

Machine Learning with Digital Signal Processing for Classification of Mouse Genotypes

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Mus subspecies (40);

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Machine Learning (ML) Applied to the Classification of Genomic **Information Uncovers a Wealth of Information**

Genomes have individual, pervasive signatures of primary sequence organization. Kari et al. *PLoS One*. 2015 May 22;10(5):e0119815

ML is a powerful tool for classification of thousands of genomic signatures Randhawa et al. BMC Genomics. 2019 Apr 3;20(1):267

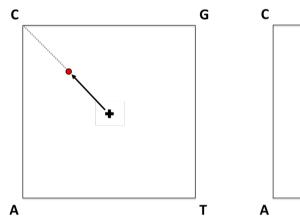
Here, classification of genomic signatures using ML is extended for the first time to single nucleotide polymorphic (SNP) genotypes to test accuracy in classification of genetic relatedness across a spectrum of origins and breeding histories.

The wealth of diversity in mouse genetic backgrounds provides benchmark testing for the power of ML and SNP genotypes to classify and identify different mouse genetic backgrounds.

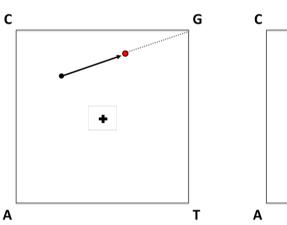
ML applied to SNP genotypes is predicted to find relevance in classifying phenotypes like cancer and inherited diseases, and in distinguishing mutation signatures of endogenous mutations and environmental mutagen exposures.

Chaos Game Representation (CGR): Two-dimensional Representation of DNA Sequence Organization in Genomic Signatures

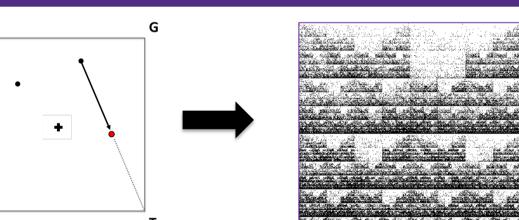
CGTA

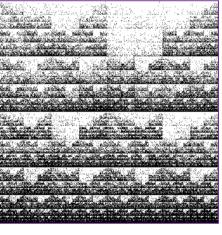


CGTA



C G T A





Human CGR 20 kb

A 2D Chaos plot uses iterative plotting of primary sequence data

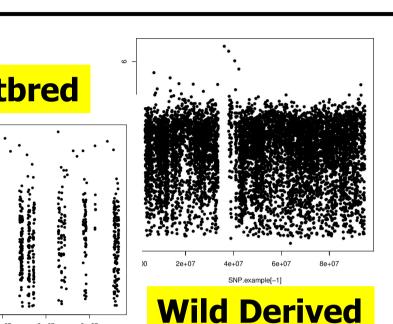
Two-dimensional CGR Representations of Mouse SNP Genotypes BB AA · · · · · · · · · · _____ ····· NC Classical Inbred **F1 NMRI** AB > Chaos plot vertices are adapted replacing single nucleotides at the vertices with AA, BB, AB and - no call (NC) SNP genotypes plotted for 500K SNP loci assayed by array technology. Plotting rules are unchanged. البوسيها إحباشاتها بالمشائد والحسا ابدك وأما CGR patterns for different mouse SNP genotypes Recombinant Wild Derived are as predicted. Inbred

Mouse Genetic Backgrounds Provide an Excellent Benchmark for a Proof-of-Concept Machine Learning Approach to Classifying Mice

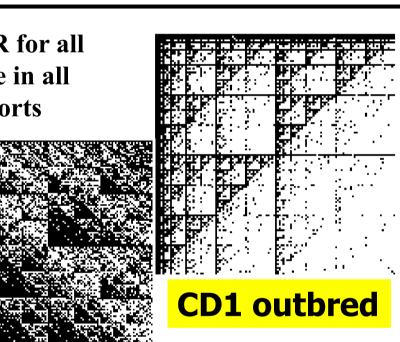
Cohorts of Mice	Heterozygosity Determined		Outl			
Classical Inbred	0.06 – 1.5 %	Between AB AB loci Between				
Recombinant Inbred	0.09 – 3.9 %	AD IOCI				
Wild-Derived	0.5 – 15.8 %	Chromosome bp position				
NMRI Outbred	5-8%	0e+00 2e+07				
CD1 Outbred	10 - 12 %	10-12 %Rainfall plots of the inter- heterozygosity across the original				
F1	19 – 46 %	striking pattern diversity	1011050			
<image/> <text></text>	ping Center for Genome Dynamic CEL image CEL image Fluorescend detection A CEL image The Jac	e SNP Genotypes:	CGR Mice f Cohor			
ML-DSP met	hodology	Molecular D	istance			
Numerical Representation Discrete Fourier Transform (DFT)	Pearson Correlation Coefficient (PCC)	Total sequences: 774				
	Map genomic sequences to	Length (# SNP loci): 493290				
	numerical sequences	Clusters (# genotypes):	0.15			
		CD-1 Outbred (100);	0.1 <			
New Sequence Obtain classification	Apply DFT to obtain	Classical Inbred (126);	N 0.05			
can be classified using trained classifiers	magnitude spectra	F1 (59); NMRI Outbred (287);	0 <			
	Obtain pairwise distance matrix using PCC	Recombinant Inbred RwwJ_TyJ(112);	-0.05 0.35 0.3 0.25			
	_	Wild Derived (50);				

