

# Identifying Clostridium Difficile in the ICU Using Bayesian Networks

## Phenome Based Analysis

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# INTRODUCTION

- ▶ Development of comprehensive electronic medical record databases has made large phenome wide association studies possible
- ▶ Prior work has tried to link phenomes with molecular information, such as SNPs
- ▶ Feasibility of these studies on the Mimic II database has been shown through association studies with other variables, such as required fluid levels
- ▶ Our project strives to link phenomes defined by ICD9 codes with lab values of patients in the ICU.

# MIMIC II

- ▶ Database with 30,000 ICU patients between 2001 and 2007.
- ▶ Comprehensive data: Lab tests, International Classification of Diseases (ICD9) discharge codes, medication orders, etc.
- ▶ 5675 distinct ICD9 codes (33.5 % of all possible)
- ▶ Mean of 8.7 ICD9 codes assigned to each admission.
- ▶ Allows for large scale phenome based analysis

## WHITE BLOOD CELL COUNT (WBC) USE CASE

- ▶ Mimic stores all measured lab events of patients (748 total)
- ▶ Use case focuses on WBC, commonly measured lab event present in most patients.

# WHITE BLOOD CELL COUNT (WBC) USE CASE

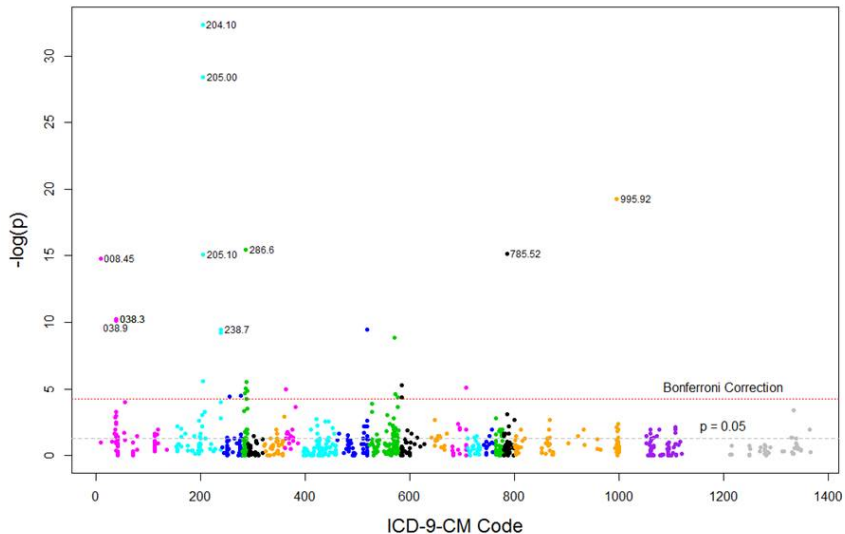
- ▶ Mimic stores all measured lab events of patients (748 total)
- ▶ Use case focuses on WBC, commonly measured lab event present in most patients.
- ▶ Method:
  - ▶ Single WBC lab result chosen for each patient by taking peak value during ICU stay
  - ▶ Patient subsets chosen by creating lower bounds from a hundred equally spaced cutoffs between counts of 0 and 100,000/ $\mu\text{L}$  (IE  $\geq 20,000/\mu\text{L}$ ,  $\geq 80,000/\mu\text{L}$ , etc)
  - ▶ Exact binomial test was performed on each subset for occurrence of each ICD9 code with  $\geq 100$  distinct cases when compared to the full database.

