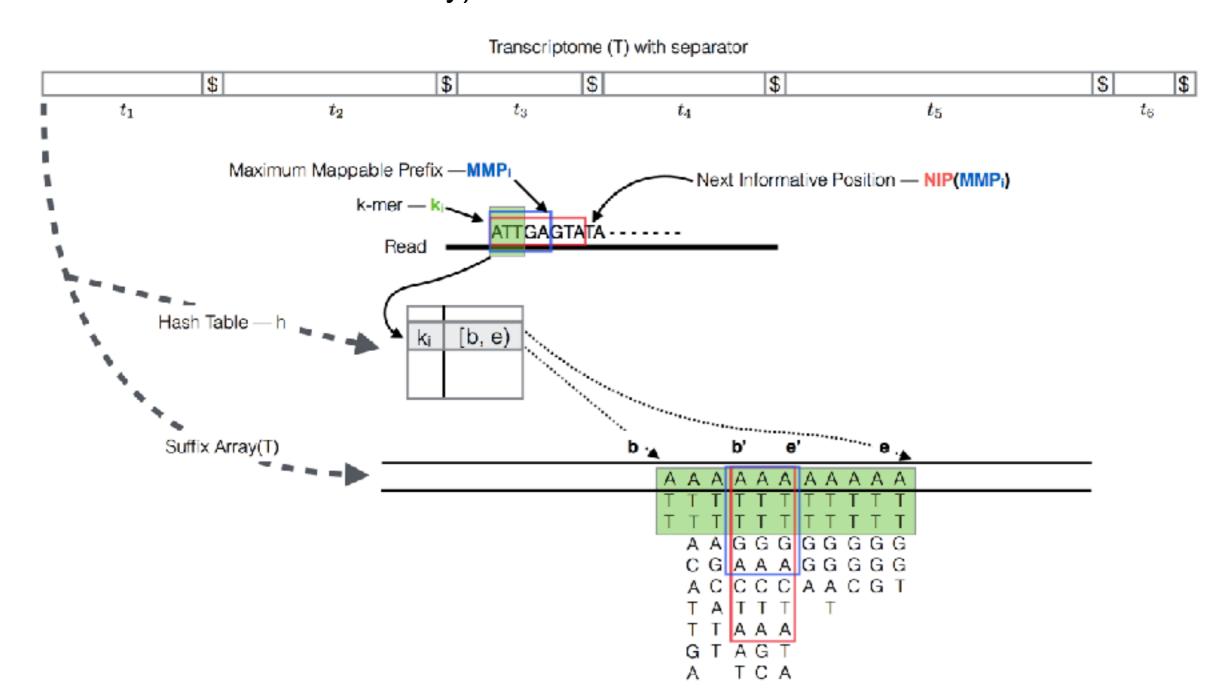


Compute NIP of this MMP — (fast) linear in read length



Compute NIP of this MMP — (fast) linear in read length

intuitively: NIP jumps you to the next exon boundary overlapping the read (need not be an actual exon boundary)

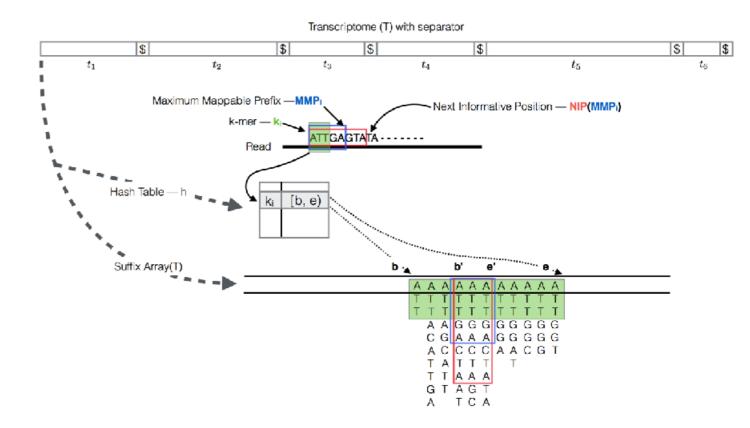


Produces a set of disjoint hits over each query (read).

