Data Analytics: Coursework 2

Pricing Dynamics Hypothesis

Nijaguna Darshana
230671566

QUESTION 1: Discuss the research area and the data set you have prepared, along with pointers to your data sources. Screen-capture part of the final version of your data set and present it here as a Figure. For example, if your data set contains 15 variables and 1,000 samples, you could present the first 10 columns and a small part of the sample size. Explain why you considered this data set to be suitable for structure learning, and what questions you expect a structure learning algorithm to answer.

Answer:

The need to study customer behaviour in today's ever shifting marketing dynamics is more than ever. This research is based on the American Customer Satisfaction Index (ACSI) dataset [3] from 2015, which includes detailed measures of customer expectations, satisfaction, loyalty, and demographics across sectors such as food, airlines, ISPs, and banking.

It is a suitable dataset for structure learning because of the rich features which makes it highly potential candidate for exploring complex causal relationships between different aspects of customer experience.

Some questions I expect a structure learning algorithm to answer are:

How does perceived value impact customer satisfaction and loyalty? Specifically, does higher perceived value enhance customer loyalty and under what conditions?

What role does price tolerance play between customer satisfaction and loyalty?

What is the impact of demographic factors?

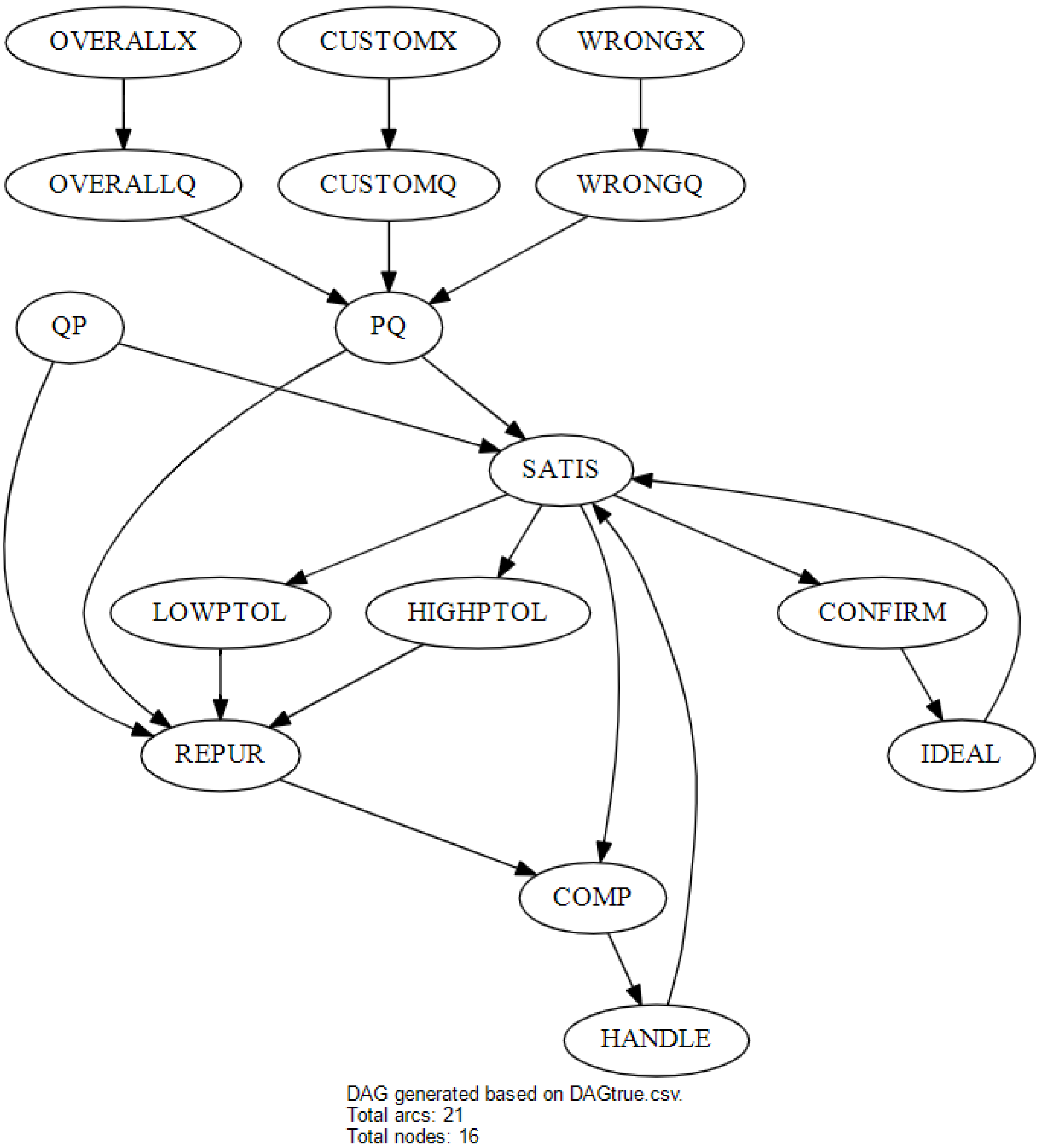
TLDR; To discover factors that drive customer loyalty and how businesses can strategically manage customer relationships based on these insights.

