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Supplemental Data

A Whole-Genome Analysis Framework

for Effective Identification of Pathogenic

Regulatory Variants in Mendelian Disease

Damian Smedley, Max Schubach, Julius O.B. Jacobsen, Sebastian Köhler, Tomasz Zemojtel, Malte Spielmann, Marten Jäger, Harry Hochheiser, Nicole L. Washington, Julie A. McMurry, Melissa A. Haendel, Christopher J. Mungall, Suzanna E. Lewis, Tudor Groza, Giorgio Valentini, and Peter N. Robinson

Note S1: Comparison of different learning approaches for the prediction of Mendelian regulatory variants

We performed an in-depth comparison of ReMM, CADD, FATHMM-MKL, GWAVA, Eigen, and DeepSEA. In order to obtain a common basis for the comparison, we rescaled all the scores in the range [0,1] through a simple linear transformation (indicated as "normalized score" in the legends to Figures S1, S2, and S3).

GWAVA displayed the best precision across the normalized scores (Figure S1 A), whereas FATHMM-MKL and DeepSEA had the best sensitivity (recall) (Figure S1 B). Nevertheless ReMM is the only method that achieves both a relatively high precision and recall (Figure S2 A and S3 A), thus achieving the best F-score (Figure S1 C) and balanced accuracy (Figure S1 D).

Although GWAVA displayed the best precision, it showed a marked decrement of the recall as a function of the normalized score (Figure S2 C), and for the highest values of the precision, the recall is close to 0 (Figure S3 C). Correspondingly, GWAVA (the second best method) showed a maximal F-score of only about 0.3, as compared to a maximum ReMM F-score larger than 0.5 (Figure S1 C).

DeepSEA achieved a high sensitivity but a very low precision, which was close to 0 for the full range of the normalized score, with a peak for the score close to 1, when the sensitivity declines close to 0 (Figure S2 F and S3 F), thus resulting in a F-score that was very close to 0 in the full range of the normalized scores.

CADD performs poorly on this task, mainly due to a low precision, with a recall that was very close to 0 for a normalized score larger than 0.5 (Figure S2 D and S3 D).

Eigen achieved the best F-score for normalized score close to 0.26 (Figure S2 E). This is the results of a peak in precision (about 0.5) close to this value of the normalized score. Unfortunately the recall declines for normalized scores larger than 0.2, thus leading to poor F-scores just for score thresholds larger than 0.26. This is due to the fact that several negative variants get an extremely high score in contrast to the regulatory mutations. Therefore a cutoff at 0.26 (normalized score) or 4 (Eigen score) for Mendelian regulatory mutations could represent an appropriate threshold to improve the performance of Eigen. In sum, Eigen has similar, but slightly lower performances than GWAVA.

FATHMM-MKL showed a low precision, but a high sensitivity with a significant decay only for normalized scores very close 1. The resulting F-score is very low also for large values of the normalized scores, due to the poor performance in precision (Figure S2 B and S3 B).

In summary, this analysis indicates that ReMM substantially outperforms the other methods in predicting non-coding Mendelian mutations. ReMM is the only method able to obtain both a relatively high precision and recall for the largest values of the normalized score (Figure S3 A). In particular, Figure S3 A indicates that ReMM, for score values higher than 0.97, can achieve an increasing precision from 0.50 to 1 while maintaining a relatively high recall between 0.3 and 0.5. This suggests that a threshold in the range of [0.95,1] may be most appropriate to search for novel Mendelian mutations in the non-coding genome. For increasing values of the normalized scores (larger than 0.95), one can choose whether to focus on precision or recall in the prediction of non-coding Mendelian mutations. Note that for scores very close to 1 the sensitivity is very low, thus leading to an F-score close to 0.

We emphasize that ReMM has been specifically designed to deal with this extremely unbalanced task, with a small, but highly reliable, set of positive examples (manually curated Mendelian mutations). The five competing methods analyzed in this work were not specifically designed for Mendelian mutations, and moreover, apart from GWAVA, they do not adopt learning strategies specifically devised to deal with extremely unbalanced data. These facts might explain their worse results with respect to ReMM in the prediction of Mendelian mutations.

