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Clustering at the Movies

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Abstract

Weekly box office revenues for approximately 100 successful motion pictures are analyzed by use of a finite mixture regression technique to determine if regular sales patterns emerge. Based on an exponential decay model applied to market share data, four clusters of movies, varying in opening strength and decay rate, are found. Characteristics of the clusters and implications for future research are discussed.

Key words: Motion pictures, product lifestyle, market segmentation, finite mixture

Introduction

The movie industry, like a number of other product categories in the entertainment and fashion industries, is characterized by regular new product or model introductions. These introductions are vital for the success of the business. In the case of movies, for instance, approximately 300 movies are released annually with an average life span (time in theatrical release) of less than 10 weeks (Radas and Shugan, 1996). Moreover, an average movie is estimated to cost $40 million to produce and $20 million to distribute and market, but less than 70% of movies are profitable (Vogel 1994). With major industries depending upon the regular introduction of new models with short life spans, it is important to understand the sales patterns of these products.

In this paper our goal is to determine if there are regular patterns in the box office revenues of major motion pictures over time. Existing approaches to the study of box office revenues emphasize specific characteristics or genre of movies—e.g., action movies need "recognizable names to ensure at least a strong opening weekend," according to a front page article in *Variety* (March 24, 1997). More generally, while motion picture executives and industry professionals appear to be able to make good predictions of a movie's success just before it opens (see Krider and Weinberg 1998 for evidence on this), attempts "to find movie characteristics that co-vary with attendance … [have had some success], but the predictive power of these variables could be poor and appears to be unstable over time." (Eliashberg and Shugan, 1997, p.69).[1] Our concern is not with prediction, but rather with understanding sales histories. In particular, our approach focuses on the actual weekly box office revenues of movies to see if there are clusters of movies which follow relatively consistent sales patterns and to see if these patterns relate to variables that are available before a movie's release.

To accomplish this goal, we analyze weekly market share data for 102 major motion pictures released between December 1990 and April 1992. We employ a finite mixture regression methodology (Jedidi, Kohli, and DeSarbo, 1996; Helsen, Jedidi, and DeSarbo, 1993) for analysis. The next section of the paper describes the data we use, followed by a brief description of the methodology. We then present our results, along with conclusions and suggestions for future research.

Data

Our focus is on major motion pictures, which account for the bulk of North American box office revenues. Each week, *Variety* publishes a list of the 50 (or 60) top grossing films for the week. We confine our analysis to films which were among the top 5 movies for at least one week during the period December 1990 to April 1992.[2] Our data include about 25% of the movies released by Hollywood, but represent about 80% of box office revenues during the time periods studied.[3]

To control for the effects of seasonality and competition, we transform our revenue data into market share terms. While the predominant pattern for major motion pictures is wide-release and mass-marketing, there are, at times, a few "sleepers," or unexpected hits which open slowly and gradually build an audience.[4] These, while memorable, are unusual; moreover, as a June 2, 1997 front page *Variety* headline speculates, "megapix may make 'sleepers' extinct." In our data set, there are only two such movies—"Driving Miss Daisy" and "Reversal of Fortune"—and they were eliminated from further analysis. The remaining 102 movies follow a consistent pattern of having their largest market share in their first week of wide release, and then declining in an approximately exponential decay pattern. (See Krider and Weinberg, 1998 for an analysis of the revenue patterns of individual movies.)

Consequently, we postulate the following exponential decay model (omitting error terms) for each movie's market share over time:

$$\text{Share}_t = e^{\alpha - \beta t}, \text{ where } t = 0, 1, 2, \ldots \tag{1}$$

and α is a parameter capturing the opening share and β is the decay constant.

