



The Human Conductome: Understanding why we make “bad” decisions

Chris Stephens,

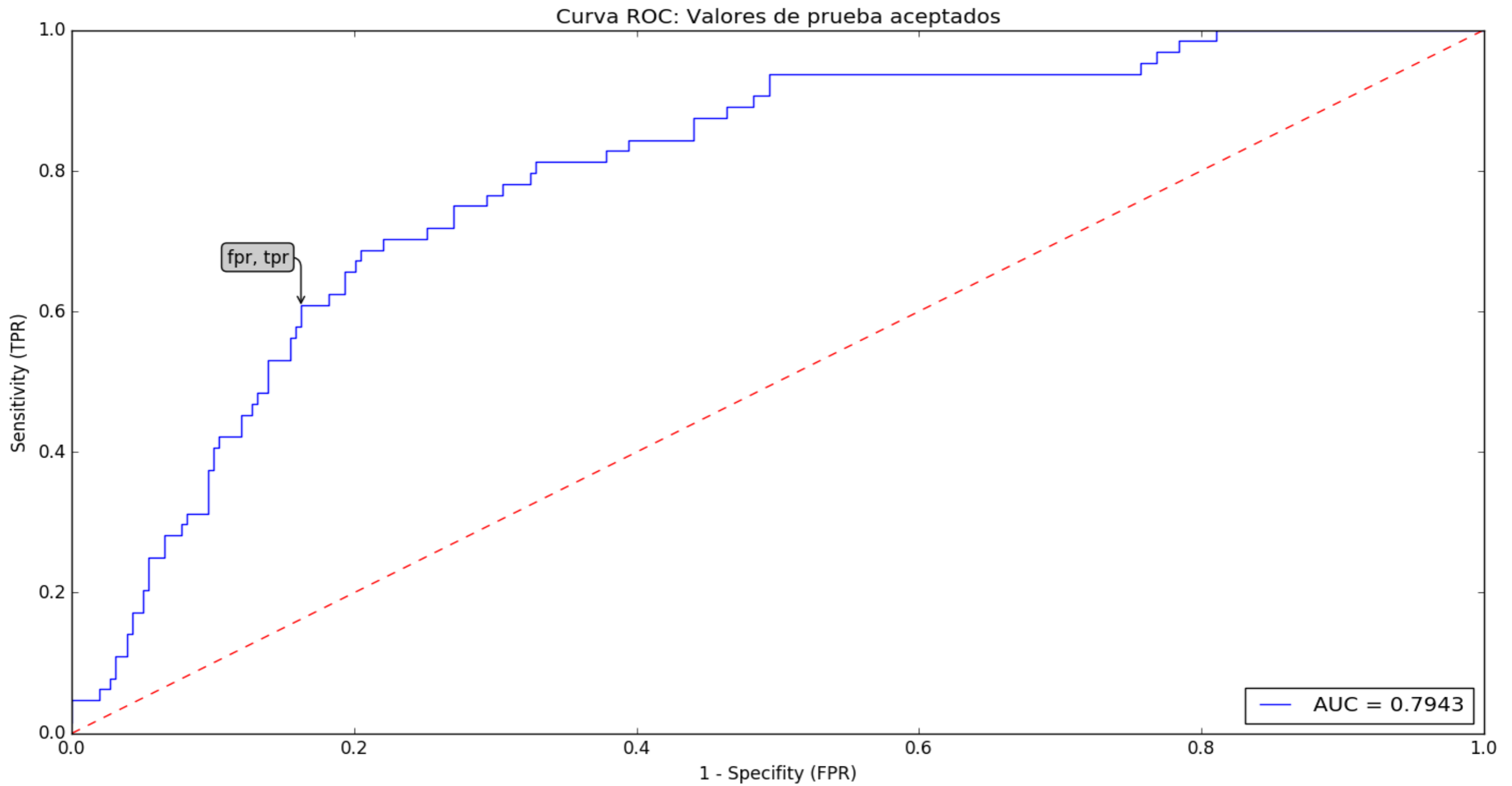
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Simposio
15 de junio 2018

FIVE NOVELS IN ONE OUTRAGEOUS VOLUME

DOUGLAS ADAMS



THE ULTIMATE
HITCHHIKER'S
GUIDE TO
THE GALAXY



= 42

Predictive model
for obesity...



Results from predictive models * based on data from a study of 1,076 non-academics and academics from the UNAM:

2,524 variables - Genetic, epidemiological, physiological,...

Epidemiological: Personal (81), **Personal history** (130), **Family History** (548), Self-health evaluation (226), **Nutrition** (220), **Lifestyle** (390), Health knowledge (293)

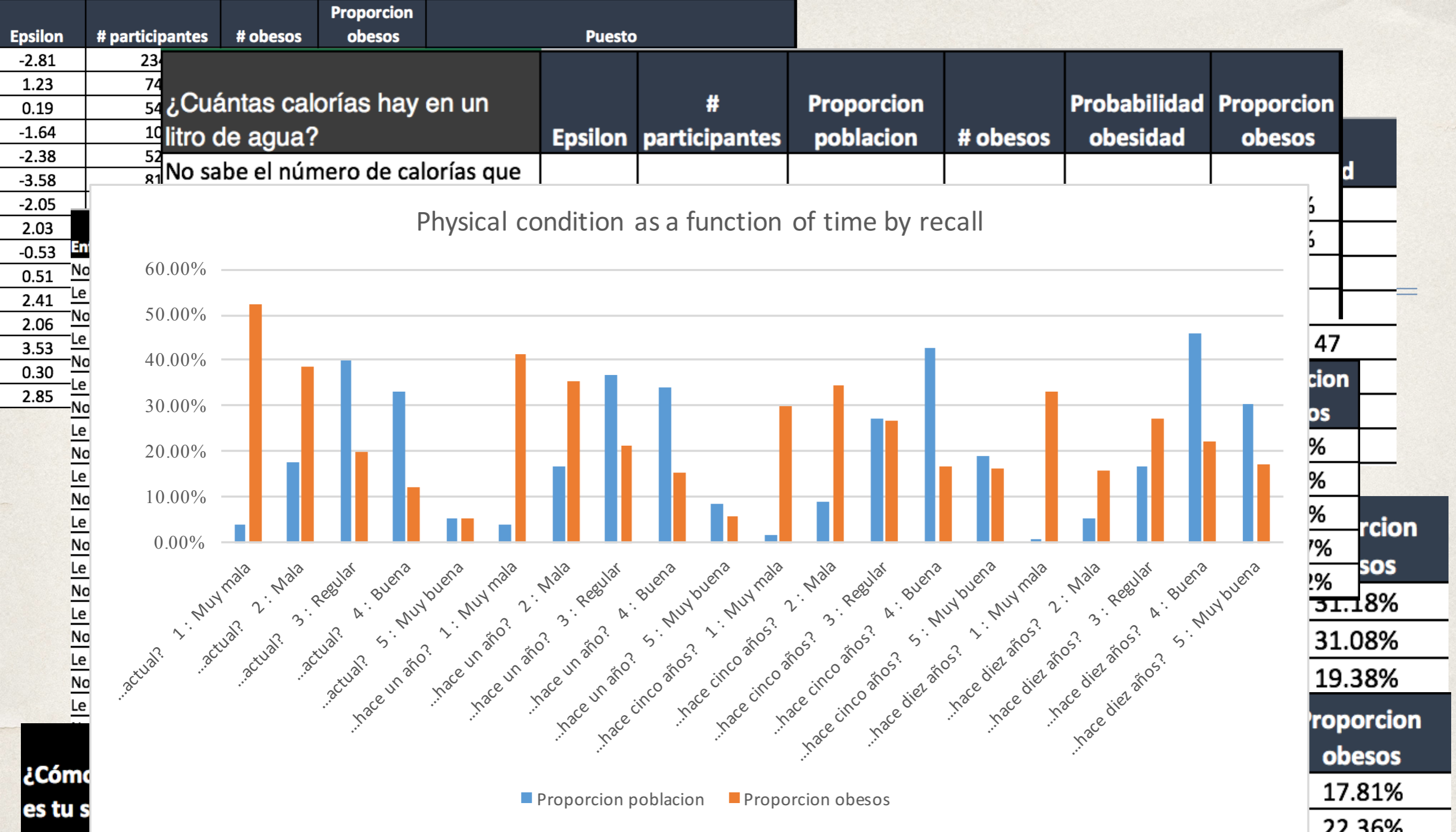
Genetic (772)

Anthropometric and physiological (49)

* Models are classification models of Naive Bayes type. Model performance is based on a 70/30 training/test split

Nutrition	
Specificity (TNR)	83.40%
1 – Specificity (SPC)	16.60%
Sensitivity (FPR)	29.69%
Accuracy (ACC)	72.76%
AUC ROC	0.63
Lifestyle	
Specificity (TNR)	84.17%
1 – Specificity (SPC)	15.83%
Sensitivity (FPR)	31.25%
Accuracy (ACC)	73.68%
AUC ROC	0.70
Lifestyle and Nutrition	
Specificity (TNR)	78.38%
1 – Specificity (SPC)	21.62%
Sensitivity (FPR)	46.88%
Accuracy (ACC)	72.14%
AUC ROC	0.71
Lifestyle and Nutrition and Personal and Family History	
Specificity (TNR)	81.08%
1 – Specificity (SPC)	18.92%
Sensitivity (FPR)	51.56%
Accuracy (ACC)	75.23%
AUC ROC	0.76

Variable	Valor	Epsilon	Nx	Nxc	N	Nc	Pc	Pxc	Descripción
Aestatura	1	4.801461	91	38	1076	228	0.2119	0.4176	Estatura que estima tener el encuestado < 1.5 : 1
Aestatura	2	-0.92449	399	77	1076	228	0.2119	0.193	Estatura que estima tener el encuestado [1.5, 1.6) : 2
Aestatura	3	-1.09413	366	69	1076	228	0.2119	0.1885	Estatura que estima tener el encuestado [1.6, 1.7) : 3
Aestatura	4	0.143796	185	40	1076	228	0.2119	0.2162	Estatura que estima tener el encuestado [1.7, 1.8) : 4
Aestatura	5	-1.63546	32	3	1076	228	0.2119	0.0938	Estatura que estima tener el encuestado [1.8, 1.9) : 5
Aestatura	6	-0.7333	2	0	1076	228	0.2119	0	Estatura que estima tener el encuestado [1.9, 2.0) : 6
Aestatura	7	1.928548	1	1	1076	228	0.2119	1	Estatura que estima tener el encuestado > 2.0) : 7
Apeso	1	-3.77209	62	1	1076	228	0.2119	0.0161	Peso que estima tener el encuestado <= 50 : 1
Apeso	2	-4.05811	79	2	1076	228	0.2119	0.0253	Peso que estima tener el encuestado (50, 55) : 2
Apeso	3	-5.74441	132	1	1076	228	0.2119	0.0076	Peso que estima tener el encuestado [55, 60) : 3
Apeso	4	-5.1211	172	9	1076	228	0.2119	0.0523	Peso que estima tener el encuestado [60, 65) : 4
Apeso	5	-1.86651	142	21	1076	228	0.2119	0.1479	Peso que estima tener el encuestado [65, 70) : 5
Apeso	6	-2.34173	138	18	1076	228	0.2119	0.1304	Peso que estima tener el encuestado [70, 75) : 6
Apeso	7	0.84116	106	26	1076	228	0.2119	0.2453	Peso que estima tener el encuestado [75, 80) : 7
Apeso	8	8.123762	143	70	1076	228	0.2119	0.4895	Peso que estima tener el encuestado [80, 90) : 8
Apeso	9	14.14686	102	80	1076	228	0.2119	0.7843	Peso que estima tener el encuestado >= 90 : 9
condi_act	1	5.045429	44	23	1076	228	0.2119	0.5227	¿Cómo consideras tu condición física actual? 1 : Muy mala
condi_act	2	5.865344	189	73	1076	228	0.2119	0.3862	¿Cómo consideras tu condición física actual? 2 : Mala
condi_act	3	-0.57931	429	86	1076	228	0.2119	0.2005	¿Cómo consideras tu condición física actual? 3 : Regular
condi_act	4	-4.18504	355	43	1076	228	0.2119	0.1211	¿Cómo consideras tu condición física actual? 4 : Buena
condi_act	5	-2.94241	57	3	1076	228	0.2119	0.0526	¿Cómo consideras tu condición física actual? 5 : Muy buena
condi_act	8	-0.7333	2	0	1076	228	0.2119	0	¿Cómo consideras tu condición física actual? 8 : No quiero re
condi1	1	3.176688	41	17	1076	228	0.2119	0.4146	¿Cómo consideras tu condición física hace un año? 1 : Muy n
condi1	2	4.71648	180	64	1076	228	0.2119	0.3556	¿Cómo consideras tu condición física hace un año? 2 : Mala
condi1	3	0.133941	396	85	1076	228	0.2119	0.2146	¿Cómo consideras tu condición física hace un año? 3 : Regula
condi1	4	-2.65254	367	57	1076	228	0.2119	0.1553	¿Cómo consideras tu condición física hace un año? 4 : Buena
ADuestu	1	-2.5817	52	4	1076	228	0.2119	0.0705	Puesto: Estudiante



¿Cómo es tu salud actualmente?

1: Muy mala	Epsilon	# participantes	# obesos	obesos
2: Mala	1.15	15	5	33.33%
3: Regular	Epsilon	# participantes	# obesos	obesos
4: Buena	Bajar de peso	5.25	771	71.65%
5: Muy buena	Esta contento con su peso	-7.54	239	22.21%
	Subir de peso	-3.50	63	5.86%
	No sabe	-0.90	3	0.28%

	Epsilon	# participantes	Proporción población	# obesos	Probabilidad obesidad	Proporción obesos
				190	45	23.68%
						22.36%
						31.18%
						31.08%
						19.38%
						Proporción obesos
						17.81%
						22.36%
						23.68%

**Why is a prediction model
important?**



Because...

**The principal purpose of living systems
and the principal purpose of science -
medicine, public health - is to...**

Predict

for

Decision making



Some important decisions...



