Non separare dopo quello che hai somministrato insieme prima: Un approccio misto per l'analisi congiunta delle misure implicite

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VS

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Implicit Association Test (IAT)

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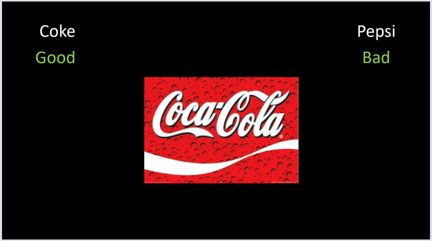
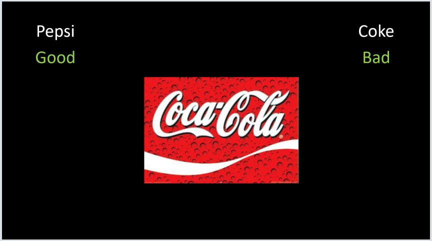
Coke Good/Pepsi Bad (CGPB)



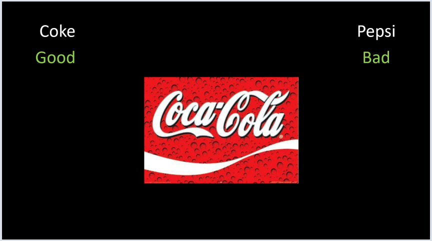
Pepsi Good/Coke Bad (PGCB)

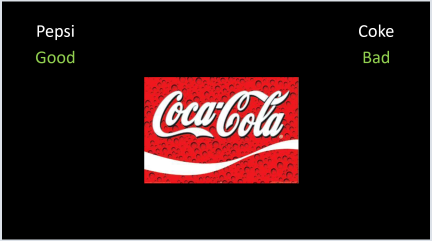


VS

Implicit Association Test (IAT)

Coke Good/Pepsi Bad (CGPB) Pepsi Good/Coke Bad (PGCB)



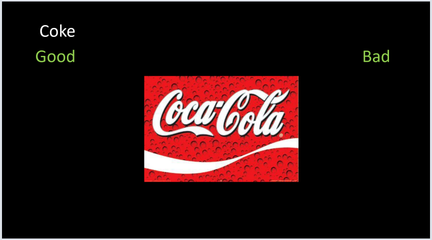


$$Dscore = \frac{M_{\text{CGPB}} - M_{\text{PGCB}}}{s_{\text{CGPB,PGCB}}}$$

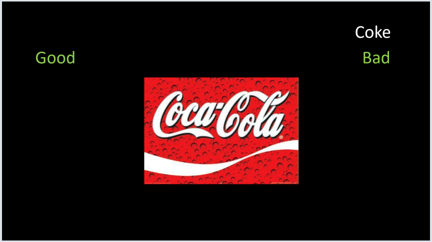
Single Category IAT

Single Category IAT

Coke-Good/Bad (CG)

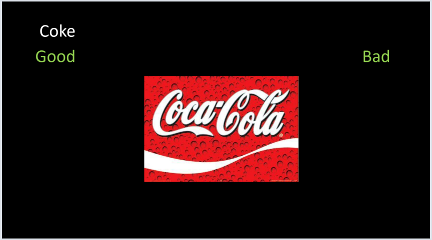


Good/Coke-Bad (CB)

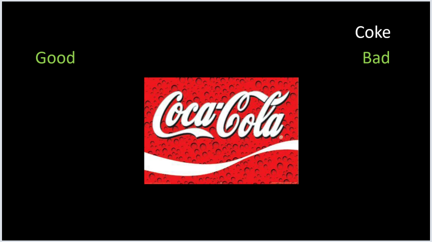


Single Category IAT

Coke-Good/Bad (CG)

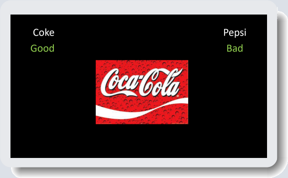


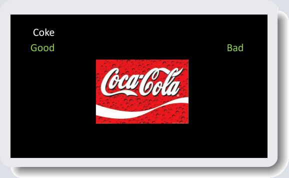
Good/Coke-Bad (CB)

