Chapter 13
Decision Models for the Movie Industry

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13.1 Introduction

The movie industry represents a challenging domain for scholarly research in general and for modelers in particular. The industry is characterized by a product (content) with multiple distribution outlets, each having a relatively short window of opportunity (see Fig. 13.1). Distribution outlets for movies include domestic and foreign theatres, home video, cable TV, and network TV. In each of these windows, many different parties and decision makers are involved. While some emphasize the creative and artistic aspects of the product, others focus on the business issues. Some industry pundits claim that the artistic nature of the product and its uncertain quality make the movie industry inherently different from others; hence, any formal methods or models employed in other industries to improve operational and commercial performance are irrelevant. Furthermore, unlike other industries where trends and consumer tastes are tracked continuously, studios see themselves more as trend setters than as trend followers. Views of industry experts are divided when it comes to reasons for recent box office declines: some blame it on deteriorating product qualities, others on changes in consumer behavior. Our experiences and perspectives are different from those who argue that movie is a form of art that cannot be understood with formal quantitative methods. Rather, we think that there is a creative tension between art and science that, if balanced properly, can lead to improvement in both the business and the artistic spheres of the industry.

Decision-making style varies across the different parties involved in the production and distribution of movies. Film makers, coming from artistic backgrounds, tend to believe in more intuitive styles. In contrast, executives in the home video sector, who interact more closely with retailers and consumers, generally see more value in formal decision models. The rise of a new breed of business-educated executives, who are starting to fill high
level positions in the supply chain, also encourages the development and application of new models, specifically addressing the unique need of the movie industry. This is the focus of this chapter.

There already exist a number of published reviews of research in the movie industry; e.g., Moul (2005), and Eliashberg et al. (2006). Unlike these reviews, our focus in this chapter is on models which have been implemented or which, we believe, have the potential for implementation. By implementation we specifically mean employed by the industry. While this review is by no means exhaustive, we survey and comment on various (published) models that have been developed to address the idiosyncratic characteristics of the movie industry. The models chosen for discussion in this chapter take the perspectives of different audiences, including academics, movie distributors, movie exhibitors, and public policy decision makers. We describe the various models in terms of the model’s (potential) users, the problem(s) it addresses, its key features, input and data requirements, and its output and main implications.

The remainder of this chapter is organized as follows. In Section 13.2, we review decision models for theatrical distribution of movies, for exhibition, and for the home video market. Section 13.3 discusses our experience in implementing marketing decision models in the movie industry and provides some insights on the implementation process. Section 13.4 provides our views on what the opportunities are for further modeling efforts.

![Fig. 13.1 Distribution outlets for movies (Vogel 2001)](image)
13.2 What Has Been Done to Date: Review

13.2.1 Theatrical Distribution Models

This section reviews models that have implications for the distributor’s decision making. In 2007, 590 movies were released in the U.S. market (http://www.mpaa.org). The movie distributors design the distribution strategy and make decisions regarding the marketing campaign, the production and distribution of copies of the movies (“prints”) to the exhibitors, and the release timing of each movie. The average cost of producing a movie is $70.8 million, while the average marketing campaign and the cost of the prints for MPAA movies amounted to $35.9 million. In light of such high (and escalating) costs, two key challenges the distributor faces are (i) forecasting the box office performance of a movie after its production but prior to its theatrical release, and (ii) deciding on a strategy of a movie’s release timing. Models reviewed in this section are listed in Table 13.1.

13.2.1.1 Forecasting Theatrical Performance

Early Regression Models

One way of approaching the distributor’s forecasting problem is through a simple regression model with the box office performance taken as the dependent variable and various factors (e.g., production budget, number of screens) as independent variables. Although more recent work typically uses more complex modeling approaches, it is worthwhile to look at some of the early approaches to this problem as they have set the stage for later work. Examples of models that used this approach include Litman and Ahn (1998) and Ravid (1999). The regression results reported in Ravid (1999) are shown in Table 13.2.

In both of these studies, (log-) cumulative domestic gross box office receipts was chosen as the dependent variable. In a separate regression equation, Ravid (1999) also considered “return-to-investment” as the dependent variable. The R-square value is low (0.25), and MPAA ratings (G, PG) are the only significant predictors.

In a more recent study, Ainslie et al. (2005) modeled the weekly market share of each movie using a “sliding window” logit model, with a gamma diffusion pattern that captures the buildup/decay of a movie over time. They define an

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1 In a separate regression equation, Ravid (1999) also considered “return-to-investment” as the dependent variable. The R-square value is low (0.25), and MPAA ratings (G, PG) are the only significant predictors.
Table 13.1 A summary of a representative sample of papers with theatrical revenue models

<table>
<thead>
<tr>
<th></th>
<th>Research Issue</th>
<th>Dependent Variable</th>
<th>Predictors</th>
<th>Data</th>
<th>Approach</th>
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<tr>
<td>Jones and Ritz (1991)</td>
<td>Forecasting box office receipts using interdependence between tickets and screens</td>
<td>Weekly box office revenue</td>
<td>Weekly number of screens</td>
<td>94 movies released between 1983 and 1984</td>
<td>Coupled differential equations</td>
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<tr>
<td>Sawhney and Eliashberg (1996)</td>
<td>Forecasting box office receipts</td>
<td>Weekly box office revenue</td>
<td>None (can also be used with covariates)</td>
<td>111 movies released between 1990 and 1991</td>
<td>Behavior-based model</td>
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<tr>
<td>Litman and Ahn (1998)</td>
<td>Forecasting box office receipts</td>
<td>Cumulative box office</td>
<td>Budget, reviews, screens, star, award, competition, distributor, seasonality, MPAA rating</td>
<td>Top 100 box office gross movies released between 1993 and 1995</td>
<td>Multiple linear regression</td>
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<td>Ravid (1999)</td>
<td>Forecasting box office receipts/ROI</td>
<td>Cumulative box office</td>
<td>Budget, reviews, stars, award, seasonality, MPAA rating, sequel</td>
<td>200 movies released between late 1991 and early 1993</td>
<td>Multiple linear regression</td>
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<td>Research Issue</td>
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<td>Eliashberg et al. (2000)</td>
<td>Forecasting box office receipts</td>
<td>Cumulative box office revenue</td>
<td>Word-of-mouth impact, advertising exposure, theme acceptability</td>
<td>Experimental data collected from “consumer clinic”</td>
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<td>Flow model calibrated using a “consumer clinic”</td>
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<td>Elberse and Eliashberg (2003)</td>
<td>Forecasting box office receipts</td>
<td>Weekly box office revenue and number of screens</td>
<td>Budget, reviews, star, distributor, seasonality, competition, director, advertising</td>
<td>Dynamic simultaneous-equations model</td>
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<td>Ainslie et al. (2005)</td>
<td>Modeling weekly market share of movies</td>
<td>Weekly market share of movies</td>
<td>Media expenditure, screens, critic rating, star, director, sequel, genre, distributor</td>
<td>Sliding-window logit model</td>
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<td>Hennig-Thurau et al. (2006)</td>
<td>Modeling movie’s commercial success based on marketing actions</td>
<td>Cumulative box office revenue</td>
<td>Reviews, seasonality, quality, advertising, sequel, seasonality</td>
<td>Latent class regression model</td>
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<tr>
<td>Einav (2007)</td>
<td>Explaining seasonality in movie box office</td>
<td>Weekly market share of movies</td>
<td>Movie “quality” as a fixed effect</td>
<td>Individual-level modeling using logit formulation</td>
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indicator variable $i$, which takes value 1 if movie $i$ is available at week $t$, and 0 otherwise. Then, they model the deterministic utility of a movie in each week using a gamma distribution (with modified parametrization), and the stochastic component using an extreme value distribution, as follows:

