# Processing Terabyte Scale Genomics Datasets with ADAM

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### **Genome Resequencing**

- When we sequence a human genome, we obtain several hundred GB of raw sequence data
- With a reference genome, we can use this sequence to compute diffs between individuals
- Two problems:
  - How do we compute this diff?
  - How do we make sense of the differences?



#### **Building Scalable Genomics Tools on ADAM**

- ADAM is an open source, high performance, distributed library for genomic analysis
- ADAM defines a:
  - Data schema and layout on disk
  - Programming interface for distributed processing of genomic data using Spark + Scala
- Goal is to enable both batch and exploratory analysis of all types of genomic data



## Genomics is built around flattened, single node tools

- Legacy flat-file formats:
  - Manually curated text/binary flat files
  - E.g., SAM/BAM → alignment, VCF → variants, BED/GTF/etc → features
- These formats scale poorly beyond single computer storage/compute capacity
- These legacy formats are functionally limiting and bug-prone:
  - What accesses can be optimized (read a full row)
  - What predicates can be evaluated (small number of genomic loci)
  - How we write genomic algorithms (sorted iterator over genome)
  - How we avoid technical lock-in (extend metadata)



#### ADAM uses a schema as a narrow waist

**Application**Transformations

Users define analyses via transformations Variant calling & analysis, RNA-seq analysis, etc.

Presentation
Enriched Models

Enriched models provide convenient methods on common models

Enriched Read/Variant

Evidence Access MapReduce/DBMS

The evidence access layer efficiently executes transformations

Spark, Spark-SQL, Hadoop

Schema Data Models

Schemas define the logical structure of basic genomic objects

Avro Schema for reads, variants, and genotypes

Materialized Data Columnar Storage

Common interfaces map logical schema to bytes on disk

Load data from Parquet and legacy formats

Data Distribution
Parallel FS

Parallel file system layer coordinates distribution of data

HDFS, Tachyon, HPC file systems, S3

Physical Storage Attached Storage

Decoupling storage enables performance/cost tradeoff

Disk, SDD, block store, memory cache



#### ADAM uses a schema as a narrow waist

```
record AlignmentRecord {
    union { null, Contiq } contiq = null;
    union { null, long } start = null;
    union { null, long } end = null;
    union { null, int } mapq = null;
    union { null, string } readName = null;
    union { null, string } sequence = null;
    union { null, string } mateReference = null;
    union { null, long } mateAlignmentStart = null;
    union { null, string } cigar = null;
    union { null, string } qual = null;
   union { null, string } recordGroupName = null;
    union { int, null } basesTrimmedFromStart = 0;
   union { int, null } basesTrimmedFromEnd = 0;
    union { boolean, null } readPaired = false;
    union { boolean, null } properPair = false;
    union { boolean, null } readMapped = false;
    union { boolean, null } mateMapped = false;
   union { boolean, null } firstOfPair = false;
    union { boolean, null } secondOfPair = false;
   union { boolean, null } failedVendorQualityChecks = false;
    union { boolean, null } duplicateRead = false;
    union { boolean, null } readNegativeStrand = false;
    union { boolean, null } mateNegativeStrand = false;
    union { boolean, null } primaryAlignment = false;
    union { boolean, null } secondaryAlignment = false;
    union { boolean, null } supplementaryAlignment = false;
    union { null, string } mismatchingPositions = null;
    union { null, string } origQual = null;
    union { null, string } attributes = null;
    union { null, string } recordGroupSequencingCenter = null;
    union { null, string } recordGroupDescription = null;
    union { null, long } recordGroupRunDateEpoch = null;
    union { null, string } recordGroupFlowOrder = null;
   union { null, string } recordGroupKeySequence = null;
    union { null, string } recordGroupLibrary = null;
    union { null, int } recordGroupPredictedMedianInsertSize = null;
    union { null, string } recordGroupPlatform = null;
    union { null, string } recordGroupPlatformUnit = null;
    union { null, string } recordGroupSample = null;
    union { null, Contig } mateContig = null;
```

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#### ADAM uses a schema as a narrow waist

- ADAM has schemas for:
  - Reads: SAM/BAM/ CRAM, FASTQ
  - Features: BED/GTF/ GFF2,3/NarrowPeak/ IntervalList



Sequence: FASTA



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### Having a stack makes it easy to accelerate genomic queries

