PREDICTING VARIANT DELETERIOUSNESS IN NON-HUMAN SPECIES: TAKING THE CADD APPROACH TO PIG

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1. OBJECTIVE

Develop a method to assign a <u>DELETERIOUSNESS</u>
<u>SCORE</u> to variants anywhere in <u>LIVESTOCK GENOMES</u>.

GTTACTAGTACAT

GTTACTCGTACAT
GTTACTAGTATAT
GTAACTAGTACAT





0.01

0.15

0.87







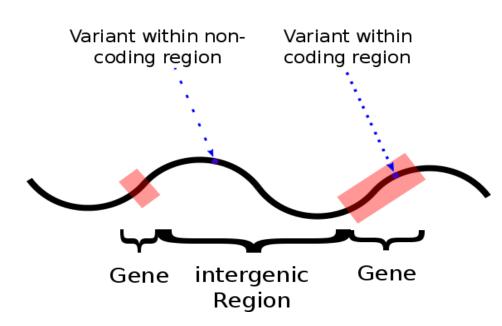
Model Objective



Standing on the Shoulders of Giants

• Kircher et al., Nature Genetics
2014

PolyPhen etc.: one model, one comparable score for variants in coding and non-coding regions



Combined Annotation Dependent Depletion (CADD)



Feasibility Study: mCADD

Research article Open Access

Predicting variant deleteriousness in nonhuman species: applying the CADD approach in mouse

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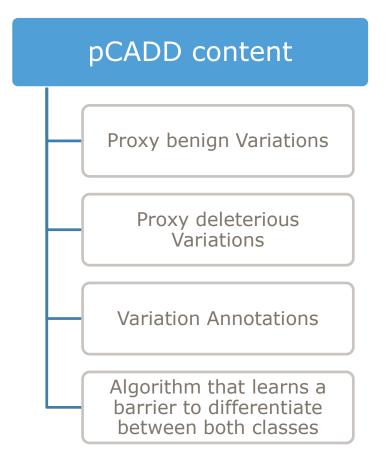
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Next step: P(ig)-CADD



