Exploring Isoform-specific Expression With R and Bioconductor

Michael Lawrence

Genentech

February 28, 2012

Michael Lawrence (Genentech)

Exploring Isoform-specific Expression

February 28, 2012 1 / 60

1 Introduction

Questions Approach

2 Implementation

Loading and Preparing the Data Finding and Annotating the Overlaps Interpreting the Results

Conclusion

Michael Lawrence (Genentech)

< (T) >

1 Introduction Questions Approach

Implementation

Loading and Preparing the Data Finding and Annotating the Overlaps Interpreting the Results

Onclusion

< 1 k

- Expression levels (from counts over exons and junctions)
- Structure (from the alignments)
- Variants (from the sequences)



February 28, 2012

- Expression levels (from counts over exons and junctions)
- Structure (from the alignments)
- Variants (from the sequences)



- Expression levels (from counts over exons and junctions)
- Structure (from the alignments)

• Variants (from the sequences)



- Expression levels (from counts over exons and junctions)
- Structure (from the alignments)
- Variants (from the sequences)



- Expression levels (from counts over exons and junctions)
- Structure (from the alignments)

Variants (from the sequences)



- Is an isoform expressed?
- What is the expression level of a particular isoform, and how can we compare it to that of other isoforms?
- Is the balance in isoform expression different across samples?



• Is an isoform expressed?

- What is the expression level of a particular isoform, and how can we compare it to that of other isoforms?
- Is the balance in isoform expression different across samples?



- Is an isoform expressed?
- What is the expression level of a particular isoform, and how can we compare it to that of other isoforms?
- Is the balance in isoform expression different across samples?



- Is an isoform expressed?
- What is the expression level of a particular isoform, and how can we compare it to that of other isoforms?
- Is the balance in isoform expression different across samples?



- Are there any unannotated isoforms present?
- How do we use them to derive novel structures? Is assembly feasible?



Questions about Isoform Structure

- Are there any unannotated isoforms present?
- How do we use them to derive novel structures? Is assembly feasible?



Questions about Isoform Structure

- Are there any unannotated isoforms present?
- How do we use them to derive novel structures? Is assembly feasible?



Introduction Questions Approach

Implementation

Loading and Preparing the Data Finding and Annotating the Overlaps Interpreting the Results

Onclusion

Michael Lawrence (Genentech)

< (T) >

- Run RNA-seq pipeline, and load concordant unique alignments
- Pind reads and isoforms with any exonic overlap
- Split the alignments into two bins: compatible with splicing, and incompatible
- ④ For the compatible, find reads that map uniquely to an isoform
- Sor the *incompatible*, find those indicating *novel* junctions or splice sites

- 1 Run RNA-seq pipeline, and load *concordant unique* alignments
- 2 Find reads and isoforms with any exonic overlap
- Split the alignments into two bins: compatible with splicing, and incompatible
- ④ For the compatible, find reads that map uniquely to an isoform
- For the *incompatible*, find those indicating *novel* junctions or splice sites



- Run RNA-seq pipeline, and load concordant unique alignments
- Find reads and isoforms with any exonic overlap
- Split the alignments into two bins: compatible with splicing, and incompatible
- ④ For the compatible, find reads that map uniquely to an isoform
- Sor the *incompatible*, find those indicating *novel* junctions or splice sites



- Run RNA-seq pipeline, and load concordant unique alignments
- 2 Find reads and isoforms with any exonic overlap
- Split the alignments into two bins: compatible with splicing, and incompatible
- ④ For the compatible, find reads that map uniquely to an isoform
- Sor the *incompatible*, find those indicating *novel* junctions or splice sites



Steps

- Run RNA-seq pipeline, and load concordant unique alignments
- Pind reads and isoforms with any exonic overlap
- Split the alignments into two bins: compatible with splicing, and incompatible
- For the *compatible*, find reads that map *uniquely* to an isoform
- For the *incompatible*, find those indicating *novel* junctions or splice sites



