

# Statistical Learning Project

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The background of the slide features a close-up of several blue and white capsules scattered on a surface. In the background, a book with the title 'Brain Stroke' is visible, along with some medical equipment like a syringe. A blue and white geometric graphic element is positioned on the left side of the slide.

# Data analysis on stroke detection

- “Stroke” is the medical term for damage to brain tissue or the death of a portion of it, due to insufficient blood supply to an area of the brain
- It is responsible for approximately 11% of total deaths
- Normal values of glucose: 60-110 mg/dl
  - > 126 diabetes
- Normal BMI range: 18.5 - 24.9
  - > 30.0 obesity

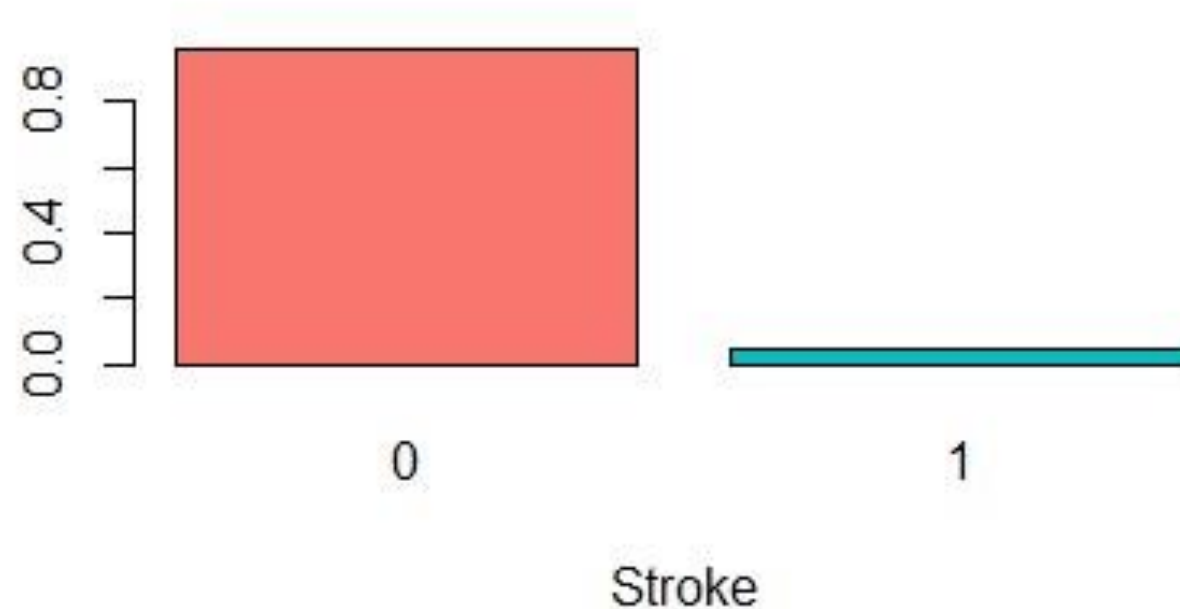
# Dataset

id	gender	age	hypert.	hd	ev_marr	work_type	res_type	glucose	bmi	smoking	stroke
9046	Male	67	0	1	Yes	Private	Urban	228.69	36.6	formerly smoked	1
51676	Female	61	0	0	Yes	Self-employed	Rural	202.21	N/A	never smoked	1
31112	Male	80	0	1	Yes	Private	Rural	105.92	32.5	never smoked	1
60182	Female	49	0	0	Yes	Private	Urban	171.23	34.4	smokes	1
1665	Female	79	1	0	Yes	Self-employed	Rural	174.12	24	never smoked	1

