Sell-Side TV Ad Optimization

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ABSTRACT
We describe a Sell-Side TV Ad Optimization system that broadcasters can use to increase relevance. The system uses set top box data to measure match between audience and ad buyer population. The impact of improved ad relevance on TV could be extremely beneficial to all parties in the TV ecosystem: advertisers, publishers and viewers.

Categories and Subject Descriptors
J.0 Computer Applications GENERAL

General Terms
Measurement.

Keywords
Television;ad;targeting;relevance.

1. INTRODUCTION
TV has a relevance problem. In 1950 TV was a mass-market, broadcast medium with only four channels in the United States. Ad placement reached a large percentage of the US population – the top-rated program in 1950 was viewed by 61.5% of the population (Brooks and Marsh, 2012). The specificity on those early TV broadcasts was limited, and so TV advertisers geared their products towards a mass consumer audience.

Today there are hundreds of channels and tens of thousands of original programs. Audiences are smaller and more fragmented and that drives the need for ads to be better matched to their programs. In this paper we will focus on what television broadcasters can do to increase ad relevance.

This paper aims to address three questions: (1) How relevant are TV ads today? (2) Why should Publishers care about ad relevance? (3) How could a Sell-side TV optimizer help Publishers to manage, sell, and increase the relevance of their inventory.

2. PREVIOUS WORK
Bing and Google utilize clickthrough rate as a measure of relevance to balance revenue generation with user experience. Ranking functions for search ads use clickthrough rate multiplied by price (Jansen, 2006; Hillard, et. al., 2010). In contrast, there has been surprisingly little work on TV ad relevance (Hanssens, et. al., 2001; Johansson, 1979; Simon and Arndt, 1980; Jones, 1997; Vakratsas, et. al., 2004). Ewing (2013) used survey methods to measure television ad relevance from 2002 to 2013. However this work did not go into networks, programs or how to improve relevance. Zigmond, Dorai-Raj, Interian and Navernioük (2009) used viewer tune-away behavior during commercial breaks as a proxy for relevance.

The current work is different from previous work in that (a) we define ad relevance on TV in a scalable and quantitative manner, (b) we undertake a study of a large amount of US TV ads, (c) we propose a sell-side optimizer that is capable of improving ad relevance. We are not aware of this work as having been done before.

3. DEFINING AD RELEVANCE
We define ad relevance *tratio* or *tr* as the match between the demographics of the media population, and that of people who have bought an advertiser's product.

$$tr(A_j, M_i) = \frac{\bar{A}_j \cdot \bar{M}_i}{|\bar{A}_j| \cdot |\bar{M}_i|}$$

where A_j is an advertiser and $\bar{A}_j$ a vector of advertiser demographics, and M_i media that could be purchased, and $\bar{M}_i$ a vector of the demographics from viewers of that media. Further detail on how this is calculated are available in (Kitts, et. al., 2013).

About 20 million television ad airings per month M_i are tracked by Nielsen Corporation, and all have product hierarchy information about advertiser and their product. From these we create a set of industries to represent groups of advertisers by manually mapping Nielsen Product Hierarchy descriptions of advertisers to particular Industries – eg. Nielsen Product Category="Charitable Orgn" maps to Industry="Charity". We used 25 industries for the work presented in this paper. Table 1 shows the industries and Table 2 shows a sample of the Nielsen hierarchy mappings to industries. For each industry we collect a random sample of 100,000 airings per industry.

The next task is to calculate the degree-of-match between the demographics of the media $\bar{M}_i$ and the demographics of the advertiser's product buyers $\bar{A}_j$. In order to determine this, we use a database of 6.8 million product purchaser persons that we also map to each industry, so about 270,000 per industry. Product purchasers are generated from (i) first party data on persons who have purchased the product which has been supplied by advertisers who are running television campaigns and using their first party data to drive targeting for television advertising; as well as (ii) demographic interest indicators (eg. persons with propensity to have a life insurance policy are regarded as buyers for the life insurance industry). In all cases, person data has been anonymized prior to us receiving the data, so we are working with persons with anonymous IDs and their demographic profiles. After completing these steps we can now report on relevance of industries, placements, and networks running ads.

