Best next offer: get ahead with predictive analytics

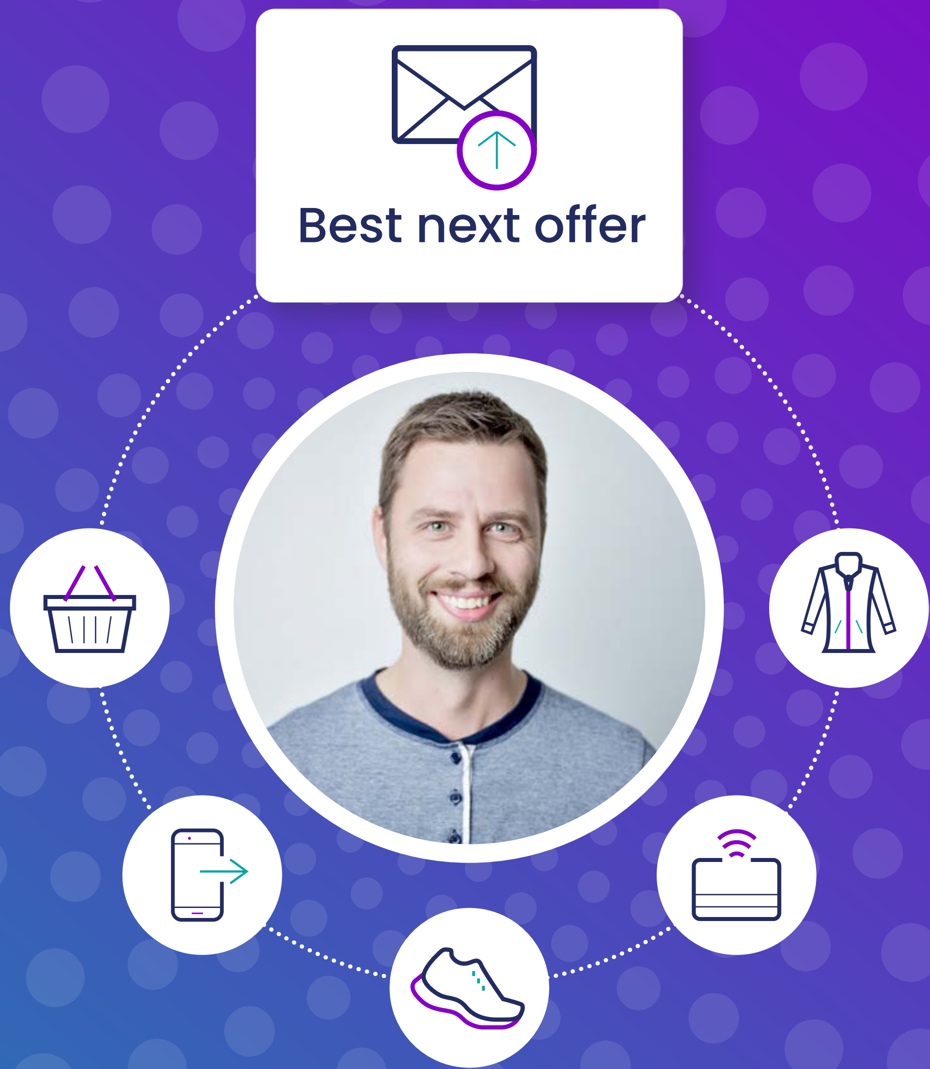
Discover how Apteco FastStats® can help you predict your customer's next purchase.

Introduction

An Apteco FastStats® system typically holds the buying history of a customer as a series of transactions. Can we use this information to predict the most likely next purchase for a customer? If so then we could highlight this product in a personalised marketing communication.

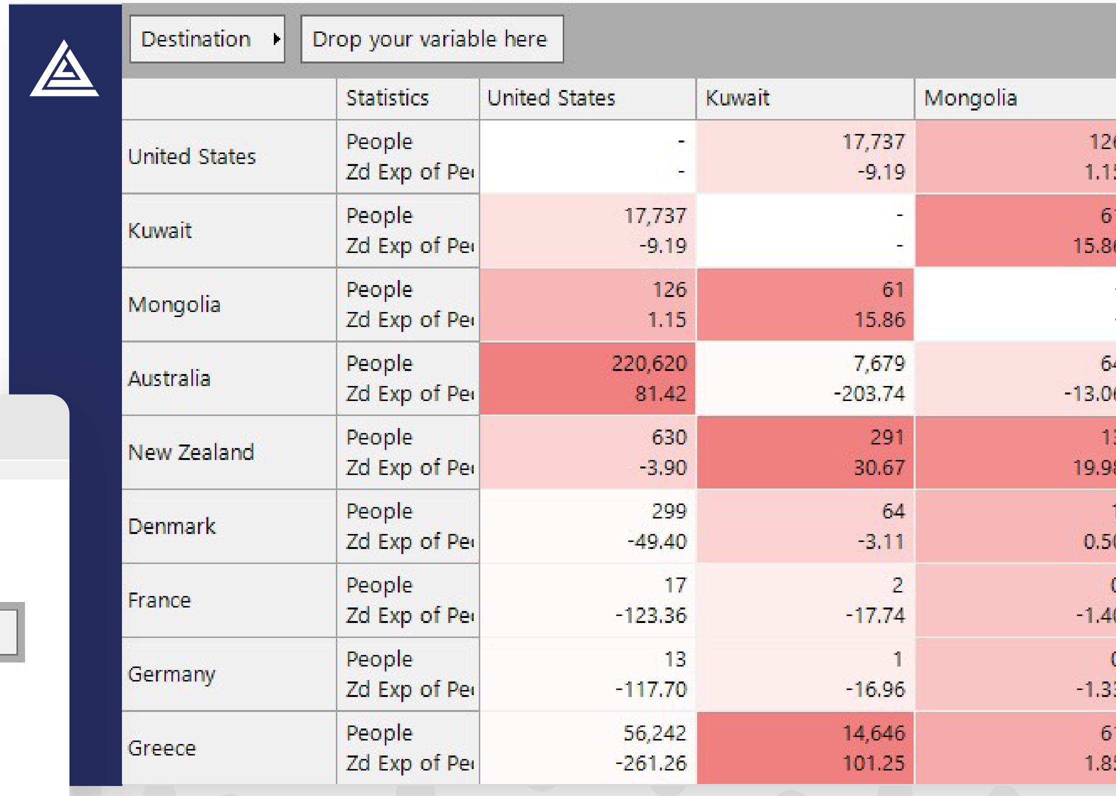
Of course we can't expect to know exactly what someone is about to purchase, but it's possible to use collaborative filtering techniques with past transactions to suggest the most likely next purchase.

