You aren't what you eat, you become what you eat: Confronting the Complexity of Obesity with Big Data

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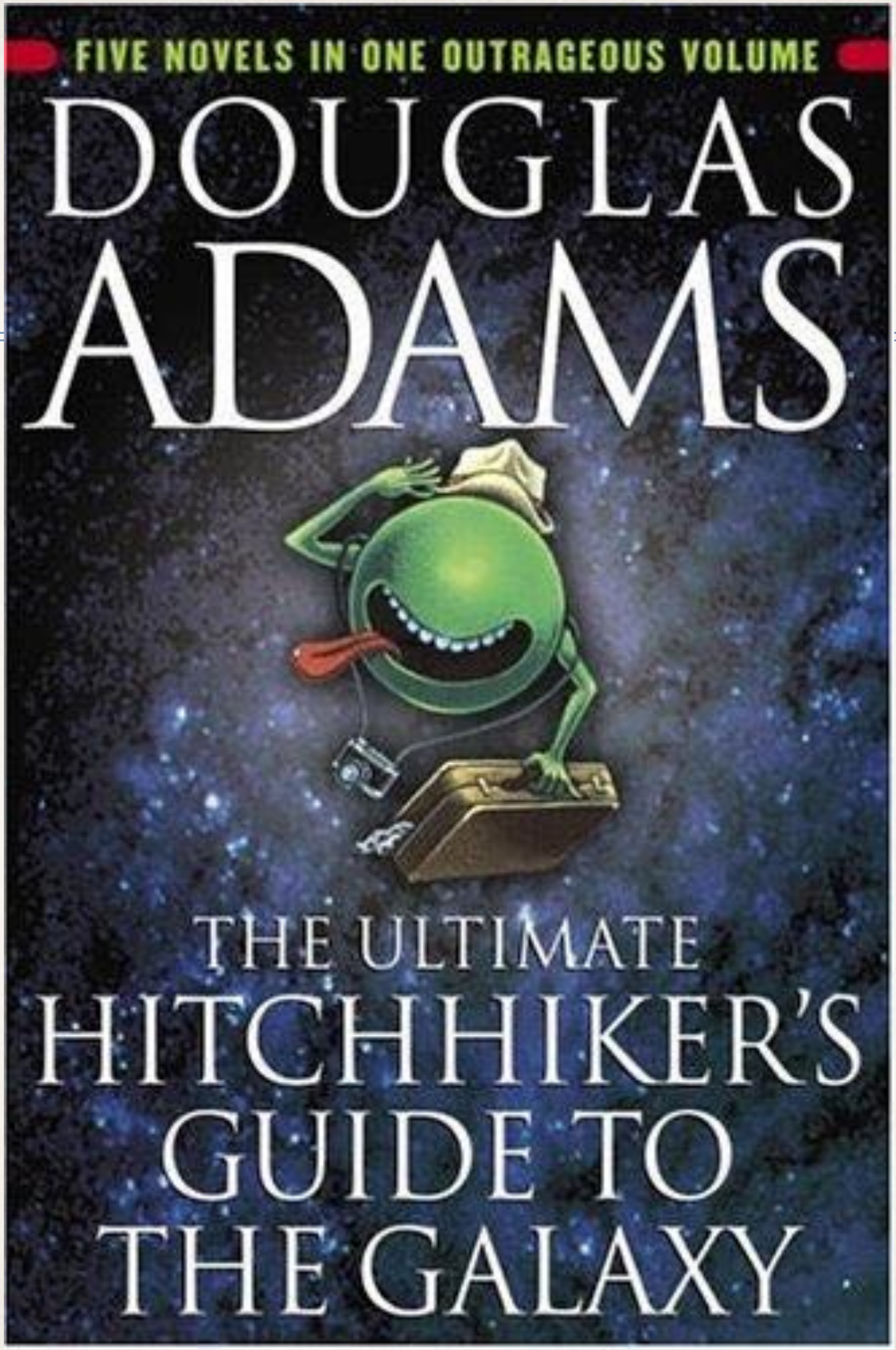
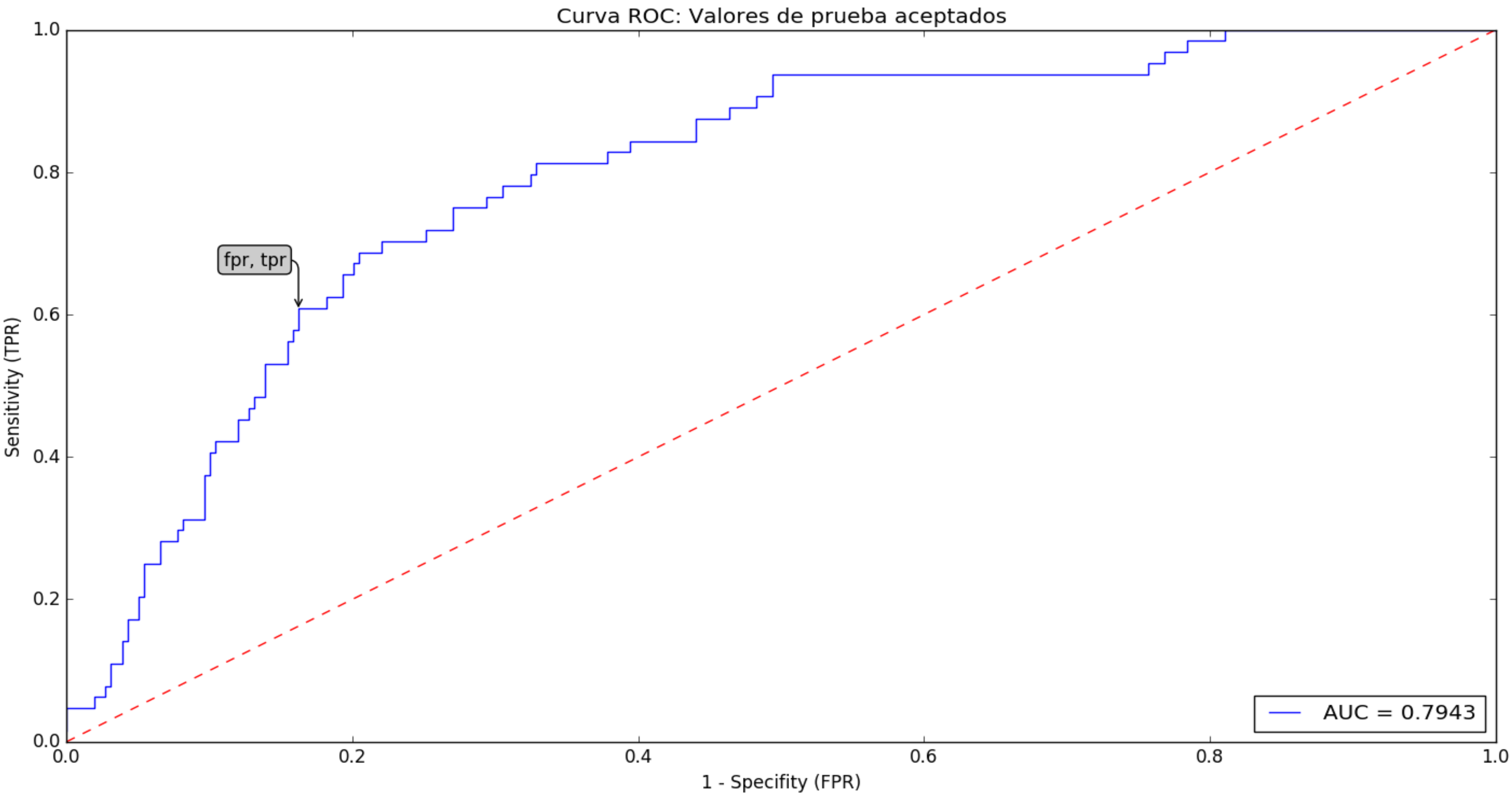
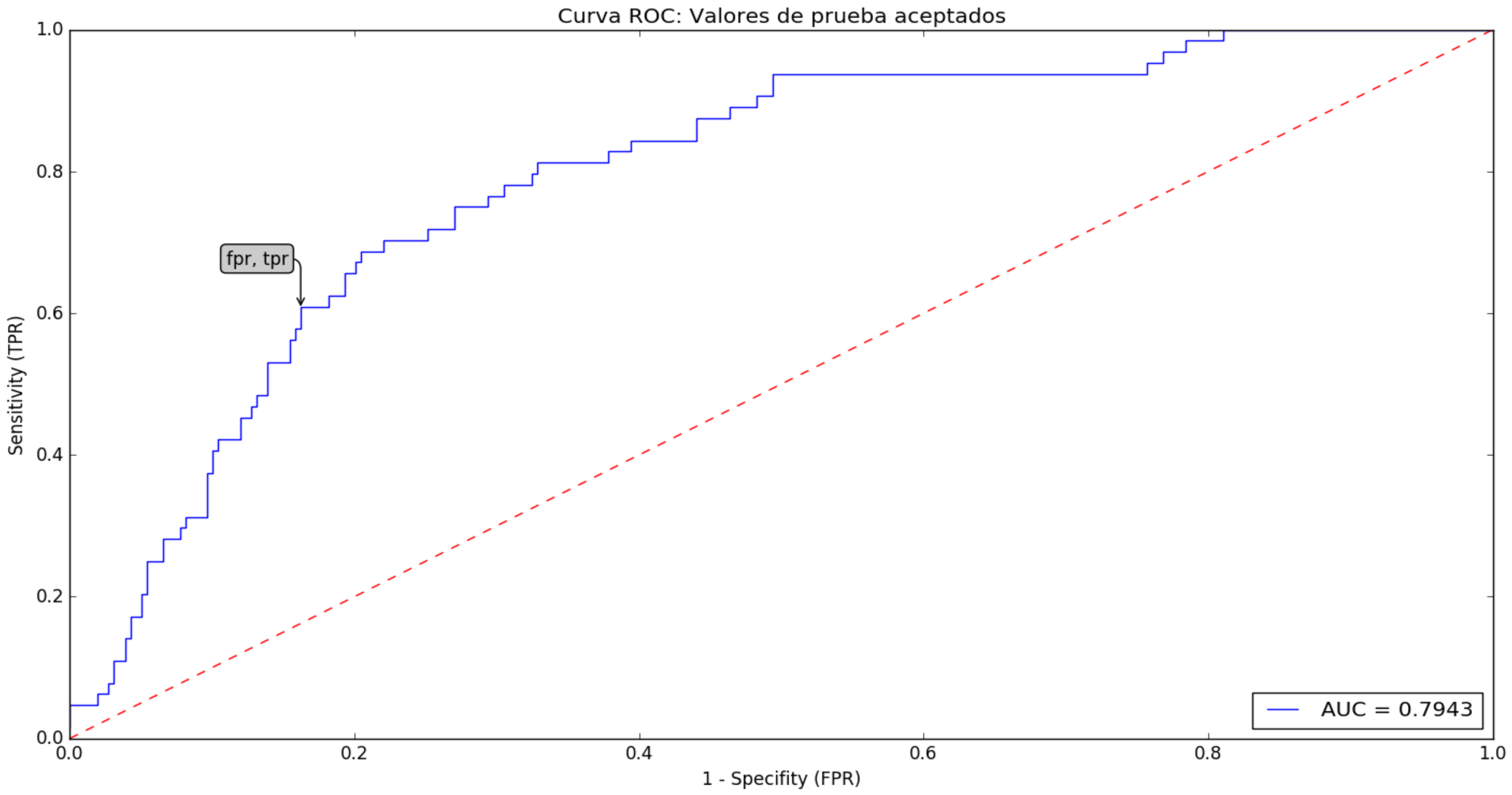

FIVE NOVELS IN ONE OUTRAGEOUS VOLUME
DOUGLAS
ADAMS
THE ULTIMATE
HITCHHIKER'S
GUIDE TO
THE GALAXY

THE ULTIMATE ANSWER
TO LIFE, THE UNIVERSE
AND EVERYTHING IS


42



Curva ROC: Valores de prueba aceptados
fpr, tpr
AUC = 0.7943
Sensitivity (TPR)
1 - Specifity (FPR)
0.0
0.2
0.4
0.6
0.8
1.0



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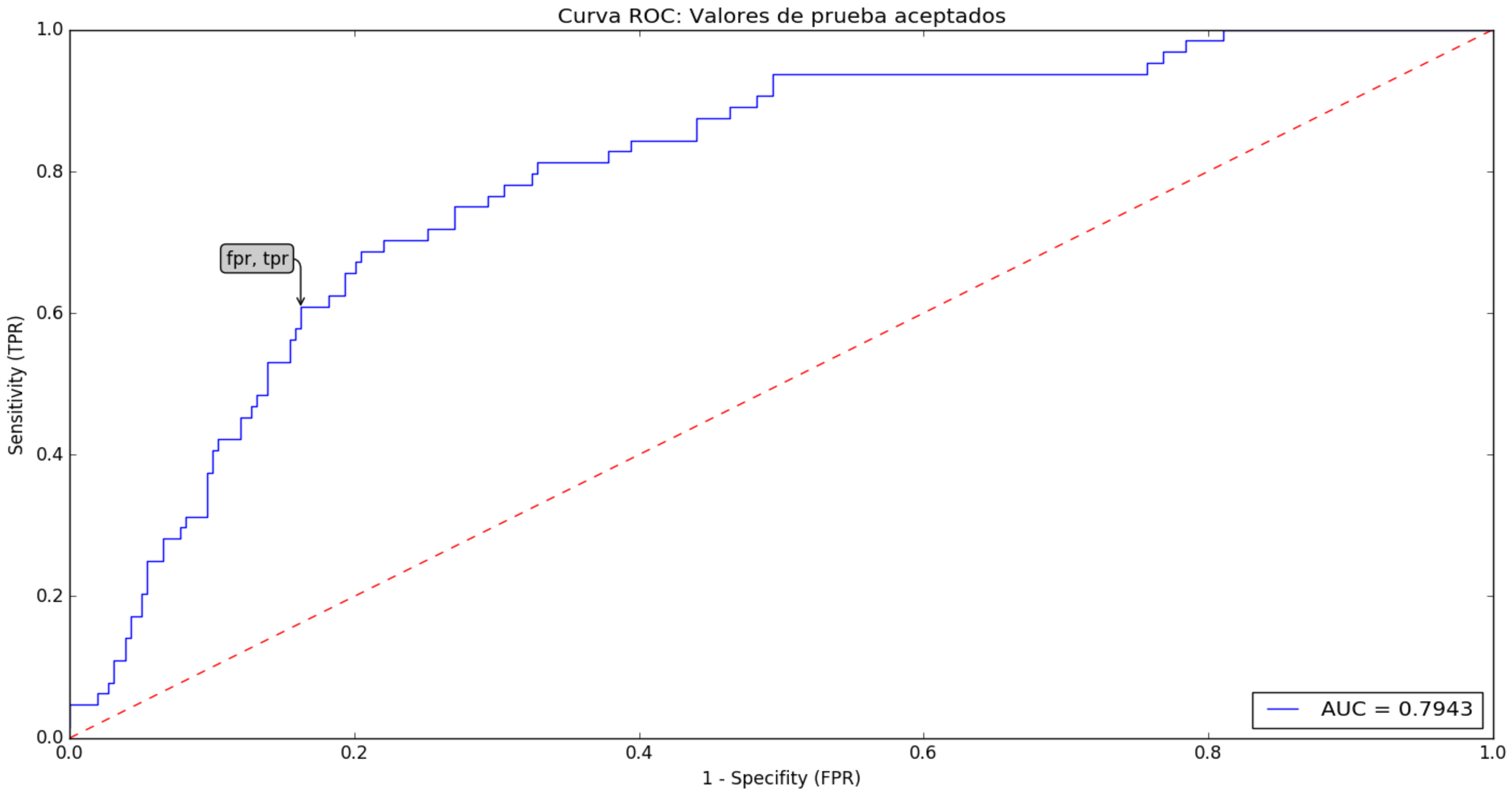
= 42



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Predictive model for obesity…

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

3,524 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)

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

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

A	B	C	D	E	F	G	H	I	J
Variable	**Valor**	**Epsilon**	**Nx**	**Nxc**	**N**	**Nc**	**Pc**	**Pcx**	**Descripción**
AAedad	1	-4.1765	122	7	1076	228	0.2119	0.0574	Edad : 19 - 27
AAedad	2	-2.7892	145	17	1076	228	0.2119	0.1172	Edad : 28 - 32
AAedad	3	0.1580	138	30	1076	228	0.2119	0.2174	Edad : 33 - 37
AAedad	4	2.2954	133	39	1076	228	0.2119	0.2932	Edad : 38 - 42
AAedad	5	1.8754	137	38	1076	228	0.2119	0.2774	Edad : 43 - 47
AAedad	6	1.4875	128	34	1076	228	0.2119	0.2656	Edad : 48 - 52
AAedad	7	1.6079	134	36	1076	228	0.2119	0.2687	Edad : 53 - 58
AAedad	8	-0.5093	139	27	1076	228	0.2119	0.1942	Edad : 59 - 81
Aestado	DF	-0.2242	981	205	1076	228	0.2119	0.2090	Estado : DF
Aestado	EMex	0.7328	86	21	1076	228	0.2119	0.2442	Estado : Estado de México
Aestado	Guan	-0.5185	1	0	1076	228	0.2119	0.0000	Estado : Guanajuato
Aestado	Hid	-0.7333	2	0	1076	228	0.2119	0.0000	Estado : Hidalgo
Aestado	Mich	1.9285	1	1	1076	228	0.2119	1.0000	Estado : Michoacan
Aestado	Mor	0.1865	4	1	1076	228	0.2119	0.2500	Estado : Morelos
Aestado	Pue	-0.5185	1	0	1076	228	0.2119	0.0000	Estado : Puebla
AIMC	1	-2.7438	28	0	1076	228	0.2119	0.0000	IMC calculado <18.5 : 1
AIMC	2	-10.6645	423	0	1076	228	0.2119	0.0000	IMC calculado 18.5-25 : 2
AIMC	3	-10.3315	397	0	1076	228	0.2119	0.0000	IMC calculado 25-30 : 3
AIMC	4	24.7727	165	165	1076	228	0.2119	1.0000	IMC calculado 30-35: 4
AIMC	5	12.9371	45	45	1076	228	0.2119	1.0000	IMC calculado 35-39 : 5
AIMC	6	8.1821	18	18	1076	228	0.2119	1.0000	IMC calculado >=40 : 6
Apuesto	Acade	-2.8129	234	32	1076	228	0.2119	0.1368	Puesto: Academico
Apuesto	Admin	1.2288	74	20	1076	228	0.2119	0.2703	Puesto: Personal Admnistrativo
Apuesto	Asi	0.1857	54	12	1076	228	0.2119	0.2222	Puesto: Asistente
Apuesto	Coo	-1.6397	10	0	1076	228	0.2119	0.0000	Puesto: Coordinador
Apuesto	E	-2.3817	52	4	1076	228	0.2119	0.0769	Puesto: Estudiante

Variable	Valor	Epsilon	Nx	Nxc	N	Nc	Pc	Pcx	Descripción
Abrazo	1	1.726919	6	3	1076	228	0.2119	0.5	Medida del brazo = 0 : 1
Abrazo	2	-7.3526447	246	5	1076	228	0.2119	0.0203	Medida del brazo (0,25] : 2
Abrazo	3	-4.6093617	294	30	1076	228	0.2119	0.102	Medida del brazo (25,27] : 3
Abrazo	4	-0.9549931	261	49	1076	228	0.2119	0.1877	Medida del brazo (27,29] : 4
Abrazo	5	12.532857	269	141	1076	228	0.2119	0.5242	Medida del brazo >= 29 : 5
Acintura	1	-6.9373884	179	0	1076	228	0.2119	0	Medida de cintura <= 80 : 1
Acintura	2	-5.7028106	181	7	1076	228	0.2119	0.0387	Medida de cintura (80,87) : 2
Acintura	3	-5.6636574	195	9	1076	228	0.2119	0.0462	Medida de cintura [87,91] : 3
Acintura	4	-4.0486085	187	17	1076	228	0.2119	0.0909	Medida de cintura (91, 97) : 4
Acintura	5	3.9869034	180	60	1076	228	0.2119	0.3333	Medida de cintura [97, 104) : 5
Acintura	6	20.18603	154	135	1076	228	0.2119	0.8766	Medida de cintura >=104 : 6
Apeso	1	-4.1481981	64	0	1076	228	0.2119	0	Medida del peso <= 50 : 1
Apeso	2	-6.8594378	175	0	1076	228	0.2119	0	Medida del peso (50, 57] : 2
Apeso	3	-6.2619858	173	3	1076	228	0.2119	0.0173	Medida del peso (57, 63] : 3
Apeso	4	-4.3473453	164	12	1076	228	0.2119	0.0732	Medida del peso (63, 68] : 4
Apeso	5	-1.2457714	168	29	1076	228	0.2119	0.1726	Medida del peso (68, 74] : 5
Apeso	6	4.9049874	166	61	1076	228	0.2119	0.3675	Medida del peso (74, 82] : 6
Apeso	7	16.680629	166	123	1076	228	0.2119	0.741	Medida del peso >82 : 7
Atalla	1	4.9555267	105	43	1076	228	0.2119	0.4095	Medida de estatura < 1.5 : 1
Atalla	2	-0.5645166	409	82	1076	228	0.2119	0.2005	Medida de estatura [1.5,1.6) : 2
Atalla	3	-1.1460552	353	66	1076	228	0.2119	0.187	Medida de estatura [1.6, 1.7) : 3
Atalla	4	-0.8280514	182	34	1076	228	0.2119	0.1868	Medida de estatura [1.7,1.8) : 4
Atalla	5	-1.2815154	27	3	1076	228	0.2119	0.1111	Medida de estatura [1.8, 1.9) : 5
Atalla	6	-1.2701211	6	0	1076	228	0.2119	0	Medida de estatura >= 1.9 : 6
Atemp	1	1.9275253	3	2	1076	228	0.2119	0.6667	Medida de temperatura <=30 : 1
Atemp	2	-1.605104	68	9	1076	228	0.2119	0.1324	Medida de temperatura (30, 35.5] : 2

Variable	Valor	epsilon	Nx	Nxc	N	Nc	Pc	Pcx	Descripción
Aami_edadpp	1	-0.57626	175	34	1075	228	0.21209302	0.19428571	Edad promedio de amigos cercanos <= 25 años : 1
Aami_edadpp	2	-1.95946	93	12	1075	228	0.21209302	0.12903226	Edad promedio de amigos cercanos (25,28] años : 2
Aami_edadpp	3	-2.17087	98	12	1075	228	0.21209302	0.12244898	Edad promedio de amigos cercanos (28,31] años : 3
Aami_edadpp	4	0.405961	87	20	1075	228	0.21209302	0.22988506	Edad promedio de amigos cercanos (31,34] años : 4
Aami_edadpp	5	-0.1976	74	15	1075	228	0.21209302	0.2027027	Edad promedio de amigos cercanos (34,36] años : 5
Aami_edadpp	6	1.008639	90	23	1075	228	0.21209302	0.25555556	Edad promedio de amigos cercanos (36,39] años : 6
Aami_edadpp	7	2.838212	97	32	1075	228	0.21209302	0.32989691	Edad promedio de amigos cercanos (39,43] años : 7
Aami_edadpp	8	1.242397	103	27	1075	228	0.21209302	0.26213592	Edad promedio de amigos cercanos (43,47] años : 8
Aami_edadpp	9	-0.63709	107	20	1075	228	0.21209302	0.18691589	Edad promedio de amigos cercanos (47,52] años : 9
Aami_edadpp	10	-0.28064	90	18	1075	228	0.21209302	0.2	Edad promedio de amigos cercanos (52,59] años : 10
Aami_edadpp	11	0.645939	61	15	1075	228	0.21209302	0.24590164	Edad promedio de amigos cercanos > 59 años : 11
Aamigos_diab	0	-0.63445	938	191	1075	228	0.21209302	0.20362473	Número de amigos diabeticos
Aamigos_diab	1	2.145029	104	31	1075	228	0.21209302	0.29807692	Número de amigos diabeticos
Aamigos_diab	2	-1.20629	26	3	1075	228	0.21209302	0.11538462	Número de amigos diabeticos
Aamigos_diab	3	-1.03766	4	0	1075	228	0.21209302	0	Número de amigos diabeticos
Aamigos_diab	4	2.72577	2	2	1075	228	0.21209302	1	Número de amigos diabeticos
Aamigos_diab	5	1.927411	1	1	1075	228	0.21209302	1	Número de amigos diabeticos
Aamigos_sobre	0	0.289564	413	90	1075	228	0.21209302	0.21791768	Número de amigos con sobrepeso
Aamigos_sobre	1	-0.04007	322	68	1075	228	0.21209302	0.21118012	Número de amigos con sobrepeso
Aamigos_sobre	2	0.616345	182	42	1075	228	0.21209302	0.23076923	Número de amigos con sobrepeso
Aamigos_sobre	3	-1.56993	90	13	1075	228	0.21209302	0.14444444	Número de amigos con sobrepeso
Aamigos_sobre	4	0.199689	40	9	1075	228	0.21209302	0.225	Número de amigos con sobrepeso
Aamigos_sobre	5	0.84319	13	4	1075	228	0.21209302	0.30769231	Número de amigos con sobrepeso
Aamigos_sobre	6	-0.6026	8	1	1075	228	0.21209302	0.125	Número de amigos con sobrepeso
Aamigos_sobre	7	-0.2722	6	1	1075	228	0.21209302	0.16666667	Número de amigos con sobrepeso
Aamigos_sobre	8	-0.51883	1	0	1075	228	0.21209302	0	Número de amigos con sobrepeso

Variable	Valor	Epsilon	Nx	Nxc	N	Nc	Pc	Pxc	Descripción
Aedad_asma	0	-0.03096	1026	217	1076	228	0.2119	0.2115	Sin ser diagnosticados con asma
Aedad_asma	1	-0.68949	31	5	1076	228	0.2119	0.16129	Edad en que fueron diagnosticados con asma (0,18] : 1
Aedad_asma	2	0.51471	3	1	1076	228	0.2119	0.33333	Edad en que fueron diagnosticados con asma (18,25] : 2
Aedad_asma	3	1.23153	11	4	1076	228	0.2119	0.36364	Edad en que fueron diagnosticados con asma (25,40] : 3
Aedad_asma	4	0.18649	4	1	1076	228	0.2119	0.25	Edad en que fueron diagnosticados con asma (40,55] : 4
Aedad_asma	5	-0.51852	1	0	1076	228	0.2119	0	Edad en que fueron diagnosticados con asma (55,70] : 5
Aedad_cardi	0	-0.27232	1022	213	1076	228	0.2119	0.20841	Sin ser diagnosticados con problemas cardiacos
Aedad_cardi	1	-1.71975	11	0	1076	228	0.2119	0	Edad en que fueron diagnosticados con problemas cardiacos (0,1
Aedad_cardi	2	1.41002	4	2	1076	228	0.2119	0.5	Edad en que fueron diagnosticados con problemas cardiacos (18,
Aedad_cardi	3	1.10819	19	6	1076	228	0.2119	0.31579	Edad en que fueron diagnosticados con problemas cardiacos (25,
Aedad_cardi	4	2.20261	13	6	1076	228	0.2119	0.46154	Edad en que fueron diagnosticados con problemas cardiacos (40,
Aedad_cardi	5	-0.27111	6	1	1076	228	0.2119	0.16667	Edad en que fueron diagnosticados con problemas cardiacos (55,
Aedad_cardi	6	-0.51852	1	0	1076	228	0.2119	0	Edad en que fueron diagnosticados con problemas cardiacos > 70
Aedad_cmama	0	-0.06603	1066	225	1076	228	0.2119	0.21107	Sin ser diagnosticados con cancer de mama
Aedad_cmama	1	-0.51852	1	0	1076	228	0.2119	0	Edad en que fueron diagnosticados con cancer de mama (0,18] :
Aedad_cmama	3	-0.7333	2	0	1076	228	0.2119	0	Edad en que fueron diagnosticados con cancer de mama (25,40]
Aedad_cmama	4	1.02927	5	2	1076	228	0.2119	0.4	Edad en que fueron diagnosticados con cancer de mama (40,55]
Aedad_cmama	5	0.99704	2	1	1076	228	0.2119	0.5	Edad en que fueron diagnosticados con cancer de mama (55,70]
Aedad_coles	0	-0.65591	781	158	1076	228	0.2119	0.2023	Sin ser diagnosticados con colesterol alto
Aedad_coles	1	-1.37189	7	0	1076	228	0.2119	0	Edad en que fueron diagnosticados con colesterol alto (0,18] :
Aedad_coles	2	0.69821	22	6	1076	228	0.2119	0.27273	Edad en que fueron diagnosticados con colesterol alto (18,25] :
Aedad_coles	3	1.66656	100	28	1076	228	0.2119	0.28	Edad en que fueron diagnosticados con colesterol alto (25,40] :
Aedad_coles	4	0.08299	135	29	1076	228	0.2119	0.21481	Edad en que fueron diagnosticados con colesterol alto (40,55] :
Aedad_coles	5	0.18953	31	7	1076	228	0.2119	0.22581	Edad en que fueron diagnosticados con colesterol alto (55,70] :
Aedad_colon	0	-0.05882	1075	227	1076	228	0.2119	0.21116	Sin ser diagnosticado con problemas de colon
Aedad_colon	4	1.92855	1	1	1076	228	0.2119	1	Edad en que fueron diagnosticados con problemas de colon (40,5

Variable	Valor	Epsilon	Nx	Nxc	N	Nc	Pc	Pxc	Descripción
Acal_agua	-1	2.8756	453	121	1076	228	0.212	0.267	No sabe el número de calorías que tiene el agua : -1
Acal_agua	0	-2.4813	567	96	1076	228	0.212	0.169	El agua contiene 0 calorías : 0
Acal_agua	1	-0.3396	27	5	1076	228	0.212	0.185	El agua contiene de 1 a 20 calorias : 1
Acal_agua	2	-0.0659	29	6	1076	228	0.212	0.207	El agua contiene más de 20 calorias : 2
Acal_hamb	-1	0.7938	705	158	1076	228	0.212	0.224	No sabe cuantas calorías tiene una hamburguesa : -1
Acal_hamb	0	-0.8981	3	0	1076	228	0.212	0	Las hamburguesas contienen 0 calorias : 0
Acal_hamb	1	0.684	18	5	1076	228	0.212	0.278	Las hamburguesas contienen [1, 100) calorías : 1
Acal_hamb	2	-0.6033	61	11	1076	228	0.212	0.18	Las hamburguesas contienen [100-350] calorías : 2
Acal_hamb	3	-1.5537	67	9	1076	228	0.212	0.134	Las hamburguesas contienen (350,500] calorías : 3
Acal_hamb	4	-0.8842	71	12	1076	228	0.212	0.169	Las hamburguesas contienen (500-1000) calorías : 4
Acal_hamb	5	0.3754	74	17	1076	228	0.212	0.23	Las hamburguesas contienen [1000,15000) calorías : 5
Acal_hamb	6	-0.0881	77	16	1076	228	0.212	0.208	Las haburguesas contienen >= 15000 calorías : 6
Acal_jugo	-1	1.0148	808	183	1076	228	0.212	0.226	No sabe el número de calorías que tiene el jugo de naranja : -1
Acal_jugo	0	0.1865	4	1	1076	228	0.212	0.25	El jugo de naranja contiene 0 calorías :
Acal_jugo	1	0.3885	29	7	1076	228	0.212	0.241	El jugo de naranja contiene (0,100) calorías :
Acal_jugo	2	-1.4798	36	4	1076	228	0.212	0.111	El jugo de naranja contiene [100, 200) calorías :
Acal_jugo	3	-1.7161	99	14	1076	228	0.212	0.141	El jugo de naranja contiene [200, 500) calorías :
Acal_jugo	4	0.0904	60	13	1076	228	0.212	0.217	El jugo de naranja contiene [500,1000) calorías :
Acal_jugo	5	-0.9579	40	6	1076	228	0.212	0.15	El jugo de naranja contiene mas de 1000 calorías :
Acal_ref	-1	0.9476	775	175	1076	228	0.212	0.226	No sabe cuantas calorías tiene un vaso de refresco : -1
Acal_ref	0	-0.8981	3	0	1076	228	0.212	0	El refreco tiene 0 calorias : 0
Acal_ref	1	0.4568	24	6	1076	228	0.212	0.25	El refresco tiene (0,100) calorías : 1
Acal_ref	2	-1.3887	22	2	1076	228	0.212	0.091	El refresco tiene [100,200) calorías : 2
Acal_ref	3	-0.3352	96	19	1076	228	0.212	0.198	El refresco tiene [200,500) calorías : 3
Acal_ref	4	-1.2275	72	11	1076	228	0.212	0.153	El refresco tiene [500, 1000) calorías : 4
Acal_ref	5	-0.7474	84	15	1076	228	0.212	0.179	El refresco tiene mas de 1000 calorías : 5

Variable	Valor	Epsilon	Nx	Nxc	N	Nc	Pc	Pxc	Descripción
Ahba	1	-2.62561	910	160	1074	227	0.2114	0.1758	HBA (valor para diagnosticar la diabetes) <= 5.6 : 1 - Normal o r
Ahba	2	5.600193	100	44	1074	227	0.2114	0.44	HBA (valor para diagnosticar la diabetes) (5.6, 6.4] : 2 - Pre diabéti
Ahba	3	2.900328	64	23	1074	227	0.2114	0.3594	HBA (valor para diagnosticar la diabetes) >6.4 : 3 - Compatibl
Ainsulina	1	-8.50928	485	26	1074	227	0.2114	0.0536	Insulina < 6.0 : 1 - Normal
Ainsulina	2	-0.31677	91	18	1074	227	0.2114	0.1978	Insulina (6.0, 7.0) : 2
Ainsulina	3	0.798506	214	50	1074	227	0.2114	0.2336	Insulina [7.0, 9.9] : 3 Deseable
Ainsulina	4	1.616042	97	27	1074	227	0.2114	0.2784	Insulina [10, 12.6) : 4
Ainsulina	5	11.90673	187	106	1074	227	0.2114	0.5668	Insulina >= 12.6 : 5 - Diabetes
Aldlc_res	1	-0.32836	101	20	1074	227	0.2114	0.198	LDLC < 79 : 1
Aldlc_res	2	1.283815	184	46	1074	227	0.2114	0.25	LDLC [79, 100) : 2
Aldlc_res	3	-1.36628	198	34	1074	227	0.2114	0.1717	LDLC [100, 115] : 3
Aldlc_res	4	-0.63123	187	36	1074	227	0.2114	0.1925	LDLC (115, 130] : 4
Aldlc_res	5	1.378526	199	50	1074	227	0.2114	0.2513	LDLC (130, 150] : 5
Aldlc_res	6	-1.17115	156	27	1074	227	0.2114	0.1731	LDLC (150, 180] : 6
Aldlc_res	7	1.42982	17	6	1074	227	0.2114	0.3529	LDLC (180, 189] : 7
Aldlc_res	8	0.378576	16	4	1074	227	0.2114	0.25	LDLC (189, 200] : 8
Aldlc_res	9	-0.44392	7	1	1074	227	0.2114	0.1429	LDLC (200, 220] : 9
Aldlc_res	10	0.896268	9	3	1074	227	0.2114	0.3333	LDLC [>= 220 : 10
chol_com	ALTO	-0.37921	12	2	1074	227	0.2114	0.1667	chol = 201 : Alto
chol_com	LTO CRITIC	0.301357	512	111	1074	227	0.2114	0.2168	chol > 202 : Alto crítico
chol_com		-0.23475	550	114	1074	227	0.2114	0.2073	chol < 100 : Normal
crs_com	LTO CRITIC	-0.26814	6	1	1074	227	0.2114	0.1667	crs [7.1, 1.31] : Alto critico
crs_com	AJO CRITIC	-0.73213	2	0	1074	227	0.2114	0	crs [0.35, 0.38] : Bajo critico
crs_com		0.051829	1066	226	1074	227	0.2114	0.212	crs [0.42, 9.65] : Normal
glu_com	ALTO	2.73168	6	4	1074	227	0.2114	0.6667	glu = 110 : Alto
glu_com	LTO CRITIC	3.648645	114	40	1074	227	0.2114	0.3509	glu [111,418] : Alto critico