Table 1. Industries

JobID	AdvertiserName
1	Charity
2	Diabetic Health insurance
3	Diet
4	Dental Insuranc
5	Home Furnishings
6	Investment Services
7	Life Insurance
8	Music
9	Power tools
10	SUVs
11	Trucks
12	Education online
52	Diabetes Health insurance
53	Luxury auto
54	Truck Pickup
55	PMIC Brand
56	HighIncomeCreditCard
57	Senior Life Insurance
58	DIY investment
59	Exercise Equipement
60	Fitness Program/Club
61	Term
62	life insurance investment
63	Cosmetics
64	Teenage extra-curricular activities
65	Technical colleges
66	Childrens learning program
67	Jewelry
68	Interior Decoration

Table 2. Example Advertiser classifications into Industries

Advertiser Name	Identifier Name	Nielsen Prod. Hierarchy
Charity	Charitable Orgn	Product Category
Dental Insuranc	Dental Services	Product Category
Investment Services	AMERIPRISE FINANCIAL INC	Subsidiary
Investment Services	CHARLES SCHWAB & CO INC	Subsidiary
Investment Services	E TRADE SECURITIES INC	Subsidiary
Investment Services	FIDELITY DISTRIBUTORS CORP	Subsidiary
Investment Services	Financial-Investment svcs	Product Category
Investment Services	GAIN CAPITAL GROUP LLC	Subsidiary
Investment Services	INTERACTIVE BROKERS LLC	Subsidiary
Investment Services	SCOTTRADE INC	Subsidiary
Investment Services	SHAREBUILDER CORP	Subsidiary
Investment Services	SPEEDTRADER.COM INC	Subsidiary
Investment Services	TD AMERITRADE INC	Subsidiary
Investment Services	TRADESTATION SECURITIES INC	Subsidiary
Investment Services	UNITED SVCS AUTOMOBILE ASSN	Subsidiary
Power tools	Power Tools-Access	Product Category

Table 3. Most relevant programming placement for a selection of industries

Ad	Program	Relevance Score
Career Education	MTV-JERSEY SHORE SSN4 REUNION	0.616
Career Education	MTV-JERSEY SHORE SSN 5	0.606
Career Education	MTV-JERSEY SHORE SSN 4	0.605
Career Education	MTV-JERSEY SHORE 2	0.605
Career Education	MTV-JERSEY SHORE SSN 6	0.605
Career Education	MTV-JERSEY SHORE SSN4 REU REC	0.604
Career Education	SYN-PUNK'D AT	0.604
Career Education	MTV-JERSEY SHORE 2B	0.602
Career Education	MTV-JERSEY SHORE	0.601
Career Education	VH1-LOVE AND HIP HOP 2	0.589
Charity	FOXB-IMUS IN THE MORNING	0.514
Charity	WILD-PACK	0.500
Charity	ESP2-TENNIS:US OPEN SRS MEN L	0.497
Charity	RFD-CROOK & CHASE	0.490
Charity	MSNB-POLITICS NATION	0.472
Charity	ETV-GRAN CINE FRI	0.470
Charity	ETV-GRAN CINE THURS	0.468
Charity	GRN-YELLOWSTONE:BATTLE FOR LI	0.467
Charity	FOXB-VARNEY & COMPANY	0.464
Charity	FOXB-IMUS MUSIC SPECIAL	0.463
Cosmetics	BRAV-FASHION HUNTERS	0.515
Cosmetics	STYL-HOT LISTINGS MIAMI	0.485
Cosmetics	BRAV-DONT BE TARDY	0.484
Cosmetics	STYL-E! NEWS	0.478
Cosmetics	STYL-WEDDINGS FROM HELL	0.478
Cosmetics	BRAV-RING LEADER, THE	0.477
Cosmetics	BRAV-K GRIFFIN: MY LIFE D-LIST	0.476
Cosmetics	BRAV-LIFE AFTER TOP CHEF	0.475
Cosmetics	STYL-FACE, THE	0.475
Cosmetics	LIFE-ON ROAD AUSTIN & SANTINO	0.472
Diet	FOOD-FAT CHEF	0.454
Diet	STYL-CLEAN HOUSE	0.442
Diet	FOOD-CHOPPED	0.434
Diet	STYL-PROJECT RUNWAY	0.425
Diet	STYL-HOW DO I LOOK	0.420
Diet	FOOD-RACHAEL VS. GUY	0.419
Diet	FOOD-CUPCAKE WARS	0.418
Diet	DFH-DR. G: AMERICAS MOST SHOC	0.414
Diet	FOOD-ACE OF CAKES	0.413
Diet	TLC-SAY YES TO THE DRESS: ATL	0.410

