Dissertation Defense of David C. Brown

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Committee: Dr. Jun-tao Guo, Dr. Alex Dornburg, Dr. Adam Reitzel



Welcome & Agenda

Defense Meeting Procedure

- Presentation
 - ~45 min. in length.
- Public Questions
 - Follow the presentation.
- Private Questions & Deliberation
 - Adjourn to the conference room.

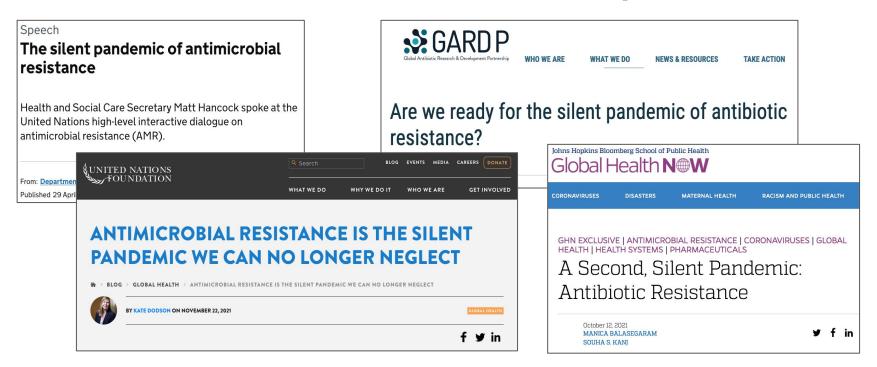
Investigating Multidrug Resistance in *Escherichia coli* with Phylogenetics and Machine Learning

David C. Brown





Global concern is increasing about the weakened efficacy of current antibiotic therapies.



Introduction

- A microbe that exhibits antimicrobial resistance (AMR) to three or more classes of antibiotics is termed multidrug resistant (MDR) (CDC, 2021)
- MDR bacteria drive the silent antimicrobial resistance (AMR) pandemic.

Antimicrobial agents used for susceptibility testing for E. coli isolates

		Years	Antimicrobial Agent Concentration Range	MIC Interpretive Standard (µg/mL)			
CLSI Class	Antimicrobial Agent	Tested	(μg/mL)	Susceptible	Intermediate*	Resistant	
Aminoglycosides	Amikacin	1997-2010	0.5-64	≤16	32	≥64	
	Gentamicin	1996-present	0.25-16	≤4	8	≥16	
	Kanamycin	1996-2013	8-64	≤16	32	≥64	
	Streptomycin†	1996-2013	32-64	≤32	N/A*	≥64	
		2014-present	2-64	≤16	N/A*	≥32	
β-lactam combination agents	Amoxicillin-clavulanic acid	1996-present	1/0.5-32/16	≤8/4	16/8	≥32/16	
Cephems	Cefoxitin	2000-present	0.5-32	≤8	16	≥32	
	Ceftiofur	1996-2015	0.12-8	≤2	4	≥8	
	Ceftriaxone [‡]	1996-present	0.25-64	≤1	2	≥4	
	Cephalothin	1996-2003	2-32	≤8	16	≥32	
Folate pathway antagonists	Sulfamethoxazole	1996-2003	16-512	≤256	N/A*	≥512	
	Sulfisoxazole	2004-present	16-256	≤256	N/A*	≥512	
	Trimethoprim- sulfamethoxazole	1996-present	0.12/2.38-4/76	≤2/38	N/A*	≥4/76	
Macrolides	Azithromycin [§]	2011–present	0.25-32 0.12-16 [¶]	≤16	N/A*	≥32	
Penems	Meropenem	2016-present	0.06-4	≤1	2	≥4	
Penicillins	Ampicillin	1996-present	1-32	≤8	16	≥32	
Phenicols	Chloramphenicol	1996-present	2-32	≤8	16	≥32	
Quinolones	Ciprofloxacin**	1996-present	0.015-4	≤0.25	0.5	≥1	
	Nalidixic acid	1996-present	0.5-32	≤16	N/A*	≥32	
Tetracyclines	Tetracycline	1996-present	4-32	≤4	8	≥16	

Current Issues



Cladistics 36 (2020) 345-347



10.1111/cla.12428

Epidemiology needs more interdisciplinary teams with expertise in molecular systematics, public health and food safety

Marc W. Allard* and Eric W. Brown

Center of Food Safety and Applied Nutrition, U. S. Food and Drug Administration, College Park, MD, 20740, USA

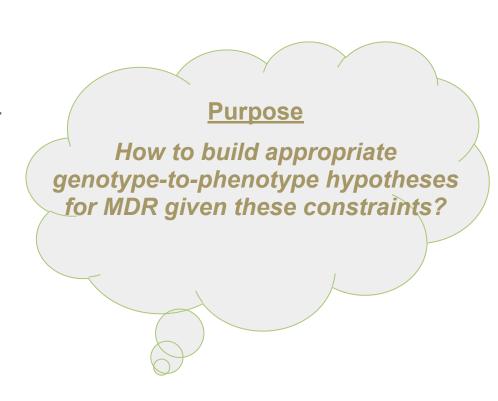
Received 7 May 2020; Revised 10 June 2020; Accepted 17 June 2020

