Conductome

Hybrid Intelligence and Complex Adaptive Systems: A Different Approach to Addressing the World's Principal Problems: Part II

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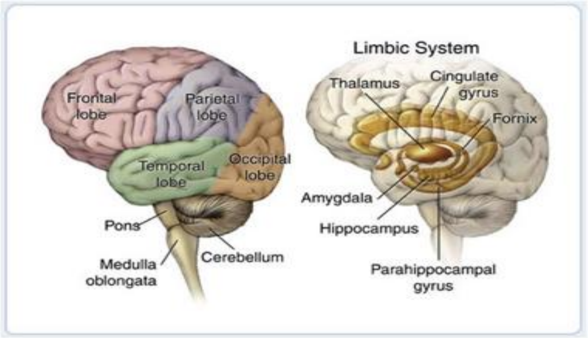
Seminar Centre for Complexity Science, Imperial College 25 February 2026

Bayesian Classifiers: A General Modelling Framework for Complex Adaptive Systems

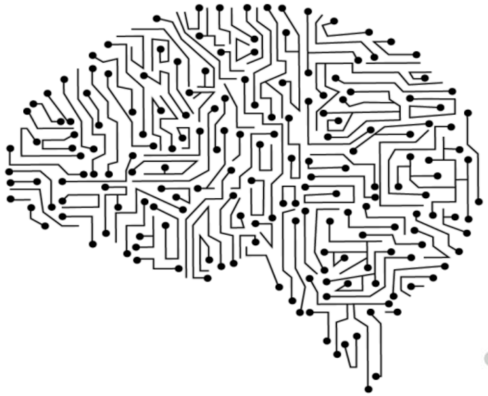


Human Intelligence:
Implicit algorithm - full of evolutionary and cultural biases

$$P(C\,|\,\mathbf{X}(t))$$

Who, What, Where, When,…

The "World"



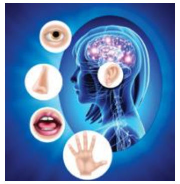
"AI" - Mathematical tools:
Explicit algorithm **-** from frequentist counts to Deep Learning

C and **X** can represent "states" and/or "rules/behaviours": obesity vs overeating; deforestation vs government subsidies; deaths from COVID19 vs labour mobility etc.

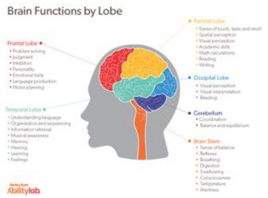
Adaptability and the Decision Cycle

Where? When? Who? What? How?

Our Goals and Objectives



VS



VS

For every decision/action there is a prediction!

How good are the predictions?

When does P(C|X) represent the complexity and adaptability of a CAS?

Two essential characteristics:

i) That **X** is of high dimension - representing the extreme multifactoriality/multicausality of CAS – this is equivalent to "complex"

ii) That C and/or (some) **X** represent rules/strategies/behaviours – this is equivalent to "adaptive"

Consider this “simple” dynamic model…

$$\mathbf{d}_i(t+\Delta t) = \sum_{j\neq i} \frac{\mathbf{c}_j(t) - \mathbf{c}_i(t)}{|(\mathbf{c}_j(t) - \mathbf{c}_i(t))|} + \sum_{j=1} \frac{\mathbf{v}_j(t)}{|\mathbf{v}_j(t)|}$$

Competition between an effective repulsion and attraction between “particles”

$$\hat{\mathbf{d}}_i(t+\Delta t) = \mathbf{d}_i(t+\Delta t)/|\mathbf{d}_i(t+\Delta t)|$$

$$\mathbf{d}_i{}'(t+\Delta t) = \frac{\hat{\mathbf{d}}_i(t+\Delta t) + \omega \mathbf{g}_i}{|\hat{\mathbf{d}}_i(t+\Delta t) + \omega \mathbf{g}_i|}$$

Equation for “charged” particles in an external field g_i

Couzin, I.D., Krause, J., Franks, N.R. & Levin, S.A. (2005) *Nature,* **433**, 513-516.

Does this represent a “complex”, “adaptive” system?

Why do fish form baitballs?

Fish form bait balls as a last-resort defensive mechanism when surrounded by predators like dolphins, sharks, or seabirds, typically in open water lacking structural cover. This phenomenon occurs when small, schooling fish (e.g., sardines, mackerel) are driven to the surface or trapped against barriers, forming dense, rotating spheres to confuse predators and protect individuals.

Key Conditions for Bait Ball Formation:

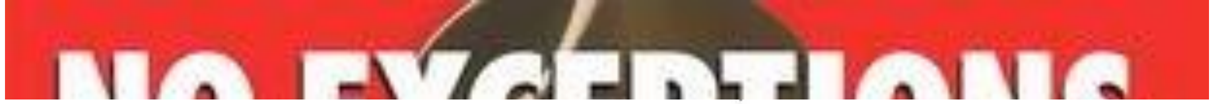
- **Intense Predation Pressure:** The primary driver is an active, coordinated attack by multiple predators from various angles (below, side, above).

