Fall | 11

Solving the Efficient Allocation Of Resources Problem in Marketing

CS224W Final Report

[This report puts forward a framework that allows marketers to make effective targeted advertisement at specific users for maximal benefit. The framework was tested on the IMDB database to great success.]

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Introduction

We would like to address the issue of efficient allocation of resources, especially in marketing campaigns. A big concern in marketing is efficiently identifying customers who would reciprocate in kind. By reciprocity, we refer to customers who – when given the right incentives – would review the product or service positively. The effect of positive review is more prominent in this highly connected world where a well-reviewed product tends to generate more consumer attention

In this paper, we propose a methodology for movie marketers to identify individuals who are likely to reciprocate in kind. Doing so would allow the marketing campaign to efficiently allocated their resources to get the maximum benefit out from it. In this context, we take good reciprocity to be the positive rating of a movie on IMDB that could feasibly propagate the name of the movie. Our methodology is built upon a hypothesis which we coined the "Taste Theory". We would first describe the background study that inspired our hypothesis. We will then explain the sociological logic behind the hypothesis before testing it on the IMDB database result. Finally, we will make a modification to the hypothesis before explaining how it can be used to identify potential positive reviewers.

Background

IMDB

IMDB is a sentiment aggregating web application that allows users to rate movies. After reading the ratings and reviews, users might decide to watch the movie if it is highly recommended by the online community. After watching the movie, users may then post their own ratings and reviews on IMDB. Ratings can be given from a scale of up to 5 stars.

In such networks, positive reviews may cascade to more positive reviews and a general positive sentiment is beneficial to drawing a larger audience for the movie. Movie marketers would want to identify users who are likely to give positive reviews and target their marketing efforts (e.g. discounts) at them. On the other hand, identifying users who are likely to give negative reviews and pay special attention (e.g. freebies) when serving these customers can help reduce bad reviews. It is our aim in this paper to develop a methodology to identify these users.

Previous works on Predicting Sign of Edges

We develop our algorithm based on concepts in previous work that analyzes the behavior of triad structures within signed networks – A triad structure is a set of 3 nodes that forms a triangle. Leskovec et al (2010) hypothesize that the sign of edges behave in context and this behavior can be explained by evaluating the connected nodes' relative status in a triad – the status theory; this postulates that, to a certain extent, we are able to predict the sign of an edge in a triad structure.

The hypothesis was tested on Epinion dataset by checking how much the behavior of an edge in a triad deviates from its baseline. Both generative surprise and receptive surprise are computed for the 16 different triads. The surprise is computed by:

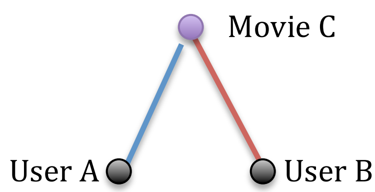
$$s_o(triad) = \frac{k - \sum_{i=1}^{n} p_o(A_i)}{\sqrt{\sum_{i=1}^{n} p_o(A_i)(1 - p_o(A_i))}}$$

Generative surprise is indicative of how much an edge is likely to be positive with respect to the empirical probability of the generating node in having a positive edge in the context of a given triad. While receptive surprise demonstrates the same idea with respect to the empirical probability of the receiving node. They successfully showed that 13 of the triads could be explained using the status theory.

We will be building a similar hypothesis to predict the outcome of a user-to-movie edge given that it exist in a certain form of network structure - which we coined "Butterfly structures". We will analyze the IMDB database using a modified form of surprise, which we will coin as "Shock".

<u>Taste Theory Proposition</u>

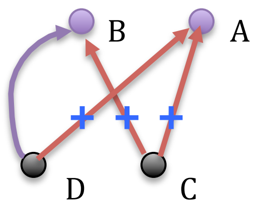
Hypothesis



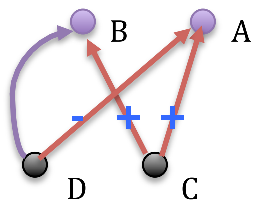
Taste theory uses the sociological idea that the more critical a user is on a common product, the higher his taste. Graphically, we observe that user A has given a positive review to movie C (blue link). User B has given a negative review to movie C (red link). The assumption in this case is that user B has held a higher expectation of C as compared to user A, resulting in him being more critical of the movie in his review. In this theory, we state that user B has a higher taste than user A. The idea is that we can use this to predict the probability that user A will give a positive or negative review on a new movie given that we know his relative taste to another user who has rated the new movie. This brings us to the idea of butterfly structures.

