Capstone Project

1 Optimizing App Offers With Starbucks

1.0.1 Capstone Proposal for Udacity's Machine Learning Nanodegree

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Submission Date: 14 May 2022

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Prepared For:

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Machine Learning Engineer Nanodegree

1.1 Abstract

This Capstone proposal proposes a notional recommendation model using a multi-model approach to provide offer recommendations to users based on the user's profile and behavior. The data used for this model will be customer and offer data provided by Starbucks in partnership with Udacity. Several data preprocessing steps will be required to generate features required for each model and optimizations are expected during the implementation process. The final product will be a web-based application where a user can input user data and receive a recommendation. This author recognizes that this interface will likely change to an in-app solution, but the suggested application provides additional verification testing to the final model.

1.2 Background

Marketing new products and offers is a difficult and critical aspect to any business endeavor. Well established companies such as Starbucks regularly require new marketing strategies in order to maintain their customer loyalty and maintain an advantage ahead of their competition.

Targeting customers with new offers and promotions can have mixed results depending on the customer's preferences and interests. While some promotions may encourage increased attendance, other promotions to the same customer base may not elicit strong responses, or perhaps elicit negative responses. Building advertising models that are careful to consider customer pervious habits and demographic information can produce tailored recommendations to deliver the most effective promotion strategy in an effort to maximize customer loyalty.

The business case for building effective marketing models are clear, additional technological implications about time-phased recommendations presents an interesting challenge to build effective models where a recommendation may differ depending on timing in addition to a customer's profile.

1.3 Problem Statement

This capstone project is targeted to build a model that can provide marketing recommendations to individuals based on personal demographics in order to maximize customer loyalty while maximizing the return on investment of the marketing materials used.

1.4 Datasets

The following data was provided by Udacity as a partnership with Starbucks (R). The data has been anonymized and separated into three datasets formatted using json. User information is held within `profile.json` and contains demographic information about users, such as `gender`, `age`, `id`, `became_member_on`, and `income`. The size of `profile.json` include 17,000 entries with 5 fields.

Field information for `profile.json`

Field	Type	Description	Null Value
gender	categorical	Gender of user (M, F, or O)	null
age	numeric	Age of user	118
id	string / hash	Unique ID of user	N/A
became_member_on	date	Date user became a member, formatted YYYYMMDD	N/A
income	numeric	Estimated income of user	null

Available offers that are sent during a 30-day test period are held within `portfolio.json`, containing 10 offers each with 6 fields. Each offer contains information about the `reward`, `channels`, `difficulty`, `duration`, `offer_type`, and `id`. Described in the table below.

Field information for `portfolio.json`

Field	Type	Description
reward	numeric	Money awarded for the amount spent
channels	list[categorical]	Where offer is available (web, email, mobile, social)
difficulty	numeric	Money required to be spent to receive reward
offer_type	string / categorical	Type of offer (bogo, discount, informational)
id	string / hash	Unique ID of offer

Information regarding key events such as offers received, offers viewed, transactions made and completed offers are stored in the `transcript.json` database. This event log contains 306,648 events each with 4 fields, including `person`, `event`, `value`, `time` data.

Field information for `transcript.json`

Field	Type	Description
person	string / hash	Unique ID of user
event	string / categorical	Category of event, (offer received, offer viewed, transaction, offer completed)
value	dictionary	Information dependent on event type including [`offer id`, `amount`, `reward`] described in table below
time	numeric	Hours after start of test

Event information is held within the `value` field of `transcript.json` and contains the following information. * `offer id` : (string / hash) not associated with any "transaction" but associated with the offer given to the user during the test * `amount` : (numeric) money spent in "transaction" * `reward` : (numeric) money gained from "offer completed" category

1.5 Proposed Solution

In order to produce an effective offer recommendation system, a multi-model approach is proposed. First, by categorizing customers into profiles and associating offer strategies to each profile and establishing successful and unsuccessful strategies to each profile. The final recommendation model will be evaluated, first if the tested user has data with a provided offer, if not the model will evaluate success based on customer profile.

1.6 Evaluation Metrics

Accuracy will be the primary metric used to evaluate model final model performance where accuracy is defined by the ratio between true negative, TN, and true positive, TP, to total events, which is the sum of TN, TP, false negatives, FN, and false positives, FP.

