

The Unreasonable Effectiveness Of Data

January, 2018
Pocket Gamer Connects, London

scientific revenue
pricing without compromise

Abstract

Over the past 4 years, Scientific Revenue has pioneered a machine-learning based approach to pricing. Simply put, Scientific Revenue uses machine learning to create segments of users that are then mapped to different price points.

Over the past year, Scientific Revenue has also used the same underlying technologies to improve other aspects of mobile video games. In particular, Scientific Revenue has used post-install behavioral data to improve both user acquisition and engagement.

In this talk Scientific Revenue's Ted Verani will share how artificial intelligence can be used to build profiles for dynamic pricing that are also useful for user acquisition. Included is a case study from a successful customer implementation.

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What if I Told You

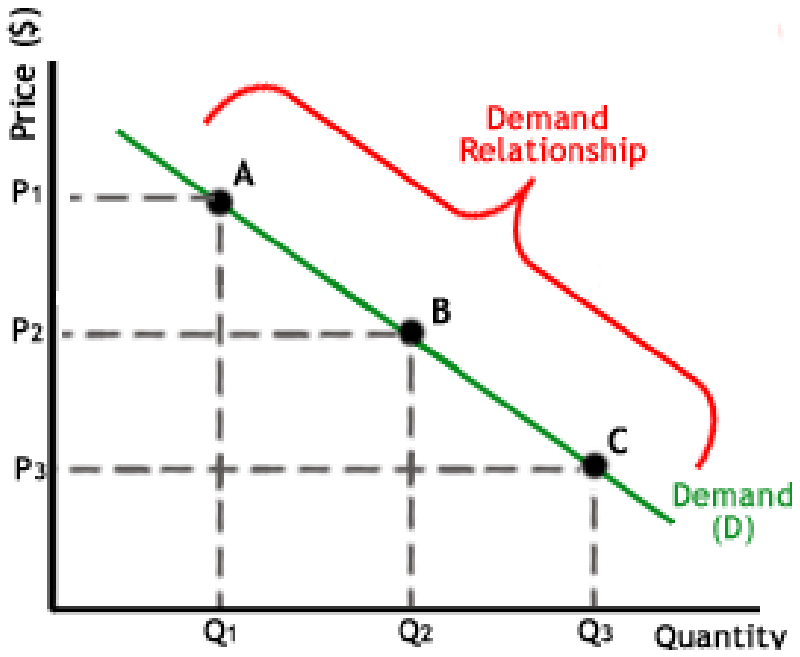
- Evidence is now clear that machine learning can dramatically improve your revenue
  - Scientific Revenue does IAP Pricing
- But also
  - Help you acquire high value users
  - Help you decide whether to monetize a specific user via ads or via IAP
  - Help you retain high spenders
  - Increase retention
  - Optimize your in-game storefronts



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What Scientific Revenue Does: Pricing to the Demand Curve



The transition from “one-size fits all” pricing to targeted pricing is a key idea to maximizing IAP Revenue.

Machine learning looks at post-install behavioral and purchase data to create a partition of the users, and send users to the right prices.

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(Slightly) More about the Pricing Piece

- At Pocket Gamer Connects in Helsinki, we gave a talk on using behavioral economics, big data and machine learning to optimize pricing
- https://www.slideshare.net/ScientificRevenue/what-makes-a-price-a-good-price



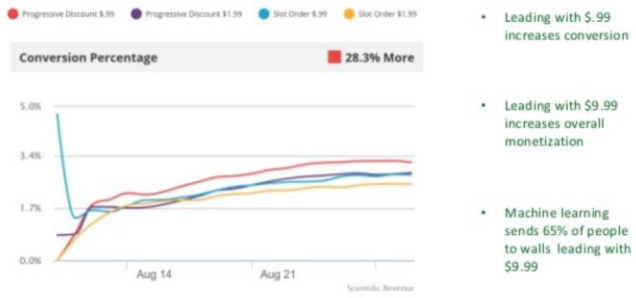
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The Biggest Takeaway from that Talk

- There's a large, and accessible body of knowledge on payment wall (aka coinstore) design
- Many walls have the same monetization across the population (ARPU)
- But they induce very different behaviors in the population.
- That means that machine learning can target end-users with the appropriate pricing

Customer Conversion and Models



- Leading with $.99 increases conversion
- Leading with $9.99 increases overall monetization
- Machine learning sends 65% of people to walls leading with $9.99

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User Acquisition and In-Game Ads

