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ACRG Applied Choice Research Group

Identifying consideration sets through search and an implementation using Shiny

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The search for information - the search for alternatives

The role that information and search plays in choice has a long history in economics

- Search models – Simon (1955), Stiegler (1961), Weitzman (1979), Gabaix et al. (2006)
- Consideration set models – Richardson (1982), Roberts and Lattin (1991)
- Information acquisition models – Hausmann and Lage (2008), Chorus et al. (2013)

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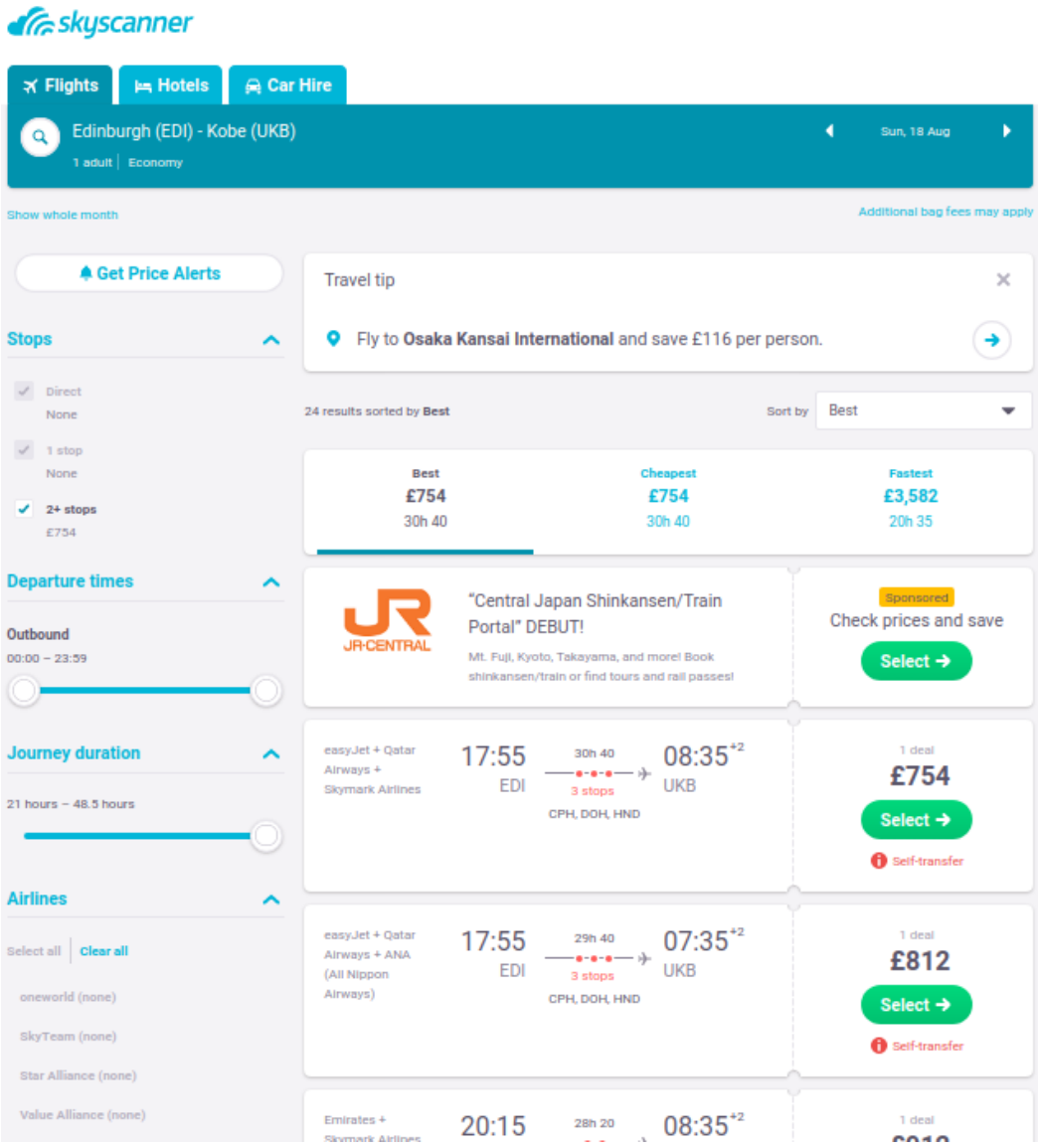
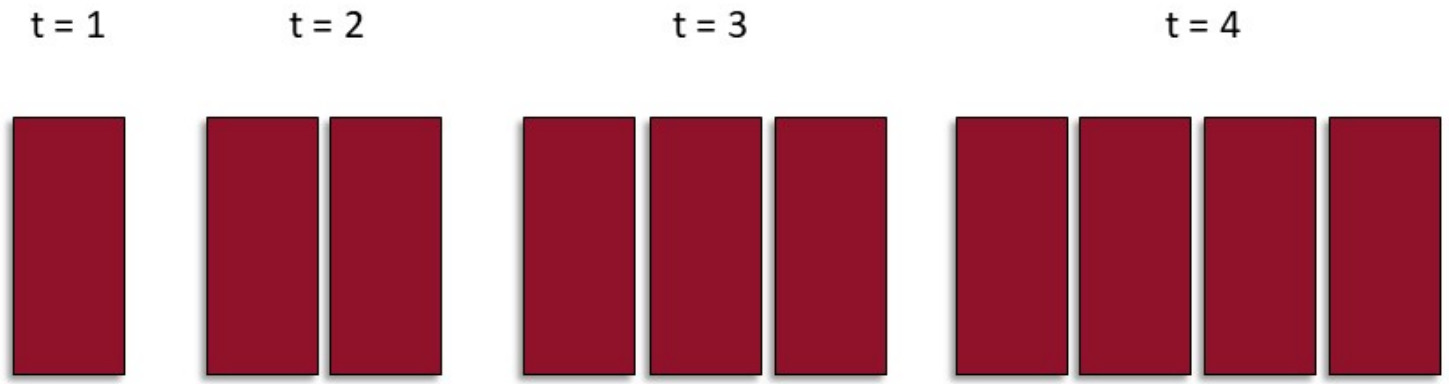


