# *SmartCampus*: Digital Financial Innovation Proposal for Hong Kong Universities


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**HKU FITE7410 Financial fraud analytics**

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## Overview

This study explores the application of machine learning techniques for detecting financial fraud transactions using a comprehensive dataset of 100,000 transactions. The analysis employs various data analytics methods, including Random Forest and Logistic Regression models, to develop an effective fraud detection system.

## 1. Background and Objectives of the Case Study

Financial fraud poses a persistent and evolving threat to the global banking system, resulting in significant monetary losses and eroding trust in financial institutions. As digital transactions continue to grow exponentially, traditional manual fraud detection methods have proven increasingly inadequate in addressing sophisticated fraudulent activities. The emergence of machine learning technologies offers a promising solution for developing automated, real-time fraud detection systems capable of processing large volumes of transactions while maintaining high accuracy (West & Bhattacharya, 2016).

The study utilizes a real-world dataset comprising 100,000 financial transactions, each characterized by 101 distinct features. Initial analysis reveals a notable class imbalance in the dataset, with 88,682 legitimate transactions (88.68%) and 11,318 fraudulent transactions (11.32%). This imbalance reflects the typical distribution observed in real-world fraud scenarios, where fraudulent activities represent a minority of total transactions.

The primary aim of this research is to develop and evaluate machine learning models capable of accurately identifying fraudulent transactions while minimizing false positives. This objective encompasses addressing the inherent class imbalance through various sampling techniques, identifying crucial features that indicate fraudulent activity, and establishing a robust framework for fraud detection. The study employs a comprehensive methodology that includes data preprocessing, implementation of class balancing techniques such as under sampling, oversampling, and SMOTE, followed by the development and evaluation of machine learning models.

Furthermore, the research seeks to provide practical insights and recommendations for financial institutions to enhance their fraud detection capabilities. By combining advanced analytical techniques with domain knowledge, this study aims to contribute to the ongoing development of more effective fraud prevention systems in the financial sector.

## 2. Description of the Dataset and Fraud Data Analytics Method

### 2.1 Dataset Overview

This study utilizes a modified version of the IEEE-CIS Fraud Detection dataset (IEEE-CIS, 2019). The dataset comprises 100,000 financial transactions with 101 features, representing real-world e-commerce transaction patterns. The dataset exhibits a significant class imbalance, with 88,682 legitimate transactions and 11,318 fraudulent transactions, reflecting the typical distribution in real-world fraud scenarios.

The analytical approach consists of three major phases: dataset preparation, handling class imbalance, and model development.

