Knowing How People are Playing Your Game Gives You the Winning Hand

Bill Grosso
(bill@scientificrevenue.com)

Abstract

This session will present the state of the art of predictive analytics for gaming, focusing on basic ideas to advanced concepts such as machine learning that can be used profitably by almost every gaming studio. We'll cover:

- An overview of the use of analytics in gaming
- Predicting churn: why and how
- Identifying unusual behavior
- Gold farming, fraud analysis, and unlocking gifting
- What's next in gaming analytics

About Bill

- Serial Entrepreneur in Silicon Valley
  - Platform-as-a-Service for 12 years
  - Analytics for 8 years
  - Gaming for the past 6 years
- Currently head of a consulting practice (Osolog) and CEO of a stealth mode startup (Scientific Revenue)
- http://www.linkedin.com/in/williamgrosso
- https://twitter.com/wgrosso

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e-mail address GO

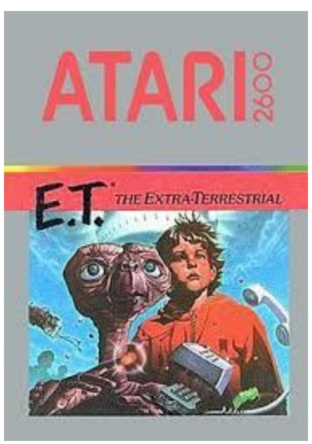
Agenda

- **The Shift in Gaming and the State of Gaming Analytics**
- Six Use Cases for Predictive Analytics
- The Importance of Data and User Segmentation
- Parting Thoughts

Game Delivery

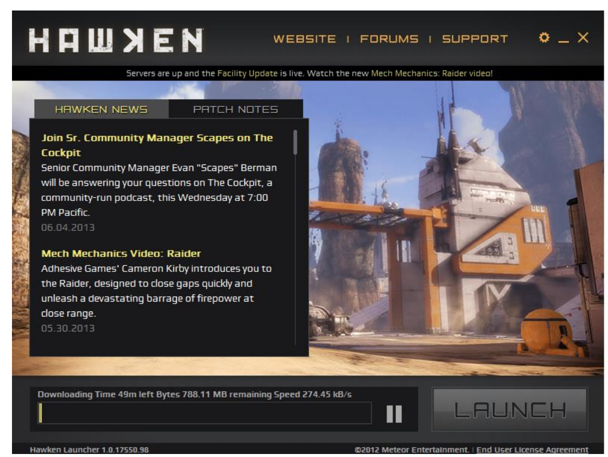
Before 2000

- Most games sold via "packaged goods" model
- Game companies made the game and handed it off to retail partners.
- They were done at that point



Today

- Download model
- Everything gets "patched" continuously (no such thing as done)
- Most games have an incremental monetization model
  - Subscriptions
  - DLC
  - Free to play



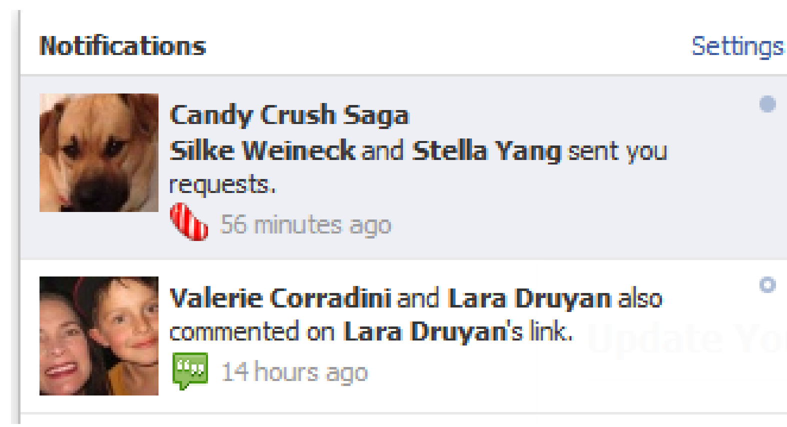
Multiplayer Gaming

Before 2000

- "Compare High Scores" model (from arcades)
- Conversation and shared tips (social model)
- Multiplayer meant "4 people around a console"

