Is this transaction fraudulent?

Kaitan Sun, Nada Liang, Duncan Wingfield, Travis Li

Machine Learning Project

Agenda

Business Problem

Dataset

Data Exploration

Models

Classification Tree
Logistic Regression (Lasso)
Random Forest
Stacking (SVM, Log)

Business Interpretation & Application

Summary

Part 1

Business Scenario

Business Problem

Who are we?

E-Commerce company

What's our Goal?

To **identify fraudulent customers** at their first transaction.

What type of question is it?

Classification: 0 (not fraudulent) or 1 (fraudulent)

Business Interpretation

		Predicted Result: Not fraudulent (0)	Predicted Result: Fraudulent (1)
Actual	Not fraudulent (0)	**TN**	**Type error I (FP):** The transaction is not fraudulent, but we predicted it was.
	Fraudulent (1)	**Type error II (FN):** The transaction is fraudulent, but we predicted not.	**TP**

Part 2

Dataset & Feature Engineering

Dataset: Each user first transaction

How large is it?

151,112 records / transactions

11 predictors

Response:

“Class”

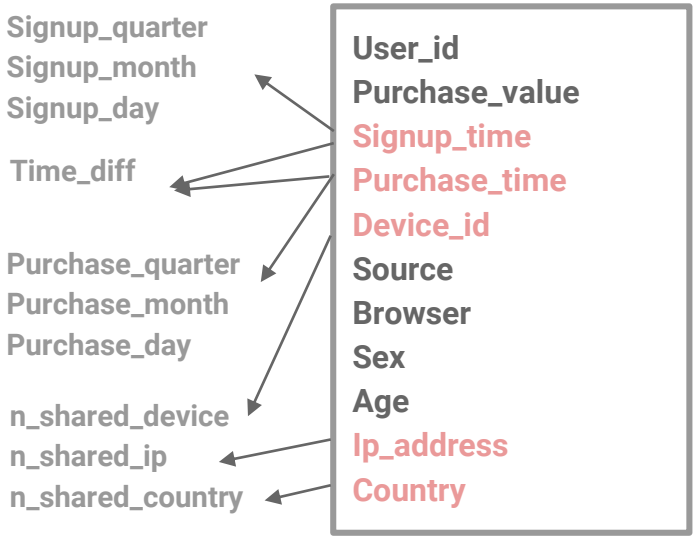
- **0 (not fraudulent)**
- **1 (fraudulent)**

User_id [numeric]	Unique User ID
Signup_time [date,time]	Time when user created account
Purchase_time [date,time]	Time when user bought an item
Purchase_value [numeric]	Cost of the item purchased
Device_id [string]	Unique physical device identification
Source [string]	How the user found and clicked on the site
Browser [string]	The internet browser the user used
Sex [string]	User sex (male/female)
Age [numeric]	User age
Ip_address [numeric]	User numeric IP address
Ip_address_to_country [string]	Shows what Country the IP address is in upon purchase

(including dummy variables)

Feature engineering: 11p → 15p → 48col

1. Delete user_ID
2. Divide time
3. Calculate Time difference
4. Transform ip, device id, country info
5. Transform string into categorical for tree based model
6. Transform categorical data to dummy variables for logistic regression
7. Scale data for logistic regression