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP}$$

where,

$$TP = TruePositive, TN = TrueNegative$$

$$FP = FalsePositive, FN = FalseNegative$$

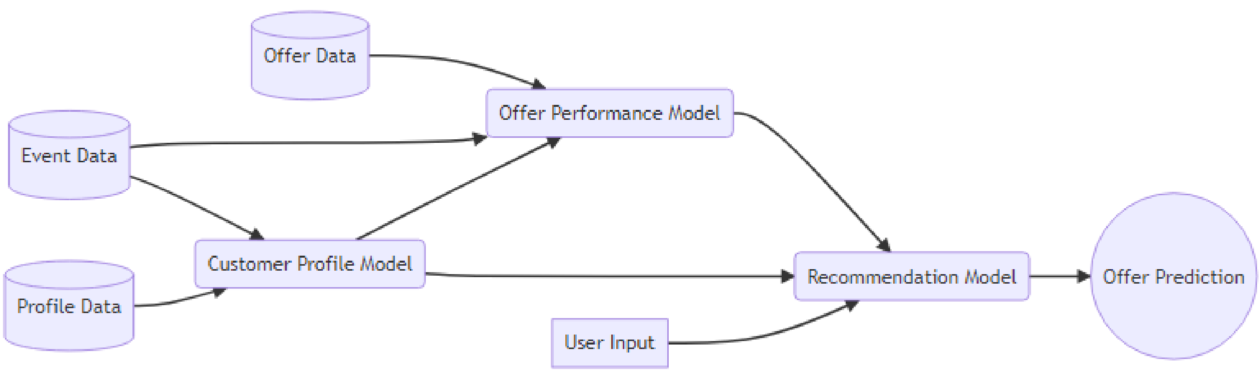
Additional metrics of bias and sensitivity were considered. However, due to the use case for this set of classification algorithms, attention to skew in performance does not seem necessary at the moment.

1.7 Project Design

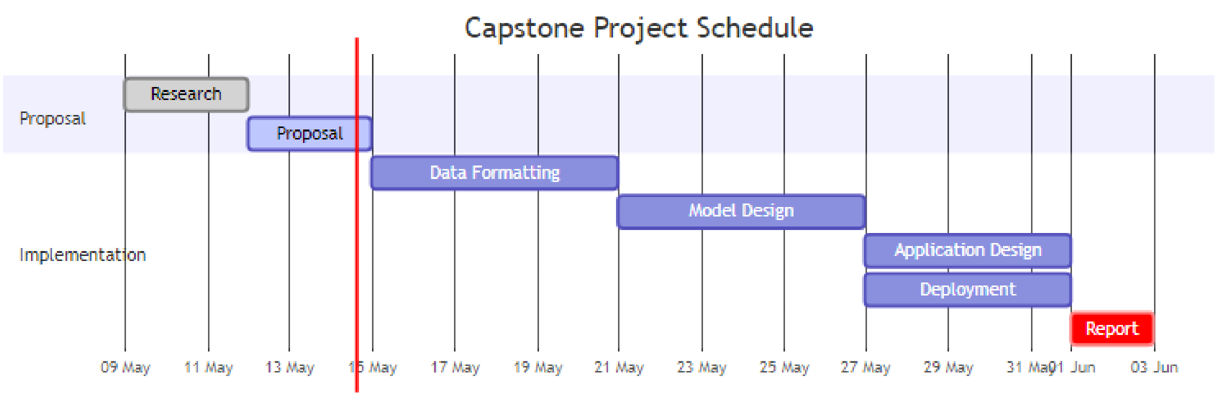
Given these three databases, information can be extracted to determine if offers are effective against specific customer portfolios. This will be done first by categorizing customers into profiles using unsupervised learning techniques such as k-means or DBSCAN, with the potential aid of dimensionality reduction techniques, such as principal component analysis. This will be known the profiling model. Once categorized, the effectiveness of offers strategies will be evaluated compared to each profile, such as time to redeeming an offer and additional useful metrics such as additional revenue generated by offer. This will be completed as a combination of data preprocessing and feature performance evaluation within a performance model.

Once complete a recommendation model can be designed using a supervised learning classifier such as Neural Network, Gaussian Naive Bayes Classifier, or Random Forest wil perform offer recommendations based a customer's demographic information, purchasing history and outputs generated from the categorization and offer performance models.

The following flow diagram depicts the data flow from one model to another that will comprise the final composite model:



As a part of the recommendation model solution, an web-based interface will be generated to allow for a user input information regarding a customer and the interface will visualize the model prediction and any additional pertinent information useful to the user. Though, the final model will likely be imbedded into an existing app such as the Starbucks phone app. This proposed html-facing application can provide additional debugging and verification interfaces.



In order to maintain task execution to the deadlines provided by Udacity's machine learning engineer nanodegree course the following schedule is proposed to maintain an schedule adherence and evaluation.