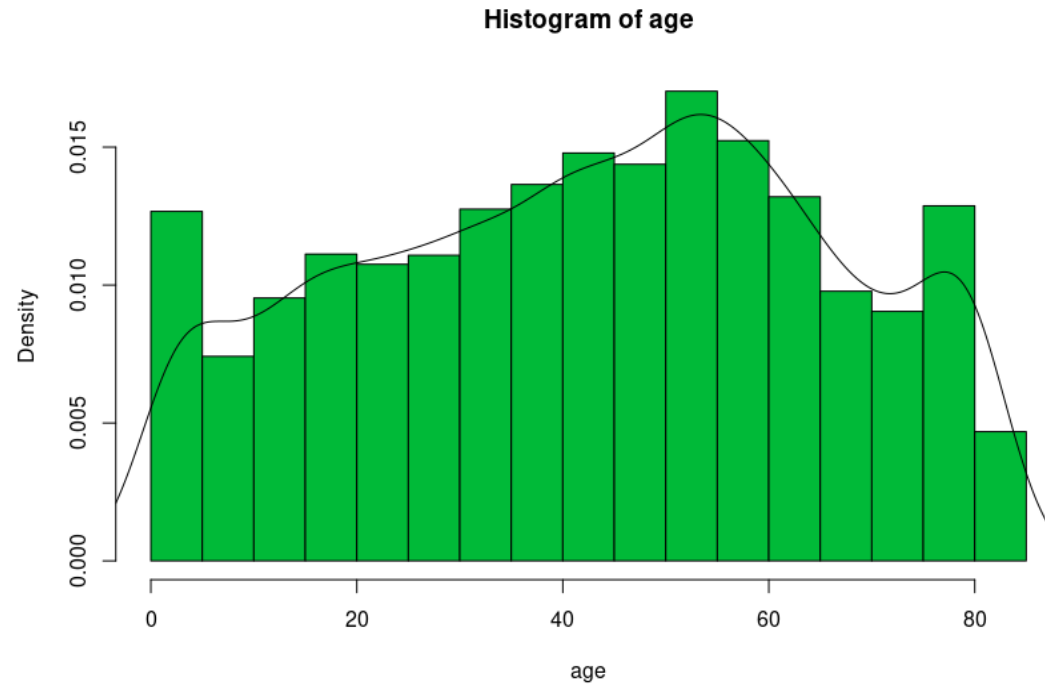


# Dataset

- **Data variables:** id, gender, age, hypertension, heart\_disease, ever\_married, work\_type, Residence\_type, avg\_glucose\_level, bmi, smoking\_status, stroke
- **Missing values**
- **Unbalanced data:**  
4,26% of the people get a stroke



