Finding Ideal Menu Items Assortments: An Empirical Application of Market Basket Analysis

Article *in* Cornell Hospitality Quarterly · November 2010

DOI: 10.1177/1938965510378254

3 authors:

Ping-Ho Ting
National Chi Nan University

Steve Pan
Singapore Institute of Technology (SIT)

Shuo-Shiung Chou
Tunghai University

Finding Ideal Menu Items Assortments: An Empirical Application of Market Basket Analysis

Ping-Ho Ting, Steve Pan and Shuo-Shiung Chou

Cornell Hospitality Quarterly 2010 51: 492 originally published online 3 August 2010
DOI: 10.1177/1938965510378254

Finding Ideal Menu Items Assortments: An Empirical Application of Market Basket Analysis

Cornell Hospitality Quarterly
51(4) 492–501

DOI: 10.1177/1938965510378254
http://cqx.sagepub.com
SAGE

By Ping-Ho Ting, Steve Pan, and Shuo-Shiung Chou

Abstract

This article applies a simplified version of market basket analysis (MBA) principles to explore menu items assortments, which are defined as the sets of most frequently ordered menu item pairs of an entrée and each of five side dishes in a prix fixe restaurant. Using the PivotTable in Excel, the authors demonstrate the analysis of 3,727 transactions for meal combinations of 24 entrées and 49 side dishes, resulting in twenty-four association rules, which suggested that guests ordering a given entrée would most likely then choose a particular side dish to go with it. Applying these association rules, guests responded favorably to servers' menu suggestions in roughly two out of three cases when the guest was "undecided" or "without preference." This article's chief purpose is to introduce the application of Excel that would otherwise require tedious computation if a restaurateur were to attempt it.

Keywords

market basket analysis (MBA); prix fixe menu; Excel PivotTable

Market basket analysis (MBA) is one of the most commonly used data analysis techniques for marketing (Marakas 2003). It derived its name from analyzing the orders assembled in grocery stores, when customers put purchases into their market baskets, also known as grocery carts and shopping trolleys. The key to this analysis is the purported connections between item choices. The analysis posits that if a customer purchases one particular item, that customer is also likely to predictably purchase a second particular item. The two items may not be directly related, so by identifying the latent relationships between items purchased, shop owners can use this information to arrange store layout so that items frequently sold together can be placed in the same retail area. In the restaurant operations, MBA has been used extensively in fast-food chains for cross- and up-selling food and beverage products. Another familiar application of MBA is in online bookstores, where customers will be presented with "associated products" when they browse certain items.

Because we have seen little application of MBA in the tourism and hospitality literature (an exception is Tang, Chen, and Hu 2008), we simplified the application of MBA to identify the association (affinity) rules of two dozen dinner meals on the prix fixe menu of a Japanese-style chain restaurant in central Taiwan. The simplification involves inputting data so that it can be analyzed with Excel's PivotTable. As often occurs in fixed-price menus, the restaurant permitted guests to choose from a limited set of side orders, which allows the modified MBA. We set out to explore the strongest association rules between entrées and appetizers, soups, starch side dishes, desserts, and drinks. Once identified, we then tested these "most frequent" associations, with restaurant employees proactively suggesting these associations to diners.

We believe that our demonstration of MBA principles with the pivot table provides an easy-to-follow and cost-efficient application to identify what might be called ideal menu item combinations for this restaurant. In this case, the definition of "ideal" is the pairs of entrées and side dishes that attract the most orders.

The article is organized as follows. After briefly reviewing the MBA literature, we demonstrate the application of PivotTable to calculate two measures (*support* and *confidence*) commonly used for selecting MBA association rules. We then show the analysis and validation results, and conclude with recommendations, limitations, and possibilities for future research.

Literature Review

Also known as association analysis or association rule mining, MBA was introduced by Agrawal, Imielinski, and Swami (1993). MBA has been applied in such areas as cross-selling, decision support, customer behavior analysis, and customer relationship management (Tang, Chen, and Hu 2008; Haughton et al. 2003). Based on data mining, it is aimed at discovering customer purchase patterns by determining associations from point-of-sale (POS) transaction data (Chen et al. 2005; Berry and Linoff 2004). The item association information thus developed can be applied in such marketing activities as catalog design, product placement, promotion, and cross-selling (Auslender 2008; Berry and Linoff 2004). Perhaps the most famous example of an association rule is the association between beer and diapers (Tsur et al. 1998; Berry and Linoff 2004), in which families commonly purchase beer (presumably for dads) and baby diapers before the weekend started.

Items ordered in a fixed-price restaurant might also have associations. If so, MBA would offer insights into what side dishes are ordered with which entrées—and hence are candidates for promotion or server recommendations. MBA data comprise customers, orders (purchases, baskets, or item sets), and items (Berry and Linoff 2004). An order is a fundamental datum representing a single purchase by a customer. The order contains total amount of the purchase, type of payment, cashier number, and store number. Most important, the items, or the contents of order, allow identification of association rules. Customer information is useful for finding association rules between customers and certain products to identify the market segment.

