

# Interacting Particle Systems

Subtitle

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## 1 Introduction

+++Motivation, particle systems and flocking in biology+++

## 2 The Model

We here elucidate the model of Buttà, Flandoli, Ottobre and Zegarlinski [1]. This is a Vicsek-type continuum model for an interacting particle system. There are three key parts to this model that together create interaction and ordered motion: a herding function, denoted  $G$ ; an averaging function, denoted  $M$ ; and an interaction function,  $\varphi$ . Each will be described before the full model is introduced. Throughout, we will be considering the phase space distribution function  $f_t(x, v)$ , where  $(x, v) \in \mathbb{T} \times \mathbb{R}$  and  $t \in \mathbb{R}$  with  $\mathbb{T} \cong \mathbb{R}/\mathbb{Z} \cong S^1$  denoting the unit one-dimensional torus. The distribution function represents the density of particles at time  $t$  at a given point in phase space  $(x, v)$ .

The interaction function,  $\varphi : \mathbb{T} \rightarrow \mathbb{R}$  acts on the smallest scale, between individual points. It is smooth and satisfies the following:

$$\varphi(x) \geq \varepsilon > 0, \quad \varphi(x) = \varphi(-x), \quad \int_{\mathbb{T}} \varphi(x) dx = 1.$$

These are quite natural ways to describe an interaction. The first means that all points interact with each other to some degree. +++ Positivity requires that all interactions are attractive, in contrast to many real-world phenomena, give examples of only attractive systems +++. The second requires symmetry when interacting, and finally the function must have unit integral – this is only for simplicity and could in fact be any value, so long as it is finite. For example, we may take  $\varphi \equiv 1$ . This will satisfy the above requirements and corresponds to all points interacting an equal amount, regardless of position on the torus. This will create space-homogeneity, which we will return to later.

The function  $M : \mathbb{R} \rightarrow \mathbb{R}$  takes a weighted average of the interactions across the space.

$$M(t, x) = \frac{\int_{\mathbb{T}} \int_{\mathbb{R}} f_t(y, w) \varphi(x - y) w dw dy}{\int_{\mathbb{T}} \int_{\mathbb{R}} f_t(y, w) \varphi(x - y) dw dy}$$

The interaction function provides the weighting. Note the argument of  $\varphi$  is the distance between two points in space and also that  $M$  depends on  $f_t$ . +++The denominator is required in the corresponding particle model to prevent the size of the group of particles from having an effect on the dynamics. It can be thought of as a normaliser. – Poor explanation.+++

Finally, the herding function  $G : \mathbb{R} \rightarrow \mathbb{R}$  is chosen such that

$$G(u) = -G(-u), \quad \begin{cases} G(u) > u & \text{if } 0 < u < 1 \\ G(u) < u & \text{if } u > 1 \end{cases}.$$

We shall consider three forms of  $G$ .

i) Step:

$$G(u) = \frac{1 + \beta \operatorname{sgn}(u)}{1 + \beta}, \quad \beta > 0$$

This is the usual choice in the biological literature, with  $\beta = \frac{1}{2}$ . It is differentiable everywhere with  $G'(u) = \frac{1}{1+\beta}$ , except at  $u = 0$ . This discontinuity makes analysis more difficult.

ii) Smooth:

$$G(u) = \frac{\arctan(u)}{\arctan(1)}$$

Here we get a much smoother curve that is everywhere differentiable. However the gradient isn't very steep and there is no way to control the shape of the curve.

iii) Sigmoid:

$$G(u) = \frac{2}{1 + e^{-\alpha u}} - 1, \quad \alpha > 0$$

The sigmoid herding function provides a middle ground between the previous two. It is smooth, but can be made as sharp as required by adjusting the parameter  $\alpha$ . However note that it only satisfies second requirement above in the limit as  $\alpha \rightarrow \infty$  as the function is bounded above by 1.

During the analysis, we will use the smooth herding function for its amenability. The role of  $G$  is to herd the mean velocity towards a fixed value – in this case plus or minus one. How it does so will become clearer when we discuss the dynamics of the model.

