Fitting Models for the Iowa Gambling Task with R

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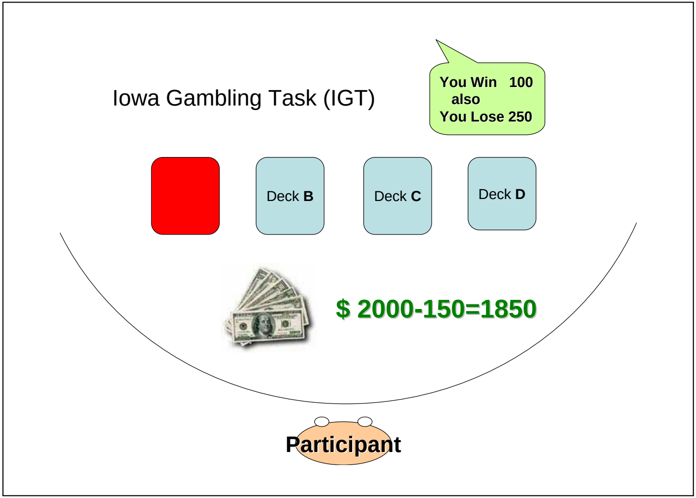
Outline

The Iowa Gambling Task(IGT, Bechara, Damasio, Damasio, & Anderson, 1994)



The Payoff Distribution

Trial	Deck A	Deck B	Deck C	Deck D
1	100	100	50	50
2	100	100	50	50
3	100,-150	100	50,-50	50
4	100	100	50	50
5	100, -300	100	50,-50	50
6	100	100	50	50
7	100,-200	100	50,-50	50
8	100	100	50	50
9	100,-250	100,-1250	50,-50	50
10	100,-350	100	50,-50	50,-1250
Mean	-25	-25	25	25

The Expectancy-Valence Model for IGT (Busemeyer & Stout, 2002)

$$\nu_t = wW_t - (1-w)L_t. \quad (1)$$

$$E\nu_{k,t} = (1-a)E\nu_{k,t-1} + a\nu_t, \quad (2)$$

$$\text{if deck } k \text{ is chosen at trial } t (k = 1,2,3,4).$$

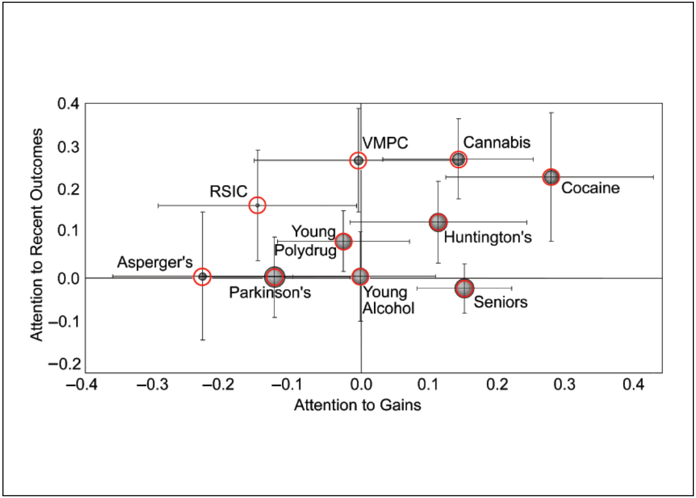
$$p_{k,t+1} = \frac{\exp(\theta_t E\nu_{k,t})}{\sum_{j=1}^{4} \exp(\theta_t E\nu_{j,t})}, \quad (3)$$

$$\text{where } \theta_t = (.1t)^c.$$

$$(p_{k,t+1} \propto E\nu_{k,t})$$

w denotes attention to gain.
a denotes attention to recent outcomes.
c denotes response sensitivity to expectancy-valence.

Yechiam, Busemeyer, Stout & Bechara, 2005



Ahn, Busemeyer, Wagenmakers & Stout(2008)

Utility	
Expectancy	$\nu_t = wW_t - (1-w)L_t$
Prospect	$\nu_t = (W_t - L_t)^\alpha$ if $W_t - L_t > 0$,
	$\nu_t = -\rho\lvert W_t - L_t\rvert^\alpha$ otherwise.

