American Airlines

A Social Media Driven Marketing Strategy

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Agenda

- Industry Background
- Market Segmentation
    - K-Means
    - Overview of the Different Clusters
- Perceptual Map
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    - Topic Modeling with LDA
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    - Perceptual Map Discussion
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    - Promotion Mix Optimization
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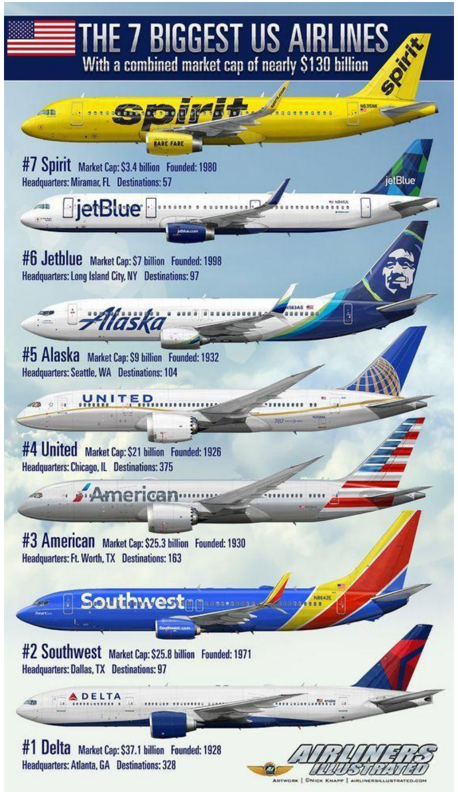
Industry Background

- In 2018, US carriers net profits amounted to 16 billion dollars
- Ultra Low cost carriers such as Spirit and Frontier have gained strong market share, growing capacity at an average rate of 15% per year
- Both Delta and American have revamped their loyalty programs to capture high yielding corporate clients and frequent flyers
- American Advertising Budget continues to increase. $128 m in 2018 vs. $ 27.8 m in 2014
- Low cost carriers such as Southwest and JetBlue have begun adding flights to high yield routes such as Hawaii
- US carriers have increased on time departures, on average, from 65% to 77% YOY



Market Segmentation

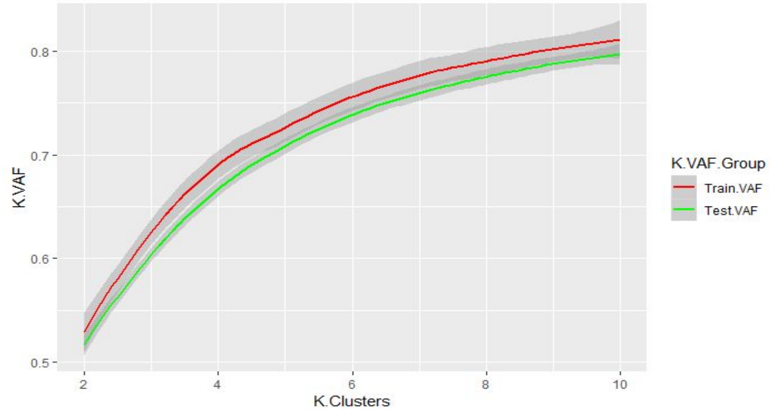
Market Segmentation Data

- Source: SkyTrax 2018 Data Set
- Data contains 3,111 reviews by unique individuals for all major US Carriers
- 5 independent parameters used to determine output variable

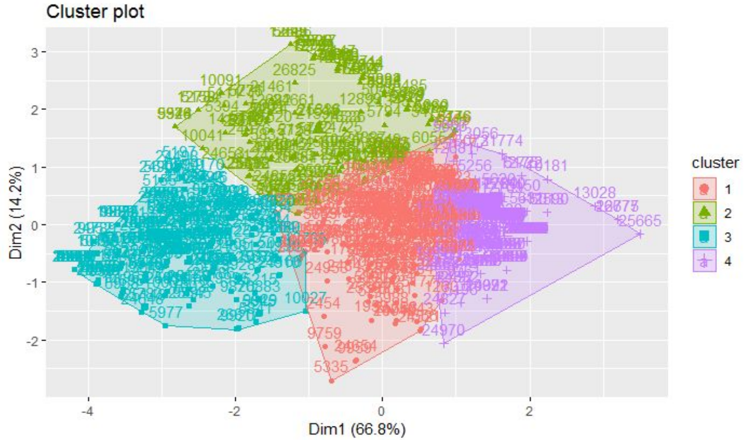
Parameters	Scale
Seat Comfort Rating	1-5
Cabin Staff Rating	1-5
Food & Beverages Rating	1-5
Inflight Entertainment Rating	1-5
Value Money Rating	1-5
Overall Rating	1-10