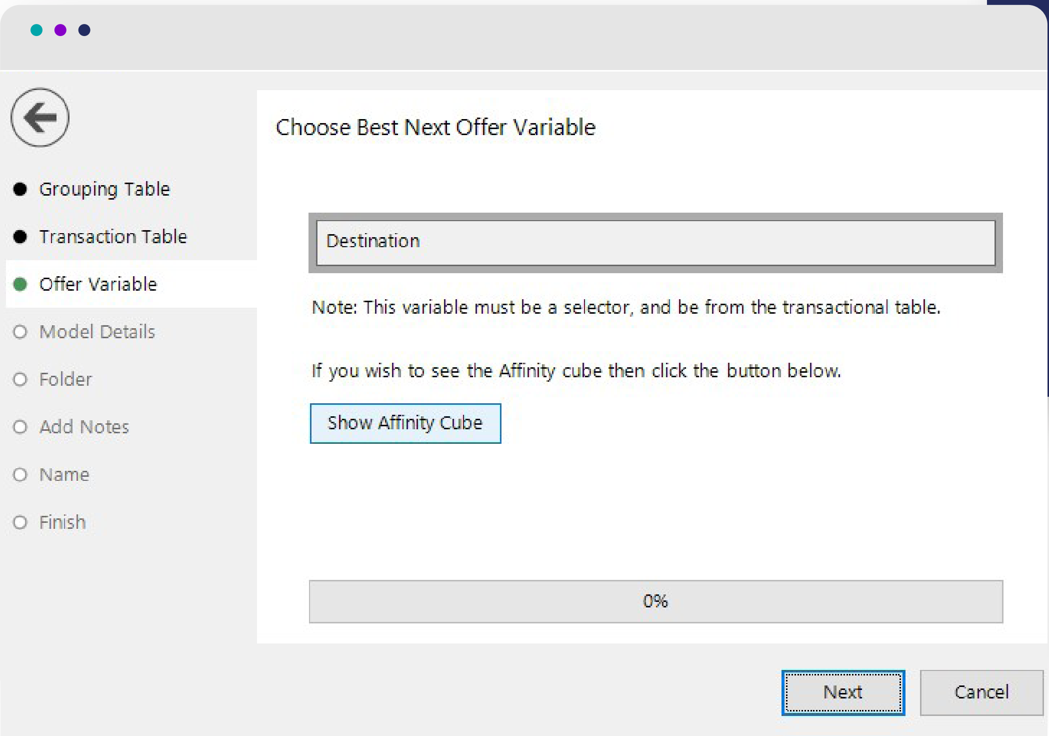
In this eGuide we'll look at how this can be achieved using the "Best Next Offer" (BNO) wizard in Apteco FastStats. First we'll look at the basics using the familiar data of the holidays system, before digging a little deeper with some real data.



Affinity Cube

The BNO wizard first generates the Affinity Cube, which explores "what is bought with what?"

