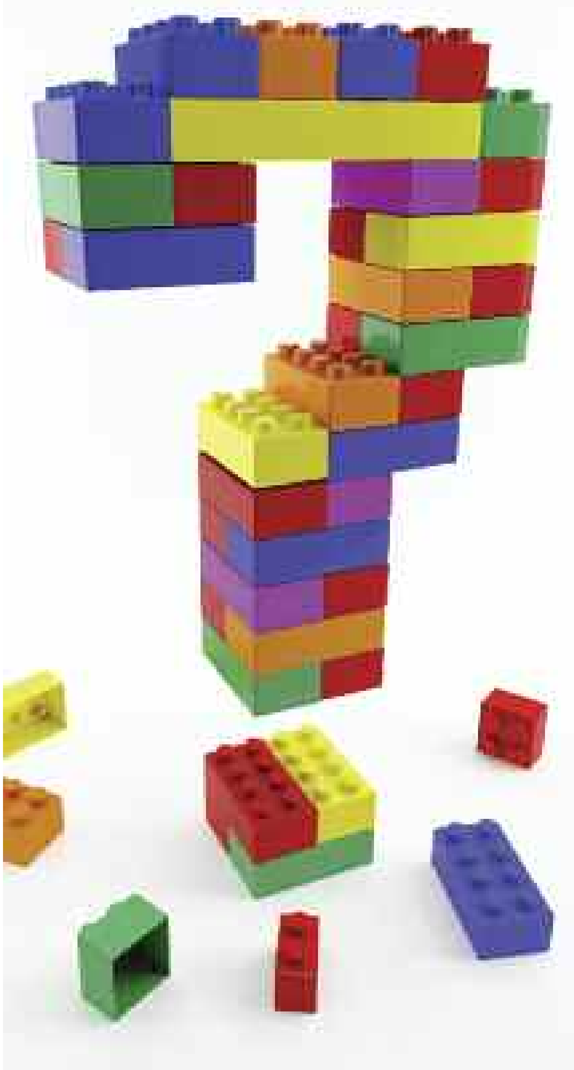
GAMING INTERACTIONS THAT DRIVE PROFITS, PT. I:

FUZZY SPATIAL ASSOCIATION AND GRAVITY MODELING

By Dr. A.K. Singh and Andrew Cardno

Authors' Note: In our previous series on market basket analysis (see Casino Enterprise Management *Vol. 6, Issue 12, and Vol. 7, Issues 1, 2, 5 and 6) we showed how individual rules can be constructed to determine relationships, including spatial relationships. This article extends this to the ocean of numbers created by the many interactions between gaming devices.*



This is the first in a new series of articles on gaming floor analysis; in these articles we will first discuss the analytical building blocks that can be used to decode the interactions between gaming devices on the casino floor. These building blocks include fuzzy spatial association rules, gravity modeling, visual representation, experimental design, mini casino management and social network analysis. This first article covers fuzzy spatial association rules and gravity modeling.

This becomes even more interesting when you add other non-spatial drivers to the data, for example, measuring the lift from a marketing campaign. The next step is to use the association rules to build models that can be used to drive yield to specific areas of the gaming floor at specific times of day. These rules offer a way of disentangling the vast dynamics of the gaming floor into a series of statistically associated patterns. This is then followed by a plan to use the association to rearrange the gaming floor and possibly push activity to areas of interest.

Fuzzy Spatial Association Rules

Spatial association rules (sARs) are association rules that involve a spatial variable[1] and, quite simply, result in a *lift* measurement. The most common spatial variable is distance. These rules establish the effective lift that one game has on another, taking into account the distance between the objects. Another way of thinking about this is to consider a market basket that is weighted by the effect of distance, so games that are spatially distant have less of an influence. This approach of using a weighted score results in a fuzzy measurement of the association effect.