Today

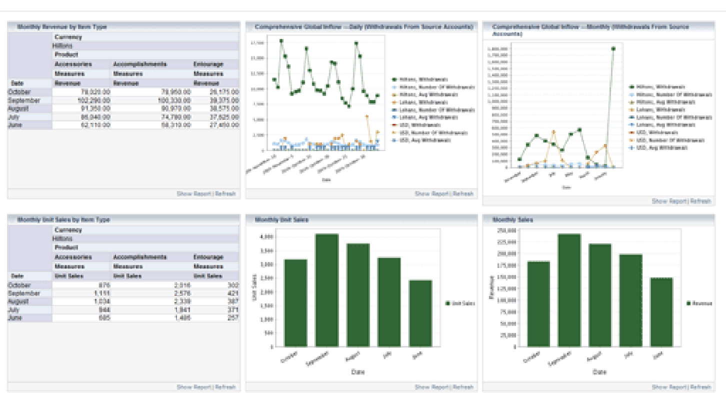
- Social on steroids
  - Tweeting
  - Facebook games
  - Shared videos
- "Always online" games becoming the norm
  - PaaS model for gaming infrastructure
- True multiplayer is still pretty rare
  - I have 60+ games on my phone
  - <10 involve simultaneous activity by people not in the same room



Analytics

Before 2000

- Entirely “historical” in nature
  - You shipped the game, then you found out how it did in the wider market
- Mostly financial
  - Sales reports
  - Very little telemetry or gameplay analytics



Now

- Growing trend of “record everything, sort it out later”
  - Though there is some skepticism about the value of doing so
- Not a lot of QA on the telemetry data
- Most reporting is still financial or “top line” metrics
  - People are very suspicious of having “too many” metrics

http://wgrosso.tumblr.com/post/23556458152/metrics-that-game-developers-use-correlations-and

The Way We Manage Games is Starting to Change

- If the game is always online and frequently updated, there’s an opportunity to change the way we make decisions
- To the extent we can make the game into a “data driven application” which use server-side logic for key decisions, we can manage the individual user experience
  - Game developer: To make better games
  - Business side: To make more money

The Next Step is A Shift In Analytics

- Pre-2000 metrics tell you how you did
  - Mostly from a financial perspective
- Current metrics tell you how you're doing
  - ARPDAU doesn't help you get better
- Next step is predicting what will happen *if you don't do something*
  - And enabling you to take action to avoid bad outcomes
  - Really the point of "predictive analytics" – if you know about bad things early enough, you can take action to prevent them

Major Companies Starting to Announce Predictive Initiatives

Big data is helping EA level up

Electronic Arts CTO Rajat Taneja on big data's growing role in the video game world.

Print

Listen

Read Later

by Ron Miller | @ron_miller | +Ron Miller | Comment | December 12, 2012

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Electronic Arts (EA) isn't the first company that comes to mind when you think of big data. Yet the gaming company is collecting increasing amounts of data about its online players, and as this data accumulates and gains steam, it falls under the big data category.

If a game maker like EA is considered a big data
might not think of as typical big data generators.
technology officer at EA and a keynote speaker
came on board with EA in 2011, he's helped stee
understanding the impact this growing data store
how to use it to provide games and services cus
if you have constantly connected online services

Our interview follows.

Sony Online Entertainment leverages Sonamine Predictive Player Scores

January 2nd, 2013 *by Nick*

Happy new year everyone!

There is a lot of industry interest in using data analytics in games. Looking at the gamasutra or linkedin job board today, I see that Ubisoft, 2K games, MachineZone, Ngmoco, Microsoft, Z2live, Activision etc are all looking for data analysts. Especially after it was revealed that the Democrats used a predictive scoring algorithm to allocate scare volunteer resources to get-out-the-vote, interest in using predictive analytics has never been higher, or more hyped.

But really, how do you actually use predictive scores in a day-to-day productionized manner to increase revenues and retention? Well, one of Sonamine's customer is Sony Online Entertainment, an industry leading MMO developer. They have successfully integrated Sonamine predictive player scores into a full fledged player relationship management program that encompasses different player touch points, a communications calendar and different offers. SOE presented their story at GDC Online in Austin. (skip to link at bottom to get presentation). Here are some of their lessons:

- Develop a player relationship management program, with calendar of communications and offers.
- Have a system that allows targeting to different sub-segments of players with appropriate messages.
- Use Sonamine predictive scores to create different player segments.
- Take the long view, it is a journey.
- Do not underestimate the resources needed to pull this off.

