An analysis of splicing variation across SRA with Rail-RNA

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Johns Hopkins University Genome Informatics 2015

in genomics

use lots
of prior
knowledge
study lots
ab initio

in RNA-seq analysis

use gene
annotation:
quantify with/
align to known
transcripts

avoid gene
annotation:
look at
expressed
regions (ERs) /
junctions in
lots of data

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Picked this side to study merits/drawbacks

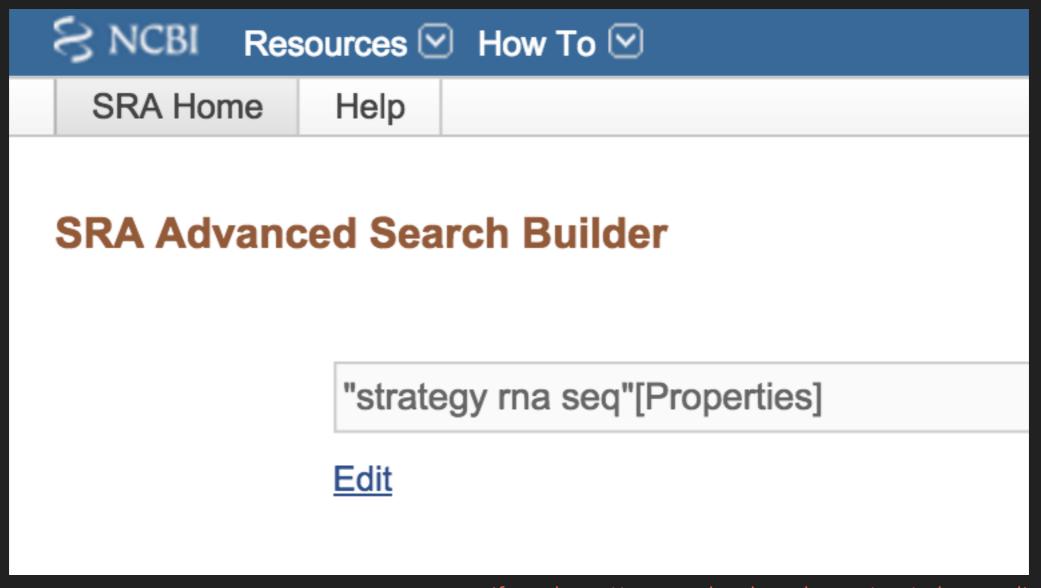
Study many RNA-seq samples

SRA: short reads hard to assemble; missing exons in 60% of transcripts
(RGASP 2013 doi:10.1038/nmeth.2714)

exon 1 exon 2 exon 3

=> Compare exon-exon junctions found across SRA RNA-seq with annotated junctions

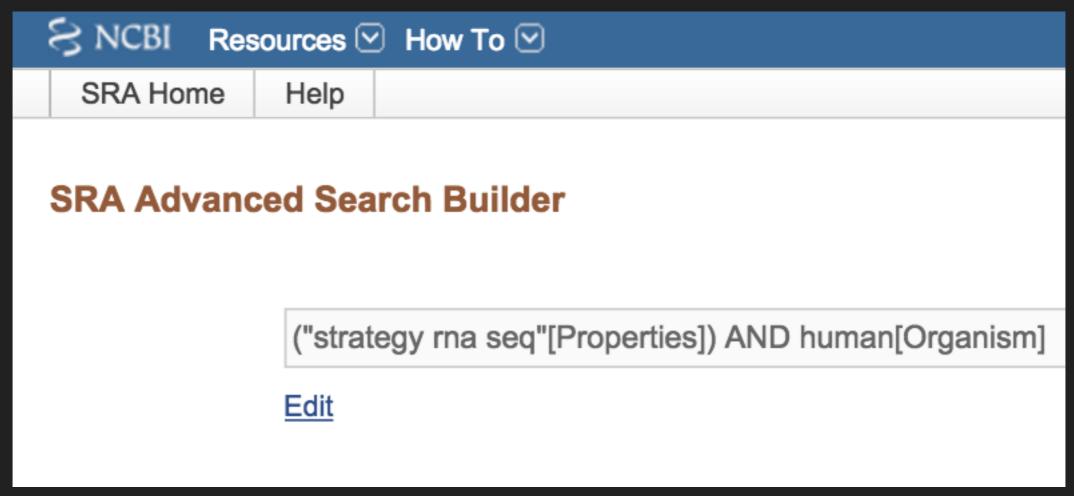
Filtering SRA



(from http://www.ncbi.nlm.nih.gov/sra/advanced)

 ≈ 180 K publicly available runs

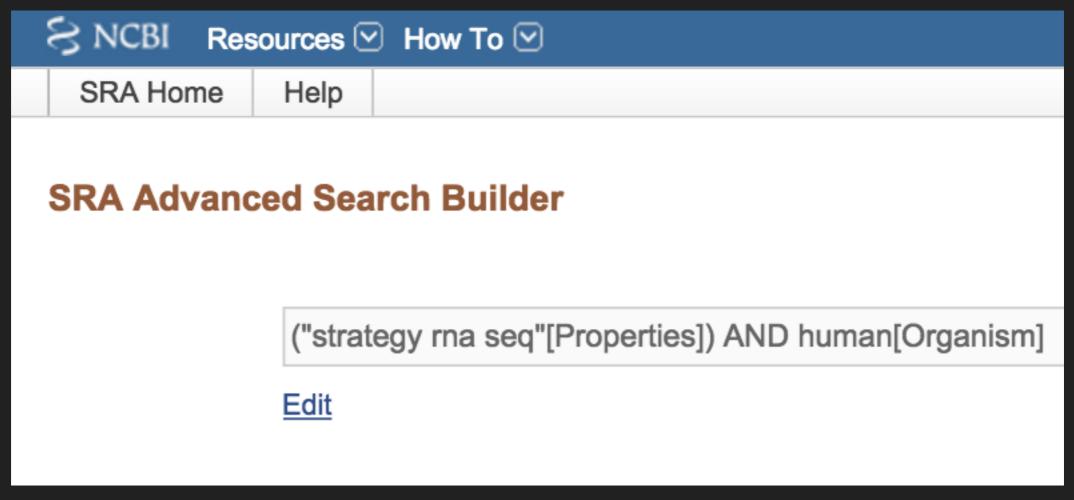
Filtering SRA



(from http://www.ncbi.nlm.nih.gov/sra/advanced)



Filtering SRA



(from http://www.ncbi.nlm.nih.gov/sra/advanced)

+ Illumina instruments[Properties]



How to find junctions across 21,504 RNA-seq runs?