Defining the Mathematics

In market basket analysis (MBA), spatial data requires additional processing. Consider the hypothesis that games on a casino floor that are placed close to an entrance get more business than those that are further away. The quality of an association rule produced by MBA is evaluated in terms of its support and confidence values. The support value of an association rule, in the case of binary variables (i.e., a yes or no value—did someone play a certain slot game or not?), is defined as the probability that someone will buy one product along with another (e.g., hotel room and table game). The confidence value is the conditional probability—if someone buys one product and they also buy the other product.[2]

Because the number of possible distances from a casino entrance is unlimited, calculating these values for MBA requires the use of a threshold and a cutoff point to obtain meaningful support and confidence values. This threshold problem also arises in other situations; the term "high coin-in" also requires a cutoff point. There is some literature available on the use of fuzzy logic describing this type of calculation,[3] where a continuous variable (e.g., coin-in) is mapped to a score in the range [0, 1]. Once distances have been converted to their corresponding scores, the support and confidence of spatial (locations) can easily be calculated as follows:

$$\text{Spatial support}(A \rightarrow C) = \frac{\sum_{x} \text{score}_A(x) \times \text{score}_C(x)}{n}$$

$$\text{Spatial confidence}(A \rightarrow C) = \frac{\sum_{x} \text{score}_A(x) \times \text{score}_C(x)}{\sum_{x} \text{score}_A(x)}$$

Table 1 shows a simulated example of spatial market basket analysis calculations in which the weekly coin-in (CI) values for 20 slot games on a casino floor, along with distances of the slot games from the closest entrance (D1) and exit (D2), are given. In this example, two spatial association rules are being compared:

sAR1 : If A1 then C (notation: A1→C)
sAR2 : If A2 then C (notation: A2 →C)

Where the antecedents of the two sARs (A1 and A2) are:

A1 = slot game is close to an entrance
A2 = slot game is close to an exit

The common consequent of the two rules is:

C = slot game has high weekly coin-in

Comparing Locations and Gravity Modeling

To further explore the effect of the fuzzy spatial association, let's consider two slot machines. The first has a high lift (H) from surrounding games, the second a low lift (L). It is likely that the machine with the high lift is played at the same time as its surrounding games, while the machine with the low lift is played at different times. This results in a reverse kind of dependence.

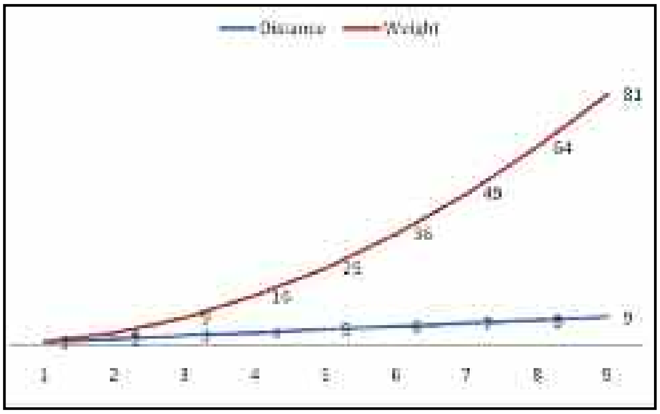
We can take this to another level by calculating the expected performance of each location. One effective way of calculating the games' performance is to build a weighted ranking of the performance of each location. In order to do this we have to find a way to generate the "average" performance of an area. This average performance is like the summation of the effect of all surrounding games, where games that are further away have less effect on the performance location ranking. Enter the inverse distance weighted[4] performance location, or gravity modeling, which, simply put, says

Table 1 – Spatial Support and Spatial Confidence of the Rules A1→C and A2→C

D1	CI	Sc(D1)	Sc(CI)	Sp(A1→C)	D2	Sc(D2)	Sp(A2→C)
6	75168	1	0.93	0.93	1	0.5	0.47
6	75722	1	1	1	1	0.5	0.5
6	73807	1	0.76	0.76	1	0.5	0.38
6	74755	1	0.88	0.88	1	0.5	0.44
7	72183	0.8	0.56	0.45	0	1	0.56
7	72620	0.8	0.61	0.49	0	1	0.61
7	72325	0.8	0.58	0.46	0	1	0.58
7	71671	0.8	0.49	0.4	0	1	0.49
7	75574	0.8	0.98	0.79	0	1	0.98
7	74075	0.8	0.79	0.64	0	1	0.79
7	72602	0.8	0.61	0.49	0	1	0.61
7	72348	0.8	0.58	0.46	0	1	0.58
6	73694	1	0.75	0.75	1	0.5	0.37
6	73575	1	0.73	0.73	1	0.5	0.37
6	74207	1	0.81	0.81	1	0.5	0.41
6	73868	1	0.77	0.77	1	0.5	0.38
11	68988	0	0.16	0	2	0	0
11	68462	0	0.09	0	2	0	0
11	69014	0	0.16	0	2	0	0
11	68411	0	0.09	0	2	0	0
Sum		14.4		10.81		12	8.52
sAR		**Confidence**					
(A1→C)	0.75						
(A2→C)	0.71						

