

# Computational Challenges in Rare Disease Analysis

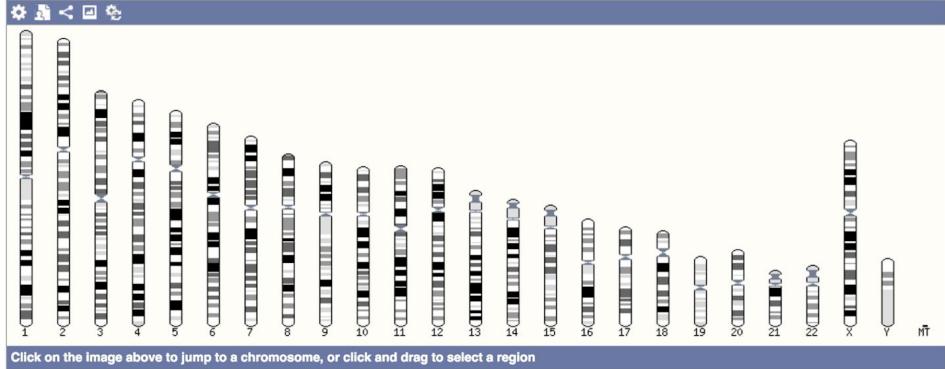
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# The human genome - basic stats



## Summary

Assembly GRCh38.p7 (Genome Reference Consortium Human Build 38), INSDC Assembly [GCA\\_000001405.22](#), Dec 2013

Database version 87.38

Base Pairs 3,547,762,741

Golden Path Length 3,096,649,726

Genebuild by Ensembl

Genebuild method Full genebuild

Genebuild started Jan 2014

Genebuild released Jul 2014

Genebuild last updated/patched Jun 2016

Gencode version GENCODE 25

## Gene counts (Primary assembly)

Coding genes 20,441 (incl 526 readthrough)

Non coding genes 22,219

Small non coding genes 5,052

Long non coding genes 14,727 (incl 214 readthrough)

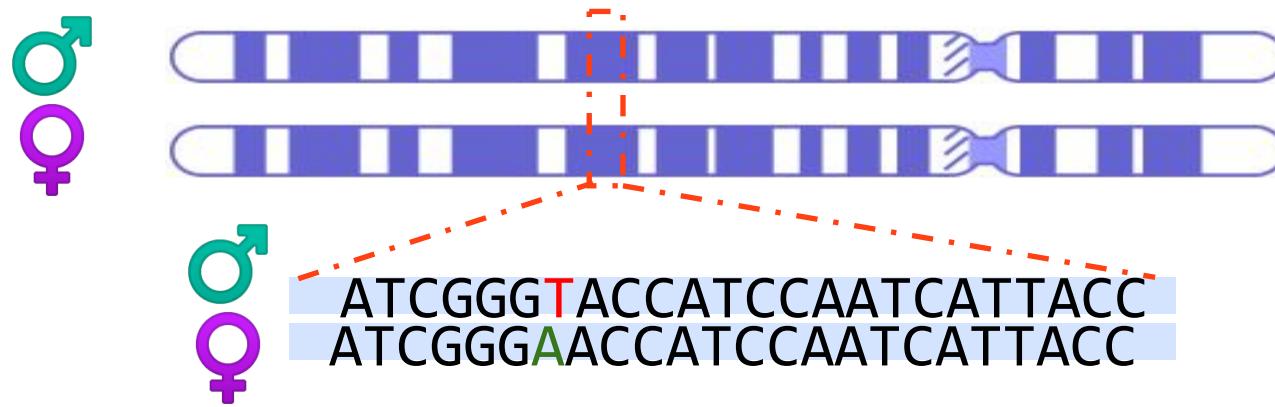
Misc non coding genes 2,222

Pseudogenes 14,606 (incl 5 readthrough)

Gene transcripts 198,002

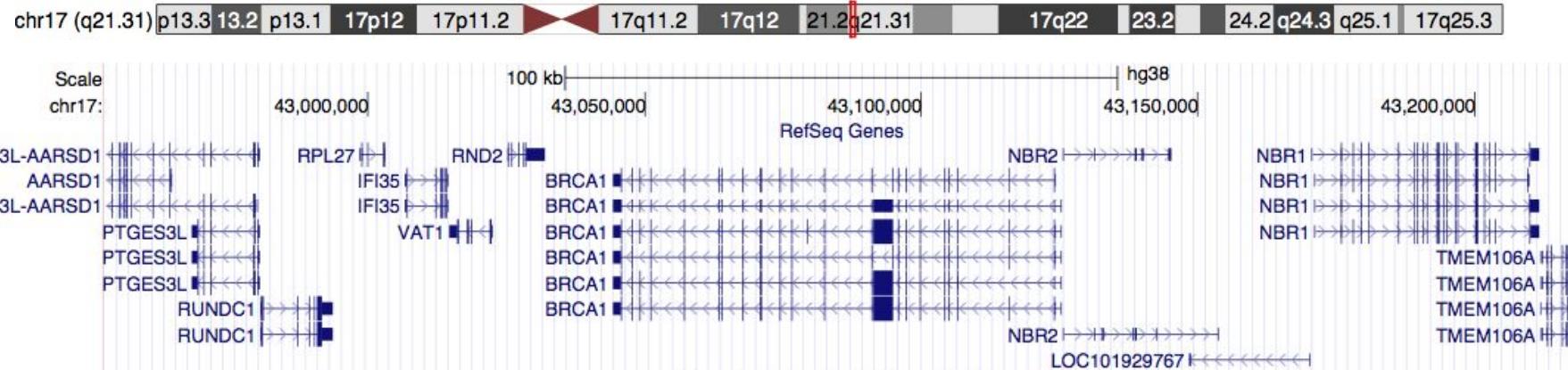
- 3.096 billion base pairs (haploid)
- ~20,000 protein coding genes
- 198,002 coding transcripts  
(isoforms of a gene that each encode a distinct protein product)

# Humans are diploid.



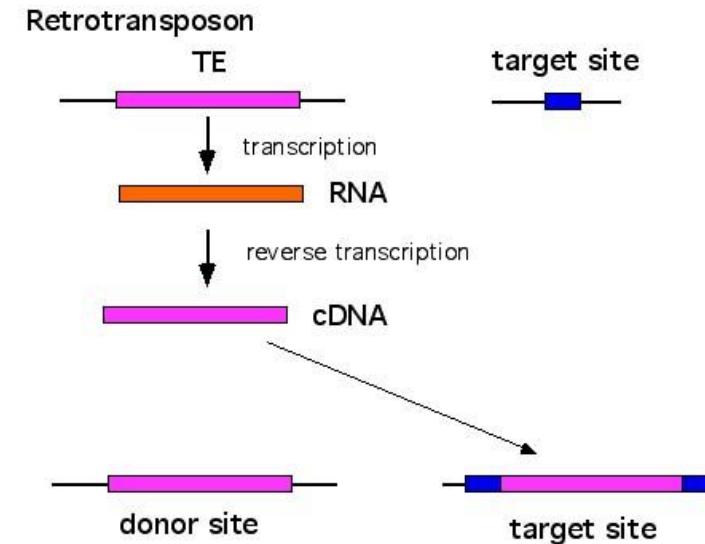
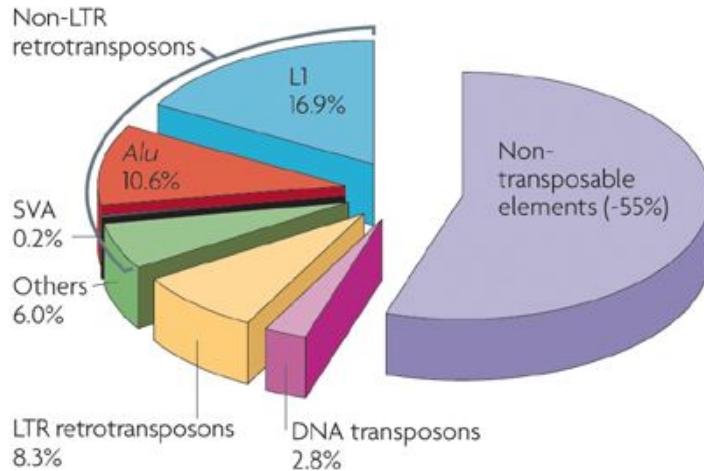
Our genome is comprised of a paternal and a maternal "haplotype". Together, they form our "genotype"

