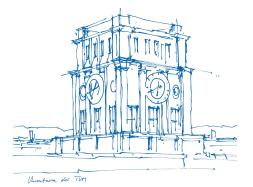


When the outlier is the signal: RNA-seq based diagnostics of rare disorders

Vicente A. Yépez, PhD Scientific researcher Gagneur lab Technical University of Munich

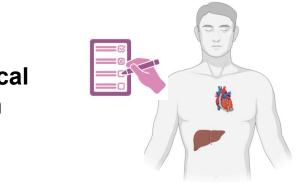
BioInfoDiag May 14th, 2024



Rare genetic diseases life-threatening, chronically debilitating conditions predominantly caused by variants in a single gene



Rare: prevalence < 1 in 2,000



Step 1: Clinical evaluation





5,000 - 8,000 rare diseases affect ~ 350 million people worldwide

The current diagnosis rate is ~50%

Amberger et al, Nuc Ac Res, 2019 EURORDIS, Rare Diseases Boycott and Ardigo, Nat Rev, 2018

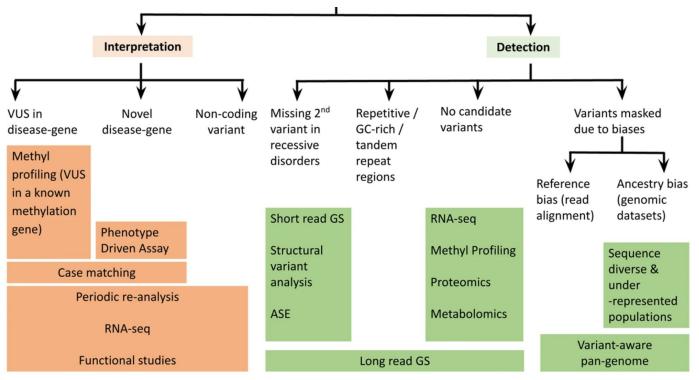
Challenges to diagnose rare disorders

From the medical side:

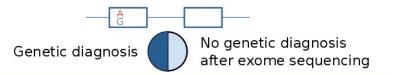
- Due to rarity of the disease, clinicians are often faced to new cases
- Overlapping phenotypes between disorders
- They're usually progressive, sometimes lethal -> time to diagnose matters
- Incomplete penetrance: same variant, different severity
- At least 2 cases are needed to prove pathogenicity of a new disease gene

Challenges to diagnose rare disorders

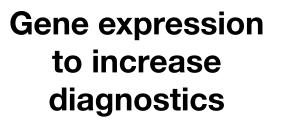
From the genetic side:



Marwaha et al, Genome Med, 2022

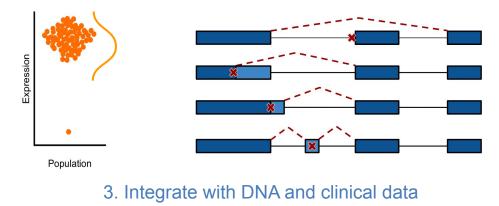


1. Sequence RNA (from clinically-accessible tissues)



~15% diagnostic increase over WES

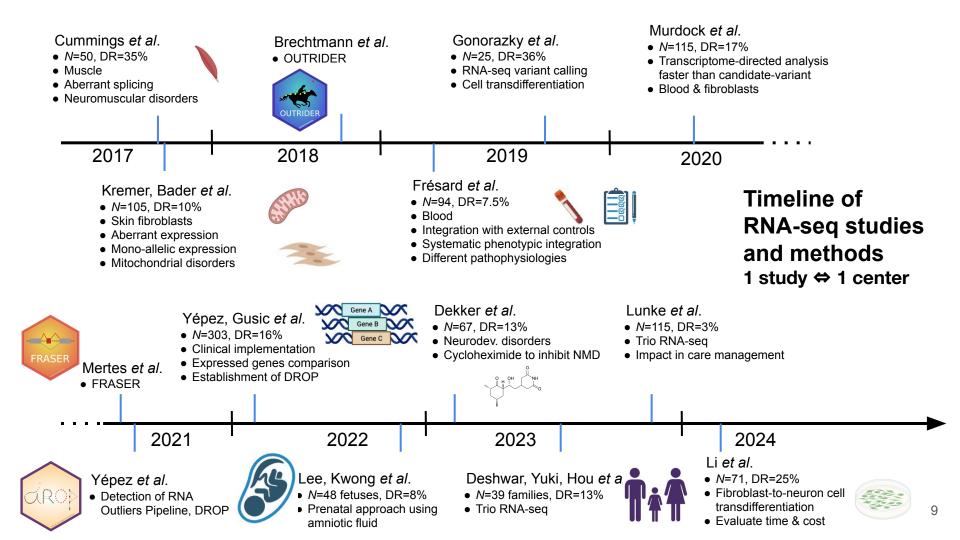
2. Aberrant (not differential!) expression & splicing detection



