Starbucks Challenge! Find Hidden Customer Segments with Unsupervised Learning.

Feb 4, 2019

Source

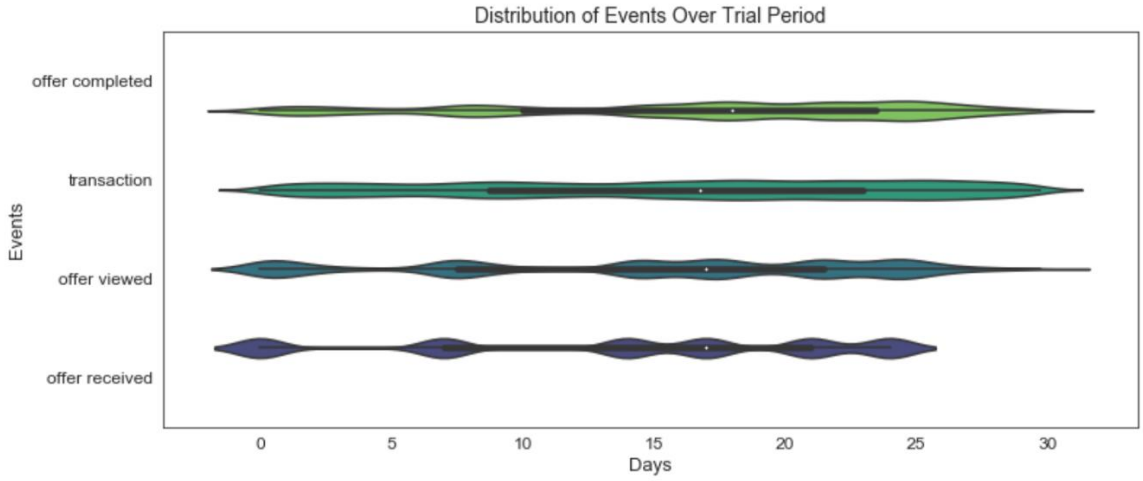
Create distinct customer segments based on purchasing behavior using unsupervised learning. Data provided by Starbucks and Udacity.

This dataset is a hard nut to crack: Complex cleaning, intense preprocessing, fine-tuned dimensionality reduction with PCA followed by some k-means clustering. Only then would it reveal some clear patterns. You can find the details and source code on GitHub.

Introduction

The data contains 3 sets of ‘events’, demographic customer data and offer data. It is simulated and mimics the behavior for 17,000 customers on the Starbucks rewards mobile app over the course of 29 days. Once every few days, Starbucks sends out an offer to users of the mobile app.

The following simple plot, showing the distribution of roughly 317,000 ‘events’ over the trial period shows that the general strategy seems to work: A release of offers is followed by offer viewings on the app, a raise in transactions and eventually, if a certain spending threshold is met, with an offer completion that leads to a reward.



There's 10 different offers that come in three types:

1. a discount offer (discount)
2. a buy-one-get-one-free offer (BOGO)
3. merely an advertisement for a drink (info)

The goal of the project is to determine which customer groups respond best to which offer type.

I will present my findings in 6 short sections:

1. Cleaning / Feature Engineering
2. High-level Comparison of Offer Types
3. PCA and Clustering
4. Segment Analysis Based on Customer Behavior
5. Conclusions on Demographic Groups
6. Learnings

But before we start, let me say that there's two things making this project a real challenge:

1) *There is no apparent experimental setup and we have no control over the variables*: Not all users receive the same offers / offer types or the same amount of offers. During certain weeks some customers may receive multiple offers at the same time, while others don't receive any at all. Also, the different offers

have different characteristics making their successful completion more or less likely.

2) *The transaction data needs extensive and pretty complex preparation*. The transactions a customer makes are not linked to any offers he has received. And even when an offer is sent to a customer, this doesn't mean he has viewed it and hence is influenced by it. Also, we have to make sure that we only count the valid offer completions which occur within the defined period of validity.

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1. Cleaning / Feature Engineering

I will skip the basic cleaning and dive right into the solution to the second problem mentioned above. I solved this in two steps:

1. Flag all events that could be linked to an offer starting from the moment it was received until the end of it's period of validity. (I did this with help of the offer's 'duration' feature).
2. Make sure that of those events flagged in step one only those count that occur after the actual viewing of the offer and only up to the moment the customer has completed the offer.