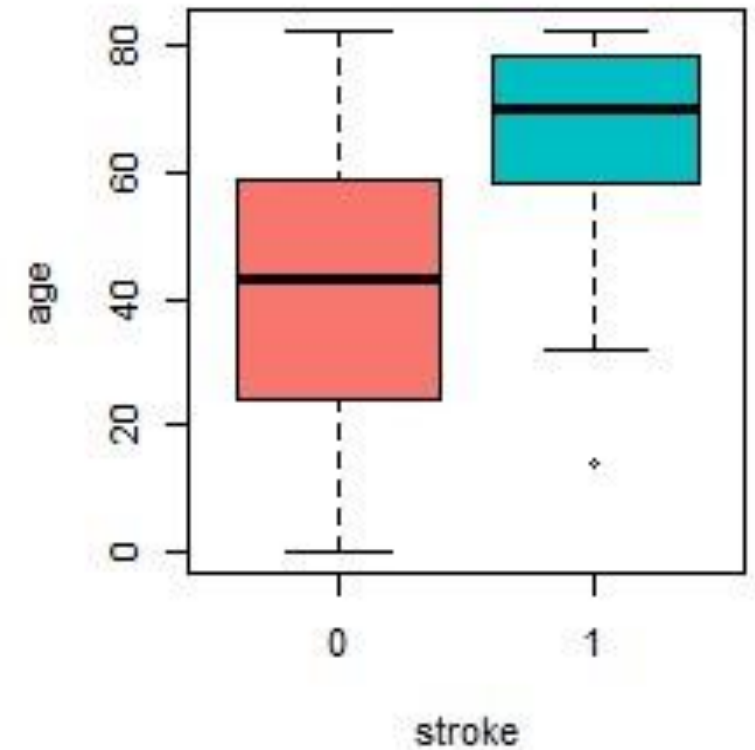
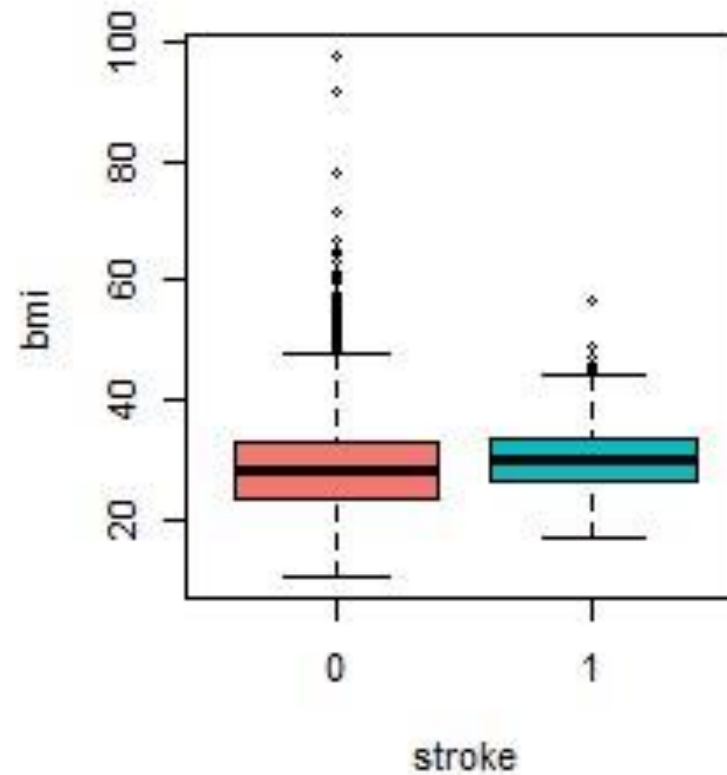
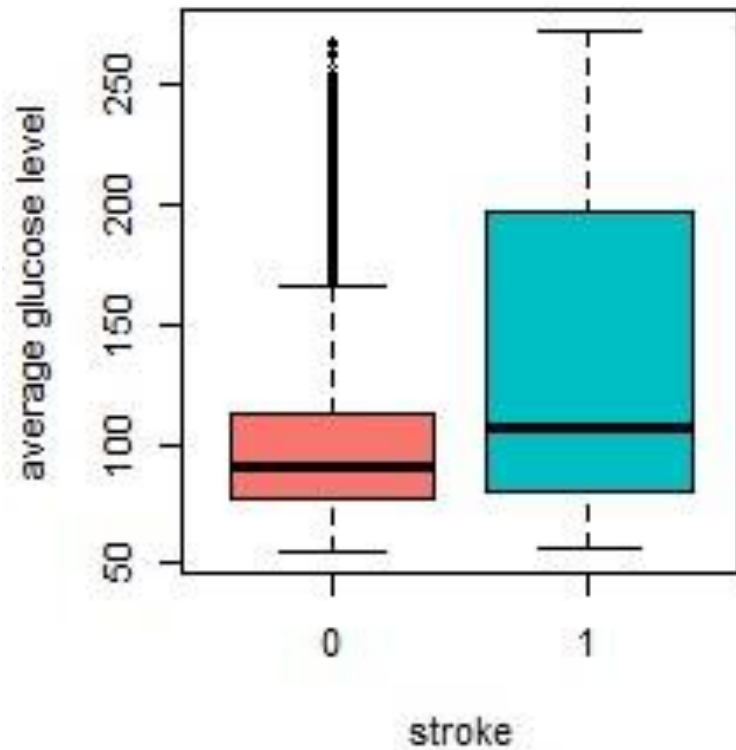
# Age distribution



