Modeling of a Dynamic Pricing Environment to Enable Success in Complex Adaptive Markets

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Abstract— Pricing for success in complex adaptive markets is a difficult problem. Established wisdom derives approaches from a view of market-equilibrium, and further from a number of pricing tactics that have worked in simpler, monopoly-like markets. This paper by contrast examines a pricing approach built on a hypotheses-driven, market-tree mechanism that due to its dynamic, flexible nature is arguably better suited for complex adaptive markets. Rapid pricing-rule prototyping based on hypotheses, and leveraging of algorithms and machine learning to appropriately search a live market-tree to decide in real-time the branches to be pruned versus grown, is the design proposed in this paper.

Keywords— Complex Adaptive Markets, Pricing, Pricing-Tree, Machine Learning

I. INTRODUCTION

Pricing of product is a complex endeavor (Nagle, 2013). At its simplest a well-chosen price should:
1. Achieve the financial goals of the company
2. Fit the realities of the marketplace so that customers will buy at that price
3. Support a product's market positioning and its value proposition, and be consistent with the other variables in the marketing mix

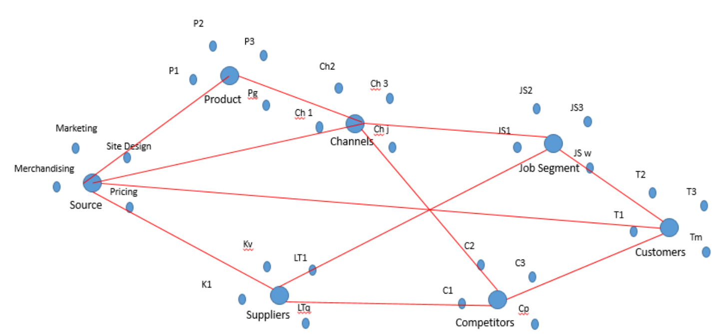
These decisions, and the setting of price, may be simpler where monopolies exist, but in today's eCommerce Retail environment (IBM, 2010), that has become the meeting place of myriad channels, niche competitors, niche markets, and increasingly well-informed customers, a fundamentally different approach to pricing will be required.

This paper explores key features of such an approach based on continued success in a complex, multi-channel, eCommerce Retail environment.

Specifically, this paper explores:
- Complexity of Markets
- Traditional Economic VS Complex Adaptive Systems View of Modeling Markets
- Hypothesis-Driven, Flexible, Pricing Rule Ecosystem
- Algorithm to Manage Complex Pricing-Rule Tree
- Place of Machine Learning in Such an Approach
- Summarizing Features of a Successful Design Environment

II. COMPLEXITY OF MARKETS

The approach to rule development and creating the right rule ecosystem is critical to managing a complex adaptive market. Markets can be thought of as consisting of various components such as Products, Suppliers, Channels, Competitors, Customers, and Job Segments as illustrated below.



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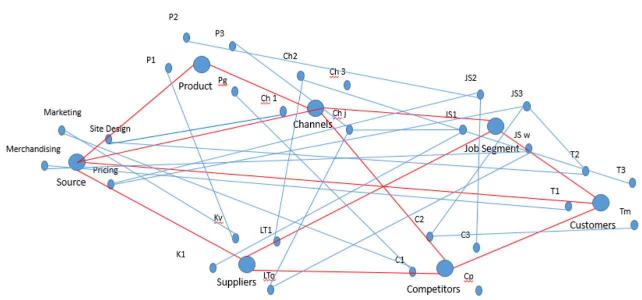
These key components show up as the bigger nodes in the illustration above. A market can be created by a subset of these nodes. But in addition, each of these key nodes will have variations and this is illustrated as the smaller nodes arranged around the bigger node. Examining the Source node, for instance one can see that the possibilities to connect with the market could be centered in Merchandising, Pricing, Site Design, and Marketing, or any combination of these.

The complexity of markets quickly increases with potential node-to-node interconnections as can be seen in the following illustration:



The complexity is directly proportional to the number of inter-connections that can be made between variations of modes. Imagine too if there is a new channel that becomes available, or a new competitor. This creates many more permutations for connection and complexity increases further.

