Telco Campaign Management Model

Summary

Running campaigns is hard especially if you are a telecom operator with lots of products and services. To build customized campaigns to engage your targeted subscribers, you need real-time data and real-time analytics - You need lightning-fast intelligence to reach the right customers with the right offers on the right channel.

Campaign Management allows you to identify your target customers, discover relevant offers for them and pinpoint the right communication channels to engage them. You can use Campaign Management to help your customers discover relevant products and services. You can drive highly personalized promotions for retention, up-selling and cross-selling to delight your users and win their loyalty.

There are various intensive operations involved in building ML models from data access from multiple sources, cleaning and preparing data relevant for ML models and finally building various experiments of models to enable decision support for retention campaigns.

The below model building demo is to illustrate HyperSense AI Studio capabilities of building the model using features such as

- No-code – drag and drop ready-made operators.
- Ease of data preparation with in-built mathematical functions.
- Quick Visualization to learn customer churn behaviour and analyze offer propensity model.
- Experimenting with various models in no time.
- Deploying churn prediction and offer propensity models for campaign management.

The case study described below has helped achieve the following ROI goals

01 The model building efforts is optimized by 13x compare traditional python coding approach as model are on distributed computing environment.

02 The model is productionized for batch prediction within minuteswhereas traditional engineering approach would have taken days.

03 The model deployed has helped reduced customer churn by 12%during the 1quarter of deployment in African region.

04 The customer retention achieved within first fiscal year is 33% due to timely offer to customers as per recommendations generated from machine learning.

05 The models in productions when managed using AI studio model hosting and performance configuration will help maintain models optimizing performance above 80% during a life-time.

The overall ML model building effort using above features has reduced to 30-45 mins.

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Telco Campaign Management Use Case Illustration

In this use case of campaign management, there is a set of customers with their Satisfaction scores, Tenure with the telco company, CLTV, Offers etc. which helps us in building the churn prediction model along with the offer propensity model.

Using the application of Machine learning (ML) on the customer data such as the type of Services they have subscribed to, Customer churn, Location data and Customer Demographic information, a prediction (classification) model is built to predict whether a particular customer will churn or not. Another classification model built is of Offer Propensity. The ML pipeline built is deployed and run-on regular basis to help the company to target and retain those customers that are likely to churn and provide them with relevant offers, in order to have huge financial implications.

In the below given implementation, we will see how to create a customer churn and offer propensity classification ML model, using 4 open sourcesample data setsfrom Kaggle website, in which each row represents a customer, and each column contains customer's attributes. These are pre-labeled data sets and in one of the data sets, the column 'Churn Label' indicates whether each customer left or not.

Data source: Kaggle dataset
Machine Learning: Two-Class Classifier
(click this link to see pipeline in A.I Studio)
Run Time: 4-5 mins
Efforts to build: Max. 45 mins

Video Demo: link

01. Inputs

The input data is sourced from 4 different data sets and combined based on primary key along with required transformations. One CSV contains the information about the services subscribed by the customers, second data setcontains the churn information, third data set has customer demographics information and the last one has customer location data, with the common key being the 'Customer ID'. The combined data consists of 7043 rows or unique customers. The data sets include information about:

- Customers who left, stayed or recently joined – the column called 'Customer Status'
- Services that each customer has signed up for – phone, multiple lines, internet, online security, online backup, device protection, tech support, and streaming TV and movies
- Customer account information – how long they've been a customer, contract, payment method, paperless billing, monthly charges, and total charges
- Demographic info about customers – gender, age range, and if they have partners and dependents

The data preparation is performed using join, missing value treatment, encoder, normalization and sampling operators. This has resulted in a clean and desired input data as summarized below.

1.1 CSV Reader
CSV Reader allows the user to load CSV files (Input) and converts the data into a readable format. We ingest the 4 CSV files into 4 separate readers.

1.2 Join
The Join operator allows the user to merge/combine two or more datasets into one single dataset, based on the key columns. The join can be of the type: inner, left, right or outer join.

1.3 Missing Value Treatment
Missing Value Treatment operator allows the user to replace the missing data with the substituted values. The data set can be either categorical or continuous. After missing value imputation, the data set can be analyzed to verify if the substituted values are matching the observed values.

1.3.1 Hypothesis Testing

Hypothesis Testingis a method of statistical inference which comes under Statistical Analysis on AIS. The test is performed on a statistical sample, with the idea of converging on the plausibility of either of the two, the null hypothesis or its counterpart the alternative hypothesis, which best supports the sample.

