

A Neural Score-Based Particle Method for the Vlasov-Maxwell-Landau Equation

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1 Introduction

- The Vlasov-Maxwell-Landau (VML) equation
- Numerical challenge and goal of this work

2 A neural score-based particle method for the VML equation

- Spatially homogeneous case
- Spatially inhomogeneous case
- Time discretization

3 Numerical results

4 Conclusion

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The Vlasov-Maxwell-Landau (VML) equation

$$\partial_t f + \mathbf{v} \cdot \nabla_{\mathbf{x}} f + (\mathbf{E} + \mathbf{v} \times \mathbf{B}) \cdot \nabla_{\mathbf{v}} f = \nu Q(f)$$

- A **kinetic model** often regarded as first-principles physics for weakly interacting plasmas
- $f = f(t, \mathbf{x}, \mathbf{v})$: electron **probability density function (PDF)**
 - $f \, d\mathbf{x} \, d\mathbf{v}$ gives the probability of finding a fixed electron at time t , position $\mathbf{x} \in \Omega_{\mathbf{x}} \subset \mathbb{R}^3$ and velocity $\mathbf{v} \in \mathbb{R}^3$ in the phase space
- **E and B: electric and magnetic fields**
 - given externally or determined self-consistently via the Maxwell's equations

$$\partial_t \mathbf{E} = \nabla_{\mathbf{x}} \times \mathbf{B} - \mathbf{J}, \quad \partial_t \mathbf{B} = -\nabla_{\mathbf{x}} \times \mathbf{E}, \quad \nabla_{\mathbf{x}} \cdot \mathbf{E} = \rho - \rho_i, \quad \nabla_{\mathbf{x}} \cdot \mathbf{B} = 0,$$

where $\rho = \int_{\mathbb{R}^3} f \, d\mathbf{v}$ is the charge density and $\mathbf{J} = \int_{\mathbb{R}^3} f \mathbf{v} \, d\mathbf{v}$ is the current density. ρ_i is the background ion density.

- $Q(f)$: **Landau collision operator** (ν is the collision frequency)
 - a nonlinear integro-differential operator modeling Coulomb collisions between charged particles
 - can be derived from the Boltzmann collision operator when all collisions become grazing (i.e., the scattering angle $\rightarrow 0$)

The Landau collision operator¹

$$Q(f)(t, \mathbf{x}, \mathbf{v}) = \nabla_{\mathbf{v}} \cdot \int_{\mathbb{R}^3} A(\mathbf{v} - \mathbf{v}_*) [f(t, \mathbf{x}, \mathbf{v}_*) \nabla_{\mathbf{v}} f(t, \mathbf{x}, \mathbf{v}) - f(t, \mathbf{x}, \mathbf{v}) \nabla_{\mathbf{v}_*} f(t, \mathbf{x}, \mathbf{v}_*)] d\mathbf{v}_*$$

where A is a semi-positive-definite matrix given by

$$A(\mathbf{v} - \mathbf{v}_*) = |\mathbf{v} - \mathbf{v}_*|^\gamma (|\mathbf{v} - \mathbf{v}_*|^2 I_3 - (\mathbf{v} - \mathbf{v}_*) \otimes (\mathbf{v} - \mathbf{v}_*)),$$

with $-3 \leq \gamma \leq 1$ ($\gamma = -3$: Coulomb collisions).

A nonlocal, quadratic, diffusive type operator **acting only in the velocity space**

Two equivalent formulations (neglecting \mathbf{x} and t dependence):

- **Rosenbluth-Fokker-Planck form:**

$$Q(f)(\mathbf{v}) = \nabla_{\mathbf{v}} \cdot (A_f \nabla_{\mathbf{v}} f - a_f f), \quad A_f = A * f, \quad a_f = \nabla_{\mathbf{v}} \cdot A_f$$

- **“log” form**

$$Q(f)(\mathbf{v}) = \nabla_{\mathbf{v}} \cdot \int_{\mathbb{R}^3} A(\mathbf{v} - \mathbf{v}_*) [\nabla_{\mathbf{v}} \log f(\mathbf{v}) - \nabla_{\mathbf{v}_*} \log f(\mathbf{v}_*)] f(\mathbf{v}) f(\mathbf{v}_*) d\mathbf{v}_*$$

¹Landau, '36.

