**Prediction in the Gaming Industry**

by [Dmitri Williams](http://www.gamasutra.com/blogs/author/DmitriWilliams/951230/) on 02/24/15

**Part 1: All About Prediction**

As a data scientist, I deal with predicting the future. Sounds fishy, right? Well, it is true that no one can truly predict the future. There is no “Minority Report.” What’s real are probabilities and patterns that play out.

I’ve already written about data and how analytics are used in games (and you can read that series here), and I briefly touched on predictive analytics. This series of articles will dive more into the topic.

With today’s advances in big data analytics, the ability to accurately predict user behavior with a fairly high degree of certainty is a reality -- that’s not just hype, and it’s what allows me to do my research at the intersection of social and computer science. In the gaming industry, specifically, this means predicting player actions and using that information to inform strategy, improve product, retain key players, and increase monetization opportunities.

We’re getting a little ahead of ourselves now, though. First, let’s back up and look at the fundamentals of predictive modeling, how it works, and how we can be sure it works.

Though the details can get confusing, there’s a fairly simple way of understanding predictive modeling. Using a gaming example, let’s say you record and monitor all of the events that happen in a game, and your computer starts to recognize patterns. Some patterns repeat, others don’t. When the computer recognizes repeated patterns, though, it “learns” and starts to look for the pattern to occur again, then begins making predictions about the next sequence.

For example, when a sequence (like A-B-C-D) repeats over and over, the computer will start to recognize it. From here, you can ask the computer to make a prediction: When an A-B-C pattern comes up, the computer will predict what will come next (in this case, “D,” of course). Beyond that, though, it can also tell you how likely this prediction is to be correct. “D” could be any number of things that are of interest to design, retention or monetization. Imagine “D” is quitting, or completing a level, or spending in the store.

How can it do that, and why is it important? Well, looking at all the previous sequences, “A-B-C” wasn’t always followed by “D” -- occasionally, the pattern is A-B-C-X. So, the more data the algorithm has access to, the more it understands likelihood, and the more it can tell you how often that guess has turned out right.

And that’s it. That’s prediction. Skeptics are right to now ask how accurate these predictions are. Well, that’s where science backs prediction up. There are a few tests that data scientists use to verify predictive models--keeping in mind that verify means “yes it worked” rather than “I can read the future and know it will work tomorrow.” If nothing changes, there’s no reason it won’t work tomorrow. Failures happen when tomorrow is different in an unaccounted for way. If there is a terrorist attack, or an end to the school year, that can throw predictions off, and we can’t see everything coming as well as everything else. The end of the school year can be built into the pattern, and the terrorist attack not as much.

One common way of testing accuracy is called cross-fold validation. Here’s how it works: a computer splits a very big data set (like your gaming data) into two halves. It takes the first half and does its analysis, looking for patterns and building its model. By the end, it comes up with a figure, like “We see A-B-C and then D happens 75% of the time.” Then it takes that model and checks its accuracy against the second, totally untouched half of the data. If A-B-C-D happens 75% in this data as well, we start feeling pretty good about the prediction. Well, we feel 75% good about it, and we report that % as a confidence number.

Why isn’t it 100%? The concept that you can’t be 100% certain might sound vaguely familiar from a high school statistics class, but there’s a slightly different reason behind predictive certainty. We’re predicting human behavior in the real world, and there are a lot of moving pieces that a computer can’t account for. For example, you might notice a pattern that John buys a large coffee every morning, and make a prediction that he’ll do the same tomorrow. Pretty safe bet, right? But what if something happens that prevents him from buying his coffee -- like poor John gets in a car accident? You had no way of knowing that will happen, and certainly didn’t plan for this in your model, but it wasn’t an incorrect model. It was just incomplete, and therefore not 100% accurate.

There’s also another reason we don’t count predictive models as 100% accurate: it’s very easy for some pseudo-scientists to cheat the system. For example, they’ll include everyone in their prediction, ignoring any false positive or false negatives. This isn’t science, because anyone could just include all the players in their model and predict that they’ll buy $10 in credits tomorrow. Since everyone is included, they’ll be 100% accurate in predicting which players will spend -- but also incorrectly predict the behavior of most of the player base.

This casts a shadow on predictive analytics, and happens more often than it should. So, to be responsible, you need proof, which comes in the form of an “F-score” (there are other metrics worth using as well). This takes one stat that allows for false positives and another that allows for false negatives and simply averages them. The result is expressed as a percentage and is extremely trustworthy. It can’t cheat, and will weed out anyone who isn’t really predicting. Games have really good data, but high scores are achieved by a team that knows what variables to include. Computer scientists are traditionally not very good at that job, by the way. Social scientists are, but usually don’t understand the tech, so the best solutions and teams combine both approaches. For reference, a good F-score in the telecommunication industry is .40. In gaming we can do better because we have richer data. Here a good score is .50 to .70. Anything over that is pretty amazing. Remember, it’s not a straight percentage since it’s an average of two scores. It’s an inherently conservative stat.

