Conductome

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


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Seminar Centre for Complexity Science, Imperial College 5 February 2026

# *MISSION: C3 – Centro de Ciencias de la Complejidad, UNAM*


*To carry out transdisciplinary frontier research in the complexity sciences, creating a space where experts from different disciplines can interact and contribute to the definition and solution of transcendent problems of national importance.*

*To train scientists in transdisciplinary teamwork and in the use of modern computer-based methods for modelling. It also aims to develop collaborations with and outreach to distinct sectors of Mexican society.*

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# CHILAM: Laboratory for the Simulation of Complex Adaptive Systems

## Mission

- To provide virtual data-based laboratories that enable research at the forefront of human knowledge on a range of problems of high social impact
- To provide open access predictive modelling engines available as Platform-as-a-Service to a wide variety of stakeholders and decision makers as well as the general public
- To promote evidence-based decision making by utilising the best of human intelligence and artificial intelligence

chilam.c3.unam.mx

## Vision

- To be a center of innovation and excellence in the use of big, deep data and the application of Artificial Intelligence to global problems in health, social welfare and sustainability.

Centro de Ciencias de la Complejidad (C3 - UNAM)

Comisión Nacional para el conocimiento y uso de la Biodiversidad (CONABIO)

Instituto de Geografía (IGg - UNAM)

Centro de Información Geográfica y Ambiental (CIGA - UNAM)

Centro de Investigaciones en Políticas, Poblaciones y Salud (CIPPS - UNAM)

Instituto de Ciencias de la Atmósfera y Cambio Climático (CCAyCC - UNAM)

Facultad de Medicina (FM - UNAM)

Instituto de Ciencias Nucleares (ICN - UNAM)

Facultad de Psicología (Fac. Psic - UNAM)

Instituto de Biología (IB - UNAM)

Facultad de Medicina Veterinaria y Zootecnia (FMVZ - UNAM)

Secretaría de Salud (SALUD)

Centro Nacional de Prevención y Control de Enfermedades

Facultad de Estudios Superiores, Zaragoza (FES-Z - UNAM)

Hospital General de México (HGM)

Hospital Juárez de México (HJM)

Instituto de Neurobiología (INB - UNAM)

Instituto Nacional De Medicina Genómica (INMEGEN)

Universidad de Guadalajara (UdG)

Universidad de Guanajuato (UGto)

Universidad Iberoamericana (Ibero)

Universidad Veracruzana

**Interdisciplinary teams**

Consejo Nacional de Ciencia y Tecnología (CONACyT)

Microsoft Academic Relations

Programa de Apoyo a Proyectos de Investigación e Innovación Tecnológica (PAPIIT, DGAPA - UNAM)

Fundación Carlos Slim

Secretaría de Educación, Ciencia, Tecnología e Innovación de la Ciudad de México (SECTEI - CDMX)

**Funding**

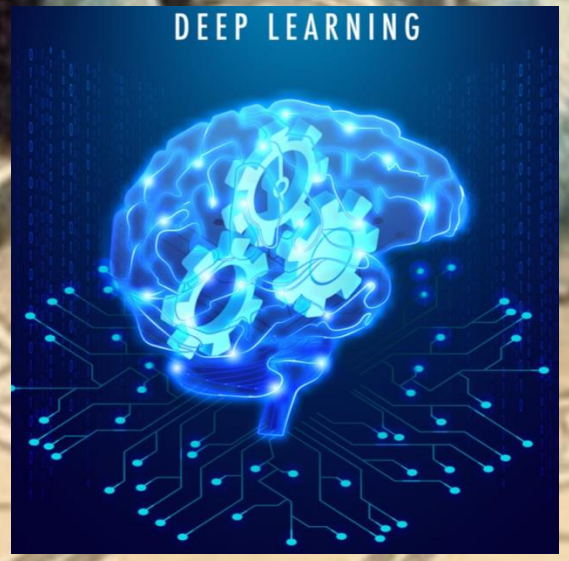
# Will I conquer the entire world?

Where are there likely to be more cases of respiratory disease next year?

Which government programs reduce deforestation?

What is the most adequate intervention for weight reduction?

Who is most likely to become diabetic?