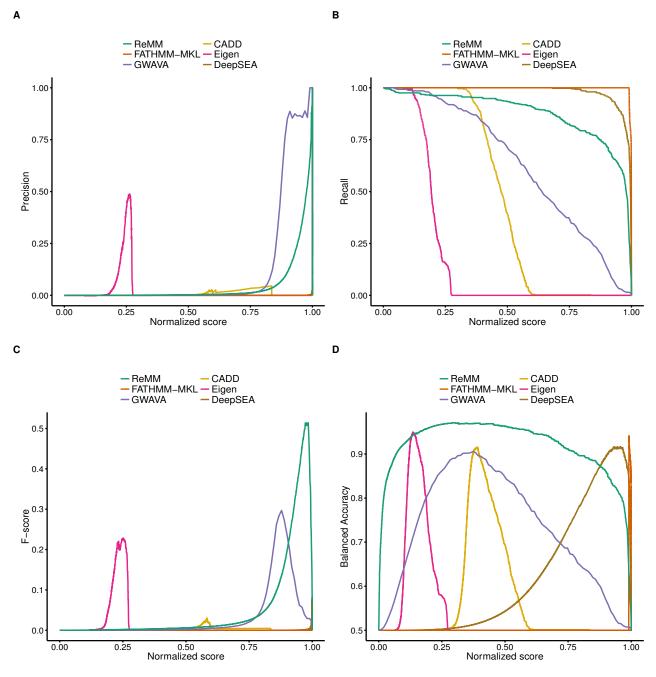


Figure S1: Performance comparison across scores. Comparison of ReMM, CADD, 1 FATHMM-MKL, 2 GWAVA, 3 Eigen, 4 and DeepSEA 5 performance, by varying the normalized score threshold. **A** precision **B** recall **C** F-score **D** balanced accuracy.

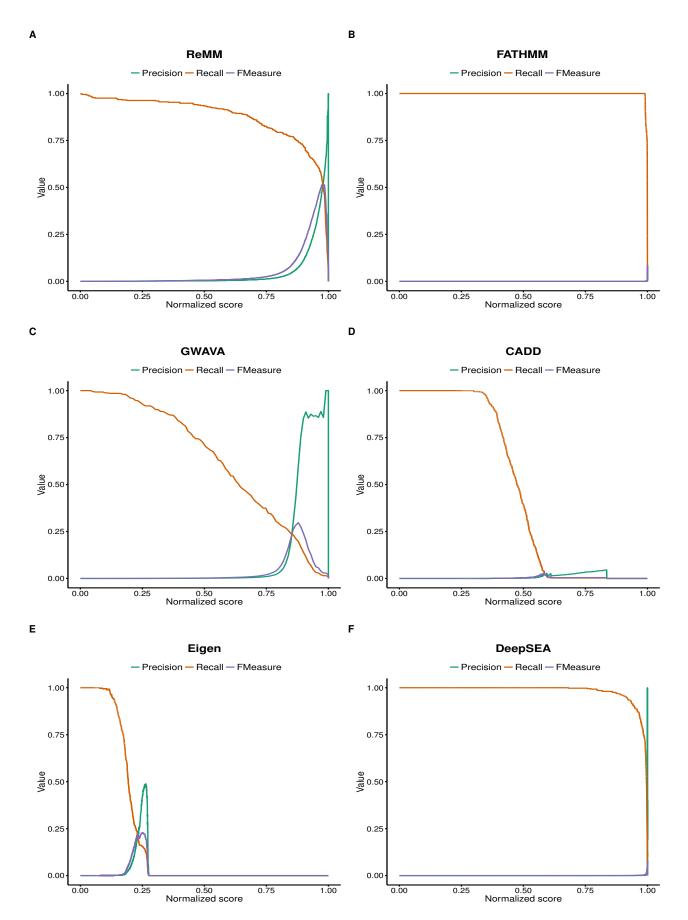


Figure S2: Precision, recall, and F-score per score. Precision, recall and F-score results as a function of the normalized score. **A** ReMM **B** FATHMM-MKL **C** GWAVA **D** CADD **E** Eigen **F** DeepSEA.