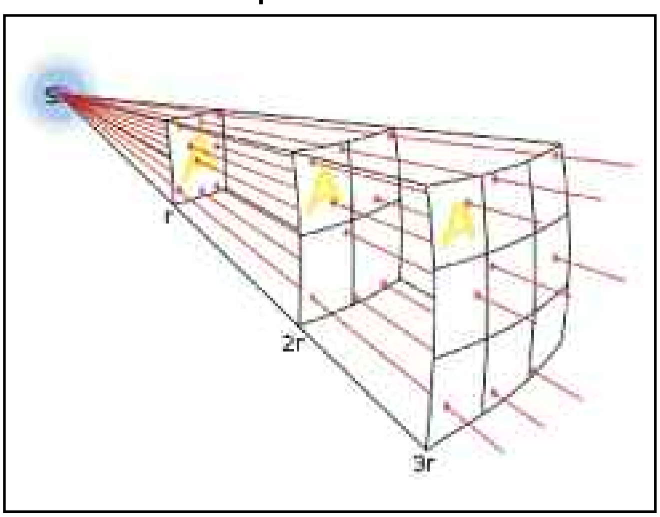
that if the distance is doubled, the weight increases by four times. Chart 1 shows the effect of this calculation.

Chart 1 – Gravity Modeling



The inverse-square law (see Chart 2) is generally applied when "some force, energy or other conserved quantity is radiated outward radially from a source. Since the surface area of a sphere (which is $4\pi r^2$) is proportional to the square of the radius, as the emitted radiation gets farther from the source, it must spread out over an area that is proportional to the square of the distance from the source."[5] When applied to the "emanation" of performance from a location, this law can be very effectively used to calculate the impact of one location on another.

Chart 2 – The Inverse-Square Law



The next step is to sum the rank times the location weight, where the sum of the weights is 1 (each weight is the percentage of the total weight). In a geographic sense, this calculation follows a model called Shepard's Method, which is the "simplest form of inverse distance weighted interpolation."[6] The equation used is as follows:

$$F(x,y) = \sum_{i=1}^{n} w_i f_i$$

where n is the number of scatter points in the set, f_i are the prescribed function values at the scatter points (e.g., the data set values), and w_i are the weight functions assigned to each scatter point.

The classical form of the weight function is:

$$w_i = \frac{h_i^{p}}{\sum_{j=1}^{n} h_j^{p}}$$

where p is an arbitrary positive value; in the case of gravity modeling, p=2.

Calculating this value for each machine on the gaming floor results in an average value for each location where it is the weighted sum of the effect of surrounding locations.

[Note: This calculation results in one calculation for the number of gaming devices squared. If you are analyzing a gaming floor with 2,000 games, for example, 4 million calculations will be needed to complete the interaction analysis.]

Combining the Gravity Model with Fuzzy sARs

The combination of these two tools gives a breakout of the games on the gaming floor into four interesting categories, as illustrated by Table 2 (average performance games are not considered interesting). This simple breakout of games by itself is probably not enough to be a basis for decisions, but it is a powerful first step in the data exploration process.

Table 2 – Post-Analysis Breakout of Games on the Casino Floor

	High Lift	Low Lift
Above Expected	Leaders	Loners
Below Expected	Laggards	Losers

Leaders

These games are outperforming the surrounding games and are lifting the surrounding games. These games may be the leaders in the area, and they are often star performers. Players may be drawn to these games and then flow on to play other games in the same area. Leaders are great candidates for further building the characteristics of a specific area of the gaming floor. They are also natural candidates for further market basket analysis, as they can be used as drawcards for other games that players who like the Leaders show a preference for.