To develop association rules, one examines the frequency with which a customer buys item B if that customer has also purchased item A. In that case, item A is the antecedent (condition), while item B is the consequent (result). MBA provides three measures of the degree of uncertainty associated with a given rule. These are support, confidence, and lift (or improvement). Support is expressed as a percentage, representing the probability that a randomly selected set of transactions from a database include items A and B. Expressed mathematically, the formula is $P(\mathrm{A} \cap \mathrm{B})$. To increase efficiency of calculation, MBA prunes support below a certain threshold, usually at 5 percent (Tan, Kumar, and Srivastava 2002; Auslender 2008). Confidence, also expressed as a percentage, is the probability that a randomly selected set of transactions will include B given that they include A. The mathematical formula is $P(\mathrm{B}|\mathrm{A})$, that is, $P(\mathrm{A} \cap \mathrm{B})/P(\mathrm{A})$. The last quantity, lift, measures the improvement in probability of B occurring in a transaction given that the transaction includes A. The mathematical formula is $P(\mathrm{A} \cap \mathrm{B})/P(\mathrm{A})P(\mathrm{B})$. That is, lift is the confidence of the combination of A and B divided by the support of B. When lift is greater than 1, item A and item B have a positive association; otherwise, they have no significant purchasing relationship (Auslender 2008).

Although we do not address this matter, this is known as the Apriori algorithm (Agrawal and Srikant 1994), which is the best-known algorithm for mining association rules from transactional databases (Chen et al. 2005). In a multistore setting, however, the Apriori algorithm is limited by its implicit assumption that purchasing patterns remain static over time and across stores. Consequently, other algorithms have been developed (see Tang, Chen, and Hu 2008; Chen et al. 2005). Rather than address the algorithm issue, this article seeks to simplify the application of traditional methods.

The ordering pattern in a prix fixe restaurant sets up an antecedent and consequent relationship (entrée followed by sides), but the association is between main course and side dish. This association is different from traditional MBA, which assumes a free association of all items. Consequently, we can simplify traditional MBA by applying the PivotTable tool in Excel.

In addition to knowledge that permits cross- and up-selling, MBA provides a comprehensive consideration of inventory, simple calculations, and usually clear results that can be quickly implemented. The drawbacks of MBA are the following: (1) it requires a large number of transactions to have meaningful data, (2) all the products need to occur with a similar frequency, and (3) the results might be caused by previous promotional campaigns (Marakas 2003).

In analyzing MBA association rules, one must discern between the following three types of rules (Pardoe 2008; Berry and Linoff 2004; Marakas 2003):

1. *actionable rules*, which provide understandable and high-quality information and suggest effective promotions (e.g., the unlikely combination of beer and diapers);
2. *trivial rules*, which amount to common sense or may reflect past marketing or product bundling (e.g., if paint, then brush); and
3. *inexplicable rules*, which seem coincidental, have no explanation, and do not suggest a course of action.

As mentioned, we have found few hospitality and tourism applications of MBA. Only Wong et al. (2006) conducted MBA to identify preferred cross-selling destination for Taiwanese outbound travelers. We did not find any applications of MBA in a restaurant.

Methodology

Difference between MBA and This Study

Although we have been discussing classic MBA, our study differs in that MBA is a co-occurrence of any products, while our study involves the pair-occurrence between entrées and side dishes that we mentioned above. The chief reason for this is that few guests would order two entrées or only side dishes, nullifying the co-occurrence concept and suggesting a pair-occurrence concept of subordinating relationships between side dishes and entrées. To explain the traditional

Exhibit 1. Co-Occurrence of Products

	Rice	Beef	Bread	Potato Chips	Milk
Rice	2	1	2	0	0
Beef	1	3	1	1	1
Bread	2	1	3	0	1
Potato chips	0	1	0	1	0
Milk	0	1	1	0	2

MBA rules, a list of five simple grocery transactions and the resulting co-occurrences is given below. No actual MBA would be based on so few transactions.

Transaction 1: Rice, beef, bread
Transaction 2: Beef, potato chips
Transaction 3: Rice, bread
Transaction 4: Beef, milk
Transaction 5: Bread, milk

Two of the five transactions include both rice and bread, giving a 40 percent support measure for the association rule "rice implies bread." The confidence in the rule "rice implies bread" is 100 percent, as two out of two transactions that include rice also contain bread. We also see that rice and bread are more likely to be purchased together than any other two items, and rice is never purchased with potato chips or milk. This analysis suggests placing rice and bread close to each other for cross-selling. Sophisticated calculations using generalized rule induction (GRI) are required to produce co-occurrence association rules (see Exhibit 1).

In contrast, five orders that demonstrate pair-occurrence calculations are given below. Items in bold are entrées.

Order 1: **Chicken fish**, corn soup, bread, red tea, pudding
Order 2: **Spicy chicken**, salad, bread, ice tea, mango cheese
Order 3: **Eel chicken**, onion soup, bread, coffee, mango cheese
Order 4: **Spicy chicken**, onion soup, bread, coffee, pudding
Order 5: **Miso salmon**, corn soup, rice, orange juice, vanilla ice cream

As shown in Exhibit 2, the pivot table consolidates individual items into categories, based on the pair-occurrence of entrées and side dishes. "Support" measures for corn soup with chicken fish and corn soup with miso salmon are both 20 percent (that is, one out of five orders). The resulting association rule "chicken fish implies corn soup" has a confidence of 100 percent (one out of one). The support rule can be used as a reference in purchasing, while the confidence rule can be a basis for recommendations by servers. This article focuses on the confidence of association rules that should allow servers to provide menu recommendations. We will use four pivot tables to produce pair-occurrence association rules.