INDUSTRY	SATIS	CONFIRM	IDEAL	OVERALLX	CUSTOMX	WRONGX	OVERALLQ	CUSTOMQ	WRONGQ	PQ	QP	COMP	HANDLE	REPUR	HIGHPTOL	LOWPTOL	AGE	EDUCAT	HISPANIC	RACE_1	INCOME	GENDER	ZIPCODE
Commercial Airlines	Satisfied	Met expectations	Close to ideal	High	Well	Often	High	Well	Very often	Good	Good	No	NoComp	Likely	Low	Unknown	Young	College graduate	0	1	<20	2	1
Commercial Airlines	Satisfied	Exceeded expectations	Close to ideal	Very high	Well	Often	High	Well	Often	Good	Good	No	NoComp	Likely	High	Unknown	Young	Post graduate	0	4	<20	2	2
Commercial Airlines	Very satisfied	Exceeded expectations	Close to ideal	High	Very well	Very often	High	Well	Often	Very good	Very good	No	NoComp	Likely	Medium	Unknown	Young	associate degree	0	2	<20	1	1
Commercial Airlines	Satisfied	Met expectations	Close to ideal	High	Well	Sometimes	High	Well	Often	Very good	Good	No	NoComp	Likely	High	Unknown	Middle-aged	Post graduate	0	1	<20	2	2
Commercial Airlines	Satisfied	Exceeded expectations	Moderately close	High	Well	Rarely	High	Well	Rarely	Good	Average	No	NoComp	Likely	High	Unknown	Young	College graduate	0	1	<20	2	1
Commercial Airlines	Very satisfied	Exceeded expectations	Close to ideal	Very high	Well	Often	Very high	Well	Often	Good	Good	No	NoComp	Very likely	High	Unknown	Young	Post graduate	0	1	<20	2	1
Commercial Airlines	Satisfied	Met expectations	Moderately close	High	Well	Sometimes	High	Well	Rarely	Good	Good	No	NoComp	Likely	Medium	Unknown	Middle-aged	College graduate	0	1	<20	1	2
Commercial Airlines	Unsure	Met expectations	Moderately close	High	Well	Rarely	High	Well	Sometimes	Average	Average	No	NoComp	Likely	High	Unknown	Senior	College graduate	0	1	<20	1	2
Commercial Airlines	Very satisfied	Exceeded expectations	Very close to ideal	Very high	Very well	Very often	Very high	Very well	Very often	Very good	Very good	No	NoComp	Very likely	Low	Unknown	Young	Post graduate	0	6	<20	1	2
Commercial Airlines	Very satisfied	Far exceeded	Very close to ideal	High	Well	Sometimes	High	Well	Rarely	Very good	Very good	No	NoComp	Very likely	Low	Unknown	Young	Post graduate	0	1	<20	1	2
Commercial Airlines	Unsure	Slightly better	Moderately close	Very high	Well	Very often	High	Very well	Rarely	Average	Average	Yes	Handled adequately	Unlikely	Unknown	High	Senior	College graduate	1	1	<20	1	3
Commercial Airlines	Satisfied	Exceeded expectations	Moderately close	High	Adequately	Rarely	High	Well	Often	Good	Good	No	NoComp	Likely	Medium	Unknown	Young	associate degree	0	1	<20	2	1