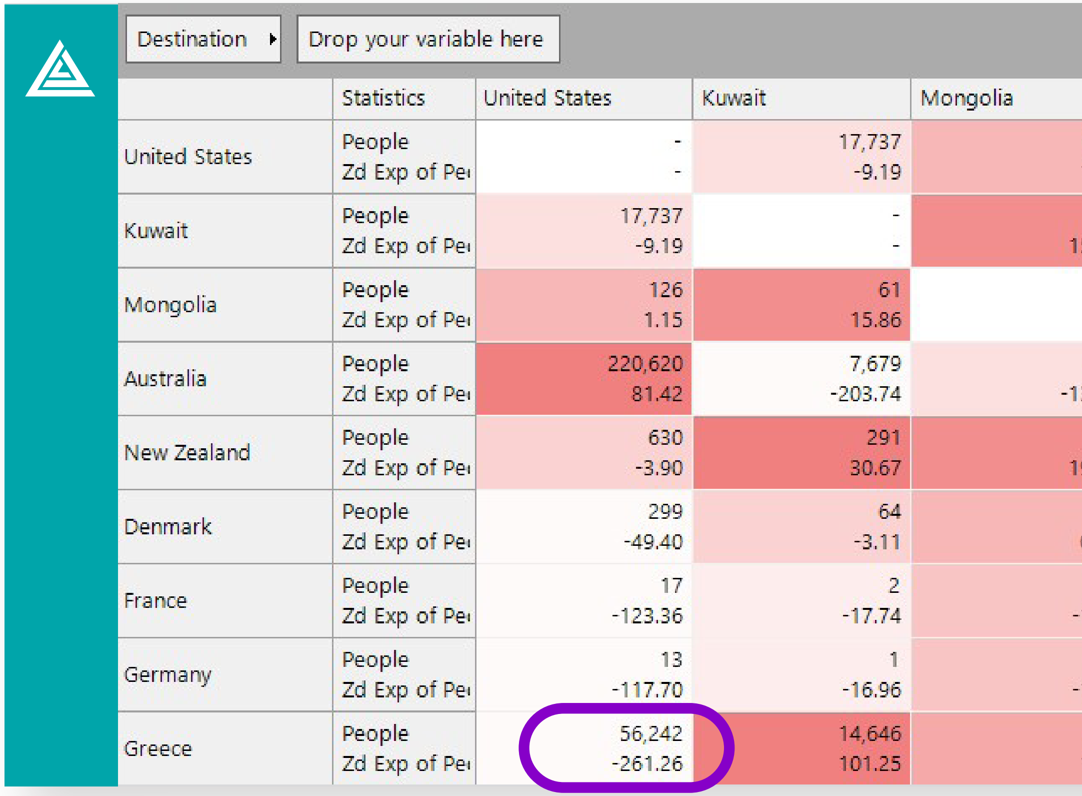




Propensity

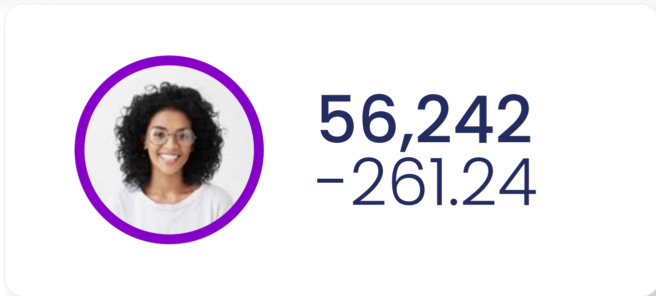
The product categories (in this case holiday destinations) are shown on both axes. Each cell shows the number of customers who have purchased both products. The highlighted cell shows that 56,242 customers bought both “Greece” and “United States” holidays. This sounds a lot but, given the number of people who have bought the two products individually, the figure is actually significantly lower than expected.

This is highlighted by the high negative cell z-score statistic, which has been used to shade the cube. In the same column we can see that Australia X United States is a higher number than expected. We can conclude that someone who has bought the US destination holiday is more likely to also buy the Australia holiday and less likely to buy the Greece holiday.



Destination | Drop your variable here

	Statistics	United States	Kuwait	Mongolia
United States	People	-	17,737	
	Zd Exp of Pe	-	-9.19	
Kuwait	People	17,737	-	
	Zd Exp of Pe	-9.19	-	
Mongolia	People	126	61	
	Zd Exp of Pe	1.15	15.86	
Australia	People	220,620	7,679	
	Zd Exp of Pe	81.42	-203.74	
New Zealand	People	630	291	
	Zd Exp of Pe	-3.90	30.67	
Denmark	People	299	64	
	Zd Exp of Pe	-49.40	-3.11	
France	People	17	2	
	Zd Exp of Pe	-123.36	-17.74	
Germany	People	13	1	
	Zd Exp of Pe	-117.70	-16.96	
Greece	People	56,242	14,646	
	Zd Exp of Pe	-261.26	101.25	



Using this approach we can calculate a measure of propensity for each combination of products (destinations in this example).

Each customer has a recorded purchase history so we can work through their transactions and look up the propensity to accumulate a score against each of the candidate products. The product with the highest score is then the one that is the best suggestion for their next offer.

Popularity

Working purely with propensity can produce less common product suggestions. Even when these are statistically significant there might be some underlying reason why a particular odd product combination was popular but only for a short time period.

In some marketing scenarios these will be interesting niches that you can exploit, but in other cases you will want to nudge the BNO suggestion towards a more popular choice even if that means a slightly lower propensity. It seems sensible to factor a measure of the overall product popularity into the BNO. This is easily calculated from the marginal totals of the Affinity Cube.

Our overall score is therefore a weighted combination of propensity and popularity.

BNO score =

(a X propensity)
+
(b X popularity)

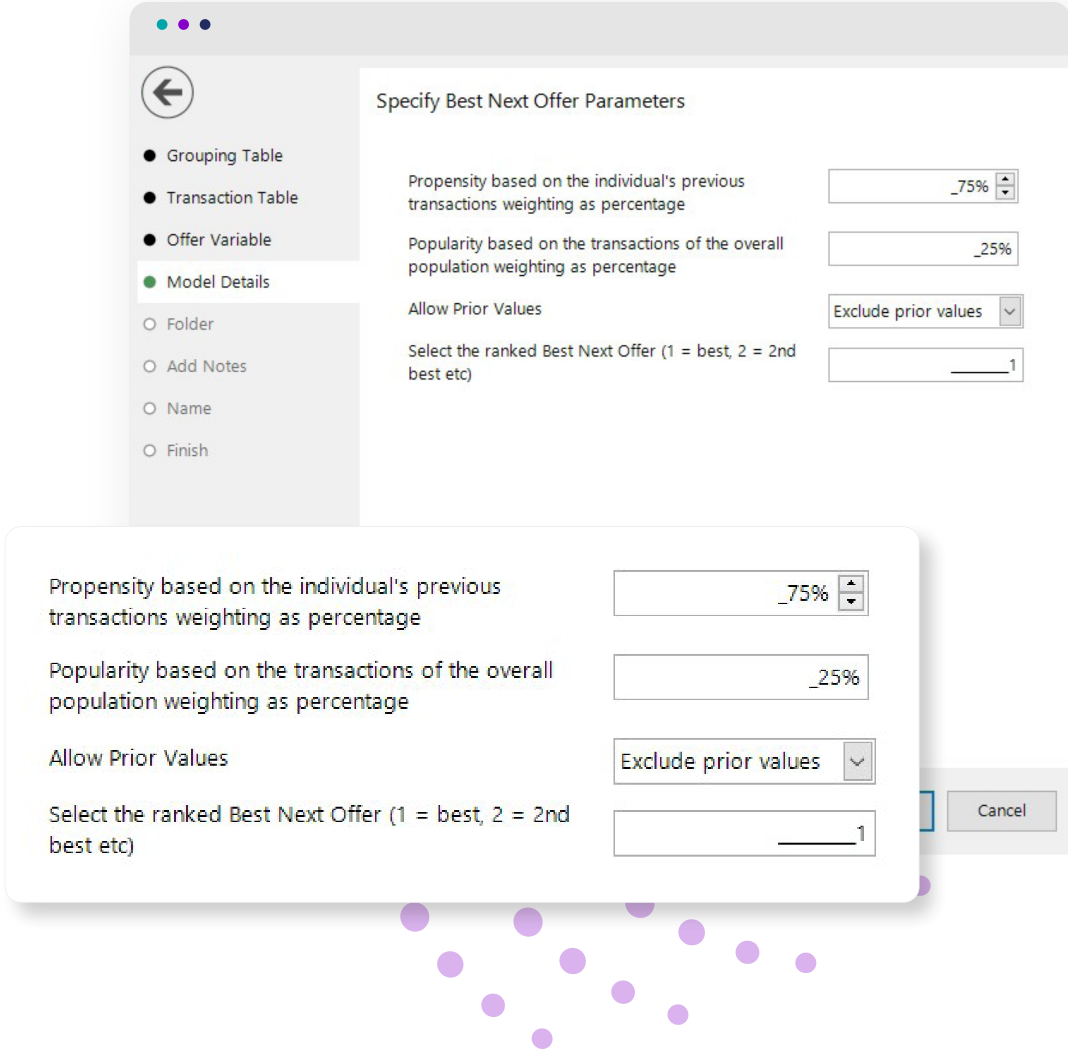
Working through a customer's past transactions we can accumulate this weighted score for each candidate product, rank them, and select the BNO for this individual.