# A measly 2% of the human genome encodes proteins.



# Half of the human genome is comprised of repeats

a



McClintock's  
"jumping  
genes" in maize

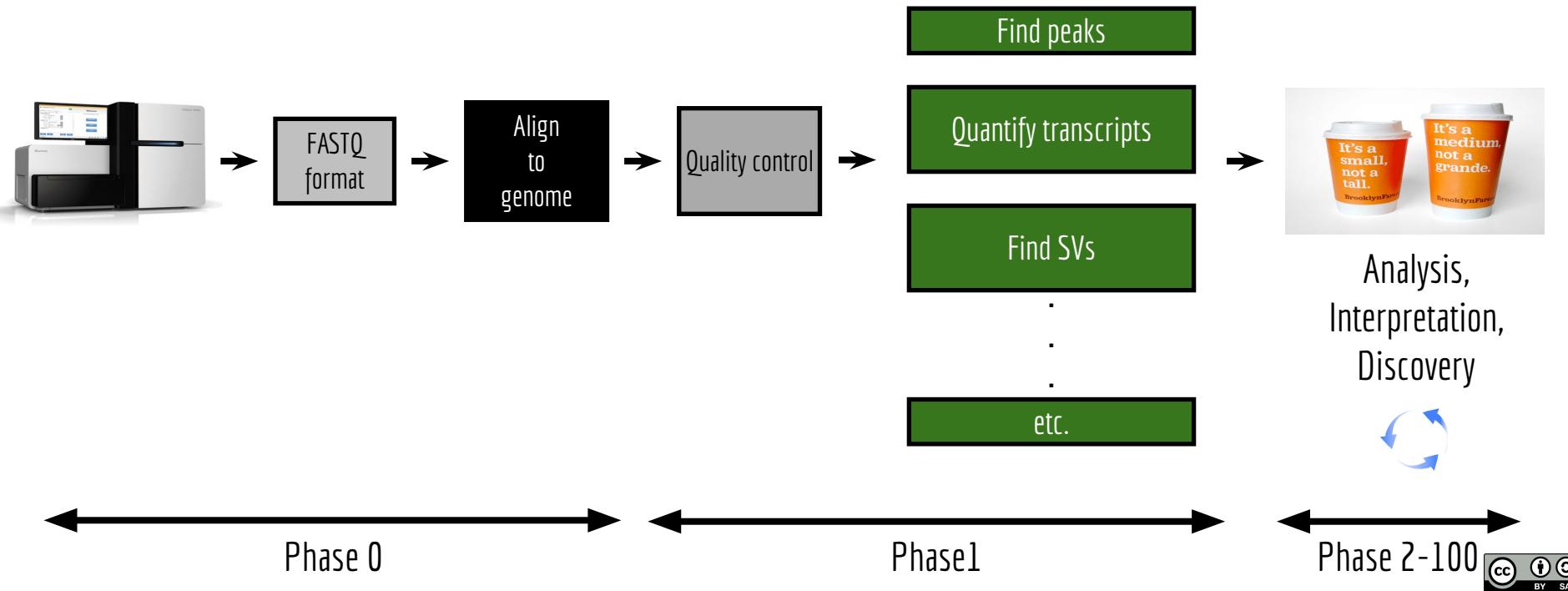
Retrotransposons use a "copy/paste" mechanism  
DNA transposons use a "cut/paste" mechanism

Problem: Half of the human genome is comprised of repeats

( first bit of human chromosome 1 )



# Alignment is central to most genomic research







# Best case scenario: an error-free sequencing technology

ATTCGAAACA  
TTCGCGCAAT  
CTGGACTCAA



ATTCGAAACA  
TTCGCGCAAT  
CTGGACTCAA



Aligner



TACCTCCAGGGGGCATCCTCCCCCA**ATTCG**  
**AAACA**ATCGTAGCCCTGGCACTACCTATG  
TGTGTCAATTGGAGAGAGAGAGATTACGAA  
AAAAAAAGT**CTGGACTCAA**CTAGGATAACACACA  
TTCGGCTACAGATAACCAAAAAAAAAAAAAAAA  
AAATTTTACCCATTGAGGCACCACCTTCTCGT  
CGCTGCGTCGCTCTGCTCGCTTGGCTAAAAA  
**TTCGCGCAAT**ACATTGGCTACAGATAACCAAA  
AAAA

Computers are rather good at finding *exact* matches.  
Think Google.

# Reality check. Errors happen. Frequently.

ATTCGAAACA



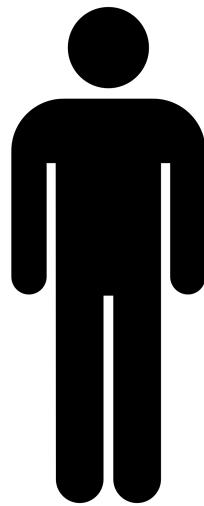
ATTTGAAACA

Aligner

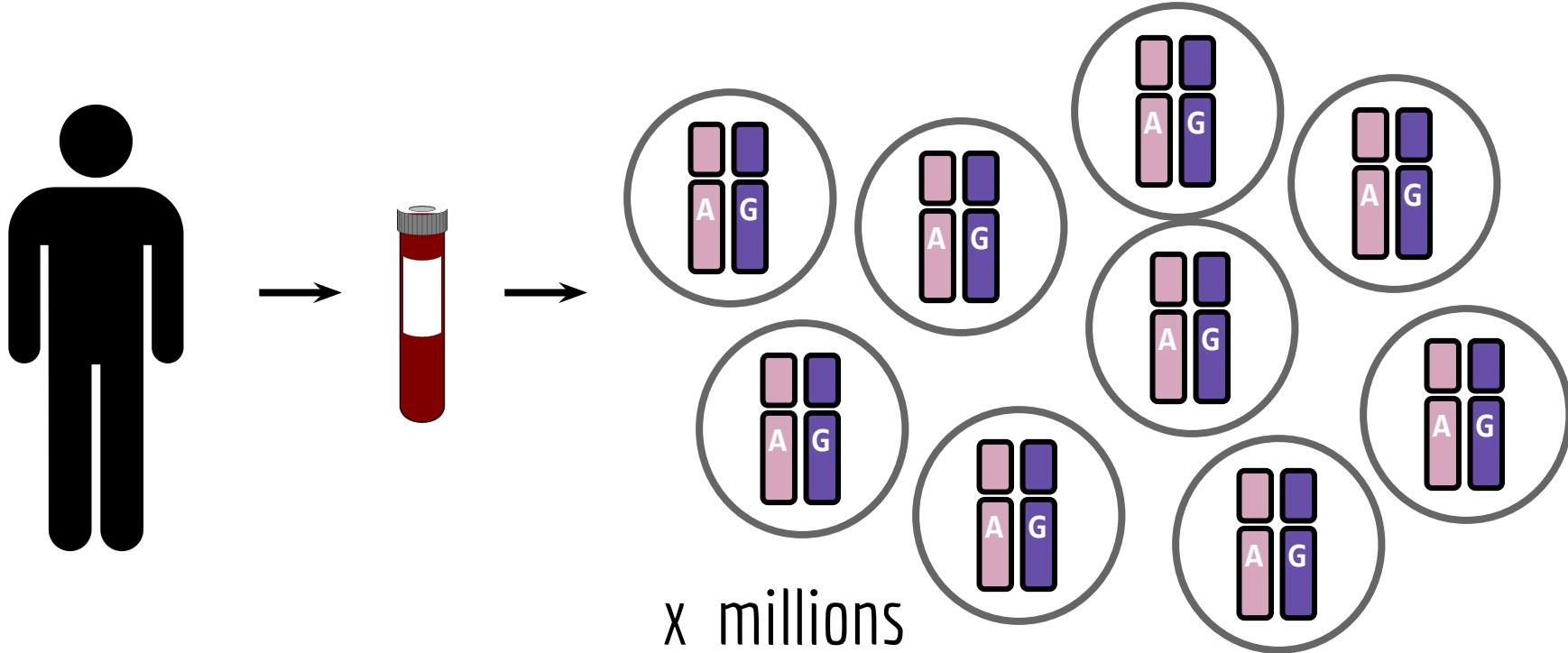
TACCTCCAGGGGGCATCCTCCCCCAATTCG  
AAACACAATCGTAGCCCTGGCACTACCTATG  
TGTGTCAATTGGAGAGAGAGAGATTGAAAC  
AAAAAAAAGTGCTACAGATACCACTAGGATACAC  
ACATTCGGCTACAGATACCAAAAAAA  
AAAAAATTTCACCATTGAGGCACCACTTCT  
CGTCGCTCGCTCGCTCGCTCGGGCTAAAAA  
ATTAGAAACACATTCGGCTACAGATACCAAA  
ATTT

“Fuzzy” matching is much more computationally expensive.  
Think Google’s “Did you mean...”

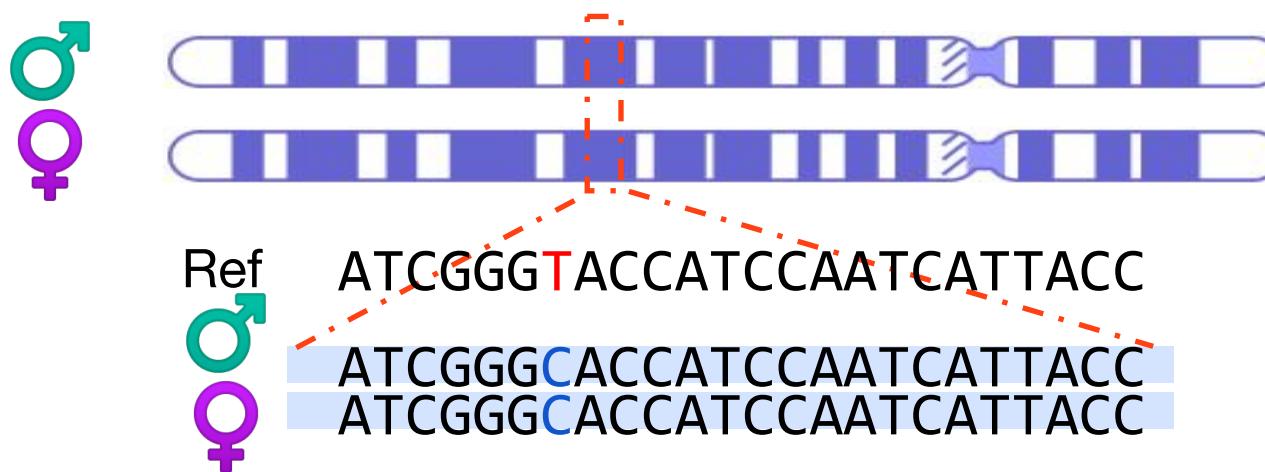
Goal: find all variants in an individual's diploid genome.



