European Research Council
Established by the European Commission

BeME

IPARCOS

UNIVERSIDAD COMPLUTENSE MADRID

ERC Project

Beyond Maximum Entropy: *A new paradigm for Modeling, Inference, and Learning Efficiency*

IPARCOS Scientific Advisory Board: Bi-Annual Review 2026

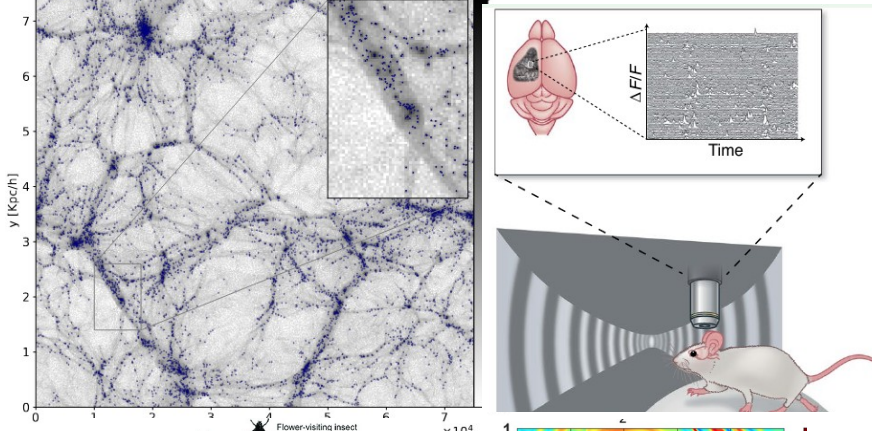
Group’s Overview

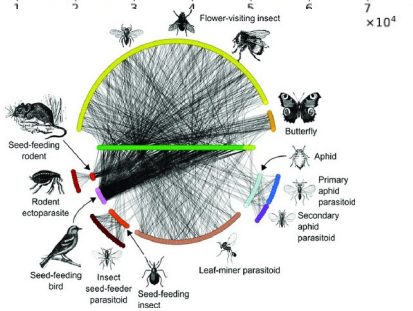
Group Snapshot

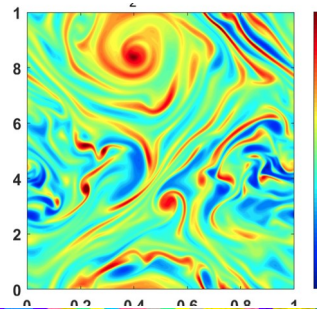
- ***Physics of Machine Learning*, PIs Aurélien Decelle (UPM) & Beatriz Seoane (UCM)**
- **Current Size:** Total members (2 Staff, 2 PhD, 4 Master, 2 visiting).
- **Key Personnel Changes:** 1 postdoc left, **new hirings 2026:** 3 postdocs + 1PhD

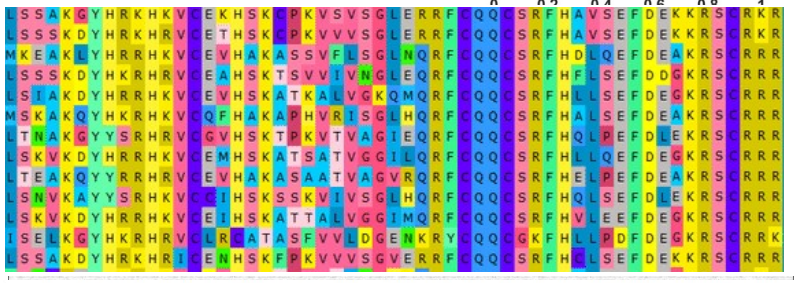
Key Performance Indicators

- **High-Impact Publications:** 15 peer-reviewed papers (10 in Q1 with 5 in D1 journals, 3 in A* conferences CS)
- **Funding Secured:** Consolidator ERC grant (2025), PID2024-158623NB-C21 (Coordinated project with the BIFI)
- **Training:** 2-PhD ongoing, one defending in 2026









	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	9046	Male	67.0	0	1	Yes	Private	Urban	228.69	36.6	formerly smoked	1
1	51676	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	NaN	never smoked	1
2	31112	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never smoked	1
3	60182	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	smokes	1
4	1665	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.0	never smoked	1
5	56669	Male	81.0	0	0	Yes	Private	Urban	186.21	29.0	formerly smoked	1
6	53882	Male	74.0	1	1	Yes	Private	Rural	70.09	27.4	never smoked	1
7	10434	Female	69.0	0	0	No	Private	Urban	94.39	22.8	never smoked	1

	point_id	process_id	s	Q	Q_min	Q_max	y	y_min	y_max	qT	...	kCut1	kCut2	eta_min	eta_max
0	A13-norm.0	1/1/1/3	169000000.0	91.0	66.0	116.0	0.0	-2.5	2.5	1.0	...	27.0	27.0	-2.5	2.5
1	A13-norm.1	1/1/1/3	169000000.0	91.0	66.0	116.0	0.0	-2.5	2.5	3.0	...	27.0	27.0	-2.5	2.5
2	A13-norm.2	1/1/1/3	169000000.0	91.0	66.0	116.0	0.0	-2.5	2.5	5.0	...	27.0	27.0	-2.5	2.5
3	A13-norm.3	1/1/1/3	169000000.0	91.0	66.0	116.0	0.0	-2.5	2.5	7.0	...	27.0	27.0	-2.5	2.5
4	A13-norm.4	1/1/1/3	169000000.0	91.0	66.0	116.0	0.0	-2.5	2.5	9.0	...	27.0	27.0	-2.5	2.5

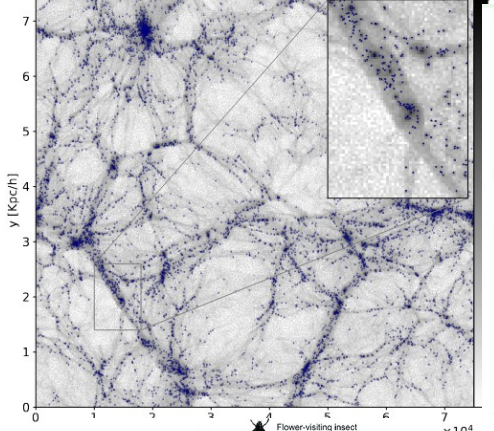
Goal: Modeling scientific data

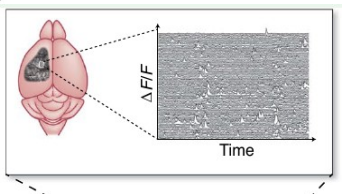
Dataset $\mathcal{D} = \{ \boldsymbol{x}^{(m)} \}_{m=1}^{M}$

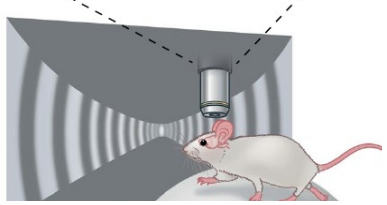
$$p_{\text{data}}(\boldsymbol{x}) = \frac{1}{M} \sum_{m=0}^{M} \delta \left(\boldsymbol{x} - \boldsymbol{x}^{(m)} \right)$$

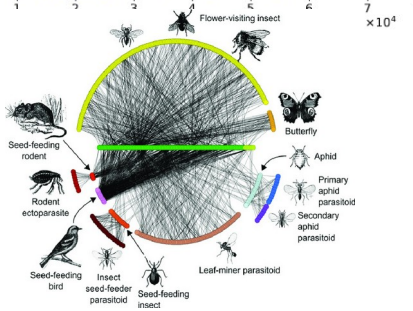
$$p_{\text{data}}(\boldsymbol{x}) \sim p_{\boldsymbol{\theta}}(\boldsymbol{x})$$