1.3.1 Correlation Testing

Correlation Testing is a bi-variate (analysis is done between two variables) statistical procedure used to identify and quantify the possible associations that might be present between the variables, and it is a part of Statistical Analysis on AIS. This operator allows the user to understand if there is positive, negative or zero correlation between 2 variables.
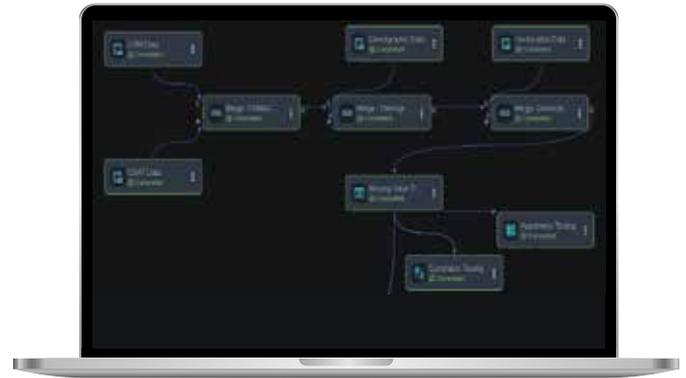
Data Summarization
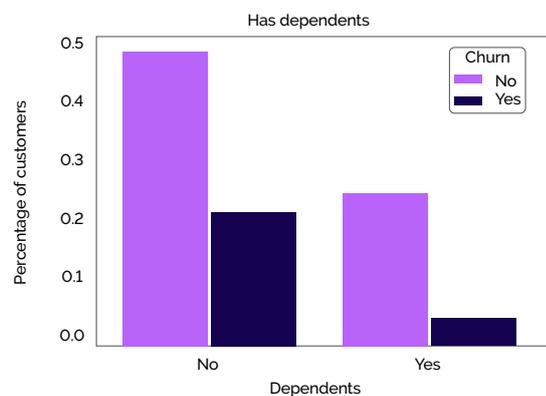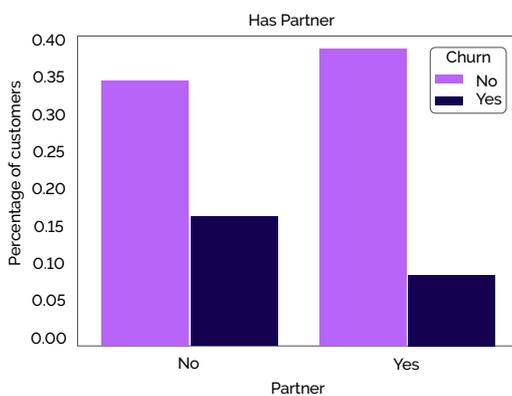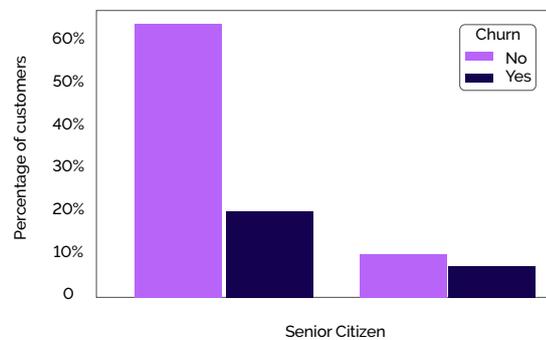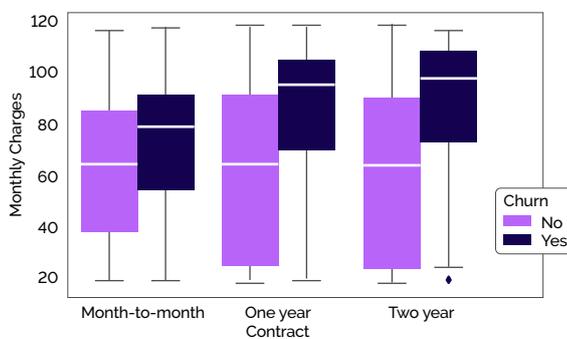
The data in some variables like Total Revenue, Monthly Charge, Total Charges etc. have varying range and requires normalization for algorithm to learn patterns sufficiently. This operation is achieved using a Normalization operator.
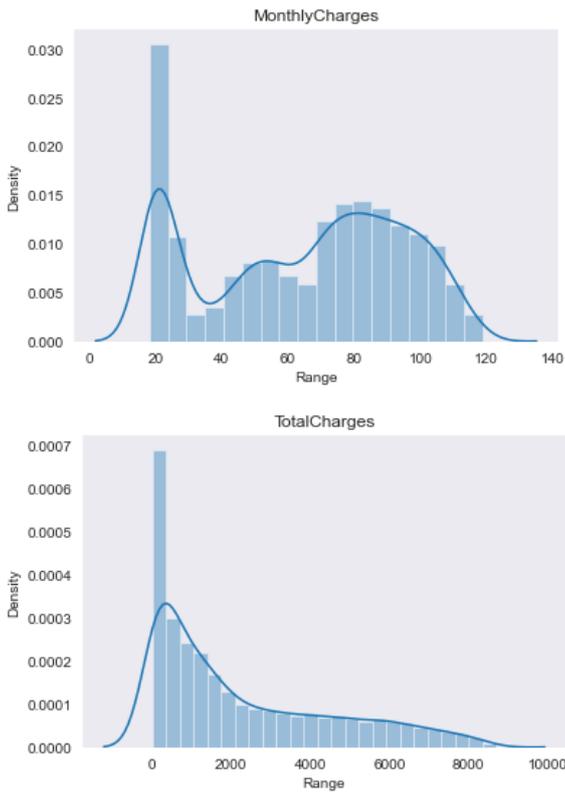
1.4 Normalization