Ideal Menu Item Association

Since all side dish orders follow the selection of an entrée in a prix fixe restaurant, the ideal association of menu items is determined by the confidence value of pairs of entrées and side dishes. We consider only sets of pairs and not individual menu items. Logically, when customers order meals in a prix fixe restaurant, they associate individual side dishes with an entrée, and they do not order just side dishes. The confidence value gives the probability that the guest will order a particular side when he or she orders a certain entrée. The combination of entrée and side dish with the greatest confidence value (among all the combinations of that entrée and any side dish) is considered the ideal association of that entrée and a side dish. We limit our calculation to the ideal pair association in part because if we allow all variables to change at the same time, we cannot use the pivot table. Instead we would need more sophisticated software.

Since the purpose of this article is to demonstrate this readily available and affordable application of Excel, we limit our analysis to entrées and sides. If we did consider all changes at the same time, the vast number of combinations would cause the final ideal menu associations to involve a small percentage of that particular entrée's sales. Additionally, as we indicated above, the situation in a fixed-price restaurant, where item choices have certain limitations, is different from that in a supermarket, with its relatively free choice. Finally, as a practical matter, it will be easier to memorize the ideal pair associations between side dishes and entrées. Based on these reasons, we believe it is justifiable to adopt this simplified association rule calculations in this study.

The procedure continues until all combinations of entrées and side dishes are considered. Overall, we identify twenty-four ideal assortments, each involving one entrée, one appetizer or soup, a starch side dish, one drink, and one dessert. Here are the PivotTable operators that we apply:

$$\text{Ideal entrée and appetizer/ Soup association (IEAS)} = \text{Max}_i[\mathit{Confidence}(\mathit{Entree}_i \rightarrow \mathit{Appetizer\ or\ Soup}_j)],\quad i = 1, 2, 3, \ldots 24; j = 1, 2, 3, \ldots 7.$$

$$\text{Ideal entrée and starch side dish association (IESSD)} = \text{Max}_i[\text{Confidence}(\mathit{Entree}_i \rightarrow \mathit{Starch\ Side\ Dish}_j)],\quad i = 1, 2, 3, \ldots 24; j = 1, 2.$$

Exhibit 2. Pair-Occurrence of Entrées and Side Dishes

Entrée	Corn Soup	Salad	Onion Soup	Bread	Rice	Red Tea	Ice Tea	Coffee	Orange Juice	Pudding	Mango Cheese	Vanilla Ice Cream
Chicken fish	1	0	0	1	0	1	0	0	0	1	0	0
Spicy chicken	0	1	1	2	0	0	1	1	0	1	1	0
Eel chicken	0	0	1	1	0	0	0	1	0	0	1	0
Miso salmon	1	0	0	0	1	0	0	0	1	0	0	1
	Pivot Table 1—Entrée and Appetizer or Soup			Pivot Table 2 -Entrée and Starch Side Dish		Pivot Table 3—Entrée and Drinks				Pivot Table 4—Entrée and Dessert		