Part 3

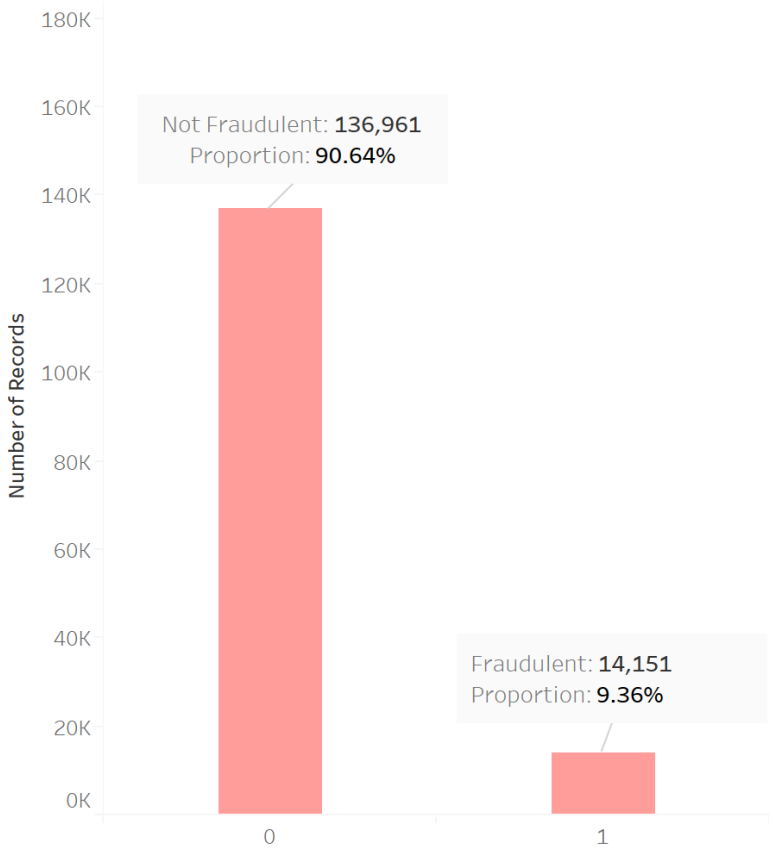
Data Exploration

Naive model

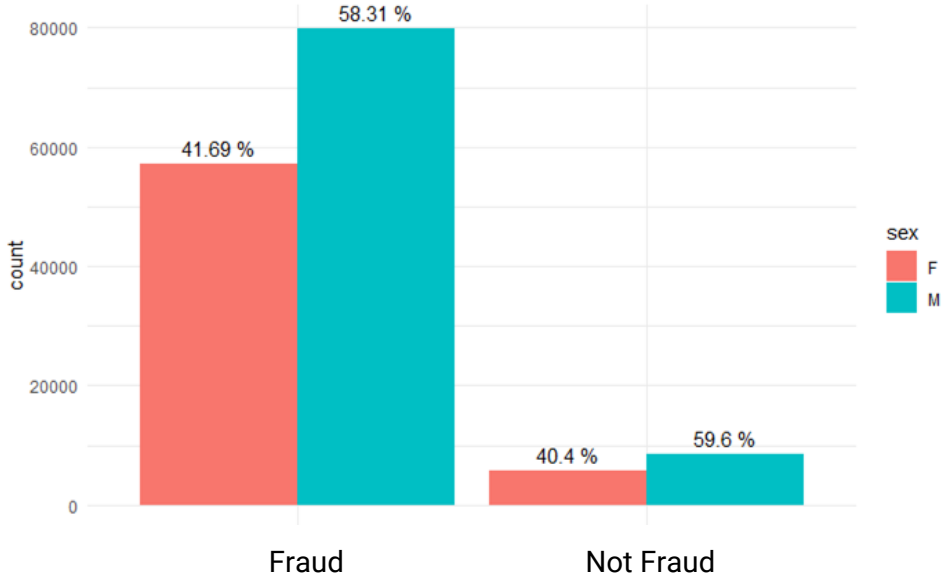
(If we predict that every transaction is not fraudulent)

