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Cinepolis: Data Science Learning Session #4

The Modeling Process and Quantitative Customer Insights

BCG GAMMA

10/22/2018

Agenda

1. Quick review of learning session purpose and agenda
2. Progress update – Flash 5 launch
3. Discussion on model creation and validation
4. Technical walkthrough

Curriculum and schedule

Our objectives for the bi-weekly learning session

Share our expertise

Collaborate and share our knowledge on modeling topics and best-in-class solutions

Provide a progress update

High level update the team on steps taken over the last two weeks and key technical developments

Identify key challenges

Discuss key challenges we have faced and steps taken to overcome those challenges

Technical deep dive/roadmaps

Code walk-through and process discussion of how the models are developed, refined, and deployed

Over the next three months we will cover a variety of topics in addition to status updates and code reviews

	Aug. 23rd	Sept. 12th	Oct. 9th	Oct. 22nd	Nov. 1st	Nov. 7th
	Introduction	Data Preparation		Modeling and Production		
Overview	Data Science overview and key topics	Sandbox creation and ERDs[1]	Experiment design and data engineering	The modeling process	Validation and selection of models	Creating production systems for models
Deep dive	Frequency challenge clustering	Menu exploration rules/propensity	Movie affinity	Quantitative Customer Insights (Proposed)	TBD Advanced Topic	TBD Advanced Topic

1. Entity-Relationship Diagram - a description of how objects are related to each other in a database and how that information can be mined for insight
2. CF - Collaborative Filtering

Many steps have to be taken before a value-adding model can be constructed and implemented

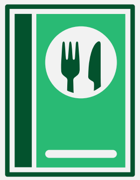
Enabling sustainable value creation | Generating and capturing value

Data exploration	Feature development	Model candidate identification	Scaling and execution
Identify what data exists	**Develop new understandings**	**Define the problem's solution**	**Scale the output and execute**
• Explore if the question can be answered with the current data • Identify which data is usable and of appropriate quality	• Combine the data create new metrics e.g. average purchases last three months, favorite product, most frequently visited location	• Determine if there's an appropriate model to predict a given outcome – for example, if a customer will purchase a given class of product Our focus for today	• Transform the entirety of the prior work into a sustainable system that can be sustained with limited updates

Typical process time is 3 to 6 months for new use cases and is highly iterative

Progress update

Going forward our focus will be primarily on flash offers

	 Frequency challenge	 Menu exploration	 Flash Offers
Description	• Unlock a reward after a personalized # of visits during a specific period of time	• Unlock a reward after purchasing a personalized set of concession products	• Offer a special discount for box office tickets during a short period of time
Hypothesis	• Using game dynamics to deliver promotions based on individual frequency levels we can increase the customer frequency	• Using game dynamics to deliver promotions based on individual consumption patterns we can increase basket size of up-sell	• Delivering short fused offers promoting movies tailored to client preferences can drive an additional impulse visit

We launched a new Flash w/ new features

Incremental steps taken as part of Flash five's launch

Added opt-in functionality for high frequency customers

Added SMS and Facebook as additional campaign components for medium and low

Deployed a new segmentation that reduces yearly variance in behavior to improve targeting

Reason for including in the next wave of pilots

Reduce the expense of running campaigns and fulfilling for any customer who happed to complete the challenge

Increase engagement with the pilots through reaching customers through other channels

