

A Cognitive Model of How People Make Decisions Through Interaction

Andrew Howes
Summer School 2017

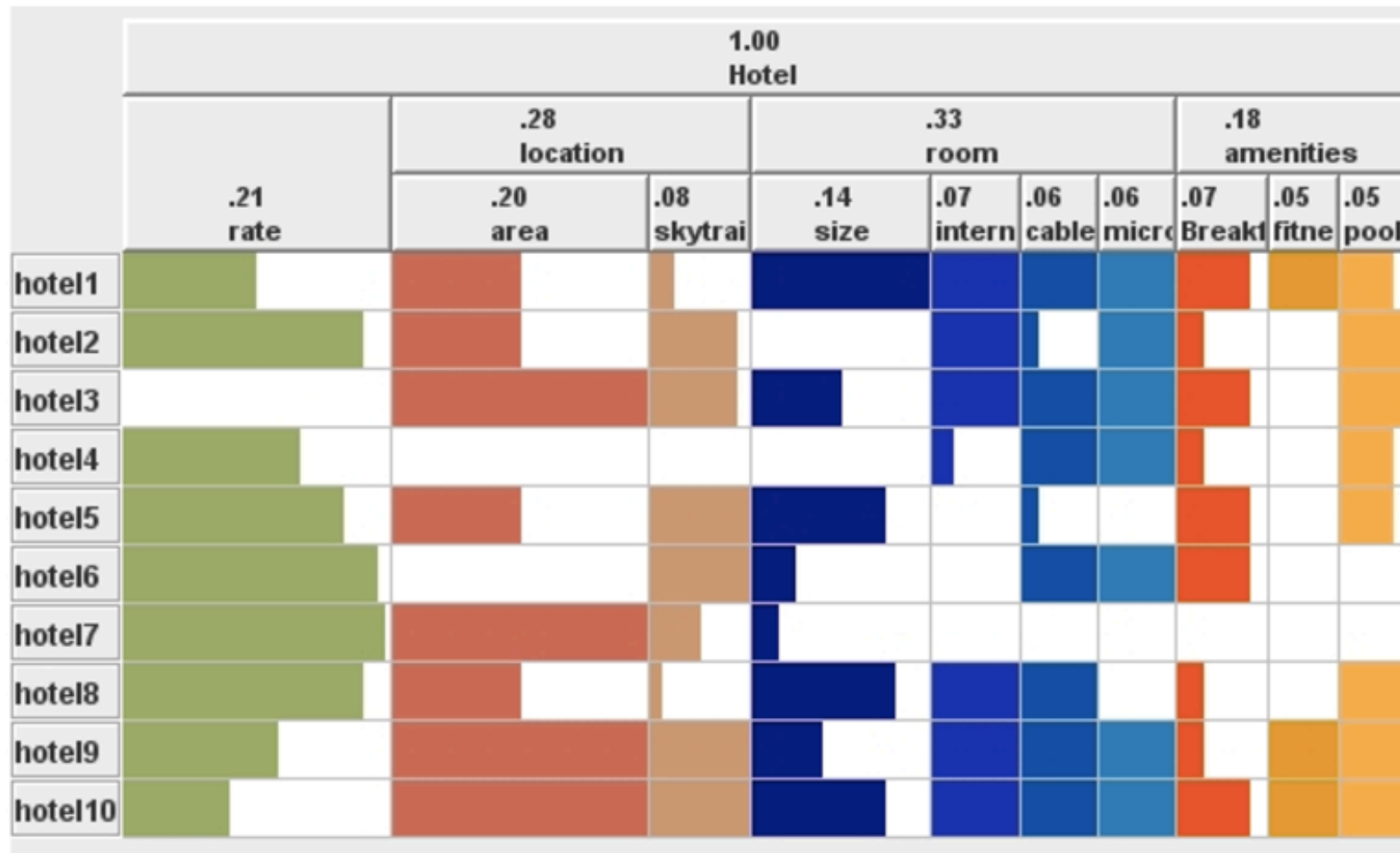
Which hotel?

- Hyatt Regency?
- Hyatt House?
- Grand Hyatt?
- Hyatt Place?

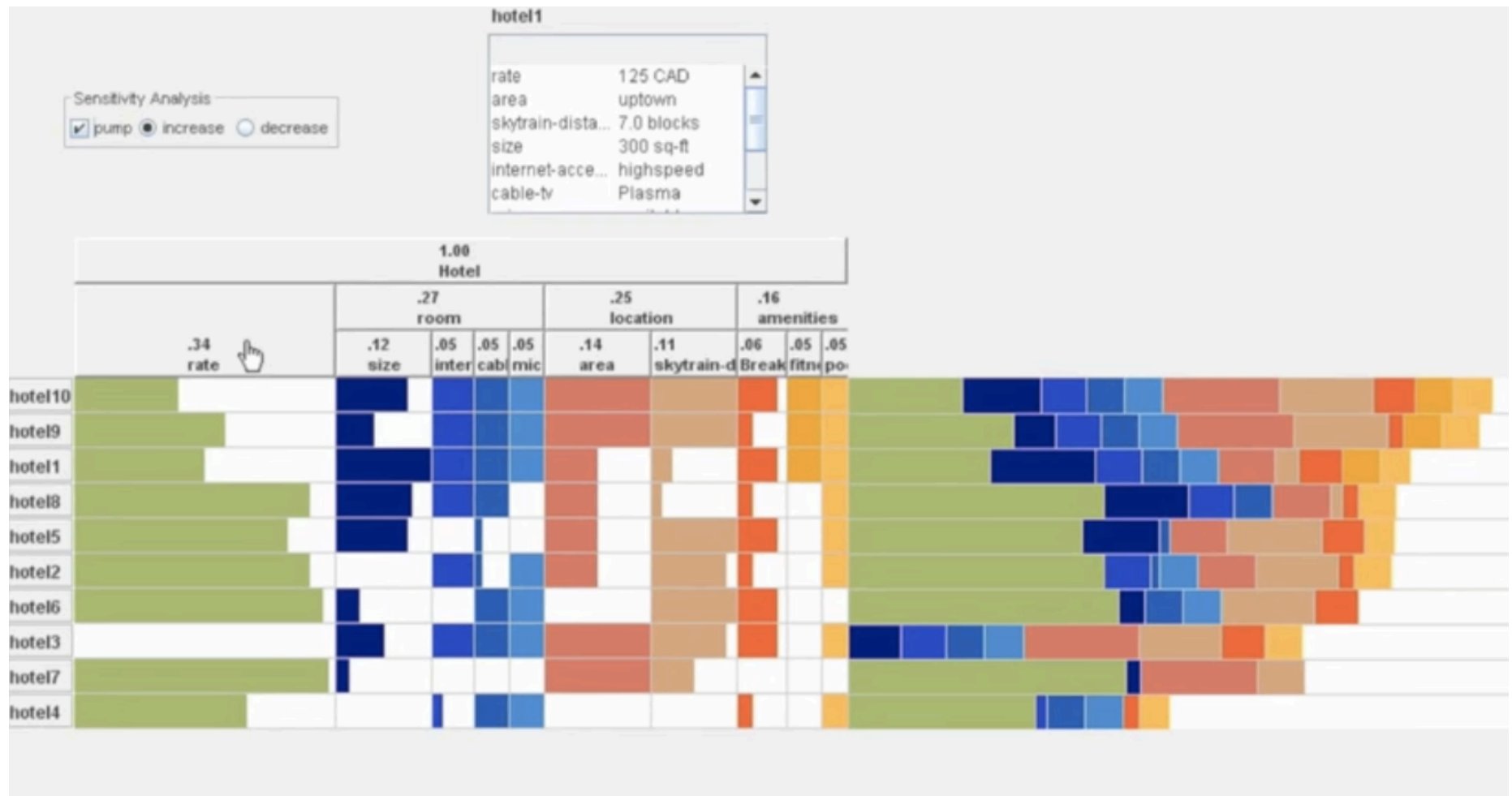


- This talk is about:
 - the application of machine learning to predicting how people use visualisations.
 - modeling users with (1) a mathematical model of visual acuity (2) Bayesian state estimation, and (3) reinforcement learning to predict strategies.
- Technical details are in the paper!