Genetic diagnosis

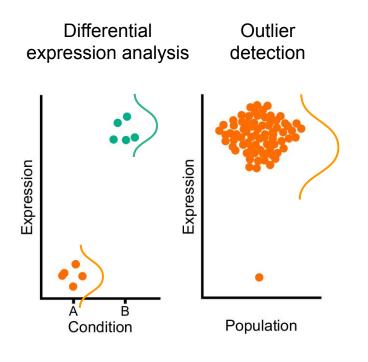


No genetic diagnosis



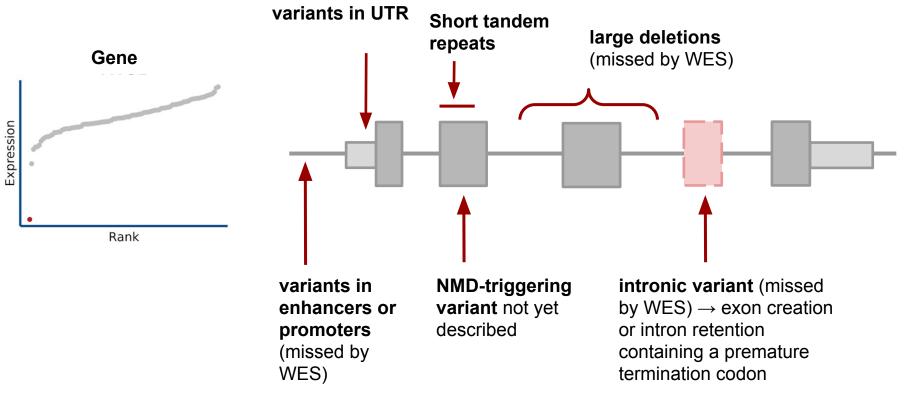
In rare disease diagnostics, the outlier is the signal

Aberrant (not differential!) expression detection



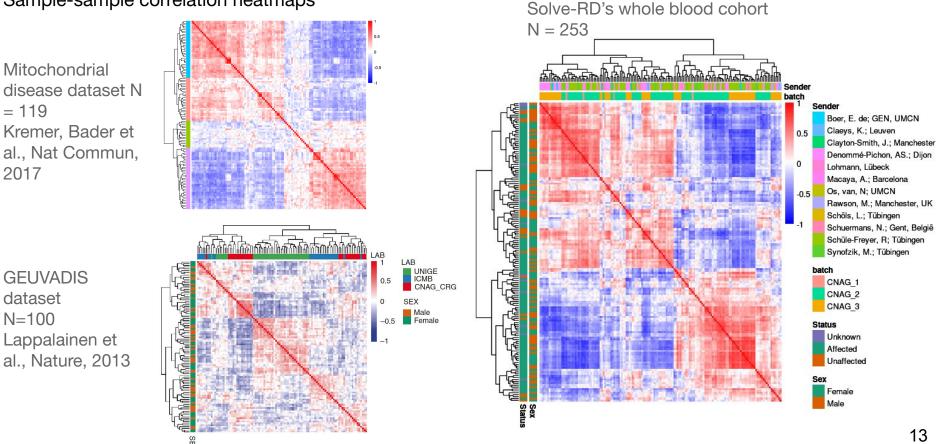
- Not interested in differential expression between 2 groups
 - Condition A vs Condition B
- Find the 'outlier' the gene whose impaired function could explain the disease
 - The population can be composed of all affected samples
 - Controls can be included to increase sample size

Detecting aberrant gene expression can lead to finding or validating disease causal variants



Gene expression data exhibits strong covariation

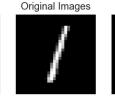
Sample-sample correlation heatmaps



Fitting denoisers with denoising autoencoders

 \mathbf{X}









Noisy Input

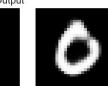


X^{corrupt}.