A word of warning: I did this the best I could, with a couple of encapsulated for-loops. On my laptop the procedure iterated for about 20 (!) hours on 317,000 rows over 10 offer columns ... No

details here (have a look at the code if you want), but let's illustrate the preparation in three steps:

	event	person	time	value
139604	transaction	55c69bafc66d4bf6a7df7f1f752c1b38	372	{'amount': 5.51}
150404	transaction	664c0533a818495781cb3a3a1c5cc5e6	402	{'amount': 24.63}
79400	transaction	2f3964e445744ce29ecd95c7656fbf22	192	{'amount': 1.29}
16671	offer viewed	2f937953414c4fc5aae319f8ba4d441c	6	{'offer id': '5a8bc65990b245e5a138643cd4eb9837'}
305641	transaction	7b74e68b25754abb968231adc71c7e3a	714	{'amount': 14.84}
265959	transaction	6bdd08b358ac44cbb9b379ff6ad6e9cc	588	{'amount': 29.99}
154639	offer received	d5059ee547a24f9a92c5c6c9892e469d	408	{'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}
2916	offer received	a3627a341176408c9512c6c6a8378458	0	{'offer id': '3f207df678b143eea3cee63160fa8bed'}
296335	transaction	c099206f76b1414db7552f163520053c	672	{'amount': 0.29}
171317	offer viewed	b527eab600344530991f159dffc3ac53	420	{'offer id': '5a8bc65990b245e5a138643cd4eb9837'}

A) A sample of the raw input data of the rougly 317'000 events. As one can see they are all assigned to a person, but the transactions are not assigned to any offers.

	event	person_id	time	amount	offer_id
48537	transaction	p_88	138	14.13	NaN
101463	transaction	p_88	282	15.20	NaN
110892	offer received	p_88	336	NaN	o_5
147228	transaction	p_88	396	24.29	NaN
147229	offer completed	p_88	396	NaN	o_5
150660	offer received	p_88	408	NaN	o_6
177275	offer viewed	p_88	432	NaN	o_6
191230	transaction	p_88	468	17.53	NaN
191231	offer completed	p_88	468	NaN	o_6
196846	transaction	p_88	486	13.72	NaN
201631	offer received	p_88	504	NaN	o_9
243239	offer viewed	p_88	570	NaN	o_9
268861	transaction	p_88	594	18.81	NaN
296332	transaction	p_88	672	33.26	NaN

B) Events for random customer 'p_88' after basic cleaning (and ID recoding). Still no assignment of transactions to offers. To get here was the easier part.

	event	person_id	time	amount	offer_id	o_1	o_2	o_3	o_4	o_5	o_6	o_7	o_8	o_9	o_10	reward
273587	transaction	p_88	138	14.13	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
273588	transaction	p_88	282	15.20	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
273589	offer received	p_88	336	NaN	o_5	NaN	NaN	NaN	NaN	0.0	NaN	NaN	NaN	NaN	NaN	NaN
273590	transaction	p_88	396	24.29	NaN	NaN	NaN	NaN	NaN	0.0	NaN	NaN	NaN	NaN	NaN	NaN
273591	offer completed	p_88	396	NaN	o_5	NaN	NaN	NaN	NaN	0.0	NaN	NaN	NaN	NaN	NaN	5.0
273592	offer received	p_88	408	NaN	o_6	NaN	NaN	NaN	NaN	NaN	0.0	NaN	NaN	NaN	NaN	NaN
273593	offer viewed	p_88	432	NaN	o_6	NaN	NaN	NaN	NaN	NaN	1.0	NaN	NaN	NaN	NaN	NaN
273594	transaction	p_88	468	17.53	NaN	NaN	NaN	NaN	NaN	0.0	1.0	NaN	NaN	NaN	NaN	NaN
273595	offer completed	p_88	468	NaN	o_6	NaN	NaN	NaN	NaN	NaN	1.0	NaN	NaN	NaN	NaN	3.0
273596	transaction	p_88	486	13.72	NaN	NaN	NaN	NaN	NaN	0.0	0.0	NaN	NaN	NaN	NaN	NaN
273597	offer received	p_88	504	NaN	o_9	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.0	NaN	NaN
273598	offer viewed	p_88	570	NaN	o_9	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0	NaN	NaN
273599	transaction	p_88	594	18.81	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0	NaN	NaN
273600	transaction	p_88	672	33.26	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

C) Events for the same customer ‘p_88’ after flagging with the two stepped process mentioned above.