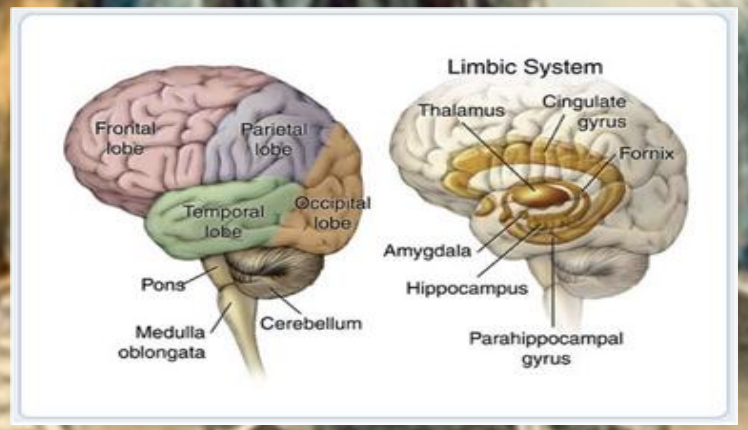
# Will I conquer the entire world?

## Am I an honest person?

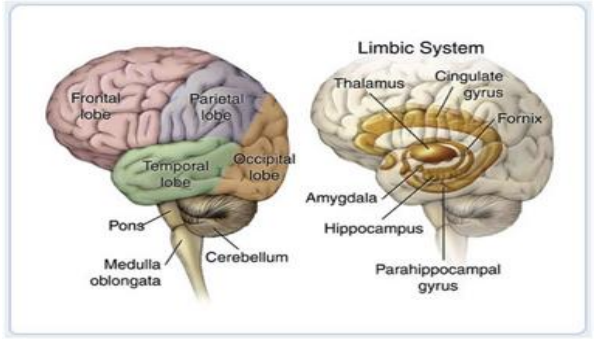
## Will I get ill if I eat this mushroom?