Updating	
Delta learning	$E\nu_{k,t} = (1 - D_{k,t}a)E\nu_{k,t-1} + D_{k,t}a\nu_k$
Decay reinforcement	$E\nu_{k,t} = (1-a)E\nu_{k,t-1} + D_{k,t}\nu_k$

Choice	$p_{k,t+1} = \dfrac{\exp(\theta(t)E\nu_{k,t})}{\sum_{j=1}^{4}\exp(\theta(t)E\nu_{j,t})}$
Trial-dependent	$\theta_t = (.1t)^c$
Trial-independent	$\theta_t = 3^c - 1$

A General Framework for IGT Models

Utility	$\nu_t = (-\rho)^{I(wW_t - lL_t < 0)} \lvert wW_t - lL_t \rvert^{\alpha}$
Expectancy	$l = 1 - w, \alpha = 1, \rho = 1$
Prospect	$w = 1, l = 1$
Updating	$E\nu_{k,t} = (1 - f_\beta a)E\nu_{k,t-1} + D_{k,t} a^\beta \nu_k$ where $f_\beta = (D_{k,t} + 1)^\beta - \beta$
Delta learning	$\beta = 1$
Decay reinforcement	$\beta = 0$
Choice	$\theta_t = \gamma t^c$
Trial t-dependent	$\gamma = .1^c$
Trial t-independent	$c = 0$

The General Framework is a Nonlinear Model.

The General Framework for IGT can be seen as a nonlinear regression model.

$$
\begin{aligned}
p_{k,t+1} &= \frac{exp((\gamma t^c \sum_{l=1}^{t} D_{l,k} a^{\beta}(1 - f_{\beta} a)^{S(k,t,l)} \nu_{k,l})}{\sum_{j=1}^{4} exp((\gamma t^c \sum_{l=1}^{t} D_{l,j} a^{\beta}(1 - f_{\beta} a)^{S(j,t,l)} \nu_{j,l})}, \\
& \quad where\ S(k,t,l) = \sum_{m=1}^{t} D_{m,k} - 1 - \sum_{m=1}^{l} D_{m,k}, \\
& \quad and\ \nu_{k,j} = (-\rho)^{I(wW_j - lL_j < 0)} |wW_j - lL_j|^{\alpha}. \\
&= f(W_1, ..., W_t, L_1, ..., L_t, D_{k,1}, ..., D_{k,t})
\end{aligned}
$$

The General Framework is also a Multinomial Logistic Model.

The General Framework for IGT can be also seen as a multinomial logistic model.

$$p_{k,t+1} = \frac{1}{1 + exp(\gamma t^c \sum_{l=1}^{t} D_{l,k} a^{\beta} (1 - f_{\beta} a)^{S(k,t,l)} (\nu_{1,l} - \nu_{k,1}))}$$

$$where\ S(k,t,l) = \sum_{m=1}^{t} D_{m,k} - 1 - \sum_{m=1}^{l} D_{m,k},$$

$$and\ \nu_{k,j} = (-\rho)^{I(wW_j - lL_j < 0)} |wW_j - lL_j|^{\alpha}.$$

Estimated Parameters of Eight Models for a Single Participant

- Step 1. Rearrange the data such that the predictors are outcomes of all previous trials.
- Step 2. Specify the parameters in the framework such that the framework will turn into a special IGT model.
- Step 3. Fitting model to individual data.
  - Minimize the loglikelihood function by nlm in R.
  - Estimate with other functions/packages for multinomial logistic regression(e.g., nnet or vgam in R).

Codes of Main Function


```
igt <- function (indigt,rho,w,l,alpha,a,beta,gamma,c) {
 if (trial==1){
     p=.25 }
 else {
     ev <- c(0,0,0,0)
     for (s in 1:(trial-1)) {
        sdvalue <- max(-1*sign(w*wvalue[s]-1*lvalue[s]),0)
        valence <- as.numeric((-1*rho)^sdvalue*abs(w*wvalue[s]-1*lvalue[s])^alpha)
        for (deck in 1:4) {
          ss <- cdeck[deck]-1
          for (m in 1:s){
            ll <- (deck==as.numeric(r[s]))
            ss  <- ss - (ll+1)^beta-beta
          }
          temp <-  a^beta*(1-a)^ss*valence[deck]
          ev[deck] <- ev[deck]+temp
        }
     }
    theta <- gamma* trial ^ c
    expev <- exp(theta*ev)
    p <- exp(ev)/sum(exp(ev))
    p[response]
 }
}
```

Estimated Parameters of Eight Models for a Single Participant - Continued.