Accuracy: 90.64%

Distribution of Response Values



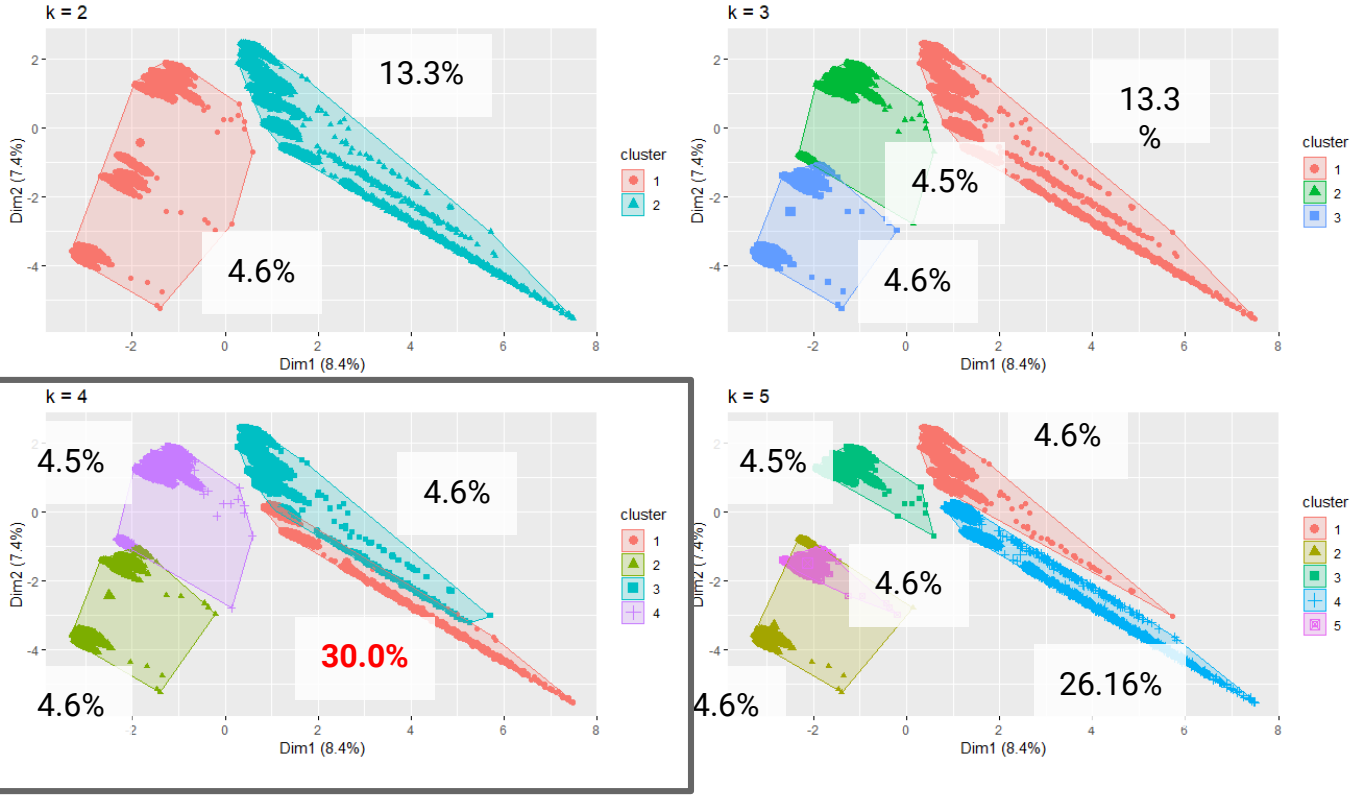
First Glimpse of Target by Age & Gender



Clustering

Method
k means (2,3,4,5)

Fraud rate:
Average: 9.36%
(k=4) Cluster1:30%



Part 4

Model & Results

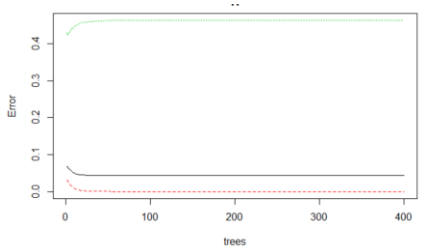
Metric Selection

1. Since the dataset is imbalanced, we are **not** going to use **ACCURACY** as the **sole metric**
2. **AUC and ROC** curve will be leveraged as a trade-off metric