This means that consideration sets grow sequentially with each period of search

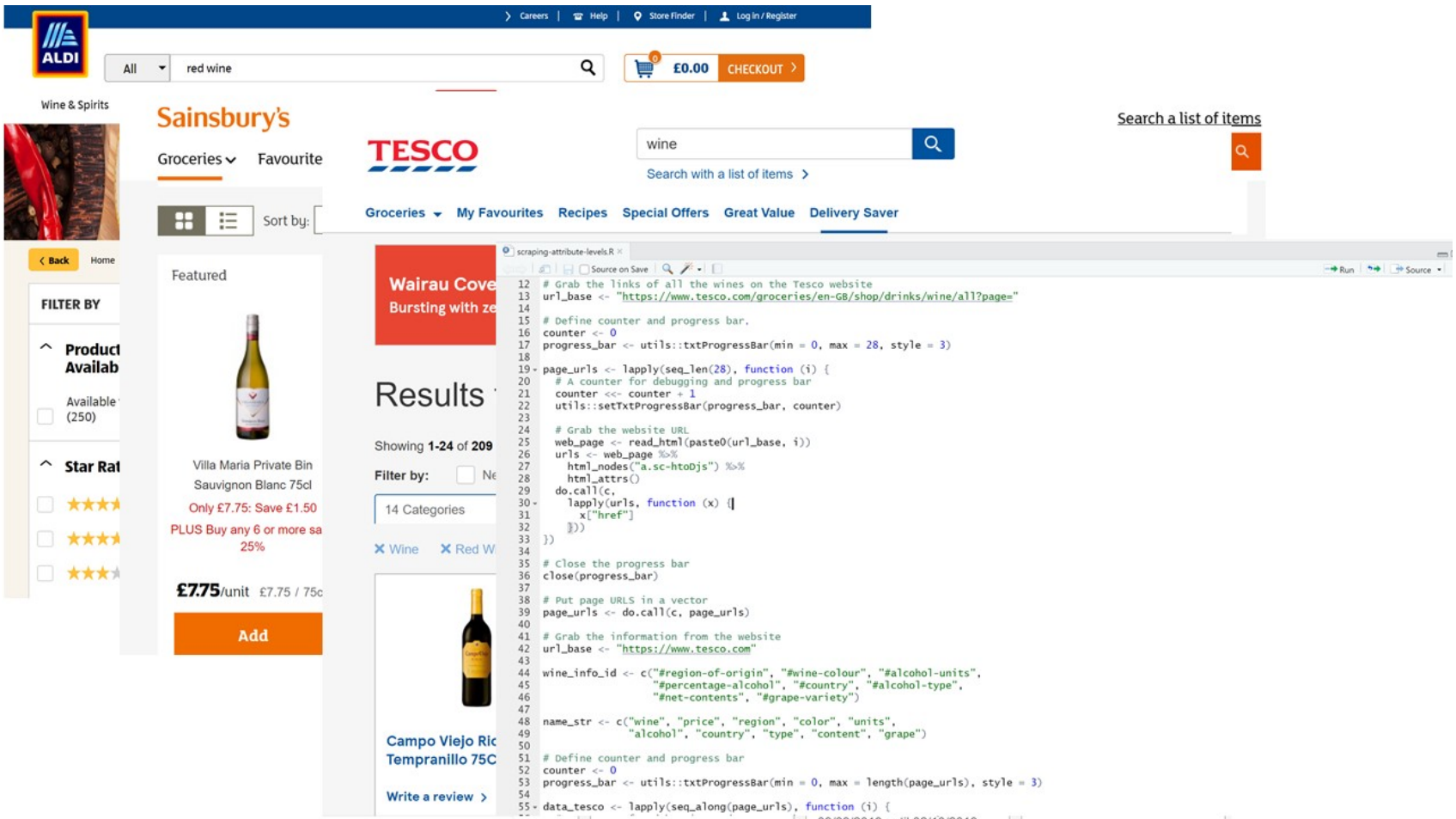


Gathering data to test hypotheses with respect to search and satisficing

A good that is familiar, reasonably priced and induces people to search

