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Video Ad Inventory Forecasting

Building customized models to enable a network to better monetize all available advertising inventory and avoid campaign under-delivery.

After a television series episodes air, networks make them available to partners to offer to viewers on demand. How and when those viewers watch the episodes has a significant impact on a network's sellable inventory. Custom data models help accurately forecast advertising inventory availability across its partners for each full episode of the season.

Background

Once a series episode airs on linear TV, our client network makes it available to its Multiple Video Programming Distributor (MVPD) and over-the-top (OTT) partners, whose users view it at their convenience. How and when those users view its full episodes off domain has a significant impact on the network's sellable inventory. Typically, in the days following the initial airing, an episode will experience a "halo bump" of views. That halo bump continues, but to a lesser degree, throughout the series, as fans seek to catch up on the season. Episodes usually experience an exponential decay in viewership, until the network removes them from the online channels and makes them available to other channels with different licensing arrangements.

Although full episodes represent the lion's share, episode clips are also an important source of inventory, and add an additional layer of complexity to the forecasting. Typically, clips have just one pre-roll ad, which makes it easier to forecast, but it is up to the individual view to initiate the start of the clip, and that is much harder to predict.

This network wanted to accurately forecast advertising inventory availability across its partners for each full episode of the season. Of particular concern was their inability to accurately forecast inventory levels three to eight weeks into the future. Doing so would allow the network's AdOps personnel to determine whether they could meet the fulfillment requirements of existing campaigns, or if corrective action was needed. But without accurate insight into mid-term inventory, they couldn't make such decisions with confidence. Due to this lack of confidence, the network regularly under-sold its inventory, leaving significant sums of money on the table.

Challenges

The network faced a number of challenges that needed to be overcome before it could achieve its forecasting goals:

- **Forecasting at the episode level**. All forecasting exercises rely on historical data, but with new shows that data simply doesn't exist. Moreover, though all episodes in a series are likely to behave similarly, variations will occur. Some episodes are more popular than others, and big events (e.g. The World Cup, the Olympics) may draw audiences away, radically changing the viewing behavior for an episode. To succeed at forecasting, the network needed to harmonize episode viewing history, which is an enormously complex task.

- **Complexity of video forecasting**. Video is inherently complex due to variances in in-week viewing consumption and consumption patterns across partners, making it extremely complex and difficult to map an episode's exponential of decay signature.

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- **Video pods**. Even if the AdOps team could accurately predict that a certain amount of impressions would be available, they couldn't say for certain how those impressions would be distributed across the pods. And that, in turn, made applying critical campaign criteria, such as frequency capping and competitive exclusions, nearly impossible to forecast.

- **Blunt tools**. All inventory forecasting tools were designed for display ads, which is a profoundly different model than video. The ad server provides some data, but the team felt this data wasn't sufficient to provide the level of forecasting needed. As a result, the network tried to forecast inventory via Excel, but Excel couldn't handle the nuances and volumes of data required. As a result, inventory was summarized, when detail was needed.

Solution

The network engaged us to create custom models to do time-series forecasting of the network's inventory, and to accurately predict availability.

We began by examining the network's FreeWheel ads-server data, which is collected when ads are shown on their partner's sites and stored in the network's Teradata database. Next, we used R to extract the viewing data from the Teradata database, in order to do the forecast modeling. R offers base-level time-series algorithms, which we customized to reflect the complexity of in-week viewing patterns per full episode.

We also used R to manage the overlap between content hierarchy (i.e. episode/show/genre/pod type/business unit/brands), as well as duration of ad pod (i.e. number of ads that may be sold in a particular pod to fill available inventory).

At the client's request, that data was then fed into an up-to-the-minute inventory report that allowed the network to forecast the amount of inventory that would be available in the mid term (a three- to eight-week time frame).

How Did it Turn Out?

As a result of accurate mid-term forecasting, the network can now take advantage of greater pools of inventory. The AdOps team is now confident they know where their pools of inventory are, and can ensure they're neither under- or over-selling. Additionally, the AdOps personnel now spend very little time correcting campaigns that have gone off track, and can focus on more strategic initiatives, such as building the business and relationships with advertisers.

About

DAS42 provides cloud-based data analytics consulting to help executives and managers reduce the time to actionable insights and empower them to make better decisions, faster.

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