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# Content Pricing in IPTV

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by

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*tűzcsap :)*

# Statement of Originality

I hereby declare that this thesis is a presentation of my original research work and that no other sources were used other than what is cited.

I furthermore declare that wherever contributions of others are involved, this contribution is indicated, clearly acknowledged and due reference is given to the author and source.

I also certify that all content without reference or citation contained in this thesis is original work. I acknowledge that any misappropriation of the previous declarations can be considered a case of academic fraud.

Tamás Jursonovics

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# Abbreviations

ACF autocorrelation.

CDF cumulative distribution function.

CRT cathode ray tube.

FTA free-to-air.

HBBTV hybrid broadcast broadband TV.

HDTV high-definition television.

IMDB Internet movie database.

IPTV Internet protocol television.

LCD liquid-crystal display.

OECD Organisation for Economic Co-operation and Development.

OIPF The Open IPTV Forum.

OTT over-the-top.

PDF probability density function.

SVOD subscription video on demand.

TVOD transactional video on demand.

VHS video home system.

VOD video on demand.

WTP willingness to pay.

# Introduction

> First thing is price elasticity – i.e. you reduce the price of something and people will consume more of it. Then, we have the ability to yield-manage, to charge prices according to demand... I'm taking that idea to cinema.
>
> —Stelios Haji-Ioannou, Founder and Chairman of easyGroup and easyCinema, 2003

Since Swinton (1908) described its theory of "Distant electric vision" in Nature, television and—as a consequence—ourselves changed dramatically. Today, television plays an important role in the day-by-day life, the broadcast industry shapes our knowledge, desire, expectation, and vision of future. It can be argued whether this development has served the intellectual or creative thinking of people, but there is absolutely no debate on its wide presence.

The technology of broadcast television has been evolving on an accelerated rate by inventions and influences from various other sectors from the first cathode ray tube (CRT) TV till hybrid broadcast broadband TV (HbbTV) (see Figure 1). For instance, several countries made a commitment to the *digital switchover*, launching a digital terrestrial television platform, and switching off the former analogue broadcast systems (see Figure 2). The legacy services were not able to compete in the last decade with the expectations of our digital generation and the efficient transport requirements of the increasing number of TV channels. Regulatory forces speed up the transition, and create demand for digital and interactive television (Adda and Ottaviani 2005; Iosifidis 2006). The age of the analogue broadcast has came to its end, and the digital services, including Internet protocol television (IPTV), will continue to emerge.

The Internet era, as the second driving factor, catalyzed this evolution. Broadband access is now widely available, customers are not required to use the local broadcast infrastructure any more, content can be transferred and consumed on a global basis. To illustrate this process with the most known over-the-top (OTT) players, Google recently introduced its interactive TV platform, which combines the television and

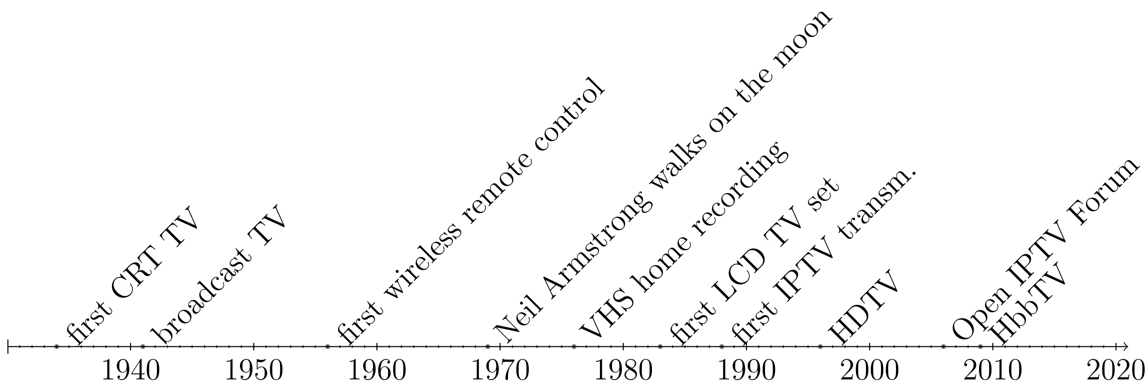


Figure 1. History of the broadcast television

web user experiences (Guardian US 2012; Choudhary 2010). Microsoft positioned the XBox One console as an equivalent gaming and home entertainment device (Microsoft 2013, 2006). Apple announced that HBO Go and WatchESPN come to AppleTV (Apple 2012a, 2013) and extended the features of its successful iTunes service (Apple 2012b). Amazon released an iPad application to access its on-demand video portal, and entered into contracts with several content owners to enlarge the content base of its video services (Amazon.com, Inc. 2013a, 2013b, 2012). It can be clearly seen that there is a big race for the customers, but it is not yet clear, which business concept will survive on long term.

The growing number of smart TV sets also challenges the traditional digital content delivery chain by creating an opportunity for content producers to bypass the middle distributors and reach consumers directly. This will allow them to capture some of that revenue, which is generated by the content aggregators (OECD 2014).

In spite of the widely available broadband connections, the revenue of the fixed line retail services of the telecommunication industry continues to decline, reported the Commerce Commission (2011). To preserve business profitability and reduce the churn of internet access products, legacy telecommunication providers extended their portfolio with various value adding services, like rich communication, mobile payment, and triple-play services to keep and attract customers. This successful strategy resulted a higher revenue, but the growing market of the new generation OTT services challenged the competitiveness of their triple-play services, therefore the telekom sector has to assess these threats with enhanced television services.

We can also observer ourselves, as we change along with television. The content consumption is slowly moving towards on-demand services, customers would like to access content everywhere and whenever on multiple devices, integrated with their

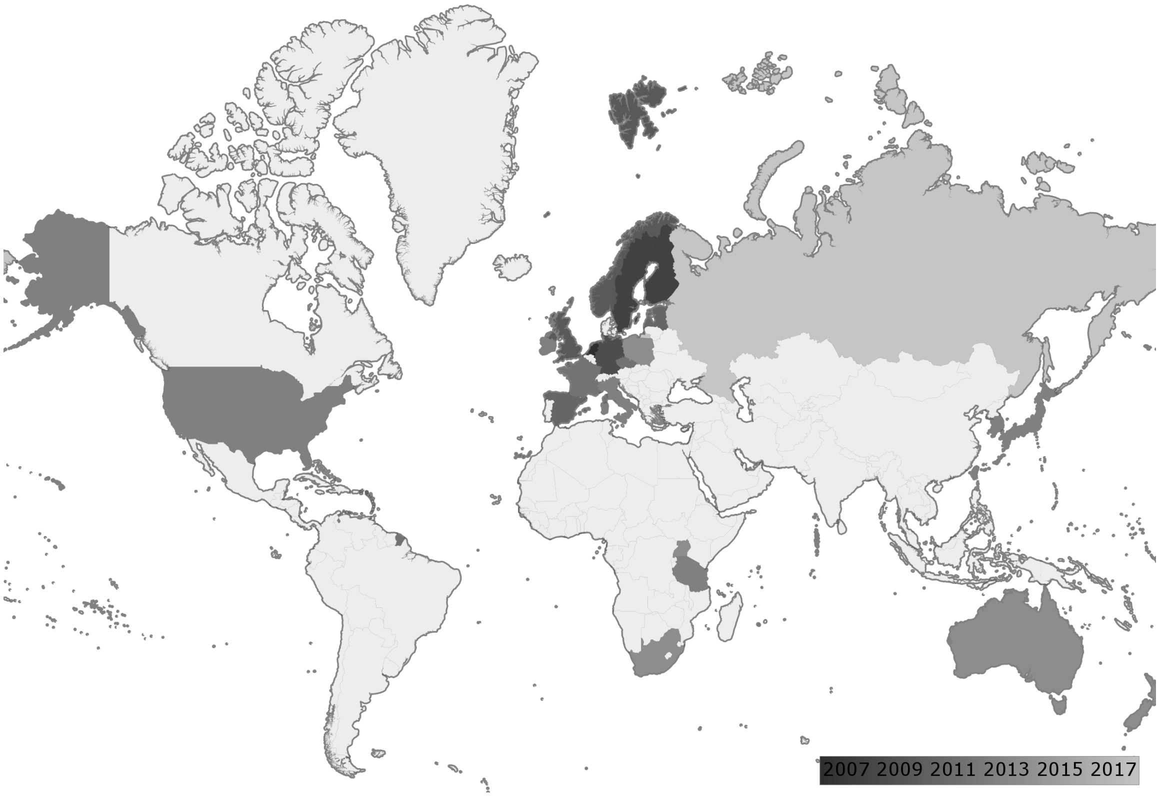


Figure 2. Analogue switch-off date in various countries. Data from DigiTAG 2013

digital social life. They are willing to pay for this privilege, however linear TV remained the main use case (Ericsson Consumerlab 2012). We understand that the on-demand market is not yet mature, OTT and telekom players have to find their way to exploit this emerging service and shape the customers needs with interactive services (Ericsson Consumerlab 2014).

The Global IPTV Forecasts report estimates that the number of subscribers, paying for IPTV service in 97 countries, will double in the next 5 years (see table 1). This means a 15% yearly growth rate between 2013 and 2018, which will be resulted by the new IPTV deployments mainly in Asia and by the increasing penetration of IPTV again the traditional broadcast technologies (Broadband TV News 2013). From financial point of view, the revenue will shoot up to $21 billion from $12.0 billion in 2018.

A recent Organisation for Economic Co-operation and Development (OECD) paper also concluded that the business prospect of the commercial digital content distribution are growing for both IPTV and over-the-top services, however the future of mobile television remains uncertain (OECD 2012, pp.5).

Table 1. Global IPTV forecasts

| | 2012 | 2013 | 2018 |
|---|---|---|---|
| TV households (thousands) | 1,438,918 | 1,461,553 | 1,580,224 |
| Pay IPTV subscribers (thousands) | 69,369 | 88,294 | 167,247 |
| IPTV penetration (%) | 4.8 | 6.0 | 10.6 |
| Revenues ($ millions) | 12,041 | 14,224 | 21,321 |

*Note:* Data from Murray 2013

> Streaming video now represents the largest component of Internet traffic. Viewers are watching a growing share of video via Internet-based distribution systems to both television sets and new endpoints such as computers and mobile devices. A substantial share of that video content is user-generated, user-selected, or otherwise outside the traditional model of professionally-produced linear programming.
>
> New entrants and services are competing with the linear broadcast paradigm and the bundling arrangements driving revenues in many content industries.

Recognizing this importance and business challenge in content on demand service, I decided to restrict my scope on only this service and I chose the

> Content Pricing in IPTV

for the topic of my research. In this thesis, I introduce (i) an idea based on disruptive innovation, and I develop and evaluate new solutions for (ii) dynamic pricing in IPTV. This is carried out in (iii) a simulation framework, which is designed and built for this purpose. In my opinion, these methods will help IPTV providers to maintain innovative services, and guide them to "cross the chasm[1]" and create the de-facto standard for future on-demand content services.

But what are the most interesting challenges of content on-demand services in IPTV today? According to the report of Ericsson Consumerlab (2014), the transactional video on demand (TVoD) service is not yet popular, customers are expecting the same free services, which they already consume in the online word. OTT entrants are continuously challenging the traditional content release window system of the movie industry. Competition is high by illegal online piracy, therefore video on

1. My research focuses on only one aspect from Moore: the price.

demand (VoD) not profitable yet (De Vinck, Ranaivoson, and Rompuy 2013; PricewaterhouseCoopers LLP 2013). I aim to provide answers to this problem.