$$U_{it} = V_{it} + \varepsilon_{it}$$

$$V_{it} = \ln(\eta_i w_{it}^{\gamma_i/\beta_i} e^{(1-w_{it})/\beta_i})$$

where $w_{it}$ represents the number of weeks since movie $i$ has been released. The movie-specific parameters $\eta_i, \gamma_i, \beta_i$ captures the attractiveness of a movie, the time when peak attractiveness occur, and the speed in which attractiveness evolves, respectively.

By including an hypothetical “outside goods” in their model to capture the underlying weekly seasonality, Ainslie et al. (2005) derived their final model from standard random utility theory:

$$M_{it} = \frac{\eta_i w_{it}^{\gamma_i/\beta_i} e^{(1-w_{it})/\beta_i} I_{it}}{e^{V_{Ot}} + \sum_j \eta_j w_{jt}^{\gamma_j/\beta_j} e^{(1-w_{jt})/\beta_j} I_{jt}}$$

where $M_{it}$ denotes the expected market share of movie $i$ in week $t$, and $V_{Ot}$ denotes the deterministic component of the utility of the outside goods,
which implicitly takes into account seasonality in the box office receipts. The model in Equation (13.2) was then linked to movie characteristics and estimated using a Hierarchical Bayes framework. They found that incorporating the impact of competition generally improves model fit and yield interesting substantive insights. Specifically, the results from the model suggested that competition from movies of the same genre and/or MPAA ratings will adversely affect a movie’s box-office revenue.

Behavioral-Based Models

The relationship between box office gross and its drivers are likely to be more complex than the linear relationship assumed in the aforementioned regression models. Other researchers recognized this complexity and developed more realistic models, based on reasonable behavioral assumptions, that relate box offices to its predictors. For instance, Zufryden (1996) captured the relationship through an awareness/intention/behavior model. His modeling approach is described graphically in Fig. 13.2. In his model, advertising increases the proportion of consumers who are aware of the movie. Awareness, together with other movie characteristics such as its genre, determines consumers’ intention to watch the movie. Finally, box office receipts are linked to intentions based on a log-linear formulation. Using awareness and intention “tracking” data to calibrate his model, Zufryden (1996) reported that the proposed model provided an excellent fit to the box office data for the 63 movies in his sample.

In a similar vein, another behavioral-based model was developed by Sawhney and Eliashberg (1996). Its behavioral premise is that the average consumer goes through two stages in executing his/her decision to attend a movie in the theater. The two stages give rise to two time periods—time to decide to attend the movie, denoted as $T$, and the time to act upon the decision, denoted as $\tau$. The sum of these two time periods, denoted as $t$, is the overall time that it takes for the consumer to enter the theatre and watch the movie. $T$ and $\tau$ are both assumed to be independent and exponentially distributed with rate parameter $\lambda$ and $\gamma$ respectively. Then, it can be shown (see Sawhney and Eliashberg 1996) that $t$ follows a Generalized Gamma distribution. Let $X$, $Y$, and $Z$ be the cumulative distribution function for $T$, $\tau$, and $t$ respectively. Formally,

![Model Framework](image)

### Fig. 13.2
A graphical summary of Zufryden (1996)'s awareness/intention/behavior model
Finally, the cumulative number of adopters by time t, \( N(t) \), is modeled as:

\[ N(t) \sim \text{Binomial}(N, Z(t)) \]  

where \( N \) denotes the market potential of the movie. From Equation (13.5), the expected number of adopters by time t, \( E(N(t)) \), is given by a three-parameter equation.

\[ E(N(t)) = \frac{N}{\lambda - \gamma} \left[ (\lambda - \gamma) + \beta e^{-\lambda t} - \beta e^{-\gamma t} \right] \]  

The three parameters, i.e., the average time to decide (\( \lambda \)), average time to act (\( \gamma \)), and the size of the market potential (\( N \)) can be estimated for each movie separately, from its previous-weeks’ box office revenues. These parameter estimates can be of potential relevance to distributors, who may then allocate their resources accordingly to influence the parameter values. The authors also showed that their model can be estimated not only on time series data that are available after a movie is released, but also on information on movie characteristics that is available before release. To predict box office performance before the release, a database containing the parameter values of other movies, along with their features (e.g., genre, sequel, sexual content, special effects, MPAA rating, stars), is prepared. Then, the distributor can forecast the gross box office performance of the new movie by “benchmarking” it against the other movies in the database (e.g., Lilien and Rangaswamy 2005) based on the characteristics of the new movie.

Models that Jointly Consider Demand and Supply

While behavioral-based models offer improved predictive performance and a richer behavioral story over simpler regression models, a key aspect that determines a movie’s performance, namely the interdependency between demand (box office receipts) and supply (number of screens), is not explicitly modeled. Empirically, the number of screens on which the movie is played and the movie’s commercial success are highly interdependent over time and across markets. This suggests that single equation-based, regression-type models may be limited in the insights that they provide, and consequently, in their predictive performance.

Jones and Ritz (1991) first tackled that problem by modeling the relationship between the number of screens and box office receipts via two coupled differential equations, as shown in Equations (13.7) and (13.8) below:
\[
\frac{dS}{dt} = \left[ c + b(S - S_0) \right] [S - S]
\] (13.7)

\[
\frac{dR}{dt} = a [pS(t) - R]
\] (13.8)

where \( S(t) \) denotes the number of screens showing the movie at time \( t \), \( S_0 \) denotes the initial number of screens, \( S \) denotes the maximum number of screens, and \( R(t) \) denotes the box office receipts at time \( t \). Equation (13.8) explicitly captures the interdependency between supply and demand by specifying that the size of the consumers’ potential market at time \( t \) is determined by the size of the supply at that time (i.e., number of screens). The authors calibrated their model with actual box office and screens data, and found that their model outperformed other benchmark models including the simple linear model, the Bass model (Bass 1969), and the NUI (non-uniform influence) model (Easingwood et al. 1983).