Selected attributes: Country of Origin, Color, Alcohol Content, Grape Variety, Characteristic, Organic and Price

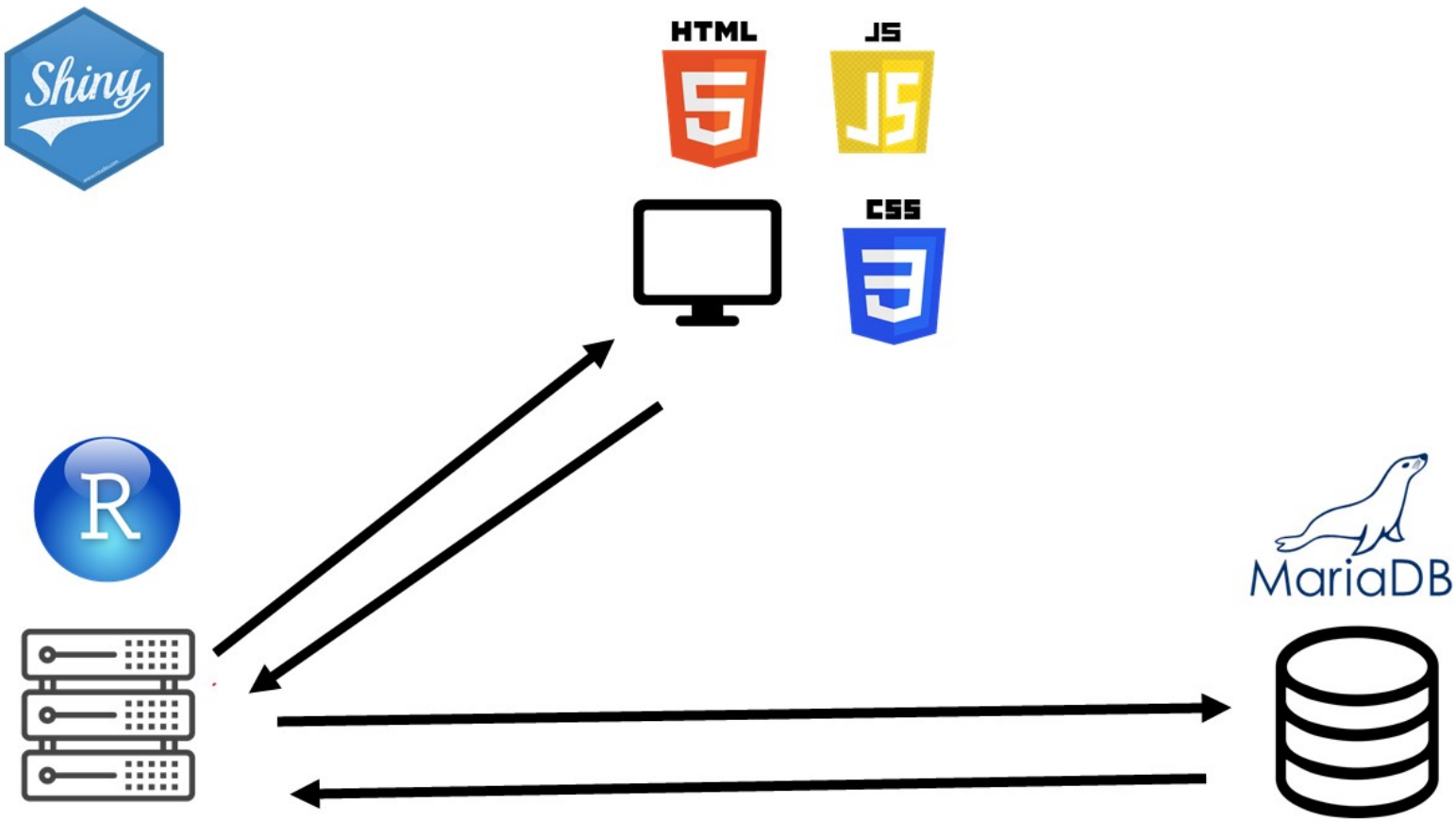
We used a web scraping algorithm to gather information on our attributes



