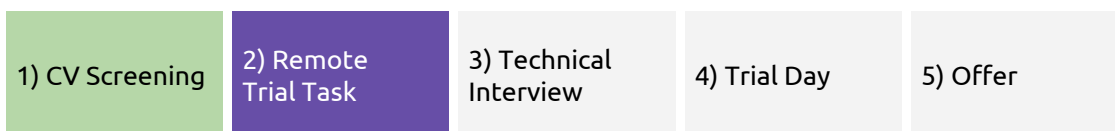


# SO1 Remote Trial Task

## Recruiting process

Thank you again for applying to SO1. As a reminder, the recruiting process for a ML position at SO1 consists of five consecutive steps:



We really liked your CV so in the next three steps (starting with this “remote task”) we want to assess whether you have the necessary skills to be successful at SO1:

1. theoretical knowledge on statistics, probability theory, and machine learning
2. experience in applying ML algorithms to real-world problems
3. good coding skills

The **remote trial task** below consists of two subtasks. In the first task you need to develop a formal probabilistic description of consumer behavior. In the second task we want you to implement a model to predict future consumer purchases. We are looking forward to your solution!

If you pass the remote task, the next step is a **technical interview**. During the interview we will discuss questions on machine learning (theory, methods, and applications), probability theory, and linear algebra. We will also ask a couple of follow-up questions on the remote task.

If you pass the technical interview stage as well, the final step in our recruiting process will be an onsite or remote **trial day** (based on where you are located). You will work closely with our ML team at the SO1 office and either spend more time on part 2 of the trial day tasks or implement a simple agent for individualised coupons within our “supermarket gym”—SO1’s homemade simulated environment for testing and developing reinforcement learning agents.

## Task 1: Formalisation of Consumer Shopping Behaviour

A consumer  $i$  shops in week  $t$  at a retailer  $r$ . The retailer carries several categories  $c$ . In each category  $c$ , the retailer offers multiple products  $j$ . The consumers decision process, that is the probability that consumer  $i$  purchases  $q_{ijt}$  units of product  $j$  in week  $t$ , can be modeled by

$$P(Q_{ijt} = q_{ijt}) = P(I_{ict} = 1) P(C_{it} = j | I_{ict} = 1) P(Q_{ijt} | I_{ict} = 1 \wedge C_{it} = j) \quad (1)$$

where  $P(I_{ict} = 1)$  is the probability of  $i$  purchasing in  $c$ ,  $P(C_{it} = j | I_{ict} = 1)$  is the probability that  $i$  purchases  $j$  conditioned on purchasing in category  $c$ , and  $P(Q_{ijt} | I_{ict} = 1 \wedge C_{it} = j)$  is the probability that  $i$  purchases  $q_{ijt}$  units of  $j$  in  $t$  conditioned on purchasing product  $j$  (in category  $c$ ). Whether the consumer buys in a category or not is independent from her purchase decisions in other categories. If she purchases in a given category, she picks exactly one product  $j$ . The probability of choosing product  $j$  in category  $c$  depends on (1) her (time-invariant) product preferences, (2) the products' prices in week  $t$ , and (3) whether product  $j$  was advertised or not (a boolean indicator). Of the chosen product  $j$ , the consumer buys  $n$  units ( $n$  is a positive integer).

*Your task:*

How would you model each of the three components: probability of category purchase  $P(I_{ict} = 1)$ , the probability of product choice within a category  $P(C_{it} = j | I_{ict} = 1)$ , and the probability for the purchased amount  $P(Q_{ijt} | I_{ict} = 1 \wedge C_{it} = j)$ ? What are suitable distributions? In your opinion, what drives the category purchase incidence? What factors besides the three mentioned above could influence product choice?

## Task 2: Predict Consumer Purchases

The data set attached to this task contains the purchase histories (i.e., shopping baskets) of 2,000 consumers over 49 weeks across 5 categories (*train.csv*). In simulating the basket data we assumed that consumers only buy one unit of a product in a given week. The data set also contains the price consumers paid for one unit of product  $j$  in week  $t$  and a boolean variable that indicates whether the purchased product was advertised (1) or not (0). We also provide the week 50 promotion schedule (discounts and advertising) for all products (*promotion\_schedule.csv*).

*Your task:*

Use the data to build a ML model for consumer purchases. With the trained model, predict week 50 purchases for all 80,000 possible consumer-product combinations (40 products x 2,000 consumers) in the data. Feel free to use any non-parametric or "black box" model you consider appropriate (i.e., you don't have to follow the formalisation from part 1). Please provide your predictions as a .csv file (cf. *prediction\_example.csv*) that contains the columns  $i$  (consumer),  $j$  (product), and prediction. We will benchmark your predictions against observed purchases using the AUC metric.