3D Plot (MoDMap)



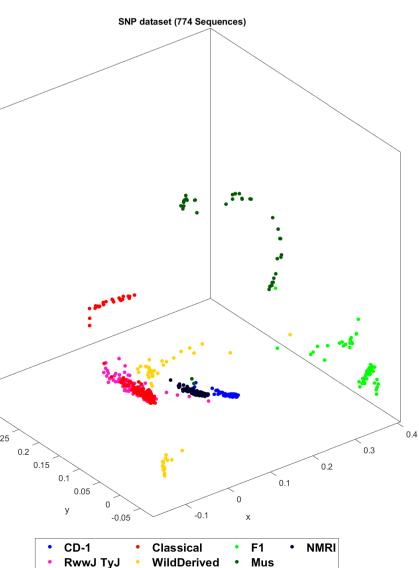


acing of mouse SNP some landscape show the



s subspecies h high heterozygosity

e Map (MoDMap)



ML-DSP Excels in Classification Accuracy for SNP Genotyping

Classification Accuracy (%)				
Linear Discriminant	97.7			
Linear SVM	93.9			
Quadratic SVM	96.8			
Fine KNN	94.4			
Subspace Discriminant	97.5			
Subspace KNN	94.1			
Average Accuracy	95.7			

Confusion Matrix Results								
TrueClass\PredictedClass	CD-1	Classical	F1	NMRI	RwwJ_TyJ	WildDerived	Mus	
CD-1	100	0	0	0	0	0	0	
Classical	0	115	0	0	10	1	0	
F1	0	0	58	0	0	0	1	
NMRI	0	0	0	287	0	0	0	
RwwJ_TyJ	0	4	0	0	108	0	0	
WildDerived	0	1	1	0	0	48	0	
Mus	0	0	0	0	0	0	40	

Inter-cluster distances

True_Predictor	CD-1	Classical	F1	NMRI	RwwJ_TyJ	Wild Derived	Mus subspecies
CD-1	0	0.1353	0.2247	0.0206	0.0909	0.0956	0.1912
Classical	0.1353	0	0.4413	0.0950	0.0781	0.1186	0.2856
F1	0.2247	0.4413	0	0.3312	0.4291	0.4303	0.2544
NMRI	0.0206	0.0950	0.3312	0	0.0476	0.0539	0.2261
RwwJ_TyJ	0.0909	0.0781	0.4291	0.0476	0	0.0736	0.2612
Wild Derived	0.0956	0.1186	0.4303	0.0539	0.0736	0	0.2835
Mus subspecies	0.1912	0.2856	0.2544	0.2261	0.2612	0.2835	0

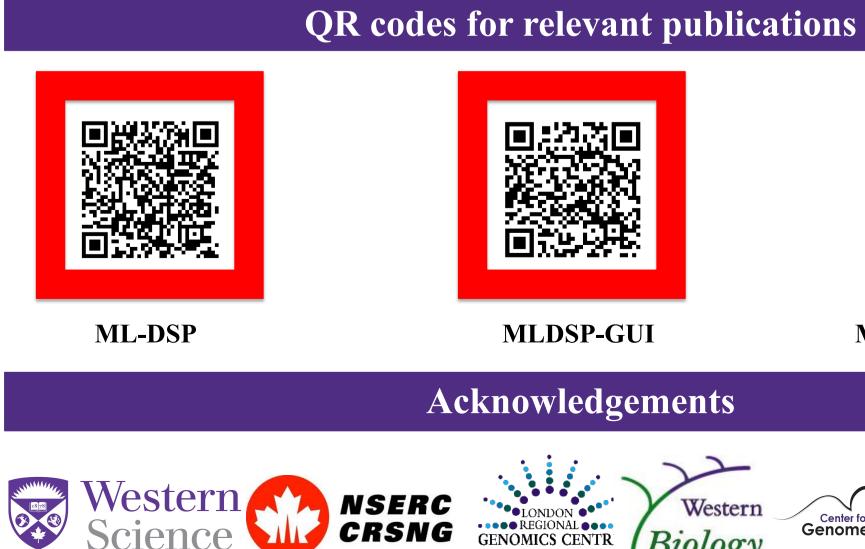
Conclusions

ML-DSP excels in classification accuracy, speed and scalability of large datasets.

ML-DSP is relevant in classifying new, unknown and wild-caught mouse genetic backgrounds using SNP genotype data.

GENOMICS CENTR

By extension, Human SNP genotype data can be classified to gain new insight into genotype associations with phenotypes of cancer and inherited disease.



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MLDSP-GUI (Software)