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 m
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

Epsilon	# participantes	# obesos	Proporcion obesos	Puesto
-2.81	234	32	13.68%	Academico
1.23	74	20	27.03%	Personal Admnistrativo
0.19	54	12	22.22%	Asistente
-1.64	10	0	0.00%	Coordinador
-2.38	52	4	7.69%	Estudiante
-3.58	81	4	4.94%	Estudiante Doctorado
-2.05	71	8	11.27%	Estudiante Maestria
2.03	110	32	29.09%	Intendencia
-0.53	85	16	18.82%	Investigador
0.51	3	1	33.33%	Investigador Emerito
2.41	96	30	31.25%	Jefe de Area
2.06	48	16	33.33%	Laboratorista
3.53	67	26	38.81%	Secretaria
0.30	57	13	22.81%	Técnico
2.85	34	14	41.18%	Vigilante

Epsilon	# participantes	# obesos	Proporcion obesos	Puesto
-2.81	234	32	13.68%	Academico
1.23	74	20	27.03%	Personal Admnistrativo
0.19	54	12	22.22%	Asistente
-1.64	10	0	0.00%	Coordinador
-2.38	52	4	7.69%	Estudiante
-3.58	81	4	4.94%	Estudiante Doctorado
-2.05	71	8	11.27%	Estudiante Maestria
2.03	110	32	29.09%	Intendencia
-0.53	85	16	18.82%	Investigador
0.51	3	1	33.33%	Investigador Emerito
2.41	96	30	31.25%	Jefe de Area
2.06	48	16	33.33%	Laboratorista
3.53	67	26	38.81%	Secretaria
0.30	57	13	22.81%	Técnico
2.85	34	14	41.18%	Vigilante

Epsilon	# participantes	# obesos	Proporcion obesos	Edad
-4.18	122	7	5.74%	19 - 27
-2.79	145	17	11.72%	28 - 32
0.16	138	30	21.74%	33 - 37
2.30	133	39	29.32%	38 - 42
1.88	137	38	27.74%	43 - 47
1.49	128	34	26.56%	48 - 52
1.61	134	36	26.87%	53 - 58
-0.51	139	27	19.42%	59 - 81

Epsilon	# participantes	# obesos	Proporcion obesos	Puesto
-2.81	234	32	13.68%	Academico
1.23	74	20	27.03%	Personal Administrativo
0.19	54	12	22.22%	Asistente
-1.64	10	0	0.00%	Coordinador
-2.38	52	4	7.69%	Estudiante
-3.58	81	4	4.94%	Estudiante Doctorado
-2.05	71	8	11.27%	Estudiante Maestria
2.03	110	32	29.09%	Intendencia
-0.53	85	16	18.82%	Investigador
0.51	3	1	33.33%	Investigador Emerito
2.41	96	30	31.25%	Jefe de Area
2.06	48	16	33.33%	Laboratorista
3.53	67	26	38.81%	Secretaria
0.30	57	13	22.81%	Técnico
2.85	34	14	41.18%	Vigilante

Epsilon	# participantes	# obesos	Proporcion obesos	Edad
-4.18	122	7	5.74%	19 - 27
-2.79	145	17	11.72%	28 - 32
0.16	138	30	21.74%	33 - 37
2.30	133	39	29.32%	38 - 42
1.88	137	38	27.74%	43 - 47
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	8
[illegible]	[illegible]	[illegible]	[illegible]	1

Epsilon	# participantes	# obesos	Proporcion obesos	Estatura en m
4.96	105	43	40.95%	< 1.5 : 1
-0.56	409	82	20.05%	[1.5,1.6) : 2
-1.15	353	66	18.70%	[1.6, 1.7) : 3
-0.83	182	34	18.68%	[1.7,1.8) : 4
-1.28	27	3	11.11%	[1.8, 1.9) : 5
-1.27	6	0	0.00%	>= 1.9 : 6

Epsilon	# participantes	# obesos	Proporcion obesos	Puesto
-2.81	234	32	13.68%	Academico
1.23	74	20	27.03%	Personal Admnistrativo
0.19	54	12	22.22%	Asistente
-1.64	10	0	0.00%	Coordinador
-2.38	52	4	7.69%	Estudiante
-3.58	81	4	4.94%	Estudiante Doctorado
-2.05	71	8	11.27%	Estudiante Maestria
2.03				
-0.53				
0.51				
2.41				
2.06				
3.53				
0.30				
2.85				

Epsilon	# participantes	# obesos	Proporcion obesos	Edad
-4.18	122	7	5.74%	19 - 27
	45	17	11.72%	28 - 32
	38	30	21.74%	33 - 37
	33	39	29.32%	38 - 42
	37	38	27.74%	43 - 47
				48 - 52
				8
				1

obesos	Proporcion obesos	Estatura en m
43	40.95%	< 1.5 : 1
82	20.05%	[1.5,1.6) : 2
66	18.70%	[1.6, 1.7) : 3
34	18.68%	[1.7,1.8) : 4
3	11.11%	[1.8, 1.9) : 5
0	0.00%	>= 1.9 : 6

Enfermedad	Epsilon	# participantes	# obesos	Proporcion obesos
No le han diagnosticado asma	-0.03	1026	217	21.15%
Le han dignosticado asma	0.14	50	11	22.00%
No le han diagnosticado problemas cardiacos	-0.27	1022	213	20.84%
Le han diagnosticado problemas cardiacos	1.18	54	15	27.78%
No le han diagnosticado cancer de mama	-0.07	1066	225	21.11%
Le han diagnosticado cancer de mama	0.68	10	3	30.00%
No le han diagnosticado colesterol alto	-0.66	781	158	20.23%
Le han diagnosticado colesterol alto	1.07	295	70	23.73%
No le han diagnosticado cancer de colon	-0.06	1075	227	21.12%
Le han diagnosticado cancer de colon	1.93	1	1	100.00%
No le han diagnosticado otra enfermedad	-0.01	1067	226	21.18%
Le han diagnosticado otra enfermedad	0.08	9	2	22.22%
No le han diagnosticado cancer de prostata	-0.01	1072	227	21.18%
Le han diagnosticado cancer de prostata	0.19	4	1	25.00%
No sabe si le han diagnosticado diabetes	-0.55	1030	211	20.49%
Le han diagnosticado diabetes	2.72	45	17	37.78%
No le han diagnosticado hipertensión	-2.46	943	169	17.92%
Le han diagnosticado hipertensión	6.54	133	59	44.36%
No le han diagnosticado problemas neuronales	0.00	1057	224	21.19%
Le han diagnosticado problemas neuronales	-0.01	19	4	21.05%
No sabe si le han diagnosticado obesidad	-7.55	741	73	9.85%
Le han diagnosticado obesidad	11.32	333	155	46.55%
No sabe si le han diagnosticado prediabetes	-0.42	993	205	20.64%
Le han diagnosticado prediabetes	1.72	79	23	29.11%
No le han diagnosticado problemas pulmonares	-0.30	1057	220	20.81%
Le han diagnosticado problemas pulmonares	2.23	19	8	42.11%
No le han diagnosticado problemas renales	-0.13	1065	224	21.03%
Le han diagnosticado problemas renales	1.23	11	4	36.36%
No le han diagnosticado problemas de retinopatia	0.05	1059	225	21.25%
Le han dignosticado problemas de retinopatia	-0.36	17	3	17.65%
No le han diagnosticado trigliceridos altos	-0.84	772	154	19.95%
Le han diagnosticado trigliceridos altos	1.35	304	74	24.34%

Epsilon	# participantes	# obesos	Proporcion obesos	Puesto
-2.81	234	32	13.68%	Academico
1.23	74	20	27.03%	Personal Admnistrativo
0.19	54	12	22.22%	Asistente
-1.64	10	0	0.00%	Coordinador
-2.38	52	4	7.69%	Estudiante
-3.58	81	4	4.94%	Estudiante Doctorado
-2.05	71	8	11.27%	Estudiante Maestria
2.03				
-0.53				
0.51				
2.41				
2.06				
3.53				
0.30				
2.85				

Epsilon	# participantes	# obesos	Proporcion obesos	Edad
-4.18	122	7	5.74%	19 - 27
	[illegible]5	17	11.72%	28 - 32
	[illegible]8	30	21.74%	33 - 37
	[illegible]3	39	29.32%	38 - 42
	[illegible]7	38	27.74%	43 - 47
		[illegible]	[illegible]	48 - 52
				[illegible]8
				[illegible]1

# obesos	Proporcion obesos	Estatura en m
43	40.95%	< 1.5 : 1

Enfermedad	Epsilon	# participantes	# obesos	Proporcion obesos
No le han diagnosticado asma	-0.03	1026	217	21.15%
Le han dignosticado asma	0.14	50	11	22.00%
No le han diagnosticado problemas cardiacos	-0.27	1022	213	20.84%
Le han diagnosticado problemas cardiacos	1.18	54	15	27.78%
No le han diagnosticado cancer de mama	-0.07	1066	225	21.11%
Le han diagnosticado cancer de mama	0.68	10	3	30.00%
No le han diagnosticado colesterol alto	-0.66	781	158	20.23%
Le han diagnosticado colesterol alto	1.07	295	70	23.73%
No le han diagnosticado cancer de colon	-0.06	1075	227	21.12%
Le han diagnosticado cancer de colon	1.93	1	1	100.00%
No le han diagnosticado otra enfermedad	[illegible]	[illegible]	[illegible]	[illegible]
Le han diagnosticado otra enfermedad				
No le han diagnosticado cancer de prosta[illegible]				
Le han diagnosticado cancer de prostata				
No sabe si le han diagnosticado diabetes				
Le han diagnosticado diabetes				
No le han diagnosticado hipertensión				
Le han diagnosticado hipertensión				
No le han diagnosticado problemas neur[illegible]				
Le han diagnosticado problemas neuronales	-0.01	19	4	21.05%
No sabe si le han diagnosticado obesidad	-7.55	741	73	9.85%
Le han diagnosticado obesidad	11.32	333	155	46.55%
No sabe si le han diagnosticado prediabetes	-0.42	993	205	20.64%
Le han diagnosticado prediabetes	1.72	79	23	29.11%
No le han diagnosticado problemas pulmonares	-0.30	1057	220	20.81%
Le han diagnosticado problemas pulmonares	2.23	19	8	42.11%
No le han diagnosticado problemas renales	-0.13	1065	224	21.03%
Le han diagnosticado problemas renales	1.23	11	4	36.36%
No le han diagnosticado problemas de retinopatia	0.05	1059	225	21.25%
Le han dignosticado problemas de retinopatia	-0.36	17	3	17.65%
No le han diagnosticado trigliceridos altos	-0.84	772	154	19.95%
Le han diagnosticado trigliceridos altos	1.35	304	74	24.34%

Número de amigos cercanos	Epsilon	# participantes	# obesos	Proporcion obesos
Cero	2.35	93	29	31.18%
Uno	2.08	74	23	31.08%
Mas que 1	-1.35	908	176	19.38%

Epsilon	# participantes	# obesos	Proporcion obesos	Puesto
-2.81	234	32	13.68%	Academico
1.23	74	20	27.03%	Personal Admnistrativo
0.19	54	12	22.22%	Asistente
-1.64	10	0	0.00%	Coordinador
-2.38	52	4	7.69%	Estudiante
-3.58	81	4	4.94%	Estudiante Doctorado
-2.05	71	8	11.27%	Estudiante Maestria
2.03				
-0.53				
0.51				
2.41				
2.06				
3.53				
0.30				
2.85				

Epsilon	# participantes	# obesos	Proporcion obesos	Edad
-4.18	122	7	5.74%	19 - 27
[illegible]	[illegible]45	17	11.72%	28 - 32
[illegible]	[illegible]38	30	21.74%	33 - 37
[illegible]	[illegible]33	39	29.32%	38 - 42
[illegible]	[illegible]37	38	27.74%	43 - 47

# obesos	Proporcion obesos	Estatura en m
43	40.95%	< 1.5 : 1

Enfermedad	Epsilon	# participantes	# obesos	Proporcion obesos
No le han diagnosticado asma	-0.03	1026	217	21.15%
Le han dignosticado asma	0.14	50	11	22.00%
No le han diagnosticado problemas cardiacos	-0.27	1022	213	20.84%
Le han diagnosticado problemas cardiacos	1.18	54	15	27.78%
No le han diagnosticado cancer de mama	-0.07	1066	225	21.11%
Le han diagnosticado cancer de mama	0.68	10	3	30.00%
No le han diagnosticado colesterol alto	-0.66	781	158	20.23%
Le han diagnosticado colesterol alto	1.07	295	70	23.73%
No le han diagnosticado cancer de colon	-0.06	1075	227	21.12%
Le han diagnosticado cancer de colon	1.93	1	1	100.00%
No le han diagnosticado otra enfermedad				
Le han diagnosticado otra enfermedad				
No le han diagnosticado cancer de prosta[illegible]				
Le han diagnosticado cancer de prostata				
No sabe si le han diagnosticado diabetes				
Le han diagnosticado diabetes				
No le han diagnosticado hipertensión				
Le han diagnosticado hipertensión				
No le han diagnosticado problemas neur[illegible]				
Le han diagnosticado problemas neuronales				
No sabe si le han diagnosticado obesidad				
Le han diagnosticado obesidad				
No sabe si le han diagnosticado prediabetes				
Le han diagnosticado prediabetes				
No le han diagnosticado problemas pulmonare[illegible]				
Le han diagnosticado problemas pulmonares				
No le han diagnosticado problemas renales				
Le han diagnosticado problemas renales				
No le han diagnosticado problemas de retinopa[illegible]				
Le han dignosticado problemas de retinopatia	-0.36	17	3	17.65%
No le han diagnosticado trigliceridos altos	-0.84	772	154	19.95%
Le han diagnosticado trigliceridos altos	1.35	304	74	24.34%

Número de amigos cercanos	Epsilon	# participantes	# obesos	Proporcion obesos
Cero	2.35	93	29	31.18%
Uno	2.08	74	23	31.08%
Mas que 1	-1.35	908	176	19.38%

Porcentaje del circulo social que tiene sobrepeso	Epsilon	# participantes	# obesos	Proporcion obesos
0-25%	-1.88	511	91	17.81%
25-50%	0.50	313	70	22.36%
50-75%	0.83	190	45	23.68%
75-100%	2.84	61	22	36.07%

Epsilon	# participantes	# obesos	Proporcion obesos	Puesto
-2.81	234	32	13.68%	Academico
1.23	74	20	27.03%	Personal Admnistrativo
0.19	54	12	22.22%	Asistente
-1.64	10	0	0.00%	Coordinador
-2.38	52	4	7.69%	Estudiante
-3.58	81	4	4.94%	Estudiante Doctorado
-2.05	71	8	11.27%	Estudiante Maestria
2.03				
-0.53				
0.51				
2.41				
2.06				
3.53				
0.30				
2.85				

Epsilon	# participantes	# obesos	Proporcion obesos	Edad
-4.18	122	7	5.74%	19 - 27
	45	17	11.72%	28 - 32
	38	30	21.74%	33 - 37
	33	39	29.32%	38 - 42
	37	38	27.74%	43 - 47

Enfermedad	Epsilon	# participantes	# obesos	Proporcion obesos
No le han diagnosticado asma	-0.03	1026	217	21.15%
Le han dignosticado asma	0.14	50	11	22.00%
No le han diagnosticado problemas cardiacos	-0.27	1022	213	20.84%
Le han diagnosticado problemas cardiacos	1.18	54	15	27.78%
No le han diagnosticado cancer de mama	-0.07	1066	225	21.11%
Le han diagnosticado cancer de mama	0.68	10	3	30.00%
No le han diagnosticado colesterol alto	-0.66	781	158	20.23%
Le han diagnosticado colesterol alto	1.07	295	70	23.73%
No le han diagnosticado cancer de colon	-0.06	1075	227	21.12%
Le han diagnosticado cancer de colon	1.93	1	1	100.00%
No le han diagnosticado otra enfermedad				
Le han diagnosticado otra enfermedad				
No le han diagnosticado cancer de prosta				
Le han diagnosticado cancer de prostata				
No sabe si le han diagnosticado diabetes				
Le han diagnosticado diabetes				
No le han diagnosticado hipertensión				
Le han diagnosticado hipertensión				
No le han diagnosticado problemas neur				
Le han diagnosticado problemas neuronales				

obesos	Proporcion obesos	Estatura en m	
43	40.95%	< 1.5 :	1

Número de amigos cercanos	Epsilon	# participantes	# obesos	Proporcion obesos
Cero	2.35	93	29	31.18%
Uno	2.08	74	23	31.08%
Mas que 1	-1.35	908	176	19.38%

Porcentaje del circulo social	# participantes	# obesos	Proporcion obesos
	511	91	17.81%
	313	70	22.36%
	190	45	23.68%
	61	22	36.07%

¿Cómo consideras que es tu salud actualmente?	Epsilon	# participantes	# obesos	Proporcion obesos
1 : Muy mala	1.15	15	5	33.33%
2 : Mala	5.15	60	29	48.33%
3 : Regular	4.41	366	112	30.60%
4 : Buena	-3.76	536	78	14.55%
5 : Muy buena	-4.30	95	3	3.16%

Epsilon	# participantes	# obesos	Proporcion obesos	Puesto
-2.81	234	32	13.68%	Academico
1.23	74	20	27.03%	Personal Admnistrativo
0.19	54	12	22.22%	Asistente
-1.64	10	0	0.00%	Coordinador
-2.38	52	4	7.69%	Estudiante
-3.58	81	4	4.94%	Estudiante Doctorado
-2.05	71	8	11.27%	Estudiante Maestria
2.03				
-0.53				
0.51				
2.41				
2.06				
3.53				
0.30				
2.85				

Epsilon	# participantes	# obesos	Proporcion obesos	Edad
-4.18	122	7	5.74%	19 - 27
	5	17	11.72%	28 - 32
	8	30	21.74%	33 - 37
	3	39	29.32%	38 - 42
	7	38	27.74%	43 - 47
				2
				8
				1

Enfermedad	Epsilon	# participantes	# obesos	Proporcion obesos
No le han diagnosticado asma	-0.03	1026	217	21.15%
Le han dignosticado asma	0.14	50	11	22.00%
No le han diagnosticado problemas cardiacos	-0.27	1022	213	20.84%
Le han diagnosticado problemas cardiacos	1.18	54	15	27.78%
No le han diagnosticado cancer de mama	-0.07	1066	225	21.11%
Le han diagnosticado cancer de mama	0.68	10	3	30.00%
No le han diagnosticado colesterol alto	-0.66	781	158	20.23%
Le han diagnosticado colesterol alto	1.07	295	70	23.73%
No le han diagnosticado cancer de colon	-0.06	1075	227	21.12%
Le han diagnosticado cancer de colon	1.93	1	1	100.00%
No le han diagnosticado otra enfermedad				
Le han diagnosticado otra enfermedad				
No le han diagnosticado cancer de prosta				
Le han diagnosticado cancer de prostata				
No sabe si le han diagnosticado diabetes				
Le han diagnosticado diabetes				
No le han diagnosticado hipertensión				
Le han diagnosticado hipertensión				
No le han diagnosticado problemas neur				
Le han diagnosticado problemas neuronales				

obesos	Proporcion obesos	Estatura en m
43	40.95%	< 1.5 : 1

Número de amigos cercanos	Epsilon	# participantes	# obesos	Proporcion obesos
Cero	2.35	93	29	31.18%
Uno	2.08	74	23	31.08%
Mas que 1	-1.35	908	176	19.38%

Porcentaje del circulo social	# participantes	# obesos	Proporcion obesos
	511	91	17.81%
	313	70	22.36%
	190	45	23.68%

¿Cómo consideras que es tu salud actualmente?	Epsilon	# participantes	# obesos	Proporcion obesos
1 : Muy mala	1.15	15	5	33.33%
2 : Mala				
3 : Regular				
4 : Buena				
5 : Muy buena				

¿Qué acciones le gustaría tomar resp	Epsilon	# participantes	Proporcion poblacion	# obesos	Probabilidad obesidad	Proporcion obesos
Bajar de peso	5.25	771	71.65%	223	28.92%	97.81%
Esta contento con su peso	-7.54	239	22.21%	3	1.26%	1.32%
Subir de peso	-3.50	63	5.86%	2	3.17%	0.88%
No sabe	-0.90	3	0.28%	0	0.00%	0.00%

Epsilon	# participantes	# obesos	Proporcion obesos	Puesto
-2.81	234	32	13.68%	Academico
1.23	74	20	27.03%	Personal Admnistrativo
0.19	54	12	22.22%	Asistente
-1.64	10	0	0.00%	Coordinador
-2.38	52	4	7.69%	Estudiante
-3.58	81	4	4.94%	Estudiante Doctorado
-2.05	71	8	11.27%	Estudiante Maestria
2.03				
-0.53				
0.51				
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-4.18	122	7	5.74%	19 - 27
	45	17	11.72%	28 - 32
	38	30	21.74%	33 - 37
	33	39	29.32%	38 - 42
	37	38	27.74%	43 - 47

Enfermedad	Epsilon	# participantes	# obesos	Proporcion obesos
No le han diagnosticado asma	-0.03	1026	217	21.15%
Le han dignosticado asma	0.14	50	11	22.00%
No le han diagnosticado problemas cardiacos	-0.27	1022	213	20.84%
Le han diagnosticado problemas cardiacos	1.18	54	15	27.78%
Le han diagnosticado diabetes				
No le han diagnosticado hipertensión				
Le han diagnosticado hipertensión				
No le han diagnosticado problemas neur				
Le han diagnosticado problemas neuronales				

¿Cómo consideras tu peso actual?	Epsilon	# participantes	Proporcion poblacion	# obesos	Probabilidad obesidad	Proporcion obesos
Muy malo	-1.47	8	0.74%	0	0.00%	0.00%
Malo	-3.70	51	4.74%	0	0.00%	0.00%
Regular	-9.66	419	38.94%	8	1.91%	3.51%
Bueno	4.65	514	47.77%	152	29.57%	66.67%
Muy bueno	13.97	80	7.43%	68	85.00%	29.82%

				Proporcion obesos
Cero	2.35	93	29	31.18%
Uno	2.08	74	23	31.08%
Mas que 1	-1.35	908	176	19.38%

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Epsilon	# participantes	# obesos	Proporcion obesos	Puesto
-2.81	23			
1.23	74			
0.19	54			
-1.64	10			
-2.38	52			
-3.58	81			
-2.05	71			
2.03				
-0.53				
0.51				
2.41				
2.06				
3.53				
0.30				
2.85				

¿Cuántas calorías hay en un litro de agua?	Epsilon	# participantes	Proporcion poblacion	# obesos	Probabilidad obesidad	Proporcion obesos
No sabe el número de calorías que tiene el agua	2.88	453	42.10%	121	26.71%	53.07%
El agua contiene 0 calorias	-2.48	567	52.70%	96	16.93%	42.11%
El agua contiene de 1 a 20 calorias	-0.34	27	2.51%	5	18.52%	2.19%
El agua contiene más de 20 calorias	-0.07	29	2.70%	6	20.69%	2.63%

Enfermedad				
No le han dia				
Le han digno				
No le han dia				
Le han diagnosticado problemas cardiacos	1.18	54	15	27.78%
No le				
Le h				
No le				
Le h				
No le				
Le h				
No le				
Le h				
No le				
Le h				
No s				
Le han diagnosticado diabetes				
No le han diagnosticado hipertensión				
Le han diagnosticado hipertensión				
No le han diagnosticado problemas neur				
Le han diagnosticado problemas neuronales				

37	38	27.74%	43 - 47

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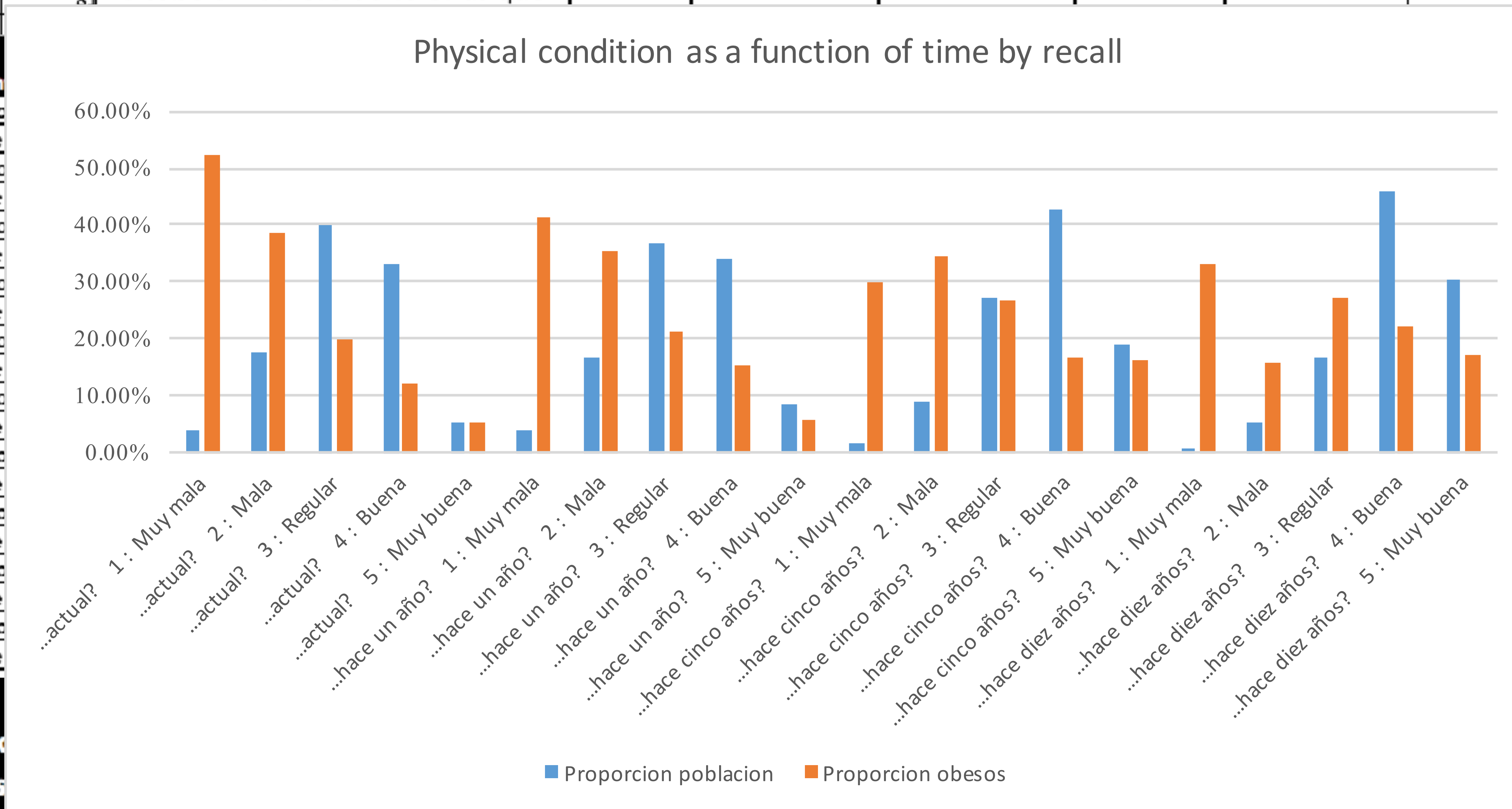
-2.05				
2.03				
-0.53				
0.51				
2.41				
2.06				
3.53				
0.30				
2.85				

¿Cuántas calorías hay en un litro de agua?	Epsilon	# participantes	Proporcion poblacion	# obesos	Probabilidad obesidad	Proporcion obesos
No sabe el número de calorías que						



47		
		31.18%
		31.08%
		19.38%
		Proporcion obesos
		17.81%
		22.36%
190	45	23.68%

¿Cómo ... es tu s... actualmente?	Epsilon	# participantes	# obesos	obesos
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No sabe	-0.90	3	0.28%	0	0.00%	0.00%

Why is a prediction model important?

Because…

Why is a prediction model important?

Because…

Predict

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

Why is a prediction model important?

Because…

Predict

Why is a prediction model important?

Because…

Predict

for

Why is a prediction model important?