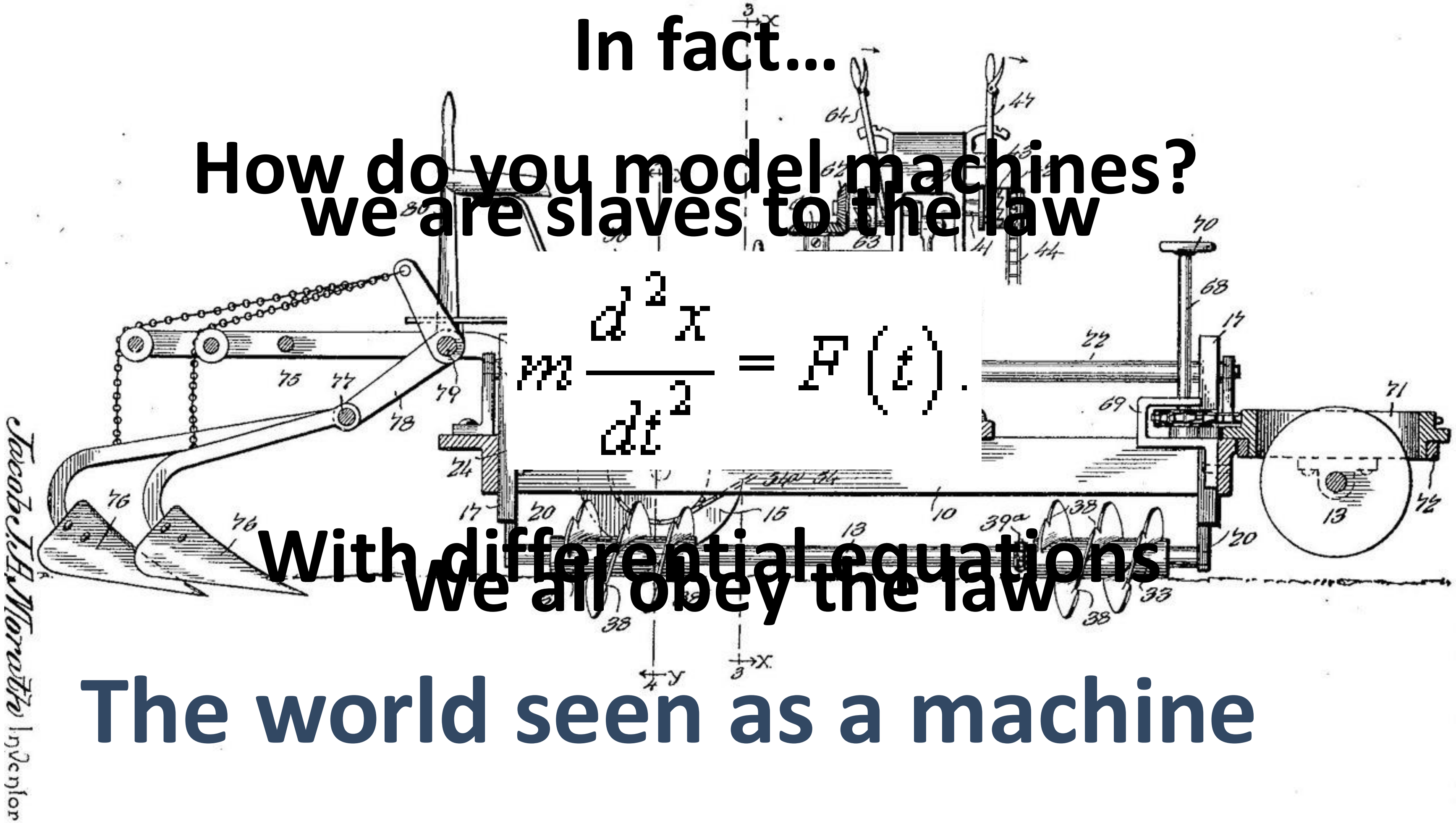
- **Lack of Shelter:** Open ocean environments where small fish cannot hide in rocks or reefs necessitate forming these defensive, tightly packed groups.

- **Physical Trapping:** Predators often drive fish to the surface, creating a "ceiling" that prevents escape, forcing them into a dense, panicked sphere.

- **Environmental Factors:** Calm, warm surface waters or low-oxygen, deep-water zones that restrict vertical movement can force fish to stay in a compact, shallow layer.

These high-energy, chaotic events are often temporary, rarely lasting more than 10 minutes.





In fact…

How do you model machines?

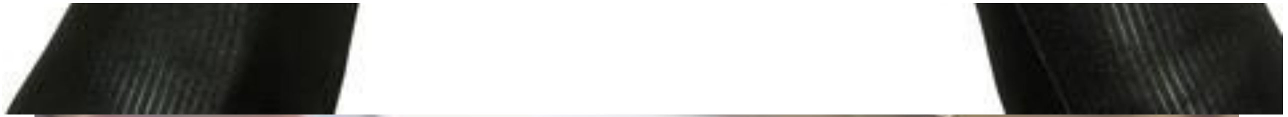
we are slaves to the law

$$m\frac{d^2x}{dt^2} = F(t).$$

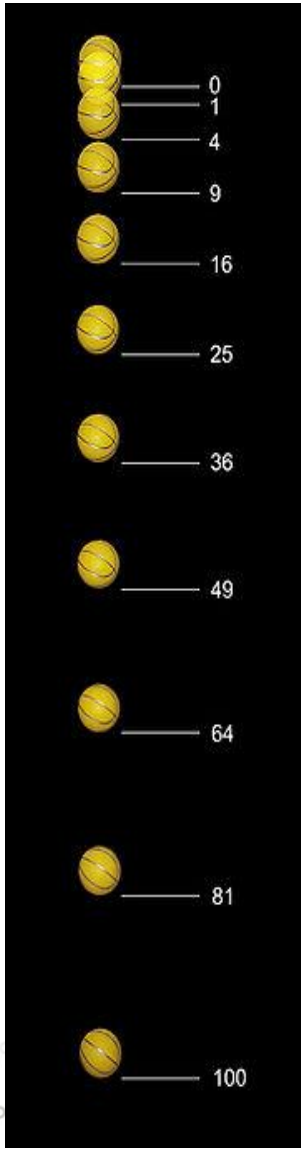
With differential equations

We all obey the law

The world seen as a machine



Mechanistic



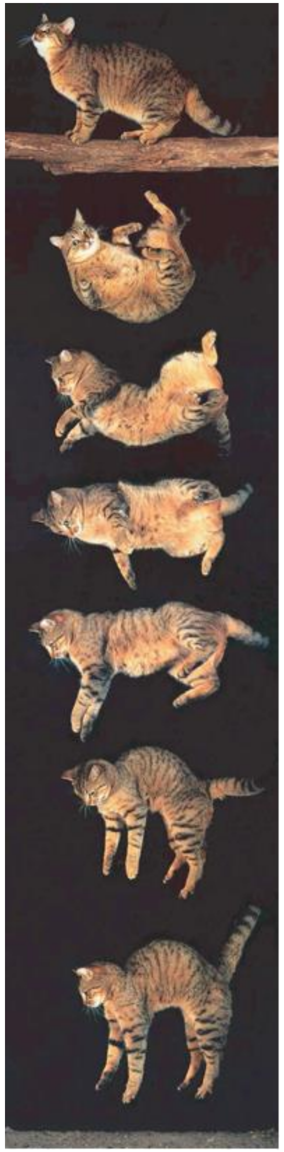
The cat obeys the same laws of physics as the ball

But its not a “slave” to them

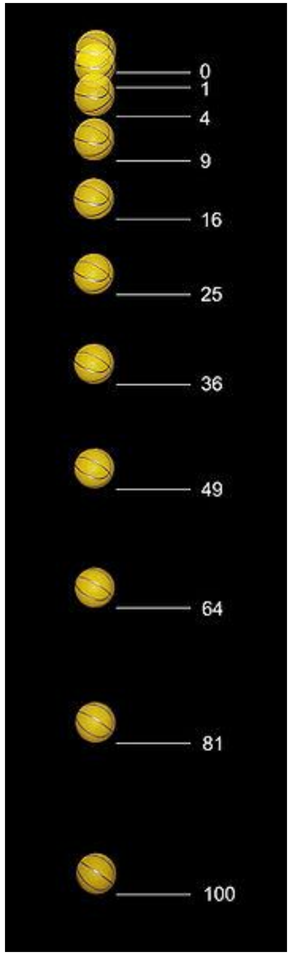
The difference between complex and simple systems is the difference between “being” and “doing”

The *evolution* of function is the revolution that allowed systems to escape the tyrrany of the laws of physics. Complexity is a consequence of that revolution.