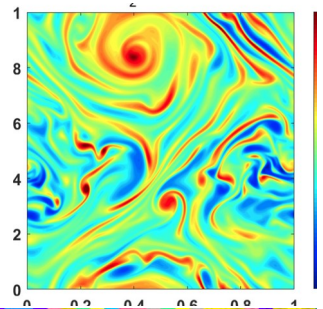
IPARCOS

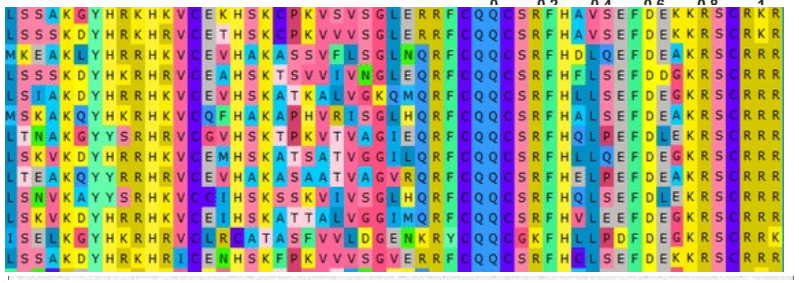












	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	9046	Male	67.0	0	1	Yes	Private	Urban	228.69	36.6	formerly smoked	1
1	51676	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	NaN	never smoked	1
2	31112	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never smoked	1
3	60182	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	smokes	1
4	1665	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.0	never smoked	1
5	56669	Male	81.0	0	0	Yes	Private	Urban	186.21	29.0	formerly smoked	1
6	53882	Male	74.0	1	1	Yes	Private	Rural	70.09	27.4	never smoked	1
7	10434	Female	69.0	0	0	No	Private	Urban	94.39	22.8	never smoked	1

	point_id	process_id	s	Q	Q_min	Q_max	y	y_min	y_max	qT	...	kCut1	kCut2	eta_min	eta_max
0	A13-norm.0	1/1/1/3	169000000.0	91.0	66.0	116.0	0.0	-2.5	2.5	1.0	...	27.0	27.0	-2.5	2.5
1	A13-norm.1	1/1/1/3	169000000.0	91.0	66.0	116.0	0.0	-2.5	2.5	3.0	...	27.0	27.0	-2.5	2.5
2	A13-norm.2	1/1/1/3	169000000.0	91.0	66.0	116.0	0.0	-2.5	2.5	5.0	...	27.0	27.0	-2.5	2.5
3	A13-norm.3	1/1/1/3	169000000.0	91.0	66.0	116.0	0.0	-2.5	2.5	7.0	...	27.0	27.0	-2.5	2.5
4	A13-norm.4	1/1/1/3	169000000.0	91.0	66.0	116.0	0.0	-2.5	2.5	9.0	...	27.0	27.0	-2.5	2.5

Goal: Modeling scientific data

Dataset $\mathcal{D} = \{ \boldsymbol{x}^{(m)} \}_{m=1}^{M}$

$$p_{\text{data}}(\boldsymbol{x}) = \frac{1}{M} \sum_{m=0}^{M} \delta \left(\boldsymbol{x} - \boldsymbol{x}^{(m)} \right)$$

$$p_{\text{data}}(\boldsymbol{x}) \sim p_{\boldsymbol{\theta}}(\boldsymbol{x})$$

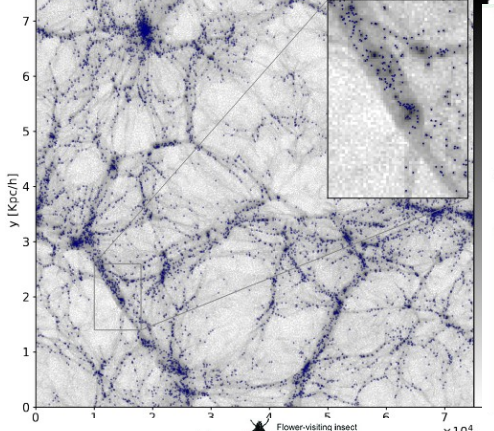
Maximum Entropy modeling

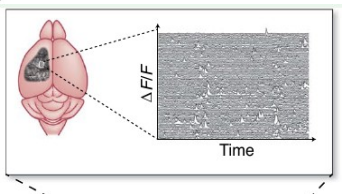
Multiple constraints $\langle \mathcal{O}_k(\boldsymbol{x}) \rangle$ with $k = 1, 2, \ldots K$

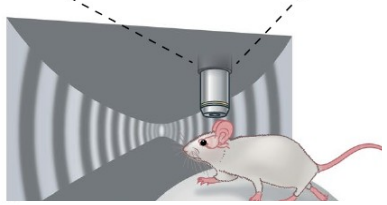
$$p_{\boldsymbol{\theta}}(\boldsymbol{x}) \propto e^{[\mu_1 O_1(\boldsymbol{x}) + \cdots + \mu_K O_K(\boldsymbol{x})]}$$

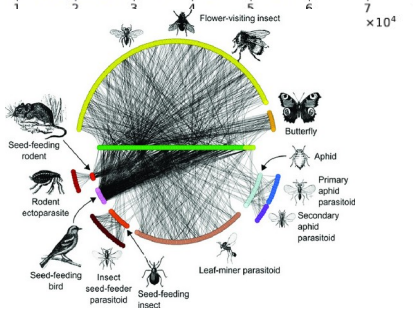
IPARCOS

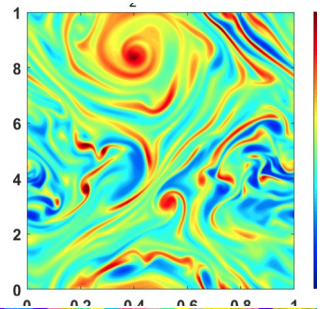
Goal: Modeling scientific data

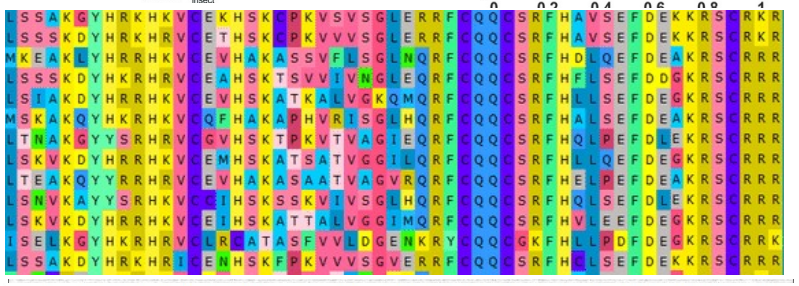












	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	9046	Male	67.0	0	1	Yes	Private	Urban	228.69	36.6	formerly smoked	1
1	51676	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	NaN	never smoked	1
2	31112	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never smoked	1
3	60182	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	smokes	1
4	1665	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.0	never smoked	1
5	56669	Male	81.0	0	0	Yes	Private	Urban	186.21	29.0	formerly smoked	1
6	53882	Male	74.0	1	1	Yes	Private	Rural	70.09	27.4	never smoked	1
7	10434	Female	69.0	0	0	No	Private	Urban	94.39	22.8	never smoked	1

	point_id	process_id	s	Q	Q_min	Q_max	y	y_min	y_max	qT	...	kCut1	kCut2	eta_min	eta_max
0	A13-norm.0	1/1/1/3	169000000.0	91.0	66.0	116.0	0.0	-2.5	2.5	1.0	...	27.0	27.0	-2.5	2.5
1	A13-norm.1	1/1/1/3	169000000.0	91.0	66.0	116.0	0.0	-2.5	2.5	3.0	...	27.0	27.0	-2.5	2.5
2	A13-norm.2	1/1/1/3	169000000.0	91.0	66.0	116.0	0.0	-2.5	2.5	5.0	...	27.0	27.0	-2.5	2.5
3	A13-norm.3	1/1/1/3	169000000.0	91.0	66.0	116.0	0.0	-2.5	2.5	7.0	...	27.0	27.0	-2.5	2.5
4	A13-norm.4	1/1/1/3	169000000.0	91.0	66.0	116.0	0.0	-2.5	2.5	9.0	...	27.0	27.0	-2.5	2.5

Dataset $\mathcal{D} = \{ \boldsymbol{x}^{(m)} \}_{m=1}^{M}$

$$p_{\text{data}}(\boldsymbol{x}) = \frac{1}{M} \sum_{m=0}^{M} \delta \left(\boldsymbol{x} - \boldsymbol{x}^{(m)} \right)$$

$$p_{\text{data}}(\boldsymbol{x}) \sim p_{\boldsymbol{\theta}}(\boldsymbol{x})$$

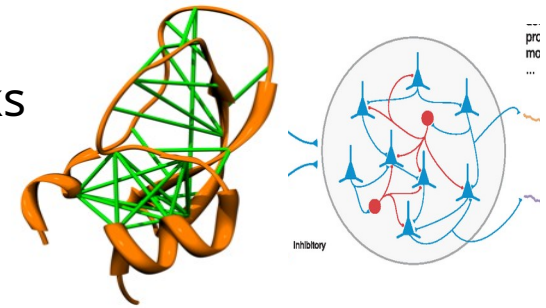
Maximum Entropy modeling

Multiple constraints $\langle \mathcal{O}_k(\boldsymbol{x}) \rangle$ with $k = 1, 2, \ldots K$

$$p_{\boldsymbol{\theta}}(\boldsymbol{x}) \propto e^{[\mu_1 O_1(\boldsymbol{x}) + \cdots + \mu_K O_K(\boldsymbol{x})]}$$