The solution could lay in peer to peer technologies (Chen et al. 2007), in new architecture (Zeadally, Moustafa, and Siddiqui 2011), or as I claim in my thesis, in advanced pricing schemes (Courcoubetis and Weber 2003). As conclusion, I formulate my research question on the following way:

> How the IPTV content pricing models could be enhanced to improve revenue?

If IPTV service providers could enhance pricing models, they can expand their customer basis and increase revenue and profitability. Pricing is a simple factor, which can be adjusted easily. Consecutively, they could also achieve progress in several other areas:

- infrastructure: increase the underlying IT infrastructure's efficiency,
- satisfaction: increase customer's satisfaction with alternatives.

But on the other hand, drawbacks have to be addressed:

- acceptance: customers may not easily accept changing prices,
- holding period: dynamic pricing is not applicable for renting and holding, customers may rent the content in a low price period, and watch it during the peak hours, therefore the renting model has to be changed radically.

In this thesis, I address my research question and develop new methods for the dynamic optimization of IPTV content pricing. Chapter 1 gives a brief overview about the materials and methods used in further sections. Then chapter 2 introduces the theoretical background on my new method, which is followed by the evaluation and discussion of my results in 2.3.

# Chapter 1

# Materials and Methods

Let me begin my thesis by describing the tools and method, used in my research with the aim of providing a solid basis to validate and reproduce my results. This chapter provides only a brief overview of the mathematical instruments, for further details, please refer to the given sources.

## 1.1 Terminology

I choose the terminology of Open IPTV Forum specification release 2 (Open IPTV Forum 2011) to describe the IPTV features in my thesis, because I experienced a wide diversity of terms in several articles, which may confuse the reader. I believe, that the The Open IPTV Forum (OIPF) terms are straightforward, and they can be easily interpreted on any IPTV solutions, though my work is independent from the standard itself.

I interpret the "IPTV" term on a broader basis, which refers to both the managed and unmanaged models, including traditional television delivery and OTT services.

Some of the terms may sound unfamiliar, therefore I provide a small excerpt in the glossary to help the reader's accommodation to these expressions.

## 1.2 Testbed

The evaluation of my research requires a framework, in which I can prove the clear benefits, advantages and disadvantages of my results. In 2, I propose novel methods and models for pricing in IPTV solutions, but due to this early research stage, I have not aimed an evaluation in a commercial implementation, instead, I have built a simulation framework to reach my conclusions. Its main components are listed in Figure 1.1.

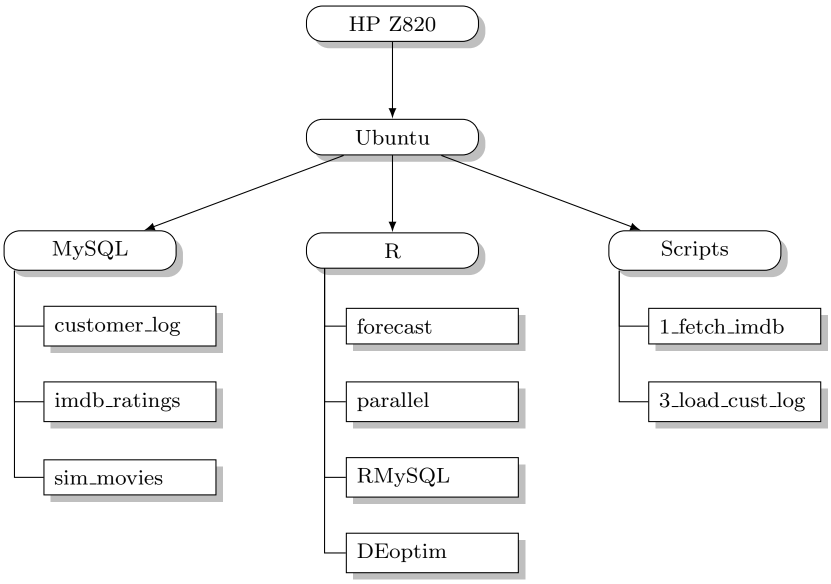


Figure 1.1. Components of the testbed

**HP Z820.** A workstation with two Intel(R) Xeon(R) E5-2697 v2 @ 2.70 GHz 12 core CPUs, running vmWare ESXi 5.5.

**Ubuntu.** To support the extensive resource requirements of my simulations, a powerful machine is required, therefore 32 logical CPUs, 200GB memory and SSD storage are allocated to this virtual instance. Leveraging parallel computing, the simulation is performed at a rate of 1000-6000 times simulation clock, however computing one round (including 3 Months of data) still takes approximately 1-2 hours. Ubuntu provides a flexible framework for all the required software components, besides I am a big fan of Linux.

**MySQL.** Due to the complex datasets, and required cross referencing I use a MySQL 5.6.19 database to store and process input data.

**customer_log.** Normalized number of VoD request over a three month long period, acquired from an anonymous tier1 IPTV service provider[1].

**imdb_ratings.** The Internet movie database (IMDb) Alternative Interface, containing ratings over thousands of movie titles.

**sim_movies.** Arbitrary selection of assets from imdb_ratings, used in simulation.

**R.** A statistical computing and graphics framework from the R project (R Core Team 2014). R provides powerful, flexible, and open source components to carry out

1. The name of the company is not disclosed on request. Data used with permission.

complex and extensive calculations. R is widely used by researchers in statistics, a good overview about its general usage is provided in Field, Miles, and Field 2012.

**forecast.** cran package for forecasting functions for time series and linear models (Hyndman and Khandakar 2008). Required by time series analysis and arima modeling, forecasting.

**parallel.** cran package for parallel computation in R. Required to leverage the multicore architecture to accelerate simulation speed.

**RMySQL.** cran package, R interface to the MySQL database.

**DEoptim.** cran package for global optimization by differential evolution.

**scripts.** My own script collection.

**1_fetch_imdb.** Download and ingest of IMDb data into the database.

**3_load_cust_log.** Process and load of customer logs into the database.

## 1.3 Data Sources

My simulation framework introduced in 2.2.2 requires input values for customer choice simulation. In my work I am using the following two sources, which are online available according to the given references.

### Customer Logs

Figure 1.2 shows the hourly aggregated number of VoD accesses in an IPTV system over three months. In order not to expose any business relevant information, this dataset was normalized to 1. To get realistic, industry relevant numbers, I arbitrary upscale this normalized dataset with a 2,000 factor[2]. I also perform a 5 hours timeshift to fit the minimum points of the periodic function to the beginning of every day to ease the interpretation of my results. This constant transformation has no effect on my results.

### IMDb

IMDb provides an alternative interface for accessing its full movie database[3]. In my research, I used the *Distribution* and *Votes* columns in the *ratings.list* file. An excerpt from the file is showed in Figure 1.3

2. 2000 is personal choice based on my experiences
3. Information courtesy of IMDb (http://www.imdb.com). Used with permission.

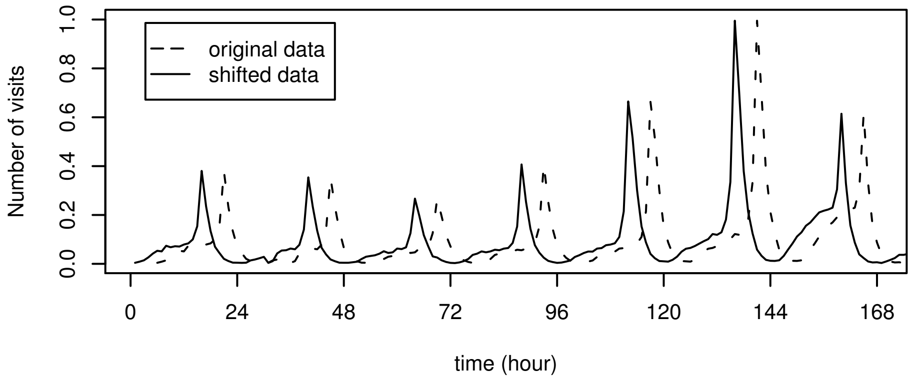


Figure 1.2. IPTV hourly visits. Part of 3 months. Data used with permission

```
New  Distribution  Votes  Rank  Title
      0000001123  320382   8.3  2001: A Space Odyssey (1968)
      0000001223  116584   8.3  Jodaeiye Nader az Simin (2011)
      0000001222  721506   8.3  Batman Begins (2005)
      0000001222   87682   8.3  Metropolis (1927)
      0000001322  452961   8.3  Toy Story (1995)
```

Figure 1.3. Excerpt form the IMDb ratings.list file

According to its description, the values possess the following meanings:

> In this list, movies have been rated on a scale of 1 to 10, 10 being good and 1 being bad. For each movie, the total number of votes, the average rating, and the vote distribution are shown. New movies are indicated by a "*" before their entry.
>
> The vote distribution uses a single character to represent the percentage of votes for each ranking. The following characters codes can appear:
>
> "." no votes cast "0" 1-9% of the votes
> "1" 10-19% of the votes
> "2" 20-29% of the votes
> "3" 30-39% of the votes
> "4" 40-49% of the votes
> "5" 50-59% of the votes
> "6" 60-69% of the votes
> "7" 70-79% of the votes
> "8" 80-89% of the votes

"9" 90-99% of the votes
"*" 100% of the votes

I performed a small adjustment on the *Distribution* column, after I inserted the data into my table. I define the rate of a movie as a discrete random variable: $d \in \mathbb{N}, 1 \leq d \leq 10$, to allow customers rate the same movie differently. I interpreted the discrete probability density function of $d$ on this column according to the following mapping:

$$P(d = i) = \begin{cases} 0 & \text{if } e_i \text{ is "."}, \\ 1 & \text{if } e_i \text{ is "*"}, \\ e_i/10 + 0.05 & \text{for all other cases,} \end{cases} \qquad \forall i \in \mathbb{N}, 1 \leq i \leq 10, \tag{1.1}$$

where $e_i$ is the $i$-th character in the distribution column. The 0.05 additive tag moves $e_i$ value in the middle of his range, and requires further normalization on the probability density function (pdf), because after the addition, the values does not sum up to 1.

## 1.4 Algorithms

In this section, I summarize the most relevant algorithms used in my research and I overview several alternatives for their realization.

### Forecasting complex time series

The appropriate modeling and forecasting of time series are required by the nature of my work. This topic is very well explained by the great book of Hyndman and Athanasopoulos (2014), which is freely available online[4]. I strongly recommend this to everyone, who is unfamiliar with the basics of time series analysis.

As I describe in 2.2.1, my model has to cover double seasonal time series with exogenous covariates. R provides several packages for time series purposes:

- tbats {forecast}: Captures double seasonality very well, but does not implement external regressors (Livera, Hyndman, and Snyder 2011).