Because…

Predict

for

Decision making

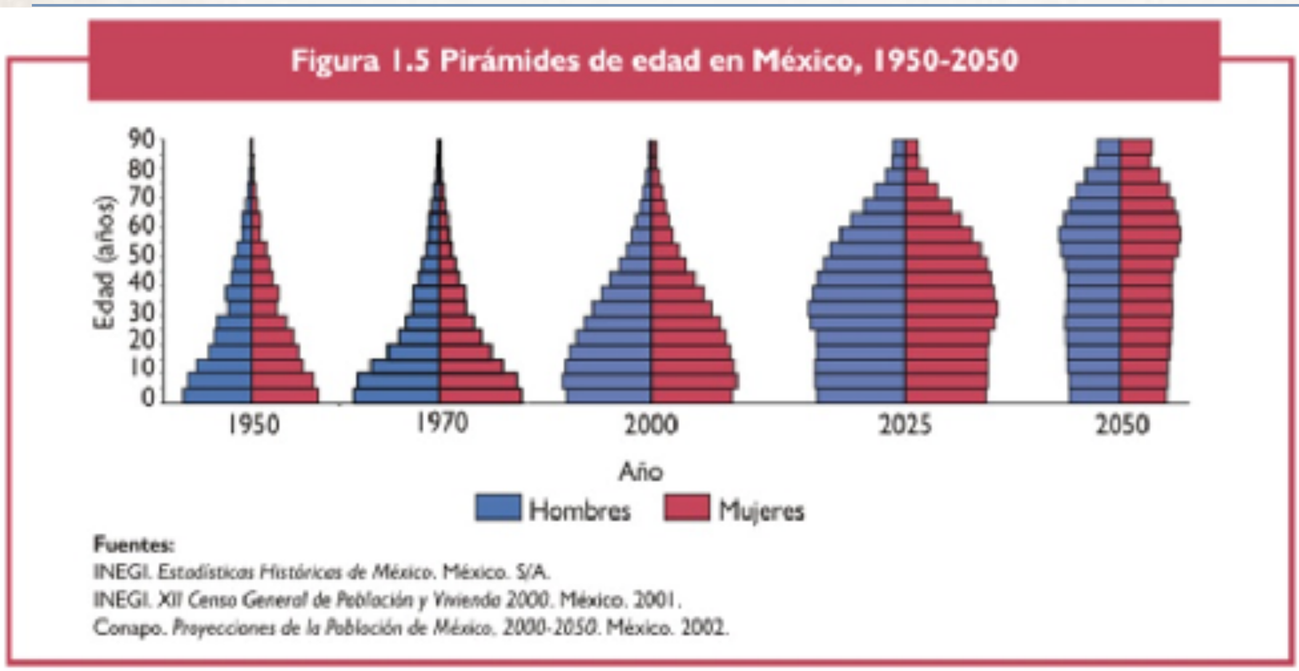
Predict for individuals…

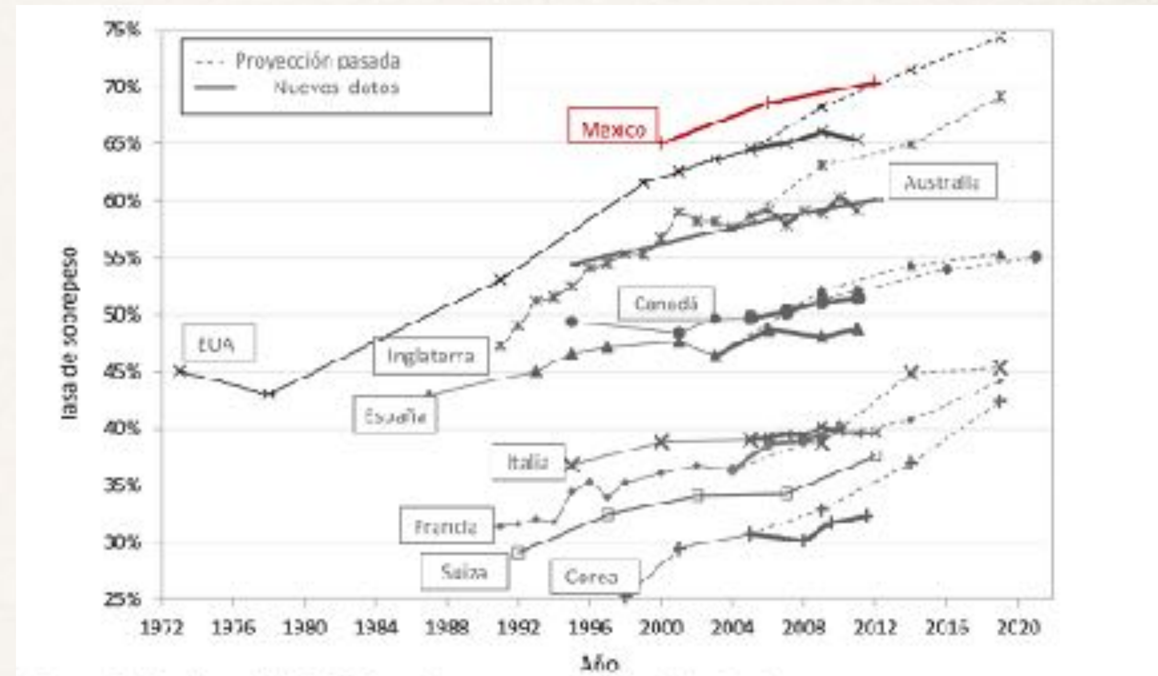
Diagnostics

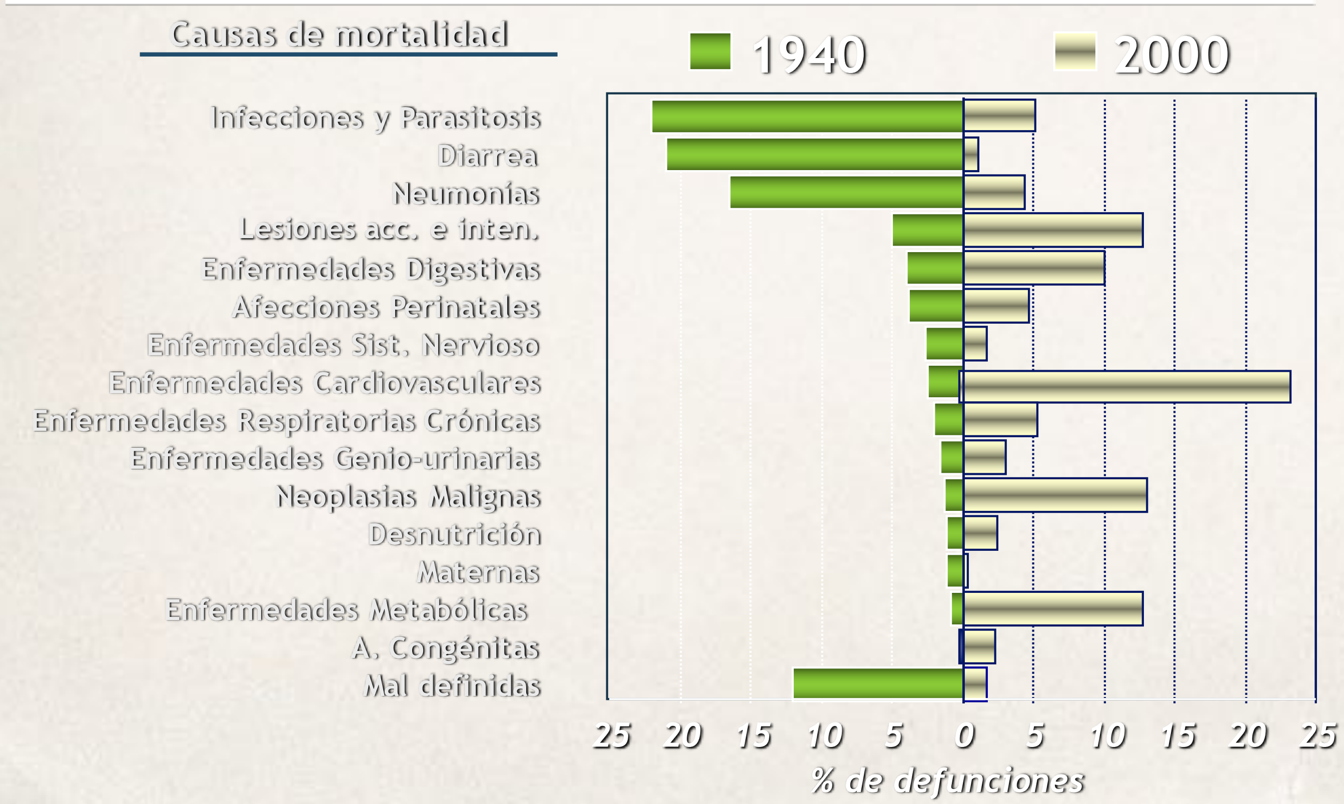
Treatments

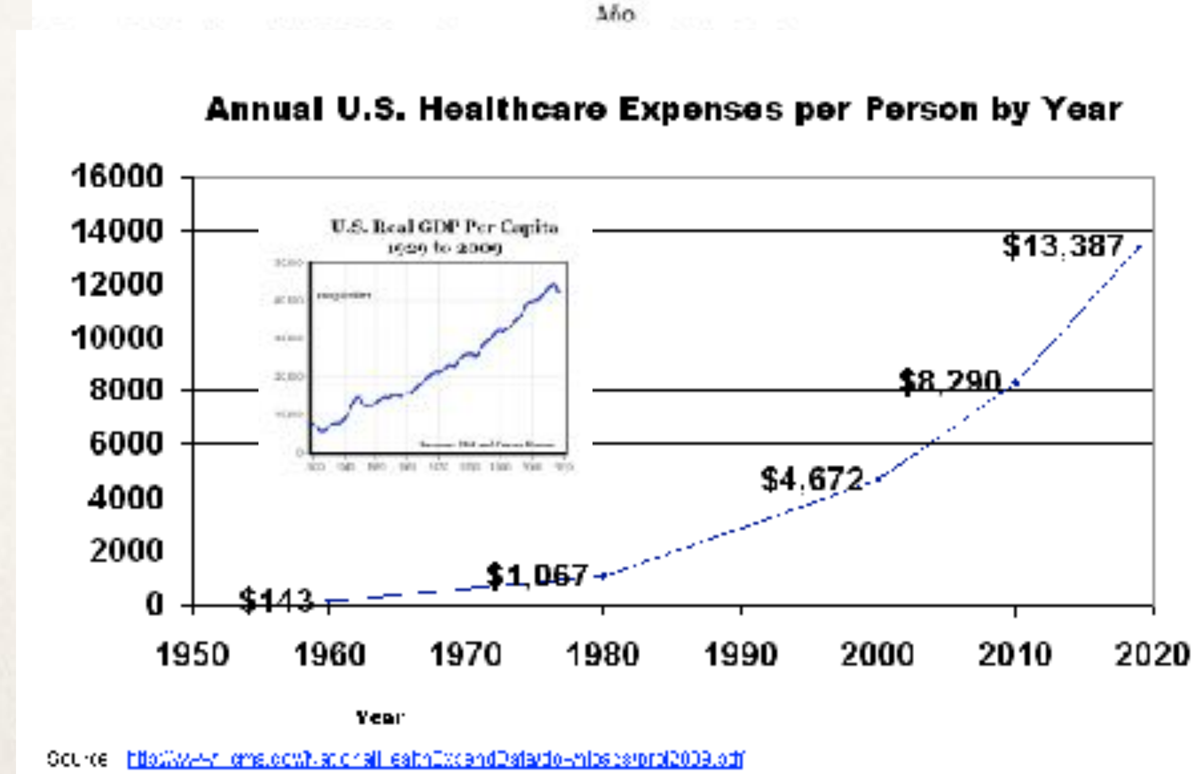
Predict for populations…

Demography, Epidemiology, Economics,…







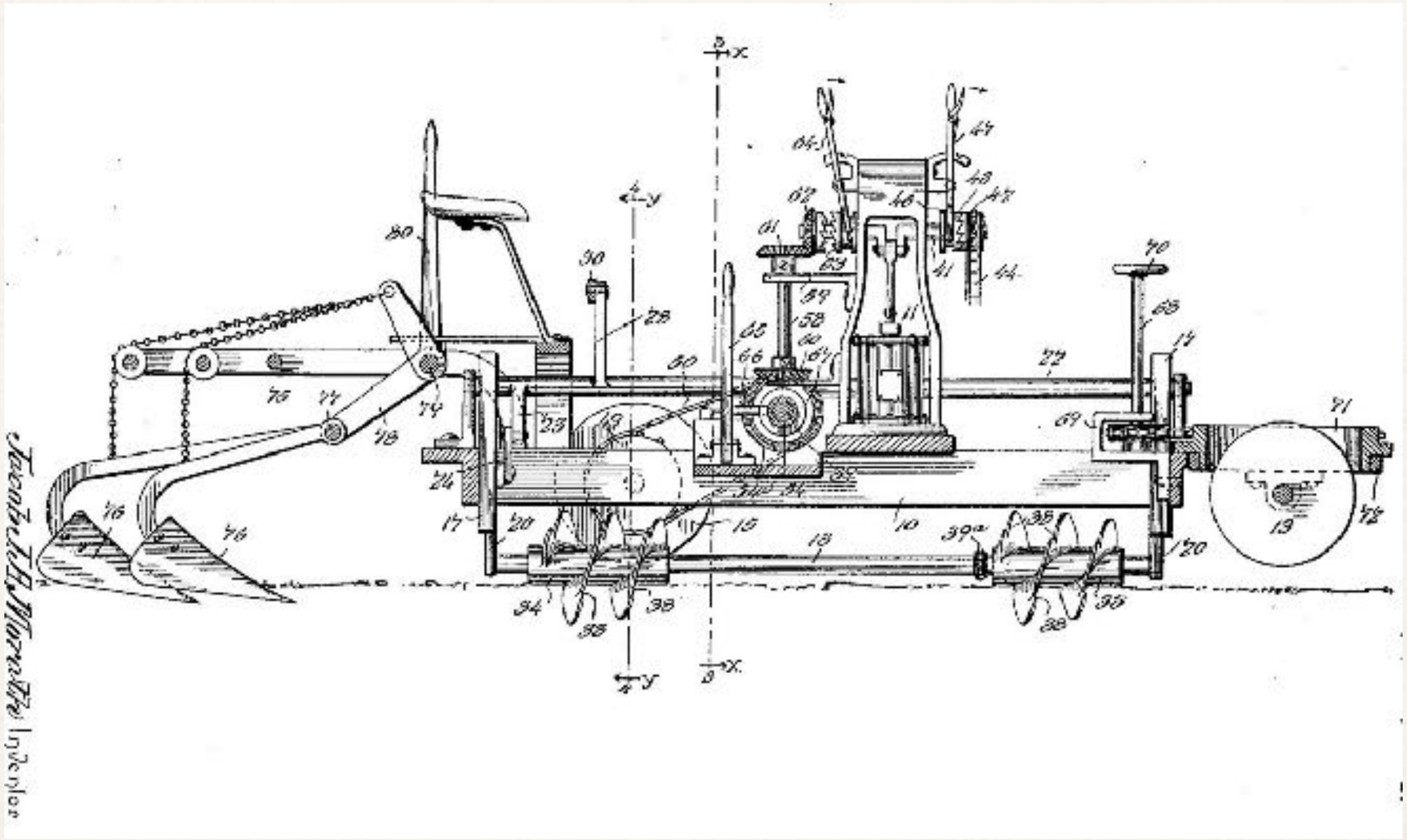


Modelling: “Cause and effect”

The standard paradigm

Modelling: “Cause and effect”

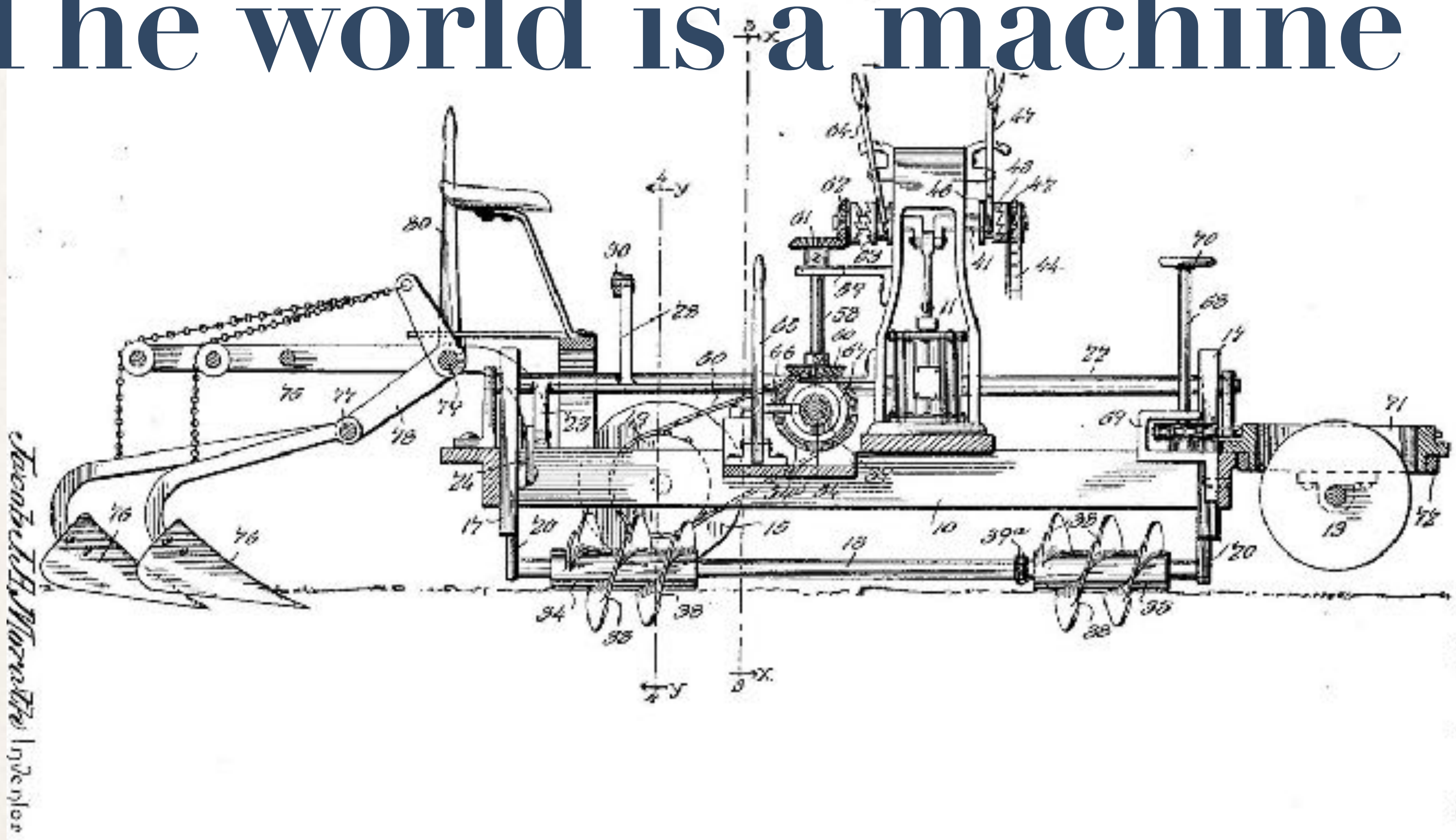
The standard paradigm



Modelling: "Cause and effect"

The standard paradigm

The world is a machine



Modelling: “Cause and effect”

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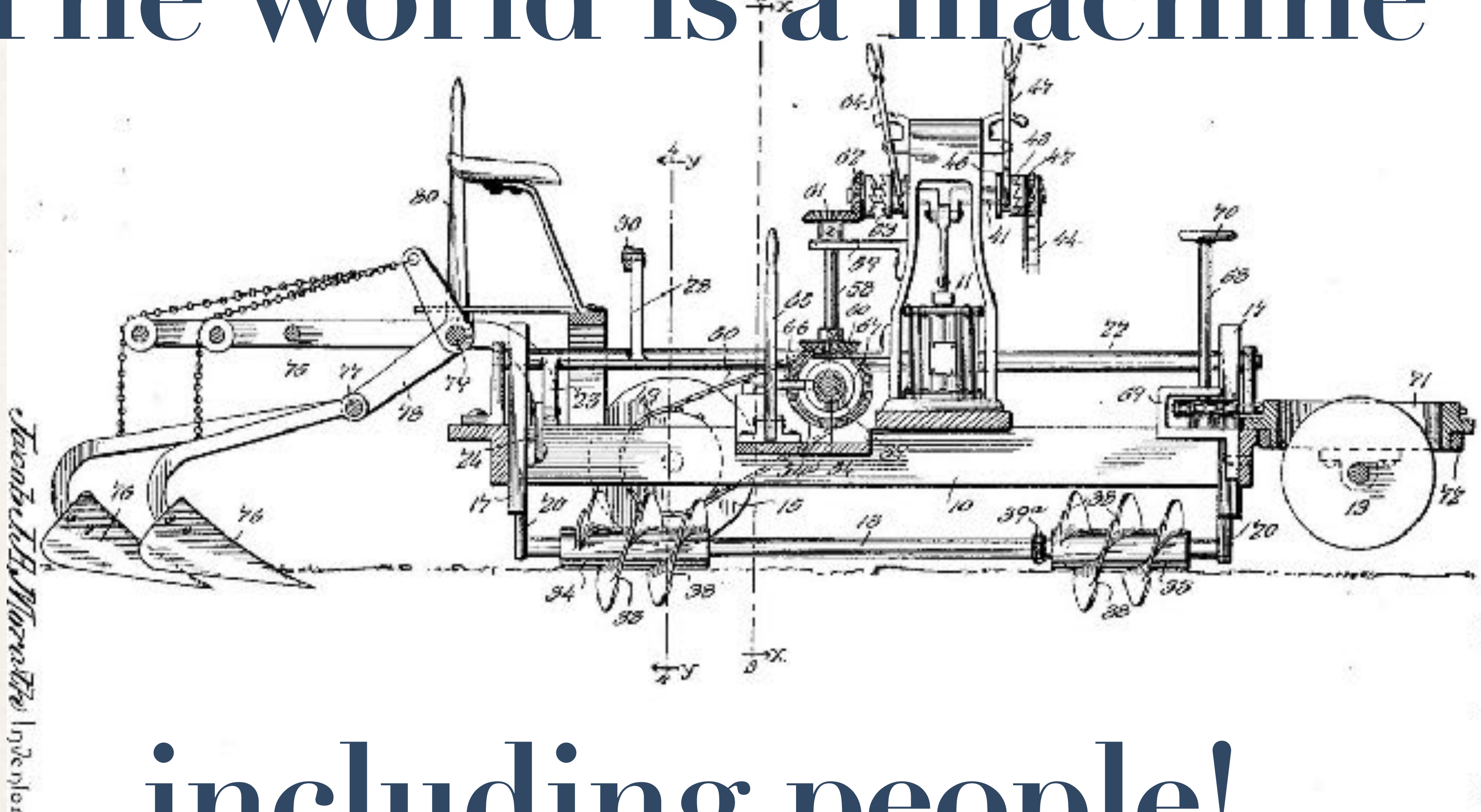
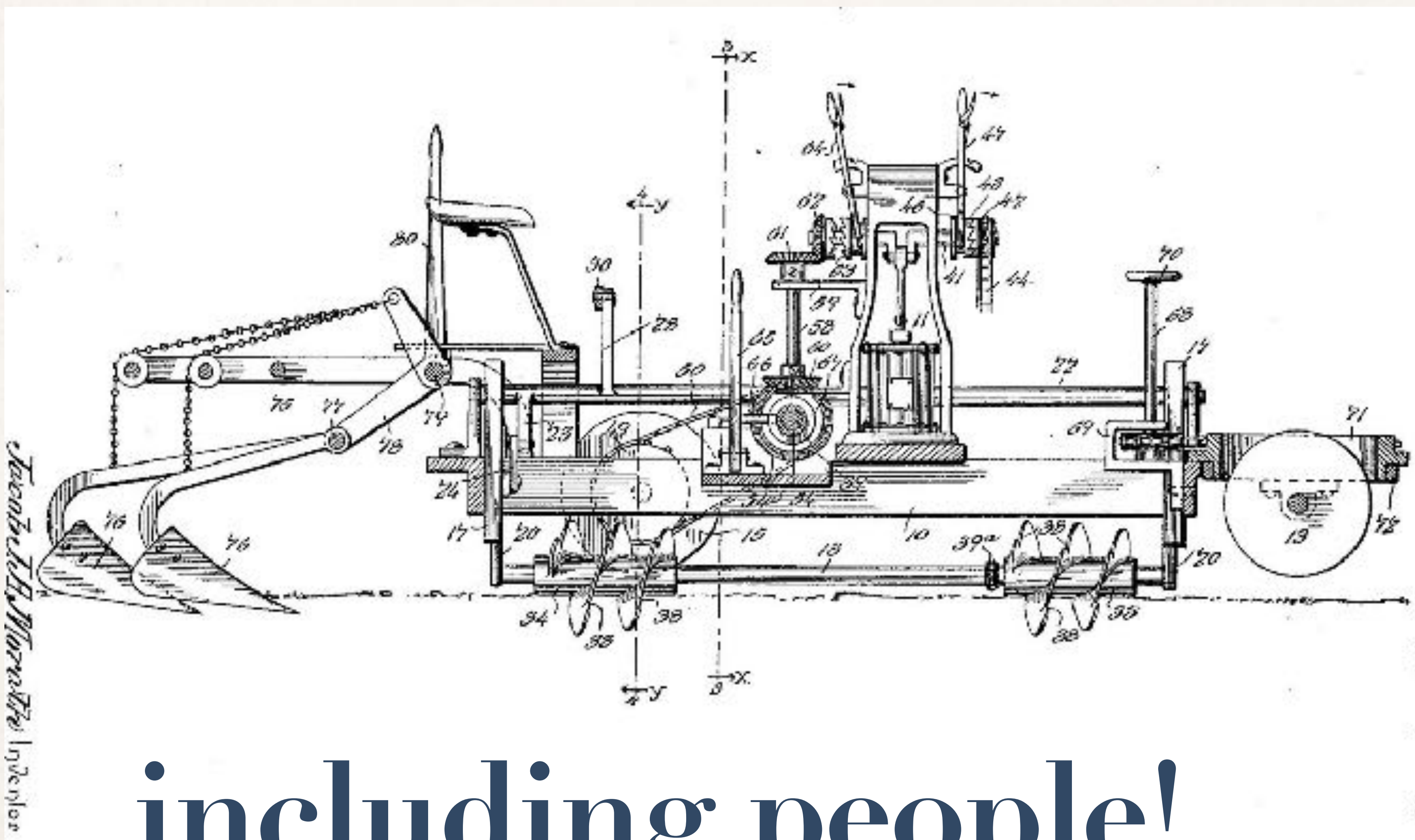
The world is a machine



including people!

Modelling: “Cause and effect”

The standard paradigm



including people!

Modelling: “Cause and effect”

The standard paradigm

including people!

Modelling: “Cause and effect”

The standard paradigm

Modelling: “Cause and effect”

The standard paradigm

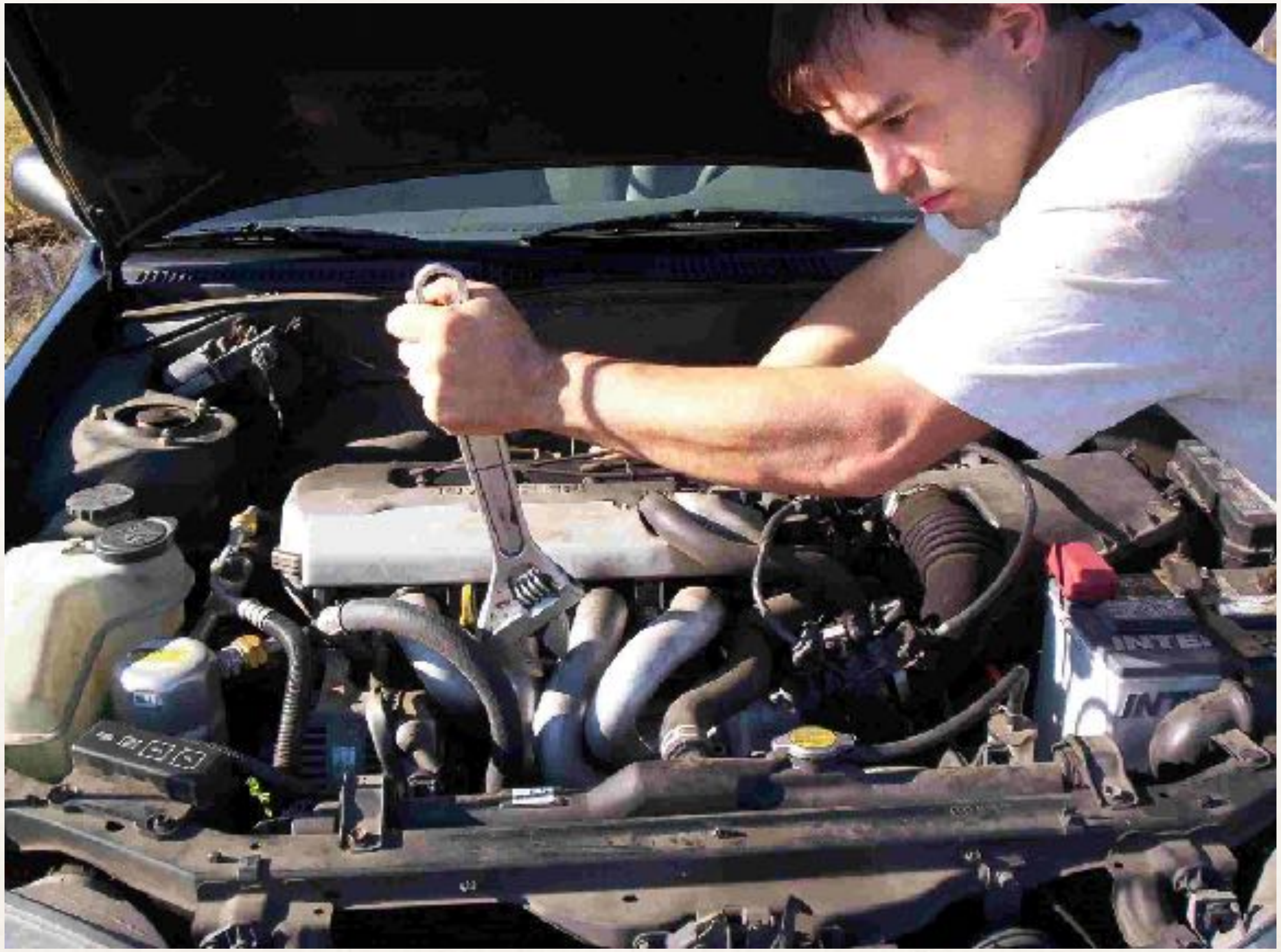
It is the paradigm of curative medicine

Modelling: “Cause and effect”

The standard paradigm

Modelling: “Cause and effect”

The standard paradigm



Modelling: "Cause and effect"

The standard paradigm

Modelling: “Cause and effect”

The standard paradigm

versus

Modelling: "Cause and effect"

The standard paradigm

Modelling: “Cause and effect”

The standard paradigm

Modelling: “Cause and effect”

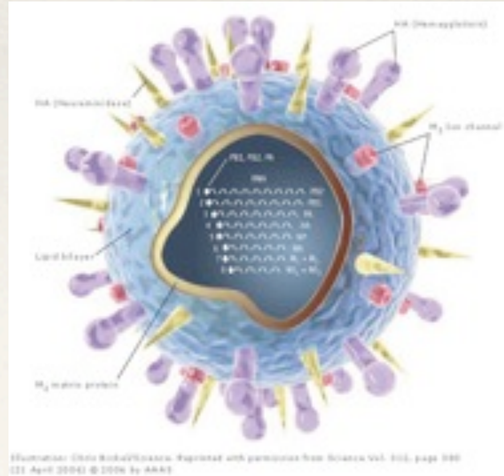
The standard paradigm

Modelling: “Cause and effect”

The standard paradigm

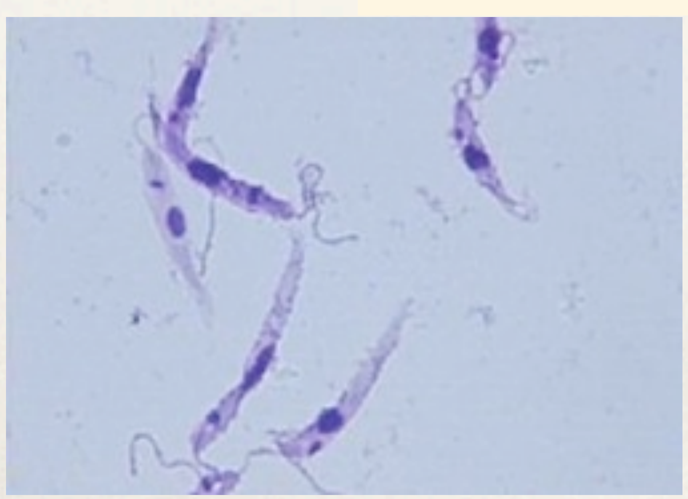
Its been very successful.