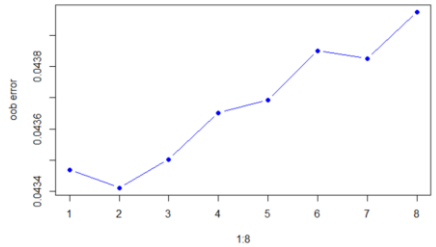
Model 1: Random Forest

Type I error	0.00%
Type II error	45.97%
Accuracy	95.68%
AUC	0.848

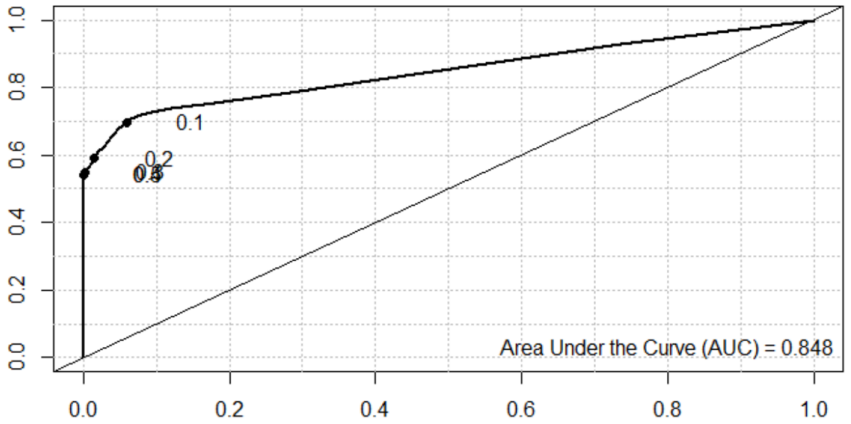
ntree: 97



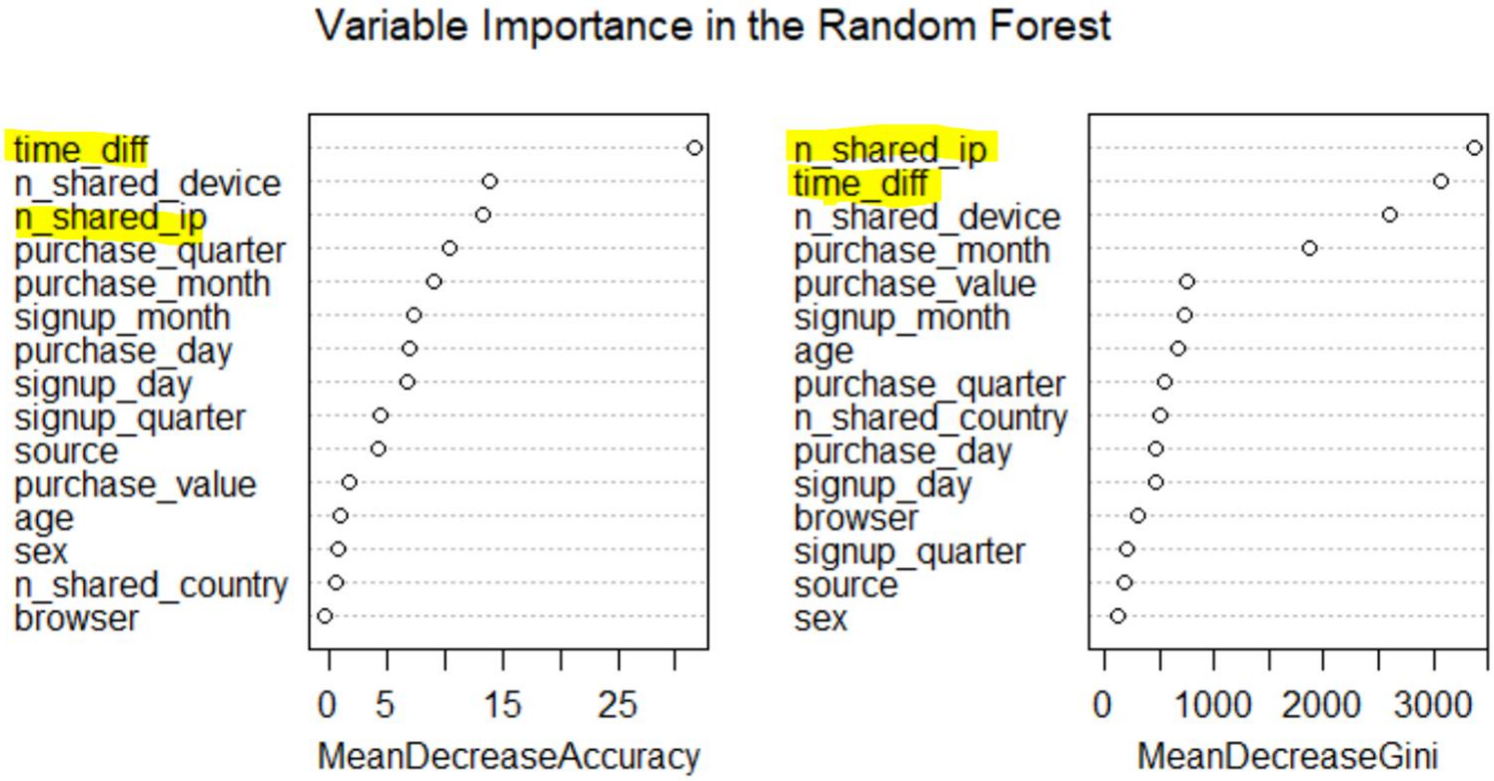
mtry: 2



		Prediction	
		Not fraud	Fraud
Actual	Not fraud	27380	0
	Fraud	1307	1536



