Predicting Stroke Likelihood:
A Bayesian Analysis

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DS 6040 - Bayesian Machine Learning
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Problem Description - Background & Motivation

Stroke is the 2nd leading cause of death according to the **WHO** (2021).

Commonly neglected and misdiagnosed as other conditions.

Ongoing studies regarding salient factors contributing to stroke risk.

Problem Description - The Data

~5000 observations with 10 clinical features

- Health metrics: *bmi*, *avg_glucose_level*
- Pre-existing conditions: *hypertension*, *heart_disease*, *smoking_status*
- Demographic information: *gender*, *age*, *ever_married*, *work_type*, *residence_type*

Data originally curated and distributed over Kaggle.

Probability Model - Bayesian Logistic Regression

Binary classification (stroke: 0/1)

Some possible models:

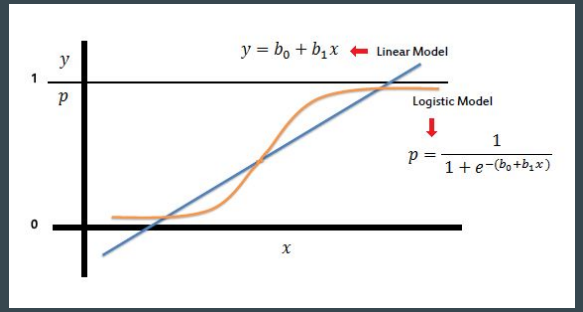
- LDA, QDA, Naïve Bayes, SVM

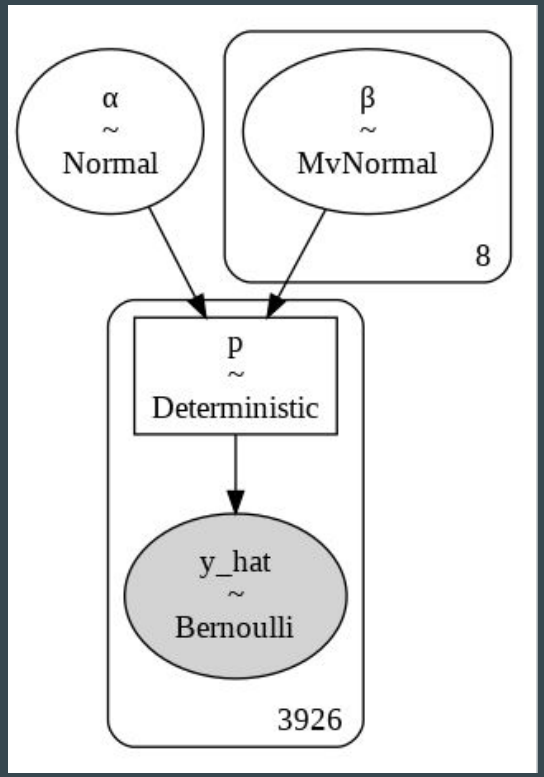
Numeric and categorical features

Bayesian Logistic Regression

- Inference
- Prediction
- Uncertainty

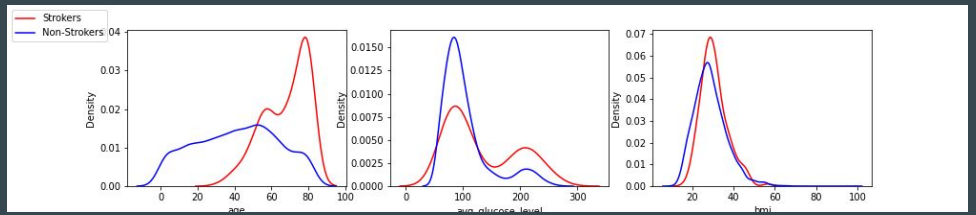
$$ln\left(\frac{p}{1-p}\right) = b_0 + b_1 x$$