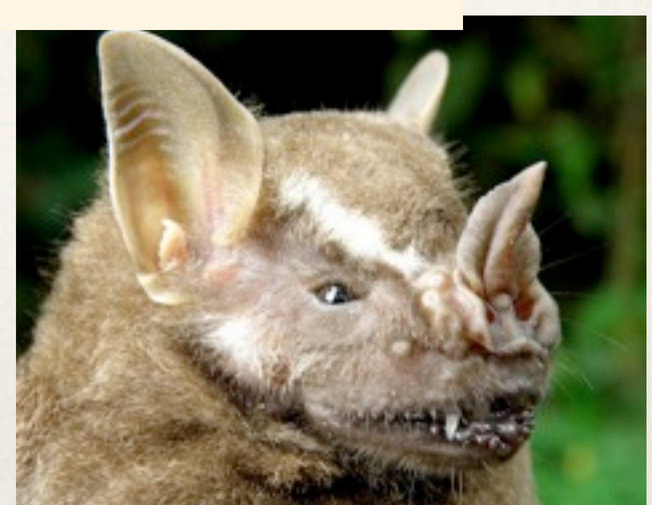
But…



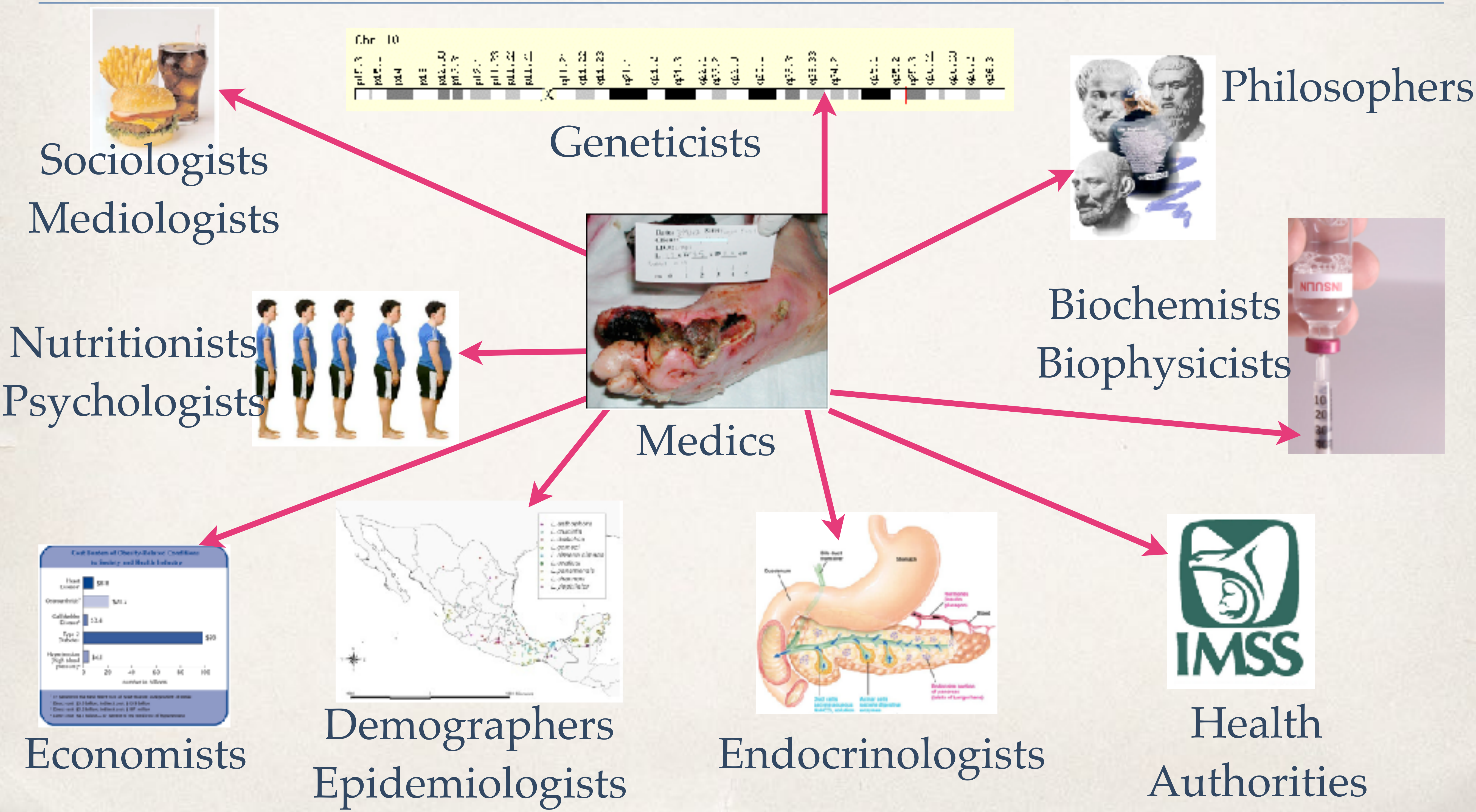
Diseases are

Complex Adaptive Systems





They are complex



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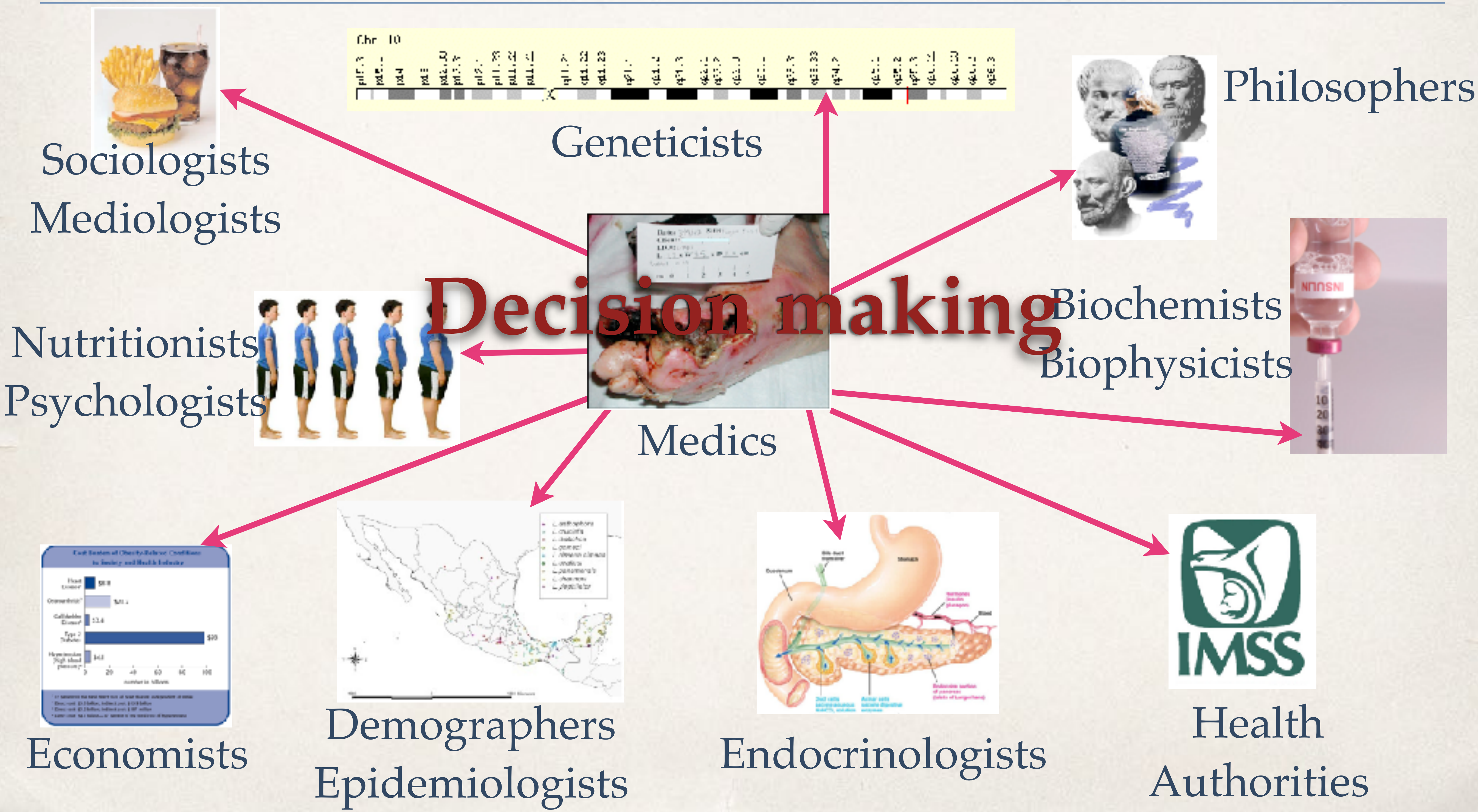
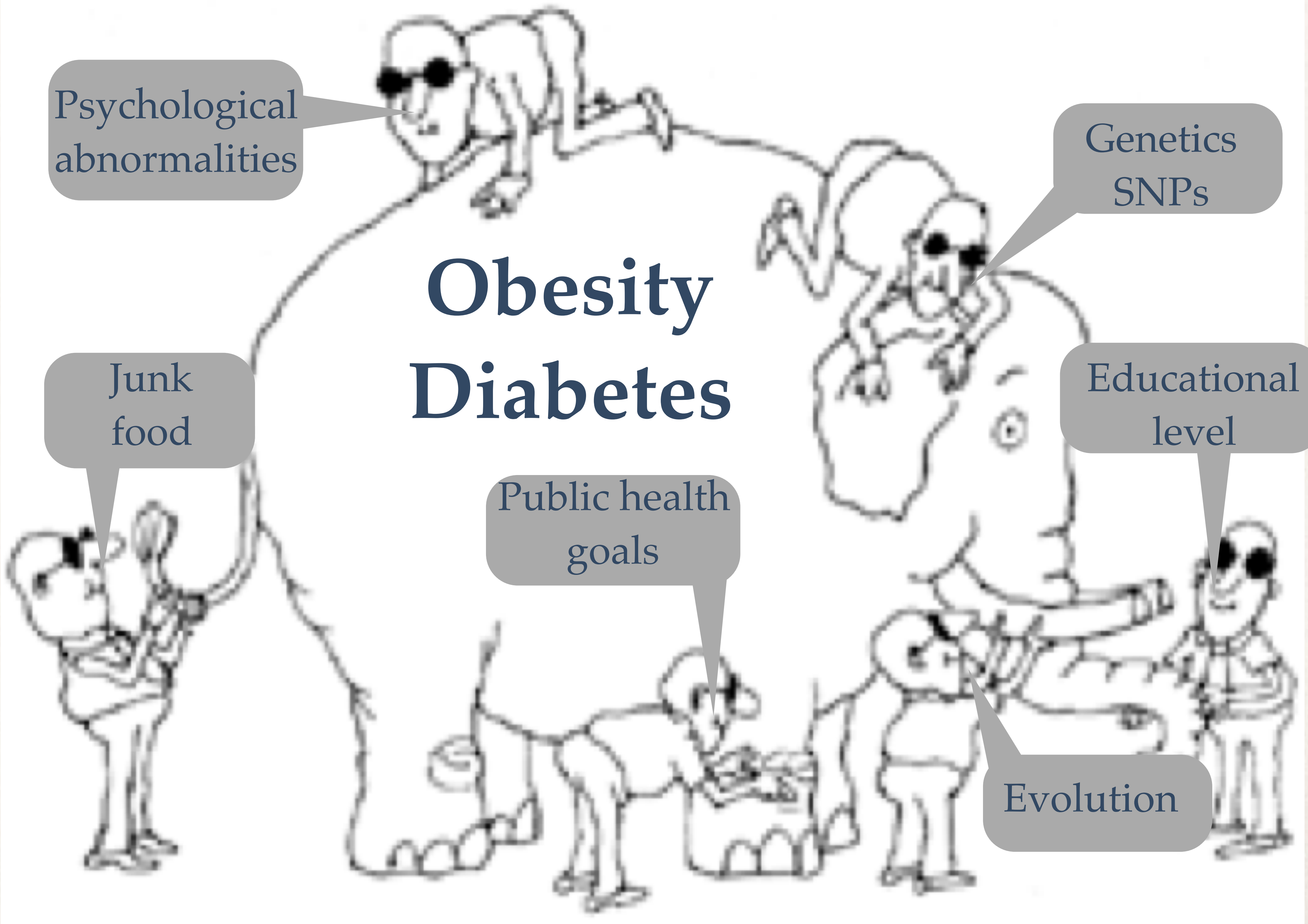
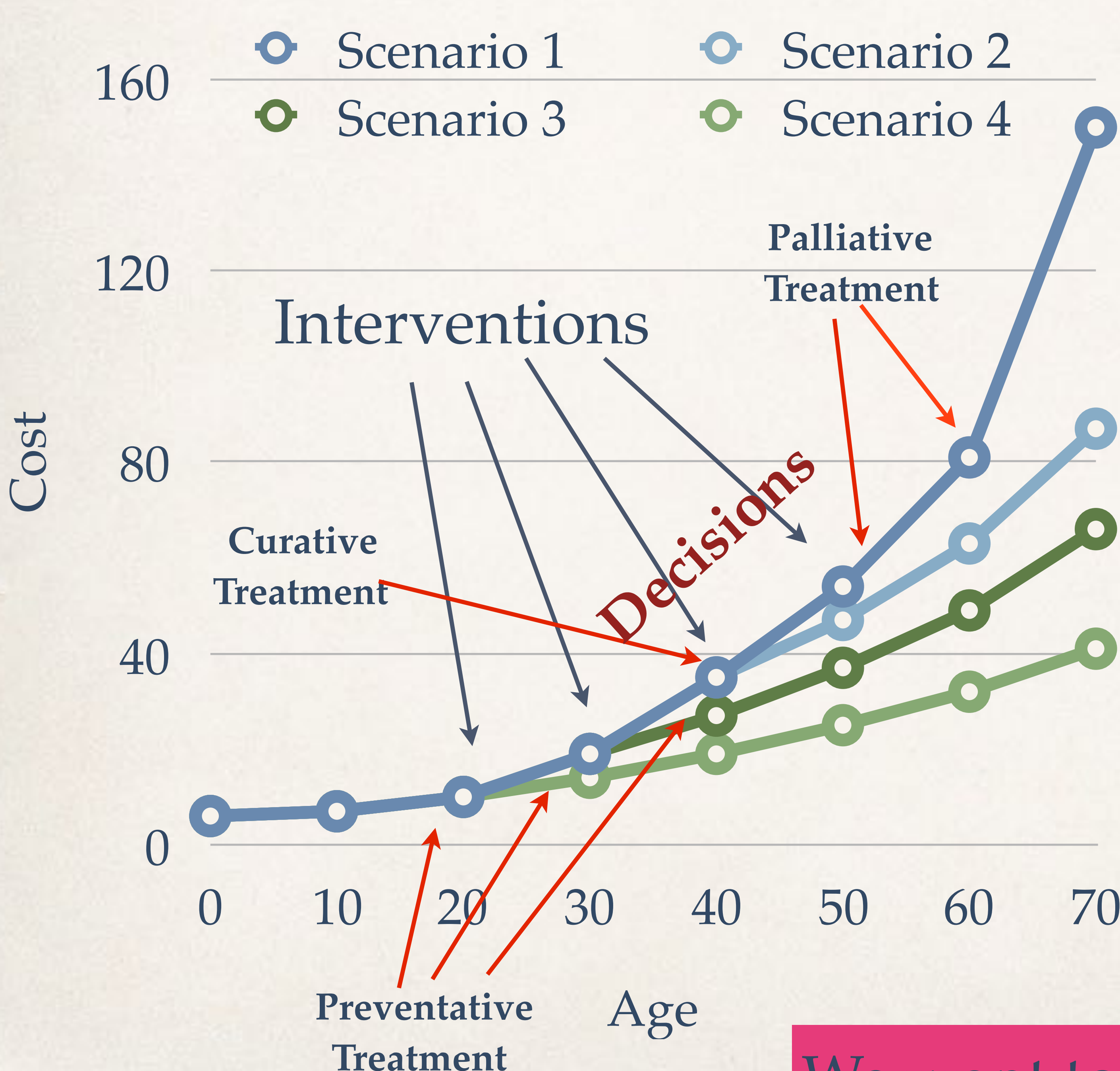


Disease and the need to work in interdisciplinary groups



They are dynamical and adaptive



Scenario 1: Onset of obesity at 20
Continued obesity and onset of metabolic syndrome at 40
Onset of diabetes at 50
Onset of renal failure at 60
Death at 70

Scenario 2: Onset of obesity at 20
Continued obesity and onset of metabolic syndrome at 40
Onset of diabetes at 50
Adequate control and treatment of comorbilities at 60
Bad health and high cost at 70

Scenario 3: Overweight at 20
Obesity at 40
Onset metabolic syndrome at 50
Onset of diabetes at 60
Continued diabetes but no serious comorbilities at 60
Ill health and moderate cost at 70

Scenario 4: Overweight at 30
Obesity at 50
Onset of metabolic syndrome at 60
Onset of diabetes at 70 but relative health

We want to predict and understand "histories"

Adaptation, health and decision making

Adaptation, health and decision making

Complex Adatptive Systems...
make “decisions”

Adaptation, health and decision making

Complex Adatptive Systems...
make "decisions"

at both the individual
and collective levels

Adaptation, health and decision making

at both the individual
and collective levels

Adaptation, health and decision making

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Adaptation, health and decision making

Adaptation, health and decision making

Adaptation, health and decision making

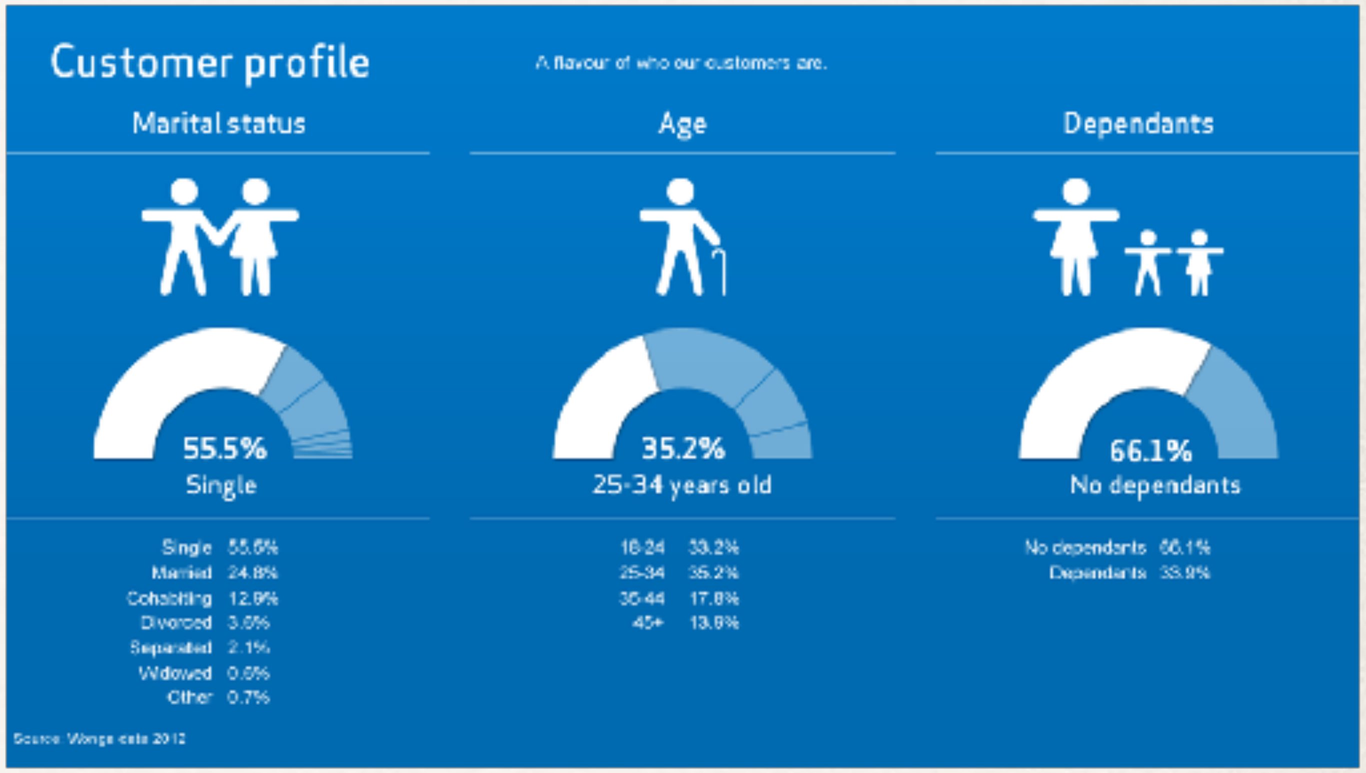
Your Prediction/Decision Heuristic/Algorithm depends on…

Your Prediction/Decision Heuristic/Algorithm depends on…

“Who” you are

Your Prediction/Decision Heuristic/Algorithm depends on…

“Who” you are



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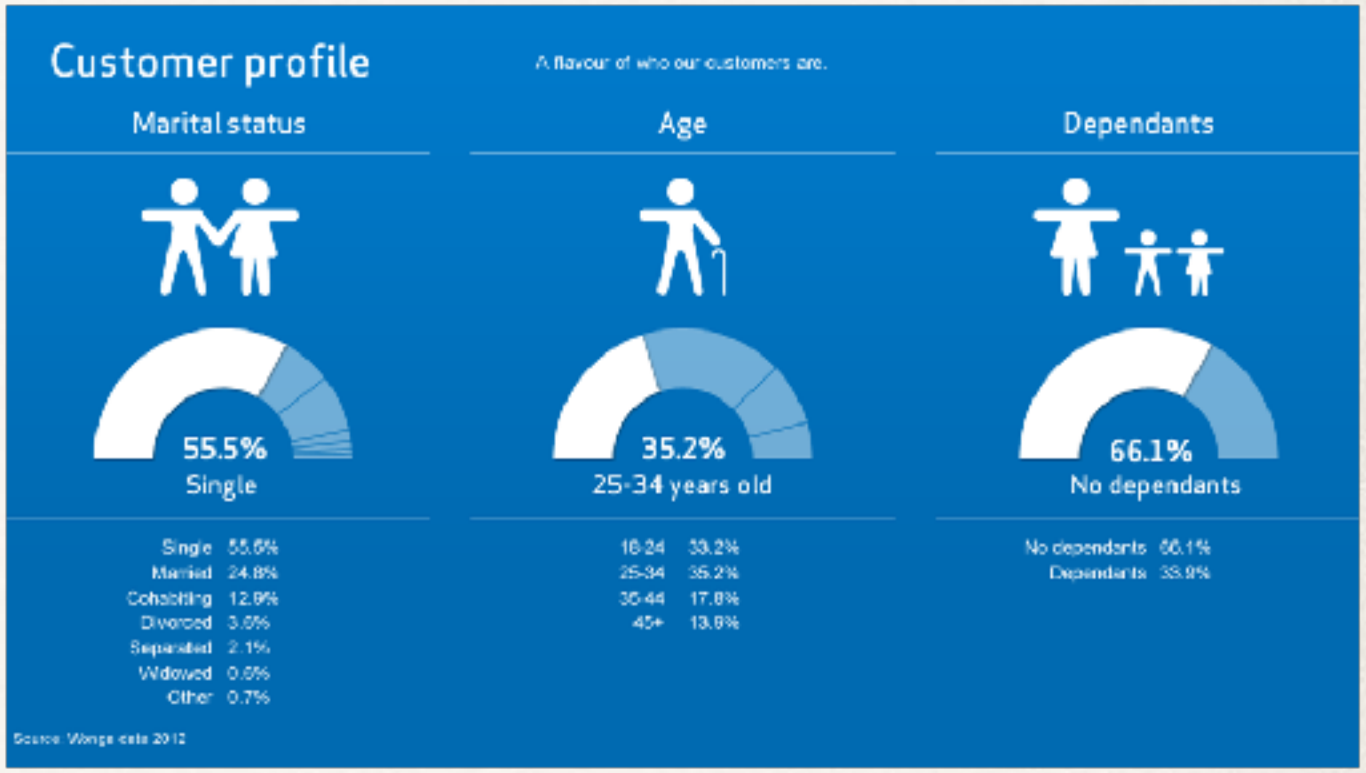


Your Prediction/Decision Heuristic/Algorithm depends on…

Your Prediction/Decision Heuristic/Algorithm depends on…

What and how
you “think”

Your Prediction/Decision Heuristic/Algorithm depends on…

What and how
you "think"

Your Prediction/Decision Heuristic/Algorithm depends on…

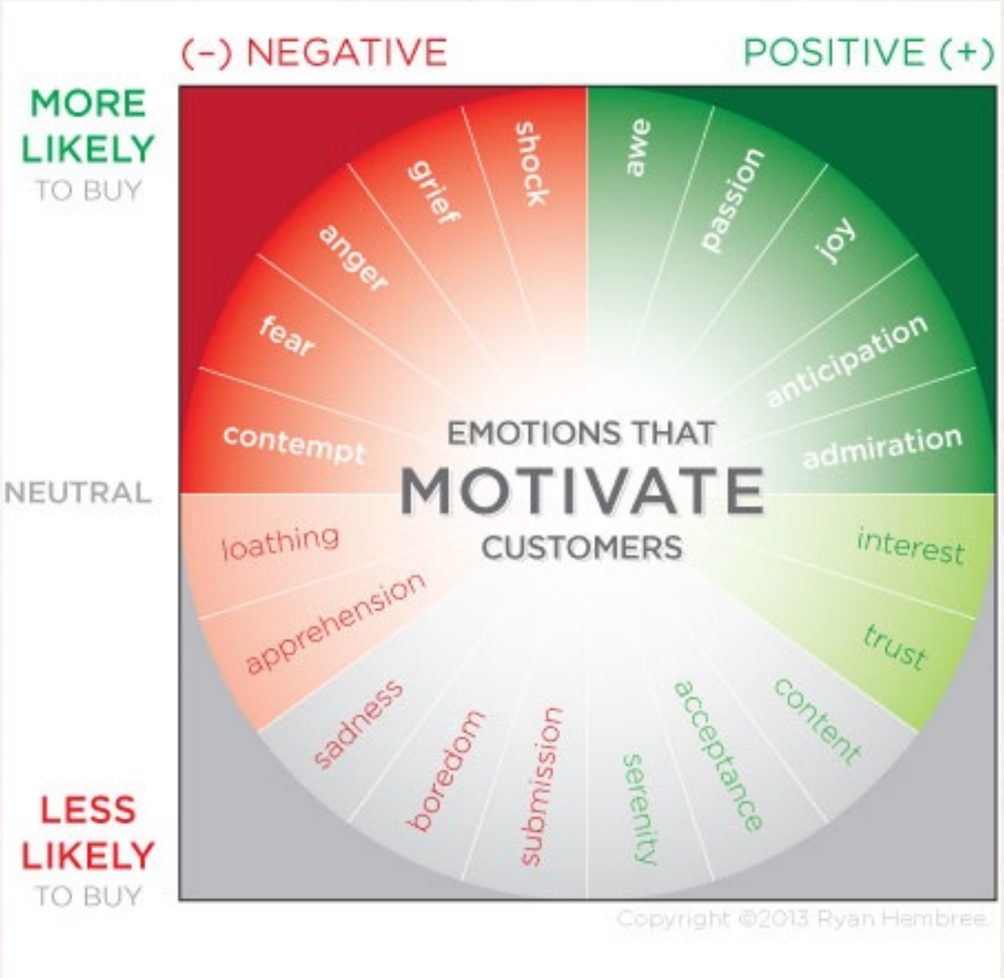
Your Prediction/Decision Heuristic/Algorithm depends on…

Your Prediction/Decision Heuristic/Algorithm depends on…

What and how you “feel”

Your Prediction/Decision Heuristic/Algorithm depends on…

What and how you "feel"



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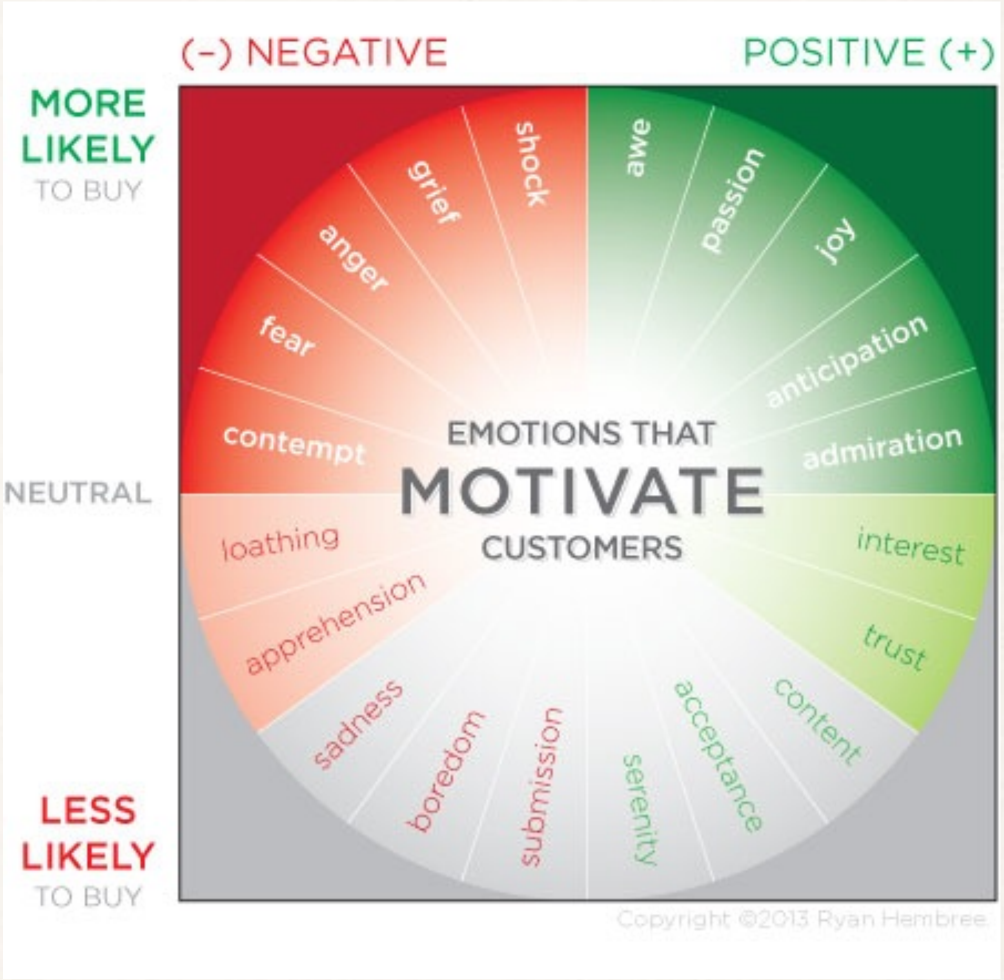

Your Prediction/Decision Heuristic/Algorithm depends on…

Your Prediction/Decision Heuristic/Algorithm depends on…

Your Prediction/Decision Heuristic/Algorithm depends on…

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

Your Prediction/Decision Heuristic/Algorithm depends on…

Your Prediction/Decision Heuristic/Algorithm depends on…

What is a decision?

A "decision"

$$P(C \mid X(t))$$

Probability of C given X

Prediction

In the exact sciences, predictions tend to be **algoríthmic**

In medicine and public health, predictions tend to be **heurístic**

Curative Medicine
Less complex, less adaptative

Preventative Medicine
More complex, more adaptative

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

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

What degree of multi-factoriality is there?

Preventative medicine requires a lot more data.

Where do we get that data…? from the data revolution

Deep Data and the Data Revolution

Deep Data and the Data Revolution

Deep Data and the Data Revolution

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Deep Data and the Data Revolution


A revolution in the generation of data

Deep Data and the Data Revolution

A revolution in the generation of data

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

Deep Data and the Data Revolution


A revolution in the generation of data

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= 1GB (200)
CT image
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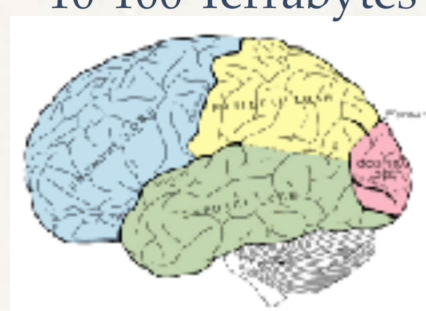
Deep Data and the Data Revolution

A revolution in the generation of data

Human brain
10-100 Terrabytes



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Deep Data and the Data Revolution


A revolution in the generation of data

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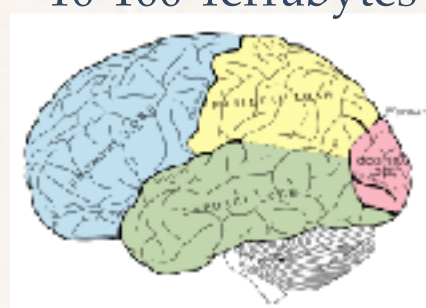


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Deep Data and the Data Revolution

A revolution in the generation of data

Human brain
10-100 Terrabytes

All the books in the world 30-50 Terrabytes

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Deep Data and the Data Revolution

A revolution in the generation of data

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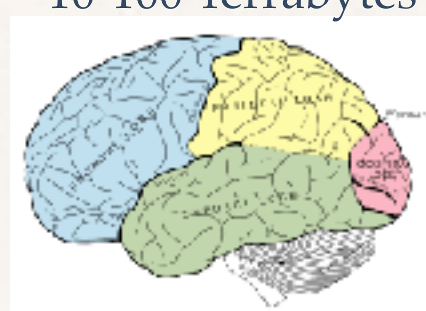
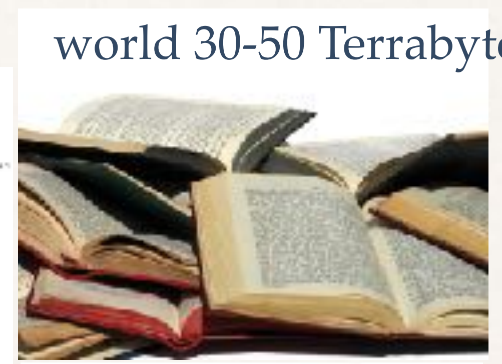


All the books in the world 30-50 Terrabytes



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

Deep Data and the Data Revolution

A revolution in the generation of data

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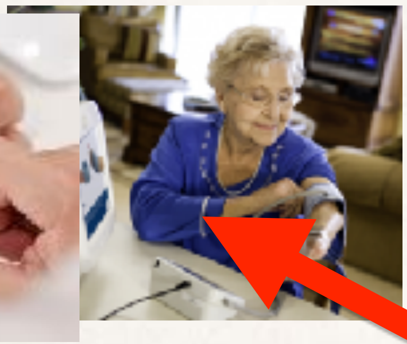

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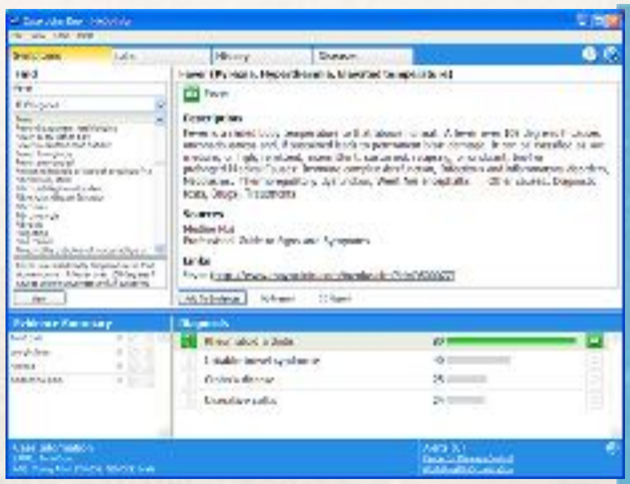

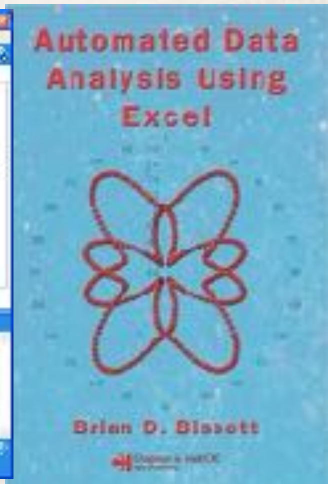

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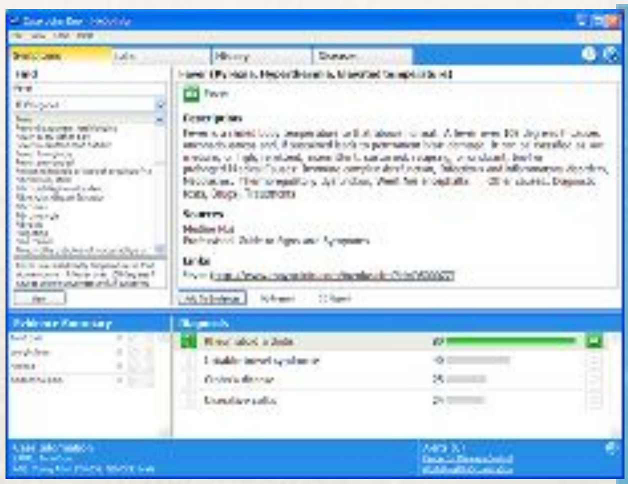

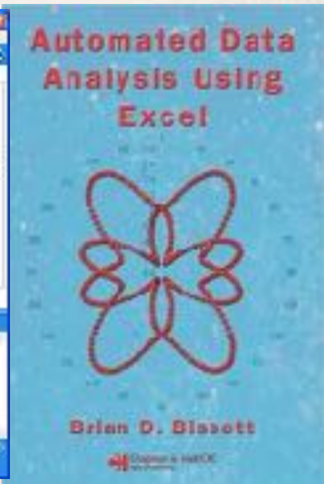

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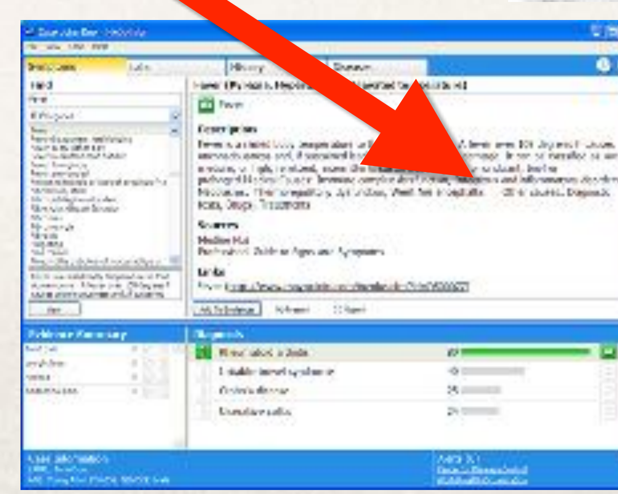
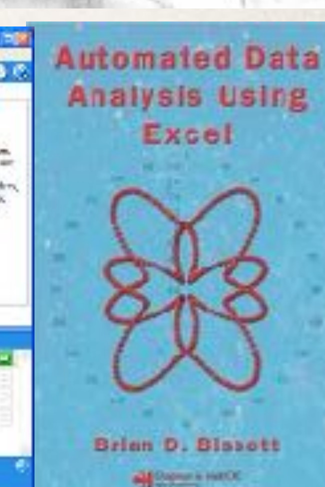
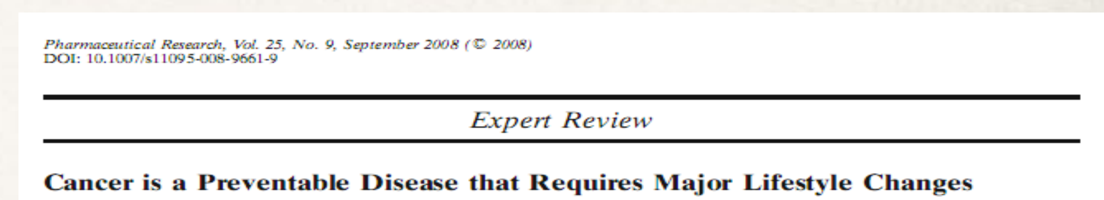




A revolution in data storage

The Obesity Pandemic

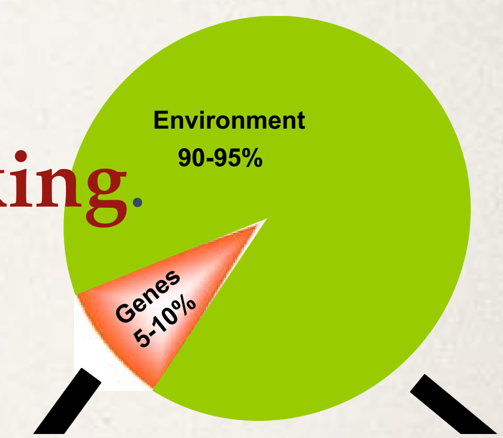
Obesity, type 2 diabetes, heart disease, strokes, cancer etc. are diseases associated with "lifestyle" and therefore are "preventible" (?)

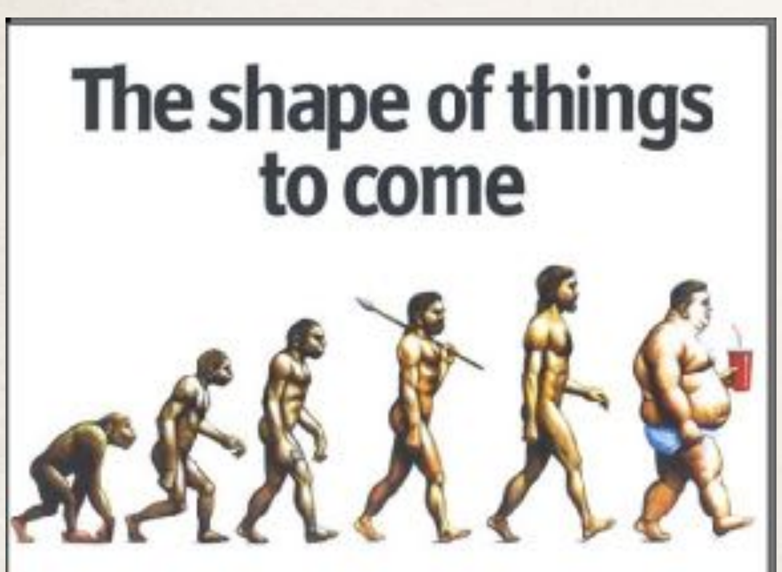

Pharmaceutical Research, Vol. 25, No. 9, September 2008 (© 2008)
DOI: 10.1007/s11095-008-9661-9

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**".