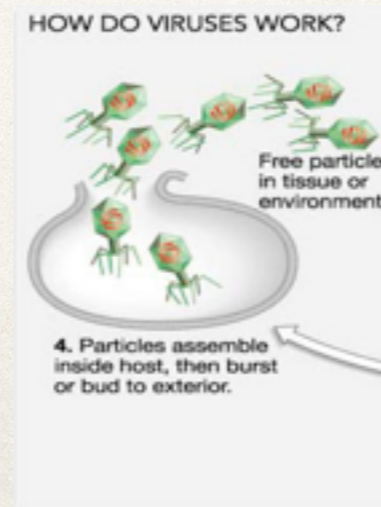
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a collective level



A grid of 50 images of a tabby cat, arranged in 10 rows and 5 columns. The top row shows the cat walking on a wooden branch. The remaining 49 images show the cat in various poses, including lying on its back, on its side, and on its stomach. The text "There are 'good' decisions and there are 'bad' ones" is overlaid in the center of the grid.

There are "good" decisions
and there are "bad" ones

Predictability and Decision Making



¿Qué es una decisión?

Una selección entre alternativas implicando un cambio de estado

- Asociada con una acción no con cosas
- Asociada con una “estrategia”
- ¿Cómo enumerar las alternativas?
- ¿Cómo ponderar las alternativas?
 - ¿Qué factores se toma en cuenta?
 - Escalas de tiempo
- “Racional” versus “irracional”
- “Emocional” versus “lógico”
- Explicito versus implícito

Predictibilidad en los Sistemas Simples versus los Sistemas Complejos

1) Suelto un objeto de mi mano. ¿Qué pasará?

Cae al suelo 100% Se queda colgado en el aire 0%

2) Dejo dos objetos de distintas masas caen de mis manos.
¿Cuál tocará piso primero?

Lo mas pesado 0% Lo menos pesado 0% Ambos al mismo tiempo 100%

3) Empujo este objeto con mi mano. ¿Qué pasa?

Se mueve 100% Se queda sin mover 0%

Fenomenología: experiencia cotidiana Las leyes de Newton

¿Qué es predecible?

¿Los seres humanos?



1) No han tomado agua (ningún líquido) en tres días. Alguien te ofrece un litro de agua o una caja de hojuelas. ¿Qué seleccionas?

Agua 100%

Hojuelas 0%

2) Hay un incendio grave en el auditorio y suena la alarma. Yo les invito esperar hasta el final de mi plática o se huyen. ¿Qué haces?

Huyes 100%

Se queda 0%

3) Tienen mucho, mucho hambre. Alguien les ofrece una comida de 1500 calorías para satisfacerles. Pueden seleccionar entre carnitas, enchiladas suizas y frijoles negros; o puro apio (7.5kg). ¿Qué seleccionas?

Carnitas etc. 100%

Apio 0%

¿Qué es predecible?

¿Los seres humanos?



4) No han tomado agua (ningún líquido) en tres días. Alguien te ofrece un litro de Coca-cola o un litro de Pepsi. ¿Qué seleccionas?

Coca cola 70%

Pepsi 30%

5) Hay un incendio grave en el auditorio y suena la alarma. Llegaste a la salida pero notas alguien quien no conoces atrapado. Regresas para tratar de ayudarles arriesgando tu propia vida o sigues corriendo?

Si regresas 50%

No regresas 50%

6) Tienen mucho, mucho hambre. Alguien les ofrece una comida de 1500 calorías para satisfacerles. Pueden seleccionar entre carnitas, enchiladas suizas y frijoles negros; o barbacoa, chicharrón y arroz ¿Qué seleccionas?

Carnitas etc. 50%

Barbacoa etc. 50%

¿Qué es predecible?



- 1) ¿Quién de ustedes será obeso en 20-30 años?
- 2) ¿Quién de ustedes padecerá de diabetes en 30-40 años?
- 3) ¿Quién de ustedes morirá antes de 70 por un mal estilo de vida?
- 4) ¿Cuánta biodiversidad perderá México en los próximos 50 años?
- 5) ¿Qué acciones (factibles) resultarán en una reducción del número de personas en situación de calle?
- 6) ¿Habrá computadoras inteligentes (estilo Hal2000 de la película 2001 A Space Odyssey) en 20 años?

y muchísimas otras

Predictabilidad y la toma de Decisiones



“Decisiones”

Normalmente pensamos en las decisiones como algo más humano asociado con la voluntad libre

¡Somos autómatas! En la mayoría...

Una bola en un campo gravitacional

Un gato en un campo gravitacional

Un ser humano en un campo gravitacional

¿Porqué tomamos malas decisiones?

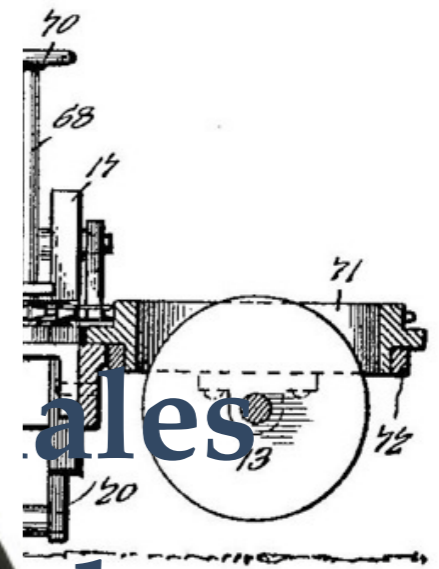
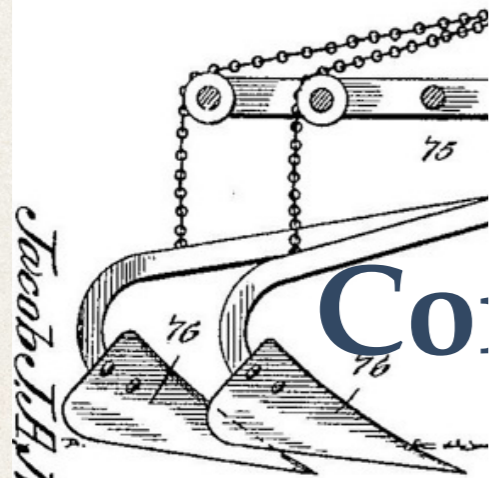


What Doesn't Make Decisions? Prediction and science: the last 3 centuries



¿Cómo

...inas?



Co:
El murosomos esclavos de la ley.

ales
la ley.





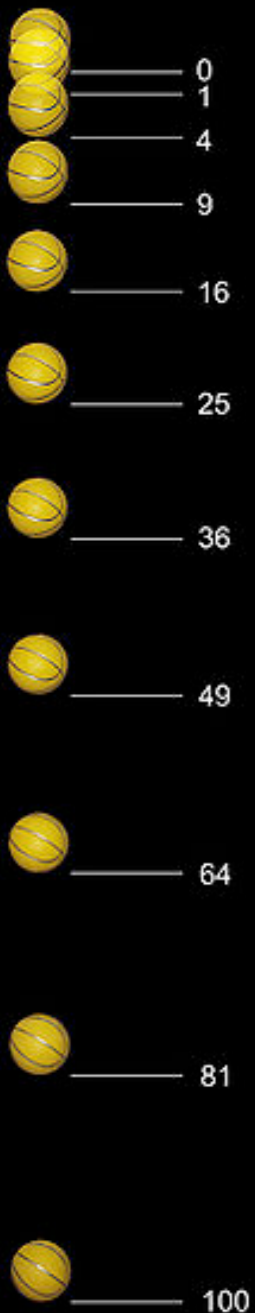
Predictability in Simple Systems versus Complex Systems

Mechanistic

Adaptive

The *evolution* of function
The difference between complex and simple systems is the difference between systems that do the same thing in the same way and those that have done them in a different way.

Complexity is a consequence
of that revolution.



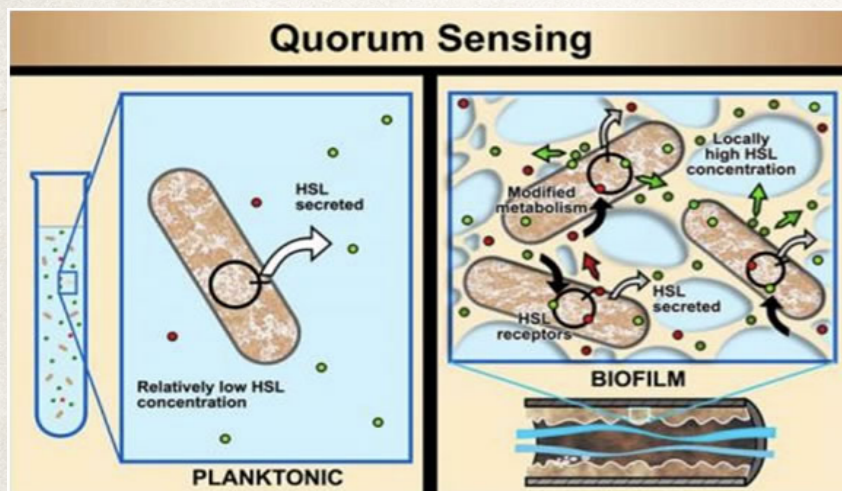
Every Living Thing Makes Decisions: Every living thing is a “data miner”



What's the difference/same between human decision making and that of a worm or even a bacterium?

They all use prediction models for decision making.

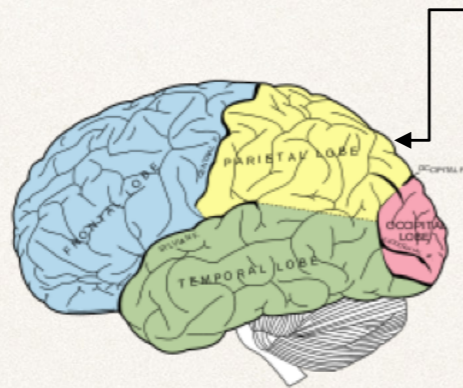
However, the complexity and richness of the set of possible behaviours and the probability distribution on them - the decision “landscape”



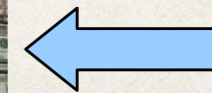
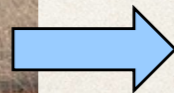
What is the Difference Between them?



Different data, different data processors and different inference algorithms



Same goal of modeling a **complex** world for **decision making** and **“optimization”**



CREDIT SUISSE FX TWAP Algo	
Type	Spot
Pair	EURUSD Buys EUR
Tenor	SPOT 09/10/2008
Amount	12,000,000.00 EUR
Order Type	Limit
Limit Price	1.4125
Start Time	10:00:00
End Time	14:00:00
Execution Style	Normal
<input type="button" value="Submit"/> <input type="button" value="Close"/>	

Deep Data, the Data Revolution and Decision Making

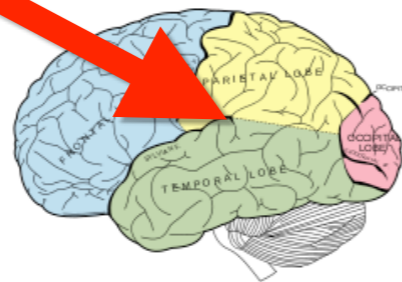


A revolution in the generation of data



Human brain
10-100 Terrabytes

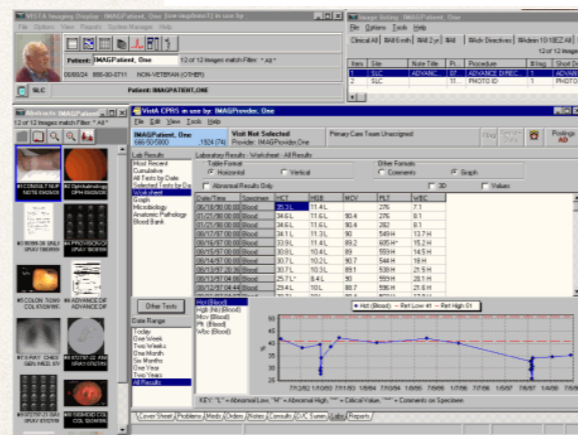
All the books in the world
30-50 Terrabytes



A revolution in data analysis

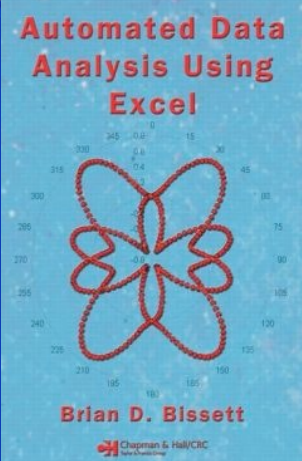
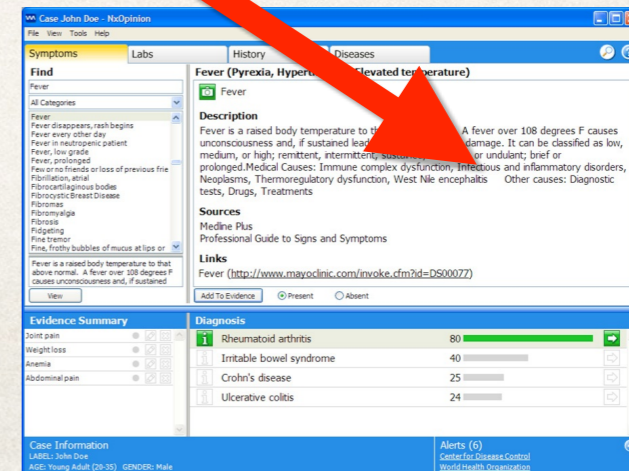


1 human genome
= 1GB (200)
CT image
= 10MB
MRI image
= 40MB



In electronic form
1 zettabyte

A revolution in data storage



How do we measure the “value” of a decision?



❖ First, what is the goal or purpose of the decision?

❖ Second, can we determine a metric of success?

❖ Great experience? Movie, meal,...

❖ Long and happy marriage?

❖ Higher salary?

❖ Vote?

❖ Increased sales?

❖ More children?

❖ Longer life?

❖ Other...

❖ More than one?

INCREASE YOUR ...