Table 4. Most and Least Relevant Ads

Industry	Most Relevant Programs	Rel	Least Relevant Programs	Rel
Luxury auto	HDNET-AUTO TRADER	0.546	TNT-CHARMED	-0.473
Luxury auto	HDNET-AMERICAN ICON - THE HOT R	0.527	TNT-SUPERNATURAL	-0.419
Luxury auto	GOLF-GOLF IN AMERICA	0.522	TV1-HUGHLEYS	-0.419
Luxury auto	ESP2-PTI SPECIAL	0.517	STYL-AMERICAS NEXT TOP MODEL	-0.413
Luxury auto	ESP2-BOXING SERIES L	0.513	SYFY-URBAN LEGENDS	-0.390
Luxury auto	GOLF-BIG BREAK XVI: IRELAND	0.510	TV1-AMEN	-0.380
Luxury auto	GOLF-USGA	0.506	TRAV-DEAD FILES	-0.373
Luxury auto	HDNET-MOTORWEEK	0.505	TV1-DIVORCE COURT	-0.370
Luxury auto	ESPN-COLLEGE FOOTBALL PRIME L	0.502	TV1-MOVIE	-0.368
Luxury auto	GOLF-HANEY PROJECT	0.498	BET-MY BLACK IS BEAUTIFUL 2	-0.351
Power tools	MILI-QUEST FOR SUNKEN WARSHIPS	0.661	WE-I DO OVER	-0.692
Power tools	MILI-WINGS OVER VIETNAM	0.659	WE-MY FAIR WEDDING	-0.674
Power tools	MILI-WINGS OF THE LUFTWAFFE	0.654	WE-SINBAD: ITS JUST FAMILY	-0.647
Power tools	MILI-COMBAT TECH	0.642	OXYG-REAL HW ATLANTA	-0.645
Power tools	MILI-CARRIER - FORTRESS AT SEA	0.639	WE-BRAXTON FAMILY VALUES	-0.639
Power tools	MILI-NAZIS: OCCULT CONSPIRACY	0.638	WE-PLATINUM WEDDINGS	-0.635
Power tools	MILI-DECISIONS SHOOK THE WORLD	0.635	BET-WENDY WILLIAMS SHOW, THE	-0.599
Power tools	MILI-ULTIMATE GUIDE:PLANES	0.632	OXYG-BEST INK	-0.583
Power tools	MILI-ANATOMY OF	0.630	OXYG-TORI & DEAN HOME SW HLYWD	-0.580
Power tools	MILI-WORLD AT WAR	0.627	OXYG-AMERICAS NXT TOP MODEL	-0.578

4. RELEVANCE OF US TELEVISION ADS

After completing the above steps, we performed some analyses on TV relevance. In order to help illustrate what relevant ads look like, Table 3 shows the top relevant ads for each Industry based on the composition of the audience viewing the Station-Program which is hosting the ad pod.

For example, Career Education ads on "MTV-Jersey Shore SSN4 Reunion" had the highest degree of audience match. It is ironic that diet purchasers match the audience for Food Network programs such as "FOOD-Fat Chef" and "FOOD – Chopped".

TV relevance as a whole has increased from 2010 – 2013 by about 4.1% per year (Figure 1). In 2013 the networks with the most relevant ads were: UPTV, TVL, INSP, CNBC, MTV2, WGNA (Table 9). Of the broadcast stations, CW has the most relevant advertising, possibly due to its more focused programming on young adults. Fox is next in relevance. CBS has the least relevant advertising (Table 8).

TV media prices as measured by cost per thousand impressions (CPM) have actually increased by about 5.1% per year over the same period, and so we speculate that advertisers are organically moving into better placements under price pressure. If tratio is approximately equal to buyers per impression reached and advertiser revenue per impression, and cost per impression increased by 5%, then we would expect advertisers to make a similar increase on tratio in order to maintain a constant Cost per acquisition.

Approximately 40% of television ads have a relevance that is *worse than random*. We define this as reaching fewer product purchasers than one would reach if an ad was targeted randomly in placements on television. This is a surprising result although it could be the result of saturation or price pressure forcing advertisers into less desirable placements.

The top irrelevant ads are shown in Table 4. For example, the most irrelevant ad for Luxury auto was TNT's "Charmed". In the

Power tools industry, the most relevant ad was on Military Channel's "Quest for Sunken Warships". The most irrelevant ad for Power tools ads were Women's Entertainment Network's "I Do Over" and "My Fair Wedding".