Obesity - risk factors
What you do
You aren’t what you eat you become what you eat

Epidemiological data from ENSANUT 2006

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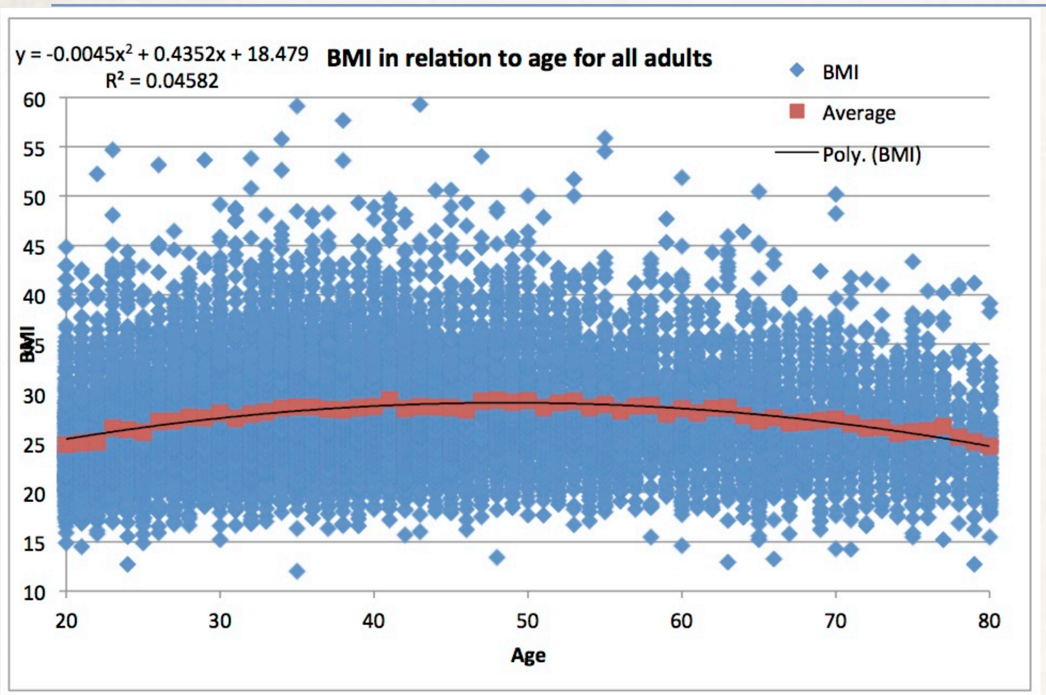

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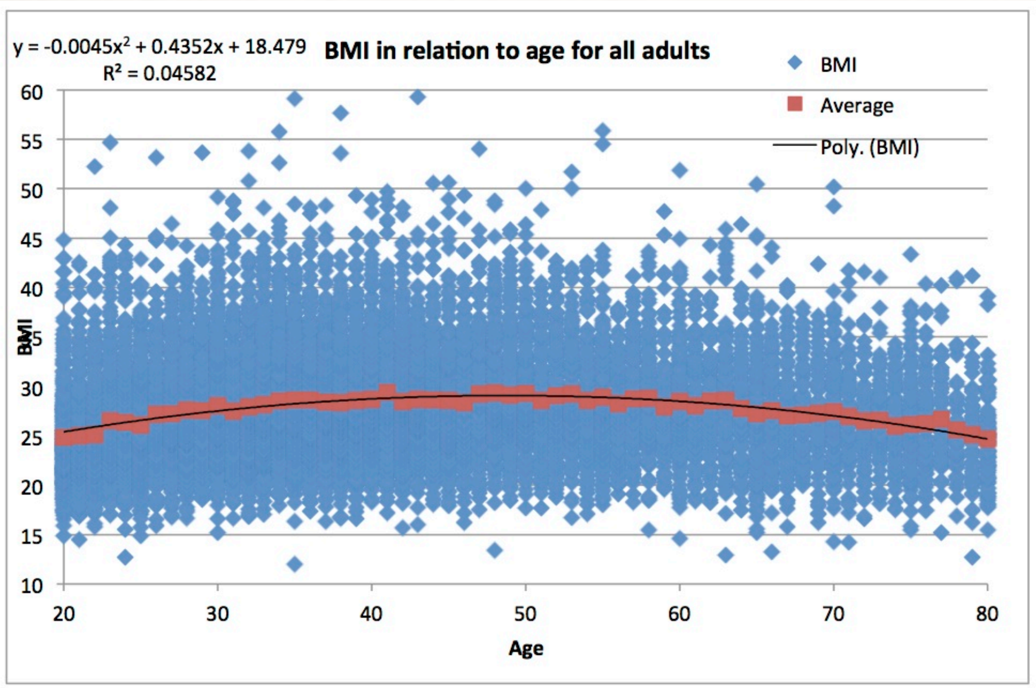

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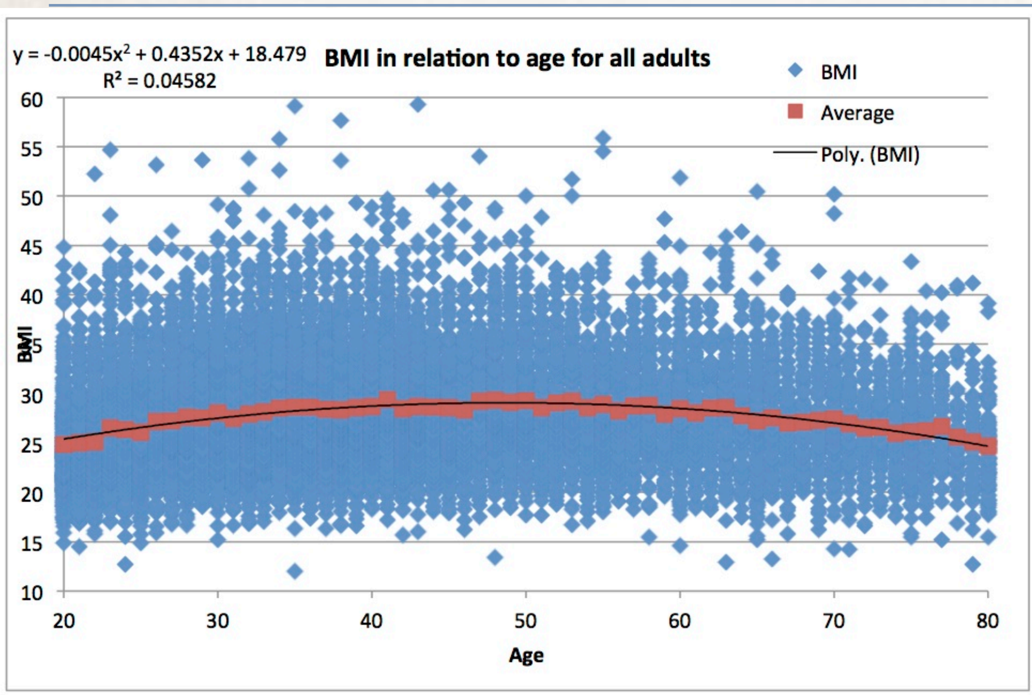

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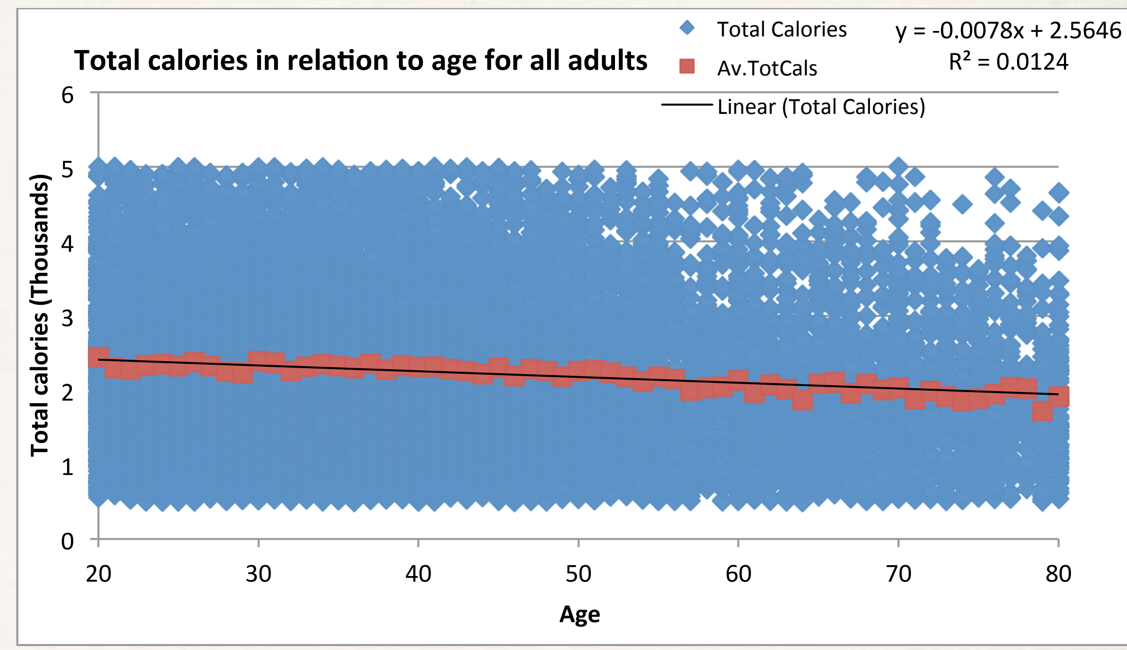

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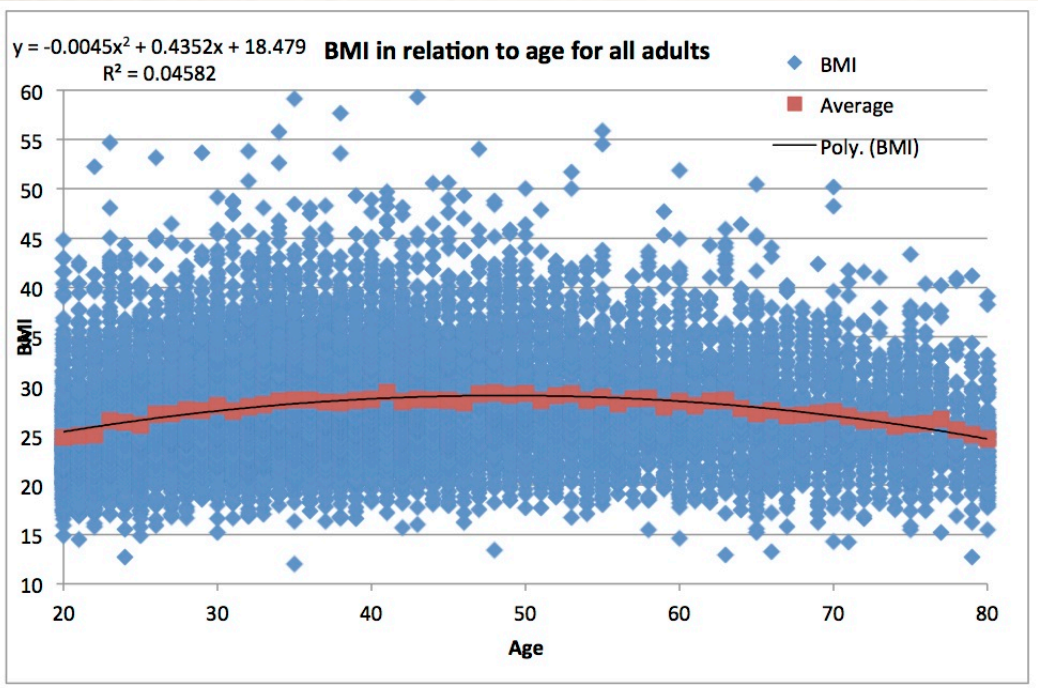

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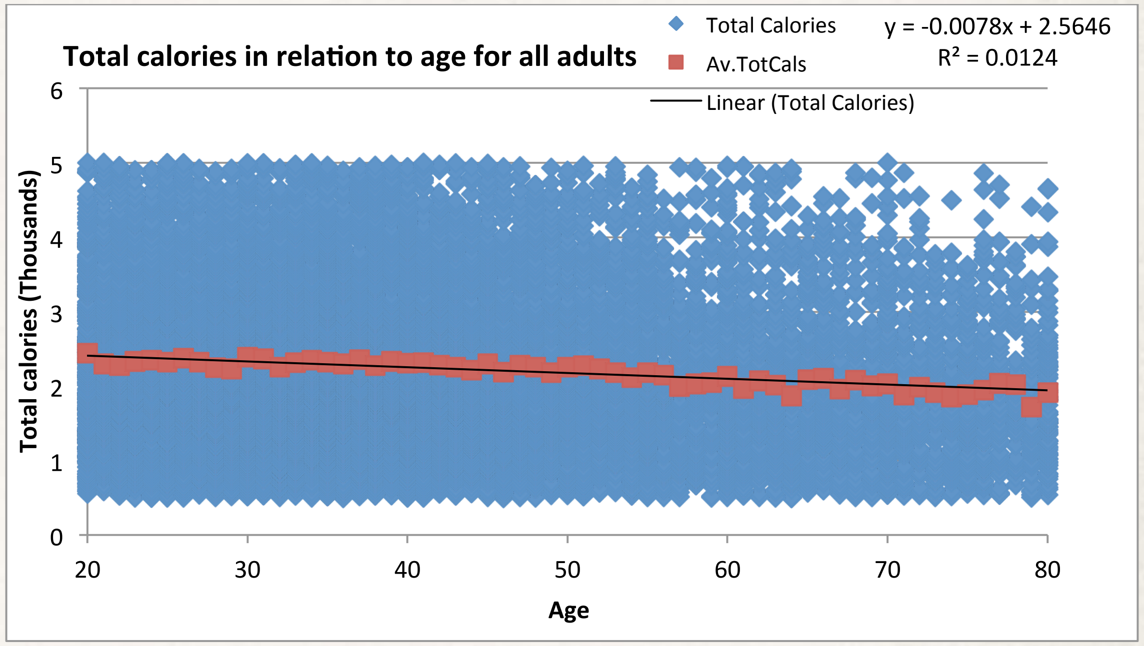

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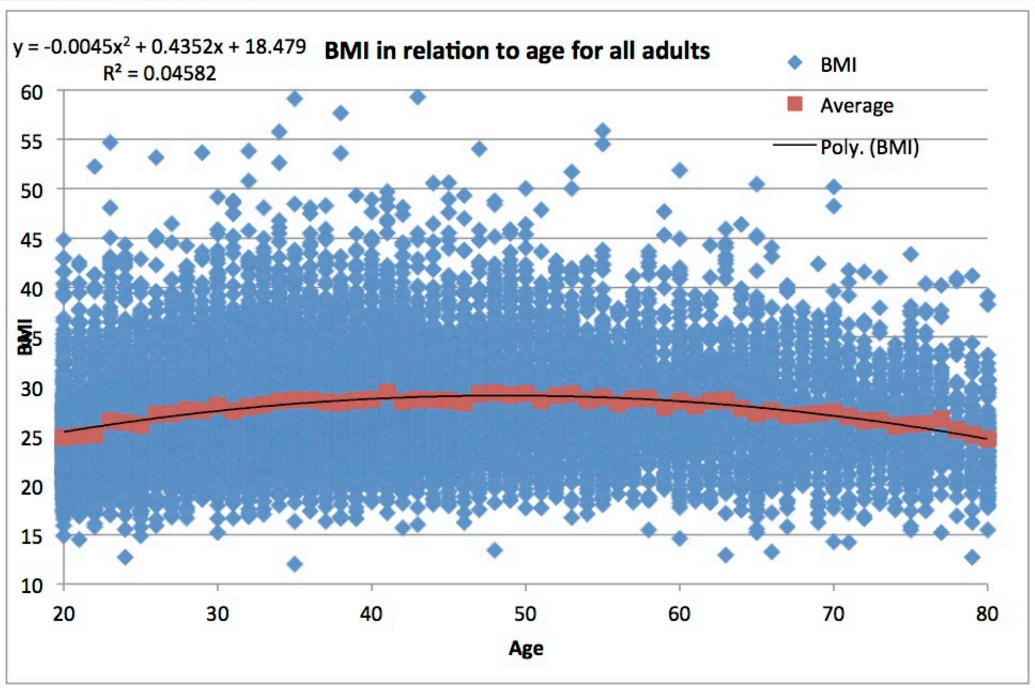

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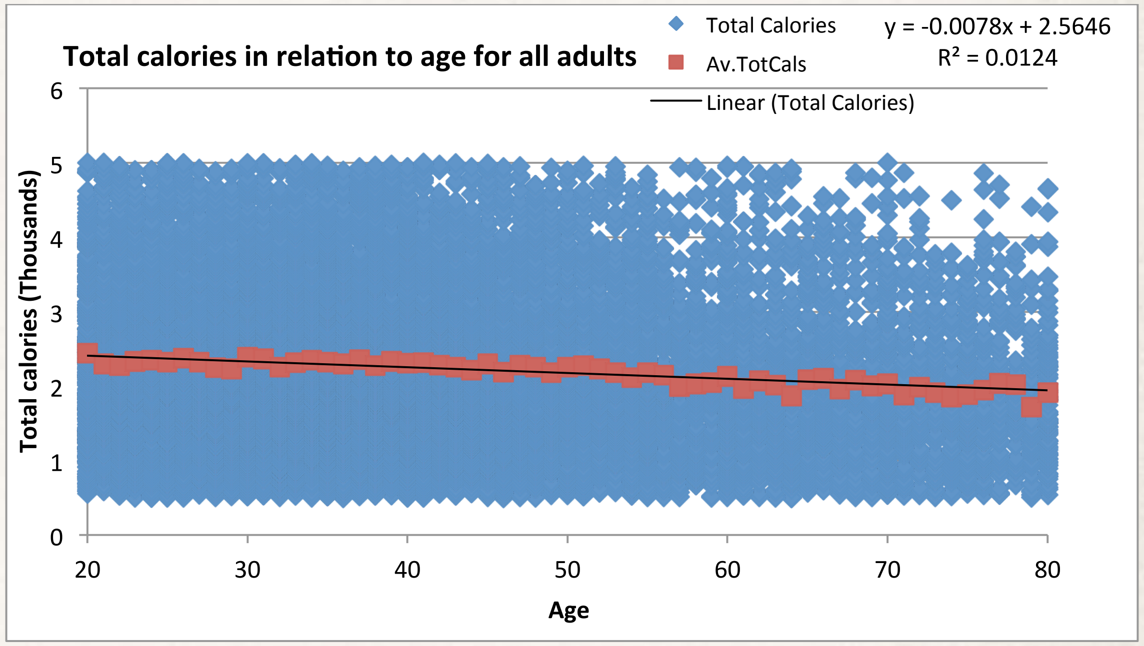
Its not "noise"its multifactoriality



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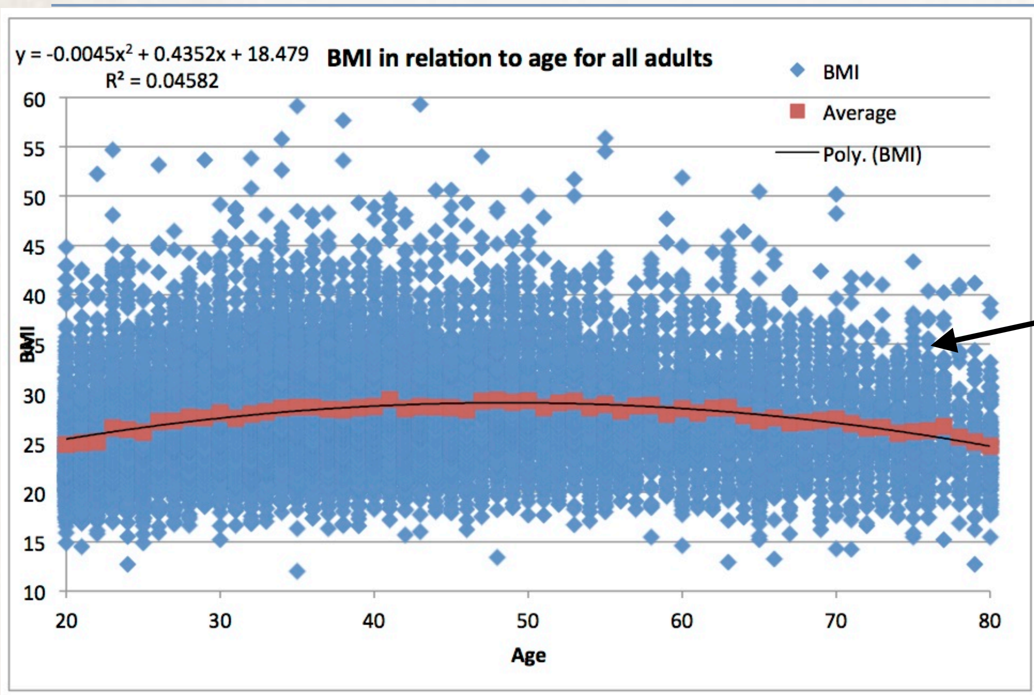

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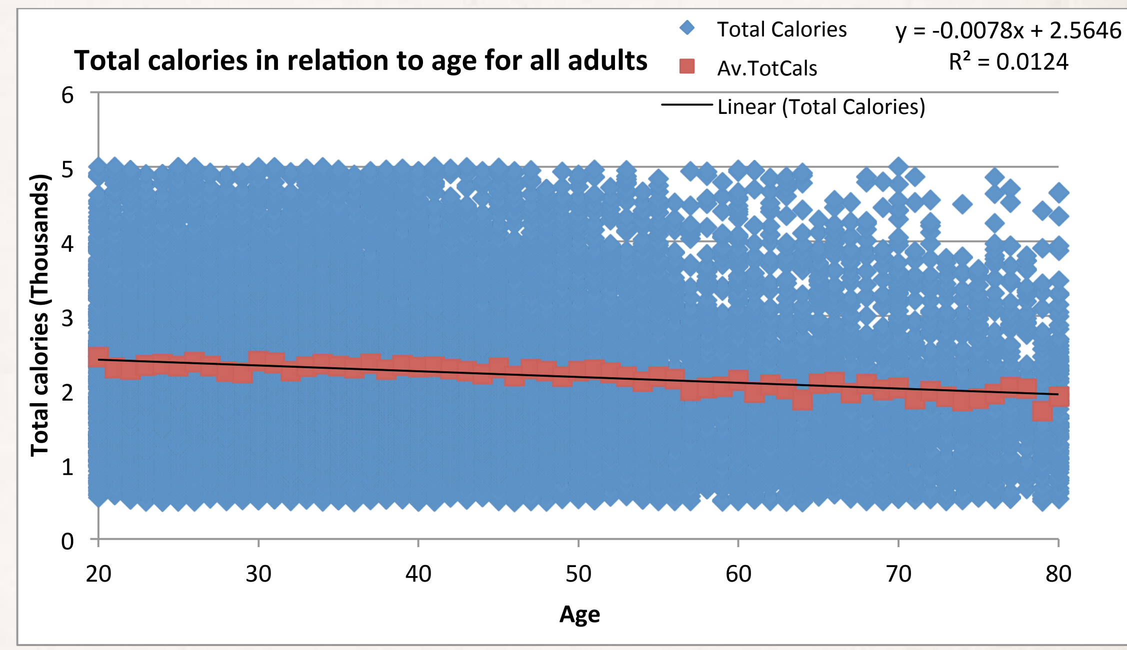

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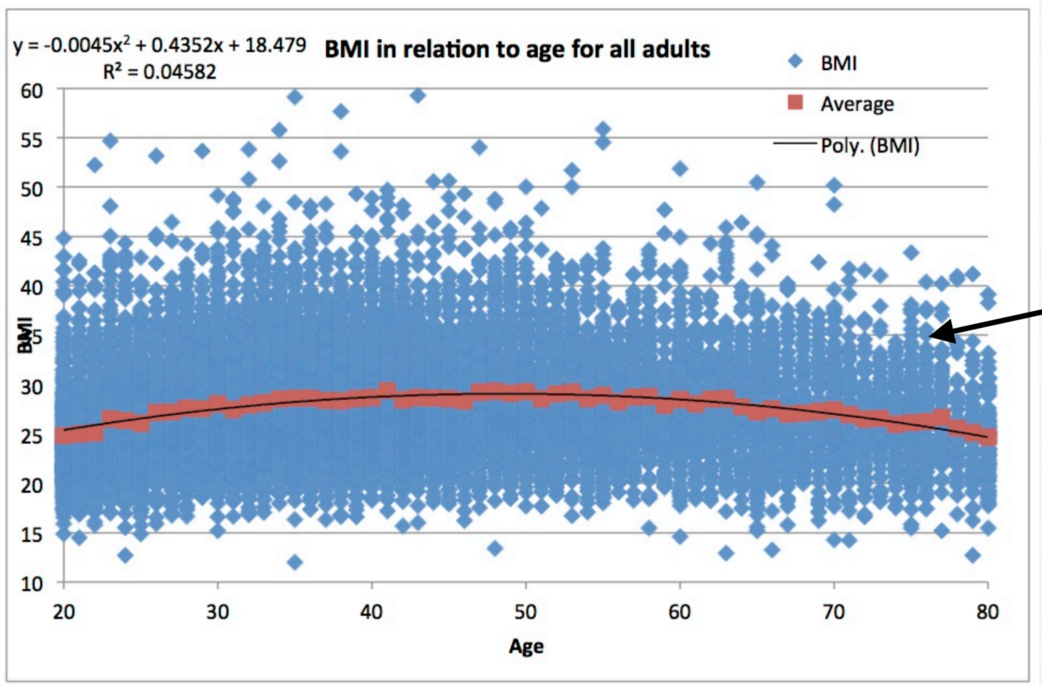

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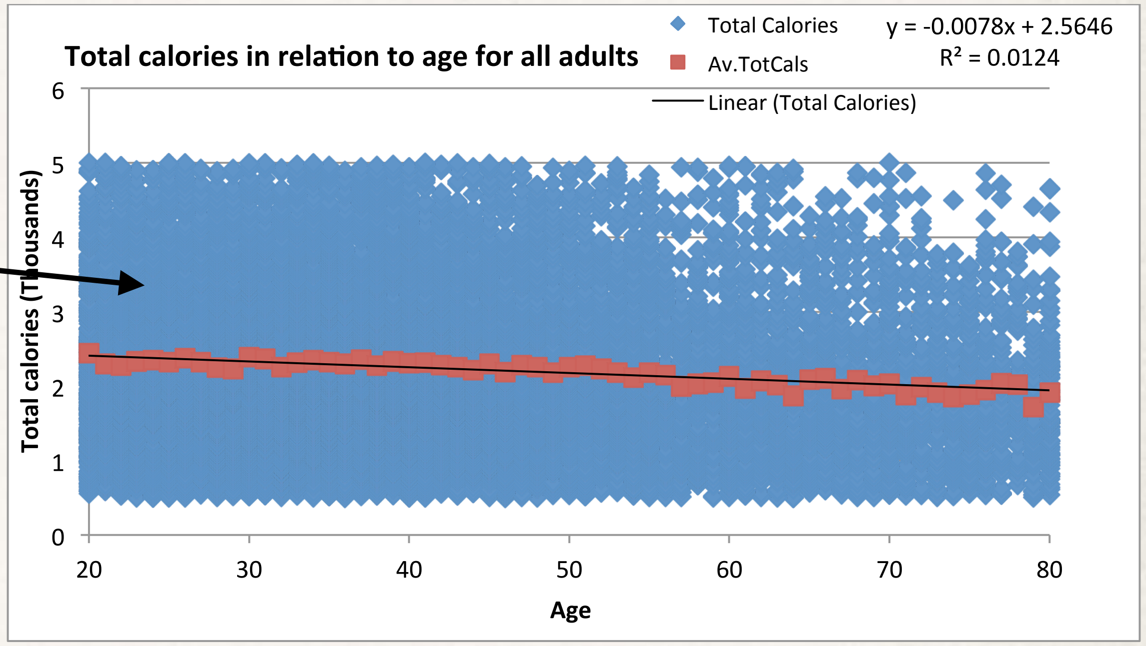

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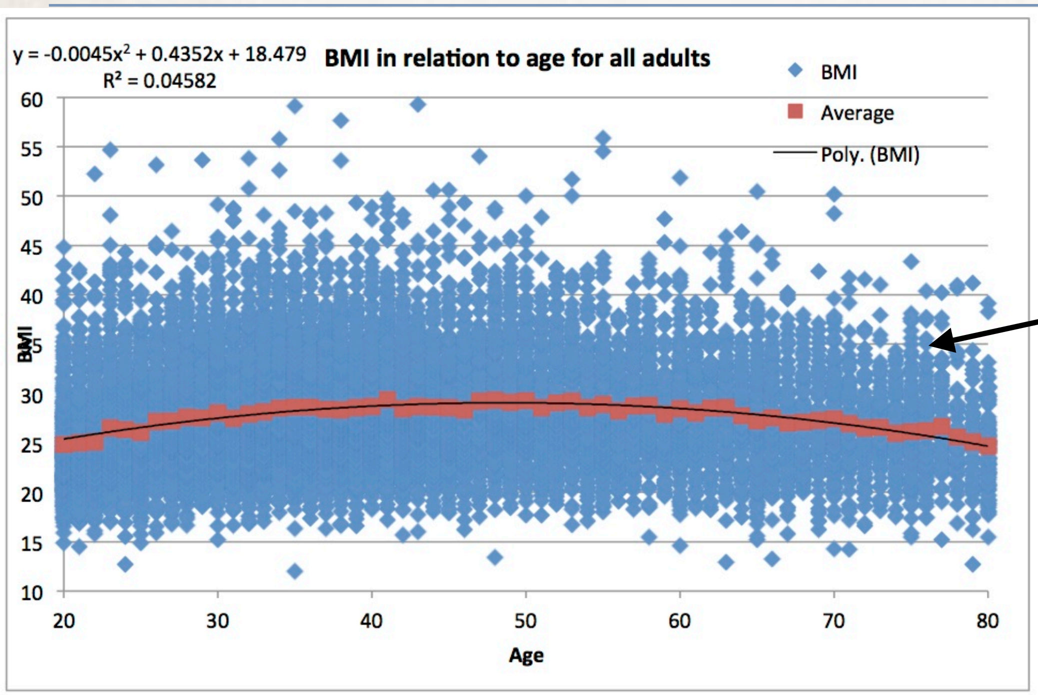

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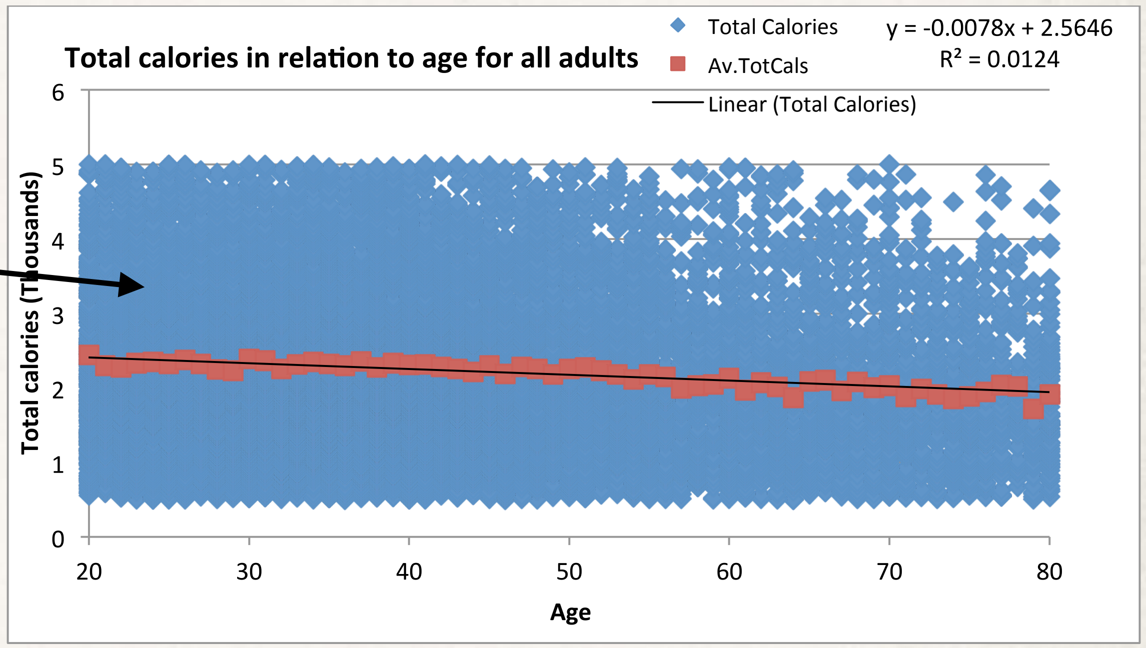

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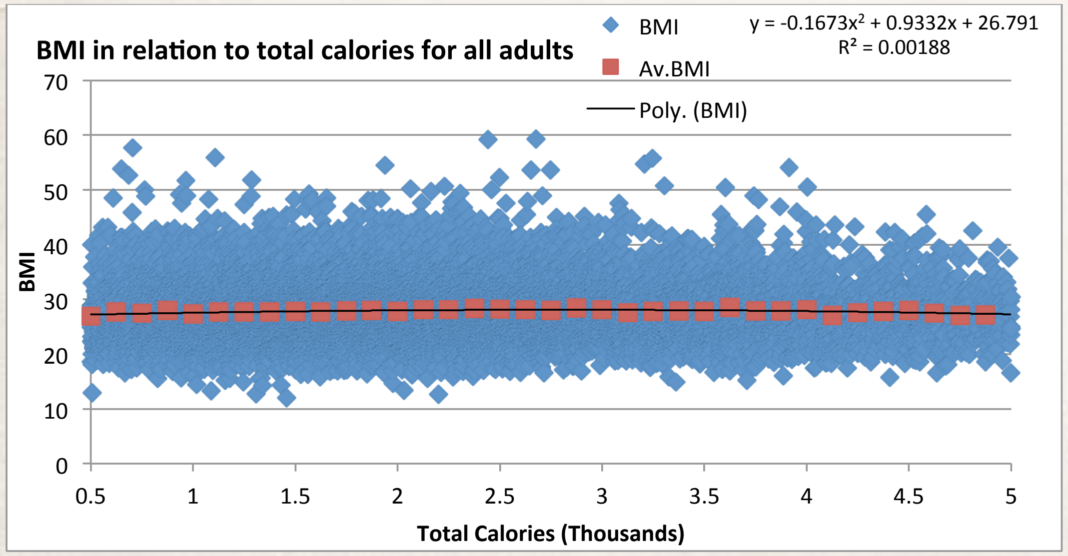

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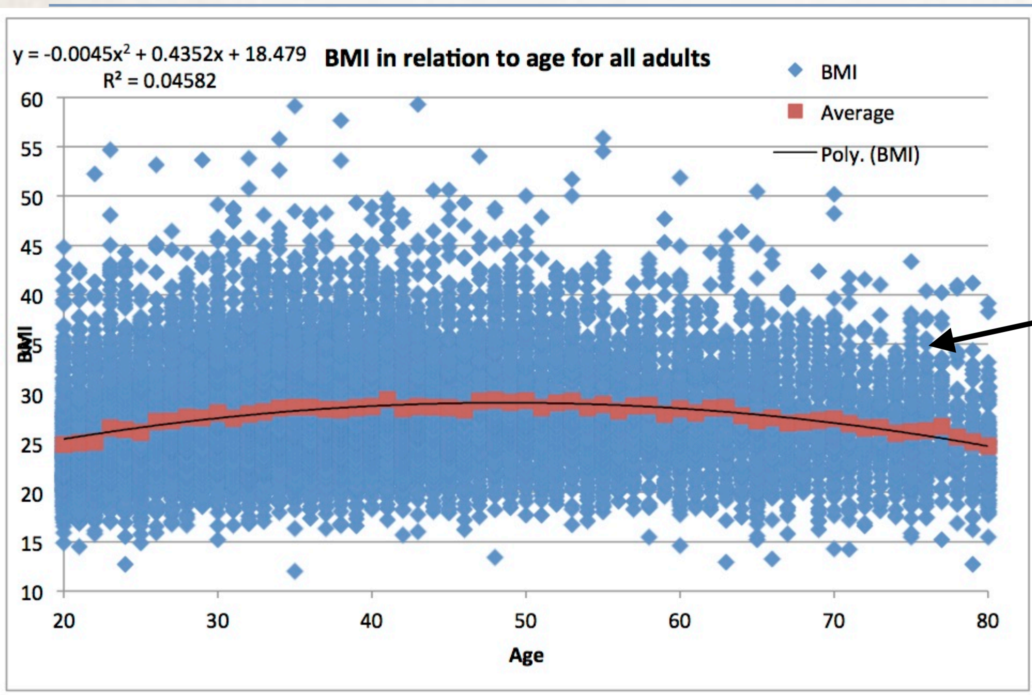