Methodology

One approach to looking for clusters in movie share-of-revenue patterns would be to conduct a regression analysis for each of the movies and then cluster the movies on the basis of the resulting parameter values. However, as discussed by Helsen, Jedidi, and DeSarbo (1993), a finite mixture approach has a number of advantages over this traditional approach. In particular, it helps to overcome problems of short time series and limited data for each movie by simultaneously determining movie clusters and parameter estimates. In addition, the number of clusters is determined based on statistical tests that involve the use of various information criteria, the most popular of which is the Bayesian Information Criterion (BIC) which penalizes for overparametrization. This requires estimating the finite mixture model for different number of clusters and then choosing the solution with minimum BIC. The methodology is described in detail in Jedidi, Kohli, and DeSarbo (1996) and Helsen, Jedidi, and DeSarbo (1993).

We applied the finite mixture regression procedure, modified for the exponential decay function, equation (1), and generated parameter estimates and BIC measures while varying the number of clusters from 1 to 5.

Results

For the 102 movies that we analyzed, the most appropriate structure involves 4 clusters (see Table 1). This structure has the minimum BIC; it also exhibits an elbow in its likelihood function and almost all movies have a posterior probability greater than 90% of belonging to a primary cluster as reflected by the high 0.925 entropy measure.[5] (See Table 1.) Appendix A reports the classification results for the movies. Thus, the four cluster structure appears to discriminate well among the movies, at the same time that it accounts for a substantial portion of the variability among movies.

Table 2 presents the parameter estimates for each of the four clusters. We use these estimates to compute opening shares and decay rates. The clusters differ both in opening share and in decay rate, as shown in Figure 1.

Clusters 1 (what we call "Hollywood Heros") and 2 ("Mega Movies") represent the most successful movies. Cluster 1, (the larger cluster) accounting for 19% of the movies, opens with a 22.6% share and declines at a rate of 20% per week. In contrast, Cluster 2

Table 1. Summary statistics for model selection

Number of Clusters	Number of Parameters	Ln Likelihood	BIC**	Entropy
1	3	−1444.5	2902.9	—
2	7	−991.1	2014.6	0.918
3	11	−687.5	1426.1	0.929
4	15	−554.3	1177.9*	0.925
5	19	−550.6	1189.1	0.934

* Denotes minimum BIC
** AIC and CAIC also pointed to a four-cluster solution

Table 2. Characteristics of clusters for model: Share $= e^{\alpha - \beta t}$; $t = 0, 1, 2, \ldots$

	CLUSTER NUMBER			
	1	2	3	4
α	−1.484	−1.614	−2.520	−2.255
Standard Error	0.027	0.135	0.065	0.034
β	0.224	0.110	0.439	0.258
Standard Error	0.002	0.009	0.009	0.004
Error Variance Estimates	0.310	0.948	0.784	0.492
Fraction of Movies in Cluster	0.191	0.068	0.378	0.364
Opening Share*	22.6%	20.0%	8.0%	10.5%
Decay Rate**	20.0%	10.4%	35.5%	22.7%
Cumulative Share for Median (12.5 week) run	113%	192%	23%	47%

* Opening Share $= e^{\alpha}$
** Decay Rate $= 1 - e^{-\beta}$

accounting for 7% of the movies, opens with a slightly smaller opening share of 20% but declines at a very low rate of only 10% per week. The next two clusters, approximately equal in size, account for nearly three quarters of the movies in our sample. The third cluster, representing 38% of the movies in our sample, opens with a market share of 8%, which then falls at a fairly rapid rate of 36% per week. This set of movies, which we term