Butterfly Structures

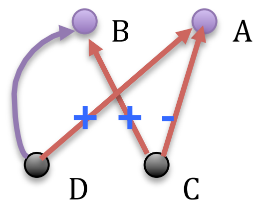
The idea is the following. We are given two movie nodes A, B and two user nodes C, D. User C has given a review respectively to movie A and B. User D has given a review to movie A. We would like to use this context to predict the review that user D will give to movie B. Given that there are 2 possible edges on each of the 3 links, we have a total of 8 possible Butterfly Structures.



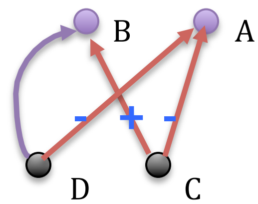
Butterfly 1



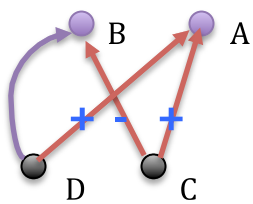
Butterfly 2



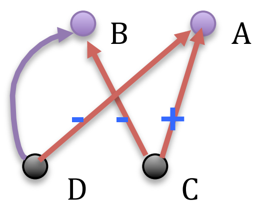
Butterfly 3



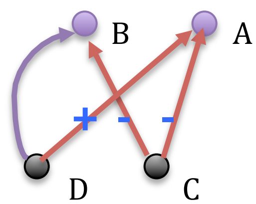
Butterfly 4



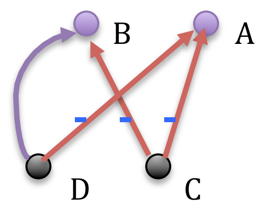
Butterfly 5



Butterfly 6



Butterfly 7



Butterfly 8

Butterfly 1: Expected "+"
Both users have similar tastes as they both offered positive reviews to a common movie A. Thus, user D is expected to follow user C in rating movie B positive.

Butterfly 2: Expected "+/-"
User C has given a positive review to movie A, which was negatively rated by user D. Thus, user D has a higher taste than user C. However as user C has given a positive rating to movie B, it remains ambiguous as user D can rate movie B less positively or negative.

Butterfly 3: Expected "+"
User D has lower taste than user C as he rated less critically than user D on the common movie A. As such, since C has rated B positive, user D would be less critical and would be expected to rate movie B positively.

Butterfly 4: Expected "+"
User C and user D both have common taste as both of them rated common movie A negatively. Thus, user D is expected to follow user C in rating movie B positive.

Butterfly 5: Expected "-"
We observe that both users have rated common movie A positively. By similar tastes, user D should follow user C in rating movie B negative.

Butterfly 6: Expected "-"
User D is has higher taste than user C as he rated more critically than user D on common movie A. Hence, since C has rated B negative, D would be more critical and rate movie B negative.

Butterfly 7: Expected "+/-"
User D has lower taste than user C. However, user C has rated movie B negative. Thus, it remains ambiguous as user D with lower taste is more forgiving and can rate movie B less negatively or positive.

Butterfly 8: Expected "-"
Both user C and D are similarly critical of movie D. By similar taste, user D should be equally critical as user C in rating movie B negative too.

Methodology
Our methodology has 3 main components driven at deriving how to predict users behavior when rating movies.

The initial analysis is to test for occurrence of Butterfly structures and demonstrate that the certain Butterfly structures occur with a higher frequency than others. We will tally this against Taste Theory and check for anomaly. We do not expect this result to be conclusive, as it does not incorporate the inherent biasness that each user possesses in giving positive reviews. In our next step, we want to remove this biasness to demonstrate that users are affected by the structure they exist in when giving positive reviews.