We now have all the necessary ingredients to give the full continuum model. The evolution of the distribution is described by

$$\partial_t f_t(x, v) = -v \partial_x f_t(x, v) + \partial_v v f_t(x, v) - \partial_v [G(M(t, x)) f_t(x, v)] + \sigma \partial_{vv} f_t(x, v), \quad (1)$$

where  $\sigma > 0$  is a constant describing the rate of diffusion. At its heart, this is just an advection-diffusion equation. The first term illustrates the movement around the torus, the second describes a damping effect and the fourth gives a diffusive effect in velocity. The third term is where the interest lies as it contains all the information on interaction and herding.

### 3 Dynamics

To better understand the dynamics of (1), first let  $G \equiv 0$ . This removes any interaction between particles and the equation becomes

$$\partial_t f_t(x, v) = -v \partial_x f_t(x, v) + \partial_v v f_t(x, v) + \sigma \partial_{vv} f_t(x, v). \quad (2)$$

This is the Fokker-Planck equation for the following system:

$$\begin{cases} dx_t = v_t dt \\ dv_t = -v_t dt + \sqrt{2\sigma} dW_t. \end{cases} \quad (3)$$

Here,  $W_t$  is a standard one-dimensional Wiener process. We recognise this as overdamped Langevin dynamics, and so we can exactly calculate the unique invariant measure. To do so it is necessary to solve  $\partial_t \rho_t = 0$ , that is, when is the density not changing in time. The evolution in  $v$  is described by an Ornstein-Uhlenbeck process so it is known that the unique stationary distribution is Gaussian with mean 1 and variance  $\sigma$ . The position  $x$  depends only on  $v$  with no noise. There is no reason to assume any sort of mean reverting behaviour and expect the density to spread out uniformly on the torus. A guess at the solution would then be  $\rho(x, v) = \frac{1}{2\pi} \exp(\frac{-v^2}{2})$ , with some normalising constant. Notice that this equation does not depend on  $x$ . By substitution into the stationary Fokker-Planck equation, this is indeed a solution.

Similarly, when  $G \neq 0$  the density  $f_t(x, v)$  of (1) is the Fokker-Planck equation of the two dimensional SDE,

$$\begin{cases} dx_t = v_t dt \\ dv_t = [G(M(t, x_t)) - v_t] dt + \sqrt{2\sigma} dW_t. \end{cases} \quad (x_t, v_t) \in \mathbb{T} \times \mathbb{R} \quad (4)$$

This is a McKean-Vlasov equation as the function  $M(t, x_t)$  conceals a dependence on the law of the process.

$$M(t, x) = \frac{\mathbb{E}[v'_t \varphi(x - x'_t)]}{\mathbb{E}[\varphi(x - x'_t)]}$$

The pair  $(x'_t, v'_t)$  is a random variable equal in distribution to  $(x_t, v_t)$ . This representation of  $M(t, x)$  is the same as the one given previously, however in this setting it is natural to use expectation notation over integrals. To illustrate the necessity of introducing another random variable, albeit one that is equal in law, consider the case when the interaction function is the indicator on the interval  $[-b, b]$ ,  $\varphi(x) = \mathbb{1}_{[-b, b]}(x)$ . This does not meet the requirements in Section 2, in particular it is neither strictly positive nor does it have unit integral.

$$\begin{aligned} M(t, x) &= \frac{\int_{\mathbb{T}} \int_{\mathbb{R}} f_t(y, w) \varphi(x - y) w dw dy}{\int_{\mathbb{T}} \int_{\mathbb{R}} f_t(y, w) \varphi(x - y) dw dy} \\ &= \frac{\int_{\mathbb{T}} \int_{\mathbb{R}} f_t(y, w) \mathbb{1}_{[-b, b]}(x - y) w dw dy}{\int_{\mathbb{T}} \int_{\mathbb{R}} f_t(y, w) \mathbb{1}_{[-b, b]}(x - y) dw dy} \\ &= \frac{\mathbb{E}[v'_t \mathbb{1}_{[-b, b]}(x - x'_t)]}{\mathbb{P}(x' \in [x - b, x + b])} \\ &= \mathbb{E}[v'_t | x' \in [x - b, x + b]] \end{aligned}$$

It makes no sense to consider  $\mathbb{P}(x \in [x - b, x + b])$  as it is always equal to one so the auxiliary variable  $(x'_t, v'_t)$  is used. +++More detail?+++ This calculation also illustrates how  $\varphi$  describes the interaction or 'where to look' while  $M$  acts as a average velocity of the points 'within range'. The transport term,  $\partial_v ([v - G(M(t, x))] f_t(x, v))$  then acts to change the velocity towards the local average given by  $M$ . It is in this sense that  $G$  is the herding function 'herding' the system towards a common velocity.