4. https://www.otexts.org/book/fpp

- arima {forecast}: An arima model with external regressors (Hyndman and Khandakar 2008). The package supports only single seasonal time series, but double seasonality can be covered by additional Fourier terms according to (De Livera, Hyndman, and Snyder 2011).
- auto.arima {forecast}: My preferred choice, a function with automatic arima model selection based on several information criteria.
- arimax {TSA} Extends the basic arima model with transfer functions, which can capture complex models rather than linear regression (Shumway and Stoffer 2011). It promises a great value, the model fitting is quite straightforward, but unfortunately, the author of the TSA package have not provided an implementation of the forecast function for the arimax model. This means, that the model can be fitted well, but no out of the box forecast is available. Due to the time constraint of my thesis, I rejected the usage of this model, however it would be interesting (and really useful for the research community) to extend the TSA package with the appropriate forecast function.
- {expsmooth}: Exponential smoothing provides also comprehensive forecasting methods (Hyndman and Athanasopoulos 2014, chapter 9), but as Osman and King (2011) pointed out in his conference presentation, there is a theoretical issue with forecastability, if regressors have to be included into the model.
- {dynlm}: A dynamic linear approach could also provide the desired results (Zeileis 2014). Petris, Petrone, and Campagnoli (2009) gives an extensive overview about the usage of this method in R.
- {nnet}: There is always a way to use neural networks, R provides several packages, including nnet (Venables and Ripley 2002).

## Multidimensional optimization

R provides many parameter optimization packages, which I need to find the optimal price set for maximal revenue.

- optim {stats}: Works well, but implemented on a single thread. My function to be optimized includes a call on fitted arima model forecasting, therefore finding a minimum involves several, computational exhausting iterations, and this function was simply too slow for my setup.
- DEoptim {DEoptim}: My preferred choice, a packet for global optimization by differential evolution (Price, Storn, and Lampinen 2006). Provides similar results as optim, but it realizes parallel computing. (In my testbed, DEoptim

required approximately 1 minute to find the minimum with 24 input parameters, on the other hand optim needed more than 10.)

- optimx: A new packet to replace optim. I have not addressed it yet.

# Chapter 2

# Variable Pricing in IPTV

Variable pricing in IPTV rarely (if never, to my knowledge) have been implemented in commercial products, which promises an exciting research area and new, complex challenges. In my view, the goal is not only to develop a new method or create competing service, but to be the first, who cracks this idea and founds a successful business, which may radically transforms today's VoD market.

In this chapter, I ask and answer the most important questions related to this idea. *Why the movie prices do not reflect demand?* A blockbuster movie at Friday night costs exactly the same as a mid-range film Monday early afternoon. This phenomena is unique for the movie industry, and the rational sense should tell us that movie theaters leave cache on the table by widely implementing this concept. *Is IPTV different from cinemas?* There are key differences in IPTV solutions, which allows to threat IPTV on a different way and implement new concepts. *What is the role of TVoD?* The IPTV industry is struggling to find its position in the content delivery chain due to the shrinking role of the content aggregator, caused by the new and dynamic over-the-top entrants. *Which sophisticated pricing scheme could offer advantages? How to forecast customer behavior and consumption?*

Consequently, I develop a new content pricing solution for IPTV services, which includes a disruptive innovation core. Then to prove its clear benefits, I create a new model for describing VoD consumption. Due to the fact that this is a green field development, I was not able to leverage an existing data-set for model evaluation, therefore I also create a novel framework for customer choice simulation to asses my claims.

Before I introduce all these instruments, let me overview the most important literature to give the reader a first glimpse of the underlying business mechanics and problems.

## 2.1 Literature Review

My attention was first drawn to dynamic pricing, when I was listening a Planet Money podcast[1] from National Public Radio in late September (Goldstein and Smith 2014). In their report, Jacob Goldstein and Robert Smith argue that in spite of the obvious success or failure of a movie, the ticket prices seem to be identical. Customers may think, that movie theaters do not reflect the demand in their prices, as it would be expected according to other industries, like petrol, online retail, sports event.

They conclude that demand is mirrored by cinemas: the location of the cinema, number of rooms, available seats, playing period of a movie do vary according to the demand. The reason, behind the uniform price, lays in several other factors. First of all, studios will never admit that a film does not worth to watch by allowing to put a lower price tag on it (however critics and movie ratings are usually signaling a failure in advance). Besides, cinemas try to avoid changing rooms: customers, buying a low cost ticket and inside the cinema entering the room of a higher priced movie.

On the top of these arguments, studios are negotiating over every single movie title individually, they enforced a revenue sharing model usually with in advance payments. This creates tension with cinemas, and they are not interested in variable pricing (yet).

### 2.1.1 Uniform Pricing

Barak Y. Orbach is a professor on the University of Arizona, who he studied pricing in the movie-theater industry. He argues that in many cases there are solid reasons for uniform pricing (McMillan 2005), but they do not apply for this particular industry. By lifting the legal constraints on vertical arrangements between studios and theaters, they could increase profit via variable pricing (Orbach 2004; Orbach and Einav 2007).

In his papers, he provides a comprehensive historical overview on US ticket prices over the last century . He shows, that prices were strongly differentiated before 1948 by distributors engaging in price fixing, which was ended by the Supreme Court decision in *United States* vs. *Paramount*[2]. As a consequence of the second world war, demand dropped for entertainment services, therefore B & C movies[3] were less produced, which caused less price dispersion in the post-Paramount era. The today

1. A great radio program, explaining actual and interesting developments in economy.
2. 334 U.S. 131 (2948)
3. are low-budget commercial movies, usually two tickets were sold for the price of one.

known uniform pricing scheme appeared in 1972 with the premiere of *The Godfather*[4], when all distributors (independently?!) decided to charge the same price for the movie. Since then, prices remained uniform.

Orbach identifies three main dimensions of uniform pricing across (i) movies that run at the same time, (ii) show times, a movie playing on weekdays and weekends, and (iii) the screen life time. He claims that the introduction of variable pricing among these dimensions could increase revenue. His analysis contradicts several possible causes besides uniform pricing like perceived fairness, unstable demand, demand uncertainty, menu and monitoring costs, agency problems, and double marginalization. He concludes that the unique characteristic of the motion-picture industry is the legal constraints on the relationships between distributors and retailers, which restrict the price alignment mechanisms along the supply chain. This prevents studios benefiting from variable pricing.

This argumentation supports my goal to find an enhanced pricing system for IPTV services, and shows that there are no economical reasons against variable pricing, if the current barriers could be lifted in an appropriate legal framework.

Variable pricing is well known in the airline industry, especially for low cost carriers, like easyJet, but it is less known that this company has already tried to take over the cinema business (Easen 2004; Clark 2006; Greenslade 2003; Smart and Lettice 2004). After the promising initial launch, easyCinema, a newly established company in the easyGroup, had to give up its vision due to the current legal system, which protects the intellectual property of the big studios, who most of the times dictates the price policies for cinema owners through their own distribution companies.

The story of easyCinema started by questioning the traditional model of ticket pricing: why costs a mid-week afternoon movie the same as another on Saturday night? easyCinema believed in its successful disruptive strategy, and in 2003 opened a 10-screen movie theater in Milton Keynes, United Kingdom. Its radical pricing strategy allowed early bookers to pay less, while late purchase costed extra according to the actual demand. This new business idea was not welcomed by film distributors and studios, and in spite of easyCinema's negotiation effort, no blockbusters could be acquired, which led to (beside an investigation of the Office of Fair Trading) low customer interest. In 2012, the building used by easyCinema was demolished.

I have to make it clear, that according to my view, IPTV is different than cinema, because IPTV occupies an other content release window. Blockbusters in TVoD form

4. A 1972 American crime film directed by Francis Ford Coppola and starring Marlon Brando and Al Pacino.

do not carry high value, as they do at first release. Studios should tend to ease their legal systems along the release cycles.

De Vinck interviews 54 stakeholders involved in the movies and European film policy making in her PhD thesis (De Vinck 2011). His work investigates the transition in the European cinema industry caused by the appearance of new technologies, shrinking release windows, online piracy, and revenue distribution deals. Among two other aspects, she evaluates the European film (support) policies and reveals the (i) horizontal ties with other European-level film-related policies and (ii) vertical relations with national, subnational and international actors and policies in the same field.

She concludes in chapter 3 that in spite of Hollywood strong position, developed by its interplay of factor conditions, rivalry, and close relationship with related and supporting industries, there is opportunity for smaller firms to settle, in which an important factor is diversity (pp.174):

> Innovation and adaptability are particularly important virtues in this regard - and less evident for bigger, established players as the Hollywood studios.

She also claims, that there is a possibility to lift the legal barriers in front of innovation and economical concerns have to be balanced to keep the interest of the audience (pp.175).

> We have shown that there exist both economic and cultural legitimizing factors for government intervention.

Her argumentation proves to me that a disruptive idea even in this historical industry can be successful!

### 2.1.2 Role of VoD in IPTV Systems

The European market for VoD services is not mature yet, it is continuously increasing without knowing its limits. This conclusion was drawn by De Vinck, Ranaivoson, and Rompuy (2013), who discuss the IPTV (VoD) service provider's view on this area. They argue that the audiovisual value network became more complex with the emergence of online services, which catalyzed new hybrid revenue models. The traditional content release system is still in place, but its clear borders are diminishing. TVoD services can now acquire the latest VoD releases, while different payment methods are introduced.

During their interview, most of the VoD service providers explained, that the VoD service is not yet profitable. Among many reasons, the most important are the strong presence of piracy and the unwillingness of customers to play for online content. They also point out that the costs of establishing a VoD service is high, which can be mitigated by the economies of scale offering contents in many countries within the European Union.

I find this concrete argumentation outdated, because today, there are several hosted IPTV platform provider, who offers a pay as you grow model (Aggarwal et al. 2011), therefore the initial infrastructural investments can be transferred into operational expenses. Inevitably, they provide a comprehensive overview on the VoD offerings in Europe. Up to a point, they show that an opportunity exists for new, innovative business models for VoD services in a changing market environment.

### 2.1.3 Dynamic Pricing Models

Dynamic pricing and revenue management is well known methods for profit maximization. I discuss this area only briefly, because there are several research papers presenting different approaches. For instance, Tereyağoğlu, Fader, and Veeraraghavan (2012) discuss the pricing strategies of theater shows, and develop a revenue management framework that models the dynamic effects of an organization's show and time related pricing decisions on the customer's propensity to purchase a ticket. They demonstrate the model's descriptive and forecast capabilities and provide a discount decision, which increases the revenue from each performance.

Their work is based on the model of customer arrival process with the proportional hazard model , which can capture the non-stationary of the arrivals. Their method is indeed a valid approach, which is supported by his results, where revenues are approximately with $2000 and $9000 higher than the revenues normally obtained.

An good book on dynamic pricing was written by Christ (2011). He present a Bayesian approach for the low cost airline industry and details his customer choice models. Similarly, Brooks et al. (2001) presents an other book on dynamic pricing of internet goods. They all have something in common: historical data, on which they can build a model. During my research, I have faced the problem of lack of existing information as I point out in 2.2.2, therefore these approaches are not one to one applicable for my case.

Furthermore, there are dynamic pricing methods, which are not targeting revenue and profit maximization. Yagi et al.; Basu and Little; Niu et al. (2002; 2000; 2011) introduce methods to manage the infrastructure capacity of an IPTV subsystem by adjusting service price. In my view, this is not an applicable approach, because today, the infrastructure cost for content delivery is extremely low, major CDN providers can offer as low as .40-.05 USD per GB transport costs[5], which invalidates the choice of building an expensive IPTV system instead of using hosted services. Even in some special case, when the service quality demands own infrastructure, a business goal of an enterprise cannot be placed behind IT problems.

The accurate forecast of customer's behavior is an important element of dynamic pricing. Casier et al. (2008) introduces a model, which addresses competition from other IPTV providers, the effect of analog switch off, and threats from OTT players based on game theory. He compares various pricing policies, like flat rate, time of day, congestion control, and auction based. I disagree with one of his finding, especially with the multicast-unicast shift. Today, the main use case of IPTV is linear TV, which will shift towards on-demand services according to the evolution in content consumption rapidly, but the increasing bandwidth demand of emerging technologies, like 3D, 4K[6], and future holographic broadcasts will always require the maximum available access bandwidth, which will force network operators to continuously use cost efficient multicast (even in the far future).