K-Means & PCA

- Elbow method recommends 4 clusters
- Present clusters of PCA components



Importance of Components		
	Comp. 1	Comp. 2
Proportion of Variance	67%	14%
Cumulative Proportion	67%	81%



Loadings		
	Comp. 1	Comp. 2
Seat Comfort Rating	0.45	0.18
Cabin Staff Rating	0.47	0.4
Food & Beverages Rating	0.41	-0.37
Inflight Entertainment Rating	0.38	-0.75
Value Money Rating	0.51	0.33

Linear Mixed Models

	Cluster 1	Cluster 2
Parameter Coefficients	(see table below)	(see table below)
Demographics	• Age: 23-30 • On average, salaries range from 60k to 100k	• Age: 18-25 • One Time Travellers
Desires & Needs	• Looking to get to their destination at a reasonable price. • Willing to pay more to fly with a more reliable and reputable carrier	• Looking to get to their destination at the lowest possible cost
Primary Airline(s)	jetBlue	spirit™ LESS MONEY. MORE GO.

Cluster 1

Parameter	Coefficient	Sig
Seat Comfort Rating	0.4	***
Cabin Staff Rating	0.5	***
Value Money Rating	0.87	***

Cluster 2

Parameter	Coefficient	Sig
Seat Comfort Rating	0.1	***
Cabin Staff Rating	0.2	***
Value Money Rating	0.6	***

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Linear Mixed Models

	Cluster 3	Cluster 4
Parameter Coefficients	Parameter / Coefficient / Sig: Seat Comfort Rating 0.7 ***; Cabin Staff Rating 1.1 ***; Value Money Rating 1.6 ***	Parameter / Coefficient / Sig: Cabin Staff Rating 0.7 ***; Value Money Rating 0.7 ***
Demographics	• Are sensitive to price changes, but they are looking for premier experiences	• Individuals are less sensitive to pricier tickets in exchange to fly with their favored carriers
Desires & Needs	• Expect the carrier to resolve issues in a respectful and efficient manner	• Looking to commit to a certain carrier who has strong connectivity domestically and internationally • Will probably stay with said carrier for an extended period of time
Primary Airline(s)	Southwest	DELTA

Cluster 3

Parameter	Coefficient	Sig
Seat Comfort Rating	0.7	***
Cabin Staff Rating	1.1	***
Value Money Rating	1.6	***

Cluster 4

Parameter	Coefficient	Sig
Cabin Staff Rating	0.7	***
Value Money Rating	0.7	***

Perceptual Map

Twitter US Airline Sentiment Data

- 14,640 Tweets Scraped in February 2015 from Travelers
- Breakdown of Tweets by Airline

Airlines	Number of Tweets
United	3,822
US Airways	2,913
American	2,759
Southwest	2,420
Delta	2,222
Virgin America*	504

* *Due to limited data, Virgin America Tweets were not used in the analysis.*

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Perceptual Map Process

1. Cleaning all the tweets in the dataset
2. Using Topic Modeling (Latent Dirichlet Allocation) to figure out what are some of the overarching topics (product attributes) discussed in the tweets
3. Once the topics are identified, using keywords to find the tweets for each topic
4. Performing sentiment analysis on all the tweets
5. Calculating the percent of positive, negative, and neutral tweets for each product attribute identified to get product attribute scores for each airline
6. Applying multidimensional scaling to generate the perceptual map from the product attribute scores

