

# A Probabilistic Graphical Model for Major Adverse Cardiac Event Prediction

Sakin Kirti and Joshua Freeze  
CSDS 491: Probabilistic Graphical Models



# Contents

**INTRODUCTION**

**MOTIVATION**

**APPROACH & RATIONALE**

**RESULTS**

**CONCLUSION**

Data Availability

Logistic Regression

Deep Neural Network

Bayesian Model

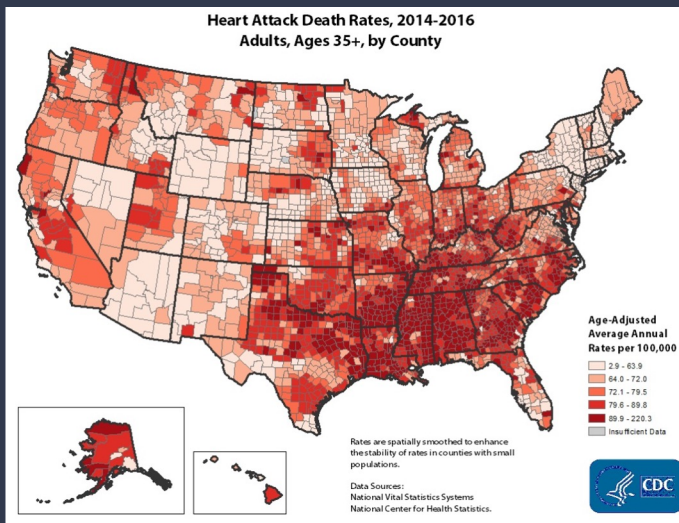
Classification

MACE Prediction

Survival Analysis

# Introduction

## Heart Disease



- Leading cause of death in the US
- Costs the US \$229 billion annually
- Strongly tied to other medical disorders like diabetes and obesity
- Coronary artery disease causes 50% of heart disease-related deaths

# Introduction

## MACE Events



- **Major Adverse Cardiovascular Events:** a set of events used by clinicians and researchers to track and investigate deadly outcomes relating to cardiovascular health
  - Acute myocardial infarction
  - Stroke
  - Cardiovascular death

# Motivation

- Current methods for MACE event prediction is formulaic
- Time-to-event analysis is done in the same way
- More advanced techniques are needed
  - Can be used in a more general sense
- Heart calcification can lead to atherosclerosis and eventually to strokes, needing bypass surgery
  - Creating early warning systems

# Approach & Rationale

## Data Availability



- Biomedical Imaging lab work provided the data for use
  - 23 features (general heart health)
  - 61 features (heart calcification)
- Permission from lab before using any data
- Dataset contained little missing data <5% of 3900 samples
  - Imputation
- Dataset was imbalanced
  - 90% no MACE, 10% MACE
  - SMOTE was used to increase size of underrepresented class

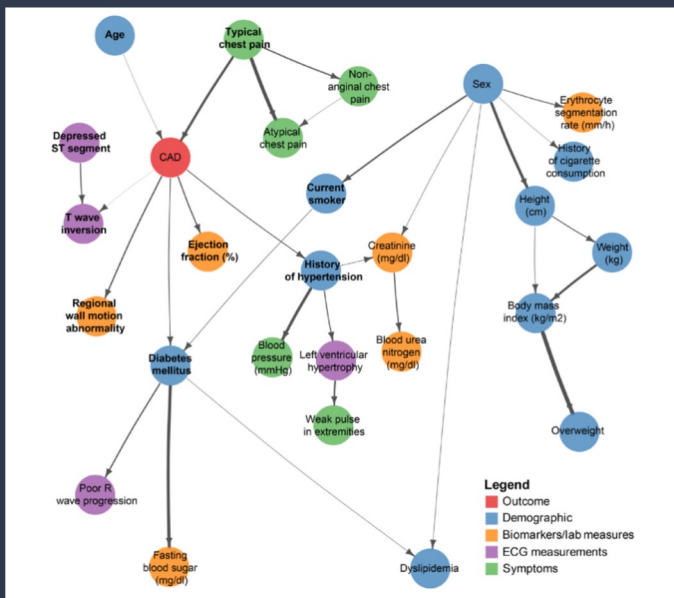
# Approach & Rationale

## Model Metrics

- Each model was measured based on several outputs
  - Classification power
    - Risk prediction
  - Model metrics
    - Accuracy, ROC curves, AUC
  - Time-to-event analysis
    - Survival analysis