Our next further analysis uses a variation of "surprise" proposed by Leskovec et al (2010) to calculate the propensity of a user to give a positive or negative review after removing his inherent biasness. By inherent biasness we refer to the fact that some users tend to be more generous in giving positive or negative reviews. Our proposed formulae computes the "Shock Ratio", which represents the percentage of users giving positive/negative reviews after removing their inherent biasness to give positive/negative review. This information will be used as a more refined proof of our hypothesis.

We then proceed to investigate the effect of movies by segregating our data into 3 cases: when the movie is ranked higher than the other, when the movie is ranked same as the other, and when the movie is ranked lower than the other. We will attempt to show that this movie effect comes into play for Butterfly structures that has ambiguous states.

Next, we will investigate how certain Butterfly structures contain users that are more critical. We will prove this by calculating user criticalness within each Butterfly structure and comparing it against the average user criticalness.

Our final step is to modify our Taste Theory to include a weak and strong form of the theory. We will explain with all our results how this modified Taste Theory can be used to explain all 8 butterflies. We will finally explain how the Butterfly structures can be used to predict users behavior.

Initial Data Analysis

Results

We counted the number of times each of the 8 Butterfly structures occurs in the network. For each Butterfly structure, we calculate how many times it closes with a positive edge and with that data compute P(+), the probability of the Butterfly closing with a positive edge. We limit the genre of the movie to only Drama so that users are not affected by genre preferences in their reviews.

Here we define a positive review as more than equals to 4 stars. (In the *Appendix* we have included our results for the case when a positive review equals more than or equals to 3 stars and our results for the entire set of IMDB data.) The results shown in the *Appendix* demonstrates similar relative P(+) as our results in *Table 1*. For sake of conciseness, we shall only discuss this set of results.

Genre: Drama	≥4stars considered "+"		Expected	Consistent
BF	Counts	P(+)		
1	33278860	0.7391253	+	✓
2	11745791	0.6195808	±	?
3	11745791	0.8546498	+	✓
4	6606716	0.6390501	+	✓
5	13743395	0.6753474	−	✗
6	3995208	0.5170565	−	✓
7	7211848	0.6590092	±	?
8	3731622	0.5261379	−	✓

Table 1: Results for initial analysis

Discussion

The results show that there is a general generosity amongst users in IMDB database to give positive reviews; the minimum probability of closure with a positive edge, $P(+)$, is 0.51.

Our results also show that Butterfly 1,3,4 demonstrates a higher (>0.63) $P(+)$ while Butterfly 6,8 demonstrates a lower (<0.53) $P(+)$; which is consistent with what our Taste Theory expects.

Butterfly 5, however, demonstrates a much higher (0.67) $P(+)$, which is inconsistent with Taste Theory. At this point, we suspect that this is a result of the overall highly positive reviewers that pushes Butterfly 5's $P(+)$ high. We would expect this to be corrected in our further analysis when we remove inherent user biasness in reviewing.

It is interesting now to note that in Butterfly 2 and 7, cases where Taste Theory is ambiguous about the expected closure, $P(+)$ is quite high (>0.61). However, noting that this could well be a result of the inherent generosity in user reviews, we will not make any conclusion at this point.

Further Data Analysis

Shock Analysis

In the following section, we incorporated the idea of shock in our calculations. The idea of shock should be thought of as the tendency for a user to express a particular opinion beyond what he usually does. In order to do that, we implemented the following algorithm for butterflies k = 1 to 8:

$$Shock\ ratio_k(\#) = \frac{\sum_{i=1}^{n} shock_{i,k}(\#)}{n}$$

$$Shock_{i,k}(\#) = \begin{cases} 1 & if\ tendency_{i,k}(\#) - baseline_i(\#) > \varepsilon \\ 0 & otherwise \end{cases} for\ i = 1\ to\ n$$

where:

$$tendency_{i,k}(\#) = \frac{number\ of\ \#\ reviews\ user\ i\ gave\ out\ in\ butterfly\ k}{total\ number\ of\ reviews\ user\ i\ gave\ out\ in\ butterfly\ k}$$

$$baseline_i(\#) = \frac{total\ number\ of\ \#\ reviews\ user\ i\ gave\ out\ in\ all\ butterfly\ situations}{total\ number\ of\ reviews\ user\ i\ gave\ out\ in\ all\ butterfly\ situations}$$

$$\# = \begin{cases} + for\ calculation\ of\ positive\ shock \\ - for\ calculation\ of\ negative\ shock \end{cases}$$

Results

We did calculation for both positive shock (# = +ve) and negative shock (# = -ve). The idea is to analyze whether people tend to review positive or negative for any of the butterflies. The table below summarizes our findings for the database.