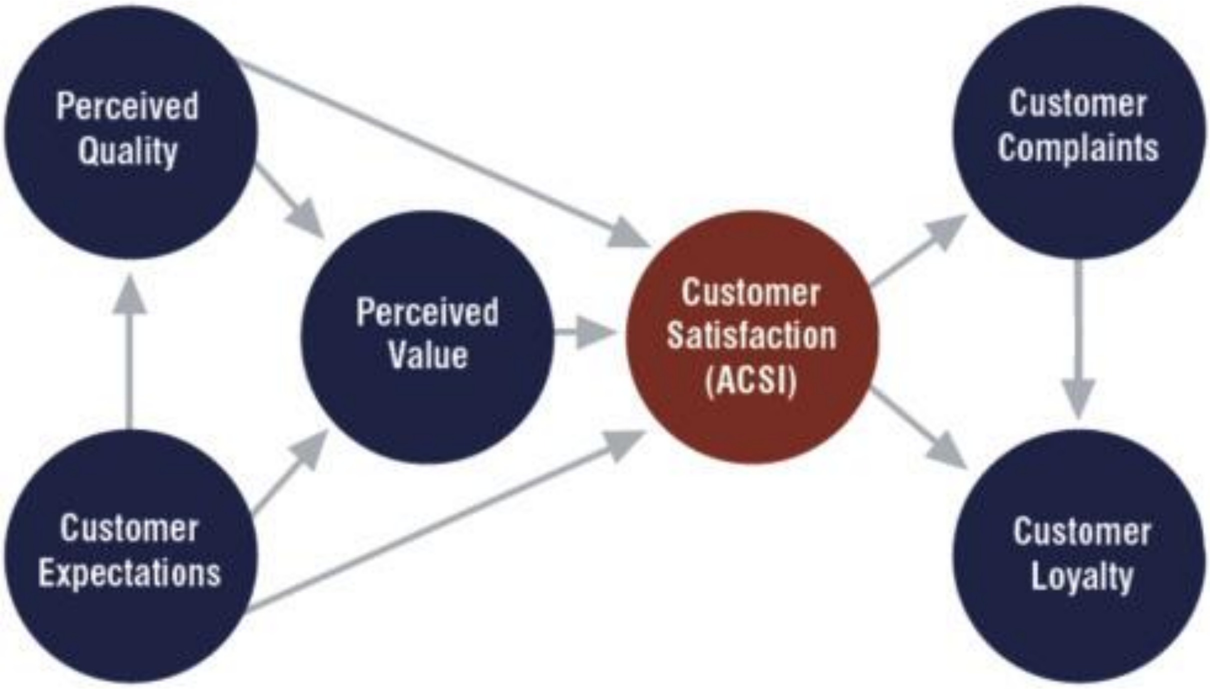
Processed ACSI Dataset Sample

QUESTION 2: Present your knowledge-based DAG (i.e., DAGtrue.pdf or the corresponding DAGtrue.csv graph visualised through the web editor), and briefly describe the information you have considered to produce this graph. For example, did you refer to the literature to obtain the necessary knowledge, or did you consider your own knowledge to be sufficient for this problem? If you referred to the literature to obtain additional information, provide references and very briefly describe the knowledge gained from each paper. If you did not refer to the literature, justify why you considered your own knowledge to be sufficient in determining the knowledge-based graph.