# Approach & Rationale

## Models



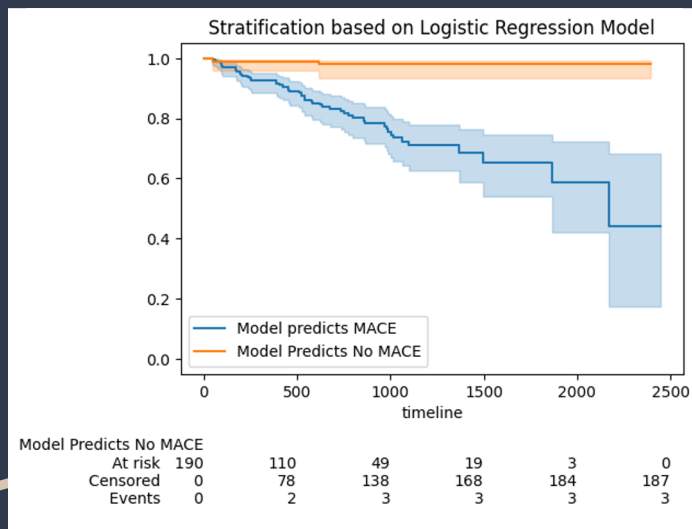
Built 3 models, wanted to understand the pros/cons of each

- Logistic regression → easy, quick
- Neural network → powerful classification
- Bayesian model → understanding of node connections



# Approach & Rationale Results

## Logistic Regression



## Approach & Rationale

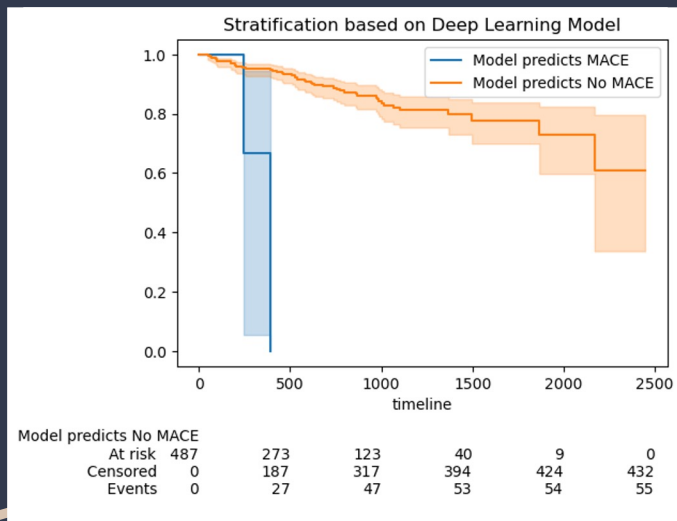
- Logistic Regression a good first model
  - Examine any correlation in the dataset
  - Simple, quick, easy (with scikit-learn)

## Results

- Accuracy: 66.1%
- AUC: 0.685
  - Vastly overpredicted MACE (57 MACE, 200+ predicted)
- Survival analysis:
  - Working separation between classes

# Approach & Rationale Results

## Neural Network



## Approach & Rationale

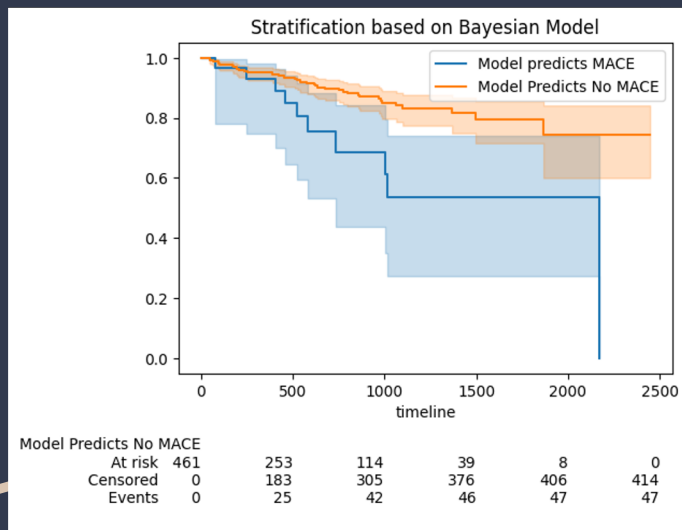
- Model architecture which output logits
- Step up from logistic regression
- Known for powerful classification
- For comparison with Bayesian model