You can google and find videos of the talks, and the slides

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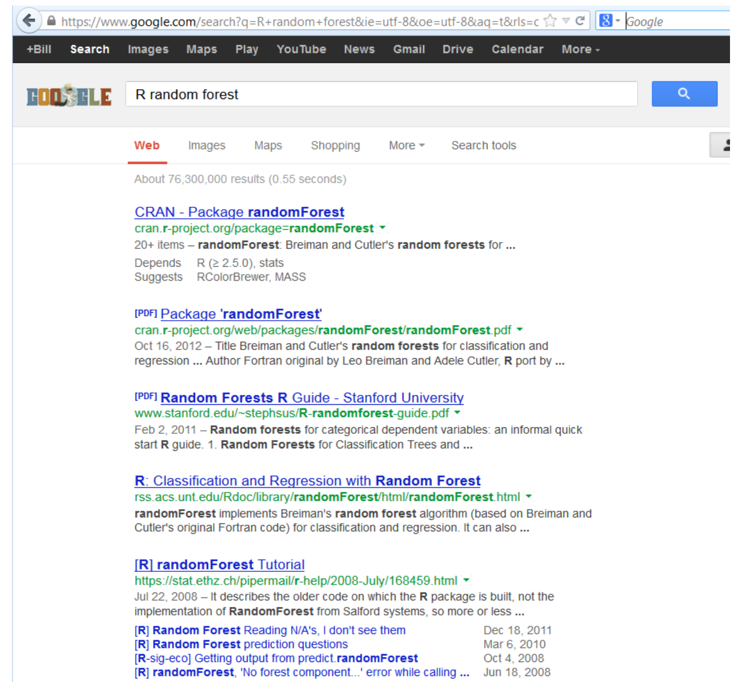
- **Six Use Cases For Predictive Analytics**
- The Importance of Data and User Segmentation
- Parting Thoughts

Use Case 1: Noob Churn Prediction

- Goal: predict whether a new player will return for a second day
- Idea: Carefully record player events and actions during the first day. Record whether users come back. Then use supervised learning to build a predictive model.
- What would you do if you knew:
  - Cancel bad advertising campaigns
  - Pro-actively cross-market other games
  - Try harder to get a purchase
  - Show more ads



Use Case 2: Vet Churn Prediction

- Goal: predict whether a veteran player is losing interest
- Idea: Track simple time-based engagement in many different ways using multiple mathematical transformations and then use supervised learning
- What would you do if you knew:
  - Pro-actively cross-market other games
  - Try harder to get a purchase (the “gosh I loved this game” nostalgia buy)

www.gamasutra.com/view/feature/176747/predicting_churn_when_do_veterans_.php?pri

GAMASUTRA
The Art & Business of Making Games

PRINT

Predicting Churn: When Do Veterans Quit?

By Dmitry Nozhnin

***In the follow-up to his original article on predicting player churn, Dmitry Nozhnin, head of analytics and monetization at Russian MMO publisher Innova, shares his methodology for predicting when veteran players will quit the game -- identifying when players will drop two to three weeks before they do with 95 accuracy, all carried out in the live environment of the Russian version of NCSoft's* Aion.**

In my previous article, I showed the process we developed for predicting churn of our freshest users, who just registered for the game, based on data collected during the first couple of days of their adventures. However, on the other end of spectrum are seasoned gamers who have spent months and months in the game, but for various reasons decided to abandon it. Predicting their desire to leave the game is possible, and in this article, we're sharing our data mining methodology.

Tech Side

Nothing changed from the first data-mining project; we were still on two Dual Xeon E5630 blades with 32GB RAM, 10TB cold and 3TB hot storage RAID10 SAS units. Both blades were running MS SQL 2008R2 -- one as a data warehouse, and the other for MS Analysis Services. Only the standard Microsoft BI software stack was used.

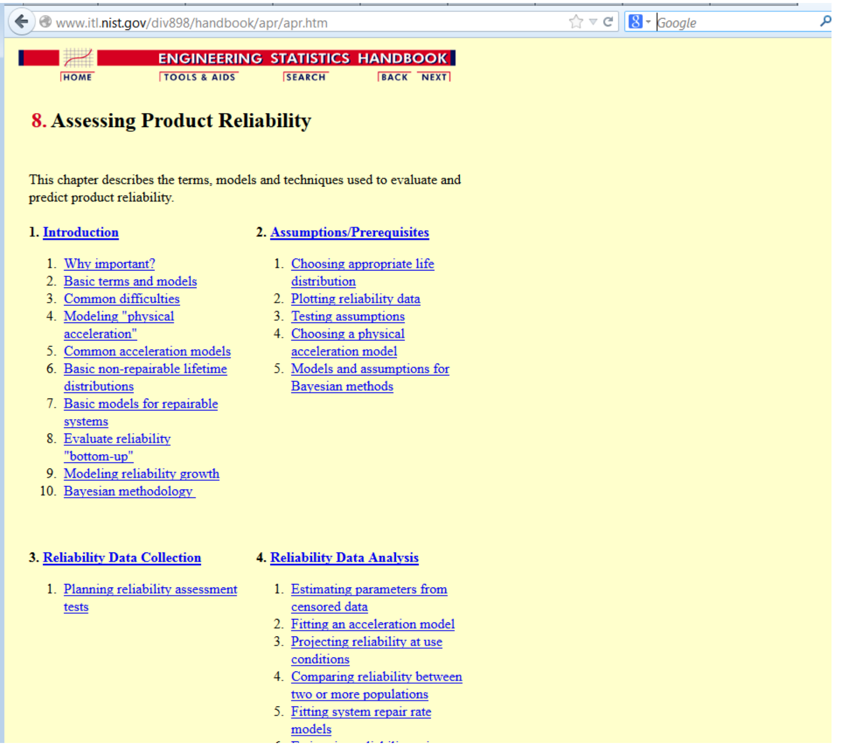
Our dataset had up to six months of recorded gameplay for about 38,000 veteran players.