At the end of the day, seeing that confidence value in a predictive model is key. You need to know how certain you can be taking actions on it. That’s going to depend on the business case and how much is at stake. The nice thing about these scores is that they get you to the scientific values of transparency and provability. There’s no “take my word for it.” I like to say that we should let the data tell the story, and then we should listen to what it says rather than what we want it to say.

**Part 2: Prediction and Gaming (Or, How to Know Your Players)**

If you haven’t read my first article on prediction in the gaming industry, stop here: [go back to part one](http://gamasutra.com/blogs/DmitriWilliams/20150109/233717/Prediction_in_the_Gaming_Industry_Part_1_All_About_Prediction.php) for a background on predictive analytics, modeling and confidence estimates.

Now that we’ve covered the basics, it’s time to delve into how game developers, specifically, can use prediction to their advantage. Prediction can be a crystal ball of sorts for game developers, but only if you have the right information in place. So the first step is to start collecting data -- and a lot of it. If your game doesn’t have data hooks, you aren’t going anywhere.

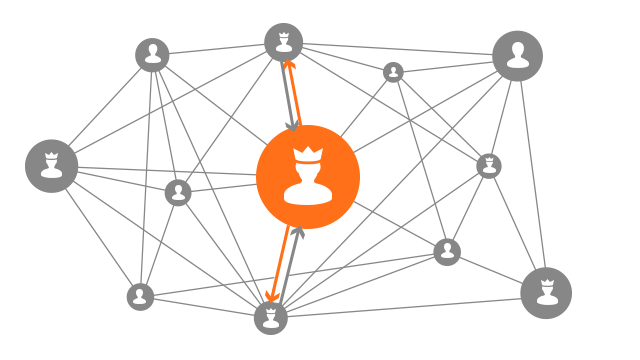
Once you have your data ready to analyze, analytics get to work. There are countless ways to slice and dice the information you have -- basic metrics like looking at Daily Active Users, Average Revenue Per User and Average Session Length -- but the metric that’s most pertinent to prediction and gaming is player lifetime value (LTV). This is basically a sum of how much a player is expected to spend in a game before they leave, or churn out. Some people look at spending to date, but what we really care about is either total, or future spending.

What we’re trying to get at here, of course, is who your most valuable players are. Not every player is created equal: For every hardcore gamer who has an LTV of thousands, there will be many more players who never spend a dime. And from a developer’s perspective, you obviously want to target the players with a high value to keep them happy, longer.

Back to metrics. LTV is a great metric to use to get the lay of the land (assuming you’re using a good model, of course), but it only goes so far. It’s kind of like looking at your players in a bubble, and just looking at how each player interacts with the game.

If you’re a developer, you’re probably shaking your head right now. Players don’t just sit down and play the game in a vacuum! They interact with other people and talk to the other players. They have clans, guilds, networks. That has to count for something, right?

This is incredibly important for prediction, and is known as Social Value. Like LTV, Social Value is a dollar amount. How can you quantify a player’s social network?  If you have an online game, think of your player network like a giant web, with players all connected to each other based on their social connections. Traditional LTV metrics look at each node in the web to determine who’s the most valuable to you, and social value takes into account the entire web and all of its interactions.



Say you have a player, Player A, who spends $5 in game, and another player, Player B, who spends $1. Who’s worth more? Traditional metrics would say Player A. But your analytics program discovers that for every $1 Player B spends, Player C spends $3, Player D spends $2, and Player E spends $3. Add it all up, and Player B doesn’t look so little anymore.

Prediction is a science, but you can’t underestimate the power of human influence -- and Social Value takes that into account. Add the Social Value to LTV and you get the true Total Value of a player, which is the best of both worlds. And this is where you can see who the really big players are.

It’s worth noting that the most valuable players often aren’t who you think. Players who can spend a lot, and whose LTVs are high, are almost never most valuable players in terms of influence. The ones predicted to have the greatest net worth based on social connection and LTV don’t spend that much, but are highly influential and cause a huge ripple effect with the little they do spend. They’re known as Social Whales, and are the ones you should be targeting.

And this, for a game developer, is the million dollar question (or maybe more, depending on the game) is: Who will quit, and how can I stop them?

Of course, you can’t stop everyone from quitting. And, as you probably guessed, an answer to the first half of the question lies in predictive analytics. This is where churn rates come in.  Aside from telling you who’s already quit, predictive models can tell you who’s at risk of quitting, and how much is at stake if they do. That’s an expected value number where the amount at risk is the total value of the player X their likelihood of quitting. For example, Suicide Bob has a total value of $100, and we think he’s 65% likely to quit. If there were 1,000 of him, we’d know that over time the amount at risk for any one of them would be $65 on average. So that’s the number we assign to Bob, and on average, we’re going to be right.

From there, you can take action. A casual gamer with no social upside is at medium risk of churning? Well, maybe you can let that one slide. If you have a Social Whale about to churn, though? It’s time to pull out the big guns and rethink your retention strategy, because they’ll take their whole network with them. And what number do you use? The expected value ($65 for Bob, for example).

The opposite of churn is conversion. This is when your players start to bring in money and monetize, the dream for any freemium developer. Basic analytics programs will be able to show which players have converted, and predictive analytics takes it a step further and asks who will convert, and then how much revenue they’re likely to bring in. With the right system this can also predict who will become the Social Whale, and who to target to reach everyone else.