In summary, I am convinced that variable pricing is a feasible approach for IPTV services, it is not yet present due to the industry specific legal barriers, but every research induces that they can be lifted and they will be lifted over time, therefore only one question remains: when to "cross the chasm", because in the next section I show how to!

## 2.2 Theory

This section introduces my idea for variable pricing in IPTV and provides an overview on the theoretical principles of my model and simulation framework.

VoD contents are offered in several ways in IPTV systems according to the age and release window of the content, showed in Figure 2.1. Free-to-air (FTA) content can be accessed without any payment, but as the first release date is closer to the access date, the content is more expensive. Subscription video on demand (SVoD) is offered on a subscription basis, allowing the customers to access hundreds of titles on a fix, monthly price. TVoDs are released parallel or just right after the DVDs, and users have to pay on a transaction basis, either purchasing the movie for ever, or renting

5. According to several online posts, blogs. In this context, only the price magnitude is relevant.
6. Ultra HD television, using 3840x2160 pixels

```
[Cinema] [DVD/TVoD] [SVoD] [FTA] Release window
                   (-------------) Lovefilm
      ()       (----------------) Netflix
```

Figure 2.1. Content release windows

it for 24-48 hours. Some IPTV service providers engaged in content production as well, for instance Netflix is producing own content to be present in the first release window and increase the value of his content chain.

According to the report of (Ericsson Consumerlab 2014), on the one hand, the popularity of SVoD is increasing, however in this category, only low value movies are offered, on the other, TVoD is not yet mature, as I pointed out in my literature review. This gap seems to be growing, therefore to increase profitability of the TVoD service, a new approach has to emerge, because current trends and increasing pressure from online piracy could jeopardize the success of this release window.

To provide a solution, I am addressing the existing pricing scheme of TVoD and introduce the following dynamic pricing model.

- First, I restrict the renting window of TVoD contents to 30 minutes[7]. The shorter renting period is necessary to avoid fraud by renting an asset in a low price period and watching it later on, and in my view, this is in alignment with the current online trends, customers are more and more engaged with instantaneous entertainment rather than downloading or consuming later on.
- I use a sophisticated model to capture the dependency between customer choices and external factors of price and time of transaction.
- Then according to price optimization, based on the forecast of my model, I yield manage.

Based on the same argumentation, the dynamic pricing for VoD purchases is not feasible. This product is less frequently used and has significantly higher price range. I believe that this new model could radically change the whole landscape of VoD services, and may provide a real alternative.

To achieve this transition, the following prerequisites has to be addressed:

- Legal barrier: as i discussed in the literature review, there is a legal barrier ahead of the variable pricing for movie content, which can and should be lifted.

7. Assuming hourly price changes, according to Nyquist–Shannon.

- Model training: before the model can be used for forecasting, the relevant covariates have to be determined, which can be achieved by slowly variing the price for a training period. This will cause short term losses in revenue, but this is compensated on the long term.

On the resource site, this new model would require additional developments.

- Display of spot price: the IT infrastructure used in IPTV systems does already enable interactivity and spot pricing with a marginal investments.

### 2.2.1 Model

There are several statistical methods to capture the dynamic behavior of customer transactions over time. To implement my idea introduced in the previous section, such a method has to be selected, which assess the following IPTV specific features:

- Non-stationarity: customer choices clearly possess several time dependent attributes, like prime time, holiday patterns, and growth trend.
- Seasonality: there are significant and good observable hierarchical periods in the consumption of IPTV services. Early daily usage is very low compared to the evening hours, and the same difference can be seen on weekdays vs. weekends.
- Time dependent exogenous covariates: customer purchase decisions depend on several external factors, like price, weather, and subjective valuation of the content.
- Forecasting: the model should provide guidelines for future events in order to make optimal decisions.

The main challenge in variable pricing is to model the customer purchases along the time and price dimensions. A good model would accurately estimate the customer choices in advance, and based on this information, an appropriate action could be determined and carried out. After short consideration, I chose the arima model family from time series analysis, because it possesses all the required attributes[8], it is widely discussed, easy to understand, and several statistical software had already implemented it. I recall the general form of an arima model,

$$y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1 e_{t-1} + \cdots + \theta_q e_{t-1} + e_t, \tag{2.1}$$

8. I provide an overview and discuss the drawbacks of other models in 1.4.

where $y'_t$ is the differenced series (can be differenced d times as well), $p$ is the order of the autoregressive part, $q$ is the order of the moving average. In a short notation form: ARIMA$(p, d, q)$

To help understanding, how I build my model, I use and analyze a sample sequence from my simulation. The arima model requires stationary time series, for which the trend components have to be removed, therefore I apply a log() transformation on my sample series.

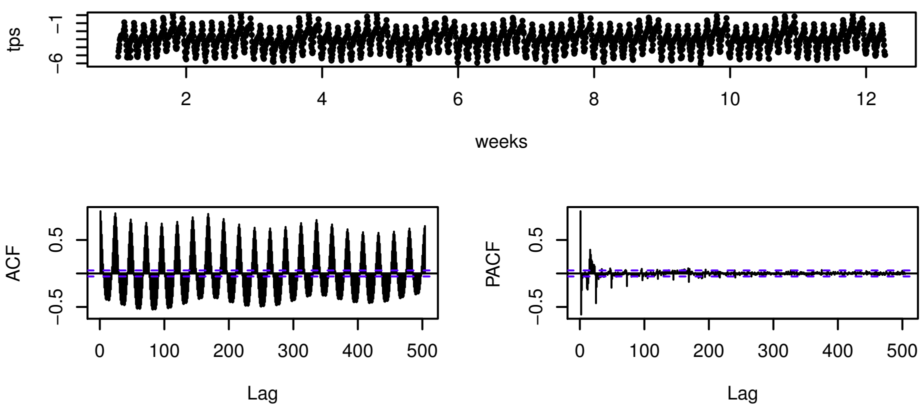


Figure 2.2. Sample time series. Applying log() transformation, the autocorrelation (ACF) diagram signals periodicity, a double seasonal term can be easily observed in the time domain. Data from own simulation

A daily and weekly double seasonality can be easily recognized, observing the ACF diagram in Figure 2.2. To eliminate this pattern, the arima model has to be extended with seasonal components[9].

$$\begin{aligned}
&(1 - \phi_1 B - \dots - \phi_p B^p) \\
&\quad (1 - \Phi_1 B^{m_1} - \dots \Phi_{P_1} B^{m_1 + P_1})(1 - \Phi_1 B^{m_2} - \dots \Phi_{P_2} B^{m_2 + P_2}) \\
&\quad (1 - B^d)(1 - B^D) y_t = \\
&\quad (1 - \theta_1 B + \dots + \theta_q B^q) \\
&\quad (1 - \Theta_1 B^{m_1} + \dots + \Theta_{Q_1} B^{Q_1 + m_1})(1 - \Theta_2 B^{m_1} + \dots + \Theta_{Q_2} B^{Q_2 + m_2}), \quad (2.2)
\end{aligned}$$

where $m_1$ and $m_2$ are the lengths of the seasonal periods, $P_1, P_2, Q_1, Q_2$ are the orders of the seasonal parts. In a shorter form:

9. Au, Ma, and Yeung 2011 compare models for double seasonality time series, and in their specific case show, that the arima models outperform exponential smoothing.

$$\mathrm{ARIMA}(p,d,q)(P_1,D_1,Q_1)_{m_1}(P_2,D_2,Q_2)_{m_2}. \tag{2.3}$$

I cannot use this model, because as I already explained in 1.4, the arima function implemented in R does not handle double seasonality. Instead, I am going to use trigonometric seasonal model with Fourier terms according to De Livera, Hyndman, and Snyder[10]. To achieve that, I use a linear regression (2.4), where the $n_t$ noise is allowed to have autocorrelation according to an arima model.

$$y_t = a + \sum_{k=1}^{K} \left( \alpha \sin(2\pi kt/m) + \beta \cos(2\pi kt/m) \right) + \gamma price_t + n_t, \tag{2.4}$$

$$n'_t = c + \phi_1 n'_{t-1} + \cdots + \phi_p n'_{t-p} + \theta_1 e_{t-1} + \cdots + \theta_q e_{t-1} + e_t. \tag{2.5}$$

Figure 2.3 shows the fitted arima model accordingly.

```
Series: tps.lts
ARIMA(2,1,1)

Coefficients:
         ar1     ar2      ma1     S1-24    C1-24   S2-24    C2-24   S3-24    C3-24    S4-24    C4-24   S5-24
              C5-24
      0.4854  0.2068  -0.9863  -0.5651  -1.3104  0.1945  -0.7078  0.0613  -0.0003  -0.1669  -0.0617  0.0305
           -0.0495
s.e.  0.0233  0.0232   0.0052   0.0133   0.0132  0.0088   0.0087  0.0065   0.0065   0.0053   0.0053  0.0046
       0.0046
        S6-24   C6-24    S7-24    C7-24   S8-24    C8-24    S9-24   C9-24   S10-24   C10-24   S1-168  C1-168
              S2-168
      -0.0017  0.0571  -0.0489  -0.0308  0.0232  -0.0151  -0.0018  0.0330  -0.0276  -0.0139  -0.4866  0.1921
            -0.1781
s.e.   0.0043  0.0043   0.0041   0.0041  0.0041   0.0041   0.0041  0.0041   0.0042   0.0042   0.0192  0.0192
        0.0178
       C2-168   S3-168   C3-168   S4-168   C4-168  S5-168   C5-168
      -0.1052  -0.0700  -0.0532  -0.0498  -0.0774  0.0196  -0.0894
s.e.   0.0177   0.0169   0.0169   0.0160   0.0160  0.0151   0.0151

sigma^2 estimated as 0.02974:  log likelihood=640.91
AIC=-1213.82   AICc=-1212.54   BIC=-1025.23

Training set error measures:
                       ME     RMSE       MAE        MPE     MAPE      MASE          ACF1
Training set 0.0007631684 0.172374 0.1249521 -0.8759606 7.654437 0.3305843 -0.0007348634
```

Figure 2.3. The arima fit results

Based on several tests, the $(10,5)$ values for $K$ provides the best results to cover double seasonality, the residuals of the arima model (remaining $e_t$ error term) seem to behave like random noise, the ACF and PACF functions shows only a few significant spikes in Figure 2.4. Indeed, further extension with volatility models could provide better results, but I assume that this complexity fits my research purpose, therefore I accept the above introduced model for double seasonality. (In view of my results, I will come back to this decision in 2.3, till that keep in mind.)