Big data methods and tools (Janies, 2019) to rapidly parse through these growing genomic databases also are greatly needed (Ford et al. their Figure 1) as much of the data are globally publicly released and shared almost entirely in real-time so that critical life-saving and timely phylogenetic-based decisions can be made.

in *E. coli* lineages. Their results also may have direct applications for optimal drug use to combat antibiotic resistant strains and in understanding a crucial problem in public health due to the rise of antimicrobial resistance and the limited choice of available drugs.

Current Issues - cont.

- MDR is a phenotypic description, not a specific or unique AMR genetic trait.
- Many potential combinations of AMR genes could lead to an MDR phenotype.
- Reticulate evolutionary mechanisms like horizontal gene transfer (HGT) can cloud the vertical (ancestor to descendant) signal commonly sought in phylogenetic analyses.



Literature Review



DOMAIN 6 EVOLUTION AND GENOMICS

Salmonella Genomics in Public Health and Food Safety

ERIC W. BROWN, AREBECCA BELL, GUODONG ZHANG, TUTH TIMME, SIE ZHENG, THOMAS S. HAMMACK, AND MARC W. ALLARD

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diversity that has accrued during a contamination event. It is the high-resolution WGS data, combined with detailed and structured metadata, that may be used by artificial intelligence (AI) and machine learning (ML) tools to make even more predictive models for the accurate prediction of food, animal source (172), and or geographic location. Published WGS data have shown that most *Salmonella* and *Listeria* isolates exhibit a very strong phylogeographic signal that is

modify the protein and affect the phenotype. By combining cladistics, character optimization, and WGS, investigators may be able to identify genotype-to-phenotype changes that specific bacterial lineages have acquired and that allow foodborne pathogens to survive and contaminate foods, animals, and the environment (177). In several examples, investigators have predicted which genomic changes correlate with outbreaks in Italian-style meats (178) and in eggs (115, 116,

Literature Review - cont.

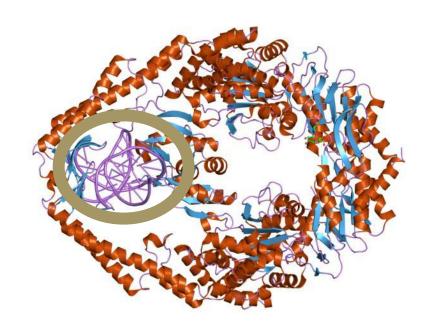
- Bacteria with deficient mismatch repair mechanisms have been described as having a "hypermutable phenotype".
- This highly adaptive phenotype is suggested to drive the acquisition of antimicrobial resistance.
- A main component of the methyl-directed mismatch repair (MMR) system in bacteria is Mutator S (gene mutS, protein MutS).

ORIGINAL RESEARCH article Front. Microbiol., 08 May 2020 | https://doi.org/10.3389/fmicb.2020.00770 Genes and Proteomes Associated With Increased Mutation Frequency and Multidrug Resistance of **Naturally Occurring Mismatch** Repair-Deficient Salmonella **Hypermutators** Huanjing Sheng¹, Jinling Huang¹, Zhaoyu Han², Mi Liu¹, Zexun Lü¹, Qian Zhang¹, Jinlei Zhang¹, Jun Yang¹, Shenghui Cui³ and Raowei Yang^{1*} ¹College of Food Science and Engineering, Northwest A&F University, Xianyang, China ²School of Pharmaceutical Sciences, Jiangnan University, Wuxi, China ³National Institutes for Food and Drug Control, Beijing, China

Literature Review - cont.

Two forces known to govern genetic change are the mutation of nucleotide sequences within a genome and the horizontal transfer of existing sequences among genomes. In certain mutator phenotypes, namely those deficient in methyl-directed mismatch repair (MMP) these forces converge to increase the rate of genetic veriation. MMR is a postreplicative repair system that corrects errors on newly synthesized DNA strands to ensure the precision of shromosome replication (3). MMR is also major barrier to interspecies gene exchange (4). Consequently, pacteria defective in MMR show both an enhanced rate of mutation (a hypermutable phenotype) and an increase in recombination of diverged sequences; that is, they are more promiscuous (4). It therefore becomes relevant to the problem of emerging pathogens to determine the frequency of such mutator phenotypes among human pathogens.

SCIENCE • VOL. 274 • 15 NOVEMBER 1996





Research Questions

Does defective MMR explain the development of MDR in *E. coli*?

How well does WGS *E. coli* data predict categories of MDR?