Autoencoder Output





 $f(\mathbf{X^{corrupt.}}, \boldsymbol{\theta})$





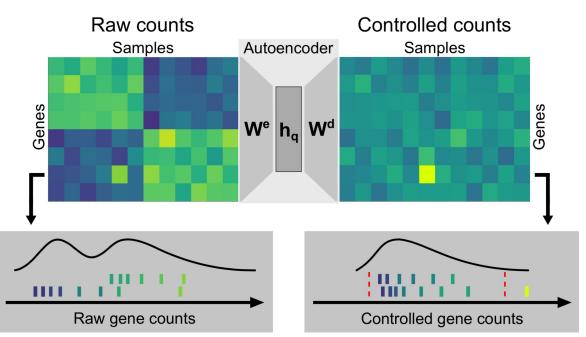


 $\min_{\boldsymbol{\theta}} ||\mathbf{X} - f(\mathbf{X^{corrupt.}}, \boldsymbol{\theta})||^2$

OUTRIDER: denoising autoencoder for RNA-seq data

- Negative Binomial loss
- Number of latent factors (q) set to maximise precision-recall of artificially injected outliers
- P-value per sample gene combination

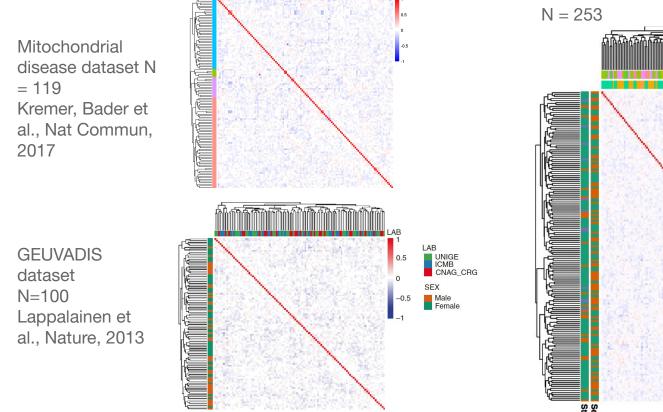


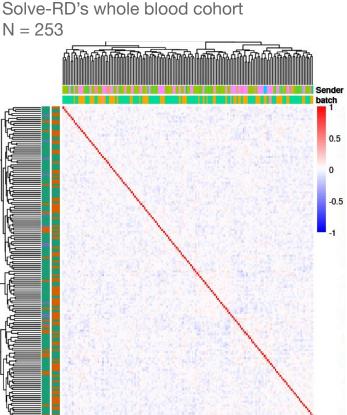


Brechtmann, Mertes, Matuseviciute, et al., AJHG, 2018

OUTRIDER successfully removes sample covariation

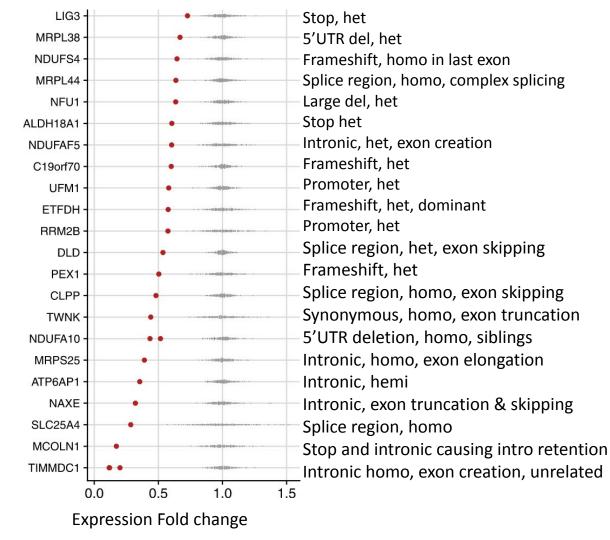
Sample-sample correlation heatmaps after correction