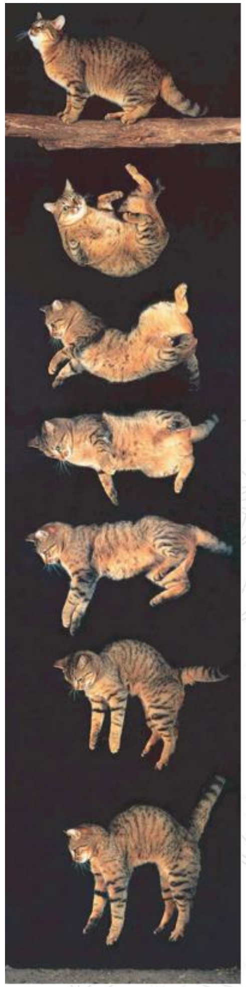
Adaptive



Mechanistic



Adaptive



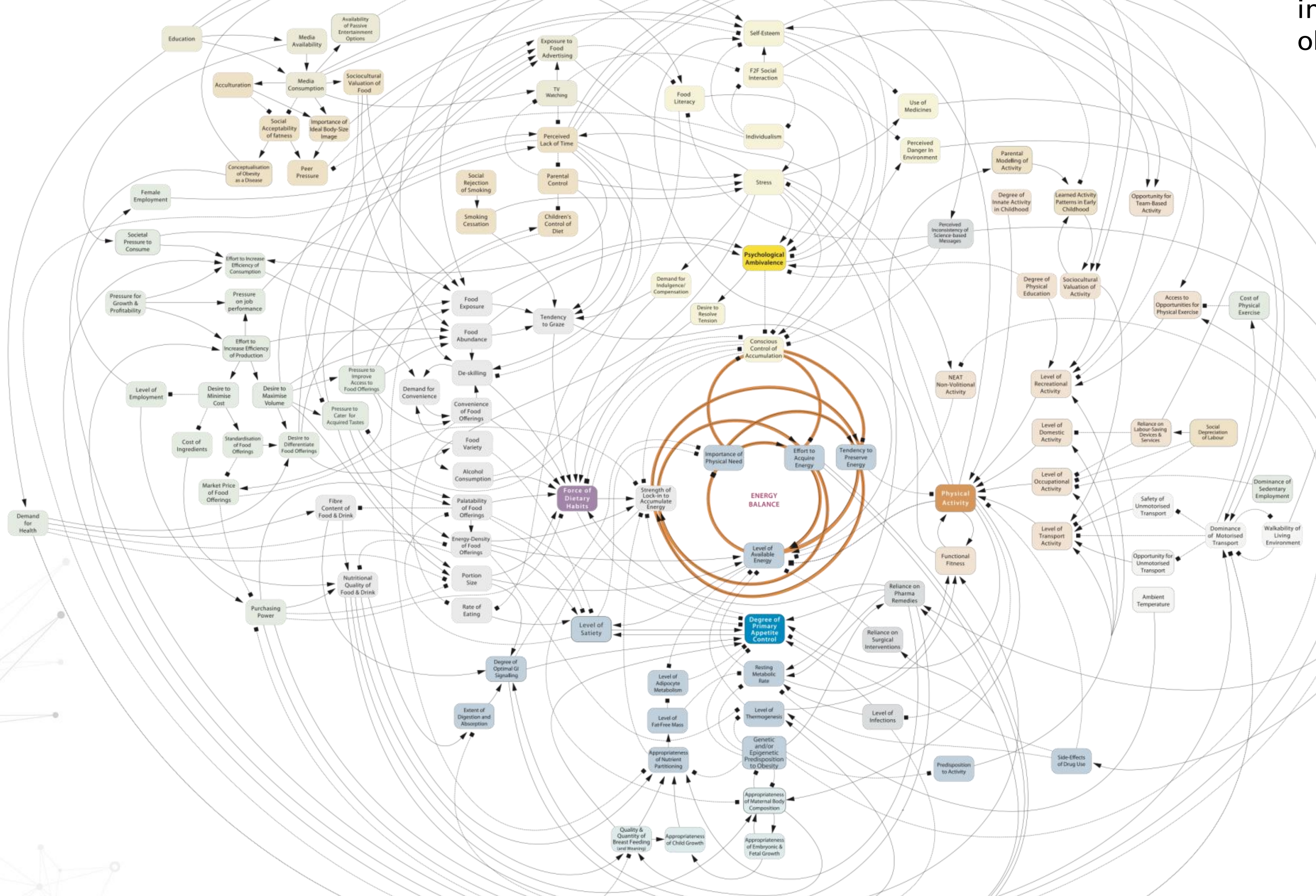
Both systems obey Newton's 2^{nd} Law. This is enough to describe the motion of their centers of gravity but doesn't tell us how or why the cat lands feet first.

In the first case Newton's laws explain the phenomenon but in the second case they become a restriction to be obeyed.

Dogs, cats and balls all have different rules when falling from a tree. For CAS we can call them **behaviours**

Foresight

Obesity System Map



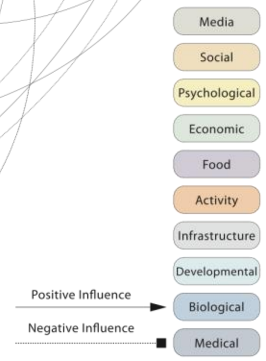
"The obesity system is therefore pragmatically defined here as the sum of all the relevant factors and their interdependencies that determine the condition of obesity for an individual or a group of people."

A causal loop model is a device to describe the systemic structure of a complex problem. As such, it serves three very general purposes:

• **to make sense of complexity.** Individuals who have been deeply involved in the construction or study of a causal loop model will appreciate its considerable heuristic power. In particular, once the top-level architecture of a model (rather than its fine detail) has been thoroughly absorbed, it becomes a powerful filter for identifying relevant variables and an aid to thinking about the issue.

• **to communicate complexity.** The anatomy of a system map – particularly with a fairly large number of variables and many causal linkages between them – is a clear confirmation of the inescapably systemic and messy nature of the issue under study. This approach highlights the need for broad and diversified policies or strategies to change the dynamics of the system.

