Biological Foundation of Choice and Memory

Aldo Rustichini

Economics, Minnesota

The State of Mind in Economics
Outline

1 A mechanistic model of choice
Outline

1 A mechanistic model of choice

2 Adaptive Coding
Outline

1. A mechanistic model of choice
2. Adaptive Coding
3. Intelligence and strategic behavior
The goal of positive science is prediction out of sample.
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The method is the *as if*: we can make unrealistic assumptions, as long as data agree with predictions obtained as if the model was real.
Replace *as if* models with mechanistic models
Replace as if models with mechanistic models

A mechanistic model is a relationship between variables in the data set where

- **Biological process**: The nature of the relationship is fully specified in terms of a biological processes that produces the data;
- **Parameter independence**: All the parameters in the model have biological definitions and should be measured independently of the data set.
The method of Neuroeconomics
Neuroeconomics: The Consilience of Brain and Decision, Glimcher, Rustichini, Science, 2004

1. Replace as if models with mechanistic models

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- **Biological process:** The nature of the relationship is fully specified in terms of a biological processes that produces the data;
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2. A mechanistic model will explain “paradoxes”:

   *Once this reconstruction of decision science is completed, many of the most puzzling aspects of human behavior will become formally and mechanistically explicable.*
The method of Neuroeconomics


- Replace *as if* models with mechanistic models
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- A mechanistic model will explain “paradoxes”:
  
  *Once this reconstruction of decision science is completed, many of the most puzzling aspects of human behavior will become formally and mechanistically explicable.*

- We will apply this method in this talk to
  - Explain stochastic choice
  - Explain the *reference dependence effect*
  - Another application is the *recency effect*. 
Padoa-Schioppa Assad, 2006: task, subjects and data
Padoa-Schioppa Assad, 2006: task, subjects and data

A mechanistic model of choice

Data

Fixate 0.5 s
Offer on, 1-2 s Delay
Go
0.75 s, Juice

Firing Rate (sp/s)

1A = 4.1B

Percent 'B' choice

0% to 100%

grape
peppermint

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Data mining identifies three types of neurons
Offer value, Chosen Juice, Chosen Value
Three types of neurons

- **Offer value neurons** are good specific and respond to the value of the offer of that good in the trial.
Three types of neurons

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2. **Chosen Juice neurons** are good specific and have high firing rate if that good is chosen, low if it is not.
A mechanistic model of choice

How the model works

### Three types of neurons

1. **Offer value neurons** are good specific and respond to the value of the offer of that good in the trial.

2. **Chosen Juice neurons** are good specific and have high firing rate if that good is chosen, low if it is not.

3. **Chosen value neurons** fire proportionally to the value of the chosen option.
A mechanistic model of choice

How the model works


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A mechanistic model of choice

How the model works

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Stochastic choice: when the two options are equally good
Stochastic choice: when the $x$-option is better
Choice and firing patterns in experimental data

- **Offer value cells**
  - Graph showing firing rate vs. offer value B
  - Graph showing offer value vs. firing rate

- **Positive encoding**
  - Graphs showing average firing rate for high, medium, and low conditions

- **Negative encoding**
  - Graphs showing average firing rate for high, medium, and low conditions

- **Chosen juice cells**
  - Similar graphs to offer value cells

- **Chosen value cells**
  - Similar graphs to offer value cells
A mechanistic model of choice

How the model works

Match of real data and model
Now we can prove theorems like these:

**Cardinal Utility**

**Theorem** we have a cardinal utility *because* neurons communicate information in an additive way.
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**Cardinal Utility**

*Theorem* we have a cardinal utility *because* neurons communicate information in an additive way.

**Adaptive Coding**

*Theorem* we have adaptive coding *because* the spike process is Poisson.
Adaptive Coding (Padoa-Schioppa, 2009)

The evidence

- Adaptive Coding
- Population firing rate
- Activity ranges
- Distribution of activity ranges
- Average firing rate
- Offer value
- Delta V

![Graphs showing adaptive coding](image)
Why Adaptive coding: how not to find an answer (Wong & Wang 2006)

Wang's model first eliminates noise using mean field analysis; then it reintroduces it assuming an Ornstein-Uhlenbeck process with fixed variance. This procedure assumes a fixed unexplained exogenous relation between mean and SD of firing rate; Adaptive coding in this way is either useless or impossible; instead we want to explain it from first principles.