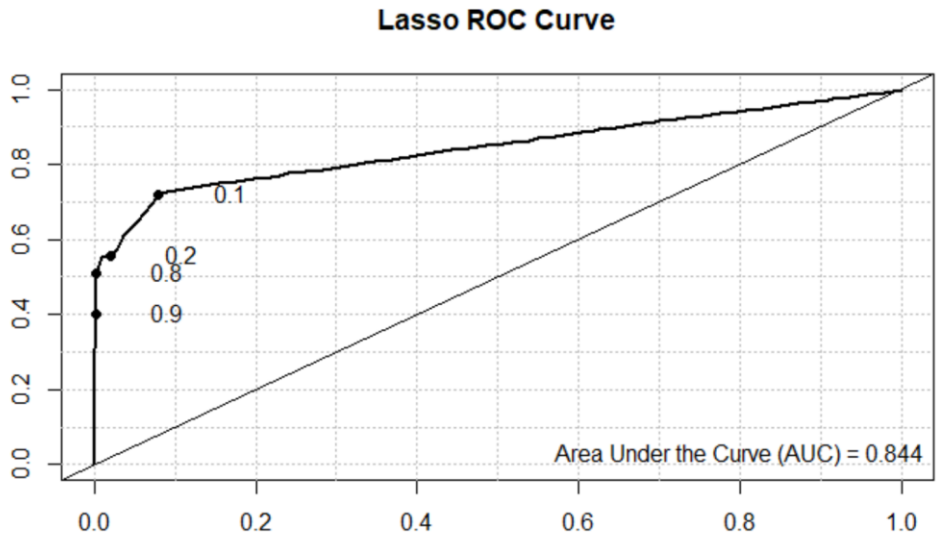
Model 1: Random Forest



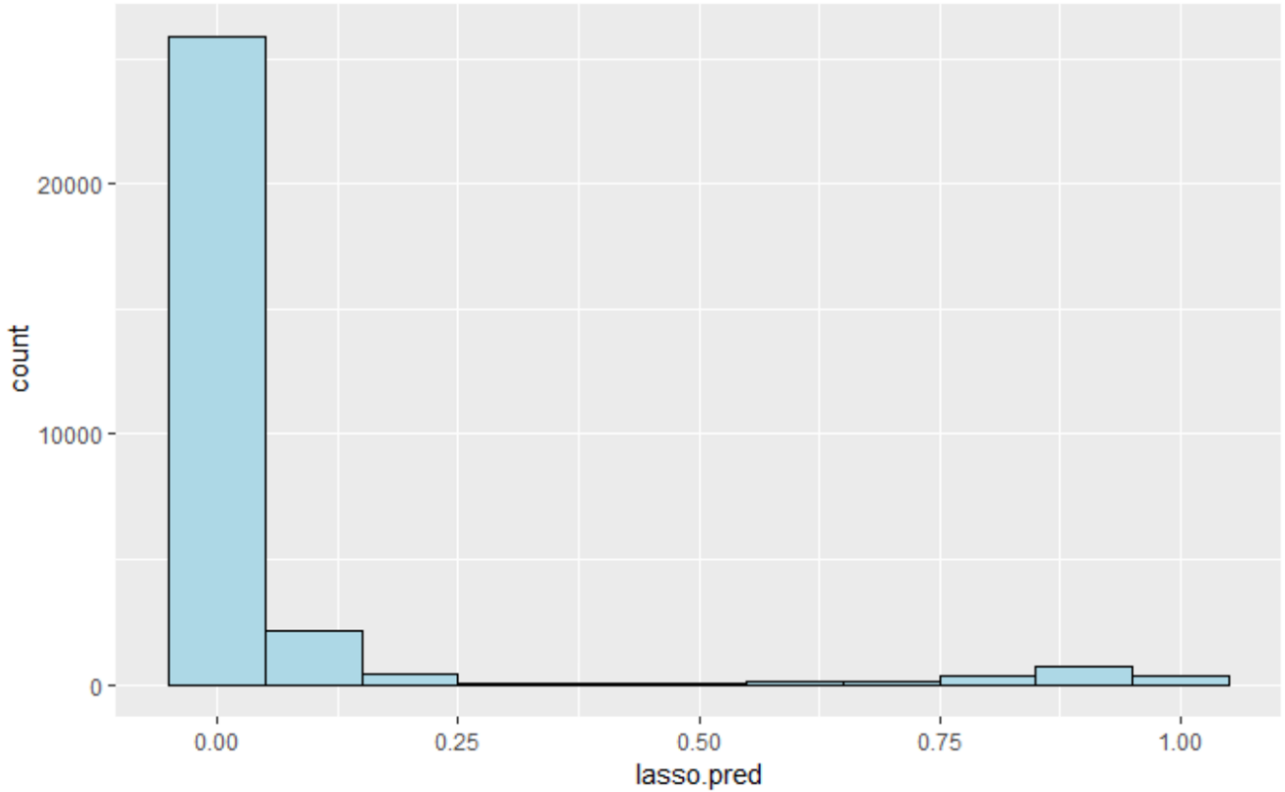
Model 2: Logistic Regression (Lasso)

Type I error	0.46%
Type II error	45.48%
Accuracy	95.30%
AUC	0.844

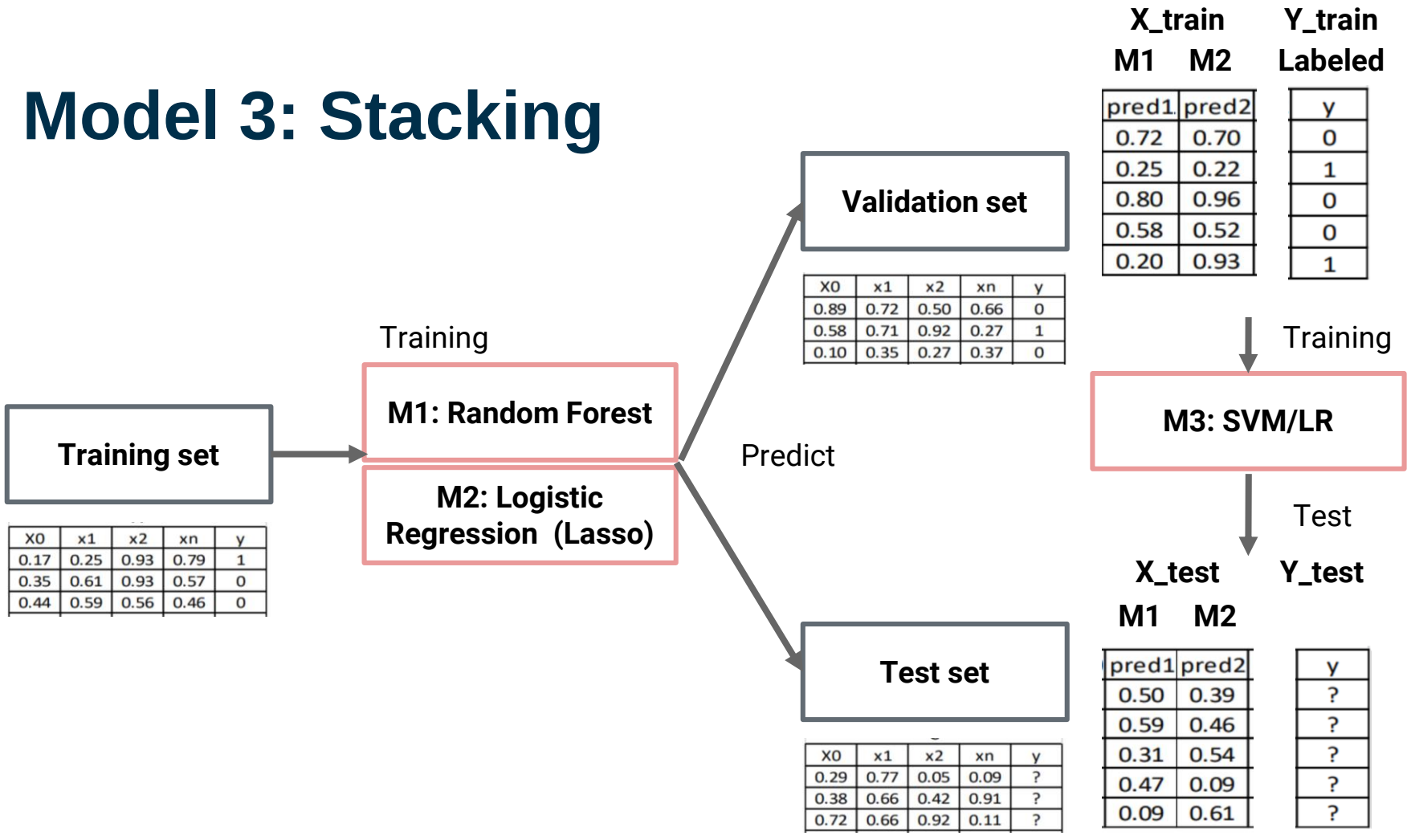
		Prediction	
		Not fraud	Fraud
Actual	Not fraud	27253	127
	Fraud	1293	1550