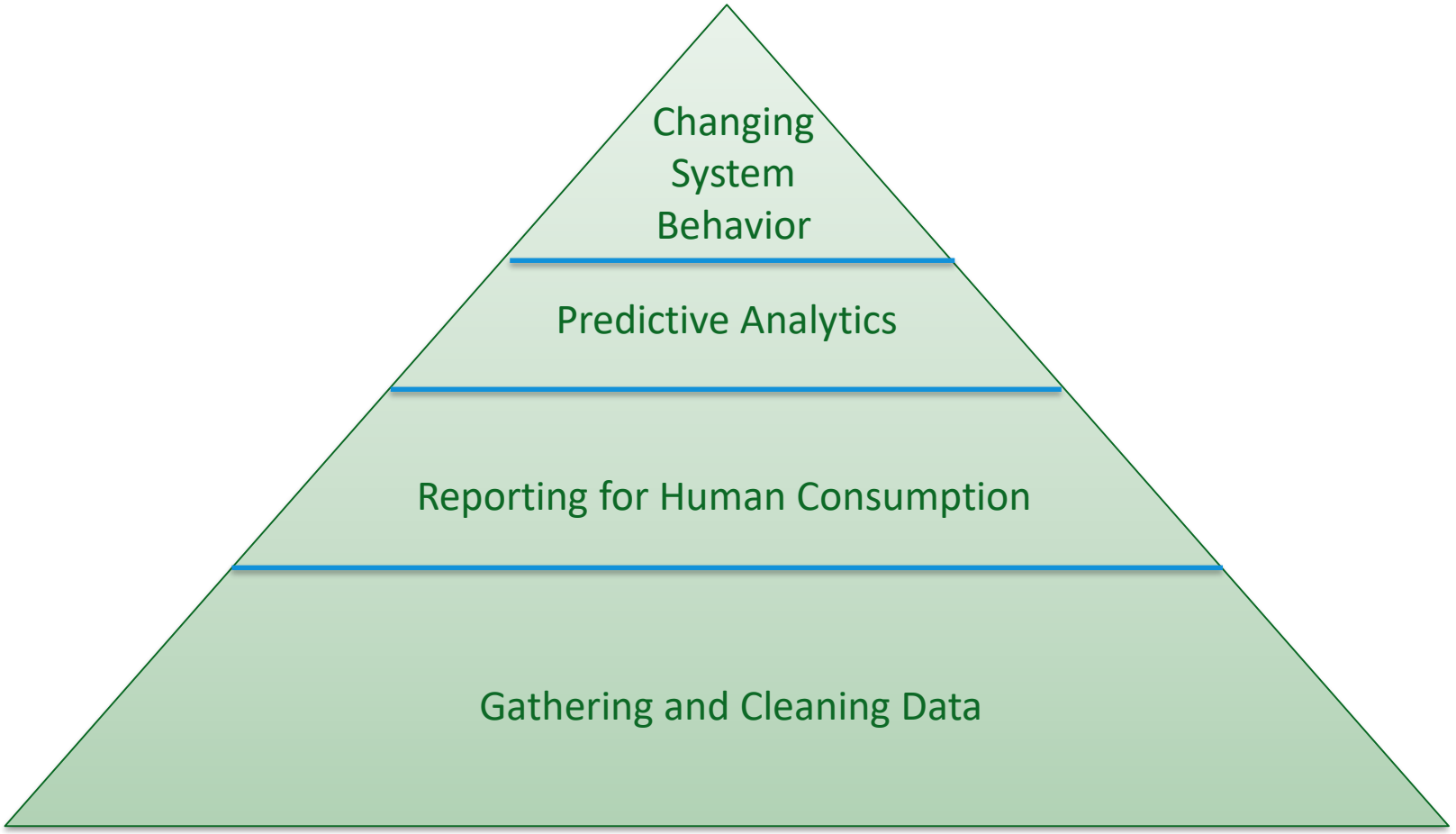


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The Machine Learning Pyramid



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The Predictive Questions

- Is this user about to churn?
  - When will this user churn?
  - How many more minutes will this user play?
  - Will this user be here a week from now?
- Will this user buy an IAP?
  - Will this user buy more than one IAP?
  - How much money will the user spend?
  - Will this be a high value user?



Solved, in the literature



Solvable, not in the literature (yet)

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The Literature

- Churn prediction is solved.
  - **Churn Prediction for High-Value Players in Casual Social Games** – Runge et al.
  - **Churn Prediction in Mobile Social Games: Towards a Complete Assessment Using Survival Ensembles** – Perianez et all

Dataset	Final Feature Set
Diamond Dash	Time series of rounds played, accuracy, invites sent; days in game, last purchase, days since last purchase
Monster World	Time series of logins, level, in-game-currency 1 balance (WooGoo), currency 2 balance (Magic Wands)

Table 2. Final Feature Set

Additionally, we want to implement our model in a data science product running in an operational business environment. Thus, the feature selection takes into account limitations in terms of memory and processing capabilities that might not be considered in a pure research environment.