Defining the Moment of Churn

For new players, defining churn was dead simple -- they just leave the game after a couple of minutes or hours. That's it. The last day of play was clearly defined, and data mining models on such churn factors were already well established. However, for veterans, it took us several iterations to define churn correctly. Our first assumption was this: the player is enjoying the game for some time, but then he decides to quit and leaves. Marking his play days with green, we expected something like this:

Use Case 3: Survival Analysis

- Goal: get a simple, top-level, measure of population dynamics
- Idea:
  - Installing a game is like getting a terminal disease
  - Stopping playing is like dying
  - Fit ether Cox PH or a Weibull distribution to the data
- What would you do if you knew:
  - Use the survival curves to perform top-line assessment of game changes



8. Assessing Product Reliability

This chapter describes the terms, models and techniques used to evaluate and predict product reliability.

1. Introduction
   1. Why important?
   2. Basic terms and models
   3. Common difficulties
   4. Modeling "physical acceleration"
   5. Common acceleration models
   6. Basic non-repairable lifetime distributions
   7. Basic models for repairable systems
   8. Evaluate reliability "bottom-up"
   9. Modeling reliability growth
   10. Bayesian methodology

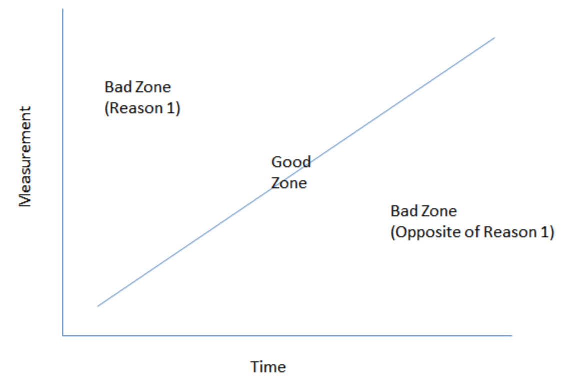
2. Assumptions/Prerequisites
   1. Choosing appropriate life distribution
   2. Plotting reliability data
   3. Testing assumptions
   4. Choosing a physical acceleration model
   5. Models and assumptions for Bayesian methods

3. Reliability Data Collection
   1. Planning reliability assessment tests

4. Reliability Data Analysis
   1. Estimating parameters from censored data
   2. Fitting an acceleration model
   3. Projecting reliability at use conditions
   4. Comparing reliability between two or more populations
   5. Fitting system repair rate models

Use Case 4: Gameplay Analysis

- Goal: figure out if a user is getting stuck, failing to learn a crucial skill, or picking up bad habits
- Secondary goal: finding cheaters or other sources of gameplay imbalance.
- Idea:
  - Carefully record player events and actions.
  - Measure increasing-skill / success of players.
  - Then perform supervised learning to see if there are early predictors of skill-acquisition or success
- What would you do if you knew:
  - Focused tutorials and interventions
  - Different pairings during matching algorithms
  - Dynamically adjusting the game



Use Case 5: Fraud Detection

- Goal: Spot people who are performing a fraudulent action (gold-farming, selling goods outside of game, …)
- Idea: Apply anti-money laundering techniques (unsupervised learning to detect outliers, usually via support vector machines)
- What would you do if you knew:
  - Shut down the gold-farmers
  - Open up gifting and third-party gifting channels

2009 International Conference on Computer Engineering and Applications
IPCSIT vol.2 (2011) © (2011) IACSIT Press, Singapore