Table 1. Broadcast relevance as measured by tratio, 2010-2013

Network	2010	2011	2012	2013	Total
CW	0.248	0.202	0.187	0.162	0.199
FOX	0.198	0.196	0.173	0.169	0.184
ABC	0.144	0.160	0.170	0.172	0.161
NBC	0.137	0.146	0.142	0.139	0.141
CBS	0.128	0.132	0.133	0.127	0.130
Mean	0.171	0.167	0.161	0.154	0.163

Table 9. Most Relevant Cable Networks 2010-2013*

Row Labels	2010	2011	2012	2013	Grand Total
MTV	5	5	5	5	5
GOLTV	5	5	5	5	5
SPD	5	5	5	5	5
CNBC	5	5	5	5	5
MILI	5	5	5	5	5
ESQR	5	5	5	5	5
MTV2	5	5	5	5	5
FOXB		5	5	5	5
GOLF	5	5	5	5	5
HDNET	5	5			5
SCI	5	5	4	5	4.75
NFLN	5	4	5	5	4.75
ESPD	4	5	5	5	4.75
ESPN	4	5	5	5	4.75
SPK	4	4	5	5	4.5
DFH	4	5	5	4	4.5
MLB	5	4	5	4	4.5
NBCSN	5	5	4	4	4.5
NKTN		4	5	4	4.333333333
VEL		5	4	4	4.333333333

*For easy viewing, tratio for this list was converted into a "5 star rating" showing effectively the percentile of tratio for each network; a score of 5 means that the tratio for the network was in the top 20th percentile of all networks for that year, and 1 means it was in the lowest 20th percentile.

Table 10. Ad Relevance and Prices by Industry

	CPM 30	T-Ratio	T-CPM30	Impressions per Airing	Cost30 per Airing
Luxury auto	$12.94	0.229	$56.47	447,697	$5,792
DIY investment	$11.78	0.212	$55.62	402,442	$4,740
Truck Pickup	$11.13	0.196	$56.86	484,196	$5,391
SUVs	$10.16	0.153	$66.43	540,640	$5,494
Investment Services	$9.12	0.222	$41.01	382,821	$3,491
Power tools	$8.14	0.231	$35.25	394,389	$3,209
Term	$7.97	0.227	$35.13	306,677	$2,445
Charity	$7.41	0.121	$61.09	544,432	$4,034
High Income Credit Card	$7.23	0.178	$40.67	321,503	$2,323
Life Insurance	$6.95	0.256	$27.12	291,572	$2,027
Fitness Program/Club	$6.32	0.267	$23.69	326,092	$2,062
Interior Decoration	$6.17	0.179	$34.51	310,786	$1,918
Cosmetics	$6.15	0.127	$48.53	469,170	$2,885
Diet	$5.73	0.133	$43.09	306,175	$1,755
Technical colleges	$5.71	0.237	$24.11	323,743	$1,848
Home Furnishings	$5.17	0.120	$43.19	301,218	$1,559

5. THE ECONOMICS OF RELEVANCE

Why should TV networks care about ad relevance? Three functions define the value to advertiser, publisher and viewer:

$$R_{PUB}(M_i) =\cdot I(M_i)\cdot \sum_j \Pr(W|CPM(A_j,M_i))\cdot CPM(A_j,M_i)$$

$$R_{VIEW}(M_i) =\cdot I(M_i)\cdot \sum_j \Pr(W|CPM(A_j,M_i))\cdot g(tr(A_j,M_i))$$

$$R_{ADV}(M_i) = I(M_i)\cdot \sum_j \Pr\left(W\middle|CPM(A_j,M_i)\right) \cdot \left(f(tr(A_j,M_i)) - CPM(A_j,M_i)\right)$$

where R_{PUB} is Publisher revenue, R_{VIEW} is viewer relevance, and R_{ADV} is advertiser revenue, $CPM(A_j,M_i)$ is a clearing price, $\Pr(W|CPM(A_j,M_i))$ is the probability that the advertiser will win the auction and pay the clearing price, and *f* is the revenue per impression that the advertiser is generating and which is sealed from the publisher and *g* is viewer relevance as a function of tratio. If we assume that media with a higher tratio increases advertiser revenue per impression $f(tr(A_j,M_i)) > f(tr(A_j,M_i) - \varepsilon)$, then as media are selected with higher tratios $tr(A_j,M_i)$, the $CPM(A_j,M_i)$ paid by the advertiser can also increase as long as $f(tr(A_j,M_i)) > CPM(A_j,M_i)$. We presented empirical data supporting this hypothesis in Kitts et. al. (2013) showing that higher TRPs and tratio generated higher observed response per impression. Thus better ad relevance could have the effect of increasing advertiser revenue per impression, publisher CPM, and viewer judged relevance.

6. SELL-SIDE OPTIMIZER

We will now propose a "Sell-side Optimizer" which will enable the TV network to increase both ad relevance and auction density. In order to optimize ad placement, we now need to score every possible ad insertion for each piece of inventory M_i

$$M_i \in DateTime \times S \times G$$

where *DateTime* is a 30 minute time period during a broadcast week, *S* is Television Network and *G* is geography – either DMA or National. In order to generate the buyable media we create a Cartesian product of Station, Day, Hour for the week under consideration. We then execute a TV schedule lookup to find the appropriate program that would be airing during a given week. We then score each media asset M_i against every possible advertiser industry A_j that could be inserted for that media. There are approximately 32,000 Station-Day-Hours during any given week, so the Cardinality of the above is about 32,000 * 25 = 800,000. This is small enough to fit into memory for OLAP operations.