Utility	Updating	Choice	w or α	ρ	a	c or γ
expec	delta	dep	.743		.172	9.725
expec	decay	dep	.693		.067	.873
expec	delta	ind	.714		.083	9.833
expec	decay	ind	.693		.069	.926
prosp	delta	dep	1.096	.028	.557	2.987
prosp	decay	dep	1.197	.236	.080	.594
prosp	delta	ind	1.222	.126	.204	4.082
prosp	decay	ind	1.164	.255	.076	.654

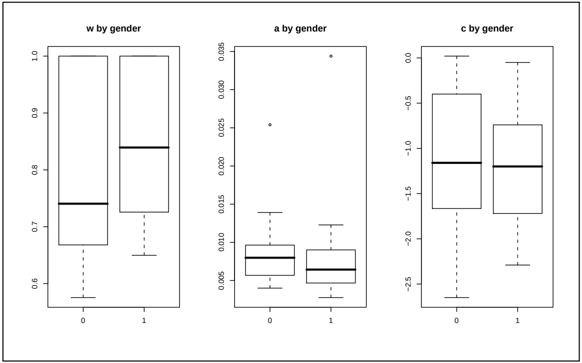
Learning Models

Some learning models are special cases of framework.

- The Rescorla-Wagner model (1972)
- The stochastic learning model of Bush and Mosteller (1955)
- The Hullian learning model(Bush and Mosteller, 1959)
- A logistic regression model of avoidance learning (Gelman, et al., 2002)

Estimated Parameters of EV Model for Different Genders(13 females, 15 males).

There are inter-subject variabilities in IGT data, mixed effect approach may gain additional power.
We should try to implement mixed-effects version of the framework for group diference in R.



A Mixed-Effects General Framework for IGT Models

Utility	$\nu_t = (-\rho_i)^{I(w_i W_t - l_i L_t < 0)} \lvert w_i W_t - l_i L_t \rvert^{\alpha_i}$
Updating	$E\nu_{k,t} = (1 - f_\beta a_i) E\nu_{k,t-1} + D_{k,t} a_i^\beta \nu_k$ where $f_\beta = (D_{k,t} + 1)^\beta - \beta$
Choice	$\theta_t = \gamma_i t_i^c$

Assume all parameters follow multivariate normal distribution.
The mixed-effects version of the framework is a special case of the mixed-effects multinomial regression models.

Mixed Effects Implementation

Glmm and nlme are two popular functions/packages dealing with mixed effect in R.

- Because "the glm() function cannot handle multinomial models"(retrieved from Agresti's homepage, 2009/7/5), glmm may be not handle mixed-effects multinomial regression model.
- "The nlme 3.0 library does not have facilities for generalized linear mixed models.....I think the preferred method for estimating glmm's is that in the new PROC NLMIXED of SAS version 7."(Bates's post, 1999, retrieved from S-news 2009/7/5).

Note: These two functions/packages may not work for mixed effect IGT models.

Gender differences in IGT using EV model(n = 13, 15)

Mixed-Effects EV model

	Mean(SD) Female	Mean(SD) Male	CI of Difference
w	.740(.074)	.797(.074)	(.016,.099)
a	.009(.002)	.007(.002)	(-.004,.006)
c	.033(.236)	.028(.236)	(-.068,.058)

We implemented the estimation procedure with SAS/NLMIXED(Cheng, Sheu, & Yen, 2009).
So far we did not find solutions in R, but we will try to implement mixed-effects version of the framework in R.

Summary

- A framework for eight IGT models and four learning models is proposed.
- A unified parameter estimation procedure for single participant is obtained for the entire class of models within the framework using nlm in R.
- Mixed effect approach gains additional power. Our future study is to implement the mixed effect version of the framework in R (I heard mlogit yesterday.).

Thank you!

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