Infer effective interaction networks

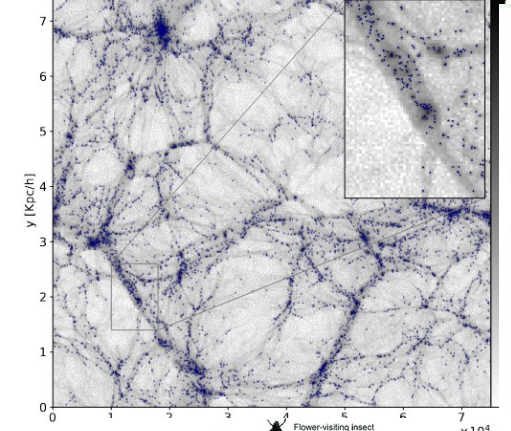
$\langle \sigma_i \rangle \, \langle \sigma_i \sigma_j \rangle$

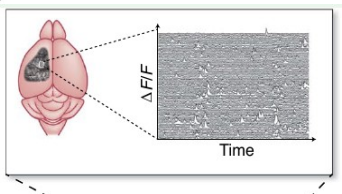


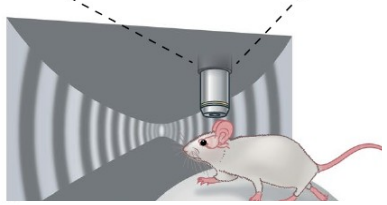
$$p_{\boldsymbol{\theta}}(\boldsymbol{\sigma}) \propto e^{\sum_{i<j} J_{ij} \sigma_i \sigma_j + \sum_i h_i \sigma_i}$$

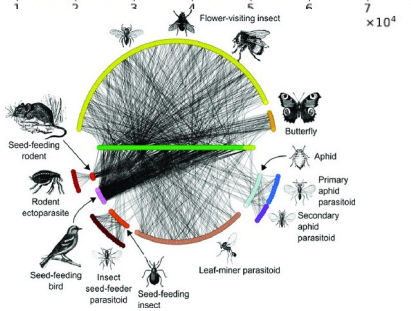
IPARCOS

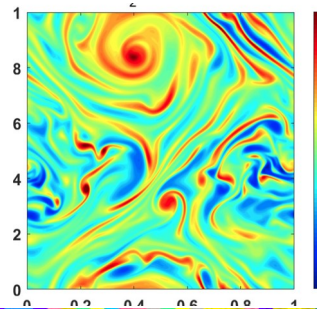
Goal: Modeling scientific data

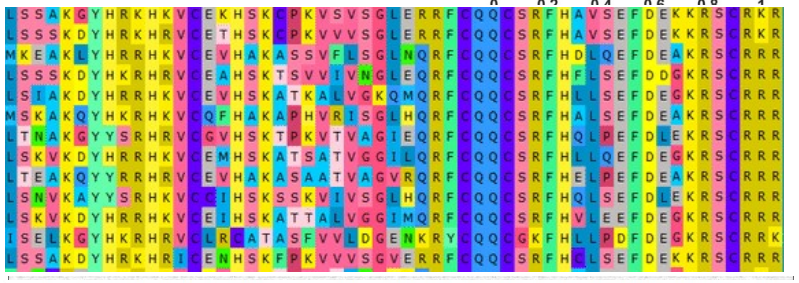












	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	9046	Male	67.0	0	1	Yes	Private	Urban	228.69	36.6	formerly smoked	1
1	51676	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	NaN	never smoked	1
2	31112	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never smoked	1
3	60182	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	smokes	1
4	1665	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.0	never smoked	1
5	56669	Male	81.0	0	0	Yes	Private	Urban	186.21	29.0	formerly smoked	1
6	53882	Male	74.0	1	1	Yes	Private	Rural	70.09	27.4	never smoked	1
7	10434	Female	69.0	0	0	No	Private	Urban	94.39	22.8	never smoked	1

	point_id	process_id	s	Q	Q_min	Q_max	y	y_min	y_max	qT	...	kCut1	kCut2	eta_min	eta_max
0	A13-norm.0	1/1/1/3	169000000.0	91.0	66.0	116.0	0.0	-2.5	2.5	1.0	...	27.0	27.0	-2.5	2.5
1	A13-norm.1	1/1/1/3	169000000.0	91.0	66.0	116.0	0.0	-2.5	2.5	3.0	...	27.0	27.0	-2.5	2.5
2	A13-norm.2	1/1/1/3	169000000.0	91.0	66.0	116.0	0.0	-2.5	2.5	5.0	...	27.0	27.0	-2.5	2.5
3	A13-norm.3	1/1/1/3	169000000.0	91.0	66.0	116.0	0.0	-2.5	2.5	7.0	...	27.0	27.0	-2.5	2.5
4	A13-norm.4	1/1/1/3	169000000.0	91.0	66.0	116.0	0.0	-2.5	2.5	9.0	...	27.0	27.0	-2.5	2.5

Dataset $\mathcal{D} = \{ \boldsymbol{x}^{(m)} \}_{m=1}^{M}$

$$p_{\text{data}}(\boldsymbol{x}) = \frac{1}{M} \sum_{m=0}^{M} \delta \left(\boldsymbol{x} - \boldsymbol{x}^{(m)} \right)$$

$$p_{\text{data}}(\boldsymbol{x}) \sim p_{\boldsymbol{\theta}}(\boldsymbol{x})$$

Maximum Entropy modeling

Multiple constraints $\langle \mathcal{O}_k(\boldsymbol{x}) \rangle$ with $k = 1, 2, \ldots K$

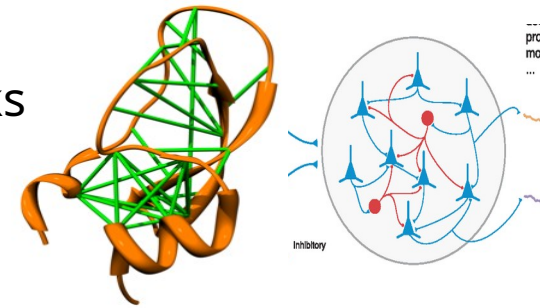
$$p_{\boldsymbol{\theta}}(\boldsymbol{x}) \propto e^{[\mu_1 O_1(\boldsymbol{x}) + \cdots + \mu_K O_K(\boldsymbol{x})]}$$

Advantages:
Simple models → Very interpretable
Few parameters → Reliable scarce data

Disadvantages:
Too simple models → Limited expressivity

Infer effective interaction networks

$\langle \sigma_i \rangle \langle \sigma_i \sigma_j \rangle$



$$p_{\boldsymbol{\theta}}(\boldsymbol{\sigma}) \propto e^{\sum_{i<j} J_{ij} \sigma_i \sigma_j + \sum_i h_i \sigma_i}$$

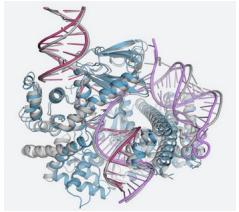
IPARCOS

Alternative : Generative models

Deep Learning

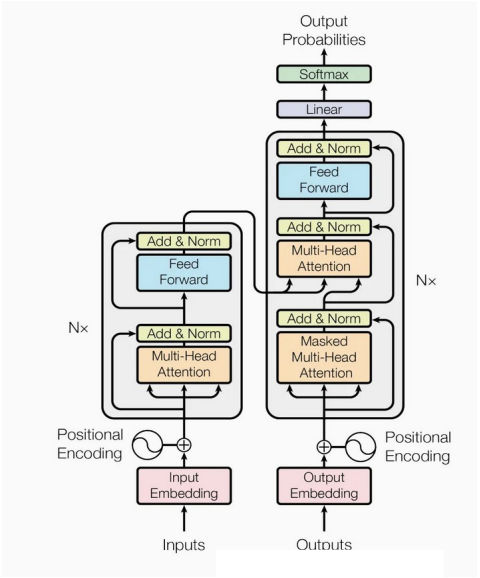
Computer Science: Generative models





Advantages:
Very expressive

Disadvantages:
Unsustainable
Data-hungry
Black-boxes



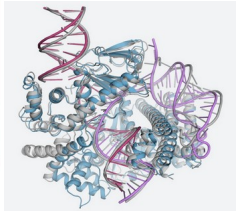
IPARCOS

Alternative : Generative models

Deep Learning

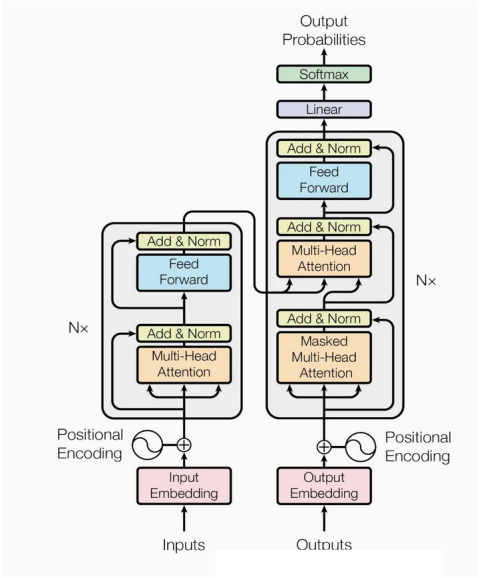
Computer Science: Generative models





Advantages:
Very expressive

Disadvantages:
Unsustainable
Data-hungry
Black-boxes

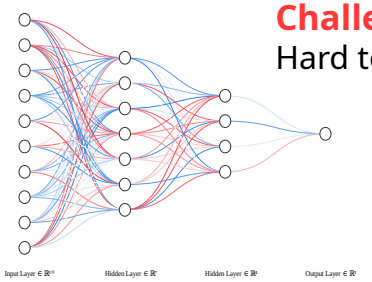


Energy-based models (EBMs)

$$p_{\text{data}} \sim p_{\boldsymbol{\theta}}(\boldsymbol{\sigma}) = \frac{e^{-\mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{\sigma})}}{Z_{\boldsymbol{\theta}}}$$