The McKean-Vlasov representation of the system is also the weak limit of an  $N$ -body particle system described by

$$\begin{cases} dx_t^{i, N} = v_t^{i, N} dt \\ dv_t^{i, N} = -v_t^{i, N} dt + G \left( \frac{\frac{1}{N} \sum_{j=1}^N \varphi(x_t^{i, N} - x_t^{j, N}) v_t^{j, N}}{\frac{1}{N} \sum_{j=1}^N \varphi(x_t^{i, N} - x_t^{j, N})} \right) dt + \sqrt{2\sigma} dW_t^i \end{cases}, \quad i = 1, \dots, N. \quad (5)$$

This gives another view of the full system (1), and one that is particularly amenable to analysis. It also allows a more intuitive view of the system – rather than thinking of how a density changes over time, we can think of particles moving around a torus and interacting according to  $\varphi$ .

### 3.1 Invariant Measures under Space Homogeneity

Thus far, we have found the invariant measure for only the rather uninteresting case when  $G \equiv 0$ . To progress further, we must simplify the system. One way to do this is to impose that the density does not depend on the position in space and set  $\varphi \equiv 1$ . The weighted local average velocity  $M$  becomes neither local nor weighted. In the particle system, this means that each particle interacts with every other particle, irrespective of the distance between them. Indeed,

$$\begin{aligned} M(t, x) &= \frac{\int_{\mathbb{T}} \int_{\mathbb{R}} f_t(y, w) \varphi(x - y) w \, dw \, dy}{\int_{\mathbb{T}} \int_{\mathbb{R}} f_t(y, w) \varphi(x - y) \, dw \, dy} \\ &= \frac{\int_{\mathbb{T}} \int_{\mathbb{R}} f_t(y, w) w \, dw \, dy}{\int_{\mathbb{T}} \int_{\mathbb{R}} f_t(y, w) \, dw \, dy} \\ &= \int_{\mathbb{T}} \int_{\mathbb{R}} f_t(y, w) w \, dw \, dy \\ &:= \langle w \rangle_{f_t}. \end{aligned}$$

So the weighted local average velocity is just the average of the distribution  $f_t(v)$  or equivalently, the average velocity of all particles in the system. The evolution is then described by

$$\partial_t f_t(v) = \partial_v v f_t(v) - \partial_v G(\langle w \rangle_{f_t}) f_t(v) + \sigma \partial_{vv} f_t(v). \quad (6)$$

The above problem's well-posedness can be shown as follows. Let

$$h_t(v) = f_t(u), \text{ where } u = v + \int_0^t G(\langle w \rangle_{f_s}) \, ds.$$

To find an equation that  $h_t(v)$  solves, we use the chain rule.

$$\begin{aligned} \partial_t f_t(u) &= \partial_t f_t(u) + G(\langle w \rangle_{f_t}) \partial_v f_t(u) && \text{as } \frac{\partial g}{\partial v} = 1, \frac{\partial g}{\partial t} = G(\langle w \rangle_{f_t}) \\ &= \partial_v v f_t(u) - \partial_v G(\langle w \rangle_{f_t}) f_t(u) + \sigma \partial_{vv} f_t(u) + G(\langle w \rangle_{f_t}) \partial_v f_t(u) && \text{as } f_t \text{ solves (6)} \\ &= \partial_v v h_t(v) + \sigma \partial_{vv} h_t(v), && h_0(v) = f_0(v). \end{aligned}$$

So  $h_t$  solves the Fokker-Planck equation for the one-dimensional Ornstein-Uhlenbeck process which is well posed [cite]. Therefore the solution  $f_t(v)$  of (6) exists and is unique given initial data. To find invariant measures of this evolution, set the transient term to zero and solve the remaining PDE, which can be written in gradient form. First note that if  $G \equiv 0$ , this system for  $f_t$  is the same as that for  $h_t$ , and so has a unique invariant measure  $\mathcal{N}(0, \sigma)$ . When the herding function is non-zero, other measures are also stationary as we will now show. For brevity, we omit the dependence on  $v$  of  $f$  and write  $\langle w \rangle_{f_t} = M_1$ . The latter is natural as it denotes the first moment of the distribution.

