# JP Morgan MLCOE TSRL 2026 Internship Question 3:

# Discrete choice model and credit card offers

Bank credit cards frequently run campaigns together with vendors and service providers to promote sales volume. These offers provide tangible benefits in the form of redemptions when consumers choose to redeem them. Typically structured as "spend x then get y back," or as some form of discount, these offers carry a clear dollar value, incentivizing consumers to engage with them (See <https://www.chase.com/personal/merchant-offers> for more context.). Clearly these campaigns can be costly to both the vendors and the banks issuing the cards. Hence estimating the demand of the consumers under different marketing conditions is crucial for the success of these promotional campaigns. The various forms of discrete choice models can be very useful tools in forecasting the demand.

## Part 1:

One possible choice is the deep context-dependent choice model of Zhang(25).

* Could you please implement, the corrected version if there are any errors, their model in choice-learn <https://artefactory.github.io/choice-learn/> using Tensorflow and Tensorflow probability?

Hint: choice-learn has Halo MNL implemented, feel free to use it as a reference to start.

* Can you write a report discussing the following?
  1. Are there any errors or unclear parts in the paper? If there are, please point them out and explain the unclear parts in the report.
  2. Do you get the same results as their synthetic data test?
  3. What additional tests could you come up with to verify the results?
  4. Comparing to the reproducing kernel Hilbert Space Choice model of Yang(25), what are the pros and cons of Zhang(25)?
  5. Do you think these models are suitable for the task of demand estimation of credit card offers? What are the potential problems or challenges?
  6. What are other models, traditional non-neural network based, or ML models that you think are more suitable or at least worth trying? Why?

## Part 2:

In the estimation problem in part 1, the problem of market-product level demand shocks (a.k.a. unobserved market-product characteristics) are not considered. Lu(25) proposed a new method to handle this problem instead of the traditional instrumental variable method.

* Could you please implement, the corrected version if there are any errors, their model in choice-learn <https://artefactory.github.io/choice-learn/> using Tensorflow and Tensorflow probability?
* Please continue the report discussing the following:
  1. Are there any errors or unclear parts in the paper? If there are, please point them out and explain the unclear parts in the report.
  2. Can you replicate their results (BLP with & without cost IV, Shrinkage) as in the simulation section (Section 4)? If not, do you have any hypotheses on why?
  3. Explain the benchmark models used in detail. What are the assumptions needed for the BLP + IV to work in the case of price endogeneity? Delineate key variables that may or may not be observed in choice model data that justifies the IV approach, and how to find suitable instruments that satisfy the required assumptions (which you should state). Provide and justify at least three examples of viable instruments in the credit card offer setting. Can you think of another benchmark model that could be used?
  4. How can we modify the deep context-dependent choice model of Zhang(25) with the same assumption as in Lu(25)? Can you design a simulation study and implement your idea in choice-learn to show that your modification is correct?
  5. Do you think the sparse assumption of Lu(25) applies to the credit card offer problem? ￼

## Bonus question 1: Storable goods and stockpiling

Some of the goods, such as detergent or other goods, can be stored. As pointed out in Ching(20), this changes majorly the choice modeling.

* How can we design a similar dynamic discrete choice model that can take into account the context, as well as unobserved market-product characteristics as discussed in part 1 and 2 to handle storable goods demand estimation?
* Can you design synthetic tests and implement your model in choice-learn to verify your model above?

## Bonus Question 2: Habit formation and peer group effect

After building a habit, such as going to a particular gym or going to a particular coffee house, we may continue to consume the service or product without any further discount. Furthermore, we tend to enjoy some activities more when going with friends. Our desire to watch a particular movie increase when our friends have watched it. Even better, we love watch movies with friends together. For credit card offers, we may give a series of discounts on different days to promote habit formation. Sometimes we offer discounts if people go in groups.

* What kind of choice models in the literature can handle habit formation?
* What kind of choice models in the literature can handle peer group effects?
* Which ones do you think are the most sensible ones for our problem? Can you design synthetic tests and implement your models in choice learn to show the effectiveness?

## Bonus Question 3: Constrained assortment optimization

Given the choice models developed above, we would like to optimize some metric by presenting the best set of offers to the credit card holder. However, there are frequent constraints we must observe. For example, some offers must be presented with some others, e.g. coffee with sandwiches together, or some goods, such as goods of rival competitors, never together.

* What are the algorithms in the literature for this kind of constrained assortment optimization problem given the model you have developed in part 1 and part 2?
* Given your literature survey above, which one do you think is the most suitable? What are the reasons?
* Can you implement this in choice-learn and design a set of synthetic tests to test your algorithm?

# References

[Ching(20)] Ching, Andrew T., Matthew Osborne (2020) Identification and Estimation of Forward-Looking

Behavior: The Case of Consumer Stockpiling. Marketing Science 39(4):707-726.

[Lu(25)] Lu Zhentong and Kenichi Shimizu, “Estimating Discrete Choice Demand Models with Sparse Market-Product Shocks”, 2025 <https://arxiv.org/abs/2501.02381>

[Yang(25)] Yang Yiqi, Zhi Wang, Rui Gao, Shuang Li, “Reproducing Kernel Hilbert Space Choice Model”, <https://dl.acm.org/doi/10.1145/3736252.3742630> 2025

[Zhang(25)] Zhang, Shuhan, Zhi Wang, Rui Gao and Shuang Li, “Deep Context-Dependent Choice Model”, ICML learning work shop, 2025, <https://openreview.net/forum?id=bXTBtUjb0c>