## Was the earthquake an act of God?

## Is this seminar worth listening to?



# Bayesian Classifiers: A General Modelling Framework for Complex Adaptive Systems

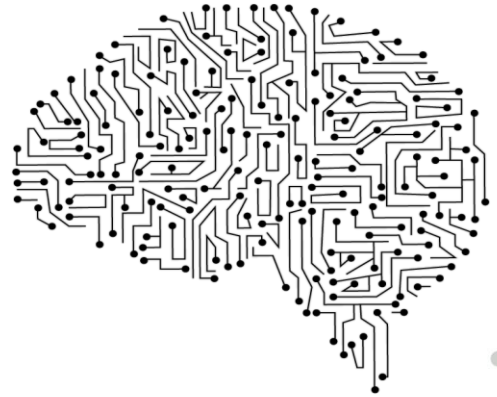



**Human Intelligence:**
Implicit algorithm - full of evolutionary and cultural biases

$$P(C \mid \mathbf{X}(t))$$

**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.

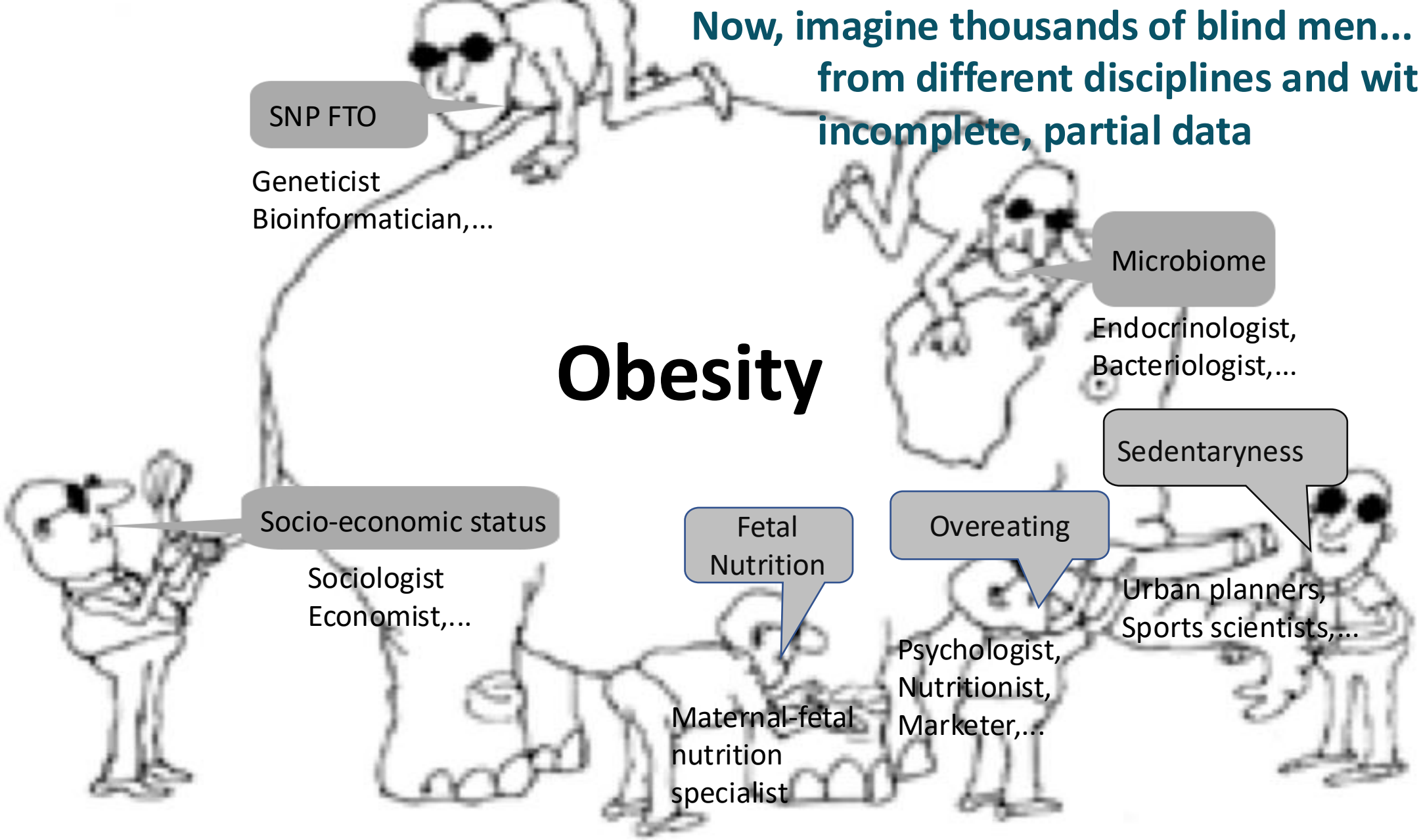
# When does P(C|X) represent the complexity and adaptability of a CAS?

## 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"

## Now, imagine thousands of blind men... from different disciplines and with incomplete, partial data



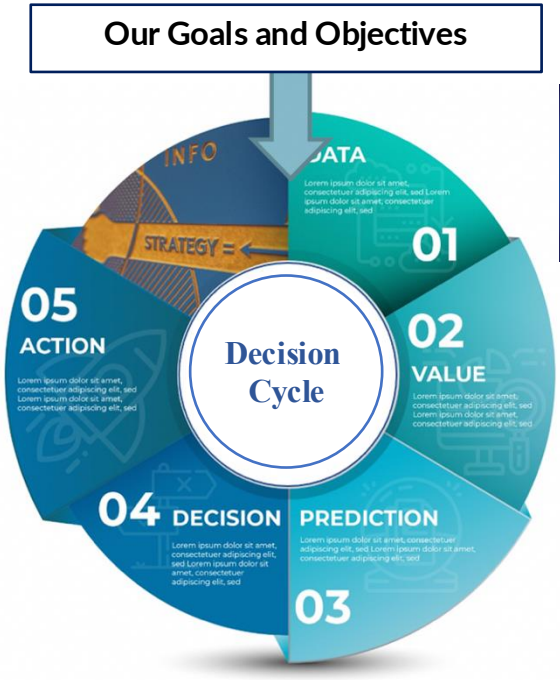
# Of all these factors…

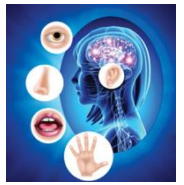
- What factors should we put in our model? DEEP data versus BIG data.
- Can we disentangle them? Black box versus white box. Explainable AI
- Which are important?
  - “Quality” versus “Quantity”; Intensive versus Extensive
- Which are statistically significant?
- What does a factor “mean”?
- Which are 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**

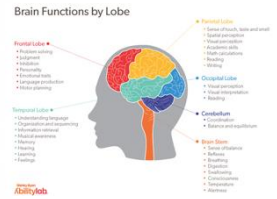
# Adaptability and the Decision Cycle


Where? When? Who? What? How?