Data Source

National Library of Medicine National Center for Biotechnology Information

Health > Pathogen Detection

- NCBI Pathogen Detection (NCBI PD) is a project to monitor bacterial pathogens.
- Used by the GenomeTrakr program for international food safety surveillance.
- Represents value in the study of the silent AMR pandemic.

Pathogen Detection **BETA**





To assist the National Database of Antibiotic Resistant Organisms (NDARO), NCBI Pathogen Detection identifies the antimicrobial resistance, stress response, and virulence genes found in bacterial genomic sequences. This enables scientists to track the spread of resistance genes and to understand the relationships between antimicrobial resistance and virulence.

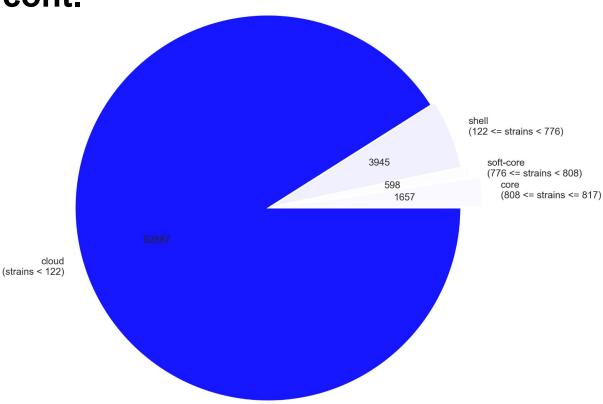
NCBI Pathogen Detection integrates bacterial pathogen genomic sequences originating in food, environmental sources, and patients. It quickly clusters and identifies related sequences to uncover potential food contamination sources, helping public health scientists investigate foodborne disease outbreaks.

Data Processing

- Used the same 29,255 isolate *E. coli* data set and metadata table as Ford et al. (2020).
- Filtered the data set for:
 - NCBI:txid562 (*E. coli*).
 - Complete Genome and Chromosome levels of assembly.
 - A RefSeq identifier (GCF_########).
- Requested 911 isolates from NCBI FTP site
 - Downloaded 875 WGS FASTA files
- Quality controlled with CheckM to 817 E. coli of high confidence, completeness, and quality.

Data Processing - cont.

- Annotated the 817
 E. coli with Prokka
- Constructed the pangenome with Roary
 - Core gene alignment file for phylogenetics
 - Gene presence absence file for ML



Characterizing MDR - 3 or more Resistance Categories

E. coli

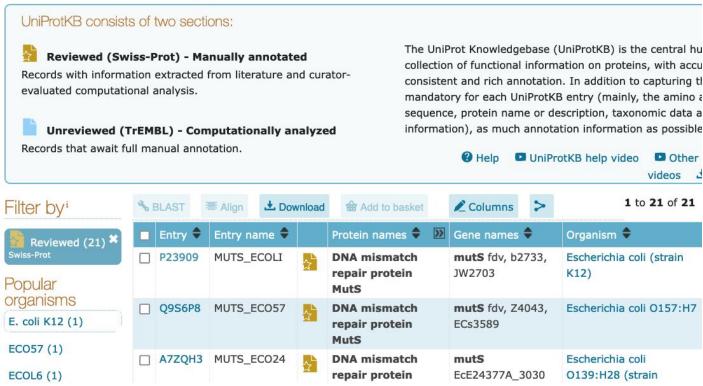
Antimicrobial agents used for susce

CLSI Class	Antimicrobial Agent			
Aminoglycosides	Amikacin			
	Gentamicin			
	Kanamycin			
	Streptomycin†			
β–lactam combination agents	Amoxicillin-clavulanic acid			
Cephems	Cefoxitin			
	Ceftiofur			
	Ceftriaxone [‡]			
	Cephalothin			

Resistance Category	3 Letter Resistance Gene Prefix				
aminoglycosides	aac, aad, ant, aph, arm, rmt				
beta-lactam combination agents	bla				
cephems	abc				
folate pathway antagonists	dfr, sul				
macrolides	ere, erm, mef, mph, msr				
nucleosides	sat				
penicillins	amp				
phenicols	cat, flo				
quinolones	qep				
tetracyclines	tet				
others	arr, ble, cml, fos, lnu, mcr, oqx, qac				

Characterizing MMR - MutS Protein Variants

UniProtKB 2021_04 results



Methodology - Correlating evolution for MutS & MDR

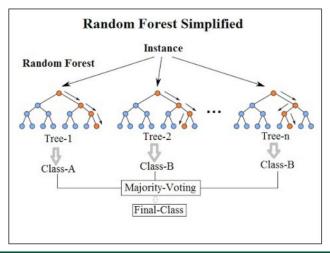
- Built phylogenetic tree with RAxML on the core genome file from Roary.
- Analyzed MutS and MDR characters with Mesquite and R, specifically fitPagel() from phytools.

