Using Response Surface Methodology(RSM) to Find the Optimal Solution in Netflix Case

Author: Minyu Zhang

Executive Summary

Problem:

Netflix is the experiment subject. This experiment will optimize the homepage of Netflix by way of minimizing browsing time. There are infinitely many things that likely influence the amount of time someone spends browsing Netflix, but only the Tile Size, Preview Size and Preview Length will be explored in this experiment. The range of each factor is below:

Factor:	Tile Size	Preview Size	Preview Length
Range:	[0.1,0.5]	[max(Tile Size,0.2),0.8]	[30,120]

Experimental Journey:

There are three phases in this experiment:

phase name	aim	desire result
Factor Screening	Find active factors	Factors with small p-values
Methods of Steepest Descent	Find the vicinity of the optimum	Find step with lowest MOI
Response Optimization	Find the location of the optimum	Optimum

Findings:

Active factors: Preview Length, Preview Size

The location of the optimum is: Preview Length=100, Preview Size=55%

The value of the optimum is: 15.09756 [14.244,15.9512]

Introduction

Netflix is is an American technology and media services provider. The homepage of Netflix is laid out in a grid system and different categories are appearing as tiles. When users hover their mouse on a tile, it will automatically display a preview with a lager size. When more options presented, it becomes harder for a user to make decisions. This phenomenon is known as decision paralysis. The browsing time on Netflix homepage is the metric of interest in the experiment. Minimizing the browsing time is a way to optimize Netflix's homepage. Preview Length, Preview Size, and Tile Size are the factors will be concerned. This experiment will find the optimal combination of those factors that provides the minimum average browsing time.

Response Surface Methodology can help to construct a surface which represents the relationship between the factors and the Metric of Interest. It seeks to characterize the relationship between the expected response and the active factors. Effective experimentation is sequential, and future experiments can be informed by the information gained in one experiment. The goals of RSM are to help to find the optimum, and this location of the optimal point will give the minimum browsing time.

Factor Screening

Aim: Using the factor screening is to find the active factors so the complexity of the experiment will be reduced.

Plan: There are three factors in this design. If 2^{K-p} design is used, then the alias will be $factor_3 = factor_1 * factor_2$. This is inappropriate here since the 2-way interaction effect is highly likely to be significant. To achieve a higher accuracy, the efficiency will be sacrificed. 2^K factorial design will be used to determine which factors significantly influence the response.

Data: Using information provided:

Factor	Low	High
Preview Length	30	90
Preview Size	0.3	0.5
Tile Size	0.1	0.3

Conditions by all the combinations of each factor:

Prev.Length	Prev.Size	Tile.Size
30	0.3	0.1
90	0.3	0.1
30	0.5	0.1
90	0.5	0.1
30	0.3	0.3
90	0.3	0.3
30	0.5	0.3
90	0.5	0.3

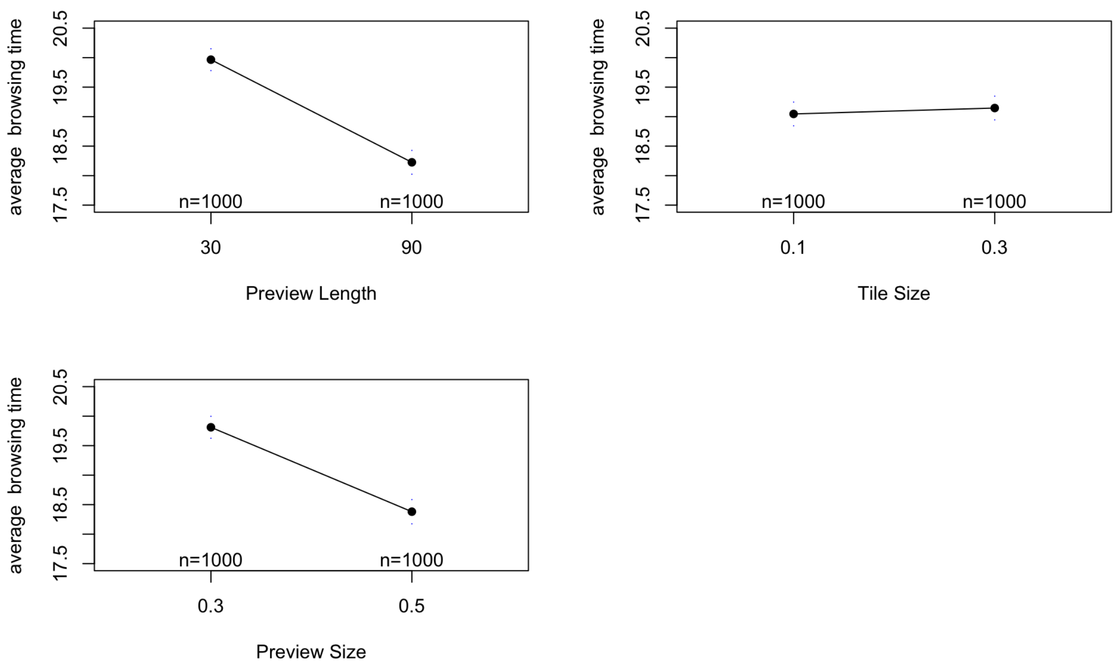
To receive the browsing time, the conditions file was uploaded to the simulator which provided by professor Stevens. The results of 2000 experimental units received. The following table summaries the estimates of each factors' main effect and corresponding p-values:

factor	estimate	p-value
Prev.Length	-0.869906	$<$2e-16
Prev.Size	-0.715188	$<$2e-16
Tile.Size	0.050129	0.447

Using formal hypothesis tests to check the significance of each factor.

null hypothesis	alternative hypothesis	p-value	conclusion
$H_0 : \beta_{Prev.Length} = 0$	$H_0 : \beta_{Prev.Length} \neq 0$	<2e-16	Reject
$H_0 : \beta_{Prev.Size} = 0$	$H_0 : \beta_{Prev.Size} \neq 0$	<2e-16	Reject
$H_0 : \beta_{Tile.Size} = 0$	$H_0 : \beta_{Tile.Size} \neq 0$	0.447	Do not reject

From the table above, Prev.Length and Prev.Size are active factors. Main effect plots can be used to check the result.



From the figures above, the Tile Size has very weak impact on average browsing time. It is not an active factor.

Conclusion: at phase 1,three factors Prev.Length, Prev.Size and Tile.Size have been successfully tested their significance. Active factors are Prev.Length and Prev.Size, and only those two factors will be used in the following experiments.

Method of Steepest Descent

Aim: using the method of steepest descent to find the vicinity of the optimum.

Plan: use two active factors to do the curvature test. If the test gives the significance result of pure quadratic effect(β_{PQ}), move to phase 3 directly. If β_{PQ} is not significant, which means it is not at the vicinity of the optimum, the steepest descent method will be used.

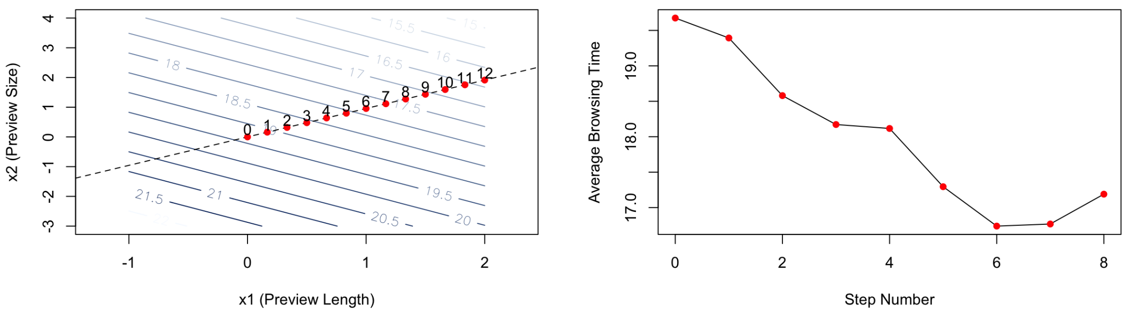
Data: Uploading the following conditions to the simulator and receive the browsing time. [60,0.4]is the center point. The results of 2250 experimental units received.

Prev.Length	Prev.Size
30	0.5
30	0.3
90	0.5
90	0.3
60	0.4

The significance of β_{PQ} will be mainly concerned because it indicates whether it is at the vicinity of the optimum. The following table is the partial summary of the result.

coefficient	estimate	p-value	conclusion
β_{PQ}	-0.48431	0.024	Do not reject

Since β_{pQ} is not significant, it means it is not at the vicinity of the optimum. Now to find the step size and the direction. Since the Preview Length can only be increments of 5 seconds,the step size $= \frac{\Delta x_i}{|\hat{\beta}_1|} = \frac{1/6}{|\hat{\beta}_1|} = 0.2117258$. The step direction $= (\frac{\partial y}{\partial x_1}, \frac{\partial y}{\partial x_2})$. The direction is (-0.7871816, -0.7528539) by using R code. Then run the R code to get each step with corresponding MOI. To make the graph more descent, the parameter asp was changed to 0.25 in contour function; however there should be a perpendicular relationship between the MOI lines and the step line.