Explanation: ‘0’ denotes events that can be assigned to an offer (‘o_1’ to ‘o_10’), be it because there is an offer ID attached to them, or, in the case of transactions, because they occured within the valid offer duration. If a customer has received several offers at the same time, a transaction can be assigned to more than one offer (for example the transaction at hour 486). Now ‘1’ denotes events that occurred after the customer has viewed an offer and before it expires or is completed (whatever comes first). Let’s again look at transaction 486: I have not counted it for offer 5 because the customer already completed that offer and even if he had not, he actually never saw that offer in his app (so was never influenced by it). And I did not count it for offer 6 because the customer already completed that one before, too. (But in this case he has seen the offer, so I counted the transaction at time 468, that led to the completion and the reward).

This tricky data preparation has given me a solid base for the subsequent steps.

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2) High-level Comparison of Offer Types

But let's first have a look at the different offers and their characteristics. I believe there are too many uncontrolled variables for a direct comparison. Although some general trends can be spotted (have a look at my EDA notebook if you want) this will not help to solve the problem.

offer_id	difficulty	duration	offer_type	reward
o_1	10	7	bogo	10
o_2	10	5	bogo	10
o_3	5	7	bogo	5
o_4	5	5	bogo	5
o_5	20	10	discount	5
o_6	7	7	discount	3
o_7	10	10	discount	2
o_8	10	7	discount	2
o_9	0	4	informational	0
o_10	0	3	informational	0

The 10 offers: 'difficulty' is the amount to be spent within the 'duration' (in days) to get the 'reward'. (As can be seen informational campaigns don't have spending thresholds and rewards.)

There is a somewhat more robust trend becoming visible, if we aggregate the offers by type and compare some key metrics:

offer_type	difficulty	duration	reward	prop_rewards	rel_difficulty	view_to_complete
bogo	7.50	6.0	7.5	1.000000	1.285714	0.437114
discount	11.75	8.5	3.0	0.269643	1.357143	0.561783
informational	0.00	3.5	0.0	NaN	0.000000	0.000000

Offers aggregated by type, with mean values and additional key metrics

*First let me explain **the view-to-complete rate (vtc rate), the most important metric for me in this project**. I have calculated it as the amount of offers that a customer has actually viewed and validly completed, divided by the amount of the offers he has viewed. It can range from one (all viewed offers have also been completed in time by the respective customer, meaning he reacts well to offers) to zero (none of the viewed offers have been completed in time, meaning the customer does not react well to offers).*

Let's forget about the informational offers for a moment and compare discounts and BOGOs only. **It is clear to see, that the average vtc rate is significantly higher for discounts than for BOGOs. And that's even though the monetary rewards for BOGOs are much higher.** (Note: The higher difficulty (= spending threshold) of discounts is mostly offset by their longer duration: I calculated this as the 'relative difficulty', the mean amount to be spent per day to reach the completion threshold before the offer ends.)

So, this is interesting—why would a company want to send out expensive BOGO offers when it can have a better activation of it's customer with the cheaper discount offers?

Now *two questions* should be answered:

- Have the two offer types been viewed by approximately the same groups of customers?
- Are there certain customer segments that are responsible for the difference or is this a general trend?

Despite diving deep into EDA after this finding, I was not able to find clear patterns or distinctive segments that I could identify as being especially pro the one type or the other. So that's where Machine Learning comes into play.

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3. PCA and Clustering

The dataframe I worked with now had a row for every customer with his events aggregated in total and by offer type specifically. I also added the non-promo condition as a kind of fourth offer type.
As my end goal was to find out if the purchasing patterns differ for different demographic groups, I removed all demographic features (age, gender, income and also the

duration of membership) from the set. I think this is important to note and something that often get's done wrong.