BeME

$\mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{\sigma})$



Advantages:
Highly expressive → Model complex systems
Energy & data efficient → meet scientific needs
Interpretable → Learn from data

Challenge:
Hard to train and sample from

IPARCOS

Ill. Niklas Elmehed © Nobel Prize Outreach

John J. Hopfield

Prize share: 1/2

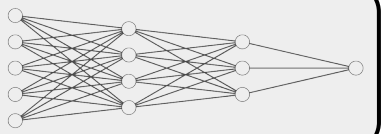
Ill. Niklas Elmehed © Nobel Prize Outreach

Geoffrey Hinton

Prize share: 1/2

Energy Based Models (EBMs)

$$p_{\text{data}} \sim p_{\boldsymbol{\theta}}(\boldsymbol{\sigma}) = \frac{e^{-\mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{\sigma})}}{Z_{\boldsymbol{\theta}}} \qquad \mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{x}) =$$



Main challenge : They are very hard to train, evaluate, and sample

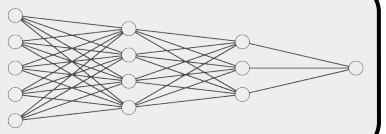
IPARCOS

Ill. Niklas Elmehed © Nobel Prize Outreach
John J. Hopfield
Prize share: 1/2

Ill. Niklas Elmehed © Nobel Prize Outreach
Geoffrey Hinton
Prize share: 1/2

Energy Based Models (EBMs)

$$p_{\text{data}} \sim p_{\boldsymbol{\theta}}(\boldsymbol{\sigma}) = \frac{e^{-\mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{\sigma})}}{Z_{\boldsymbol{\theta}}} \qquad \mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{x}) =$$



~~**Main challenge :** They are very hard to train, evaluate, and sample~~ No longer true

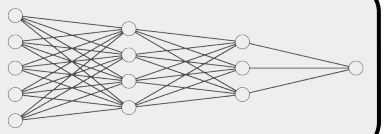
IPARCOS

Ill. Niklas Elmehed © Nobel Prize Outreach
John J. Hopfield
Prize share: 1/2

Ill. Niklas Elmehed © Nobel Prize Outreach
Geoffrey Hinton
Prize share: 1/2

Energy Based Models (EBMs)

$$p_{\text{data}} \sim p_{\boldsymbol{\theta}}(\boldsymbol{\sigma}) = \frac{e^{-\mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{\sigma})}}{Z_{\boldsymbol{\theta}}} \qquad \mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{x}) =$$



~~**Main challenge :** They are very hard to train, evaluate, and sample~~ No longer true

1) Diagnosis
Uncontrolled Monte Carlo

- Decelle, Furtlehner, **S**, **NeurIPS** (2021)
- Agoritsas, Catania, Decelle, **S**, **ICML** (2023)

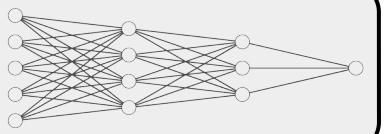
IPARCOS

Ill. Niklas Elmehed © Nobel Prize Outreach
John J. Hopfield
Prize share: 1/2

Ill. Niklas Elmehed © Nobel Prize Outreach
Geoffrey Hinton
Prize share: 1/2

Energy Based Models (EBMs)

$$p_{\text{data}} \sim p_{\boldsymbol{\theta}}(\boldsymbol{\sigma}) = \frac{e^{-\mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{\sigma})}}{Z_{\boldsymbol{\theta}}} \qquad \mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{x}) =$$



~~**Main challenge :** They are very hard to train, evaluate, and sample~~ No longer true

1) Diagnosis
Uncontrolled Monte Carlo

2) Physical origin
Metastability
Cascade of Phase Transitions

- Decelle, Furtlehner, **S**, **NeurIPS** (2021)
- Agoritsas, Catania, Decelle, **S**, **ICML** (2023)
- Béreux, Decelle, Furtlehner, **S**, **SciPost Phys**. (2023)
- Bachtis, Biroli, Decelle, **S** **NeurIPS** (2024)

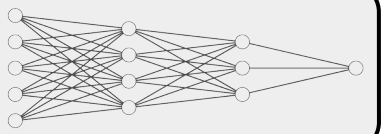
IPARCOS

Ill. Niklas Elmehed © Nobel Prize Outreach
John J. Hopfield
Prize share: 1/2

Ill. Niklas Elmehed © Nobel Prize Outreach
Geoffrey Hinton
Prize share: 1/2

Energy Based Models (EBMs)

$$p_{\text{data}} \sim p_{\boldsymbol{\theta}}(\boldsymbol{\sigma}) = \frac{e^{-\mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{\sigma})}}{Z_{\boldsymbol{\theta}}} \qquad \mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{x}) =$$



~~**Main challenge :** They are very hard to train, evaluate, and sample~~ No longer true

1) Diagnosis
Uncontrolled Monte Carlo

- Decelle, Furtlehner, **S**, **NeurIPS** (2021)
- Agoritsas, Catania, Decelle, **S**, **ICML** (2023)

2) Physical origin
Metastability
Cascade of Phase Transitions

- Béreux, Decelle, Furtlehner, **S**, **SciPost Phys**. (2023)
- Bachtis, Biroli, Decelle, **S** **NeurIPS** (2024)

3) Accurate methods
Training
Likelihood estimations
Generating

- Carbone, Decelle, Rosset, **S**, **IEEE TPAMI** (2025)
- Béreux, Decelle, Furtlehner, Rosset, **S**, **ICLR** (2025)

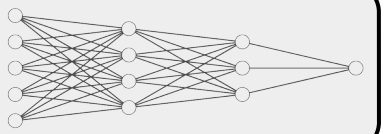
IPARCOS

Ill. Niklas Elmehed © Nobel Prize Outreach
John J. Hopfield
Prize share: 1/2

Ill. Niklas Elmehed © Nobel Prize Outreach
Geoffrey Hinton
Prize share: 1/2

Energy Based Models (EBMs)

$$p_{\text{data}} \sim p_{\boldsymbol{\theta}}(\boldsymbol{\sigma}) = \frac{e^{-\mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{\sigma})}}{Z_{\boldsymbol{\theta}}} \qquad \mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{x}) =$$



~~**Main challenge :** They are very hard to train, evaluate, and sample~~ No longer true

1) Diagnosis
Uncontrolled Monte Carlo

2) Physical origin
Metastability
Cascade of Phase Transitions

3) Accurate methods
Training
Likelihood estimations
Generating

- Decelle, Furtlehner, **S**, **NeurIPS** (2021)
- Agoritsas, Catania, Decelle, **S**, **ICML** (2023)

- Béreux, Decelle, Furtlehner, **S**, **SciPost Phys**. (2023)
- Bachtis, Biroli, Decelle, **S** **NeurIPS** (2024)

- Carbone, Decelle, Rosset, **S**, **IEEE TPAMI** (2025)
- Béreux, Decelle, Furtlehner, Rosset, **S**, **ICLR** (2025)

It's time to bring **EBMs** back !

BeME

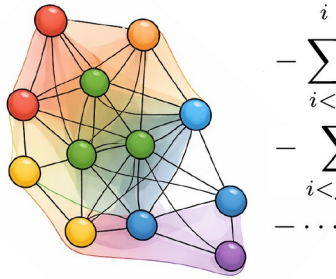
IPARCOS

Why EBMs ?

$$p_{\theta}(\boldsymbol{\sigma}) = \frac{e^{-\mathcal{H}_{\theta}(\boldsymbol{\sigma})}}{Z_{\theta}}$$

Why EBMs ?