**Application**Transformations

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Enriched Models

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Schema
Data Models

Materialized Data Columnar Storage

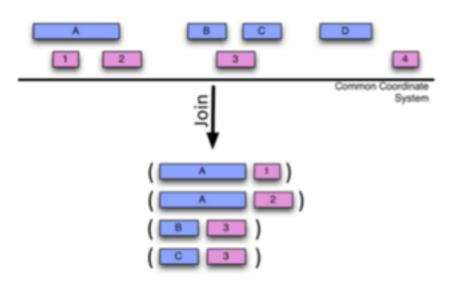
Data Distribution
Parallel FS

Physical Storage Attached Storage



#### ...while also providing higher level abstractions

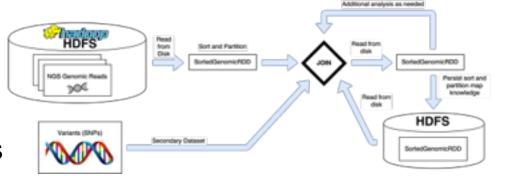
- ADAM eliminates need to use "genome walker":
  - Use region join for overlap computation
  - Use group/reduceByKey functions from Spark to process features aligned at a genomic coordinate point
- Can reduce targeted regions across a genome via sort + fold
- Higher level primitives enable optimizations:
  - Can leverage indices/sort orders
  - Can push down join/filter queries into storage

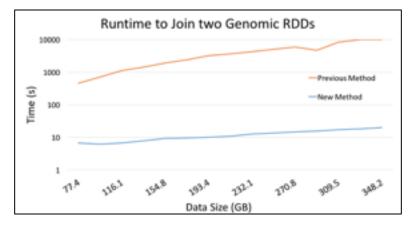




#### Higher level primitives enable optimizations

- Maintain sort order across runs and optimize to reduce data skew
- Leverage indices/sort orders
- Push down join/filter queries into storage
- Use join optimizations to develop BEDtools equivalent







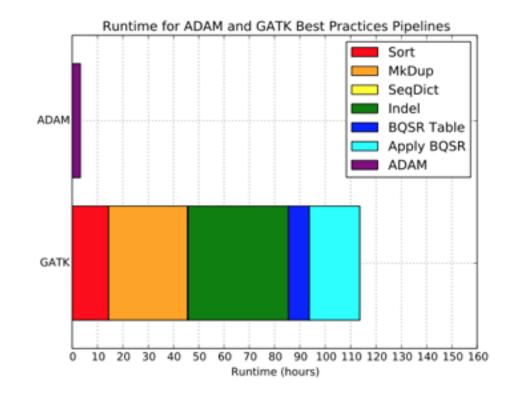
### **Big Data Genomics Stack**

gnocchi: avocado: mango: ADAM Scalable Parallel Fast, multi-Transforms: variant variant sample Read ETL analysis visualization calling Core ADAM APIs Apache spork Toil Apache GA4GH Legacy file formats Parquet (BAM/VCF) Schemas



### **Benchmarking ADAM**

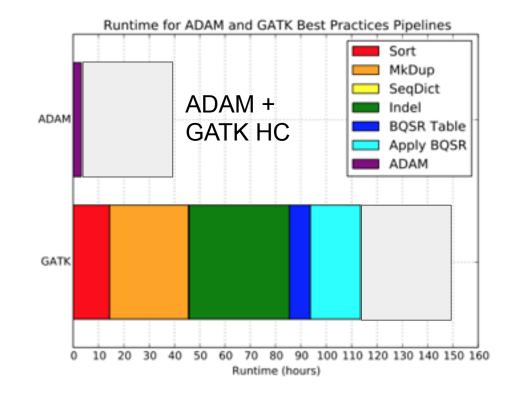
- ADAM produces statistically equivalent results to the GATK best practices pipeline
- Read preprocessing is >30x faster and 3x cheaper





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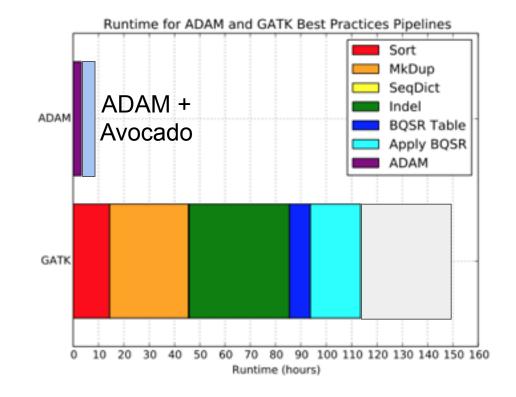
- ADAM produces statistically equivalent results to the GATK best practices pipeline
- Read preprocessing is >30x faster and 3x cheaper, end-to-end pipeline is 4x faster, 3.5x cheaper