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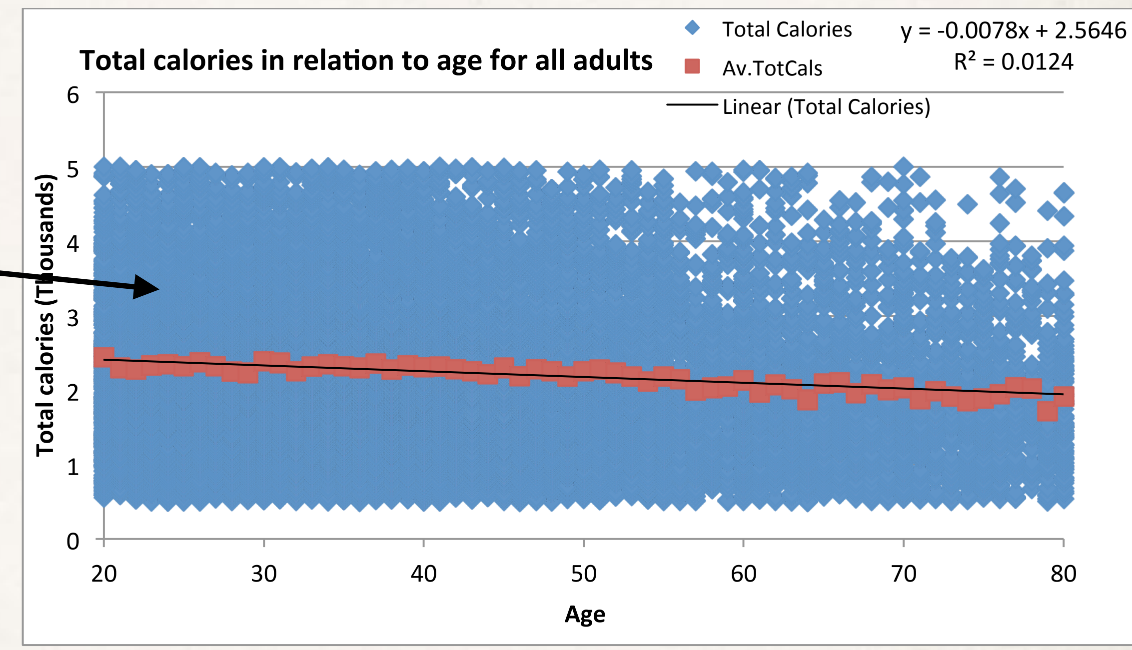

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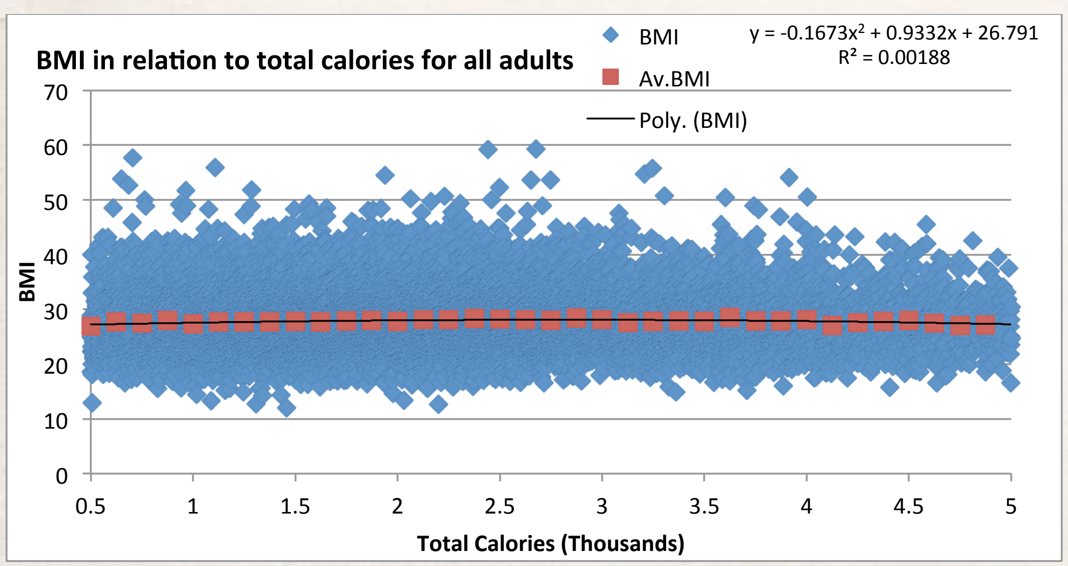

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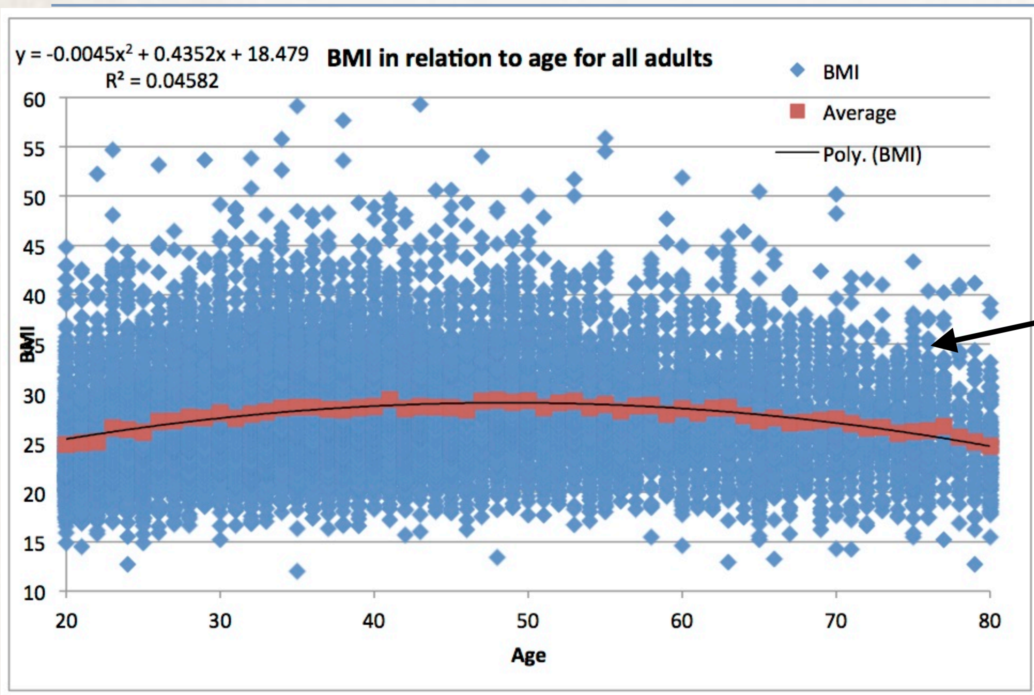

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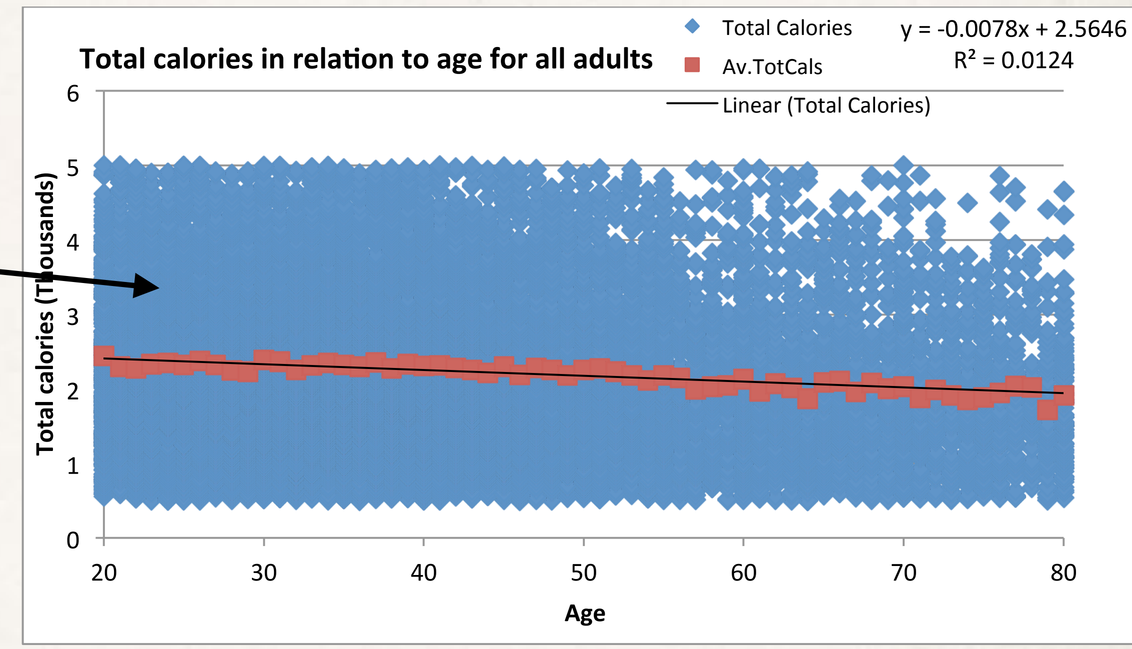

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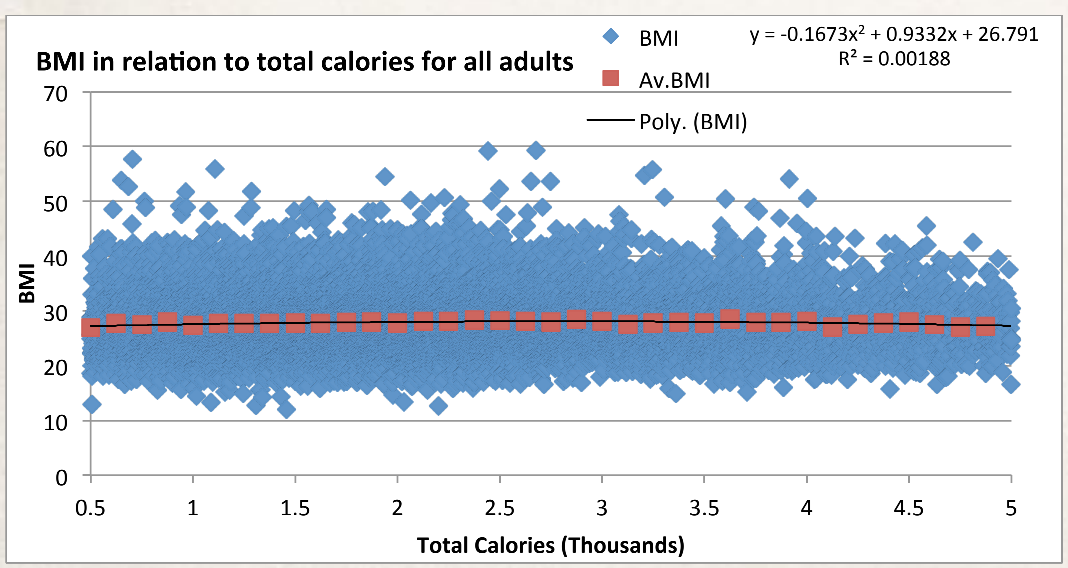

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Moving Av.					29.236	0.343	0		
BMI Change	Constant	-1.954	0.362	-5.392			0	-2.68	-1.228
ALL	Total_Cals	0.904	0.167	5.407			0	0.569	1.239
	Variable(s)	Unstd. B	Std. Error	t	f	R^2	Sig	Lower	Upper
Moving Av.					13.397	0.193	0.001		
BMI Change	Constant	-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

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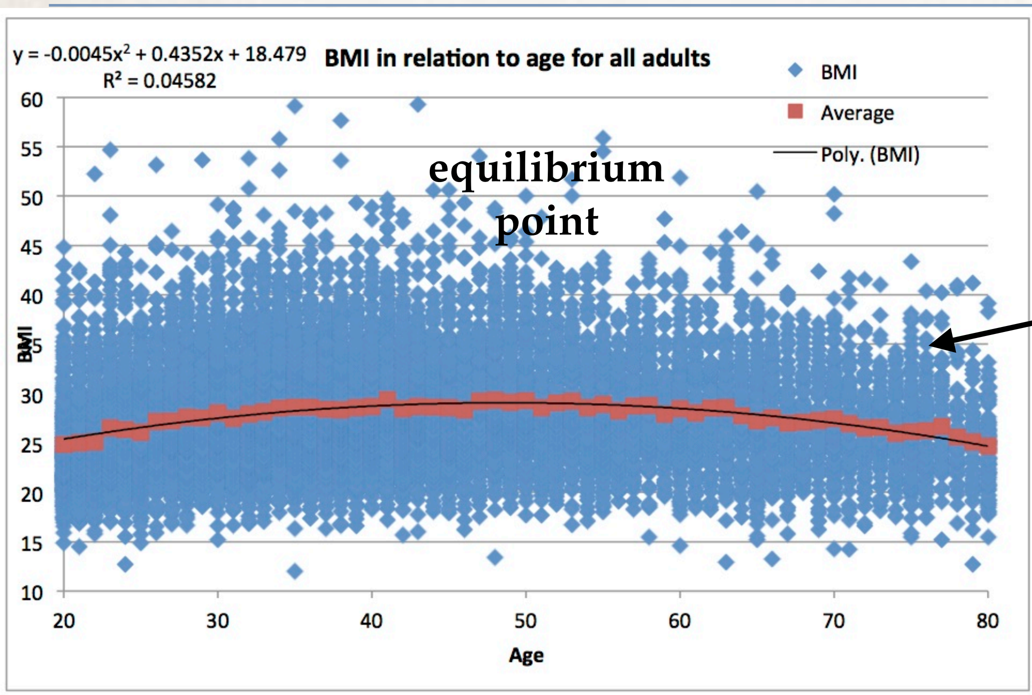

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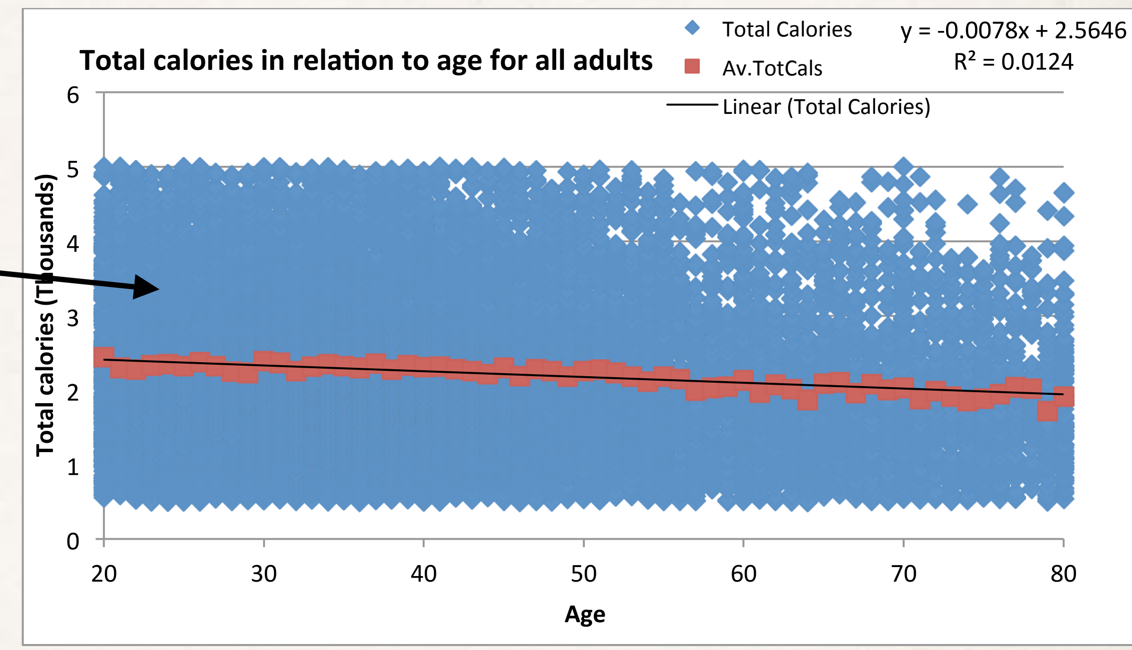

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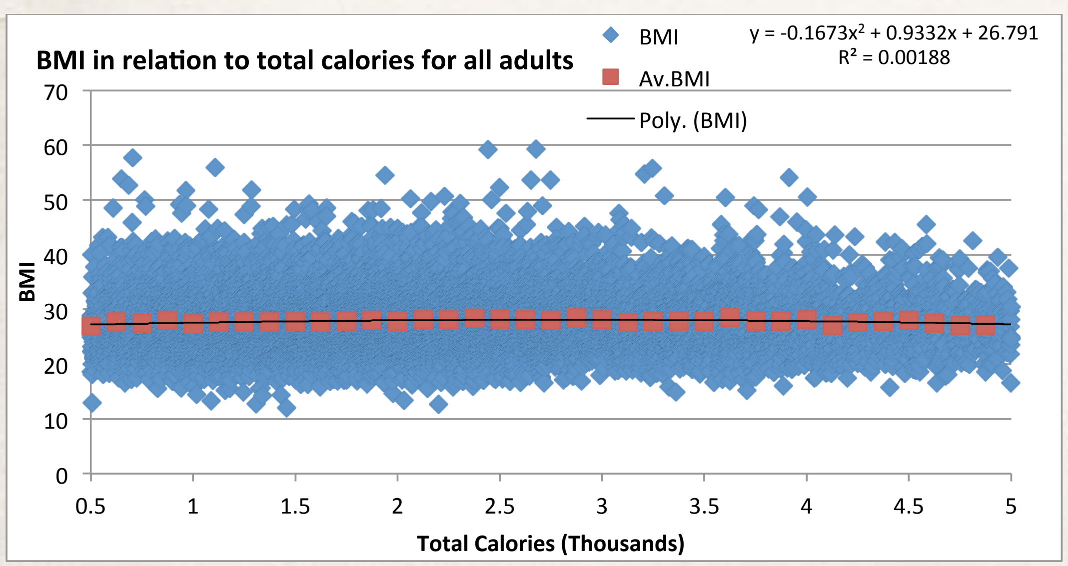

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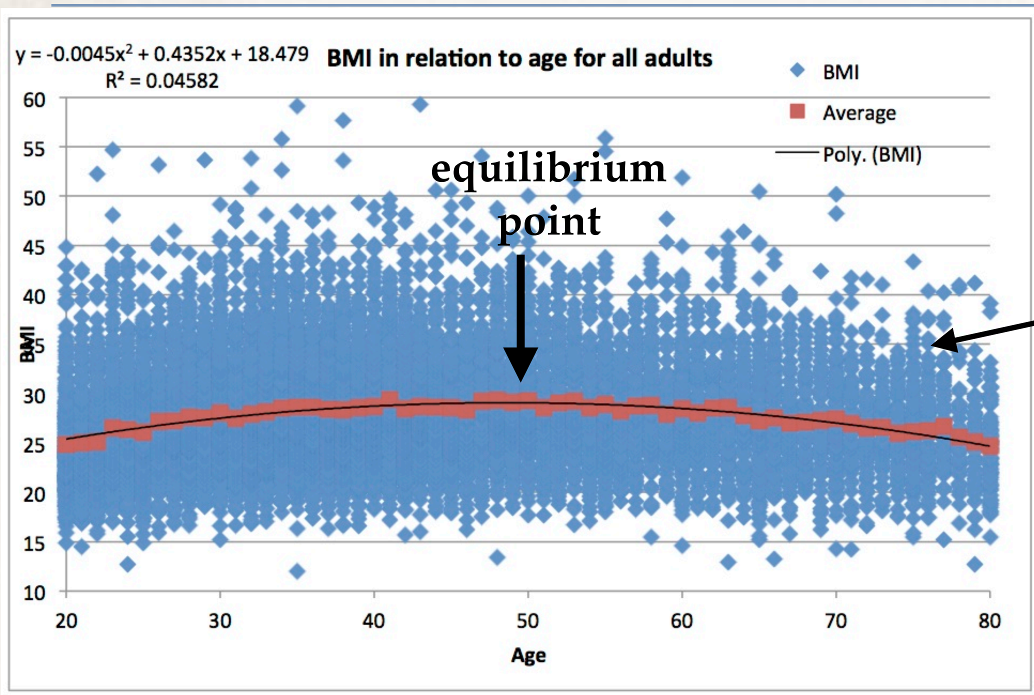

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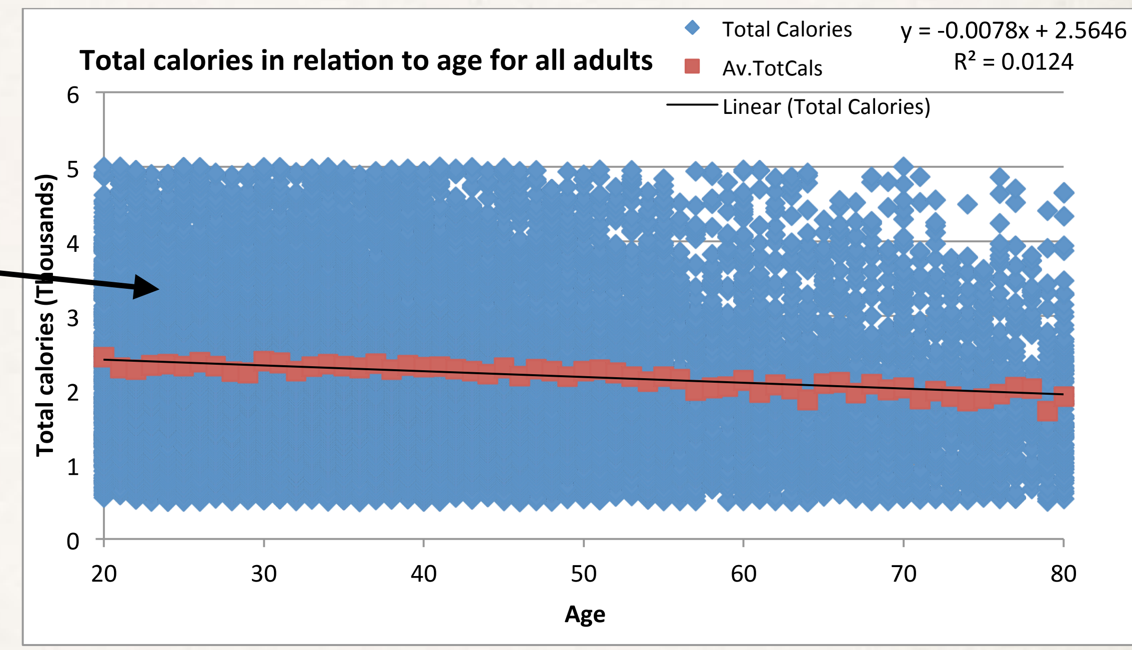

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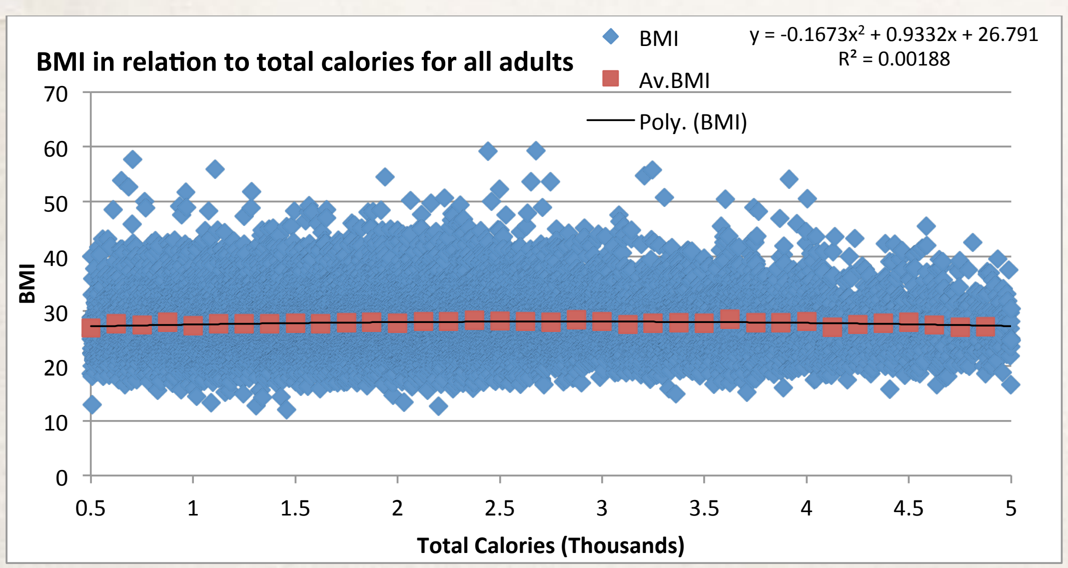

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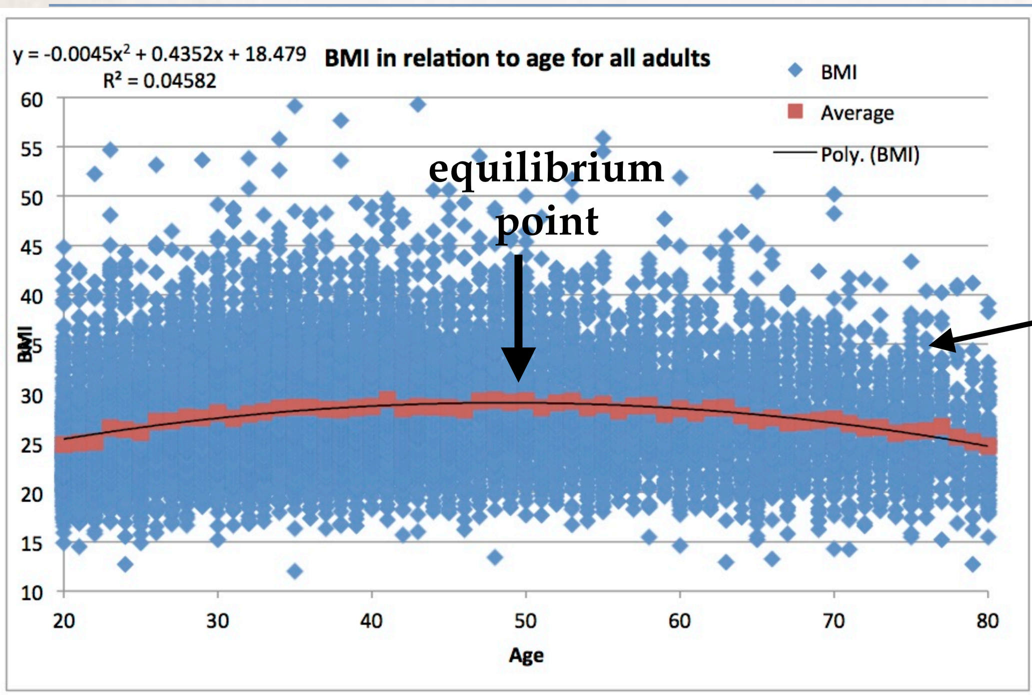

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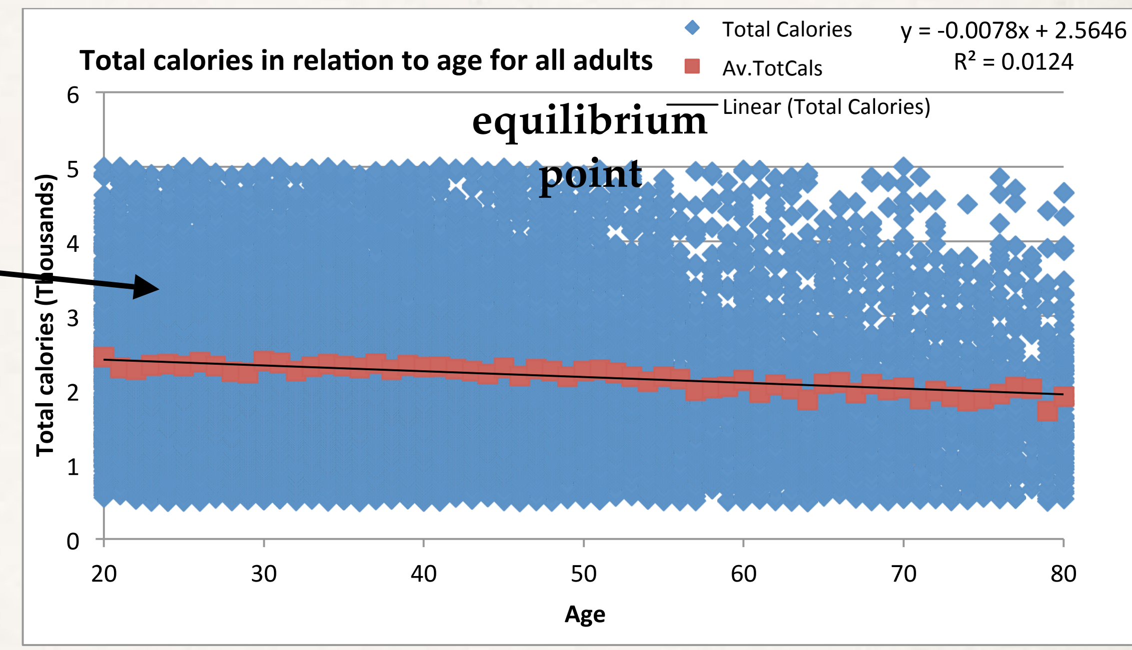

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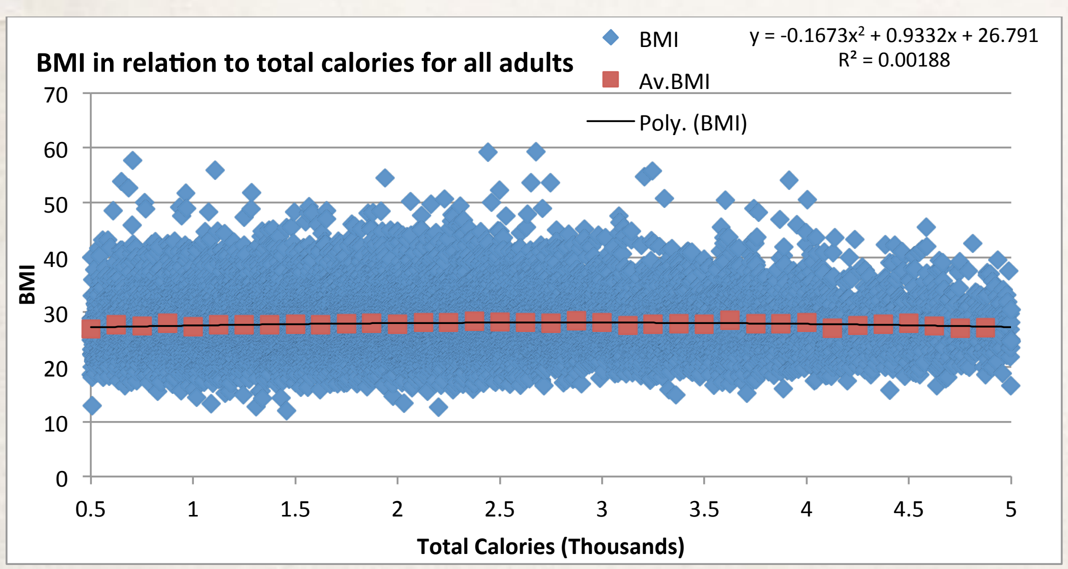

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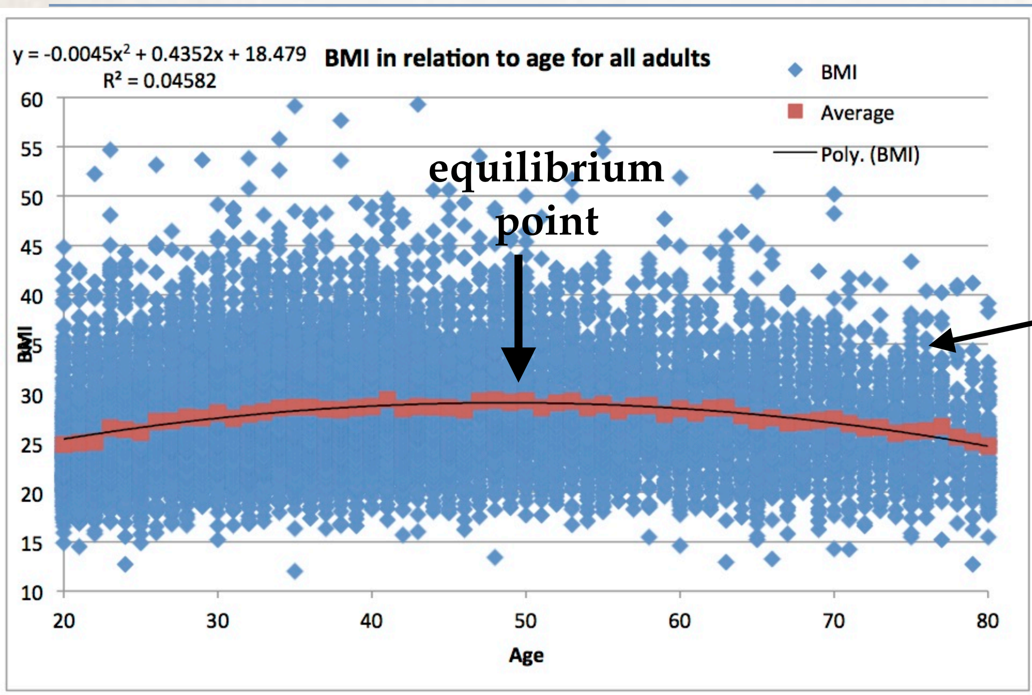

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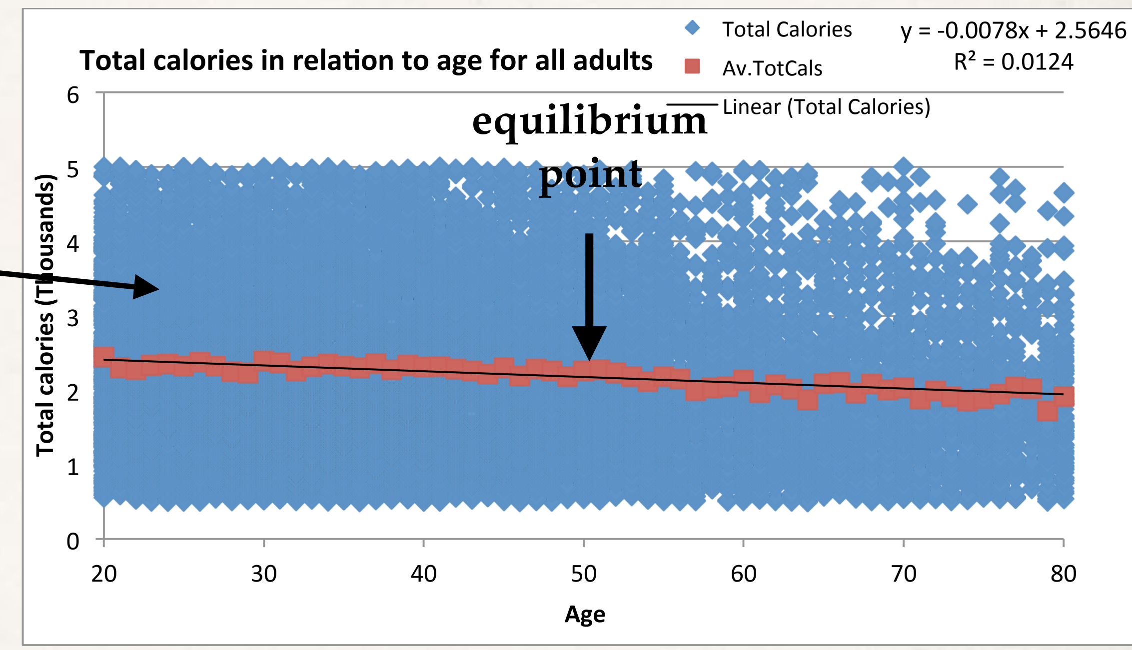