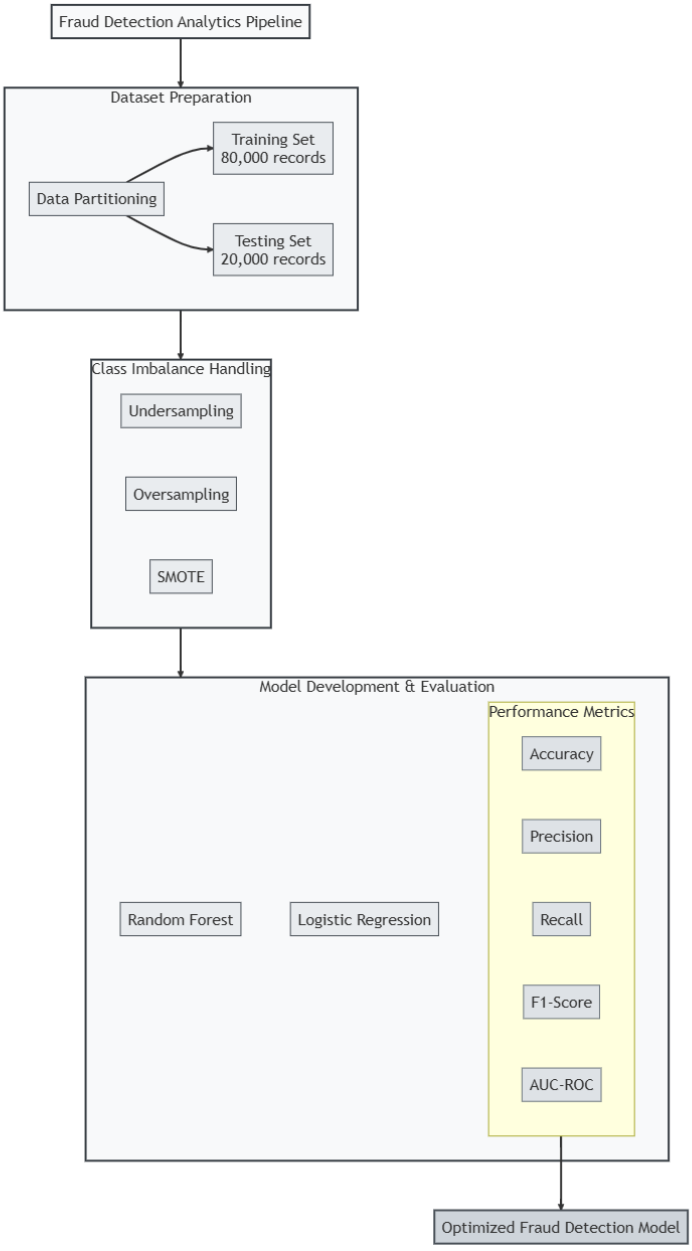



*Fig.1 Data Analytics Pipeline*

### 2.2 Dataset Preparation

The initial dataset was partitioned using an 80:20 split ratio, creating a training set of 80,000 transactions and a test set of 20,000 transactions. This split was implemented using random sampling with a fixed seed (123) to ensure reproducibility. The distribution of fraud cases was maintained proportionally across both sets, with the training set containing 70,896 legitimate and 9,104 fraudulent transactions, while the test set comprised 17,786 legitimate and 2,214 fraudulent transactions.

To mitigate the substantial class imbalance, three distinct techniques were implemented:

- *Under sampling*: The majority class (legitimate transactions) was reduced to match the minority class size, resulting in balanced but smaller dataset.
- *Oversampling*: The minority class (fraudulent transactions) was replicated to match the majority class size, maintaining all original data while achieving balance.
- *SMOTE (Synthetic Minority Over-sampling Technique)*: This advanced approach generated synthetic fraud cases based on the characteristics of existing fraudulent transactions. The process involved:
  - Converting categorical variables to numeric format
  - Handling missing values through median imputation
  - Creating synthetic samples using K=5 nearest neighbors
  - Generating a balanced dataset while preserving data integrity

### 2.3 Model Development

In this study, we employed two distinct machine learning algorithms, selected based on their complementary characteristics and demonstrated efficacy in financial fraud detection applications.

The primary methodology implemented was Random Forest, an ensemble learning algorithm that synthesizes multiple decision trees to construct a robust classification framework (Breiman, 2001). The selection of this methodology was predicated on several theoretical and empirical considerations. Random Forest demonstrates superior capability in capturing non-linear relationships inherent in transaction data, a critical factor given the intricate patterns characteristic of fraudulent activities. The algorithm's intrinsic feature importance quantification mechanism facilitates the identification of salient transaction attributes indicative of fraudulent behavior. Furthermore, Random Forest exhibits efficient handling of high-dimensional feature spaces, particularly pertinent to our dataset's multifaceted nature. The ensemble architecture inherently mitigates overfitting through bootstrap aggregation, thereby enhancing generalization performance on novel transaction instances.

As a comparative baseline, we implemented Logistic Regression, a well-established statistical learning method. Despite its relative algorithmic simplicity, Logistic Regression serves as a fundamental benchmark and offers distinct methodological advantages. The model's primary strength lies in its mathematical interpretability, a crucial consideration in financial domains where algorithmic decisions necessitate transparent explanation to regulatory entities. The probabilistic outputs generated by Logistic Regression enable flexible threshold adjustment for fraud classification. Notably, while structurally straightforward, the model demonstrates substantial computational efficiency in processing large-scale financial datasets and maintains widespread adoption in empirical studies due to its consistent performance characteristics.