VS




VS

**For every decision/action there is a prediction!**

**How good are the predictions?**

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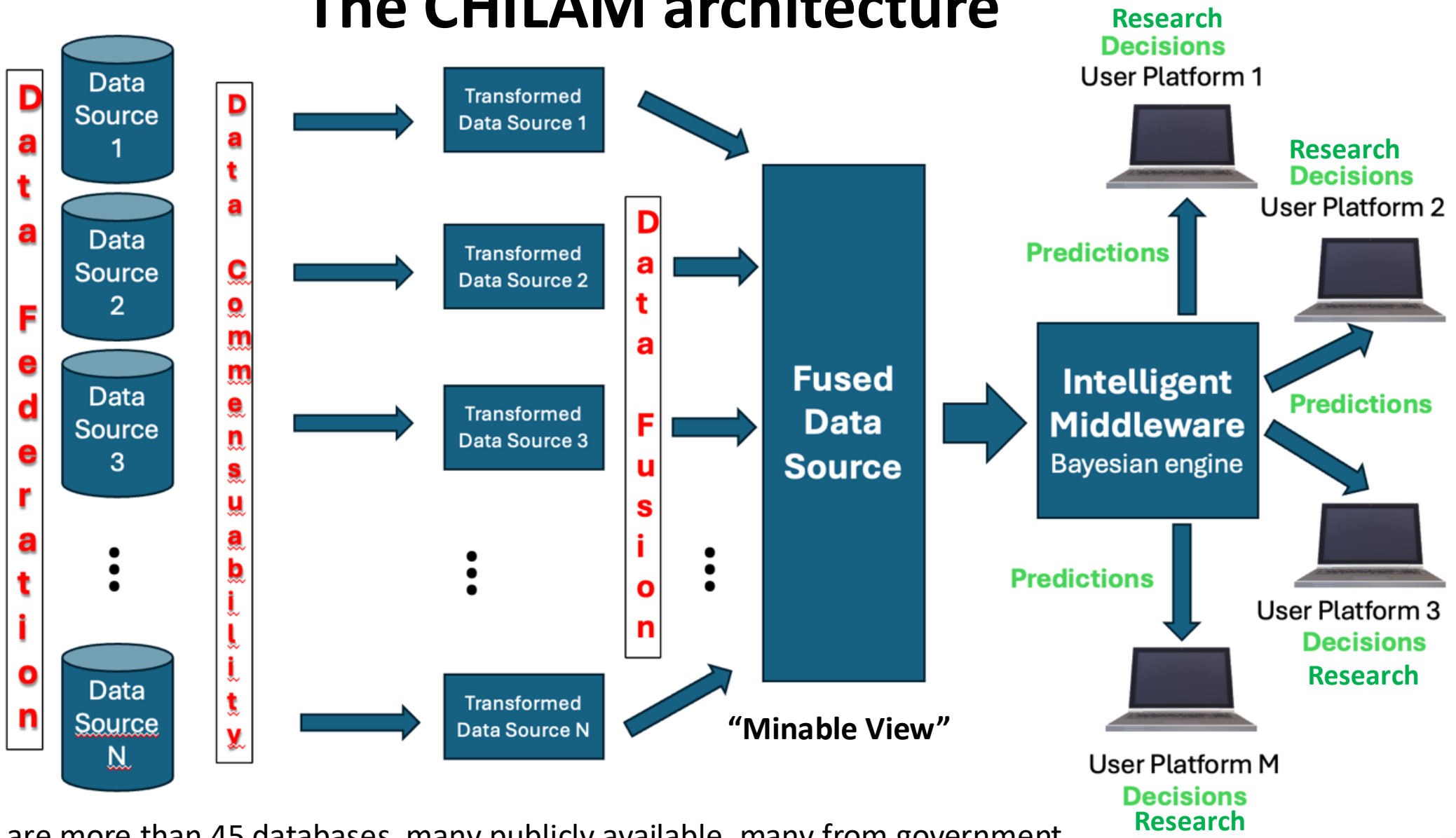
**SPECIES** (Niche and community ecological analysis) https://species.conabio.gob.mx/
**EpI-SPECIES** (10 emerging/neglected diseases) https://epispecies.c3.unam.mx/
**EpI-PUMA** (COVID19) https://covid19.c3.unam.mx/ and https://epipuma20.c3.unam.mx/
**Project42** (obesity and metabolic disease) https://project42.c3.unam.mx/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

Project 42 | Data

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

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

| 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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Sonar, so good using “AI”

# The Bayesian Models

$P(C|\mathbf{X}) = P(C|X_1, X_2, \ldots, X_N)$ $\quad\quad$ $\mathbf{X} = (X_1, X_2, \ldots, X_N)$

