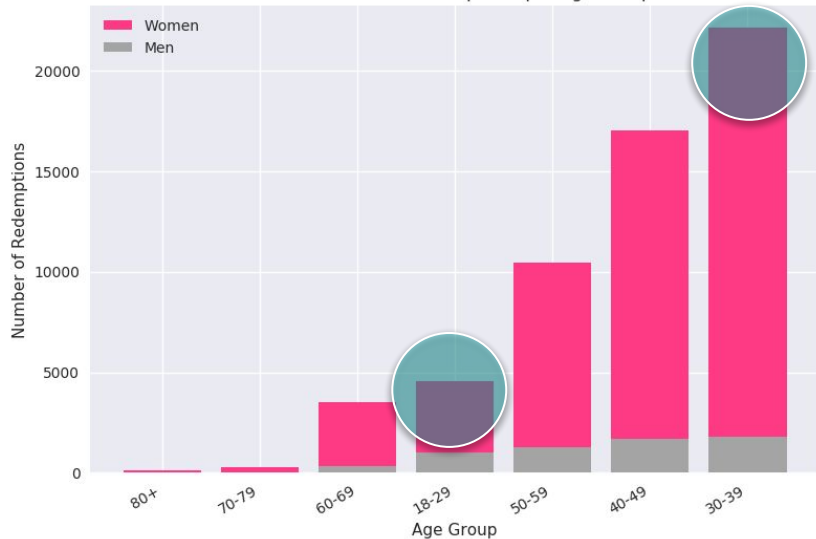


REDEMPTION TRENDS BY AGE

Most Frequent Users: 30-39

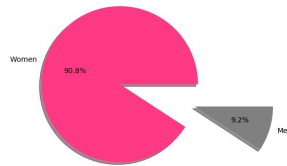
Target Audience: 18-29

Total Number of Redemptions per Age Group



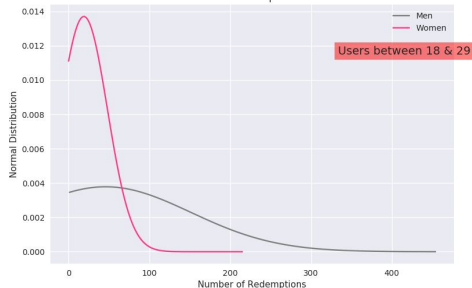
The global average redemption per customer is 25.7 with a Standard Deviation of 41.1

Percentage of Men Vs Women



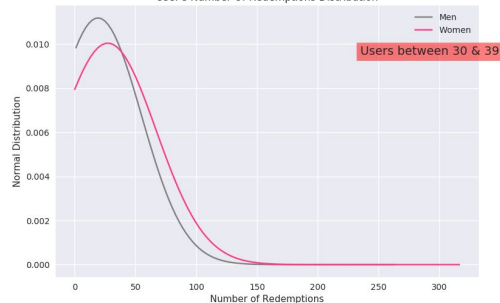
Majority of redeemers are women

User's Number Of Redemptions Distribution



Men between 18 and 29 have the most diverse spread of redemptions. Additionally the standard deviation is more than double the population

