Contact Center Management Using Data Analytics

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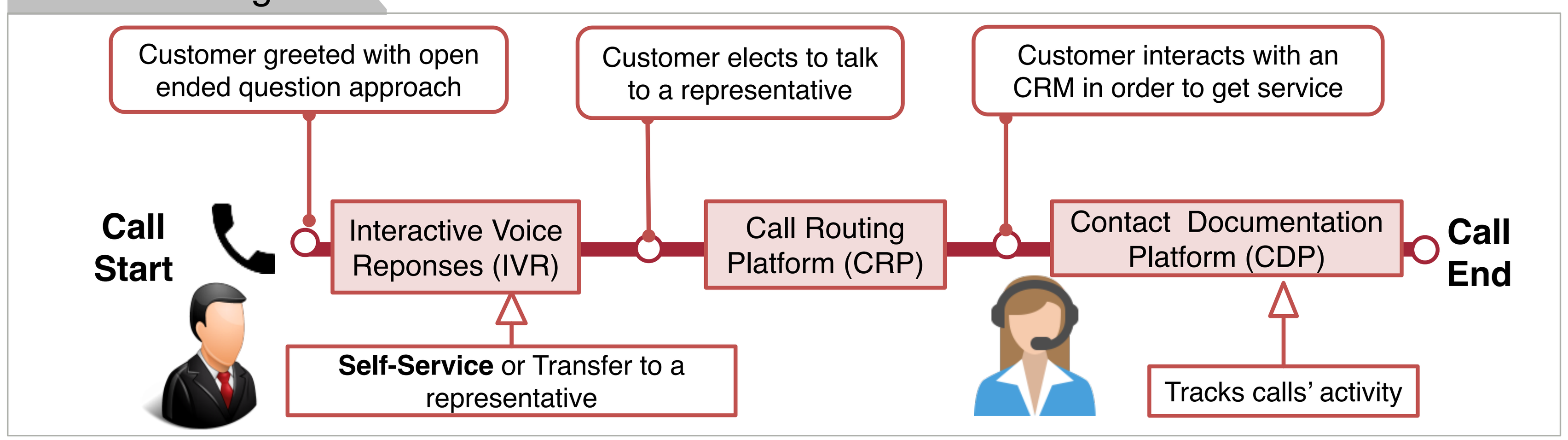
Introduction

- This research studies a Contact Center data set of a **major U.S. insurance company**
- The **key properties** of this study:
  - **Richness of Data** covering multiple phases of calls with detailed attributes, e.g., transactions originated from different medium of contacts such as web and the Interactive Voice Response (IVR) system, Caller intent (both Nominal and Actual), detailed call reasons subtypes
  - **Massive Data** sets with more than **62 million records**
  - **Predictive models** using customers' profile for **target variables**, beyond estimating the arrival rate, which has been the typical target variable studied in the call center analytics literature
- Research with these key properties in contact center and customer management data analytics is of need to deal with the curse of dimensionality, when analyzing **thousands of** different **interaction patterns** for policyholders and crafting aggregate features.

Research Goals:

- Determine the **outcome** of a call arriving at the IVR system
- **Predict** how likely a policyholder will call in different time horizons: next hour, days, or weeks

Call Flow Diagram:

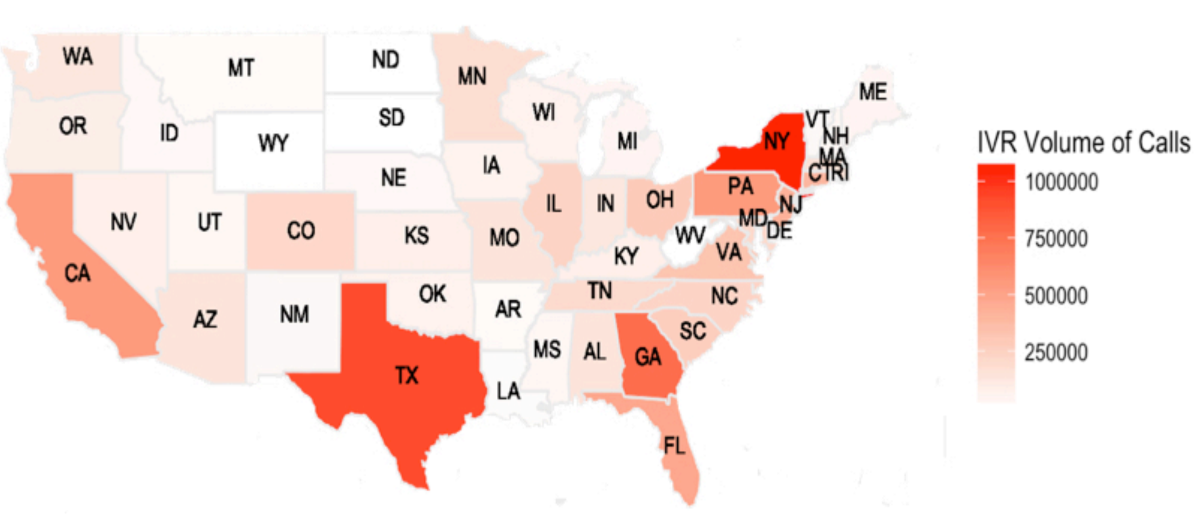


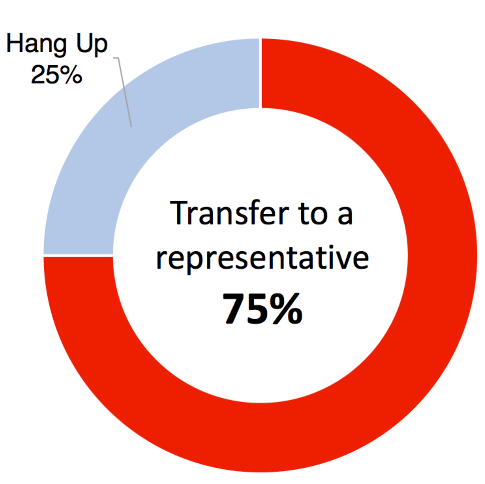
Data Description

From 1-Jan-2015 to 31-Dec-2015 for all states in the United States and Canada

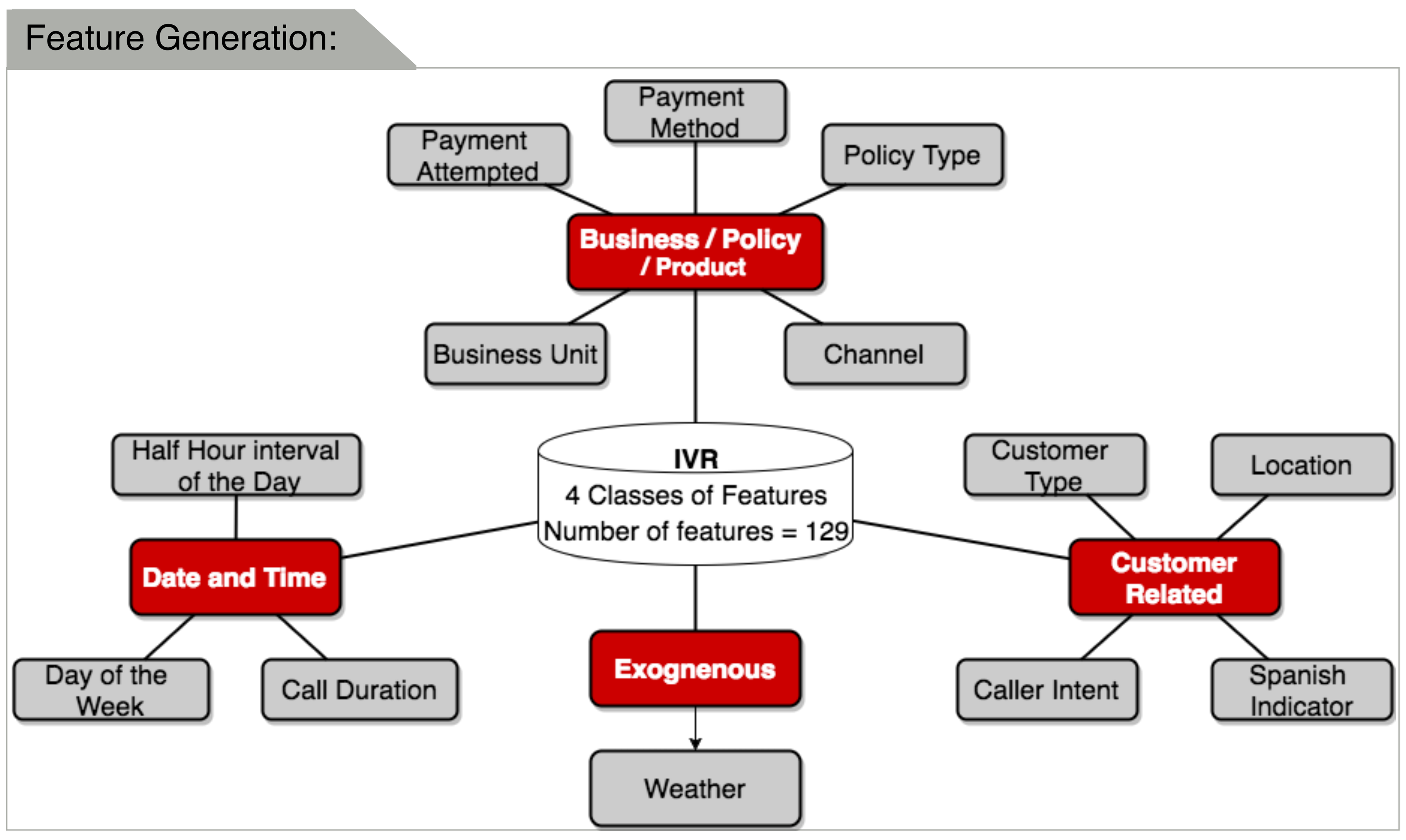
Insurance Company

Data Set	Communications	Attributes
IVR	9,951,063	67
CRP	12,053,570	173
CDP	40,500,486	19





Feature Generation:



Literature Review

Target Variable: Call Arrival Counts

Univariate Models

References	Data
Brown et al. (2005)	Call Center of Israel's Bank.
Avramidis et al. (2004)	Bell Canada Call Center
Weinberg et al. (2007)	North American commercial bank.
Shen and Huang (2008a)	Northeastern U.S. bank call center.
Shen and Huang (2008b)	Northeastern U.S. financial firm.
Taylor (2008)	Retail bank in the UK
Taylor (2012)	NHS in England and Wales, and UK credit card company
Ibrahim and L'Ecuyer (2013)	Canadian Telecom. company

Models used: variablities of Doubly Stochastic Poisson Processes, and autoregressive models such as ARIMA

Multivariate Models

References	Soyer and Tarimcilar (2008)	Aldor-Noiman et al. (2009)
Data	Consumer electronics producer	Israel Telecom company
Model(s)	Two-way multiplicative Bayesian model.	Mixed Poisson Process and GLMM
Features	Media dollars, print media type (weekly or monthly), offer type	6 for days of the week, 8 for billing cycle

Target Variable: Call Outcome

Multivariate Models

Outbound Call Center	Inbound Call Center
Moro et. al. (2014)	Our Study
Data: Portuguese retail bank	Data: U.S. Insurance Comp.
Models: • Logistic regression • Decision Trees • Neural Network • SVM	Models: • Mixed-effect logistic model
N. of features: 150 Commonly used bank client and product attributes, and generic social and economic indicators	N. of features: 129 Features related to the call record, business, policy, product, and to customer profile and behavior. Additionally considers the weather as exogenous variable.