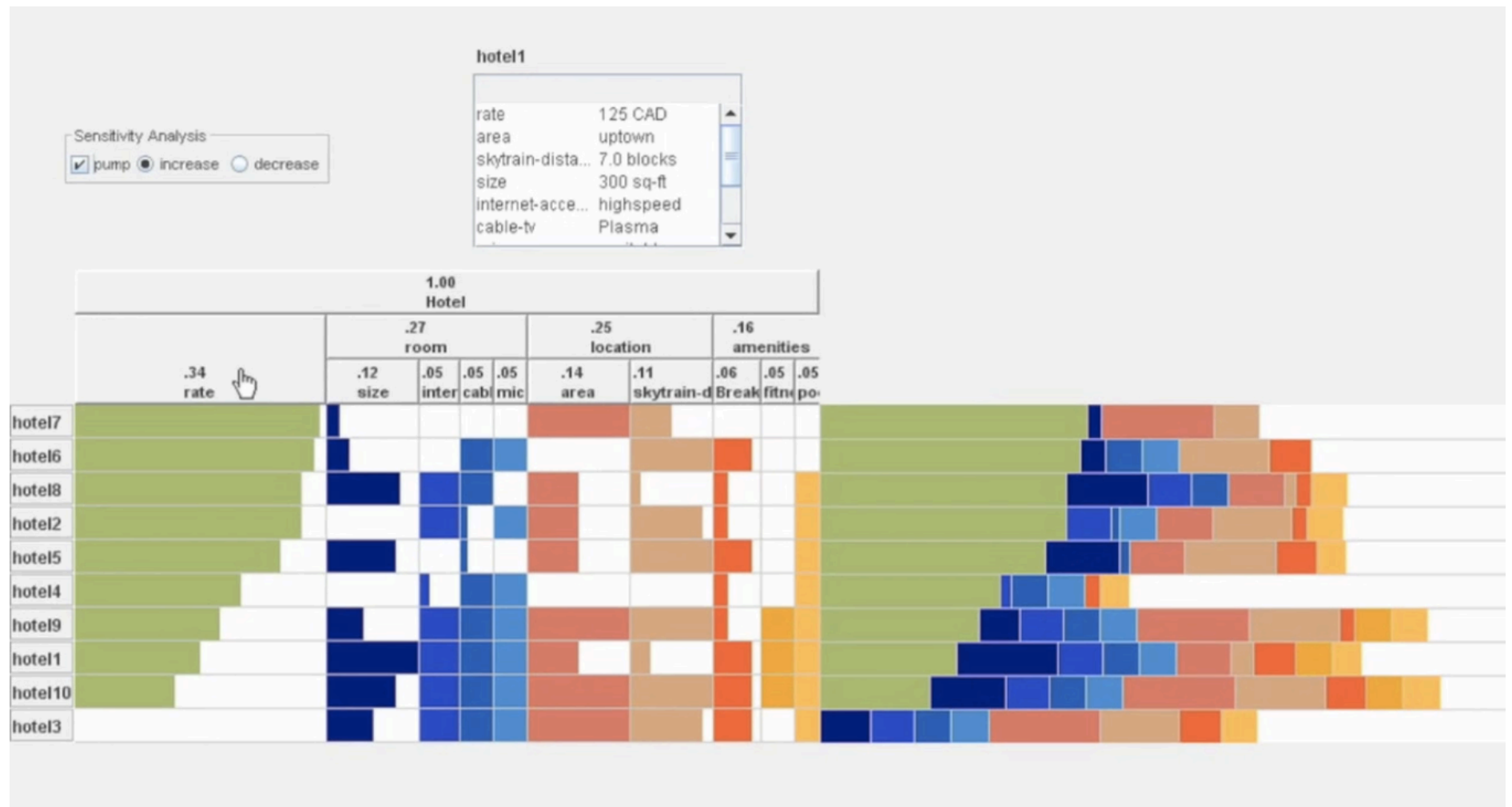
value charts



Conati et al., 2014

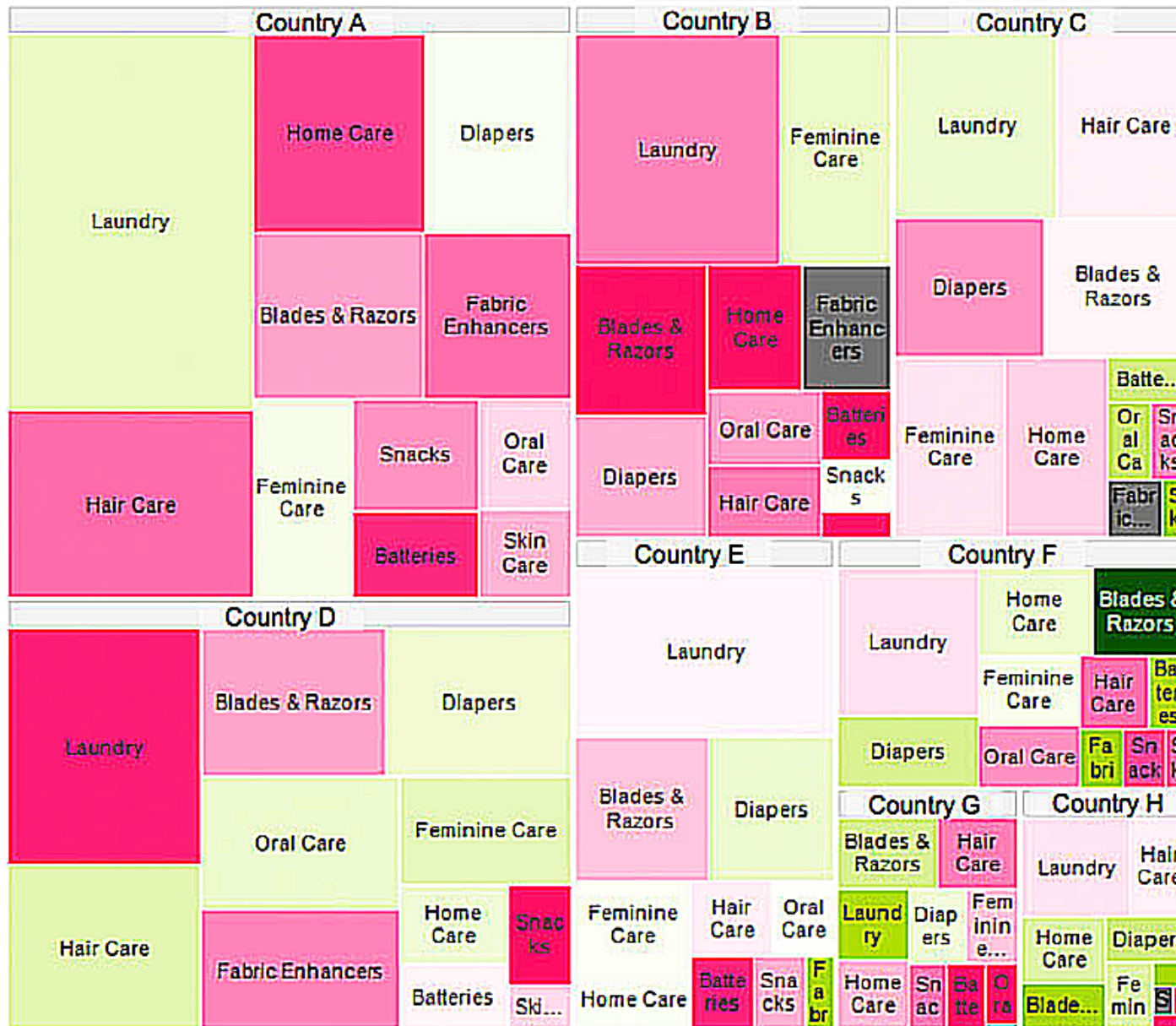


Choose a hotel based on all attributes
Supports a Weighted Additive (WADD) Strategy.

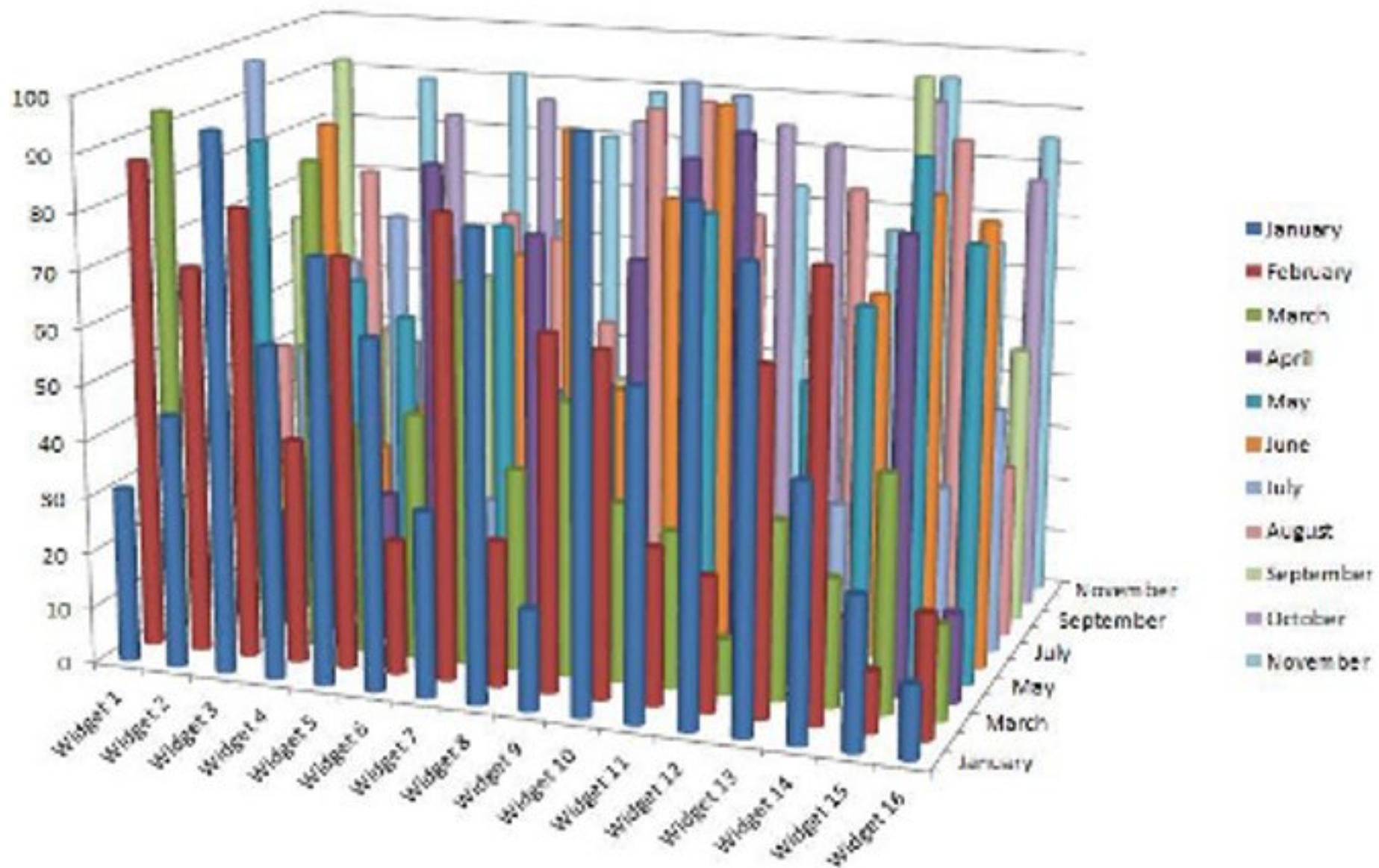


Choose a hotel based on a single attribute.
Supports a Take-the Best Strategy (TTB).

Proctor and Gamble color map



Choose an investment opportunity based on colour and size



But not all visualisations work...