Normalization is a scaling technique in which values are shifted and rescaled so that they end up ranging between 0 and 1 (in case of min-max scaling) or -1 to 1 (in case of Z score).
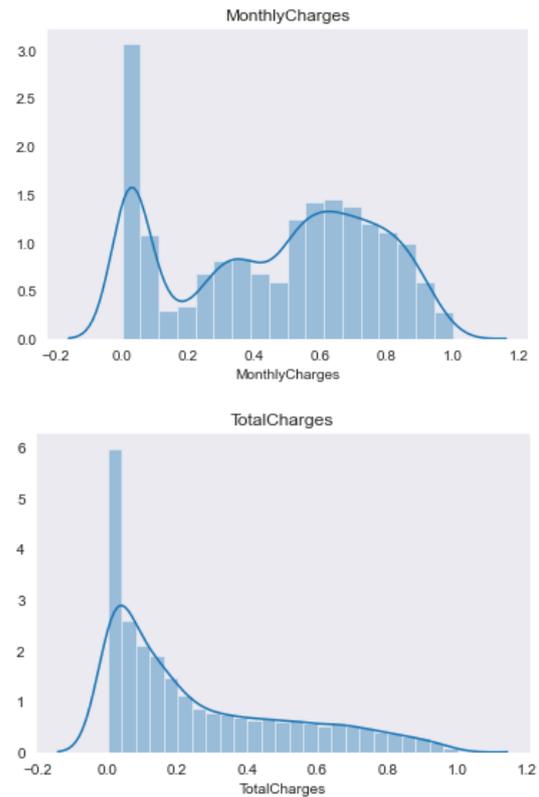
1.5 Encoder

Encoder determines the existence of a string value in a selected column within each row in the data set. It converts categorical values to numeric values (only 0 and 1).

Prior Normalization

*The scale for Range is different for different variables.

Post Normalization

*The scale for Range is normalized (0-1) without affecting the distribution density.

1.6 Sampling

Sampling Operator allows the user to divide the data set into train and test set to fit and evaluate a ML model. User can divide the data set using any of these 3 methods: linear, random or stratified sampling.
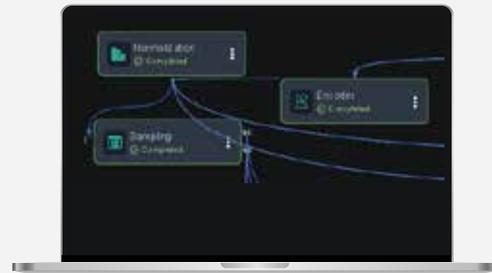
2. Auto ML

2.1 Auto CASH

Combined Algorithm Selection and Hyperparameter Optimization (CASH) allow the user in finding a high-performing hyper parameter configuration for a machine learning model on a given data set. The tool provides several algorithms for both classification and regression methods.

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3. ML Model Building

3.1 Clustering

Clustering is an unsupervised learning algorithm which allows dividing the population or data points into a number of groups, such that data points in the same groups are more similar to each other than those in other groups. In our campaign management problem, customer segmentation is done using clustering operator to segment high and low valued customers.

3.2 Classifier

A classifier is a hypothesis or discrete-valued function that is used to assign (categorical) class labels to particular data points. This operator essentially contains the classification prediction model which will be used to carry out the predictions. In our campaign management problem, we built 2 classifier models:

i) In our customer churn classification problem, classifier is treated as a hypothesis for labelling each customer as likely to churn or not.

ii) With the offer propensity classification model, we want to evaluate the right kind of offer which should be provided to each customer.

3.3 Model Saving

Model Saving operator is used to save the trained ML model into a pickle file. A JSON containing features used to build ML model, results of the model, description of data, with actual model pickle file is passed. So, the next operator can use it in production.
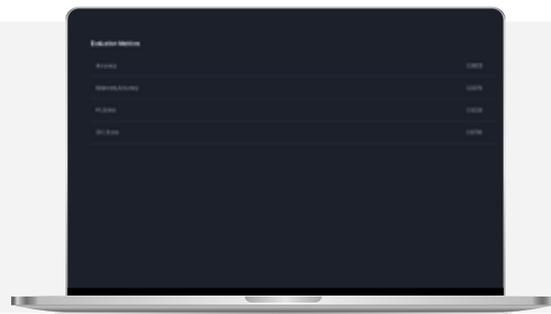

Final End-to-end Pipeline

4. Model Insights

4. 1 Model Validation (Metrics)

The model built has a decent accuracy of around 96%, which means more than 9 out of 10 times, it's going to identify the correct churn behaviour.