This dual-methodological approach enables the exploitation of complementary algorithmic strengths: the sophisticated pattern recognition capabilities inherent in Random Forest, coupled with the interpretability and computational efficiency of Logistic Regression. The methodology synthesis establishes a robust analytical framework while maintaining the requisite transparency for financial applications. Both models were trained on the SMOTE-balanced dataset and evaluated using a comprehensive set of metrics including accuracy, precision, recall, F1-score, and AUC-ROC curves.

## 3. Results and Model Performance Analysis

The empirical results demonstrate the effectiveness of our dual-model approach in fraud detection, with both models showing distinct performance characteristics after training on the SMOTE-balanced dataset.

### 3.1 Class Imbalance Resolution

Our initial data analysis revealed a significant class imbalance in the dataset, necessitating the implementation of balanced learning techniques. We evaluated three distinct approaches to address this imbalance:

```
## Method 1: Undersampling
undersampled_majority <- majority_class[sample(nrow(majority_class), nrow(minority_class)), ]
undersampled_data <- rbind(undersampled_majority, minority_class)


## Method 2: Oversampling
oversampled_minority <- minority_class[sample(nrow(minority_class), nrow(majority_class), replace = TRUE), ]
oversampled_data <- rbind(majority_class, oversampled_minority)
```

After careful evaluation, we selected the SMOTE (Synthetic Minority Over-sampling Technique) algorithm as our primary approach. This decision was driven by several critical considerations. Unlike traditional undersampling, which potentially discards valuable majority class information, or simple oversampling, which may lead to overfitting due to exact

replication of minority instances, SMOTE generates synthetic examples in the feature space through interpolation (Chawla et al., 2002). This synthetic sample generation preserves the statistical properties of the minority class while introducing beneficial variations. Furthermore, SMOTE's approach of creating synthetic samples along the line segments joining nearest minority class neighbors helps prevent the overfitting problems associated with simple oversampling, while maintaining the full information content of the majority class.

```
# 1. Data Preparation for SMOTE
X <- as.data.frame(train_data[, -which(names(train_data) == "isFraud")])  # Features
Y <- train_data$isFraud  # Target variable

# 2. SMOTE Application with Key Parameters
smote_result <- SMOTE(X, Y, K = 5, dup_size = 7)
smote_data <- smote_result$data
```

The SMOTE-based balanced dataset demonstrated effective resolution of the initial class imbalance problem. The original dataset exhibited a significant imbalance ratio, which was successfully addressed through SMOTE, resulting in balanced class distributions (70,896 non-fraudulent vs. 72,832 fraudulent cases). This balanced distribution contributed to the models' improved learning capabilities and reduced bias towards the majority class.

### 3.2 Model Training Evaluation

```
evaluate_model <- function(predictions, actual, probabilities = NULL) {
  conf_matrix <- confusionMatrix(predictions, actual)

  metrics <- c(
    Accuracy = conf_matrix$overall["Accuracy"],
    Precision = conf_matrix$byClass["Precision"],
    Recall = conf_matrix$byClass["Recall"],
    F1 = conf_matrix$byClass["F1"],
    AUC = if(!is.null(probabilities)) auc(roc(actual, probabilities)) else NA
  )

  return(metrics)
}
```

The model training phase was executed with meticulous attention to methodological rigor and comprehensive evaluation metrics. We implemented a sophisticated evaluation framework to ensure robust model assessment.