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  - ▶ Exact binomial test was performed on each subset for occurrence of each ICD9 code with  $\geq 100$  distinct cases when compared to the full database.
  - ▶ Results filtered using Bonferroni Correction  
 (p value less than  $\frac{0.05}{\text{number of ICD9 codes}}$  )

# SINGLE LOWER BOUNDED RUN

## Diagnostic Codes Associated with WBC > 50k/uI



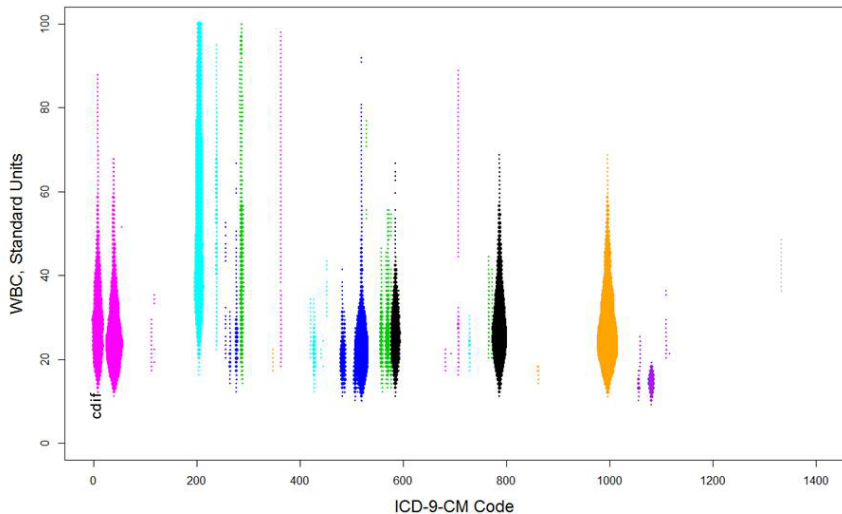
# SIGNIFICANT ICD9 CODES

ICD9 Code	Description	P value
204.10	Chronic lymphoid leukemia (CLL)	$4.3 \times 10^{-33}$
205.00	Acute myeloid leukemia (AML)	$4.0 \times 10^{-29}$
995.92	Severe sepsis	$5.3 \times 10^{-20}$
286.6	Disseminated intravascular coagulation (DIC)	$3.7 \times 10^{-16}$
785.52	Septic shock	$7.3 \times 10^{-16}$
205.10	Chronic myeloid leukemia (CML)	$7.7 \times 10^{-16}$
008.45	<b>Intestinal infection due to Clostridium difficile</b>	$1.7 \times 10^{-15}$
038.3	Septicemia due to anaerobes	$6.0 \times 10^{-11}$
038.9	Unspecified septicemia	$7.2 \times 10^{-11}$
238.70	Neoplasm of uncertain behavior of other lymphatic and hematopoietic tissues	$3.4 \times 10^{-10}$



# PHENOME MAP

2-D Phenome Map, Showing Significant Diagnoses



## *Clostridium difficile*

- ▶ Bacterial infection, usually brought on through the use of antibiotics
- ▶ Symptoms range from mild diarrhea to extreme dehydration, inflammation of the colon, kidney failure, etc
- ▶ Infection can be tested for through growing microbiology cultures, but take up to 24 hours to get results. Lab tests results could come back within 5 hours.
- ▶ 723 total patients with ICD9 code for *C. diff* in MimicII database
- ▶ Phenome map shows *C. diff* to be a highly probable occurrence in patients with WBC in the range between 15,000/ $\mu$ L and 45,000/ $\mu$ L

## EARLY AND LATE *C. diff*

Clostridium Difficile can occur in two different ways in the ICU:

- ▶ Early *C. diff*: Clostridium Difficile infection is found in the patient before admission to the ICU.
- ▶ Defined as:
  - ▶ Any patients who had a positive microbiology test within 72 hours of admission
  - ▶ Patients given treatment within 48 hours of admission. ICD9 code required if treatment was Metrodiazole but no code required if Vancomycin
- ▶ Late *C. diff* (Hospital Acquired): Patient acquires *C. diff* infection during ICU stay
  - ▶ Positive microbiology test more than 72 hours after admission
  - ▶ Order for Vancomycin more than 48 hours after admission
  - ▶ Order for Metrodiazole more than 48 hours after admission along with positive ICD9 code