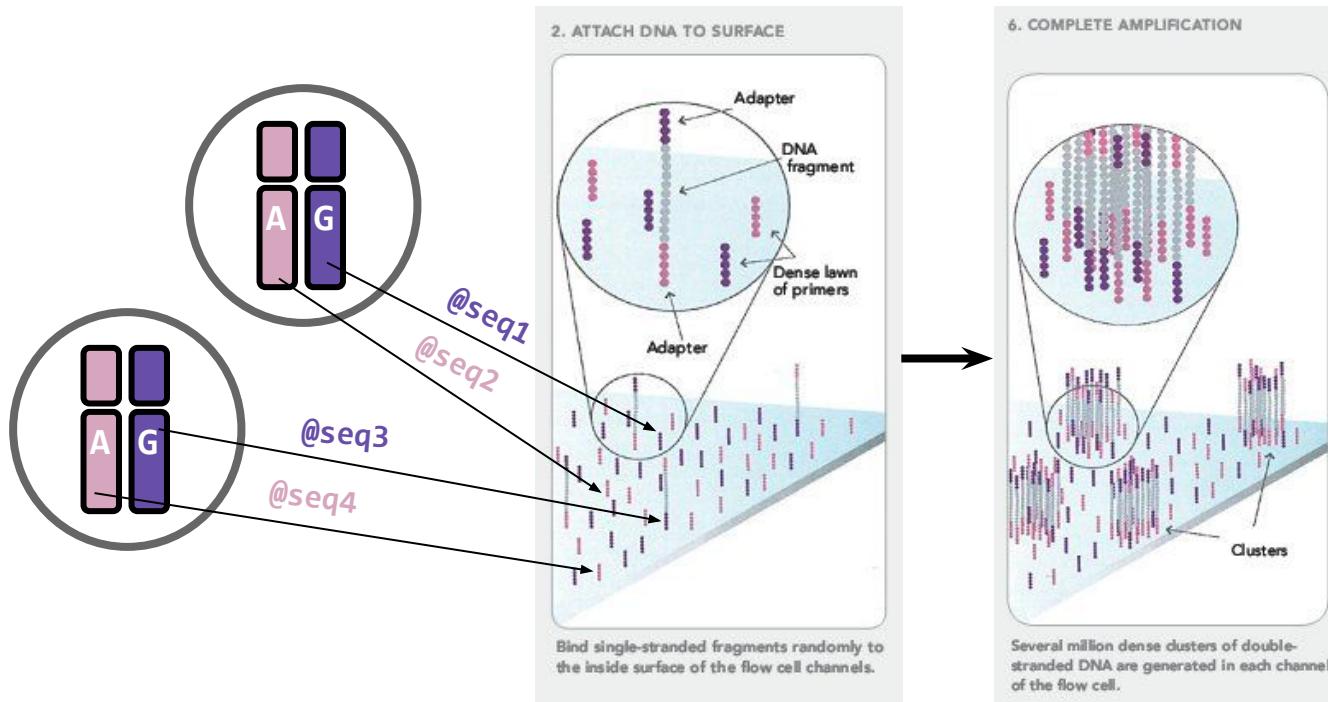
# Find inherited genetic variation by sequencing DNA from millions of cells



# What if an individual is homozygous for an "alternate" allele?

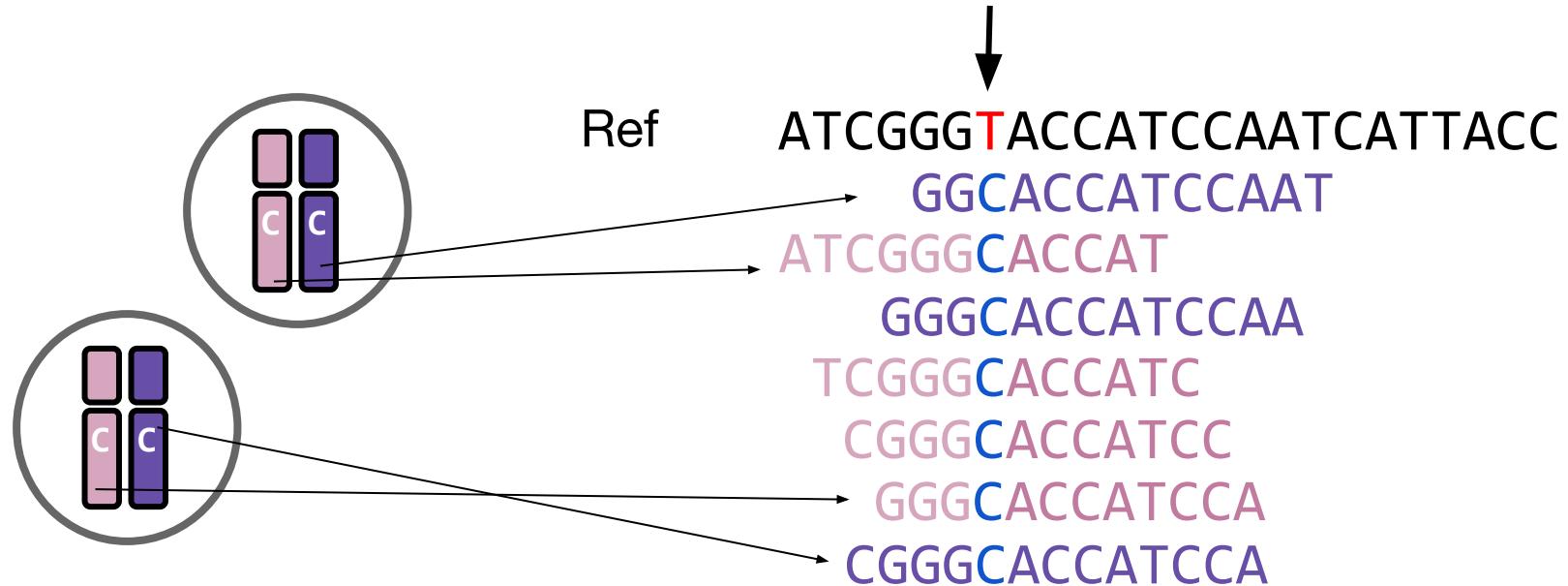


Each DNA cluster is amplified from a single strand from a single haploid chromosome from a single cell.

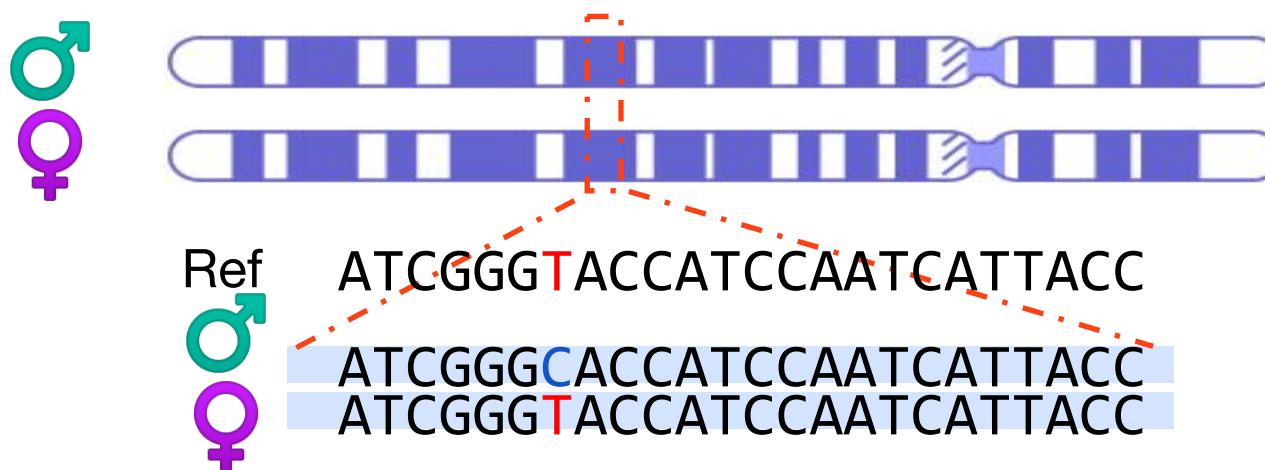


@seq1  
ACCTTCGAACGGCGGGGGTTACAA  
+  
! ' \*((( (\*\*+))%%++).1\*\*\*  
@seq2  
TGGAACCGAACGGCCCCGGTTACAT  
+  
! ' \*!!!!\*\*+))+++++).1\*\*\*  
@seq3  
ACCTTCGAACGGCGGGGGTTACAA  
+  
! ' \*((( (\*\*+))%%++).1\*\*\*  
@seq4  
TGGAACCGAACGGCCCCGGTTACAT  
+  
! ' \*!!!!\*\*+))+++++).1\*\*\*