User's Number Of Redemptions Distribution



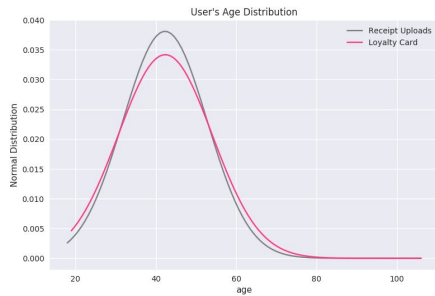
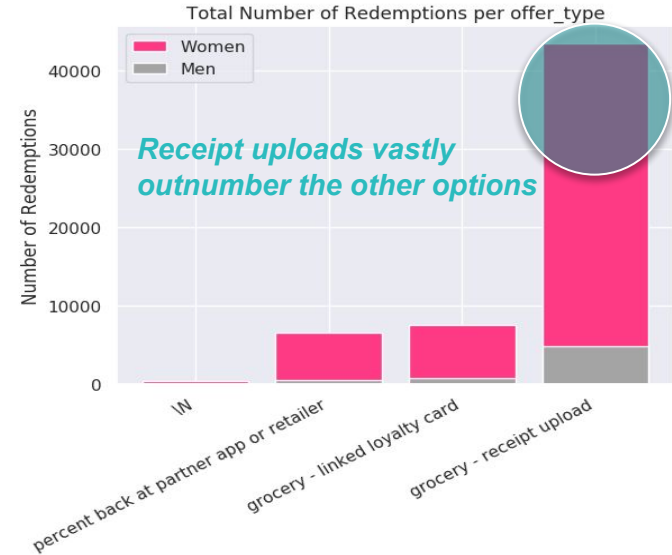
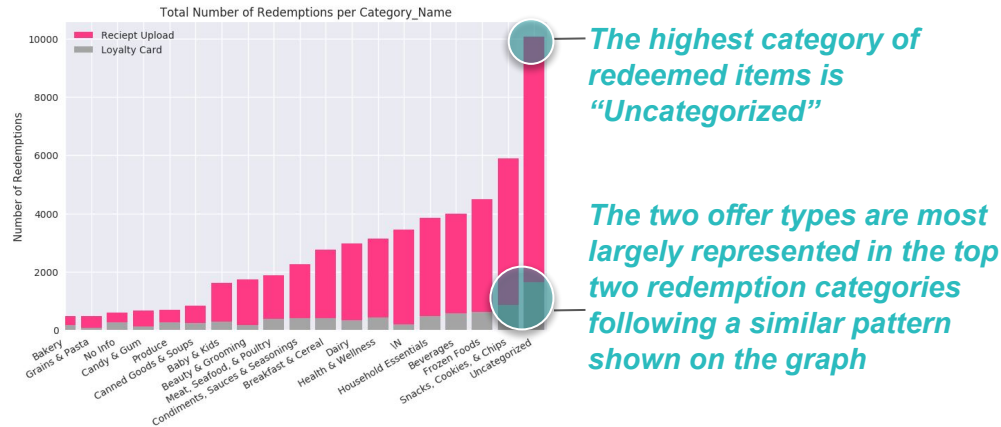
STATISTICS

	AVG	STD
Men 18-29:	45.7	100.5
Women 18-29:	18.9	29.1
Men 30-39:	19.1	35.7
Women 30-39:	27.2	39.8

The distribution for males between the ages of 18 and 29 is not consistent with the rest of the data. Young adult men could be identified as a target audience to increase total number of redemptions. It is important to note that young adult men tend to redeem more than double the women in the same age group.

REDEMPTION TRENDS BY OFFER TYPE

Receipt Uploads account for 71% of the total redemptions

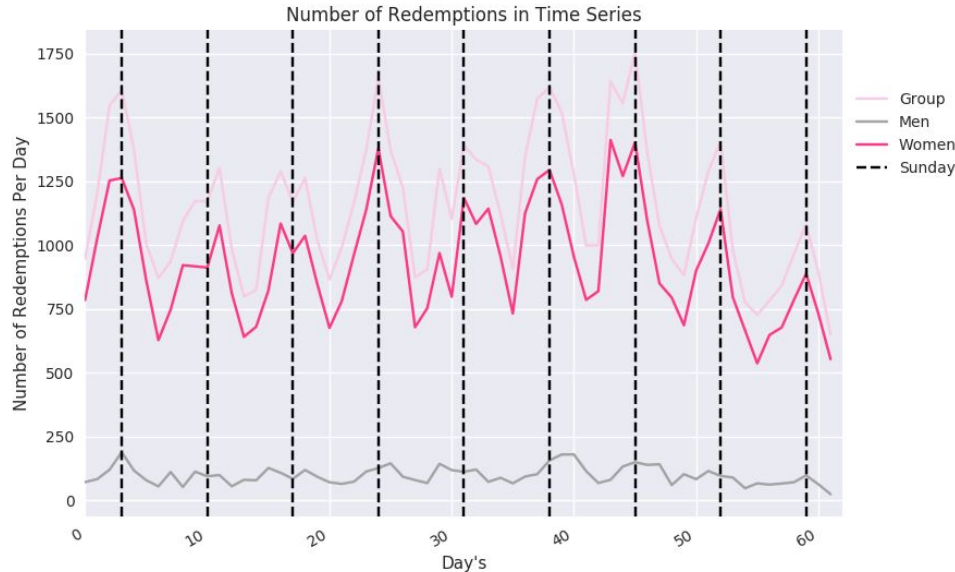


The age distribution graph shows the users near the mean user age of 41 tend to use the receipt uploads more. While those further away from the mean tend to use the loyalty card more but only slightly compared to those near the mean.