10. For a deeper analysis, please refer to De Livera, Hyndman, and Snyder 2011.

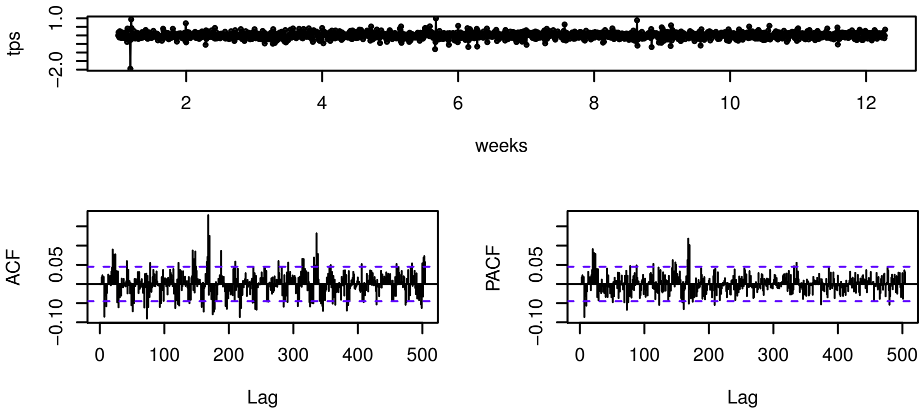


Figure 2.4. Residuals of arima fit. The modes is accepted in spite of the significant spikes in the afc and pacf. Data from own simulation

As the final step, to keep my model simple, I include only the price, as external influencing factor to my model, and I assume that the price elasticity follows a linear equation.

Axiom 1 (Price elasticity follows a linear equation).

$$q(price, h, i) = h - i \cdot price, \tag{2.6}$$

$$re(price, h, i) = q \cdot q(price, h, i), \tag{2.7}$$

where $h$ and $i$ are form parameters. My model includes its effect in the $\gamma \cdot price_t$ term in (2.4). The optimal price can be calculated on the following, well known way:

$$\frac{\mathrm{d}}{\mathrm{d}p} q(p, h, i) = 0, \tag{2.8}$$

$$p = \frac{h}{2i}. \tag{2.9}$$

Below is the source code of the above described model. The optimal price parameter set for maximal revenue is determined by a minimum searching algorithm of DEopzim. I use an additive term to push all values above 1 before the log() transformation, because otherwise the DEoptim function results strange values for negative inputs. This is compensated during forecast.

```
if ( method == 7405 ){  #final method
  #model
  tps.ts <- msts(log(tps+1),    #log(), +1: avoid neg. values
    seasonal.periods=c(24,168)) #double seasonality
```

```
  fit <- auto.arima(tps.ts,
    xreg=cbind(fourier(tps.ts,K=c(10,5)),price=price),
    seasonal=FALSE,     #disable season. (covered by F. terms)
    approximation=TRUE, #increase speed for long time series
    stepwise=FALSE,     #disable for parallel computing
    parallel=TRUE,      #increase speed by parallel computing
    num.cores=getDoParWorkers())

  #forecast
  p.fx <-function(par) {
    fc<-forecast(fit, xreg=cbind(fourierf(tps.ts, K=c(10,5), h=24),
        price=par))
    -sum(par*(exp(fc$mean)-1))         #-: turn to maximization
                                       #exp()-1: back from log space
  }

  #optimize
  opt<- DEoptim(p.fx,
    lower=rep(5*0.95,24),              #set overprice limit
    upper=rep(5*1,24),                 #set discount limit
    DEoptim.control(strategy = 2,itermax=200,parallelType=2,
      foreachArgs=list(.packages=c("forecast"))))

  price <- c(price,opt$optim$bestmem) #max. revenue next 24h
}
```

The arima model requires a training set, for which I allocate prices randomly over 4 weeks of training period. The variable pricing model will be activated only after this period.

```
if ( method == 7405 ) { #final method
  price <- c(price,runif(1,min=1,max=7)) #random for training
}
```

### 2.2.2 Simulation Framework

I face a serious issue, while I am thinking on the evaluation of my new model. To assess its properties and prove, that my idea has definite benefits, I have to demonstrate its function on customer data, but this data is not existing, because dynamic pricing have not been implemented in IPTV yet. Computer simulation could provide a solution, but such a framework requires also a model, on which the simulated data could be generated. I have a model, but if I would plug it in to the simulation then I would use my model to evaluate the same model... This is clearly a no-go, therefore I have to find an other approach. I reach back and I summarize the requirements, which a simulation framework should fulfill. According to my personal expectation and independent studies, these criteria are:

- Non-stationarity: the customer choices clearly possess several time dependent attributes (Qiu et al. 2009; Abrahamsson and Nordmark 2012; Traverso et al. 2013; Qiu et al. 2009).
- Power law: the watching statistics of movie assets follow a Zipf distribution (Breslau et al. 1999; Jagannathan and Almeroth 2001; Lorenz 2009).

Now, it is more clear, what to do. I decide to build my framework on existing data originated from uniform pricing, and I independently simulate the customer's choice process for my model. I gained permission and access to the log files of one tier-1 IPTV provider in Europe, and I recently discovered, that IMDb offers an open access database for movie titles. Based on these two data sources, I create a second model for customer choice simulation, which is showed by Figure 2.5.

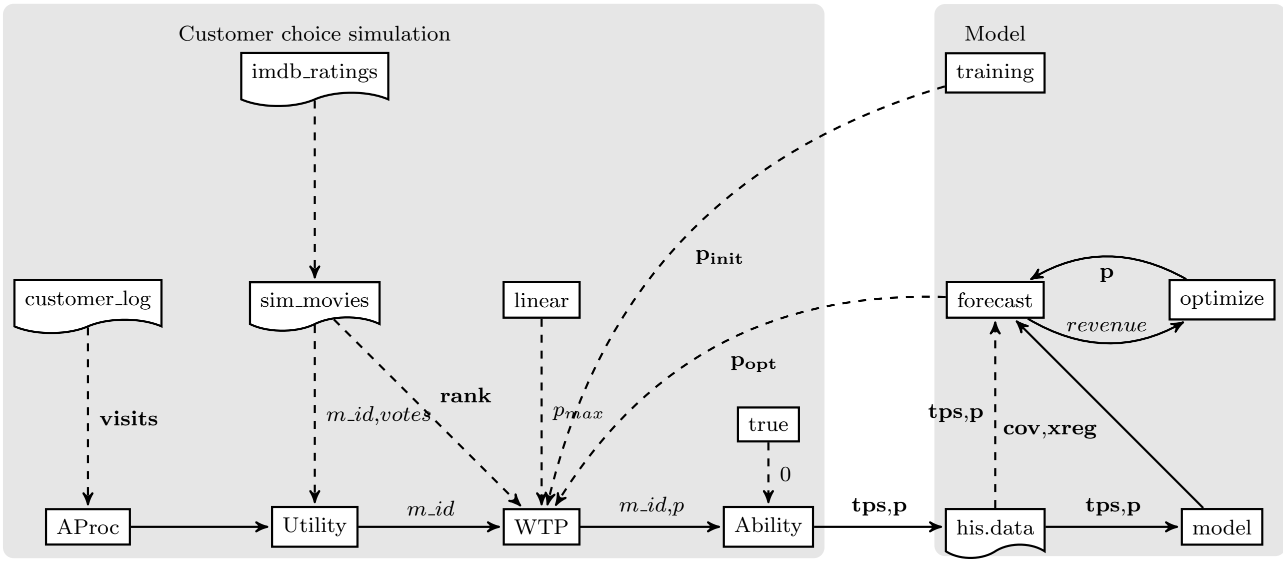


Figure 2.5. Workflow for customer choice simulation and prediction

The customer simulation block consists of 4 modules, each representing one step in the customer choice model.

The *AProc* function simulates the customer arrivals at the IPTV system according to the *customer_log* dataset. Remember, that this dataset was normalized to remove any business specific information on the IPTV provider, therefore it has to be scaled up with an arbitrary value (in my case 2000). This process triggers the individual choice procedure.

```
AProc <- function(visits,k){
  #visits - number of visits at period k (customer_log)
  #k      - simulation period (hour)

  result <- visits$visit[k]*2000  #arbitrary upscale

  return(result)
}
```

The *Utility* function represents a single customer choice by selecting one movie from the *sim_movies* movie set. This set is an 10000 pieces excerpt from the *imdb_ratings* database to use a realistic asset base size. The selection is performed by random sampling over *sim_movies* data set weighted by the number of votes (and not by the rating) for each movie. This step is by design, and it is important to pay some time to understand it.

What I am assuming is that a low rated movie can be also chosen several times, because before selecting a movie, customers have limited knowledge on its content. After watching it, a customer may conclude that a movie was not worth to see, and he may assign a rate accordingly, but as a consequence, the number of votes correlates better to the number of choices for a movie. I do not support this claim with analysis, therefore I am asking the acceptance of this axiom.

AXIOM 2. *The number of votes positively and strongly correlates with the number of choices.*

High voted movies should statistically fulfill the customer's utility to entertain better, therefore I use random sampling in my function. Finally, the utility function return the attributes of the chosen movie.

```
Utility <- function(movies){
  #movies - vector, the movie set

  #movie index (i) is selected on a random basis, weighted by the
     number of votes
  i <- sample(1:nrow(movies), size = 1, replace = TRUE, prob =
     movies$votes)
```

```
  result <- list(m_id=movies$m_id[i],     # movie id
                 p=movies$p[i],           # price, not used
                 rank=c(movies$d1[i],     # distribution of ranks (
                    sim_movies)
                       movies$d2[i],
                       movies$d3[i],
                       movies$d4[i],
                       movies$d5[i],
                       movies$d6[i],
                       movies$d7[i],
                       movies$d8[i],
                       movies$d9[i],
                       movies$d10[i]))

  return(result) #return the attributes of the selected movie
}
```

The *WTP* function implements the willingness to pay criteria. Based on the $r$ movie rating, it determines a $p_{max}$ maximal price, above which the customer will not spend his money. I use linear assumption and arbitrary, but industry relevant values for this function according to (2.10).

$$p_{max} = \frac{7 - 0.5}{10 - 1} r. \tag{2.10}$$

It is hard to determine the rate of a movie. For some customers, the *Return of the Jedi*[11] is an absurd science-fiction movie, for me it is the greatest film ever made. To capture this difference in opinion, I use the rate distribution.

AXIOM 3. *The utility of watching a movie is represented by the rate distribution of the movie.*

Let $r \in \mathbb{R}, 1 \leq r \leq 10$ denote a random variable, representing the rate of a movie and $f_r(r)$ the probability density of $r$:

$$f_r(r) = \mathcal{N}(d, 0.4), \tag{2.11}$$

$$P(d = i) = \frac{d_i}{\sum_j d_j}, \forall i \in (N), 1 \leq i \leq 10, \tag{2.12}$$

where $\mathcal{N}(r, 0.4)$ is the probability density function of the normal distribution with $\sigma = 0.4$ and $\mu = d$, where $d \in \mathbb{N}, 1 \leq d \leq 10$ is a discrete random variable, with

11. George Lucas's 1983 epic space opera film directed by Richard Marquand and starring Mark Hamill, Harrison Ford, Carrie Fisher, and others.

discrete density function of $P(d=i)$, where $d_i$ is the number of votes with rate $i$ over $j$ number of all rates for a single movie.

I admit that this could be a bit challenging to understand it at first! My intention here is to avoid a simulation problem: at first, I used the $d$ discrete random variable to model opinion differences by simply assuming that a customer would rate a movie according its rate distribution from imdb_rating. This had an unfortunate effect in the max price criteria function: it restricted the function's values to a discrete set. This caused non-linearity, the customer's decision (therefore the revenue function) had sudden steps, which jeopardized the forecast accuracy (and therefore the optimization effort) of my model. Thinking through this problem, in real life, I would also not expect harsh changes in the customer willingness to pay (WTP) function.