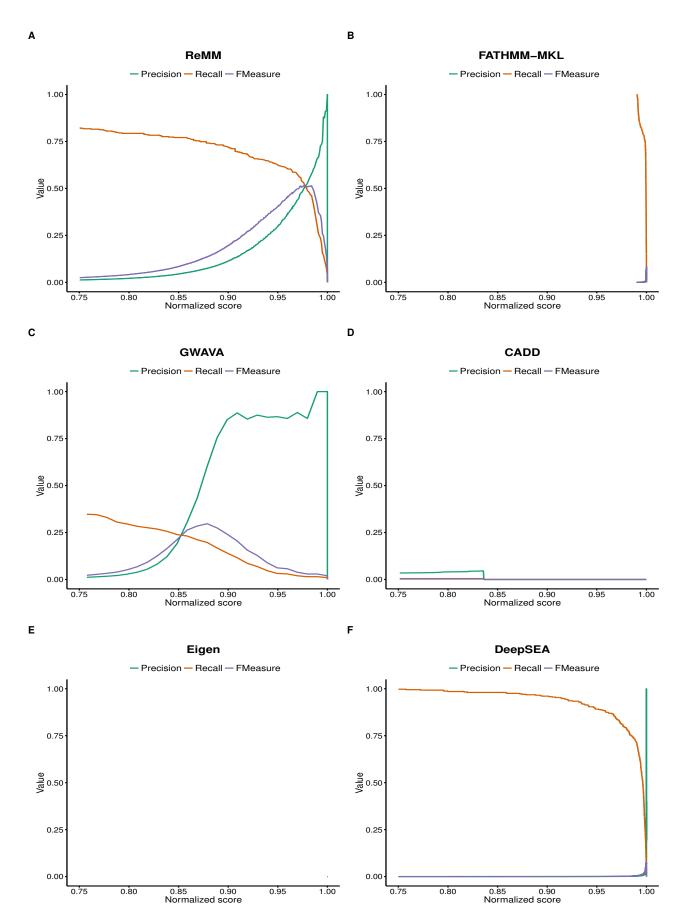


Figure S3: Details of precision, recall, and F-score per score on the highest range. Details of precision, recall and F-score results depending on [0.75,1] values of the normalized scores. A ReMM B FATHMM-MKL C GWAVA D CADD E Eigen F DeepSEA.

Category	All	High quality	Fixed	High-quality & Fixed
CDS	49599	44885	43420	38706
CDS (syn)	57708	52656	52189	47137
Unclassified sequence variant	11408	10675	11408	10675
Splice	12520	12553	12430	11218
5' UTR	764719	711934	692943	640158*
3' UTR	121014	112740	109034	100760*
Intron	5954014	5600983	5383124	5030093*
Upstream/Downstream	224128	198554	203737	178163*
Noncoding (exon)	67704	58236	62038	52570
Noncoding (intron)	858848	782486	782720	706358*
Intergenic	9908106	8989024	9018749	8099667*
Total	18029768	16574726	16371792	14915505

Table S1: Negative training set for the ReMM score. Distribution of variant categories for single nucleotide positions in Homo sapiens that differ from the inferred sequence of the last common primate ancestor. An asterisk (*) marks variant categories that were used to calculate the ReMM score. Variants were chosen from the Sequence Ontology⁶ categories NON_CODING_TRANSCRIPT_INTRON_VARIANT, COD-FIVE_PRIME_UTR_VARIANT, ING TRANSCRIPT INTRON VARIANT, THREE PRIME UTR VARIANT, UPSTREAM_GENE_VARIANT, DOWNSTREAM_GENE_VARIANT, INTERGENIC VARIANT, TF_BINDING_SITE_VARIANT, REGULATORY_REGION_VARIANT, CONSERVED_INTRON_VARIANT, IN-TRAGENIC VARIANT, CONSERVED INTERGENIC VARIANT, and INTRON VARIANT. Variants were defined at positions in which the human genome differs from the inferred genome sequence of the last common primate ancestor (ancestral allele sequences downloaded from http://ftp.ensembl.org/pub/release-71/fasta/ ancestral_alleles/homo_sapiens_ancestor_GRCh37_e71.tar.bz2). For fixed variants we rejected variants ants if the ancestral allele is present in more then 5% in the individuals of the 1000 Genomes Project. Variants are annotated using Jannovar⁷ version 0.14 using transcript definitions from the NCBI Reference Sequence Database⁸ (annotation release 105).