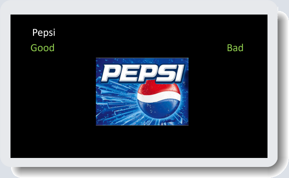


$$Dscore = \frac{M_{\text{CB}} - M_{\text{CG}}}{s_{\text{CB, CG}}}$$

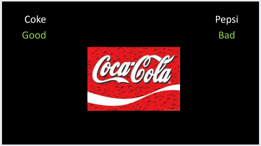
VS

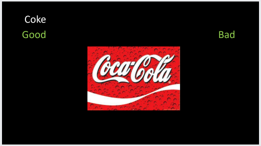






VS





D-score

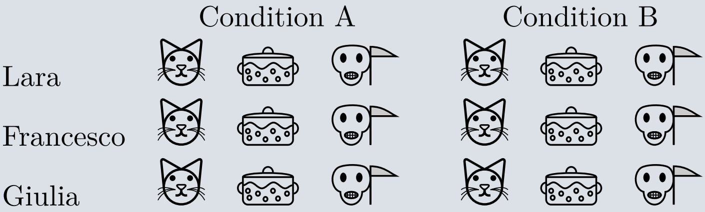
D-Coke

D-Pepsi

Stand alone measures:

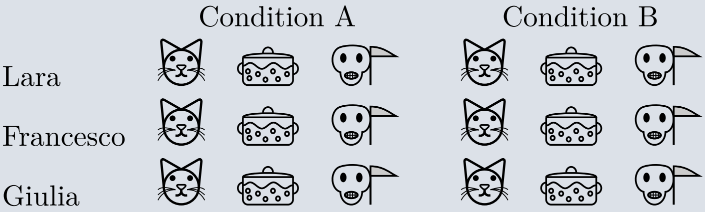
Multiple measures:

Stand alone measures:

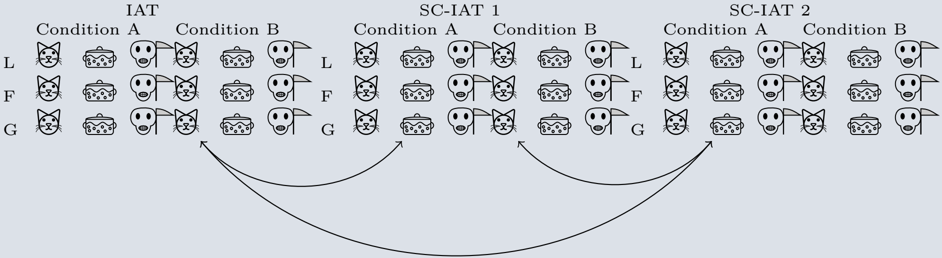


Multiple measures:

Stand alone measures:



Multiple measures:



Linear Mixed Effect Models (LMMs) allow for:

- Accounting for (potentially) all the sources of variability and dependency
- Gathering information at the stimuli level

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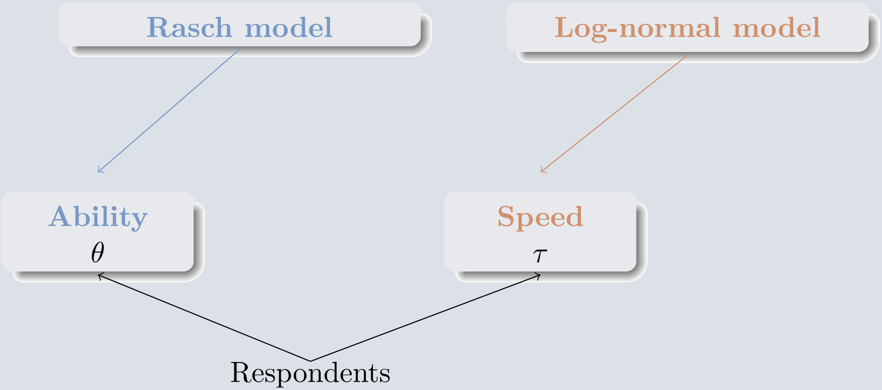
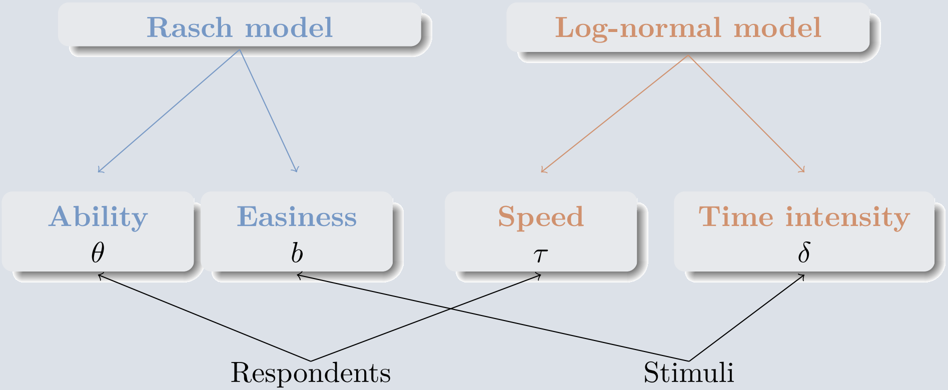
- Gathering information at the stimuli level
- **Rasch Model** & **Log-normal Model** estimates