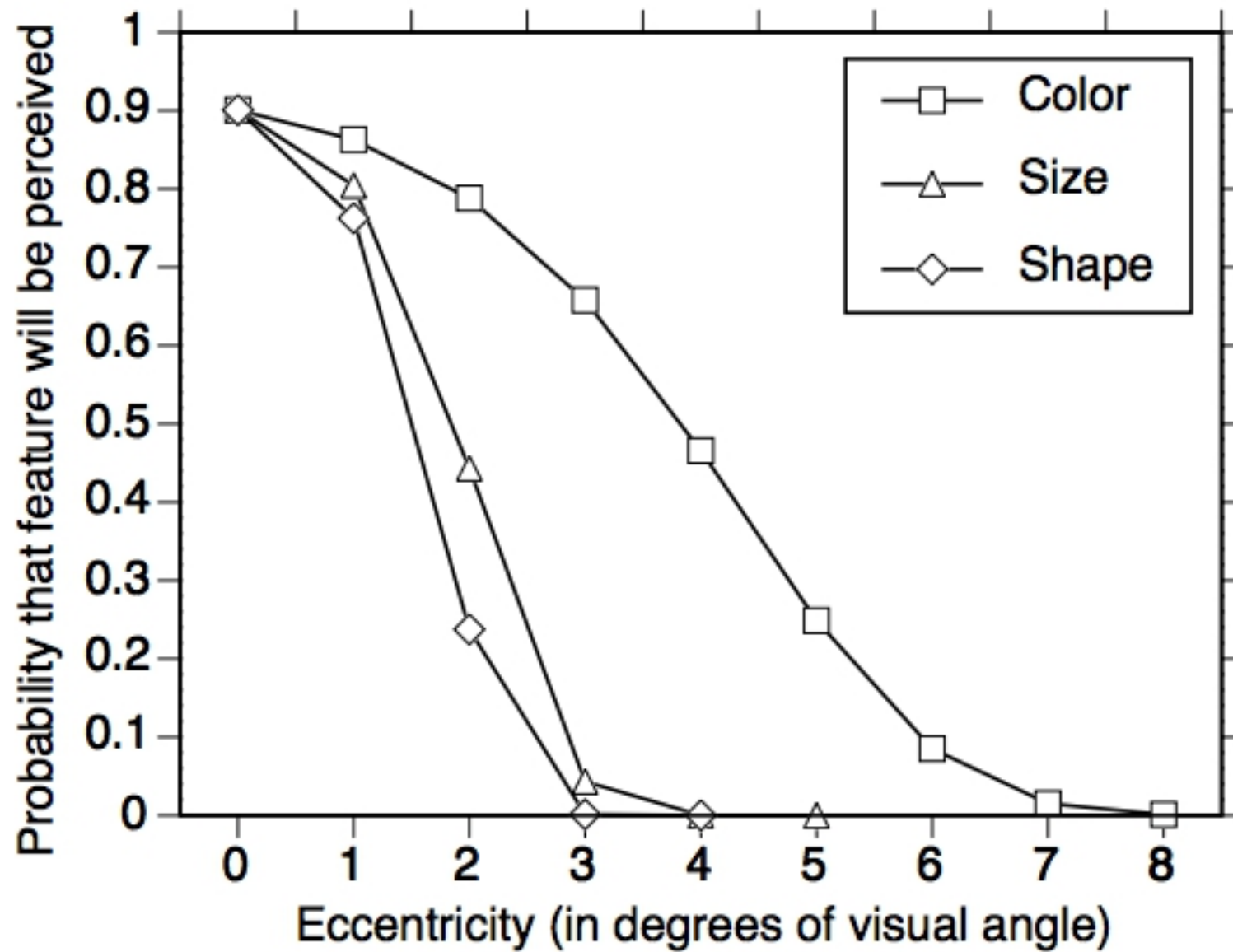
- How should designers make use of organisation, size, text, colour, dimensions, in visualisations?
- Empirical studies (e.g. Conati et al., 2014).
- Theory and models (e.g. Russell, Stefik, Pirolli & Card, 1993; Gigerenzer & Gaissmaier, 2011).
 - Cost of knowledge function
 - Adaptive toolbox — simple heuristics that make us smart (for example, WADD versus TTB).

What do we need to model interactive decision making?

- a model of (1) **human vision** (the costs of acquiring information)
- a model of (2) the **strategies** that determine what to look at and when to stop.

(1) Human Vision

- It is limited
- eye movements are required to bring the high acuity fovea to bear on useful elements of the display.
- peripheral vision can be used to distinguish some types of attribute better than others, e.g. colour better than shape (Kieras and Hornof, 2014).



Kieras and Hornof (2014)

We can formalise this and code it in a computer program:

$$P(\textit{available}) = P(\textit{size} + X > \textit{threshold}) \quad (1)$$

Where X is a random variable and threshold reduces with eccentricity.

We can also formalise the duration required to move the eyes (saccade to a new location):

$$D = 37 + 2.7A \quad (2)$$

(2) The strategies

- Which eye movements will a person make and when will they have gathered enough information to make a decision?
- Strategies are adaptive to the limitations of the visual system and to the design of the visualisation.

- Fortunately, there is a sequential decision making framework that is suitable for learning approximately optimal strategies...

Partially Observable Markov Decision Process (POMDP)

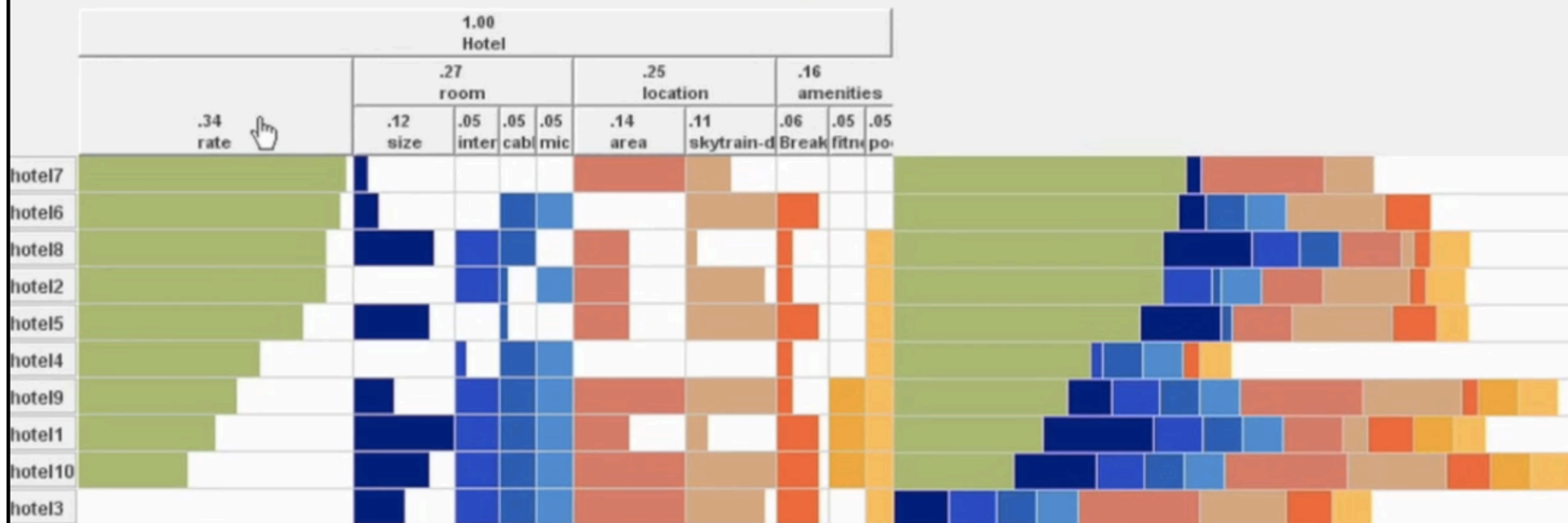
- **POMDP** is a framework for modeling decision making processes where:
- **Observations** are made by partial or limited perceptual systems, e.g., as bounded by the visual acuity function.
- **Actions** are costly and have probabilistic outcomes.
- The problem is to find strategies that maximise **reward** where reward is a trade-off between speed and accuracy