Model 2: Logistic Regression + New Loss



Model 3: Stacking

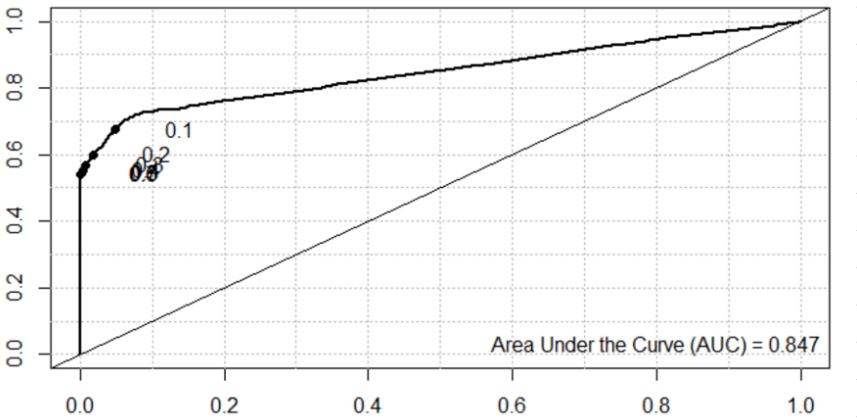


Model 3: Stacking

M3: logistic regression

Type I error	0.18%
Type II error	45.55%
Accuracy	95.55%
AUC	0.847

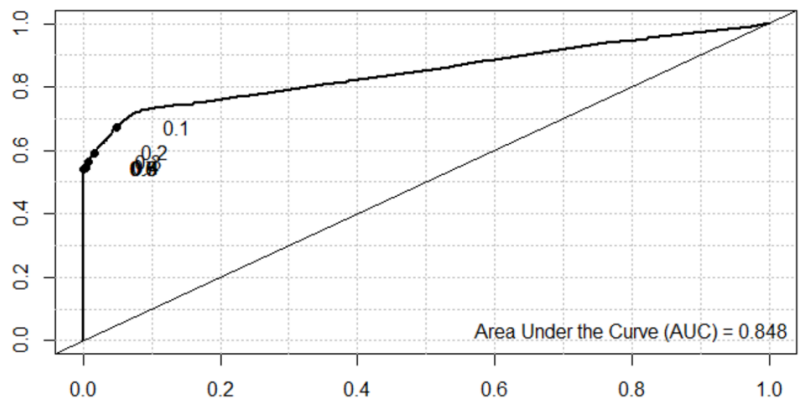
Actual	Prediction: Not fraud	Prediction: Fraud
Not fraud	27330	50
Fraud	1295	1548



M3: SVM

Type I error	0.00%
Type II error	45.97%
Accuracy	95.68%
AUC	0.848

Actual	Prediction: Not fraud	Prediction: Fraud
Not fraud	27380	0
Fraud	1307	1536



Summary of Models

Random Forest is the best model.