### 3.3 Random Forest Implementation and Feature Importance Analysis

The Random Forest model was implemented utilizing optimized hyperparameters (ntree = 500, mtry = sqrt(number of features)) based on established methodological principles (Breiman, 2001). The model demonstrated exceptional predictive performance, achieving an accuracy of 0.982 and an AUC score of 0.996 on the test dataset. The high precision (0.972) and recall (0.991) values indicate robust performance in both fraud detection and false positive minimization.

```
# Random Forest Implementation
rf_model <- randomForest(isFraud ~ .,
                         data = train_balanced,
                         ntree = 500,
                         mtry = sqrt(ncol(train_balanced)),
                         importance = TRUE)

# Model Evaluation
rf_pred <- predict(rf_model, test_balanced)
rf_evaluation <- evaluate_model(rf_pred, test_balanced$isFraud, rf_prob)
```

Feature importance analysis revealed that TransactionAmt (MeanDecreaseAccuracy = 71.91) and behavioral indicator C1 (MeanDecreaseGini = 6979.39) were the most influential predictors, suggesting the significance of both transaction characteristics and derived features in fraud detection.

### 3.4 Logistic Regression Analysis

The logistic regression model was implemented as a baseline comparison, employing a binomial distribution with a logit link function. The model achieved moderate performance metrics with an accuracy of 0.812 and an AUC of 0.884.

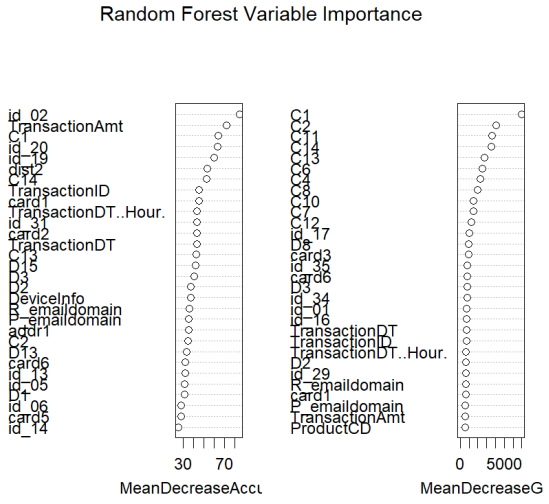
```
# Logistic Regression Implementation
lr_model <- glm(isFraud ~ .,
                data = train_balanced,
                family = "binomial")

# Model Evaluation
lr_prob <- predict(lr_model, test_balanced, type = "response")
lr_pred <- as.factor(ifelse(lr_prob > 0.5, "1", "0"))
lr_evaluation <- evaluate_model(lr_pred, test_balanced$isFraud, lr_prob)
```

### 3.5 Model Comparison and Recommendations

| | Random Forest | Logistic Regression |
|---|---|---|
| Accuracy | 0.9815279 | 0.8116955 |
| Precision | 0.9721020 | 0.8157388 |
| Recall | 0.9912416 | 0.8018498 |
| F1 | 0.9815785 | 0.8087347 |
| AUC | 0.9959672 | 0.8840700 |

*Table.1 Model Comparation*



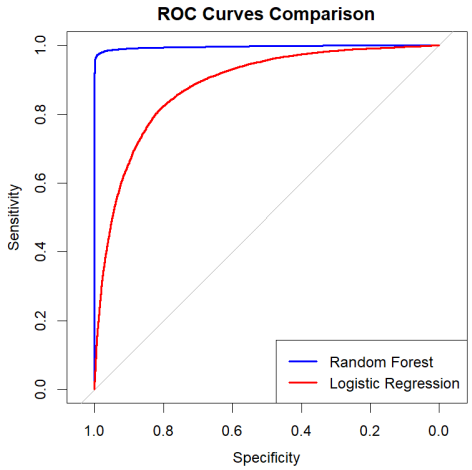




*Figure.2 Random Forest Variable Importance* *Figure.3 ROC Curves Comparison*

A comprehensive evaluation of the implemented models reveals distinct performance characteristics (Table 1). The Random Forest model demonstrated superior predictive capabilities across all evaluation metrics, achieving an accuracy of 0.982 and an exceptional AUC score of 0.996. This performance significantly outperformed the logistic regression baseline, which achieved an accuracy of 0.812 and an AUC of 0.884.