Properties of the Landau operator

From the “**log**” form one can easily derive the **weak form**: for a test function $\phi(\mathbf{v})$

$$\begin{aligned} & \int_{\mathbb{R}^3} \mathcal{Q}(f)(\mathbf{v}) \phi(\mathbf{v}) \, d\mathbf{v} \\ &= -\frac{1}{2} \iint_{\mathbb{R}^6} [\nabla_{\mathbf{v}} \phi(\mathbf{v}) - \nabla_{\mathbf{v}_*} \phi(\mathbf{v}_*)]^T A(\mathbf{v} - \mathbf{v}_*) [\nabla_{\mathbf{v}} \log f(\mathbf{v}) - \nabla_{\mathbf{v}_*} \log f(\mathbf{v}_*)] f(\mathbf{v}) f(\mathbf{v}_*) \, d\mathbf{v} \, d\mathbf{v}_* \end{aligned}$$

- **Conservation** of mass, momentum, and energy:

$$\int_{\mathbb{R}^3} \mathcal{Q}(f) \, d\mathbf{v} = \int_{\mathbb{R}^3} \mathcal{Q}(f) \mathbf{v} \, d\mathbf{v} = \int_{\mathbb{R}^3} \mathcal{Q}(f) |\mathbf{v}|^2 \, d\mathbf{v} = 0$$

- **Decay of entropy** (H -theorem):

$$\int_{\mathbb{R}^3} \mathcal{Q}(f) \log f \, d\mathbf{v} \leq 0$$

where “=” holds iff f is the **Maxwellian** $\mathcal{M}[f] := \frac{n}{(2\pi T)^{3/2}} e^{-\frac{|\mathbf{v}-\mathbf{u}|^2}{2T}}$

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Particle-in-cell (PIC) method

Due to high dimensionality of the VML equation (6 dimension + time), the predominant numerical method is the **particle-in-cell method**²:

$$f^N(t, \mathbf{x}, \mathbf{v}) = \sum_{p=1}^N w_p \delta(\mathbf{x} - \mathbf{x}_p(t)) \delta(\mathbf{v} - \mathbf{v}_p(t))$$

where \mathbf{x}_p : particle position, \mathbf{v}_p : particle velocity, w_p : particle weight, N : number of particles.

$$\begin{cases} \frac{d\mathbf{x}_p}{dt} = \mathbf{v}_p \\ \frac{d\mathbf{v}_p}{dt} = \mathbf{E}(t, \mathbf{x}_p) + \mathbf{v}_p \times \mathbf{B}(t, \mathbf{x}_p) \end{cases}$$

— trace \mathbf{x}_p , \mathbf{v}_p by following the characteristics and update \mathbf{E} and \mathbf{B} by solving the field equations on a mesh

- Natural to treat the Hamiltonian system (**Vlasov equation without collisions**)
- “Gold standard” in today’s large scale plasma simulations
- Modern PIC can preserve the conservation properties³

²Birdsall and Langdon, '18. Hockney and Eastwood, '10.

³Chen, Chacon, and Barnes, '11. Lapenta, '17. Kraus, Kormann, Morrison, and Sonnendruker, '17.

Numerical challenge when including collisions

- Coulomb collisions are an integral and important aspect of plasma dynamics but are often neglected due to their high complexity
- Some collisional algorithms:
 - **Monte Carlo Collisions (MCC)**⁴
 - **Direct Simulation Monte Carlo (DSMC)**⁵
 - **Langevin dynamics (SDE)**⁶

Collisions are added as a separate step via time splitting. Stochastic nature, introducing statistical noise. First-order temporal accuracy at best. Nice properties preserved in the (collisionless) PIC are not guaranteed.

⁴Birdsall, '91.

⁵Takizuka and Abe, '77. Bobilev and Nanbu, '00. Dimarco, Caflisch, and Pareschi, '10.

⁶Manheimer, Lampe, and Joyce, '97.

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Goal of this work: Introduce a particle method to handle Coulomb collisions in plasmas, which can be naturally coupled with the classical PIC to create a structure-preserving particle method for the full Vlasov-Maxwell-Landau system.

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⁵Takizuka and Abe, '77. Bobilev and Nanbu, '00. Dimarco, Caflisch, and Pareschi, '10.