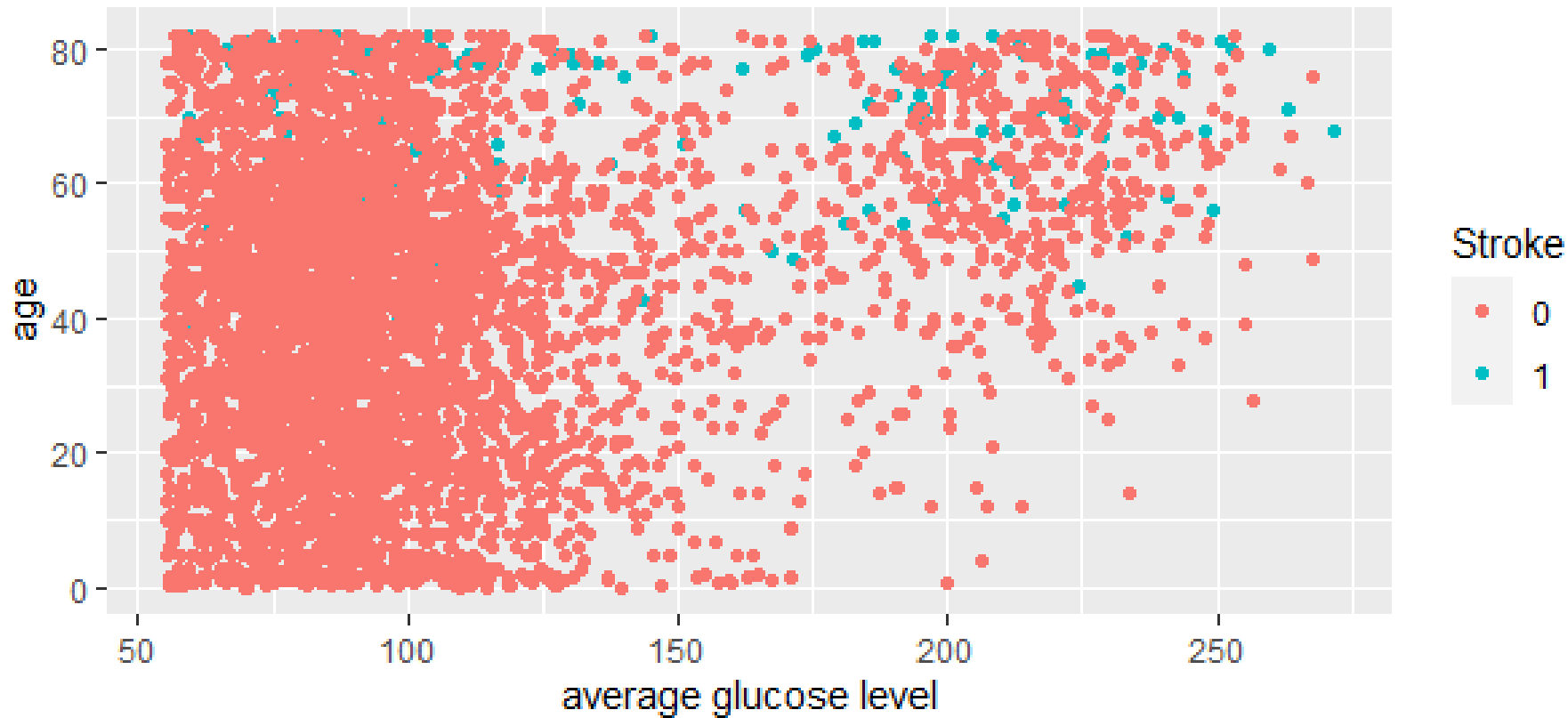
Data cover people of all ages from babies of 8 days to seniors of 82 years old

# Explanatory Data Analysis (EDA)

- High glucose level and bmi do not imply directly a stroke
- Rare/interesting cases of stroke
- Strong relation between age and stroke