Energy function

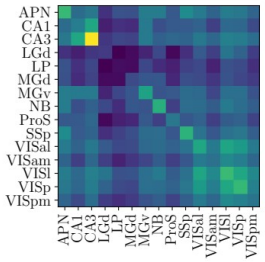


$$\mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{S}) = -\sum_i h_i(\boldsymbol{\theta})\, S_i - \sum_{i<j} J^{(2)}_{ij}(\boldsymbol{\theta})\, S_i S_j - \sum_{i<j<k} J^{(3)}_{ijk}(\boldsymbol{\theta})\, S_i S_j S_k - \cdots$$

$$p_{\boldsymbol{\theta}}(\boldsymbol{\sigma}) = \frac{e^{-\mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{\sigma})}}{Z_{\boldsymbol{\theta}}}$$

Ising - Decelle, Furtlehner, Navas Gómez, **S**, ***SciPost Phys.*** (2024)
Potts - Decelle, Navas-Gómez, **S**, *accepted in* ***Physical Review Letters*** (2025)

Multi-body interaction inference



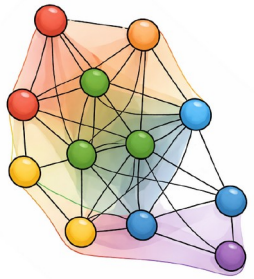
Neural Activity - Béreux, Catania, Decelle, Mignacco, Navas Gómez, **S**. ArXiv (2026)

IPARCOS

Why EBMs ?

Energy function

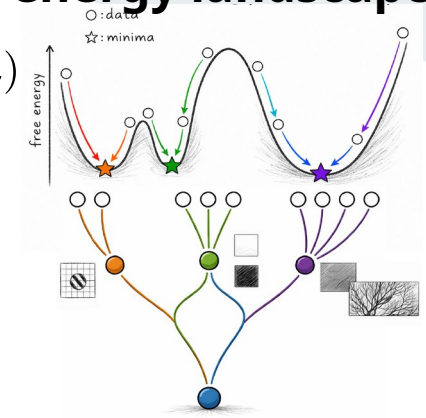
$$\mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{S}) = -\sum_i h_i(\boldsymbol{\theta})\, S_i - \sum_{i<j} J^{(2)}_{ij}(\boldsymbol{\theta})\, S_i S_j - \sum_{i<j<k} J^{(3)}_{ijk}(\boldsymbol{\theta})\, S_i S_j S_k - \cdots$$



$$p_{\boldsymbol{\theta}}(\boldsymbol{\sigma}) = \frac{e^{-\mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{\sigma})}}{Z_{\boldsymbol{\theta}}}$$

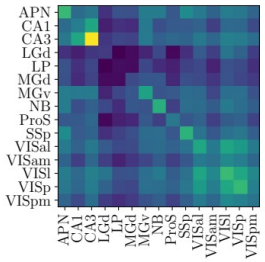
Free-energy landscape

$\mathcal{F}_{\boldsymbol{\theta}}(\boldsymbol{m})$



Ising - Decelle, Furtlehner, Navas Gómez, **S**, ***SciPost Phys.*** (2024)
Potts - Decelle, Navas-Gómez, **S**, *accepted in* ***Physical Review Letters*** (2025)

Multi-body interaction inference



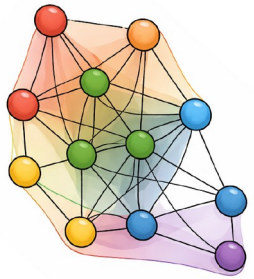
Neural Activity - Béreux, Catania, Decelle, Mignacco, Navas Gómez, **S**. ArXiv (2026)

IPARCOS

Why EBMs ?

Energy function

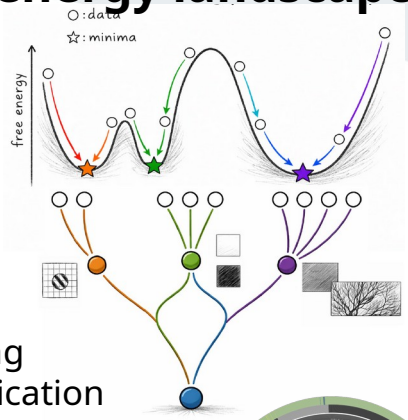
$$\mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{S}) = -\sum_i h_i(\boldsymbol{\theta})\, S_i - \sum_{i<j} J^{(2)}_{ij}(\boldsymbol{\theta})\, S_i S_j - \sum_{i<j<k} J^{(3)}_{ijk}(\boldsymbol{\theta})\, S_i S_j S_k - \cdots$$



$$p_{\boldsymbol{\theta}}(\boldsymbol{\sigma}) = \frac{e^{-\mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{\sigma})}}{Z_{\boldsymbol{\theta}}}$$

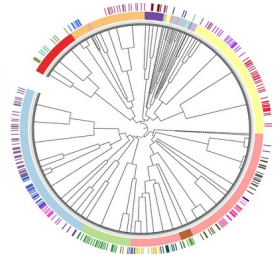
Free-energy landscape

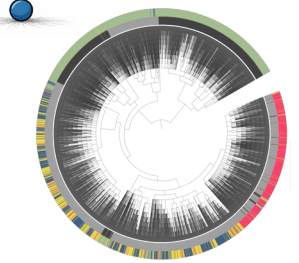
$\mathcal{F}_{\boldsymbol{\theta}}(\boldsymbol{m})$



Decelle, Rosset, **S**,
Physical Review E (2023)

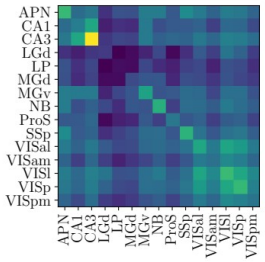
Hierarchical clustering
Unsupervised classification



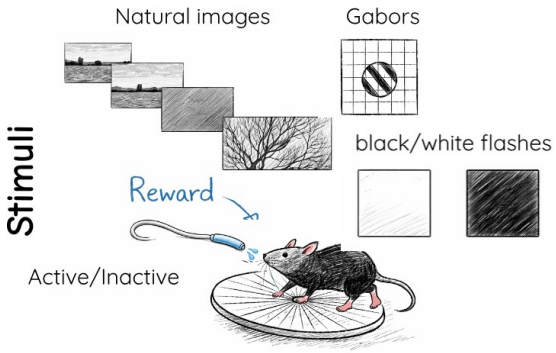


Ising - Decelle, Furtlehner, Navas Gómez, **S**, ***SciPost Phys.*** (2024)
Potts - Decelle, Navas-Gómez, **S**, *accepted in* ***Physical Review Letters*** (2025)

Multi-body
interaction
inference



Neural Activity - Béreux, Catania, Decelle, Mignacco, Navas Gómez, **S**. ArXiv (2026)

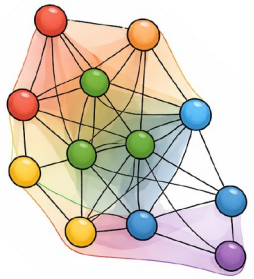


IPARCOS

Why EBMs ?

Energy function

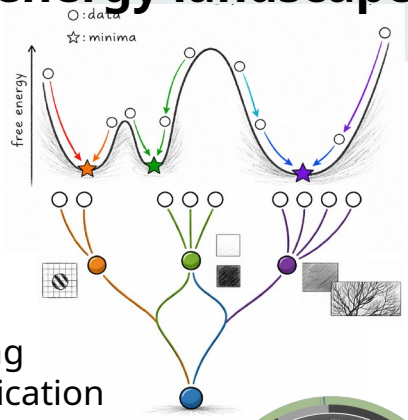
$$\mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{S}) = -\sum_i h_i(\boldsymbol{\theta})\, S_i - \sum_{i<j} J^{(2)}_{ij}(\boldsymbol{\theta})\, S_i S_j - \sum_{i<j<k} J^{(3)}_{ijk}(\boldsymbol{\theta})\, S_i S_j S_k - \cdots$$



$$p_{\boldsymbol{\theta}}(\boldsymbol{\sigma}) = \frac{e^{-\mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{\sigma})}}{Z_{\boldsymbol{\theta}}}$$

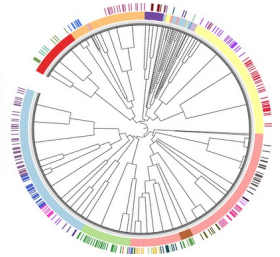
Free-energy landscape

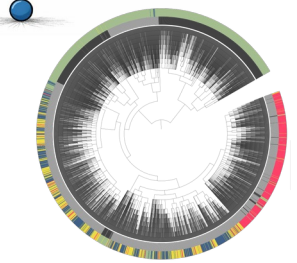
$\mathcal{F}_{\boldsymbol{\theta}}(\boldsymbol{m})$



Decelle, Rosset, **S**,
Physical Review E (2023)