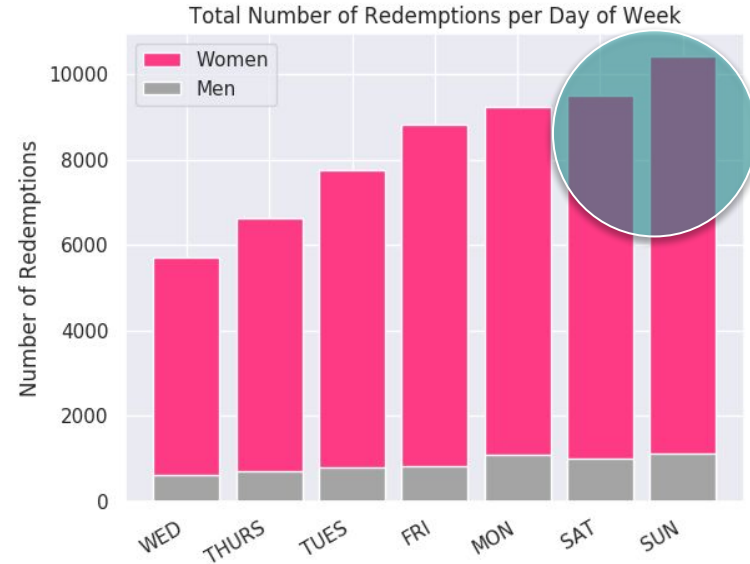
There is much unknown about the “Uncategorized” redeeming category, making it difficult to identify further trends. The next steps would be to identify unique offer names categorized in more than one category. With this information, more insight could be gathered on the types of redemptions and if it's possible to categorize the offers in either an existing category or a new one.

REDEMPTION TRENDS AND TIME

The majority of redemptions occur on weekends



Most peaks are on Sunday, indicating the weekends are a popular time for people to use the app



The above graph also indicates that the majority of redemptions occur Friday through Monday, with Saturday and Sunday being the highest

The weekends are the highest redeeming days, and Wednesdays are lowest redeeming days. The data provided by the men show less variance in peaks and valleys which could be due to the small number of users in this data population.

Personalizing the App Experience for Each User

Personalization Idea Overview

customer_id	age	gender	age group	Number of Redemptions	Top Category Count	Top Category	Top Offer Count	Top Offer
180508	47	F	40-49	108.666667	6.0	Beverages	2.0	7UP~Æ
189508	33	F	30-39	81.000000	13.0	\N	5.0	Amazon Home, Kitchen, & Garden
122608	34	F	30-39	117.587662	1.0	Uncategorized	3.0	Applegate Naturals~Æ Deli Meat
171508	49	F	40-49	5.000000	4.0	Uncategorized	3.0	BELVITA Breakfast Biscuits
162308	36	F	30-39	4.000000	6.0	\N	3.0	BELVITA Breakfast Biscuits

For customer 180508 their most redeemed category is “Beverages”, and their most redeemed offer is “7UP~Æ”

customer_id	offer_name	category_name
3108	Pearls~Æ Olives To Go~Æ	Condiments, Sauces & Seasonings
3108	RXBAR~Æ	Health & Wellness
3108	RXBAR~Æ	Snacks, Cookies, & Chips
3108	RXBAR~Æ	Uncategorized
18734108	Rachael Ray, Ñe Nutrish~Æ Dry Dog Food	Pets
18734108	Rachael Ray, Ñe Nutrish~Æ Dry Dog Food	Uncategorized
18734108	SweetARTS~Æ	Candy & Gum
18734108	SweetARTS~Æ	Uncategorized
18682508	Figgin' Fruit	Snacks, Cookies, & Chips
18682508	Figgin' Fruit	Uncategorized

Addressing the “Uncategorized” values can greatly increase the information in the other categories, showing a truer representation of this population

The table above shows numerous times where an offer_name was classified as “Uncategorized” when it was previously labeled into a category

Plan of Action

1. Address the misclassification issues in the category names
 - a. This will allow for a true representation of the data population
2. Determine the most redeemed offer name and category for each user
3. Develop a recommendation feature for the app that will suggest redeemable offers based on the users and various group populations top redeeming offers or categories.
 - a. Group populations can be based on demographics like age or gender
 - b. Group populations can be more tailored to each user through a short questionnaire about the users' lifestyles