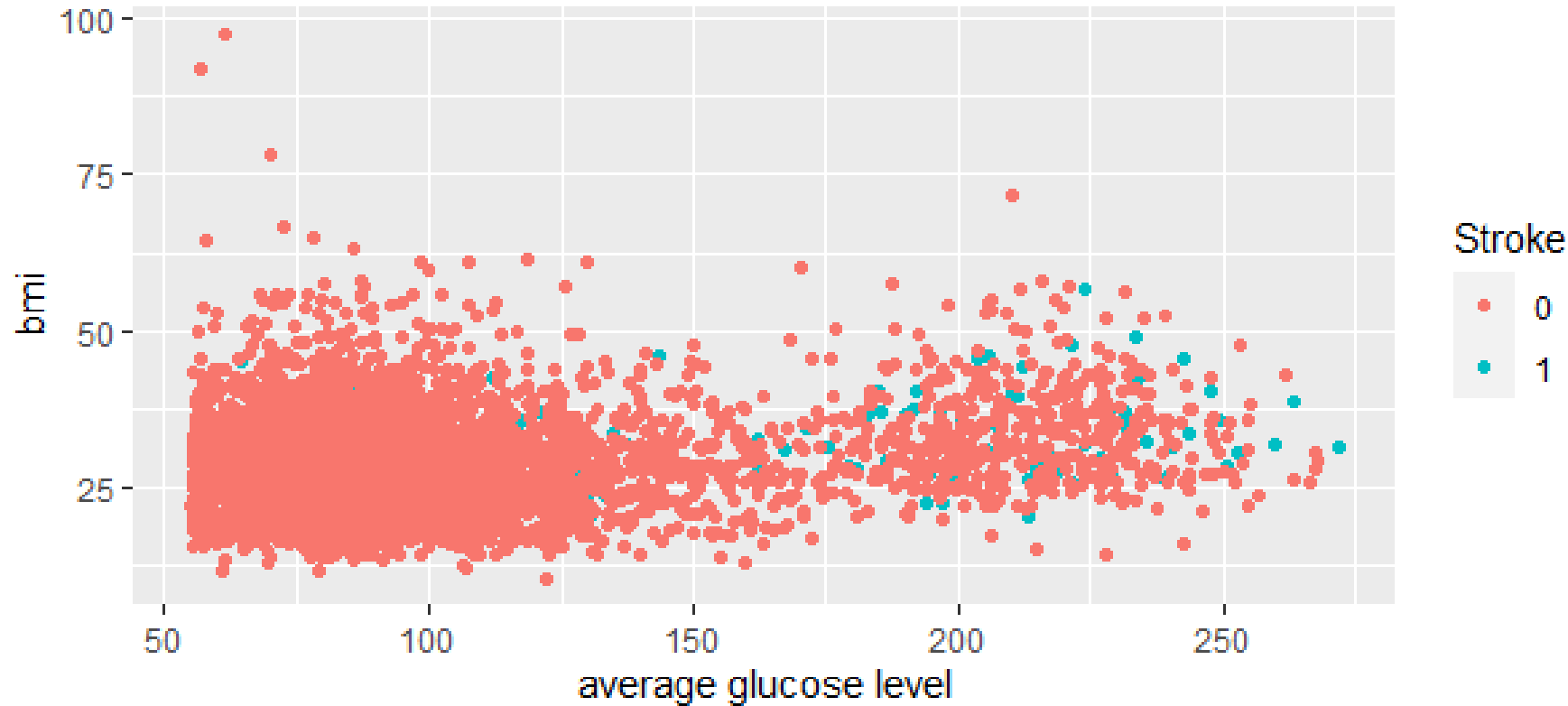


# Not an easy problem



- Non-linear separable
- Not easy to identify a direct relationship with stroke diseases

# Not an easy problem



*Glucose levels* and *Bmi* could not be so strictly related to the disease but maybe correlated to other illnesses linked to it.



# Not an easy problem



- Strong correlation with *age*
- Weak correlation with *Bmi*

# Correlation between features

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- Presence of collinearity:
  - Age ~ Ever married : 0.68
  - Age ~ Work type : 0.54
  - Age ~ Smoking status : 0.39
  - Ever married ~ Bmi: 0.34
- Correlated variables:
  - Stroke ~ Age: 0.23
  - Stroke ~ Hypertension: 0.14
  - Stroke ~ Avg. glucose level: 0.14



# Relevant Questions:

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- Which factors are the most related to the stroke disease?
- How strong are the relations between the features?
- Are the given variables enough to predict a good accuracy of some possible person affected by stroke?
- Is it possible to prevent the stroke?