4. 2 Model Validation (Report)

The model is able topredict non-churners and churners with a precision of 96%.

4.3 Feature Importance Analysis

This helps user understand what customer behaviours-based variables are leading to possible churn behaviour.


4.4 Model Predictions

The output are the predictions which indicates whether a customer will churn or not, and the scoring probability.

Similarly, we can also evaluate these for offer propensity model.

4.5 Customer Retention Strategy

This decision tree analysis helps identify what variables related to customer behaviour are influentialin order to reduce churn possibility or in other words improve customer retention. Similarly, decision tree can also be evaluated for offer propensity model.

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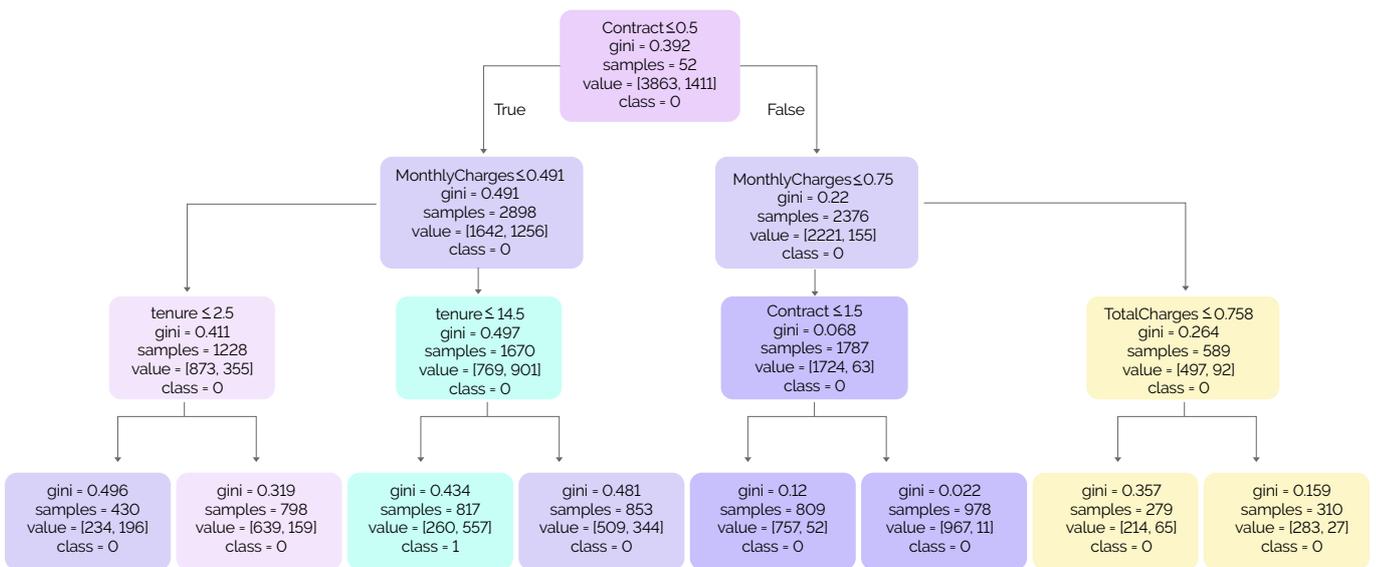
HyperSense™

About HyperSense

HyperSense is an AI Orchestration platform that helps enterprises operationalize AI enabling scalability and growth. It gives you the AI automation capabilities to build, test, deploy, and operationalize AI models in minutes. It is a no-code platform with an intuitive drag-and-drop framework that makes AI/ML accessible to various organizational stakeholders and empowers them to become citizen data scientists. You can get lightning-fast insights, predict outcomes accurately, automate complex workflows, optimize operations, and discover new business opportunities. With HyperSense AI, you can work faster, smarter, and better.

HyperSense AI Capabilities

Ideate
Let enterprises design, explore, and validate business problems to find appropriate solutions.

Create
Collect data from multiple sources, databases, and business functions to build, deploy, and scale AI in minutes without coding.

Operationalize
Create complex business rules and quickly deploy AI-critical processes that convert data into actionable insights in real time.

Innovate
Let businesses continuously investigate, collaborate, and drive innovations based-on model insights.

For more information email **hypersense@subex.com** or visit, **www.hypersense.subex.com**