Other considerations

For many applications we will want to exclude the possibility of suggesting a product that has already been bought. For example, if a customer has already bought a washing machine then don't try to sell them another – at least not for a few years. The wizard therefore defaults to Allow Prior Choice = No.

If your system can highlight more than one product then you could select rank two in the wizard to get the "second best next offer" and so on.

In this simple example we have included all transactions in the analysis. The wizard allows us to specify a transaction filter that will often be required. For example, we might sensibly exclude transactions for products that were returned or rated badly.



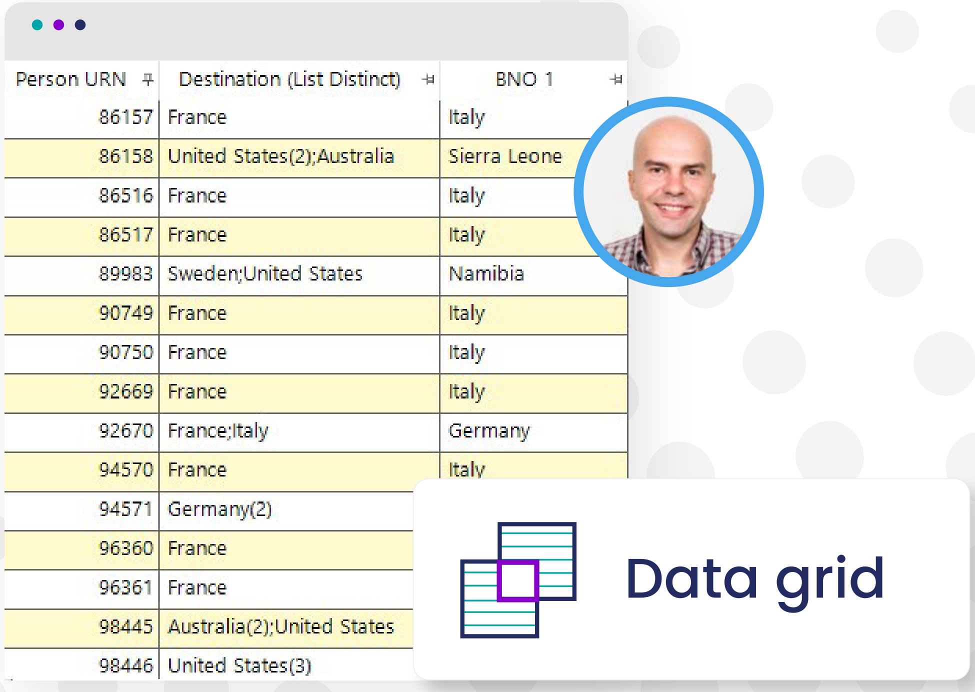
Using the BNO

The BNO product for each customer is written into a virtual variable. This can then be used to personalise the next marketing communication to the customer to highlight this product.

This datagrid shows the customer's past holiday destinations along with the BNO suggestion using a Propensity / Popularity weighting of 75%/25% as described above.

It will often be more practical to work at a higher level "product group" than, say, a low level SKU code. The BNO can then be used to suggest the product group and you can use other criteria (stock level, profitability, seasonal effects) to target a particular product from within that group.

You can also use BNO in combination with other models like Recency-Frequency-Value (RFV). In this case your marketing communication could use the RFV to promote the customer's "usual choice" with the BNO result as a "or why not try something new" option.