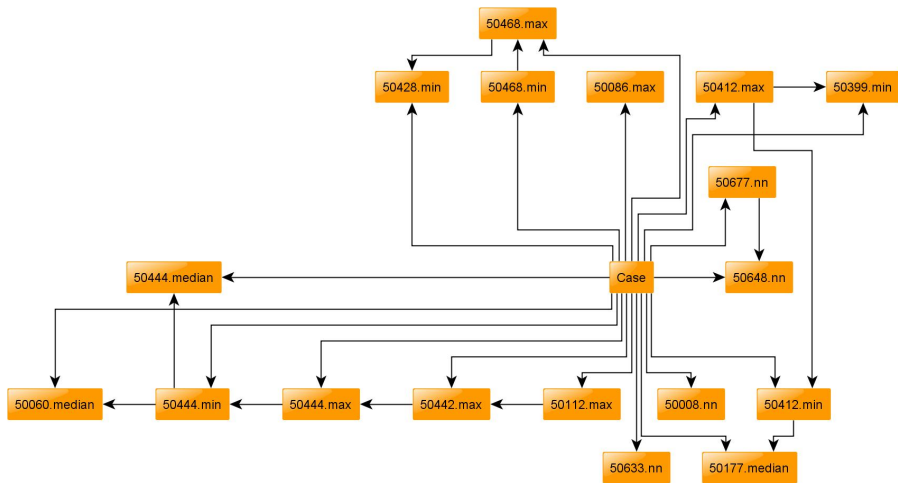
# WHAT ARE BAYESIAN NETWORKS?

- ▶ A Bayesian Network is a graphical model for determining probabilistic relationships among a set of variables. Represented by a directed acyclic graph
- ▶ Utilizes machine learning and bayesian probabilities to identify relationships among independent and dependent variables
- ▶ Each node is represented by a probability function which determines the probability of a variable given the values of its parents

# METHODS

- ▶ Bayesian networks generated using WEKA
  - ▶ Java based program created by University of Waikato for machine learning
- ▶ Patient lab data extracted through taking maximum, minimum, and median lab values throughout duration of hospital stay
- ▶ Equal number of negative control patients taken from MimicII
- ▶ Data discretized into three equal frequency bins to convert numeric lab data into nominal ranges
- ▶ Bayesian network generated through two parent K2 search algorithm and evaluated by 10 fold cross validation
- ▶ Attribute selection performed on datasets to reduce the amount of data required for accurate identification

# EARLY *C. diff* - ALL LABS



EARLY *C. diff***Full Data**

Correctly Classified Instances 593 77.6178 %  
 Incorrectly Classified Instances 171 22.3822 %

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.801	0.249	0.763	0.801	0.782	0.846	Y
	0.751	0.199	0.791	0.751	0.77	0.846	N
Weighted Avg.	0.776	0.224	0.777	0.776	0.776	0.846	

**Attribute Selected (All Labs)**

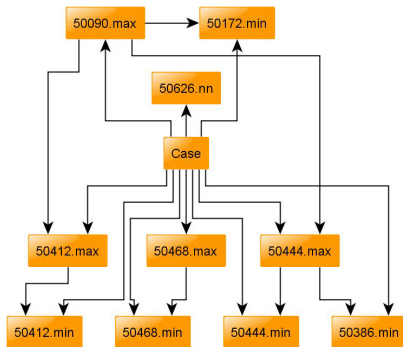
Correctly Classified Instances 551 72.1204 %  
 Incorrectly Classified Instances 213 27.8796 %

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.751	0.309	0.709	0.751	0.729	0.783	Y
	0.691	0.249	0.735	0.691	0.713	0.783	N
Weighted Avg.	0.721	0.279	0.722	0.721	0.721	0.783	