We also define $MostFreqAd(M_i)=A_j$ to be the most frequent historical ad inserted into this media M_i calculated by simply counting the number of occurrences of A_j in past airings of media M_i. We will often use the *MostFreqAd* to compare current ad insertion to improved ad insertion.

We can now support several applications:

6.1 Most Relevant Inventory for an Advertiser

If a publisher is trying to advise an advertiser on how to reach the most buyers per impression, they can provide a list of recommended media by sorting inventory in order of *tr*:

$$M_i\colon \max_N tr(A_j,M_i)$$

It is also possible for the publisher to recommend media that is most relevant for the advertiser, below a particular CPM or Cost threshold.

6.2 Most Economical Inventory for an Advertiser

If a publisher is trying to advise an advertiser on the most cost effective media for their ad, they can provide a list by sorting inventory in order of the cost per targeted impression or *tCPM*:

$$M_i: \min_N tCPM(A_j, M_i) = \frac{CPM(A_j, M_i)}{tr(A_j, M_i)}$$

6.3 Agencies to contact to sell inventory

Publishers have to sell through all of their inventory, and as an air date approaches, it becomes increasingly important to find a buyer. If a buyer cannot be found, the Publisher will need to give away the inventory in the form of bonus or in the form of a Public Service Announcements Therefore it is important that Publishers know which advertisers to contact, in order of likelihood of purchase, to monetize their inventory. We can do this by ordering the top advertiser industries for each media:

$$A_j: \max tr(A_j, M_i)$$

In addition to helping to connect to buyers, it is in the Publisher's interest to have more bidders on their market interested in their inventory. A key result from auction theory is that as the number of bidders increase, so should the average price for the goods under auction. Therefore, increasing awareness of desirable media with potential buyers should also help to increase auction density.

6.4 Inventory that will be More Performant than another Network's

Publishers are in competition with other publishers, and have to make the case to an Advertiser that they should buy their inventory rather than someone else's. Relevance scores enable a Publisher to compare their inventory to programs on other networks and show which of their inventory are are perhaps better targeted or have better value per dollar. These in effect allow the Publisher to provide comparisons in a currency which is customized for each advertiser's industry.

Substitues work in a similar way, but with the advertiser's own inventory: perhaps an advertiser wanted to buy a particular program that is unavailable. The same mechanism can enable the Publisher to provide a list of inventory back to the Advertiser which are as good or better than the program that they requested, both in price and targeting, but which are available for purchase:

$$M_i: \max_N tr(A_j, M_i) \geq tr(A_j, M_k) \forall k$$

$$M_i: \min_N tCPM(A_j, M_i) \leq tCPM(A_j, M_k) \forall k$$

6.5 Maximum increases in relevance

The Publisher often has a lot of flexibility when scheduling their ads. Advertisers tend to buy packages in rotations, which represent time ranges when their ad is requested to air. This means that the Publisher can optimize within those rotations. Given a set of media, a publisher can identify the ad insertion improvements that would result in the greatest increase in overall relevance by calculating the quantity below:

$$A_j, M_i: \max\left(tr(A_j, M_i) - tr(MostFreqAd(M_i), M_i)\right)$$

6.6 Yield Maximization: Advertiser Pricing

The objective of this application is to improve publisher yield by charging more appropriate prices for their inventory.

There are two primary markets for selling inventory in television: Upfront and Scatter. The Upfront market occurs each September and is a large event where new programs and premium media is sold in a short period of time. The Scatter market occurs continuously throughout the year and involves any media that wasn't sold during Upfronts.

We will begin with Scatter applications. Price setting on Scatter inventory is similar to airline ticket prices. As demand for inventory goes up, price should also go up. As an air-date is approaches, price may have to drop to ensure that a sale occurs. If the inventory is left unsold then the Publisher loses revenue.

In trying to set an effective price for their media, the Publisher needs to set a price for each advertiser which is low enough to clear, but which also is high enough that the publisher could generate a reasonable yield. In setting the price, Publishers often set a single price for their media in what is known as a "Rate Card". The Rate card is often published weekly.

However it would be useful to have a more dynamic Rate Card price. Knowledge of the advertiser, their interest in the media, and their historical prices paid, should greatly inform pricing – the Publisher should be able to avoid over-discounting on media which the advertiser would want to buy, and on media which is not ideal for an advertiser, the Publisher should have some insight that they will need to lower the price of the media.