Hierarchical clustering
Unsupervised classification

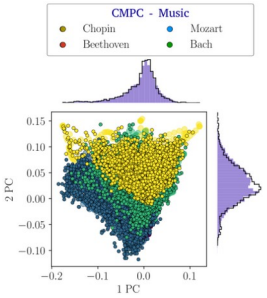


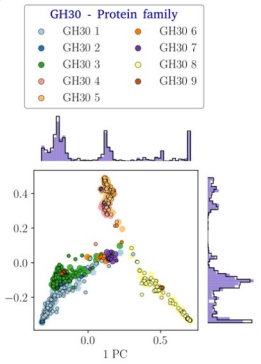


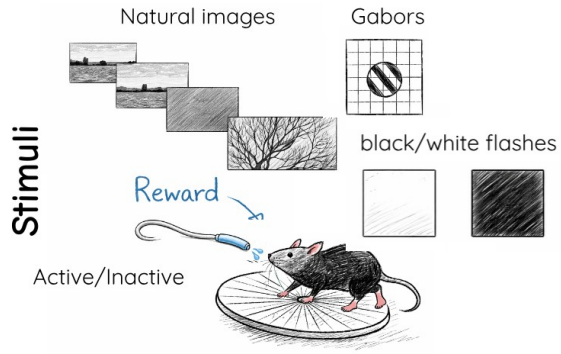
$p_{\boldsymbol{\theta}}(y)$ $p_{\boldsymbol{\theta}}(\boldsymbol{x}|y)$

Conditional generation

Carbone, Decelle, Rosset, **S**,
IEEE TPAMI (2025)

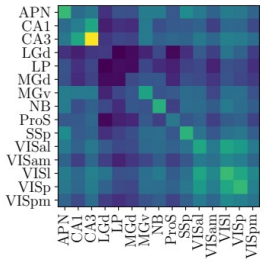






Ising - Decelle, Furtlehner, Navas Gómez, **S**, ***SciPost Phys.*** (2024)
Potts - Decelle, Navas-Gómez, **S**, *accepted in* ***Physical Review Letters*** (2025)

Multi-body interaction inference



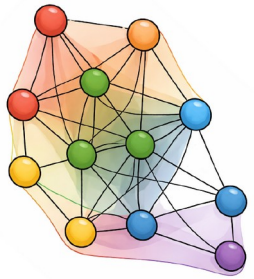
Neural Activity - Béreux, Catania, Decelle, Mignacco, Navas Gómez, **S**. ArXiv (2026)

IPARCOS

Why EBMs ?

Energy function

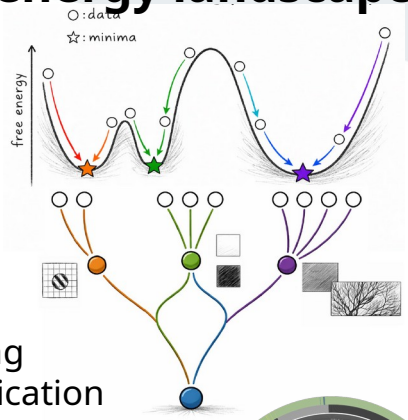
$$\mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{S}) = -\sum_i h_i(\boldsymbol{\theta})\, S_i - \sum_{i<j} J^{(2)}_{ij}(\boldsymbol{\theta})\, S_i S_j - \sum_{i<j<k} J^{(3)}_{ijk}(\boldsymbol{\theta})\, S_i S_j S_k - \cdots$$



$$p_{\boldsymbol{\theta}}(\boldsymbol{\sigma}) = \frac{e^{-\mathcal{H}_{\boldsymbol{\theta}}(\boldsymbol{\sigma})}}{Z_{\boldsymbol{\theta}}}$$

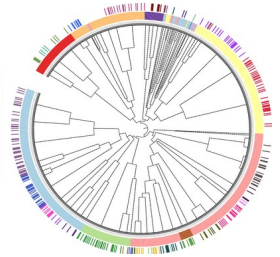
Free-energy landscape

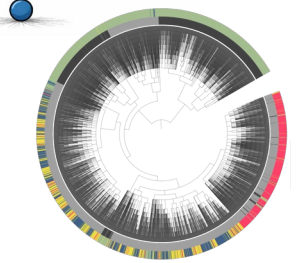
$\mathcal{F}_{\boldsymbol{\theta}}(\boldsymbol{m})$



Decelle, Rosset, **S**,
Physical Review E (2023)

Hierarchical clustering
Unsupervised classification

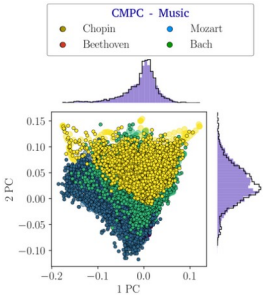


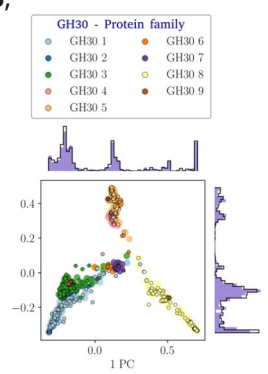


$p_{\boldsymbol{\theta}}(y)$ $p_{\boldsymbol{\theta}}(\boldsymbol{x}|y)$

Conditional generation

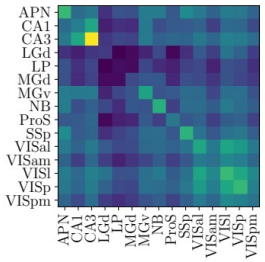
Carbone, Decelle, Rosset, **S**,
IEEE TPAMI (2025)



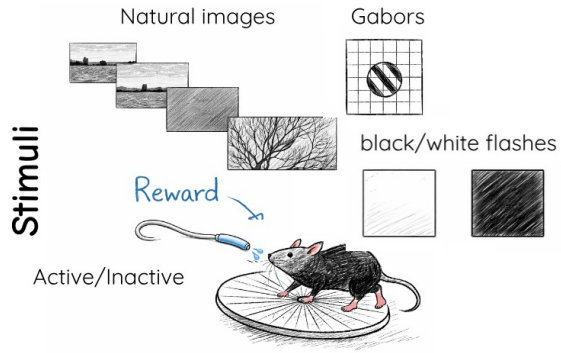


Ising - Decelle, Furtlehner, Navas Gómez, **S**, ***SciPost Phys.*** (2024)
Potts - Decelle, Navas-Gómez, **S**, *accepted in* ***Physical Review Letters*** (2025)

Multi-body interaction inference



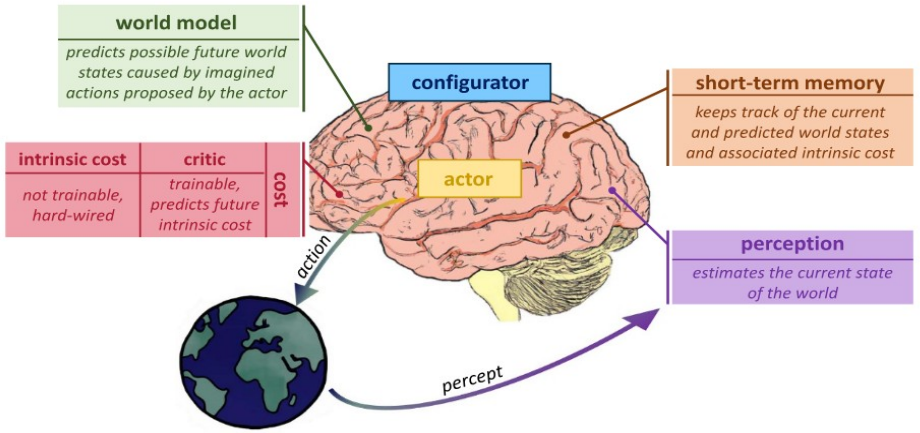
Neural Activity - Béreux, Catania, Decelle, Mignacco, Navas Gómez, **S**. ArXiv (2026)



Universal toolbox for data-driven studies across fields

IPARCOS

Why EBMs ?