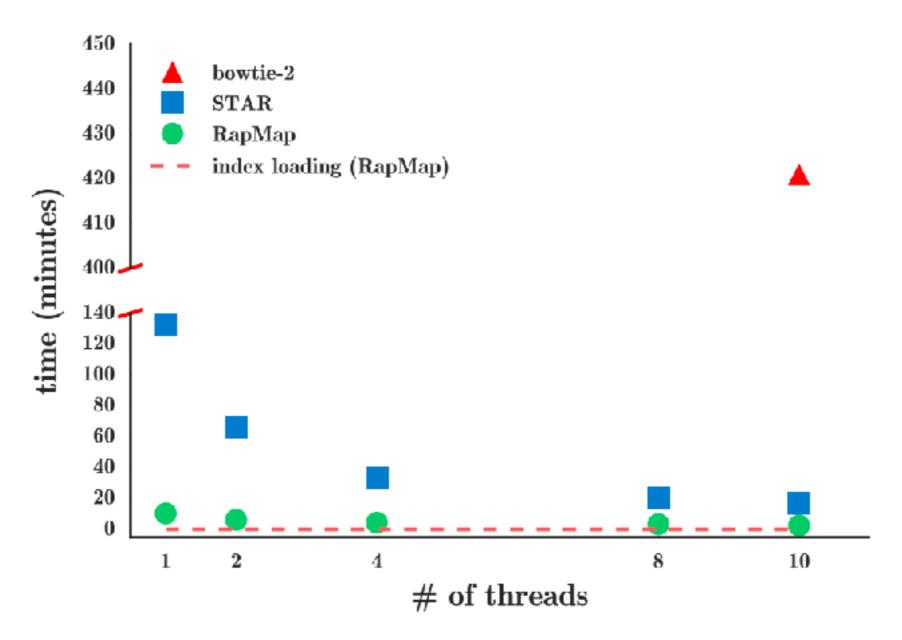
A hit is a tuple — (query offset, orientation, length, SA-interval)

Mappings are determined by a *consensus* mechanism over hits:

- default: a read maps to a transcript if that transcript appears in every hit for that read.
- other (stricter or looser) mechanisms are trivial to enforce (e.g. co-linearity of hits wrt read & reference).



Quasi-mapping is Fast



Can map **75 million paired-end reads** (76 bp) to the human transcriptome in matter of **minutes**; even with few threads.

Note: High degree of multi-mapping and inability to report top "stratum" means Bowtie2 is often reporting more than the "best" mapping (though it's commonly used in this context).

Quasi-mapping is Accurate

	Bowtie 2	Kallisto	RapMap	STAR
reads aligned	47579567	44804857	47613536	44711604
recall	97.41	91.60	97.49	91.35
precision	98.31	97.72	98.48	97.02
F1-score	97.86	94.56	97.98	94.10
FDR	1.69	2.28	1.52	2.98
hits per read	5.98	5.30	4.30	3.80

Bowtie 2: BWT-based aligner RapMap: SA-based quasi-mapper

Kallisto: dBG-based pseudoaligner STAR: SA-based aligner

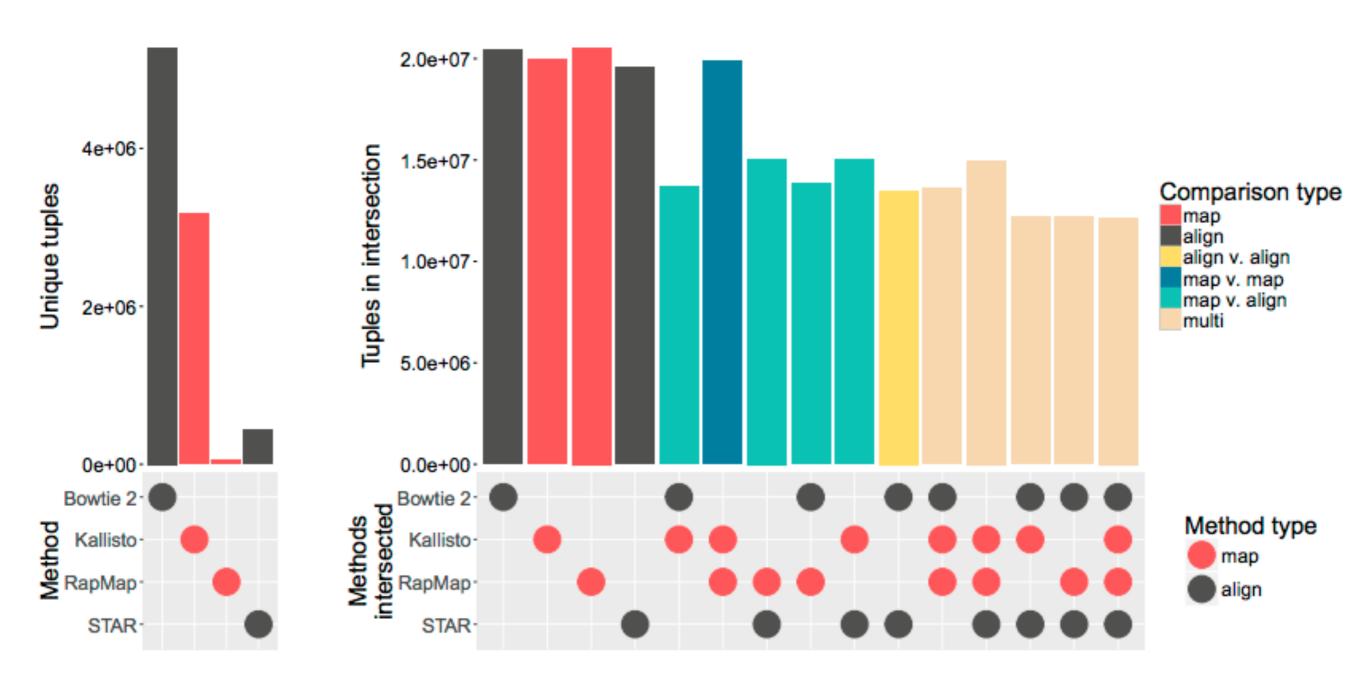
TP = True transcript of origin was in the set returned by the method