A key limitation of Jones and Ritz (1991)’s model is that the number of screens is allowed to affect box office receipts but not vice versa. It does not allow for the possibility that the number of screen may be endogenous, i.e., a distributor may change the number of screens based on the observed box office performance of a movie. Elberse and Eliashberg (2003) recognized this limitation and developed a dynamic simultaneous-equations model that explicitly captures this interrelationship. More specifically, their model consists of two equations capturing the weekly box-office revenues (opening and beyond the opening week) and two similar equations representing the dynamics of screens allocation. The box office revenues are modeled as a function of the number of screens, time-varying covariates (e.g., word of mouth and competition for the attention of the audience), as well as time-invariant covariates (e.g., star and director), as shown in Equations (13.9) and (13.10):

\[
\ln(\text{REVENUE}_{it}) = \alpha_0 + \alpha_1 \ln(\text{SCREEN}_{it}) + \alpha_2 \ln(X_{Rit}) \\
+ \alpha_3 \ln(Z_{Ri}) + \varepsilon_{Rit} \quad \text{for } t = 1
\] (13.9)

\[
\ln(\text{REVENUE}_{it}) = \alpha_0 + \alpha_1 \ln(\text{SCREEN}_{it}) + \alpha_2 \ln(X_{Rit}) \\
+ \alpha_3 D_{Rit} + \varepsilon_{Rit} \quad \text{for } t \geq 2
\] (13.10)

where \( X_{Rit} \) is a vector of time-varying (e.g., word of mouth), and \( Z_{Ri} \) denotes time-invariant covariates (e.g., star and director) which is assumed to affect only the opening week box office. \( D_{Rit} \) denotes (t-1) time dummies used for estimation.

Similarly, the dynamics of the screens are also modeled as functions of time-varying and time-invariant covariates that includes expected opening box office
revenues, actual previous week box office revenues, competition on screens from new and ongoing movies, advertising and production expenditures, stars, and directors, as shown in Equations (13.11) and (13.12) below:

\[
\begin{align*}
\ln(SCREEN_{it}) &= \beta_0 + \beta_1 \ln(REVENUE_{it}^{**}) + \beta_2 \ln(X_{Si}) + \beta_3 \ln(Z_{Si}) \\
& \quad + \beta_4 D_{Si} + \varepsilon_{Sit} \quad \text{for } t = 1 \\
\ln(SCREEN_{it}) &= \beta_0 + \beta_1 \ln(REVENUE_{it}^{**}) + \beta_2 \ln(X_{Si}) + \beta_3 D_{Si} + \varepsilon_{Sit} \quad \text{for } t \geq 2
\end{align*}
\]

Elberse and Eliashberg (2003) estimated their model using a three-stage least-square (3SLS) procedure. Their results indicated high level of R-squared values (0.8 and above). While most of their results are consistent with the previous literature, they found that contrary to previous results, variables such as movie attributes and advertising expenditures do not influence audiences directly. Instead, those factors generally affect box office indirectly through their impact on the exhibitors’ screens allocations.\(^2\)

Note that some researchers have empirically studied the effect of marketing actions (e.g., promotion activities, release schedules) on a movie’s commercial success. For instance, Hennig-Thurau et al. (2006) used a structural equations model to study the extent to which marketing actions and movie quality affect a movie’s box office performance, both for the opening week and thereafter. Their conceptual framework is depicted in Fig. 13.3. Their results suggested that (i) both the studio’s action and movie quality have a positive impact on the box office, both for the opening-week and for the “long-term,” and (ii) the studio’s action have a stronger impact than movie quality on the opening week, and a weaker impact on the long term box office.

Pre-test Market Approaches

The models discussed above rely on “hard” data, that is, box office ticket sales. However, prior to distributing the movie in theaters, the distributor has the option of playing the new movie to a sample of moviegoers, and surveying them for their reactions. This is in line with pre-test market approaches that have been used extensively in consumer goods context (Silk and Urban 1978). Testing the movie under a simulated test market environment can provide the distributor with a box office forecast as well as with diagnostic information.

\(^2\) In a related study, Krider et al. (2005) used a graphical approach to model the lead-lag relationship between distribution and demand for motion pictures. They found that, after the first week, the number of theatres a movie is shown is influenced by its performance in the previous week.
concerning the effectiveness of the contemplated distribution strategy. This is the key objective of Eliashberg et al. (2000) who developed the MOVIE MOD decision support system. The approach taken by the authors is that of a flow model where the target audience is broken down into sub-groups (e.g., unaware consumers, aware but waiting for the opportunity to attend the theater, and positive/negative spreaders of word of mouth) and probabilistic flows that move consumers across the different sub-groups, as shown graphically in Fig. 13.4.

Some of these flows are influenced directly by the distributor’s strategic decisions (e.g., advertising, number of prints). The inputs required to implement the model are: consumer responses (e.g., tendency to talk about movies, degree of liking the tested movies), collected via simulated test market and under a contemplated “base” marketing strategy. The output provided by the model indicates that expected box office grosses under the base strategy, as well as the incremental increases/decreases that are likely to occur as a result of deviations from the base strategy. An implementation of the model in The Netherlands led to a change in the distributor’s base strategy and predicted the resulting box office performance with a reasonable degree of accuracy.

The major movie studios have access to weekly surveys conducted by private research firms. While these studies are influential in theatrical distribution decision making, as far as we can determine, there are no published studies of formal models that incorporate such data into forecasting structures. While the published models surveyed here have reported good forecasting performance,
systems incorporating both hard and soft data are likely to improve results, and hence encourage managerial usage.

Having reviewed the different forecasting approaches proposed in the literature, we conclude this section with an intriguing question: how early in the production/distribution process of a movie can researchers make prediction of its success? Not only is this issue of academic interest, but it is also of huge economic importance for major distributors, who are often also participate in the production of movies. To answer this question, Eliashberg et al. (2007) forecasted the theatrical performance at the very early stage of the production process, when movie makers are reviewing and selecting scripts for possible production. Combining domain knowledge in scriptwriting with techniques from natural language processing and machine learning, Eliashberg et al. (2007) extracted textual and content information from the storyline of a script and used it to predict the return-on-investment of a motion picture. In the future, we expect to see more models that enable forecasting earlier in the production process.

13.2.1.2 Theatrical Release Timing

The aforementioned models do not explicitly recognize the strategic nature of the distributor’s release timing. However, a movie’s box office performance in a certain week depends not only on the demand side (i.e., consumers’ leisure time and willingness to see the movie), but also on the supply of movies that is available in that week. The latter is the aggregate result of the competing distributors’ release strategies. Taken together, those two factors determine the seasonality observed in the data. Einav (2007) attempted to separate out
the extent of the two effects using a panel of weekly box office grosses that contains 1956 movies from 1985 to 1999. He started by assuming that a consumer’s utility to see a movie is a function of the (unobserved) quality of the movie and its “age.” More specifically, the utility that consumer \( i \) receive from going to movie \( j \) on week \( t \) is given by

\[
u_{ijt} = \theta_j - \lambda(t - r_j) + \xi_{jt} + \zeta_{it} + (1 - \sigma)\varepsilon_{ijt}\]  

(13.13)

where \( \theta_j \) denotes the (unobserved) quality of the movie \( j \), \( t - r_j \) is the number of weeks that have elapsed since the movie’s release, \( \xi_{jt} \) is a movie-week random effect, while \( \zeta_{it} + (1 - \sigma)\varepsilon_{ijt} \) is an individual error term. The utility of the corresponding “outside option”, i.e., not watching any movies, is given by

\[
u_{i0t} = -\tau_t + \zeta'_{it} + (1 - \sigma)\varepsilon_{i0t}\]  

(13.14)

where \( \tau_t \) is a week fixed effect that captures the underlying seasonality of the demand.