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Spatially homogeneous Landau equation

$$\partial_t f = \mathcal{Q}(f) = \nabla_{\mathbf{v}} \cdot \int_{\mathbb{R}^3} A(\mathbf{v} - \mathbf{v}_*) [\nabla_{\mathbf{v}} \log f(\mathbf{v}) - \nabla_{\mathbf{v}_*} \log f(\mathbf{v}_*)] f(\mathbf{v}) f(\mathbf{v}_*) d\mathbf{v}_*$$

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$$= \nabla_{\mathbf{v}} \cdot \{ \mathbf{U}[f] f \}, \quad \text{a transport operator with "collision force" } \mathbf{U}[f]$$

where

$$\mathbf{U}[f] := \int_{\mathbb{R}^3} A(\mathbf{v} - \mathbf{v}_*) [\nabla_{\mathbf{v}} \log f(\mathbf{v}) - \nabla_{\mathbf{v}_*} \log f(\mathbf{v}_*)] f(\mathbf{v}_*) d\mathbf{v}_*$$

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The particle method seeks a (weak) solution of the form:

$$f^N(t, \mathbf{v}) = \sum_{p=1}^N w_p \delta(\mathbf{v} - \mathbf{v}_p(t)),$$

then \mathbf{v}_p satisfies

$$\frac{d\mathbf{v}_p}{dt} = -\mathbf{U}[f^N](\mathbf{v}_p) = -\sum_{q=1}^N w_q A(\mathbf{v}_p - \mathbf{v}_q) [\nabla_{\mathbf{v}} \log f^N(\mathbf{v}_p) - \nabla_{\mathbf{v}} \log f^N(\mathbf{v}_q)]$$

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Key observation: The collision force $\mathbf{U}[f^N]$ depends on the distribution function through the **score function** $\nabla_{\mathbf{v}} \log f^N$.

Score approximation

Therefore, if we know a good approximation $s(\mathbf{v})$ to $\nabla_{\mathbf{v}} \log f^N(\mathbf{v})$, we are done!

$$\frac{d\mathbf{v}_p}{dt} = -\mathbf{U}[f^N](\mathbf{v}_p) \approx -\sum_{q=1}^N w_q A(\mathbf{v}_p - \mathbf{v}_q) [s(\mathbf{v}_p) - s(\mathbf{v}_q)]$$

Q: Given particle samples $\{\mathbf{v}_p\}_{p=1}^N$, how can we approximate the score $\nabla_{\mathbf{v}} \log f^N$?

⁷Degond and Mustieles, '90.

⁸Carrillo, Craig, and Patacchini, '19.

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Q: Given particle samples $\{\mathbf{v}_p\}_{p=1}^N$, how can we approximate the score $\nabla_{\mathbf{v}} \log f^N$?

- **Traditional particle (blob) method**⁷:

$$s(\mathbf{v}) = \nabla_{\mathbf{v}} \log(\varphi^\varepsilon * f^N),$$

where φ^ε is a mollifier (typically Gaussian). Need to choose the bandwidth ε properly.

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- **Entropy-decaying (blob) particle method**⁸:

Noting that $\nabla_{\mathbf{v}} \log f = \nabla_{\mathbf{v}} \frac{\delta H}{\delta f}$, where $H(f) = \int f \log f \, d\mathbf{v}$

$$s(\mathbf{v}) = \nabla_{\mathbf{v}} \frac{\delta H^\varepsilon}{\delta f} [f^N], \quad H^\varepsilon = \int f \log(\varphi^\varepsilon * f) \, d\mathbf{v}$$

⁷Degond and Mustieles, '90.

⁸Carrillo, Craig, and Patacchini, '19.

Score approximation

- If we view the problem as **score matching**⁹:

$$\min_{s \in \mathcal{F}} \int |\nabla_{\mathbf{v}} \log f - s|^2 f \, d\mathbf{v} \implies \min_{s \in \mathcal{F}} \sum_{p=1}^N w_p [2\nabla_{\mathbf{v}} \cdot s(\mathbf{v}_p) + |s(\mathbf{v}_p)|^2]$$

$$\begin{aligned} \int |\nabla_{\mathbf{v}} \log f - s|^2 f \, d\mathbf{v} &= \int (|\nabla_{\mathbf{v}} \log f|^2 - 2\nabla_{\mathbf{v}} \log f \cdot s + |s|^2) f \, d\mathbf{v} \\ &= \int (2\nabla_{\mathbf{v}} \cdot s + |s|^2) f \, d\mathbf{v} + C \end{aligned}$$

Choosing \mathcal{F} as the neural network leads to the

score-based transport modeling (SBTM)¹⁰

Remark: The network is pretrained on the known analytic score of the initial condition. At each subsequent time step, perform a fixed number of steps of gradient descent.

⁹Hyvarinen, '05. Maoutsa, Reich, and Opper, '20.

¹⁰Boffi and Vanden-Eijnden, '23.