(62 terabases of reads)







- No competition for compute
- Rapid: 8 days to data
- Reproducible:
 - http://github.com/nellore/gi2015 for commands (& goodies!)
- Cheap: ~\$0.70/sample

What gene annotation says

For *hg19*,

Ensembl v75 GENCODE v19 RefSeq

(almost subsumed by Ensembl v75)

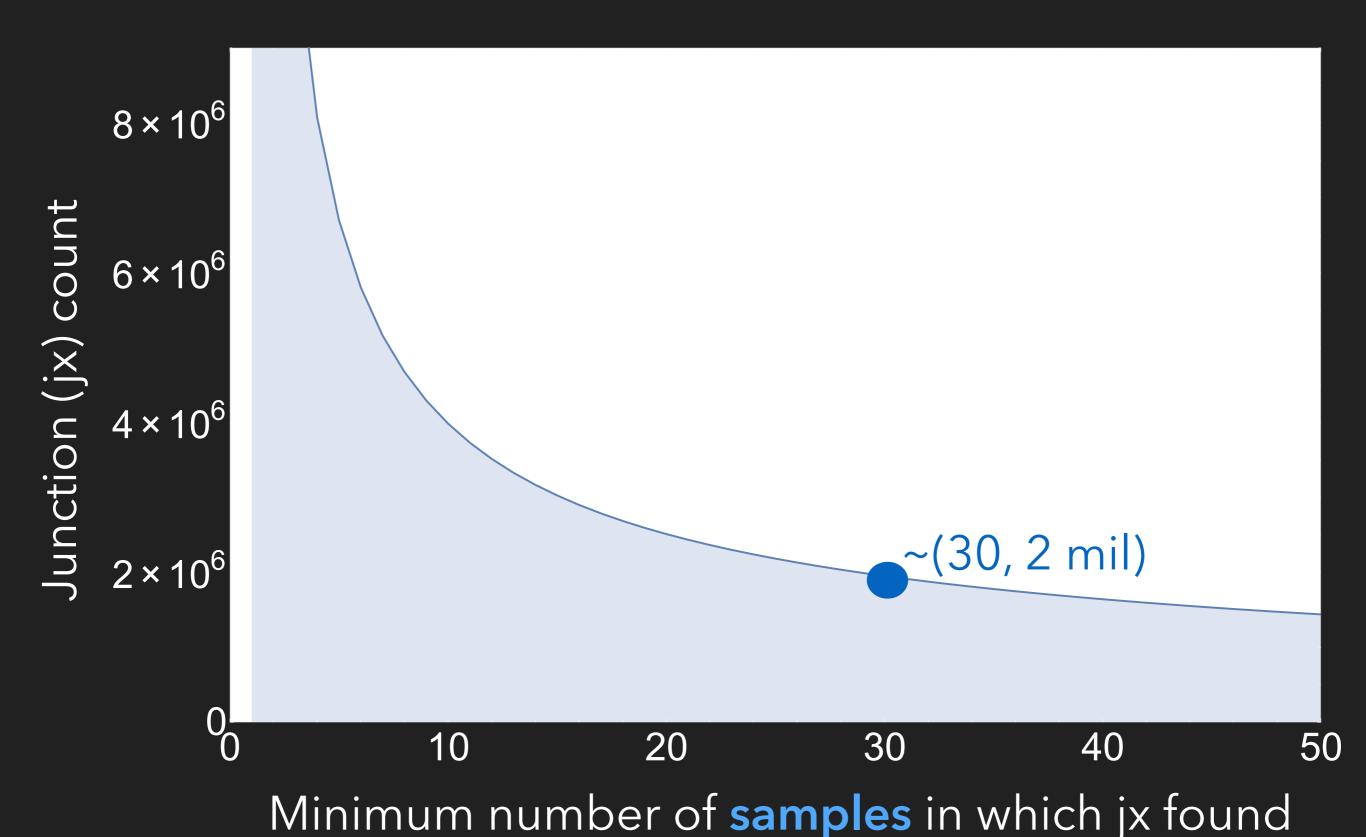
junctions

2 commands X 43 batches gave, across 21,504 samples

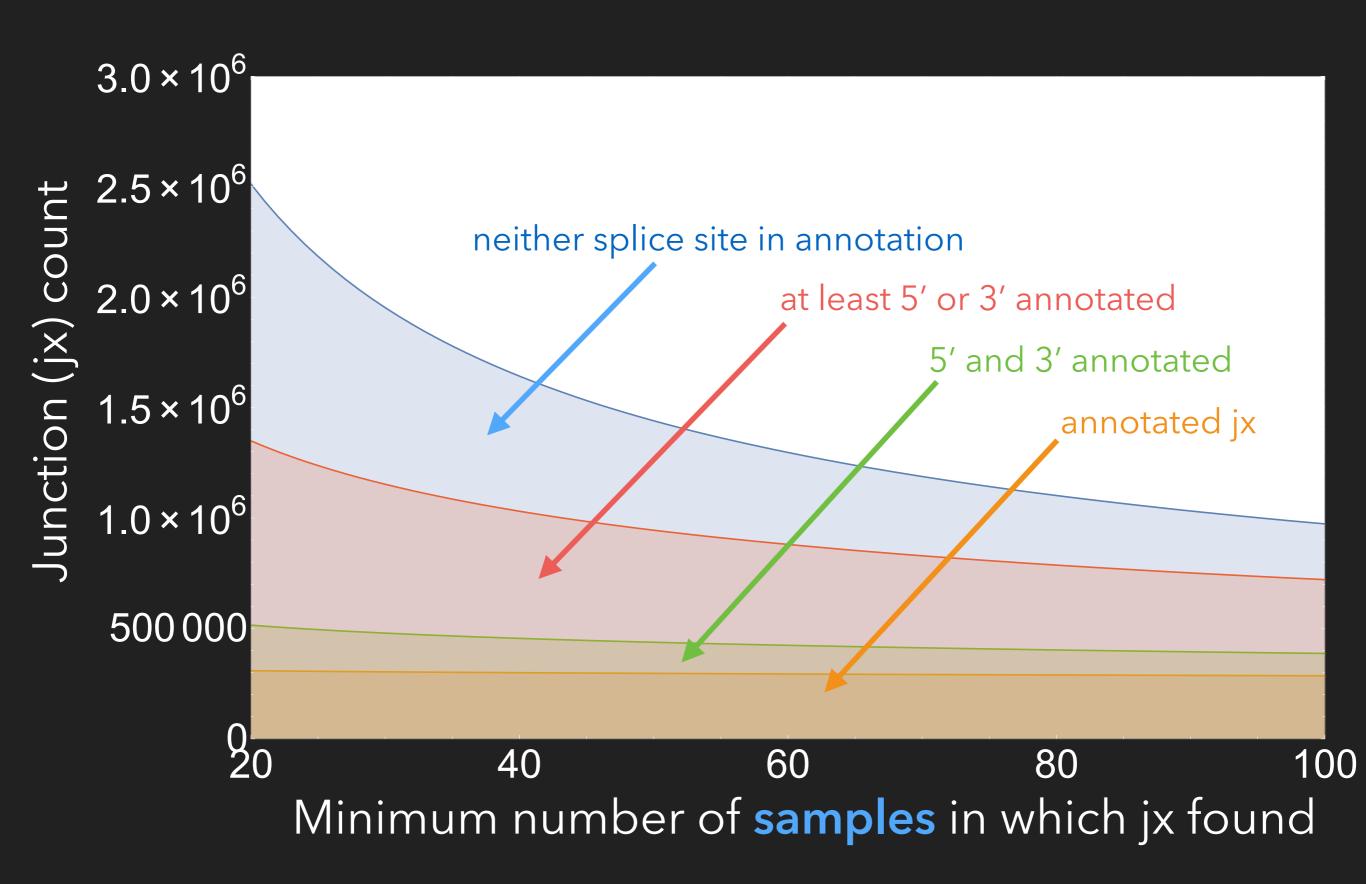
One 7-GB tsv.gz

junctions

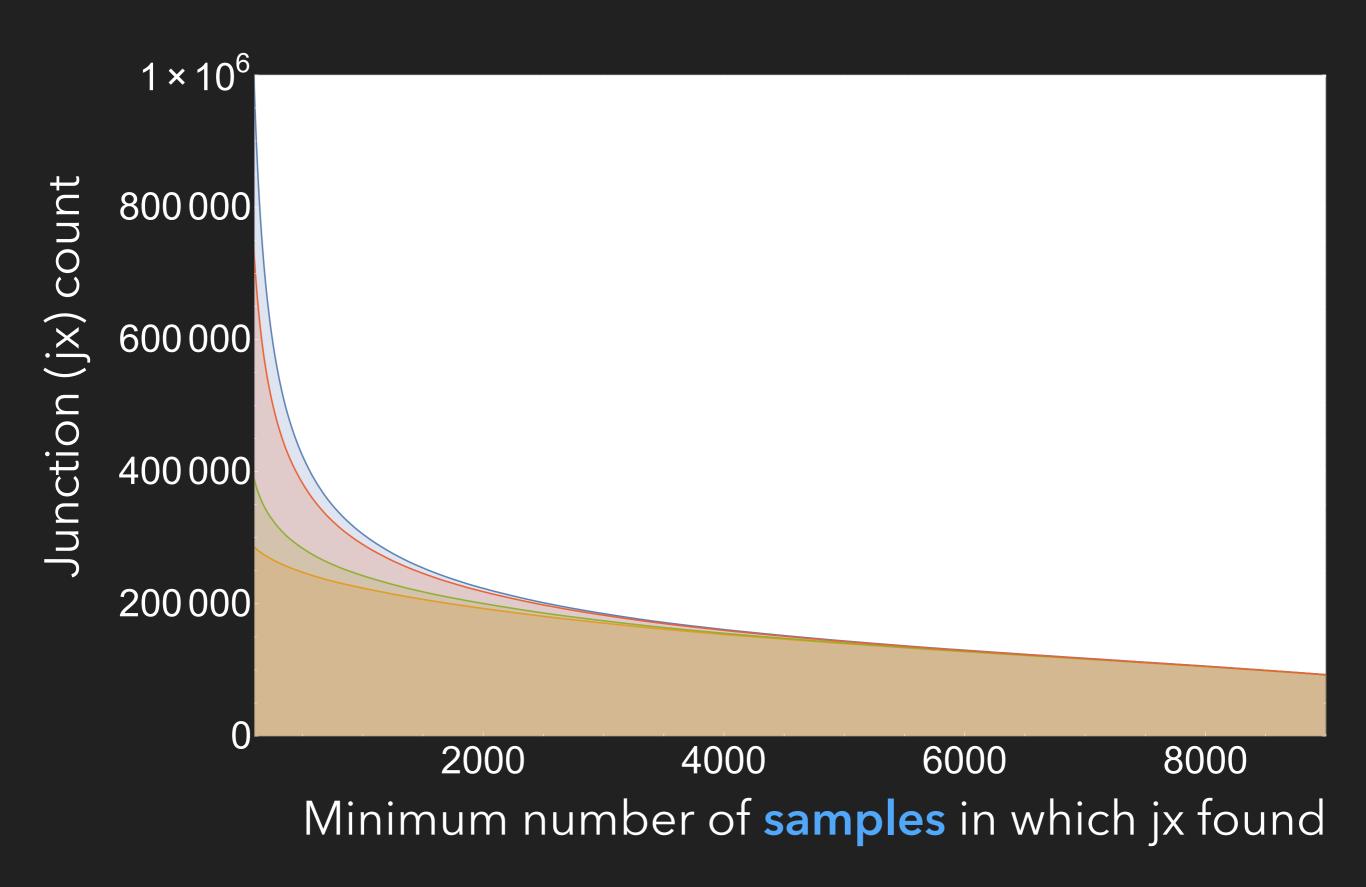
A steep dropoff



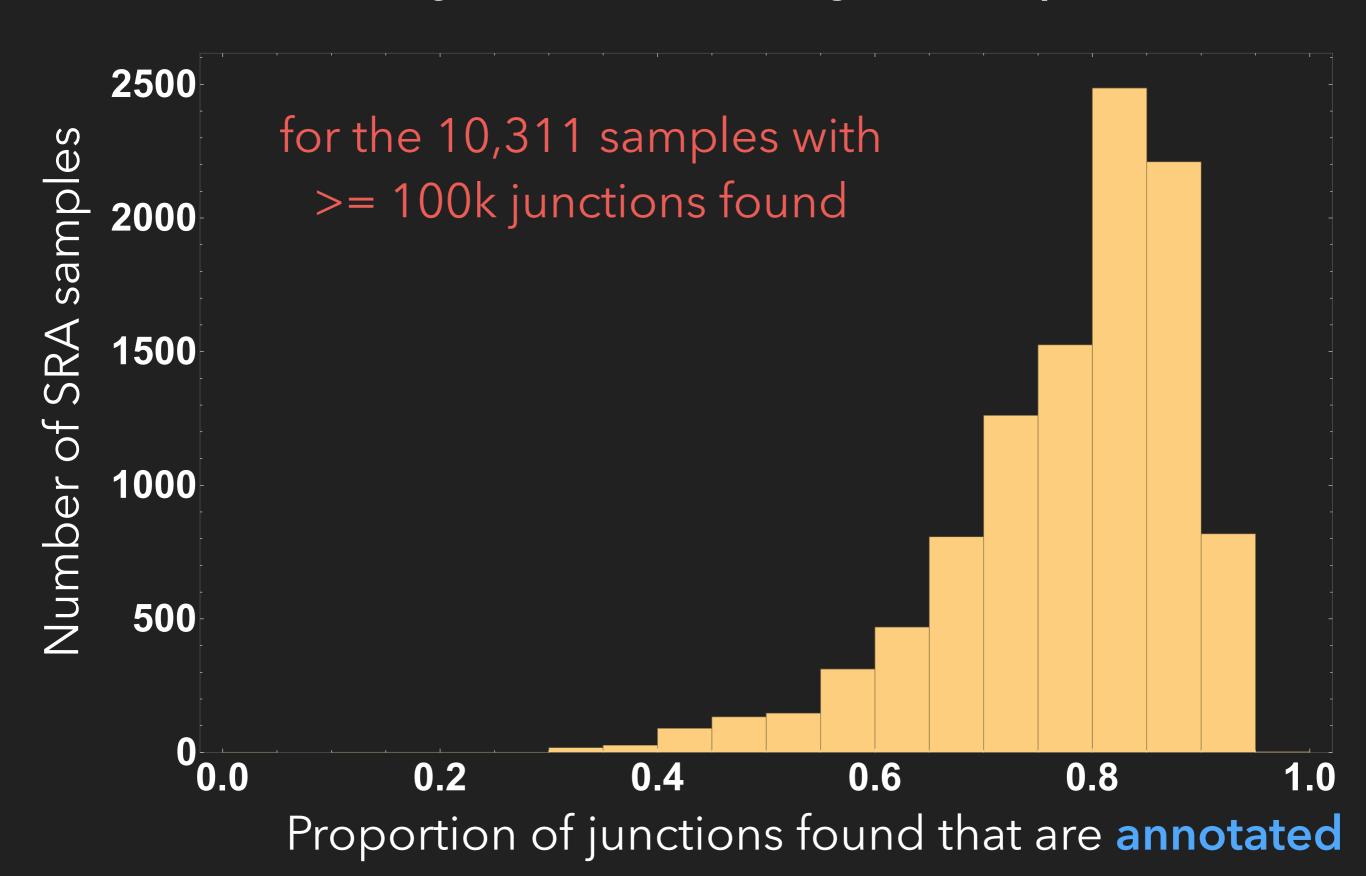
Increasing evidence in annotation



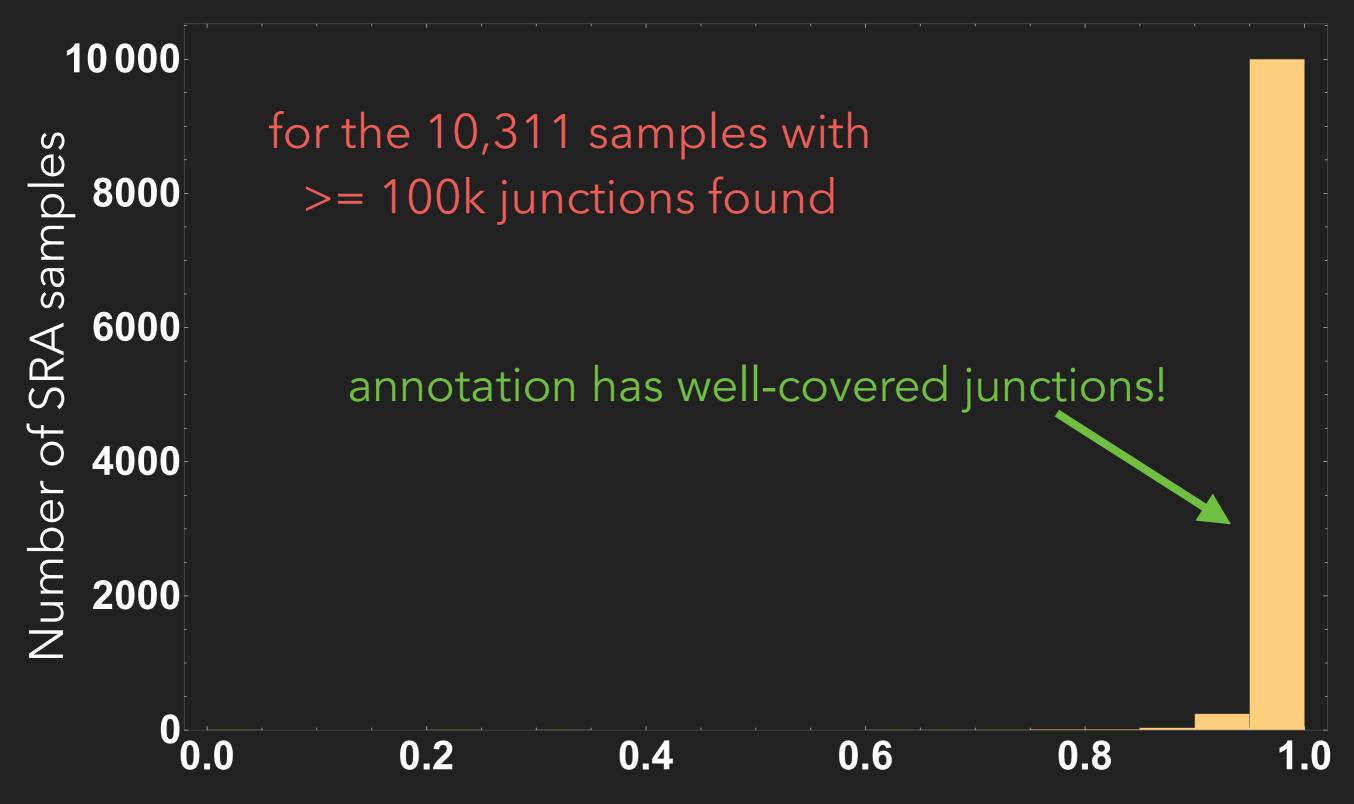
