

# Predictive Compression Dynamics: A Methodological Framework for Computable Information-Motivated Modeling

Mats Helander<sup>1</sup> and Jeeves<sup>1</sup>

<sup>1</sup>Independent Research

Dated: October 21, 2025

## Abstract

We present *Predictive Compression Dynamics* (PCD), a methodological recipe for constructing *computable*, local functionals  $\hat{\Phi}$  and driving dynamics by gradient flow  $\dot{x} = -\nabla\hat{\Phi}(x)$  with preregistered parameters. Two concrete instances are given: (i) a fixed-graph pair functional and (ii) a smooth compact-support kernel; both yield an attractive inverse-square two-body form (after calibration) and admit Lyapunov descent. These models serve as methodological demonstrations of computable, information-motivated dynamics. We make the MDL split  $L_{\text{tot}} = L(M) + L(D \mid M)$  explicit, give a minimal coding scheme linking  $-\hat{\Phi}$  descent to achievable  $\Delta L_{\text{tot}}$ , address well-posedness (smooth-kernel variant), recommend robust integrators (BAOAB for Langevin), and provide a preregistration/model-card template and falsifiers for a chosen model instance. The goal is a reproducible toolbox for compression-driven dynamics across domains.

## 1 Positioning and Commitments

A disciplined workflow to construct and test *computable* local functionals  $\hat{\Phi}$  whose gradients define dynamics, with explicit preregistration (domain, discretization, kernels, parameters) and sanity checks.

## 2 Operational Domain and Notation

We consider  $N$  point agents with positions  $x_i \in \mathbb{R}^3$  and positive weights  $m_i$ . Computations use finite precision: lattice spacing  $a_{\text{grid}}$  and  $b$  bits/axis, stated *a priori*. A global calibration constant  $G_{\text{eff}} > 0$  maps dimensionless forces to physical units. *Design choice*: we use the same  $m_i$  in the interaction and as inertial mass; this incidentally yields accelerations independent of  $m_i$  by construction.

## 3 Model–Data Decomposition and Coding Link

Following MDL, we split description length as

$$L_{\text{tot}} = L(M) + L(D \mid M), \quad (3.1)$$

where  $L(M)$  encodes modeled regularities and  $L(D \mid M)$  encodes residuals given  $M$ . A decrease  $\Delta L_{\text{tot}} < 0$  corresponds to realized compression. PCD treats a computable, local  $\hat{\Phi}$  as a proxy for (the negative of) an achievable  $\Delta L_{\text{tot}}$ ; thus  $\dot{x} = -\nabla\hat{\Phi}$  implements a descent in achievable codelength under the chosen surrogate. This identification is heuristic and intended only as a modelling analogy.

**Minimal explicit coding scheme.** Let  $(i, j)$  range over a symmetric set of “near” pairs. A two-part code describes (i) a shared pairwise template per distance bin and (ii) residual offsets:

- Partition distances into bins  $\{B_k\}$  with centers  $r_k$ ; encode the histogram counts with a prefix-free code.
- For each pair  $(i, j)$  with  $r_{ij} \in B_k$ , encode a residual offset relative to a shared template; the expected residual codelength per pair is a decreasing function  $\ell(r_{ij})$ .

Then, for fixed binning overhead and under mild regularity,

$$L_{\text{tot}} \approx \text{const} + \sum_{(i,j)} \ell(r_{ij}). \quad (3.2)$$

Choosing  $\hat{\Phi} \propto -\sum_{(i,j)} \ell(r_{ij})$  makes  $-\nabla \hat{\Phi}$  a proxy for the gradient of achievable compression. A smooth choice  $\ell(r) \approx (r^2 + a^2)^{-1/2}$  yields closed-form forces below.

## 4 Information-Motivated Functionals

### 4.1 Fixed-graph functional (corrected notation)

Let  $E \subset \{(i, j) : 1 \leq i < j \leq N\}$  be a symmetric, degree-bounded edge set. Define

$$\hat{\Phi}_E(x) = - \sum_{(i,j) \in E} \frac{m_i m_j}{\sqrt{\|x_i - x_j\|^2 + a^2}}, \quad a > 0. \quad (4.1)$$

The minus sign ensures attraction under descent;  $a$  regularizes collisions. The force on  $i$  is

$$F_i^{(E)}(x) = -\nabla_{x_i} \hat{\Phi}_E(x) = - \sum_{\substack{j: \\ (i,j) \in E}} m_i m_j \frac{(x_i - x_j)}{(\|x_i - x_j\|^2 + a^2)^{3/2}}. \quad (4.2)$$

Two-body,  $a \rightarrow 0$ ,  $(i, j) \in E$  gives the attractive inverse-square form:

$$F_i^{(E)} \rightarrow -m_i m_j \frac{x_i - x_j}{\|x_i - x_j\|^3}. \quad (4.3)$$

### 4.2 Smooth-kernel functional (well-posedness)

To avoid neighbor-set discontinuities, choose a compactly supported,  $C^1$  radial kernel  $K_\sigma : [0, \infty) \rightarrow \mathbb{R}_{\geq 0}$  with support  $\subset [0, R\sigma]$ . Define

$$\hat{\Phi}_K(x) = - \sum_{i < j} m_i m_j K_\sigma(\|x_i - x_j\|), \quad (4.4)$$

so  $F_i^{(K)}(x) = -\nabla_{x_i} \hat{\Phi}_K(x)$  is continuous and locally Lipschitz off collisions. If  $K_\sigma(r) \sim (r^2 + a^2)^{-1/2}$  near  $r = 0$ , one recovers the regularized two-body form (4.3).