Loners

These games are beacons of performance that is drawing play but not lifting the other games in the immediate area. Consider actions such as adding more of the same game or running a market basket analysis to find other products that the players who play this game like and are therefore likely to flow on to if they are placed close together. A comparison of the demographics of the players who like a Loner game to the players who like its neighbors will give insight into why the players in the area are not mixing.

For example, one real-world gaming floor optimization analysis showed that there was a salt-and-pepper arrangement of two games in a bank of slot machines (alternating themes). Both of these themes were giving similar theoretical win numbers, but further analysis showed that the players were not mixing products. Analysis into the demographics of the two games showed that the two groups of players had quite different profiles. The very profitable response to this insight was the creation of two areas of gaming, one for players who preferred the "salt" themes and one for players who preferred "pepper" themes. The result was stronger play for both games; the cost was that of moving an existing product and a simple communication to the two customer groups informing them where their favorite games were now located.

Laggards

The Laggards are games that have a positive lift effect on the games around them but that are played less than their surrounding games. The link these games have with their surroundings indicates we should treat them with care. One approach is to apply a "Why We Buy"[7] survey to gain some understanding of the way players are playing these games. Questions such as "Are we oversupplied with this product in this area?" or "Is the game priced correctly?" should be considered in the first round of the follow-up analyses.

Losers

These are the games that have a negative effect on the surrounding areas and are under performing. This kind of game is a great candidate for removal, but one should not jump to conclusions: Sometimes further analysis using a market basket approach can show clusters of these games that have isolated players.

If the players are isolated to a particular product, then it might be better to setup a separate playing area focused on this small group. We once found a group of keno machines that were low performers and had low (in fact, near zero) lift on the surrounding games. However, customer surveys showed that a core of players was extremely loyal to this product. Instead of removing the product, we turned one of the most isolated and underperforming areas into a special keno room. This, accompanied by a marketing program that invited those players to their new special area, was successful; moreover, the space that was made available became one of the highest performing on the floor.

Final Thoughts

Often the gaming floor is seen as a mass of bright lights and colors, but applying these techniques, and the techniques we will describe in the following installments of this series, will introduce you to an analytical framework that can change the way you see a gaming floor. In today's world of diminishing returns, adapting the floor to give customers what they want, where they want it is rapidly becoming a science. The challenge lies in that there are ever more products and increasing flexibility—and vastly increasing volumes of data collected from the gaming floor. As operators we can either exploit that data and learn to utilize that newfound flexibility, or we can choose to rely on luck.

1 P. Laube, M. de Berg, M. van Kreveld (2008). *Headway in Spatial Data Handling* (Eds. Anne Ruas, Christopher Gold), Lecture Notes in Geoinformation and Cartography Series, pp. 575–593.

2 Bart Lewin, A. K. Singh, Andrew Cardno. "Let's Talk Turkey: Applying Retail MarketBasket Analysis to Gaming." *Casino Enterprise Management*, December 2008.

3 L.A. Zadeh (1965). "Fuzzy sets," *Information Control* Vol. 8, pp. 338-353.

4 Edward H. Isaaks, R. Mohan Srivastava (1989). *Applied Geostatistics*, Oxford University Press.

5 http://en.wikipedia.org/wiki/Inverse-square_law

6 www.emsi.com/gmshelp/Interpolation/Interpolation_Schemes/Inverse_Distance_Weighted/Shepards_Method.htm

7 *Why We Buy*, Puco Underhill, 2000.

ONLINE EXTRA

Singh and Cardno open up the discussion on fuzzy spatial associations and gravity modeling with a new ACEME blog. Be sure to check out www.aceme.org/blogs to join in the discussion.

ANDREW CARDNO

Andrew Cardno has more than 16 years of experience in business analytics, ranging from modeling health care drive times to casino gaming floor analytics. He often presents on the future of analytics across the world and has spent the last seven years living in the United States and working with corporations around the world. He can be reached at andrewcardno@yahoo.com.

DR. A. K. SINGH

Dr. A. K. Singh has taught statistics, mathematics and operations research courses at New Mexico Tech, Socorro, N.M., and statistics and mathematics courses at University of Nevada, Las Vegas. He has more than 75 publications in theoretical and applied statistics and can be reached at aksingh@unlv.nevada.edu.