Addressing the Misclassification Issues

The Personalization Model

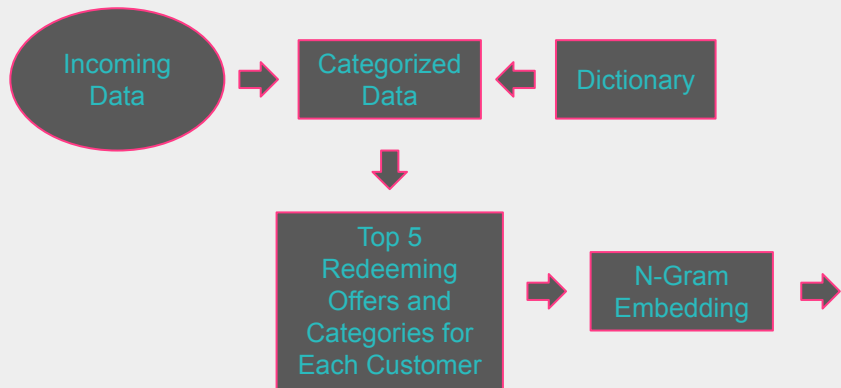
The first step is to address the misclassification issues in the category names, primarily for “Uncategorized”. We can store a dictionary of unique offers and their respective category names. Using the offer name from the transaction we can find its category name derived from our dictionary.

Taking the top 5 offers and/or categories for redemptions we can embed this data in various N-grams and build a model like word2vec to predict based on the top N offers and/or categories.

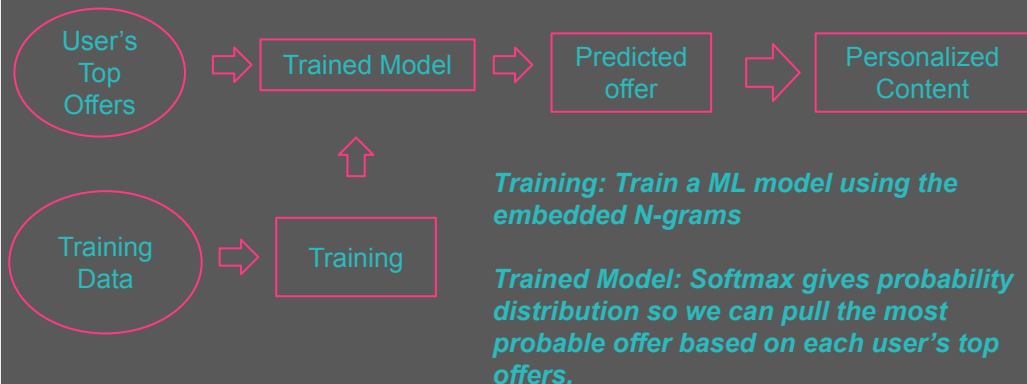
*Example Training data: [n-gram, unique offer]
[{offer 1, offer 34, offer 23} , offer 2]*

The live data to be predicted with: [Users Top 3 Offers]

Dictionary Look up and Categorization Cleanup



Machine Learning (ML) Model



Personalization of the User Experience

The Personalization Model - Scalable

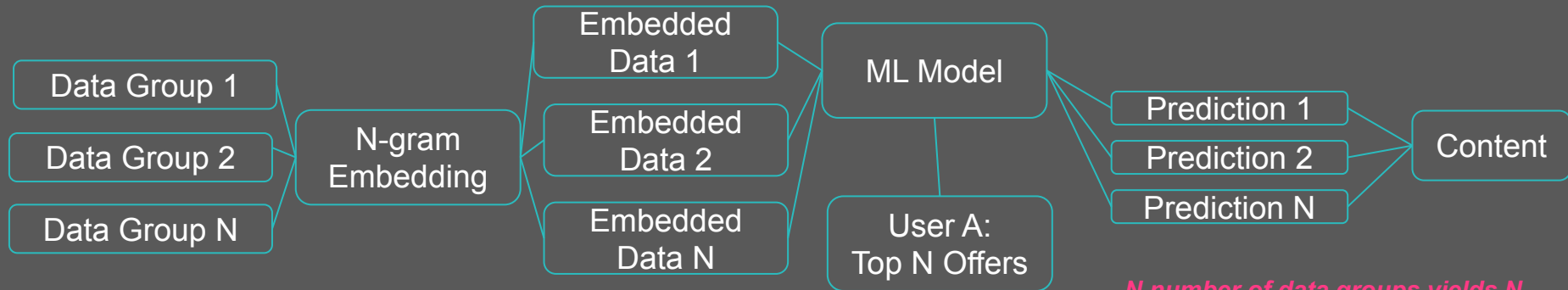
The predicted offer gives a suggestion based on the context of the global data's top offers. The offer can be fed into content of the app to receive personalized recommendations.

Designed so gathering predicted offers is scalable based on the different populations of the data

Data Group 1 could be all of the users

Data Group 2 could be all of users in their age group

Data Group 3 could be based on their gender



N number of data groups yields N number of offer names predict by our model