From the graph on the right, the step6 corresponds to the lowest observed average browsing time. Another test of curvature in this region will be performed. Step6 corresponds to [90, 0.5]. This point will be used as the center point. From the center point, the preview length is plus and minus 15. The preview size is plus and minus 0.1.The following conditions will be used to test the curvature.

Prev.Length	Prev.Size
75	0.4
75	0.6
105	0.4
105	0.6
90	0.5

The following table is the partial summary of the result.

coefficient	estimate	p-value	conclusion
β_{PQ}	1.02501	1.27e-06	Reject

Conclusion: Since β_{PQ} is significant, now it is at the vicinity of the optimum.

Response Optimization

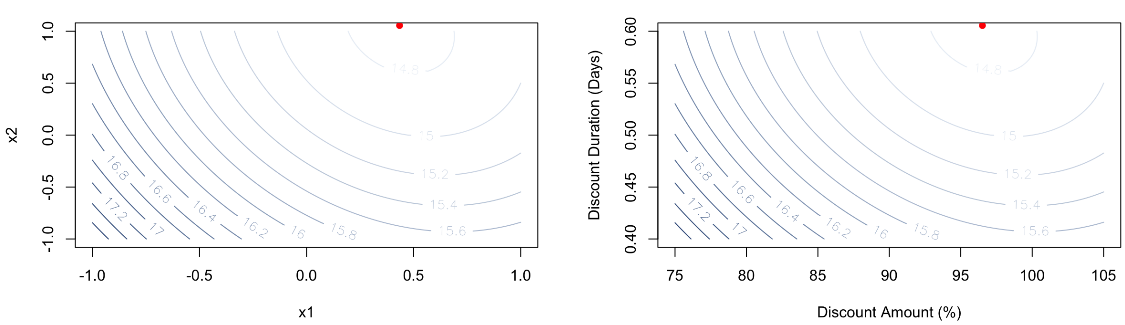
Aim:fitting a 2nd-order surface to find the optimal point.

Plan: central composite design(CCD) will be used to find the stable point. The following table shows the conditions which will be uploaded to the simulator. Two-level factorial conditions and the center point are derived from phase2. The axial conditions which will be used is $a = \sqrt{K}$, since it ensures that the estimate of the response surface at each condition is equally precise.

Data: Uploading the following conditions to the simulator and receive the browsing time. [60,0.4]is the center point. The results of 2250 experimental units received.

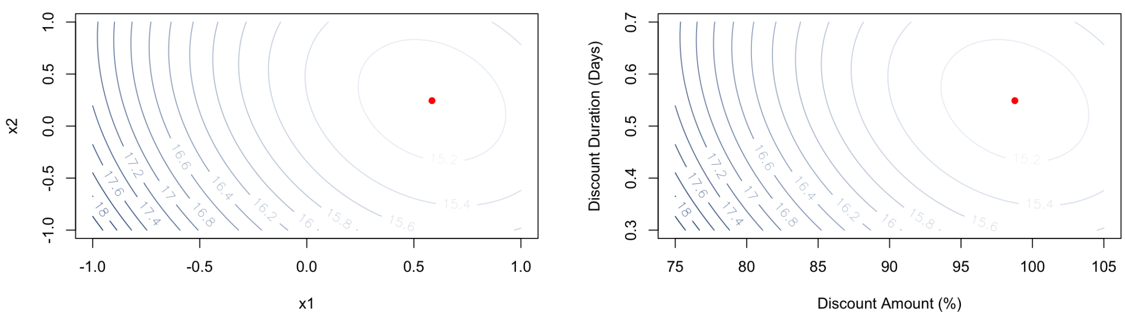
Prev.Length	Prev.Size
75	0.4
75	0.6
105	0.4
105	0.6
90	0.5
110	0.5
70	0.5
90	0.36
90	0.64

Analysis: The second order effects for both Prev.Length and Prev.Size are significant, now plot the response surface.



However the outcome is not satisfactory, expand the width of the Pre.Size to make the response surface more descent. The following conditions will be uploaded to receive data from the simulator.

Prev.Length	Prev.Size
75	0.3
75	0.6
105	0.4
105	0.6
90	0.5
110	0.5
70	0.5
90	0.2
90	0.8



Conclusion: Now a descent contour of the response surface with optimal points is observed. The 95% confidence interval for this optimal point is [14.244,15.9512].The optimal is at [100,0.55] for 15.09756 as lowest browsing time.