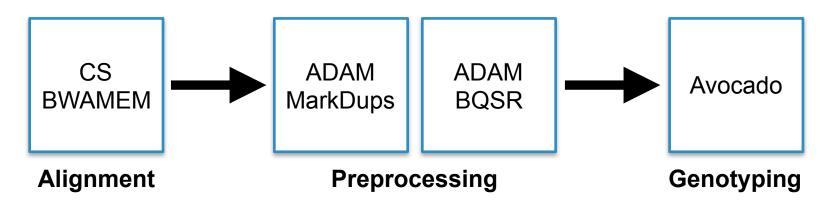
### **Benchmarking ADAM + Avocado**

- Avocado outperforms GATK at SNP calling, slightly behind on INDELs
- Overall pipeline is >17x faster and 2x cheaper
- Avocado relies on novel, efficient INDEL canonicalization engine, drops INDEL discovery cost by 5x





#### **End-to-end variant analysis in Spark**



- Can process a 65x whole genome in <2hrs on 1,024 cores</li>
- CS-BWAMEM: <a href="https://github.com/ytchen0323/cloud-scale-bwamem">https://github.com/ytchen0323/cloud-scale-bwamem</a>



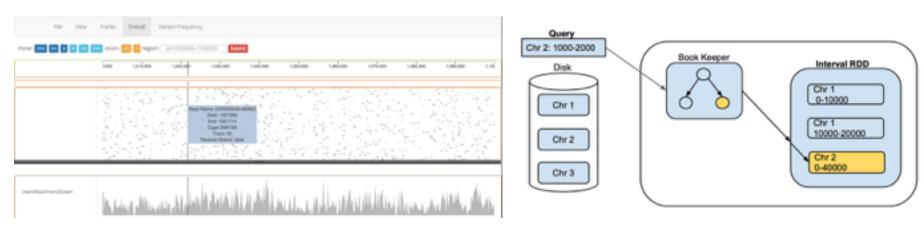
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### **Optimizing for genomic EDA**

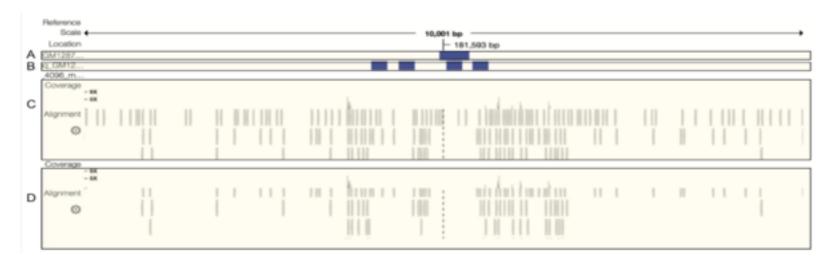


#### Narrow waist in stack → can swap in/out levels of stack

- For interactive queries against genomic loci, swap in RDD implementation optimized for point/range queries
- Persistent store optimizations minimize initial overhead for fetching raw data
- Memory optimizations minimize latency for genomic range queries



#### Benefit of stack: intersection of technologies



- Apply the model interactively to a new dataset using Mango, use join query to overlap "ground truth" data against predictions
- 10kbp query+apply latency: ~400ms



#### Ongoing work: variant warehousing

- Reads yield genotypes, but we're often interested in statistical aggregates across genotypes:
  - Probability of seeing a genotype in a population
  - Probability of a genotype associating with a phenotype
- Data typically is arriving (near) continuously



#### Demonstrating Incremental Update in Gnocchi

- Problem: want to compute associations between genotypes and phenotypes (linear/logistic regression)
- Solution: Incremental update of many small GnocchiModels
  - Train each distributed model using standard methods
  - When new data added, build locally optimized model on new data and merge resulting model with old model (do not need old data!)
- Work in progress:
  - Requires periodic recomputes over entire cohort to remain close to full recompute solution
  - Can limit the number of recomputes by being smart about haplotype blocks



### Acknowledgements

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- And many other open source contributors, especially Neil Ferguson, Andy Petrella, Xavier Tordior, Deborah Siegel, Denny Lee
- Over 60 contributors to ADAM/BDG from >12 institutions



### Thank You.

Check out the code: https://github.com/bigdatagenomics
Check out a demo: https://databricks.com/blog/2016/05/24/
genome-sequencing-in-a-nutshell.html
Run ADAM in Databricks CE: http://goo.gl/xK8x7s