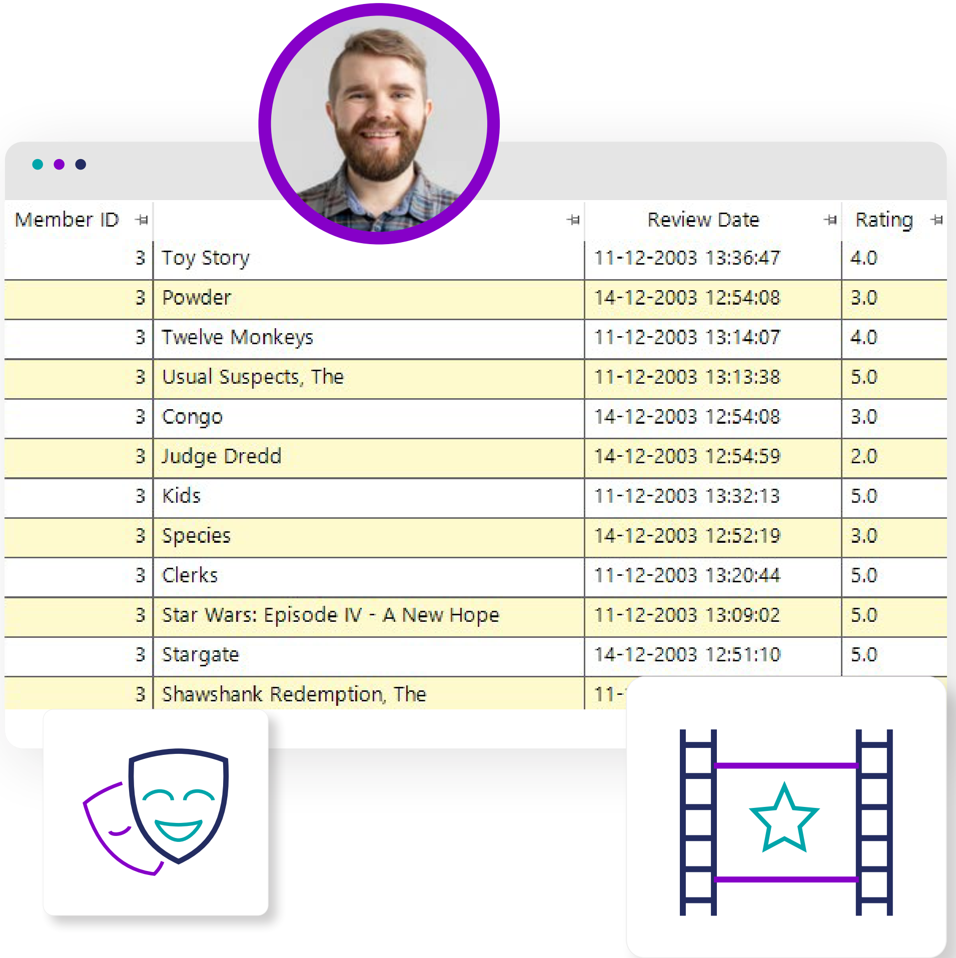
Person URN	Destination (List Distinct)	BNO 1
86157	France	Italy
86158	United States(2);Australia	Sierra Leone
86516	France	Italy
86517	France	Italy
89983	Sweden;United States	Namibia
90749	France	Italy
90750	France	Italy
92669	France	Italy
92670	France;Italy	Germany
94570	France	Italy
94571	Germany(2)	
96360	France	
96361	France	
98445	Australia(2);United States	
98446	United States(3)	

Application to real data

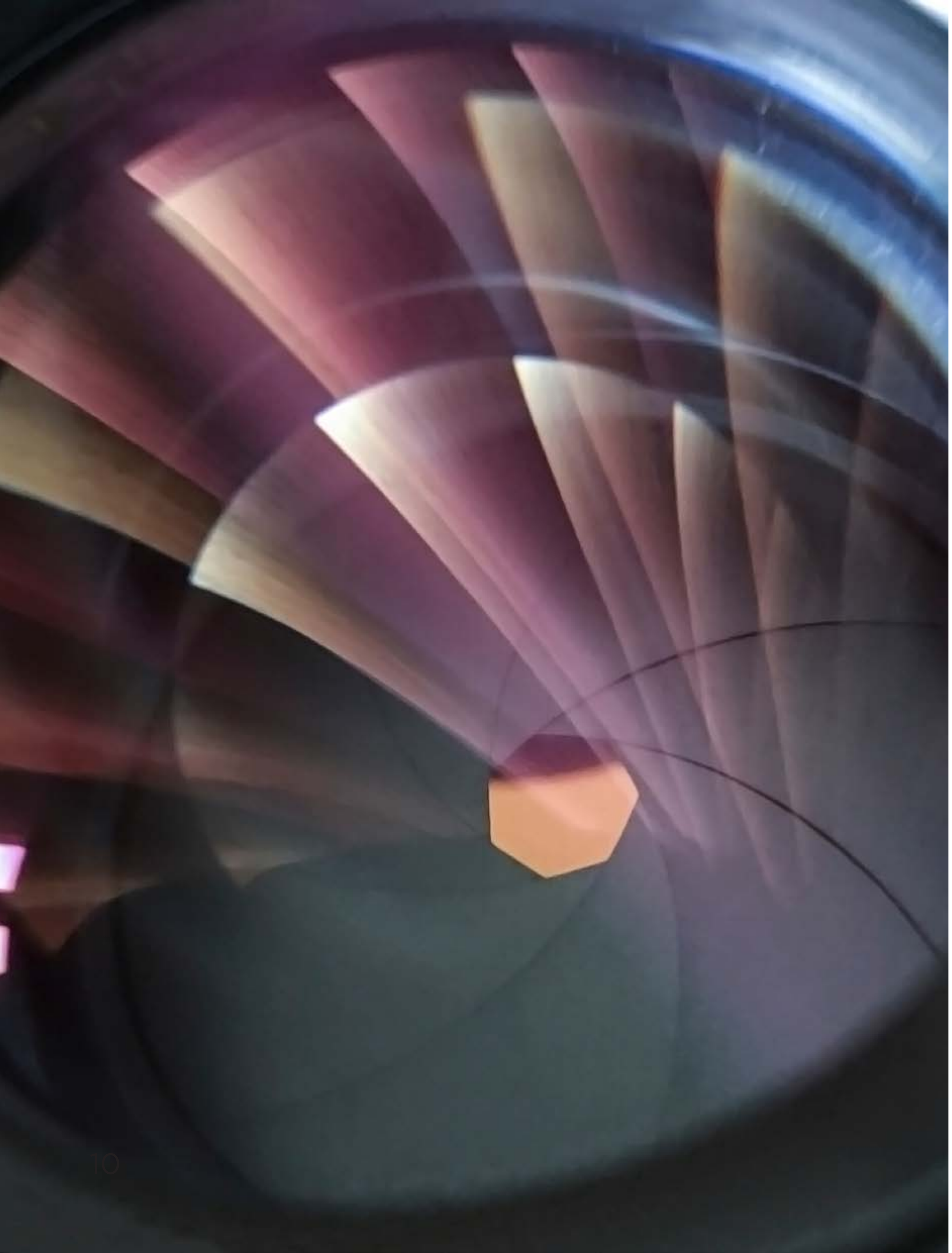
Transactional data with real purchase history tends to be closely guarded by our clients for obvious reasons. However, we can illustrate some of the practical considerations when using the BNO techniques by looking at some real but public film review data (sourced from the MovieLens project https://movielens.org/).