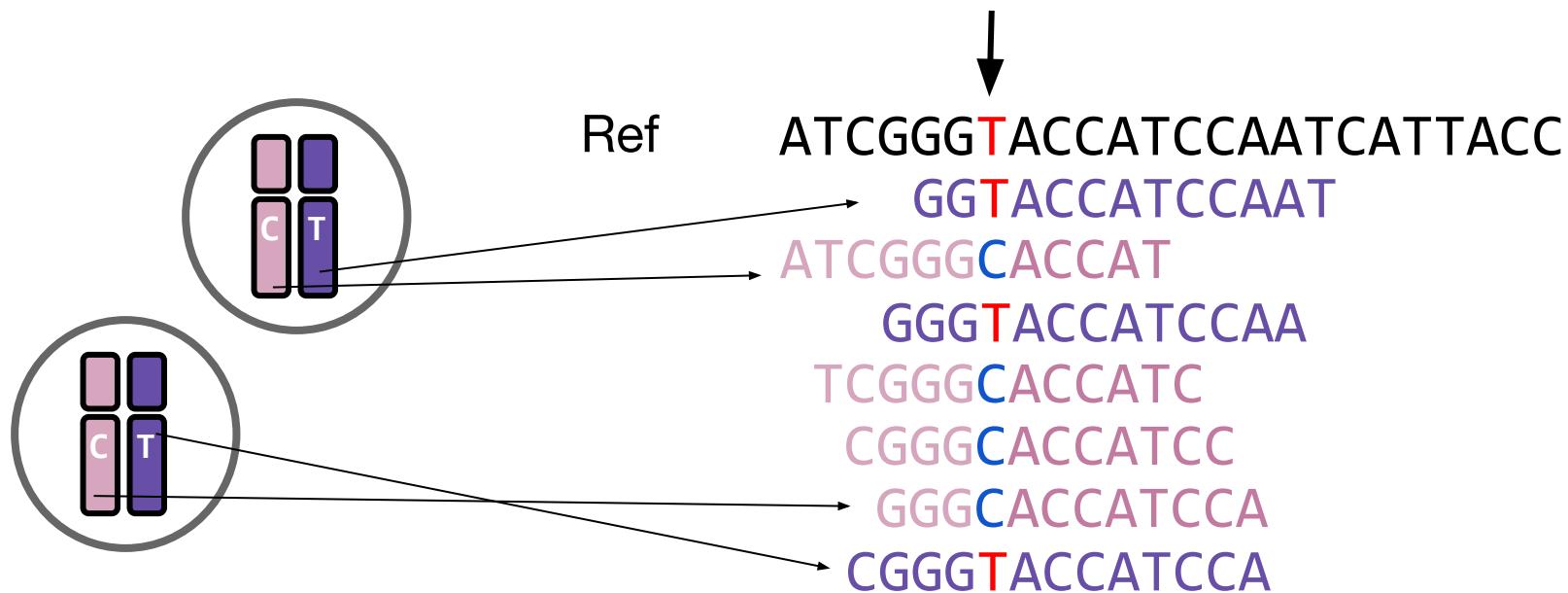
# What if an individual is homozygous for an "alternate" allele?



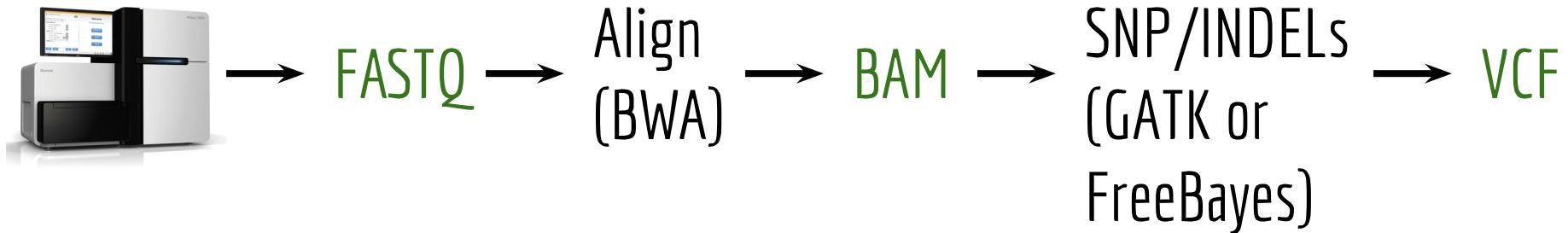
# What if an individual is heterozygous for an "alternate" allele?



# What if an individual is heterozygous for an "alternate" allele?

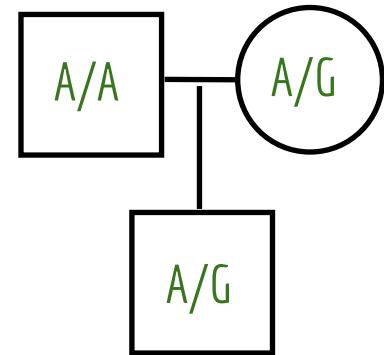


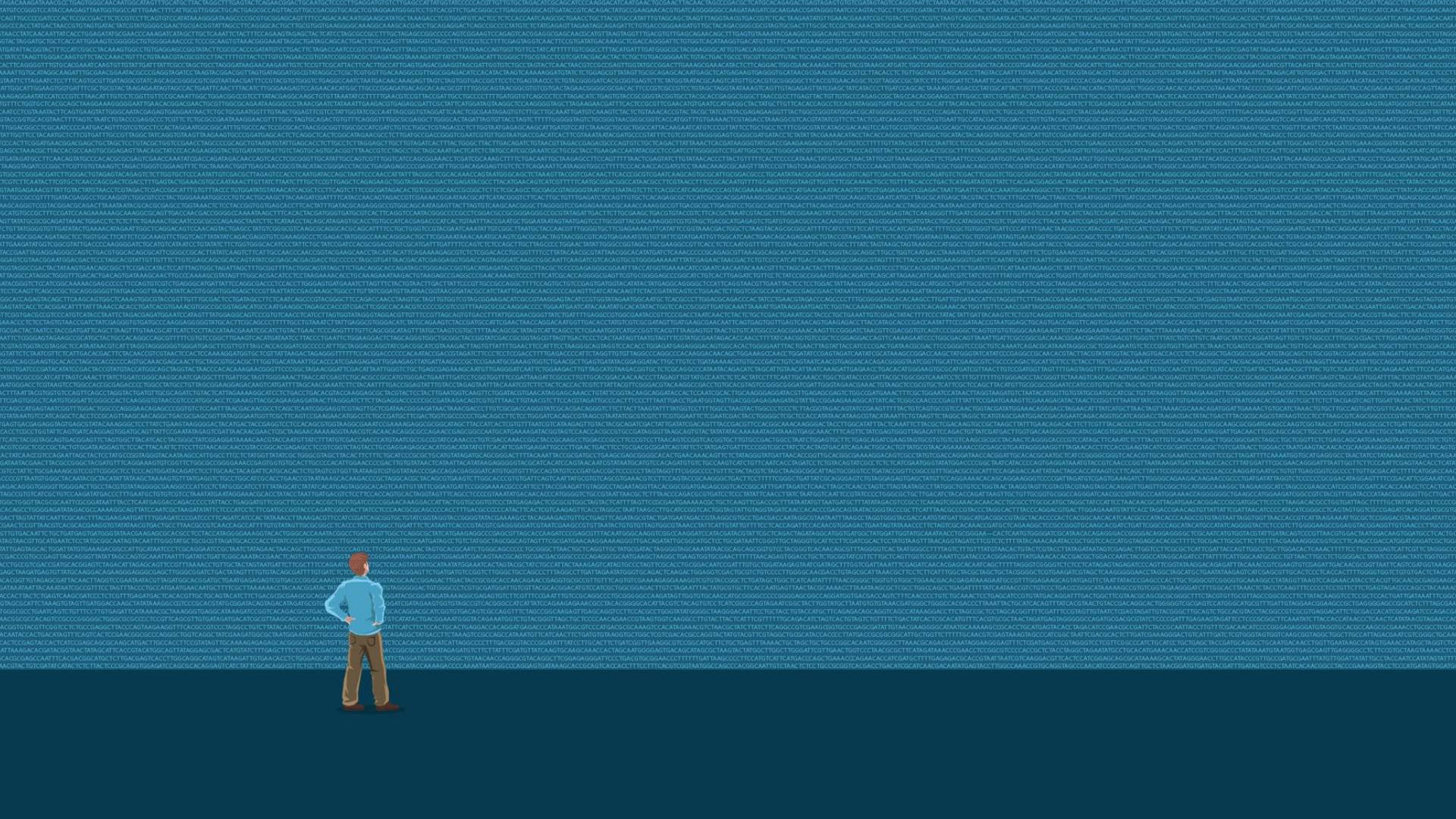
# Variant Calling Overview



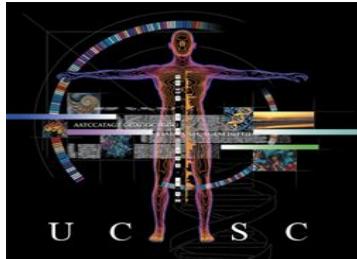
# Raw VCF files are naked. Interpretation requires annotation.

```
##fileformat=VCFv4.3
##fileDate=20090805
##source=variantcallerXYZ
##reference=file:///seq/references/1000GenomesPilot-NCBI36.fasta
##contig=<ID=20,length=62435964,assembly=B36,md5=379d618ff66beb2da,species="Homo sapiens",taxonomy=x>
##phasing=partial
##INFO=<ID=NS,Number=1,Type=Integer,Description="Number of Samples With Data">
##INFO=<ID=DP,Number=1,Type=Integer,Description="Total Depth">
##INFO=<ID=AF,Number=A,Type=Float,Description="Allele Frequency">
##INFO=<ID=AA,Number=1,Type=String,Description="Ancestral Allele">
##INFO=<ID=DB,Number=0,Type=Flag,Description="dbSNP membership, build 129">
##INFO=<ID=H2,Number=0,Type=Flag,Description="HapMap2 membership">
##FILTER=<ID=q10,Description="Quality below 10">
##FILTER=<ID=s50,Description="Less than 50% of samples have data">
##FORMAT=<ID=GT,Number=1,Type=String,Description="Genotype">
##FORMAT=<ID=GQ,Number=1,Type=Integer,Description="Genotype Quality">
##FORMAT=<ID=DP,Number=1,Type=Integer,Description="Read Depth">
##FORMAT=<ID=HQ,Number=2,Type=Integer,Description="Haplotype Quality">
#CHROM POS ID REF ALT QUAL FILTER INFO FORMAT MOM DAD KID
20 14370 rs6054257 G A 29 PASS NS=3;DP=14; GT:GQ:DP:HQ 0|0:48:1:51,51 1|0:48:8:51,51 1/1:43:5:..
20 17330 . T A 3 q10 PASS NS=3;DP=11; GT:GQ:DP:HQ 0|0:49:3:58,50 0|1:3:5:65,3 0/0:41:3
20 1110696 rs6040355 A G,T 67 PASS NS=2;DP=10; GT:GQ:DP:HQ 1|2:21:6:23,27 2|1:2:0:18,2 2/2:35:4
20 1234567 microsat1 GTC G,GTCT 50 PASS NS=3;DP=9; GT:GQ:DP 0/1:35:4 0/2:17:2 1/1:40:3
```