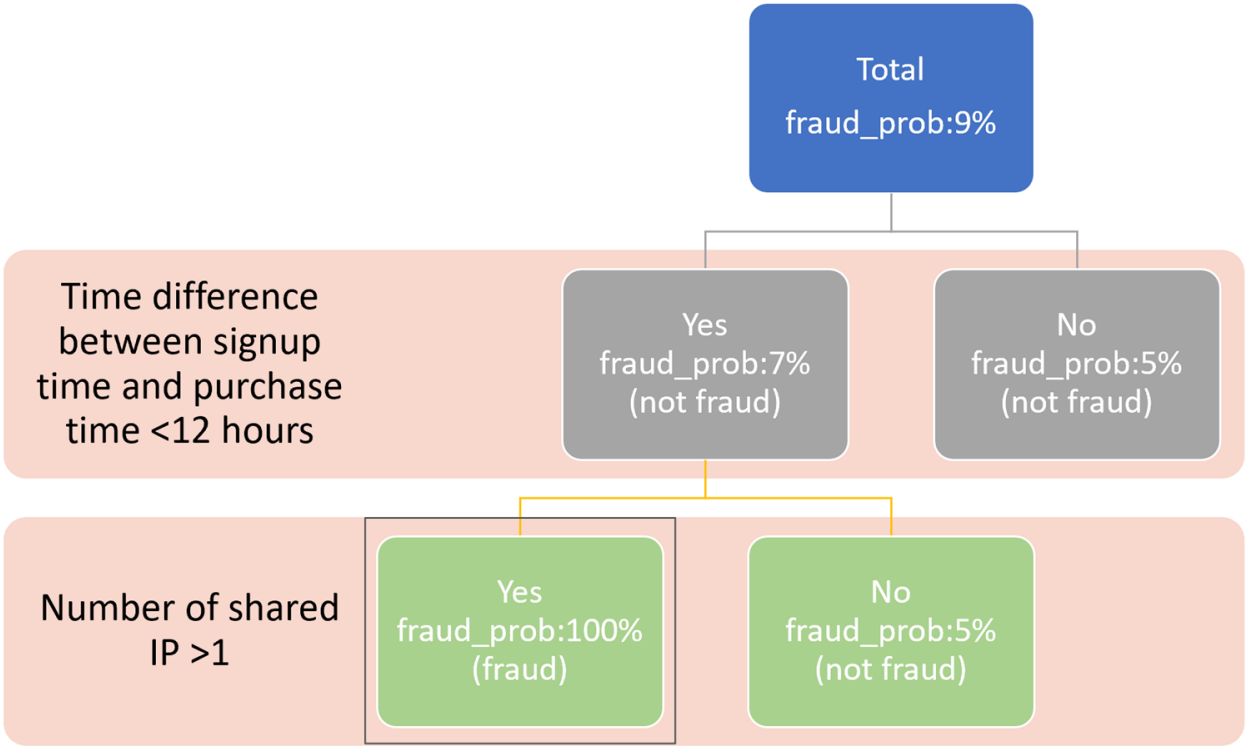
(overall performance is great, more simple than stacking)

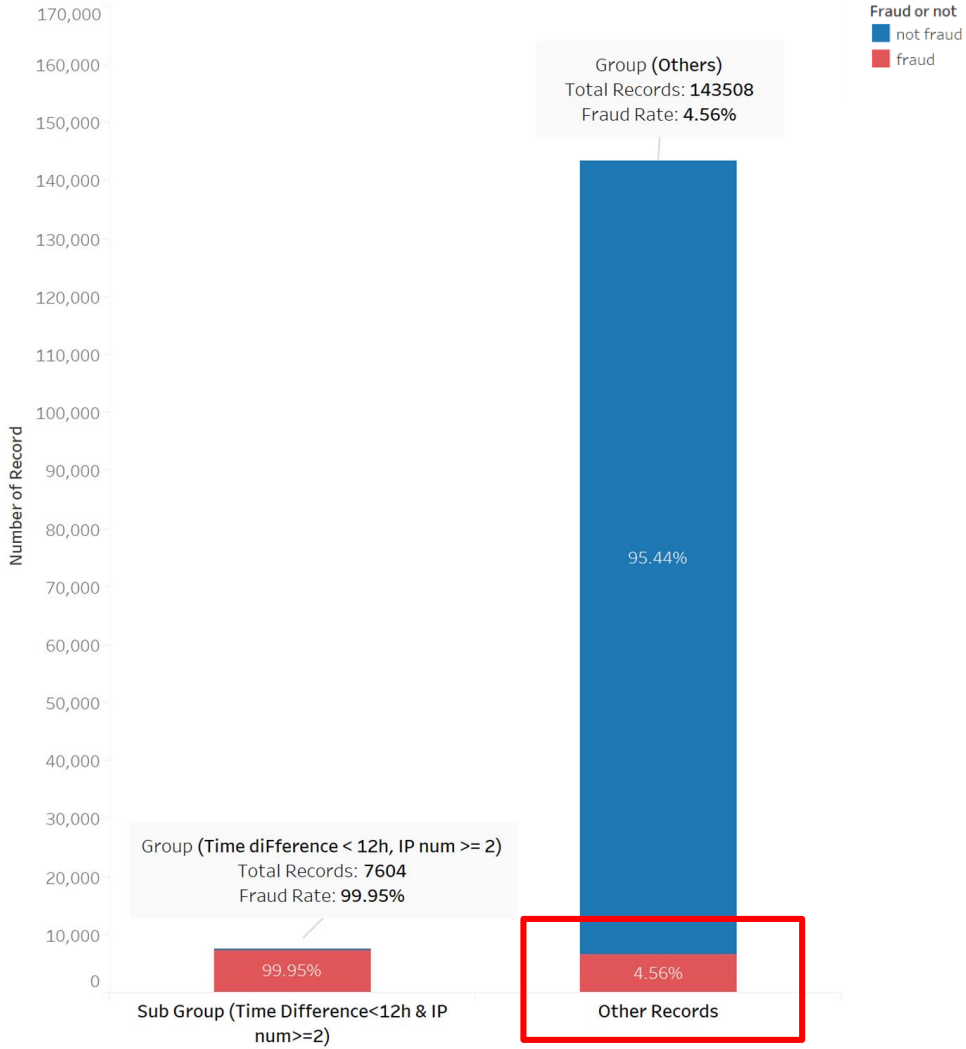
	Classification Tree	Logistic Regression	Random Forest	Stacking-SVM	Stacking-Logistic Regression
Type I error	0.00%	0.46%	0.00%	0.00%	0.18%
Type II error	45.94%	45.48%	45.97%	45.97%	45.55%
Accuracy	95.68%	95.30%	95.68%	95.68%	95.55%
AUC	0.7704	0.844	0.848	0.848	0.847