Combining Equations (13.13) and (13.14) yield a logit formulation for the share of each movie in each week. After some algebraic manipulations, the author showed that the share for movie \( j \) in week \( t \), denoted by \( s_{jt} \), can be written as

\[
\log(s_{jt}) = \log(s_{0t}) + \theta_j + \tau_t - \lambda(t - r_j) + \sigma \log\left(\frac{s_{jt}}{1 - s_{0t}}\right) + \xi_{jt}
\]  

(13.15)

The estimated seasonality and the observed seasonality are shown in the top and bottom panel of Fig. 13.5, respectively. By comparing the two panels in the figure, one can see that the underlying seasonality observed in the movie market is amplified by the release decisions of movie studios. Apparently, the best movies are scheduled in the most favorable seasons, which magnifies the seasonality observed in the data. In particular, if the fixed effect terms that represent movie quality are omitted from the model, the standard deviation of the estimated week dummy variable \( \tau_t \) increases from 0.236 to 0.356. Based on this result, the author claimed that the endogeneity of movie quality amplifies seasonality by about 50%.

Krider and Weinberg (1998) utilized a game-theoretical approach to model the strategic competition between two distributors. Under their model, each movie is characterized by its “marketability” parameter \( (\alpha) \) and “playability” parameter \( (\beta) \). The revenue generated by each movie is then captured using a share-attraction model. The attraction of movie \( i \) at time \( t \) is assumed to follow an exponential model, given by

\[
A_i(t) = e^{\alpha_i - \beta_i(t-t_0)} , \quad t_0i \ (= 0 \text{ otherwise})
\]  

(13.16)
where $t_{0i}$ denotes the release time for the movie $i$. While the empirical analysis in the paper considered all movies available in a week, the release timing game was based on two (major) movies that might be released in the same week. Thus, $i$ may take value 1 or 2 only. In the 2-movie model, the total revenue for picture $i$ can be written as:

$$R_i = \int_{t_{0i}}^{t_f} \frac{A_i(t)}{A_1(t) + A_2(t) + 1} dt$$

(13.17)

where $t_f$ is the planning horizon under consideration. With this model set-up, Nash equilibrium strategies were identified; the precise solution was found

![Fig. 13.5 Top panel: Estimated seasonality; bottom panel: observed seasonality of movies (Einav 2007). As can be seen, the observed seasonality is amplified compared to the estimated seasonality](image-url)
using numerical techniques, since no closed form solutions are available. Three different equilibrium strategies emerged: (1) a single equilibrium strategy with both movies opening simultaneously at the beginning of the season, (2) a single equilibrium with one movie opening at the beginning of the season and one delaying, and (3) dual equilibria, with either movie delaying opening. In particular, the model predicted that stronger movies, i.e., movies that have high opening strength ($\alpha$) and/or longer legs ($\beta$), will open earlier in the peak summer season. This prediction is confirmed by an empirical analysis of the actual release pattern of movies for one summer season. In addition, the authors found that most movie studios appeared to place, appropriately, a great deal of emphasis on the opening strength of a movie, but underestimated the importance of the decay rate in deciding when to release their movies.

### 13.2.2 Exhibition Models

In this section, we focus on models whose potential users are the exhibitors. Two key decisions that a movie exhibitor has to make are theatre location and movie schedule; we review works that study each of these issues below.

#### 13.2.2.1 Facility Location

From 1990 to 2000, the number of movie theater screens in the U.S. grew from 23,814 to 36,280, an increase of 50%, while the box office revenues increased only by 16% from $6.6 to $7.6 billion (Davis 2006). Such asymmetrical expansion proved to be unhealthy. In the early 2000s, a number of theater chains went bankrupt; by 2004, the exhibition industry had undergone a period of consolidation, and at the end five major chains controlled more than 50% of the U.S. movie screens (Variety 2004). While we could identify no published papers which directly looked at what we believe is a very important decision—how many theaters and screens to have in an area and where they should be located—a number of researchers have looked at the effects of location on revenues obtained by theaters. These papers are primarily useful for public policy decision makers who are typically concerned about the competitive effects of horizontal and vertical mergers.

Davis (2006) is a representative study. In this paper, the author modeled the revenue received at a particular theatre as a function of the number of local competitors (i.e., the other theatres owned by the same or other chains). The estimation equation proposed is as follows:

$$\text{Revenue} = \alpha \times \text{Number of Competitors} + \beta \times \text{Other Effects} + \epsilon$$

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3 In the paper, the author also estimated other specifications that are similar (and some slightly more general) than Equation (13.18). Interested readers are encouraged to see Davis (2006) for more details.
where $R_{hmt}$ denotes the revenue for theater $h$, in market $m$, and at time $t$. $\alpha_h$ is a theater fixed effect, $\tau_t$ is a time fixed effect, and $\xi_{hmt}$ is a normally distributed error term. $\bar{W}_{hmt}^{d,own}$ represents the number of screens, owned by the same chain, that is within distance $d$ of the focal theater. $\bar{W}_{hmt}^{d,rival}$ represents the number of screen owned by a different chain within distance $d$ of the focal theater. Thus, the third and fourth term of Equation (13.18) represents the degree of “cannibalization” by own theatres and “business stealing” by rivals respectively.

Davis (2006) also estimated a potential “market expansion” effect by modeling (using a separate equation), the aggregate revenue across all theatre in a market as a function of total number of screens. More specifically, the total revenue for all theatres in market $m$, at time $t$ (denoted as $R_{mt}$) is given by:

$$R_{mt} = \alpha_1 \text{screens}_{mt} + \alpha_2 \text{screens}^2_{mt} + \mu_m + \tau_t + \varepsilon_{mt}$$  \hspace{1cm} (13.19)
the short life cycles of movies, the changing level of demand over time, the
carcity of screens, and the complex revenue sharing contract between the
exhibitor and the distributor.

Swami et al. (1999) developed a decision support system called SilverScreener
to tackle this movie scheduling problem, by relating it to the “parallel
machine problem” (Baker 1993) considered in operations research. In their
analogy, screens are *machines*, and movies are *jobs*. The problem of assigning
a specific movie to play on each screen can thus be viewed as analogous to the
problem of assigning jobs to machines. Although there are a number of differ-
ences between the two problems, this powerful analogy allowed Swami et al.
(1999) to set up a formal mathematical programming model to solve for the
optimal (dynamic) allocation of movies to screen. While readers are encouraged
to refer to the original paper for full mathematical details, we briefly outline the
key modeling approach here. The objective function that the exhibitor seeks to
maximize is the total profit over the planning horizon, taking into account the
revenue sharing contract between the exhibitor and the distributor. The action
space is the movies to show and how long to keep each of the selected movies on
screen. The objective function is maximized subject to two key constraints, as
follows:

(i) A movie must be played only on consecutive weeks. For example, a movie
cannot be shown on week 1, withdrawn on week 2, and subsequently re-
introduced in week 3.