• **to support the development of a strategy to intervene in a complex system.** Careful study of a causal loop model will reveal features that help in deciding where to intervene most effectively in the system. These features are: leverage points, feedback loops and causal cascades.



https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/296290/obesity-map-full-hi-res.pdf

https://assets.publishing.service.gov.uk/media/5a7b8811ed915d4147620fb2/07-1177-obesity-system-atlas.pdf

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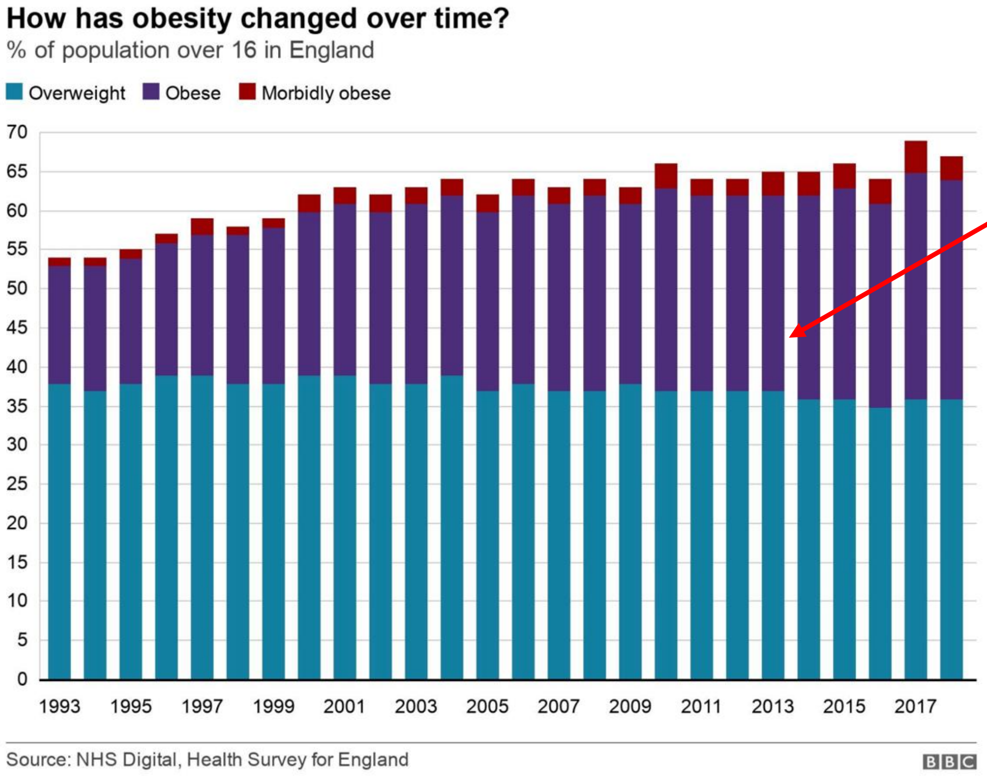
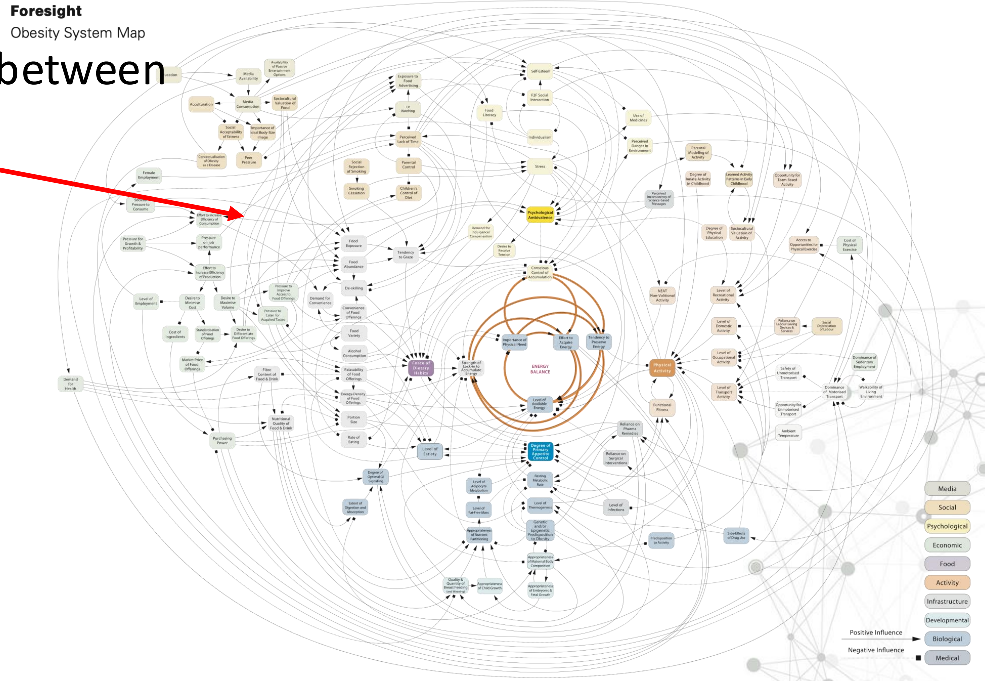


What is the relationship between this and this?