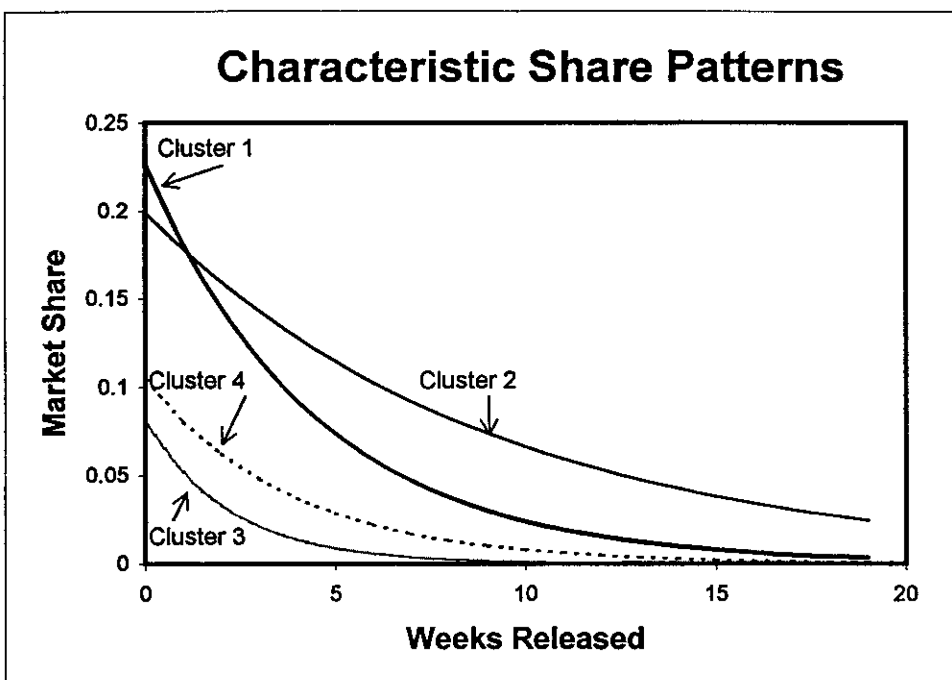


Figure 1. Estimated share patterns over time for the four-cluster solution.

"Fast Fade," is the least successful set of movies in our study. Most of these movies achieve a highest ranking of fourth or fifth for one week, and then decline rapidly. Our final cluster ("Fair Flicks"), consisting of 36% of the movies, declines at a rate of 23% after obtaining an opening week share of 10.5%. Interestingly, while the smallest cluster (Mega Movies) has the highest cumulative share per movie, the largest cluster in terms of number of movies (Cluster 3), has the smallest cumulative share per movie.

By calculating the cumulative share over the median run length (12.5 weeks) for movies in our sample, it can be seen that the effect of a slower decline is substantial. Cluster 2 opens at a slightly lower share (20%) than Cluster 1 (23%), but the slower declining Cluster 2 movies have cumulative revenue nearly 70% (192/113) greater than those for Cluster 1. The rapidly declining Cluster 3 earns about one-third of its revenue in the first week of wide-release and will usually have a brief theatrical release. The positive effect of a slow decay is reinforced further, since slowly declining movies are likely to be shown for a longer period of time in theaters.

Posterior analysis

Table 3 presents characteristics of the movies in each of the four clusters. While we would not suggest that the overall appeal of a movie can be reduced to a weighted summation of its characteristics, previous research (Wallace, Seigerman, and Holbrook 1993; Sawhney and Eliashberg 1996) has reported some success in forecasting revenues based on such characteristics. Based on this literature, we selected a set of variables that would be available before a movie is released, a set that would reflect the overall quality of the movie, and a set of variables external to the movie. The first set of variables included the genre of the movie, whether the movie included major stars (as classified by Quigley's *Motion Picture Almanac*, Klain, 1990), the Motion Picture of America Association's (MPAA) classification of the movie as R, PG-13, or G/PG (none of the [successful] movies in our sample were rated X and too few were rated G to be kept as a separate category), and whether the movie was a sequel or not. A number of measures of quality are available. To capture the industry's view, we used a variable indicating whether or not the movie was nominated for one of the major (Best Picture, Best Director, Best Leading or Supporting Male or Female Actor) academy awards. To capture the public's view more generally, we relied on the 5 point rating (1 = lowest, 5 = highest) provided by Blockbuster Entertainment (Castell, 1996). External factors were measures of competitive intensity, distribution, and seasonality. Since competing movies have the strongest draw in the earliest parts of their runs, our competitive intensity measures focused on newly opened competing movies. One measure (OPENST) looked at movies competing with the target movie at the time of opening. It is the number of competing movies that are in either their first or second week when the target movie opens. (Two other measures—counting movies in their first week only, or in first, second or third weeks—led to results similar to those reported below). This measure focuses on competition at a movie's opening. Because the target movie is described in terms of its opening and decay, a second measure of competitive intensity was the average number of new movies opening per week over the