(ii) The total number of movies scheduled in any week of the planning horizon
has to equal to the total number of screens in the multiplex.

Given these two constraints, this mathematical program was then solved using
integer programming techniques to recommend an optimal schedule. Thus,
SilverScreener is able to help select and schedule movies for a multiple-screens
theater over a fixed planning horizon to optimize the exhibitor’s cumulative
profit.

To demonstrate the applicability of their model, Swami et al. (1999) provided
various ex-post analyses of optimal versus actual decision making, based on
publicly available data for a specific theater in New York City. Although the
modelers did not collaborate with the management of that theater, their ana-
lyses provided a number of important insights:

(i) Based on SilverScreener’s recommendations, the exhibitor can achieve
substantially higher cumulative profit.

(ii) The improvement over actual decisions in terms of profitability appears to
result from a combination of both *better selection* and *improved scheduling*
of the movies.

(iii) The general structure of the exhibitor’s normative decision as compared to
current practice is: *choose fewer “right” movies and run them longer*.

A more extensive testing of the SilverScreener system was undertaken by
Eliashberg et al. (2001) (henceforth ESWW), who implemented SilverScreener
in collaboration with the Pathé theaters chain in Holland. They presented comparative results for the movie theater in which managers used the SilverScreener model and for two comparable theaters which did not. They found that the “SilverScreener theater” outperformed the other two theatres in 9 out of 12 weeks, the length of the implementation period. Further, the researchers reported that the use of decision support systems was increasingly valued by managers over time; at the end of the study, the exhibitor asked the authors to develop a revised model for use in a new major multiplex. Later in Section 13.3, we will discuss the details of the implementation and key lessons learned.

A critical portion of the SilverScreener model is the forecasts for each week’s movie attendance, in each theater that is under consideration. Thus, the problem of movie scheduling is closely related to the revenue forecasting models discussed in the previous section. See ESWW and Section 13.3 for a discussion of how both objective and subjective elements were incorporated into the decision support system designed for Pathé.

### 13.2.3 Models for the Home Video Market

The total revenue from the U.S. home video market (including both the sale and rental of videos, which encompasses both DVDs and video tapes) exceeds that of theatrical distribution by a wide margin. For instance, in 2005, the home video market generated around $23.8 billion in total revenues (Standard and Poor’s 2006), while tickets from theatrical distribution only generated around $9.0 billion (http://www.mpaa.org). Despite its economic importance, the home video market has received surprisingly little attention from marketing researchers. This may be because published data on the home video market are, in general, more difficult to obtain than data for the theater market, or perhaps, because most researchers view theatrical release as the “glamour” industry. Among the handful of published models in this area, three major aspects of decision making have been investigated: (i) the timing of video release (how long after the theatrical release of the movie should the video be released), (ii) the revenue sharing arrangement between the video distributor and the video retailer, and (iii) the video retailer’s decision on price and quantity.

#### 13.2.3.1 Home Video Release Timing

Once a movie is released, one of the most important questions is how long to wait before issuing the corresponding video, in the so-called video “window.” If the video is released too long after the movie, then the excitement and hype surrounding the movie’s release may dissipate. On the other hand, if the video window is too short, movie fans may feel that it is not worthwhile to go to the movie theater and instead just wait to see the video. In other words, to what extent does the movie serves as a promoter of the video, and to what extent does
the video cannibalizes box office revenues? Lehmann and Weinberg (2000) and Prasad et al. (2004) addressed this question from two different perspectives.

Lehmann and Weinberg (2000) approached the modeling task from the viewpoint of a distributor who needs to decide when to release the video. They developed a descriptive statistical model of a movie’s box office revenue and home video revenue over time. Consistent with previous work that we reviewed earlier in this chapter, they used an exponential model to characterize the declining box-office ticket sales over time for a movie, and then extended the same functional form to the video rental market. Formally, let \( t_2 \) be the release time of the video, \( M(t) \) and \( V(t, t_2) \) be the revenue of the theatre and video over time respectively. The authors specified that

\[
M(t) = \begin{cases} 
  m_B^1 e^{-m_B t} & 0 \leq t < t_2 \\
  m_A^1 e^{-m_A t} & \text{otherwise} 
\end{cases}
\]

and

\[
V(t, t_2) = v_1 e^{-v_B t_2} e^{-v_A (t-t_2)}
\]

(13.21)

where \( m_B^1 > m_A^1 \geq 0 \). The difference between the two decay rates \( m_B^1 \) and \( m_A^1 \) thus represents the degree of cannibalization of theatre revenue by the introduction of home video, which is also depicted graphically in Fig. 13.6. As can be seen, the revenue from movie theatre is assumed to drop once the video is introduced. The extent of the drop, i.e., cannibalization, is then estimated from actual data.

To obtain analytical results to guide management thinking, Lehmann and Weinberg (2000) made two critical assumptions in their model. First, when the video of a movie is released, all of the corresponding theater revenue is assumed
to be cannibalized. Second, the opening strength of a video is assumed to depend on the opening strength and decay rate of the movie’s box office, and the length of the video window; typically, a longer video window often leads to a lower opening strength for the home video.

Lehmann and Weinberg (2000) then incorporated their empirical model into a normative framework in order to determine the optimal time to release a video. They solved for the optimal release time of the video using a backward analysis algorithm, which consists of two steps. In the first step, the retailer’s optimal order quantity for videos is derived. This optimal quantity is then used in the second step to derive the optimal “window” between the release of the movie and the video. The researchers applied their model to a dataset of 35 movies. For each movie, they collected information on the weekly box office revenue, the marketing activities (e.g., pricing strategy) for the video, and the weekly rentals of the video. They reported a good fit for their model, and suggested two recommendations for distributors. First, using movie ticket sales to forecast video revenues will lead to better predictive accuracy. Second, distributors may adjust the release timing of the video to maximize their profit margins. While the optimal release time varies for each movie, in most cases the analysis suggested that a shorter window between the movie and the video’s release is preferred. In particular, the researchers reported that studios may increase their profits on average by 37% if they follow the release timing recommended by the model.

Prasad et al. (2004) studied the issue of optimal release timing of the video from a different perspective. They explored the issue using a theoretical framework and did not offer any empirical test for their model. The focus of their work, therefore, is on understanding how altering various model assumptions will lead to different analytical conclusions under their analytical framework. A key contribution of their model is that they focus on the role of consumer expectation, which is not considered in Lehmann and Weinberg (2000). That is, consumers anticipate the time of a video’s release based on their past experience with video rentals. In conjunction with Lehmann and Weinberg (2000), their model gives us a more complete understanding about the issue and competitive dynamics surrounding the home video market. Both papers conclude that for most movies, earlier release of the video is a more profitable strategy.

Papers in this area typically assume that the decisions when to release a movie and when to release a video are independent; however, a broader view may be required. The decision may better be framed as a joint one of when the movie and the video should be released (see Krider and Weinberg 1998), allowing for the decision to be updated after weekly movie revenues are observed.