Isolate	MutS-	MDR+
GCF_000000001	0	0
GCF_000000002	1	1
GCF_000000003	0	1
GCF_000000004	1	0
GCF_00000005	0	0

Methodology - Identifying best predictors of MDR

- Trained random forest classifiers with scikit-learn library in Python 3
 - Feature Matrix: gene presence/absence file from Roary
 - Label Matrix: presence/absence of AMR genes from NCBI PD, compressed into resistance categories

Isolate	Gene 1	Gene 2	Gene 3	Gene n	ami +	fol +	mac +	tet +
GCF_000000001	1	0	1	0	0	0	1	1
GCF_000000002	1	1	0	1	1	1	1	0
GCF_000000003	1	1	1	1	0	1	1	1
GCF_000000004	1	1	1	1	1	0	1	0
GCF_000000005	1	0	1	1	0	0	0	1



Limitations

Data

- Lack of expression data collected by GenomeTrakr.
- Heavy reliance on accurate metadata from NCBI PD.

Methods

- Did not employ a reference sequence.
- Did not count mutations.
- High computational resource demands.



First Research Question and Hypothesis

Does defective MMR explain the development of MDR in E. coli?

H

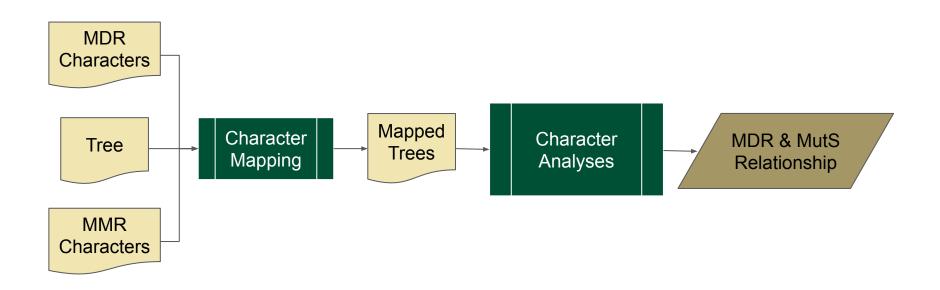
No relationship (independence) between repair deficient MutS variants and MDR.

 H_1

Repair deficient MutS variants correlate with MDR.



Evolutionary Relationship of MDR & MutS - Workflow



No mutS Genes Match LeClerc's Deficient Definition

```
Location/Oualifiers
FEATURES
                     1..69
     source
                     /organism="Escherichia coli str. K-12 substr. MG1655"
                     /mol type="genomic DNA"
                     /strain="K-12"
                     /sub strain="MG1655"
                     /host="Homo sapiens"
                     /db xref="taxon:511145"
                     /country="USA: Boston"
                     /collection date="2017-01-15"
                     /note="C321.deltaA"
                     1..69
     gene
                     /locus_tag="CXP41_14995"
                     /pseudo
                     1..69
     CDS
                     /locus tag="CXP41 14995"
                     /inference="COORDINATES: similar to AA
                     sequence:RefSeq:WP 007663512.1"
                     /note="incomplete; partial on complete genome; missing
                     start; Derived by automated computational analysis using
                     gene prediction method: Protein Homology."
                     /pseudo
                     /codon start=1
                     /transl table=11
                     /product="DNA mismatch repair protein MutS"
ORIGIN
        1 ctcgaaggct ttaatttgca agctcgtcag gcgctggagt ggatttatcg cttgaagagc
       61 ctggtgtaa
11
```

Change to Protein Space: MutS Consensus Sequence

Is late	MutS-	MDR+
GCF_000c20001	0	0
GCF_000000002	1	1
GCF_000000003		1
GCF_000000004	1	0
GCF_000000005	0	0

Isolate	pos_1	pos_2	pos_3	pos_n	MDR+
GCF_000000001	1	0	1	0	0
GCF_000000002	1	1	0	1	1
GCF_000000003	1	1	1	1	1
GCF_000000004	1	1	1	1	0
GCF_000000005	1	0	1	1	0



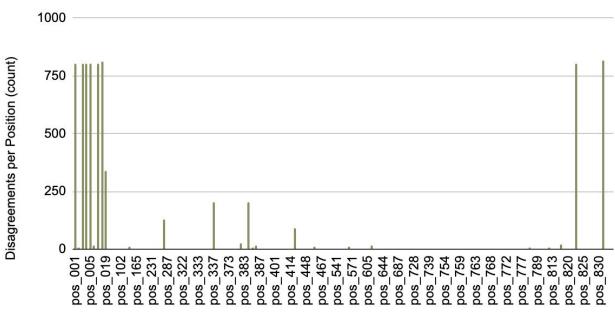
Weighted AIC Supports Independent Model of Correlation Between MutS Residues and MDR