I carefully selected which of the remaining features I would pass for PCA and clustering to avoid high correlation and bias. It took me two or three runs and some feature tweaking to get a good configuration:

```profile.columns = ['viewed_received', 'total_trans', 'total_amount', 'prop_np_trans', 'prop_bogo_viewed', 'bogo_vtc', 'prop_bogo_amount', 'prop_discount_viewed', 'discount_vtc', 'prop_discount_amount', 'prop_info_viewed', 'prop_info_amount', 'prop_by_accident']```

- viewed_received: ratio of offers viewed to offers received
- total_trans / totaol_amount: total transactions and amount spent
- prop_np_trans: proportion of transaction when no promo was active
- prop_by_accident: proportion of completed offers that were not viewed
- for every offer type: the proportion of viewed offers of that type, the view-to-complete rate, the proportion of amount spent under offer conditions

There is also a lot of experimentation documented in my repository considering pre-processing, and fine-tuning of the
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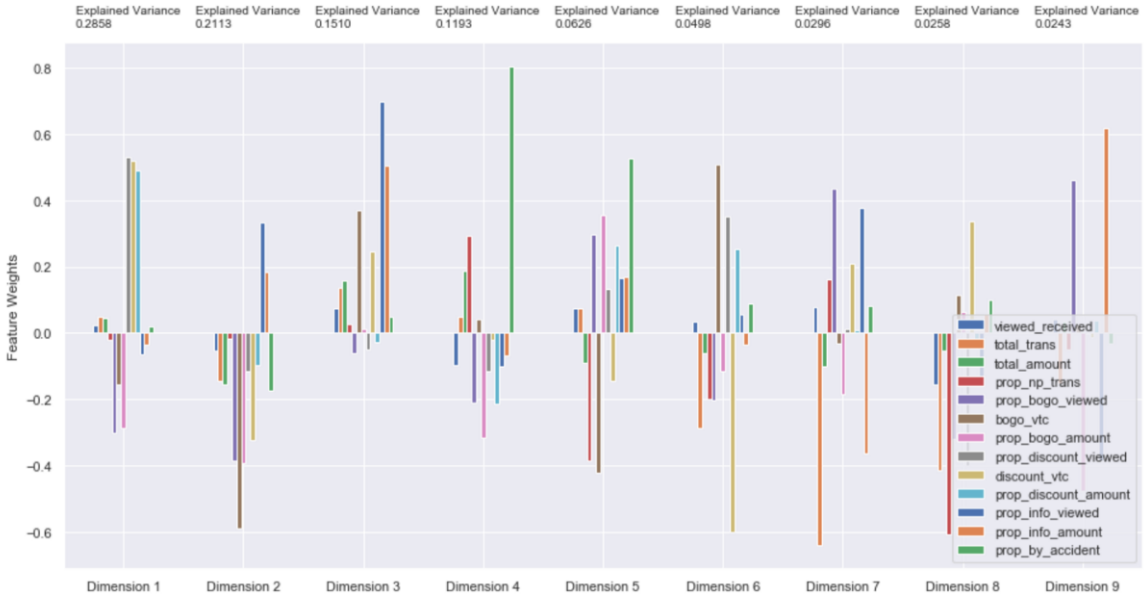
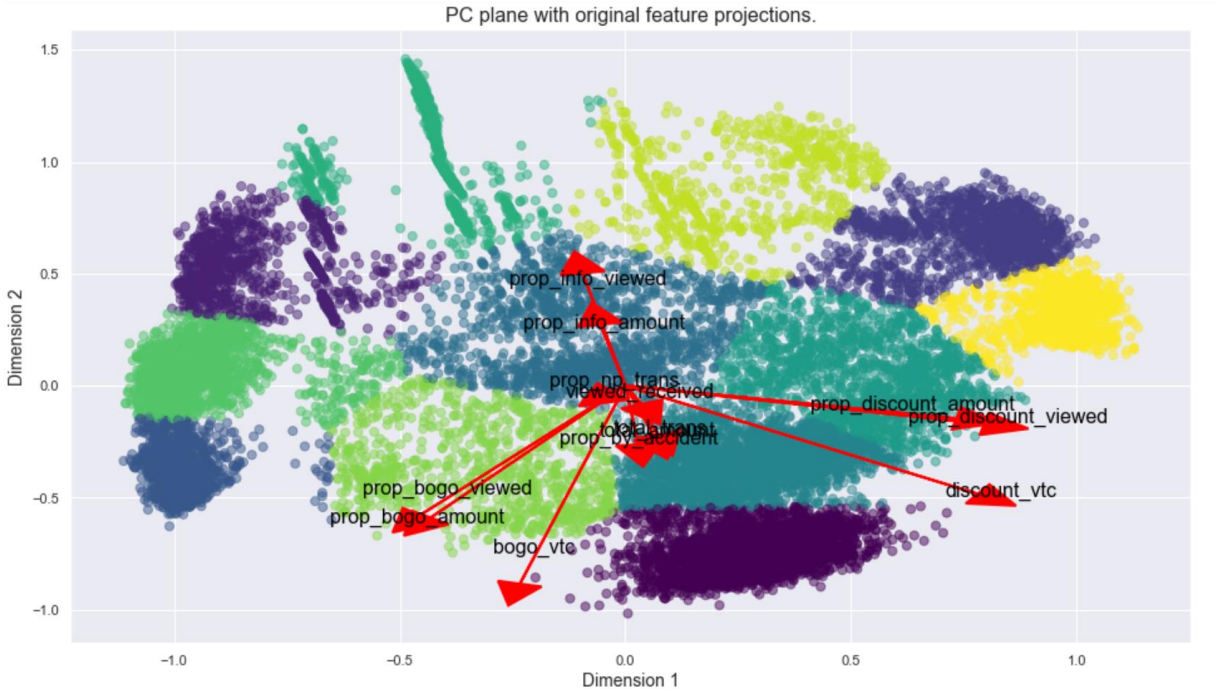
PCA and clustering. It was especially interesting to see how different feature transformations (log, yeo-johnson, box-cox) led to slightly different patterns after the application of PCA.



9 Dimensions of PCA with 95% of original variance retained on log transformed data. Explanation: The first dimension separates customers that spent heavily on BOGOs or discounts. The fourth dimension separates customers who spent above average and do not respond well to offers.

To make a long (and interesting) story short: In the end I log-transformed my data, removed some outliers, scaled it to a range of 0,1, applied a PCA to reduce the feature space to 2 dimensions and then clustered with k-means to have 12 segments.