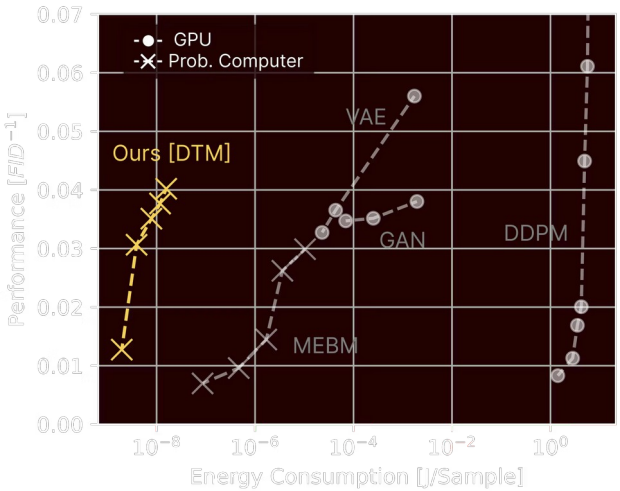


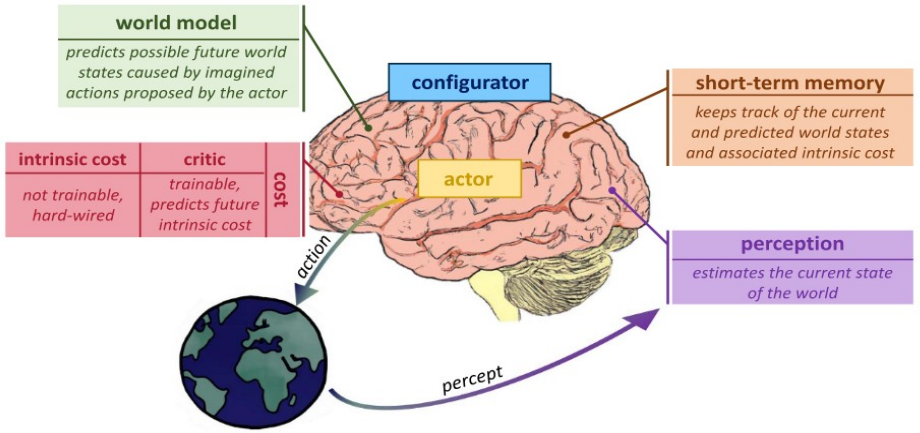
LeCun, Y. (2022). Open Review, 62(1), 1-62.
Dawid, A., & LeCun, Y. (2024). Journal of Statistical Mechanics: Theory and Experiment, 2024(10), 104011.

IPARCOS

Why EBMs ?

Thermodynamic sampling units (TSUs)





LeCun, Y. (2022). Open Review, 62(1), 1-62.
Dawid, A., & LeCun, Y. (2024). Journal of Statistical Mechanics: Theory and Experiment, 2024(10), 104011.

IPARCOS

ML Challenges

1) Making neural networks **interpretable** and **transparent**

2) Challenge the prevailing **“bigger is better”** paradigm

3) Ensure reliability even with **limited data**

IPARCOS

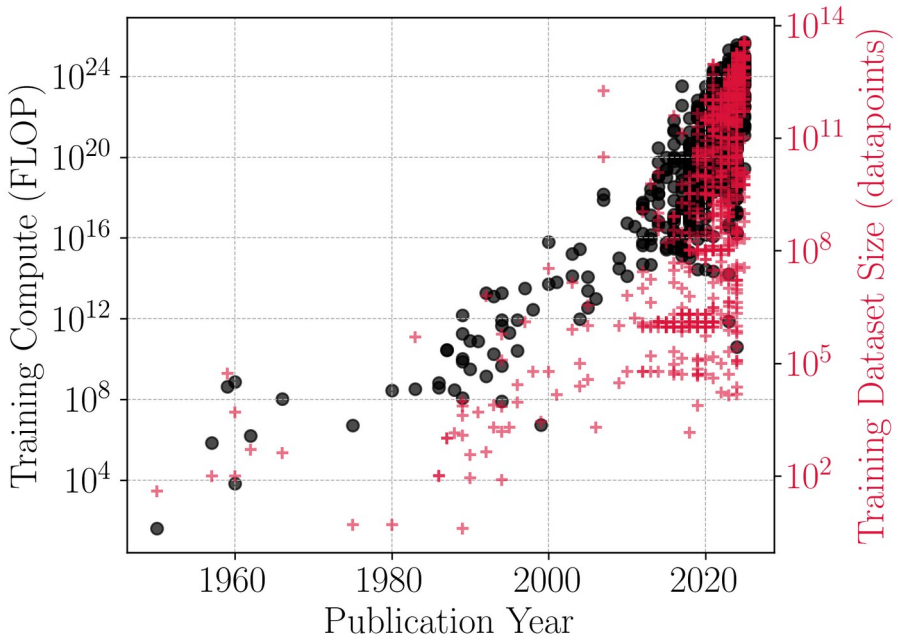
ML Challenges

1) Making neural networks **interpretable** and **transparent**

2) Challenge the prevailing **“bigger is better”** paradigm

3) Ensure reliability even with **limited data**

BeME



Data taken from Sevilla *et al.* epoch.ai/blog/compute-trends

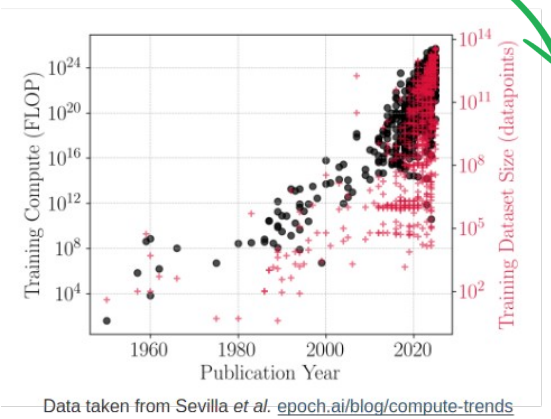
IPARCOS

ML Challenges

1) Making neural networks **interpretable** and **transparent**

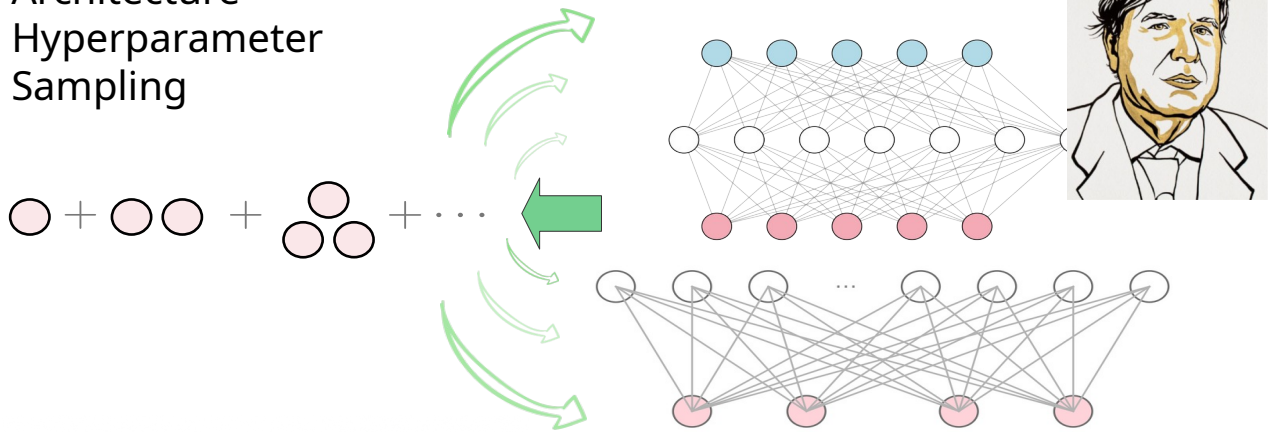
2) Challenge the prevailing **"bigger is better"** paradigm

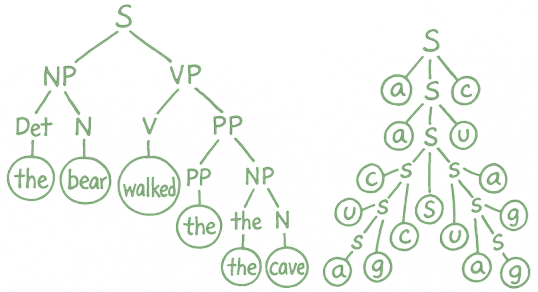
3) Ensure reliability even with **limited data**

