REAL-TIME FRAUD DETECTION IN TELECOMMUNICATION NETWORK USING CALL PATTERN ANALYSIS

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Degree of Master of Science

Department of Computer Science and Engineering

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December 2017

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Dissertation submitted in partial fulfillment of the requirements for the degree

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DECLARATION

Candidate:

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Abstract

Telecommunication service providers are losing considerable percentage of their annual revenue due to fraudulent activities. Such activities also deteriorate customer experience. Therefore, real-time detection of such fraudulent activities is required to minimize the revenue loss and to preserve customer experience. Illegal termination of International calls (aka. SIMbox fraud) and extreme usage scenarios related to International revenue share fraud are two major fraudulent activities which make highest impact. While such activities can be detected by identifying behavioral and calling patterns of subscribers, they need to be detected in real time so that subscriber connections linked with an ongoing fraud activity can be terminated to minimize the impact of threat or revenue loss, Call Detail Records (CDRs) produced by telecommunication equipment contains attributes that are specific to a phone call or other communication transactions handled by the device could be used to detect behavioral and calling patterns of subscribers. However, traditional CDR analysis techniques do not facilitate time-sensitive monitoring and analytical requirements. Therefore, we propose a Complex Event Processing (CEP) based solution for the real-time identification of fraudulent and extreme usage subscriber patterns. We identified a rich set of features and set of call patterns, and then combined batch analytics with real-time analytics to increase the detection accuracy. We demonstrated the utility of the proposed solution using a real dataset from a service provider. The proposed solution achieved an accuracy of 99.9% with average latency of 16 call attempts per detection at input event rate of 230 events per second with modest hardware.

Keywords: Complex Event Processing, Data analytics, Call Detail Records, call patterns

ACKNOWLADGEMENT

My sincere gratitude goes to my family members for the continuous support and motivation given to make this thesis a success. I also express my heartfelt appreciation to Dr. Dilum Bandara, my supervisor, for the supervision, advice and valuable feedback given throughout to make this research a success. I also thank to Mr. Ruchira Yasaratne, Mr. Sampath Ilesinghe and Mr. Pradeep De Almeida of the Dialog Axiata PLC, for providing approvals to proceed this project by keeping trust on me. Last but not least I also thank my friends who supported me in this whole effort.

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LIST OF ABBREVIATIONS

ANN Artificial Neural Networks

ASCII American Standard Code for Information Interchange

BAM Business Activity Monitor

BI Business Intelligence

BSC Base Station Controller

CDR Call Detail Record

CEP Complex Event Processor
CLI Calling Line Identification

CTR Click-through Rate

CUP Current User Profile

DAHP Database-Active Human-Passive

DAS Data Analytics Server

DBMS Database Management System

DDOS Distributed Denial of Service

DOS Denial of Service

DSMS Data Stream Management System

EDGE Enhanced Data rates for GSM Evolution

FDT Fraud Detection Tool

GPRS General Packet Radio Service

GSM Global System for Mobile Communications

GT Global Title

HADP Human-Active Database-Passive

HSPA High Speed Packet Access

HTTP Hypertext Transfer Protocol

IDD International Direct Dialing

IMEI International Mobile Equipment Identity

IMSI International Mobile Subscriber Identity

ISC International Switching Center

ISDN Integrated Services Digital Network

ISUP ISDN User Part

LTE Long Term Evolution

LKR Sri Lankan Rupee

MCC Mobile Country Code
MLP Multi-Layer Perception
MNC Mobile Network Code

MO Mobile Originated

MSC Mobile Switching Center

MSISDN Mobile Station - ISDN

MT Mobile Terminated

NFA Non-Deterministic Finite Automata

NN Neural Networks

OCS Online Charging Node

PABX Private Automatic Branch Exchange

QoS Quality of Service

RFID Radio Frequency Identification

SIM Subscriber Identity Module

SIP Session Initiation Protocol

SMS Short Message Service

SOM Self-Organizing Map

SVM Support Vector Machine

TDM Time Division Multiplexing

TMSC Tandem Mobile Switching Center

UPH User Profile History

UTMS Universal Mobile Telecommunications System

VLR Visitor Location Register

VoIP Voice over Internet Protocol