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$$\begin{aligned} Q(f)(\mathbf{x}, \mathbf{v}) &= \nabla_{\mathbf{v}} \cdot \int_{\mathbb{R}^3} A(\mathbf{v} - \mathbf{v}_*) [\nabla_{\mathbf{v}} \log f(\mathbf{x}, \mathbf{v}) - \nabla_{\mathbf{v}_*} \log f(\mathbf{x}, \mathbf{v}_*)] f(\mathbf{x}, \mathbf{v}) f(\mathbf{x}, \mathbf{v}_*) d\mathbf{v}_* \\ &= \nabla_{\mathbf{v}} \cdot \{\mathbf{U}[f]f\} \end{aligned}$$

where

$$\mathbf{U}[f](\mathbf{x}, \mathbf{v}) := \int_{\mathbb{R}^3} A(\mathbf{v} - \mathbf{v}_*) [\nabla_{\mathbf{v}} \log f(\mathbf{x}, \mathbf{v}) - \nabla_{\mathbf{v}_*} \log f(\mathbf{x}, \mathbf{v}_*)] f(\mathbf{x}, \mathbf{v}_*) d\mathbf{v}_*$$

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For a particle solution of the form

$$f^N(t, \mathbf{v}) = \sum_{p=1}^N w_p \delta(\mathbf{x} - \mathbf{x}_p(t)) \delta(\mathbf{v} - \mathbf{v}_p(t)),$$

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$$\frac{d\mathbf{v}_p}{dt} = \mathbf{E}(t, \mathbf{x}_p) + \mathbf{v}_p \times \mathbf{B}(t, \mathbf{x}_p) - \nu \underbrace{\mathbf{U}[f^N](\mathbf{x}_p, \mathbf{v}_p)}_{??}$$

Regularized Landau operator

$$\mathbf{U}[f](\mathbf{x}, \mathbf{v}) = \int_{\mathbb{R}^3} A(\mathbf{v} - \mathbf{v}_*) [\nabla_{\mathbf{v}} \log f(\mathbf{x}, \mathbf{v}) - \nabla_{\mathbf{v}_*} \log f(\mathbf{x}, \mathbf{v}_*)] f(\mathbf{x}, \mathbf{v}_*) d\mathbf{v}_*$$

We propose to regularize $\mathbf{U}[f]$ as¹¹

$$\mathbf{U}^h[f](\mathbf{x}, \mathbf{v}) = \iint_{\Omega_{\mathbf{x}} \times \mathbb{R}^3} \psi_h(\mathbf{x} - \mathbf{x}_*) A(\mathbf{v} - \mathbf{v}_*) [\nabla_{\mathbf{v}} \log f(\mathbf{x}, \mathbf{v}) - \nabla_{\mathbf{v}_*} \log f(\mathbf{x}_*, \mathbf{v}_*)] \\ \times f(\mathbf{x}_*, \mathbf{v}_*) d\mathbf{v}_* d\mathbf{x}_*$$

- When considering collisions at a spatial point \mathbf{x} , we first *localize* particles to the neighborhood of \mathbf{x} ; then within this neighborhood, we *delocalize* to associate each particle with a distinct position.
- We choose $\psi_h(\mathbf{x})$ as the B-spline (h is the cell size)

¹¹Bailo, Carrillo, and H., '24.

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- When considering collisions at a spatial point \mathbf{x} , we first *localize* particles to the neighborhood of \mathbf{x} ; then within this neighborhood, we *delocalize* to associate each particle with a distinct position.
- We choose $\psi_h(\mathbf{x})$ as the B-spline (h is the cell size)

Now if we plug in f^N , we obtain

$$\mathbf{U}^h[f^N](\mathbf{x}_p, \mathbf{v}_p) = \sum_{q=1}^N w_q \psi_h(\mathbf{x}_p - \mathbf{x}_q) A(\mathbf{v}_p - \mathbf{v}_q) [\nabla_{\mathbf{v}} \log f^N(\mathbf{x}_p, \mathbf{v}_p) - \nabla_{\mathbf{v}} \log f^N(\mathbf{x}_q, \mathbf{v}_q)]$$

¹¹Bailo, Carrillo, and H., '24.

Replacing $\nabla_{\mathbf{v}} \log f^N$ by the score approximation...