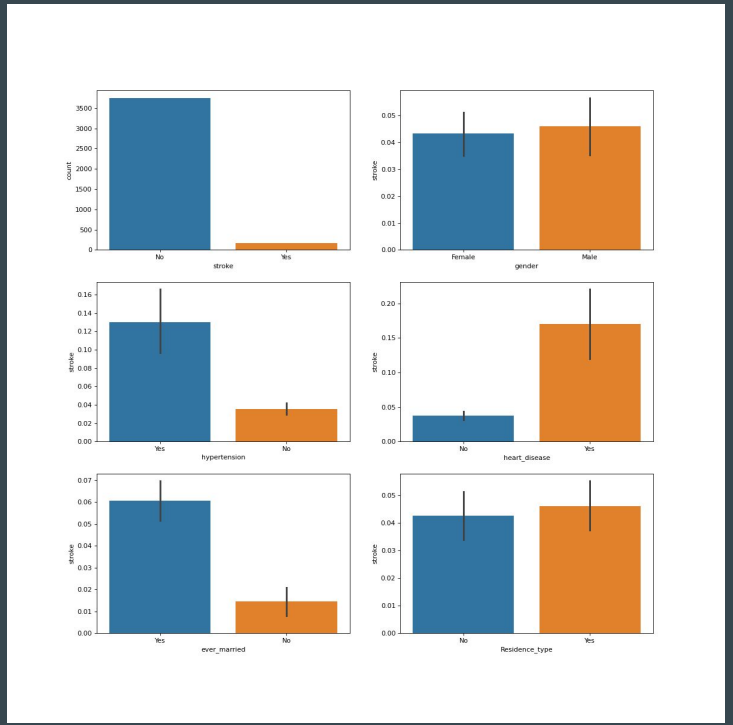




Approach - Exploratory Data Analysis

- Assessed the relationship between each of the predictors and the target variable.
- Potentially notable features:
  - *age*
  - *hypertension*
  - *heart_disease*
  - *ever_married*





Approach - Data Cleaning

Dropped 201 observations containing NAs

Features removed:

- *id* (unique patient identifier)
- *work_type* and *smoking_status* (multi-class categorical predictors)

Features converted into binary variables:

- *gender* (male: 1, female: 0)
- *ever_married* (yes: 1, no: 0)
- *Residence_type* (urban: 1, rural: 0)

Final features:

- 5 binary variables (*gender*, *hypertension*, *heart_disease*, *ever_married*, *Residence_type*)
- 3 numeric variables (*age*, *avg_glucose_level*, *bmi*)

80/20 Train-Test Split

- 3926 training observations
- 982 test observations

Approach - General Trajectory

Full Model

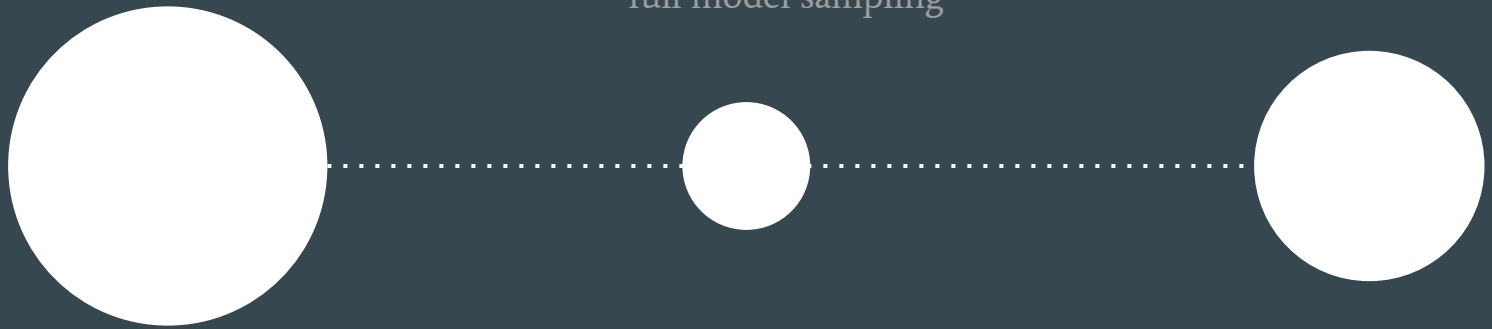
Uses all available features which can be incorporated effectively