Answer:



ACSI Knowledge Graph



ACSI Foundation Model

The ACSI's foundational model was developed by Professor Claes Fornell [1], capturing the interaction between customer expectations, perceived quality and value, satisfaction, complaints, and loyalty. The DAGtrue knowledge graph is an amalgamation of my experience with marketing and inspired by the foundational model and literature like 'Do managers know what their customers think and why?' [2]

My approach was to integrate this robust ACSI framework with the hypothesis that price tolerance acts as a mediator between customer satisfaction and loyalty, further influenced by perceived value. The graph was constructed to which elucidate how satisfaction is not merely a direct outcome of service quality and value but also a precursor to loyalty and complaint behaviour. In addition to this, scholarly work and empirical studies have been considered to understand the nuances of price tolerance and its role within the satisfaction-loyalty nexus, especially across different industries.

The resultant DAG true model encapsulates this interconnection of variables, weaving in the hypothesis that the perception of quality and value, moderated by individual customer experiences and expectations, leads to satisfaction, which then influences loyalty through the prism of price tolerance, with these pathways being potentially moderated by various industry contexts.

QUESTION 3: Complete Table Q3 below with the results you have obtained by applying each of the algorithms to your data set during Task 4. Compare your CPDAG scores produced by F1, SHD and BSF with the corresponding CPDAG scores shown in Table 3.1 (page 13) in the Bayesys manual. Specifically, are your scores mostly lower, similar, or higher compared to those shown in Table 3.1 in the manual? Why do you think this is? Is this the result you expected? Explain why.

Answer:

Algorithm	CPDAG scores			Log-Likelihood (LL) score	BIC score	# free parameters	Structure learning elapsed time
	BSF	SHD	F1				
HC	0.162	36.5	0.309	-109503.035	-111866.063	383	12 seconds
TABU	0.152	37.5	0.304	-109477.095	-111889.481	391	12 seconds
SaiyanH	0.057	39.5	0.232	-109326.693	-112343.719	489	24 seconds
MAHC	-0.001	36	0.167	-110804.037	-112439.03	265	11 seconds
GES	0.152	37.5	0.304	-109477.095	-111889.481	391	12 seconds

Table Q3

The results were not expected to be this low, but I was not expecting it to be too good either because of the oversimplification of the data. The most surprising result is the negative BSF score for MAHC, which suggests a re-evaluation of the algorithm’s settings, the data, or the model structure might be necessary. SaiyanH's lower F1 score prompts further investigation into the data characteristics or algorithm configuration.