In order to develop dynamic pricing that takes into account advertiser value, we can develop a model that predicts, based on advertiser historical prices paid, and relevance to the advertiser, the expected clearing price $CPM30(A_j, M_i)$. The model below has the following terms:

$CPM30(A_j, M_i)^* =$

$$\sum w_1 \cdot SQADCPM30(m_i) \cdot SQADDiscount \quad (1)$$

$$+\sum w_2 \cdot CPM30(m_i) \quad (2)$$

$$+\sum_{m_i} w_3 \cdot SQADCPM30(A_j, m_i) \cdot SQADDiscount(A_j) \quad (3)$$

$$+\sum w_4 \cdot CPM30(A_j, m_i) \quad (4)$$

$$+\sum_{m_k} w_5 \cdot \left|tr(A_j, m_i) - tr(A_k, m_k)\right| \cdot CPM30(A_j, m_k) \quad (5)$$

$$+\sum w_6 \cdot CoView(m_i, m_k) \cdot CPM30(A_j, m_k) \quad (6)$$

1. Historical SQAD price for a media pattern $SQADCPM30(m_i)$ that matches the inventory that is being priced M_i (eg. If M_i =CNN-Tues-8pm was being priced, then m_i=CNN-Weekday-Prime would match), adjusted by an overall SQAD adjustment.
2. Historical clearing price for this media pattern $CPM30(m_i)$.
3. $SQADCPM30(A_j, m_i)$ that the advertiser has logged for patterns of media m_i that match the inventory being priced M_i, scaled by the typical percentage off SQAD that this advertiser historically achieves $SQADDiscount(A_j)$.
4. The historical actual clearing price for a pattern of media that has similar tratio or audience composition, scaled by the similarity
5. The historical actual clearing price for a pattern of media that has similar a high probability of having the same set top box persons viewing the pattern as the media being priced
6. The historical actual clearing price for a pattern of media that matches the inventory being priced.

The above model is trained on historical observations of inventory M, Advertiser A, SQAD price SQADCPM30, and actual clearing price CPM30. In Adap.tv we have over 250,000 clearing prices.

6.7 Yield maximization: Advertiser win probability landscape / negotiation support tool

After building the model above, we can estimate whether the advertiser is likely to accept a price which is above or below their expected clearing price. The publisher can use this to inform their negotiation strategy. For example, if we are close to an on-air date, and the publisher needs to sell their inventory lest it go unsold, they might be able to use this data to know that they should drop their price by 20% which will increase their win probability with the advertiser by 2x. This may enable the publisher to avoid over-discounting their inventory because they estimate that an advertiser will probably buy the inventory at the reduced price. In order to calculate this win probability landscape we can measure the empirical probability of win versus difference from expected:

$$\Pr\left(Z \middle| x \cdot CPM30\left(A_j, M_i\right)^*\right) = \frac{occ}{N} : CPM30\left(A_j, M_i\right) \geq x \cdot CPM30\left(A_j, M_i\right)^*$$

Where *occ* are the number of observations of an advertiser paying more than $x \cdot CPM30\left(A_j, M_i\right)^*$ and *N* are total observations.

7. SELL-SIDE OPTIMIZER: LIVE EXPERIMENTS

We implemented a Sell-side optimizer prototype to explore these use cases. The Sell-side optimizer uses SQL code to score every combination of Station-day-hour-advertiser, scores the inventory, and then outputs the scored inventory to be displayed in a web-based Graphical User Interface (GUI) written in HTML5 and D3. This enables a network to view which advertiser to insert against their inventory.

The GUI is organized into a grid which has TV inventory running down the page, and candidate advertisers who could be inserted against media inventory running across the page. A series of linked filters are available on the left and right-hand panes. The GUI supports *two-dimensional sorting* – vertical sorting enables the user to sort by schedule, cost of media, gain in relevance, or relevance, or units available, so that they can quickly review which inventory to work on. Horizontal sorting allows the user to sort advertisers who could be inserted into each position by tratio relevance, or other metrics.