Scatterplot showing the 12 segments and the original feature projections on the PCA-reduced data (2 dimensions).

A note on PCA: Because a reduction to 2 dimension means quite a loss of information / variance in the data, I tried to cluster with less reduced data (say to 4 or 6 dimensions) but then I could not get good clusters (by measure of their silhouette score).

A note on outlier removal: I removed approx 5% of the customers who spent way more than the rest. This may be controversial, but I always prefer to have a more general model than to make compromises for customers that behave so special that your proposed treatments probably don't apply to them anyway. And for PCA outlier removal is crucial (believe me, I tried without).

4. Segment Analysis Based on Customer Behavior

First, please remember that the 12 segments have been based on purchasing behavior only. The cool thing is that the segmentation let's us control for the exposure of the customers to different offer types. The findings are listed below in somewhat simplified form (e.g. I won't mention info offers in the segment descriptions, but will add a remark and plots regarding them at the end).

First group of segments—customers that have viewed both BOGO offers and discounts in a more or less similar share:

- **Seg 1 (15.4% of total customers, biggest segment)**: Customers with highest spending / net revenue, react very well to discounts (mean view-to-complete rate of 0.9) and nearly as good to BOGOs (0.8). Top!
- **Seg 2 (14%, 2nd biggest segment)**: Customers with 2nd highest spending / net revenue, same vtc rate on discounts as Seg 1 but BOGO vtc rate drops to 0.6. Probably increase discount share.
- **Seg 5 (5.1%)**: Now that's interesting. These customers react well on BOGO offers (vtc rate 0.7), but seem totally unimpressed by discounts (vtc rate 0.05). Go for BOGO then.