# Tested Models

- **Logistic Regression**
  - Full and Reduced Models
  - Interaction Models
  - Polynomial Models
- **Bayesian Models**
  - LDA Model
  - QDA Model





# LOGISTIC REGRESSION

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- A type of Generalized linear model (GLM)
- The dependent variable is binary

0 NO STROKE

1 STROKE

## Model selection:

- Hypothesis
- p-value
- AIC



# Reduced Model

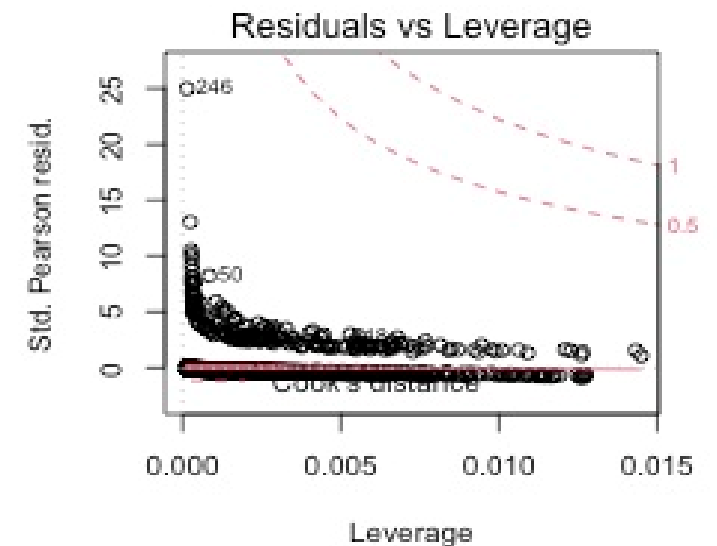
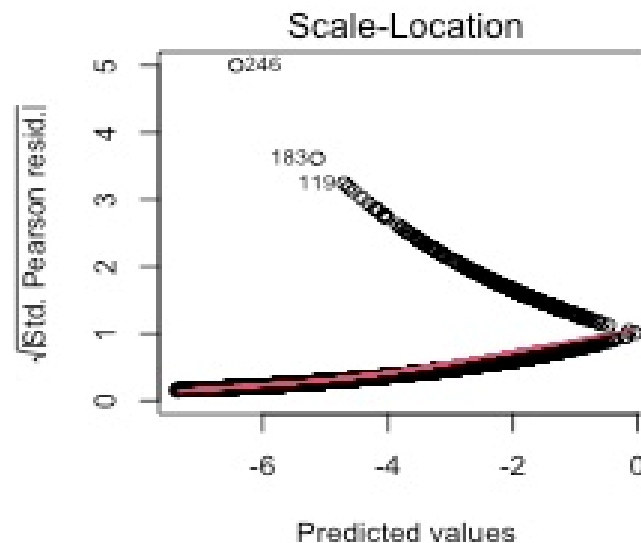
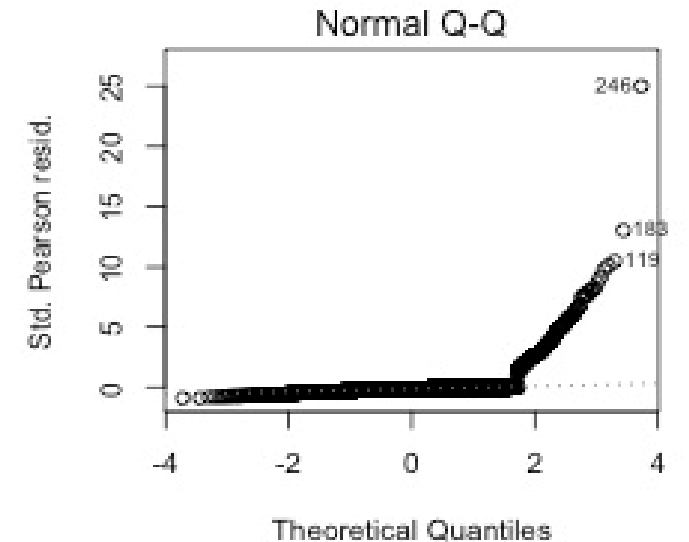
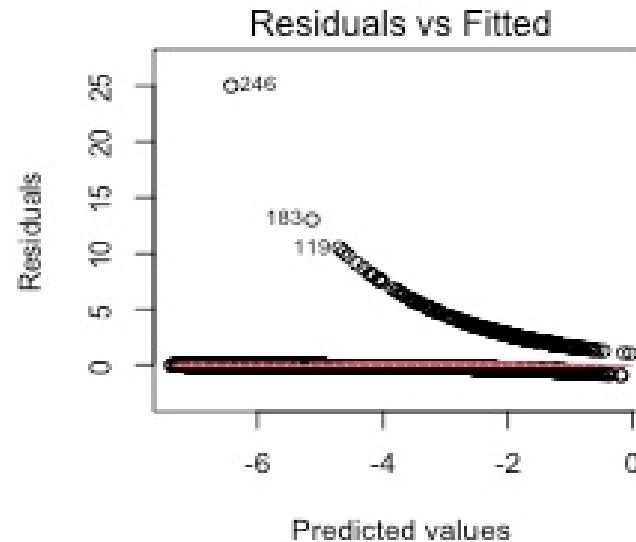
Feature	Coef.	Level of significance
Age	0.067547	$< 2e-16$
Avg. Glucose level	0.004802	0.000129
Heart disease	0.404298	0.046895
Hypertension	0.539613	0.001820