Attribute	Description
GCContent	GC-content in a window of ± 75 nt
CnGnerGC	Percentage of island that is C or G.
CpGperGC	UCSC table cpgIslandExt
CpGperCpG	Percentage of island that is CpG.
оророгора	UCSC table cpgIslandExt
CpGobsExp	Ratio of observed to expected CpG in island.
'	UCSC table cpgIslandExt
priPhyloP46way	Primate PhyloP score.
	http://hgdownload.soe.ucsc.edu/goldenPath/hg19/phyloP46way/primates Vertebrate PhyloP.
verPhyloP46way	http://hgdownload.soe.ucsc.edu/goldenPath/hg19/phyloP46way/vertebrate
	Mammalian PhyloP score.
mamPhyloP46way	http://hgdownload.soe.ucsc.edu/goldenPath/hg19/phyloP46way/placentalMammals
	Primate PhastCons conservation score
priPhastCons46way	http://hgdownload.soe.ucsc.edu/goldenPath/hg19/phastCons46way/primates
DI1010	Vertebrate PhastCons conservation score
verPhastCons46way	http://hgdownload.soe.ucsc.edu/goldenPath/hg19/phastCons46way/vertebrate
mamPhastCons46way	Mammalian PhastCons conservation score
mamrnasicons40way	http://hgdownload.soe.ucsc.edu/goldenPath/hg19/phastCons46way/placentalMammals
GerpRS	GERP++ element score
derprio	http://mendel.stanford.edu/SidowLab/downloads/gerp/hg19.GERP_elements.tar.gz
GerpRSpv	GERP++ element p-Value
G.G. P. 10P	http://mendel.stanford.edu/SidowLab/downloads/gerp/hg19.GERP_elements.tar.gz
EncH3K27Ac	Maximum ENCODE H3K27 acetylation level
	http://hgdownload.cse.ucsc.edu/goldenPath/hg19/encodeDCC/wgEncodeRegMarkH3k27ac
EncH3K4Me1	Maximum ENCODE H3K4 methylation level
	http://hgdownload.cse.ucsc.edu/goldenPath/hg19/encodeDCC/wgEncodeRegMarkH3k4me1 Maximum ENCODE H3K4 trimethylation level
EncH3K4Me3	http://hgdownload.cse.ucsc.edu/goldenPath/hg19/encodeDCC/wgEncodeRegMarkH3k4me3
	DnaseClustered V3 hypersensitivity score
DnaseClusteredHyp	http://hgdownload.cse.ucsc.edu/goldenPath/hg19/encodeDCC/wgEncodeRegDnaseClustered
D 01 1 10	Number of DnaseClustered V3 hypersensitive cells
DnaseClusteredScore	http://hgdownload.cse.ucsc.edu/goldenPath/hg19/encodeDCC/wgEncodeRegDnaseClustered
fantom5Perm	FANTOM 5 permissive enhancers
lantomorenn	http://enhancer.binf.ku.dk/presets/permissive_enhancers.bed
fantom5Robust	FANTOM5 robust enhancers
เลเนอกาอกออนรถ	http://enhancer.binf.ku.dk/presets/robust_enhancers.bed
numTFBSConserved	Number of overlapping transcription factor binding sites.
\/	UCSC table tfbsConsSites
rareVar	Number of rare 1000 Genome variants ($\leq 0.5\%$ AF) in a window of ± 500 nt
commonVar fracRareCommon	Number of common 1000 Genome variants ($>0.5\%$ AF) in a window of ±500 nt Ratio rare to common variants
nacrialecommon	Overlapping ISCA CNVs
	http://www.ncbi.nlm.nih.gov/dbvar/studies/nstd75
ISCApath	http://www.ncbi.nlm.nih.gov/dbvar/studies/nstd46
	http://www.ncbi.nlm.nih.gov/dbvar/studies/nstd37
	Overlapping dbVAR CNVs
dbVARCount	ftp://ftp.ncbi.nlm.nih.gov/pub/dbVar/data/Homo_sapiens/
	by_assembly/GRCh37.p13/gvf/GRCh37.p13.remap.all.germline.ucsc.gvf.gz
DGVCount	Overlapping DGV CNVs
2 d v Oodin	http://dgv.tcag.ca/dgv/app/downloads?ref=GRCh37/hg19

Table S2: Genomic attributes used by the ReMM score. Genomic attributes used for calculating the ReMM Score with UCSC table or web-link of the source.