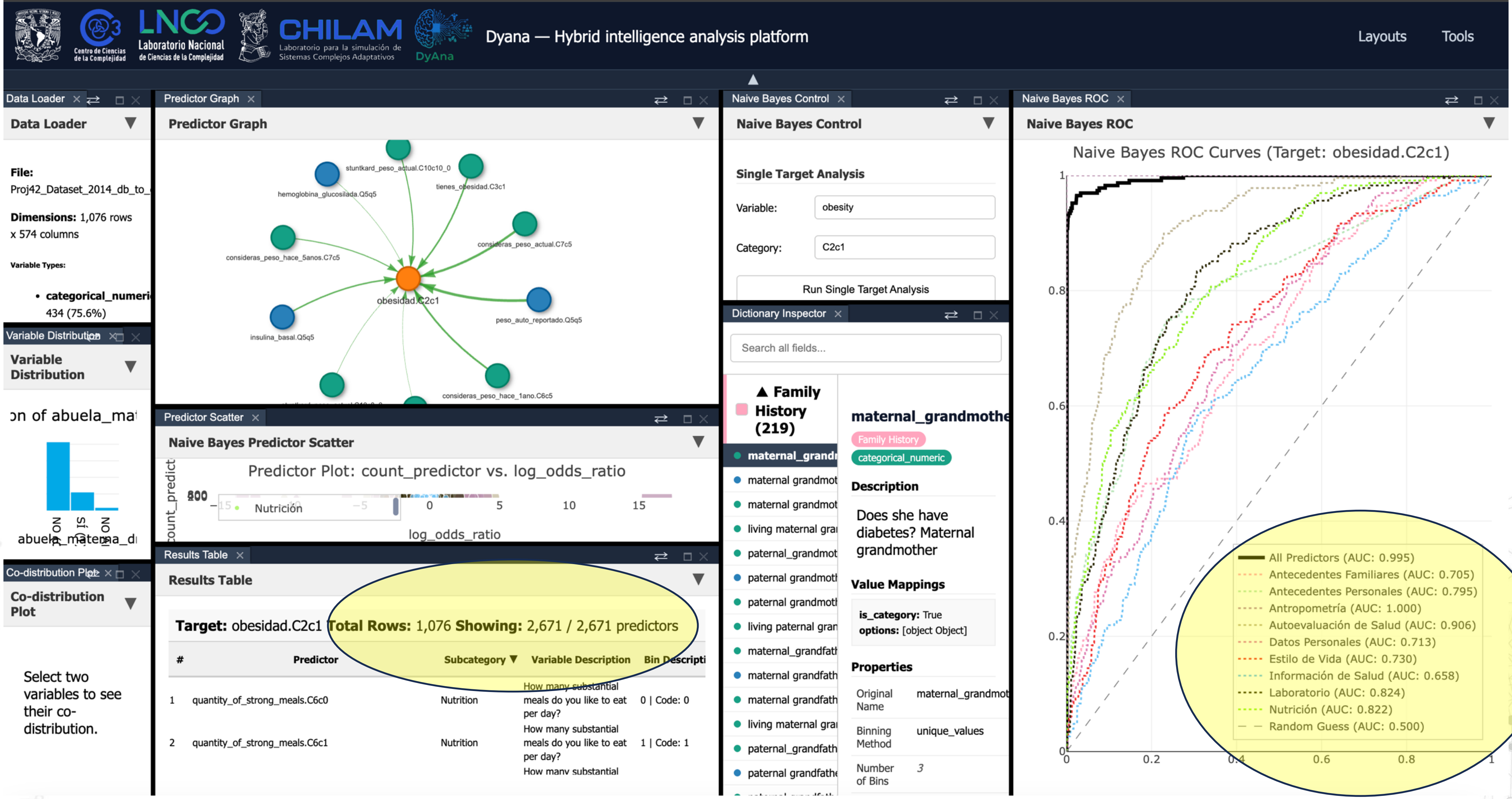


$$P(C|\mathbf{X})!$$

Of all these factors…

- What factors should we put in our model? DEEP data versus BIG data.
- Can we disentangle them? Black box versus white box. Explainable AI
- Which are important?
  - “Quality” versus “Quantity”; Intensive versus Extensive
- Which are statistically significant?
- What does a factor “mean”?
- Which are causes?
  - Direct/indirect; Proximal/distal
- Which are “actionable”?
  - Degree of feasibility; Cost-benefit
- How do we integrate into a model factors with very different:
  - Spatio-temporal scales
  - Formats
  - Types
  - Regions/time periods

Fusion and commensurabilty



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This is 90% Artificial Intelligence. Understanding what it means, what it implies and how it can be used is 90% Human Intelligence. That’s why we need HYBRID Intelligence.

The Bayesian Models

P(C|**X**) = P(C|X_1, X_2,…, X_N) **X** = (X_1, X_2,…, X_N)

As a number this can tell us the probability of the "effect" given the "causes" **X**. It won't tell us the "whys".

For the Decision Cycle we need to know the "whys" - which X_i are:

- Important
- Believable (statistically)
- Causal (direct, indirect, very indirect,…)
- Actionable (is it a variable we can change, e.g., climate or age = no, government program or diet = yes)

Use a Bayesian approach: P(C|**X**) = P(**X**|C)P(C)/P(**X**). And then P(C|**X**,**X'**) = P(**X**´|C,**X**)P(C|**X**)/P(**X**´|**X**). And then…

P(**X**|C) → $\prod_{i=1}^{M} P(\xi_i|C)$ Assume a factorization of the likelihood (weight of evidence)

$$S(C|\boldsymbol{X}) = \ln\left(\frac{P(C|\boldsymbol{X})}{P(\bar{C}|\boldsymbol{X})}\right) = \sum_{i=1}^{M} s_i + s_0. \qquad s_i = \ln(P(\xi_i|C)/P(\xi_i|\bar{C})). \qquad s_0 = \ln\left(\frac{P(C)}{P(\bar{C})}\right).$$

This is a generative not a discriminitive classifier – depends on the distribution of X

Importance/effect size.
The "Weight of Evidence" in favour of C versus $\bar{C}$

Bayesian prior

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The Bayesian Models

$P(\xi_i|C) = \frac{N(C\xi_i)}{N(C)}$; $P(C) = N(C)/N; P(\bar{C}|X) = (N(\xi_i) - N(C\xi_i))/N(\xi_i);\ P($

$(N - N(C))/N; P(\xi_i) = \frac{N(\xi_i)}{N}.$

Are the Building Blocks of everything . Everything is just counting!

New data → New counts: $N \to N + 1; N(C) \to N(C)\ or\ N(C) + 1;\ N(\xi_i) \to$
$1; N(C\xi_i) \to N(C\xi_i)\ or\ N(C\xi_i) + 1;$

Dynamics/**Adaptation**: $C\ or\ \xi_i$ can be states or rules.

But is the correlation between C and ξ_i statistically reliable? Use:

$$\varepsilon(C|\xi_i) = N(\xi_i)(\mathrm{P}(\mathrm{C}|\xi_i) - P(C))/\sqrt{N(\xi_i)(P(C)(1 - P(C))}$$

We are comparing the relation between C and ξ_i with the null hypothesis P(C)

The Bayesian Models

What are we counting?

- There are two basic types of ensemble:
  1. “People” (“things”)
  2. “Places” (”events” in spacetime)

- People and places have descriptors X_i
  1. These can change in space and time
  2. Are multimodal/multiformat/multiscale (ordinal, nominal, interval etc.)
  3. Are located in very different data sources
  4. Are properties of what the ensemble element “is” (weight, sex, father has diabetes, etc.) and what the element “does” (exercises regularly, eats more than the recommended amount etc.)

- ALL variables are discretised into a number of bins at the same scale with each bin treated as an independent variable.