We sample alternatives according to how common they are in the store

	A	B	C	D	E	F	G	H
1	country	color	alcohol	grape	characteristic	organic	price	weight
2	New Zealand	White	11.50%	Pinot Grigio	2 - Semi dry	No	8	3.02E-16
3	South Africa	Red	13%	Tempranillo	5 - Full bodied	Yes	4.5	2.39E-15
4	Chile	Red	14%	Malbec	5 - Full bodied	Yes	5.5	5.26E-16
5	New Zealand	RosÃ©	10.50%	Merlot	1 - Dry	Yes	5.5	2.62E-17
6	Italy	White	14.50%	Blend	1 - Dry	Yes	15	1.63E-16
7	South Africa	Red	11%	Malbec	5 - Full bodied	Yes	5.5	3.56E-16
8	USA	RosÃ©	12%	Pinot Noir	3 - Medium dry	No	5.75	2.83E-16
9	Italy	RosÃ©	14%	Tempranillo	4 - Semi sweet	Yes	9.5	7.08E-17
10	Australia	Red	11.50%	Blend	1 - Light bodied	Yes	7.25	1.12E-15
11	New Zealand	RosÃ©	13%	Cabernet Sauvignon	3 - Medium dry	No	16.5	6.16E-17
12	Italy	Red	12%	Blend	1 - Light bodied	Yes	8.5	6.13E-16
13	France	White	10%	Sauvignon Blanc	3 - Medium dry	No	5	4.96E-16
14	USA	White	12%	Pinot Grigio	2 - Semi dry	Yes	8.75	4.44E-16
15	New Zealand	RosÃ©	12%	Pinot Noir	4 - Semi sweet	Yes	5	3.84E-16
16	New Zealand	White	13%	Pinot Grigio	1 - Dry	Yes	17.5	2.89E-16
17	South Africa	Red	12.50%	Merlot	4 - Full bodied	No	6.5	1.07E-15
18	Italy	RosÃ©	14%	Merlot	3 - Medium dry	Yes	6.25	7.08E-17
19	New Zealand	Red	15%	Tempranillo	4 - Full bodied	Yes	11	2.19E-17
20	Italy	RosÃ©	12%	Pinot Noir	4 - Semi sweet	No	5.5	3.67E-16

We implement the survey using Shiny and host it on shinyapps.io



An example using Shiny

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Question 1: Please choose your most preferred wine

	None of these wines	Wine 1	Wine 2	Wine 3
Country		Australia	Chile	Australia
Color		White	White	Red
Alcohol		12%	13.5%	12.5%
Grape		Chenin Blanc	Blend	Tempranillo
Characteristic		1 - Dry	3 - Medium dry	5 - Full bodied
Organic		No	Yes	Yes
Price		5	9	13
I choose	○	○	○	○

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Economics Division

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Econometric model

Utility can be described by a separable and additive utility function

$$u_{nis} = \beta x_{nis} + \varepsilon_{nis}$$

U_{nis} Utility

β Vector of parameters to be estimated

X_{nis} Levels of the attributes

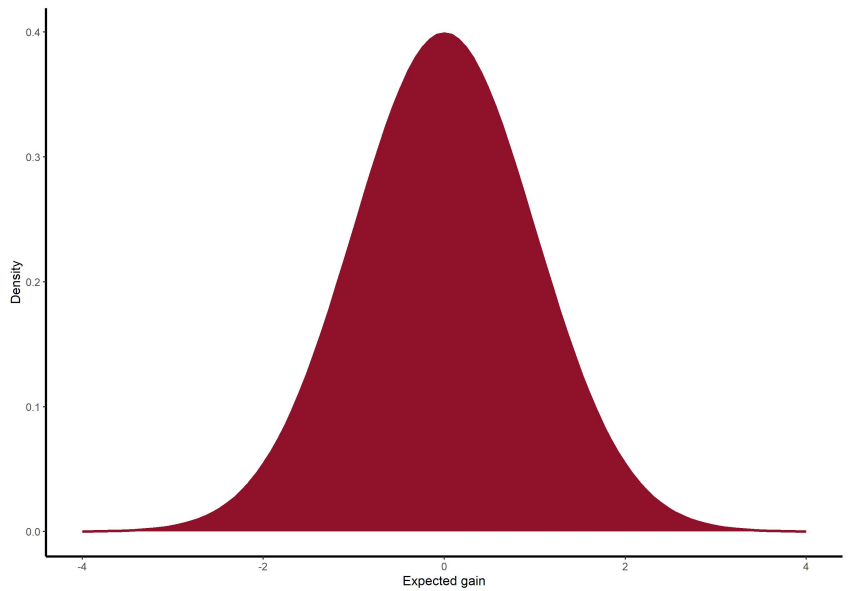
ε Type I Extreme value distributed error term with variance $\pi^2/6$