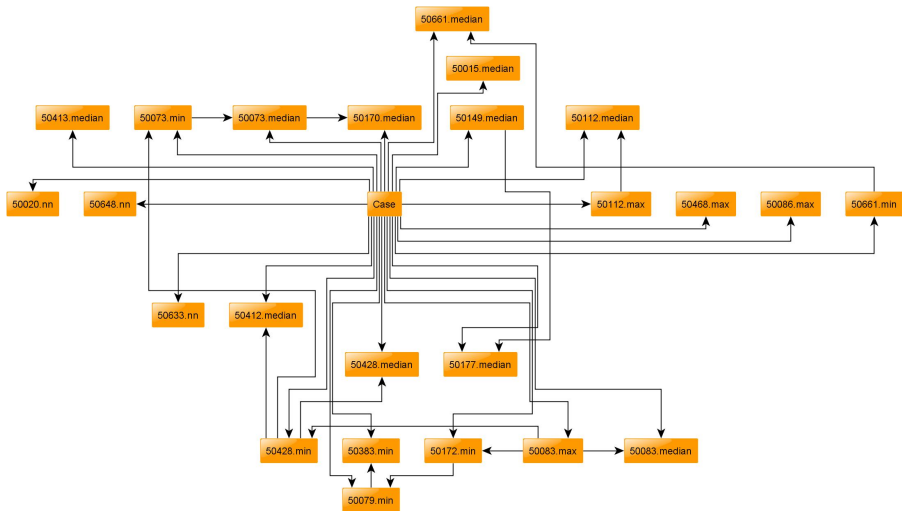
**Attribute Selected (25% NA or less)**

Correctly Classified Instances 532 69.6335 %  
 Incorrectly Classified Instances 232 30.3665 %

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.709	0.317	0.691	0.709	0.7	0.78	Y
	0.683	0.291	0.702	0.683	0.692	0.78	N
Weighted Avg.	0.696	0.304	0.696	0.696	0.696	0.78	



# LATE *C. diff* - ALL LAB DATA UP TO TREATMENT





# LATE *C. diff* - ALL LAB DATA UP TO TREATMENT

## Full Data

Correctly Classified Instances 599 65.9692 %  
 Incorrectly Classified Instances 309 34.0308 %

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Clas
	0.584	0.264	0.688	0.584	0.632	0.696	Y
	0.736	0.416	0.639	0.736	0.684	0.696	N
Weighted Avg.	0.66	0.34	0.663	0.66	0.658	0.696	

## Attribute Selection (All Labs)

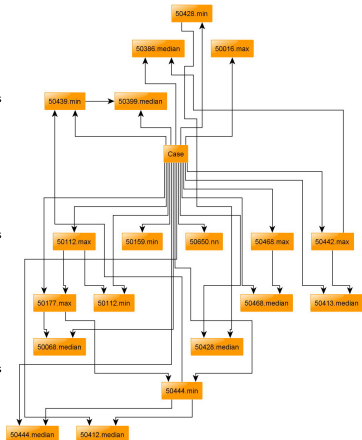
Correctly Classified Instances 547 60.2423 %  
 Incorrectly Classified Instances 361 39.7577 %

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Clas
	0.586	0.381	0.606	0.586	0.596	0.656	Y
	0.619	0.414	0.599	0.619	0.609	0.656	N
Weighted Avg.	0.602	0.398	0.603	0.602	0.602	0.656	

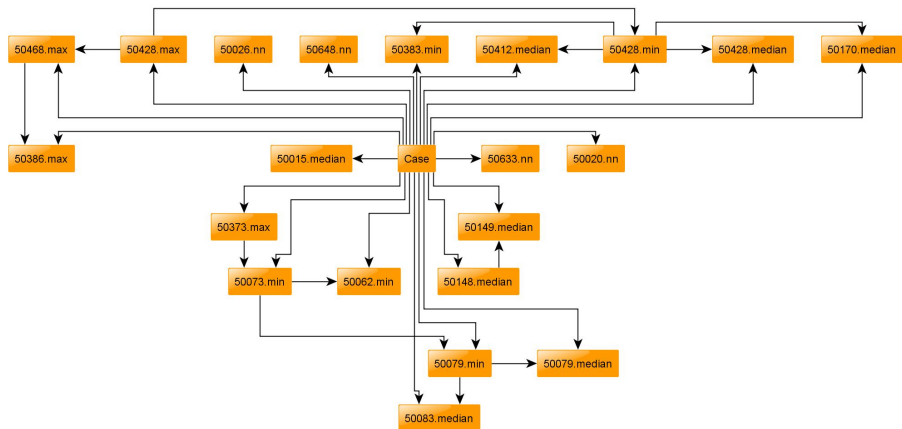
## Attribute Selection (25% NA or less)