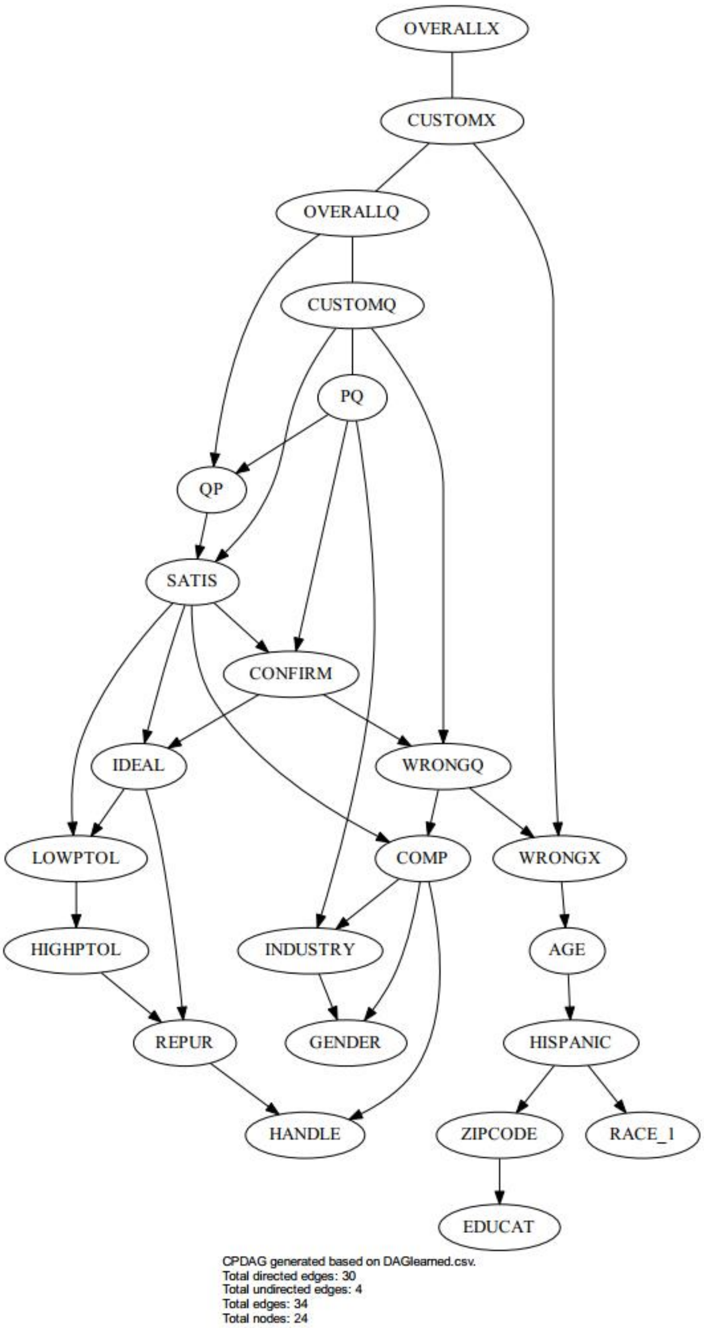
However, when comparing the results of the table 3.1 of the manual, which states were obtained using clean synthetic data. Synthetic data often lacks the noise and complexity of real-world data, potentially making the algorithms appear more accurate in the manual than when applied to our real-world dataset. This can partly explain why some algorithms may not perform as well on our dataset. Also, the sensitiveness of the variable order might have influenced their performance on our dataset if the variable ordering significantly deviated from the ordering used in the manual's experiments.

The HC and GES algorithms show F1 scores that are competitive with those presented in the manual. he SaiyanH algorithm’s F1 score is notably lower, indicating that it may not be capturing the true structure as effectively as others. The TABU algorithm gives a slightly lower BSF score compared to HC and GES, which might imply a less optimal fit to the data.

TLDR; while the results from HC and GES were within expectations, those from SaiyanH and especially MAHC were not.

Question 4: Present the CPDAG generated by HC (i.e., CPDAGlearned.pdf or the corresponding CPDAGlearned.csv graph visualised through the web editor). Highlight the three causal classes in the CPDAG. You only need to highlight one example for each causal class. If a causal class is not present in the CPDAG, explain why this might be the case.

Answer:



CPDAG by HC Algorithm

The CPDAG from HC algorithm has all three causal classes, in fact also has a few causal relations not established nodes as well. The three causal classes in the above graph are as follows:

1. Ancestor Nodes: These nodes have only outgoing edges and can be considered as independent variables in the graph. They are not influenced by any other variable within the CPDAG. 'OVERALLX' is the ancestor nodes since they do not have any incoming edges.

2. Descendant Nodes: Nodes that receive only incoming edges and are influenced by other variables in the graph. They do not exert influence on any other variable in the CPDAG. 'EDUCAT' is a descendant node, being at the receiving end of an edge from 'ZIPCODE'.

3. Intermediary Nodes (Mediators): These are the nodes that have both incoming and outgoing edges, suggesting they mediate the influence between other variables. 'SATIS' is a prominent mediator in the CPDAG graph as it receives influences from 'PQ' and 'QP' and transmits influences to 'CONFIRM', 'IDEAL', 'COMP', 'LOWPTOL', and 'HIGHPTOL'.