## Results

- Accuracy: 87.4%
- AUC: 0.907
  - Note: did not do well with classifying positive cases (57 MACE, only 11 detected)
  - Still significantly better than the logistic regression model
- Survival analysis
  - Classification and low numbers cause sharp drop in time-to-event analysis

# Approach & Rationale Results

## Bayesian Model



## Approach and Rationale

- Outputs probability of MACE occurring
  - Risk score/calculation
- Node relationships based on
  - Gupta et al for general heart features
  - Conversations with Josh's PI for heart calcification data

## Results

- Accuracy (rounded): 90.5%
- AUC: 0.720
- Survival Analysis
  - Accurate separation of classes

# Conclusion

## Project Models

### 3 Models built

- Logistic Regression
  - good insight into the data
- Deep Neural Network
  - classification power and comparison for Bayesian Model
- Bayesian Model
  - classification and confidence for predictions

### Project-specific Outcomes

- Deep neural model did the best and created risk scores in the process (probability proxy)
- Neural network did well with classification

### Next Steps

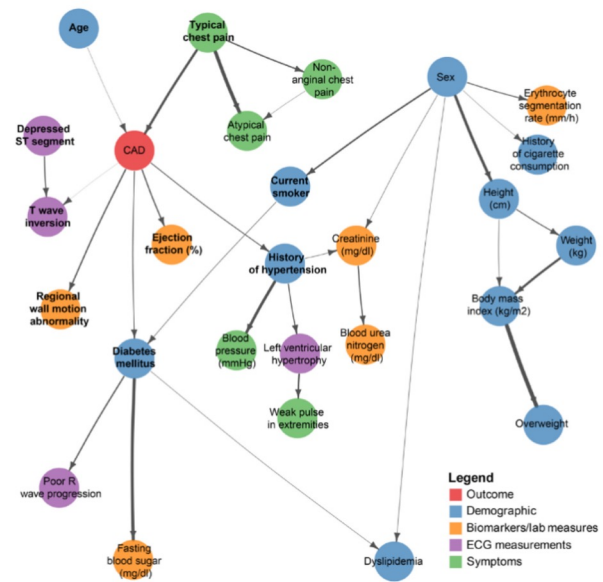
- Rethink node classifications and maybe reduce the number of nodes
- Spend some time on hyperparameter tuning