# Annotation provides context for interpretation.

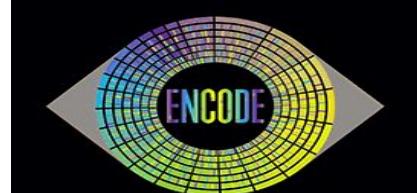


Pfam



gnomAD browser

ClinVar

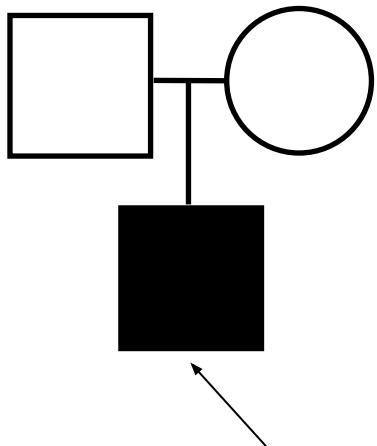


Genetic variation  
...CCTCATG**C**ATGGAAA...  
...CCTCATG**T**ATGGAAA...  
...CCTCATG**C**ATGGAAA...  
...CCTCATG**C**ATGGAAA...  
...CCTCATG**T**ATGGAAA...  
...CCTCATG**C**ATGGAAA...  
...CCTCATG**T**ATGGAAA...

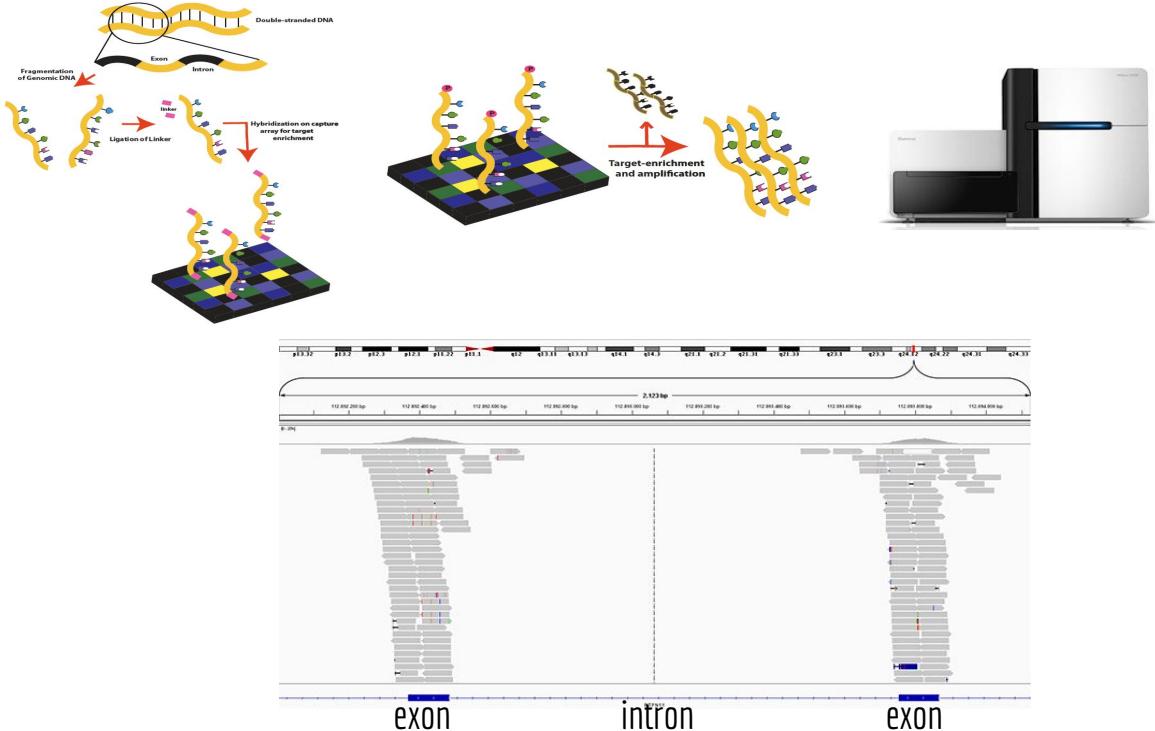


Chromatin marks  
DNA methylation  
RNA expression  
TF binding

# Case study: exome sequencing for rare disease



Mom and dad are unaffected, kid (proband) is affected with rare, Mendelian disease phenotype



>40% of developmental disorders caused by *de novo* mutation

# Prevalence and architecture of *de novo* mutations in developmental disorders

Deciphering Developmental Disorders Study\*

The genomes of individuals with severe, undiagnosed developmental disorders are enriched in damaging *de novo* mutations (DNMs) in developmentally important genes. Here we have sequenced the exomes of 4,293 families containing individuals with developmental disorders, and meta-analysed these data with data from another 3,287 individuals with similar disorders. We show that the most important factors influencing the diagnostic yield of DNM are the sex of the affected individual, the relatedness of their parents, whether close relatives are affected and the parental ages. We identified 94 genes enriched in damaging DNM, including 14 that previously lacked compelling evidence of involvement in developmental disorders. We have also characterized the phenotypic diversity among these disorders. We estimate that 42% of our cohort carry pathogenic DNM in coding sequences; approximately half of these DNM disrupt gene function and the remainder result in altered protein function. We estimate that developmental disorders caused by DNM have an average prevalence of 1 in 213 to 1 in 448 births, depending on parental age. Given current global demographics, this equates to almost 400,000 children born per year.

# Goal: find variants that disrupt gene function

## synonymous (silent)

	L	Q	T
Normal	ctg	cag	act
Mutated	ctg	caa	act

Impact sometimes hard to predict.

## non-synonymous (missense)

	L	Q	T
Normal	ctg	cag	act
Mutated	ctg	cgg	act

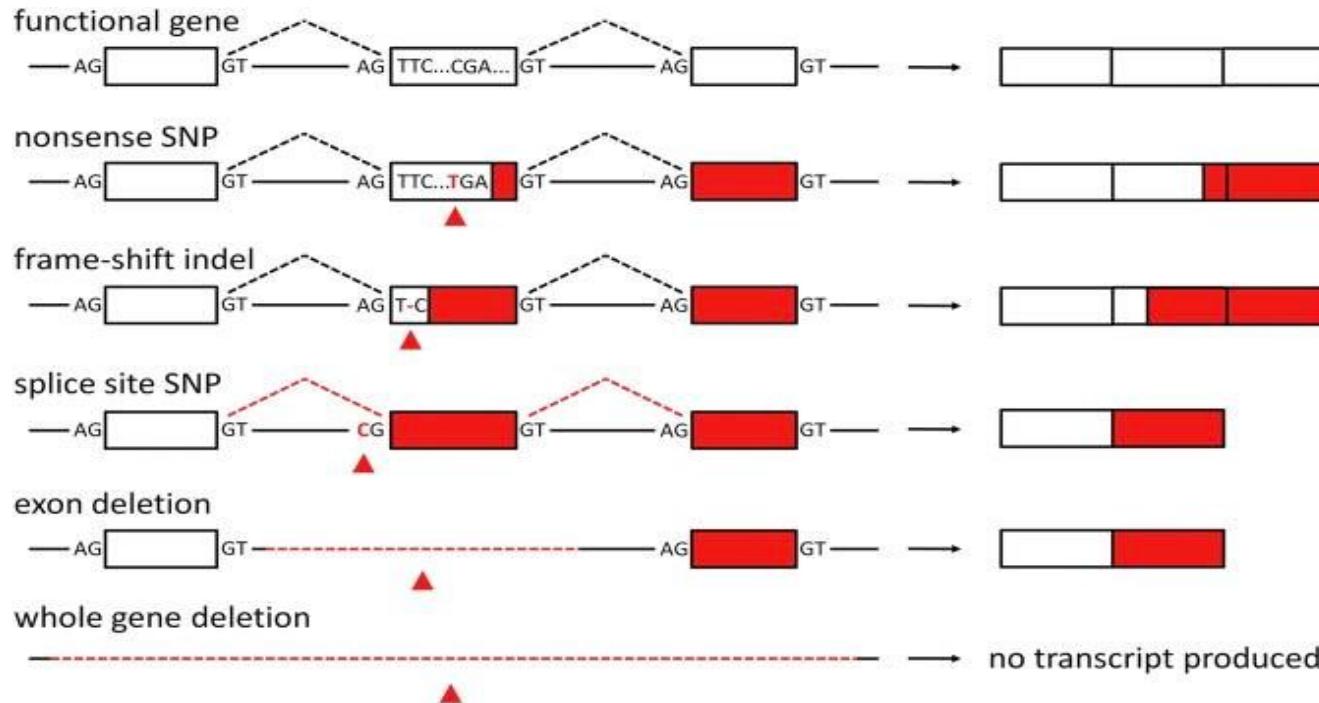
## stop-gain (nonsense)