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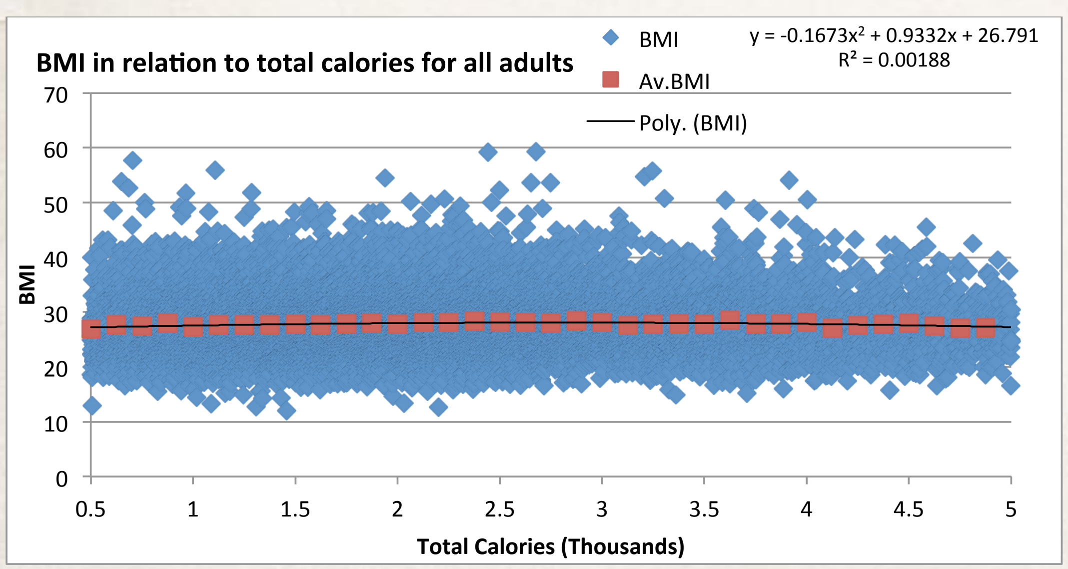

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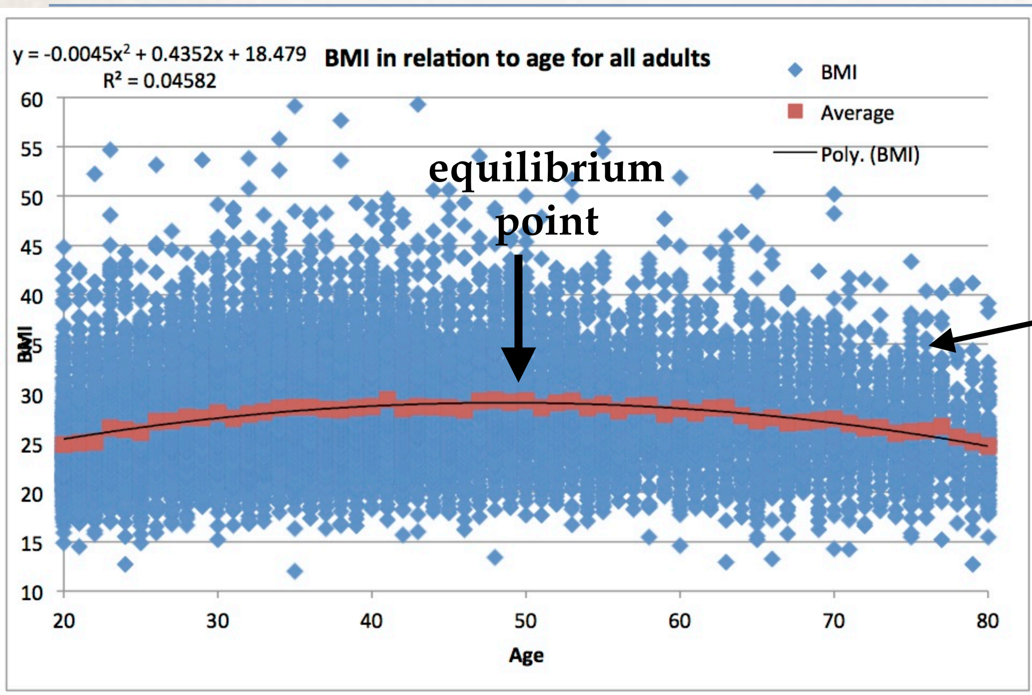
Women	Total_Cals	0.833	0.176	4.736			0	0.481	1.185

Obesity - risk factors
What you do

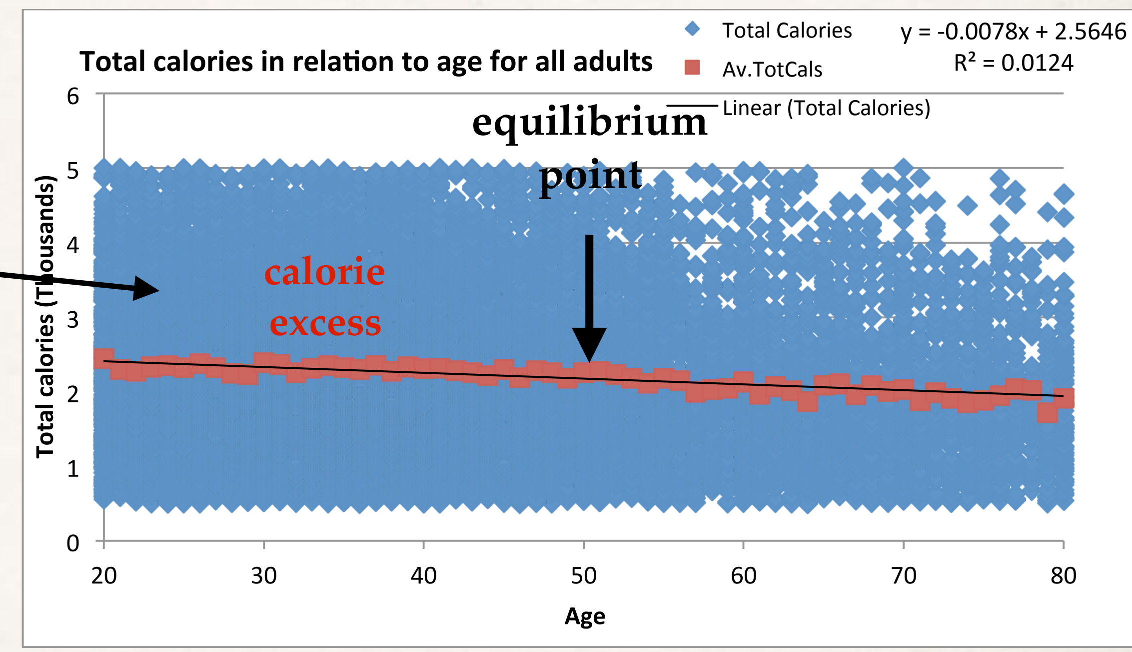
You aren’t what you eat you become what you eat

Epidemiological data from ENSANUT 2006

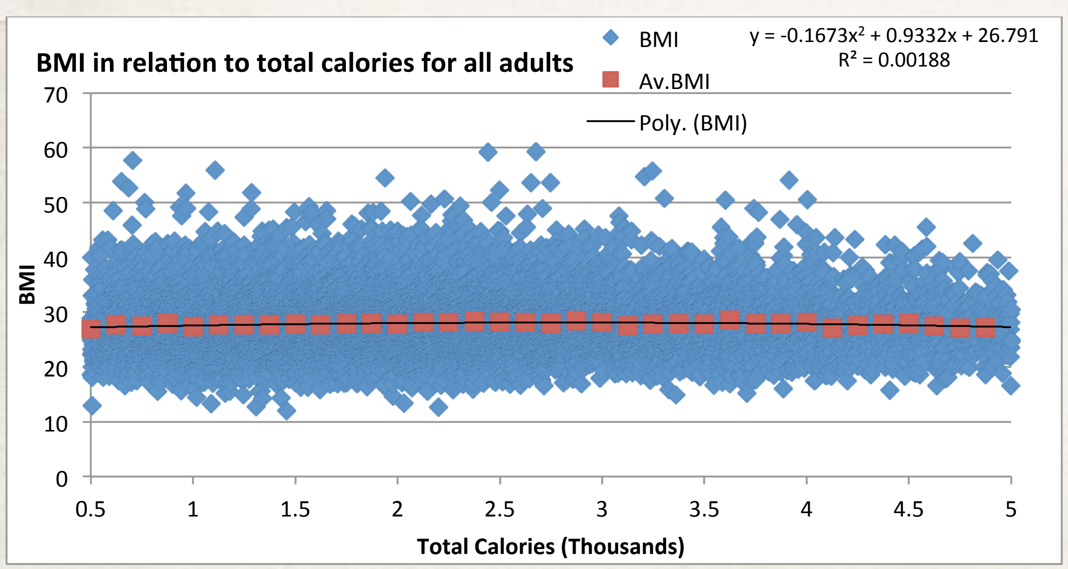


We get fatter then we get thinner

Its not “noise”its multifactoriality



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
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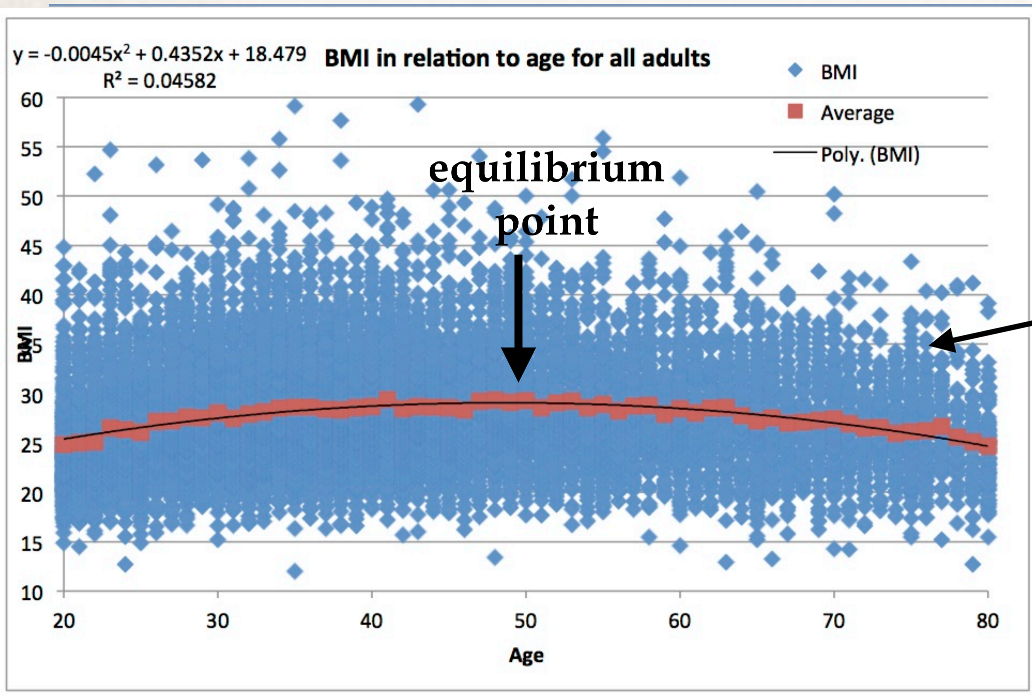
The obese eat as much as the thin

Obesity - risk factors
What you do

You aren’t what you eat you become what you eat

Epidemiological data from ENSANUT 2006



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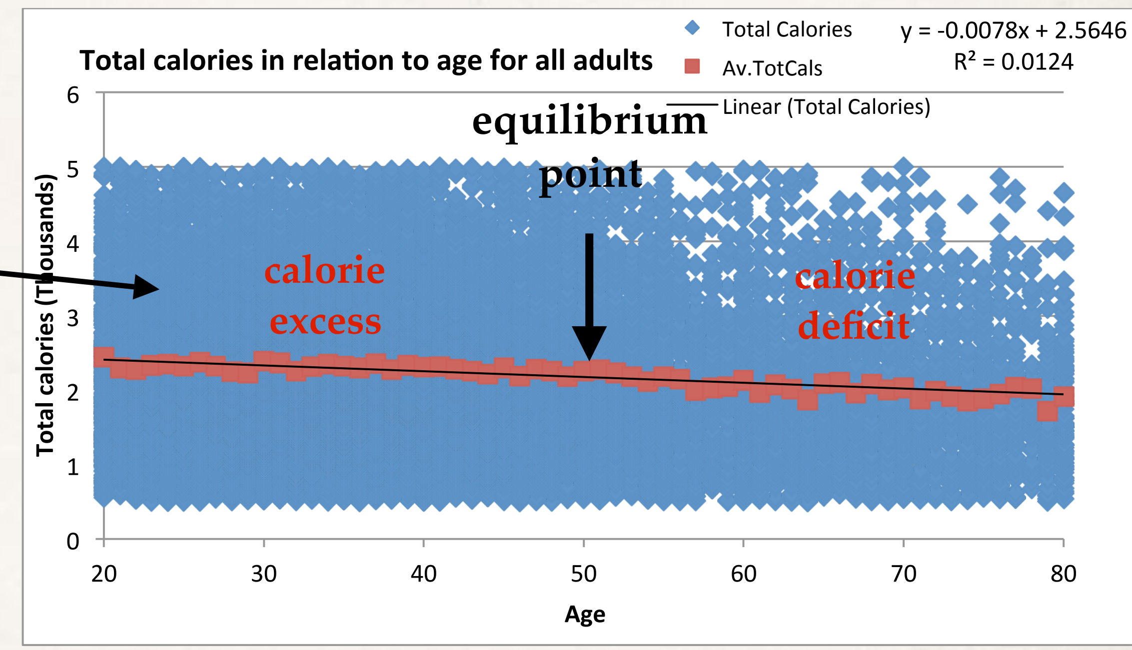

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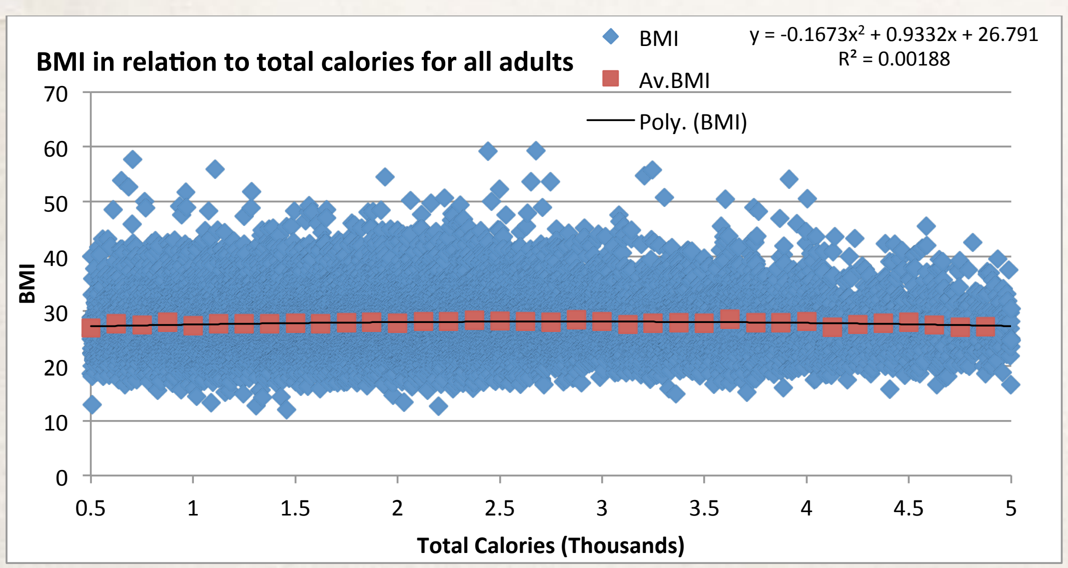

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Obesity - risk factors
What you do

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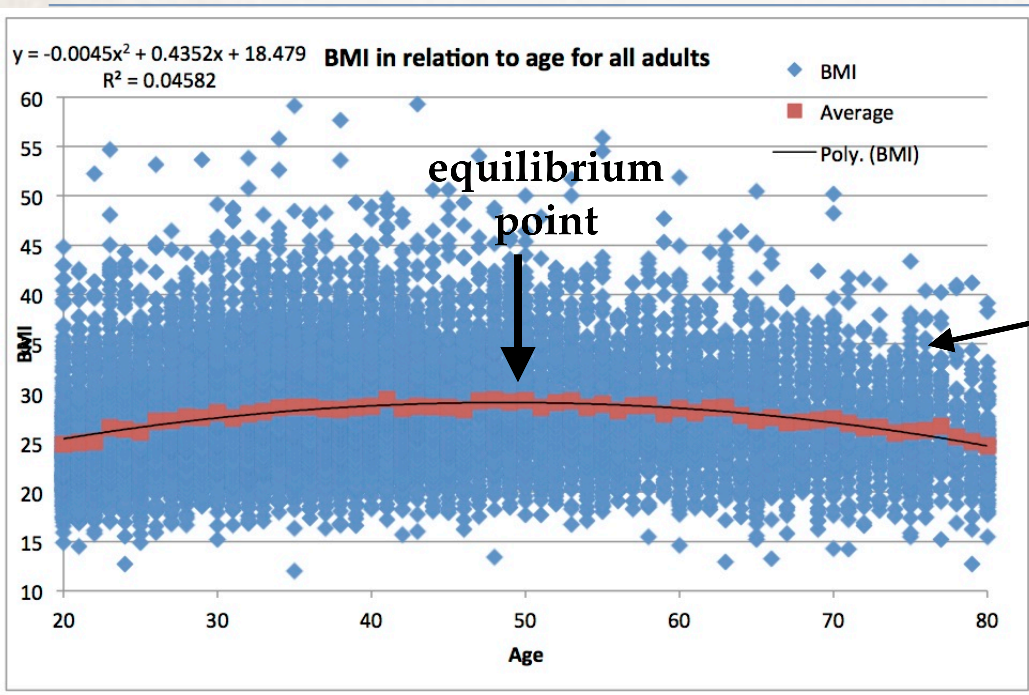
Epidemiological data from ENSANUT 2006



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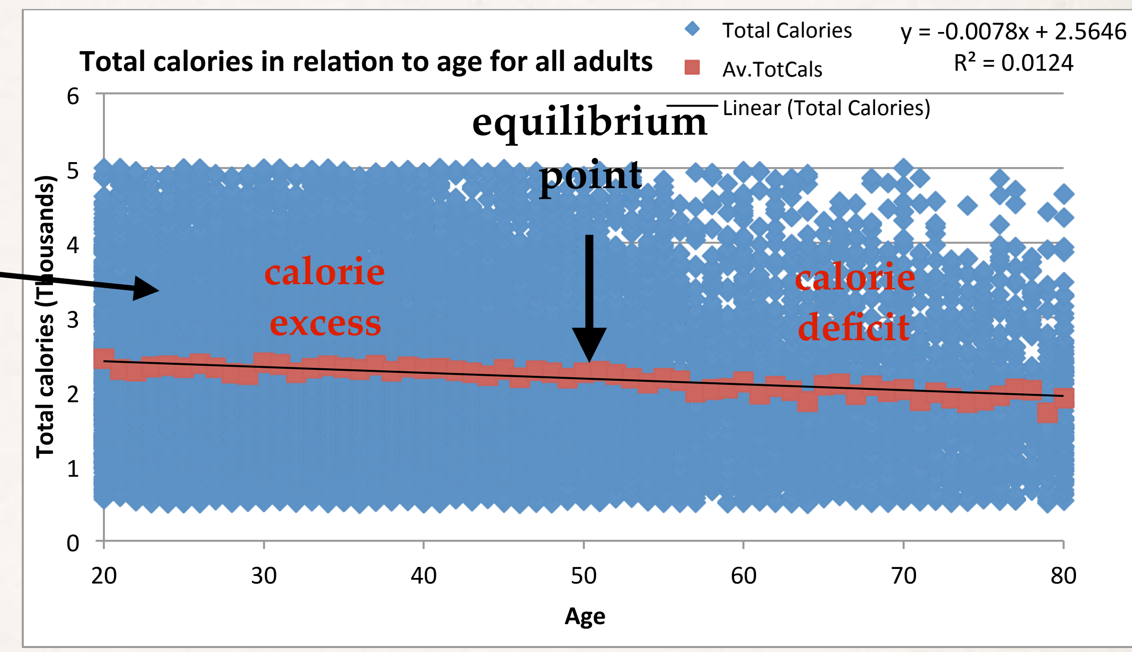
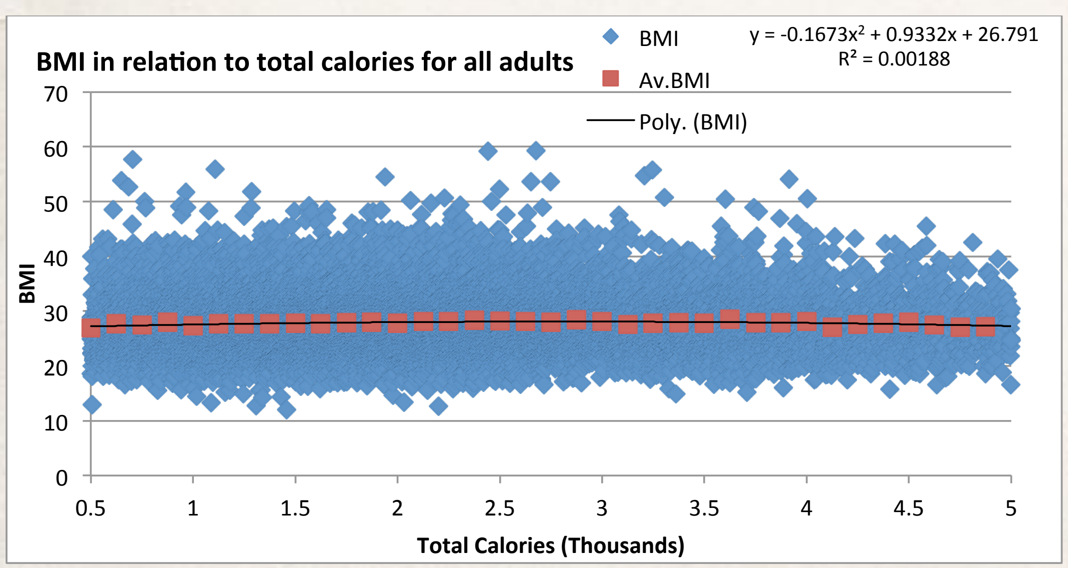


We eat less the older we get



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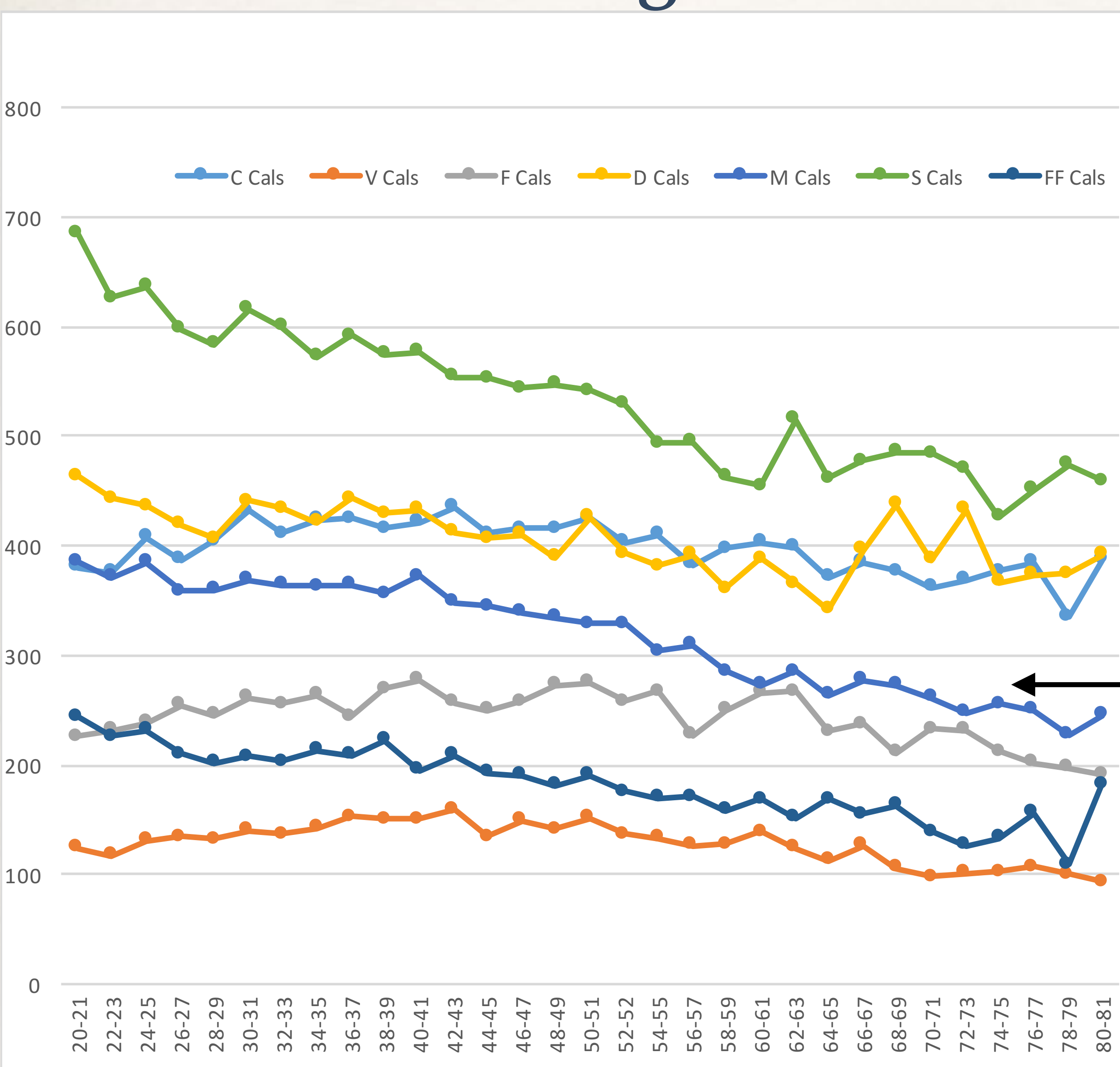
Its the excess of calories that is the motor for obesity. The motor is more active at 20 and stops at 50 and then goes in reverse.

Obesity - risk factors
What you do

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

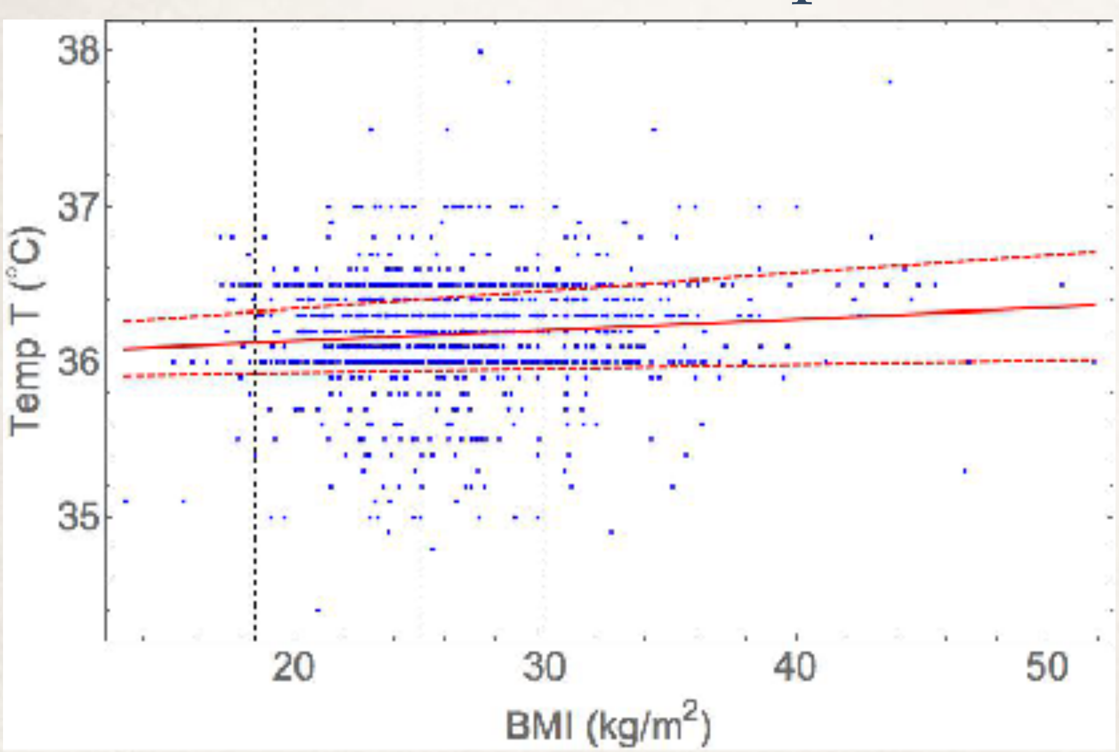
Do you become what you eat?

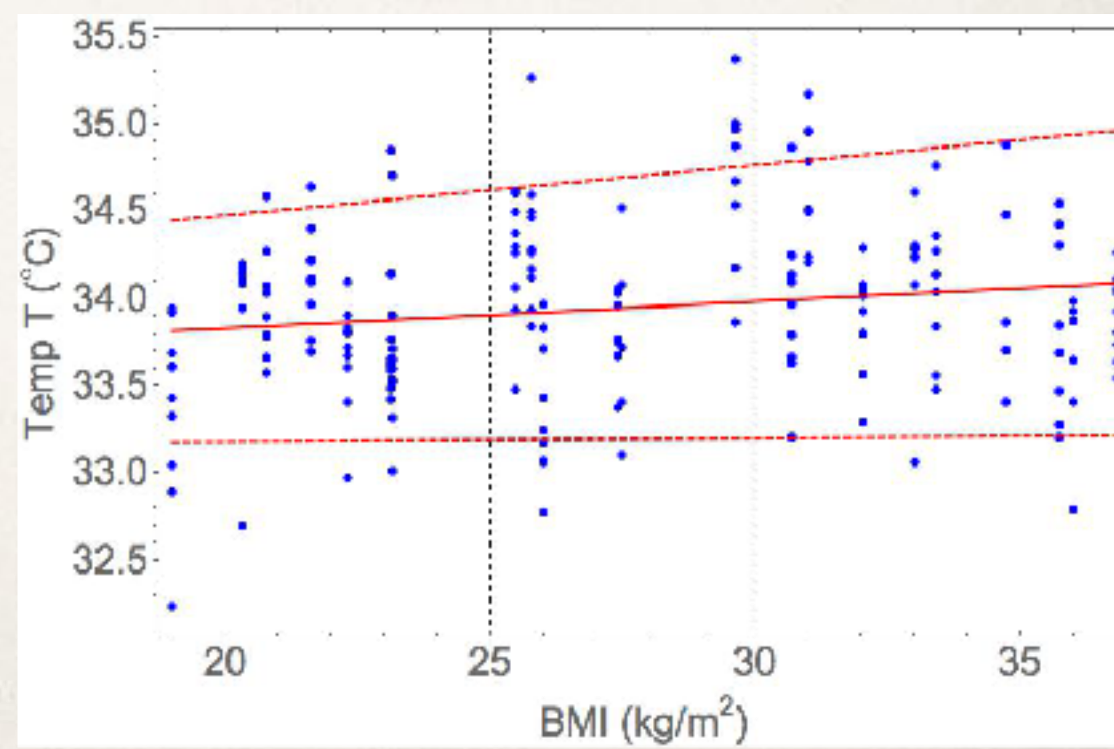
The data shows an overconsumption of 200-300 Cals/day at age 20-30. 8 Cal/day is enough (naively through the famous/infamous 3500 cal rule) to generate the observed increase in BMI. **Where do the other calories go?**

Why aren't we even fatter?