# Conclusion

## Project Models

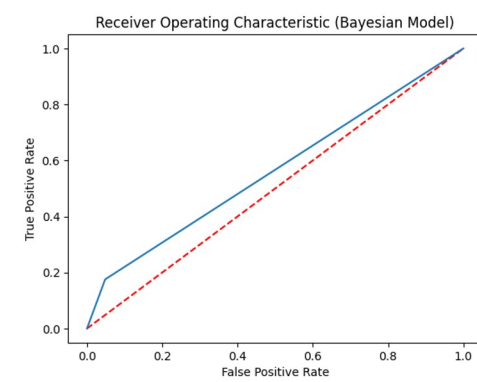
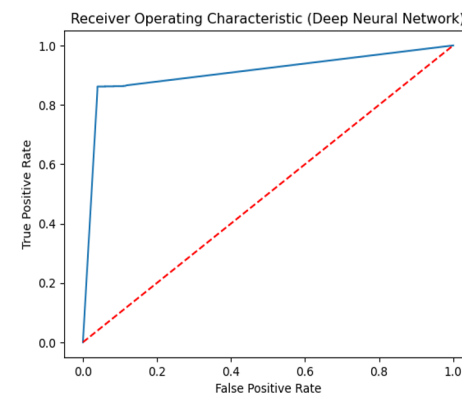
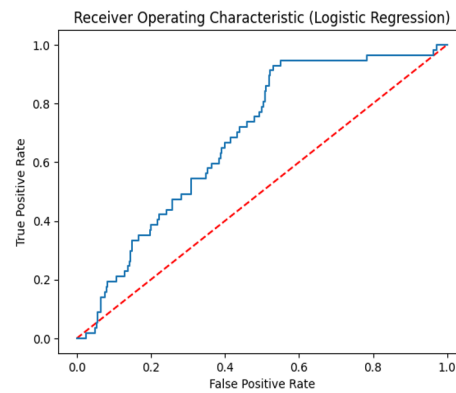
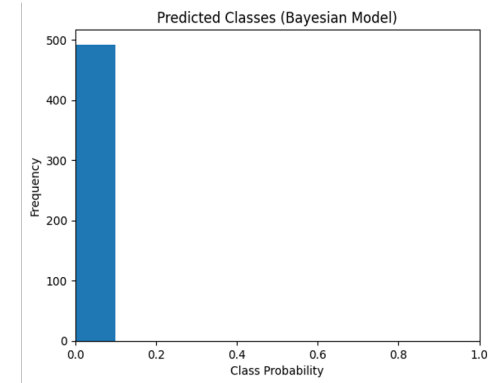
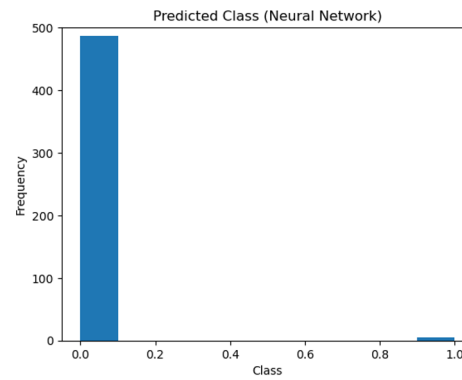
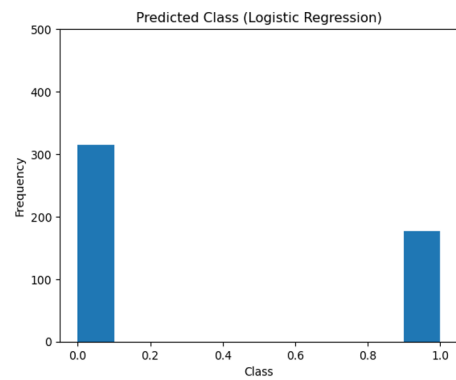
### Broad Outcomes

- Literature contains examples of probabilistic models for heart data
- We expand on this by adding calcification data

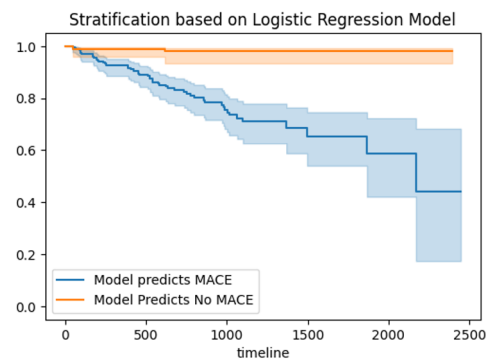


Thank you!

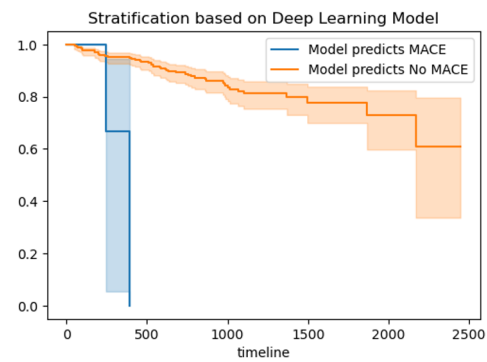




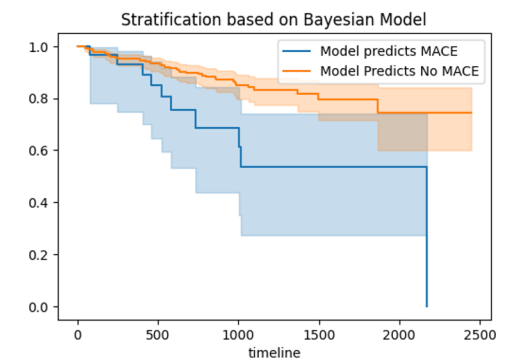
# Results Summary



Model Predicts No MACE						
At risk	190	110	49	19	3	0
Censored	0	78	138	168	184	187
Events	0	2	3	3	3	3



Model predicts No MACE						
At risk	487	273	123	40	9	0
Censored	0	187	317	394	424	432
Events	0	27	47	53	54	55



Model Predicts No MACE						
At risk	461	253	114	39	8	0
Censored	0	183	305	376	406	414
Events	0	25	42	46	47	47

## Results Summary