Reduced variance should be more predictive of actual customer behavior

How to model - potential candidates, evaluation, and deciding on a model

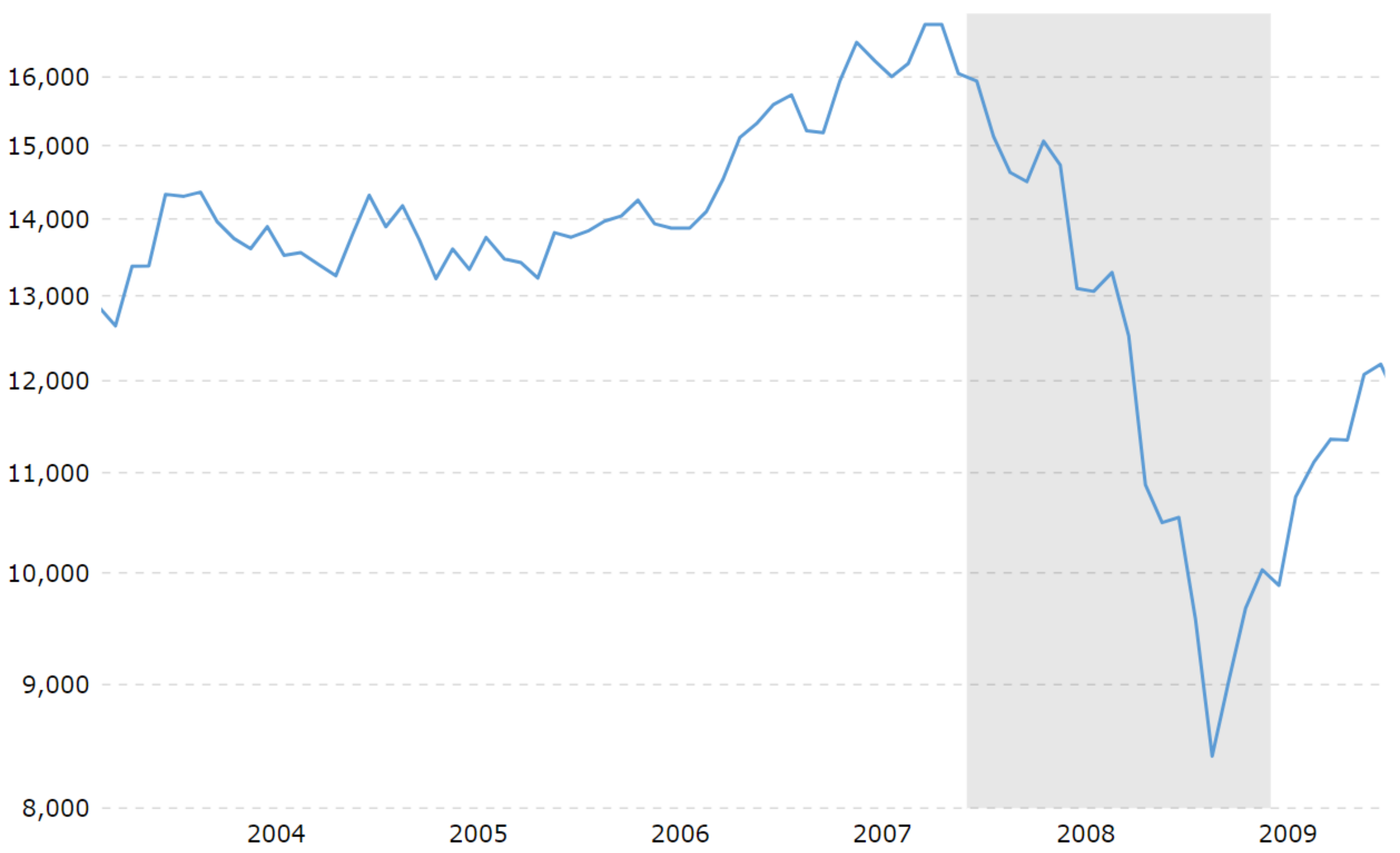
A question
How do we know what we know?

- There is a lot of information in the world and it is hard to tell what is important and not important
- Humans are bias and don't determine causal effects
- That information is constantly changing with new behaviors and new patterns that are relevant to us
- We have a common set of statistical tools to optimize and test our understanding/models of the world…
- …but often those are meaningless as new techniques, data sources, and data become available to us

Example – What would you say about the trend below?

Example The next period is actually the 'Great Recession' of 2007-2008 with a 50% decline in values

DJIA monthly closes from 2003 to mid-2009



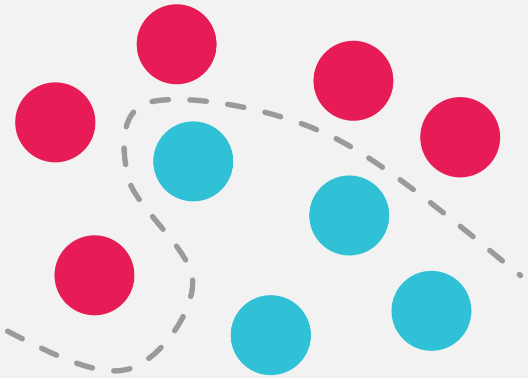
What story did you tell yourself?

Source: www.macrotrends.net/1319/dow-jones-100-year-historical-chart

we want to know the future but can only see the past

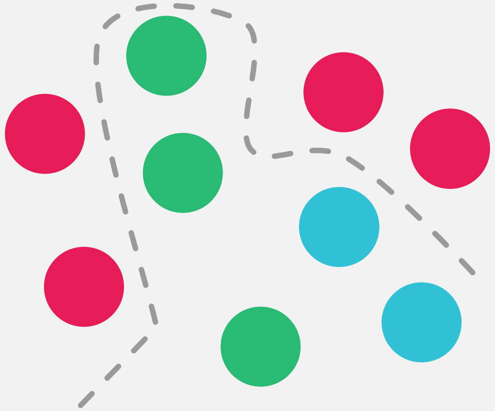
Past data is the only way we can make a decision about the future...