FP = Mappings were returned for the read, none of which were to the true transcript

FN = Read is un-mapped, but derives from the transcriptome

Hits per read = Avg. # of mappings returned for the reads How many *extra* mappings did we report?

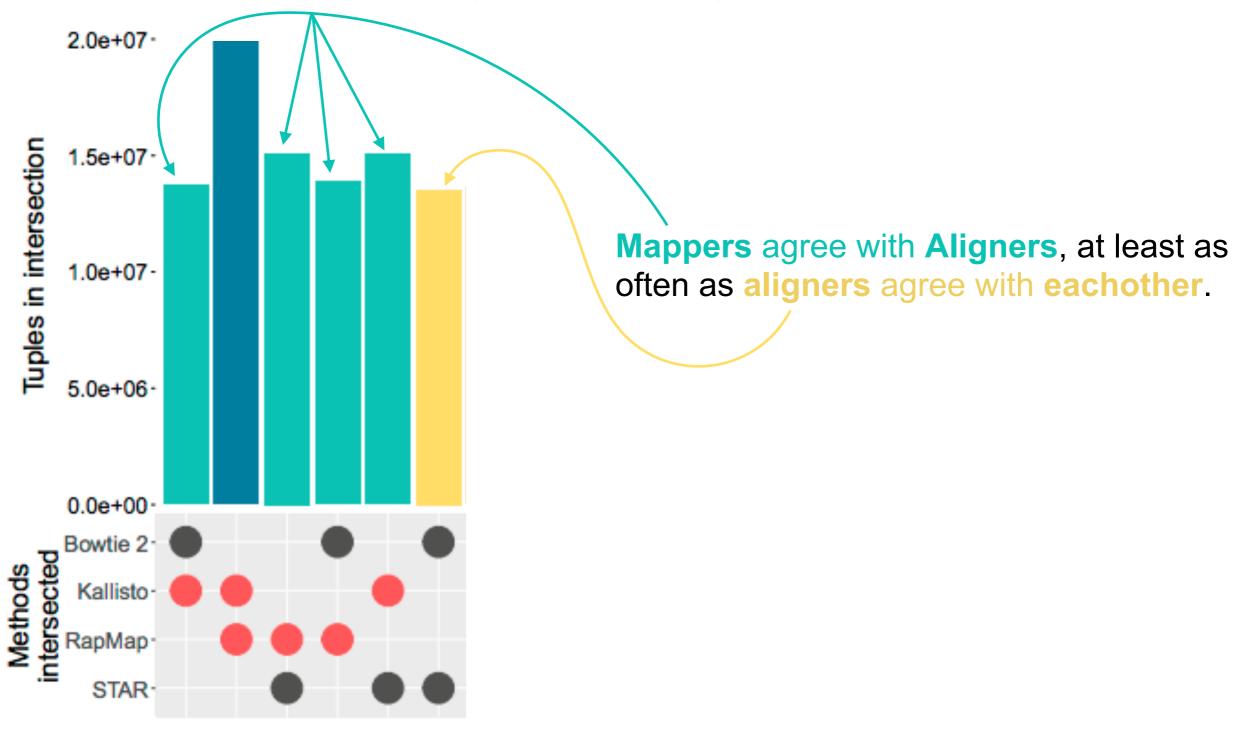
Quasi-mapping and Alignment Agree Well



A tuple consists of a read id and set of transcripts e.g. (r_i, {t₁, t₂, t₆})

Two methods *agree* on the mappings of a read if they return the same tuple; otherwise they disagree

Quasi-mapping and Alignment Agree Well



A tuple consists of a read id and set of transcripts e.g. (r_i, {t₁, t₂, t₆})

Two methods *agree* on the mappings of a read if they return the same tuple; otherwise they disagree

Where might we use quasi-mapping?

We believe there are *many* places where this replacement can be made. I'll discuss one in some depth (and mention a second):

1)Transcript-level quantification

- Determine abundance of transcripts from a collection of RNA-seq reads.
- The quasi-mapping information is sufficient to yield estimates as accurate as full alignment.

2) de novo transcript clustering

- Find groups of related contigs likely from the same transcript / gene
- Such groups help improve downstream analysis (e.g. differential expression testing)

Obviously, alignments are *necessary* for certain types of analysis (e.g. variant detection).