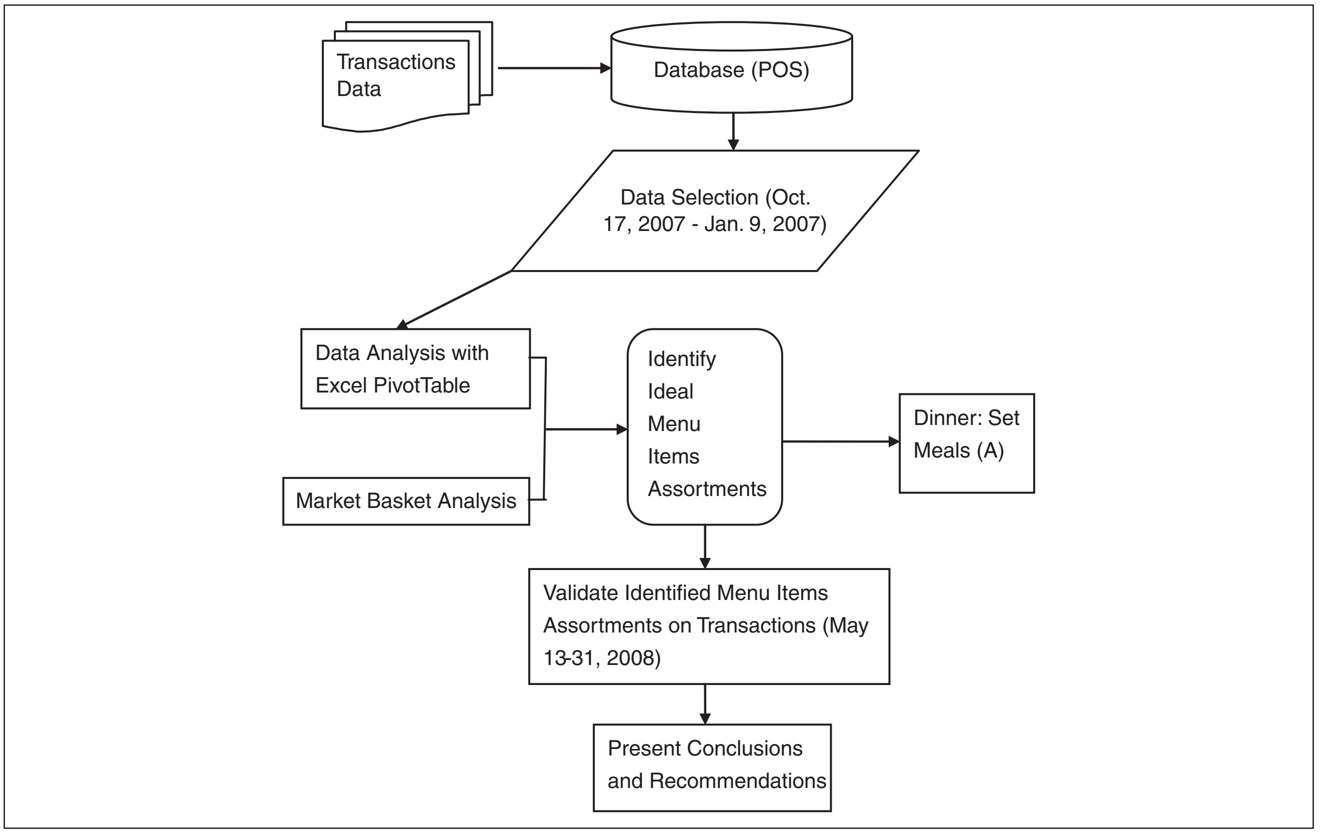

Exhibit 3. Research Framework

$$\text{Ideal entrée and drink association (IED)} = \text{Max}_i[\textit{Confidence}(\textit{Entree}_i \rightarrow \textit{Drink}_j)],$$
$$i = 1, 2, 3, \ldots 24; j = 1, 2, 3, \ldots 23.$$

$$\text{Ideal entrée and dessert association (IEDE)} = \text{Max}_i[\textit{Confidence}(\textit{Entree}_i \rightarrow \textit{Dessert}_j)],$$
$$i = 1, 2, 3, \ldots 24; j = 1, 2, 3, \ldots 17.$$

Ideal menu items assortments are [Entrée, IEAS, IESSD, IED, IEDE] based on the assumption that ideal menu items assortment is the combination of individual highest ordered pairs.

The research comprises the following five steps: (1) retrieve eighty-five days of restaurant transaction data, from October 17, 2007, to January 9, 2008; (2) analyze data with Excel's PivotTables and calculate support and confidence for each item set; (3) identify ideal menu item assortments; (4) validate the findings on real-world transactions; and (5) present conclusion and recommendations. Exhibit 3 presents the research framework.

Data Collection

The Japanese-style restaurant we studied is located in Taichung, central Taiwan, and has 144 seats. The restaurateur agreed to provide daily business data for our analysis, and the staff was willing to take part in recommending the identified menu-item

	A	B	C	D	E	F	G	H	I	J
1	Year	Month	Day	Meal Period	Holiday or Weekend	Entrée	Appetizer/ Soup	Starch Side Dish	Drink	Dessert
2	2007	Oct	17	D	N	Chicken Rice	Mushroom	B	GREEN	Sundae L
3	2007	Oct	17	D	N	Rice Hamburger	Clam	B	Cranberry	Sundae T
4	2007	Oct	17	D	N	Shrimp Hamburger	Beef	B	Iced Coffee	Pudding
5	2007	Oct	17	D	N	Rice Hamburger	Onion	R	OJ	Tea Ice Cream
6	2007	Oct	17	D	N	Rice Hamburger	Salad	B	OJ	Mango
7	2007	Oct	17	D	N	Shrimp Hamburger	Clam	B	GJ	Vanilla
8	2007	Oct	17	D	N	Shrimp Steak	Onion	B	GJ	Sundae M
9	2007	Oct	17	D	N	Filet Steak	Beef	B	TJ	Sundae L
10	2007	Oct	18	D	N	Broadway Sizzling	Onion	B	IT	Vanilla

Exhibit 4. Set Meal A Sales Data

associations to diners. Although the restaurant provided breakfast, lunch, high tea, and dinner, we present the analysis of one of the set dinners. The restaurant's main dishes include such Western-style food as steak, pork chop, chicken fillet, and sea food, as well as Japanese-style set meals.

At dinner, guests can choose from set meal A or meal B. We present the results for set A because it offers wider choices of side dishes than does meal B. For set meal A, customers select from among twenty-four entrées, seven appetizers or soups, two starch side dishes, twenty-three drinks, and seventeen desserts. Prices for set meal A range from NT$220 to NT$520 (US$7.30 to US$17.00).

First, using transaction data from the POS system, we transformed the data into a user profile, which is defined as an item set, <customer-id, entrée, appetizer or soup, starch side dish, drink, dessert>. The number of transactions for meal A during this period is 3,727, and Exhibit 4 displays the first few of nearly 4,000 rows of data.

Data Analysis

For each order, we calculated support and confidence for each entrée and its associated side dishes in pairs. For example, out of 3,727 transactions, we have 123 transactions ordering entrée "club sandwich" and 62 transactions ordering both club sandwich and ice tea, then *Support*(Club Sandwich → Ice Tea) = *P*(Club Sandwich∩Ice Tea) = 62/3,727 = 0.017, while *Confidence*(Club Sandwich → Ice Tea) = *P*(Ice Tea | Club Sandwich) = 62/123 = 0.50). Lift was not used here to determine the effectiveness of association, but we will show the calculations. Lift tends to vary inversely with the numbers (support) of individual side dishes being ordered. These numbers were not evenly distributed among side dishes.