- Player attention: the time component of the player accessing the game.
  - Time spent per day in the game, including averages over the first weeks and moving average over the last weeks.
  - Lifetime: number of days since registration until churn, in case the player churns.
- Player loyalty: the frequency of the player access to the game.
  - Number of days with at least one playing session.
  - Loyalty index: ratio of number of days played, divided by lifetime.
  - Days from registration to first purchase.
  - Days since last purchase.
- Playing intensity: the quality of the playing sessions, i.e. how a player interacts with the game.
  - Number of actions.
  - Number of sessions.
  - Number and amount of in-app purchases.
  - Action activity distance: Euclidean distance between the average number of actions over the lifetime and the average number of actions over the last days.
- Player level: the value of this variable and its evolution depends on the game. However, the concept of level is present and measurable in the majority of games, and can be then considered as a game-independent predictor that can be used in our model and applied to most other mobile social games.

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Intuitively, You Know Your Data Predicts Outcomes

- **What is the number one predictor of spend?**

  Engagement over time

- **What is the number two predictor of spend?**

  A history of previous spend

- **What is the number three predictor of spend?**

  Repeated interaction with the virtual economy

- **What is the number four predictor of spend?**

  Did your friends spend?

- **Which spends more: an iPhone or an Android Device?**

  It depends on which Android device

- **Does phone storage predict LTV?**

  Yes, weakly – more storage correlates with higher spends

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Facebook Value-based Look-a-likes

Introducing Value-Based Lookalike Audiences

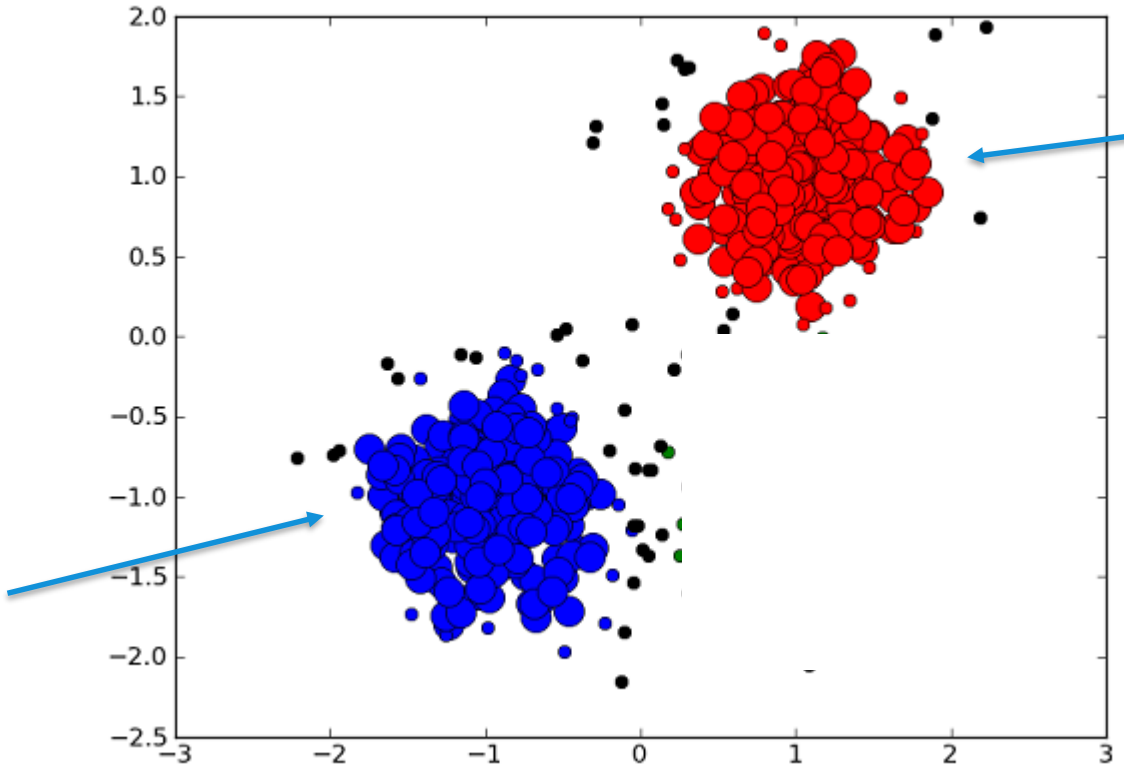
With Lookalike Audiences you can target ads to people on Facebook that are the most similar to a list of people that you already know. A common targeting strategy to acquire new customers requires you to provide a *seed* audience listing your more valuable, existing customers from a CRM. For background, see Lookalike Audiences. While this proves to be a successful strategy, it's more likely that you may value each person differently in this audience based on your business goals.