The Random Forest model's high precision (0.972) coupled with outstanding recall (0.991) suggests robust fraud detection capabilities while maintaining a low false positive rate. This balance is crucial in practical applications where false positives can lead to customer dissatisfaction and operational inefficiencies.

### 3.6 Model Limitations

- Potential overfitting despite SMOTE balancing

- Computational intensity of Random Forest in real-time applications

- Limited interpretability compared to logistic regression

## 4. Recommendation

The recommendations encompass both technical implementation and essential non-technical controls for comprehensive fraud prevention. For technical implementation, the Random Forest model should serve as the primary detection mechanism, with Logistic Regression maintained as validation backup. Real-time monitoring systems should focus on key predictive features, with threshold-based alerts for suspicious patterns. Regular model retraining and sophisticated feature engineering should be implemented, combining machine learning capabilities with traditional rule-based systems for comprehensive coverage.

From a risk management and governance perspective, we recommend implementing a three-lines-of-defense model incorporating operational controls, risk management oversight, and internal audit. This should be supported by clear escalation procedures, regular risk assessments, enhanced transaction monitoring thresholds, and strengthened KYC procedures. Internal controls should include segregation of duties in transaction processing, mandatory dual control for high-risk transactions, regular compliance reviews, and comprehensive documentation of override decisions. capital development is crucial, requiring comprehensive staff training on fraud indicators, regular updates on emerging patterns, and establishment of cross-functional fraud response teams. Clear communication channels and performance metrics should be established to ensure effectiveness. External collaboration through information sharing with other financial institutions, engagement with regulatory bodies, and partnerships with cybersecurity experts will further enhance fraud prevention capabilities. This integrated approach ensures robust fraud detection while maintaining operational efficiency and regulatory compliance.

## Summary

This comprehensive study developed an effective fraud detection framework combining advanced analytics with robust operational controls. The technical analysis of 100,000 financial transactions utilized machine learning techniques, addressing class imbalance through SMOTE sampling. The Random Forest model achieved 98.2% accuracy and 0.996 AUC score, outperforming Logistic Regression (81.2% accuracy, 0.884 AUC). Transaction amount and behavioral indicator C1 were identified as crucial predictive features. The study's success relies on integrating this technical solution with strong governance frameworks, internal controls, and human capital development. The recommended multi-layered approach combines automated detection with manual oversight, supported by clear policies, procedures, and regular training. This comprehensive strategy ensures effective fraud prevention while maintaining operational efficiency and regulatory compliance.

**Reference**

Breiman, L. (2001). Random forests. Machine learning, 45, 5-32.

Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: synthetic minority over-sampling technique. Journal of artificial intelligence research, 16, 321-357.

IEEE-CIS. (2019). IEEE-CIS Fraud Detection. Kaggle Competition Dataset. Retrieved from https://www.kaggle.com/c/ieee-fraud-detection/data

West, J., & Bhattacharya, M. (2016). Intelligent financial fraud detection: a comprehensive review. Computers & security, 57, 47-66.