✓ LEADS
✓ CUSTOMERS
✓ SALES
✓ PROFIT



Importance of “scale”:

- time
 - a decision can have different values as a function of time
- population / statistical ensemble
 - a decision may be good / bad for you and bad / good for the group
- causal chain / attribution

Importance of feedback and learning

Importance of substrate

- Genetic
- Epigenetic
- Neuronal

In Evolution Natural Selection is the ultimate arbiter of the “value” of decisions

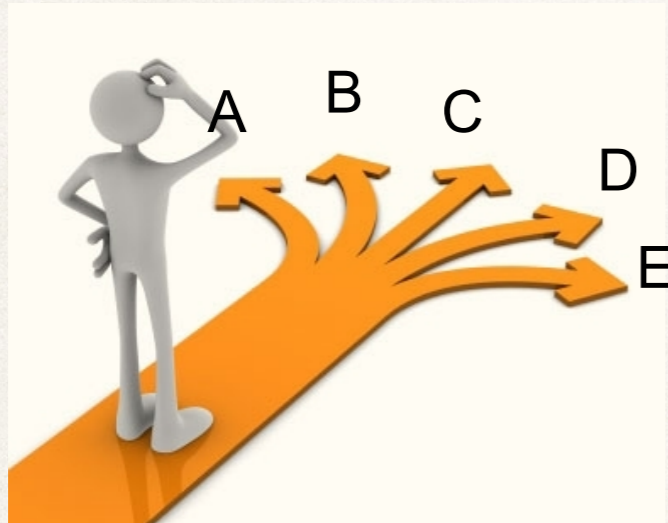


The Value of a Decision: The Rational Theory of Decision Making

Alternativas: A, B, C, D, E

Preferencias: $P(A)$, $P(B)$, $P(C)$, $P(D)$, $P(E)$

Para tomar una decisión racional se ranquea las alternativas por sus preferencias y adopta la alternativa con mayor preferencia



Puede hacer la comparación $P(i) > o < P(j)$ para todas las alternativas

Si $P(i) > P(j)$ y $P(j) > P(k)$ entonces $P(i) > P(k)$

¿Se aplica únicamente a los seres humanos?

Lo racional es siempre traicionar – ¡piensa sobre manejar en el DF!

Ejemplo de la racionalidad: El dilema del prisionero

	Prisionero B se mantiene silencioso	Prisionero B traiciona
Prisionero A se mantiene silencioso	Cada uno recibe sentencia de 6 meses	Prisionero A: 10 años Prisionero B: se libera
Prisionero A traiciona	Prisionero A: se libera Prisionero B: 10 años	Cada uno recibe sentencia de 5 años

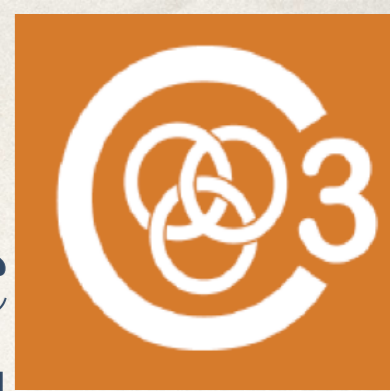


Group Decisions versus Individual Decisions

- ¿Quién toma decisiones?
 - Individuos, familias, empresas, gobiernos, muchas otras unidades organizacionales

	<i>P</i>	<i>if P then Q</i>	<i>Q</i>
Individual 1	true	true	true
Individual 2	false	true	false
Individual 3	true	false	false
Society	true	true	false

Si votamos por mayoría entonces la sociedad no es lógico/racional



An Algorithmic Representation of a Decision Requires an Algorithmic Representation of the World: A Model

A “decision” Prediction $P(C | X(t))$ Probability of C given X

In the physical world, predictions tend to be **algorithmic** ← **Prediction** → In the biological world, predictions tend to be **heuristic**

Physical world
Less complex,
less adaptative

Biological
World
More complex,
more adaptative

$X(t)$ = the information used
to make the decision (predict)

How much information do you need or use to make a “good decision”?

What degree of multi-factoriality is there?

The biological world requires a lot more data.

Algorithmic Representation of a Decision



$P(C|X(t))$ represents our model of reality and perception



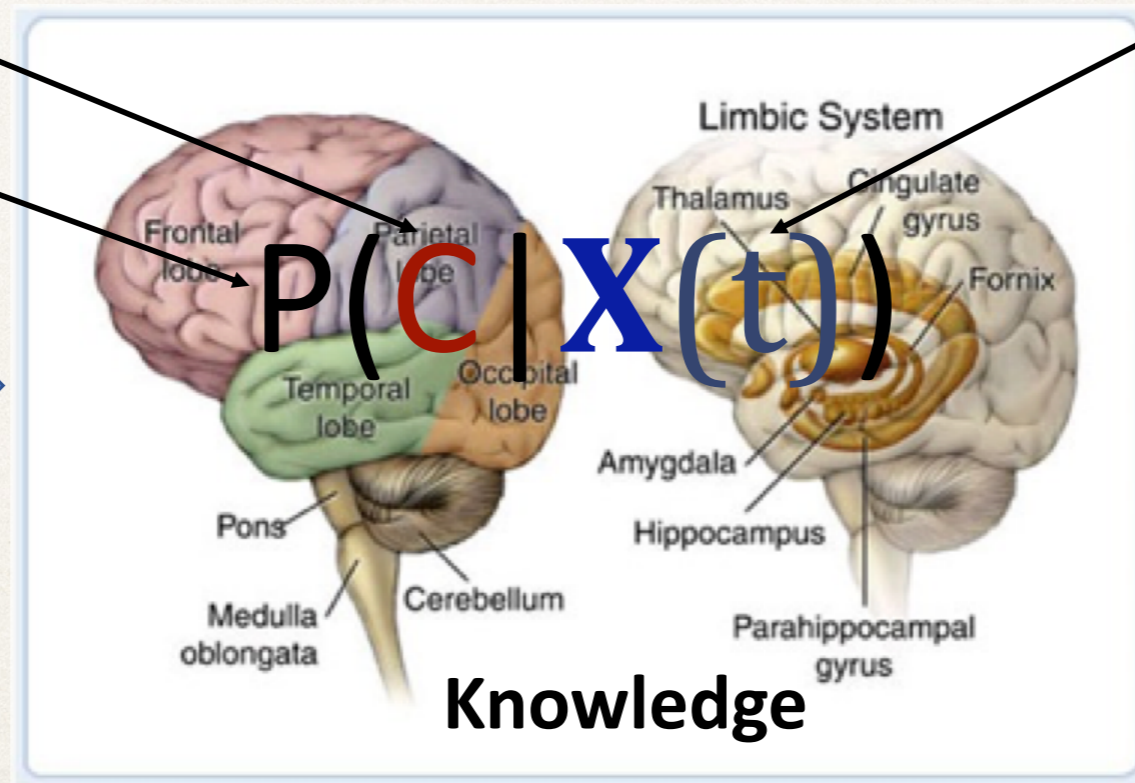
Data + Information + Knowledge

Prediction --> Decision + Action

Human Intelligence

Heuristic: we don't know what it is in humans. It's a model of the world.

Data + Information



Decision + Action

There are many Alternatives to be considered in Decisions And many possible actions

Did it work?

The decision+action is judged to be good or bad with respect to A performance indicator

Algorithmic Representation of a Decision



$P(C|X(t))$ represents the algorithm's model of reality and perception



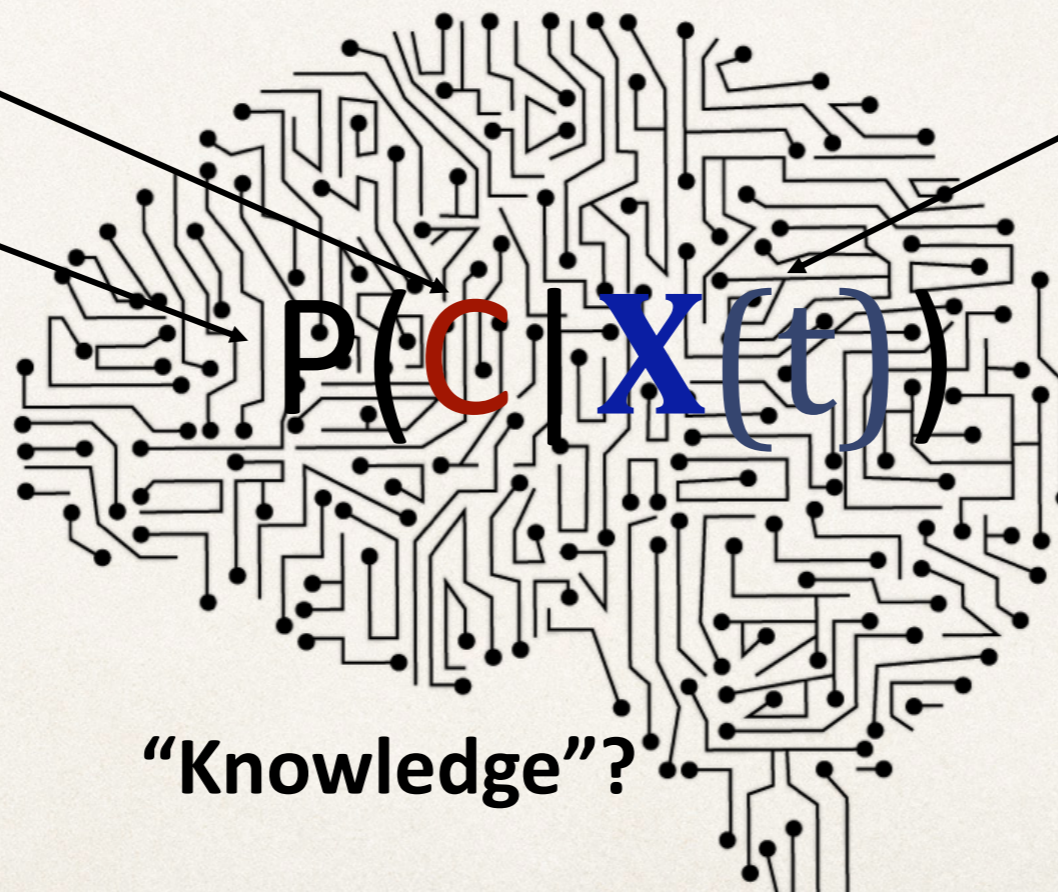
Data + Information + Knowledge

Prediction --> Decision + Action

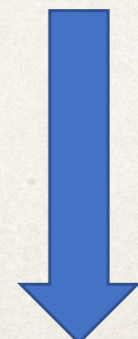
Artificial Intelligence

Heuristic: we don't know what it is in humans. It's a model of the world.

Data + Information



Decision + Action



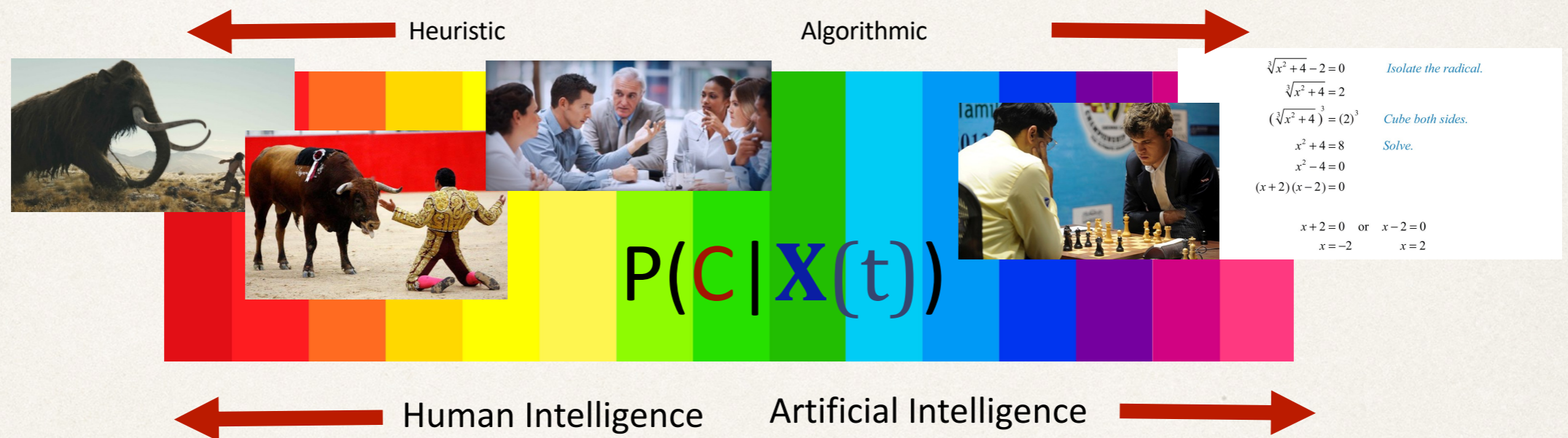
Did it work?

The decision+action is judged to be good or bad with respect to A performance indicator

Algorithmic Representation of a Decision



Human Intelligence versus Artificial Intelligence



As examples of this function for humans we have: Roger Federer making a tennis shot; Sergio Perez deciding when to brake; Octavio Paz deciding which words to use; you reading a memo from the CEO; You deciding whether to invest in a new hardware set up; you deciding whether to hire a new Chief Data Architect;...