We have a simple neural score-based particle method for the VML equation¹²:

$$\begin{cases} \frac{d\mathbf{x}_p}{dt} = \mathbf{v}_p \\ \frac{d\mathbf{v}_p}{dt} = \mathbf{E}(t, \mathbf{x}_p) + \mathbf{v}_p \times \mathbf{B}(t, \mathbf{x}_p) - \nu \mathbf{U}^h[f^N](\mathbf{x}_p, \mathbf{v}_p) \end{cases}$$

where

$$\mathbf{U}^h[f^N](\mathbf{x}_p, \mathbf{v}_p) = \sum_{q=1}^N w_q \psi_h(\mathbf{x}_p - \mathbf{x}_q) A(\mathbf{v}_p - \mathbf{v}_q) [s(\mathbf{x}_p, \mathbf{v}_p) - s(\mathbf{x}_q, \mathbf{v}_q)]$$

- Learn $s(\mathbf{x}_p, \mathbf{v}_p)$ from $\{\mathbf{x}_p, \mathbf{v}_p\}_{p=1}^N$

$$\min_{s \in \mathcal{F}} \int_{\Omega_{\mathbf{x}} \times \mathbb{R}^3} |\nabla_{\mathbf{v}} \log f - s|^2 f \, d\mathbf{v} \, d\mathbf{x} \implies \min_{s \in \mathcal{F}} \sum_{p=1}^N w_p [2\nabla_{\mathbf{v}} \cdot s(\mathbf{x}_p, \mathbf{v}_p) + |s(\mathbf{x}_p, \mathbf{v}_p)|^2]$$

- Compared with the traditional particle (blob) method, it does not require regularization/mollification in velocity space

$$s(\mathbf{x}_p, \mathbf{v}_p) = \nabla_{\mathbf{v}} \log \left(\sum_{q=1}^N w_q \varphi_{\varepsilon}(\mathbf{v}_p - \mathbf{v}_q) \psi_h(\mathbf{x}_p - \mathbf{x}_q) \right)$$

¹²Ilin and H., 2026.

Preserving the properties

For the regularized “collision force” $\mathbf{U}^h[f^N](\mathbf{x}_p, \mathbf{v}_p)$, one can show that for a test function $\phi(\mathbf{x}, \mathbf{v})$:

$$\begin{aligned} \sum_p w_p \phi(\mathbf{x}_p, \mathbf{v}_p) \cdot \mathbf{U}^h[f^N](\mathbf{x}_p, \mathbf{v}_p) &= \frac{1}{2} \sum_{p,q} w_p w_q \psi_h(\mathbf{x}_p - \mathbf{x}_q) [\phi(\mathbf{x}_p, \mathbf{v}_p) - \phi(\mathbf{x}_q, \mathbf{v}_q)]^T \\ &\quad \times A(\mathbf{v}_p - \mathbf{v}_q) [s(\mathbf{x}_p, \mathbf{v}_p) - s(\mathbf{x}_q, \mathbf{v}_q)] \end{aligned}$$

— This is the **discrete weak form** of the regularized Landau operator.

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— This is the **discrete weak form** of the regularized Landau operator.

- **Conservation** of momentum and energy:

$$\sum_p w_p \mathbf{U}^h[f^N](\mathbf{x}_p, \mathbf{v}_p) = 0, \quad \sum_p w_p \mathbf{v}_p \cdot \mathbf{U}^h[f^N](\mathbf{x}_p, \mathbf{v}_p) = 0$$

- **Estimated entropy decay:**

$$-\sum_p w_p s(\mathbf{x}_p, \mathbf{v}_p) \cdot \mathbf{U}^h[f^N](\mathbf{x}_p, \mathbf{v}_p) \leq 0$$

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How about the time discretization?

We have obtained a (semi-discrete) particle method for the VML equation:

$$\begin{cases} \frac{d\mathbf{x}_p}{dt} = \mathbf{v}_p \\ \frac{d\mathbf{v}_p}{dt} = \mathbf{E}(t, \mathbf{x}_p) + \mathbf{v}_p \times \mathbf{B}(t, \mathbf{x}_p) - \nu \mathbf{U}^h[f^N](\mathbf{x}_p, \mathbf{v}_p) \end{cases}$$

Provided the Maxwell's equations are discretized properly (e.g., Yee's lattice), this scheme can conserve the total (semi-discrete) energy of the system:

$$E_{\text{total}} := \sum_{p=1}^N w_p \frac{1}{2} |\mathbf{v}_p|^2 + \sum_h \left(\frac{1}{2} |\mathbf{E}(t, \mathbf{x}_h)|^2 + \frac{1}{2} |\mathbf{B}(t, \mathbf{x}_h)|^2 \right) h^3 = \text{const}$$

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Q: Can we design a time discretization such that the fully discrete scheme is energy-conserving?

— An implicit scheme can achieve so (e.g., implicit midpoint); however, collisions are the most computationally expensive part of the simulation and are better treated explicitly.