Cleaning the Tweets

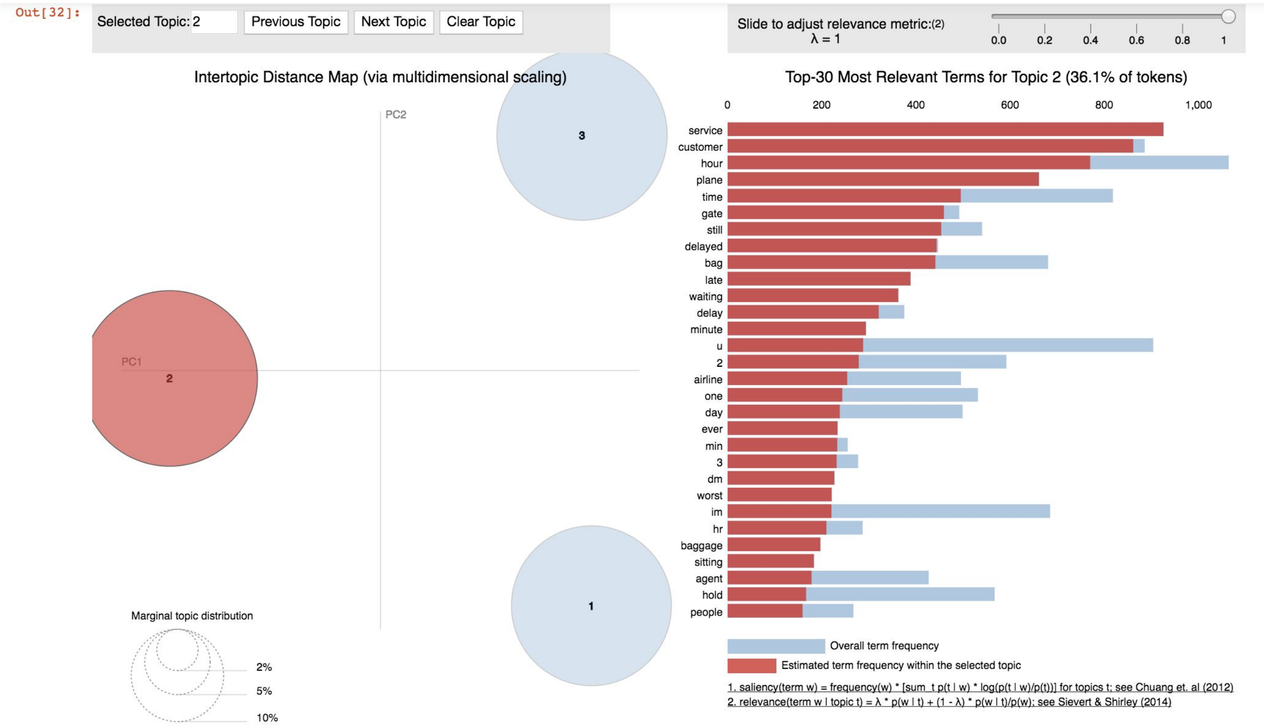
text	text_clean
@AmericanAir Flight 236 was great. Fantastic c...	americanair flight 236 was great. fantastic ca...
@AmericanAir Flight 953 NYC-Buenos Aires has b...	americanair flight 953 nycbuenos aires has bee...
@AmericanAir Flight Cancelled Flightled, can't...	americanair flight cancelled flightled, cant g...
Thank you. “@AmericanAir: @jlhalldc Customer R...	thank you. americanair: jlhalldc customer rela...
@AmericanAir How do I change my flight if the ...	americanair how do i change my flight if the p...
@AmericanAir Thanks! He is.	americanair thanks he is.
@AmericanAir thx for nothing on getting us out...	americanair thx for nothing on getting us out ...
“@AmericanAir: @TilleyMonsta George, that does...	americanair: tilleymonsta george, that doesnt ...
@AmericanAir my flight was Cancelled Flightled...	americanair my flight was cancelled flightled,...
@AmericanAir right on cue with the delays👌	americanair right on cue with the delays
@AmericanAir thank you we got on a different f...	americanair thank you we got on a different fl...
@AmericanAir leaving over 20 minutes Late Flig...	americanair leaving over 20 minutes late fligh...
@AmericanAir Please bring American Airlines to...	americanair please bring american airlines to ...
@AmericanAir you have my money, you change my ...	americanair you have my money, you change my f...
@AmericanAir we have 8 ppl so we need 2 know h...	americanair we have 8 ppl so we need 2 know ho...