This is by no means a comprehensive guide to all the capabilities of predictive analytics, even within the gaming industry. Eventually, prediction will get to a point where developers will be able to predict virality, monetization, and even return on advertisements.

So, where is the industry heading? I’ll cover that in the final article of the series.

**Part 3: Predictions for the Prediction Industry**

By now, you should have a fairly good understanding of predictive modeling and how it relates to games -- if not, see part 1 and part 2 of this series. We’ve set a good baseline, and this final installment does a little predicting on prediction, and looks to the future of the burgeoning industry.

After all is said and done, big data prediction is still new. We’re just in the beginning stages of discovering what this technology is capable of. So if you’re thinking about utilizing prediction in your gaming company now, that’s great news -- you’re getting in on the ground floor and you’re ahead of a lot of your competitors.

The bad news is that this is so new, there aren’t a lot of qualified analysts out there to interpret the data you’re churning out -- and there isn’t a lot of data to begin with. To create these models, you need power users. In social predictive analytics (discussed in the last post), these are the social whales. They’re the big names spewing out lots of value, and are therefore teaching the models a lot by proving or disproving their predictions. Prediction gets better by learning from player actions (the repeated patterns), and power users are at the core of these models. Without them, we can’t improve on models.

For a lot of game developers, the real gating item is not a lack of data, but a lack of qualified analysts. The academy (and I’m part of that problem) just doesn’t train people for these roles well yet. We either train good technicians who can handle data, or good interpreters, but rarely those who can do both. [Here’s](http://mobiledevmemo.com/memo/the-marketing-analytics-practice-is-evolving-how-can-you-adapt/?d=e) someone else’s deeper thinking on the issue. From my vantage point, the biggest shortage is in people who understand the right questions. Technical skills are easier to find, but taking business processes and fitting data to them is tougher. That’s where social scientists can shine.

The problem for everyone, though, is a lack of frictionless lay-friendly tools. These models aren’t the “Up and running in 30 minutes!” analytics programs that you can install in an afternoon. They’re big, bulky and take time to implement. Right now, it isn’t an easy thing for game developers to roll out: you have to be committed to knowing your players, and take the time to gather good data before you start seeing a return. You need to deal with an integration or an SDK, and once it’s up, the tools need to be understandable and accessible to all levels of management. Easier said than done, but possible

Sounds pessimistic, right? Like I’ve said before, prediction isn’t magic -- gaming prediction, in particular, is lots of science and hard work. It’s not all bleak, though: there are good tools coming online and best practices are starting to take shape. There are researchers in the trenches right now, interpreting data and building better models to bring this industry up to speed. And once it gets going, it won’t stop.

Eventually, we’ll get to a point where prediction is commodified, and will be a standard part of every dashboard. It’s my hope that a [Social Value score](http://www.ninjametrics.com/social-value) will be right up with a K-Score or LTV in terms of measurement.

But if prediction is so valuable, you might ask, aren’t analytics companies all making the transition over to prediction?

Well, there’s a continuing struggle between power and understandability. To put it simply (as you might have picked up from the series so far), analytics are becoming increasingly complex. As this happens, we get more powerful and accurate results -- but those results often come at the expense of comprehension.

The new computer science models we’ve been discussing for predictions, for example, beat regular social science and business school approaches. Hands down. The proof is in the pudding: We’re getting over 90% accuracy levels with some models, which you would never be able to get with “traditional” approaches (e.g. regression, logit models).

There is a flipside, though. These models aren’t traditional, so we aren’t getting understandable results: The results come out in tables, if-then statements, rule sets and other long, unfathomable formats. Literally no human being can intuit it -- I’ve spent the better portion of my career figuring out data and the human nature of gamers and after 2 solid pages of if-then statements, I have no idea what it means.

So how can we place our faith in models that we don’t understand? Because, thanks to all of our research and testing, we know that it just “is.” However the sausage is made, it tastes good. It’s accurate and stands up to testing and repeated trials. It’s a black box that works.

To put it directly in the context of gaming, imagine you want to know if Player A is going to spend money next month. You have two models: one that will tell you if she will with an 85% accuracy rate, but you can’t know why, and another with a 40% accuracy rate and a full explanation. Which box do you want?

From a practical, actionable point of view, it’s actually an easy question to answer. I would choose the model with a high accuracy rate, every time. If you’re thoughtful and going to run interventions and test their effectiveness anyway, you’re going to develop a theory and get to the “why” eventually.

Don’t get me wrong: I’m a long-time modeler who likes to know the “why”. But if I can get 80%+ confidence levels without it, the price is often worth paying. I would prefer to have other parts of my dashboard focus on “why” issues, and I’ll focus my energies on making those parts accessible to the design and community teams. They understand the game context best, so they need tools they can grok. It’s the smarter, more actionable entrance to the rabbit hole.

As I said when I started the series, no one can truly predict the future. But by taking observations of patterns and predictions, and adding a heavy dose of data science, we’re getting pretty darn close.