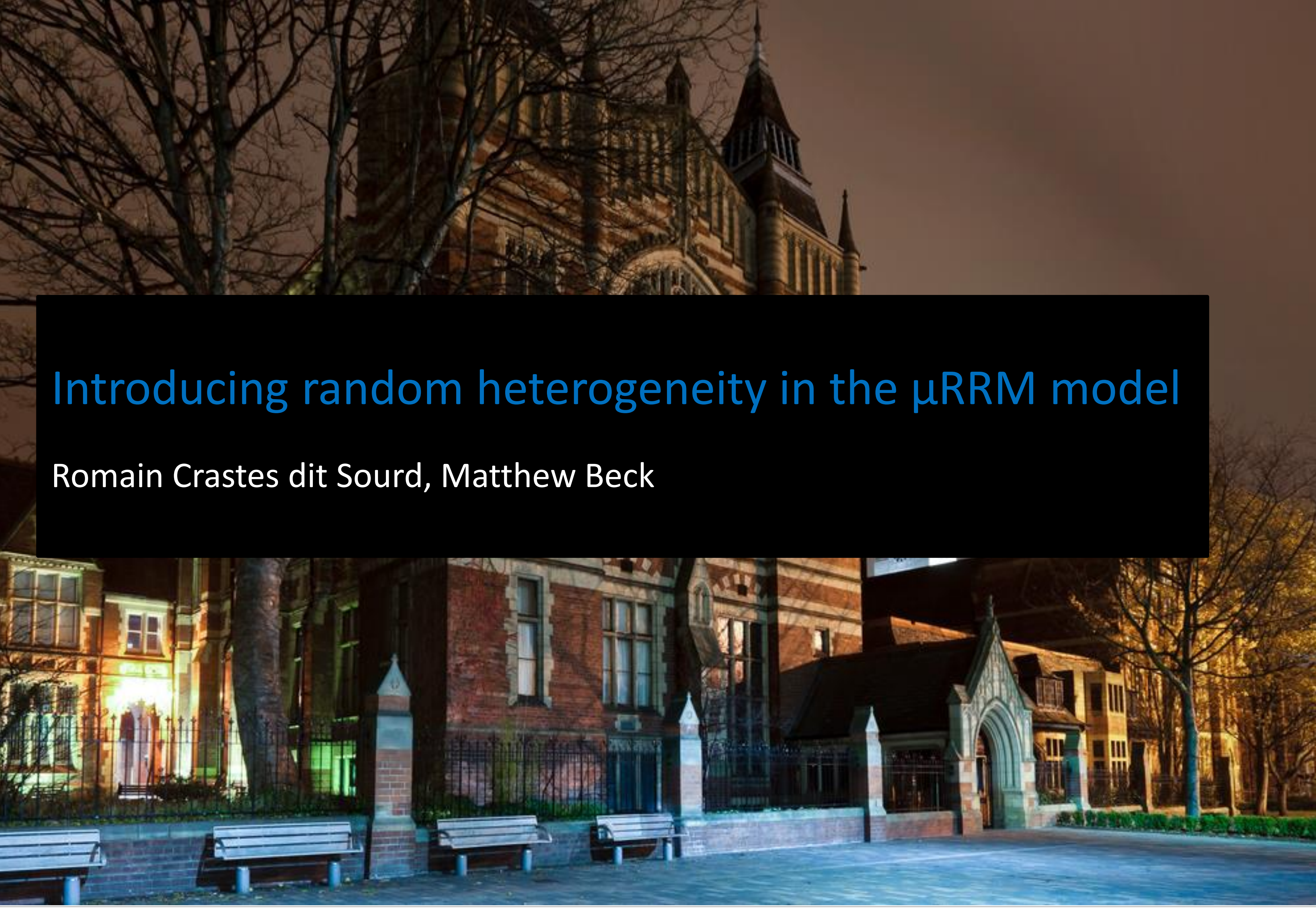

Introducing random heterogeneity in the µRRM model

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Outline

- The μRRM model
- Potential evolutions
- Application
- Conclusions

Let's first introduce the classical RRM model (Chorus, 2010)

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$$RR_{in} = \sum_{j \neq i} \sum_m \ln(1 + \exp(\beta_m [x_{jmn} - x_{imn}]) + \varepsilon_{in}$$

- ε_{in} is i.i.d type I EV distributed with variance $\pi^2/6$

- Choice probabilities correspond to

$$\frac{e^{-R_{in}}}{\sum_j e^{-R_{jn}}}$$

Now let's move to the μRRM model (Cranenburgh *et al.*, 2015)

- This approach generalizes the classical RRM model
- The variance of the error term can be estimated
- The size of the scale parameter corresponds to the profundity of regret imposed by the μRRM model
- « *the notion of profundity of regret refers the extent to which RRM models impose regret minimization behaviour* »

The μRRM model

- $RR_{in} = \sum_{j \neq i} \sum_{m} \ln(1 + \exp(\frac{\beta_m}{\mu}[x_{jmn} - x_{imn})] + \varepsilon_{in}$

With $\varepsilon_{in} \sim i.i.d.EV(0,\mu)$

- Choice probabilities now correspond to

$$\frac{e^{-\mu R_{in}}}{\sum_j e^{-\mu R_{jn}}}$$

The μRRM model – special cases

- When μ is arbitrarily large, the μRRM model exhibits linear additive random utility maximization

- When μ is arbitrarily small, the difference between the utility one gets from a gain and the regret one gets from a loss is very strong. In this case, the μRRM model takes the form of the P-RRM model

- When μ is close to 1 the model corresponds to a normal RRM model

Why using the the µRRM model rather than a Latent class RUM-RRM model?