III. Traditional Economic VS Complex Adaptive Systems View of Modeling Markets

To handle such complexity the market needs to be thought of differently. The following illustration summarizes two philosophies for managing a complex market, Traditional and Complex Adaptive System (CAS) views (Beinhocker, 2007):

Concept/Filter	Traditional	CAS View
Dynamics	Closed, generally static, linear systems in equilibrium	Open, dynamic, nonlinear systems, far from equilibrium
Market Components	Collective modeling, use of deductive calculations to make decisions, assume complete information, no biases, no need for adaptation	Individual modeling, use of inductive reasoning, incomplete information, subject to bias, adaptation
Networks	Assume market-components interact indirectly through market mechanisms	Explicitly model interactions between market-components, network changes quickly over time
Emergence	Micro and macro analyses / patterns distinct	Macro-patterns are emergent result of micro-plays
Evolution	Reliance on exogenous mechanisms to create novelty, or growth in complexity	Evolutionary process of differentiation, selection, amplification provides endogenous novelty and growth

Recent research indicates that the Traditional view is inadequate in modeling and managing complex markets. The CAS view is proving to be more accurate in both modeling and managing complex markets and is the view adopted in the set up, and management of the prototype dynamic pricing environment. Each of the points of view for each row in the preceding table are examined and key principles surfaced that inform our approach to managing the prototype dynamic pricing environment.

In the Traditional approach 'Dynamics' (first row in table) of the market are viewed as closed, static, and as a linear system in equilibrium. This implies that the market "knows best" and that due to that a price that is settled at, will be the best price possible. Further the dynamics settle into an equilibrium which implies that once this is reached there is no further movement in the market. In such a view, there is perfect information and infinite computing power available at all nodes to figure all possibilities in real-time. Further, linear systems will be adequate to figure out next steps in the market since everything is inevitably moving toward a market equilibrium. This is an idealistic view of overall market dynamics and may be true sometime in the future but for now the alternative Complex Adaptive Systems (CAS) view in the second column is more realistic and suggests that markets should be viewed as open, dynamic, driven by nonlinear systems, and existing far from equilibrium. A market being open implies that that there is always a source for additional energy or change to be injected into the market. By definition such a market has low entropy as opposed to a closed market as envisioned by traditional economics that has higher entropy. This is an important difference when thinking about pricing and managing the market, because the CAS view implies that a well-structured pricing-ecosystem can itself be the source of injecting energy into a market thereby ensuring its sustainability. Dynamics in the CAS view require nonlinear modeling since there can be multiple sources of change that defy notions of linear causality. Such markets also tend to be far from equilibrium implying that there is never a "right" or a "single" approach, but in fact multiple approaches that may settle on finitely-existing local equilibria. The key is to know when to move out of such equilibria so that an organization is not coaxed into thinking of itself as "successful". Dynamic pricing is important in such a view, and is ideally coupled with other simultaneous market impacting levers an organization may have available to it, such as merchandising and portfolio optimization, site redesign, or multiple approaches to marketing.

In a Traditional approach 'Market Components' (second row in table) are viewed through collective modeling – that is assuming that the market can be modeled as a whole. By contrast in the CAS approach each individual node is modeled – typically through some simple set of rules – and then the nodes are allowed to interact to determine the overall dynamics of the market. Traditional economic modeling relies more on deductive reasoning and this is consistent with the philosophy that generally the key things in a market are known and therefore some additional things can be deduced. By contrast in CAS modeling the inductive, rule-of-thumb type reasoning is used. Such reasoning is also consistent with the notion that any node or set of nodes has only incomplete information, is subject to bias, and as a general modus operandi will need to iteratively adapt. By contrast in traditional economic modeling approaches it is believed that perfect information always exists, there are no biases, and adaptation is inefficient since the right solution should be reached the first time. The CAS view of market components suggests an iterative, experimental approach to pricing-rule evolution.

In a Traditional economic approach, 'Networks' (third row in table) are assumed to comprise of nodes that do not directly interact with each other, but only through efficient market mechanisms such as auctions. By contrast in the CAS view it is assumed that nodes interact directly with each other and that the network therefore changes over time. The latter view is again more consistent with dynamics in a market and points to the reality of pricing-rules potentially being able to successfully make sub-markets in their area of foci. This too is a key principle in the design of our pricing rule ecosystem.