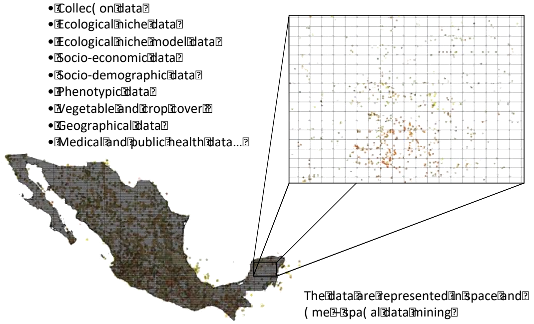
ENSANUT CONTINUA 2021

What can be said, X, about a person? "**Epidemiological**” perspective

What can be said, X, about a person? ”**Epi-Ecological**” perspective

$$P(C\,|\,X(t))$$

What can be said, X, about a person? ”**Eco-Epidemiological**” perspective



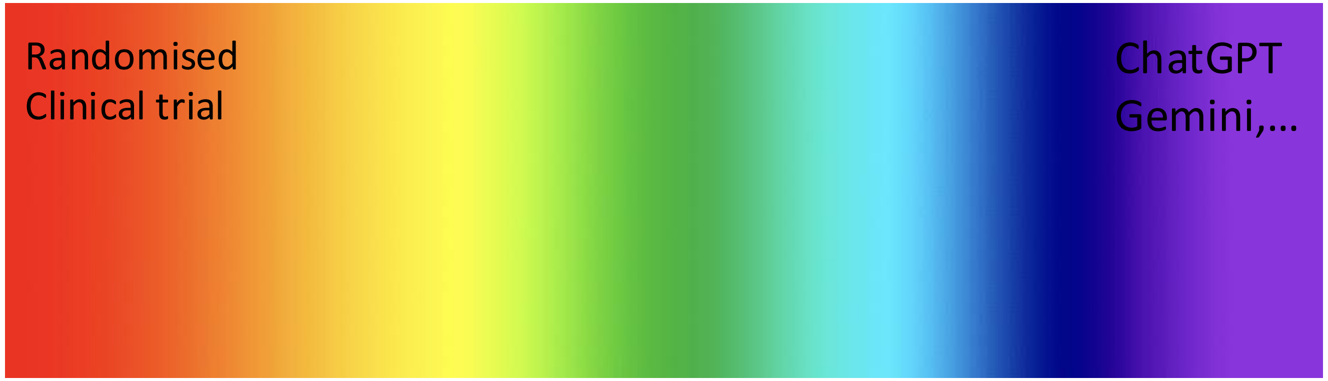
What can be said, X, about a place? ”**Ecological**" perspective

2020 censo de Población y Vivienda

The virtues of factorised Bayesian models

- They are naturally adaptive in the presence of new data – using Bayes theorem – retraining is done automatically
- Human intuition (and bias) can be incorporated in terms of a Bayesian prior
- Updating is done by pure counts
- 100% explainable – the effect size, coverage and statistical significance of every variable, or combination of variables, is clear
- Human Intelligence can easily be incorporated
- Can naturally be adapted into a causal inference framework
- Can be applied to any statistical ensemble – places, people, events,...
- Naturally incorporate rules (behaviours) as outputs or inputs as well as states

What does all this tell us about how we do science?



← Hypothesis driven

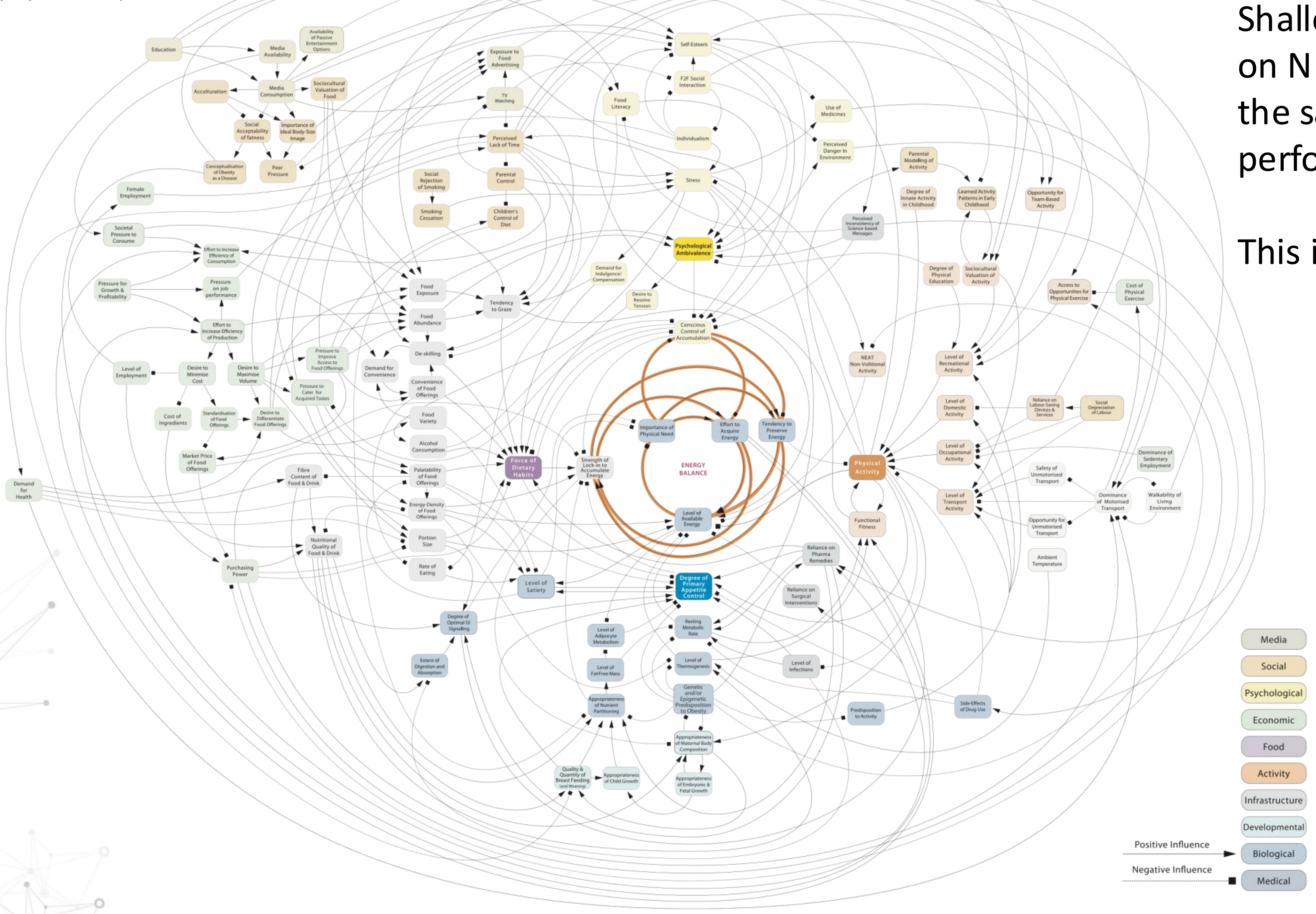
"Shallow" Data

Data driven →

"Deep" data

- Complex Adaptive Systems can be studied in a Hypothesis driven way with shallow data or deep data, or in a Data driven way with shallow data or deep data.
- Shallow means few variables and from a single or small number of scales/disciplines are used. Deep means many variables and from many scales/disciplines are used.
- With shallow/deep data few/many questions can be posed and hypotheses considered.