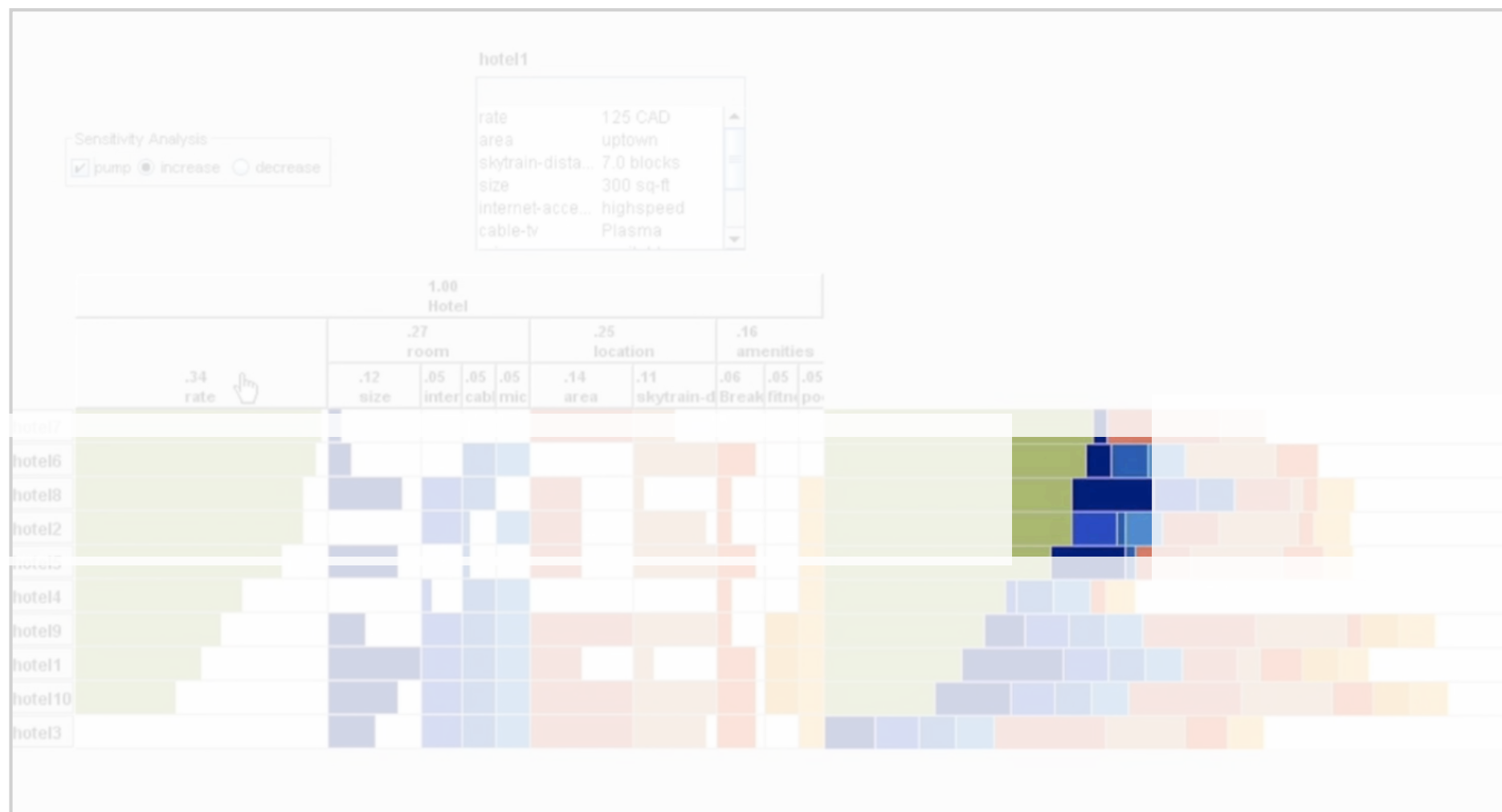
Sensitivity Analysis

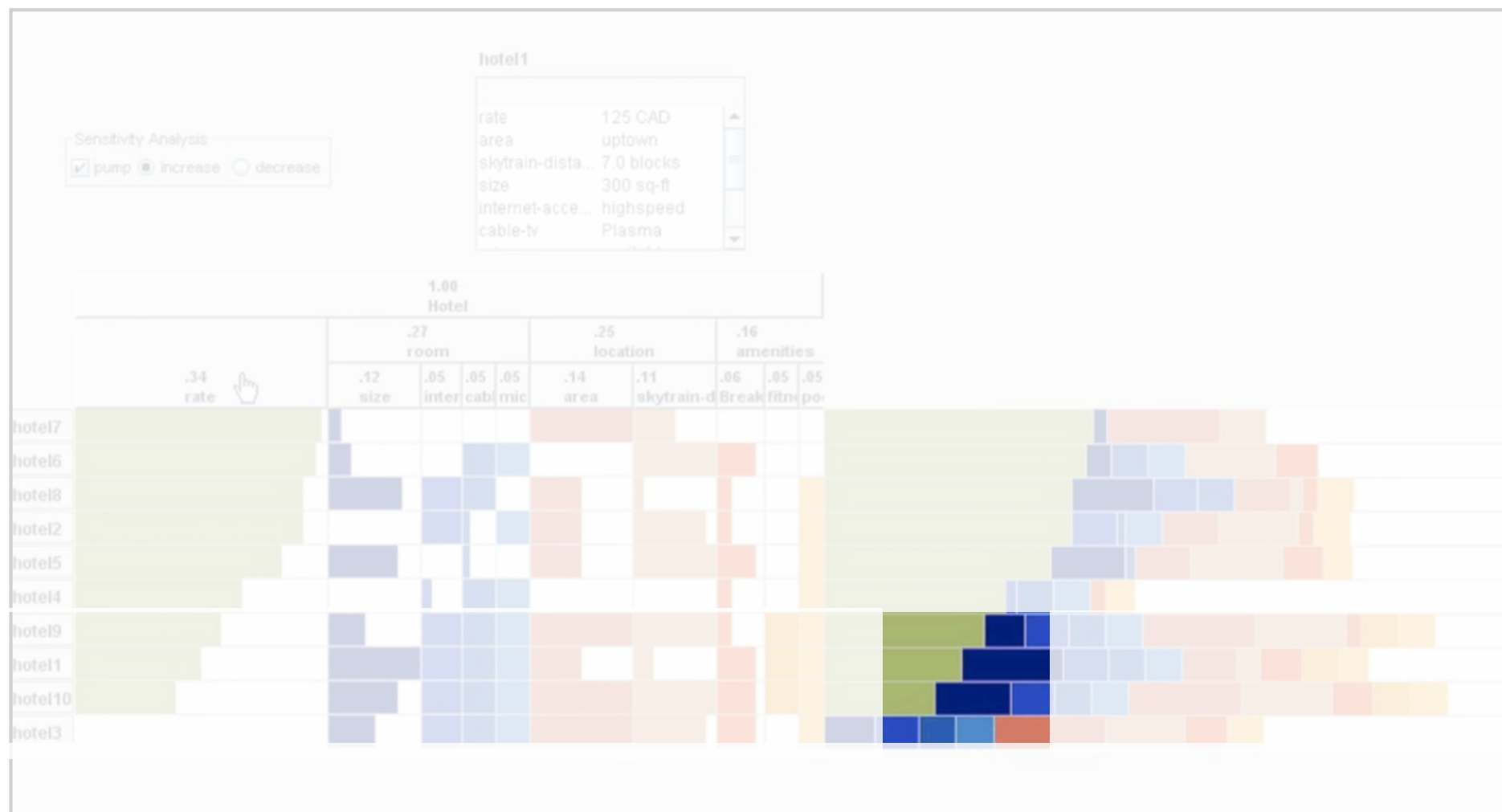
☒ pump ☒ increase ☐ decrease

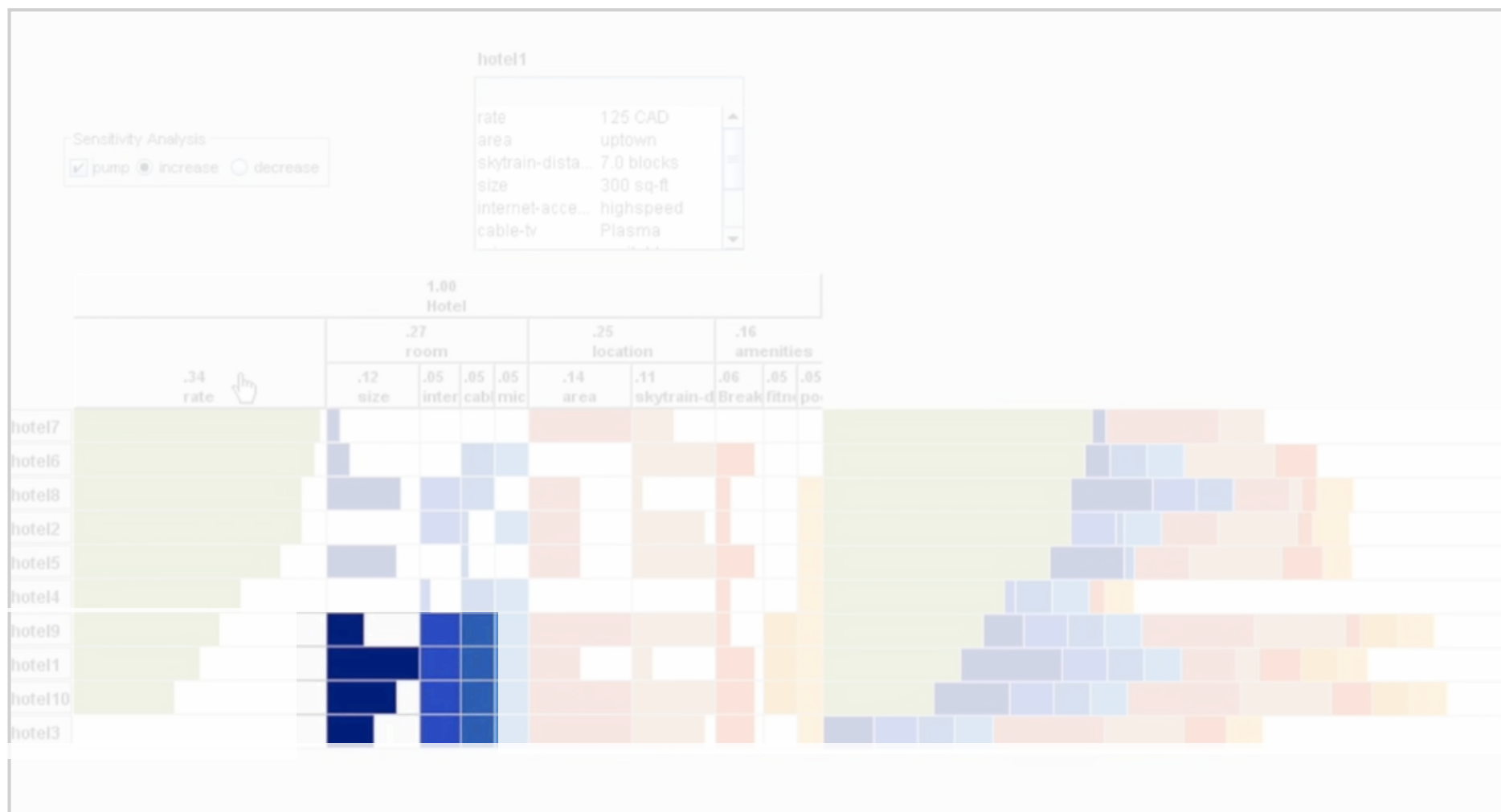
hotel1

rate 125 CAD
 area uptown
 skytrain-dista... 7.0 blocks
 size 300 sq-ft
 internet-acce... highspeed
 cable-tv Plasma









Bayesian Belief update

$$b_{t+1}(s_i) = \frac{b_t(s_i) \times p(o_{t+1} \mid s_i, a_{t+1})}{\sum_{s_i \in S} p(o_{t+1} \mid s_i, a_{t+1}) b_t(s_i)} \quad (5)$$

Learning strategies

- Because we framed the problem as a POMDP we were able to use **reinforcement learning** to acquire strategies for performing the task.
- We used Q-learning to learn strategies that **approximately maximize reward**,
- ... where a bigger reward was given for good quality fast decisions.

$$Q(s_t, a_t) \leftarrow \underbrace{Q(s_t, a_t)}_{\text{old value}} + \underbrace{\alpha_t}_{\text{learning rate}} \cdot \left(\overbrace{\underbrace{r_{t+1}}_{\text{reward}} + \underbrace{\gamma}_{\text{discount factor}} \cdot \underbrace{\max_a Q(s_{t+1}, a)}_{\text{estimate of optimal future value}}}_{\text{learned value}} - \underbrace{Q(s_t, a_t)}_{\text{old value}} \right)$$

Reward: 100 correct trials must be performed as quickly as possible.

build a computer model of human vision



use machine learning to find
approximately optimal strategies for using
a visualisation given this model of human
vision



execute the strategies and record their
performance characteristics

Testing the model

The fraud detection task

- Decision makers (student participants) were presented with **9 cues** (e.g. transaction amount, location etc.)
- Cues differ in the reliability (**validity**) with which they determine whether or not a transaction is a fraud.
- Users need to decide which cues are worth looking at and then whether or not a card should be blocked.

Conditions