An investigation into Data Mining approaches for Anti Money Laundering

Nhien An Le Khac, Sammer Markos, M. O'Neill, A. Brabazon and M-Tahar Kechadi
University College Dublin, Ireland
{an.lekhac,sammer.markos, m.oneill, anthony.brabazon, tahar.kechadi}@ucd.ie

Abstract. Today, money laundering (ML) poses a serious threat not only to financial institutions but also to the nation. This criminal activity is becoming more and more sophisticated and seems to have moved from the cliché of drug trafficking to financing terrorism and surely not forgetting personal gain. Most of the financial institutions internationally have been implementing anti-money laundering solutions (AML) to fight

Use Case 6: Whale Spotting

- Goal: Sport high spending customers as soon as possible
- Idea:
  - Carefully record player events and actions.
  - Measure the life-time spend of players.
  - Then perform supervised learning to see if there are early predictors of significant spend.
- What would you do if you knew:
  - Lots of possibilities here

R is the Right Tool

- The six use cases mentioned
  - Supervised learning
  - Unsupervised learning
  - Anti-money laundering
  - Cox-PH / Weibull models
  - Mathematical data transformations
- R is the single best tool for exploratory data analysis using a wide-variety of machine learning algorithms

<<Poll Question>>

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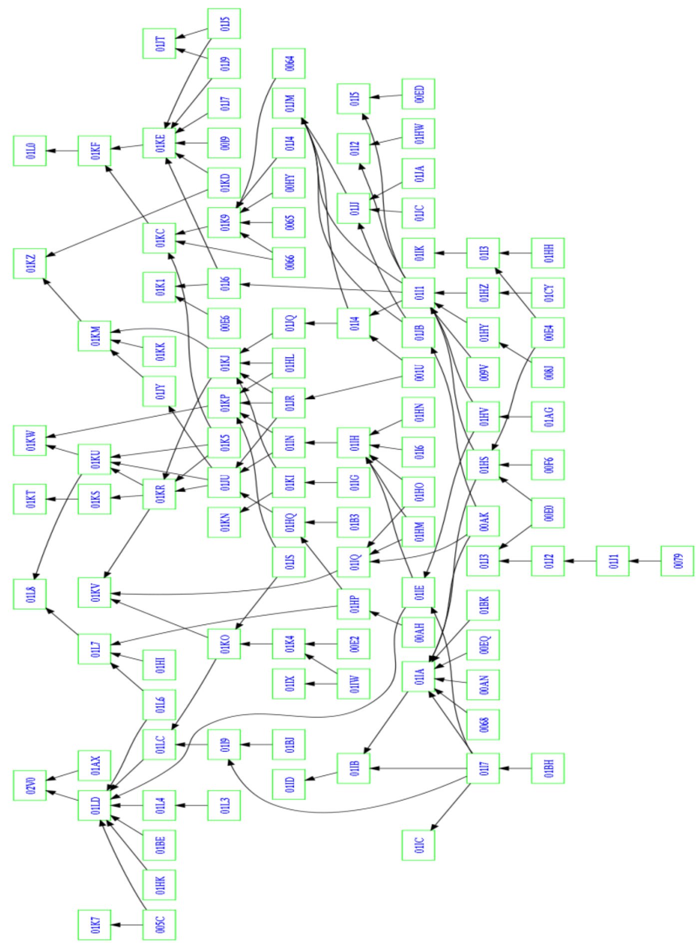
The Basic Idea

- Create a detailed model of the user
  - A user is a point in 2000 dimensional space
- Create a set of questions
  - You would like the answers to these predictively
  - You can measure the answers to these historically
- Create a training data set
  - Historical Users x Measured Outcomes
- Sample your data and use standard algorithms
  - CRAN is your friend
  - This is just supervised learning. Random Forests and Neural Nets rule the world.



Historically Measured Outcomes

- Supervised learning means you need to know the outcome
  - You can’t learn much on day 1
- Not a bad thing. This lets you
  - Baseline behavior
  - See how far “Two standard deviations” style reasoning can take you
  - Then mix in machine learning

The Literature is Extremely Helpful

- **Model 1 (Player Attribute Based Features):** These features are based on the attributes of the player's character in the game e.g., character race, character gender, distribution of gaming activities etc. Th same features which were used by Ahmad et al
- **Model 2 (Item Based Features):** These are t which are derived from items bought and sol consignment network. These features are bas frequency of the frequent items sold or boug farmers.
- **Model 3 (Player Attribute & Item Based Fea** the attributes from the previous two models.
- **Model 4 (Item Network Based Features)** which are derived from the item network in analogous to Model 2.
- **Model 5 (Player Attribute & Item-Netwo Features):** A combination of features from M Model 4.
- **Model 6 (Item Network & Item-Netwo Features):** A combination of features from M Model 4.
- **Model 7 (Player Attribute, Item & Iten Based Features):** Union of all the features above.