Correctly Classified Instances 528 58.1498 %  
 Incorrectly Classified Instances 380 41.8502 %

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Clas
	0.568	0.405	0.584	0.568	0.576	0.621	Y
	0.595	0.432	0.579	0.595	0.587	0.621	N
Weighted Avg.	0.581	0.419	0.582	0.581	0.581	0.621	



# LATE *C. diff* - ALL LAB DATA UP TO 72 HOURS BEFORE TREATMENT



# LATE *C. diff* - ALL LAB DATA UP TO 72 HOURS BEFORE TREATMENT

## Full Data

Correctly Classified Instances 582 66.8966 %  
 Incorrectly Classified Instances 288 33.1034 %

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.575	0.237	0.708	0.575	0.635	0.722	Y
	0.763	0.425	0.642	0.763	0.697	0.722	N
Weighted Avg.	0.669	0.331	0.675	0.669	0.666	0.722	

## Attribute Selected (All Labs)

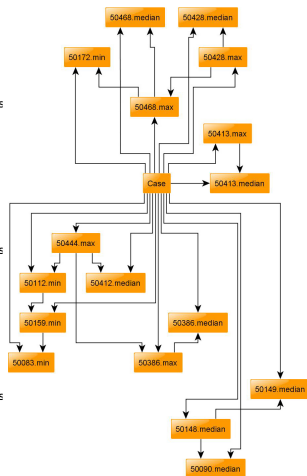
Correctly Classified Instances 588 67.5862 %  
 Incorrectly Classified Instances 282 32.4138 %

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.637	0.285	0.691	0.637	0.663	0.739	Y
	0.715	0.363	0.663	0.715	0.688	0.739	N
Weighted Avg.	0.676	0.324	0.677	0.676	0.675	0.739	

## Attribute Selected (25% NA or less)

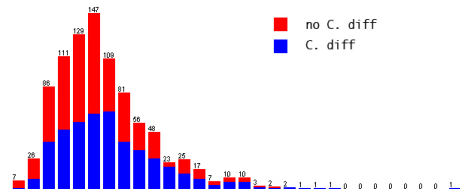
Correctly Classified Instances 563 64.7126 %  
 Incorrectly Classified Instances 307 35.2874 %

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.584	0.29	0.668	0.584	0.623	0.684	Y
	0.71	0.416	0.631	0.71	0.668	0.684	N
Weighted Avg.	0.647	0.353	0.65	0.647	0.646	0.684	



# BAYES NET RESULTS

- ▶ Results show that our classifiers are able to maintain relatively good levels of accuracy even using minimal amounts of lab tests ( $\leq 15$ )
- ▶ Accuracies are not perfect in the Bayes nets but are significant enough to provide new information in clinical applications
- ▶ Causes:
  - ▶ Database has a large percentage of NA, meaning most patients don't get every single lab test taken for them
  - ▶ Some errors in database: Impossible values which lead to development of outliers that introduce noise to the data. Much of the lab data has extremely high skew.



# CONCLUSION

- ▶ Phenome Wide Analysis using WBC allowed us to identify *C. diff* as a commonly occurring diagnosis in a specific range
- ▶ Further refining of phenotypic definitions allowed us to identify existence of community acquired and hospital acquired *Clostridium difficile*
- ▶ Bayes net classifiers generated were able to accurately identify *Clostridium Difficile* cases using minimal lab tests

# FUTURE WORK

- ▶ Expand method into identifying and finding associations within other phenomes
- ▶ Identification of waveforms in lab records
- ▶ Inclusion of additional data available in MimicII cohort

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