To eliminate this problem, the discrete probability density function $P(d=i)$ has to be transferred to a continuous probability density function ($f_r(r)$). This can be achieved by inverse transform sampling, but the inverse form of the desired cumulative distribution function (cdf) has to be calculated. This has a complex form and requires long expressions, instead, I used my own method. (The distribution of movie ratings is very well analyzed in Lorenz 2009.)

(2.11) is not else, just a skinny, jumping normal distribution. $\mathcal{N}(d, 0.4)$ has always a fix, 0.4 standard deviation, but its mean ($\mu = d$) changes according to the discrete rate distribution with every drawn from it. This implies, that a customer rating will be near to the 1-10 natural values, but more likely will be around that rate, which has higher probability. With this simple step, the overall pdf ($f_r(r)$) will be the weighted averages of the normal pdfs ($\mathcal{N}(d, 0.4)$), therefore a continuous pdf. Figure 2.6 shows the continious and discrete pdfs according to 4 arbitrary selections, and confirms my goal.

As the last step, the willingness to pay is chosen by a simple comparison. The price used in the *WTP* function is set equally for all movies, but changed over time by either the training or optimize functions according to my model described in 2.2.1.

```
WTP <- function(p,rank){
  #p    - price of the asset (set externally)
  #rank - vector, distribution of ranks (sim_movies)

  linear <- function(r){ #lin. appr. of the rank-max.price relation
    (7-0.5)/(10-1)*r
  }

  #rank (of the asset) is determined on a stochastic basis
  r<-rnorm(1,mean=sample(1:10,size=1,replace=TRUE,prob=rank),sd=0.4)

  if( p<=linear(r) )
```

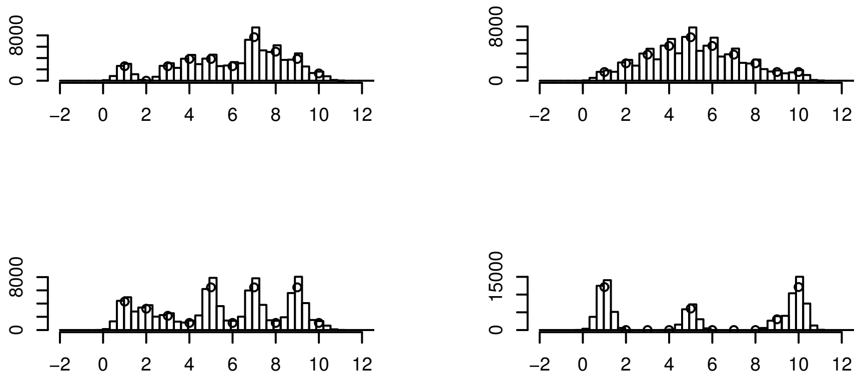


Figure 2.6. Discrete-continuous pdf transformation. The discrete pdfs are set by my custom choice, the histograms are determined on 100000 random samples each.

```
    result <- T
  else
    result <- F

  return(result)              #willingness to pay (TRUE/FALSE)
}
```

The last step of the customer choice model is the customer's *Ability* to purchase, where I used a constant true function to reduce my model's complexity.

```
Ability <- function(t,c_id,m_id) {
  result <- T
  return(result)                    #returns constant true
}
```

### 2.2.3 Orchestration

Now, I put all the pieces together for a working simulation.

1. My routine begins with a `for` cycle over the hours of the simulation period: `cycles_sim`.

2a. If the training period has not been ended yet (`k <= training_weeks*7*24`), the price is set randomly: `runif(1,min=1,max=7)`.

2b. If the training period is over (`else`),

2b.1. my arima model is fit on the existing transaction logs (`#model`),

2b.2. the prices of the next 24 hours are optimized to maximize revenue (`#optimize`)

2b.3. by forecasting the customers transaction with the fitted model's coefficients (`#forecast`).

3. According to the customer arrival process (`AProc()`), customer simulations are started (`foreach`) with the hourly price,

3.1. then a movie is selected for each customer: `Utility`,

3.2. the willingness to pay is checked: `WTP()`,

3.3. and according to the ability to pay (`Ability()`), the movie is purchased or rejected.

4. The logs of the transactions are stored: `tps <- c(tps,nrow(ret)/60/60)`.

```
cycles_sim <- 1897                   #about three months
training_weeks <- 4                  #length of training weeks

for(k in 1:cycles_sim){              #run cycles_sim cycles

  #init cycle
  if ( k <= training_weeks*7*24 ){  #training period
    if ( method == 7405 ){
      price <- c(price,runif(1,min=1,max=7))   #random prices
    }
  }
  else{                              #simulation period
    if ( k%%24==1 ){                 #beginning of a day
      if ( method == 7405 ){
        #model
        ...
        #forecast
        ...
        #optimize
        ...
        price <- ...                 #max. revenue next 24h
      }
    }
  }

  #run simulation cycle
  ret <- foreach(i=1:(AProc(visits,k)), #arrival process
    .combine='rbind',
    .inorder=FALSE) %dopar%{         #parallel computation

    utility <- Utility(movies)       #select a movie (based on
                                     #number of votes)

    spend <- Wtp(price[k],           #check willingness to pay
      utility$rank)                  #(based on rank and price)

    if(spend == TRUE){
      if( Ability() == TRUE){
```

```
        data.frame(m_id=utility$m_id,p=price[k])
      }
    }
  }

  #store data
  tps <- c(tps,nrow(ret)/60/60)
}
```

## 2.3 Results and Discussion

Let me answer your long tingling questions first!

### How much can we earn by this method?

It depends! To calculate the result, a reference method has to be chosen, to which my model can be compared. Let perform 10 measurements with identical input parameters and with 5 euro uniform price. Averaging these 10 results yields a revenue curve (105-4), on which my model can be evaluated. Table 2.1 shows the results of several revenue streams, simulated with my variable pricing method compared to the above defined reference curve.

Table 2.1. Simulation results – 1st round

| Simulation id[12] | Price range (E) | Total revenue (thousand E) | Gain (thousand E) |
|---|---|---|---|
| 105-4 | 5.0 | 2,007 | 0 |
| 7405-8001 | 4.75-5.0 | 2,024 | 16.5 |
| 7405-8002 | 4.75-5.0 | 2,027 | 18.2 |
| 7405-8003 | 4.75-5.0 | 2,018 | 10.5 |
| 7405-8004 | 4.75-5.0 | 2,024 | 17.1 |
| 7405-8005 | 4.75-5.0 | 2,023 | 15.7 |
| 7405-8000 | 4.75-5.0 | 2,023 | 15,6 |
| 7405-7001 | 4.5-5.0 | 2,027 | 20.5 |
| 7405-7002 | 4.5-5.0 | 2,028 | 21.1 |
| 7405-7003 | 4.5-5.0 | 2,028 | 20.8 |
| 7405-7004 | 4.5-5.0 | 2,028 | 20.2 |
| 7405-7005 | 4.5-5.0 | 2,028 | 20.4 |
| 7405-7000 | 4.5-5.0 | 2,028 | 20,6 |

Each simulation round yielded better revenue values on an 8 week period. A simple, 5% dynamic discount on the 5 euro basic price provides 10,000-16,000 euro more income than a constant 5 euro price (7405-800x). 10% discount would allow up to 21,100 euro gain (7405-700x). Let recognize, that the prices were not increased. Figure 2.7 shows the gain in the revenue streams.

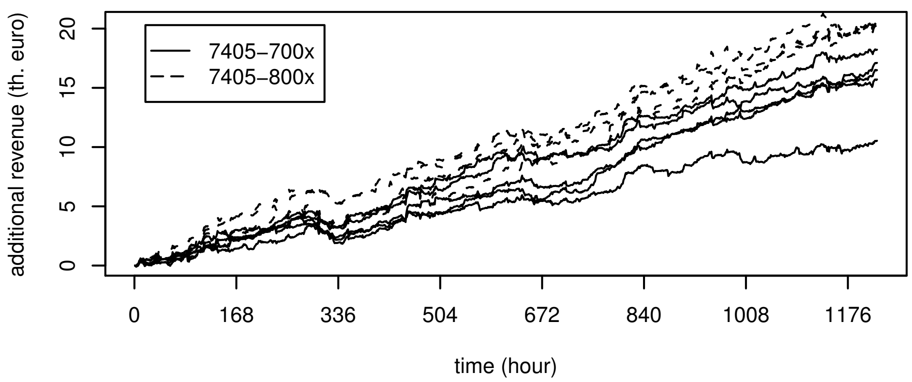


Figure 2.7. Revenue

This is achieved by my algorithm, which allocated the a-priory optimal price set for every day, to maximize the revenue on that day. Figure 2.8 shows this price allocation. As I expect, the algorithm prefers to assign high prices for peak hours and discounts for the early hours in a day to maximize revenue.

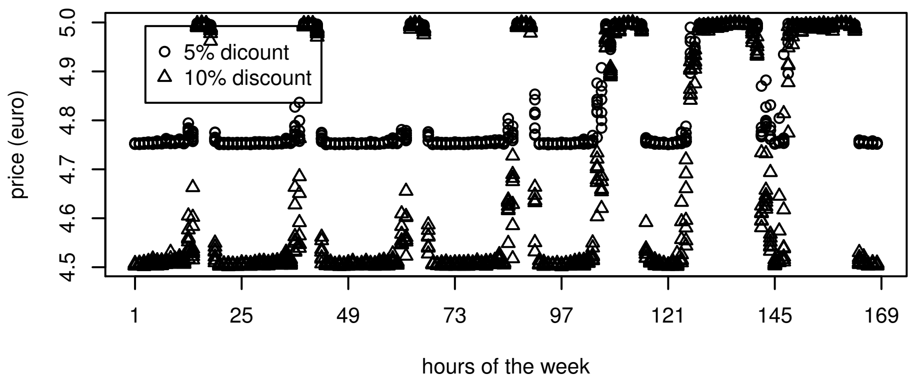


Figure 2.8. Price allocation

12. method-seed

## Is this the maximum?

No, definitely not. If we test the simulated system with different uniform prices, then the price elasticity and maximal revenue can be easily determined. Figure 2.9 shows the overall revenue in reflection to the price.

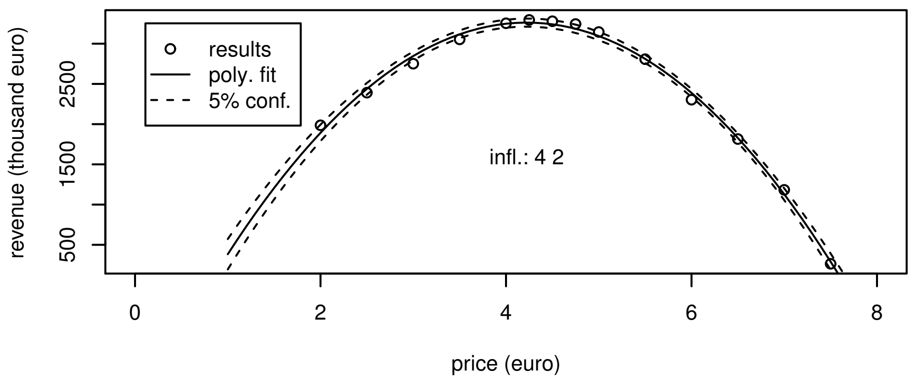


Figure 2.9. Optimal price

My basic assumption is correct, the price demand is linear, which is also confirmed by the price elasticity curve in Figure 2.10.