Scalable Data Analytics Method

Mixed-effect logistic model

$$\mathrm{E}(y_i|b_i) = g^{-1}(\boldsymbol{x}_i^T\boldsymbol{\beta} + b_i)$$

Lasso Method

$$L(\boldsymbol{\beta},\sigma) = \prod_{i=1}^{I}\int_{-\infty}^{\infty}\left(\frac{e^{\boldsymbol{x}_i^T\boldsymbol{\beta}+b_i}}{1+e^{\boldsymbol{x}_i^T\boldsymbol{\beta}+b_i}}\right)^{y_i}\cdot\left(\frac{1}{1+e^{\boldsymbol{x}_i^T\boldsymbol{\beta}+b_i}}\right)^{1-y_i}\frac{e^{(-b_i^2/2\sigma^2)}}{\sqrt{2\pi\sigma^2}}db_i$$

$$(\boldsymbol{\beta}^*,\sigma^2) = \arg\min_{\boldsymbol{\beta},\sigma}\left\{-\log L(\boldsymbol{\beta},\sigma) + \lambda\sum_k |b_i|\right\}$$

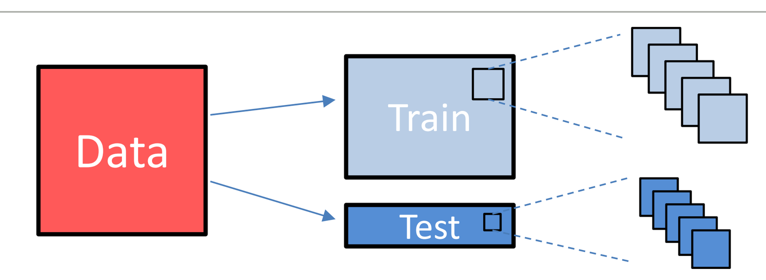
$$\lambda^* = \arg\min_{\boldsymbol{\beta},\sigma}\left\{-2\log L\big(\boldsymbol{\beta}(\lambda),\sigma(\lambda)\big) + |\mathcal{A}(\lambda)|\cdot\log N\right\}$$

Subsampling

Subsample size $M = N^{\gamma}, \quad 0.5 \le \gamma \le 1$

Nº of subsamples $S = \frac{N}{M}$

kth feature is included if $\frac{1}{S}\sum_{s=1}^{S} 1_{k\in\mathcal{A}(\lambda^*)} \le \rho, \quad 0.5 \le \rho \le 1$



Feature Ranking and Selection Results

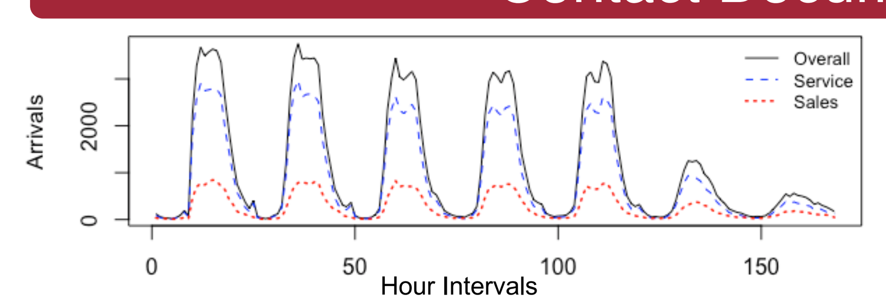
Top 10 Features Selected – All States
$\rho = 0.5$
Training Accuracy = 85.59%
Test Accuracy = 85.63%