	L	Q	T
Normal	ctg	cag	act
Mutated	ctg	tag	act

## stop-loss

	L	STOP	T
Normal	ctg	tag	act
Mutated	ctg	cag	act

# Loss of function variants



# Uh oh. Needle in a haystack problem.

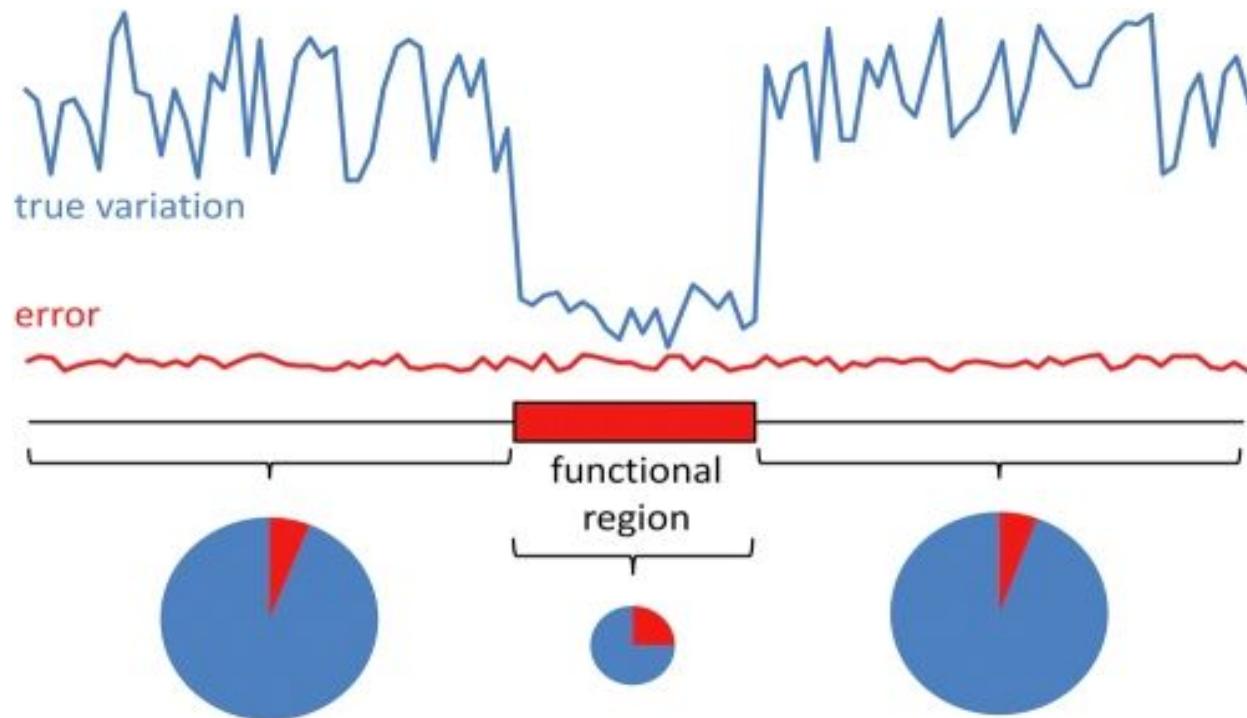
Table 1 | Median number of protein-coding variants and effects among world super-populations\*

Super-population code	Synonymous (het; hom alt)	Missense (het; hom alt)			Frameshift (het; hom alt)	Stop gain (het; hom alt)	Start lost (het; hom alt)	Splice donor (het; hom alt)	Splice acceptor (het; hom alt)
	Total	SIFT Del	PP Del						
EUR	6961; 4317	7220; 4452	116; 55	116; 38	151; 146	93; 35	61; 52	184; 99	114; 72
AFR	9296; 4673	9347; 4820	163; 56	156; 31	196; 150	123; 32	78; 51	231; 116	150; 80
AMR	7257; 4314	7449; 4479	121; 56	121; 38	154; 145	96; 34	62; 50	187; 101	117; 76
SAS	7180; 4397	7366; 4550	123; 56	121; 39	159; 148	93; 36	68; 49	186; 103	117; 78
EAS	6502; 4759	6802; 4908	105; 66	113; 45	143; 149	89; 38	62; 54	171; 112	115; 86

AFR, individuals of African descent; AMR, individuals of admixed descent from the Americas; EAS, individuals of East-Asian descent; EUR, individuals of European descent; PP Del, PolyPhen2 predicted the missense variant to be deleterious; SAS, individuals of South-Asian descent; SIFT Del, SIFT predicted the missense variant to be deleterious. \*We measured the average number of heterozygous (het) and homozygous alternate (hom alt) genotype counts among the 2,504 individuals sequenced by the 1000 Genomes Project. All genetic variants affecting genes were annotated with the Variant Effect Predictor and categorized by their most deleterious predicted effect.

Many predicted loss of function variants observed in a typical human.  
Even as a homozygote!!!

# Apparent loss-of-function variants are enriched for error.



MacArthur DG, Tyler-Smith C. (2010) Loss-of-function variants in the genomes of healthy humans. *Hum Mol Genet.* 19(R2):R125-130.

If a disease phenotype is rare, the causal variant should also be similarly rare

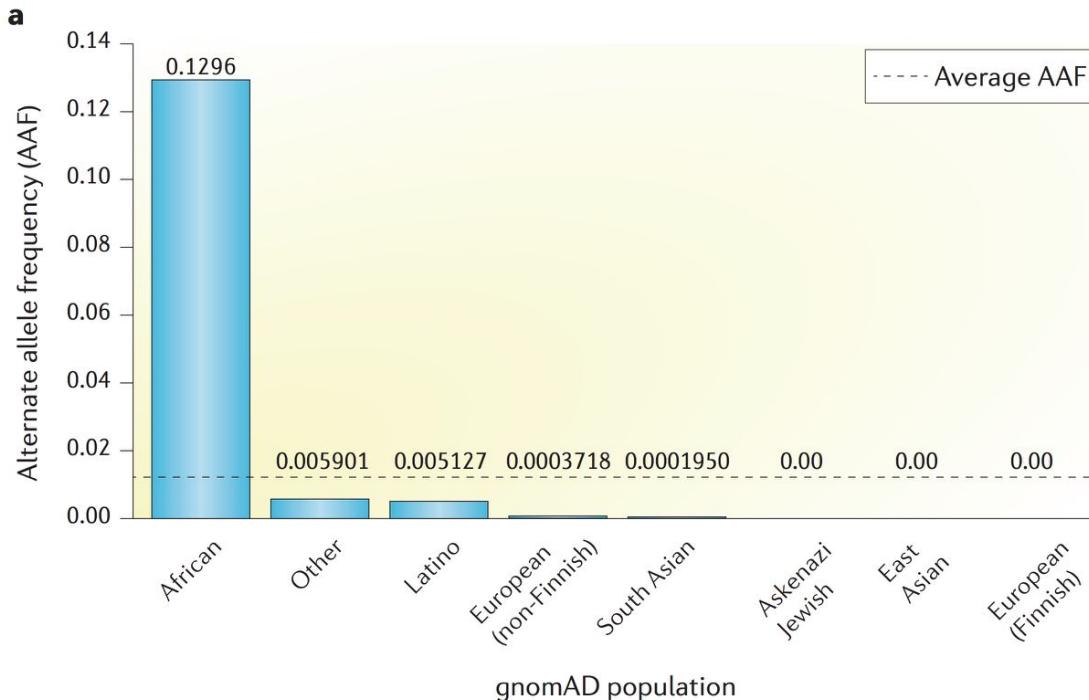
## Analysis of protein-coding genetic variation in 60,706 humans

Monkol Lek<sup>1,2,3,4</sup>, Konrad J. Karczewski<sup>1,2,\*</sup>, Eric V. Minikel<sup>1,2,5,\*</sup>, Kaitlin E. Samocha<sup>1,2,5,6\*</sup>, Eric Banks<sup>2</sup>, Timothy Fennell<sup>2</sup>, Anne H. O'Donnell-Luria<sup>1,2,7</sup>, James S. Ware<sup>2,8,9,10,11</sup>, Andrew J. Hill<sup>1,2,12</sup>, Beryl B. Cummings<sup>1,2,5</sup>, Taru Tukiainen<sup>1,2</sup>, Daniel P. Birnbaum<sup>2</sup>, Jack A. Kosmicki<sup>1,2,6,13</sup>, Laramie E. Duncan<sup>1,2,6</sup>, Karol Estrada<sup>1,2</sup>, Fengmei Zhao<sup>1,2</sup>, James Zou<sup>2</sup>, Emma Pierce-Hoffman<sup>1,2</sup>, Joanne Berghou<sup>14,15</sup>, David N. Cooper<sup>16</sup>, Nicole Deflaix<sup>17</sup>, Mark DePristo<sup>18</sup>, Ron Do<sup>19,20,21,22</sup>, Jason Flannick<sup>2,23</sup>, Menachem Fromer<sup>1,6,19,20,24</sup>, Laura Gauthier<sup>18</sup>, Jackie Goldstein<sup>1,2,6</sup>, Namrata Gupta<sup>2</sup>, Daniel Howrigan<sup>1,2,6</sup>, Adam Kiezun<sup>18</sup>, Mitja I. Kurki<sup>2,25</sup>, Ami Levy Moonshine<sup>18</sup>, Pradeep Natarajan<sup>2,26,27,28</sup>, Lorena Orozco<sup>29</sup>, Gina M. Peloso<sup>2,27,28</sup>, Ryan Poplin<sup>18</sup>, Manuel A. Rivas<sup>2</sup>, Valentin Ruano-Rubio<sup>18</sup>, Samuel A. Rose<sup>6</sup>, Douglas M. Ruderfer<sup>19,20,24</sup>, Khalid Shakir<sup>18</sup>, Peter D. Stenson<sup>16</sup>, Christine Stevens<sup>2</sup>, Brett P. Thomas<sup>1,2</sup>, Grace Tiao<sup>18</sup>, Maria T. Tusie-Luna<sup>30</sup>, Ben Weisburd<sup>2</sup>, Hong-Hee Won<sup>31</sup>, Dongmei Yu<sup>6,25,27,32</sup>, David M. Altshuler<sup>2,33</sup>, Diego Ardiissino<sup>34</sup>, Michael Boehnke<sup>35</sup>, John Danesh<sup>36</sup>, Stacey Donnelly<sup>2</sup>, Roberto Elosua<sup>37</sup>, Jose C. Florez<sup>2,26,27</sup>, Stacey B. Gabriel<sup>2</sup>, Gad Getz<sup>18,26,38</sup>, Stephen J. Glatt<sup>39,40,41</sup>, Christina M. Hultman<sup>42</sup>, Sekar Kathiresan<sup>2,26,27,28</sup>, Markku Laakso<sup>43</sup>, Steven McCarroll<sup>6,8</sup>, Mark I. McCarthy<sup>44,45,46</sup>, Dermot McGovern<sup>47</sup>, Ruth McPherson<sup>48</sup>, Benjamin M. Neale<sup>1,2,6</sup>, Aarno Palotie<sup>1,2,5,49</sup>, Shaun M. Purcell<sup>19,20,24</sup>, Danish Saleheen<sup>50,51,52</sup>, Jeremiah M. Scharf<sup>2,6,25,27,32</sup>, Pamela Sklar<sup>19,20,24,53,54</sup>, Patrick F. Sullivan<sup>55,56</sup>, Jaakko Tuomilehto<sup>57</sup>, Ming T. Tsuang<sup>58</sup>, Hugh C. Watkins<sup>44,59</sup>, James G. Wilson<sup>60</sup>, Mark J. Daly<sup>1,2,6</sup>, Daniel G. MacArthur<sup>1,2</sup> & Exome Aggregation Consortium†