TABLE I. A MODEL OF PLAYER MOTIVATIONS [25]

Achievement	Social	Immersion
Advancement Progress, Power, Accumulation, Status	*Socializing* Casual Chat, Helping Others, Making Friends	*Discovery* Exploration, Lore, Finding Hidden Things
Mechanics Numbers, Optimization, Templating, analysis	*Relationship* Personal, Self-disclosure, Find and Give, Support	*Role-playing* Story Line, Character History, Roles, Fantasy
Competition Challenging Others, Provocation, Domination	*Teamwork* Collaboration, Groups, Group achievement	*Customization* Appearances, Accessories, Style, Color schemes
		Escapism Relax, Escape from Real Life, Avoid Real Life problems

Features (computed from Everquest II® log-files)

- Experience points, number of monster kills, messages sent between players, leveling up, fighting, number of items sold or traded, ...

Features:

- Game time completion, total number of deaths, total number of heal on demand actions, number of death by falling ...

- **Causes of death:** TRU features a variety of ways in which players can die, which can be grouped into three tegories that encompass all possible ways n die. The total number of times a player ach of the three following categories and onding percentages over the total number of calculated:

  ient; the percent of total number of deaths l by any computer-controlled opponent exis- 1 the game over the total number of deaths, ying from opponents comprises 28.9% of the umber of deaths across the 1365 data sam- The best player died only 6.32% of the times opponents, while 60.86% is the maximum observed for D_o.

  onment; the percent of total number of deaths l by the environment over the total number ths, D_e. Environment-related causes of death e player drowning, being consumed by fire, led in a trap, comprising 13.7% of the to- mber of deaths across all players. The best died 2.43% of her total number of deaths from environment-related effects, while the highest recorded value of D_e is 45.31%.

  – Falling; the percent of total number of deaths caused by a failed jump over the total number of deaths, D_f. Dying from falling comprises 57.2% of all death events making it the dominating cause of death in TRU. This is expected since the core of the gameplay consists of jumping, climbing and navigating in 3D environments. The minimum and maximum values of D_f are 27.19% and 83.33% respectively.

Growing Body of Research Papers

- Started with Dmitri Williams in 1990's
- Small body of productive researchers
  - Dmitri Williams
  - Anders Drachen
  - Christian Thurau
  - Alessandro Canossa
  - Jeremy Gow

Illicit Bits: Detecting and Analyzing Contraband Networks in Massively Multiplayer Online Games

How Players Lose Interest in Playing a Game: An Empirical Study Based on Distributions of Total Playing Times

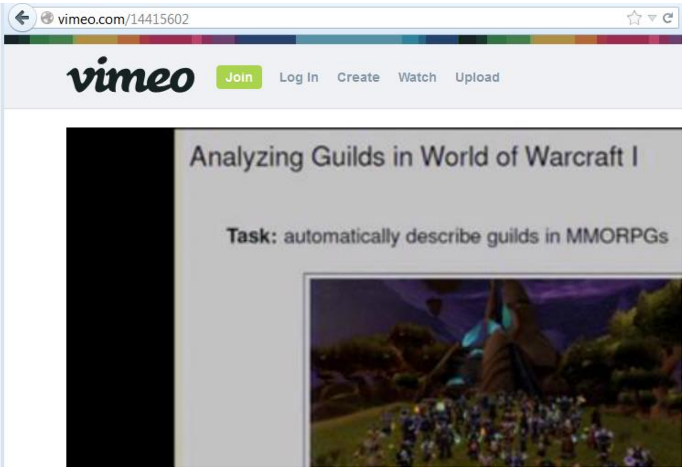
Guns, Swords and Data: Clustering of Player Behavior in Computer Games in the Wild

Churn Prediction in MMORPGs using Player Motivation Theories and an Ensemble Approach