The possible gain from search is the difference between any alternative and the current best

$$g = u - u_{\max}$$

The value of all possible gains is the area under the "gain" curve

$$\bar{g} = \int_{-\infty}^{+\infty} gP(g)\mathrm{d}g,$$

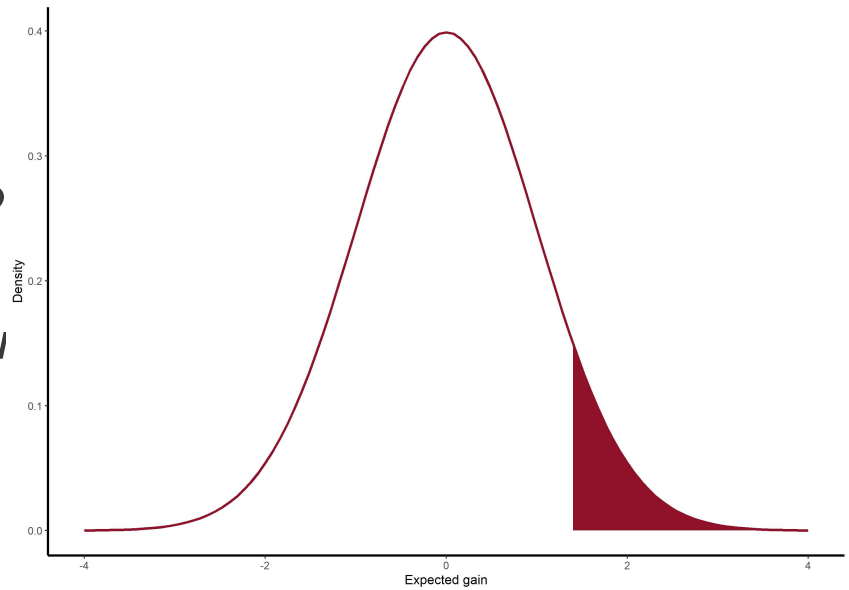


With recall you cannot lose utility by searching for another alternative

$$g = \begin{cases} u - u_{\max} & \text{if } u \geq u_{\max} \\ 0 & \text{if } u \leq u_{\max} \end{cases}$$

The gain from searching is the area under the "gain" curve above the current best

$$
\begin{aligned}
\bar{g} &= \int_{u_{\max}}^{+\infty} (u - u_{\max})\, \phi(u) \mathrm{d}u \\
&= \int_{u_{\max}}^{+\infty} u \phi(u) \mathrm{d}u - \int_{u_{\max}}^{+\infty} u_{\max} \phi \\
&= \phi(u_{\max}) - u_{\max} \int_{u_{\max}}^{+\infty} \phi(u) \mathrm{d}u
\end{aligned}
$$



where

$$u_{\max} = (U_{\max} - \mu_t) / \sigma_t$$

An individual will search as long as expected gains are higher than the marginal cost of searching

$$\bar{G} - \bar{c} > 0$$

where

$$\bar{G} = \bar{g}\sigma$$

i.e. the non-standardized gain to be compared with the marginal cost of search $\bar{c}$, e.g. time, money, cognitive cost of maintaining a consideration set

The log likelihood function

$$P(i_s|C_{ns}) = \prod_{t=1}^{T=J} \left[\frac{\exp(\beta x_{nis})}{\sum_{j \in C_{ns}^t} \exp(\beta x_{njs})} \right]^{I_t}$$

where

$$I_t = \begin{cases} 1 & \text{if } \bar{G}_t - \bar{c}_t < 0 \quad t = t* \\ 0 & \text{if } \bar{G}_t - \bar{c}_t \geq 0 \quad \forall \quad t \neq t^* \end{cases}$$

and t^* is the first time the condition is TRUE.