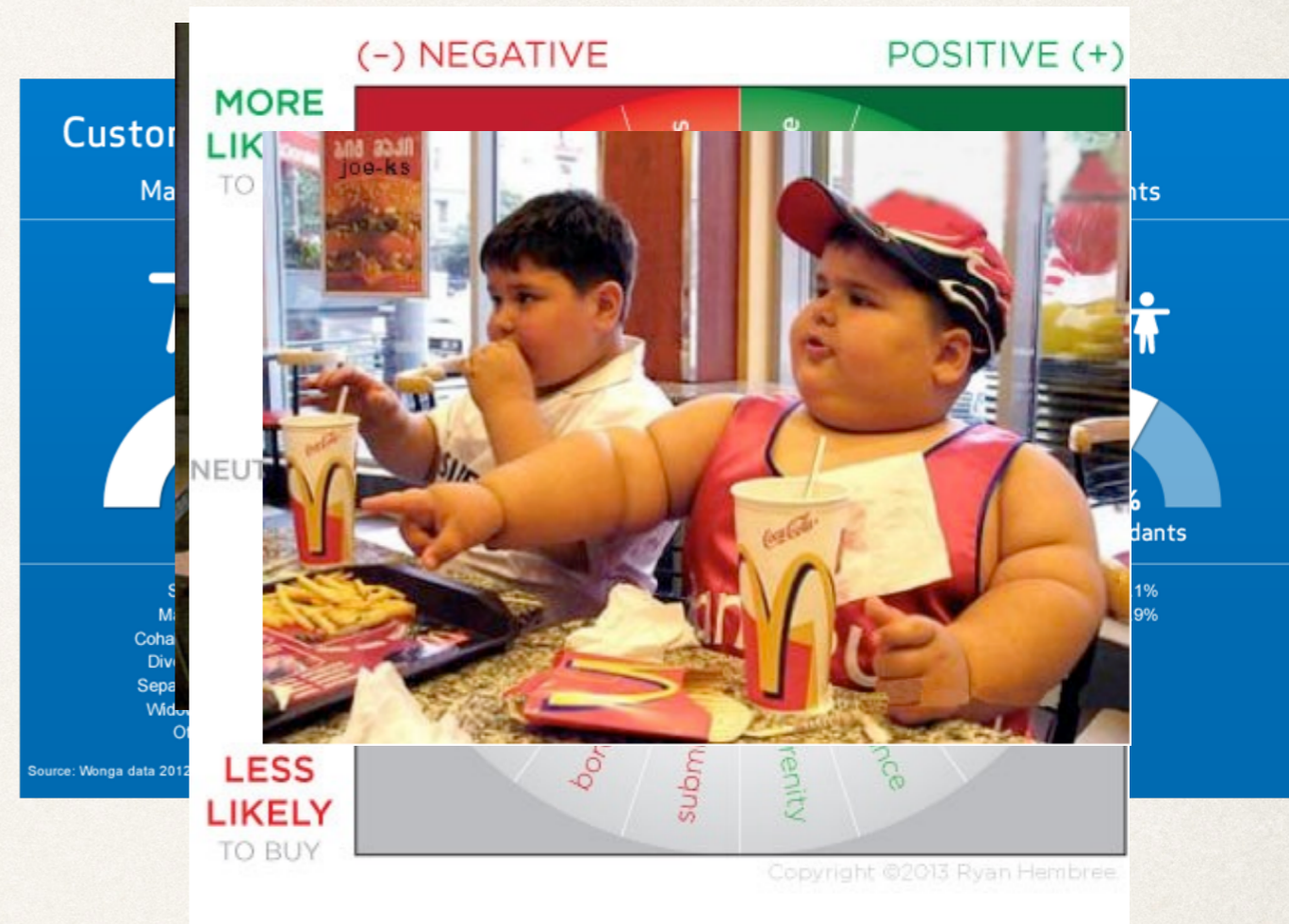
Every decision/action we take requires and uses a DIFFERENT $P(C|X)$, whether we use HI or AI!

How we arrive at this function is a deep mystery. How we convince ourselves we arrive at a decision often doesn't have much to do with reality because there are many subjective elements to it.



Your Prediction/Decision Heuristic/Algorithm depends on...

**“Who” you are
What and how
you think
you “feel”**

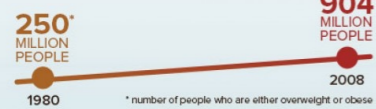


**Your prediction/decision heuristic/algorithm
then determines your behaviour - what you do**

Decision Making and the Obesity Pandemic



THE WORLD IS GETTING FATTER



HOW DO I KNOW WHETHER I AM OVERWEIGHT?

Calculate your body mass index (BMI) using this formula



OBESITY KILLS!

- 7 common diseases due to obesity:
- Arthritis
 - Cancer
 - Infertility
 - Heart Diseases
 - Back Pain
 - Diabetes
 - Stroke



A B C TO OBESITY PREVENTION

SIMPLE RULES TO STAY IN SHAPE

A dopt New Healthy Habits



B alance Your Calorie Intake



C ontrol Your Weight Gain



source: World Health Organization ©2014 Health Buzz www.healthbuzz.asia

Obesity, type 2 diabetes, heart disease, strokes, cancer etc. are diseases associated with “lifestyle” and therefore are “preventible” (?)

Pharmaceutical Research, Vol. 25, No. 9, September 2008 (© 2008)
DOI: 10.1007/s11095-008-9661-9

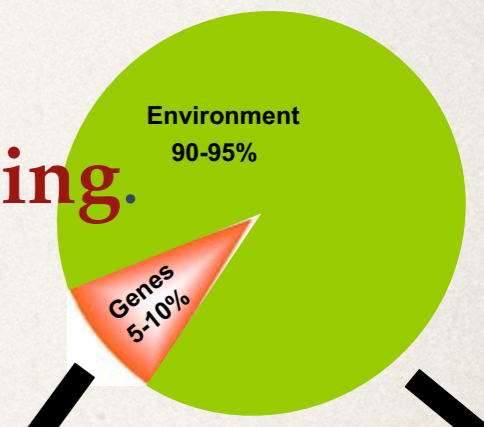
Expert Review

Cancer is a Preventable Disease that Requires Major Lifestyle Changes

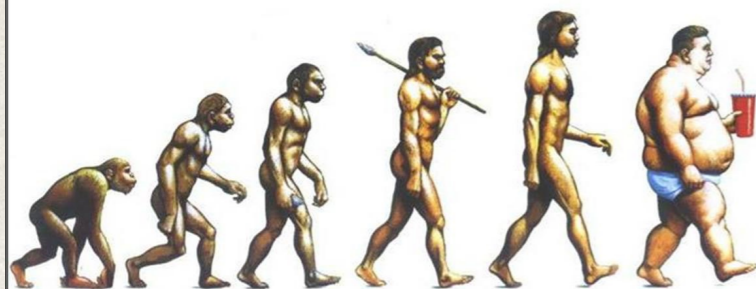
They are **behavioral** diseases, i.e. diseases arising from **decision making**.

Human behavior is **complex**

and requires “**deep data**”.



The shape of things to come



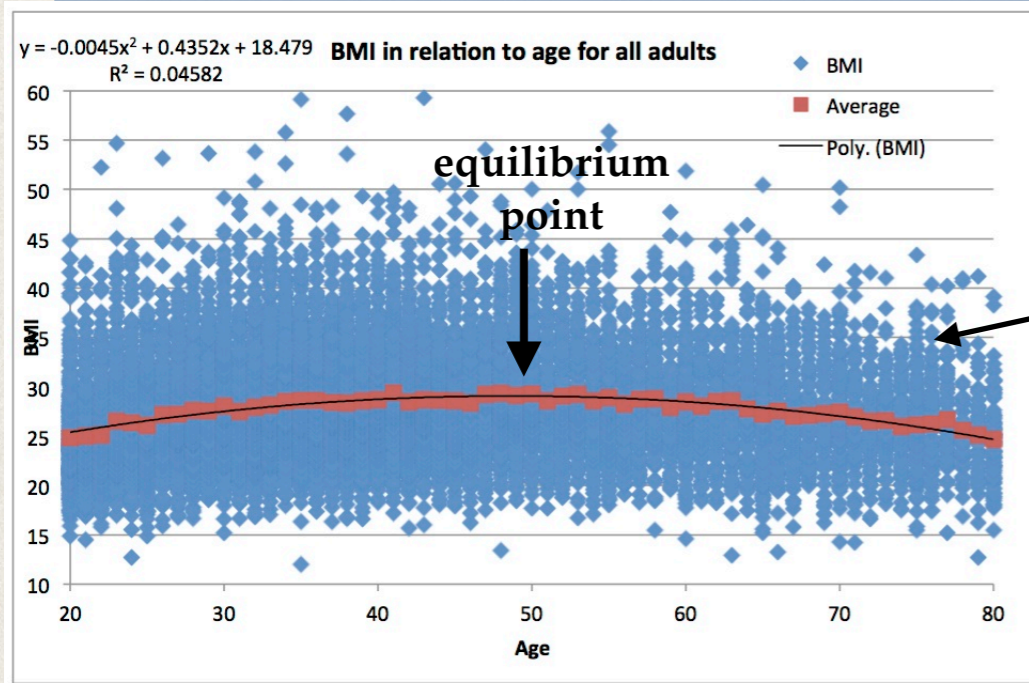


Obesity - risk factors: What you do

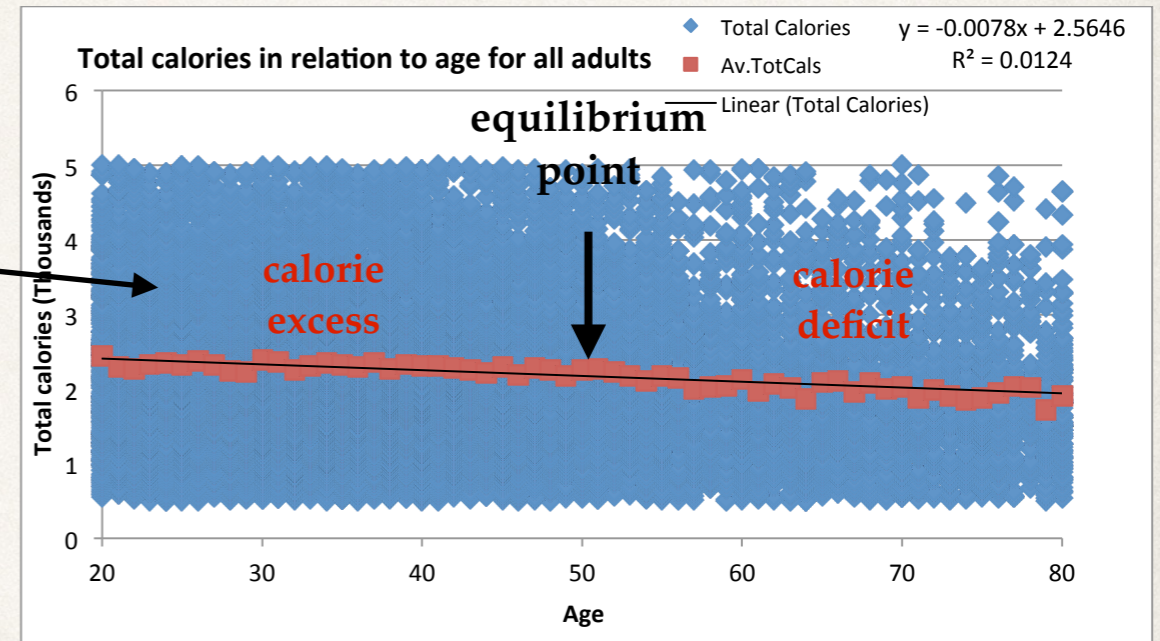
You aren't what you eat you become what you eat

We "decide" to eat too much

Epidemiological data from ENSANUT 2006

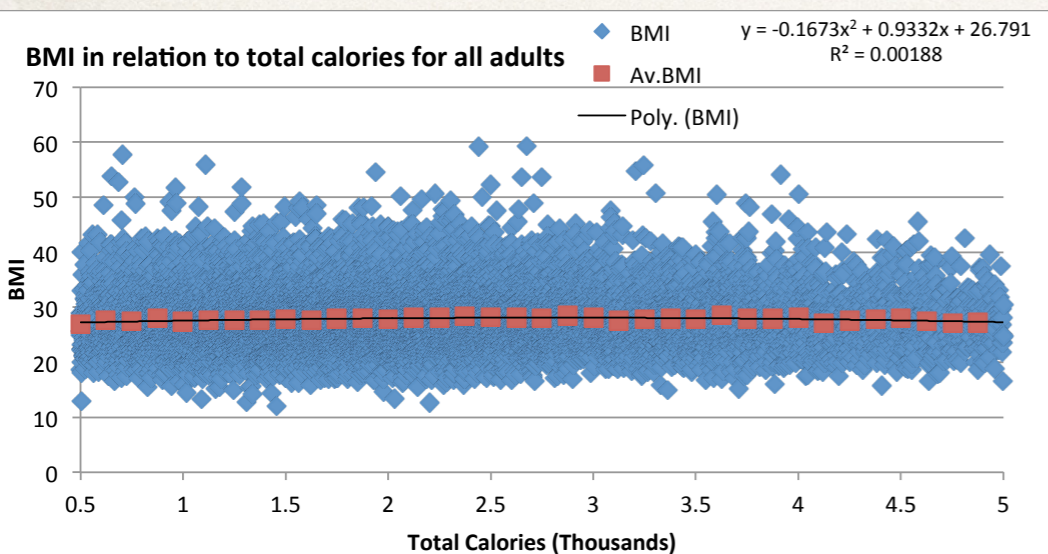


Its not "noise" its multifactoriality



We get fatter then we get thinner

We eat less the older we get



	Variable(s)	Unstd. B	Std. Error	t	f	R ²	Sig	Lower	Upper
Moving Av.					29.236	0.343	0		
BMI Change	Constant	-1.954	0.362	-5.392			0	-2.68	-1.228
ALL	Total_Cals	0.904	0.167	5.407			0	0.569	1.239
	Variable(s)	Unstd. B	Std. Error	t	f	R ²	Sig	Lower	Upper
Moving Av.					13.397	0.193	0.001		
BMI Change	Constant	-1.625	0.444	-3.656			0.001	-2.515	-0.734
Men	Total_Cals	0.724	0.198	3.66			0.001	0.328	1.121
	Variable(s)	Unstd. B	Std. Error	t	f	R ²	Sig	Lower	Upper
Moving Av.					22.429	0.286	0		
BMI Change	Constant	-1.754	0.372	-4.711			0	-2.5	-1.008
Women	Total_Cals	0.833	0.176	4.736			0	0.481	1.185

The obese eat as much as the thin

Its the excess of calories that is the motor for obesity. The motor is more active at 20 and stops at 50 and then goes in reverse.