Imagine a model trained to identify red and blue...



...but future preferences are unknown and likely to change!

...what happens when we introduce green into our model?



Since the model was not trained to "see" green, it will identify it as blue or red!

Takeaways

There is no such thing as a 'right' or 'correct' model, models are as good as can be given constrained time, resources, data

Just because something has been modeled once doesn't mean the same model will work next time

The same human biases exist in models but can be reduced

So where should we even start our understanding?

The beginning
A very good place to start

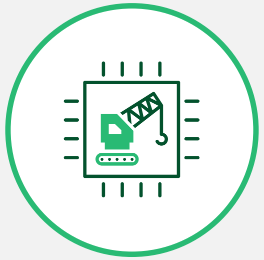
- **Identify the question we are actually trying to answer!**
- Do we want to understand a likelihood? A grouping? Similar behaving customers? Film aficionados? The loyalty program?
- Having a crisp clear question is critical to getting a meaningful answer – not all models will work the same or can answer the same questions
- Determine what is actually a 'good' result – does this model need to be highly accurate or are their asymmetric costs for accuracy

Once we understand the question we'd like to answer, we look to our resources: data, features, and models

Data

Information we currently have about the state of the world – facts that are known to exist and be true for a given point-in-time

Features



Pieces of information that represent novel information derived from the data and constructed in a way for a model to ingest

Models

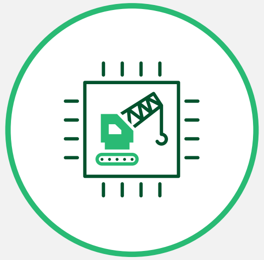
A set of rules about how information that is given to it will be processed and which outputs can be obtained from those inputs

We must make decisions across all three categories in order for us to build an understanding of the world…

…and decisions always have trade-offs

We need to make trade-offs in each of these categories to triangulate on potential candidate models

For example, imagine a small data set with 100 records…

	Potential action	Pros	Cons
Data 	Gather more data!	Would increase the size of the data set and give more information	How much do we need to increase by is unknown as is the cost
Features 	Develop some interesting features!	Potential to improve model accuracy at no cost	No idea if those features would be relevant or actually improve the model
Models 	Use a resampling technique!	Would solve the data size issue and give better results	Potentially missing an entire population that could change the outcome

When resources are known then set the evaluation and testing criteria

Evaluation

Evaluation refers to the metric used to determine how well a model is doing against a set of data in relation to some criteria

E.g. Accuracy, AUC, AIC, BIC, Recall, Precision

Testing

Testing is how we validated that a model is stable not only against data we've seen but also unseen data

E.g. Hold back/test sets, control

Our end goal

An model that correctly reflects the future state of the world to make better decisions about it

Once we have an understanding of the question, evaluation, and testing, we create a benchmark model

Simple model to create and deploy

Almost always a linear regression model with a few features

First 'check' that there exists a model that will fit the problem

Same evaluation as future models

Check that our intuition about the problem is correct as there has to be some outcome