	Study 1		Study 2	
	points	deciles	7-day mean	1-day mean
slope	0.0072	0.0067	0.0093	0.015
intercept	35.99	36.00	33.69	33.524
CIslope	0.0028	0.0024	-0.019	0.0019
	0.012	0.011	0.038	0.029
CIintercept	35.88	35.89	32.88	33.15
	36.11	36.12	34.51	33.90
tslope	3.18	3.56	0.68	2.25
tintercept	590.34	708.93	86.9	174.92
F	10.15	12.64	0.46	5.06
p	0.0015 (*)	0.0074 (*)	0.50	0.026 (*)
R2	0.0094	0.61	0.022	0.027

Relation between temperature and BMI

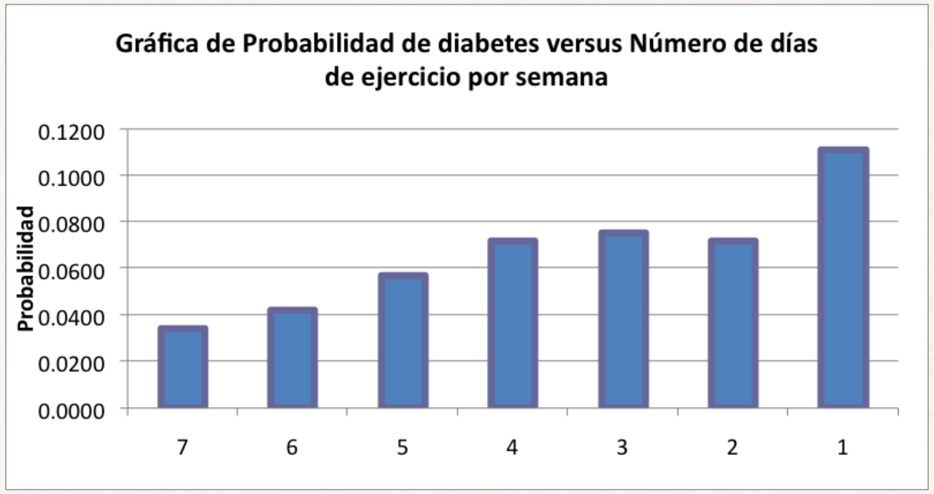


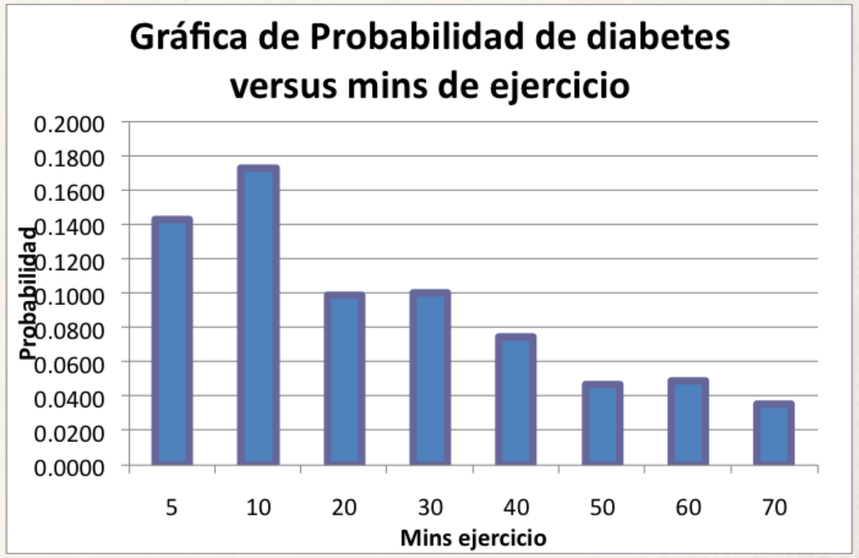


R. Fossion
DH17

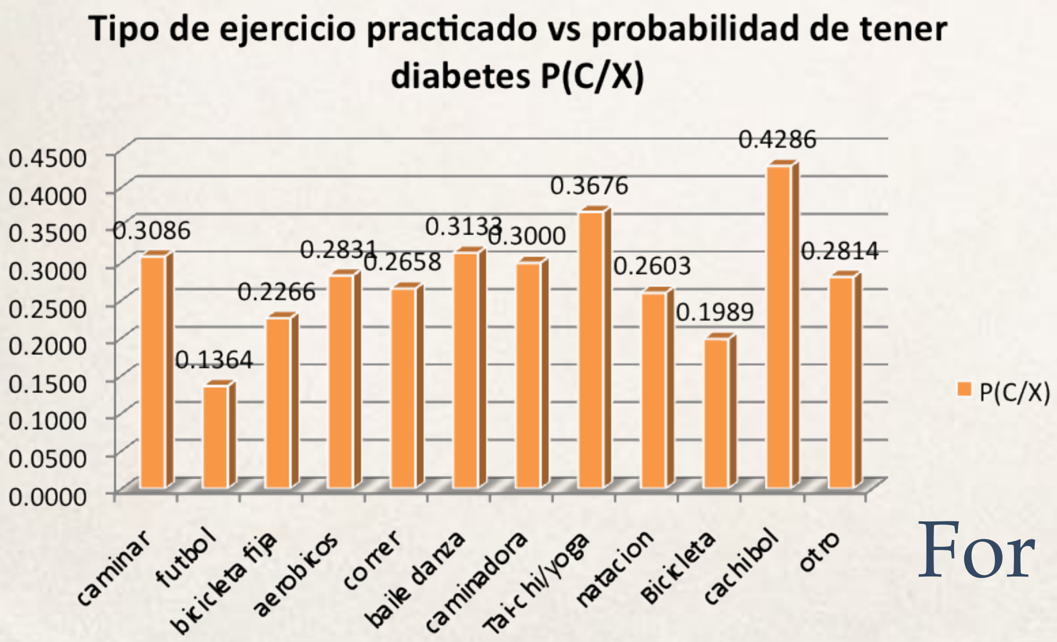
Chronic disease - Risk factors

What you do Exercise

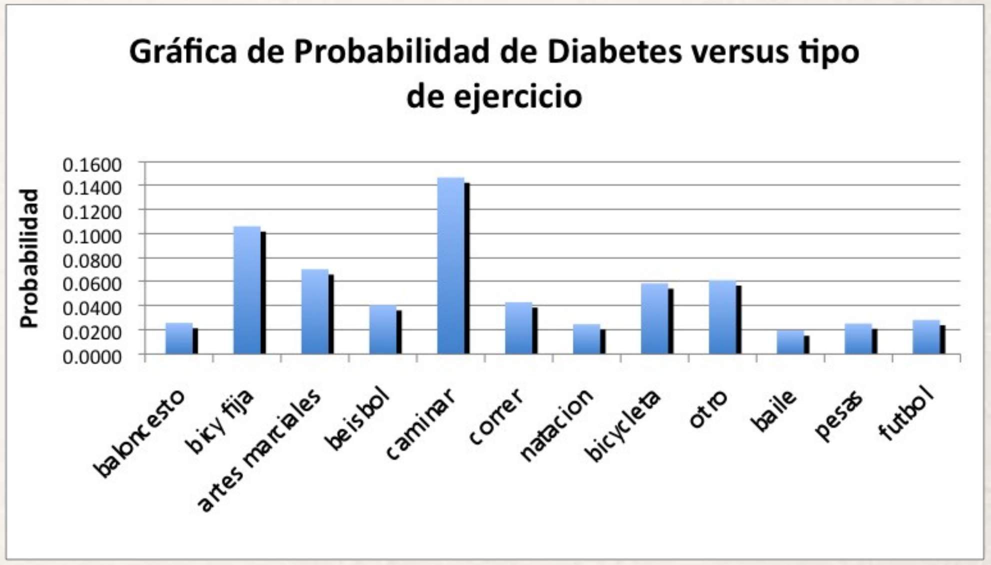




For men 20-59 de PREVENIMSS 2006



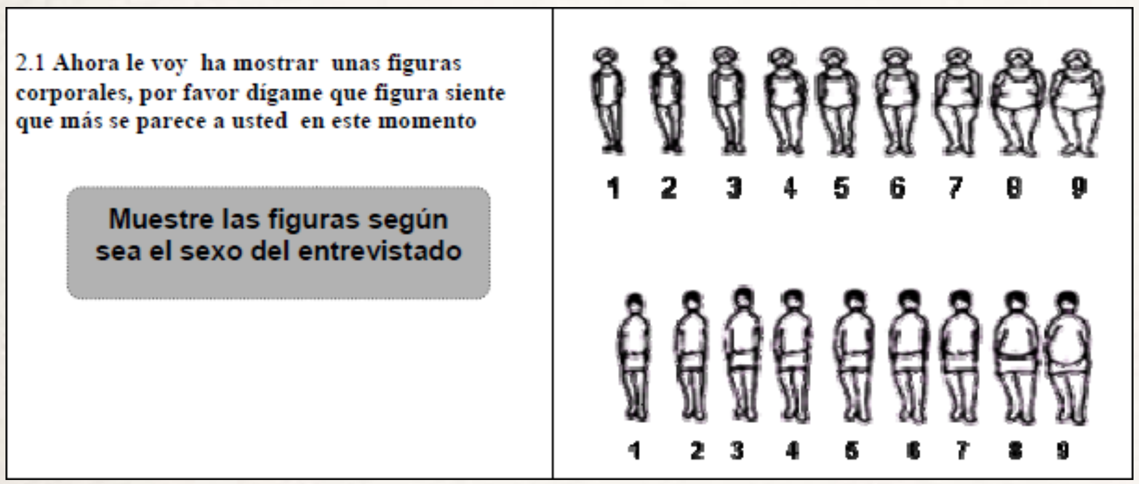
For seniors > 59

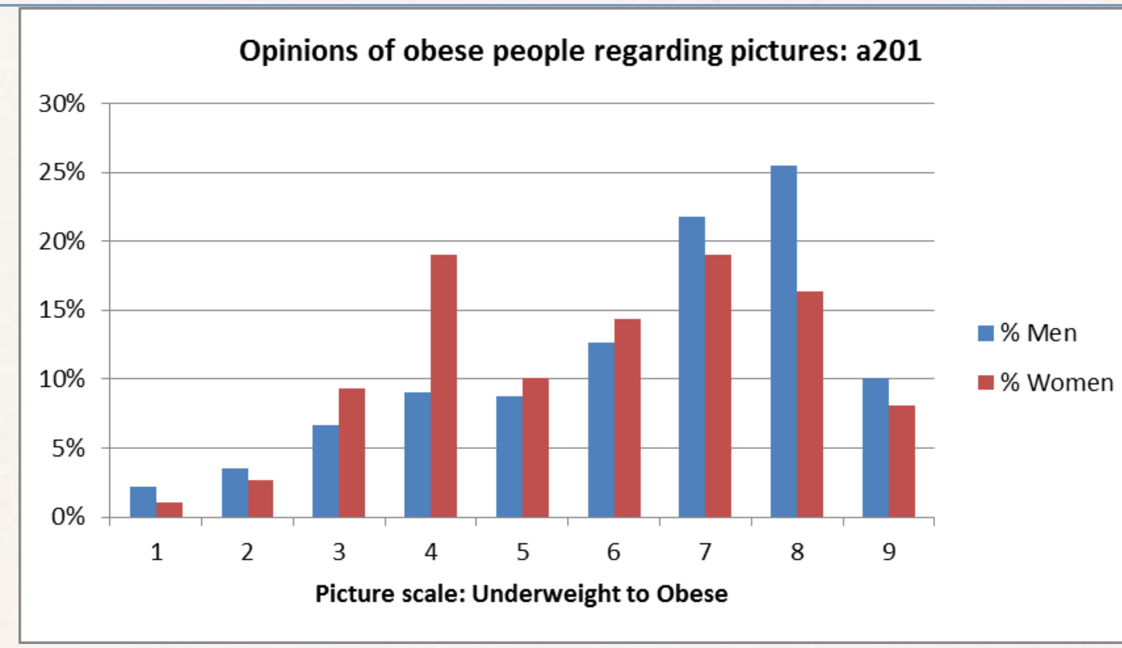


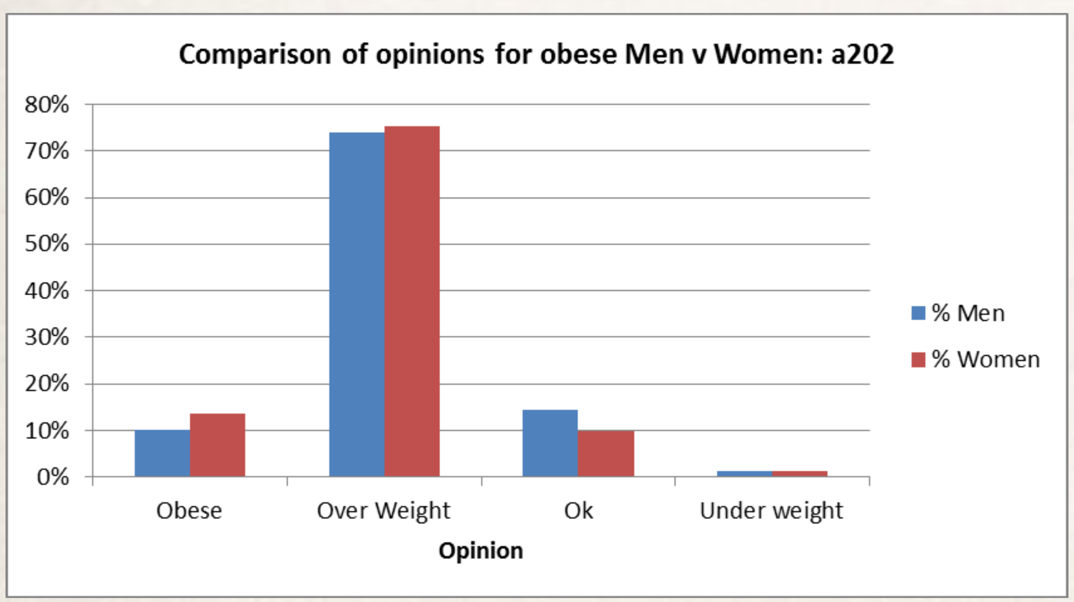
Is it riskier to walk than do nothing?

Obesity- risk factors
What you think/feel
Obesity is unrecognised by the sufferer in spite of the symptoms

Epidemiological data from ENSANUT 2006







People think they're less overweight/obese than they are. Symptom severity is under-estimated.

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

J. Easton, H. Sicilia - BMC, Frontiers in Public Health

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

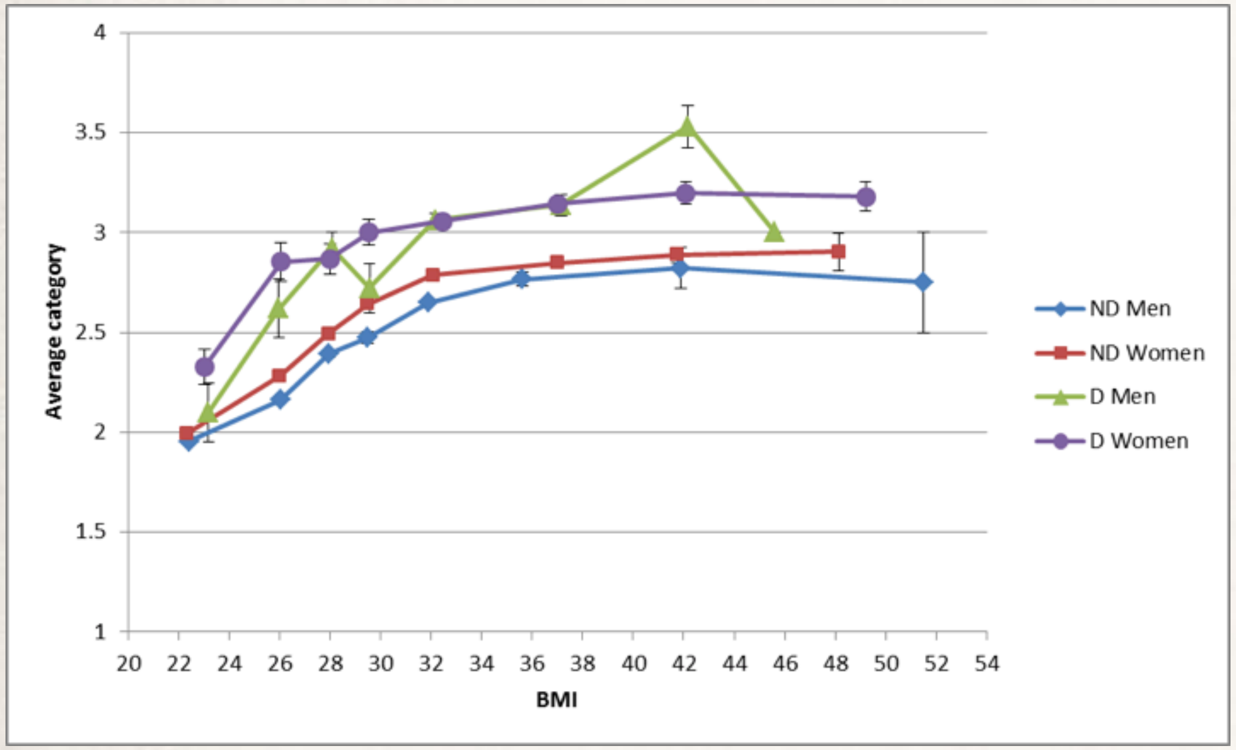


Figure 2. Comparison of non-diagnosed (ND) versus diagnosed (D) obese mean responses for the category self-perception question by gender.

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

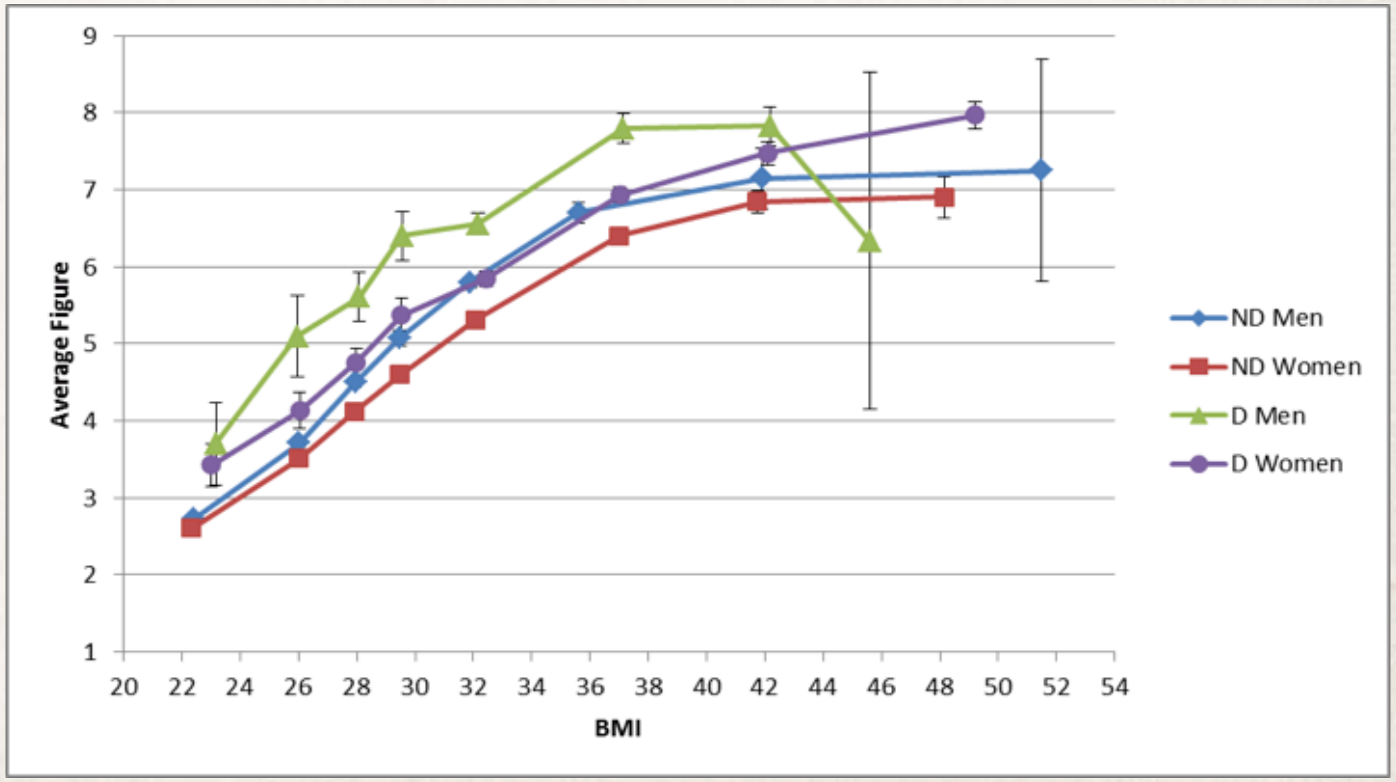


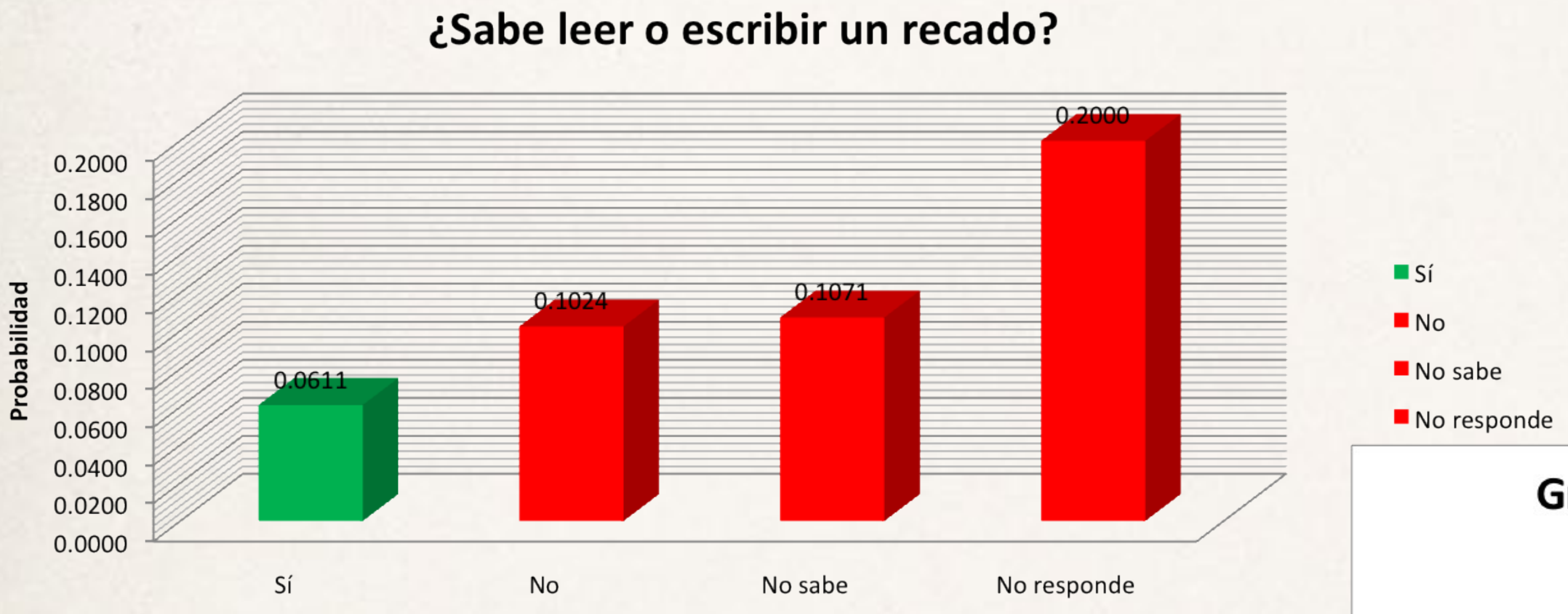
Figure 3. Comparison of non-diagnosed (ND) versus diagnosed (D) obese mean responses for the Stunkard figure rating scale question by gender.

Self-serving bias
Anchoring bias

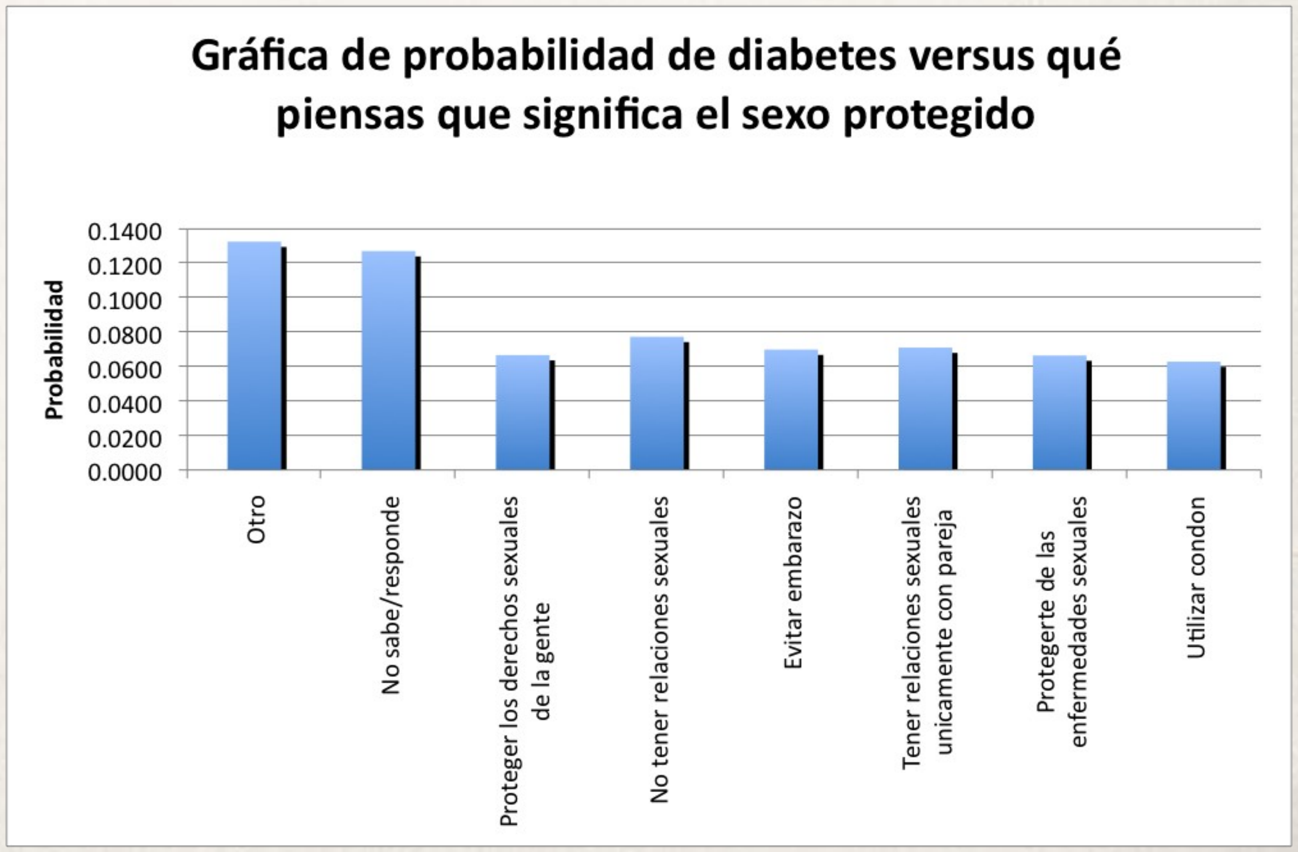
Chronic disease - risk factors

What you think (know): Ignorance can kill

Epidemiological data from ENCOPREVENIMSS 2006



For men 20-59 from PREVENIMSS 2006



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

Obesity -risk factors
Who you are

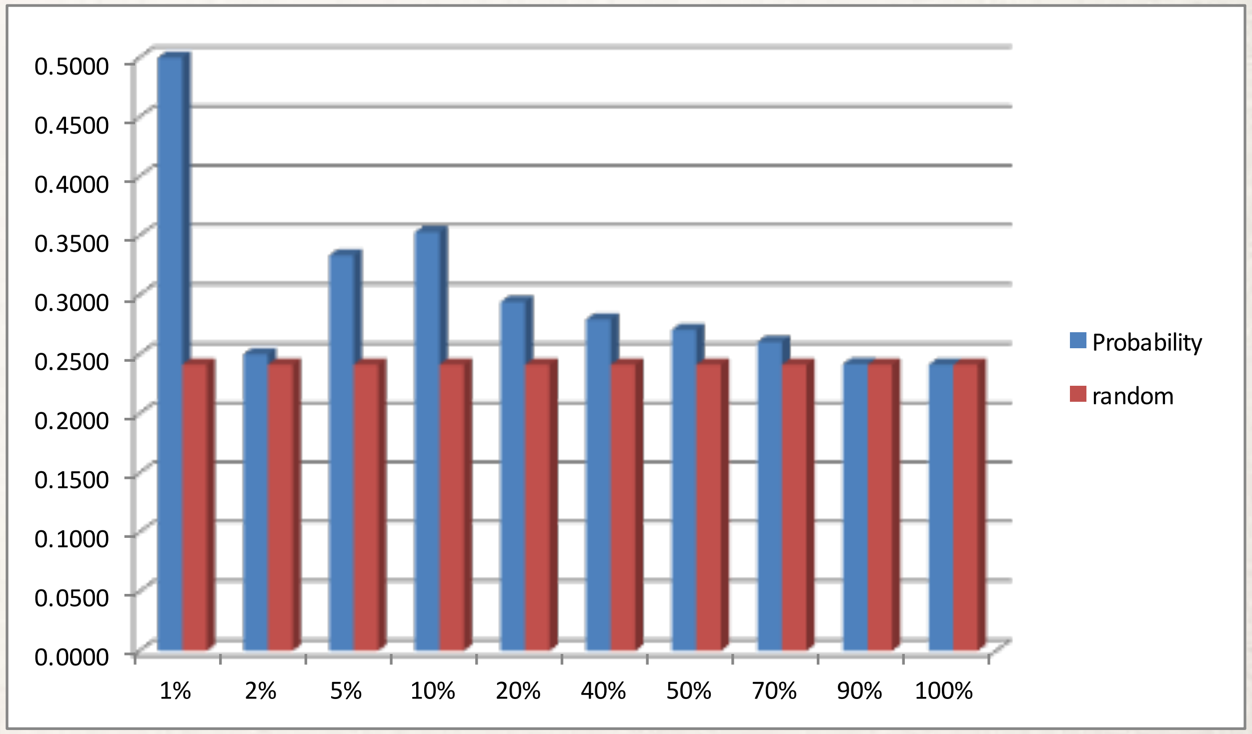
772 SNPs considered
Subsets with obesity, DM2, lipids, hepatic

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

UNAM Study 2014: Genetic analysis

obesity (score = 0.904, predictive but scarce)

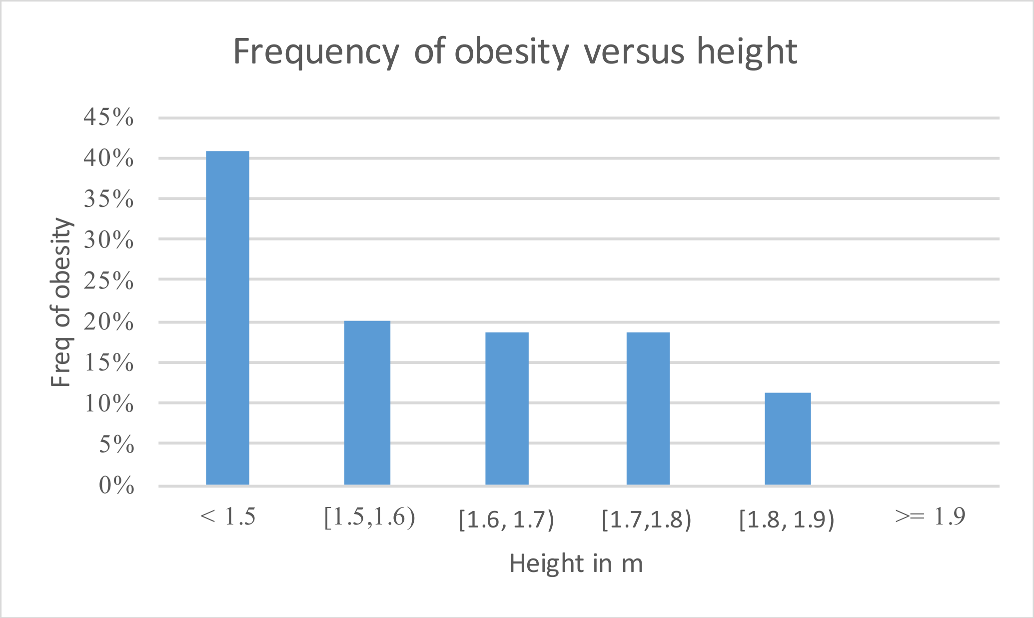
obesity (score = 0.105, not so predictive but common)

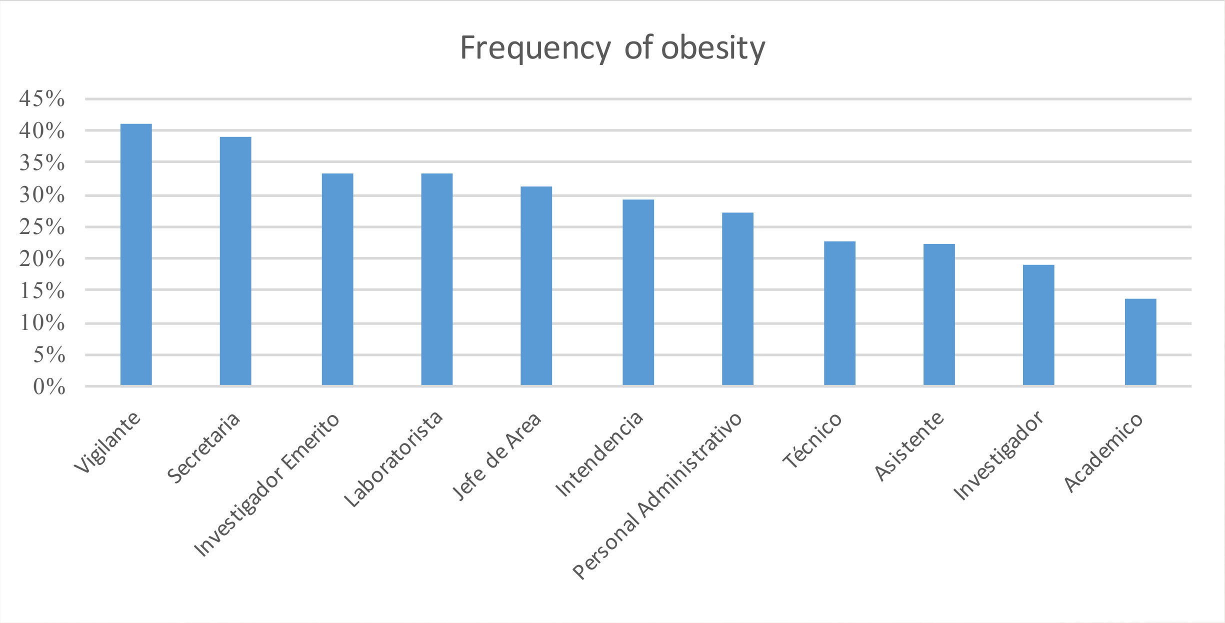


Doesn’t give a good model on its own

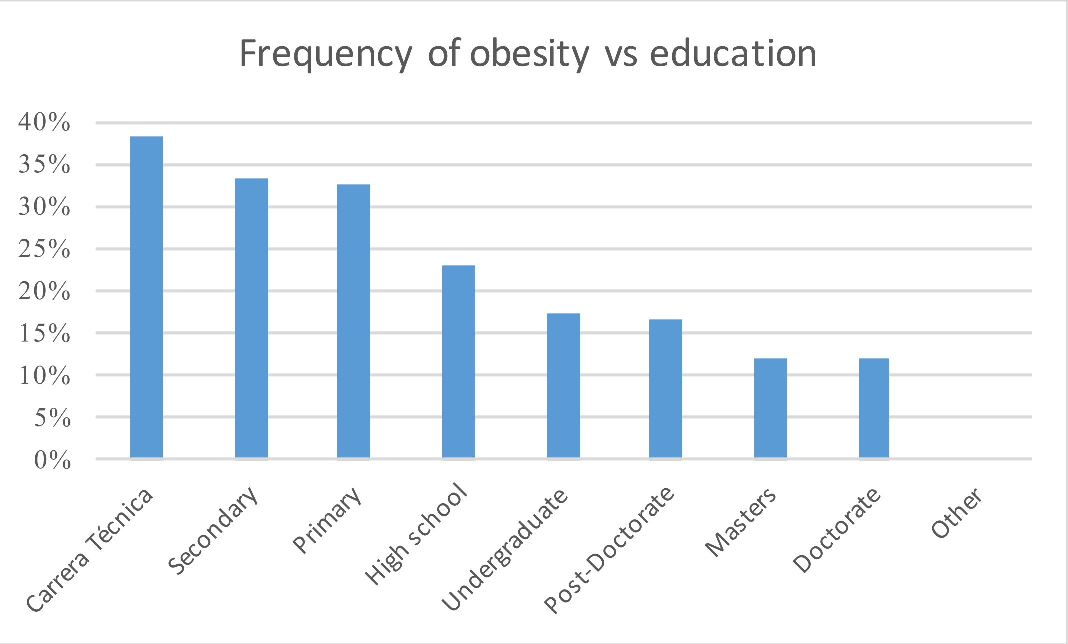
Obesity -risk factors

Who you are, what you think, what you do





Why are short people so prone to obesity?
Unit bias?*



The crucial role played by "education"
But what does it really mean?

* Katherine Stephens

Chronic diseases

To understand the physiology and genetics of such diseases is important. However, these diseases are predominantly “behavioural” diseases, associated with “bad” decisions.
Why do we make “bad” decisions? What behaviour is plastic?

Establishing and untangling causal chains is very difficult. Causality must be respected…e.g.,
overeating —> overweight —> inflammation…
Not
inflammation —> overeating…

The Challenges of Modelling Human Health

Human health, and any disease, is a CAS. To model such systems is on the very forefront of science. We don't do it well.

- CAS are extraordinarily multifactorial, requiring big data across multiple scales: genetics, epigenetics, physiology, psychology, neuroscience, epidemiology, sociology,… We don't have it.
- CAS require appropriate frameworks for generating data and sharing data. We don't have them.
- CAS require interdisciplinary teams to analyse and model the data. We don't have them.
- We need a more data science centered medicine and health science, requiring a shift in emphasis from curative medicine to preventative medicine

We have the technology to do the data "plumbing" but not the data semantics.
We have a lot of interesting work to do over the coming months, years, decades, …

You're all invited!

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

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