Question 5: Rank the six algorithms by score, as determined by each of the three metrics specified in Table Q5. Are your rankings consistent with the rankings shown under the column "Rankings according to the Bayesys manual" in Table Q5 below? Is this the result you expected? Explain why.

Rank	BSF (single score)	SHD (single score)	F1 (single score)	BSF (average score)	SHD (average score)	F1 (average score)
1	SaiyanH (0.057)	HC (36.5)	HC (0.309)	SaiyanH (0.559)	MAHC (50.96)	SaiyanH (0.628)
2	GES (0.152)	TABU (37.5)	GES (0.304)	GES (0.506)	SaiyanH (57.98)	MAHC (0.579)
3	TABU (0.152)	GES (37.5)	TABU (0.304)	MAHC (0.503)	HC (62.36)	GES (0.552)
4	HC (0.162)	MAHC (36)	MAHC (0.167)	TABU (0.499)	TABU (62.63)	TABU (0.549)
5	MAHC (-0.001)	SaiyanH (39.5)	SaiyanH (0.232)	HC (0.498)	GES (63.2)	HC (0.548)

Table Q5

The poor performance was not expected, but it is not a surprise as well to see such performance when comparing to the Bayses manual data, reasons below:

1. The Bayesys manual utilizes synthetic data to benchmark algorithm performance, while the ACSI dataset is derived from real-world customer satisfaction surveys. Real data can be noisier and more complex, affecting the algorithms' performance and their rankings accordingly.
2. The knowledge graph incorporates a nuanced understanding of industry-specific customer satisfaction, including additional demographic and segmentation variables. These add layers of complexity that the algorithms must navigate, which can impact their efficiency and accuracy differently.
3. As noted in the manual, certain algorithms like HC and TABU are sensitive to variable ordering, which I wasn't aware while applying the algorithm. Meanwhile, algorithms like SaiyanH and MAHC, which are less sensitive to variable ordering, show disparities in performance due to the structural complexity and mostly are overfitting.
4. The randomness in structure learning algorithms, especially when applied to complex, real-world data, can lead to variations.

In conclusion, while the results from the Bayesys provide a valuable baseline, the real-world application of these algorithms to the ASCI dataset can lead to different outcomes.

QUESTION 6: Refer to your elapsed structure learning runtimes and compare them to the runtimes shown in Table 3.1 in the Bayesys manual. Indicate whether your results are consistent or not with the results shown in Table 3.1. Explain why.

Answer:

My runtime for all the algorithms except for SaiyanH is 12s and 24s respectively. My dataset consists of 5.2K rows and 24 features. And most of the variables are in 3 categories. Comparing this to the Diarrhoea 28 68 104, runtime which take 4 secs for SaiyanH, and by halving it is just 2s. So, it has got to do with the dataset, the processor, and the complexity of the graph.

Also, since my ACSI data is from a real-world dataset, it has the noise, the complexity, and the randomness of the survey even though it has been cleaned.

QUESTION 7: Compare the BIC score, the Log-Likelihood (LL) score, and the number of free parameters generated in Task 3, against the same values produced by the five structure learning algorithms you used in Task 4. What do you understand from the difference between those three scores? Are these the results you expected? Explain why.

Algorithm	Task	BIC score	Log-Likelihood (LL) score	Free parameters
Knowledge-based graph	3	-112439.03	-110804.037	265
HC	4	-111866.063	-109503.035	383
TABU	4	-111889.481	-109477.095	391
SaiyanH	4	-112343.719	-109326.693	489
MAHC	4	-112439.03	-110804.037	265
GES	4	-111889.481	-109477.095	391

Table Q7

Yes, the results seen above is expected as the structure learning algorithms would generally perform well in terms of discovering the underlying pattern within the data. Notably, the BIC scores across the algorithms, except for MAHC, show a less penalized (lower) score compared to the knowledge-based graph. This indicates that the algorithms, to various extents, found simpler model structures that still adequately explain the data, resulting in a favorable balance between model complexity and goodness of fit.