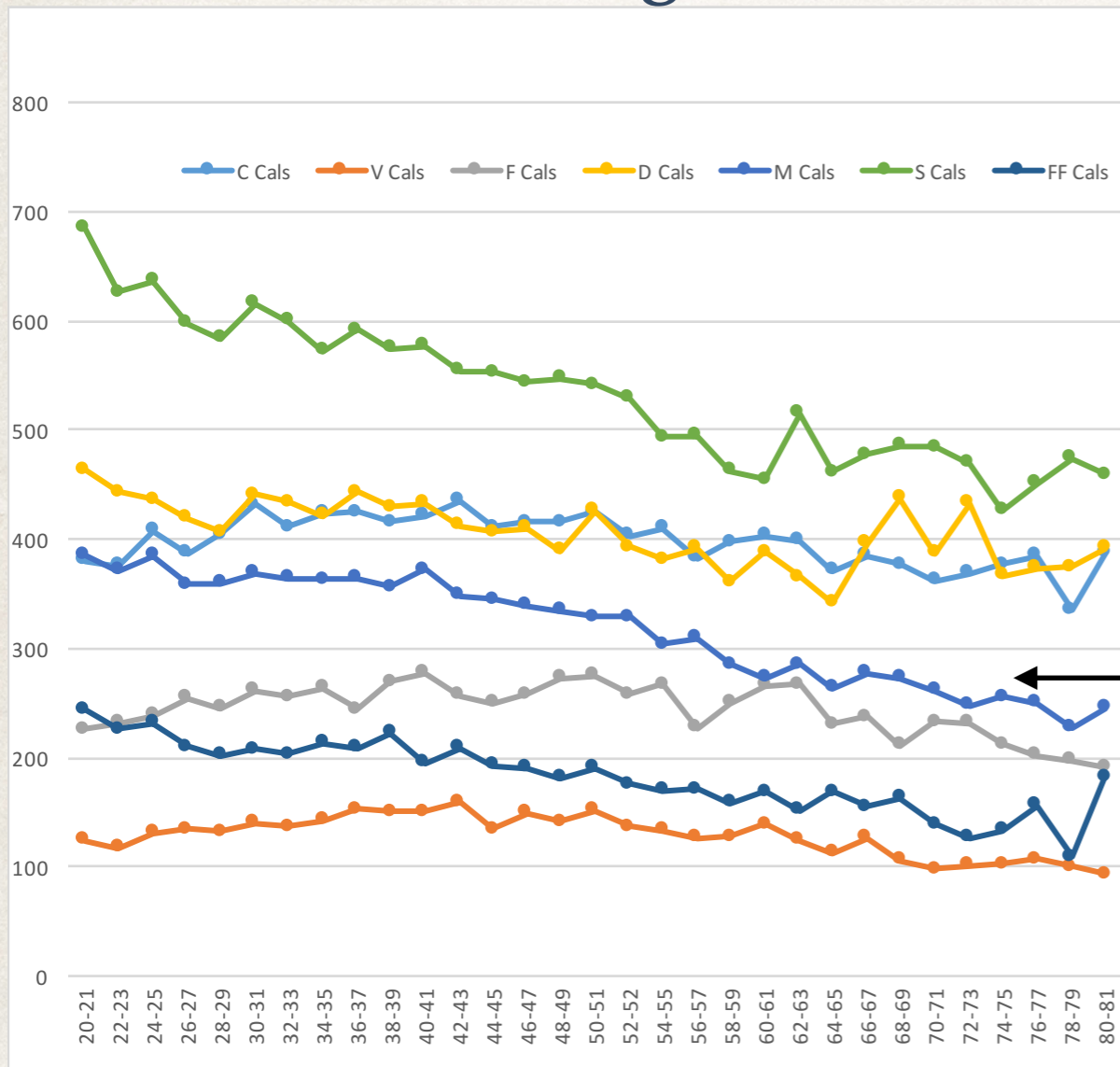


Obesity - risk factors: What you do

We “Decide” to eat the “wrong” things

Epidemiological data from ENSANUT 2006

The motor changes its fuel...



	Edad 20	Edad 50	Edad 80	Diff 50 20	Diff 80 20	Diff 80 50	Edad 20	Edad 50	Edad 80
S	650	540	460	16.92%	29.23%	14.81%	26.75%	23.38%	24.73%
FF	230	185	140	19.57%	39.13%	24.32%	9.47%	8.01%	7.53%
M	370	330	240	10.81%	35.14%	27.27%	15.23%	14.29%	12.90%
D	450	415	370	7.78%	17.78%	10.84%	18.52%	17.97%	19.89%
F	230	270	200	-17.39%	13.04%	25.93%	9.47%	11.69%	10.75%
V	120	150	90	-25.00%	25.00%	40.00%	4.94%	6.49%	4.84%
C	380	420	360	-10.53%	5.26%	14.29%	15.64%	18.18%	19.35%
	2430	2310	1860	4.94%	23.46%	19.48%			

The fuel mix at age 20 consists of 51.5% sugars, junk food and meat and 30% fruit, vegetables and cereals. At age 50 its 45.5% and 36.5%.

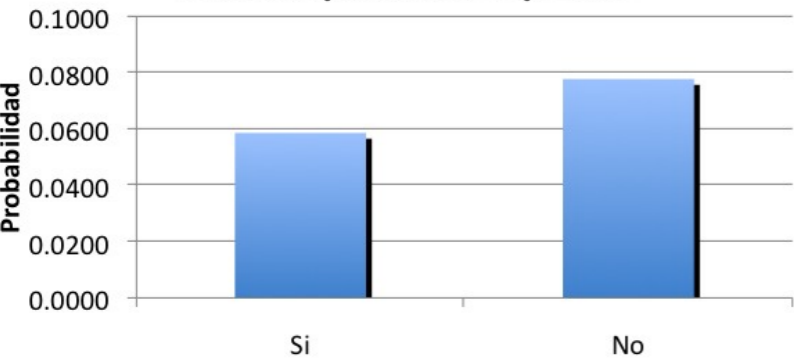
Accelerated reduction in meat consumption in the aged

Chronic disease - Risk factors What you do

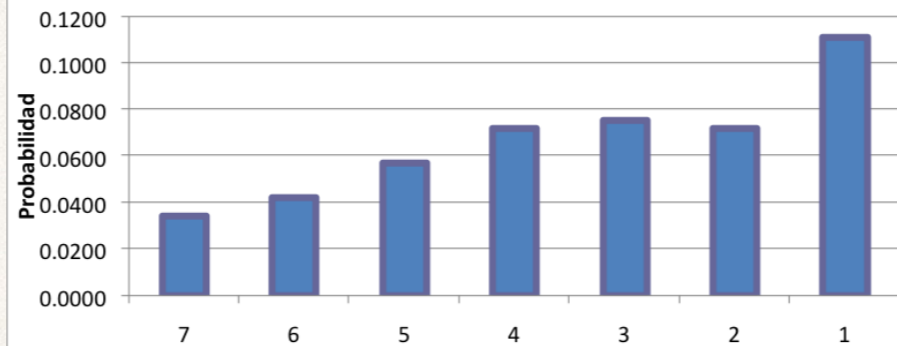
We “Decide” when to exercise, what type, how often,...



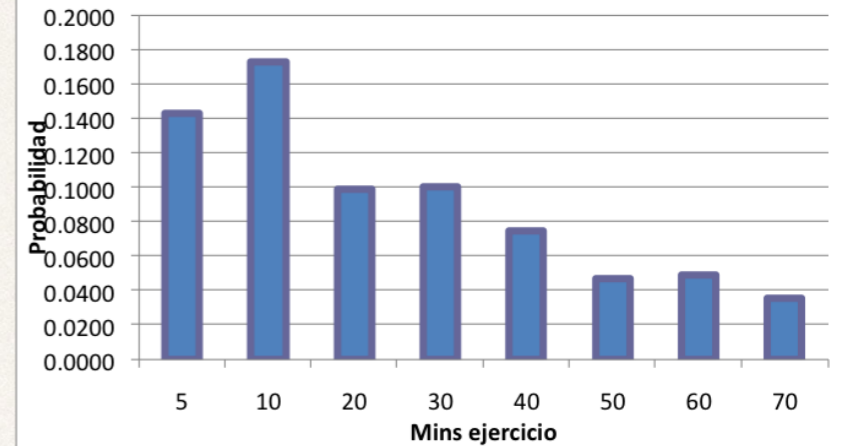
Gráfica de Probabilidad de Diabetes versus si practicas deportes



Gráfica de Probabilidad de diabetes versus Número de días de ejercicio por semana

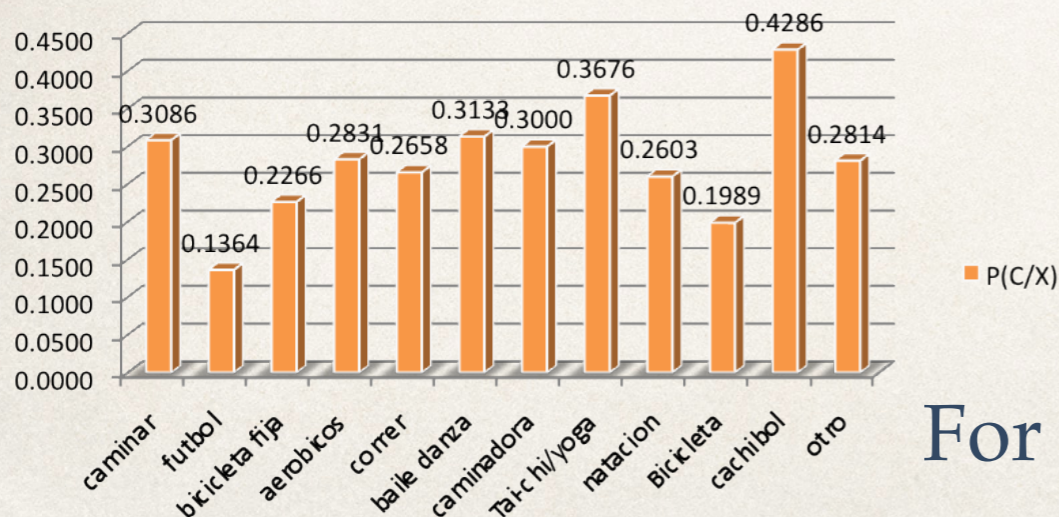


Gráfica de Probabilidad de diabetes versus mins de ejercicio

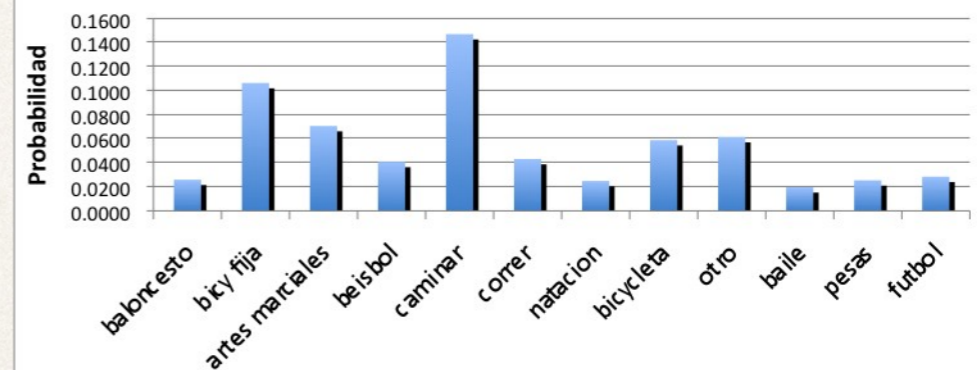


For men 20-59 de PREVENIMSS 2006

Tipo de ejercicio practicado vs probabilidad de tener diabetes P(C/X)



Gráfica de Probabilidad de Diabetes versus tipo de ejercicio



For seniors > 59

Is it riskier to walk than do nothing?



-
- ❖ So, there is ample evidence that we eat too much, too much of the wrong things and we don't exercise enough. These are all associated with "bad" decisions?
 - ❖ Why do we make these decisions?
 - ❖ Are our decisions rational? Depends on:
 - ❖ What value function our decision making is based on
 - ❖ What processing model $P(\cdot | \cdot)$ we use
 - ❖ What information $\mathbf{X}(t)$ we have available

Rational Decision Making: The Information $X(t)$



- ❖ Do we have the information available to make a “rational” decision?

Pregunta	Epsilon	# participantes	Proporcion poblacion	# obesos	Probabilidad obesidad	Proporcion obesos
Hacer ejercicio no tiene importancia	0.51	3	0.28%	1	33.33%	0.44%
Hacer ejercicio es poco importante	-0.90	3	0.28%	0	0.00%	0.00%
Hacer ejercicio es importante	-1.45	115	10.69%	18	15.65%	7.89%
Hacer ejercicio es muy importante	0.56	953	88.57%	209	21.93%	91.67%

What information is necessary and what information, if any, is sufficient?

Pregunta	Epsilon	# participantes	Proporcion poblacion	# obesos	Probabilidad obesidad	Proporcion obesos
Si sabe del nuevo impuesto en alimentos de alta densidad	-0.81	814	75.72%	163	20.02%	71.49%
No sabe del nuevo impuesto en alimentos de alta densidad	1.47	261	24.28%	65	24.90%	28.51%

Pregunta	Epsilon	# participantes	Proporcion poblacion	# obesos	Probabilidad obesidad	Proporcion obesos
Si conoce el IMC para un peso normal	-3.07	141	13.12%	15	10.64%	6.58%
No conoce el IMC para un peso normal	1.21	934	86.88%	213	22.81%	93.42%