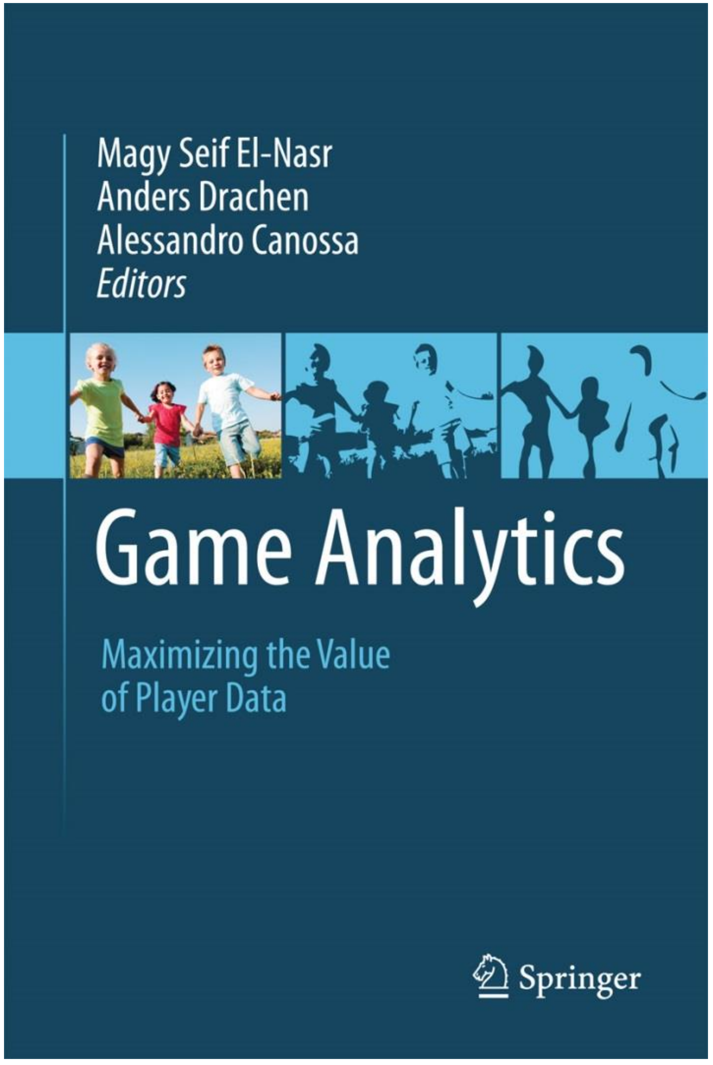
Zoheb Borbora, Jaideep Srivastava
Dept. of Computer Science and Engineering
University of Minnesota
borbo001@umn.edu, srivasta@cs.umn.edu

Kuo-Wei Hsu
Dept. of Computer Science
National Chengchi University
Taipei, Taiwan
hsu@cs.nccu.edu.tw

Dmitri Wiliams
School for Communication and Journalism
University of Southern California
Los Angeles, USA
dcwillia@usc.edu



There's a Very Good Book Too



And, of Course, Thousands of Papers from the Telcos

- Literally thousands of fairly straightforward and easy to understand papers

Attribute	Data Type	Description
category_Id	Text	Category id of phone account.
Category	Text	Category of phone account.
Sec_dep	Currency	Security deposit

Table 2: Attributes from customer file

Attribute	Data Type	Description
Late_pay	Number	Count of late pay
Extra_charges	Number	Count of bills with extra charges.

Table 3: Attributes from billing information section

Attribute	Data Type	Description
Max_Units	Currency	Maximum no of units charged in any two week period during the study period.
Min_Units	Currency	Minimum no of units charged in any two week period during the study period.
Max_dur	Number	Maximum total duration for the calls in any two week period during the study period.
Min_dur	Number	Minimum total duration for the calls in any two week period during the study period.
Max_count	Number	Maximum no. of calls in any two week period during the study period.
Min_count	Number	Minimum no. of calls in any two week period during the study period.
Max_dif	Number	Maximum no. of different numbers are called in any two week period during the study period.
Min_dif	Number	Minimum no. of different numbers are called in any two week period during the study period

Table 4: Attributes from call detail record

Predicting customer churn in mobile networks through analysis of social groups

Yossi Richter * Elad Yom-Tov † Noam Slonim ‡

Abstract

Churn prediction aims to identify subscribers who are about to transfer their business to a competitor. Since the cost associated with customer acquisition is much greater than the cost of customer retention, churn prediction has emerged as a crucial Business Intelligence (BI) application for modern telecommunication operators.