SNP_pos	independent_aic	weighted_independent_aic	dependent_x_aic	weighted_dependent_x_aic	dependent_y_aic	weighted_dependent_y_aic	dependent_both_aic	weighted_dependent_both_aic	aic_sum_check
pos_001	972.674191	0.73850	976.425098	0.11320	976.157236	0.12943	980.008335	0.01887	1.00000
pos_002	937.020127	0.72062	940.029061	0.16007	941.019181	0.09757	944.022361	0.02174	1.00000
pos_003	964.976440	0.76582	968.933036	0.10592	968.806119	0.11286	972.788963	0.01540	1.00000
pos_004	956.967060	0.77511	960.956773	0.10544	960.963009	0.10511	964.946896	0.01434	1.00000
pos_005	972.674191	0.73850	976.425098	0.11320	976.157236	0.12943	980.008335	0.01887	1.00000
pos_007	983.221111	0.15289	998.103538	0.00009	980.192509	0.69507	983.233381	0.15195	1.00000
pos_008	972.674191	0.73850	976.425098	0.11320	976.157236	0.12943	980.008335	0.01887	1.00000
pos_009	935.186074	0.76140	938.655002	0.13438	939.425851	0.09140	943.355416	0.01281	1.00000
pos_019	1084.630053	0.73699	1087.917985	0.14240	1088.601191	0.10119	1091.902770	0.01942	1.00000
pos_026	895.860034	0.69515	899.853922	0.09437	898.503629	0.18537	902.501635	0.02511	1.00000
pos_073	895.860034	0.69515	899.853922	0.09437	898.503629	0.18537	902.501635	0.02511	1.00000
pos_086	906.358058	0.68833	909.673777	0.13116	909.361772	0.15330	912.819764	0.02721	1.00000
pos_102	912.172833	0.56689	915.020106	0.13653	914.699345	0.16028	915.023333	0.13631	1.00000
pos_110	906.619284	0.70849	910.029034	0.12880	909.899289	0.13743	913.285171	0.02528	1.00000
pos_140	1048.579427	0.00000	913.056810	0.16496	910.077542	0.73168	913.991884	0.10336	1.00000
pos_156	909.546683	0.74668	912.946782	0.13640	913.586195	0.09908	917.014972	0.01784	1.00000
pos_165	906.648843	0.82548	910.107767	0.14642	1044.494424	0.00000	913.409630	0.02809	1.00000
pos_167	906.136171	0.68873	909.625882	0.12030	909.000245	0.16448	912.652268	0.02649	1.00000

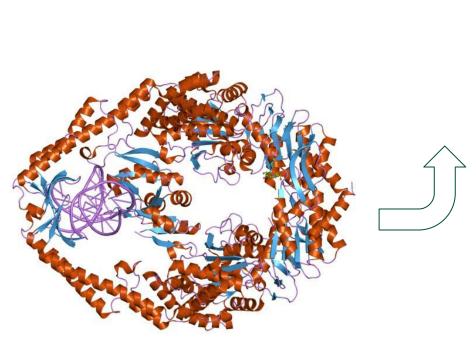
Only exceptions were the residue variants at positions 7 (domain I - mismatch binding), 140 (domain II - connector), and 804 (near final HTH motif).

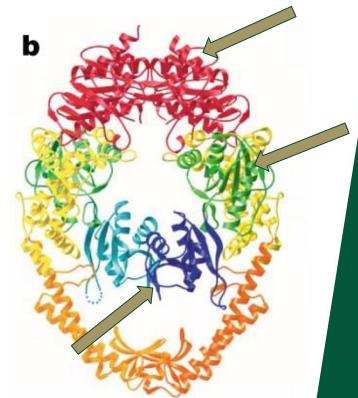
Position & Frequency of Residue Variants in MutS





Locations Where MDR Depends on MutS Residues





Left image of MutS protein (PDB 10h6) from previous slide. Right image Muts modified from Figure 3 by Obmolova et al., 2000. Similar colors represent same domain in the respective MutS dimer. Approximate positions of residues 7, 140, and 804 added for emphasis.





Summary & Discussion

<u>Does defective MMR explain</u> the development of MDR in *E. coli*?

- No observation of LeClerc's definition of hypermutable mutS.
- Generally independent evolutionary correlation between MutS residue variants and MDR. (H₀)
- Three positions support a dependent evolutionary correlation for MutS and MDR, potentially indicating novel definitions for repair deficient MutS or MDR development in *E. coli*.



Second Research Question and Hypothesis

How well does WGS E. coli data predict categories of MDR?