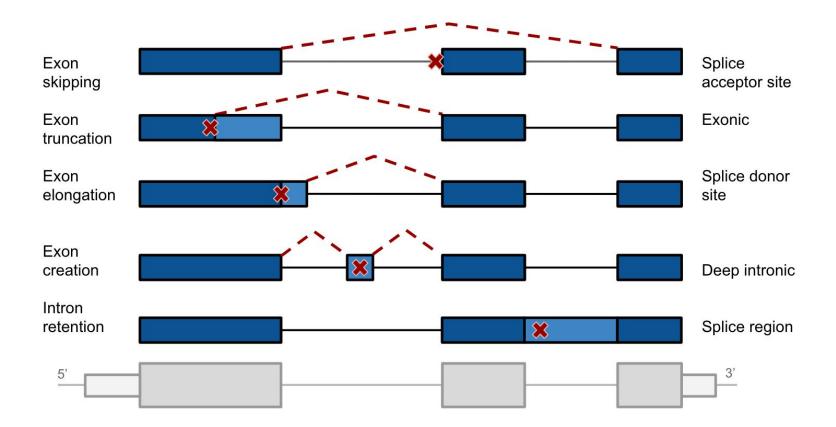


Reduction in expression suggests mono- or biallelic LoF variants

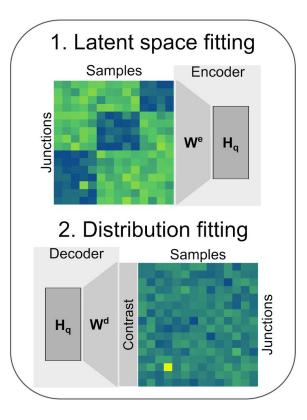
Yépez, Gusic, et al, Genome Med, 2022

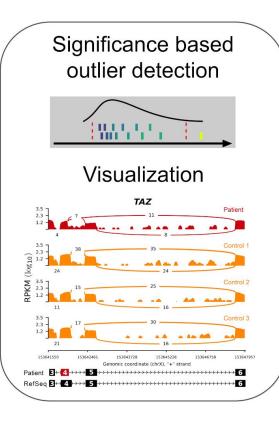


Detecting aberrant splicing, in its many forms, can also lead to finding or validating disease causal variants



FRASER to detect aberrant splicing



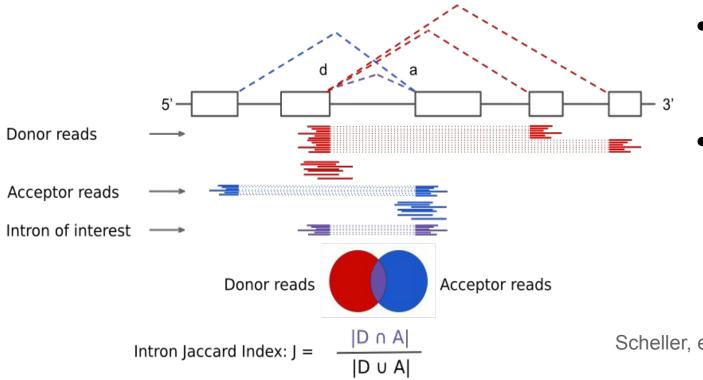


- Splice-site centric metrics $(\psi_5, \psi_3, \text{SE}_5 \text{ and SE}_3)$
- Similar as OUTRIDER but with Beta Binomial loss on each metric
- *P*-value per sample junction - metric combination



Mertes, Scheller, et al., Nat Commun, 2021

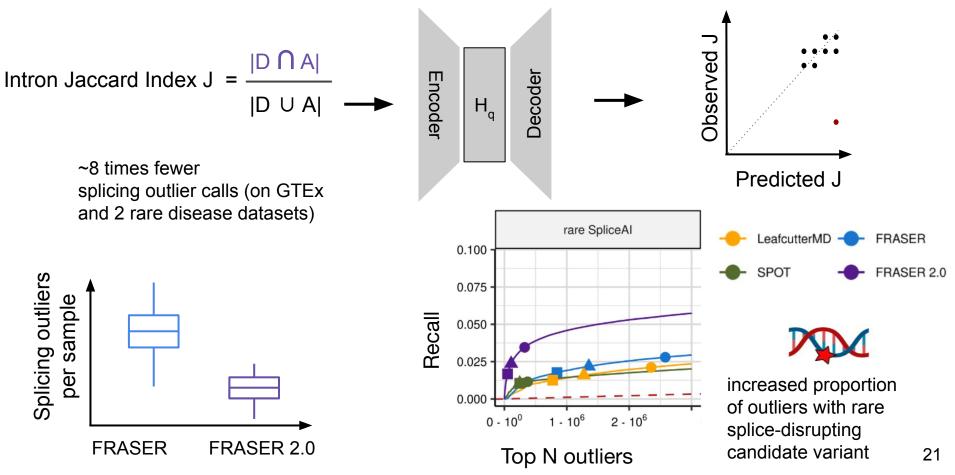
Novel intron-centric metric to quantify splicing: Intron Jaccard Index