- **Seg 12 (8.4%)**: And here it's exactly the other way round: Discounts are ok (vtc rate 0.7), but viewed BOGOs are completed at less than 1%.

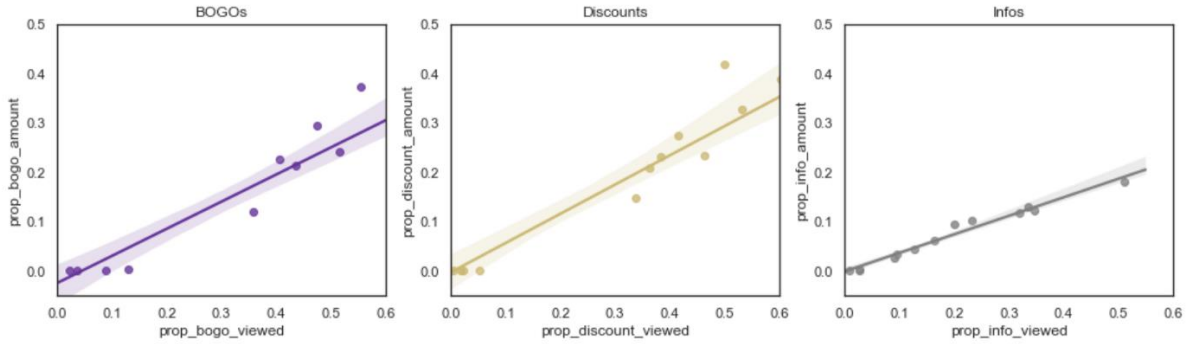
Second group of segments—medium spending customers that have either been exposed to BOGO offers or to discounts only:

- **Seg 3 (6.7%) and Seg 6 (9.9%)**: Have seen BOGO only. Seg 3 reacts ok with vtc rate of 0.7, Seg 6 considerably less with a vtc rate of 0.4.
- **Seg 4 (6%) and Seg 8 (7.2%)**: Have seen discounts only. Both Segments react ok with a vtc of 0.8 and 0.7 respectively. *(One bigger difference here is that Segment 8 was exposed to a high share of info offers.)*

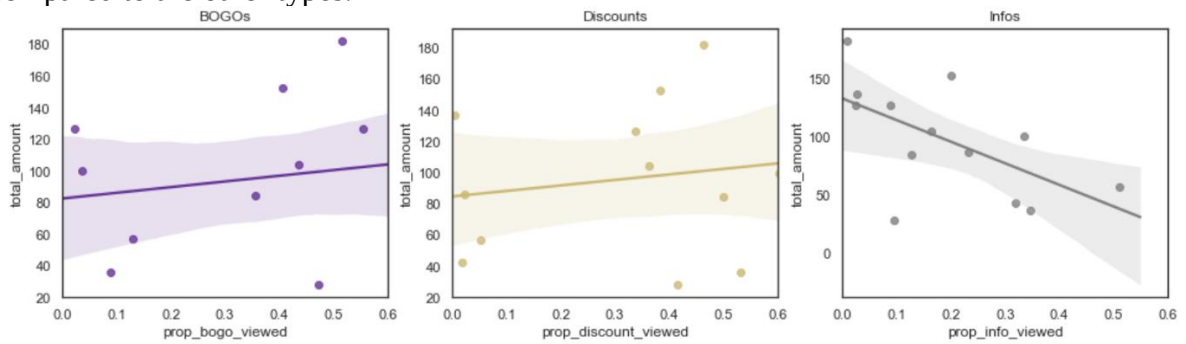
3rd group of segments—low spenders that could not be activated through offers:

- **Seg 10 (8.7%)**: Quite regular customers (6 transactions a month vs. overall mean of 8), but spending small amounts only (total spending is only 25% of overall mean). They view the offers on the app regularly, but complete neither BOGOs nor discounts (vtc rate close to 0 for both).
- **Seg 11 (5.7%)**: Similar to Seg 10 but have viewed no discounts. The average transaction amount is a little higher, so maybe there would be a chance to tickle them with some discounts. But probably they won't move to much.
- **Seg 2 (3.8%)**: Similar to 11 but have viewed no BOGO. Maybe worth a try to send them some BOGOs?.

What about the **informational offers**? To be honest, I didn't analyze them in great detail, because as far as I can see, their effect seems limited compared to BOGOs and Discounts. Here are two plots for why I think so (but, really, I didn't check this in detail and the following plots show correlations and not necessarily causations):