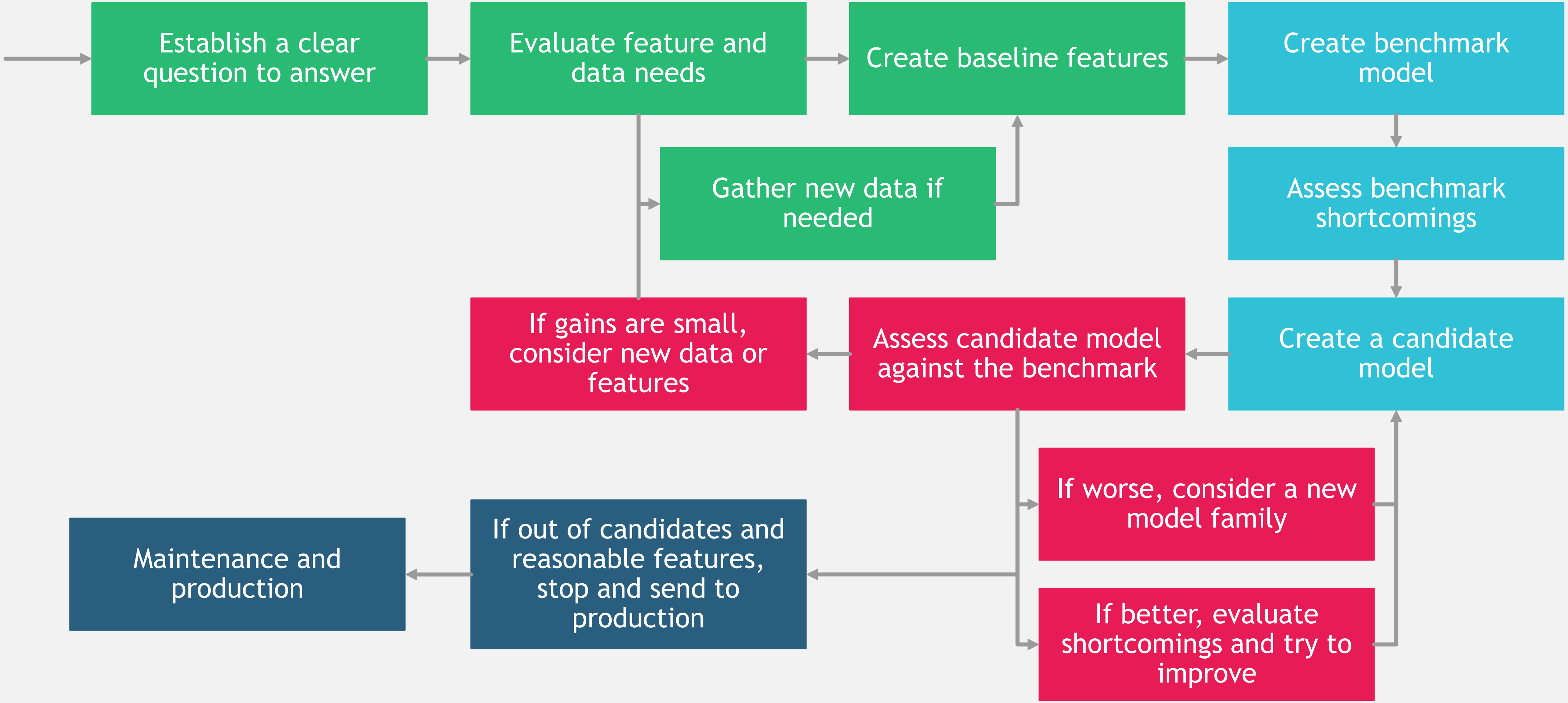
Provides a baseline for all additional steps

Points the way to complex models

Exploratory data analysis gives us idea what the next steps are

Additionally informs us if it's worthwhile to add new features to our model

A holistic process incorporates all elements and is iterative since model performance is not know a priori



“I was gratified to be able to answer promptly, and I did. I said I didn’t know.”

Mark Twain, American Humorist

Quantitative Customer Insights

The goals of customer insights

Understand the fundamental drivers of customer behaviors in making a visit or redeeming an offer

Utilize insights to improve targeting of personalized offers to customers at the individual level

Deliver sustainable value through continuing to adapt our understand and update our offers based on the individual

Recall We launched 3 use cases to influence customer visits and concessions behavior

Use Cases

Frequency Challenge

Flash Offer

Menu Challenge

Experimental Design

Test different offer variants on different treatment/test cells

Freeze all comms to control group

Offer Validation

Test for a statistically significant difference in a key metric between test cells and control group

Outcomes

Many early pilot results are directional but not significant

Requires us to develop a deeper understanding of our customers

Leveraging insights from customer reactions to pilot offers is the critical last step for personalization

1 — Assign offer to customers

- Assign customers to various use case offers based on launch schedule
- Split customers into multiple test cells within each use case that differ based on difficulty, reward type, reward amount
- Products of the offer are personalized to the customer (i.e. movies, concessions)

2 — Measure changes in customers' behaviors

- Analyze changes in customers' behavior based on the offers sent to them
- Measure effectiveness of offers at influencing behavior

3 — Learn customers' preferences and sensitivities to offers

- Readjust offer assignment to customer based on historic propensity to visit or redeem offers
- Offer assignment attributes can be personalized to each customer to maximize for propensity to visit or redeem:
  - Use case
  - Difficulty
  - Reward type
  - Reward amount

Code walkthrough - interlude

We developed models for each use case to study how customer behavior changes in response to an offer

Visits
Propensity Model

Calculate the probability of a customer to make a visit

Redemptions
Propensity Model

Calculate the probability of a customer to redeem an offer

Freq1

Visits Propensity Model estimates customer probabilities to visit

Customers included:
- Treatment A, C, F
- N = 166k

Testing Data	
Accuracy	62%
AUC	61%

Demographic
- Gender is not statistically significant
- Increasing age decreases probability by <1%
- Tenure[1] is not statistically significant