Attribute	AUC	AUPRC	TP Rate	FP Rate
priPhyloP46way	0.96407	0.02496	0.87685	0.06908
verPhyloP46way	0.92481	0.11445	0.81773	0.08782
mamPhyloP46way	0.92085	0.21589	0.82266	0.10174
priPhastCons46way	0.89792	0.00363	0.74631	0.05408
mamPhastCons46way	0.85730	0.00148	0.73153	0.02982
verPhastCons46way	0.84801	0.00103	0.71921	0.03874
GerpRS	0.84290	0.00035	0.65025	0.03898
GCContent	0.82194	0.00034	0.71182	0.24562
EncH3K4Me3	0.80195	0.00060	0.59852	0.04158
EncH3K27Ac	0.79835	0.00026	0.52217	0.06235
EncH3K4Me1	0.74378	0.00007	0.48522	0.17776
DnaseClusteredScore	0.73638	0.00029	0.59606	0.08874
DnaseClusteredHyp	0.73173	0.00081	0.50000	0.04383
fracRareCommon	0.67290	0.00006	0.65271	0.40319
numTFBSConserved	0.63509	0.00060	0.29803	0.00936
CpGperGC	0.61854	0.00088	0.39655	0.00595
CpGperCpG	0.61734	0.00095	0.39655	0.00595
CpGobsExp	0.61715	0.00094	0.39655	0.00595
commonVar	0.58439	0.00004	0.65025	0.51394
ISCApath	0.52920	0.00004	0.36946	0.23349
rareVar	0.50331	0.00025	0.35961	0.32046
fantom5Robust	0.49221	0.00003	0.49754	0.51007
GerpRSpv	0.49083	0.00003	0.02709	0.00588
fantom5Perm	0.48692	0.00003	0.79310	0.83444
DGVCount	0.40812	0.00002	0.36453	0.50823
dbVARCount	0.40812	0.00002	0.36453	0.50823

Table S3: Univariate logistic regression model of genomic attributes. Performance results of an univariate logistic regression model⁹ of the genomic attributes using all Mendelian non-coding regulatory mutations and the differences between primates and humans. The model and results were computed with an in-house Java program using the Weka library.¹⁰

Score	ROC AUC	p-value
CADD	0.9519	$< 2.2 \cdot 10^{-16^*}$
GWAVA	0.9563	$4.471 \cdot 10^{-7^*}$
DeepSEA	0.9733	$4.696 \cdot 10^{-4*}$
Eigen	0.9812	$< 2.2 \cdot 10^{-16^*}$
FATHMM-MKL	0.9847	0.1045

Table S4: Statistical comparison of ROC curves. Comparison of the area under the ROC curve between ReMM (AUC = 0.9894) and other state-of-the-art scoring methods: CADD, GWAVA, DeepSEA, Eigen, and FATHMM-MKL. Tests were performed using the one-sided DeLong test, and asterisks (*) mark statistically significant differences (significance level $\alpha = 0.05$)