Steps:

- removing all special characters (@, emojis, etc.)
- lowercase only

Topic Modeling using LDA

First Potential Topic Identified: Customer Service



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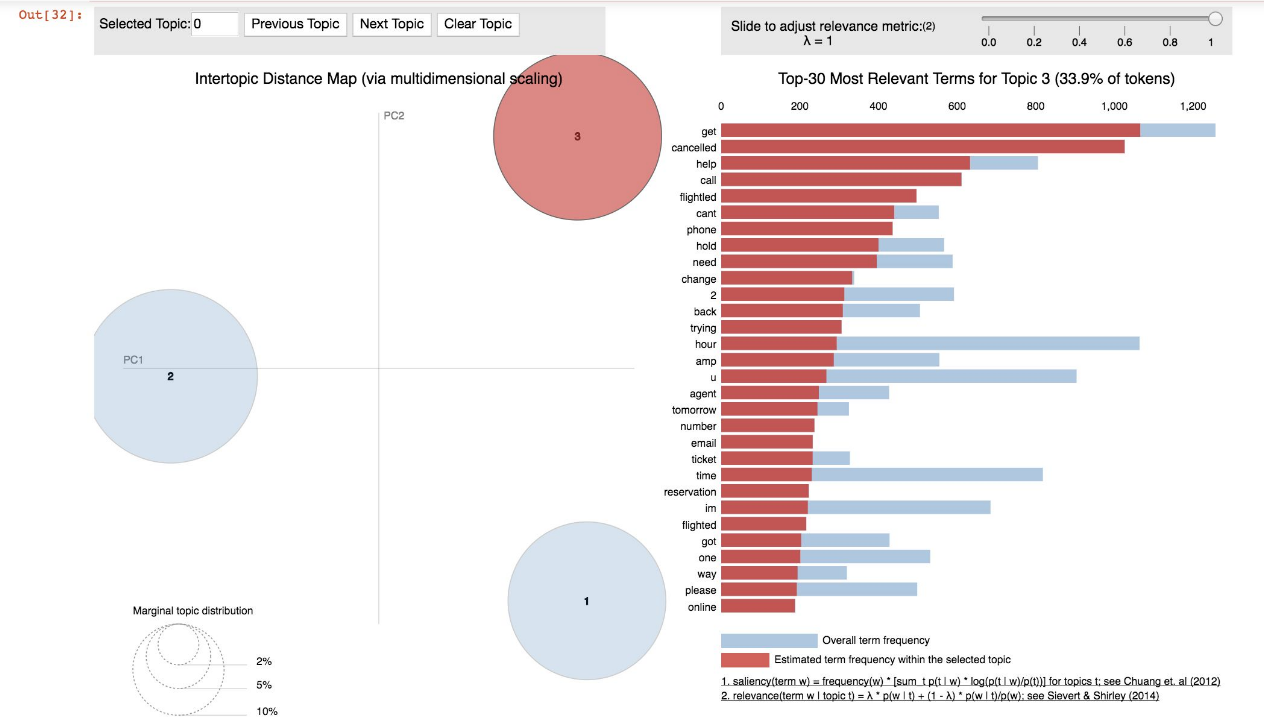
Topic Modeling using LDA

Second Potential Topic Identified: Flight Cancellations, Delays, etc.