- More robust than splice-site centric metrics (ψ₅, ψ₃, SE₅ and SE₃)
- ~120K introns / cohort are tested also using Beta Binomial

Scheller, et al., AJHG, 2023

FRASER 2.0 improves over FRASER and other methods

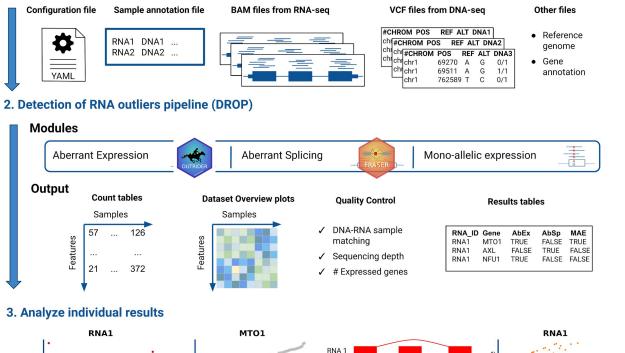


Detection of RNA outliers pipeline - DROP

1. Input

Significanc

Amplitude



RNA 2 RNA 3

RefSe

Expression

Rank

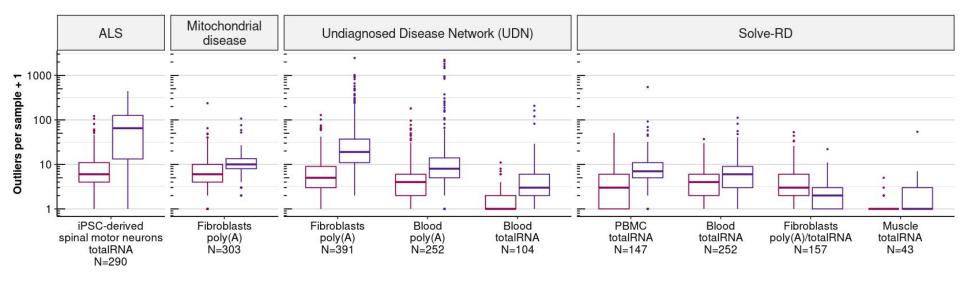
- Easy to install through GitHub including all dependencies
- After set-up, runs each module with 1 command
- Runs cohorts of few hundreds of samples in < 1 day
- Used by centers all over the world



github.com/gagneurlab/drop₂₂ Yépez et al, Nat Protoc, 2021

Handful of outliers per sample across multiple rare disease cohorts

OUTRIDER
FRASER 2.0



Median expression outliers: 3 Median splicing outliers: 8







Solving the Unsolved Rare Diseases

Need to upscale and standardize RNA-seq methods for big consortia













More to come!

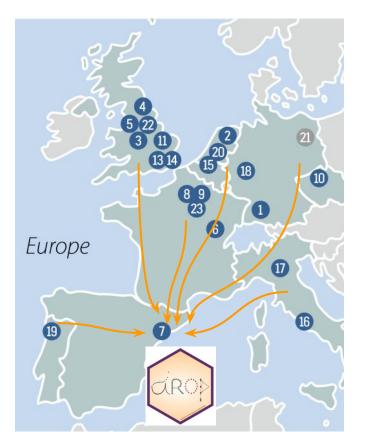
Major challenge: cope with large number of senders