Asymptote to annotation



Annotated junctions by sample

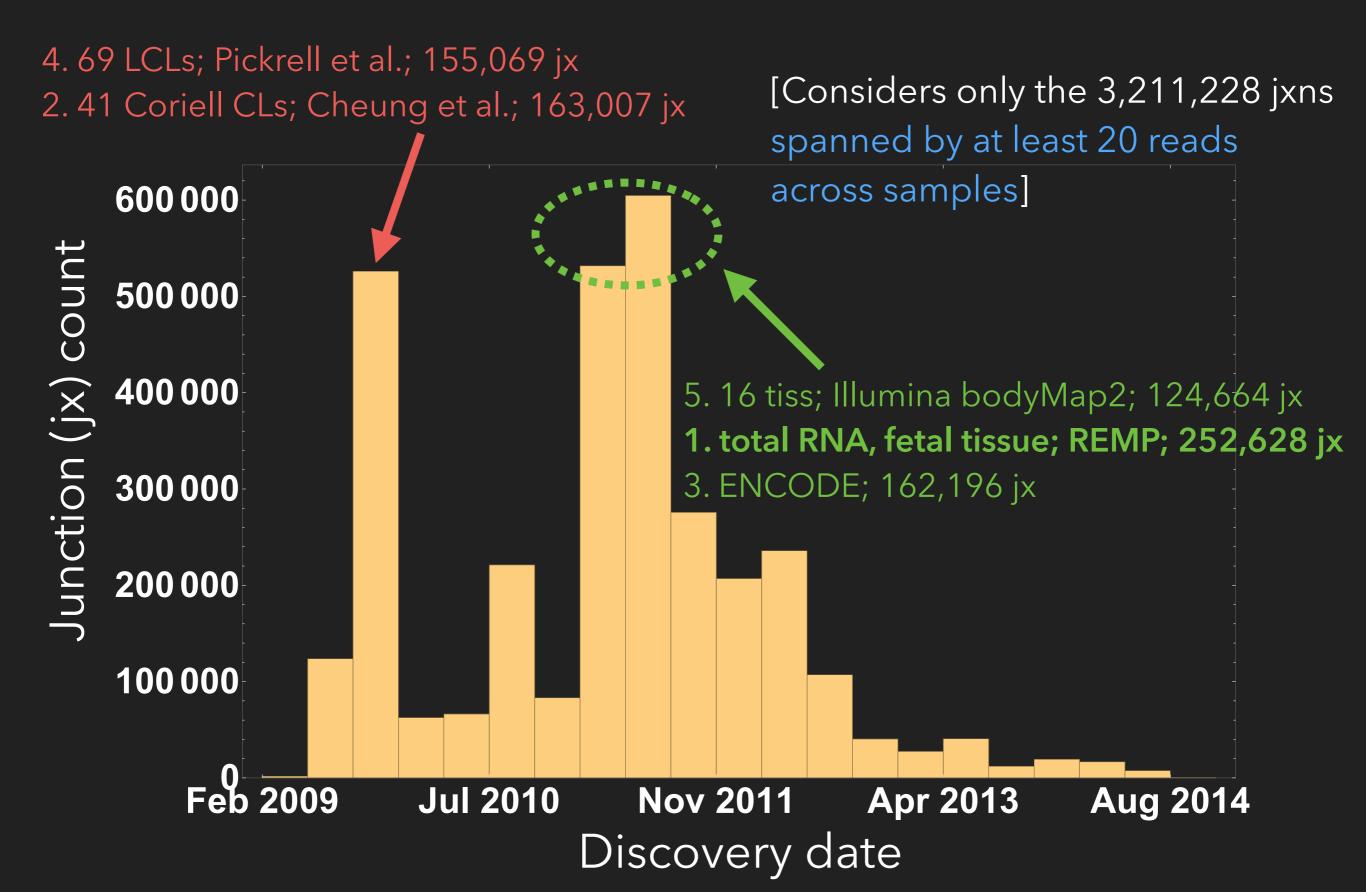


Junction (jx) overlaps by sample



Proportion of jx overlaps for which jx is annotated

Are we still finding new junctions?



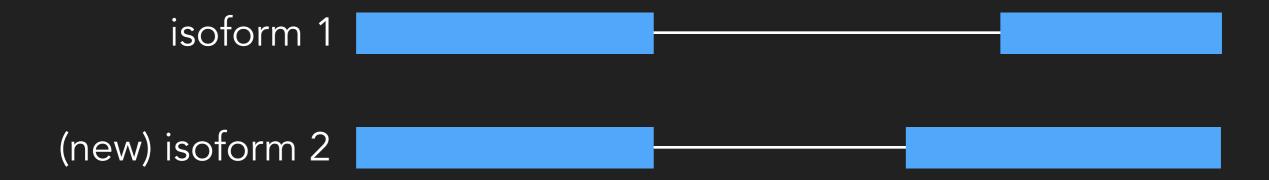
So just make annotation better!

Not so fast.

Gedankenexperiments

More complete annotation = better! Increased sensitivity

(Can detect isoform 2 now!)



More complete annotation = worse!

Decreased specificity

(What if isoform 2 is really rare?)

Rail-RNA's approach

Realign after collecting and filtering a list of junctions across **SIMILAR** samples.