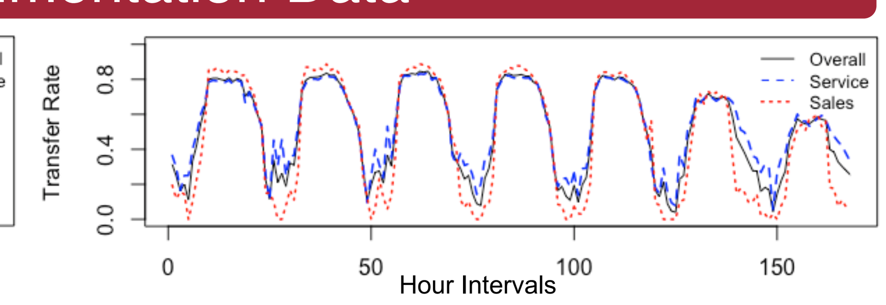
Rank	Features	States
1	Call Duration	50
2	Avg. Temp	49
3	Payment Attempted	48
4	Intent 'No intent'	48
5	Channel 'Service'	48
6	Channel 'Billing'	42
7	Intent 'Payment'	40
8	Cust. Type 'Potential Customer'	19
9	Channel 'Affinity Sales'	7
10	Cust. Type 'Third Party'	5

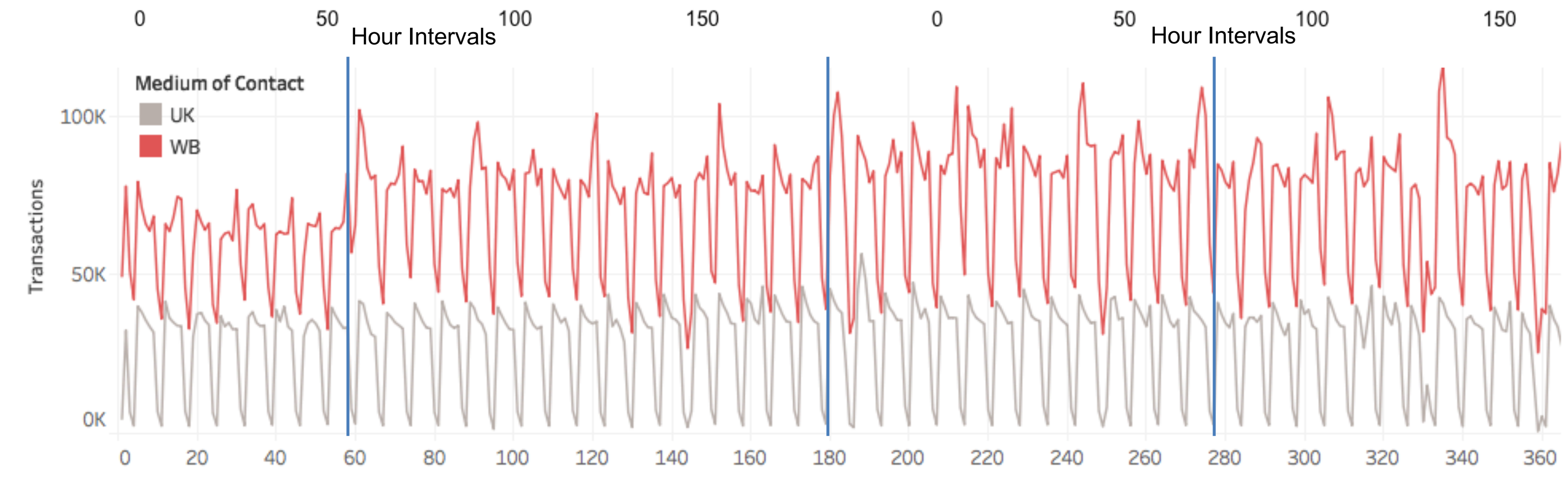
Model for the New York State (1.1M communications)
$\rho = 0.5$
Training Accuracy = 85.59% Test Accuracy = 85.63%