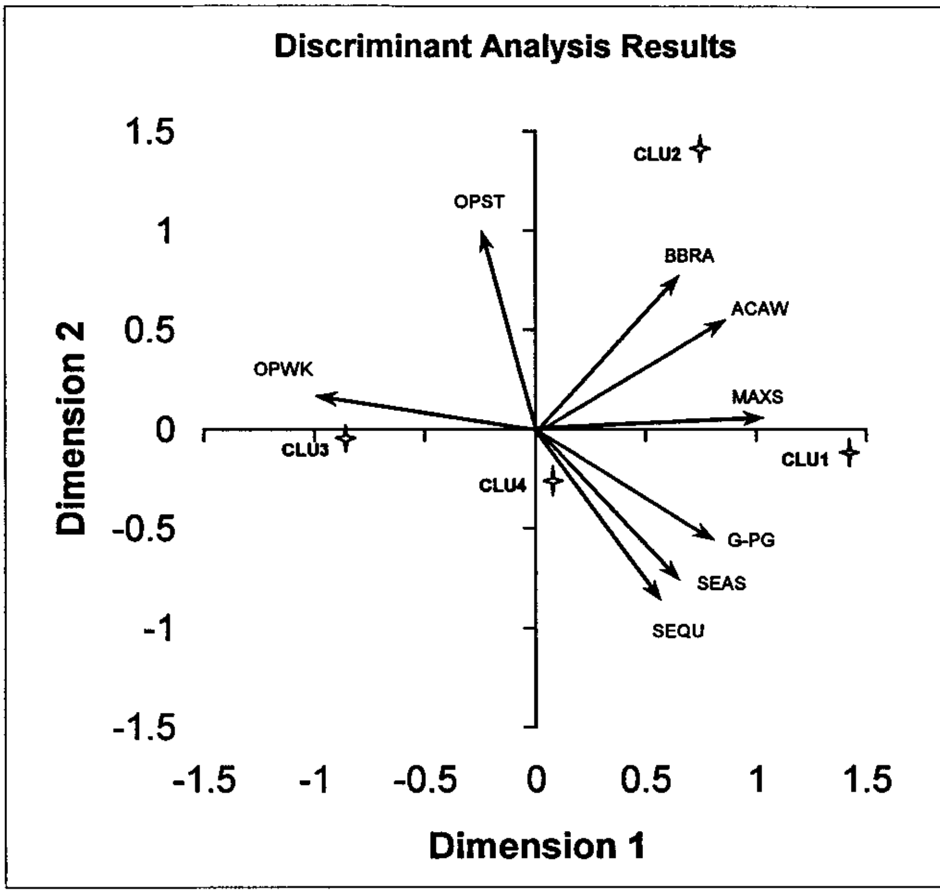
Table 3. Characteristics of clusters

Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Overall
GENRE:					
Comedy	30%	29%	26%	39%	31%
Family	15%	14%	5%	11%	10%
Drama	20%	29%	18%	14%	18%
Horror	10%	0%	18%	3%	10%
Crime	10%	29%	10%	11%	12%
Action	15%	0%	20%	14%	16%
Others	0%	0%	3%	8%	4%
MPAA Classification:					
PG13	20%	57%	26%	33%	29%
R	45%	29%	67%	42%	51%
PG&G	35%	14%	8%	25%	20%
HAVING STARS:	35%	29%	15%	28%	25%
SEQUEL:	35%	0%	13%	11%	16%
ACADEMY AWARD:	15%	14%	0%	0%	5%
Blockbuster's Movie RATINGS:					
(from 1 lowest to 5 highest):	3.75	4.15	3.08	3.26	3.34
HIGH SEASON:	55%	29%	18%	47%	36%
MAXIMUM NUMBER OF SCREENS:	1773	1699	1414	1611	1574
COMPETITION:					
OPENST	2.0	3.3	2.5	2.2	2.35
OPENWK	1.2	1.3	1.4	1.3	1.36