Large-scale reference data sets of human genetic variation are critical for the medical and functional interpretation of DNA sequence changes. Here we describe the aggregation and analysis of high-quality exome (protein-coding region) DNA sequence data for 60,706 individuals of diverse ancestries generated as part of the Exome Aggregation Consortium (ExAC). This catalogue of human genetic diversity contains an average of one variant every eight bases of the exome, and provides direct evidence for the presence of widespread mutational recurrence. We have used this catalogue to calculate objective metrics of pathogenicity for sequence variants, and to identify genes subject to strong selection against various classes of mutation; identifying 3,230 genes with near-complete depletion of predicted protein-truncating variants, with 72% of these genes having no currently established human disease phenotype. Finally, we demonstrate that these data can be used for the efficient filtering of candidate disease-causing variants, and for the discovery of human 'knockout' variants in protein-coding genes.



# An allele underlying a rare disease should be rare in all ancestries!



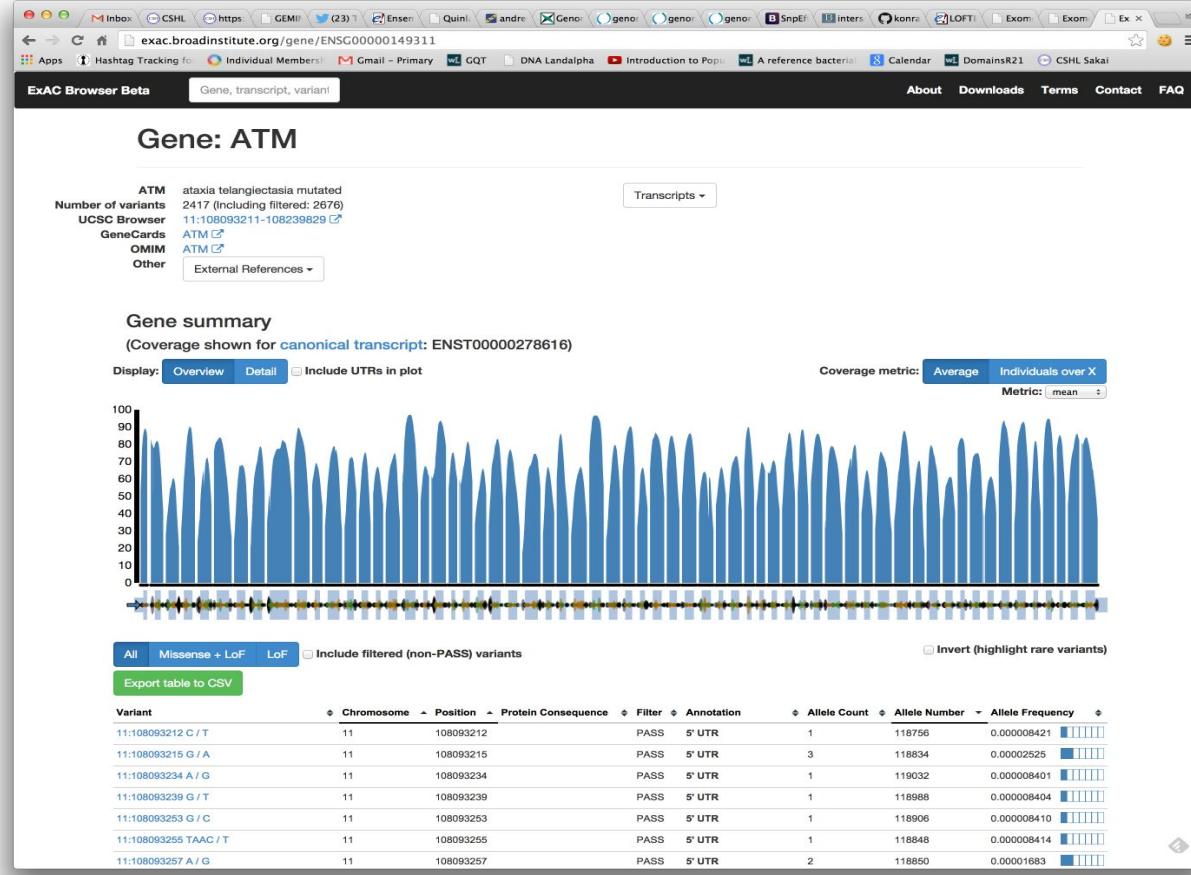
## Settling the score: variant prioritization and Mendelian disease

Karen Eilbeck<sup>1</sup>\*, Aaron Quinlan<sup>1,2</sup>\* and Mark Yandell<sup>2</sup>

**Abstract** | When investigating Mendelian disease using exome or genome sequencing, distinguishing disease-causing genetic variants from the multitude of candidate variants is a complex, multidimensional task. Many prioritization tools and online interpretation resources exist, and professional organizations have offered clinical guidelines for review and return of prioritization results. In this Review, we describe the strengths and weaknesses of widely used computational approaches, explain their roles in the diagnostic and discovery process and discuss how they can inform (and misinform) expert reviewers. We place variant prioritization in the wider context of gene prioritization, burden testing and genotype–phenotype association, and we discuss opportunities and challenges introduced by whole-genome sequencing.

Nature Reviews Genetics, 2017

# gnomAD reports the allele frequency from diverse ancestries



exac.broadinstitute.org  
gnomad.broadinstitute.org

# Why are only 30% of rare disease cases diagnosed?

# Hypothesis 1: we cannot detect the causal variant

ARTICLE

OPEN

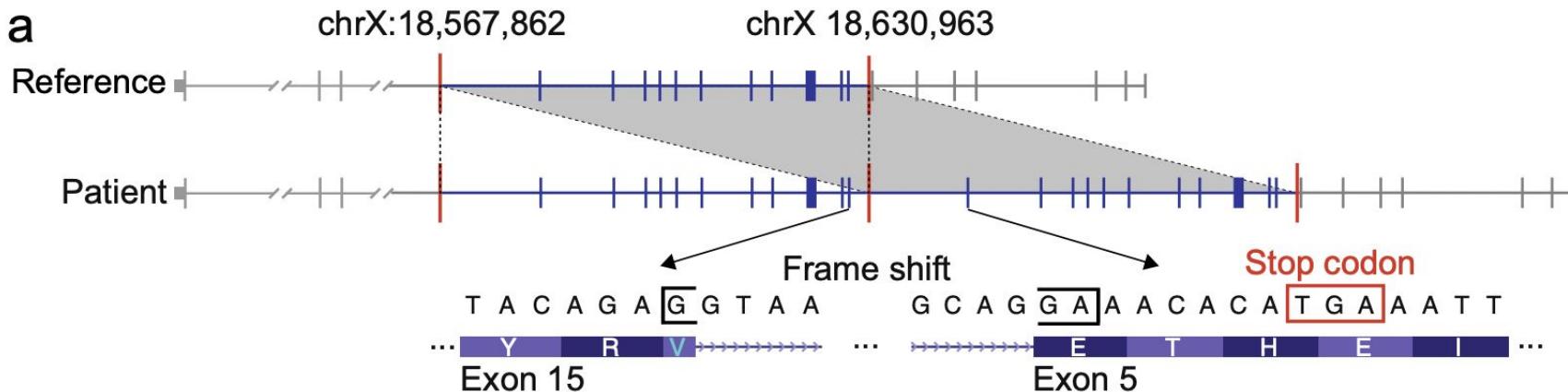
## Whole-genome analysis for effective clinical diagnosis and gene discovery in early infantile epileptic encephalopathy

Betsy E. P. Ostrander<sup>1</sup>, Russell J. Butterfield , Brent S. Pedersen<sup>2</sup>, Andrew J. Farrell<sup>2</sup>, Ryan M. Layer<sup>2</sup>, Alistair Ward<sup>2</sup>, Chase Miller<sup>2</sup>, Tonya DiSera<sup>2</sup>, Francis M. Filloux<sup>1</sup>, Meghan S. Candee<sup>1</sup>, Tara Newcomb<sup>2</sup>, Joshua L. Bonkowsky<sup>1</sup>, Gabor T. Marth  and Aaron R. Quinlan 