Rasch model

Log-normal model


Rasch model
Log-normal model
Ability
θ
Speed
τ
Respondents


Rasch model
Log-normal model
Ability
θ
Easiness
b
Speed
τ
Time intensity
δ
Respondents
Stimuli

LMMs on implicit measures responses:

LMMs on implicit measures responses:

GLMMs on
Accuracy responses

Rasch model estimates

LMMs on implicit measures responses:

GLMMs on
Accuracy responses

LMMs on
Log-time responses

Rasch model estimates

Log-normal model estimates

LMMs on implicit measures responses:

GLMMs on
Accuracy responses

LMMs on
Log-time responses

Rasch model estimates

Log-normal model estimates

Predictive ability of behavioral outcomes

Classic scoring vs Model estimates

The expected response y for the observation $i = 1, \dots, I$ for respondent $j = 1, \dots, J$ on stimulus $k = 1, \dots, K$ in condition $l = 1, \dots, L$ of measure $m = 1, \dots, M$:

Model 1:

$$y_i = \alpha + \beta l_i + \alpha_{j[i]} + \alpha_{k[i]} + \epsilon_i$$

Fixed Effect

$$\alpha_j \sim \mathcal{N}(0, \sigma_j^2),$$
$$\alpha_k \sim \mathcal{N}(0, \sigma_k^2).$$

Model 2:

$$y_i = \alpha + \beta l_i + \alpha_{k[i]} + \beta_{j[i]} m_i + \epsilon_i$$

Random structure

$$\alpha_k \sim \mathcal{N}(0, \sigma_k^2),$$
$$\beta_j \sim \mathcal{MVN}(0, \Sigma_{jm}).$$

Model 3:

$$y_i = \alpha + \beta l_i + \alpha_{k[i]} + \beta_{j[i]} m_i l_i + \epsilon_i$$

$$\alpha_k \sim \mathcal{N}(0, \sigma_k^2),$$
$$\beta_j \sim \mathcal{MVN}(0, \Sigma_{jml}).$$

Accuracy: $\epsilon \sim \mathcal{L}(0, \sigma^2)$
Log-time: $\epsilon \sim \mathcal{N}(0, \sigma^2)$

Accuracy model (Rasch Model estimates):

	Respondents' parameters	**Stimuli parameters**
Model 1	Overall (θ_j)	Overall (b_k)
Model 2	Measure–specific (θ_{jm})	Overall (b_k)
Model 3	Condition–specific (θ_{jml})	Overall (b_k)

Log-time model (Log-normal Model estimates):

	Respondents' parameters	**Stimuli parameters**
Model 1	Overall (τ_j)	Overall (δ_k)
Model 2	Measure–specific (τ_{jm})	Overall (δ_k)
Model 3	Condition–specific (τ_{jml})	Overall (δ_k)

$j = 1, \ldots, J$ Respondents
$k = 1, \ldots, K$ Stimuli

$l = 1, \ldots, L$ Condition
$m = 1, \ldots, M$ Measure

Stimuli:

14 Object Stimuli (7 *Dark*, 7 *Milk*)

26 Evaluative attributes (13 *Good*, 13 *Bad*)

Chocolate IAT
Conditions:

MGDB: 60 trials
DGMB: 60 trials

Dark SC-IAT
Conditions:

DB: 72 trials
DG: 72 trials

Milk SC-IAT
Conditions:

MB: 72 trials
MG: 72 trials

$n = 152$, (F $= 63.82\%$, Age $= 24.03 \pm 2.82$ years)
Milk Chocolate Choice: 48.03%

	Accuracy			Response times		
Model	AIC	BIC	Deviance	AIC	BIC	Deviance
1	22990.85	23036.02	22980.85	44623.69	44677.9	44611.69
2	22905.80	22996.15	22885.80	43448.31	43547.70	43426.31
3	22364.85	22617.83	22308.85	38932.55	39194.56	38874.55

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Rasch model:
Model 3

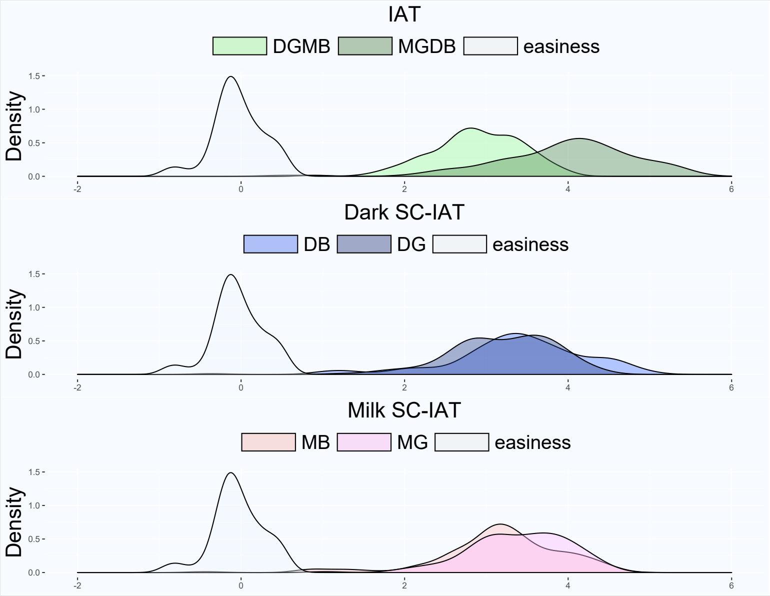
b_k: Overall stimuli estimates, across respondents/conditions/measures.

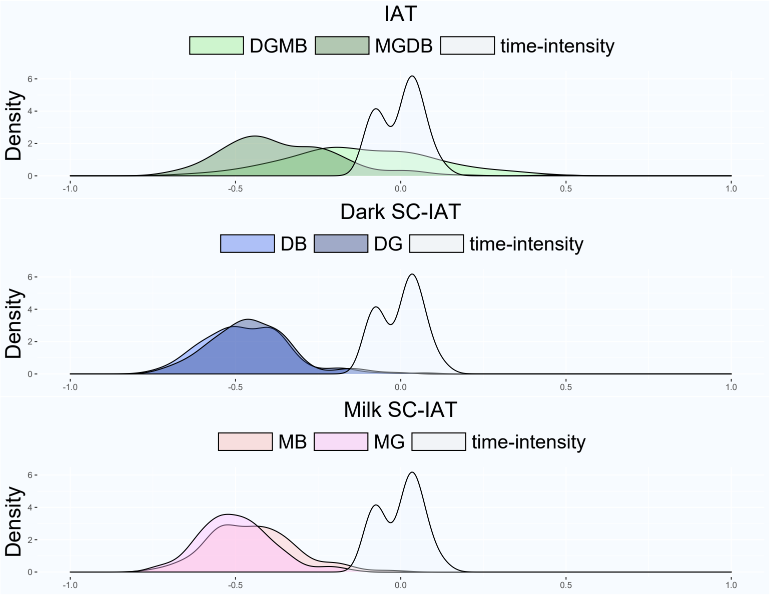
θ_{jml}: Measure-Condition specific respondents' estimates.