- The µRRM approach allows to model the profundity of regret in a continuous manner

- It gives a measure of « how much regret there is » rather than « what is the percentage of people expressing a regret minimisation behaviour »

- The µRRM can emulate the results from a LC RUM-RRM while avoiding the estimation issues when µ is set up to be random

Going beyond the µRRM model (1)

- In this work, we propose a series of extensions for the µRRM model
- We seek to accomodate heterogeneity in the profundity of regret
- Different people use different decision rules
- Different attributes trigger different choice strategies

Going beyond the µRRM model (2)

- We propose the following extensions:

- The random µRRM model
  - µ is allowed to be normally distributed across respondents

- The multiple random µRRM model
  - Different, randomly distributed µ are estimated for each attribute

The random μRRM model

- $RR_{in} = \sum_{j \neq i} \sum_{m} \ln(1 + \exp(\frac{\beta_m}{\mu}[x_{jm} - x_{im}]) + \varepsilon_i$

- μ now corresponds to mean_μ + sd_u ∗ random draws

- The random draws are normally distributed

- It is a very straightforward change to implement

The multiple random μRRM model

- $RR_{in} = \sum_{j \neq i} \sum_m \mu m \, . \ln(1 + \exp(\frac{\beta_m}{\mu m}[x_{jm} - x_{im}]) + \varepsilon_i$

- Each μm now corresponds to mean_μm + sd_um ∗ random draws

- This model does not seem to converge well unless we estimate a full variance_covariance matrix for the random draws

- In this case, the choice probability correspond to:

$$\frac{e^{-R_{in}}}{\sum_j e^{-R_{jn}}}$$

Application

- Our dataset comes from an Australian regional mobility survey. Each respondent faced 10 choice tasks involving a choice between four labelled alternatives: plane and taxi, plane and shuttle, car, coach and taxi

- <u>Attributes:</u>
  - departure time
  - average travel time
  - travel time early
  - travel time late
  - Cost
  - wait time for transfer service
  - cost of transfer service
  - Duration for transfer service

- 811 respondents

	uRRM		Random uRRM		Multiple random uRRM	
	est	t ratio	est	t ratio	est	t ratio
bdepatime	**1.74**	**9.44**	**1.65**	**5.21**	**1.95**	**8.49**
btravtime	**-0.76**	**-11.51**	**-0.81**	**-4.48**	**-0.84**	**-3.01**
bearlymin	-2.47	-1.55	-2.56	-1.78	**-2.99**	**-3.03**
blatemin	**-1.41**	**-8.33**	**-1.44**	**-4.45**	-1.45	-1.61
btravcost	**-2.06**	**-11.70**	**-2.04**	**-10.45**	**-2.02**	**-13.16**
bwaittime	**-2.52**	**-3.99**	**-2.45**	**-3.99**	**-2.73**	**-3.27**
btrantime	**6.36**	**2.20**	**5.25**	**4.12**	**4.95**	**3.99**
btrancost	**-3.55**	**3.11**	**-3.01**	**2.54**	**-2.86**	**-2.05**
alt1	**-0.16**	**-7.89**	**-0.19**	**-5.58**	**-0.44**	**-2.51**
alt2	-0.65	-1.47	-0.48	-1.42	0.19	1.12
alt3	**-0.52**	**-6.47**	**-0.52**	**-5.54**	**-1.75**	**-22.25**

	uRRM		Random uRRM		Multiple random uRRM	
	est	t ratio	est	t ratio	est	t ratio
mu1	**1.21**	**3.92**	**1.14**	**3.87**	**3.10**	**3.15**
mu2					**23.38**	**3.80**
mu3					**-0.34**	**-2.89**
mu4					-0.65	-1.49
mu5					6.27	0.01
mu6					**-0.05**	**-2.56**
mu7					**-0.16**	**-2.25**
mu8					**-0.26**	**-2.00**
sdmu1			0.08	0.78	-0.05	0.01
sdmu2					0.11	**2.87**
sdmu3					0.34	**1.99**
sdmu4					-0.43	-1.36
sdmu5					0.14	-0.93
sdmu6					**0.14**	**2.24**
sdmu7					0.26	0.89
sdmu8					**0.15**	**1.94**
AIC	17963.13		179851.54		17880.81	
LL	-8969.565		-8958.781		-8885.404	

Discussion

- First results look promising:
  - ➢ Significant observed heterogeneity in the profundity of regret
  - ➢ Significant rando heterogeneity
- Model performed (much) better than a LC RUM RRM
  - ➢ More convenient way to introduce heterogeneity in decision rules in SP survey
- Some challenges: « more convenient » doesn’t mean perfect (lots of issues with local optimas)


ANY
QUESTIONS
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