< A >

February 28, 2012 8 / 60

∃ ► < ∃ ►

Steps

- Run RNA-seq pipeline, and load concordant unique alignments
- Pind reads and isoforms with any exonic overlap
- Split the alignments into two bins: compatible with splicing, and incompatible
- Generation For the compatible, find reads that map uniquely to an isoform
- For the *incompatible*, find those indicating *novel* junctions or splice sites



글 🕨 🖌 글

Steps

- Run RNA-seq pipeline, and load concordant unique alignments
- 2 Find reads and isoforms with any exonic overlap
- Split the alignments into two bins: compatible with splicing, and incompatible
- Generation For the compatible, find reads that map uniquely to an isoform
- For the *incompatible*, find those indicating *novel* junctions or splice sites



- 4 回 ト - 4 回 ト

- To be *compatible* a read must align completely within the exons and the read gaps should exactly match the introns over the read extent
- To be *uniquely mapped* a read must be compatible with only a single isoform



- To be *compatible* a read must align completely within the exons and the read gaps should exactly match the introns over the read extent
- To be *uniquely mapped* a read must be compatible with only a single isoform



- To be *compatible* a read must align completely within the exons and the read gaps should exactly match the introns over the read extent
- To be *uniquely mapped* a read must be compatible with only a single isoform



- To be *compatible* a read must align completely within the exons and the read gaps should exactly match the introns over the read extent
- To be *uniquely mapped* a read must be compatible with only a single isoform



- To be *compatible* a read must align completely within the exons and the read gaps should exactly match the introns over the read extent
- To be *uniquely mapped* a read must be compatible with only a single isoform



Levels of novelty

- Inconclusive
- Novel combination of events
- Novel junction
- Novel splice site



Levels of novelty

- Inconclusive
- Novel combination of events
- Novel junction
- Novel splice site



Levels of novelty

- Inconclusive
- Novel combination of events
- Novel junction
- Novel splice site



Levels of novelty

- Inconclusive
- Novel combination of events
- Novel junction
- Novel splice site



Levels of novelty

- Inconclusive
- Novel combination of events
- Novel junction
- Novel splice site



Levels of novelty

- Inconclusive
- Novel combination of events
- Novel junction
- Novel splice site



Introduction Questions Approach

2 Implementation

Loading and Preparing the Data Finding and Annotating the Overlaps Interpreting the Results

Onclusion

- Illumina paired-end 75nt RNA-seq reads from two matched human tissue samples: tumor and normal
- Strand inferred during alignment from splice directions
- Stored in a BAM file
- Subset to the ALDOA (aldolase) gene
Introduction Questions Approach

2 Implementation

Loading and Preparing the Data

Finding and Annotating the Overlaps Interpreting the Results

Conclusion

We need two types of data for the analysis:

- 1 Transcript annotations (gene models)
- 2 Read alignments from the two samples

For this demonstration, we will focus on the ALDOA gene.

To load the data, we need the genomic interval of ALDOA.

```
> aldoa_eg <- org.Hs.egSYMBOL2EG$ALDOA
> txdb <- TxDb.Hsapiens.UCSC.hg19.knownGene
> aldoa_gr <- exons(txdb, vals = list(gene_id = aldoa_eg),
+ columns = c("tx_id", "gene_id"))
> aldoa_range <- range(aldoa_gr)</pre>
```

Simplest method is calling exonsBy, but its API does not support restrictive queries, or extra columns. Thus, we form our models directly from aldoa_gr:

- > aldoa_vals <- values(aldoa_gr)</pre>
- > values(aldoa_gr) <- NULL</pre>
- > tx <- multisplit(aldoa_gr, aldoa_vals\$tx_id)</pre>
- > tx_to_val <- match(names(tx), unlist(aldoa_vals\$tx_id))</pre>
- > values(tx)\$gene_id <-</pre>
- + rep(unlist(aldoa_vals\$gene_id),
- + elementLengths(aldoa_vals\$tx_id))[tx_to_val]

> values(tx)\$tx_id <- names(tx)</pre>

As an alternative to last slide, use exonsBy and subsetByOverlaps to get the basic transcript structures for the ALDOA gene. *Bonus: get the gene_id my merging with transcripts return value.*

As an alternative to last slide, use exonsBy and subsetByOverlaps to get the basic transcript structures for the ALDOA gene. Bonus: get the gene_id my merging with transcripts return value.