Value-based Lookalikes are an enhancement of Lookalike Audiences. You can use it to include an arbitrary, numeric value for each person. We use this to determine which people in the list are most valuable to your business, in a quantifiable way.

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Use Machine Learning to Define Distinct Classes of Users



Bad

Good

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Empirical Results

- Scientific Revenue has now engaged in a systematic exploration of Facebook Look-a-likes for the past year
  - Scientific Revenue generates a value-based look-a-like set using predictive LTV.
  - The data set is actually overweighted with low-value users (so that Facebook can focus away from zero-value users)
- Example results (from a typical game):
  - Organic users are lowest value
  - Acquired users (done by outsourced UA) are worth 2X organic users
  - Look-a-like users cost 1.5X the professionally acquired users, but generate 6x the ARPU (on a 45 day basis)

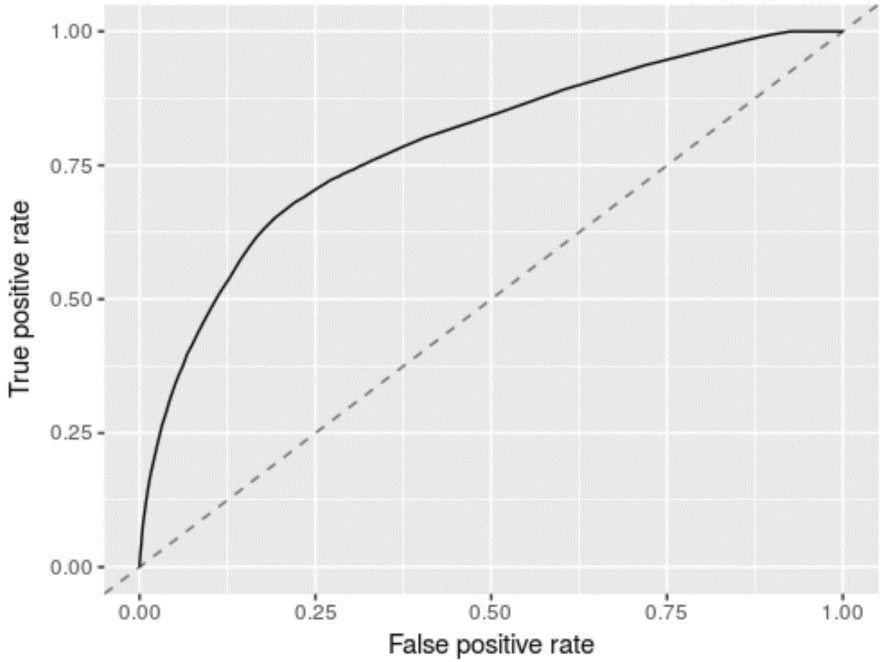
    —*Monetize much better, retain much longer.*

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Key Point: You Don't Have to Be Perfect, Just Better

- Your systems are already making predictions (you are advertising, and you are setting prices)
- Only question is: are you using your data?



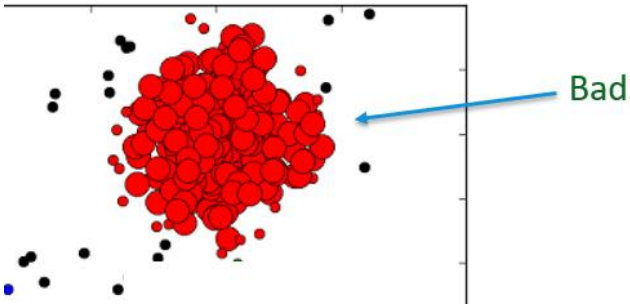
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Putting it All Together: Ad Control

- Take that red cluster from a few slides ago
- Users in that cluster are *never* going to spend
  - We have a good idea of “never going to spend” within 3 days
  - We have a great idea of “never going to spend” within 7 days
- So .,.. as the predictive models become more certain about a user., we can turn on ads.



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Summary

- There is a set of monetization-related best practices which are susceptible to machine learning techniques.
- They all rely on the same basic practices: fine-grained data collection and cleaning, accurate and meaningful reporting, and predictive analytics.
  - They have a 90% overlap in the first three stages of the pyramid
- Each practice gives you additional incremental revenue
- The cumulative impact is potentially enormous

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Thank You

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