AIC: 1384.6



# Reduced Model Plots

- Non-linearity in dataset
- Residuals do not follow normal distribution
- Heteroscedasticity
- Leverage points
- Outliers



# "Outliers"

Able to infer some particular stroke cases, *anomaly detection*.

	gender	age	hypert.	hd	ev_marr	work_type	res_type	glucose	bmi	smoking	stroke
119	Female	38	0	0	No	Self-employed	Urban	82.28	24.0	formerly smoked	1
183	Female	32	0	0	Yes	Private	Rural	76.13	29.9	smokes	1
246	Female	14	0	0	No	children	Rural	57.93	30.9	Unknown	1

# Interaction between features

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- $\text{age} * \text{heart\_disease}, \text{avg\_glucose\_level}, \text{bmi}, \text{hypertension}$
- $\text{avg\_glucose\_level} * \text{heart\_disease}, \text{bmi}, \text{hypertension}$
- $\text{heart\_disease} * \text{hypertension}$
- $\text{bmi} * \text{hypertension}$



# Best Interaction Model

Feature	Coef.	Level of significance
Age	0.070133	$< 2e-16$
Avg. Glucose level	0.004702	0.000176
Heart disease	2.765299	0.047694
Hypertension	0.536550	0.001880
Age:heart disease	-0.032872	0.091604

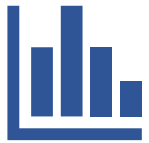
AIC: 1384

# Best Model Selection

To choose the best model among the electives ones we used Training and Validation testing method.

Data splits should be done carefully cause of unbalanced issue.