Offer:
- Hurdle is not statistically significant
- Reward is not statistically significant

Past Behavior:
- Higher loyalty tier decreases probability by 76%
- Lower segments (Lapsed, Low, Medium, New) decreases probability by 34/26/19/7%
- Higher # of visits in past 1/3/6 month increases probability by 19/13/16%
- Redeeming points, buying popcorn, using 2x1 increases probability by 16/20/6% [2]
- Higher avg items per visit in past year decreases probability by 2%

1. Tenure = # of months in Club Cinepolis
2. Redeeming points, buying popcorn, or using a 2x1 In last 8 visits

Key takeaways

- Freq1 offers did not change customers' behaviors in making visits
- Recent visit behavior is very informative of visit behavior in the coming month
- Evidence present for burnout effect amongst loyalty program members.
- Reward type past behaviors are more indicative of engagement than customer preference for reward type
- More items purchased per visit is less likely to visit. Consumers make tradeoff between visits and concession spend.
- Running model with only Treatment A and C produces identical results

Flash4

Visits Propensity Model estimates customer probabilities to visit

Customers included:
- Treatment B, F
- N = 139k

Testing Data	
Accuracy	55%
AUC	61%

Demographic
- Gender is not statistically significant
- Increasing age increases probability by <1%
- Tenure is not statistically significant

Offer:
- Hurdle is constant for all customers
- Reward type = 'product' increases probability by 7%

Past Behavior:
- Loyalty tier is not statistically significant
- Lower segments (Lapsed, Low, Medium) decreases probability by 23/25/19% each
- Higher # of visits in past 1/3/6 month increases probability by 14/11/16%
- Redeeming points and buying popcorn increases probability by 15/17%
- Avg items per visit in past year is not statistically significant

Key takeaways

- In aggregate, sending Flash4 did not change visiting behavior. However sending a Flash4 with 'product' as reward type did slightly increase probability
- Past points redemption and popcorn purchasing behavior makes it more likely to visit
- Older customers slightly more likely to visit
- Loyalty tier does not influence probability of visiting when sent a flash offer
- Segment and recent visit behavior are very informative of visit behavior in the coming month
- Running model with only Treatment A and C produces identical results

We developed models for each use case to study how customer behavior changes in response to an offer

Visits
Propensity Model

Calculate the probability of a customer to make a visit

Redemptions
Propensity Model

Calculate the probability of a customer to redeem an offer

Freq1

Redemption Propensity Model estimates customer probabilities to redeem

Customers included:
- Treatment A, C
- N = 152k

Testing Data	
Accuracy	71%
AUC	67%

Demographic
- Gender is not statistically significant
- Increasing age decreases probability by <1%
- Tenure is not statistically significant

Offer:
- Increasing hurdle decreases probability by 64%
- Reward is not statistically significant

Past Behavior:
- Higher loyalty tier decreases probability by 76%
- Lower segments (Lapsed, Low, Medium) decreases probability by 31/25/18%
- Higher # of visits in past 1/3/6 month increases probability by 22/15/15%
- Redeeming points, buying popcorn, using 2x1 increases probability by 17/22/8%
- Higher avg items per visit in past year decreases probability by 3%
- # of tickets purchased in past 1/3/6 month is not statistically significant

Key takeaways

- Higher hurdle made the challenge more difficult and less likely to be completed
- # of tickets bought in past has no influence on probability to redeem an offer
- Similar results to Visits Propensity Model

Flash4

Redemption Propensity Model estimates customer probabilities to redeem

Customers included:
- Treatment B
- N = 125k

Testing Data	
Accuracy	55%
AUC	61%

Demographic
- Gender is not statistically significant
- Increasing age increases probability by 2%
- Tenure is not statistically significant

Offer:
- Hurdle is constant for all customers
- Reward type = 'product' increases probability by 10%

Past Behavior:
- Loyalty tier is not statistically significant
- Lower segments (Lapsed, Low, Medium) decreases probability by 20/25/21% each
- Higher # of visits in past 1/3/6 month increases probability by 19/8/16%
- Redeeming points and buying popcorn increases probability by 17/18%
- Avg items per visit in past year is not statistically significant
- Higher # of tickets purchased in past 1 month decreases probability by 4%

Key takeaways

- Higher # of tickets purchased in past month means less likely to redeem Flash offer
  - Inverse relationship between avg # of tickets purchased per visit and # of visits
- Similar results to Visits Propensity Model

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Key questions to ask

- How is our data being managed/what is our process for data governance?
- How will we develop the data management practices?
- What will our data engineers be working on in the near term?
- How do we have access to a system which this work can be done and what are those systems?