entire run of the movie (OPENWK). Distribution intensity was captured by the maximum number of screens (MAXSCREENS) the movie played on in any week, over its run. Seasonality was measured by a dummy variable that takes the value one for movies released in the high Christmas season (the four weeks starting mid-December), and the summer season, (mid-May to the first week in September), and zero for those released in the remainder of the year.

To determine whether these characteristics were associated with cluster membership, we ran a discriminant analysis in which each of the categories for genre and MPAA ratings were treated as 0, 1 dummy variables.[6] Two discriminant functions were significant, with the first dimension accounting for 74% of the variance (see Figure 2). The overall hit rate of 58% is much higher than chance as well as being higher than the maximum chance criterion (Cluster 3 has 38% of movies). The following eight variables were selected at a significance level of $p < 0.05$ by the stepwise discriminant analysis procedure:

- SEQUEL
- G/PG (MPAA dummy for G or PG ratings)
- ACADEMY AWARD WINNER
- Blockbuster's Movie RATINGS
- SEASONALITY
- MAXSCREENS



SEQU :Sequel
ACAW :Academy Award Winner
G-PG :G/PG Rating
SEAS :Seasonality
MAXS :Maximum Number of Screens
BBRA :Block Buster Movie Ratings
OPST :Competitive openings at Start of Movie
OPWK :Competitive openings per Week over Run

Figure 2. Plot of discriminant analysis. Cluster coordinates are cluster means on discriminant axes. Variable coordinates are discriminant coefficients normalized to unit length.

- OPENST (Number of competitive openings during the first two weeks)
- OPENWK (Average number of new movies opening per week)

Interestingly, none of the genre classifications are significant. While Cluster 2 (“Mega Movies”) does not include certain categories (e.g., Horror), genre does not contribute significantly to the overall categorization scheme.

The characteristics of the clusters are quite intriguing and reveal potentially interesting patterns both in industry strategy and audience characteristics. Starting with Cluster 3, “Fast Fade,” we see that almost half of these movies are in the crime, horror, and action categories. This cluster, accounting for more movies than any other, has the lowest opening share and the highest decay rate. While some of the movies in this cluster are undoubtedly those for which more was hoped, most of the movies are targeted at a (probably male) segment that wants action. Movie producers appear to have recognized this; as shown in Figure 2, the movies do not earn academy award nominations or high ratings from critics. The data in Table 2 show that they infrequently use stars in their movies. Moreover, the producers seem to know that these movies are unlikely to gather a showing in a high number of screens. Thus, Cluster 3 movies tend to avoid the high season; they appear at a time when there are more likely to be a significant number of other (presumably also of lower quality) movies in distribution. Just as the movies in this cluster are characterized by action, so is the audience. With a high decay rate, the audience quickly moves on to other movies.[7]

And where do these people go? Most people go to the seven movies in Cluster 2, the Mega Movies. What distinguishes this cluster from the others, as indicated by Dimension 2, is that it produces high quality movies. However, there are other factors as well. Aside from one movie, Little Mermaid, it avoids the G-PG classification and thus appeals to a wide audience who wants at least a little “edge” in their movies. This cluster contains no sequels, thus appearing “fresh” to its audience. Interestingly, the movies in this cluster tend to avoid the high season, which may provide them with sufficient strength to overcome the competition they face in the early weeks of their release. Presumably it is the quality of these movies (BBRA) which provides them with a very low decay rate. As indicated in Figure 1, the maximum number of screens is about equally important for both Clusters 1 and 2, but it is Cluster 2’s quality which allows it to sustain an audience.