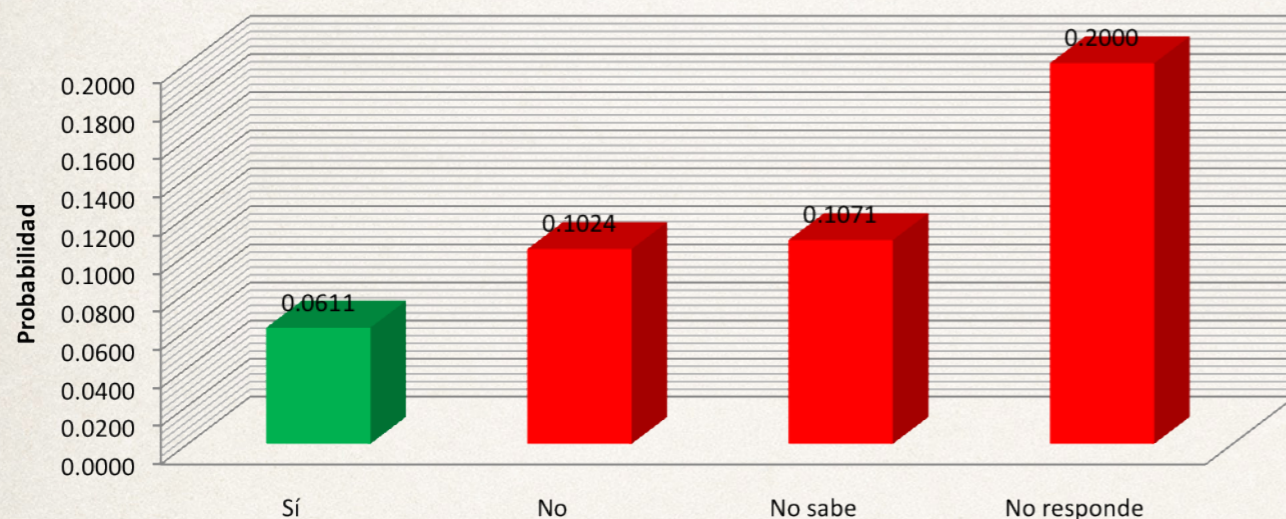


Chronic disease - risk factors

What you think (know): Ignorance can kill

Epidemiological data from ENCOPREVENIMSS 2006

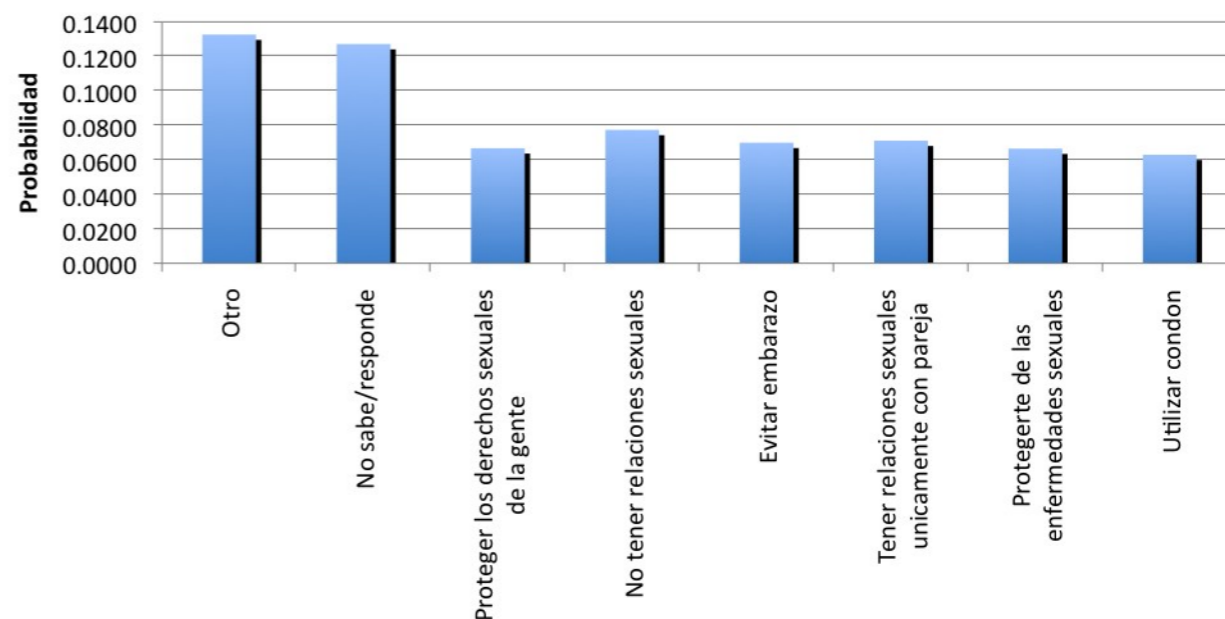
¿Sabe leer o escribir un recado?



For men 20-59 from
PREVENIMSS 2006

- Sí
- No
- No sabe
- No responde

Gráfica de probabilidad de diabetes versus qué piensas que significa el sexo protegido

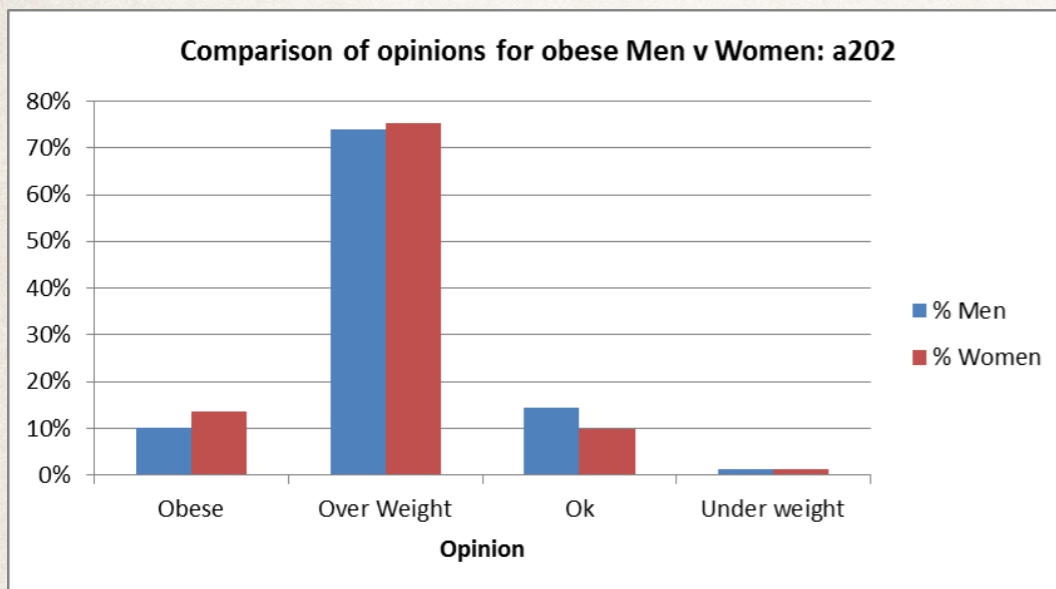
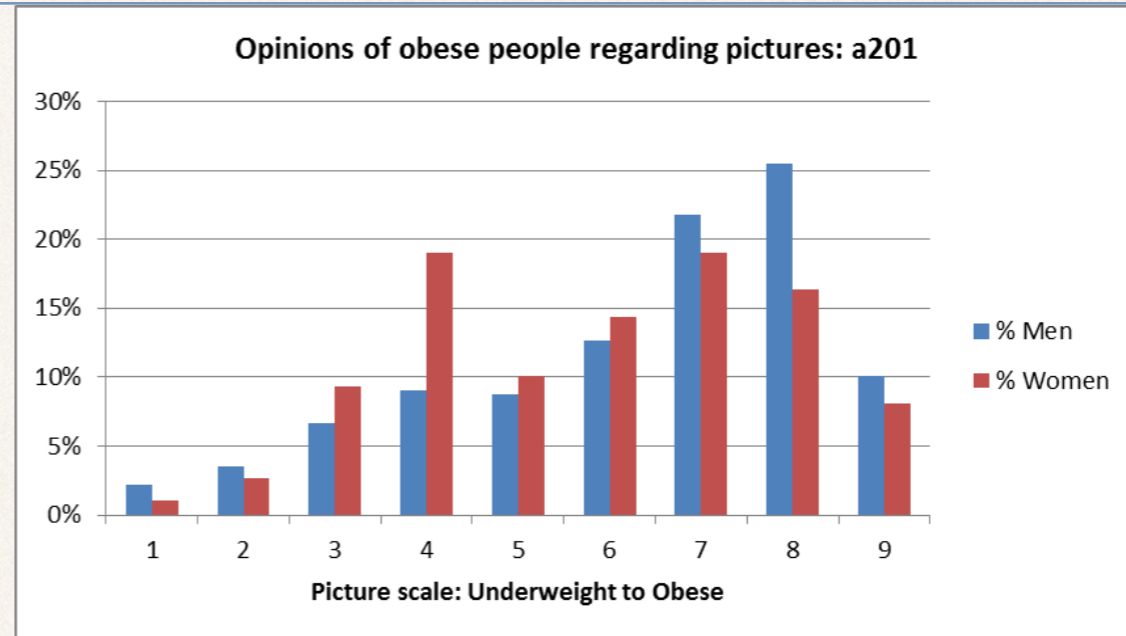
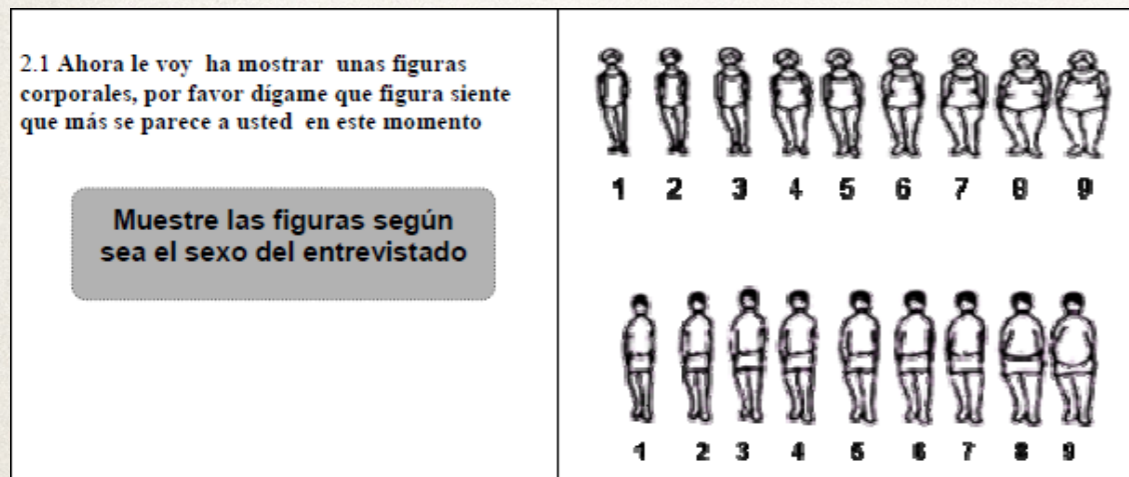


Ignorance and especially about health issues is as important a risk factor as obesity

Rational Decision Making:

Our processing unit - misperception by image

Epidemiological data from ENSANUT 2006



People think they're less overweight/obese than they are. Symptom severity is underestimated.

Fundamental question: Why do we "lie" to ourselves?

Perception of weight and Cognitive Biases - What you think/feel

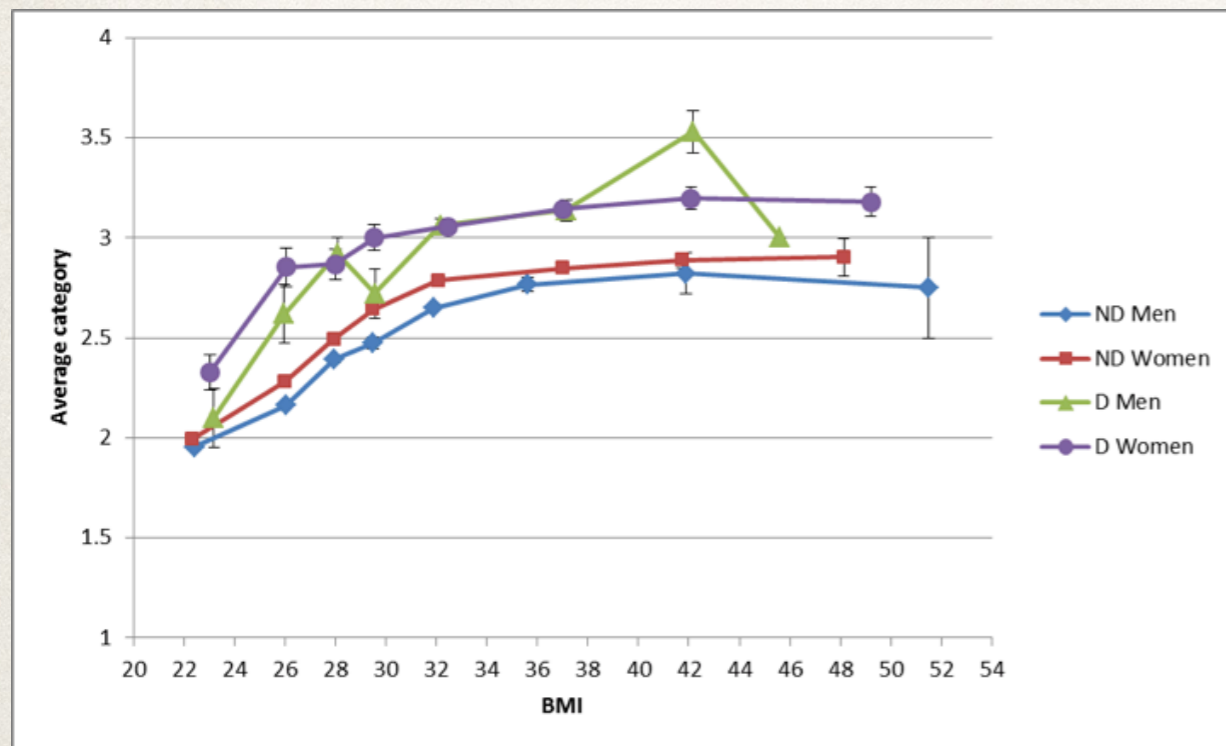


Figure 2. Comparison of non-diagnosed (ND) versus diagnosed (D) obese mean responses for the category self-perception question by gender.