# Appendix 1. Random Forest Feature Importance

| | 0 | 1 | MeanDecreaseAccuracy | MeanDecreaseGini |
|---|---|---|---|---|
| TransactionID | 34.884854 | 37.365342 | 45.581115 | 689.247589 |
| TransactionDT | 33.067035 | 43.889886 | 43.054855 | 692.765196 |
| TransactionDT..Hour. | 33.749792 | 40.817563 | 43.652833 | 666.865836 |
| TransactionAmt | 54.006843 | 60.793650 | 71.907005 | 568.875911 |
| ProductCD | 15.830910 | 17.403315 | 18.123600 | 556.483904 |
| addr1 | 17.906797 | 37.394764 | 35.234313 | 187.285161 |
| addr2 | 10.921628 | 24.948450 | 24.627491 | 43.438705 |
| dist2 | 27.680794 | 49.058108 | 53.047108 | 195.203748 |
| card1 | 28.250076 | 48.638807 | 45.199446 | 607.920483 |
| card2 | 28.280898 | 43.967164 | 43.305117 | 538.387150 |
| card3 | 13.646817 | 19.636159 | 17.176057 | 933.609279 |
| card4 | 14.117710 | 35.723888 | 21.174707 | 220.123817 |
| card5 | 18.058549 | 34.254728 | 27.882665 | 370.403336 |
| card6 | 25.333395 | 38.150431 | 32.305444 | 822.363190 |
| P_emaildomain | 26.689395 | 38.295263 | 35.489293 | 573.775230 |
| R_emaildomain | 26.274879 | 35.734926 | 36.147881 | 623.978650 |
| C1 | 38.508529 | 64.533538 | 64.267956 | 6979.389052 |
| C2 | 26.726094 | 31.520485 | 34.410567 | 4066.925969 |
| C3 | 11.775886 | 7.824405 | 8.991947 | 7.495277 |
| C4 | 16.129383 | 20.244606 | 20.323048 | 2267.169829 |
| C5 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| C6 | 16.815297 | 19.684959 | 20.505470 | 2500.962295 |
| C7 | 17.607203 | 16.654880 | 20.235220 | 1512.517247 |
| C8 | 18.629355 | 19.865996 | 21.151964 | 1981.384911 |
| C9 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| C10 | 14.824824 | 15.332445 | 16.279084 | 1526.837910 |
| C11 | 20.168601 | 23.723988 | 24.627794 | 3624.378215 |
| C12 | 16.257799 | 15.772639 | 18.684653 | 1257.282804 |
| C13 | 37.963361 | 36.902379 | 42.651451 | 2748.959029 |
| C14 | 47.151323 | 37.429288 | 52.808078 | 3538.353541 |
| D1 | 20.439557 | 33.419885 | 31.214183 | 501.590302 |
| D2 | 23.938838 | 37.517491 | 37.605262 | 662.219647 |
| D3 | 32.172324 | 39.209240 | 40.575206 | 767.253753 |
| D4 | 10.811096 | 20.753878 | 15.552964 | 270.685984 |
| D5 | 12.699694 | 18.649730 | 19.699992 | 93.661961 |
| D6 | 10.610027 | 24.426549 | 15.245731 | 369.292877 |
| D7 | 12.933513 | 22.447496 | 20.704800 | 123.252303 |
| D8 | 18.749501 | 34.414845 | 21.816479 | 946.413243 |
| D9 | 12.030678 | 48.194209 | 16.733453 | 236.868566 |
| D10 | 8.785498 | 15.400613 | 13.996333 | 83.991289 |
| D12 | 6.055969 | 18.938245 | 8.064197 | 273.710395 |
| D13 | 17.759032 | 35.064410 | 33.234883 | 212.766047 |
| D14 | 13.767576 | 25.584742 | 21.915753 | 185.540583 |
| D15 | 31.656731 | 35.831517 | 41.737517 | 192.901449 |