An explicit energy-conserving time discretization¹³

$$\begin{aligned}\mathbf{x}_p^* &= \mathbf{x}_p^n + \frac{\Delta t}{2} \mathbf{v}_p^n, \\ \mathbf{v}_p^* &= \mathbf{v}_p^n + \frac{\Delta t}{2} \mathbf{E}_p^{n,*} - \frac{\Delta t}{2} \nu \mathbf{U}^h[f^N](\mathbf{x}_p^*, \mathbf{v}_p^n), \\ \mathbf{x}_p^{n+1} &= \mathbf{x}_p^n + \Delta t \mathbf{v}_p^*, \\ \mathbf{E}_h^{n+1} &= \mathbf{E}_h^n - \Delta t \mathbf{J}_h^{*,*}, \\ \mathbf{v}_p^\dagger &= \mathbf{v}_p^n + \Delta t \mathbf{E}_p^{n+\frac{1}{2},*} - \Delta t \nu \mathbf{U}^h[f^N](\mathbf{x}_p^*, \mathbf{v}_p^*), \\ \mathbf{v}_p^{n+1} &= \Gamma_p^n \mathbf{v}_p^\dagger, \quad \Gamma_p^n = \sqrt{1 + 2(\mathbf{v}_p^* - \frac{\mathbf{v}_p^\dagger + \mathbf{v}_p^n}{2}) \cdot (\mathbf{v}_p^\dagger - \mathbf{v}_p^n) / |\mathbf{v}_p^\dagger|^2}.\end{aligned}$$

Can show that $E_{\text{total}}^{n+1} = E_{\text{total}}^n$ – a key property used to achieve energy conservation

$$\sum_p w_p \mathbf{v}_p^* \cdot \mathbf{U}^h[f^N](\mathbf{x}_p^*, \mathbf{v}_p^*) = 0 \iff \text{exactly satisfied by our particle method!}$$

Remark: Second order accuracy; can be extended to the electromagnetic case.

¹³Yoo, H., and Ricketson, '25 (arXiv:2510.03960).

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Numerical results – Landau damping

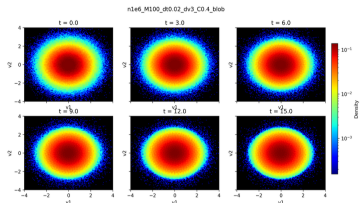
We initialize the plasma as

$$f_0(x, \mathbf{v}) = \frac{1 + \alpha \cos(kx)}{(2\pi)^{3/2}} \exp\left(-\frac{|\mathbf{v}|^2}{2}\right)$$

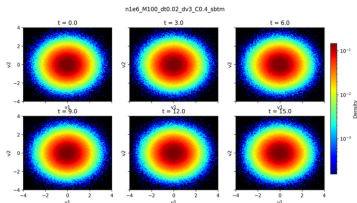
with wavenumber $k = 0.5$ and domain $L = 2\pi/k$, $\alpha = 0.1$, $M = 100$ spatial cells, $\Delta t = 0.2$, $\nu = 0.4$, $t_{\text{final}} = 15$, $K = 100$ gradient steps, sweeping over particle numbers $N = 5 \times 10^5, 10^6, 3 \times 10^6$.

We compare SBTM and the blob method. Forward Euler is used for simplicity.

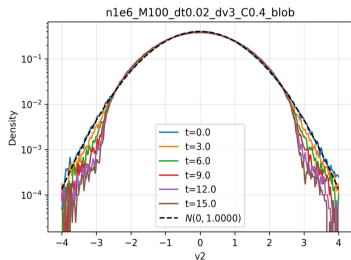
Numerical results – Landau damping



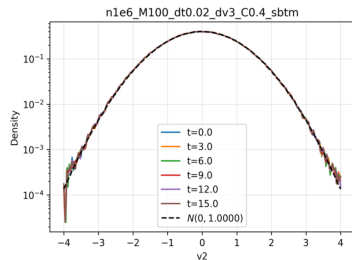
(a) Blob, $\nu = 0.4$



(b) SBTM, $\nu = 0.4$



(c) Blob, v_2 -marginal (log), $\nu = 0.4$



(d) SBTM, v_2 -marginal (log), $\nu = 0.4$

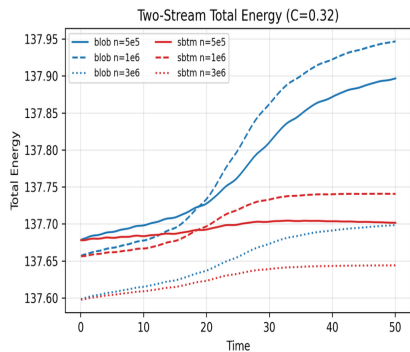
Numerical results – Two stream instability