Slopes in the linear range are 35-50% less than one would expect if people could gauge their weight accurately! The lobster in the pot syndrome



Self-serving bias
Anchoring bias

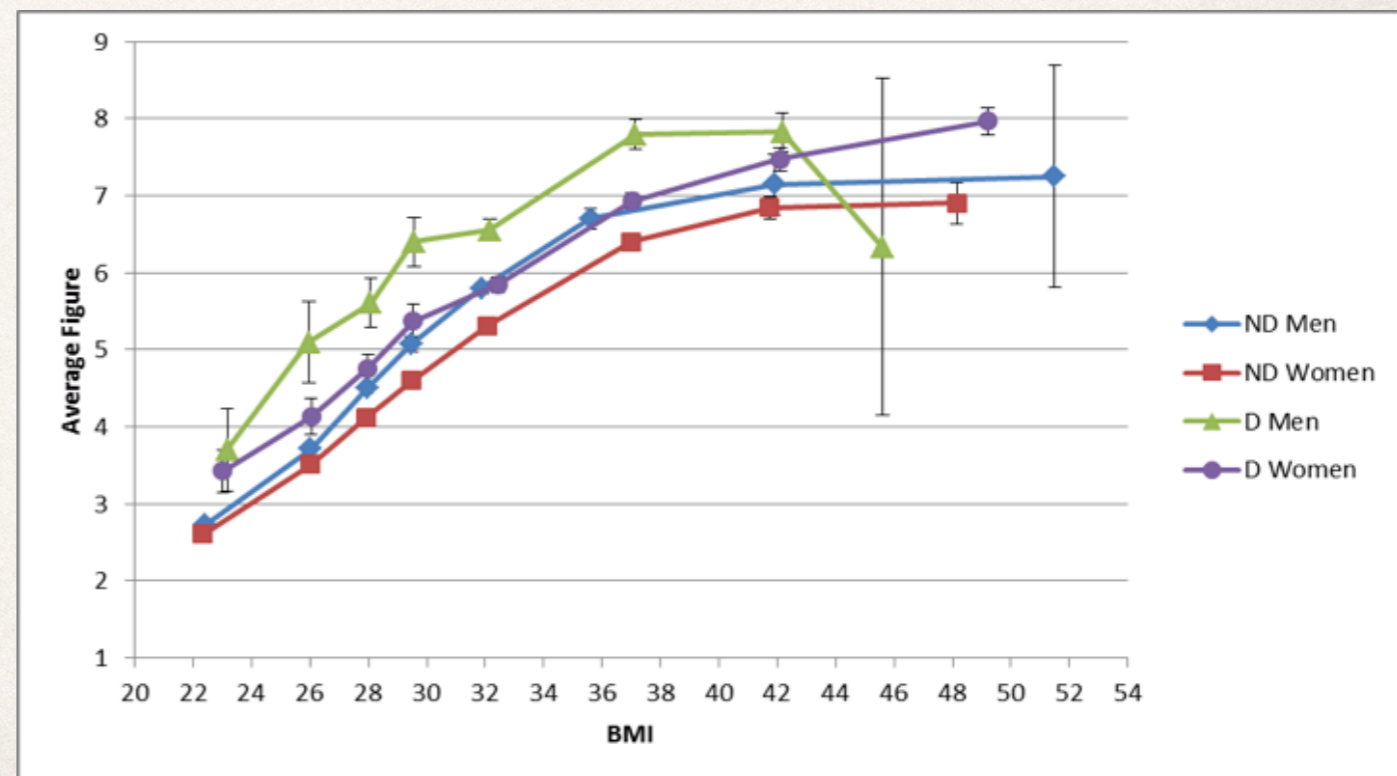
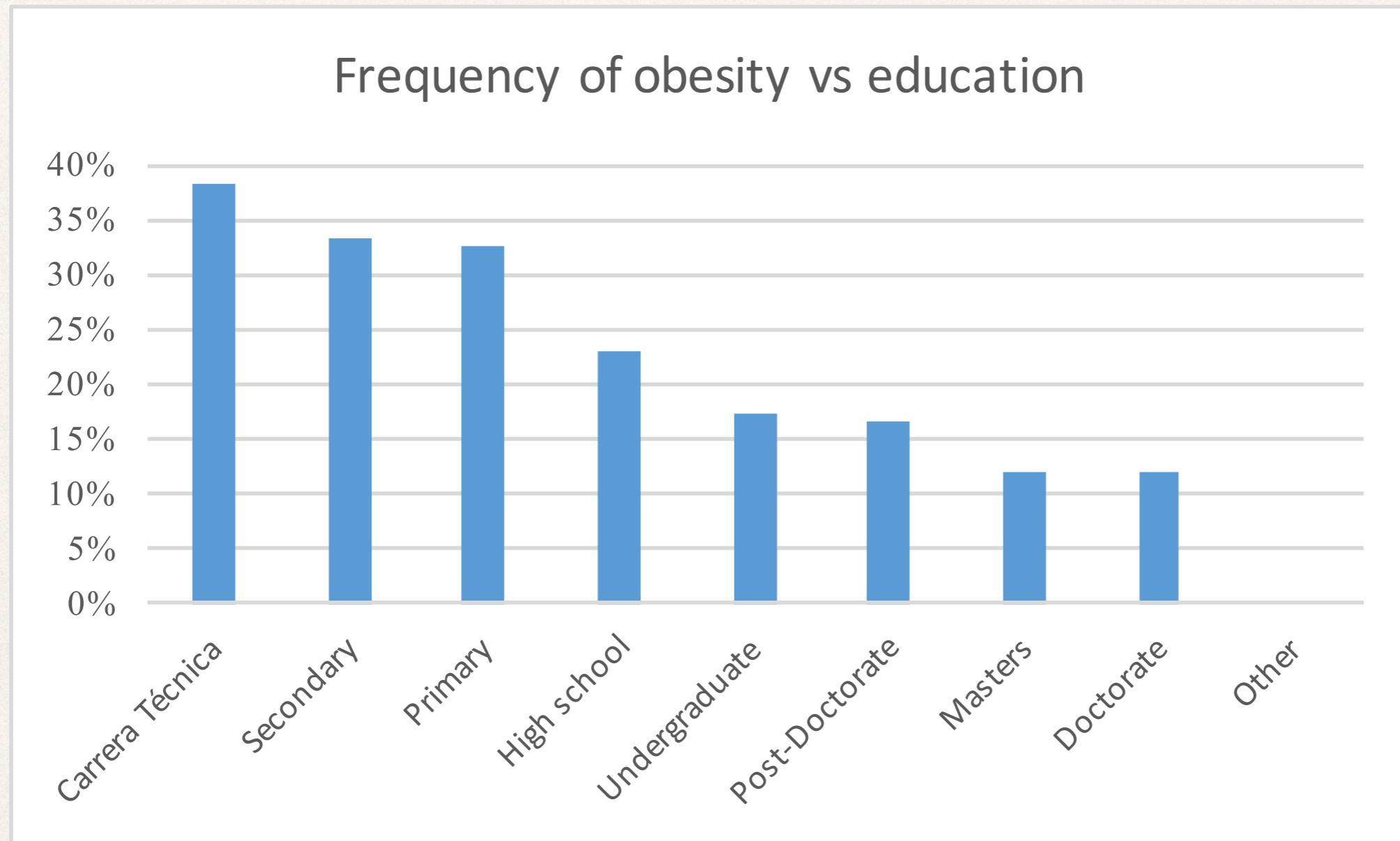


Figure 3. Comparison of non-diagnosed (ND) versus diagnosed (D) obese mean responses for the Stunkard figure rating scale question by gender.



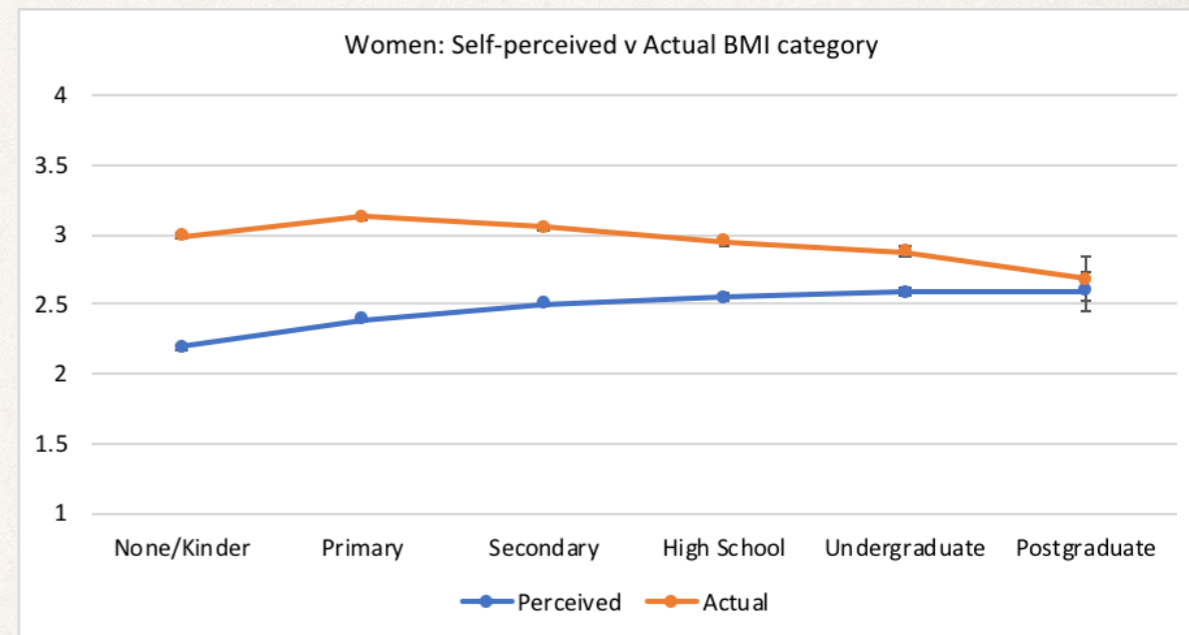
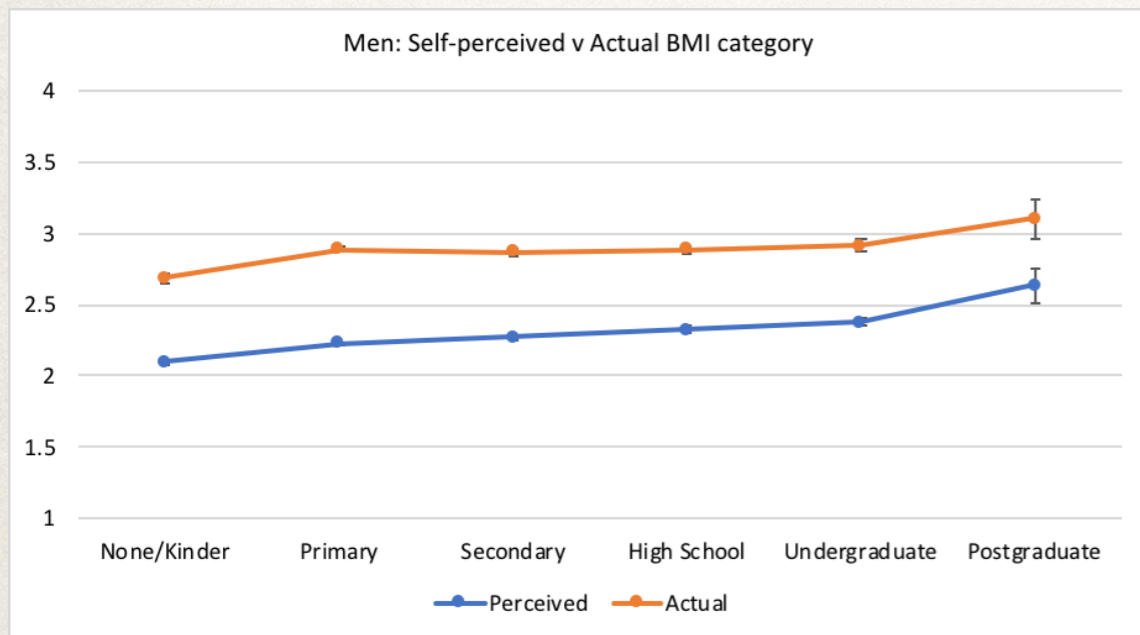
The Role of Education

What Decisions are Taken Differently?

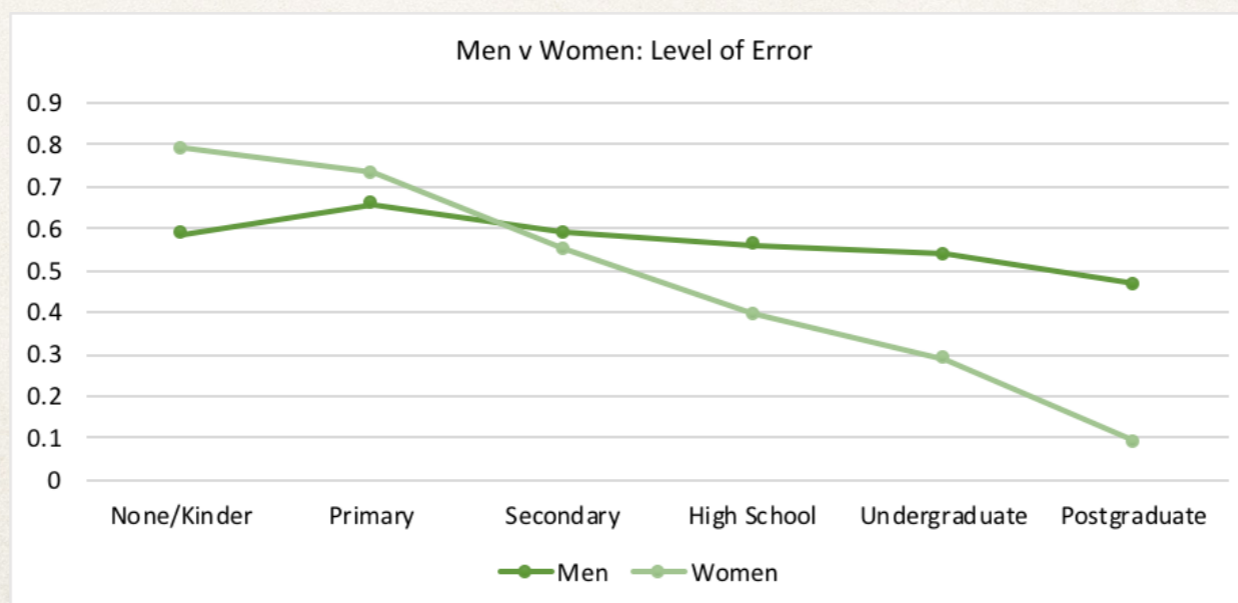


UNAM 2014 Study: 1,076 participants

Perception, Educational Level and Gender



“Do you consider yourself to be...? 1) Overweight, 2) Obese, 3) Underweight, 4) Normal”



People of different educational levels have different models of themselves and their environment

Gender difference for BMI versus height

ENSANUT 2006

Perception, Educational Level and Gender

All BMI Obese	Education level (n; %)					
Self-Perception	None/Kinder	Primary	Secondary	High School	Undergraduate	Postgraduate
Obese	13; 2.3	87; 3.3	54; 5	29; 7.1	19; 7.4	1; 6.7
Overweight	338; 59.5	1845; 69.8	830; 77.4	326; 80.3	209; 81.3	13; 86.7
Normal	200; 35.2	672; 25.4	177; 16.5	50; 12.3	28; 10.9	1; 6.7
Underweight	17; 3	38; 1.4	12; 1.1	1; 0.2	1; 0.4	0; 0
BMI Obese Men	Education level (n; %)					
Self-Perception	None/Kinder	Primary	Secondary	High School	Undergraduate	Postgraduate
Obese	4; 3.7	14; 2.2	13; 4.6	10; 6.8	3; 2.5	1; 9.1
Overweight	65; 60.2	406; 62.8	196; 68.8	110; 75.3	98; 81.7	9; 81.8
Normal	38; 35.2	217; 33.5	69; 24.2	26; 17.8	18; 15	1; 9.1
Underweight	1; 0.9	10; 1.5	7; 2.5	0; 0	1; 0.8	0; 0
BMI Obese Women	Education level (n; %)					
Self-Perception	None/Kinder	Primary	Secondary	High School	Undergraduate	Postgraduate
Obese	9; 2	73; 3.7	41; 5.2	19; 7.3	16; 11.7	0; 0
Overweight	273; 59.3	1439; 72.1	634; 80.5	216; 83.1	111; 81	4; 100
Normal	162; 35.2	455; 22.8	108; 13.7	24; 9.2	10; 7.3	0; 0
Underweight	16; 3.5	28; 1.4	5; 0.6	1; 0.4	0; 0	0; 0

ENSANUT 2006

Number and percentage of actual BMI obese by self-perceived BMI category and educational level.