Ho

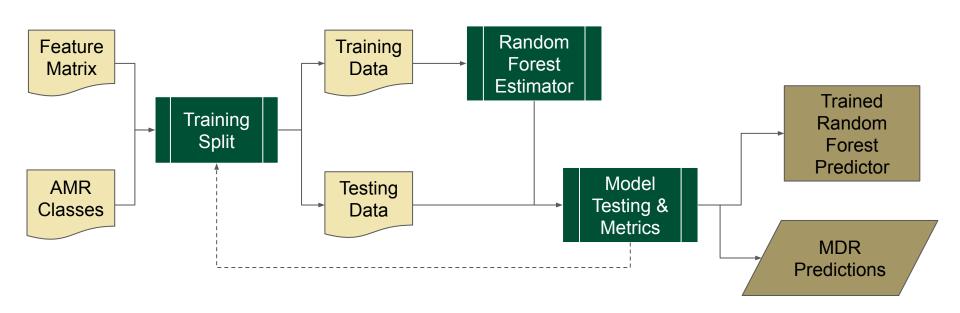
A random forest classifier trained on annotated *E. coli* gene features will reveal *mutS* or its paralog as the best predictor of MDR.

H

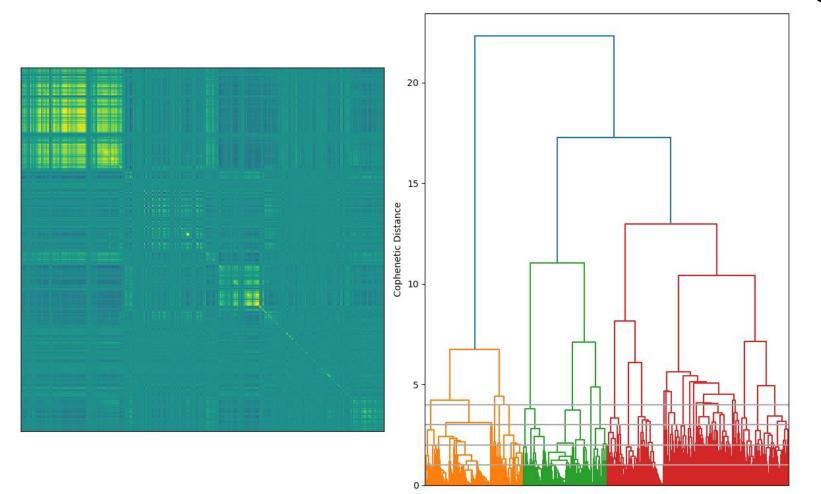
Gene features other than *mutS* best predict MDR.