| M4 | 12.621115 | 12.460323 | 13.409861 | 544.932040 |
| V310 | 14.102345 | 19.278045 | 18.349778 | 183.412594 |
| V311 | 11.840169 | 18.229415 | 16.038058 | 33.360251 |
| V312 | 11.820550 | 18.875316 | 14.282190 | 111.911933 |
| V313 | 11.377004 | 25.381247 | 13.832707 | 102.227249 |
| V314 | 13.259849 | 22.388445 | 17.534847 | 117.107980 |
| id_01 | 13.734320 | 35.472859 | 22.548066 | 716.081223 |
| id_02 | 65.088200 | 61.810435 | 84.723952 | 437.536904 |
| id_03 | 14.018014 | 27.953429 | 18.279077 | 81.087447 |
| id_04 | 13.919909 | 12.563040 | 17.479974 | 9.864744 |
| id_05 | 20.874894 | 37.907323 | 31.642748 | 283.697556 |
| id_06 | 21.912547 | 28.718750 | 28.088603 | 300.125153 |
| id_07 | 8.100192 | 13.466701 | 14.714356 | 25.138057 |
| id_08 | 8.202623 | 19.983522 | 16.366644 | 25.149979 |
| id_09 | 15.611569 | 22.034961 | 19.136161 | 113.209088 |
| id_10 | 9.196563 | 15.813186 | 15.911778 | 12.732216 |
| id_11 | 12.741998 | 23.342279 | 17.944203 | 59.732050 |
| id_12 | 19.161955 | 16.638106 | 21.203441 | 473.849074 |
| id_13 | 18.661457 | 39.544796 | 31.813942 | 217.405481 |
| id_14 | 10.933596 | 28.946357 | 25.335122 | 127.031499 |
| id_15 | 15.540459 | 22.504318 | 18.419502 | 423.858216 |
| id_16 | 12.546688 | 16.786462 | 14.481404 | 699.733908 |
| id_17 | 16.291963 | 14.762220 | 16.937885 | 1000.393899 |
| id_18 | 15.312227 | 21.928616 | 24.915054 | 99.999778 |
| id_19 | 27.270857 | 60.134240 | 60.329794 | 316.865589 |
| id_20 | 29.903313 | 67.192357 | 63.627515 | 350.620129 |
| id_21 | 7.135591 | 11.775428 | 13.632003 | 18.852418 |
| id_22 | 6.765472 | 10.023101 | 11.685438 | 5.168167 |
| id_23 | 12.232072 | 10.607533 | 14.588712 | 22.807675 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| id_24 | 6.756599 | 9.543708 | 11.034142 | 6.649893 | id_33 | 15.059409 | 21.393496 | 17.815346 | 414.020459 |
| id_25 | 6.776582 | 17.658186 | 16.182085 | 18.575117 | id_34 | 17.387083 | 12.845364 | 20.140397 | 760.678377 |
| id_26 | 10.895643 | 16.543014 | 17.240517 | 20.892893 | id_35 | 14.794683 | 10.185767 | 15.460830 | 826.071587 |
| id_27 | 9.106379 | 9.151726 | 12.814077 | 19.654212 | id_36 | 9.732228 | 19.344671 | 21.206939 | 32.068579 |
| id_28 | 19.809217 | 17.017693 | 22.052136 | 519.302796 | id_37 | 13.691049 | 16.223785 | 19.366427 | 106.118380 |
| id_29 | 16.040338 | 15.710109 | 17.996203 | 635.992003 | id_38 | 12.025296 | 23.428746 | 19.518577 | 105.650870 |
| id_30 | 17.009420 | 13.845847 | 20.741816 | 538.918381 | DeviceType | 16.148520 | 31.116230 | 20.640251 | 356.661231 |
| id_31 | 21.457255 | 56.135072 | 43.423705 | 362.076781 | DeviceInfo | 26.465615 | 36.988317 | 37.415889 | 334.121449 |
| id_32 | 16.300141 | 18.628934 | 18.820638 | 209.065222 | | | | | |