It turns out that the essential feature is that the process is Poisson.
Why Adaptive coding: how not to find an answer (Wong & Wang 2006)

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Poisson process

Three Poisson processes, rate 5, 10 and 15
Poisson process
Poisson process

Three Poisson processes, rate 5, 10 and 15

- Frequency vs. Number of spikes
It all follows from the Poisson property Mean = Variance
What does this property do for you? A simple example

You are given two offers in quantities \((x, y)\), with known joint distribution.
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1. You are given two offers in quantities \((x, y)\), with known joint distribution.
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3. You do not observe \(x\) or \(y\), but before the choice, two signals \(X \sim N(s_x, s_x)\) and \(Y \sim N(s_y, s_y)\) are drawn and you observe the difference between the two,

\[ D \equiv X - Y \]
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\[ D \equiv X - Y \]

4. You can choose the **common** slope \(s\), and optimize. Optimize what?
What do we want to optimize? Laughlin 1981, ZN
Visual perception: Entropy
What do we want to optimize? Laughlin 1981, ZN: the fit
Visual perception: Entropy
An explanation of Adaptive coding: theory and test

*Optimal coding and neuronal adaptation in economic decisions*, Rustichini, Conen, Cai, Padoa-Schioppa *Nature Communications*
An explanation of Adaptive coding: theory and test

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The system maximizes expected payoff
An explanation of Adaptive coding: theory and test

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1. **The system maximizes expected payoff**

2. To do this you can pick any $s \in S$ (say $s$ smaller than a given maximum), and after the observation of $D$ you can choose 1 or 2.

3. The probability of choosing $x$ is:

$$Q_{(x,y)}(R^+|s) = P\left(Z \geq -\frac{(x-y)\sqrt{s}}{\sqrt{x+y}} | Z \sim N(0,1)\right)$$

so increasing $s$ makes the probability of choosing $x$ almost equal to 1 when $x > y$, and the probability of choosing $x$ almost 0 when $y > x$. 


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so increasing $s$ makes the probability of choosing $x$ almost equal to 1 when $x > y$, and the probability of choosing $x$ almost 0 when $y > x$.

Hence the payoff increases with $s$ and the optimal policy is to choose $s$ as large as possible, thus:

Theorem We have adaptive coding because the spike process is Poisson.
Slope of the response function and steepness of the softmax

Theory predicts: larger range, shallower slope of softmax
Slope of the response function and steepness of the softmax

\[ \text{Sigmoid steepness } (n) \]

\[ \text{Mean value range } (\Delta) \]

\[ \text{Corr} = -0.41 \]
\[ p = 0.00035 \]

\[ \text{Corr} = -0.26 \]
\[ p = 0.014 \]
A potential problem

Max rate

X
Good A

Y
Good B
A potential problem

Adaptive Coding

Good A

Max rate

x y

Good B

Aldo Rustichini (Economics, Minnesota)
A potential problem
A potential problem

Max rate

x

y

Good A

Good B

Aldo Rustichini (Economics, Minnesota)
A potential problem: HUGE environment bias
But is the bias there?
But is the bias there?

We run the same experiment as Padoa-Schioppa Assad 2006, but systematically in some sessions **double** the range of the A good, keep the range of the good B the same.
But is the bias there?

1. We run the same experiment as Padoa-Schioppa Assad 2006, but systematically in some sessions **double** the range of the A good, keep the range of the good B the same.

2. Check whether the relative value of the two goods is affected in the “×2” sessions compared to the “×1” sessions.
But is the bias there?

1. We run the same experiment as Padoa-Schioppa Assad 2006, but systematically in some sessions **double** the range of the $A$ good, keep the range of the good $B$ the same.

2. Check whether the relative value of the two goods is affected in the “$\times 2$” sessions compared to the “$\times 1$” sessions.

3. Then plot the pair of relative values in the “$\times 1$” and “$\times 2$” sessions.
But is the bias there?
But is the bias there? NO!