Reduced Model

Uses a subset of features determined by the results of the full model sampling

BMA Model

Weights the predictions of the other models based on their WAIC scores



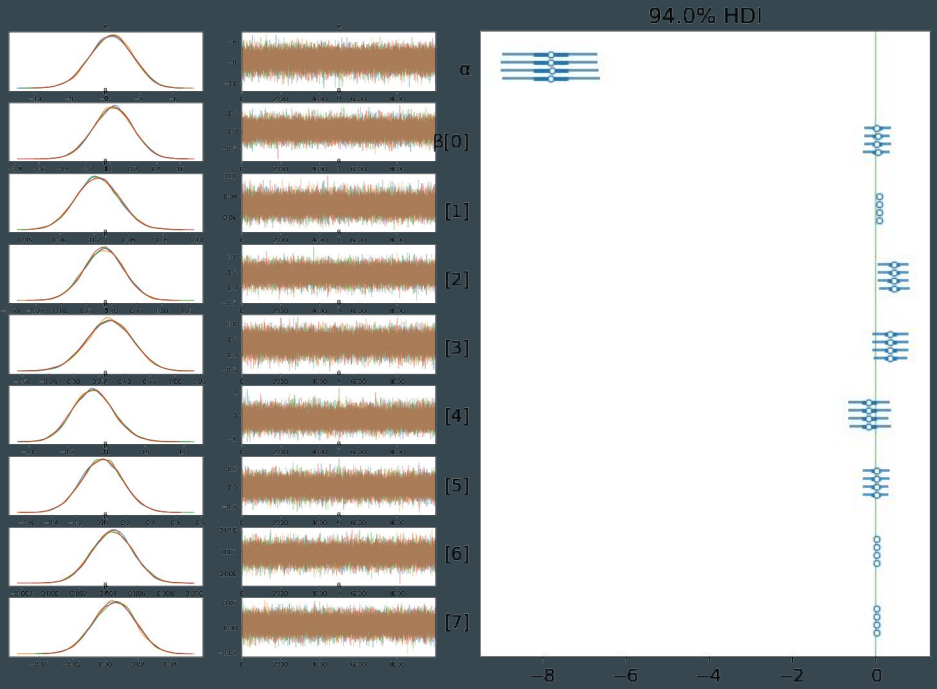
Approach - The Full Model

Predictor variables:

- 5 binary categorical
- 3 numeric

HMC Sampling

- Very slow process
- Good trace plot convergence
- Forest plots and summary table revealed many predictors were not statistically significant



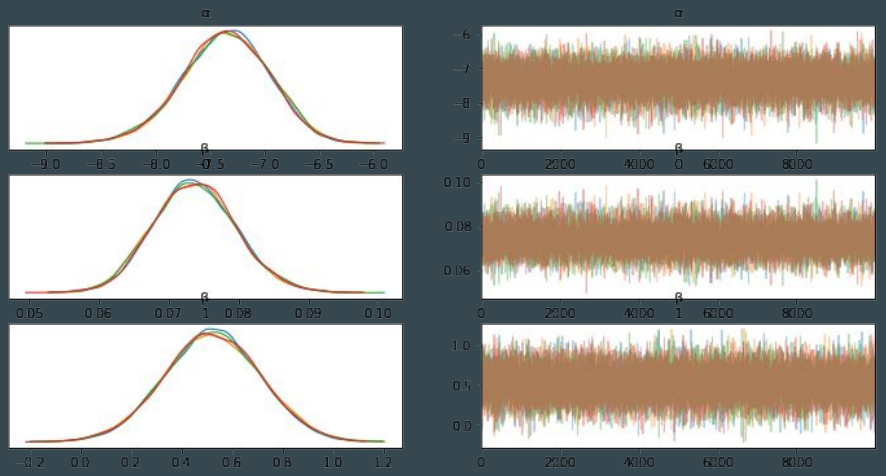
Approach - The Reduced Model and BMA Model

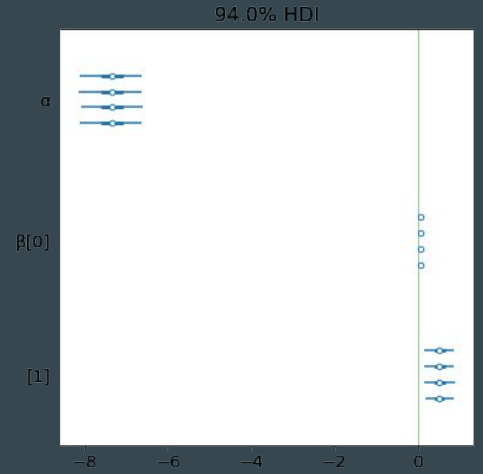
2 predictor variables: *age* & *hypertension*

Strong convergence and statistically significant posterior parameter estimates

WAIC comparison:

- 55.94% full model
- 44.06% reduced model





Modeling Objectives

Minimizing Misclassification Cost

Lower Threshold

- Liberal on diagnosing as ‘positive’ (0.04)
- Impact of misdiagnosing as ‘negative’ (False Negative) is huge
- FP cost = 1, FN cost = 50

Focusing on Recall than Accuracy and Precision

- Huge class imbalance on response variable
- What proportion of actual positives identified correctly?