Cluster 1 also contains movies of high quality. However, in this case, while these movies received an equivalent percentage of academy award nominations, the overall reaction to these movies as measured by Blockbuster’s ratings is not as strong. Moreover, Cluster 1 movies seem to follow a releasing strategy that avoids competition both in the opening weeks (OPENST) and throughout its run.

Cluster 4 movies are in many ways similar to Cluster 1 movies, except they don’t achieve the same quality standard. This weakness to a large part may be recognized early on, as they are released to fewer screens and face stiffer competition than Cluster 1 movies. Market forces thus exacerbate the difficulties, but are not the underlying cause.

To explore further this intuition, we re-ran the analysis without the external factors (SEASONALITY, MAXSCREENS, OPENST, OPENWK) and found that virtually the same movie-related factors remained significant, and that the qualitative structure of the map was nearly identical.[8] One difference is that without OPENWK, the average competitive intensity over the run, Clusters 3 and 4 are not as strongly separated.

Conclusions, limitations, and future research

While not all major movies are alike, neither are their sales patterns all different. We find that the market share patterns for major North American movies (released between December 1990 and April 1992) can be grouped into four main clusters, involving differences in both opening strength and decay rate. We focus on major movies because they account for the vast majority of revenues, and presumably profits, although Hollywood accounting is, at times, baffling. (See Vogel 1994.)

Our research has a number of limitations. Movies with lower box office revenues would undoubtedly add different patterns. One such pattern would be a very small opening share followed by a rapid decay, but there may be other patterns as well. The approach we develop here could be applied to a much larger sample size.

In addition to being limited to major movies, we also look at only one time period (i.e., December 1990–April 1992) and only one market. The study could be replicated over other data sets to determine the stability of the clusters over time. Since Hollywood generally opens its movies in North America and then distributes them to other countries at a later date, it would be interesting to see if other countries have similar cluster structures.

Differences in cluster structures across countries could be explained by distribution characteristics in each country, cultural factors or other elements. In a preliminary analysis, we found that data for movies shown in Hong Kong also form four clusters, but that the clusters seem to have different opening share and decay patterns. This result is not unexpected, given that movie runs are defined in Hong Kong by days rather than by weeks.

An interesting area of future research, following the direction established by Helsen, Jedidi, and DeSarbo (1993), would be to examine sales patterns across countries and determine if groups of countries emerge which have similar patterns. This might help movie producers develop an international releasing strategy that is sensitive to market factors. This is particularly important, since Hollywood earns more box-office revenues from outside North America than from North America itself.

If consistent clustering patterns can be established, either country-by-country or globally, then an interesting next step would be to determine how accurately movie characteristics can be used to estimate cluster membership. In turn, if movies can be assigned to clusters on a reliable basis, then this information can perhaps be used to improve early forecasts of a movie's eventual revenue streams.

Acknowledgment

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APPENDIX A. List of movies and primary cluster assignment[a]

Cluster 1	Cluster 2	Cluster 3	Cluster 4
Awakening	Dances With Wolves	Adventure of Ford Fairlane	Air America
Back to the Future Part III	Ghost	Bad Influence	Always
Back to the Future Part II	Goodfellas	Blue Steel	Another 48 Hours
Born on the Fourth of July	Home Alone	Cadillac Man	Arachnophobia
Die Hard 2	Little Mermaid	Career Opportunities	Bird on a Wire
Edward Scissorhands	Pretty Woman	Child's Play 2	Class Action
Flatliners	Silence of the Lambs	Darkman	Days of Thunder
Hunt for Red October		Death Warrant	Defending Your Life
Kindergarten Cop		Exorcist III	Dick Tracy
Misery		Fantasia	Doors
New Jack City		Fire Birds	Ernest Goes to Jail
Out for Justice		First Power	Godfather Part III
Presumed Innocent		Flashback	Gremlins
Sleeping With the Enemy		Flight of the Intruder	Hard to Kill
Tango and Cash		Funny about Love	Hard Way
Teenage Mutant Ninja Turtles		Graveyard Shift	House Party
Teenage Mutant Ninja Turtles II		Guardian	Internal Affairs
Three Men and A Lady		Jacob's Ladder	Jetsons: The Movie
Total Recall		Lionheart	Joe Versus the Volcano
War of the Roses		Loose Cannons	Jungle Book