Predicting MDR from WGS Annotations - Workflow

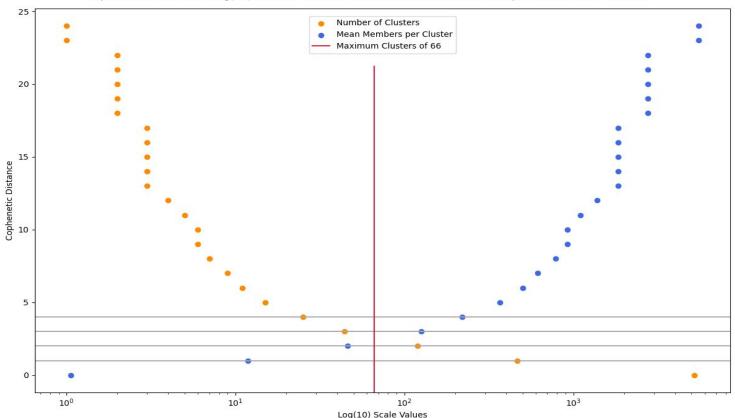


Feature Correlation Matrix and Hierarchical Clustering

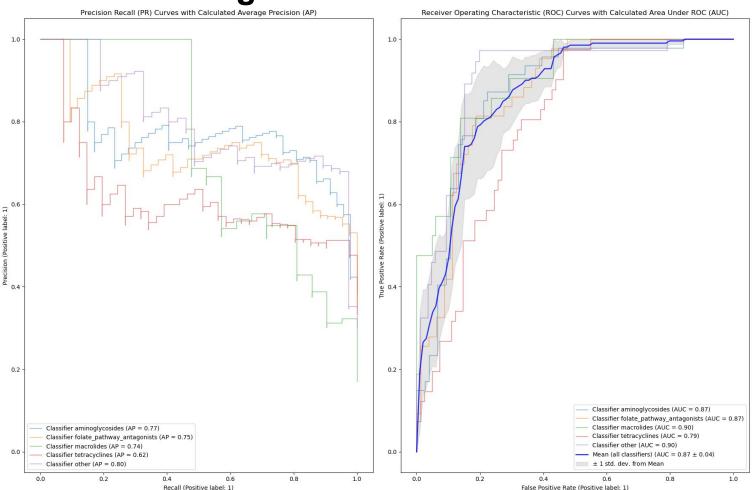


Solving Collinearity by Clustering Features

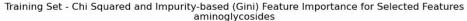


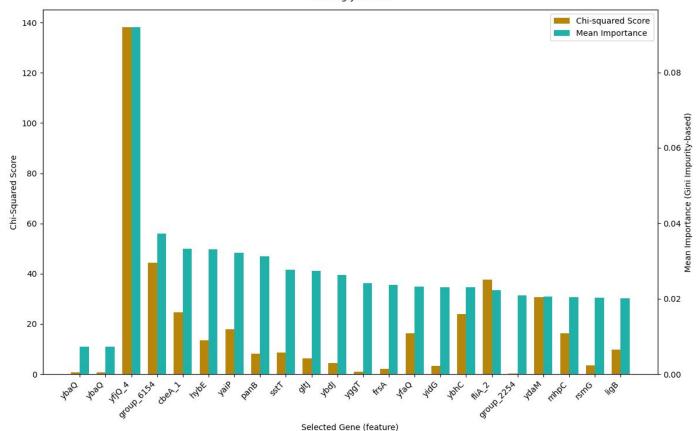


Evaluating the Predictive Classifiers



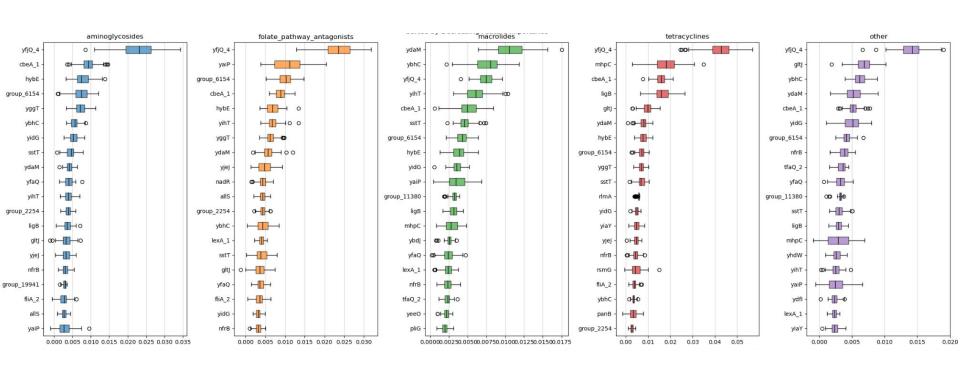
Comparing Feature Importance Measures







Permutation Importance for Classifiers





Summary & Discussion

How well does WGS *E. coli* data predict categories of MDR?

- The mutS gene and its paralogs do not occur in the feature clusters that best predict any category of AMR.
- Gene features other than mutS best predict MDR. (H₁)
- Mean classifier AUC = 0.87 ± 0.04; 0.62 ≤ AP ≤ 0.80



Third Research Question

What are the gene contents of the feature clusters that best predict MDR?

- Avoid self-evidence from known AMR genes.
- Investigate three highly ranked feature clusters.
- Evaluate model explainability against literature.

Top Ranked Cluster yfjQ_4 Annotations

Gene (Roary)	Annotation (Roary)	Protein names (independent BLAST)
group_16177	hypothetical protein	LPD25 domain-containing protein
group_10103	hypothetical protein	Protein Trbl
group_10424	hypothetical protein	TraK lipoprotein
group_12760	hypothetical protein	Protein TraQ
group_7878	hypothetical protein	Protein TraW
group_19502	hypothetical protein	Protein TraJ
group_4098	hypothetical protein	Protein TraB
group_24638	hypothetical protein	Terminase
group_9019	hypothetical protein	Protein TraE
group_11161	hypothetical protein	Protein TrbG
group_5897	hypothetical protein	Protein TraP
group_4701	hypothetical protein	Protein TrbJ
group_9337	hypothetical protein	Protein TraV
group_17382	hypothetical protein	Protein TraL
group_2543	hypothetical protein	Protein TrbB
group_4818	hypothetical protein	X polypeptide, ORF 19, ORF 169, P19 protein
umuC_2	SOS mutagenesis and repair	
traM	Relaxosome protein TraM	
traY	Relaxosome protein TraY	
group_2526	hypothetical protein	
ccdB	hypothetical protein	
traA	Pilin	
yfjQ_4	CP4-57 prophage; predicted protein	
group_5903	hypothetical protein	

ydaM Includes Rac Prophage & Transcription Genes

SCIENTIFIC REPORTS

Published: 04 November 2015

Received: 29 May 2015 Accepted: 07 October 2015

OPEN Physiological Function of Rac Prophage During Biofilm Formation and Regulation of Rac Excision in Escherichia coli K-12

> Xiaoxiao Liu^{1,*}, Yangmei Li^{1,2,*}, Yunxue Guo¹, Zhenshun Zeng^{1,2}, Baiyuan Li^{1,2}, Thomas K. Wood^{3,4}, Xingsheng Cai¹ & Xiaoxue Wang¹



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How macrolide antibiotics work

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Abstract

Macrolide antibiotics inhibit protein synthesis by targeting the bacterial ribosome. They bind at the nascent peptide exit tunnel and partially occlude it. Thus, macrolides have been viewed as 'tunnel plugs' that stop synthesis of every protein. More recent evidence, however, demonstrates that macrolides selectively inhibit translation of a subset of cellular proteins and that their action critically depends on the nascent protein sequence and on the antibiotic structure. Therefore, macrolides emerge as modulators of translation rather than global inhibitors of protein synthesis.