The share of offers per type viewed by the 12 segments, compared to the proportion of amount spent under conditions of that offer type. Infos don't seem to trigger much purchases compared to the other types.



What's even worse, the total mean amount spent for a segment decreases with more Infos in the mix. It's not that they don't work at all, but they perform worse than the other types.

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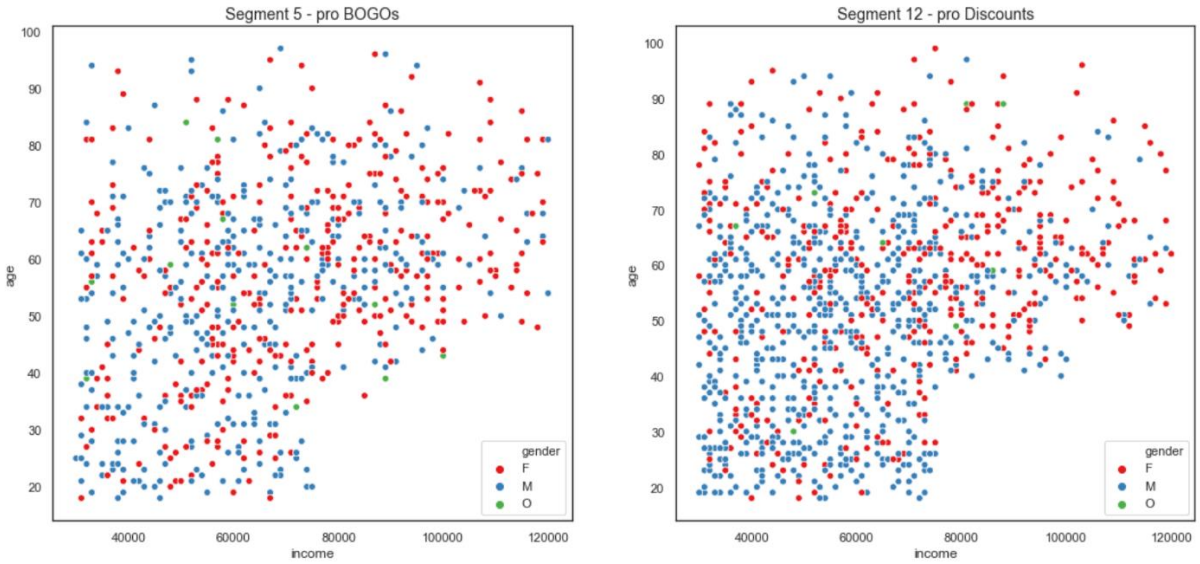
5) Conclusions on Demographic Groups

The next step includes appending the segment predictions to the demographic customer data. (Note: There are 2'175

customers for which we have no demographic info. I dropped them all. Because we removed some outliers too in the last step, only 14,167 of the original 17,000 customers are left for this part of the analysis. Should be enough to get valid results.)

Again, the focus is on preferences of specific user groups for BOGOs vs. discounts. *In that respect the comparison of segment 5 (completed more than two thirds of viewed BOGOs, but no discounts) and segment 12 (just the opposite) seem the most promising to show a clear difference in user groups.*

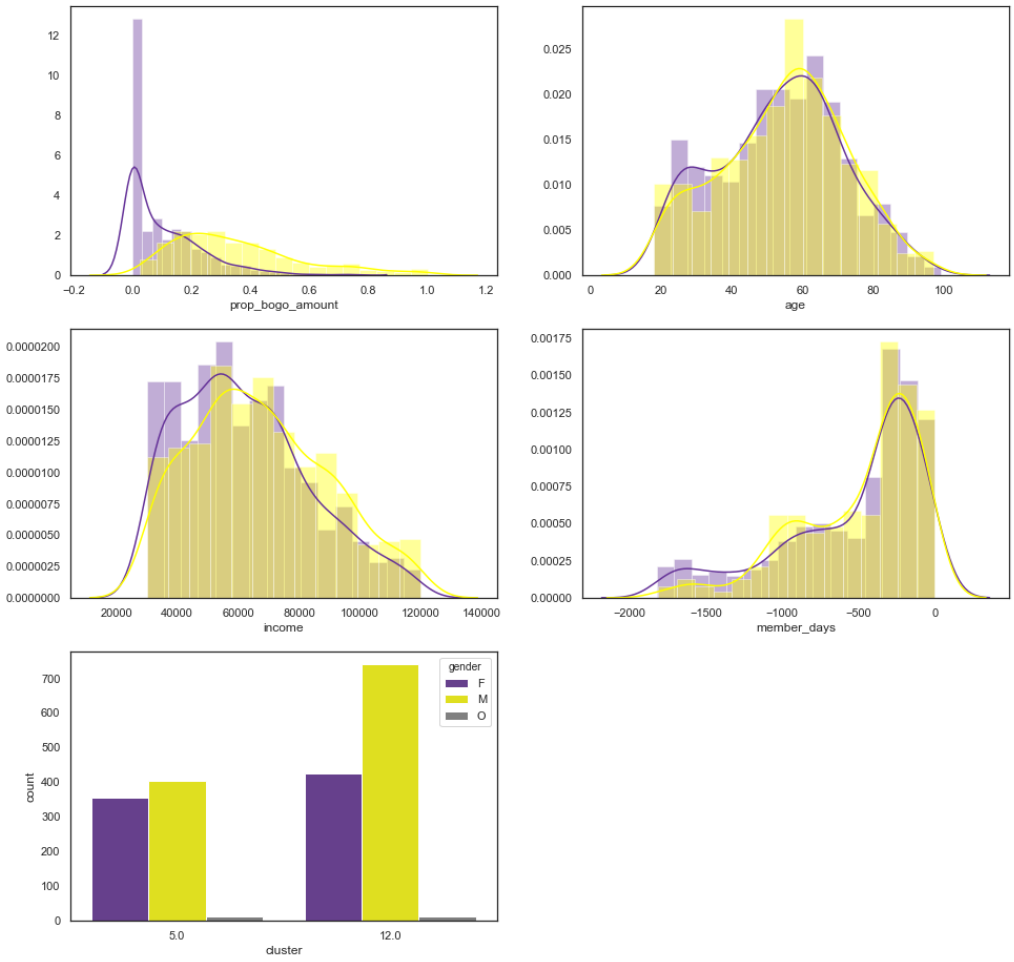
I hoped for a clear pattern doing some scatterplots with different combinations of demographic features for members of those segments—unfortunately nothing was to be seen:



Hard to spot any patterns for combined demographic data between BOGO lovers and BOGO haters.

But looking at the features in isolation, a tendency becomes visible (and it is very consistent for different pairs of segment

comparisons, as can be seen here). The younger, lower income and male customers are, the more they prefer discounts to BOGOs:



Segment 12 in purple vs. Segment 5 in yellow, the first Subplot shows the amount spent under BOGO conditions (customer has viewed BOGO offer) to make the distinction clear.