Gene	Transcript	Disease	Reference
ADSL	NM_000026.2	Adenylosuccinase deficiency	Marie S (2002), PMID:12016589
	 Coding 	c.1277G>A:p.Arg426His	chr22:40760969G>A
	 Non-coding 	c49T>C	chr22:40742514T>C
ALDOB	NM_000035.3	hereditary fructose intolerance	Coffee EM (2010), PMID:20882353
	Coding	c.448G>C:p.Ala150Pro	chr9:104189856C>G
	Non-coding	Promoter (-132)	chr9:104198194C>T
DBT	NM_001918.2	Maple syrup urine disease, type II	Brodtkorb E (2010), PMID:20570198
	Coding	c.901C>T:p.Arg301Cys	chr1:100680411G>A
CEDT1	Non-coding	c.*358A>C	chr1:100661453T>G
GFPT1	NM_001244710.1	Myasthenia, congenital, 12	Dusl M (2015), PMID:25765662
	CodingNon-coding	c.595G>T:p.Val199Phe c.*22C>A	chr2:69583638C>A chr2:69553299G>T
GHRHR	NM 000823.3	Growth hormone deficiency, isolated, type IB	Salvatori R (2002), PMID:11875102
amm	• Coding	c.985A>G:p.Lys329Glu	chr7:31016054A>G
	Non-coding	Promoter (-124)	chr7:31003560A>C
GJB2	NM 004004.5	Deafness, autosomal recessive 1A	Matos TD (2007), PMID:17660464
GODE	• Coding	c.250G>A:p.Val84Met	chr13:20763471C>T
	Non-coding	Promoter (-3438)	chr13:20767158G>A
GRHPR	NM 012203.1	Hyperoxaluria, primary, type II	Fu Y (2014), PMID:25410531
<i>C</i>	Coding	c.694del:p.Gln232Argfs*3	chr9:37430601TC>T
	 Non-coding 	3	chr9:37422744GC>AT
HBB	NM_000518.4	beta thalassemia	Athanassiadou A (1994), PMID:7803275
	Coding	c.118C>T:p.Gln40*	chr11:5248004G>A
	 Non-coding 	c41delT	chr11:5248291GA>G
HBB	NM_000518.4	beta thalassemia	Calvo SE (2009), PMID:19372376
	 Coding 	c.25_26delAA (p.Lys9Valfs)	chr11:5248225CTT>C
	 Non-coding 	c29G>A	chr11:5248280C>T
HBB	NM_000518.4	beta thalassemia	Van de Water (2008), PMID:18473240
	 Coding 	c.126_129del:p.Phe42Leufs*19	chr11:5247992CAAAG>C
	 Non-coding 	c43C>T	chr11:5248294G>A
HBB	NM_000518.4	beta thalassemia	Ma (2001), PMID:11722440
	 Coding 	c.126_129del:p.Phe42Leufs*19	chr11:5247992CAAAG>C
	 Non-coding 	c.*108A>C	chr11:5246720T>G
HBB	NM_000518.4	beta thalassemia	Jacquette (2004), PMID15481893
	Coding	c.28_29insTA:p.Ser10Leufs*11	chr11:5248223G>GTA
	Non-coding	c.*110T>A	chr11:5246718A>T
HBB	NM_000518.4	beta thalassemia	Ho (1996), PMID:8562944
	Coding	c.118C>T:p.Gln40*	chr11:5248004G>A
HBB	Non-coding Non-coding	c18C>G	chr11;5248269G>C
пвв	NM_000518.4	beta thalassemia	Chen (2007), PMID:17516066
	CodingNon-coding	c.126_129del:p.Phe42Leufs*19 Promoter (-73)	chr11:5247992CAAAG>C chr11:5248374T>A
HBB	•	beta thalassemia	
ПОО	NM_000518.4 • Coding	c.20A>T:p.Glu7Val	Al Zadjali S (2011), PMID:21801233 chr11:5248232T>A
	Non-coding	Promoter (-71)	chr11:5248372G>A
HK1	NM 033497	Hemolytic anemia due to hexokinase deficiency	de Vooght KM (2009), PMID:19608687
	• Coding	c.293G>A:p.Arg98Gln	chr10:71119707G>A
	Non-coding	Promoter (-193)	chr10:71075518A>G
PROC	NM 000312	protein C deficiency	Millar DS (2000), PMID: 10942114
	Coding	c.814C>T:p.Arg272Cys	chr2:128185950C>T
	 Non-coding 	Promoter (-32)	chr2:128175983A>G
RAPSN	NM 005055.4	Myasthenic syndrome, congenital, 11	Ohno K (2003), PMID:12651869
	 Coding 	c.264C>A:p.Asn88Lys	chr11:47469631G>T
	 Non-coding 	c199C>G	chr11:47470715G>C
TH	NM_199293	Segawa syndrome, recessive	Verbeek MM (2007), PMID:17696123
	 Coding 	c.1147C>A:p.Leu383Met	chr11:2187270G>T
	 Non-coding 	Promoter (-71)	chr11:2193087G>A
UROS	NM_000375.2:	Porphyria, congenital erythropoietic	Solis C (2001), PMID:11254675
	 Coding 	c.217T>C:p.Cys73Arg	chr10:127503630A>G
	 Non-coding 	c26-177T>C (Promoter)	chr10:127505271A>G
UROS	NM_000375.2:	Porphyria, congenital erythropoietic	Solis C (2001), PMID:11254675
	 Coding 	c.673G>A:p.Gly225Ser	chr10:127477562C>T
	 Non-coding 	c26-197C>A (Promoter)	chr10:127505291G>T
UROS	NM_000375.2:	Porphyria, congenital erythropoietic	Solis C (2001), PMID:11254675
	 Splice 	c.63+1G>A:	chr10:127505005C>T
	Non-coding	c26-193C>A (Promoter)	chr10:127505287G>T

Table S5: Compound heterozygous mutations. 22 cases were identified in the literature with one coding or splice site mutation and one mutation in a non-coding sequence. Where applicable, the effect of the mutation on a representative transcript is shown. The chromosomal coordinates of the variants are shown using abbreviated VCF-like notation. For instance, chr9:104198194C>T corresponds to CHROM chr9, POS 104198194, REF C, and ALT T. These cases were used to test the performance of Genomiser on combinations of coding/non-coding mutations. Note that the 22 non-coding mutations were also included in the main training data set of 453 non-coding mutations.

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