Transcription

RNA

Translation

Polypeptide

Highly Ranked Cluster cbeA_1 Annotations

ami	fol	mac	tet	oth	Gene (Roary)	Non-unique	Annotation (Roary)	Protein names (BLAST)
1	3	4	2	4	group_13421		hypothetical protein	Zinc ribbon domain-containing protein
1	3	4	2	4	group_4945		hypothetical protein	RelB antitoxin
1	3	4	2	4	group_22310		hypothetical protein	Uncharacterized protein
1	3	4	2	4	group_7475		hypothetical protein	DUF3310 domain-containing protein
1	3	4	2	4	group_9598		hypothetical protein	Chemotaxis protein
1	3	4	2	4	yfjJ		hypothetical protein	Uncharacterized protein YagK
1	3	4	2	4	group_7384		hypothetical protein	Regulatory protein
1	3	4	2	4	group_5273		hypothetical protein	Phospholipase
1	3	4	2	4	group_6844		hypothetical protein	C8 domain-containing protein
1	3	4	2	4	group_13325		hypothetical protein	Lipoprotein
1	3	4	2	4	group_4579		hypothetical protein	
1	3	4	2	4	cbeA_1		CP4-44 prophage; antitoxin of the CbtA-CbeA toxin-antitoxin system	
1	3	4	2	4	yeeS_1		CP4-44 prophage; predicted DNA repair protein	
1	3	4	2	4	php_1		putative hydrolase	
1	3	4	2	4	group_684		hypothetical protein	
1	3	4	2	4	group_257	yfjQ_1	CP4-57 prophage; predicted protein	
1	3	4	2	4	group_1508	yeeP_1	CP4-44 prophage; predicted GTP-binding protein	



Comparison of Best Predictors Across Classifiers

0-based Rank	aminoglycosides (ami)	folate pathway (fol)	macrolides (mac)	tetracyclines (tet)	others (oth)
0	yfjQ_4	yfjQ_4	ydaM	yfjQ_4	yfjQ_4
1	cbeA_1	yaiP	ybhC	mhpC	gltJ
2	hybE	group_6154	yfjQ_4	cbeA_1	ybhC
3	group_6154	cbeA_1	yihT	ligB	ydaM
4	yggT	hybE	cbeA_1	gltJ	cbeA_1



Summary & Discussion

What are the gene contents of the feature clusters that best predict MDR?

- Absence of known AMR gene determinants in best features.
- HGT, phage, and transcriptional regulation genes best predict MDR.
 - Induced mutable states (SOS) vs. structurally deficient hypermutators (MMR)
- Concerning presence of tra family (F plasmid) genes in cluster yfjQ_4.
- Unique combinations of feature clusters (gene sets) differentiate between categories of AMR.



Conclusion

MDR does not correlate dependently with deficient MMR (MutS).

The proliferation of AMR genes into MDR phenotypes is driven by horizontal gene transfer and temporary states of increased mutation.

Phylogenetics and machine learning combine well to generate genotype-to-phenotype hypotheses for polygenic traits.

Future Work

- Investigate the three exceptional positions in MutS for:
 - Protein conformational changes due to amino acid substitutions.
 - Count and compare mutations between isolates with those specific substitutions.
- Further explore the gene feature clusters that best predict MDR.
 - Find SNPs and amino acid substitutions from same genes that clustered differently.
 - Identify a genetic signature that indicates presence of mutations that allow MDR.

Significance

Intellectual Merit

- Refine current understandings of multidrug resistance in enteric bacteria.
- Demonstrate underutilized data sets from NCBI PD.
- Explore combining phylogenetic and machine learning approaches to build improved genotype-to-phenotype hypotheses.

Broader Impacts

- Improve current disease surveillance analyses.
- Insights for anticipating the direction of the silent pandemic.
- Prolong the efficacy of current antibiotics.

Thank you for your kind attention.



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Committee Members

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- Dr. Alex Dornburg
- Dr. Adam Reitzel

Attendees

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List of Abbreviations & Terms

- AMR
 - Antimicrobial resistance
- CDC
 - Centers for Disease Control and Prevention
- CFSAN
 - Center for Food Safety and Applied Nutrition
- CRE
 - Carbapenem-resistant Enterobacteriaceae
- E. coli
 - Escherichia coli
- FDA
 - U.S. Food and Drug Administration

- MDR
 - Multidrug resistance
- MMR
 - Methyl-directed mismatch repair
- MutS
 - MutatorS
- Pathogenicity
 - Potential ability to produce disease
- SNP
 - Single nucleotide polymorphism
- Virulence
 - Degree of disease producing power

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