Inferences on Variability

The Main Goal of Bayesian Statistics

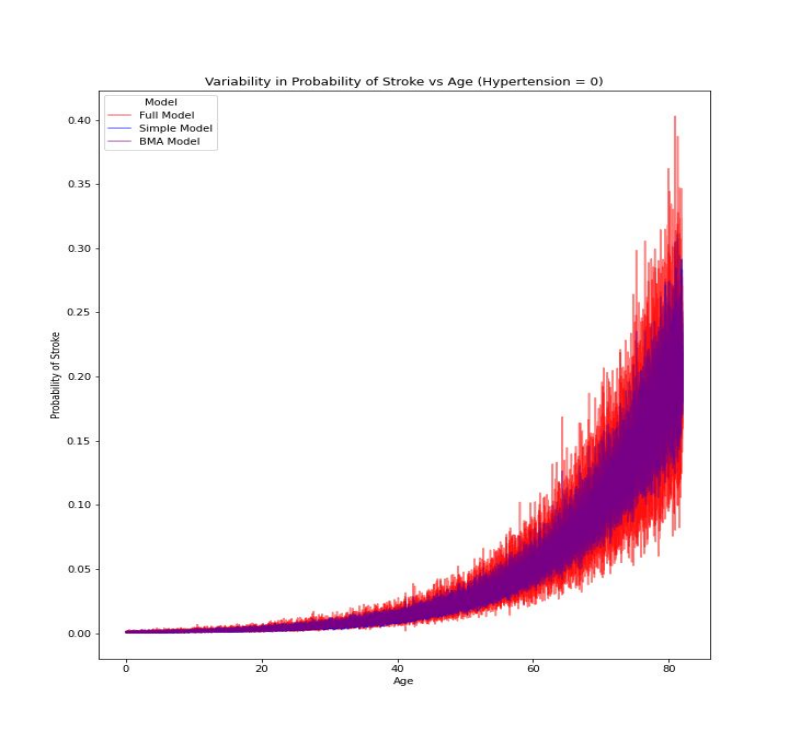
- Identify uncertainty in each model
- Checking mean of posterior graph to get pointwise probability

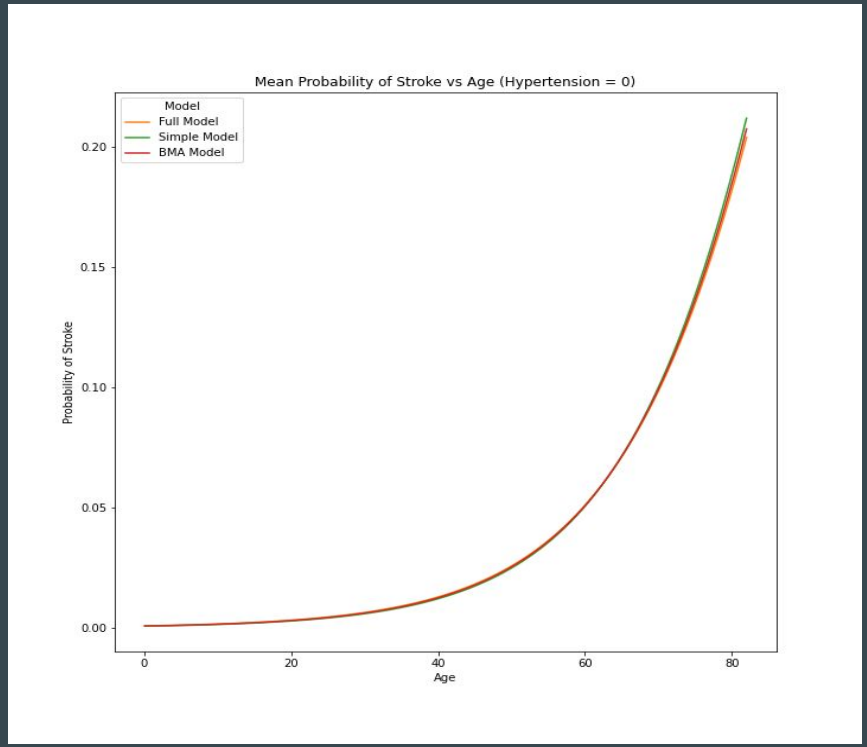
Results

Models / Metrics	AUC	Confusion Matrix	Precision	Accuracy	Recall
Full Sampling	0.854	[[33, 2], [280, 667]]	0.105	0.713	0.943
Reduced Sampling	0.836	[[33, 2], [306, 641]]	0.097	0.686	0.943
BMA	0.847	[[33, 2], [292, 655]]	0.102	0.701	0.943