This data has a table of members of a movie review website. Each member has added reviews of a number of films rating them from one to five stars and these form a transaction table in the FastStats system. We will try to use BNO to suggest the next film that should appeal to the member given their viewing history.

Here is a data grid with the reviews by one member.



Member ID		Review Date	Rating
3	Toy Story	11-12-2003 13:36:47	4.0
3	Powder	14-12-2003 12:54:08	3.0
3	Twelve Monkeys	11-12-2003 13:14:07	4.0
3	Usual Suspects, The	11-12-2003 13:13:38	5.0
3	Congo	14-12-2003 12:54:08	3.0
3	Judge Dredd	14-12-2003 12:54:59	2.0
3	Kids	11-12-2003 13:32:13	5.0
3	Species	14-12-2003 12:52:19	3.0
3	Clerks	11-12-2003 13:20:44	5.0
3	Star Wars: Episode IV - A New Hope	11-12-2003 13:09:02	5.0
3	Stargate	14-12-2003 12:51:10	5.0
3	Shawshank Redemption, The	11-	



Limit the number of products

This database lists over 10,000 films. The BNO technique depends on building the Affinity Cube and this won't be possible for more than a few thousand categories (the maximum cube size allowed in a system is configurable and can be increased especially in 64bit implementations but is ultimately limited by resources).

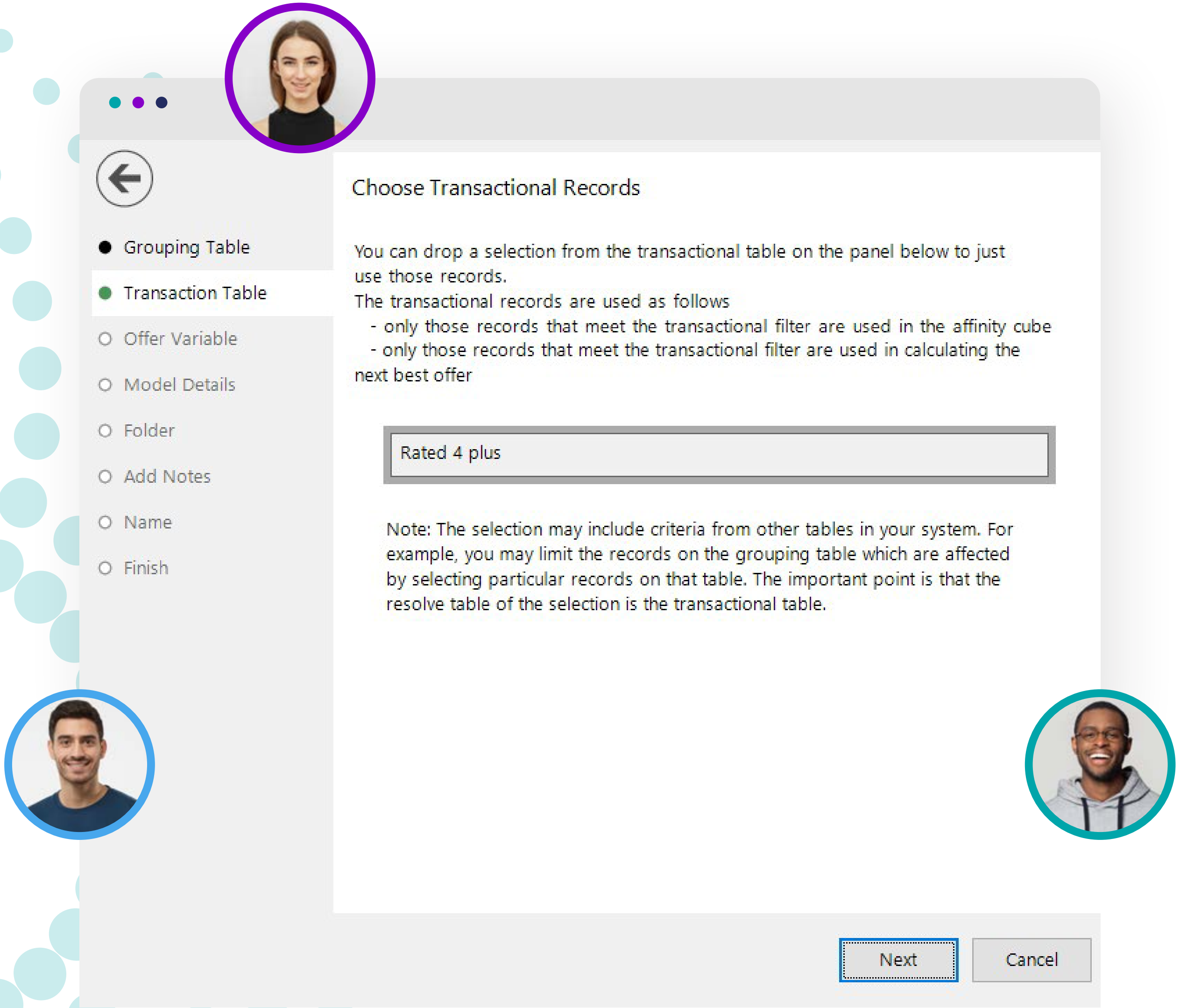
There are several approaches to reducing the number of product categories:

- Use a product grouping to combine similar products.
- Limit the products to the most popular N – in this case the top 100 films by viewings.
- Limit the products to those that feature at least N times – in this case the films that have been rated at least 500 times.