Butterfly	Positive Shock	Negative Shock	Closure	Expected	Consistent
1	0.57794	0.19618	+	+	✓
2	0.84942	0.038176	++	±	?
3	0.62248	0.19088	+	+	✓
4	0.84517	0.043478	++	+	✓
5	0.077413	0.82397	−−	−	✓
6	0.25239	0.63097	−	−	✓
7	0.078473	0.82715	−−	±	?
8	0.25027	0.61824	−	−	✓

Table 2: Results with the inclusion of shock

This represented a very interesting result for analysis for various reasons. For one, there is a greater difference in the numbers we get in *Table 2* as compared to *Table 1*, making the distinction clearer in terms of whether the butterfly should expect a higher positive closure or negative closure.

Next, we observed that this is in fact consistent with 6 out of 8 of our proposed butterfly structures. In the 2 ambiguous states, we make the following observations: for butterfly 2, we observe that there is a tendency to give positive reviews while for butterfly 7, we observe a tendency to give negative reviews. We believe that in these ambiguous state when Taste Theory has little effect, the natural ranking of the movies has a huge influence on how people rank. In our next analysis we will investigate the effect of this.

Movie Effect

To investigate the effect of the natural ranking of movies on reviews, we first rank the movies according to the ratio of positive reviews that the movie has obtained, and split the movies into 2 different bins. A movie with a higher ratio of positive reviews is naturally better received and ranks higher. We then run the Shock analysis on data from each of these 2 bins.

Bin 1 (A<B)	Movie A has a smaller proportion of positive reviews as compared to new movie B. A<B by 0.05
Bin 2 (A>B)	Movie A has a larger proportion of positive reviews as compared to new movie B. A>B by 0.05.

Table 3: Definition of the 2 bins we will be using for our calculations

Results

The following results were generated:

Butterfly	Bin 1 (A<B)		Bin 2 (A>B)		Total Data	
	Positive Shock	Negative Shock	Positive Shock	Negative Shock	Positive Shock	Negative Shock
1	0.78791	0.15695	0.13998	0.75822	0.57794	0.19618
2	0.83563	0.12619	0.24496	0.70201	0.84942	0.038176
3	0.77094	0.16543	0.12407	0.79958	0.62248	0.19088
4	0.82078	0.12831	0.24708	0.70626	0.84517	0.043478
5	0.71686	0.19724	0.11241	0.83139	0.077413	0.82397
6	0.79958	0.13574	0.193	0.76776	0.25239	0.63097
7	0.69671	0.193	0.11453	0.82821	0.078473	0.82715
8	0.65429	0.19618	0.19406	0.76776	0.25027	0.61824

Table 4: Results inclusive of shock and segregation into bins

On the first cut, these numbers in *Table 4* highly support the fact that the relative strength of the movie has a clear effect on the way the users rate the movies. For cases where A < B, (recall B is the new movie to be rated) there is a significantly higher positive shock for all users. Similarly in the other case where movie A is better than the new movie B, we see a significantly higher negative shock for all users. The effect of the relative ranking of the movie is thus apparent and we will call this the movie effect.

From *Table 4*, we can easily see the movie effect on the results of butterfly 2 and 7. Recall that butterflies 2 and 7 were predetermined to be the ambiguous butterflies.

Thus, it becomes understandable that the shock of the full data will be highly influenced by the movie effect. For the case of butterfly 2, we observe that the value of positive shock of Bin 1 (0.83563) dominated the positive shock of butterfly 2. Similarly in the case of butterfly 7, the dominating effect of negative shock in Bin 2 (0.82821) resulted in the extremely low positive shock that we see in this butterfly.