Part 5

Business Interpretation & Application

Patterns of Fraudulent Transactions





Transactions that were difficult to identify:

6551/151112

4.3% of total records → acc 95.66%

6551/14151

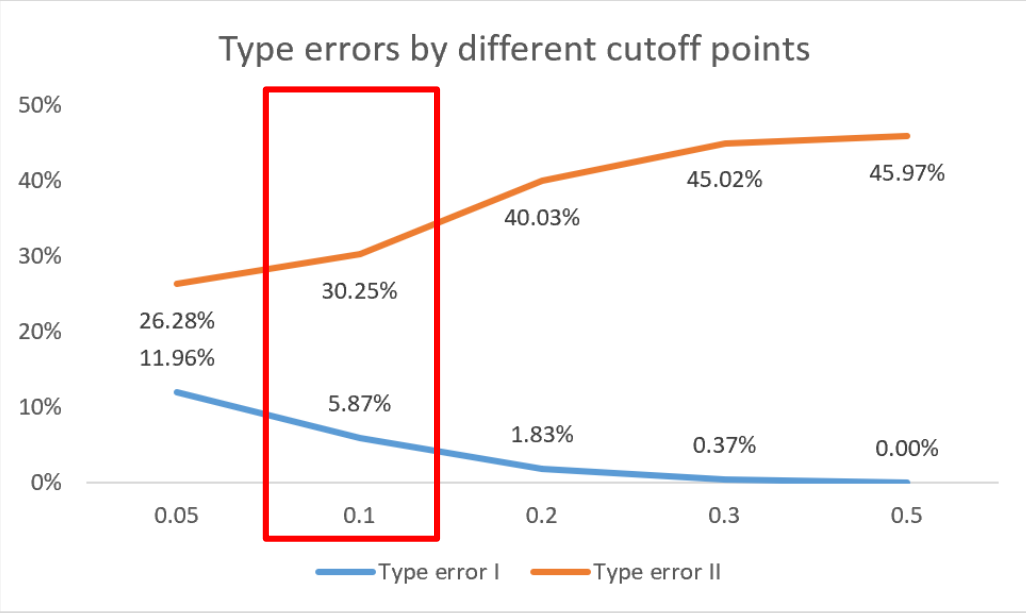
46.3% of fraud records → type error II

Lower Cutoff

To Get a Lower Type II Error

Based on Random Forest:

Cutoff Points	0.05	0.1	0.2	0.3	0.5
Accuracy	86.69%	91.83%	94.58%	95.43%	95.68%
Type error I	11.96%	5.87%	1.83%	0.37%	0.00%
Type error II	26.28%	30.25%	40.03%	45.02%	45.97%



Action Plan

Based on the fraud probability from our model, set **ALERT 1** (0.1) and **ALERT 2** (0.5)

Cutoff Points	0.1	0.5
Accuracy	91.83%	95.68%
Type error I	5.87%	0.00%
Type error II	30.25%	45.97%

If p < ALERT 1:
Normal, no alert

If ALERT 1 < p < ALERT 2:
The purchase is suspicious, we will ask the customer for additional authorization. For example, send email or SMS to the customer, let him/her authorize the purchase.

If p > ALERT 2 :
Then the purchase is highly suspicious. Not only ask the customer for additional authorization via email or SMS, but also put the purchase on hold and send the purchase information to relevant departments for further investigation.

Part 6

Summary

Summary and Recommendations

- In this scenario, **type II error** is more important.
- **Random forest** is our best model
- We lowered the **cutoff points** and deigned two alert levels based on 0.1 and 0.5 cutoff points.
- There is always a fraction of fraud that we can not distinguish (46%). Therefore, **more data** should be collected.

- For those who have had more than one IP address and purchased the products before signing up for 12 hours:

99.95% are **fraudulent**.

- Important variables:
  - **Time difference between purchase time and sign-up time**
  - **Number of shared devices**
  - **Number of shared IPs**
  - **Purchase value**
  - **Purchase time (month/quarter)**