All of these groupings can be built using the Combine Categories wizard.

Let's work with the top 100 films.

Include	Code	Description	Viewings
☐	...	Unclassified	16,414,780
☐	Pulp...	Pulp Fiction	67,310
☐	Forre...	Forrest Gump	66,172
☐	Shaw...	Shawshank Redemption, The	63,366
☐	Silen...	Silence of the Lambs, The	63,299
☐	Juras...	Jurassic Park	59,715
☐	Star...	Star Wars: Episode IV - A New H...	54,502
☐	Brav...	Braveheart	53,769
☐	Term...	Terminator 2: Judgment Day	52,244



Filter people

The BNO model is going to reflect the behaviour of the people that are fed into the tool so we need to consider carefully who to include.

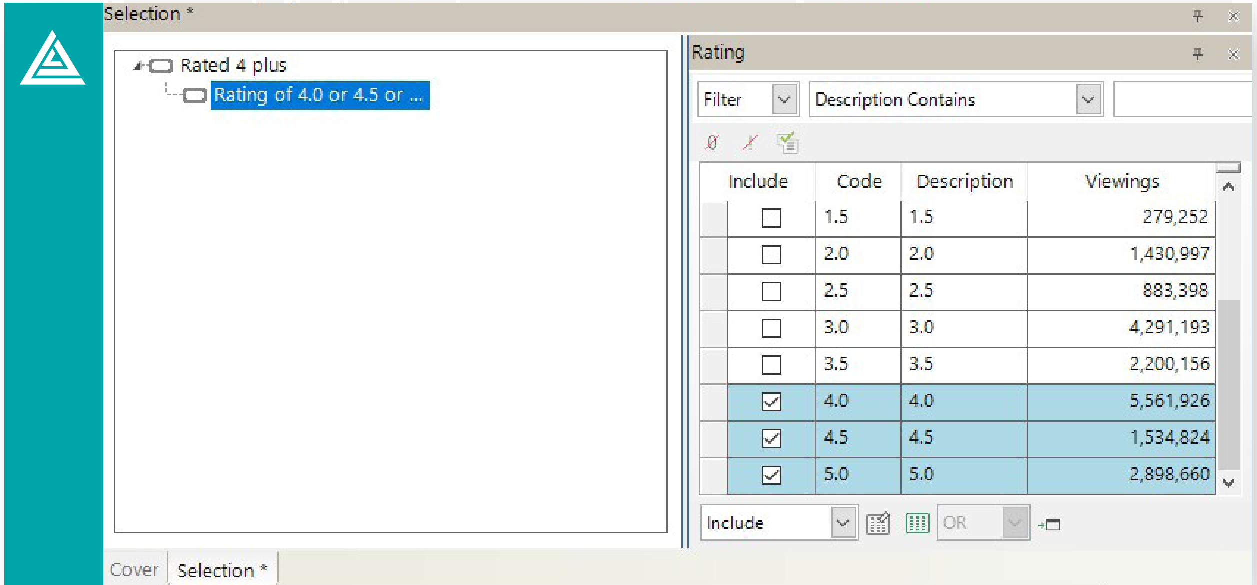
People who have bought less than two products will automatically be excluded from the Affinity Cube. Depending on the task it might make sense to exclude certain types of non-typical customer e.g. corporate customer of consumer business, lapsed customer.

In this case let's include all people.

Filter transactions

The BNO model is going to be built directly from the transactions that are fed into the tool so we need to consider carefully which to include. In many cases it will be a good idea to remove older transactions, judging the cut-off from your knowledge of the market sector. Refunds, free offers, seasonal deals might be other candidates for exclusion.

Here the goal is to recommend a film that the customer will enjoy so we will filter the transactions to include only four to five star ratings.