As described above, we used Excel's PivotTable to analyze the data and to calculate support and confidence. As indicated in Exhibit 2, this tool arranges and summarizes information from selected fields of a data source (Dodge and Stinson 2007). To use this tool, click Excel's Insert tab and click PivotTable in the Tables group. With a pivot table, one simply drops the data into one of the four areas, as shown in Exhibit 5. For this study, we first drag field "entrée" and "∑ Values" and drop them to area "row labels," drop individual side dishes (appetizer or soup, starch side dish, drink, and dessert) to "column labels," and drop individual side dish in question four times to "∑ Values." For example, if we want to create a pivot table for entrées and drinks, we drop field "entrée" to "row labels," drop field "drink" to "column labels," and drop "drink" four times to area "∑ Values" (see Exhibit 5). The first "drink" in the area "∑ Values" is "Count/Drink," which counts the frequency of both entrée and individual drink appear in the data base (3,727 transactions). The name of the second "drink" in the same area needs to be changed by right-clicking on it and selecting "Value Field Settings" to change the "Custom Name" into "Support." By default, "Count" will be selected in "Summarized by," and in the "Show Value as" field select "% of total." This will calculate support for each association. For the third "drink," repeat the same procedures to change the name to "Confidence" and select "% of row" in "Show Value as" field (see Exhibits 6 and 7). The fourth "drink" is changed to the name "Lift," and "Index" needs to be selected in the "Show Value as" field. "Index" uses a formula (Dodge and Stinson 2007) that

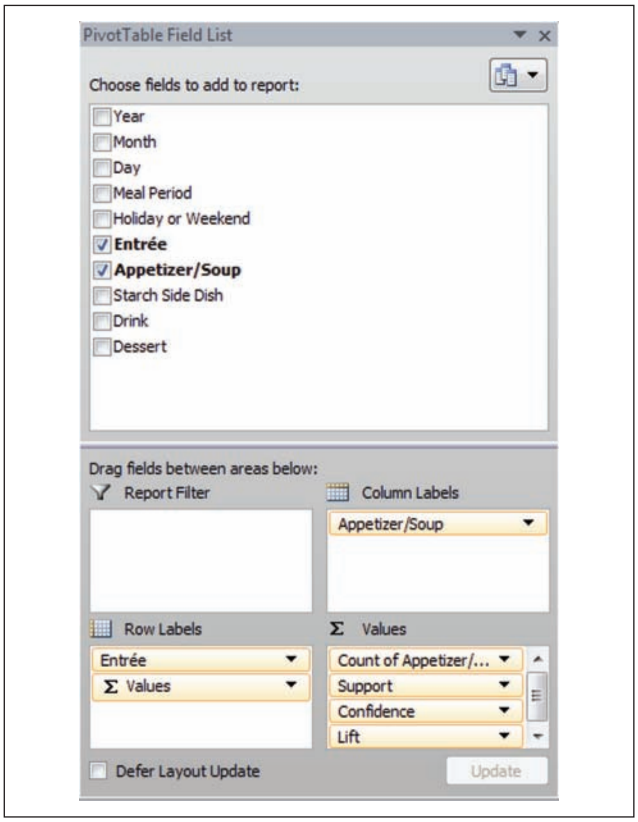

Exhibit 5. The Four Areas of a Pivot Table

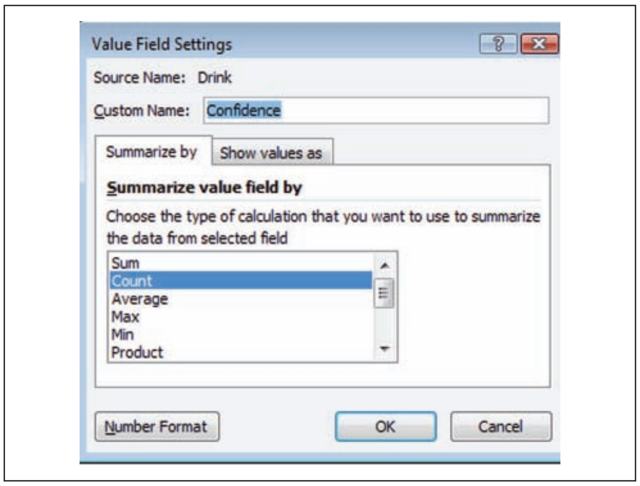

Exhibit 6. Change "Custom Name"

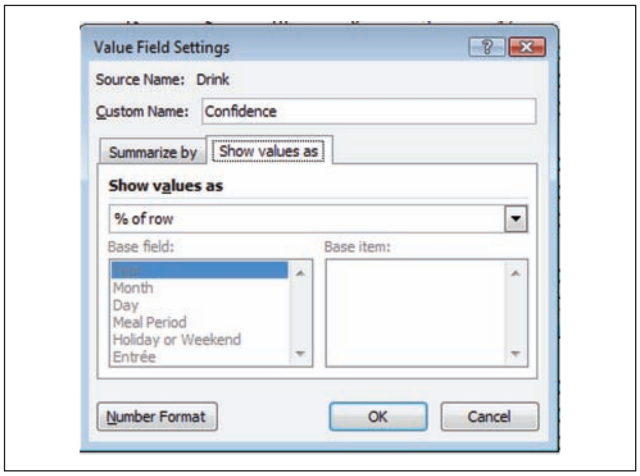

Exhibit 7. Change "Summarized By" and "Show Value As"

is the same as that in calculating the "Lift" in MBA. Partial calculation results are displayed in Exhibit 8.