We initialize the plasma as

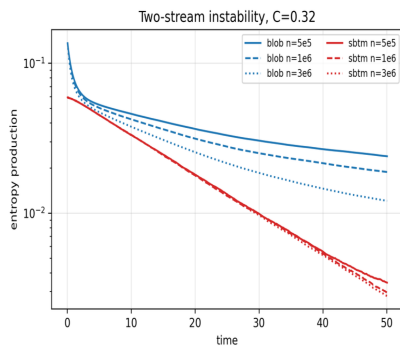
$$f_0(x, \mathbf{v}) = \frac{1 + \alpha \cos(kx)}{2} [\mathcal{N}(v_1; c, 1) + \mathcal{N}(v_1; -c, 1)] \prod_{j=2,3} \mathcal{N}(v_j; 0, 1)$$

with $c = 2.4$, wavenumber $k = 1/5$ and domain $L = 2\pi/k$, $\alpha = 1/200$, $M = 100$ spatial cells, $\Delta t = 0.05$, $\nu = 0.32$, $t_{\text{final}} = 50$, $K = 100$ gradient steps, sweeping over particle numbers $N = 5 \times 10^5, 10^6, 3 \times 10^6$.

Numerical results – Two stream instability

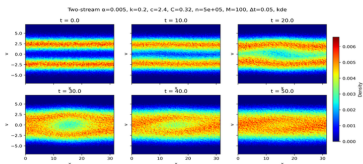


(c) Total energy

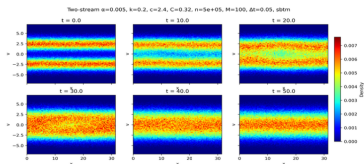


(d) Estimated entropy production

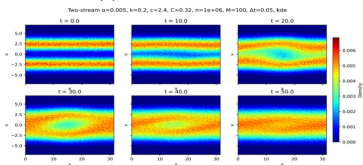
Numerical results – Two stream instability



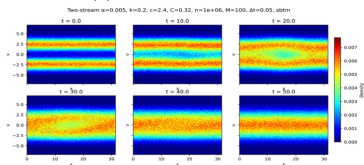
(a) Blob, $n = 5 \times 10^5$



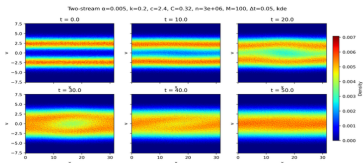
(b) SBTM, $n = 5 \times 10^5$



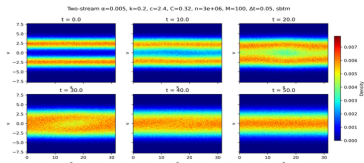
(c) Blob, $n = 10^6$



(d) SBTM, $n = 10^6$



(e) Blob, $n = 3 \times 10^6$



(f) SBTM, $n = 3 \times 10^6$

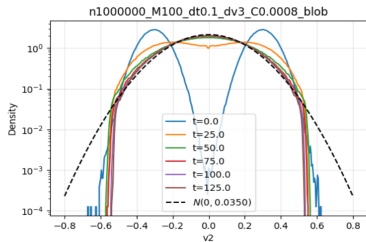
Numerical results – Weibel instability

We initialize the plasma as

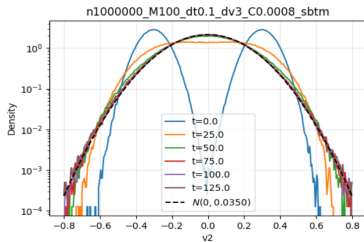
$$f_0(x, \mathbf{v}) \propto \exp\left(-\frac{v_1^2}{\beta}\right) \left[\exp\left(-\frac{(v_2 - c)^2}{\beta}\right) + \exp\left(-\frac{(v_2 + c)^2}{\beta}\right) \right] \exp\left(-\frac{v_3^2}{\beta}\right)$$

with $c = 0.3$, $\beta = 0.01$, $B_3(0, x) = \alpha_B \sin(kx)$, $\alpha_B = 10^{-3}$, wavenumber $k = 1/5$ and domain $L = 2\pi/k$, $M = 100$ spatial cells, $\Delta t = 0.1$, $N = 10^6$, $t_{\text{final}} = 125$, $K = 100$ gradient steps, sweeping over collision frequencies $\nu = 10^{-4}, 2 \times 10^{-4}, 4 \times 10^{-4}, 8 \times 10^{-4}$.