We now present some examples of the prototype in action on live media for some well-known television networks below:

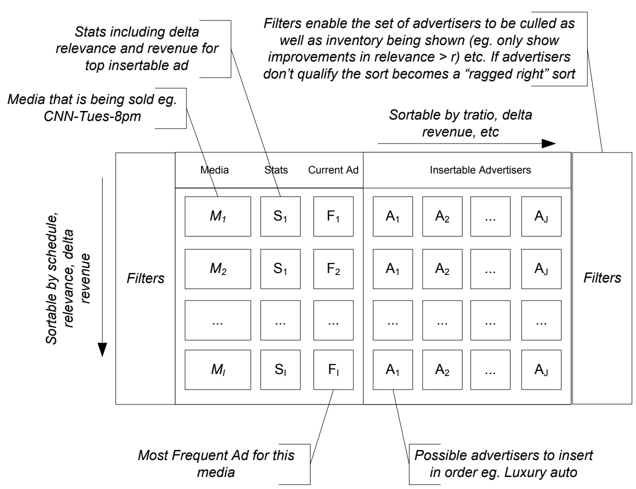

Figure 2. Sell-Side Optimizer Graphical User Interface

7.1 Best Media for an Advertiser

Figure 11 shows an American Broadcasting Corporation (ABC) Saturday schedule with the best inventory to recommend for an SUV advertiser.

An SUV advertiser would reach few buyers in "The Chew" or "General Hospital", (1pm-2pm Saturday) or even "Shark Tank" or "Last Man Standing" (8pm-10pm). However they would do well in College Football from 3pm-6pm.

This would enable the advertiser to fine-tune their rotation boundaries to include Football and yet avoid the other programming.

7.2 Advertisers to Contact

We noted earlier that Publishers could use the optimizer to get insight into the list of advertisers who would be interested in a particular media placement. Figure 9 shows a real contact list for Discovery Channel's Animal Planet.

In the early morning "Music players" would be best to insert since that appeals to young people, and young people tend to be up in the early mornings. If that advertiser couldn't participate, then Online Education, Auto and Trucks would be next in order of relevance and so would be next to contact to sell the inventory.

As we continue down the schedule, we notice some curious changes due to the time of day – "Fitness" (Heart icon) becomes the most relevant ad at about 6am in the morning, and then "Senior Life Insurance" around 11am and noon. The shift to Senior Life insurance is related to daytime viewing audience being much more elderly. For this inventory, if Senior Life Insurance wasn't interested in buying, the next in order would be Family Life Insurance, Term Life Insurance, and Dental Insurance – all products favored by more mature advertisers.

7.3 Increasing Ad Relevance

7.3.1 Schedule Improvements

Figure 7 shows a TV schedule for Music Television (MTV). Currently "Cosmetics" industry ads are being aired against "Ridiculousness" in the wee hours of the morning including midnight and 5am. What should the Cable Network for MTV insert with its programming? The relevance scores indicate that "Cosmetics" only scores a tratio of 0.092, where-as the highest tratio ad industry is "Music". The reason why "Cosmetics" scores poorly is because Ridiculousness is similar to Jackass and appeals to young males. It doesn't appeal to young females. Instead, "Music" would be a far more relevant ad for this audience.

MTV is also airing "Charity" ads for the movie "Step Up". However "Education online" would be a far better ad to insert – the buyers of this product are young and skew female, and so to viewers of "Step Up".

7.3.2 Largest gains

We next show another use case where we will sort in order of largest gains in relevance (Figure 8). We use WGN for this example. WGN tends to be viewed by an older audience, however has an unusual mix of programming.

We sort by the largest increase in relevance. The largest potential gain would be by replacing "Online Education" ads against WGN News at Nine. The WGN News tends to be viewed by an older audience, and so Online Education was a poor match since it appealed to mainly young people. Instead a Power tools ad would have been a better choice to air with WGN News at Nine.

The next highest relevance improvement would be from optimizing the ad for Futurama at 3am. At this time in the morning, the only people watching tend to be very young. In addition, Futurama is a program that is viewed by younger people. Yet a Colonial Penn Life Insurance ad was the one most frequently run. It would have been better to show a Music Player ad.

8. CONCLUSION

The impact of improved ad relevance on TV could have significant benefits to the TV ecosystem. Recent studies sponsored by ABC suggest that 75% of consumers are okay with ad-supported, free, television content. However they just would like there to be fewer ads (Goetzl, 2011). It is possible that ad tolerance may increase with more relevant ads, tune-away could decrease with more relevant ads, and more impressions may be credited to networks using these techniques to manage relevant ads. With Sell-side optimization technology we hope that increased ad relevance will be “coming soon” to TV screens everywhere.