Perception, Educational Level and Gender



All	Education Level (n; %)					
Actual BMI	None/Kinder	Primary	Secondary	High School	Undergraduate	Postgraduate
Obese	13; 2.3	87; 3.3	54; 5	29; 7.1	19; 7.4	1; 6.7
Overweight	154; 19.5	1116; 34.7	652; 45.3	323; 50.1	213; 57	12; 66.7
Normal	543; 72.4	1621; 73.2	750; 70.1	315; 64.2	262; 77.5	14; 73.7
Underweight	11; 36.7	17; 34.7	20; 69	11; 64.7	5; 41.7	N/A
MEN	Education Level (n; %)					
Actual BMI	None/Kinder	Primary	Secondary	High School	Undergraduate	Postgraduate
Obese	4; 3.7	14; 2.2	13; 4.6	10; 6.8	3; 2.5	1; 9.1
Overweight	50; 18.1	364; 28.8	189; 34.1	104; 38.7	88; 45.8	7; 63.6
Normal	229; 74.8	753; 81	340; 77.3	132; 65	127; 84.1	7; 87.5
Underweight	4; 33.3	7; 38.9	3; 33.3	3; 42.9	3; 75	N/A
WOMEN	Education Level (n; %)					
Actual BMI	None/Kinder	Primary	Secondary	High School	Undergraduate	Postgraduate
Obese	9; 2	73; 3.7	41; 5.2	19; 7.3	16; 11.7	0; 0
Overweight	104; 20.3	752; 38.5	463; 52.4	219; 58.2	125; 68.7	5; 71.4
Normal	314; 70.7	868; 67.6	410; 65.1	183; 63.5	135; 72.2	7; 63.6
Underweight	7; 38.9	10; 32.3	17; 85	8; 80	2; 25	N/A

ENSANUT 2006

Number and percentage of participants correctly identifying their BMI category by educational level for all four standard BMI categories.



Perception and Action

- 1) “In the last year have you lost or gained weight?”
- 2) “Was this weight loss intentional?”

BMI Obese	Education level (n; %)					
Intention to lose	None/Kinder	Primary	Secondary	High School	Undergraduate	Postgraduate
All	17; 6.3	100; 7.1	61; 9.2	28; 10.9	24; 15.7	2; 25.0
Men	2; 3.9	23; 8.0	10; 6.4	10; 12.2	10; 16.1	1; 25.0
Women	15; 6.8	77; 6.8	51; 10.0	18; 10.3	14; 15.4	1; 25.0

Mis-perception has consequences

ENSANUT 2006

Do We Always Misperceive our Weight?



MHAS Study
Collaboration with INGER

Measured BMI (n; %)	Self-Reported BMI				Total
	Underweight	Normal	Overweight	Obese	
Underweight	4; 57.1	3; 42.9	0; 0.0	0; 0.0	7; 100.0
Normal	4; 1.8	178; 80.2	38; 17.1	2; 0.9	222; 100.0
Overweight	2; 0.5	81; 19.4	292; 69.9	43; 10.2	418; 100.0
Obese	0; 0.0	4; 1.4	71; 24.6	213; 73.9	288; 100.0

There are systematic misperceptions in terms of image and linguistic concept, but not numbers. Why?

Are “Bad” Decisions in our Genes?



Driver	Value	Epsilon	P(C/X)	P(C)	N(X/C)	N(X)	N(C)	NTotal
rs2943641_A	2	2.9391	0.6000	0.2169	6	10	123	567
rs2972146_C	2	2.9391	0.6000	0.2169	6	10	123	567
rs2943650_G	2	2.9391	0.6000	0.2169	6	10	123	567
rs12629908_A	2	2.6981	0.3116	0.2169	43	138	123	567
rs870347_C	2	2.2200	0.2914	0.2169	44	151	123	567
rs1407434_G	0	2.1617	0.2841	0.2169	50	176	123	567
rs972283_A	2	2.1543	0.3085	0.2169	29	94	123	567
rs10496971_C	2	1.9688	0.3011	0.2169	28	93	123	567
rs2241766_C	1	1.9472	0.2741	0.2169	54	197	123	567
rs10885122_A	2	1.9426	0.5000	0.2169	4	8	123	567
rs2986742_G	2	1.9121	0.4545	0.2169	5	11	123	567
rs1799884_A	2	-2.0385	0.0000	0.2169	0	15	123	567
rs3943253_A	2	-2.0502	0.1364	0.2169	15	110	123	567
rs4607517_A	2	-2.1053	0.0000	0.2169	0	16	123	567
rs4880436_A	2	-2.1388	0.0870	0.2169	4	46	123	567
rs174537_C	2	-2.1927	0.0851	0.2169	4	47	123	567
rs174546_G	2	-2.1927	0.0851	0.2169	4	47	123	567
rs174550_A	2	-2.1927	0.0851	0.2169	4	47	123	567
rs972283_A	0	-2.3181	0.1521	0.2169	33	217	123	567
rs2073821_A	2	-2.3502	0.1170	0.2169	11	94	123	567
rs1513181_G	2	-2.3605	0.1250	0.2169	14	112	123	567
rs2237895_A	2	-2.3836	0.1308	0.2169	17	130	123	567
rs7803075_G	2	-2.4635	0.0847	0.2169	5	59	123	567
rs896854_A	0	-2.5528	0.1398	0.2169	26	186	123	567
rs7809589_C	2	-2.5964	0.1231	0.2169	16	130	123	567
rs1111875_A	0	-3.2065	0.1211	0.2169	23	190	123	567

obesity (score = 0.904, predictive but scarce)

772 SNPs considered

Subsets with obesity,
DM2, lipids, hepatic

obesity (score = 0.105, not so predictive but common)

Thrifty Gene Hypothesis - Neel 1962

Adaptations that were useful in our evolutionary past are now harmful.

Physiological versus behavioural focus - what genes are associated with generic behaviours. Looking for a “haystack-in-a-needle”.

Evolutionary Psychology versus Evolutionary Just-so stories...

Agent Based Models for the Study of Food Strategy in Obesogenic Environments

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Introduction

Obesity and Overweight are complex phenomena with genetic, endocrine and behavioral components (Bray 2007). The positive **Energy Imbalance** that gives place to overweight occurs when consuming more energy than is spent. Consuming food involves **Decision Making** restricted by availability of sources, time and competition. The main objective of a **Food Strategy** is survival of individuals and populations. Then avoid negative long-term energy imbalance is a priority.

An optimal strategy seeks energy balance. It can regulate consumption, perception and movement across the environment. Nonetheless the extended epidemic of obesity and overweight is evidence of a generalized deviation of an optimal energetic plan.

Johnson and Andrews (2010) suggest a prehistoric mutation of human ancestors to increase fat stores. Such that mechanism, originally a survival advantage against starvation, could explain partially the resilient tendency to overweight in **Obesogenic Environments**. There is no accessible data to test directly such that hypothesis. However those inaccessible scenarios can be investigated in a generative manner by agent system simulations (Epstein 2006).

The aim of this work is to investigate the origin and development of bias in food strategies with **Agent Based Modeling (ABM)**. The Agent Model presented here exhibits the competition between two kind of agents: A perceptive one (Type II) that can observe a larger local environment at an energetic cost and other that only can perceive for free the cell where is situated (Type I). Agents were provided with three capacities: To eat, to move and to reproduce themselves. Perceptive agents' strategy is more complex and can be considered cognitively superior. To measure system's performance we obtain in each simulation the extinction time (if is the case), the final fraction of agents of type I and the time when diversity is lost (if is the case).

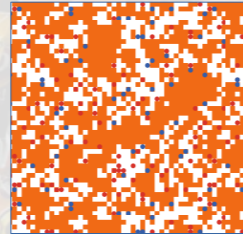


Figure 1. View of a typical simulation of ABM. This was implemented in NetLogo.

Design of Agents System

- Environment:** 41 X 41 Square Grid in a Torus (PBCs), each cell can grow a **source of energy**.
- Agents:** Two types according food strategy: **Perceptive** and **non-perceptive**.
- Agents have move, eat and intend to reproduce every time.
- Each time-step agents spent energy in a basal metabolism and in a cost of movement proportional to their energy. If the agent is perceptive pays a fixed cost of perception. Both agents consume the energetic sources in their consumption area.



Agent Type I (non-perceptive)

- Perceives only the cell where is placed
- Eat only the sources in the cell is placed (A = 1).
- Moves randomly to a neighbour cell

Agent Type II (perceptive)

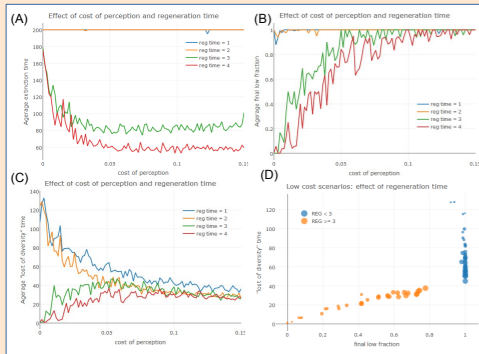
- Perceives the cell where is placed and the first eight neighbours
- Eat only the sources in the cell is placed (A = 1).
- Moves to a neighbour cell with energetic sources available. It reduces uncertainty when looking for energy but it has a cost.

$$E_{\alpha}(t) = \begin{cases} (E_{\alpha}(t-1) - M_b + A^{(I)} E_s) (1 - C^{(m)}), & \text{if } \alpha \text{ is type I} \\ (E_{\alpha}(t-1) - M_b - \Delta M^{(p)} + A^{(II)} E_s) (1 - C^{(m)}), & \text{if } \alpha \text{ is type II} \end{cases}$$

Figure 2. Sketch of ABM environment, agent type I and II and Energy of agent at time t.

Parameters	Symbol
Basal Metabolism	M_b
Cost of Perception	$\Delta M^{(p)}$
Cost of Movement	$C^{(m)}$
Source Energy	E_s
Consumption Area	$A^{(I)}, A^{(II)}$

Table 1. Parameters and symbols of ABM.



Effect of Cost of Perception and Regeneration of Sources

- Rapid regeneration of resources can make the population survive indefinitely (Fig. 3A). This also causes the scenarios with perceptual agents to disappear while slow regeneration allow diversity in the ensemble of simulations (Fig. 3B).
- Final stages where both type of strategies coexist are scarce. Most scenarios finish with homogeneous populations.
- Perceptive agents can live longer than non-perceptive only if the cost of perception is low (Fig. 3B). In those scenarios with rapid regeneration an increase in cost of perception makes the minority agents (perceptive) to disappear faster. If regeneration is slow an increase on the cost makes the minority agents to disappear a little bit more slowly (Fig. 4B).

Cost of movement and reproduction

- Reproduction consists in the division of an agent when it exceeds a limit of energy (20). It makes more pronounced the effect of the cost of movement in the final distribution of agents: This favors one of the two types depending on their value: If the cost of movement is lower than 0.02 agents type II are predominant. When is greater than 0.02 agents type I survive more oftenly (Fig. 4A).
- In general, reproduction changes changes the distribution of types in final states (Fig. 4B)
- The dynamics of the types distribution have a similar characteristic behavior: Cost of movement determines the final type of agent and reproduction helps the predominant agent (Fig. 5).

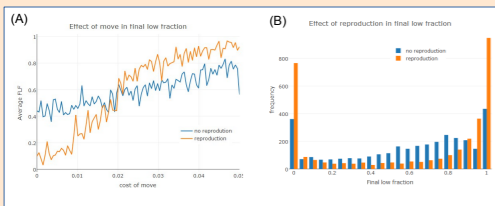


Figure 4. Effect of cost of movement and reproduction in (A) average final low fraction (type I fraction) and (B) histogram of final low fraction.

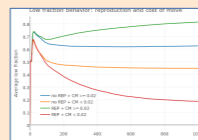


Figure 5. Effect of cost of movement and reproduction in the average fraction of type I agents at every generation.

Let's try and recreate the world of 200,000 years ago and see what behaviours were useful in environments then versus environments now.

Recreate environments with scarcity / plenty and find which adaptations are favoured / disfavoured

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Johnson, R. J., & Andrews, P. (2010). *Fructose, uricase, and the Back-to-Africa hypothesis*. *Evolutionary Anthropology: Issues, News, and Reviews*, 19(6), 250-257.

Aknowledgments

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Conclusions

- * The Human Conductome is the entirety of factors which control human behavior: **Behaviour ← Strategies ← Decisions ← Predictions**
- * It is extraordinarily multifactorial and adaptive. It requires big, deep data across multiple scales to understand it: genetics, epigenetics, physiology, psychology, neuroscience, epidemiology, sociology,... We don't have such data, but the Data Revolution is helping.
- * A crucial ingredient of the Conductome is how we evaluate decisions, the different concepts of value and to understand why we make "bad" decisions.
- * Another crucial ingredient is how we create a model of reality that may be substantially different from reality itself. Such deviations can have severe psychological, social and other health consequences.

The goal of Project 42 is to obtain and model data in order to better understand the Conductome and predict human behavior. We have a lot of interesting work to do over the coming months, years, decades,... We need a lot of help!

You're all invited!



Partial list of members of the C3 research program in Obesity and Diabetes

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