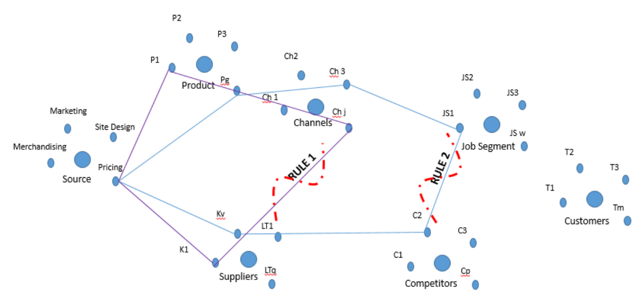
In Traditional economics micro and macro analyses are distinct, whereas in CAS-based economics macro analyses and patterns are seen to be dependent on micro patterns. In other words markets can move in a direction based on a number of micro-type pricing-like adjustments. This means that pricing has to be dynamic, adaptive, and follow the right set of values and money trail consistent with company goals, and is so doing may even be able to shape the outcome in markets and the way the market itself evolves. This is important to keep in mind when managing a dynamic pricing-rules ecosystem.

In Traditional economics and market modeling market evolution is primarily a result of exogenous factors, as it has to be in a market that is perceived to be at equilibrium. By contrast in a CAS view evolution is caused by endogenous factors and hence adaptability, experimentation at the pricing-rule level becomes important.

IV. HYPOTHESES-DRIVEN, FLEXIBLE, PRICING RULE ECOSYSTEM

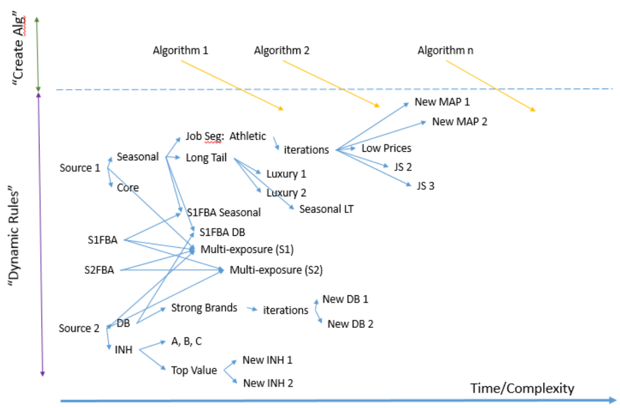
Taken together the implications for a CAS view of market, is that a pricing-rules ecosystem has to be flexible, adaptable, and proceed along hypothesis-driven, and possibly re-traceable and re-direct-able, trajectories. This is explored in further detail below.

But first the following illustrates the structure of a current and typical pricing rule:



Rule 1 is structured so as to focus on Product-set P1, Channel-set Ch 1, and Supplier-set K1. In addition, the rule only utilizes standard metrics already available in the pricing engine environment of the nature of sales, inventory, and some life-cycle type dates. A key feature of this rule is that it is dynamic and therefore in CAS terms becomes a "strange attractor" in the market with a higher likelihood of successfully making a sub-market due to local equilibria converging to the dynamic price possibilities generated by the rule. If the rule were static, which is what happens when rules are created using the Event Manager, then essentially the rule is 'stating' that the market has an established equilibrium and the prices set by the rule are the "right" prices. For such an approach to begin to work the rule would have to have been created using 'infinite' computing power to establish all possibilities and price at the best price to maximize returns over the time period that the rule has been set for.

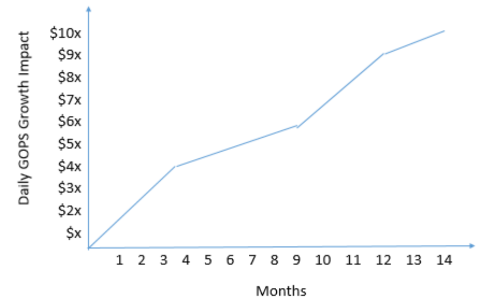
For a dynamic pricing environment to work it ideally needs to be proceed based on a hypotheses-driven approach. The following illustrates the evolving dynamic-rule tree with each fork being generated through hypotheses:



Hence, for example in the top right hand corner an established hypothesis is that pricing rules should be specific to core and seasonal product. Hence the fork from "Source 1" to Seasonal and Core. But further, there is a fork to Multi-Exposure which is driven by the hypothesis that some "Source 1" product will be better served by simultaneously existing on multiple channels beyond just the primary "Source 1" channel. Detailed analyses contrasting before and after results of such hypothesis and consequent rules either prove or disprove the hypothesis that may then result in new forms and new branches for the dynamic-rule tree.