Schüle-Freyer, R; Tübingen Denommé-Pichon, AS.; Dijon Synofzik, M.: Tübingen Roos, A.; Essen, Duitsland Mei, D.; Florence Vossler-Wolf, C.; Tübingen · Kleefstra, T.; KG, UMCN Minardi, R.: Bologna Zaharieva, I.: Londen, UK · Schuermans, N.; Gent, België -Magrinelli, F.; Londen Morsy, H.; Londen Macken, W: Londen Cilio, R: Louvain -Canafoglia, L.; Milaan · Os. van. N: UMCN -Sender Natera, D. / Nascimiento, A.; Barcelona -Natera de Benito, D.; Barcelona -Zaganas, I.; Heraklion, Greece -Topf, A.; Newcastle upon Tyne -Khan, A.: Londen, UK -Nelson, I.; Parijs -Horvath, R.; Cambridge -Gijn, ME. van.; UMCG Boer, E. de: GEN, UMCN -Schöls, L.; Tübingen -Renieri, A.; Siena, Italië -Lohmann, Lübeck -Cavalleri, G.: Dublin -Rawson, M.; Manchester, UK -Clayton-Smith, J.; Manchester -Udd, B.: Helsinki · Macava, A.; Barcelona Claeys, K.; Leuven · 25 50 75 100 n **RNA** samples

Extremely important to:

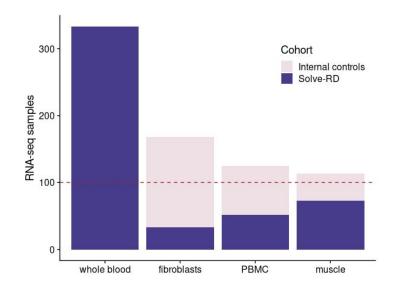
- Compile all results in one place (DNA, RNA & phenotype)
- Minimize manual inspection
- Instruct how to interpret results following similar criteria
- Standardize all steps

Centralized data preprocessing and results generation



Detection of RNA Outliers Pipeline, Yépez et al, Nat Protoc, 2021

- Same criteria for sample inclusion
- Standardize all steps from raw data to results
- Increased statistical power
- Minimize data transfer agreements



Instead of sending tables

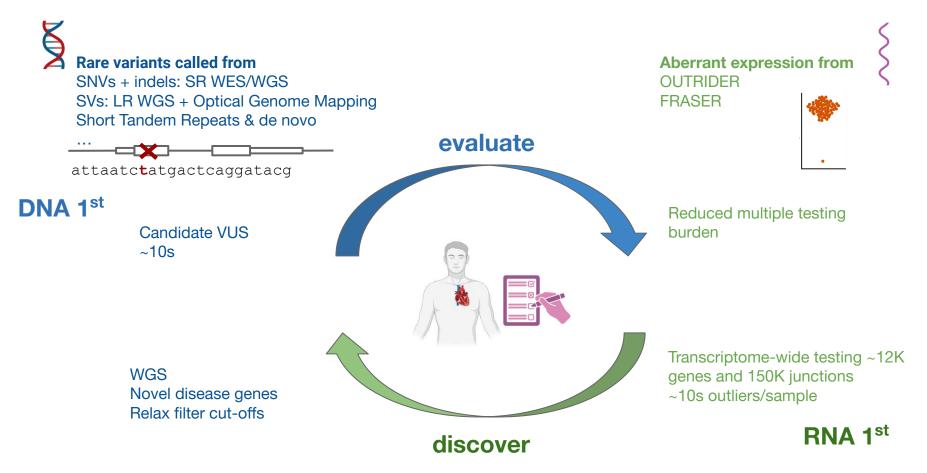


⇒ organize Solvathons!

- 3-days on-site and online event
- Multidisciplinary: bioinformaticians, biologists, clinicians, geneticists, group leaders, postdocs, PhDs, ...
- Goals:
 - Instruct on how to analyze the results
 - Diagnose samples!
- Great starting point for follow-up analyses!



DNA 1st and RNA 1st as two avenues for diagnostics

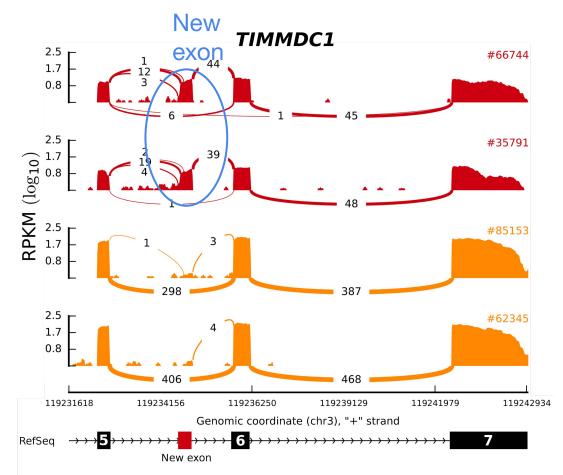


DNA 1st and RNA 1st as two avenues for diagnostics



(In the next slides I showed our current diagnostic rate in Solve-RD of 20 samples, including (unbalanced) translocations, insertions & deletions. As it is unpublished data, I unfortunately cannot share it. Keep updated for the preprint!)