In fact, the surprising thing is that the remaining result from the other butterflies in the total data column seems to be independent of the effect of the ranking of the movies. This highly supports the butterfly theory, implying in a way that the taste theory dominates over the movie effect except in the ambiguous butterfly structures. The butterfly theory seemed to have an aggregating effect over all the possible cases of movies and returns a result that is independent of the ranking of the movies.

Criticality Effect and Weak Taste Theory

We now want to seek to understand the differences in degree of shock that each butterfly obtained. We believe that the users in butterfly demonstrate different levels of criticality and this results in the different degrees of shock in our results.

In order to prove our belief, we calculate the inherent criticality of individual users that the taste theory hypothesized. We first do a quick check on the average positive baseline for all users. The positive baseline of a user would be the $baseline_i(+)$ of user i, ie the proportion of positive reviews user i gives. We then plotted a histogram.

Results

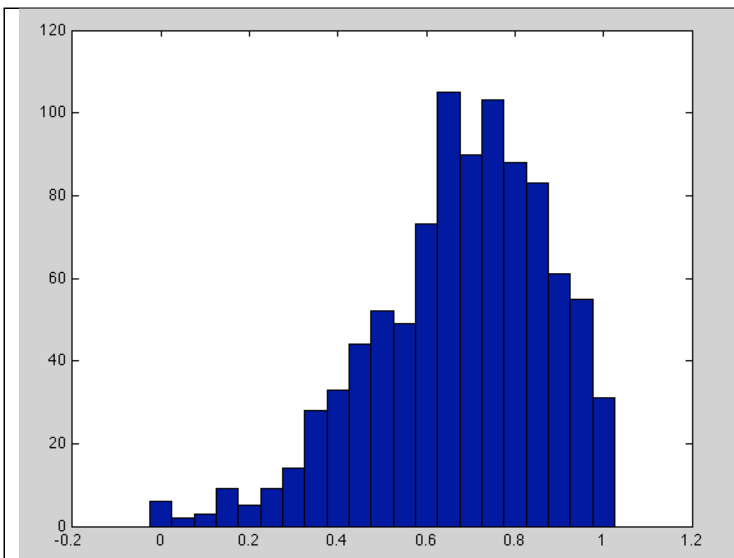


Figure 5: plot of histogram of baseline positive reviews of all users (943 users). Average = 0.6742

We thus showed the tendency of the people in this database to generally provide positive reviews with an average of 0.6742. We want to proof that the butterfly acts as a natural selection to splice out users with different baseline positive reviews. This could potentially help us understand the various fluctuations we observed in the calculations of the shock. We proceed as follows.

For butterfly k = 1 to 8

$$Criticality\ of\ user\ D_k = \frac{\sum_{i=1}^{n} Participation_i \times baseline_i(+)}{\sum_{i=1}^{n} Participation_i}$$

where

$$baseline_i(\#) = \frac{total\ number\ of\ \#\ reviews\ user\ i\ gave\ out\ in\ all\ butterfly\ situations}{total\ number\ of\ reviews\ user\ i\ gave\ out\ in\ all\ butterfly\ situations}$$

$$Participation_i = Total\ number\ of\ times\ user\ i\ participates\ in\ butterfly\ k$$

The above formula is a weighted sum of participating user's $baseline_i(\#)$ weighted by the proportion of user i's participation. It provides us the baseline criticality of the user D in any butterfly k. Its interpretation would be the inherent baseline tendency of user D to give out a positive review in butterfly k. The higher this value, the less critical the user D would be as he gives out more positive review than average. We obtained interesting results as follows:

Butterfly	Criticality/Butterfly Baseline	Criticality-Average
1	0.7106	+ve (less critical)
2	0.5866	-ve (more critical)
3	0.715	+ve (less critical)
4	0.59611	-ve (more critical)
5	0.70388	+ve (less critical)
6	0.57687	-ve (more critical)
7	0.70868	+ve (less critical)
8	0.58601	-ve (more critical)

Table 6: Analysis of the criticality of the user D in the butterfly structures

We then classify the criticality of user D by asking a comparison of the criticality with the average baseline of 0.6742. It is thus interesting that we see a split in that users who are more critical tend to be found in butterflies 2,4,6 and 8, and the users who are less critical are found in butterflies 1,3,5 and 7. In fact, this is perfectly in agreement with the taste theory, which hypothesized that users who give out negative reviews are generally more critical than those who gave out positive reviews.