intron

 $exttt{..}$ ATACATCAGACTAGACCGTACCACA $exttt{GT}$ AGTTCATGACCCTC $exttt{AG}$ CAGCATGACAGTCATTCGACGTACTGGTATCGATACAGTACAGTAGCC $exttt{..}$

chr1

CATAGCATGACAGTCATTCGACGTACTCGTATCGATACAGTACAGTAGCC

read 2 found to overlap junction on realignment



similar: same feature to which you want to be sensitive

cell line, tissue type, population, experimental condition...

Junction (jx) filter

Keep a junction if and only if it's initially detected in:

(1) 5% of samples

OR

(2) at least 5 reads in any one sample

grabs common jx

so we don't miss jx
 that are probably
 there but unique to
 a sample

Comparison

Simulate from annotation, then give competitors annotation

112 simulated LCLs (based on GEUVADIS)

mean overlap accuracy value I mean junction accuracy value

	Precisions	Recalls	F-scores
TopHat 2 ann	.815 .947	.839 .982	.826 .964
STAR ann	.882 .977	.874 .980	.878 .979
HISAT ann	.895 .922	.857 .982	.875 .951
Rail	.969 .976	.858 .939	.910 .957

(http://j.mp/rail-pre)

annotation-agnostic pipeline



http://rail.bio

derfinder

biocLite("derfinder")



Leo Collado-Torres



Alyssa Frazee

sidesteps
assembly &
annotation limitations
resolves
isoform-level
features

derfinder finds unannotated (D)ERs

8.3% of age-associated DERsoutside annotated genes across72 prefrontal cortex samples:

Jaffe et al. (Nat Neuro, doi:10.1038/nn.3898)

6.9% of ERs outside annotated genes across 465 GEUVADIS LCLs: Nellore et al. (j.mp/rail-pre)

scripts for recovering junctions



processed data



http://github.com/nellore/gi2015

Collaborators



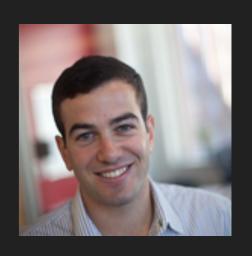
Jeff Leek



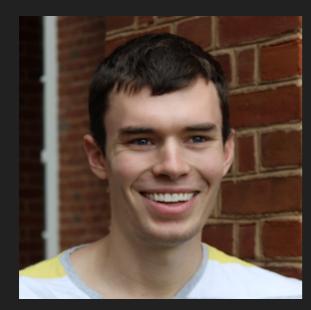
Ben Langmead



Leo Collado-Torres



Andrew Jaffe



Jacob Pritt



Chris Wilks



José Alquicira Hernández

Summer interns: Nishika Karbhari, James Morton, Robert Phillips, Sara Wang

Why so many junctions?