APPENDIX A. (Continued)

Cluster 1	Cluster 2	Cluster 3	Cluster 4
		Lord of the Flies	King Ralph
		Madhouse	L.A. Story
		Miami Blues	Look Who's Talking Too
		My Blue Heaven	Marked for Death
		Narrow Margin	Marrying Man
		Navy Seals	Memphis Belle
		Never Ending Story II	Men at Work
		Once Around	National Lampoon's Christmas V
		Opportunity Knocks	Pacific Heights
		Predator 2	Postcards from the Edge
		Revenge	Problem Child
		Rocky V	Quigley Down Under
		Rookie	Rescuers Down Under
		Sibling Rivalry	Robocop 2
		Spaced Invaders	White Fang
		Stella	Young Guns II
		Tales From the Darkside	
		Tremors	
		White Palace	

a. For these 102 movies, all had a greater than 90% posterior probability of cluster membership except the following: Career Opportunities (69% Cluster 3, 31% Cluster); Darkman (62% Cluster 3, 38% Cluster 4); Death Warrant (82% Cluster 3, 18% Cluster 4); Defending Your Life (26% Cluster 3, 71% Cluster 4); Edward Scissorhands (76% Cluster 1, 24% Cluster 4); First Power (71% Cluster 3, 29% Cluster 4); Loose Cannons (85% Cluster 3, 15% Cluster 4); Madhouse (72% Cluster 3, 28% Cluster 4); Marrying Man (34% Cluster 3, 66% Cluster 4); Men at Work (38% Cluster 3, 62% Cluster 4); New Jack City (73% Cluster 1, 27% Cluster 4); Out of Justice (68% Cluster 1, 8% Cluster 2, 8% Cluster 3, 17% Cluster 4); Silence of the Lambs (34% Cluster 1, 66% Cluster 2).

Notes

1. New approaches, based on innovative marketing research models, appear to hold promise for improvement in forecasting accuracy. See, for example, Sawhney and Eliashberg, (1996). In addition, in some specific instances, successful forecasting and planning models have been developed and implemented. For example, in the performing arts, see Weinberg (1986).
2. The same set of movies was analyzed by Krider and Weinberg (1998).
3. The distinction between the "two Hollywoods," one aiming to produce high grossing blockbusters and the other, more independent sector is now accepted. The latter sector, often appealing to a tightly targeted audience, can be highly profitable. The artistic merits of such a separation are debatable, as Gabler (1988, p.78) notes: "There are now small films for older arty audiences and big films for younger action-oriented ones, which puts the movies exactly where literature, music, dance and art are: split. Even more important, the segregated audience has allowed film makers to segregate themselves, too. … Now that the independents have relieved their film makers of the obligation to reach a large audience and studios have relieved theirs of the obligation to make intelligently crafted pictures, the split between art and entertainment is larger than ever and, one fears, never the twain shall meet."
4. There are also disappointments; in 1997, these included "Volcano" (with a loss of $40 million) and "Father's Day." Klady, 1997).
5. Entropy is bounded by 0 and 1. A value close to 0 indicates that the posterior probabilities are not well separated (i.e., it is difficult to classify movies into distinct groups).
6. All movie characteristics are standardized to have zero mean and unit variance to facilitate comparison of effects.
7. DeVany and Walls (1997), while using a different approach, also obtain results which imply "that audiences have a taste for variety, (p. 795)."
8. The dummy variable for G/PG was replaced by the dummy variable for *R*.

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