### 13.2.3.2 Channels Contractual Arrangements

The contractual agreement between an independent manufacturer and an independent retailer has long been an important area of study in industrial organization, and has been applied to many marketing settings (e.g., Jeuland
and Shugan 1983; McGuire and Staelin 1983). The basic underlying problem is that the retailer, driven by its own profit incentive, may take actions that deviate from those preferred by the manufacturer. These deviations may reduce profits for the channel as a whole. In the case of the video rental industry, the retailer has to make two key decisions, the number of copies of a video placed in stocks, and the rental price. To make these decisions, retailers need to allow for demand uncertainty and the cost of stock out. As video demand declines over time, a special feature of the models is that the retailer orders the video only once, making the problem a variant of what is called the “news vendor” problem in the operations research literature.

One reason that this problem has drawn the attention of researchers is that since the late 1990s, the terms of the contract between the distributor and the video store have changed dramatically. Prior to 1998, most videos were sold to retailers by distributors at a flat price of about $70. After that, the contract for many movies switched to a two-part tariff: retailers were typically charged a price of about $5 per video, but had to remit more than 50% of the rental income back to the distributor (see Mortimer 2006 for more details). This provides a fertile testing ground for the theoretical development and empirical examination of contract theories.

Dana and Spier (2001) is representative of the theoretical approach taken by economists to study this problem. Since the theoretical derivations in their paper are fairly involved, we only provide an overview of their model set up, the assumptions, and the key results. Interested readers are encouraged to refer to the original paper for the full mathematical details. The channel set up in Dana and Spier (2001) consists of a monopolistic studio distributor, who produces each unit of output with cost \( c > 0 \), and retailers whose cost of renting out a movie is \( d > 0 \). The retailing market is assumed to be perfectly competitive, and each consumer is assumed to have unit valuation \( V > d + c \).

To mimic the situation in the video rental market, the researchers make a number of assumptions. First, consumer demand is assumed to be uncertain, with the uncertainty captured by allowing the number of consumers to be drawn from a generic distribution \( F(\cdot) \). Second, a planning horizon of only one period is considered. Third, retailer can set both the rental price and the quantity to order.

With these assumptions, Dana and Spier (2001) showed that a “revenue sharing contract” \( \left\{ \left( \frac{d}{1 + \eta} \right) c, \left( \frac{-d}{1 + \eta} \right) \right\} \) will optimally “coordinate” the channel, i.e., obtain an outcome equivalent to that of a vertically integrated channel. A revenue sharing contract denoted by \( \{ t, r \} \) means that the retailer pays an upfront fee of \( t \) per unit, and on top of that pays a fraction, denoted by \( r \), of his/her rental revenue to the distributor. While this theoretical result is, like in many other studies, dependent upon many simplifying assumptions which abstract away from the real world, the primary message has powerful managerially implications. It shows that revenue sharing contracts solve the coordination problems generated by vertical separation, demand uncertainty, and
downstream competition, and thus lead to improved results for manufacturers. With the use of revenue sharing contracts, retailers will tend to increase their inventory holding, and to be involved in less intense price competition. Finally, Dana and Spier (2001) compared revenue sharing contracts with other mechanisms for channel coordination, including return policies, resale price maintenance, and two-part tariffs, and found that revenue sharing contracts avoid many potential problems associated with the other mechanisms. In particular, revenue sharing contracts typically involve lower transaction cost and logistical burden; thus, Dana and Spier (2001) recommended their use in the video industry.

From a theoretical standpoint such as Dana and Spier (2001), a two-part tariff (and other mechanisms such as revenue sharing) leads to better channel coordination, and thus higher profits, than a fixed price contract. Demonstrating such effect empirically, however, requires a detailed dataset and an econometric methodology that adequately controls for the endogeneity of the retailer’s contract choice. Mortimer (2006) presents an empirical test of the impact of the two-part tariffs now implemented in the video industry. Her main goal is to compare the difference in profits, both for the upstream distributor and the downstream retailer, that results from a fixed price contract versus a two-part tariff. In addition, she also investigated the effect of the introduction of two-part tariff on social welfare.

Mortimer (2006) began by constructing a theoretical model of firms’ behavior. Assuming a linear demand function, she derived the profit maximizing conditions for a retailer who maximizes his expected profit by first choosing a contractual form, and then an inventory level. She then derived the equilibrium choice of level of inventory and of contract. This theoretical model is then calibrated with actual data by a structural econometric model at the store-title level, using the Generalized Method of Moments (GMM) approach. Her estimation approach is based on a set of six moment conditions, which jointly incorporates consumers’ demand, retailers’ inventory and profit maximization considerations, and the relationship between rentals and inventory.

The dataset used is very rich and disaggregated; it contains weekly information, such as price, inventory, rentals, for each title in each store. While her results vary for specific titles and settings, her results are well represented by her own summary statement: For popular movies, both distributor’s and retailer’s profits are improved by about 10% under two-part tariff. This improvement in profit is even larger for unpopular titles.

We believe that work such as Mortimer (2006) is a key step forward towards applying theory to practice, and is thus particularly important for both researchers and for decision makers. For researchers, this paper contributes to the academic literature by presenting an empirical test for the theoretical predictions with a rich dataset in the context of the video industry.
market. It also complements the previous theoretical studies (e.g., Dana and Spier 2001) that have examined the adoption of revenue sharing contracts in the video rental industry. As for decision makers, while such work does not provide information to distributors at the tactical level to suggest the amount of fixed fee and the specific revenue sharing terms to set for a specific movie, it does provide overall strategic guidance as to the type of contracts that should be used, and provides incentives for distributors to consider in changing current practice.

13.2.3.3 Home Video Retailer’s Decision on Price and Quantity

While the above cited contracting papers model some aspects of the retailer’s decision with regard to ordering policy (rental price and order quantity), the retailer’s decision is usually not the primary focus. In this section, we briefly mention literature that studied the price and quantity decisions from a retailer’s standpoint.

The video rental industry has been studied by many researchers in operations management (e.g., Drezner and Pasternack 1999; Lariviere and Cachon 2002). In particular, Gerchak et al. (2006) provided the link between this section and the previous section on contract agreements. In this paper, the researchers took the view of a retailer who has to decide how many copies of a specific video to order and how long to keep it on the shelf in the face of uncertain demand that is exponentially declining, on average, over time. With decreasing demand, the retailer needs to balance the costs of holding inventory and of lost sales in choosing the optimal policy. The authors derived the optimal recommendations for the order quantity and the time to hold a video for the retailer, and showed that it depends upon the nature of the contract offered by the distributor. Referring back to the previous section, the authors showed that when order quantity and shelf-retention timing is considered, even a two-part tariff may not be sufficient to coordinate the channel. Instead, a third term, a license fee (or subsidy) per movie title may be required to achieve channel coordination.