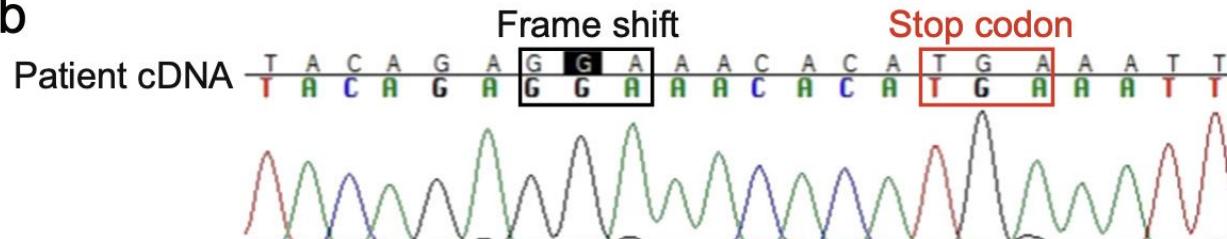


# Hypothesis 1: e.g., structural variants

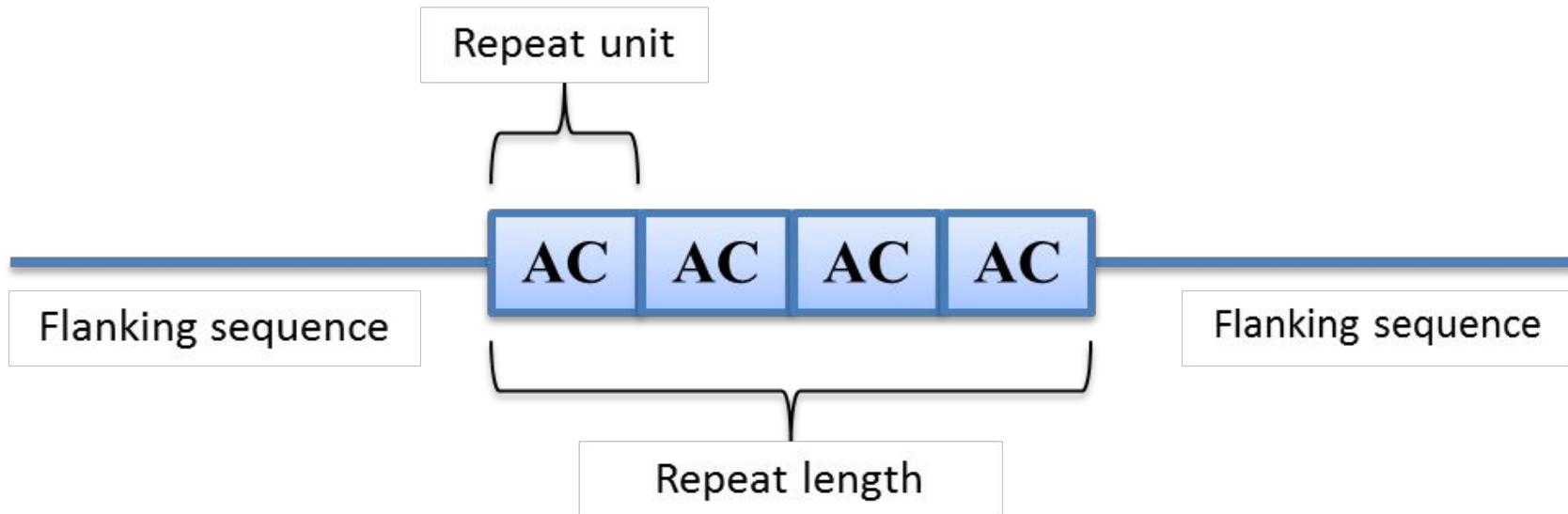
a



b



# Hypothesis 1: e.g., Novel Short Tandem Repeats



- 1-6bp repeat units
- AKA microsatellites
- ~3% of the human genome
- High mutation rate,  
high polymorphism

# Hypothesis 1: e.g., Novel Short Tandem Repeats

Disease	Gene	Repeat unit	Inheritance	Location	Pathogenic range	Reference
CANVAS	RFC1	AAGGG	AR	intronic	400-2000	Cortese 2019
Baratela-Scott Syndrome	XYLT1	CCG	AR	5' non-coding		LaCroix 2019
BAFME1/FAME1	SAMD12	TTTCA	AD	intronic	225-458	Ishiura 2018
BAFME6/FAME6	TNRC6A	TTTCA	AD	intronic		Ishiura 2018
BAFME7/FAME7	RAPGEF2	TTTCA	AD	intronic		Ishiura 2018
SCA37	DAB1	ATTTC	AD	intronic	31-75	Seixas 2017
SCA31	BEAN	TGGAA	AD	intronic		Sato 2009

# Hypothesis 2: We don't know what to make of a variant (VUS)

## Predicting Splicing from Primary Sequence with Deep Learning

Kishore Jaganathan,<sup>1,6</sup> Sofia Kyriazopoulou Panagiotopoulou,<sup>1,6</sup> Jeremy F. McRae,<sup>1,6</sup> Siavash Fazel Darbandi,<sup>2</sup> David Knowles,<sup>3</sup> Yang I. Li,<sup>3</sup> Jack A. Kosmicki,<sup>1,4</sup> Juan Arbelaez,<sup>2</sup> Wenwu Cui,<sup>1</sup> Grace B. Schwartz,<sup>2</sup> Eric D. Chow,<sup>5</sup> Efstathios Kanterakis,<sup>1</sup> Hong Gao,<sup>1</sup> Amirali Kia,<sup>1</sup> Serafim Batzoglou,<sup>1</sup> Stephan J. Sanders,<sup>2</sup> and Kyle Kai-How Farh<sup>1,7,\*</sup>

<sup>1</sup>Illumina Artificial Intelligence Laboratory, Illumina, Inc., San Diego, CA, USA

<sup>2</sup>Department of Psychiatry, University of California, San Francisco, San Francisco, CA, USA

<sup>3</sup>Department of Genetics, Stanford University, Stanford, CA, USA

<sup>4</sup>Broad Institute of MIT and Harvard, Cambridge, MA, USA

<sup>5</sup>Department of Biochemistry and Biophysics, University of California, San Francisco, San Francisco, CA, USA

<sup>6</sup>These authors contributed equally

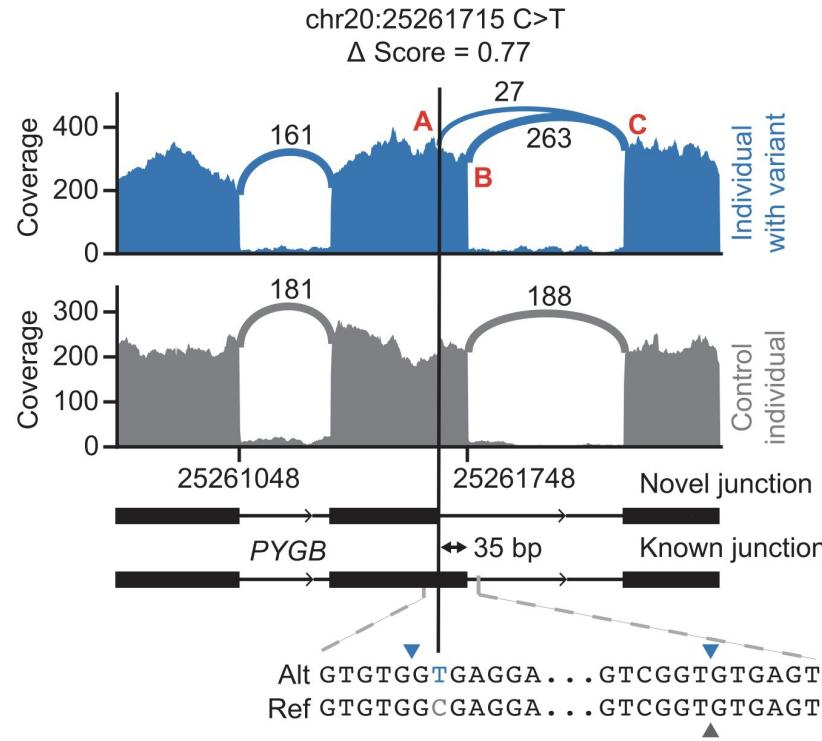
<sup>7</sup>Lead Contact

\*Correspondence: kfarh@illumina.com

<https://doi.org/10.1016/j.cell.2018.12.015>



# Hypothesis 2: e.g. splice-altering predictions



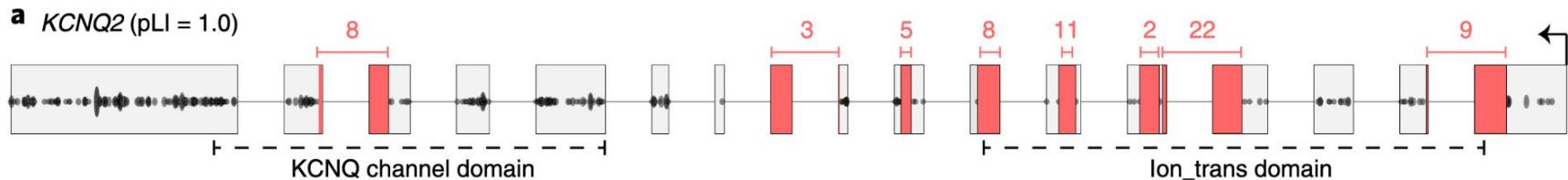
# Hypothesis 2: genetic "constraint" (intolerance to mutation)



# Hypothesis 2: genetic constraint

## A map of constrained coding regions in the human genome

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# Summary and things to ponder

- Modern DNA sequencing and advanced software can rapidly diagnose 33-50% of rare disease cases, often in just a few days
- The majority of cases are caused by loss-of-function variants in protein coding exons or splice sites.
- **Why are 50% of cases undiagnosable with the same assay, information?**
  - We are far from predicting phenotype directly from genotype.
  - We have a poor understanding of the consequence of genetic variation outside of exons
  - Often we have one interesting variant, but are missing the other (AR inheritance). How do we find it?
  - Some patients may in fact have multiple phenotypes. This complicates interpretation.