Solution

+

- > exons_grl <- exonsBy(txdb)</pre>
- > ans <- subsetByOverlaps(exons_grl, aldoa_range)</pre>
- > values(ans)\$tx_id <- names(ans)</pre>
- > tx_gr <- transcripts(txdb, columns = c("tx_id", "gene_id")</pre>
- > values(ans)\$gene_id <-</pre>
- + drop(values(tx_gr)\$gene_id)[match(names(ans),
 - values(tx_gr)\$tx_id)]

3

Would be trivial in our case, but here is a general demonstration:

```
> gene_id_keys <-
+ values(tx)$gene_id[!is.na(values(tx)$gene_id)]
> tx_gene_sym <- rep.int(NA, length(tx))
> tx_gene_sym[!is.na(values(tx)$gene_id)] <-
+ unlist(mget(gene_id_keys, org.Hs.egSYMBOL,
+ ifnotfound = NA),
+ use.names = FALSE)
</pre>
```

> values(tx)\$gene_sym <- tx_gene_sym</pre>

Just take my word for it:

> tx <- tx[c(2, 4, 5, 7)]

Reading the Alignments

We obtain the normal BAM file for demonstration purposes:

```
> extdatadir <- system.file("extdata",
+ package = "isoformExprTutorial")
> files <- tools::list_files_with_exts(extdatadir, "bam")
> names(files) <- tools::file_path_sans_ext(basename(files))
> bamFiles <- Rsamtools::BamFileList(files)
> bam <- bamFiles$normal</pre>
```

And read it into a GappedAlignments object:

> param <- ScanBamParam(tag = "XS", which = aldoa_range)
> ga <- readGappedAlignments(path(bam),
+ use.names = TRUE,
+ param = param)</pre>

We request the XS tag, the strand as determined by the aligner from the splice directions.

Michael Lawrence (Genentech)

The grglist function returns the alignment ranges as a GRangesList.

- > reads <- grglist(ga)</pre>
- > metadata(reads)\$bamfile <- bam</pre>

We store the BAM path in the metadata to track provenance.

Store the ScanBamParam object in the metadata.

æ

Store the ScanBamParam object in the metadata.

Solution

> metadata(reads)\$param <- param</pre>

э

We use a custom function, elementGaps, to find the gaps within each element of the *GRangesList*:

- > splices <- elementGaps(reads)</pre>
- > values(splices)\$XS <- values(reads)\$XS</pre>

All metadata needs to be carried over explicitly.

```
> elementGaps <- function(reads) {
+    psetdiff(unlist(range(reads), use.names=FALSE), reads)
+ }</pre>
```

Problem: the call to range(reads) is painfully slow.

24 / 60

elementGaps: Optimization via partitioning

>	<pre>elementGaps <- function(x) {</pre>
+	x_flat <- unlist(x, use.names = FALSE)
+	egaps <- gaps(ranges(x))
+	first_segment <- start(PartitioningByWidth(x))
+	<pre>sn <- seqnames(x_flat)[first_segment][togroup(egaps)]</pre>
+	<pre>strand <- strand(x_flat)[first_segment][togroup(egaps)]</pre>
+	<pre>relist(GRanges(sn, unlist(egaps, use.names = FALSE),</pre>
+	<pre>strand, seqlengths = seqlengths(x)),</pre>
+	egaps)
+	}

Assumption

Strand and chromosome is the same within the elements, i.e., no trans-splicing, genomic rearrangements, etc.

Use a *PartitioningByWidth* to find the start of the first exon in each transcript.

Use a *PartitioningByWidth* to find the start of the first exon in each transcript.