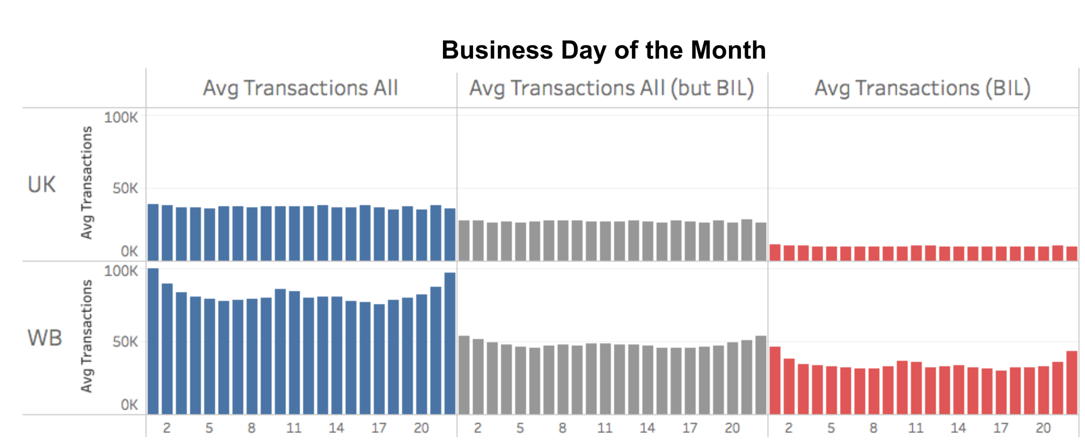
Rank	Features	Avg. Coef.	S.E.	p-value
1	intercept	3.2099	1.6661	0.0135
2	Call Duration	0.0005	0.0000	0.7829
3	Payment Attempted	-5.5251	7.1739	0.0402
4	Intent 'No Intent'	-2.7114	0.8690	0.0040
5	Average Temperature	0.0054	0.0000	0.3660
6	Channel 'Billing'	-1.4147	0.2279	0.0033
7	Intent 'Payment'	-0.5125	0.0471	0.0190
8	Cust. Type 'Potential Cust.'	-1.1461	0.5477	0.1227
9	Channel 'Service'	0.9646	0.5063	0.1764
10	Channel 'Affinity Sales'	1.7656	0.9153	0.0662
11	Cust. Type 'Customer'	0.2876	0.0722	0.2857