Card present <input type="button" value="Reveal"/>	CVV entered No	Type of goods Travel agent	Your overview Goal:42 out of 100 Accuracy: 66% Completed trials: 64
Expiry check transaction date: 10-sep-2015 card expiry: 11-sep-2015	Transaction amount <input type="button" value="Reveal"/>	Issued bank <input type="button" value="Reveal"/>	Your classification <input type="button" value="Block"/> <input type="button" value="Allow"/>
Transaction time 15:04	Transaction history <input type="button" value="Reveal"/>	Purchase made in Europe	Feedback: Correct Confirm: <input type="button" value="Submit"/> <input type="button" value="Next"/>








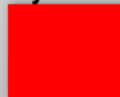

(a) Covered-Text (CT)

Card present <input type="button" value="Reveal"/>	CVV entered 	Type of goods 	Your overview Goal:42 out of 100 Accuracy: 66% Completed trials: 64
Expiry check 	Transaction amount <input type="button" value="Reveal"/>	Issued bank <input type="button" value="Reveal"/>	Your classification <input type="button" value="Block"/> <input type="button" value="Allow"/>
Transaction time 	Transaction history <input type="button" value="Reveal"/>	Purchase made in 	Feedback: Correct Confirm: <input type="button" value="Submit"/> <input type="button" value="Next"/>

(b) Covered-Color (CC)

Card present Yes	CVV entered No	Type of goods Travel agent	Your overview Goal:42 out of 100 Accuracy: 66% Completed trials: 64
Expiry check transaction date: 10-sep-2015 card expiry: 11-sep-2015	Transaction amount £976.41	Issued bank Hanford	Your classification <input type="button" value="Block"/> <input type="button" value="Allow"/>
Transaction time 15:04	Transaction history £6.30 £6.98 £8.20 £138.50 £61.37 £145.08	Purchase made in USA	Feedback: Correct Confirm: <input type="button" value="Submit"/> <input type="button" value="Next"/>

(c) Visible-Text (VT)