This last result raises an important modeling challenge, i.e., how complexly by a model should be specified. Obviously, more complicated models will be able to better capture reality and generate more detailed recommendations on managerial policies; however, they are also more susceptible to unrealistic assumptions. In addition, the policies recommended may be too difficult for managers to implement, especially as managers need to contend with a number of real world limitations as well. The appropriate level of model complexity, therefore, is a delicate issue that must be considered carefully and should be tailored to the specific application at hand. In the next section, we will discuss the application issues faced when the SilverScreener system was implemented.
13.3 Application Issues and Implementation Experience

Many marketing models have been successfully implemented in industry, and marketing researchers have recently placed more emphasis on the impact of their models on industry practice. With the increased attention to real-life applications (e.g., the commencement of the ISBM Practice Prize), we expect to see more successful implementation of marketing models in the near future.

To date, the most prominent application of marketing decision models has been in the area of sales-force models. For instance, Sinha and Zoltners (2001) reported on a long history of successful models in that area; Lodish (2001) discussed the successful use of CallPlan and other models. Outside the sales-force area, however, there has still been relatively little work that discusses the application of decision models, as many cases remained unreported in the existing literature. The movie industry, in particular, is far less receptive to the idea of applying quantitative decision models. Two of the authors of this chapter (Eliashberg and Weinberg) jointly with Sanjeev Swami and Berend Wierenga were involved in that implementation. For expositional convenience, the term “we” is used in this section to refer to the members of the implementation team. In particular, to encourage the use of decision models in this area, we report our experience obtained from the implementation of SilverScreener in Holland and the United States. By sharing the lessons learned during the implementation process, we hope to provide a useful guide to future researchers who may wish to apply their models in the movie industry.

SilverScreener, as discussed in Section 13.2.2, is a mathematical programming routine (used in conjunction with a weekly revenue forecast system) that recommends which movies an exhibitor should show in each week. ESSW described the first implementation of SilverScreener in detail and carefully specified the measures of implementation success. Our implementation was guided by Wierenga et al. (1999) systematic framework for decision support system implementation, which requires a careful match between decision makers and the decision making environment. In the discussion below, we highlight the key lessons learned from the implementation process.

Lesson 1: Managers Are Often Reluctant to Give Predictions

At first, we hoped to use managerial assessment as an input to the forecasting system in SilverScreener. However, we learned that managers are often reluctant to provide predictions due to at least two reasons: First, providing weekly forecast for each movie for each theatre requires a lot of effort; sometimes, managers just use very simple heuristics to guide their decisions. Second, a manager may prefer not to make forecast because of
the worry that potential loss in revenue due to forecast error would be held against them personally.

Since the goal of a decision support system is to help managers make better decisions, it must be designed with the end user in mind according to his/her personal preferences. In our case, the implementation of a decision support system should depend on the manager’s willingness to provide forecasting inputs. If the manager is reluctant to provide forecasts, a system should be developed with minimal managerial involvement. In contrast, if a manager provides detailed information and forecasts based on domain knowledge, this information should be incorporated as much as possible into the decision support system.

Lesson 2: A Successful Decision Support System Must Take into Account the Degree of Centralization in the Organization

In the exhibition sector, decision making is usually very centralized: One booker typically makes the scheduling decisions for all the chain’s screens. It is unlikely that this person, even if he/she is highly motivated, will have the basis for developing judgmental forecasts for the box office performance of each movie, in each of the local theaters. In our assessment, although the local theater manager may be more aware of the needs of the local clientele, he/she is not the person who is asked to provide forecasts for our system. This situation is in sharp contrast with the traditional retailing industry where decentralized decision making is more common and there is more local control. For example, two chain stores located in the same city may carry very different assortments, depending on the local clientele and the local manager’s familiarity with the store patrons’ preferences. We believe that for a decision support system to be successful, it must take into account the degree of centralization in the decision making mechanism in the target organization.

Lesson 3: Researchers Should Use All Available (and Appropriate) Data When Building a Decision Support System

Even when a field is data rich like the movie industry, managers may not use all the data available when they make decisions on a daily basis. For example, SilverScreener utilizes data that managers had access to but did not regularly use. These data included detailed box office reports and the results of market research on upcoming movies. Sometimes, the data that managers focused on are different from the data required by the decision support system. For instance, managers we spoke to typically pay more attention to gross box office revenues than to net revenues (which includes the effects of concessions and the deduction of sliding scale payments to distributors) although the latter is more directly linked to profitability.
In addition, presumably due to the need to make multiple decisions within a short horizon, managers often base their decision on heuristics rather than on data. This is precisely why models are valuable: though computationally intense at times, they can overcome some heuristic biases by forcing managers to take a hard look at the data available, and thus confront their decisions quantitatively and objectively. Therefore, it is important for modelers to identify and use all available data, even if such data are not regularly used by managers.

**Lesson 4: The Goal of a Decision Support System is to Assist in, but not Automate, Decision Making. Thus, Researchers Must Carefully Balance Complexity and Parsimony**

Researchers must keep in mind that models are only incomplete maps of the world, and many factors still remain outside the model. Such factors may occur too rarely to be included, and thus would add much complexity with little managerial gain; they may be unexpected and only revealed after the model was completed, perhaps because the manager or modeler may not want to reveal certain information. For example, in one instance, a manager chose not to show a movie that SilverScreener recommended because a distributor for another movie wanted a movie shown now, with the implicit bargain that when a very popular movie was available later on, this manager would have access to that movie. This “contract” is not considered by the SilverScreener system.

SilverScreener also involves several simplifying assumptions. For instance, it does not explicitly consider the seating capacities of the different screening rooms. Since sellouts rarely occur, this simplifying assumption may be justifiable even if it does not correspond exactly to the real world. This raises an important question: how complex should a model be, and how closely should the manager follow the model’s recommendations, given that it is an abstract of the actual situation? In one of our implementations, managers followed our recommendations of which movies to play in which screens about 60% of the time; this is consistent with Blattberg and Hoch’s (1990) recommendation that a 50-50 weighting between model and expert judgment is a reasonable balance. In any case, in an area as complex as movie scheduling, we believe that the goal is to assist the managers in making decisions, rather than to completely automate the decision process.

**Lesson 5: Researchers Should Keep the Managers Involved During the Model Building Process**

From our experience, most progress is made when managers stay involved in the model building and testing process. While implementing models is time consuming on the part of the manager, it is necessary to continually
monitor the process by which inputs and outputs are provided, identify new factors that may emerge, or even take into account changes in the management structure. In addition, perhaps due to the background of the managers in the movie industry, the managers with whom we interacted were more interested in the outputs of the model than the process by which models were generated. However, we think that managerial involvement is vital not only when we interpret output, but also during model development. Since not all managers are naturally inclined towards the use of analytical procedures, it is critical to make sure that models maintain face validity and adapt to changing circumstances, so that the model will continue to be useful for managers over time. Nevertheless, as the organizational history deepens, there is less need for continual contact over time and the burden on the managers will be reduced.