## 5 Dynamics and Integrators

With  $\dot{x} = -\nabla \hat{\Phi}(x)$ ,

$$\frac{d}{dt} \hat{\Phi}(x(t)) = -\|\nabla \hat{\Phi}(x(t))\|^2 \leq 0, \quad (5.1)$$

so  $\hat{\Phi}$  is a Lyapunov function. We preregister all parameters  $(a_{\text{grid}}, b, a, \sigma, \Delta t, m_i, \gamma, T, \text{seeds})$ .

**Deterministic gradient flow.** Explicit Euler:

$$x_i^{(t+\Delta t)} = x_i^{(t)} + \Delta t F_i(x^{(t)}), \quad F_i \in \{F_i^{(E)}, F_i^{(K)}\}. \quad (5.2)$$

For stability, use adaptive  $\Delta t$  or semi-implicit variants.

**Underdamped Langevin (BAOAB recommended).**

$$m_i \ddot{x}_i = F_i(x) - \gamma \dot{x}_i + \xi_i(t), \quad \langle \xi_i(t) \xi_j(t') \rangle = 2\gamma k_B T \delta_{ij} \delta(t - t'). \quad (5.3)$$

We recommend the BAOAB integrator with reported weak/strong orders.

## 6 Sanity Checks

With  $a \rightarrow 0$  and a single pair, (4.3) holds (after one calibration  $G_{\text{eff}}$ ). For  $r \gg a$ ,

$$\frac{r}{(r^2 + a^2)^{3/2}} = \frac{1}{r^2} \left( 1 - \frac{3a^2}{2r^2} + O\left(\frac{a^4}{r^4}\right) \right), \quad (6.1)$$

so

$$\|F_i^{(E)}\| = m_i m_j \frac{r}{(r^2 + a^2)^{3/2}} \approx m_i m_j \frac{1}{r^2} \left( 1 - \frac{3a^2}{2r^2} \right). \quad (6.2)$$

These expansions serve purely as numerical consistency checks.

## 7 Well-posedness

For  $a > 0$  and bounded degree,  $\hat{\Phi}_E \in C^1(\mathbb{R}^{3N} \setminus \{x_i = x_j\})$  and  $F^{(E)}$  is locally Lipschitz off collisions. For  $C^1$  kernels with bounded  $K'_\sigma$ ,  $F^{(K)}$  is continuous and locally Lipschitz. Existence and uniqueness follow by Picard–Lindelöf on compact intervals. For dynamic  $k$ NN, forces are piecewise smooth; employ hysteresis or prefer the smooth kernel.

## 8 Preregistered Model Card (example)

**Domain.**  $a_{\text{grid}} = 10 \mu\text{m}$ ,  $b = 16$ .

**Functional.**  $\hat{\Phi}_K$  with Wendland  $C^2$  kernel ( $\sigma = 0.5 \text{ mm}$ ); softening  $a = 50 \mu\text{m}$ .

**Dynamics.** BAOAB underdamped with ( $m_i \equiv 1, \gamma = 0.1, T = 300 \text{ K}$ ),  $\Delta t = 1 \times 10^{-3} \text{ s}$ .

**Calibration.** Single  $G_{\text{eff}}$  fit in a dilute two-body sandbox at  $r \gg a$ .

**Sanity checks.** Verify (4.3) and the far-field expansion; report seeds and residuals.

## 9 Falsifiers for a chosen instance

Given fixed  $(\hat{\Phi}, \text{params})$ , declare the instance falsified if:

- (F1) Two-body trajectories disagree with the calibrated inverse-square form beyond numerical error.
- (F2) Smooth-kernel vs fixed-graph variants differ systematically at small  $r$  beyond topology effects.
- (F3) The code-length proxy correlates poorly with realized compression in controlled tests (e.g.  $-\hat{\Phi}$  vs measured  $L_{\text{tot}}$ ).

## 10 Discussion and Scope

PCD supplies a reproducible route from *computable* information-motivated functionals to concrete dynamics. Future work will extend this framework to broader estimator families under the same preregistration discipline.

## Acknowledgments

We thank colleagues for discussions on local estimators, kernels, integrators, and  $N$ -body numerics. Earlier drafts that explored alternative framings are superseded by this methodological formulation.

## References

## References

- [1] C. E. Shannon, “A mathematical theory of communication,” *Bell Syst. Tech. J.* (1948).
- [2] J. Rissanen, “Modeling by shortest data description,” *Automatica* (1978).
- [3] L. A. Levin, “On the notion of a random sequence,” *Sov. Math. Dokl.* (1971).
- [4] S. Amari, *Information Geometry and Its Applications*, Springer (2016).
- [5] R. Jordan, D. Kinderlehrer, F. Otto, “The variational formulation of the Fokker–Planck equation,” *SIAM J. Math. Anal.* **29** (1998).
- [6] A. Caticha, *Entropic Inference and the Foundations of Physics*, (2012).
- [7] H. Wendland, “Piecewise polynomial, positive definite and compactly supported radial functions,” *Adv. Comput. Math.* **4** (1995) 389–396.
- [8] B. Leimkuhler, M. Matthews, “Rational construction of stochastic numerical methods for molecular sampling,” *Appl. Math. Res. eXpress* (2013).
- [9] B. Leimkuhler, C. Matthews, *Molecular Dynamics*, Springer (2016).
- [10] R. C. Prim, “Shortest connection networks and some generalizations,” *Bell Syst. Tech. J.* **36**, 1389–1401 (1957).
- [11] L. Hernquist, “An analytical model for spherical galaxies and bulges,” *ApJ* **356**, 359–364 (1990).
- [12] H. C. Plummer, “On the problem of distribution in globular star clusters,” *MNRAS* **71**, 460–470 (1911).