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: $P(C|\mathbf{X}) = P(\mathbf{X}|C)P(C)/P(\mathbf{X})$. And then $P(C|\mathbf{X},\mathbf{X}') = P(\mathbf{X}'|C,\mathbf{X})P(C|\mathbf{X})/P(\mathbf{X}'|\mathbf{X})$. And then…

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

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

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

# 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 $\xi_i$ 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 $\xi_i$ 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)

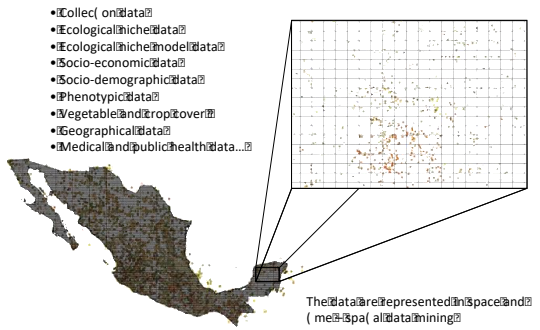
- People and places have descriptors $X_i$
  1. These can change in space and time
  2. Are multimodal/multiformat/multiscale (ordinal, nominal, interval etc.)
  3. Are located in very different data sources
  4. Are properties of what the ensemble element “is” (weight, sex, father has diabetes, etc.)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


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


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

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

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

# Causality

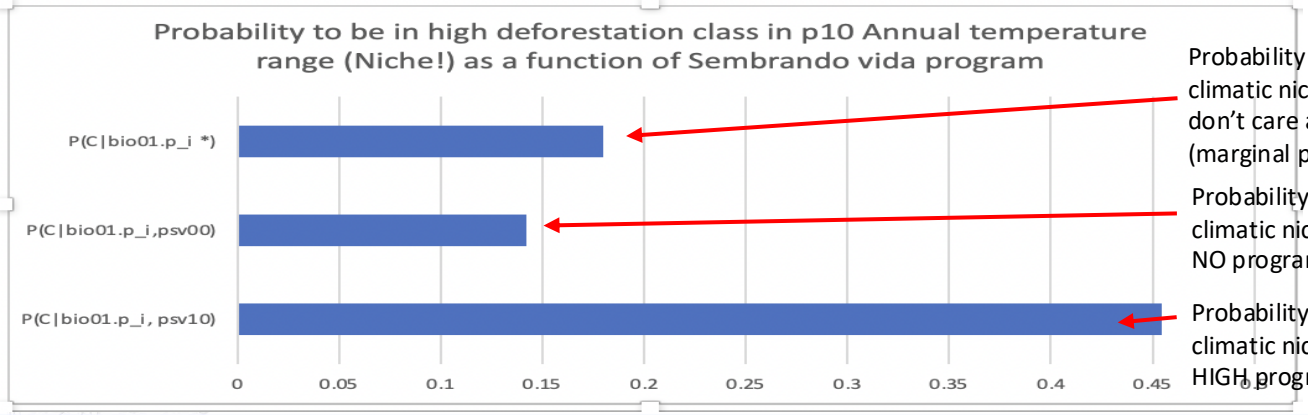
*Strength* (effect size): A small association does not mean that there is not a causal effect, though the larger the association, the more likely that it is causal. Bradford Hill 1965

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)

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

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

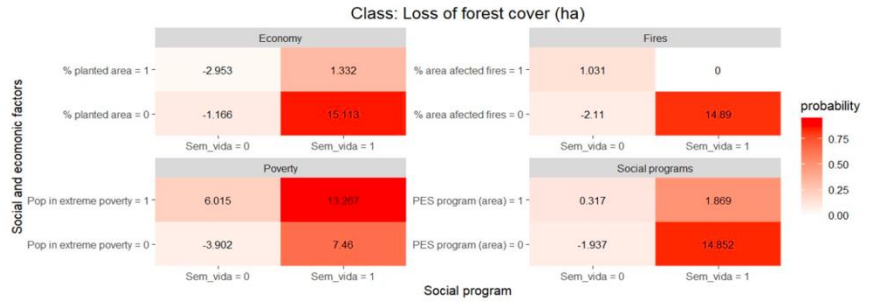



Figure 4: Visualization of $P(C|X_{ij}X_{kl})$ and $\varepsilon(C|X_{ij}X_{kl})$ for $C$ = the top 10% of municipalities with the highest degree of deforestation in ha, with $X_{ij}$ being the presence or absence of the *Sembrando Vida* program and $X_{kl}$ representing the presence/absence of other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

# 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)