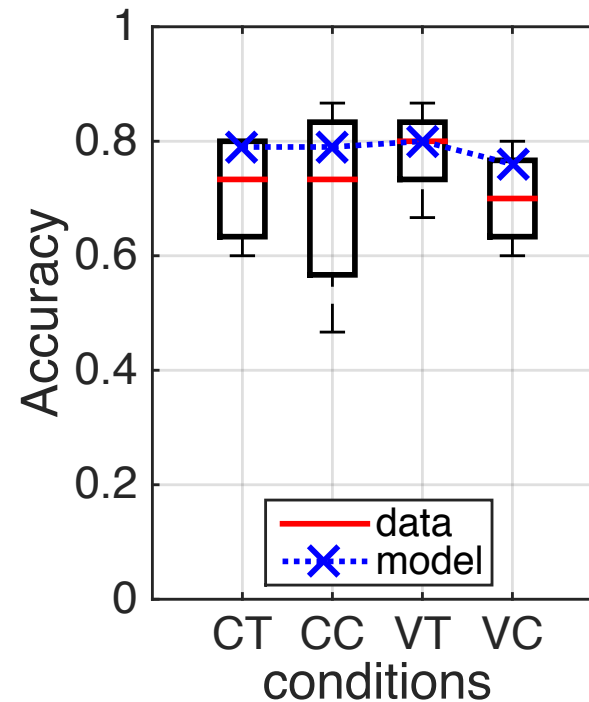
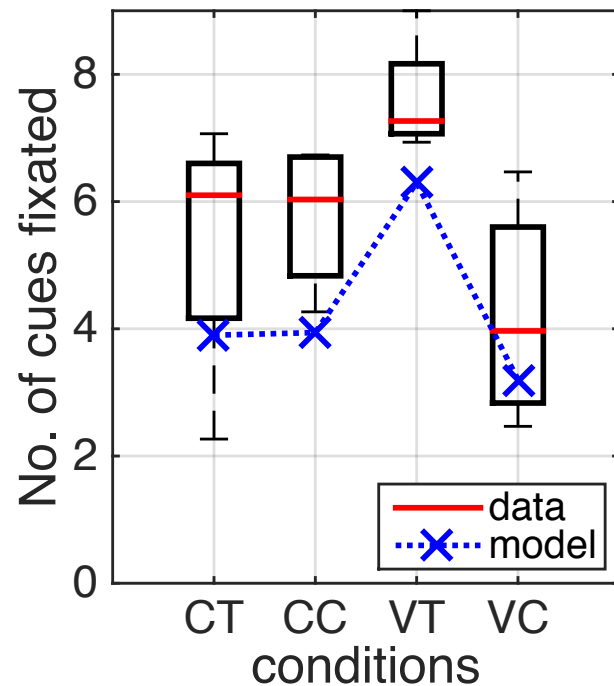
Card present 	CVV entered 	Type of goods 	Your overview Goal:42 out of 100 Accuracy: 66% Completed trials: 64
Expiry check 	Transaction amount 	Issued bank 	Your classification <input type="button" value="Block"/> <input type="button" value="Allow"/>
Transaction time 	Transaction history 	Purchase made in 	Feedback: Correct Confirm: <input type="button" value="Submit"/> <input type="button" value="Next"/>

(d) Visible-Color (VC)

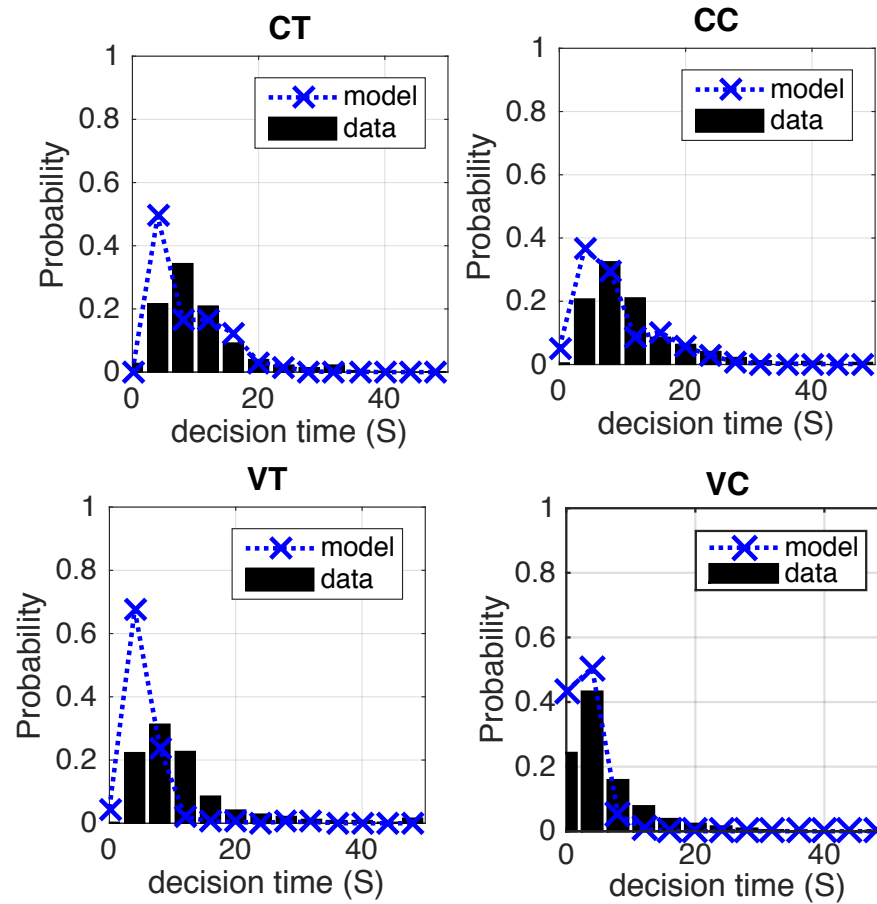
Model and data

- The model makes predictions
- In what follows the predictions are plotted on the same graphs as the aggregated human data.