At this point, it is important to understand how criticality affects shock and the social meaning behind that. From the formula for shock, if a butterfly contains users with higher criticality (butterfly 2,4,6,8), users in that butterfly is likely to have a higher $baseline_i(\#)$ value, thus it becomes harder to obtain positive shock. In the same vein, if a butterfly contains users with lower criticality (butterfly 1,3,5,7), it becomes harder to obtain negative shock. The social meaning is that we are less shocked when a generous (less critical) user gives out positive reviews or negative reviews.

Weak form of Taste Theory

From our observation above, we arrive at the weak form of Taste Theory. The theory states that within the context of Butterfly structures, we can tell user D's critically based on his rating of Movie A, independent of user C.

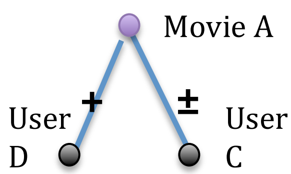
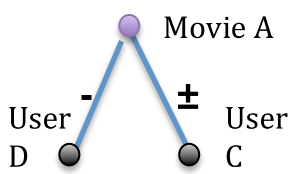
Structure	Weak Taste Theory	Found in Butterfly
	User D is less critical (independent of User C)	1,3,5,7
	User D is more critical (independent of User C)	2,4,6,8

Table 7: Definition of the weak form of taste theory

Note here that we can only tell how critical user D is, but not able to predict the outcome of his review on Movie B. We will see next that the Weak form of Taste Theory, when coupled with the Strong form of Taste Theory, can explain why certain Butterfly structures shows a higher degree of positive/negative shock

Strong form of Taste Theory

We now propose a small modification to the original proposed taste theory to give the Strong form of Taste Theory:

- ❖ Butterfly structure predicts the closure of user D with new movie B, purely based on his relative taste to user C, (explained in original Taste Theory), independent of the relative ranking of movie A and B.
- ❖ Strong form of Theory precludes Butterfly structure 2 and 7, which are affected by the relative rank of the movies.

Combined Taste Theory

We will now show how our results obtained can be explained by both the Weak and the Strong form of the taste theory. We juxtapose our results for criticality and shock to get the following table. The detailed full analysis of each butterfly will then follow:

Butterfly	Criticality/Butterfly Baseline	Weak Theory	Total Data			Strong Theory
			Positive Shock	Negative Shock	Net Shock	
1	0.7106 (less critical)	✓	0.57794	0.19618	+	✓
2	0.5866 (more critical)	✓	0.84942	0.038176	++	*Mov.Eff*
3	0.715 (less critical)	✓	0.62248	0.19088	+	✓
4	0.59611 (more critical)	✓	0.84517	0.043478	++	✓
5	0.70388 (less critical)	✓	0.077413	0.82397	−−	✓
6	0.57687 (more critical)	✓	0.25239	0.63097	−	✓
7	0.70868 (less critical)	✓	0.078473	0.82715	−−	*Mov.Eff*
8	0.58601 (more critical)	✓	0.25027	0.61824	−	✓

Table 8: Combined results

<u>Butterfly 1</u>
Butterfly 1 naturally attracts users who less critical, in agreement with the weak taste theory. This immediately leads to a smaller chance of positive shock. The fact that we still obtained a healthy positive shock of 0.58 (~200% higher than butterflies 5 and 7) meant that the butterfly structure does further boost the tendency that generous users in such butterflies will be even more generous. Note this result is based on total data, independent of the relative rank of movies A and B, and is thus in agreement with the strong taste theory.