Solution

- > tx_part <- PartitioningByWidth(tx)</pre>
- > tx_flat <- unlist(tx, use.names = FALSE)</pre>
- > start(tx_flat)[start(tx_part)]
- [1] 30064411 30075600 30075818 30076994

We depend on each end of a pair sharing the same name:

```
> pairs <- split(unlist(reads, use.names=FALSE),
+ factor(names(reads)[togroup(reads)],
+ unique(names(reads))))
> metadata(pairs) <- metadata(reads)</pre>
```

XS information is shared within pairs:

```
> xs <- values(reads)$XS
> has_xs <- !is.na(xs)
> pair_xs <- setNames(rep.int(NA, length(pairs)),
+ names(pairs))
> pair_xs[names(reads)[has_xs]] <- xs[has_xs]
> values(pairs)$XS <- unname(pair_xs)</pre>
```

The mapping is direct, except NA maps to *.

```
> xs <- values(pairs)$XS
> strand <- ifelse(!is.na(xs) & xs != "?", xs, "*")
> strand(pairs) <- relist(Rle(strand, elementLengths(pairs))
+ pairs)</pre>
```

We have factored the preceding code into two functions.

- > splices <- pairReadRanges(splices)</pre>
- > splices <- strandFromXS(splices)</pre>

- > normal <- readReadRanges(bamFiles\$normal)</pre>
- > tumor <- readReadRanges(bamFiles\$tumor)</pre>

Introduction Questions Approach

2 Implementation

Loading and Preparing the Data Finding and Annotating the Overlaps Interpreting the Results

Onclusion

-

Steps

- Run RNA-seq pipeline, and load concordant unique alignments
- 2 Find reads and isoforms with any exonic overlap
- Split the alignments into two bins: compatible with splicing, and incompatible
- G For the compatible, find reads that map uniquely to an isoform
- For the *incompatible*, find those indicating *novel* junctions or splice sites



Steps

- Run RNA-seq pipeline, and load concordant unique alignments
- Pind reads and isoforms with any exonic overlap
- Split the alignments into two bins: compatible with splicing, and incompatible
- Generation For the compatible, find reads that map uniquely to an isoform
- For the *incompatible*, find those indicating *novel* junctions or splice sites



> hits <- findOverlaps(pairs, tx)</pre>

æ

Michael Lawrence (Genentech)

- > hit_pairs <- ranges(pairs)[queryHits(hits)]</pre>
- > hit_splices <- ranges(splices)[queryHits(hits)]</pre>
- > hit_tx <- ranges(tx)[subjectHits(hits)]</pre>

Memory inefficient, but permits vectorized operations

Steps

- Run RNA-seq pipeline, and load concordant unique alignments
- Pind reads and isoforms with any exonic overlap
- Split the alignments into two bins: compatible with splicing, and incompatible
- G For the compatible, find reads that map uniquely to an isoform
- For the *incompatible*, find those indicating *novel* junctions or splice sites



Steps

- Run RNA-seq pipeline, and load concordant unique alignments
- 2 Find reads and isoforms with any exonic overlap
- Split the alignments into two bins: compatible with splicing, and incompatible
- ④ For the compatible, find reads that map uniquely to an isoform
- For the *incompatible*, find those indicating *novel* junctions or splice sites



Compatibility Checking

- > read_within <-</pre>
- + elementLengths(setdiff(hit_pairs, hit_tx)) == OL
- > tx_within <-
- + elementLengths(intersect(hit_tx, hit_splices)) == OL
- > compatible <- read_within & tx_within</pre>



Steps

- Run RNA-seq pipeline, and load concordant unique alignments
- 2 Find reads and isoforms with any exonic overlap
- Split the alignments into two bins: compatible with splicing, and incompatible
- ④ For the compatible, find reads that map uniquely to an isoform
- For the *incompatible*, find those indicating *novel* junctions or splice sites



Steps

- 1 Run RNA-seq pipeline, and load concordant unique alignments
- 2 Find reads and isoforms with any exonic overlap
- 3 Split the alignments into two bins: *compatible* with splicing, and incompatible
- 4 For the compatible, find reads that map *uniquely* to an isoform
- **5** For the *incompatible*, find those indicating novel junctions or splice sites



February 28, 2012 37 / 60

э

We find the compatible hits where the read is represented only once:

> compat_hits <- hits[compatible]</pre>

- > reads_unique <- tabulate(queryHits(compat_hits),</pre>
- + queryLength(compat_hits)) == 1L
- > unique <- logical(length(hits))</pre>
- > unique[compatible] <- reads_unique[queryHits(compat_hits)]</pre>

Like any other Vector, Hits can have element metadata:

```
> strand_specific <-
+ all(strand(pairs) != "*")[queryHits(hits)]
> values(hits) <- DataFrame(strand_specific,
+ compatible,
+ unique)</pre>
```

Add a column to the hits element metadata indicating whether the read had a splice (ignoring XS tag and assuming all reads are paired).

February 28, 2012

40 / 60

Add a column to the hits element metadata indicating whether the read had a splice (ignoring XS tag and assuming all reads are paired).

Solution

- > values(hits)\$spliced <-</pre>
- + (elementLengths(pairs) > 2)[queryHits(hits)]

Steps

- Run RNA-seq pipeline, and load concordant unique alignments
- 2 Find reads and isoforms with any exonic overlap
- Split the alignments into two bins: compatible with splicing, and incompatible
- For the *compatible*, find reads that map *uniquely* to an isoform
- For the *incompatible*, find those indicating *novel* junctions or splice sites


Overview of Algorithm

Steps

- 1 Run RNA-seq pipeline, and load concordant unique alignments
- 2 Find reads and isoforms with any exonic overlap
- 3 Split the alignments into two bins: *compatible* with splicing, and incompatible
- 4 For the compatible, find reads that map *uniquely* to an isoform
- **5** For the *incompatible*, find those indicating *novel* junctions or splice sites



< 47 ▶

- ∢ ∃ → February 28, 2012 41 / 60

э

Junction Counting

Simplest algorithm: form keys from GRanges and hashing.

Key generator

```
> gr2key <- function(x) {
+ paste(seqnames(x), start(x), end(x), strand(x),
+ sep = ":")
+ }</pre>
```

Key Parser

```
> key2gr <- function(x, ...) {
+ key_mat <- matrix(unlist(strsplit(x, ":", fixed=TRUE)),
+ nrow = 4)
+ GRanges(key_mat[1,],
+ IRanges(as.integer(key_mat[2,]),
+ as.integer(key_mat[3,])),
+ key_mat[4,], ...)
+ }</pre>
```

- > introns <- elementGaps(tx)</pre>
- > introns_flat <- unlist(introns, use.names = FALSE)</pre>
- > tx_keys <- gr2key(introns_flat)</pre>
- > splices_flat <- unlist(splices, use.names = FALSE)</pre>
- > splice_table <- table(gr2key(splices_flat))</pre>
- > splice_summary <-</pre>
- + key2gr(names(splice_table),
- + score = as.integer(splice_table),
- + novel = !names(splice_table) %in% tx_keys,
- + seqlengths = seqlengths(splices))

< 4 → <

```
> countByTx <- function(x) {
+ tabulate(subjectHits(hits)[x], subjectLength(hits))
+ }
> compatible_strand <-
+ countByTx(with(values(hits),
+ compatible & strand_specific))
> counts <- DataFrame(compatible_strand,
+ lapply(values(hits)[-1], countByTx))</pre>
```

- > normal_hits <- findIsoformOverlaps(normal)</pre>
- > normal_counts <- countIsoformHits(normal_hits)</pre>
- > normal_splices <- summarizeSplices(normal)</pre>
- > tumor_hits <- findIsoformOverlaps(tumor)</pre>
- > tumor_counts <- countIsoformHits(tumor_hits)</pre>
- > tumor_splices <- summarizeSplices(tumor)</pre>

Introduction Questions Approach

2 Implementation

Loading and Preparing the Data Finding and Annotating the Overlaps Interpreting the Results

Conclusion

We reshape the data into a *SummarizedExperiment*:

> assays <- mapply(cbind, normal_counts, tumor_counts, + SIMPLIFY = FALSE)

- > colData <- DataFrame(tumorStatus = c("tumor", "normal"))</pre>
- > rownames(colData) <- colData\$tumorStatus</pre>
- > se <- SummarizedExperiment(assays, tx, colData)</p>

We use a Fisher Test to check whether the balance is shifting between top two isoforms (by uniquely mapped reads), between tumor and normal.