Validation of Assortments

To validate our findings, we tested the association rules on real-life transactions, with the restaurant's cooperation. We tested a total of 145 transactions involving set meal A selected randomly during the period of May 13 to 31, 2008. When a customer ordered a certain entrée, restaurant employees would recommend the "ideal" accompaniments, as indicated by the pivot table analysis. For each suggested side dish recommendation that the diner accepted (that is, appetizer or soup, starch side dish, drink, or dessert), we added 25 percent to the recommendation rate. We further categorized these data into three groups according to customers' evident preferences: (1) customers with preferences (clearly knew what they wanted), (2) undecided customers (who were evaluating competing choices), and (3) customers without preferences (who had no clue as to what to order).

To empirically validate our findings, we would have to conduct an experiment in which we divide undecided customers into three groups. Each group would have a different "suggestion condition." One group would receive essentially random suggestions, one group would receive the ideal suggestions, and one group would receive no suggestions. Unfortunately, a study like this is impossible to arrange. Nevertheless, we did ask servers to suggest sides for those who seemed undecided, and we believe that the results of this validation process (described later) offer a certain degree of credibility to our findings. Moreover, it makes sense to offer customers a well-founded recommendation based on in-depth analysis.

Analysis Results: Market Basket Analysis

Exhibit 9 shows the four pivot table reports generated by our analytical procedure, resulting in twenty-four sets of ideal menu items assortments. The first column shows entrée support levels (the percentage of total orders). Columns 2 through 5 display the most popular side dish for that entrée, with its confidence level. (Again, this is the quantity of the particular side dish ordered divided by the number of the particular entrées ordered.)

Row Labels	Column Labels Seasonal Soup	Beef	Corn
Chicken Fish			
Count of Appetizer/Soup	29	22	58
Support	0.78%	0.59%	1.56%
Confidence	10.86%	8.24%	21.72%
Lift	1.166585716	0.919442015	0.751727472
Spicy Chicken			
Count of Appetizer/Soup	16	29	53
Support	0.43%	0.78%	1.42%
Confidence	6.53%	11.84%	21.63%
Lift	0.70142916	1.320823659	0.748606295
Eel Chicken			

Exhibit 8. Pivot Table for Entrees and Appetizer/Soup
Note: The names of all the dishes in this study are either a rough translation of the Chinese names or codes used in the daily operations of the restaurant in question.

Ten of the twenty-four entrees had extremely weak sales. If we apply menu engineering classification guidelines (Kasavana and Smith 1990; LeBruto, Ashley, and Quain 1997), the unpopular items have support below 3 percent: $(1/24) \times 0.7 = 2.92$ percent. The top three entrées sold were vanilla chicken (13.93 percent), rice hamburger (10.54 percent), and shrimp hamburger (9.55 percent), accounting for more than one-third (34.02 percent) of all sales of set meal A (see Exhibit 10).

Despite the relatively wide variety of items available at this restaurant (a total of 131,376 choices), customers who ordered meal A focused narrowly on sides. More than two-thirds of diners eating meal A (70.92 percent) selected corn, onion, or clam soup. Bread was far more popular than rice; and diners were most likely to order one of three drinks (a total of twenty-three), namely, iced tea, hot coffee, or orange juice. Once they see the ordering patterns, restaurant operators can examine why a particular item sells better than others on the menu. When we asked restaurant employees about the bread-rice discrepancy, they suggested that the bread had a strong reputation that made it popular among the diners. With regard to the beverages, the restaurant has a free-refill policy for hot coffee, while the iced tea offers the largest portion size among all drinks. Additionally, it is fair to say that mango cheese (33.24 percent) is customers' favorite dessert because one does not have to pay extra for it.

Our data partially support the contention by Myung, McCool, and Feinstein (2008) that diners in a prix fixe restaurant prefer to choose the most expensive menu items because they attach greater importance to value for price. An independent sample *T*-test shows that the popular menu-item associations (defined as those bundle choices whose sales volume exceed 2.92 percent) have a mean price of NT$392.86 and a mean quantity sold of 249.07, while the mean price for the unpopular ones is NT$352.50 and the average quantity is 28.62. The mean difference for price ($p = .233$) is not statistically significant, but the difference for quantity is significant ($p = .000$), both at the .05 significance level. It is fair to say that popular menu items with a higher price were significantly higher than their counterparts in terms of sales volume. We can also argue that the small price difference (NT$40, roughly US$1.20) creates an impression that by paying a little more, diners would receive a higher value, that is, a higher marginal utility.

Empirical Validation

The validation approach we used was to have servers suggest sides for 145 guests in one meal period. Of the 145 diners in this test, based on restaurant employees' judgment, 61 (42.06 percent) were undecided and 44 (30.34 percent) had no preference about their sides. (The other 40 clearly knew their preferences.) As shown in Exhibit 11, the employees' suggestions largely fell on deaf ears for those with definite preferences. On the other hand, compared to those with definite preferences, undecided customers and those without preferences were nearly three times more likely to accept the staff's recommendations.