The dominant approach to churn prediction is to

1 Introduction

1.1 Overview Over the last two decades, we have seen mobile telecommunication become the dominant communication medium. In many countries, especially developed ones, the market has reached a degree of saturation where each new customer must be won over from the competitors. At the same time, public regulations and the standardization of mobile communication now allow customers to easily move from one carrier to an-

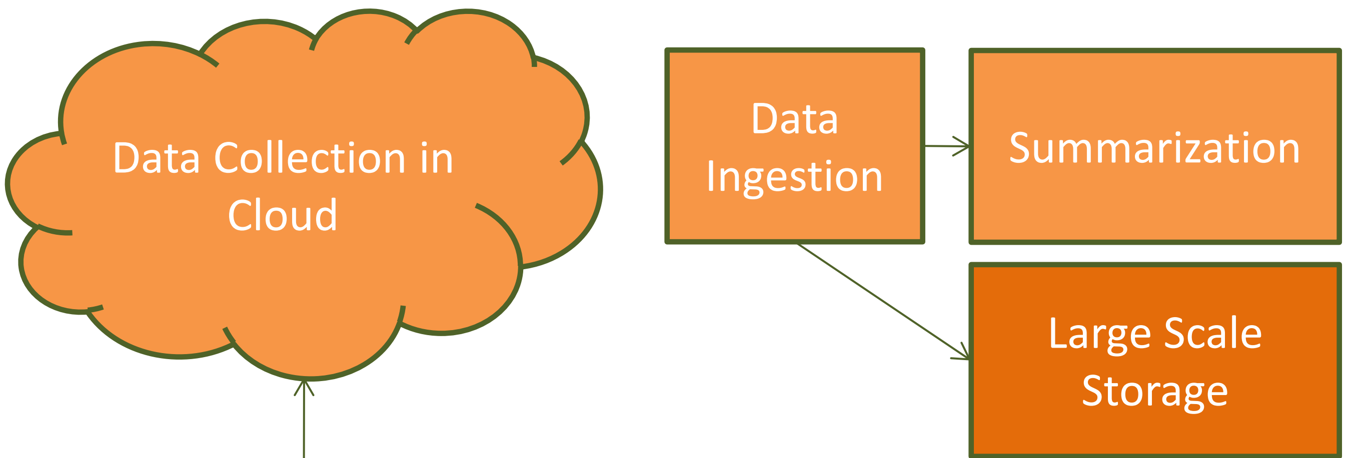
There’s a Lot of Data to Record

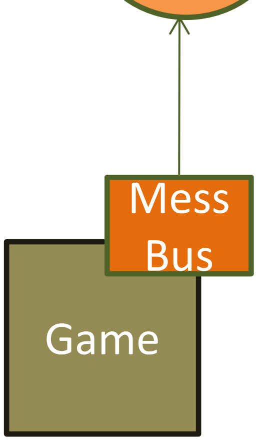
- Events and activities.
- Outcomes
  - Win / lose subgame
  - Made it to dungeon level 4
  - Completed tutorial
  - *Achieved goal*
- Model skills acquisition
  - People generally get better as they play games
  - But the idea of “level” is often much too coarse
  - Leveling up is frequently not the full story
  - User satisfaction is often strongly related to skills acquisition

Sample, Summarize, Model

- You’re going to be storing a ton of data
- Player activity streams are verbose
  - Every chat generates an event
  - Every time a gun gets fired, an event gets generated.
    - And data about them (headshot!)
- Nobody actually reasons about individual events
  - Store counts and ratios at the “session” level
  - Choose representative samples of users to reason about
- Generally speaking, we’re talking about >100 fine-grained measurements that you use to build a model

Example Architecture





- Game is fully instrumented
- Messages sent to server via message bus architecture (in background and batched)

- Standard “NoSQL” stack (storage with Hadoop/Pig layered on top)
- Streaming event aggregation often done by aggregating into in-memory caching (memcached or elasticcache).
- Often the large-scale storage is simply json files stored in S3
- Large scale storage can run into tens of gigabytes a day. Can be significant cost over time

- What we know and love

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The World is Non-Stationary

- Games are now online services with constant tuning
- The people who install a game are constantly changing
  - Early adopters → mass market
- Social and environmental expectations change constantly
- You can't create a model, tune it, get some answers, and move on
- And you really really *really* can't do this on the beta version of your game

Cross-Game Doesn't Work Well

- Games are very different
- There is no generic "across all games" model that will work perfectly without game-specific tuning
- Figure that "data scientist per game" (more for larger games) plus a team to build data pipelines is what you're looking at

Technology is No Longer the Reason for Failure

- You might fail
  - You might not have budget
  - You might not have data
  - You might not get executive buy-in
  - You might run into "cultural issues" or find out that you're upsetting someone's applecart
  - But ….

If you have budget and data and buy-in

You will be able to deliver results

<<Poll Question>>