junctions

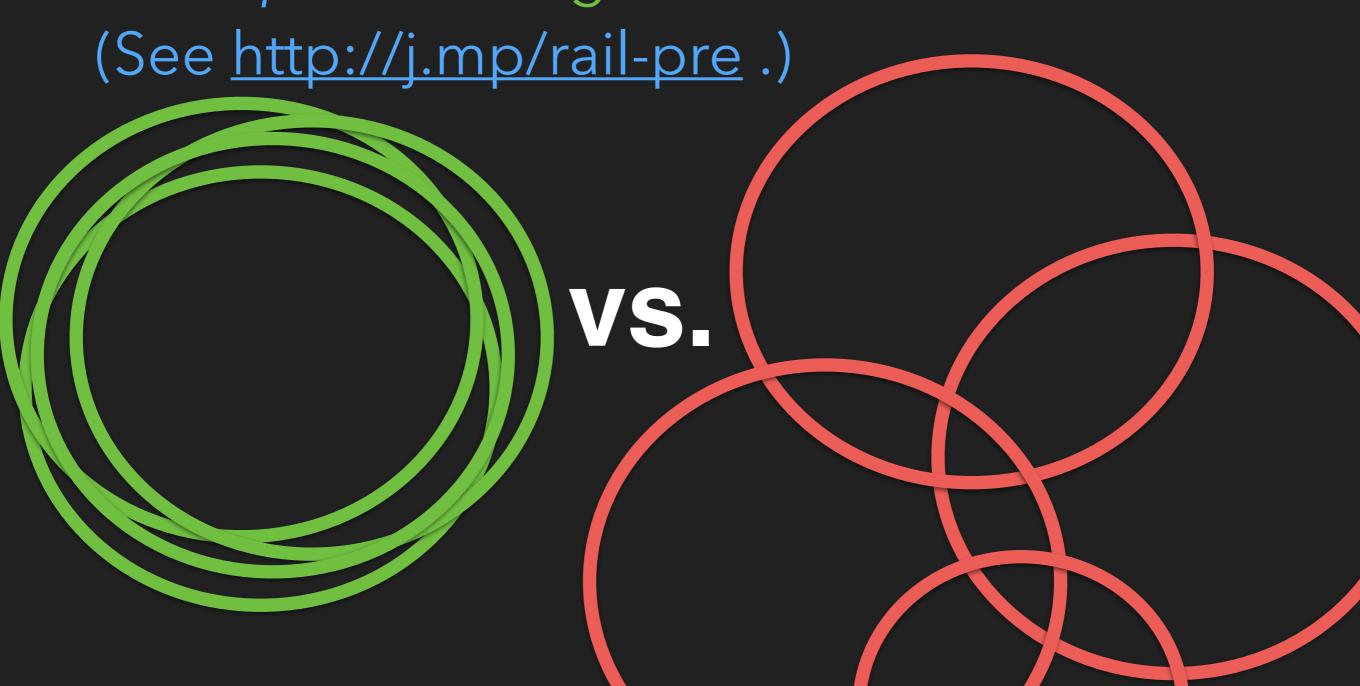
duds

goods

On a single sample, every aligner will find some good junctions and some duds (or very rare junctions).

Why so many junctions?

Comparing the junctions found in many simulated samples, there is *much more overlap* between goods than between duds.



Why so many junctions?

junctions junctions duds duds So as you add samples... goods goods

We ran

```
(~500 runs)
rail-rna prep elastic
--manifest batch X.tsv
--core-instance-count 20
--output s3://bucket/batch X prepped
--core-instance-bid-price 0.13
--master-instance-bid-price 0.13
--core-instance-type c3.2xlarge
--master-instance-type c3.2xlarge
       for X \in \{0, ..., 42\}
```