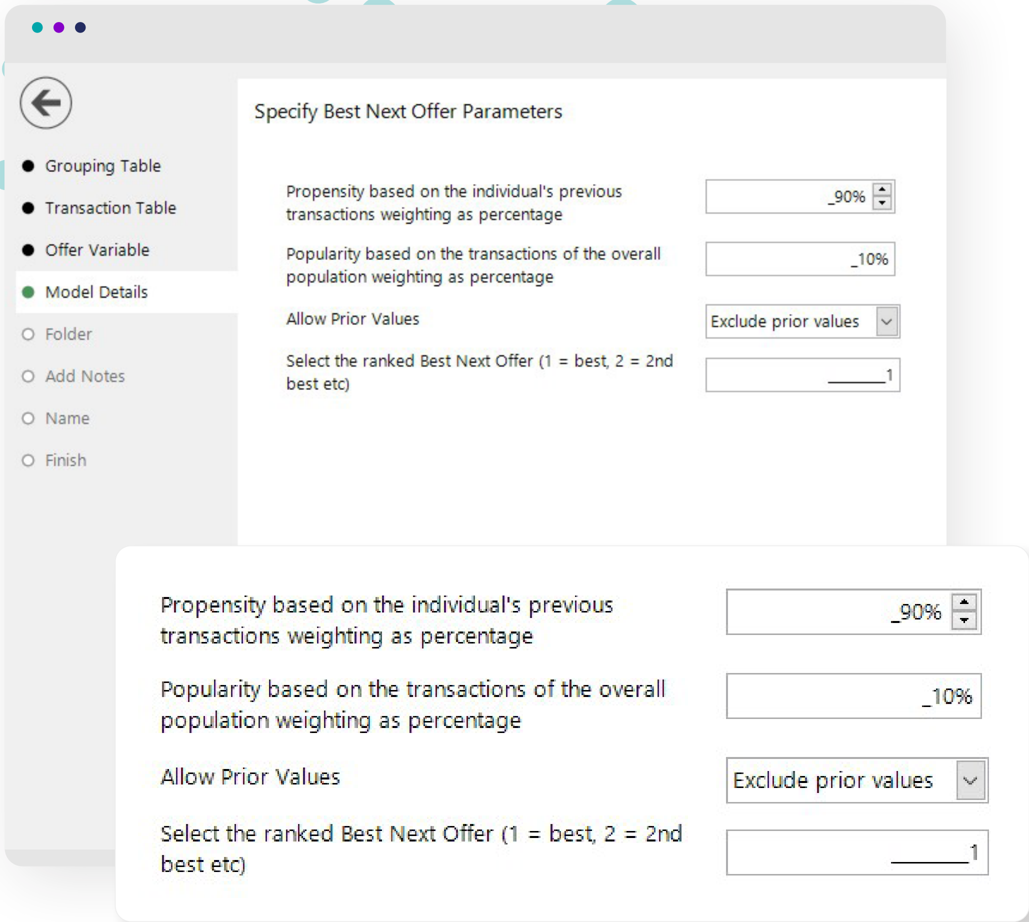
Affinity Cube

It is always a good idea to study the Affinity Cube. In this case it shows some believable correlations between films. In some cases this might have achieved your analysis objective to gain understanding and visualise products that are purchased together. Remember that you can also use Basket Analysis to investigate multiple product lines that are most frequently bought in the same transaction or by the same customer.

Continuing with the wizard will build a BNO model and use it to produce individual product suggestions.

Top 100 Movie(Rated 4 plus) | Drop your variable here

	Statistics	2001: A Space Odyssey	Ace Ventura: Pet Detective	Aladdin
2001: A Space Odyssey	Members	-	1,414	3,315
	Zd Exp of Members	-	-0.57	3.95
Ace Ventura: Pet Detective	Members	1,414	-	4,388
	Zd Exp of Members	-0.57	-	64.18
Aladdin	Members	3,315	4,388	-
	Zd Exp of Members	3.95	64.18	-
Alien	Members	9,579	2,352	4,795
	Zd Exp of Members	140.14	12.19	12.61
Aliens	Members	7,703	2,242	4,520
	Zd Exp of Members	115.87	17.33	19.54
American Beauty	Members	8,135	3,045	5,963
	Zd Exp of Members	64.50	3.77	-5.30
Apollo 13	Members	5,021	4,837	11,044
	Zd Exp of Members	17.10	53.91	92.54



Adjust weightings

As discussed, general weighting towards propensity will favour niche combinations of products that might not always be desirable. However, here we have already restricted the analysis to more popular products by using the top 100 films.

Therefore we have chosen to weight more by propensity as the candidate films are all popular. We have also forced the BNO suggestion to be a film not seen before by setting “Allow Prior Choice” No.

Review results

The BNO suggestion is produced as a virtual variable so all the usual FastStats analysis tools can be used to explore and review the results.

Here we've used a datagrid to show the film's transactions for a person along with the BNO suggestion. Remember to apply the same filtering selection to the datagrid if you want to see transactions that were used to model the BNO.

In this case the films are limited to those in the top 100 for which the member had awarded a rating of four or five stars.

Member ID : 39 (9 items)

Top 100 Movie	BNO 1
Fargo	Die Hard
Independence Day	Die Hard
Mission: Impossible	Die Hard
Rock, The	Die Hard
Star Wars: Episode IV - A New Hope	Die Hard
Toy Story	Die Hard
Twelve Monkeys	Die Hard
Twister	Die Hard
Willy Wonka & the Chocolate Factory	Die Hard

Member ID : 40 (7 items)

Top 100 Movie	BNO 1
Batman	Ocean's Eleven
Fargo	Ocean's Eleven

Tip – You will often want to go back to tweak the weightings and transaction filters. If you avoid closing the wizard then you can use the back button and change the setting.

Cubes are the obvious way to explore the distribution of the BNO suggestions, and of course you can break these down by other variables and use Charting to visualise further.

Die Hard
Members **11,486**

	Members
Die Hard	11,486
Indiana Jones and the Last Crusade	9,469
Reservoir Dogs	9,075
There's Something About Mary	7,853
Aliens	7,001
Terminator, The	6,979
Cliffhanger	6,267
Shawshank Redemption, The	5,951
Firm, The	4,916
Ocean's Eleven	4,604
Ghostbusters	4,571
Goodfellas	4,419
X-Men	4,005

Using the BNO result

The BNO suggestion is stored as a virtual variable and so can easily be exported in a datagrid or included in an Apteco PeopleStage™ output. The BNO code can be used to specify the product offered within the marketing communication.

Of course there are other methods of choosing a product to offer the individual, including:

- Selection based on individual's RFV history e.g. last/most frequent product bought
- Selection based on the demographic cluster of an individual
- Selection based on the season, topical event or brand promotion

Depending on your sector some of these methods are probably already in use. It makes sense to introduce the BNO suggestion as an alternative alongside these established options.

BNO is a flexible technique but the application above shows that it's crucial to set the parameters carefully, experiment, and test the results.

Book an Apteco demo to discover how understanding your customers' most likely next purchase can boost your campaigns.

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