# Appendix 2. Logistic Regression Coefficients

| | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| (Intercept) | -1.306447e+02 | 3.236720e+00 | -40.36329253 | 0.000000e+00 |
| TransactionID | 2.836794e-05 | 8.512847e-07 | 33.32367656 | 1.753318e-243 |
| TransactionDT | -1.082508e-05 | 8.118022e-06 | -1.33346221 | 1.823802e-01 |
| TransactionDT..Hour. | 3.550692e-02 | 2.922704e-02 | 1.21486515 | 2.244175e-01 |
| TransactionAmt | 5.576493e-03 | 1.142908e-04 | 48.79213665 | 0.000000e+00 |
| ProductCD | -3.912044e-01 | 2.151514e-02 | -18.18274316 | 7.070676e-74 |
| addr1 | -2.740023e-04 | 1.275815e-04 | -2.14766427 | 3.174044e-02 |
| addr2 | 3.191092e-02 | 2.685887e-03 | 11.88096311 | 1.486448e-32 |
| dist2 | 6.990064e-05 | 3.041916e-05 | 2.29791461 | 2.156665e-02 |
| card1 | -3.182195e-05 | 1.747294e-06 | -18.21213341 | 4.135148e-74 |
| card2 | -1.363677e-03 | 5.277795e-05 | -25.83800811 | 3.318613e-147 |
| card3 | 2.000482e-02 | 6.794886e-04 | 29.44098585 | 1.642163e-190 |
| card4 | 1.762985e-01 | 1.213856e-02 | 14.52383589 | 8.558387e-48 |
| card5 | -2.834586e-04 | 1.966990e-04 | -1.44107822 | 1.495626e-01 |
| card6 | -7.496723e-01 | 1.762126e-02 | -42.54362297 | 0.000000e+00 |
| P_emaildomain | -1.071387e-01 | 5.918579e-03 | -18.10210510 | 3.067181e-73 |
| R_emaildomain | 1.949259e-02 | 5.196267e-03 | 3.75126914 | 1.759417e-04 |
| C1 | -1.975651e-02 | 9.698473e-04 | -20.37074607 | 3.040112e-92 |
| C2 | -1.433965e-02 | 8.111359e-04 | -17.67847578 | 6.143470e-70 |
| C3 | -5.024076e+00 | 2.809783e-01 | -17.88065521 | 1.668645e-71 |
| C4 | 5.218057e-02 | 1.505627e-02 | 3.46570352 | 5.288461e-04 |
| C6 | -1.975210e-01 | 1.582605e-02 | -12.48074682 | 9.509054e-36 |
| C7 | 2.861594e-01 | 1.597861e-02 | 17.90890611 | 1.004911e-71 |
| C8 | 5.933458e-02 | 2.549988e-03 | 23.26856900 | 9.228774e-120 |
| C10 | 1.721245e-02 | 1.623649e-03 | 10.60109173 | 2.945218e-26 |
| C11 | 4.686890e-01 | 1.399275e-02 | 33.49512266 | 5.675912e-246 |
| C12 | -3.766570e-01 | 1.436178e-02 | -26.22635288 | 1.330496e-151 |
| C13 | -3.000674e-03 | 1.330115e-03 | -2.25595107 | 2.407370e-02 |
| C14 | -4.780982e-01 | 7.924804e-03 | -60.32933525 | 0.000000e+00 |
| D1 | -3.730999e-03 | 3.102907e-04 | -12.02420632 | 2.651234e-33 |
| D2 | -2.779085e-03 | 3.560089e-04 | -7.80622374 | 5.892693e-15 |
| D3 | 2.080040e-03 | 3.633383e-04 | 5.72480223 | 1.035543e-08 |
| D4 | -2.724397e-03 | 4.793304e-04 | -5.68375680 | 1.317676e-08 |
| D5 | -3.669376e-03 | 5.965485e-04 | -6.15101070 | 7.699072e-10 |
| D6 | -2.586539e-04 | 2.516720e-04 | -1.02774222 | 3.040711e-01 |
| D7 | -2.347655e-04 | 5.911210e-04 | -0.39715299 | 6.912546e-01 |
| D8 | -2.347321e-03 | 7.487127e-05 | -31.35143184 | 9.301491e-216 |
| D9 | -5.253919e-02 | 3.350255e-02 | -1.56821445 | 1.168311e-01 |
| D10 | -1.839330e-03 | 2.969900e-04 | -6.19323983 | 5.893994e-10 |
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| D14 | 3.495552e-04 | 8.885611e-05 | 3.93394695 | 8.356223e-05 |
| D15 | 4.445064e-04 | 1.431139e-04 | 3.10596308 | 1.896604e-03 |
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