9. ACKNOWLEDGMENTS

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Program	Day-Hour	Recommended Ad	Current Ad	Recommended tratio	Current tratio
Ridiculousness	1-0	Music	Cosmetics	0.493	0.092
Ridiculousness	1-1	Music	Charity	0.500	0.056
Ridiculousness	1-2	Music	Charity	0.491	0.081
Ridiculousness	1-3	Music	Charity	0.467	(0.030)
Ridiculousness	1-4	Music	Charity	0.471	0.112
Ridiculousness	1-5	Music	Cosmetics	0.465	0.311
Ridiculousness	1-6	Music	Charity	0.394	0.000
Ridiculousness	1-7	Music	Cosmetics	0.386	0.130
Ridiculousness	1-8	Music	Cosmetics	0.401	0.132
Ridiculousness	1-9	Music	Cosmetics	0.434	0.186
Awkward.	1-10	Music	Cosmetics	0.236	0.184
Ridiculousness	1-11	Music	Charity	0.438	0.105
Step Up	1-12	Education online	Charity	0.349	0.173
The Pacifier	1-13	Education online	Charity	0.383	0.164
The Pacifier	1-14	Education online	Cosmetics	0.405	0.209
Catfish: The TV Show	1-15	Music	Charity	0.353	0.148
16 and Pregnant	1-16	Education online	Charity	0.285	0.080
16 and Pregnant	1-17	Education online	Charity	0.270	0.141
Catfish: The TV Show	1-18	Music	Charity	0.320	0.146
Catfish: The TV Show	1-19	Music	Charity	0.328	0.180
The Fast and the Furious: To	1-20	Education online	Education online	0.412	0.211
Catfish: The TV Show	1-21	Music	Charity	0.353	0.135
Catfish: The TV Show	1-22	Music	Cosmetics	0.362	0.173
Catfish: The TV Show	1-23	Music	Cosmetics	0.356	0.202
Catfish: The TV Show	2-0	Music	Charity	0.389	0.066
Ridiculousness	2-1	Music	Charity	0.504	0.075
Ridiculousness	2-2	Music	Charity	0.505	0.204
Ridiculousness	2-3	Music	Charity	0.522	(0.095)
Ridiculousness	2-4	Music	Charity	0.522	0.051
Ridiculousness	2-5	Music	Charity	0.522	0.199

Figure 7: Ad-relevance increases for Music Television Network MTV. Above is in schedule order (vertical sort) and showing the current and recommended top tRatio ad.

WGN News at Nine: Better to show Powertools

Futurama: Colonial Penn Insurance-Life – better to show iPhone

In the Heat of the Night – better to show dental insurance ad

Day	Hour	Program	Current Brand	Indy	CPM	Optim	ΔCPM	ΔRev	ΔtRatio	1st	2nd	3rd	4t
Saturday	10PM-11PM	Wgn News At Nine	University Of Phoenix University	-0.49	$3.0	$4.0	$1.0	$82.0	0.94	0.45	0.34	0.34	0.22
Saturday	3AM-4AM	Futurama	Colonial Penn Insurance-Life	-0.33	$1.5	$1.9	$0.4	$12.4	0.84	0.51	0.29	0.21	0.21
Friday	3AM-4AM	Futurama	Colonial Penn Insurance-Life	-0.33	$1.5	$1.9	$0.4	$12.2	0.83	0.50	0.29	0.22	0.22
Wednesday	3AM-4AM	Futurama	Colonial Penn Insurance-Life	-0.33	$1.5	$1.9	$0.4	$11.9	0.82	0.49	0.28	0.22	0.22
Thursday	3AM-4AM	Futurama	Colonial Penn Insurance-Life	-0.33	$1.6	$2.0	$0.4	$12.6	0.82	0.49	0.28	0.22	0.22
Monday	10PM-11PM	Wgn News At Nine	University Of Phoenix University	-0.39	$2.1	$2.6	$0.6	$40.2	0.79	0.41	0.34	0.34	0.34
Monday	3PM-4PM	In The Heat Of The Night	Kia Sorento Trucks	-0.14	$3.0	$3.7	$0.7	$339.7	0.78	0.64	0.63	0.63	0.63
Sunday	10PM-11PM	America's Funniest	University Of Phoenix University	-0.16	$3.2	$3.9	$0.7	$94.5	0.74	0.58	0.58	0.58	0.58

Figure 8: WGN ad optimization showing inventory that could show the highest improvements in ad relevance. To generate this view we sorted by ΔtRatio descending (vertical sort) and Advertiser tRatio descending (horizontal sort). ΔtRatio is the difference between the most frequently inserted ad, and the optimal ad.

Figure 9: Schedule for Animal Planet showing a contact list of advertisers who would be most relevant to insert into each program. The view above was generated by sorting by schedule (vertical sort), and advertiser tRatio descending (horizontal sort).

Figure 11: ABC showing the best inventory for an SUV advertiser on ABC during Saturday afternoon. The view above was generated by sorting by schedule (vertical sort) and filtering on Advertiser=SUV (so other advertisers are not shown). Green indicates relevant advertising, and red poor relevance.