pCADD - Model outline



Model outline



pCADD - proxy benign variations

pCADD content

Proxy benign Variations

Proxy deleterious Variations

Variation Annotations

Algorithm that learns a barrier to differentiate between both classes

ACATA AAAAA

Infer common ancestor with closely related species



pCADD - Simulating SNPs and their constraints

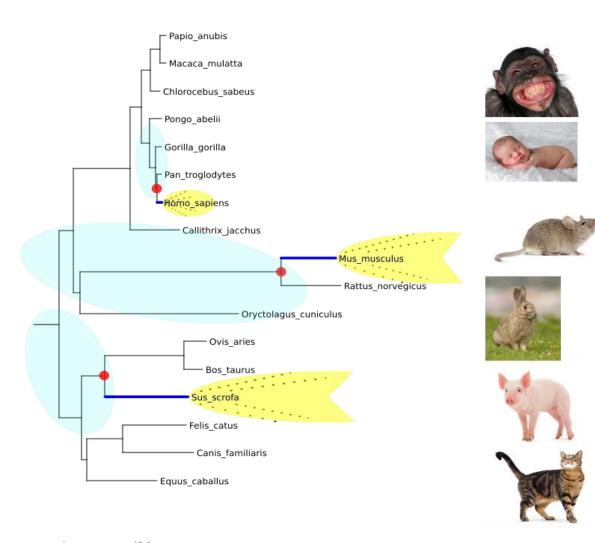
pCADD content

Proxy benign Variations

Proxy deleterious Variations

Variation Annotations

Algorithm that learns a barrier to differentiate between both classes





pCADD - Variant annotations

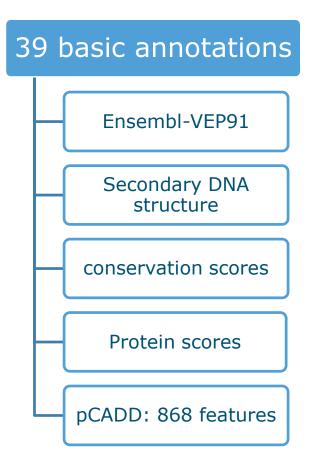
pCADD content

Proxy benign Variations

Proxy deleterious Variations

Variation Annotations

Algorithm that learns a barrier to differentiate between both classes



Annotation labels



pCADD - Generation of the Machine Learning Model

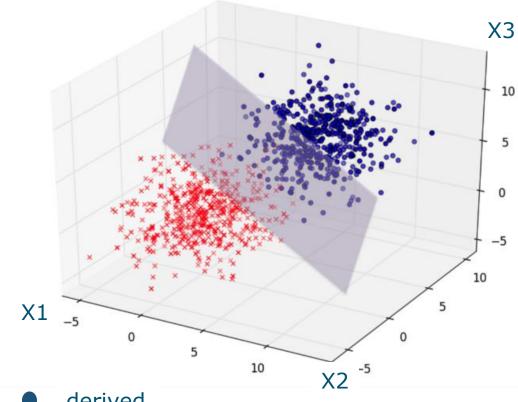
pCADD content

Proxy benign Variations

Proxy deleterious Variations

Variation Annotations

Algorithm that learns a barrier to differentiate between both classes



derived

simulated

Notes: X(n)=feature(n) In this research more than 3 features were used

Decision boundary

General representation of a Machine learning model



pCADD Model Extension - PHRED-like scores

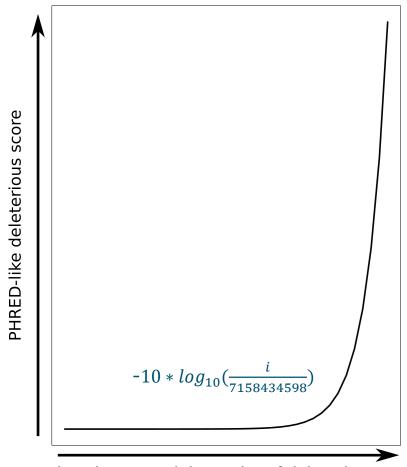
- All possible SNPs on chromosome 1-18 and X were generated and annotated (7,158,434,598).
- SNPs were ranked with respect to their deleteriousness.

Lowest 90%

• PHRED: 0-10 Lowest 99%

• PHRED: 0-20 Lowest 99.9%

• PHRED: 0-30



mutations in ascertaining order of deleteriousness

Hypothetical representation of PHRED-like score distribution



4. Results

pCADD - Evaluating Known Deleterious Variants

Нар.	Туре	SSC	Position	Ref	Alt	Gene	AA change (SIFT)	Raw-score	PHRED- score
DU1	Splice-donor	12	38,922,102	G	Α	TADA2A	-	0.95885	21.88258
LA1	Splice-region	3	43,952,776	Т	G	POLR1B	-	0.69472	10.14103
LA2	Frameshift	13	195,977,038	С	-	URB1	1961-V/X	NA	NA
LA3	Missense	6	54,880,241	Т	С	PNKP	96-Q/R (0.02)	0.9967	29.46386

small set of known variants



4. Results

pCADD - JBrowser Implementation

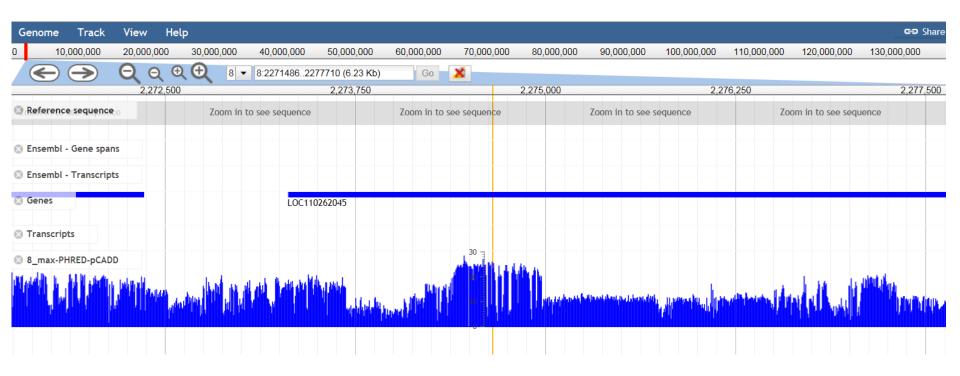






4. Results

pCADD - Identification of NCBI genebuild element



Intergenic high-impact, high frequent SNP



6. QUESTIONS?

People to Thank



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- Marcel Reinders







- Dick de Ridder
- Martijn Derks
- Mirte Bosse
- Hendrik-Jan Megens
- Martien Groenen