<u>Butterfly 2</u>
Butterfly 2 attracts users who are more critical, as predicted by the weak taste theory. Since critical users are in this butterfly, it will become easier to collect positive shock. The butterfly theory labels this as an ambiguous butterfly, just like that of butterfly 7. We thus need to look into other factors to explain the result.
As observed from the previous table, the situational butterfly A < B dominated the result. This is understandable too, since the user is already more critical, the fact that the new movie B is better, the movie effect easily overcomes his low $baseline_i(+)$ to result in high positive shock.
Thus while strong taste theory failed, the movie effect and the weak taste theory helped to explain the result obtained.

<u>Butterfly 3</u>
Butterfly 3 attracts less critical users, as predicted by the weak taste theory. However, despite the greater difficulty in obtaining good positive shock, we managed to obtain a significant positive shock of 0.62. This proved the existence of the strong taste theory governing the butterfly.
In fact for this butterfly, we notice that that the case of A > B does not make sense from the way user C has reviewed movies A and B. This means that there will naturally be more cases of A < B, which will also help in generating more positive

shock. This provides a natural boost for this butterfly to generate more positive shock.

Butterfly 4

Butterfly 4 tends to attract highly critical users, in agreement with the weak taste theory. The strong taste theory predicts that this butterfly should influence a greater closure of positive reviews, and this is what was observed. The fact that this butterfly closed with a higher positive shock than butterflies 1 and 2 once again shows the combination of both the weak and strong theory at work. The positive prediction closure by the strong theory was boosted further by the fact that we expect more critical users (ie users with low $baseline_i(+)$) in this butterfly. Thus we obtained an even greater positive shock.

In the same manner as butterfly 3, we can see that that the case of A > B does not make sense from the way user C has reviewed movies A and B. This also means that there will be more cases of A < B, which will also help in generating more positive shock. This provides a natural boost for this butterfly to generate more positive shock.

Butterfly 5

Butterfly 5 tends to attract non-critical users, as predicted by weak taste theory. The strong taste theory predicts a closure with negative for this butterfly structure, and this is supported by the data obtained. The high negative shock induced by this butterfly can be explained by a combination of the weak and the strong taste theory. The negative closure influence of the butterfly structure is easily achieved given generous users in this butterfly structure with high $baseline_i(+)$.

In addition for this butterfly, we can observe that that the case of A < B does not make sense from the way user C has reviewed movies A and B. This means that there will be more cases of A > B, which will also help in generating more negative shock. This provides a natural boost for this butterfly to generate more negative shock.

Butterfly 6

Butterfly 6 attracts more critical users, as predicted by the weak taste theory. The high level of negative shock obtained is in conjunction with the prediction by the strong taste theory. However, this level of negative shock is lower than that of butterfly 5 simply because this butterfly already attracts critical users to begin with. Like in butterfly 5, we notice that that the case of A < B does not make sense from the way user C has reviewed movies A and B. This then also means that there will be more cases of A > B, which will also help in generating more negative shock. This provides a natural boost for this butterfly to generate more negative shock.

Butterfly 7

Butterfly 7 attracts non-critical users, and this is supported by the weak taste theory. The butterfly theory labels this as an ambiguous state, just like butterfly 2. We thus need to look into other factors to explain the result.

We observe that the event B > A dominated the result of this butterfly. When the new movie is generally lousier than the old movie, there is a high probability for the user to give a poor review, leading to accumulation of negative shock in this situation. The inherent low $baseline_i(-)$ of users in this butterfly further helped amplify the accumulation of negative shock.Thus, the movie effect combined with the weak taste theory helped to explain the result of this butterfly.

Butterfly 8

Butterfly 8 attracts more critical users, as predicted by the weak taste theory. This implies that it is more difficult to obtain negative shock for this. Despite that, we observed a relatively high negative shock obtained (~200% higher than butterfly 1 and 3). This lends support to the strong butterfly theory.