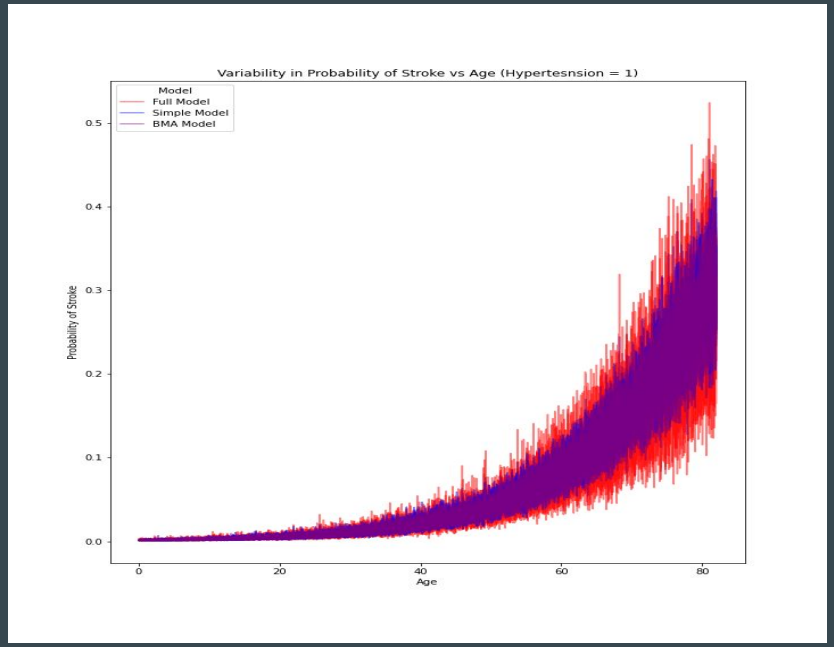
- Precision = TP / (TP+FP) = What proportion of positive identifications are actually correct?
- Recall = TP / (TP + FN) = What proportion of actual positives was identified correctly?

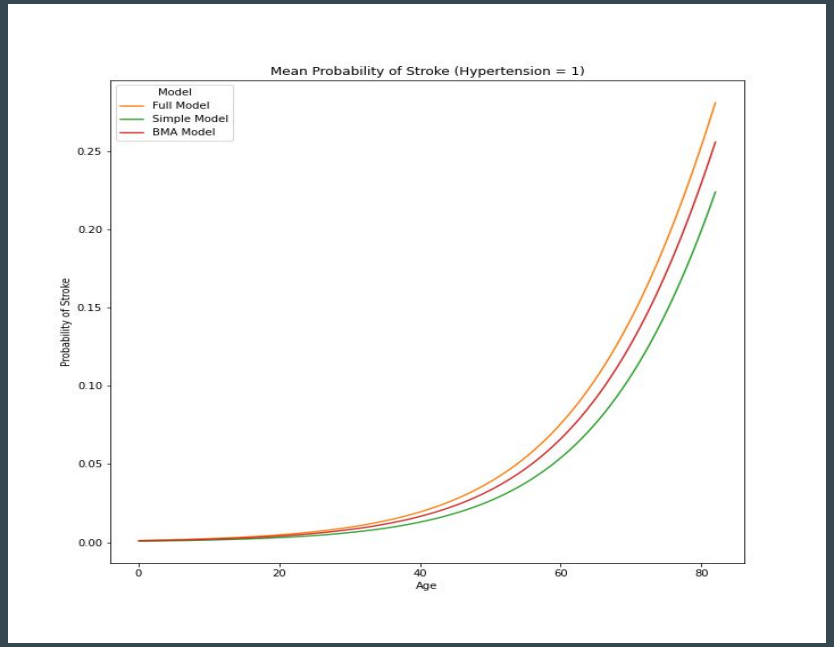
Result: Variability in Age & No Hypertension





Result: Variability in Age & Hypertension





Limitations

Observations	• The dataset only has roughly 5000 observations
Features	• The dataset only has 10 possible predictors
Regional Factors	• Did not take into account possible differences in regions, countries, etc.

Conclusions:

- Bayesian Logistic Regression can provide decent predictions for classifying patients as with or without stroke.
- Bayesian Model Averaging is effective in building a final model that balances prediction variance and overall performance.

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