Foresight
Obesity System Map



Shallow data from n experiments performed on N people divided into n populations is not the same as deep data from all n experiments performed on all N people.

This is the problem of commensurability.

Areas of Interest for potential collaboration

Theory

- Foundations of CAS – adaptation, complexity,…
- Search - No Free Lunch theorem, Predictability Landscapes, Cumulant expansion (diagrammatics)
- Intelligence – AI versus Human I versus Hybrid I
  - Bayesian brain,…; psychology (coarse graining)
- Evolution – natural and artificial – Renormalisation group/coarse graining – diagrammatic expansion (Feynman)
- Causality and causal modelling
- Information theory – language, semantics – information and predictability
- Bayesian probability – theory space versus frequency space
- Public policy – what's the right thing to do to make things better?

Areas of Interest for potential collaboration

Applications

- Obesity and metabolic diseases
- Emerging/neglected diseases (ecology, epidemiology, eco-epidemiology, epi-ecology) – Leishmaniasis, Chagas, Dengue, Zika, Lyme, Coronavirus (COVID), influenza,...
- Environmental degradation/sustainability (deforestation)
- Poverty, homelessness, unaffordability, crime,...
- Financial markets – agent-based models, “predicting the predictors”
- Marketing/sales/customer lifecycle/reputation
- Education (“dropouts”/academic performance)

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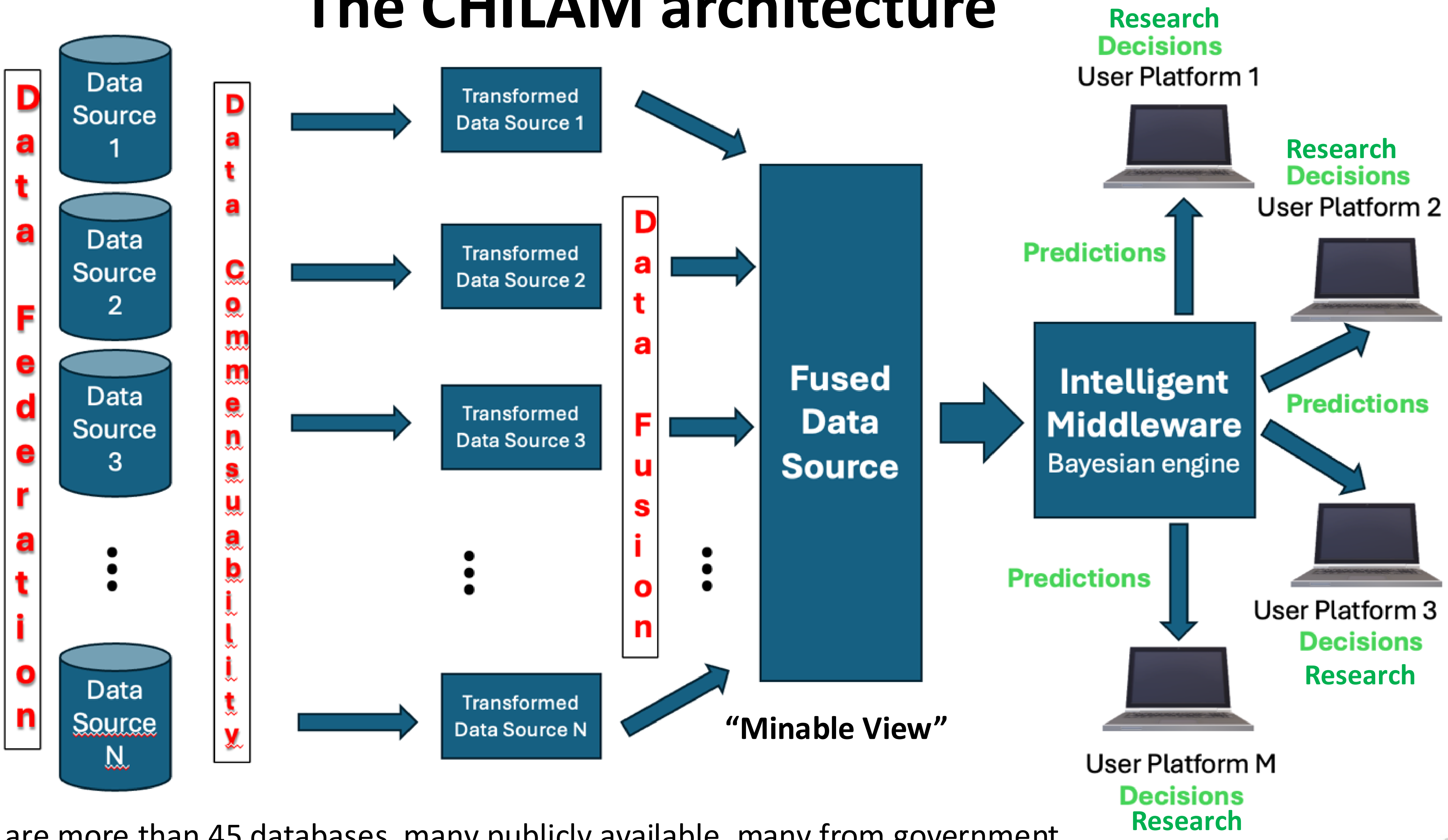
SPECIES (Niche and community ecological analysis) https://species.conabio.gob.mx/
EpI-SPECIES (10 emerging/neglected diseases) https://epispecies.c3.unam.mx/
EpI-PUMA (COVID19) https://covid19.c3.unam.mx/ and https://epipuma20.c3.unam.mx/
Project42 (obesity and metabolic disease) https://project42.c3.unam.mx/
Dyana (General purpose platform) https://dyana.c3.unam.mx

How do we do it?

What's behind the curtain?