Although there is a demographic difference for certain customers who absolutely prefer BOGOs to discounts and vice versa, there is also a lot of overlap between these groups.—And that leads us to the conclusions.

6. Conclusions

We probably could still dig a bit deeper into the demographic data and try to better single out some distinct demographic pockets of customers that react especially good on certain offer types. But the general demographic overlap is so large, that I think it makes more sense to build segments based on purchasing behavior for the vast majority of customers.

If I had to give Starbucks some advice on improving their offer strategy, then I would try to do some A/B testing on substituting a good amount of BOGOs with discount offers (there seems to be a lot of potential for that in the large Segments 1, 2 (especially), 6 and so on (actually more or less in all segments but 5).

My learnings

This project was tough work, I would say it consisted of about 65% cleaning & EDA (at least), 15% modelling, 20% analysis and report. And of course the modelling was the funniest part. I especially enjoyed the experimentation with the different feature transformations and visually inspecting the results with the PCA plots.

Keys to success: Proper cleaning and feature engineering. For this project it was especially important to calculate some ratios (like the view-to-complete rate) to control for some of the

variables, as not all customers had the chance to view the same amount of offers or the same mix of offer types.

This project is my capstone for Udacity's Data Science Nanodegree and my first with unsupervised learning. I hope I made no conceptual mistakes—if you have any doubts or questions, please make a comment and let me know.