The LL scores are higher for the algorithms compared to the knowledge-based graph, suggesting that these algorithms were better able to capture the dependencies in the data, potentially due to their ability to explore a broader solution space and iteratively refine the model based on data patterns.

The number of free parameters, which reflects model complexity, is notably higher for HC, TABU, and SaiyanH algorithms, possibly explaining why their LL scores are higher; they are not as constrained, allowing for a more nuanced fit to the data at the cost of complexity. Interestingly, MAHC's results are identical to the knowledge-based approach, suggesting that the pre-imposed structure from domain knowledge might align closely with the patterns discovered through the MAHC algorithm's learning process.

QUESTION 8: Select TWO knowledge approaches from those covered in Week 11 Lecture and Lab; i.e., any two of the following: a) Directed, b) Undirected, c) Forbidden, d) Temporal, e) Initial graph, f) Variables are relevant, and g) Target nodes. Apply each of the two approaches to the structure learning process of HC, separately (i.e. only use one knowledge approach at a time).

Knowledge approach	CPDAG scores							
	BSF	SHD	F1	LL	BIC	Free parameters	Number of Edges	Runtime
Without knowledge	0.162	36.5	0.309	-109503.035	-111866.063	383	21	12s
Initial	0.196	35	0.321	-109080.617	-111727.455	429	5	14s
Forbidden	0.162	36.5	0.309	-109475.043	-111949.127	401	19	21s

Table Q8

After trying Directed, Undirected, Forbidden, Temporal, Initial graph, I decided to stick with Initial and Forbidden as every other approach's performance diminished than the without knowledge.

Incorporating Professor Claes Fornell's ACSI model [1] into the structure learning reveals a complex network where customer loyalty is rooted in perceived value and moderated by price tolerance. The choice to use Initial and Forbidden knowledge has improved the stats. The Initial graph method improved CPDAG scores from 0.162 to 0.196 and reduced SHD from 36.5 to 35, indicating a more accurate model of customer satisfaction dynamics.

While the Forbidden constraints didn't significantly alter CPDAG scores, they ensured that our model didn't explore implausible connections, maintaining a reliable structure. This reflects in the steady CPDAG scores and subtle shifts in model complexity, as seen in the free parameters and edges.

The F1 score's rise to 0.321 for the Initial graph reflects enhanced predictive precision, while the increase to 429 free parameters suggests a richer yet more complex model. Conversely, the Forbidden approach maintained the F1 score at 0.309, indicating stability in predictions, with a slight complexity rise to 401 free parameters.

The impact of demographics is undeniable; age, income, and education distinctly affect customer expectations and perceptions, thereby shaping their value assessment and subsequent loyalty. Thus, a stratified approach to customer relationship management is essential for cultivating loyalty. The nuanced dance between understanding and strategic action suggests that businesses can foster loyalty by aligning customer satisfaction and price tolerance, taking demographic contexts into account.

Ultimately, the analysis filters the core of customer loyalty: it's constructed on the solid foundation of satisfaction, with perceived value as the foundation, and reinforced by the customer's price tolerance. Recognizing and responding to these multifaceted insights is key to unlocking sustaining customer loyalty. These findings, though expected, underscore the critical importance of integrating domain knowledge into predictive modelling for more nuanced and actionable insights.

References

1. Fornell, Claes, et al. "The American Customer Satisfaction Index: Nature, Purpose, and Findings." Journal of Marketing, vol. 60, no. 4, 1996, pp. 7–18. JSTOR, https://doi.org/10.2307/1251898. Accessed 19 Apr. 2024.
2. Hult, G.T.M., Morgeson, F.V., Morgan, N.A. et al. Do managers know what their customers think and why?. J. of the Acad. Mark. Sci. 45, 37–54 (2017). https://doi.org/10.1007/s11747-016-0487-4
3. Hult, Tomas; Morgeson, Forrest (2023), "The American Customer Satisfaction Index (ACSI): A Sample Dataset and Description", Mendeley Data, V2, https://doi.org/10.17632/64xkbj2ry5.2