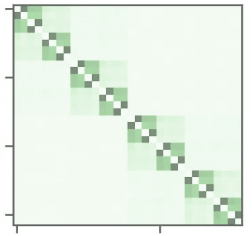


Theoretical insights

Architecture
Hyperparameter
Sampling







IPARCOS

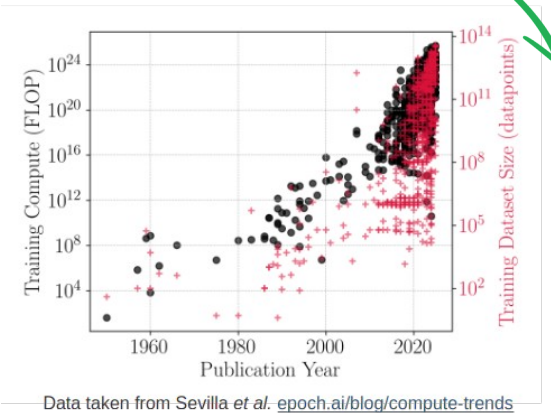
ML Challenges

BeME

1) Making neural networks **interpretable** and **transparent**

2) Challenge the prevailing **"bigger is better"** paradigm

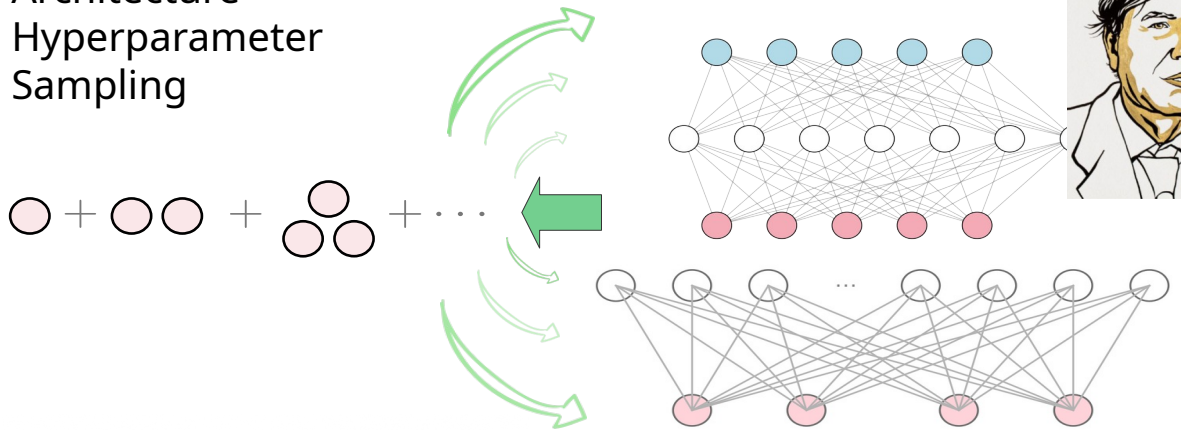
3) Ensure reliability even with **limited data**



Theoretical insights

Data cleaning
Regularization
Early-stopping protocols
Federated learning protocols

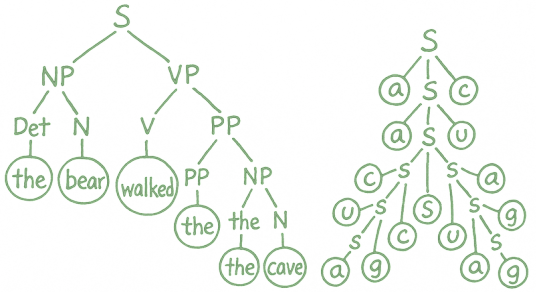
Architecture
Hyperparameter
Sampling

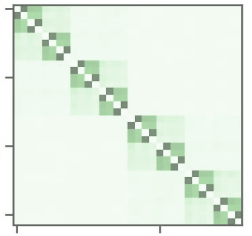


ICML 2025
International Conference On Machine Learning

A Theoretical Framework For Overfitting In Energy-based Modeling

Giovanni Catania [1] Aurélien Decelle [1 2] Cyril Furtlehner [3] Beatriz Seoane [1]

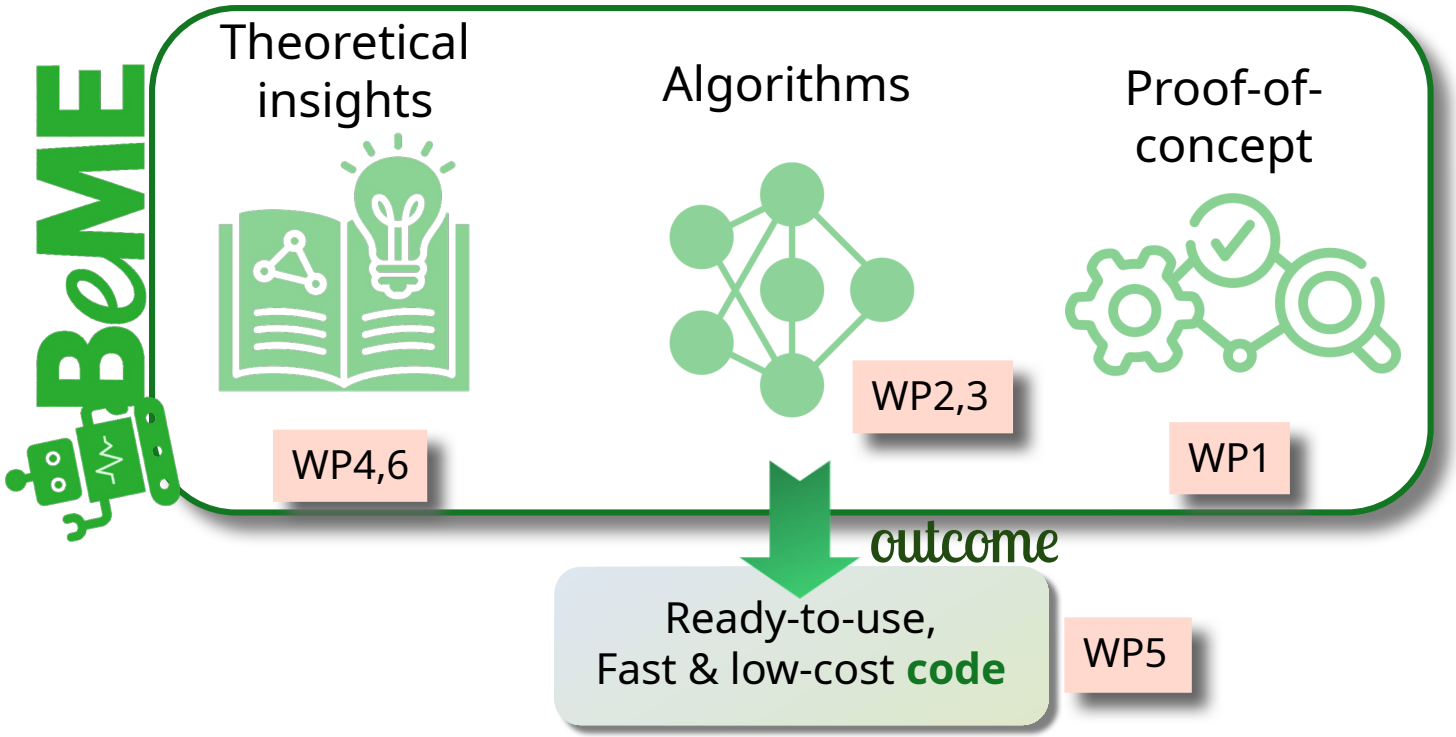




IPARCOS

IPARCOS

UNIVERSIDAD COMPLUTENSE MADRID

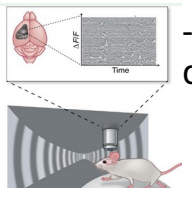


IPARCOS

UNIVERSIDAD COMPLUTENSE MADRID

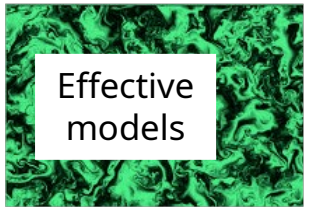
Proteins

Neuroscience

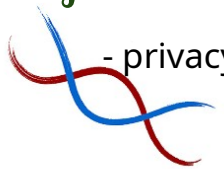


- feature detection

Turbulence



Human genome



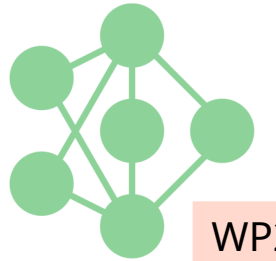
- privacy

BeME

Theoretical insights

WP4,6

Algorithms



WP2,3

Proof-of-concept

WP1

outcome

Ready-to-use,
Fast & low-cost **code**

WP5

IPARCOS

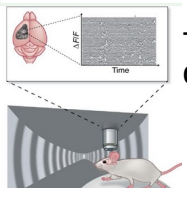
UNIVERSIDAD COMPLUTENSE MADRID

IPARCOS

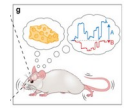
- Medical imaging
- Lattice gauge theory
- High energy experiments

Proteins

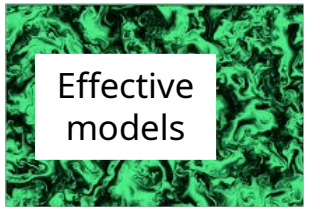
Neuroscience



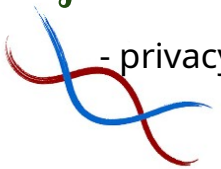
- feature detection



Turbulence



Human genome



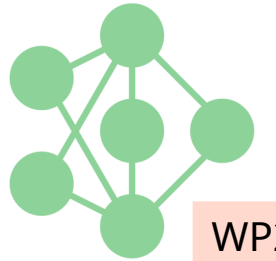
- privacy

BeME

Theoretical insights

WP4,6

Algorithms



WP2,3

Proof-of-concept

WP1

outcome

Ready-to-use,
Fast & low-cost **code**

WP5