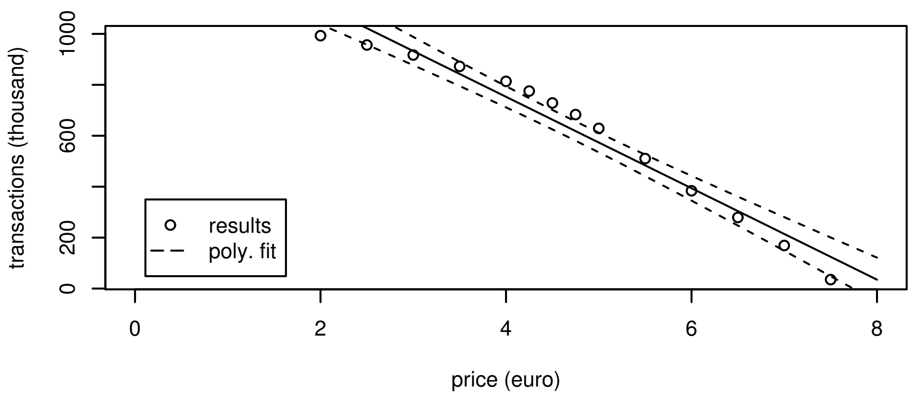


Figure 2.10. Price elasticity

The model (and simulation) is working according to the expected behavior. Now, I challenge my model around the maximal price (4.2 euro), using the uniform 4.25 euro simulation as basis, and I expect even better revenue values. Table 2.2

Table 2.2. Simulation results – 2nd round

| Simulation id[13] | Price range (E) | Total revenue (thousand E) | Gain (thousand E) |
|---|---|---|---|
| 100-425 | 4.25 | 2,104 | 0 |
| 7405-6001 | 3.825-4.25 | 2,089 | -14.5 |
| 7405-6003 | 3.825-4.25 | 2,088 | -15.5 |
| 7405-5001 | 3.825-4.675 | 2,078 | -26,2 |

The dynamic pricing method does capture the price elasticity by allocating higher and lower prices according to the demand and price elasticity curve shown by Figure 2.11,

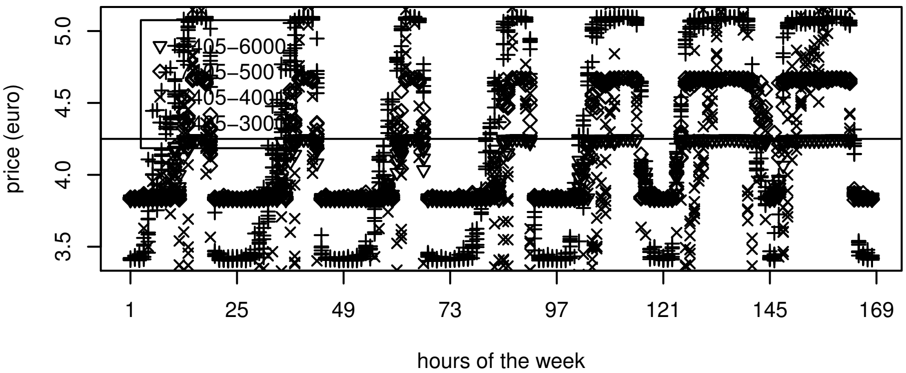


Figure 2.11. Price

but the revenue diagram in Figure 2.12 shows a steady loss.

After checking the earning per day between the uniform reference model and and 7405-5001 method, it seems that the gains or losses are following each other randomly in Figure 2.13.

The main reason for this negative effect is the accuracy of the forecast. My method sets the a priori prices for a day based on the forecast results from the arima model, if this is not accurate enough, the optimization converges to a wrong minimum due to the prediction errors.

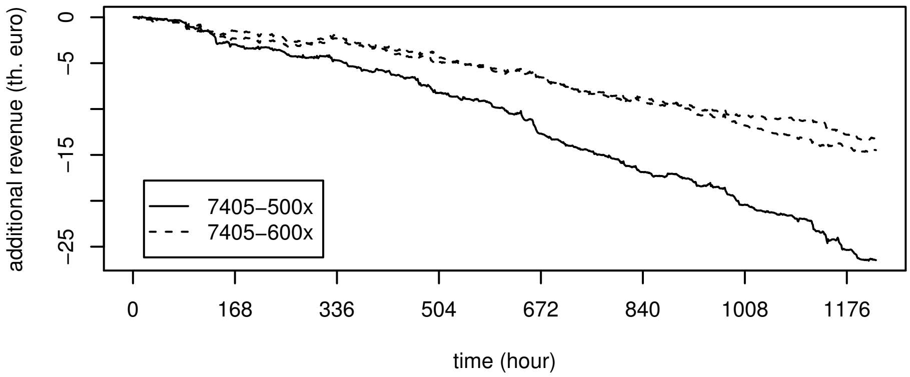


Figure 2.12. Revenue

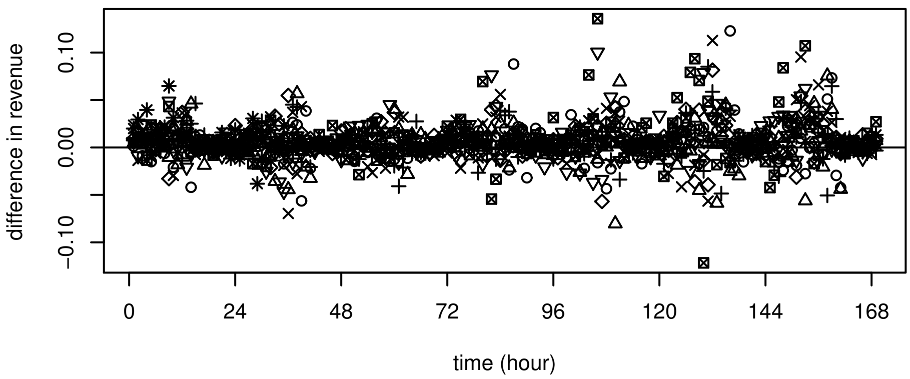


Figure 2.13. Additional gains over the reference model

### Should we expect the same results in a commercial implementation?

This depends on the accuracy of the forecast. Indeed, a non optimal price range can be signaled by fitting the model and checking the price elasticity values, but a real price adjustment has to be considered carefully. An inaccurate model fitting and consequent forecast error may decrease the overall revenue.

## 2.3.1 Required Resources

In spite of all parallel computing, simulation is performed on a 1500 times real time rate, which demands approximately 60 minutes for one full simulation round. Over one simulated day, 24 `foreach` cycles are calculated quite fast, within 5 seconds, then the auto arima process requires 20-40 seconds, but the optimization is really slow, takes 2-5 minutes due to the high number of `forecast` function calls and long time series. Reducing the timespan of the data used for model fitting could provide better performance, but less accurate predictions. Up scaling the input values by 20,000, one simulation round need 5 hours to be completed. I would like to emphasize, that I used quasi commercial input parameters for the simulation, which implies, that the in a field deployment, my method could fit hourly prices 1000 times faster, than real time!

Running simulations parallel could increase performace a bit, since the auto arima process is quite fast, but the gain is not more than 1.2-1.5. 3 parallel simulation script caused a constant 37 load for 2 hours on Ubuntu.

## 2.4 Conclusion

I carried out my research in the field of dynamic pricing for IPTV services. Variable pricing and yield management for VoD rentals have not been addressed by the research community, because there has been a strong historical legal barrier set by the big content producers 50 years ago. The digital era has a huge influence on IPTV services as well, and the way for variable pricing seems to be open in the near future. In my thesis I address this promise, and I create new methods according to my research objectives.

1. Explore the background of uniform content pricing in IPTV services.
2. Find and analyze dynamic pricing models for revenue management in IPTV services.
3. Create a simulation framework and evaluate the proposed methods.

This section will integrate my theoretical findings to answer my research objectives.

1. Explore the background of uniform content pricing in IPTV services.

   **Legal barriers.** I pointed out that due to the historical development of the movie industry, uniform pricing presents since the seventies, which has its roots in the US anti-trust regulation. Several researchers agree that today this does not serve the content business and should be lifted to catalyze revenue (in 2.1.1).

**European film policy.** I reviewed the European movie industry regulations and I emphasized the role of innovation for success (in 2.1.1).

**Special case of IPTV.** I showed the special role of IPTV in the content value chain and its differences in comparison with cinemas (in 2.1.2).

2. Find and analyze dynamic pricing models for revenue management in IPTV services.

**General aspect.** I reviewed several dynamic pricing models in context of my research (in 2.1.3) and I showed their relevance and expected gain in IPTV services (in 2.2).

**Model.** I created a new method based on ARIMA models to capture the special attributes of customer preferences in IPTV systems (in 2.2.1).

3. Create a simulation framework and evaluate the proposed methods.

**Simulation framework.** I created a model independent simulation framework based on external datasets, which allowed to simulate and evaluate complex customer choices in IPTV systems (in 2.2.2).

**Evaluation of results.** I carried out extensive simulation cycles, which shoved the benefits and limitations of my proposed algorithm.

The main empirical research was conducted on a testbed (in 1.2), built for this specific reason using the R language, integrating my own realization of the newly created entities, methods, and functions:

**Customer choice mode.** I realized four steps of the customer choice model for accurate and independent user simulation.

In further research, I am going to extend my customer behavior model for more accurate estimation. This may be achieved by including other factors, like weather condition for forecasts, and I will consider the exponential smoothing algorithm in this research context.

My study has offered an evaluative perspective on pricing in IPTV, however it encountered a number of limitations, which need to be considered:

**Scope.** I restricted my research scope to VoD, linear TV was not analyzed. I believe, that this service is already mature, therefore promises less for further advancement.

**Price elasticity.** To keep my model simple, I assumed linearity for price elasticity, which is helpful for basic research, however in commercial implementation, nonlinear effect may be considered.

**Random number generation** The independent reproduction of results is a key principle in research. This could be sometimes hard, in system with high degree of freedom (like growing and examining bacterias in a Petri disk), but computer simulation offers an easy solution by setting the seed of the pseudo random generator. This technique is widely used, but as R Core Team (2013) points out in his paper, multithreaded simulation environments have their own challenges. To speed up calculations, new threads may be created, but the synchronization of the pseudo random generator in every thread is not self evident. To achieve this goal, additional steps should be taken. During my research I was aware of this problem, but due to my time constraint to submit my thesis, I had to neglect this issue and proceed without settings, therefore my results are not 1:1 replicable, however independent researchers must come to the same conclusion on a statistical basis.