Get Uniquely Mapped Reads

```
> getUniqueReads <- function(reads, hits) {</pre>
```

```
+ sel <- values(hits)$unique &
```

```
+ subjectHits(hits) %in% c(1, 4)
```

+ reads[unique(queryHits(hits)[sel])]

```
+ }
```

+

```
> normal_uniq <- getUniqueReads(normal, normal_hits)</pre>
```

```
> tumor_uniq <- getUniqueReads(tumor, tumor_hits)</pre>
```

```
> both_uniq <- mstack(normal = unlist(normal_uniq),</pre>
```

```
tumor = unlist(tumor_uniq))
```

49 / 60

Get Uniquely Mapped Splices

> normal_uniq_splices <- summarizeSplices(normal_uniq)</pre>

> tumor_uniq_splices <- summarizeSplices(tumor_uniq)</pre>

> uniq_splices <- mstack(normal = normal_uniq_splices, + tumor = tumor_uniq_splices) We leverage the autoplot function from ggbio:

```
> read_track <- autoplot(uniq_splices, geom = "arch",</pre>
                           aes(size = score.
+
+
                               height = width / 5),
+
                           color = "deepskyblue3",
+
                           ylab = "coverage",
                           facets = name \sim .) +
+
    stat_coverage(both_uniq, facets = name ~ .)
+
> tx_16 <- keepSeqlevels(tx, "chr16")</pre>
                                                              "")
> tx_track <- autoplot(tx_16, geom = "alignment", ylab =</pre>
> tracks(read_track, tx_track, heights = c(3, 1))
```

51 / 60

Coverage Plot



◆□▶ ◆□▶ ◆臣▶ ◆臣▶ 臣 のへで

The xlim argument restricts the genomic interval:

>	<pre>tracks(read_track,</pre>
+	tx_track , heights = $c(3, 1)$,
+	xlim = c(30075000, 30080000))

Zoomed Coverage Plot



◆□▶ ◆□▶ ◆三▶ ◆三▶ ○○ のへで

Problem

Zoom to a similar region of interest by finding a window around the tallest peaks. Hint: coverage and slice would be useful here.

Problem

Zoom to a similar region of interest by finding a window around the tallest peaks. Hint: coverage and slice would be useful here.

Solution

- > cov_chr16 <- coverage(both_uniq)\$chr16</pre>
- > roi <- range(ranges(slice(cov_chr16, 1000)))</pre>
- > roi <- roi + 500
- > tracks(read_track,
- + tx_track , heights = c(3, 1),
- + xlim = roi)

Get the Novel Splices

```
> all_splices <- mstack(normal = normal_splices,
+ tumor = tumor_splices)
> novel_splices <-
+ all_splices[values(all_splices)$novel &
+ values(all_splices)$score == 9]
> uniq_novel_splices <- c(uniq_splices, novel_splices)</pre>
```

글 에 에 글 에

3

This time, we specify the color = novel aesthetic:

```
> novel_track <- autoplot(uniq_novel_splices, geom = "arch",</pre>
+
                            aes(size = score,
+
                                height = width / 5,
+
                                color = novel).
+
                            ylab = "coverage",
                            facets = name \sim .) +
+
+
    stat_coverage(both_uniq, facets = name ~ .)
  tracks(novel_track, tx_track, heights = c(3, 1),
         xlim = roi)
+
```

Coverage Plot, with Novel Junctions



◆□▶ ◆□▶ ◆□▶ ◆□▶ ● ● ●

Introduction Questions Approach

Implementation

Loading and Preparing the Data Finding and Annotating the Overlaps Interpreting the Results

3 Conclusion

э

- Use the right data structure for the right job
- Take advantage of metadata facilities
- Long ragged arrays: partitioning faster than looping over lists