- 75% Training
- 25% Validation
- Both splits have 4% of stroke cases



**Training set**



**Validation set**

# Best Model Selection

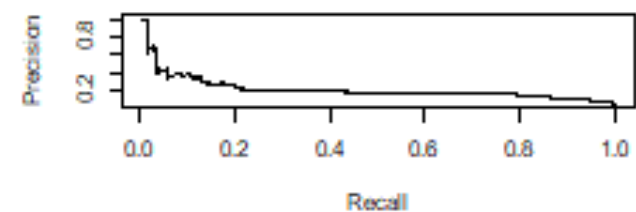
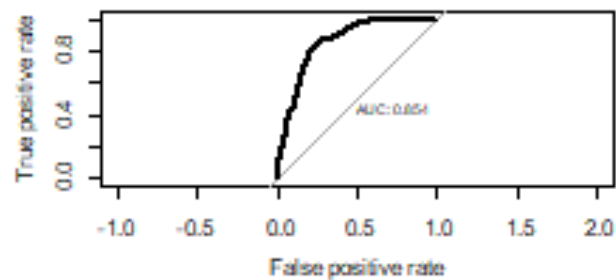
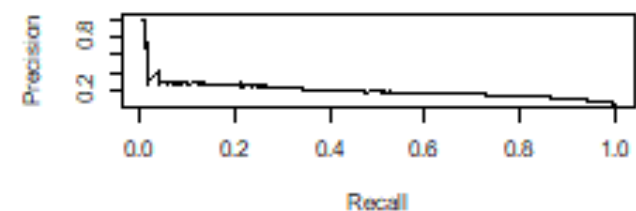
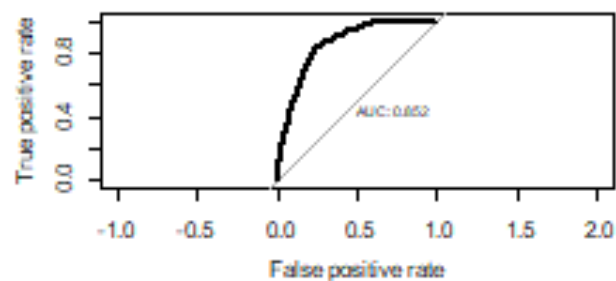
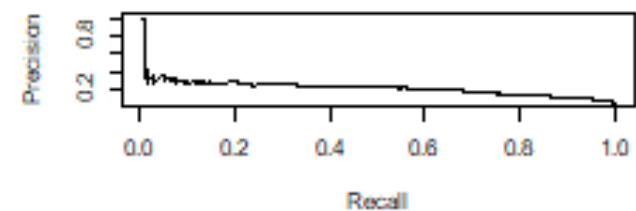
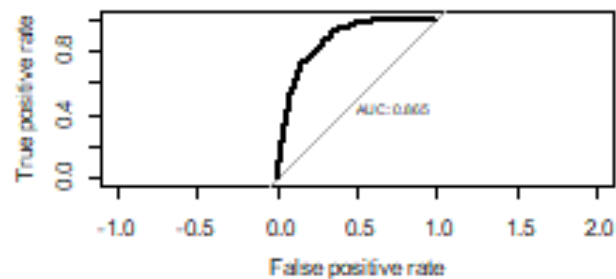
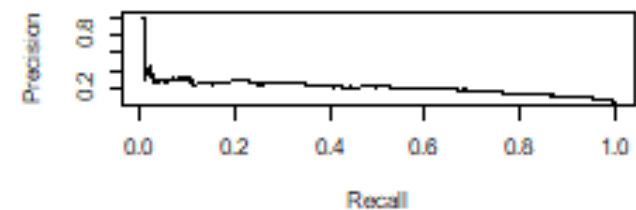
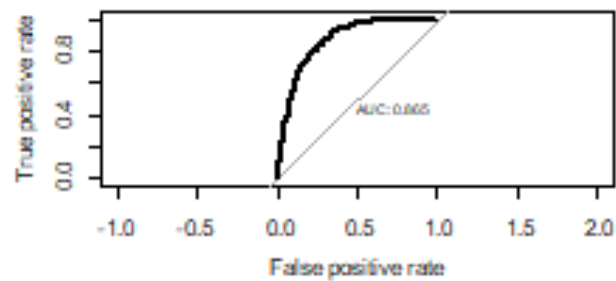
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- False Rates?
  - False negatives in medical cases
  - ROC or Precision-Recall curves?
  - Threshold





# ROC VS Prec-Recall Curves



# Best Model Selection

REDUCED MODEL			
		Predicted	
		0	1
Ground thruth	0	497	681
	1	1	48

INTERACTION MODEL			
		Predicted	
		0	1
Ground thruth	0	499	679
	1	1	48

LDA MODEL			
		Predicted	
		0	1
Ground thruth	0	490	688
	1	1	48

QDA MODEL			
		Predicted	
		0	1
Ground thruth	0	599	579
	1	4	45

# Best Model Selection

## - Error Rates -

### **REDUCED MODEL:**

- Positive rates: 0.0658
- Negative rates:  $2.01 \times 10^{-3}$

### **INTERACTION MODEL:**

- Positive rates: 0.0660
- Negative rates:  $2.0 \times 10^{-3}$

### **LDA MODEL:**

- Positive rates: 0.0652
- Negative rates:  $2.04 \times 10^{-3}$

### **QDA MODEL:**

- Positive rates: 0.0721
- Negative rates:  $6.633 \times 10^{-3}$



# Conclusions

- Interaction model is the best
- Older people have higher probability to get a stroke
- Not easy to make secure predictions
- Increase the number of data
- Find more features related with stroke
- Find out the appropriate false rate