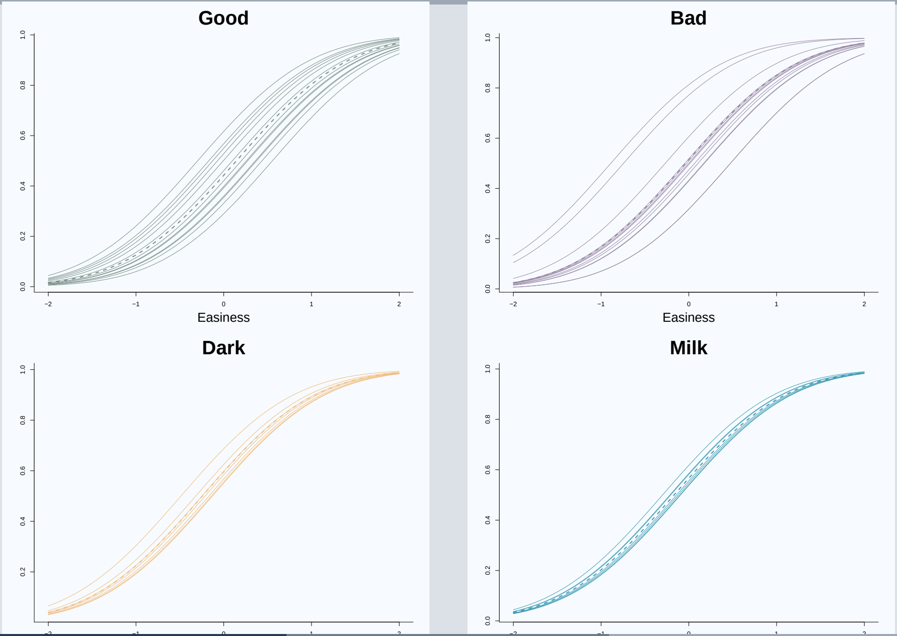
Log-normal model:
Model 3

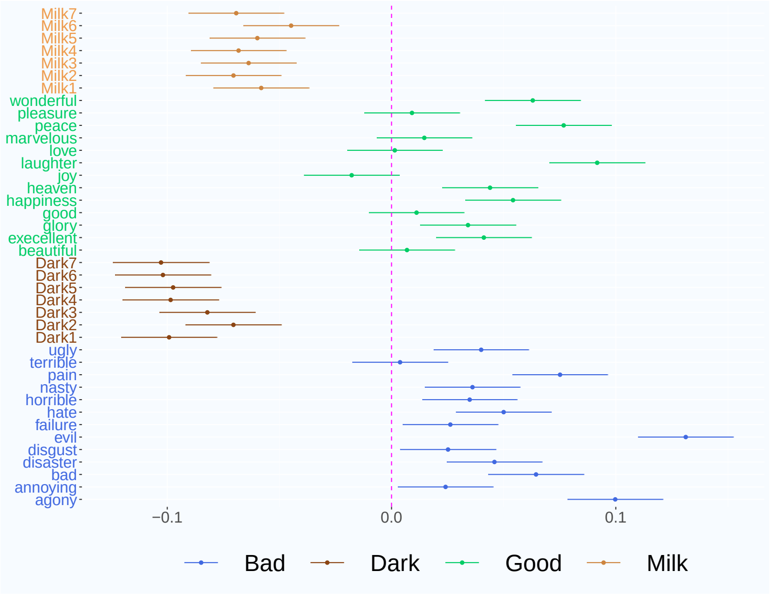
δ_k: Overall stimuli estimates, across respondents/conditions/measures.

τ_{jml}: Measure-Condition specific respondents' estimates.


IAT
DGMB
MGDB
easiness
Density
1.5
1.0
0.5
0.0
-2
0
2
4
6
Dark SC-IAT
DB
DG
easiness
Density
Milk SC-IAT
MB
MG
easiness
Density


IAT
DGMB
MGDB
time-intensity
Density
Dark SC-IAT
DB
DG
time-intensity
Density
Milk SC-IAT
MB
MG
time-intensity
Density


Good
Bad
Dark
Milk
Easiness
Easiness
0.0
0.2
0.4
0.6
0.8
1.0
−2
−1
0
1
2


Milk7
Milk6
Milk5
Milk4
Milk3
Milk2
Milk1
wonderful
pleasure
peace
marvelous
love
laughter
joy
heaven
happiness
good
glory
execellent
beautiful
Dark7
Dark6
Dark5
Dark4
Dark3
Dark2
Dark1
ugly
terrible
pain
nasty
horrible
hate
failure
evil
disgust
disaster
bad
annoying
agony
−0.1
0.0
0.1
Bad
Dark
Good
Milk