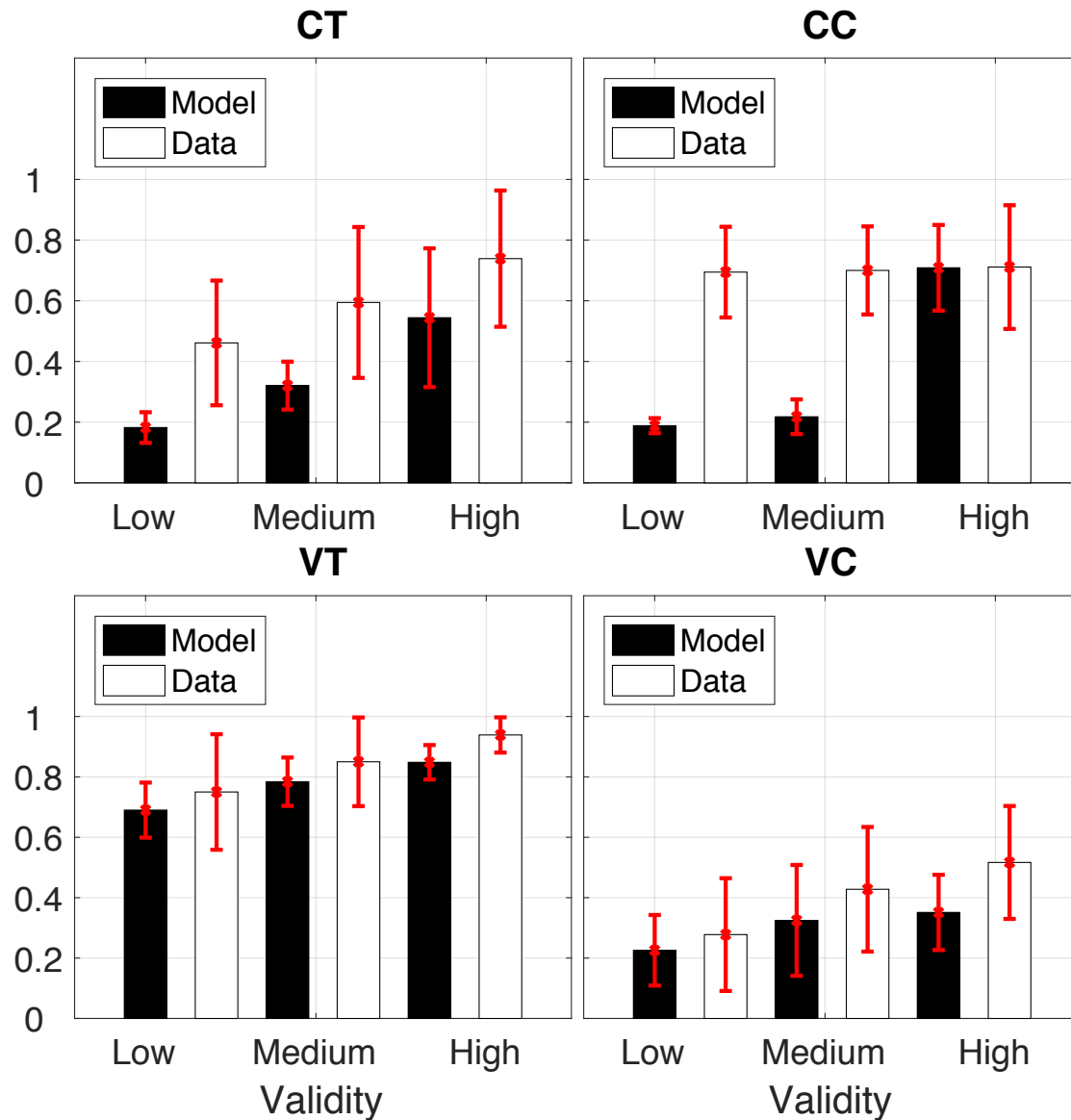
Number of cues fixated and accuracy



Distribution of decision times



Proportion of trials on which cues with each level of validity were used.



Discussion

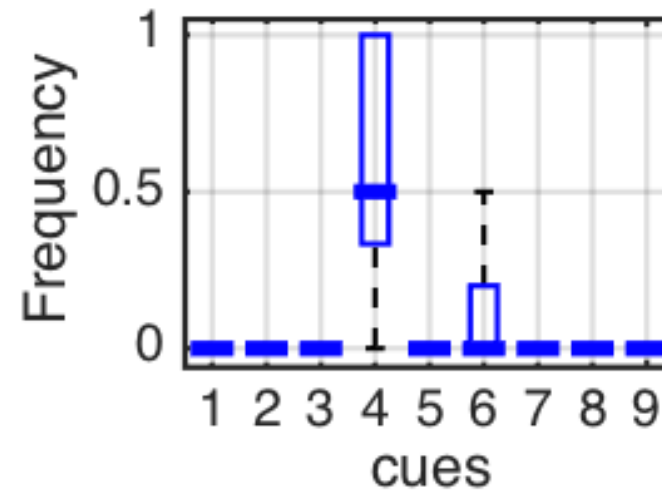
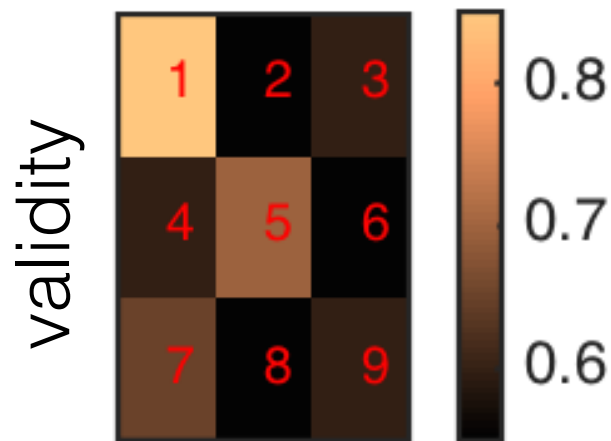
- A user's decision problem can be formulated precisely as a **POMDP** and user strategies can be predicted using machine learning.
- The “**cost of knowledge**” is reduced by the use of colour to signal meaning because people can make better use of peripheral vision.

Discussion

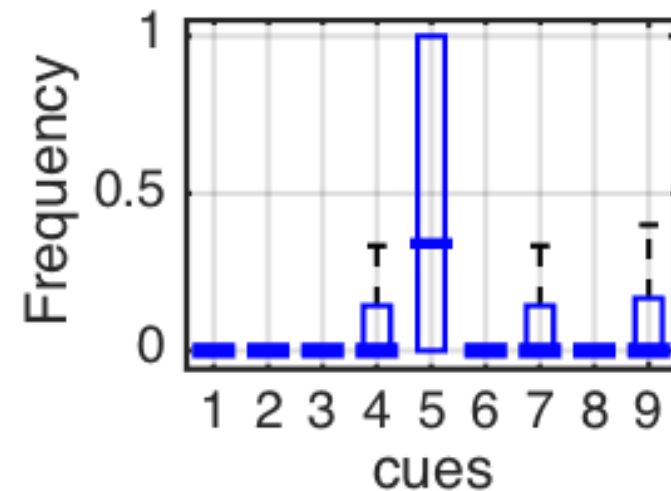
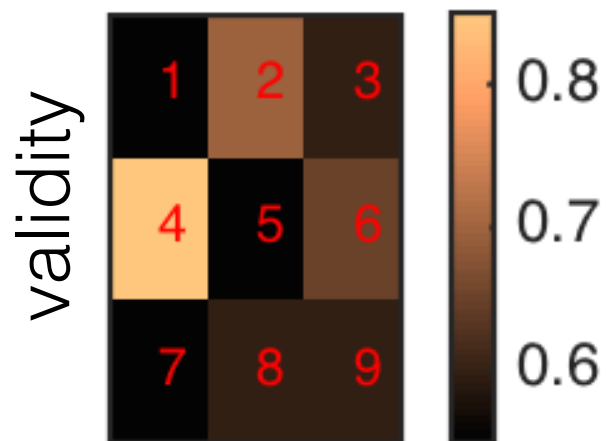
- In addition, the model predicts some, but not all well known strategies.
- It predicts inhibition of return.
- It predicts centre of gravity effects

The model exhibits centre of gravity effects

(A)



(B)



Discussion

- However, it does not predict either WADD or TTB, rather it makes use of an approximately optimal subset of the high validity cues.

Discussion

- This is an example of computational interaction (Antti Oulasvirta, Xiaojun Bi, Per Ola Kristensson, Andrew Howes, forthcoming).
- A key requirement of this approach is inferring parameters from data (Kangasrääsiö, et al. **Tuesday 9.30 room 111**)

Conclusion

- User behaviour can be explained and predicted as a POMDP.

References

- Chen, X., Starke, S.D., Baber, C., Howes, A. (2017). A cognitive model of how people make decisions through interaction with visual displays. In Proceedings of the ACM CHI'17 Conference on Human Factors in Computing Systems. ACM Press.
- Best of CHI Award: Honorable Mention Paper, awarded by SIGCHI - top 5% of submissions*.