![Graph](image-url)
Individuals are rational in different ways; how rational they are may depend on how intelligent they are.
Rationality and Intelligence

1. Individuals are rational in different ways; how rational they are may depend on how intelligent they are.

2. Intelligence affects individual performance and behavior, but how? Common intuition: higher Intelligence implies behavior closer to game theoretic equilibrium predictions. The intuition is correct in competitive games, wrong in general.
Rationality and Intelligence

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3. We study this in experimental repeated interactions: subjects are randomly matched with a partner, play a repeated game with random termination, then are matched with a different partner, and so on.
Experimental Design: create two cities
Experimental Design

**Day 1:** Test subjects on Intelligence (Raven Test) and collect demographics, risk attitude and personality measures

**In between:** Allocate subjects in *low* (below the median) and *high* (above the median) Intelligence groups

**Day 2:** Play the games repeatedly with random matching and a given continuation probability
Raven Test
Group composition

IQ: All Sessions

Low Raven Sessions - High Delta

Raven Sessions - High Delta

Low Raven Sessions - Low Delta

High Raven Sessions - Low Delta
Intelligence and strategic behavior

1. A subject has to remember the rule that deviation is followed by retaliation.
2. Lower intelligence subjects remember rules, but forget to implement them (Duncan’s Goal neglect).
A subject has to remember the rule that deviation is followed by retaliation

2. Lower intelligence subjects remember rules, but forget to implement them (Duncan's Goal neglect)

3. Prediction: In games with a tradeoff between short run gain and long run loss, lower intelligence groups will deviate, higher intelligence will not

4. The effect may be large
**Repeated Prisoner’s Dilemma**

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### Repeated Prisoner’s Dilemma: natural equilibrium outcome

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Repeateed Prisoner’s Dilemma: tradeoff

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Prisoner’s Dilemma with *High* Continuation Probability
IQ separated treatments
Prisoner’s Dilemma with *High* Continuation Probability
IQ separated treatments

**Cooperation**

**Payoffs**

**1st Period Cooperation**

**1st Period Payoff**

*Blue = High IQ; Red = Low IQ*
Prisoner’s Dilemma with *Low Continuation Probability*

IQ separated treatments

**Cooperation**

**Payoffs**

**1st Period Cooperation**

**1st Period Payoff**
### Battle of the Sexes with a Compromise

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Battle of the Sexes with a Compromise: natural equilibrium

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Intelligence and strategic behavior

Intelligence in Battle of the Sexes with a Compromise

Battle of Sexes with compromise

High continuation probability
## Stag Hunt

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Stag Hunt: no tradeoff at the natural equilibrium

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Stag Hunt
High continuation probability
## Battle of the Sexes

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Battle of Sexes

High continuation probability
Low and high Conscientiousness sessions
PD with High Continuation Probability
Low and high Agreeableness sessions
PD with High Continuation Probability

![Graphs showing cooperation and payoffs in merged supergames for low and high Agreeableness sessions.](image)
Conclusions: Neuroeconomics works

- Replace *as if* models with mechanistic models
Conclusions: Neuroeconomics works

1. Replace as if models with mechanistic models
2. A mechanistic model will explain “paradoxes”:

   Once this reconstruction of decision science is completed, many of the most puzzling aspects of human behavior, aspects that economic theory, psychological analysis, or neurobiological deconstruction have failed to explain, will become formally and mechanistically explicable.
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   Once this reconstruction of decision science is completed, many of the most puzzling aspects of human behavior, aspects that economic theory, psychological analysis, or neurobiological deconstruction have failed to explain, will become formally and mechanistically explicable.

3. We have successfully applied this method to
   - Explain stochastic choice
   - Explain the reference dependence effect
   - Explain the recency effect.

4. We open the way for a new look at the role of intelligence in cooperation
Thanks to my co-authors

1 Camillo Padoa-Schioppa, Katherine E Conen, Xinying Cai
2 Philippe Domenech, Claudia Civai, Colin DeYoung
3 Eugenio Proto, Andis Sofianos
4 Doris Pischedda, Carlo Reverberi, Johanna Strump, Marco Mantovani, John-Dylan Haynes