RNA 1st: exon creation due to intronic variant



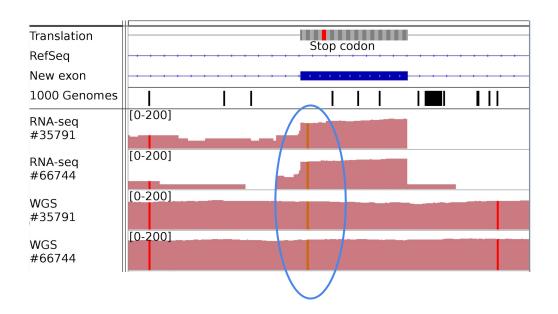
2 mitochondrial disease patients with TIMMDC1 defect

Other samples

TIMMDC1: Translocase Of Inner Mitochondrial Membrane Domain Containing 1

> Kremer, Bader et al., Nat Commun, 2017

RNA 1st: exon creation due to intronic variant



- Homozygous intronic variant missed by WES
- Gene was originally not a disease gene, but confirmed by proteomics (all complex I subunit down)











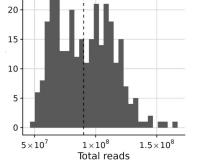
32

Kumar et al, npj Genomic Medicine, 2022

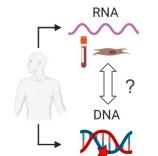
Oligonucleotide correction of an intronic *TIMMDC1* variant in cells of patients with severe neurodegenerative disorder

Extensive QC to verify that the RNA-seq samples:

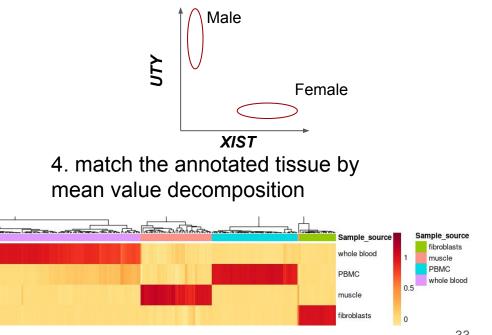
1. have comparable sequencing depth by comparing counts and size factors



3. match the annotated DNA by comparing the variants

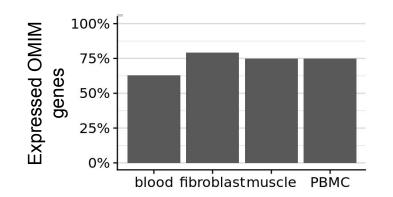


2. belong to the annotated sex by comparing the expression of XIST and UTY



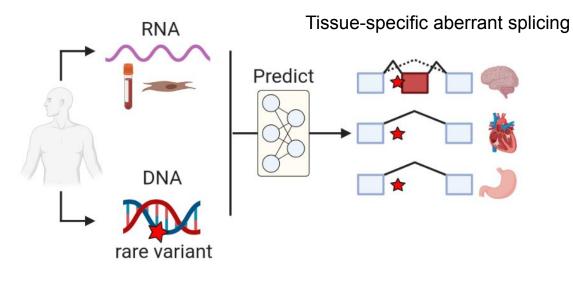
Limitations: RNA-seq is not always able to capture the effect of the variants

- Gene not expressed in probed tissue
 - Limited to accessible tissues blood, skin, muscle
 - ~60-70% Mendelian disease genes expressed
- Variant does not affect transcript (e.g. missense or synonymous)
- Expression and splicing outliers are not highly reproduced across tissues
- Cohorts of at least 100 samples are needed to detect outliers



How can we overcome this?