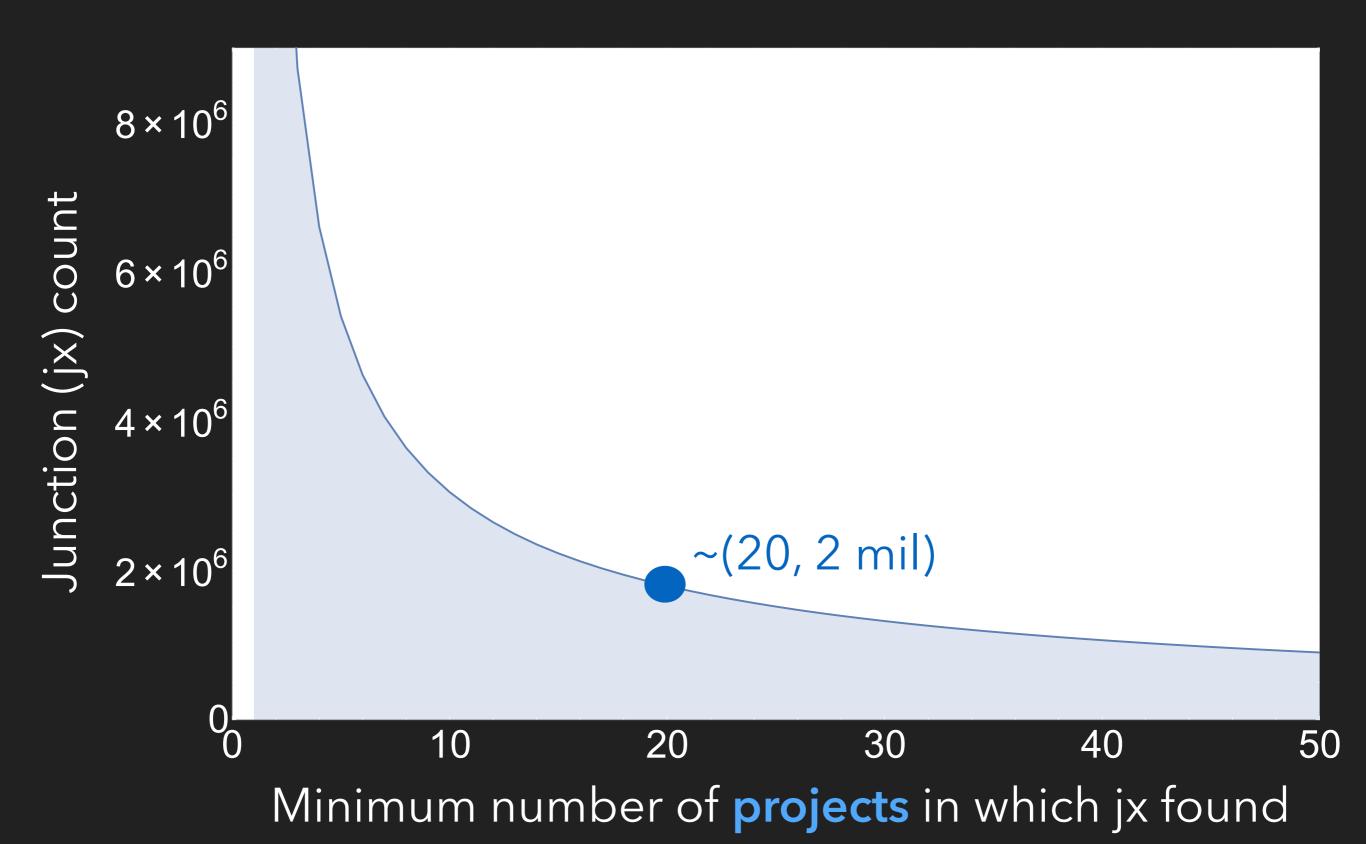
to download/preprocess data, copy to S3

We ran

```
rail-rna align elastic
--manifest batch X.tsv
--input s3://bucket/batch X prepped
--output s3://bucket/batch X itn
--core-instance-bid-price 0.60
--master-instance-bid-price 0.60
--core-instance-count 60
--core-instance-type c3.8xlarge
--master-instance-type c3.8xlarge
--deliverables itn
```

to detect junctions from one pass of alignment

A steep dropoff: project-level



Actual experiment

RGASP simulated sample 1 (40 mil read pairs)

HISAT2 2.0.0-beta

		junctions	junction overlap
fed true jx	prec: rec:	0.94 0.99	0.98
fed union of annotated jx	prec:	0.80 0.95	0.97

Actual experiment

RGASP simulated sample 1 (40 mil read pairs)

STAR 2.4.2a

junctions junction overlaps

fed true jx

prec:

0.98

0.995

rec:

0.99

0.91

fed union of annotated jx

prec:

0.90

0.98

rec:

0.97

0.87

Comparison with SEQC

SEQC/MAQC-III (Nat Biotech, doi:10.1038/nbt.2957)

1720 samples in common with Rail; universal human & brain reference samples

Rail-RNA
in at least
5 SEQC samples

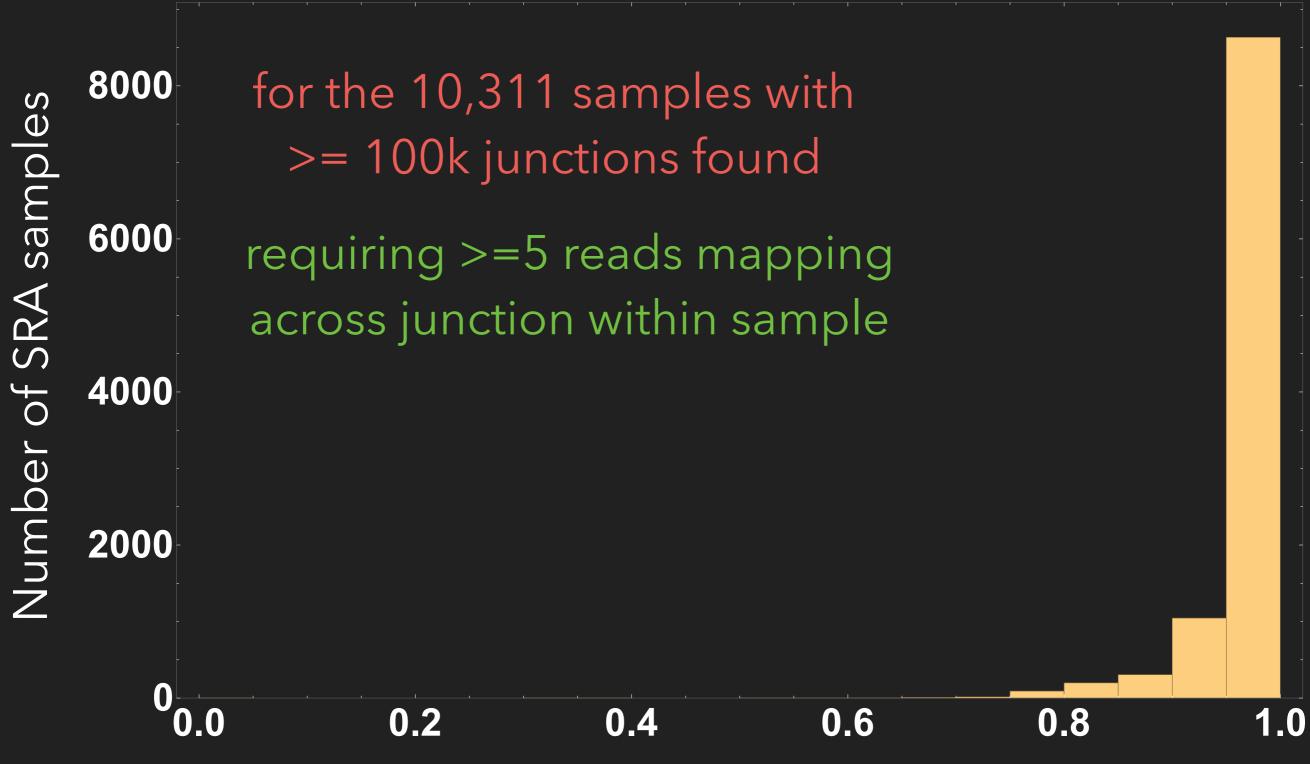
One of rmake, magic, and subread

164,086 junctions

1,068,282 junctions

2,510,072 junctions

Annotated junctions by sample



Proportion of junctions found that are annotated