Apparently, the successful recommendation rate is the highest for diners "without preference," followed by the "undecided" group. This finding suggests that servers need to pay close attention to diners' "preference status" and proactively recommend the "ideal" assortments. For restaurateurs, they need to pay attention to the composition of diners

Exhibit 9. Ideal Menu Items Associations

Entrée: Support (%)	Appetizer/Soup: Confidence (%)	Starch: Confidence (%)	Drink: Confidence (%)	Dessert: Confidence (%)
Vanilla chicken	Corn soup	Bread	Ice tea	Mango cheese
13.93	31.98	84.01	21.00	33.53
Rice hamburger	Corn or onion soup	Bread	Ice tea	Mango cheese
10.54	29.77	95.67	21.37	31.81
Shrimp hamburger	Corn soup	Bread	Ice tea	Mango cheese
9.55	27.81	76.69	25.00	30.90
Spice chicken	Corn soup	Bread	Ice tea	Mango cheese
7.46	32.37	80.58	17.27	27.70
Steak scallop	Clam soup	Bread	Ice tea	Mango cheese
7.32	24.54	87.18	19.41	38.10
Chicken fish	Onion soup	Bread	Hot coffee	Mango cheese
7.16	27.22	86.52	17.98	34.46
Spicy chicken	Onion soup	Bread	Hot coffee	Mango cheese
6.57	31.02	98.78	18.78	34.69
Shrimp steak	Onion soup	Bread	Orange juice	Mango cheese
6.47	31.54	87.55	20.75	37.76
Roast spaghetti	Corn soup	Bread	Orange juice	Mango cheese
5.55	38.16	96.62	25.60	32.37
Broadway sizzling	Corn soup	Bread	Orange juice	Mango cheese or pudding
5.39	25.87	79.10	21.89	29.35
Filet steak	Onion soup	Bread	Ice tea	Mango cheese
3.78	29.08	84.40	29.08	35.46
Sweet rice	Onion soup	Bread	Hot coffee	Mango cheese
3.33	27.42	97.58	19.35	42.74
Shrimp rice	Corn soup	Bread	Orange juice	Mango cheese
3.30	41.46	100.00	17.89	29.27
Spice pork chop	Corn soup	Bread	Ice tea	Mango cheese
3.19	38.66	82.35	36.13	30.25
Scallop hamburger	Corn soup	Bread	Ice tea	Mango cheese
2.52	36.17	69.15	18.09	32.98
Seafood pasta	Corn soup	Bread	Ice tea	Pudding
2.04	31.58	96.05	18.42	35.53
Club sandwich	Clam soup	Bread	Hot coffee	Mango cheese
0.56	33.33	100.00	23.81	47.62
Pancake	Corn soup	Bread	Hot tea	Mango cheese
0.32	50.00	100.00	33.33	41.67
Eel chicken	Onion soup	Bread	Orange juice	Pudding
0.21	75.00	100.00	50.00	75.00
Steak royal	Corn soup	Bread	Orange juice	Mango cheese
0.21	50.00	87.50	50.00	37.5
Pork chop royal	Onion soup	Bread	Hot coffee	Mango cheese
0.19	42.86	100.00	42.86	71.43
Spinach rice	Corn soup or Caesar salad	Bread	Hot coffee, grapefruit juice, hot milk tea, hot tea, orange juice, rice tea	Mango cheese
0.16	33.33	100.00	16.67	50.00
Mushroom noodle	Seasonal soup	Bread	Hot latte	Chestnut sundae
0.13	60.00	100.00	40.00	40.00
Miso salmon	Seasonal, onion, or clam soup	Bread	Hot coffee, hot tea or peach tea	Mango cheese
0.08	33.33	100.00	33.33	66.67

Exhibit 10. Percentage of Top Three Sold Menu Items

Entrée or Side Dish (Number of Choices)	Top Three Sold Items	Percentage of Total Orders
Entrée (24)	Vanilla chicken, rice hamburger, or shrimp hamburger	34.02
Appetizer or soup (7)	Corn, onion, or clam soup	70.92
Starch side dish* (2)	Bread	87.42
Drink (23)	Ice tea, hot coffee, or orange juice	49.69
Dessert (17)	Mango cheese, pudding, or vanilla ice cream	75.56

a. As there are only two choices in this item, only one is selected.

Exhibit 11. Frequencies of Recommendation Successful Rate

Successful Rate	With Preference	Undecided	Without Preference	Total
0%	11	0	0	11
25%	22	5	2	29
50%	5	29	16	50
75%	2	16	13	31
100%	0	11	13	24
Total	40	61	44	145
Average	23.75%	63.52%	71.02%	

in terms of their preferences and better understand the sales mix of entrées and sides. This can help them better control the purchasing of food and beverage inventories. The overall rate of successful suggestions for all three groups is close to 56 percent and is derived by multiplying their individual successful recommendation rate by the percentage of their segments (27.59 percent × 23.75 percent + 42.07 percent × 63.52 percent + 71.02 percent × 30.34 percent = 55.81 percent). On the other hand, the overall "unsuccessful" rate, barely more than 44 percent, indicates the difficulty in swaying diners' habitual tastes or preferences. This finding also supports the argument that customers tend to choose familiar menu items (Myung, McCool, and Feinstein 2008).

Conclusions and Implications

This article has demonstrated the application of the PivotTable tool in Excel to determine the "ideal" menu items assortments (bundle choices) in a Japanese-style prix fixe restaurant. This modified MBA helps restaurateurs better understand customers' preferences. In principle, this knowledge would allow employees to make menu recommendations backed by analysis and perhaps even shorten guests' decision and ordering time. However, we could not demonstrate those outcomes in this limited study. The reason that one can use the pivot table analysis, which differs from traditional MBA, is that in the prix fixe restaurant the products have a subordinated relationship, starting with the entrée, unlike typical MBA, which deals with free associations of product categories.

We found that three of the twenty-four entrées accounted for one-third of all entrées sold to diners who ordered set meal A, and ten out of the twenty-four entrées can be considered unpopular, in menu analysis terms. This finding is similar to that of Myung, McCool, and Feinstein (2008), who suggested that variety is not an important factor for diners in a prix fixe restaurant.