As can be seen, the tree has grown in complexity over the last 1.5 years (note the time-line starts at April 2016). Philosophically such an approach allows a dynamic portfolio of experiments to be generated and so long as a close pulse of the market is maintained the tree will better allow an organization to continue to fulfil its financial and value-based goals.

The graph below is indicative of the results that have seen over the last 1+ years which illustrates incremental daily growth in Gross Order Product Sales \$ year-over-year.



V. Algorithm to Manage Complex Pricing Rule Tree

Over the course of a few years the Pricing Rule Tree can become overwhelmingly complex with many forks, and branches, and many more tests to be performed to decide what is to be pruned, and what grown. In order to assist with the management of this complexity an algorithm that searches the tree to decide which branches are useful would be a good approach.

'Usefulness" of a branch would certainly be based on important top-of-mind micro-goals such as:

- Increase in Gross Margin %
- Increase in Gross Margin \$s
- Impact on Gross Order Product Sales
- Effect of Customer Acquisition
- Effect of Customer Retention
- Effect on Size of Customer Purchase

In addition to that other value-proposition goals such as:

- Reinforcing customer perception of right price
- Reinforcing customer perception of service

These goals would be combined together as testable criteria against hypothesis already setup. Multiple runs through the tree focused on specific testable criteria could then be compiled together to determine which of these branches is the most fruitful.

VI. Place of Machine Learning in Such an Approach

With increasing ubiquity of computing the amount of data being generated is enormous. This is fundamentally changing the direction of computing since now it is data itself that increasingly needs to drive what should be done as opposed to just programming. The role of data is therefore becoming more active. Given this, the question is how can Machine Learning (ML) be leveraged in the proposed pricing environment?

As Alpaydin points out in "Machine Learning; the New AI" (Alpaydin, 2016) typically in ML a large volume of data is processed to construct a simple model with predictive accuracy. Typically ML algorithms may differ along one or more of three dimensions. First, different models can be used in an ML algorithm where a model can be thought of as a template defining the relationships between inputs and outputs. Such models can be thought of as emulating different mathematical functions – such as a linear equation or sinusoidal equation, amongst others. Second, the model inputs or performance criteria being optimized may vary. Third, ML algorithms may vary in the way the parameters or weights of the performance criteria are adjusted during an optimization or training. Learning typically occurs along the third dimension of weighting.

In all cases though there are some potential issues that need to be called out:

- It is possible that the right attributes or factors to understand relationships in the first place may not have been captured or exist
- It is possible that the factors will change in real-time as the environment under consideration changes and while there are online ML algorithms that continually take new input this approach has yet to reach sufficient maturity to be considered robust
- It is possible that the factors may not be measured accurately, especially if they are psychological or have to do with behavior

This implies that any generated or trained ML model may apply within a fixed context only. Even within such a context an ML approach is to assume that there will always be missing factors. To compensate for this, predictions are generally specified in ranges or intervals only.

Given that ML algorithms generally tend to assume reality as fixed, the approach suggested here is to consider ML in the context of CAS. CAS as a framework allows implicit experimentation and assumes that reality is always changing. It would be possible to set up a range of experiments within specified boundaries, and within these to allow ML to generalize a model that may be best within that experiment or niche.

Even from a general computational theory approach arguably a CAS approach as opposed to an ML approach is better since it will allow for a quicker realization of the goal of the computation in a changing environment, and consequently a more appropriate abstract definition of the computational task. The ML itself may be best suited to capture the relationships between the inputs and the outputs and the specific algorithm to bring about the intended input-output transformation. From an information processing standpoint such varied levels of analyses will allow for a more robust approach (Marr, 1982).

VII. Summarizing Features of a Successful Design Environment

In summary, a successful dynamic pricing environment should contain the following features:

1. Enabling quick, deliberate experimentation
    a. Spawning of rules, variation in rules, assessment tools
2. Diverse range of variables that can be incorporated in rule logic
    a. Site experience, marketing, competitor, customer
3. Diverse range of functions that can be incorporated in rule logic
    a. Curves, lines, step functions, controlled random
4. Ability to quickly check range of outcomes
    a. Profitability, sales growth, customer acquisition, retention
5. Checking/validation of hypothesis
    a. Documentation, AB testing
6. Mapping/remapping of "forked" terrain in pricing-tree
    a. Expected go-forward, probability forks, new route generation
7. Application of niche ML in one or more of the experiments/branches that have been set up

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