**Lesson 6: It Is Important to Evaluate the Model’s Performance After Its Implementation**

Finally, managers appear to be reluctant to set up a systematic review in order to judge the level of model improvement. In our experience, managers have been quite willing to put time and effort into the modeling process and have shared extensive internal data, but it has been our initiative to set up a control design in order to evaluate the system. As a result, the evaluation system described in ESWW was entirely developed by the researchers. Yet, we feel that evaluation is a crucial step both for managers and for researchers. For managers, we believe that this is the best way to judge whether the model has led to a profit improvement. In fact, we believe that the demonstrated success reported in ESWW was critical to our continuing work with Pathé. For us as researchers, our interest is in improving the quality of our models. Both diagnostic and performance data are needed in order to improve the models that are provided.

**13.4 What Models Are Still Missing: Opportunities for Further Research**

While there has been considerable progress in modeling and addressing various managerial issues in the movie industry, many issues are still open for future research. Some of these issues arise because of the recent trends in the movie industry. We provide a list of some of these emerging trends below. While this list is by no means exhaustive, we believe that it provides a valuable guideline for future researchers.
• Increased focus on bottom line performance in movie production decision making
• Availability of multiple distribution outlets (e.g., digital cinema/movies)
• Decline in the U.S. theatrical movie attendance
• Competition from other forms of media
• Increased worldwide focus: Globalization of both supply and demand in the entertainment industry

We now explore the implications of some of these trends for modelers.

13.4.1 Increased Focus on Bottom Line Performance

Over the decades, the motion picture industry has been transformed from one dominated by entrepreneurial studio heads who relied on their own intuitive judgments, to one in which executives and companies focused predominantly on bottom line performance. Few studios are independent entities; most are a part of conglomerates with a multitude of interests inside and outside the entertainment industry. While few would argue that a systematic model will ever replace the art involved in producing a great movie, many decisions are still subject to analytical scrutiny. This provides great opportunities for modelers. To illustrate, as described in The Wall Street Journal (April 29–30, 2006), the idea of investing in the production of movies has attracted investors such as hedge funds and other money managers who, in the 2004–2006, have provided more than $4 billion in movie financing to the major film studios. As noted in the article, “armed with computer-driven investment simulations and sophisticated database analysis, [investors] think that they can pick movies with the right characteristics to make money.” This represents an opportunity for collaboration between industry and academics where new models, capable of assessing, screening, and forecasting the commercial performance of movies based on the descriptors (e.g., scripts) that are available at each point of decision-making (e.g., green-lighting). An interesting question is: to what level can the uncertainty about movies’ performances be reduced? We do not believe that the movie making process should be completely random, and it would be interesting and important for investors to quantify the associated uncertainties as precisely as possible.

13.4.2 Multiple Distribution Outlets

The number of distribution outlets for movies have increased dramatically in the recent years. Besides traditional outlets of theatres and home videos, movies can now be distributed in electronic devices (e.g., iPod, cell phones) and over the Internet (e.g., movielink.com). This leads to a number of new managerial questions that deserve modeling attention. Modelers may study the extent to
which these different outlets cannibalize each other and whether, by contrast, they reinforce each other. They may also study what type of movie and content is most appropriate for large screen (i.e., theater) movie, small-screen (i.e., home TV set), and even micro-screen (i.e., cell-phone) entertainment. More generally, one may try to match movie characteristics with distribution channels, by considering the distinct segments of consumers who engage in consuming movies in different outlets. The existence of multiple channels also encourages researchers to jointly model the multi-stage life cycle process that films go through, perhaps even starting with the “buzz” prior to a film’s release\(^4\) (e.g., Liu 2006). One particularly important and interesting question, for instance, is how word of mouth (WOM) information and the buzz surrounding a movie affect its performance in each of the distribution outlets. Already, researchers have studied the extent to which WOM drives box office performance (e.g., Eliashberg et al. 2000; Liu 2006; Zufryden 2000); extending their research to consider a multi-channel setting, and hence develop them into decision models, may appear to be a natural next step. This may also add to the long stream of research in marketing that is concerned with the modeling of new products (e.g., the very first article in *Marketing Science*, BBD&O’s News model by Pringle et al. (1982) concerned new product management). The changes in the movie industry provide both an opportunity to empirically test and implement existing approaches, and a challenge for researchers to develop new approaches.

### 13.4.3 Decline in the U.S. Theatrical Movie Attendance

Modeling opportunities are increasingly generated as managers turn from a focus on the domestic box office market to multiple distribution channels and a worldwide perspective. Such changes increase complexity and make it more difficult for managers to rely primarily on intuition to make decisions, and increase the value of models to managers. As we discussed earlier, we do not expect such models to completely automate decision making, but rather to serve as an aid to decision makers. To date, the modeling literature has largely studied movies distributed in theaters, leaving opportunities for more focused models.

Marketing analysts have a long history of separating out the characteristics of primary and secondary demand using sophisticated estimation methods. Such approaches should help answer the important question of whether the decline in North American movie attendance in the recent years is due to a change in people’s viewing tastes and habits, to a slippage in quality, or to the employment of suboptimal marketing strategies. Similarly, as movies increasingly become vehicles for product placement, models which have helped media and media buyers to develop advertising programs can be adapted to the context of motion pictures (and other entertainment products such as video games). The impact of

\(^4\) We thank Fred Zufryden for this suggestion.
product placement on the quality of movies produced and their appeal to audiences is an important issue that deserves more research attention.

13.4.4 Competition from Other Forms of Media

There is a need for models that address the modeling of competition from “outside sources” to the movie industry. Researchers have considered the competitive aspects of different movies titles in the prediction of film market shares and life cycle (e.g., Krider and Weinberg 1998; Ainslie et al. 2005). The next step forward, we believe, is to model the “higher-level” threats to the film industry from related industries such as video games. More specifically, we believe that different models are needed to capture the “passive” movie watchers’ and the “active” entertainment consumers’ behavior. Such models are likely to help in identifying fundamental differences that will have significant implications on both the appropriate content provision as well as on the marketing strategy. An important concern for managers and policy makers is the threat of piracy to the economics of the movie industry and current practice. Only limited work has been done in this area.

13.4.5 Increased Worldwide Focus

Much of the work reviewed in this chapter has focused on the United States and on the theater market. As we have already noted, this is where research attention has focused. However, as Weinberg (2005) and others have pointed out, the non-theater market accounts for more revenues than the theater market, and revenues from outside North America are approximately 50% higher than those in North America. An important challenge is determining what modeling structures will be most useful as the North American box office becomes a smaller portion of the overall market. At present, Hollywood studios—or the conglomerates that control them—continue to dominate the world wide market. One may wonder whether there are strategies, both from producers and distributors standpoints, that will allow this dominance to continue. It is too early to determine whether the development of such sites as youtube.com which allow originators to provide their content directly to users will lead to a fundamental shift in movie distribution or just another alternative to the current arrangements.

Finally, consistent with the view of other authors in this volume, we want to emphasize the importance, challenge, and the enjoyment of working with managers to apply marketing models in industry. While the literature reports on relatively few implemented models, we strongly encourage other researchers to examine for themselves whether there is “nothing as practical as a good theory”. We hope that this chapter will serve as a useful guide for future researchers in the movie industry.
Reference