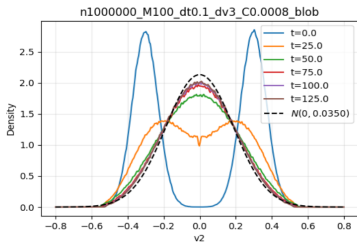
Numerical results – Weibel instability



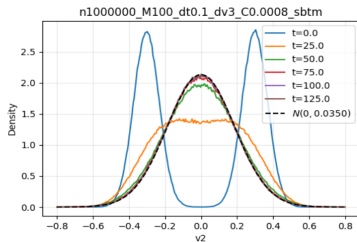
(a) Blob, log scale



(b) SBTM, log scale

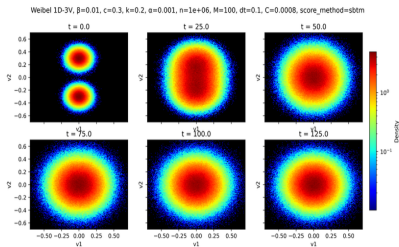
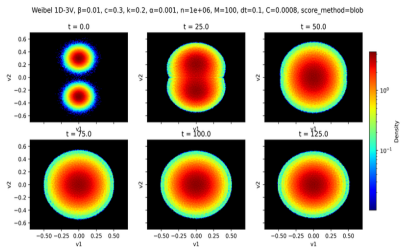
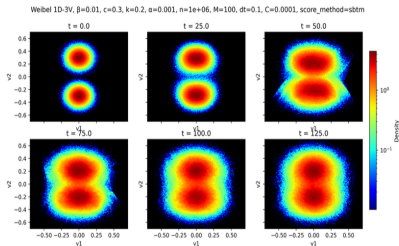
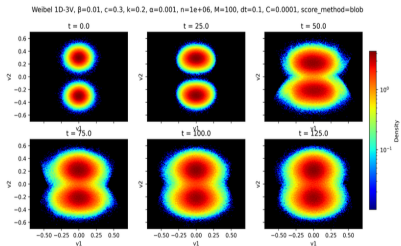


(c) Blob, linear scale

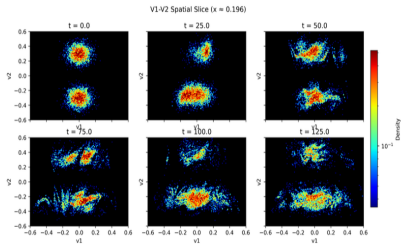


(d) SBTM, linear scale

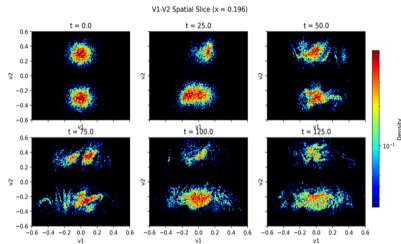
Numerical results – Weibel instability



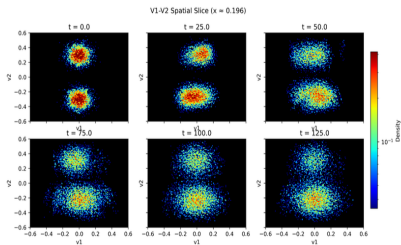
Numerical results – Weibel instability



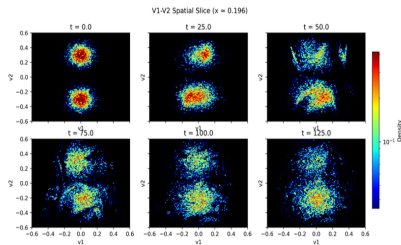
(e) Blob, $\nu = 0$



(f) SBTM, $\nu = 0$



(g) Blob, $\nu = 10^{-4}$



(h) SBTM, $\nu = 10^{-4}$

Numerical results – computational efficiency

Method	Runtime ($n = 10^6$)		Peak Memory (GB)	
	Time	Speedup	$n = 10^6$	$n = 3 \times 10^6$
Blob (KDE)	11h 27m	–	16.4	65.1
SBTM	7h 17m	1.57×	4.4	17.2

Figure: This table compares runtime and peak GPU memory for the two-stream instability test on the same architecture. SBTM achieves a 1.57× speedup at $N = 10^6$ and uses 2 – 4× less memory across all particle counts, with the memory advantage growing at larger N .

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Conclusion

A particle method is introduced for the Vlasov-Maxwell-Landau equation:

- offers a unified approach to handle transport, field effects, and collisions in a plasma system
- replaces the traditional particle/blob method by the neural score matching
- preserves the conservation and entropy decay structure of the Landau operator

arXiv:2603.25832



Thank you!