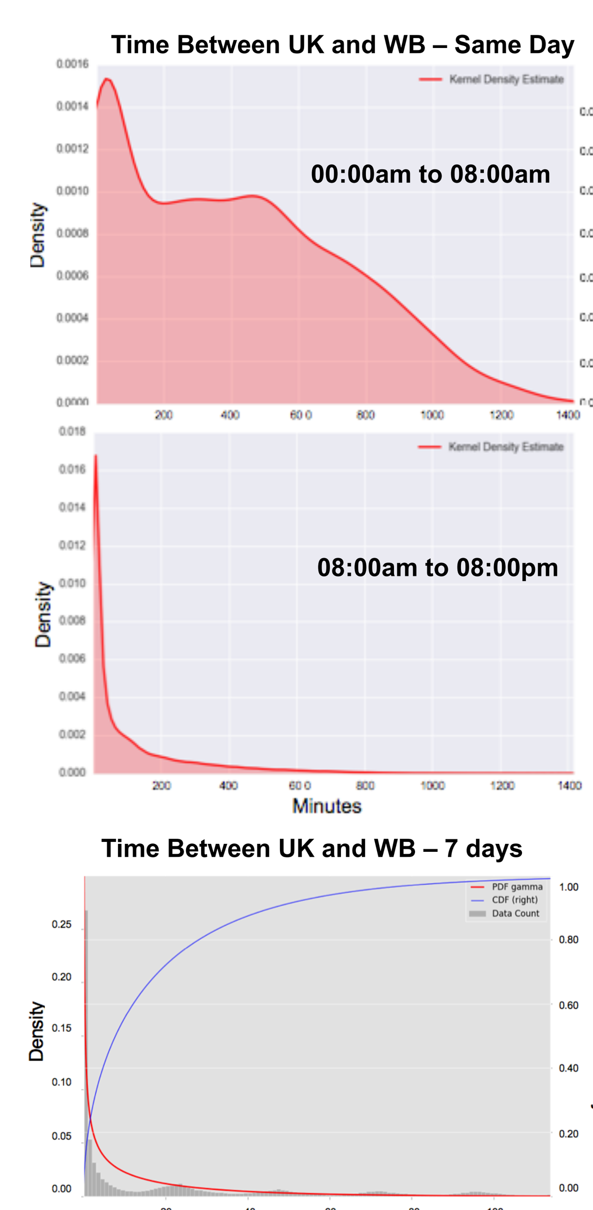
Contact Documentation Data

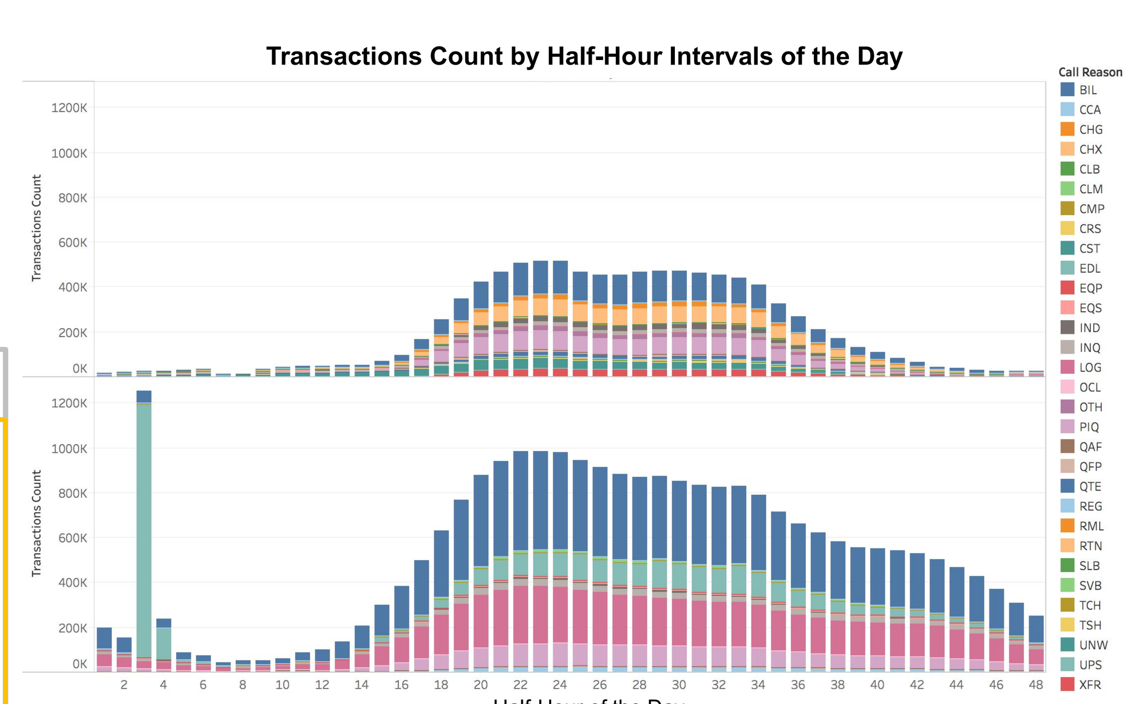












Applications

- The results can provide various managerial insights into policyholders' behavior seeking to make more effective use of customer data and segmentation.
- The selected features describing the customers and their motivations for calling and decisions such as being transferred during calls can lead to policy and operational recommendations. It guides managers to improve the waiting time of customers, to more accurately predict the number of CRMs necessary to handle calls at any time, and better understand the customers' usage of the websites, and consequently, design more effective marketing strategies according to the customers' characteristics and behavior.
- The developed algorithm is scalable and can be adopted for big data analytics in other decision making problems and business segments.