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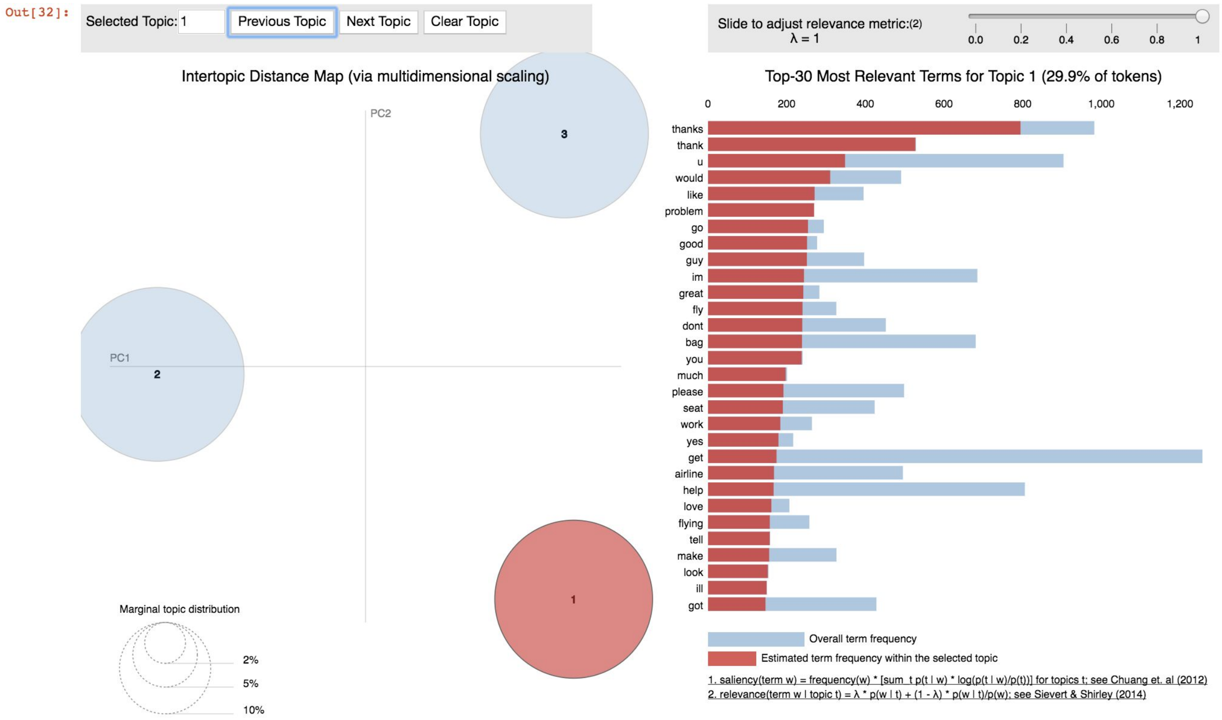
Topic Modeling using LDA

Third Potential Topic Identified: Overall Service (Luggage Issues, InFlight Experience, etc.)



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Getting the tweets for each identified product attribute (topic)

Customer Service		Cancellations and Delays		Overall Service (Luggage and Inflight Service)	
service customer hold call chone CS agent help response email message communication	cancel delay seat airplane luggage bag http	cancel,next, late, delay, wait, hour, 2, due, hr weather, degree, issue, rebook, fix, connection, stuck, day, yesterday, reschedule, tomorrow, today, miss,early, arrive, jfk, sfo, ewr, lax, ord, lga, day, problem, minute, min, time	service customer hold call phone CS agent help response email message communication luggage bag food http	lost, luggage, bag, baggage, wifi, leg, seat, device, movie, entertainment, recline, food, aircraft, plane, inflight, tv, cabin, broken, meal, space, sitting, coach, economy	customer, call, delay, cancel, time, hold, call, phone, CS, agent, help, response, email, message, communication, weather
Number of Tweets Found - 3,240		Number of Tweets Found - 4,452		Number of Tweets Found - 1,915	

Percent of positive, negative, and neutral tweets for each product attribute

Customer Service

airline	airline_sentiment	tweet_id count
American	negative	0.824134
	neutral	0.093710
	positive	0.082157
Delta	negative	0.577320
	neutral	0.175258
	positive	0.247423
Southwest	negative	0.645022
	neutral	0.158009
	positive	0.196970
US Airways	negative	0.835443
	neutral	0.084005
	positive	0.080552
United	negative	0.714472
	neutral	0.143416
	positive	0.142112