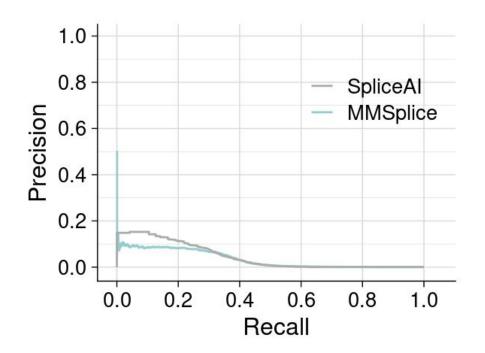
Aberrant splicing prediction in any human tissue



Having FRASER established, we generated the first benchmark dataset for tissue-specific aberrant splicing prediction using GTEx

- 16,213 post-mortem RNA-seq samples
- 946 individuals
- 49 tissues
- 8.8 million rare variants
- 21,000 aberrant splicing events

State-of-the-art sequence-based models poorly predict aberrant splicing

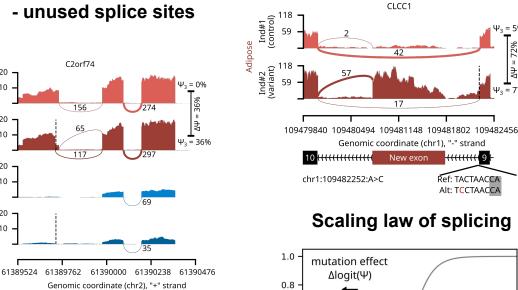


Ground truth: splicing outliers called using FRASER on all GTEx samples

SpliceAl: Jaganathan et al., 2019, Cell

MMSplice: Cheng et al., 2019, Genome Biology

Quantitative tissue-specific splice-site maps

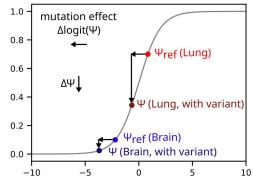


+ weak splice sites

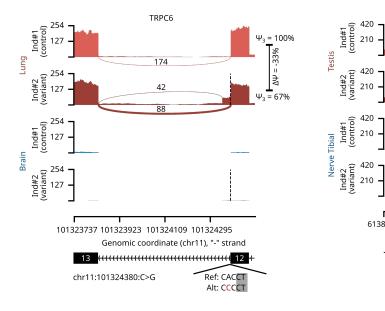
 $\Psi_{2} = 5\%$

₽

Scaling law of splicing



- unexpressed genes



- unused splice sites

Ref: GTTTTTTTATATAAATGGT

Alt: GGTTTTTTTATATAAATGGT

Δ ,,,,,

chr2:61389729:T>G

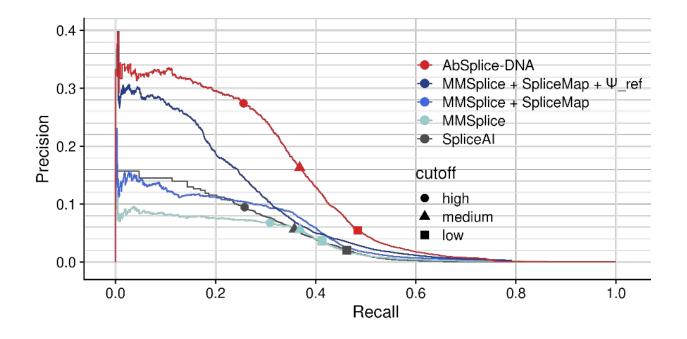
(control) (fontrol) (fontrol)

Ind#2 (variant) (variant) 420

[ud#1 (control) 210

Testis

AbSplice-DNA yields 3-fold improvement over state-of-the-art





Precomputed scores for all possible SNVs for all GTEx tissues

RNA-Seq for rare disease diagnostics - conclusion

- Added value of RNA-seq over Exome Seq / Genome Seq
- Specialized statistical methods and software to detect expression and splicing outliers
 - OUTRIDER
 - FRASER
 - DROP
- Outlook:
 - Proteomics Kopajtich et al, medRxiv 2021
 - ATAC-seq Celik et al, medRxiv 2023
 - Oncology Cao et al, Genome Med 2024
 - Splicing outlier prediction from sequence Wagner, Celik et al, Nat Genet, 2023
 - Expression outlier prediction from sequence Hölzlwimmer et al, bioRxiv, 2023

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- Other DATF and ERN members

All the patients included in the studies and their families

HELMHOLTZ MUNICI)

Solve RD Solving the Unsolved Rare Diseases

GHGA