Summary

Butterfly	Weak Taste Theory	Strong Taste Theory	Comments
1	✓	✓	
2	✓		Explained by movie effect
3	✓	✓	Helped by natural movie effect
4	✓	✓	Helped by natural movie effect
5	✓	✓	Helped by natural movie effect
6	✓	✓	Helped by natural movie effect
7	✓		Explained by movie effect
8	✓	✓	

Table 9: Summary of the adherence to the taste theory for the different butterflies

From our hypothesis and experimental results, we make the following claim:

Butterfly	Prediction	Comments
1	Positive review closure	Generally draws users who are less critical.
2	-	Generally draws users who are more critical.
3	Positive review closure	Generally draws users who are less critical.
4	Positive review closure	Generally draws users who are more critical.
5	Negative review closure	Generally draws users who are less critical.
6	Negative review closure	Generally draws users who are more critical.
7	-	Generally draws users who are less critical.
8	Negative review closure	Generally draws users who are more critical.

Table 10: Summary of prediction of each butterfly

The result obtained presents itself as a powerful framework for prediction of user behavior. This is especially so because the strong form of the taste theory shows that the prediction is highly independent of relative ranking of the two movies. This allows a new movie to easily reach out to the desired user D's who exist in butterfly structures 1,3 and 4 to obtain a higher chance of getting a good review.

Further Work

We would like to run our algorithms on other user-to-business databases such as Yelp.com and TripAdvisor.com to test if our hypothesis still holds in these databases.

Further work can also look into the actual predictive algorithm that can be use to predict the outcome of any user-to-business node. As each user-to-business node can exists in several butterfly structures - some predicting the outcome positive while others negative - we do not know the extent of the influence of each butterfly on the final outcome. We would propose using a weighted sum of predicted outcomes as follows, for user-business-edge i:

$$outcome_i = \sum_{B=1,2,3,4} w_B * n_{i,B} * prediction_{i,B} + \sum_{B=5,6,7,8} w_B * n_{i,B} * prediction_{i,B}$$

where:
B = Butterfly number
w_B= Weight attached to each Butterfly structure
$n_{i,B}$= Ratio of Butterfly B in user-business-edge i

$$prediction_{i,B} = \begin{cases} +1 \ if \ Butterfly \ B \ predicts \ positive \ closure \\ -1 \ if \ Butterfly \ B \ predicts \ negative \ closure \end{cases}$$

Research can then go into using machine learning performed on known datasets to train the weights to give better prediction power.

Conclusion

In this report, we have developed a powerful methodology in our Taste Theory to help marketers address the issue of efficient resource allocation. By adopting our framework, any marketing team can simply map out the user base and focus their resources in reaching out to users who are highly likely to give positive reviews. Doing so would help boost the effectiveness of their marketing campaign and improve the review ranking of their movies. It is also feasible that this framework can be extended to other similar review based datasets such as Yelp for adoption by businesses to experience the same benefits.

References

[1] *Signed Network In Social Media*, Leskovec, Huttenlocher & Jon Kleinberg, in CHI 2010 28th ACM Conference on Human Factors in Computing Systems, 11 Mar 2010

Appendix

Entire Data	≥3stars considered "+"		≥4stars considered "+"		Consistent
BF	Count "+"	P(+)	Count "+"	P(+)	
1	524247144	0.8899755	162282364	0.7003631	✓
2	64810775	0.7954218	69429380	0.5795190	
3	64810775	0.9421705	69429380	0.8301011	✓
4	16484244	0.8161255	53168636	0.6057307	✓
5	68788792	0.8066886	83639667	0.6113639	
6	7956034	0.6817532	28420574	0.4509201	✓
7	16668982	0.8177920	50375784	0.5927736	✓
8	3713928	0.6952884	34607381	0.4649024	✓

Genre: Drama	≥3stars considered "+"		≥4stars considered "+"		Consistent
BF	Count "+"	P(+)	Counts	P(+)	
1	90287112	0.9131680	33278860	0.7391253	✓
2	8585283	0.8203088	11745791	0.6195808	
3	8585283	0.9538344	11745791	0.8546498	✓
4	1446720	0.8356133	6606716	0.6390501	✓
5	9000810	0.8615251	13743395	0.6753474	
6	831054	0.7448983	3995208	0.5170565	✓
7	1880632	0.8685563	7211848	0.6590092	✓
8	284607	0.7528588	3731622	0.5261379	✓