Cancellations and Delays

airline	airline_sentiment	tweet_id count
American	negative	0.741401
	neutral	0.160510
	positive	0.098089
Delta	negative	0.585219
	neutral	0.220211
	positive	0.194570
Southwest	negative	0.525180
	neutral	0.280576
	positive	0.194245
US Airways	negative	0.834081
	neutral	0.106502
	positive	0.059417
United	negative	0.759812
	neutral	0.160911
	positive	0.079278

Overall Service
(Luggage and Inflight Service)

airline	airline_sentiment	tweet_id count
American	negative	0.786624
	neutral	0.127389
	positive	0.085987
Delta	negative	0.568702
	neutral	0.244275
	positive	0.187023
Southwest	negative	0.729508
	neutral	0.151639
	positive	0.118852
US Airways	negative	0.862162
	neutral	0.091892
	positive	0.045946
United	negative	0.799392
	neutral	0.124620
	positive	0.075988

Product Attribute Scores for Each Airline

Formula Used: $score = 1 - \sum {p_i}^2$

	Customer Service	Cancellations + Delays	Overall Service
American	3.05	4.15	3.58
Delta	5.75	5.71	5.82
Southwest	5.20	6.08	4.31
US Airways	2.88	2.89	2.46
United	4.49	3.91	3.40

Perceptual Map

Strategy Insights

Promotion Mix Optimization:

- **Problem Statement:** given a promotion budget, optimize budget allocation for each attribute
- **Assumptions:**
  - Attributes with lower scores will be allocated greater amounts of a promotional budget
  - Attribute scores are collected for one month and are extrapolated across the remaining months
  - American Airlines total marketing spending in 2014 ($27.8 m) is used as promotional budget for the given 3 attributes
  - Monthly and Attribute Maximum and Minimum budgets are set as constraints

Promotion Mix Optimization: LP Model

- Sets:
  - i : Attribute { 1 : Cust_Serv, 2 : Canc_Del, 3 : Overall }
  - t : Month { 1,….,12 }
- Decision Variables:
  - X_{ti} : Amount of Promotion Budget spent in month t on attribute i
- Parameters:
  - S_{ti} : Score of Attribute i in month t
- Objective function:
  - $\max \sum (10 - S_{it}) \cdot X_{it}$

Promotion Mix Optimization: LP Model cont.

- Upper-Bound Constraints:
  - Total yearly promotion budget cannot be exceeded:
    $$\sum_{i=1}^{n}\sum_{t=1}^{n} x_{it} \leq Total\ yearly\ Promotion\ Budget$$
  - Monthly promotion budget cannot be exceeded:
    $$\sum_{t=1}^{n} x_{t} \leq Monthly\ Promotion\ Budget$$
  - Individual Attribute budget cannot be exceeded:
    $$\sum_{i=1}^{n} x_{i} \leq Attribute\ i\ Max\ Promotional\ Spending$$

- Lower-Bound Constraints:
  - Total yearly promotion is greater than minimum yearly spending:
    $$\sum_{i=1}^{n}\sum_{t=1}^{n} x_{it} \geq Minimum\ yearly\ Promotion\ Spending$$
  - Monthly promotion minimum spending is exceeded:
    $$\sum_{t=1}^{n} x_{t} \geq Monthly\ Promotion\ Minimum\ Spending$$
  - Individual attribute promotion minimum spending is exceeded:
    $$\sum_{i=1}^{n} x_{i} \geq Attribute\ i\ Min\ Promotional\ Spending$$

Promotion Mix Optimization: Solution Approach

- Solved using the simplex algorithm
- Monthly and Attribute Maximum and Minimum budgets are presented