The CHILAM architecture



There are more than 45 databases, many publicly available, many from government and academic institutions - INEGI, SNIB, CONEVAL, DGE, Sec. Health., WorldClim,…

We also have our own “home grown” data that is publicly available?

https://chilam.c3.unam.mx/en/proy-42-eng/data-project42

Project 42 | Data

Clave	Nombre	Año	Población (e= estudiantes, t= trabajadores)	n	Estatus limpieza
14UNI1_CAQ	Cuestionario + Antropometría + Química Sanguínea	2014	UNAM, e, t	1075	100%
14UNI1_G	Genética	2014	UNAM, e, t	1068	100%
17MED1_CA	Med1: Cuestionario + Antropometría	2017	UNAM, medicina e	329	90%
17MED1_Q	Med1: Química Sanguinea	2017	UNAM, medicina e	291	90%
17MED2_CA	Med2: Cuestionario + Antropometría	2017	UNAM, medicina e	131	90%
17MED2_Q	Med2: Química Sanguinea	2017	UNAM, medicina e	119	90%
19MED4_CA	Med4: Cuestionario + Antropometría	2019	UNAM, medicina e	280	90%
19MED4_Q	Med4: Química Sanguinea	2019	UNAM, medicina e	201	90%
19UNI2_Cs	Cuestionario Grande seguimiento 2019	2019	UNAM, e, t	292	0%
19UNI1_Cn	Cuestionario Grande 2014 nuevo	2019	UNAM, e, t	1170	0%
19UNI2_GC	Entrega Genética y Cuestionario	2019	UNAM, e, t	182	0%
19UNI1_M	Menú	2019	UNAM, e, t	927	0%
19UNI1_F	Foto porción - Seguimiento Cuestionario 2014	2019	UNAM, e, t	834	0%
19UNI1_A	Antropometría	2019	UNAM, e, t	1070	0%
19UNI1_Q	Química Sanguinea	2019	UNAM, e, t	1242	0%
19UNI1_Cp	Cuestionario Psicológico por correo	2019	UNAM, e, t	523	0%
19PDM1_C	Cuestionario Diabetes Mellitus	2019	pacientes con diabetes	99	80%
21UNI1_C1	Cuestionario antecedentes personales	2021	UNAM, IBERO, otras universidades, e	721	100%
21UNI1_C2	Cuestionario ancestros	2021	UNAM, IBERO, otras universidades, e	704	40%
21UNI1_C3	Cuestionario hermanos	2021	UNAM, IBERO, otras universidades, e	717	0%
21UNI1_C4	Cuestionario pareja y amigos	2021	UNAM, IBERO, otras universidades, e	700	0%
21UNI1_Cp1	Cuestionario Psicológico 1	2021	UNAM, IBERO, otras universidades, e	384	100%
21UNI1_Cp2	Cuestionario Psiclológico 2	2021	UNAM, IBERO, otras universidades, e	265	100%
21UNI1_Cp2.2	Cuestionario Psicológico 2.2	2021	UNAM, IBERO, otras universidades, e	265	100%
22ISAa_C	Cuestionario Salud en tu Vida a	2022	Universidad de la Salud aspirantes	3186	10%
22ISAi_C	Cuestionario Salud en tu Vida i	2022	Universidad de la Salud ingresados	334	0%
22IRC1_C	Cuestionario Salud en tu Vida IRC	2022	Instituto Rosario Castellano aspirantes, ingresados	253	0%

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So far, so good using “AI”

Causality

Strength (effect size): A small association does not mean that there is not a causal effect, though the larger the association, the more likely that it is causal. Bradford Hill 1965

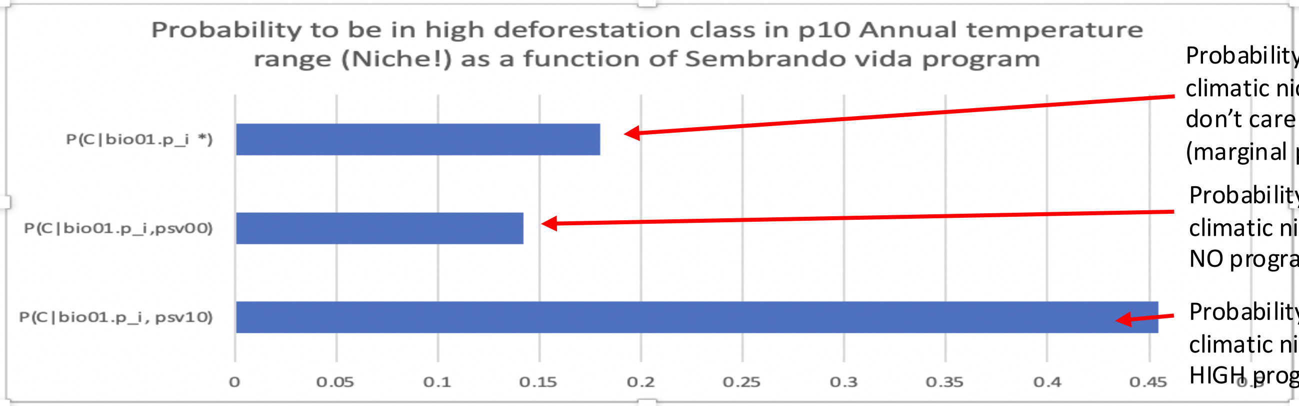
The bigger the score the more likely that it is causal

For two potential causes represented as binary variables we have:
P(C|11), P(C|10), P(C|01), P(C|00)
"AB testing" – look for where cause 1 is present without cause 2, and vice versa, where they´re both present (to look for "epistasis") and where they´re both absent (to look for other causes)

$$\varepsilon(C|X_{ij}X_{kl}) = \frac{N(X_{ij}X_{kl})(P(C|X_{ij}X_{kl}) - P_{nh})}{\sqrt{N(X_{ij}X_{kl})P_{nh}(1-P_{nh})}}$$

$P_{nh} = P(C)$, $P(C|X_{ij})$ and $P(C|X_{kl})$

This will tell us whether the associations are statistically significant



Probability given you're in climatic niche conditions and you don't care about the program (marginal probability)

Probability given you're in climatic niche conditions and NO program support

Probability given you're in climatic niche conditions and HIGH program support

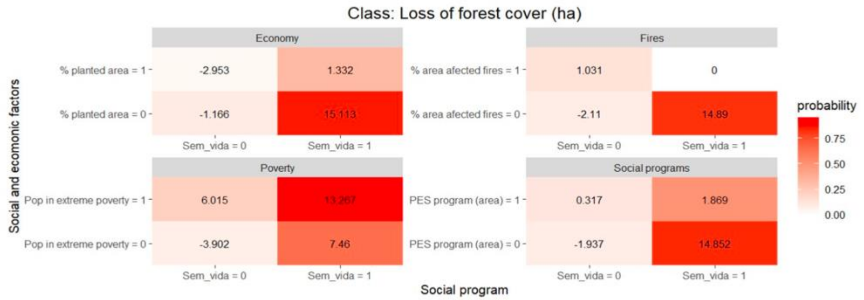


Figure 4: Visualization of $P(C|X_{ij}X_{kl})$ and $\varepsilon(C|X_{ij}X_{kl})$ for C = the top 10% of municipalities with the highest degree of deforestation in ha, with X_{ij} being the presence or absence of the *Sembrando Vida* program and X_{kl} representing the presence/absence of other social and economic competing causes of deforestation.