Although our chief purpose here is to demonstrate the use of PivotTable, we offer the following five recommendations based on our analysis.

1. Employee training. Once ideal menu combinations are identified, restaurant employees need to be informed of them. Additional confirmation of the analysis can be drawn from front staff's opinions.
2. Focusing suggestions on undecided customers and those without preference. Our small test recorded an average 67 percent success rate for suggesting "ideal" assortments to these "persuadable" customers.
3. Focusing on ideal menu items. We again note the popularity of a relatively short list of menu items.
4. Testing price demand elasticity. The mean price for popular items is about NT$40 higher than that for the unpopular ones, although this difference is not statistically significant. It is possible that the restaurateur could test price elasticity (and improve revenues) with judicious price increases for the popular entrées, to see whether demand continues strong.
5. Repeating the analysis when the menu changes.

The contribution of this article lies more in its methodology than in its findings. It applies an easy and straightforward concept and used a common spreadsheet program to identify the ideal menu items assortments. In the future, MBA may be applied to tourists who will be visiting different destinations and purchasing different products and services in destinations. The association rules found can be used to cross-promote tourism destinations and tourism-oriented products (goods and services).

The chief limitation of this study is that it focuses on a local chain restaurant in Taiwan. Although our analysis included a large number of cases, the findings cannot be generalized.

Future research can extend this analysis to different restaurants, different chains, or different cultures; or the study could involve different servers in one restaurant to find out whether ordering patterns and bundle choices exist only in connection with certain staff members. Another research possibility is the linkage between ideal menu items and guest characteristics. Also, an association rules study with information on menu item costs and combined with menu engineering will provide more managerial implications.

Disclosures

The author(s) declared no conflicts of interest with respect to the authorship and/or publication of this article.

Funding

The author(s) received no financial support for the research and/or authorship of this article.

References

Agrawal, R., T. Imielinski, and A. Swami. 1993. Mining association rules between sets of items in large databases. Paper read at ACM SIGMOD International Conference on Management of Data (SIGNOD '93), Washington DC.

Agrawal, R., and R. Srikant. 1994. Fast algorithms for mining association rules. Paper read at 20th VLDB Conference, Santiagi, Chile.

Auslender, L. E. 2008. On analytical tools for market basket (associations) analysis 2008. http://nymetro.chapter.informs.org/prac_cor_pubs/Auslender-On-market-basket-basket-analysis-May-04.pdf (accessed June 3, 2008).

Berry, M. J. A., and G. S. Linoff. 2004. *Data mining techniques—For marketing, sales, and customer support*. 2nd ed. New York: Wiley.

Chen, Y. L., K. Tang, R. J. Shen, and Y. H. Hu. 2005. Market basket analysis in a multiple store environment. *Decision Support Systems* 40 (2): 339-54.

Dodge, M., and C. Stinson. 2007. Analyzing data with PivotTable reports. In *Excel 2007 inside out*. Redmond, WA: Microsoft Press.

Haughton, D., J. Deichmann, A. Eshghi, and S. Sayek. 2003. A review of software packages for data mining. *The American Statistician* 57 (4): 290-309.

Kasavana, M. L., and D. Smith. 1990. *Menu engineering—A practical guide to menu analysis*. Rev. ed. Okemos, MI: Hospitality Publications, Inc.

LeBruto, M. S., R. A. Ashley, and W. Quain. 1997. Using the contribution margin aspect of menu engineering to enhance financial results. *International Journal of Contemporary Hospitality Management* 9 (4/6): 161-67.

Marakas, G. M. 2003. *Modern data warehousing, mining and visualizing: Core concepts*. Upper Saddle River, NJ: Prentice Hall.

Myung, E., A. C. McCool, and A. H. Feinstein. 2008. Understanding attributes affecting meal choice decisions in a bundling context. *International Journal of Hospitality Management* 27 (1): 119-25.

Pardoe, I. 2008. Data mining techniques: Market basket aalysis rules 2008. http://lcb1.uoregon.edu/ipardoe/teaching/dsc433/handouts/chapter9h.pdf (accessed June 26, 2008).

Tan, P., V. Kumar, and J. Srivastava. 2002. Selecting the right interestingness measure for association patterns. Paper read at the 8th ACM SIGKDD International Conference on KDD, Edmonton, Alberta, Canada.

Tang, K., Y. L. Chen, and H. W. Hu. 2008. Context-based market basket analysis in a multiple-store environment. *Decision Support System* 45:150-63.

Tsur, D, J. D. Ullman, S. Abiteboul, C. Clifton, R. Moteani, S. Nestoroy, and A. Rosethal. 1998. Query flocks: A generalization of association-rule mining. Paper read at the 1998 ACM SIGMOD International Conference on Management of Data, March, Seattle, WA.

Wong, J. Y., H. J. Chen, P. H. Chung, and N. C. Kao. 2006. Identifying valuable travelers and their next foreign destination by the application of data mining. *Asia Pacific Journal of Tourism Research* 11 (4): 355-73.

Bios

Ping-Ho Ting, Ph.D., is an associate professor, Department of Hospitality Management, Tunghai University (ding@thu.edu.tw). **Steve Pan**, Ph.D., is an assistant professor at the School of Hotel and Tourism Management, The Hong Kong Polytechnic University (hmstcpan@polyu.edu.hk). **Shuo-Shiung Chou** is a lecturer in the Department of Hospitality Management, Tunghai University (shchou@thu.edu.tw).