Dark Chocolate Choice (DCC) = 0

Milk Chocolate Choice (MCC) = 1

Differential measures:

$$\text{Choice} \sim \textit{D-score} + \textit{D-Dark} + \textit{D-Milk}$$
$$\text{Choice} \sim \textit{IAT-differential} + \textit{Dark-differential} + \textit{Milk-differential}$$

Single components:

$$\text{Choice} \sim M_{\text{DGMB}} + M_{\text{MGDB}} + M_{\text{DB}} + M_{\text{DG}} + M_{\text{MG}} + M_{\text{MB}}$$
$$\text{Choice} \sim \tau_{\text{DGMB}} + \tau_{\text{MGDB}} + \tau_{\text{DB}} + \tau_{\text{DG}} + \tau_{\text{MB}} + \tau_{\text{MG}}$$

$\textit{IAT-differential} = \tau_{\text{DGMB}} - \tau_{\text{MGDB}}$
$\textit{Dark-differential} = \tau_{\text{DB}} - \tau_{\text{DG}}$
$\textit{Milk-differential} = \tau_{\text{MB}} - \tau_{\text{MG}}$

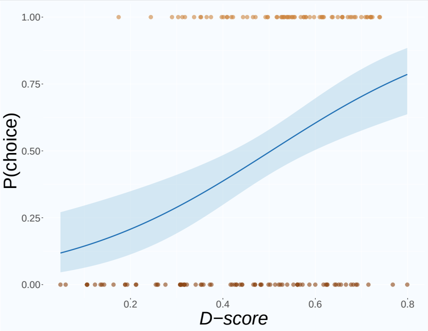
		Expected			
		Dark	Milk		
Observed	Dark	a	b	$a+b$	DCCs
	Milk	c	d	$c+d$	MCCs
		$a+c$	$b+d$		

$$\frac{a+d}{a+b+c+d}$$ General Accuracy (i.e., ratio between model correctly identified choices and total number of choices)

$$\frac{a}{a+b}$$ DCC Accuracy (i.e., ratio between model correctly identified DCCs and observed number of DCCs)

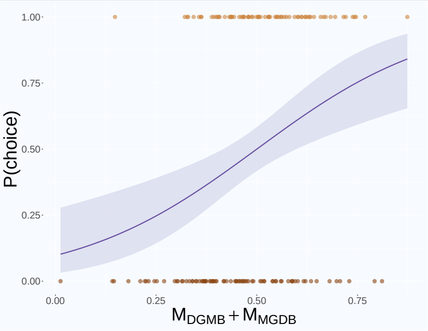
$$\frac{d}{c+d}$$ MCC Accuracy (i.e., ratio between model correctly identified MCCs and observed number of MCCs)

Differential measure



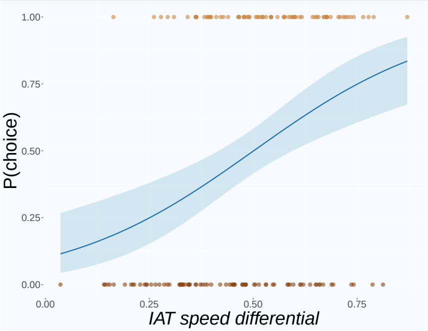
General	DCC	MCC	Pseudo R^2
0.64	0.62	0.67	0.16

Single components



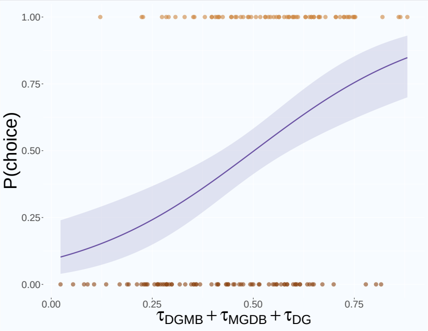
General	DCC	MCC	Pseudo R^2
0.62	0.67	0.56	0.12

Differential measure



General	*DCC*	*MCC*	*Pseudo* R^2
0.64	0.67	0.60	0.15

Single components



General	*DCC*	*MCC*	*Pseudo* R^2
0.64	0.65	0.63	0.19

Stimuli Information

- Malfunctioning stimuli
- Stimuli driving the IAT effect
- Issues related with the computation of the *D-score*

Choice prediction

- Single components vs Differential measures
- Not "How much" but "What"
- Deeper understanding of the processes underlying behaviors

Thank you!