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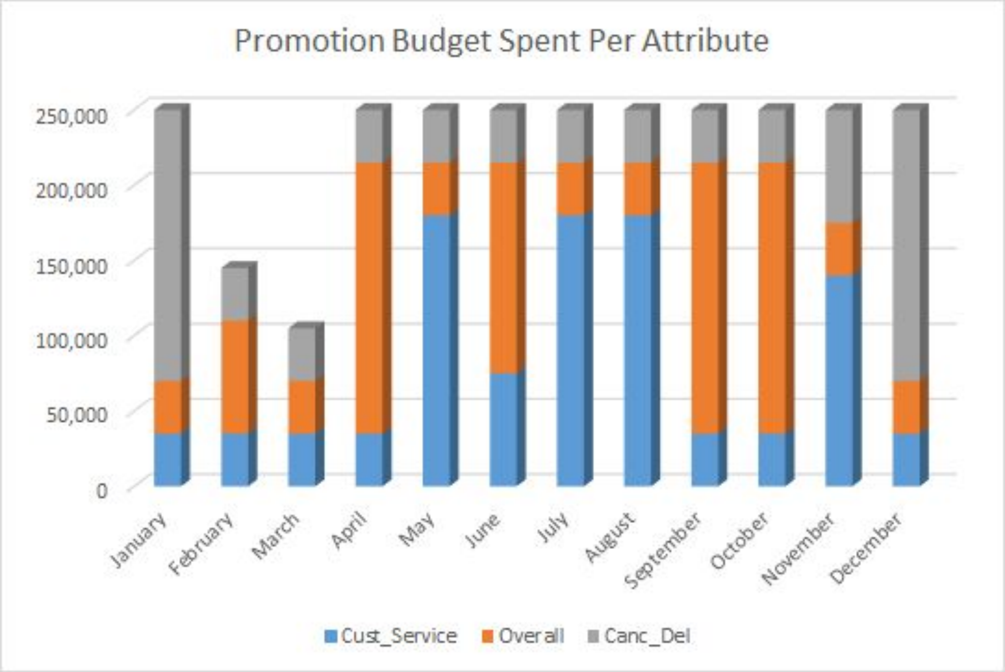
	10-Sit			
Month	Cust_Service	Canc_Del	overall	Objective Function:
1	6.09	7.07	6.42	18534050
2	5.87	6.49	6.29	Total Budget Spent
3	6.27	6.19	6.07	2750000
4	6.77	6.02	6.88	
5	6.95	5.85	6.42	
6	7.03	5.82	6.72	
7	7.53	5.79	7.02	
8	7.7	5.76	7.32	
9	5.07	5.93	6.39	
10	5.79	6.03	6.41	
11	6.95	7.03	6.43	
12	6.77	7.19	6.45	
sum	78.79	75.17	78.82	

	Xit							
Month	Cust_Service	Canc_Del	overall	SUM		Minimum		Maximum
1	35,000	180000	35000	250000	>=	100,000	<=	250,000
2	35000	35000	75000	145000	>=	100,000	<=	250,000
3	35000	35000	35000	105000	>=	100,000	<=	250,000
4	35000	35000	180000	250000	>=	100,000	<=	250,000
5	180000	35000	35000	250000	>=	100,000	<=	250,000
6	75000	35000	140000	250000	>=	100,000	<=	250,000
7	180000	35000	35000	250000	>=	100,000	<=	250,000
8	180000	35000	35000	250000	>=	100,000	<=	250,000
9	35000	35000	180000	250000	>=	100,000	<=	250,000
10	35000	35000	180000	250000	>=	100,000	<=	250,000
11	140000	75000	35000	250000	>=	100,000	<=	250,000
12	35000	180000	35000	250000	>=	100,000	<=	250,000
Sum	1000000	750000	1000000	2750000	>=	19,100,000	<=	27800000
	>=	>=	>=					
Minimum	700,000	700,000	700,000		MINUMUM X	>=	35,000	
	<=	<=	<=					
Maximum	1,000,000	750,000	1,000,000					

Promotion Mix Optimization: Optimized Mix

- **Insights:**
  - Focus Cancellation and Delay themed advertising efforts between October - February
  - Rotate Promotions between Overall theme and Canc_Delay theme March - September



