

Problem proposal for the 32nd Annual Workshop on Mathematical Problems in Industry

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Project: **Hybrid Programmatic TV Markets**

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Introduction

This problem builds on last year's so please read that [problem's description](#) for a more general introduction.¹ In a nutshell, last year's problem consisted in determining how to best place TV advertisements that target specific audiences in TV breaks that have a certain history of viewership. To do this, we need to forecast how many people that belong to a particular category (e.g., adults 21+ with a graduate degree) will watch what and when, and then we have to solve a large-scale optimization problem with hundreds of thousands of decision variables and thousands of constraints. A true big data/data science problem.

¹ The final report is available upon request if you are interested in learning about how the MPI'15 team tackled the proposed problem.

This year's problem is about finding the best pricing and/or placement of TV advertisements against a TV programmer's inventory (e.g., the breaks on CNN) when the buyers (typically advertising agencies) place their orders in one of two possible ways:

1. As generic specifications of the constraints that the desired schedule must satisfy.
2. As bids on sets of specific placements.

Since TV programmers typically accept orders of the first type only, a marketplace with these two kinds of orders at the same time is called "hybrid" for the purpose of this problem.

Order types

The buyer of TV time communicates with the seller via an order, which is a specification of the spots the buyer would like their advertisement placed in. The two kinds of orders we want to consider in this problem.

Generic constraints that a schedule must satisfy

Since the set of available breaks is best known to the TV programmer, it is usually the case that buyers encode what placements they would like using relatively broad constraints that the schedule they want to buy must satisfy. For example, a dissertation writing service (the advertiser) would probably want to target busy Ph.D. students that do not spend a lot of time watching TV except for shows like "The Big Bang Theory" and some movie shows. Thus, the advertiser would instruct its agency to place its ads on a combination of spots on CBS and TMC (Turner Movie Classics) in order to produce a schedule that reaches 40,000 people of the target audience at least 3 times each. The total price for this placement is set by CBS and TMC, but negotiated with the agency.

Bids on sets of specific placements

The traditional way TV advertising transactions happen is changing. Now, both advertising agencies and TV programmers use big data/data science tools to mine TV viewership data to discover what shows are popular among target audiences and automate the whole transaction cycle.

Thus, in this example, the advertiser agency might have discovered that students with master's degrees likely pursuing a Ph.D. degree, actually watch cooking shows more often than movies. With this information, the agency can put together an ideal schedule down to the network, day, hour level to maximize the advertiser's investment. For example, the agency's schedule might look like

Placement ID	TV network	Datetime
1	CBS	2016-06-15 20:00:00
2	Food network	2016-06-15 20:30:00
3	CBS	2016-06-22 20:00:00
4	Food network	2016-06-22 20:30:00

Since the schedule is defined by the agency without considerations such as availability (TV spots at those times might have already been sold), the agency decides the amount of money to offer, like a bid², in order to encourage the TV programmer to move around possibly previously booked spots (that were generated using broad constraints) for a greater profit.

The interesting part comes next.

The Problem

The question we want to address during MPI'16 is the following:

What is the best strategy for TV programmers to balance constraint-based and bid-based orders in order to maximize profit and the number of accepted orders?

We want to build on last year's problem formulation but enrich it with considerations such as the combinatorial nature of the bid-based orders: An agency might offer, say \$10,000, for the full satisfaction of the example order shown above. But the programmers (collectively, through clypd) might see more profitable to just satisfy placements (1,2, and 4) (and for a more advanced version of the problem, possibly offer a "lookalike spot" instead of spot 3). Because of the nature of an advertising campaign, the agency might only offer \$2,000 for those placements, (or \$8,000 with the inclusion of the substitute) possibly forcing the TV programmers to reconsider the situation and iterate the process.

The mathematical nature of the bid-based orders is akin to combinatorial auctions, where the bidder places offers on groups of items instead of placing bids on individual items³.

² See

<http://www.mediapost.com/publications/article/259946/auction-based-selling-what-tv-media-owners-need-t.html> to better understand these kinds of bids.

³ See <ftp://cramton.umd.edu/ca-book/cramton-shoham-steinberg-combinatorial-auctions.pdf> for an introduction.

Programmatic TV is not so much an engineering endeavor, as it is a data science effort. In this sense, we are looking for a sound mathematical framework to address the challenges described in this document.

The participants will not only learn about TV advertising, but also will have the opportunity to learn about how their mathematical skills are highly relevant in a typical data science project.

We also hope to learn about alternative mathematical approaches that could be used in a programmatic TV platform.