# Appendix A

# Source Codes

## The Simulation Source Code in Rs

```
#!/usr/bin/Rscript
rm(list= ls())


###################################
# DECLARE FUNCTIONS
###################################
# Arrival process
#
# Hourly arrival rate according to the dt_log arrival numbers.
###################################

AProc <- function(visits,k){
  result <- visits$visit[k]
  return(result) #return the number of visits in an hour.
}


###################################
# Utility function
#
# Simple utility function, one movie is selected on a random basis, with a probability
# weight of the number of votes.
#
# This function assumes that if a movie has a high number of votes, then
# the movie worth to watch, customers are more likely selecting movies with high
# number of votes. After watching the movie, they may give a good/bad rate.
# (please note, that the value or distribution of the votes are ignored
# in this model!)
###################################

votesUtility <- function(movies){
 i <- sample(1:nrow(movies), size = 1, replace = TRUE, prob = movies$votes)
 result <- list(m_id=movies$m_id[i], p=movies$p[i], rank=c(movies$d1[i],movies$d2[i],movies$d3[i],movies$d4[i],
      movies$d5[i],movies$d6[i],movies$d7[i],movies$d8[i],movies$d9[i],movies$d10[i]))
 return(result) #returns the selected movie id, the price of the movie and the rank distribution for WTP.
}


###################################
# Willingness to Pay function
#
# Simple model, willingness depends on the rank the movie.
# Rank is assigned on a random basis, according to the rank distribution.
# Linear model is assumed, with subjectiv slope value:
#  - max ranked movie (rank=10) --> 7 euro
#  - min ranked movie (rank=1)  --> .5 euro
###################################

linearWtp <- function(p,rank){
  wtp <- function(r){
    (7-0.5)/(10-1)*r
  }

  r<-sample(1:10,size=1,replace=TRUE, prob = rank)

  if( p<= wtp(r) )
    result <- T
  else
    result <- F
  return(result)                                #returns willingness (T/F)
```

```
}


####################################
# Ability to decide
#
# Ignored from model
####################################

constAbility <- function(t,c_id,m_id){          #simple ability function
 result <- T
 return(result)                                 #returns constant true
}


####################################
# LOAD DATA FOR SIMULATION
####################################
library(RMySQL)

paste("Opening mysql connection...")
drv <- dbDriver("MySQL")
con <- dbConnect(drv,"sim","root", "********", "127.0.0.1", "127.0.0.1")
on.exit(dbDisconnect(con))

paste("Fetching tables...")
rs <- dbSendQuery(con, "SELECT sim_movies.m_id,p,votes,d1,d2,d3,d4,d5,d6,d7,d8,d9,d10 FROM sim_movies JOIN
     imdb_ratings on sim_movies.m_id = imdb_ratings.m_id;")
movies <- fetch(rs, n=-1)
huh <- dbHasCompleted(rs)
dbClearResult(rs)

paste("Clearing sim_log...")
rs <- dbSendQuery(con, "TRUNCATE sim_log;")
huh <- dbHasCompleted(rs)
dbClearResult(rs)


####################################
# START SIMULATION
####################################
#Prepare for multithreading
library(doMC)
registerDoMC(detectCores())
paste("Registered cores: ",getDoParWorkers())
library(forecast)

#Init variables
t_sim <- as.POSIXct("2015-01-01 00:00:00")   #stat: simulation time
t_sim_start <- t_sim                         #stat:
t_real_start <- Sys.time()                   #stat:
timestamp <- Sys.time()                      #stat:
price <- NULL                                #results: price over simulation
tps <- NULL                                  #results: transaction pro sec over simulation
profit<-NULL                                 #results: profit per hour over simulation
cycles_sim=1867
seed<-56854                                  #set seed for reproduction
set.seed(seed)

method<-21                                   #choose model and forecast method

training_weeks<-4                            #length of training weeks
dev.off()                                    #clear plotting device


#Main cycle
paste("Running simulation rounds...")
tryCatch({
for(k in 1:(cycles_sim)) { #run cycles_sim weeks simulation cycle

  #init cycle
  if ( k <= training_weeks*7*24 ) { #training period
    #price <- c(price,5)                                #set prices constant
    price <- c(price,runif(1,min=1,max=7))             #set prices random for training
  }
  else { #simulation period

    if ( k%%24==1 ) { #beggining of a day
      par(mfrow=c(3,1))

      ################### constant price, optimized on the training weeks (for benchmarking)
      if ( method == 2 ) {
        #model
        profit_fc<-NULL
        for(i in seq(1,training_weeks*7*24,by=24) ){
          profit_fc<-rbind(profit_fc,c(price[i],sum(tps[i:(i+23)]*price[i])))
        }
        plot(price[1:(training_weeks*7*24)],type="p")
        fit<-lm(profit_fc[,2] ~ poly(profit_fc[,1],2,raw=TRUE))
        plot(profit_fc)

        #forecast
```

```
    points(profit_fc[,1],predict(fit),col="red")

    #control
    price <- c(price,rep(-as.numeric(coef(fit)[2])/2/as.numeric(coef(fit)[3]),24))
                                              #set prices to maximize profit in the next week
  }


  #################### constant price, manually set for manual optimization
  if ( method == 21 ) {
    #control
    price <- c(price,rep(2,24)) #manual price is set at the first parameter of rep
  }


  #################### arima with fourier terms to cover double seasonality and external regressor
  if ( method == 71 ) {
    #model
    tps.ts=ts(tps,freq=24)

    #fit <- Arima(tps.ts, order=c(2,0,1), xreg=fourier(1:(length(tps.ts)),4))
    #fit <- auto.arima(tps.ts, xreg=fourier(tps.ts,4))
    #plot(forecast(fit, xreg=fourierf(tps.ts, K=4, h=104)))

    fit <- auto.arima(tps.ts, xreg=cbind(fourier(tps.ts,K=10),xreg=price),stepwise=FALSE,parallel=TRUE,num.
         cores=getDoParWorkers())
#         plot(forecast(fit, xreg=cbind(fourierf(tps.ts, K=10, h=24),xreg=rep(5,24))))

    #forecast
    p.fx <-function(par,data) {
      fc<-forecast(fit, xreg=cbind(fourierf(data, K=10, h=24),xreg=par))
      -sum(par*fc$mean)
    }

    opt<-optim(par=rep(5,24),p.fx,data=tps.ts)
    plot(forecast(fit, xreg=cbind(fourierf(tps.ts, K=10, h=24),xreg=opt$par)))
    lines(opt$par/10,col="red")

    #control
    price <- c(price,opt$par)                                  #set prices to maximize profit in the next
         week
  }

  #################### arima with fourier terms to cover double seasonality and external regressor
  if ( method == 73 ) {
    tps.ts=ts(tps,freq=24)

    fit <- auto.arima(tps.ts, xreg=cbind(fourier(tps.ts,K=10),xreg=price),stepwise=FALSE,parallel=TRUE,num.
         cores=getDoParWorkers())
    #        plot(forecast(fit, xreg=cbind(fourierf(tps.ts, K=10, h=24),xreg=rep(5,24))))

    p.fx <-function(par,data) {
      fc<-forecast(fit, xreg=cbind(fourierf(data, K=10, h=24),xreg=par))
      -sum(par*fc$mean)
    }

    opt<-optim(par=rep(5,24),p.fx,data=tps.ts,upper = rep(7,24))
    plot(forecast(fit, xreg=cbind(fourierf(tps.ts, K=10, h=24),xreg=opt$par)))
    lines(opt$par/10,col="red")

    price <- c(price,opt$par)                                  #set prices to maximize profit in the next
         week
  }

  #################### arima last 4 weeks with fourier terms to cover double seasonality and external
       regressor
  if ( method == 74 ) {
    cat("msts...")
    tps.ts=msts(tps[(k-training_weeks*7*24):(k-1)],seasonal.periods=c(24,168))

    cat("auto.arima...")
    fit <- auto.arima(tps.ts, xreg=cbind(fourier(tps.ts,K=c(5,5)),price=price[(k-training_weeks*7*24):(k-1)])
         ,stationary=FALSE,seasonal=FALSE,approximation=TRUE,stepwise=FALSE,parallel=TRUE,num.cores=
         getDoParWorkers())
    #        plot(forecast(fit, xreg=cbind(fourierf(tps.ts, K=10, h=24),xreg=rep(5,24))))

    p.fx <-function(par,data) {
      fc<-forecast(fit, xreg=cbind(fourierf(data, K=c(5,5), h=24),price=par))
      -sum(par*fc$mean)
    }

    cat("optim...")
    opt<-optim(par=rep(5,24),p.fx,data=tps.ts,upper = rep(7,24))

    cat("plot...")
    plot(forecast(fit, xreg=cbind(fourierf(tps.ts, K=c(5,5), h=24),price=opt$par)))
    lines(opt$par/10,col="red")

    price <- c(price,opt$par)                                  #set prices to maximize profit in the next
         week
    cat("done\n")
  }
```

```
    }
  }


  #run simulation cycle
  ret <- foreach(i=1:(AProc(visits,k)),.combine='rbind',.inorder=FALSE) %dopar%{                 #parallel
       computation cycle

    utility <- votesUtility(movies)                        #select a movie (based on number of votes)

    spend <- linearWtp(price[k],utility$rank)                                   #check willingness to pay (
         based on rank and price)

    if(spend == TRUE){
      data.frame(time=visits$time[k],m_id=utility$m_id,p=price[k],sim_time=timestamp)
    }
  }


  #store data
  tps <- c(tps,nrow(ret)/60/60)
  profit <- c(profit,nrow(ret)*price[k])                                        #calculate profit


  #stat
  speed <- round(as.numeric(visits$time[k]+60*60-t_sim_start,units="secs") / as.numeric(Sys.time()-t_real_start,
       units="secs"), 0)        #stats
  print(paste( k,", sim. time:",t_sim,"speed:",speed,"x real time, proc.elem:", nrow(ret), ", price=",round(price
       [k],2),", ETA:",((cycles_sim-k)*60)%/%speed, "min"))
  t_sim <- visits$time[k]+60*60
}
}, interrupt = function(ex) {
  cat("Interrupt...")
})

paste("Closing mysql connection...")
dbDisconnect(con)

save(price,tps,profit,file=paste("simulation",method,seed,".Rda",sep="_"))

plot(tps,type="b")
plot(price,type="l")
plot(cumsum(profit),type="l")


cat(paste("######################################\nYou achieved",sum(profit),"$ profit\n
      ######################################"))
```

# Glossary

**release windows.** Systematic cycles of movie releases to the customers in chronological oder based on the type of the distribution media. Also known as media chronology. Typical release windows are theatrical (0 – 16 weeks), DVD (16 – 28 weeks), CoD (28 weeks – 2 years), free-to-air (2 years –).

**analogue switch-off (aSo).** The date, when the analogue terrestrial television is switched off.

**consumer domain.** The domain where the IPTV services are consumed. A consumer domain can consist of a single terminal or a network of terminals and related devices for service consumption. The device may also be a mobile end device; in this case, the delivery system of a network provider is a wireless network. This domain is within the scope for the Open IPTV Forum specifications.

**content on demand (CoD).** A Content on Demand service is a service where a user can select the individual content items he or she wants to watch out of the list of available content. Consumption of the content is started on user request.

**content provider.** Entity that provides Content and associated usage rights to the IPTV Service Provider.

**digital switchover.** The digital switchover is the process of launching the digital terrestrial television platform and switching off analogue terrestrial television services.

**IPTV service provider.** Entity that offers IPTV Services and which has a contractual relationship with the Subscriber.

**IPTV solution.** The specifications published by the Open IPTV Forum.

**IPTV terminal function (ITF).** The functionality within the Consumer Network that is responsible for terminating the media and control for an IPTV Service.

**network provider.** provides transport resources for delivery of authorized content to the consumer domain. It also provides the communications between the consumer domain and the Service Platform Provider. The User to Network Interface (UNI) links the Network Provider to the consumer domain.

**scheduled content service.** An IPTV service where the playout schedule is fixed by an entity other than the User. The content is delivered to the user for immediate consumption.

**service platform provider.** Entity which, based on a contractual relationship with IPTV Service Providers, provides the supporting functions for the delivery of IPTV Services, such as charging, access control and other functions which are not part of the IPTV Service, but required for managing its delivery.

**network provider domain.** The domain connecting customers to platform and service providers. The delivery system is typically composed of access networks and core or backbone networks, using a variety of network technologies. The delivery network is transparent to the IPTV content, although there may be timing and packet loss issues relevant for IPTV content streamed on IP. This domain is within the scope of the Open IPTV Forum specifications.

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