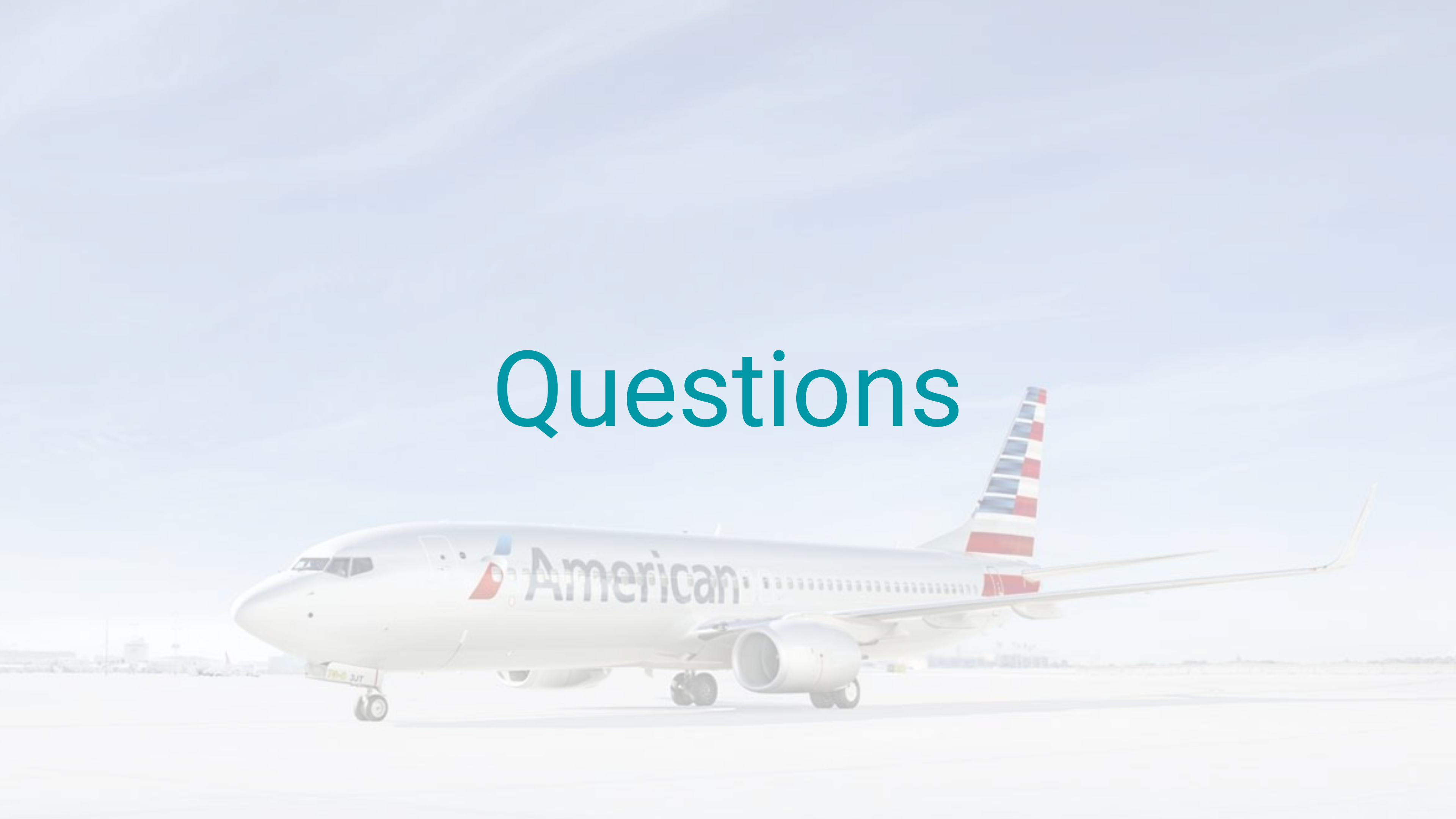
Customer Service Themed Promotion

Customer Service themed promotions like above will be pushed in months recommended by optimization model

Conclusion

01	**Evaluation**	• Limitations in identifying more unique attributes from social media • Budget allocation optimization involved many assumptions
02	**Future Improvements**	• Collect data more frequently • Better understanding of budget related constraints
03	**Key Takeaways**	• Social media perception driven strategies can help guide decision making for American Airlines

Questions



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