$$\begin{aligned} \partial_v [(-G(M_1) + v)f + \sigma \partial_v f] &= 0 \\ \implies (-G(M_1) + v)f + \sigma \partial_v f &= C_1 \end{aligned}$$

This ODE is solvable and gives

$$f(v) = C_2 \exp\left(\frac{2G(M_1)v - v^2}{2\sigma}\right).$$

Applying the constraint  $\int_{\mathbb{R}} f(w) dw = 1$  gives  $C_2 = \exp(-G^2(M_1))/\sqrt{2\pi\sigma}$ . +++note here this is a Gaussian with mean  $G(M_1)$ ? Immediately implies that  $M_1 = G(M_1)$  without need for integration  
+++ Furthermore, from the definition of space average,

$$\begin{aligned} M_1 &:= \int_{\mathbb{R}} w f(w) dw \\ &= \int_{\mathbb{R}} \frac{w \exp(-G^2(M_1))}{\sqrt{2\pi\sigma}} \exp\left(\frac{2G(M_1)v - v^2}{2\sigma}\right) \\ &= \int_{\mathbb{R}} \frac{w}{\sqrt{2\pi\sigma}} \exp\left(\frac{-(v - G(M_1))^2}{2\sigma}\right) \\ &= G(M_1) \end{aligned}$$

Using the smoothed version of the herding function from Section 2 gives  $G(M_1) = 0, \pm 1$ . Substituting this into our expression for  $f$  gives three invariant measures:

$$\rho_0 = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{v^2}{2\sigma}\right), \quad \rho_{\pm} = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{(v \pm 1)^2}{2\sigma}\right).$$

These are Gaussian densities with mean  $0, \pm 1$  and variance  $\sigma$ .

We have found three invariant measures for the evolution (6), however whether the system will converge to these distributions given initial data remains to be settled. In the space homogeneous case it is possible to close equations on the moments of the distribution. Let  $M_n = \int_{\mathbb{R}} v^n f_t(v) dv$  denote the  $n^{\text{th}}$  moment of the distribution  $f_t(v)$ . Then

$$\begin{aligned} \partial_t M_n(t) &= \int_{\mathbb{R}} v^n \partial_t f_t(v) dv \\ &= - \int_{\mathbb{R}} v^n \partial_v G(M_1) f_t(v) dv + \int_{\mathbb{R}} v^n \partial_v v f_t(v) dv + \sigma \int_{\mathbb{R}} v^n \partial_v v f_t(v) dv, \end{aligned}$$

as  $f_t$  solves the space-homogeneous PDE (6). Using integration by parts and simplifying gives, for the first three moments,

$$\begin{aligned} \dot{M}_0 &= 0, \\ \dot{M}_1 &= G(M_1) - M_1, \\ \dot{M}_2 &= 2[M_1 G(M_1) - M_2 + \sigma]. \end{aligned}$$

The first tells us there is no change in the zeroth moment over time, that is probability is conserved. The equation for the first moment has equilibria at -1, 0 and 1 for the smoothed choice of  $G$ . Figure +++ref+++ shows the phase plane diagram for this ODE. It shows that given any initial data with positive average velocity, the first moment will converge to one. By symmetry, the same is true for negative initial data, the mean will converge towards negative one. It also shows that mean zero is an unstable equilibrium – a slight perturbation will move the system from random movement to ordered motion. To find the convergence of the variance, we must look at the difference between



Figure 1: Phase plane of the first +++(and second?)+++ moment ODE

the second moment and the square of the first.

$$\begin{aligned}
 \frac{d}{dt}[M_2 - M_1^2] &= \dot{M}_2 - 2M_1\dot{M}_1 \\
 &= 2[G(M_1)M_1 - M_2 + \sigma] - 2M_1[G(M_1) - M_1] \\
 &= -2M_2 + 2\sigma + 2M_1^2 \\
 &= 2[M_2 - M_1^2 - \sigma]
 \end{aligned}$$

Solving this ODE gives  $M_2 - M_1^2 = \sigma + (\sigma_0 - \sigma)e^{-2t}$ , where  $\sigma_0$  is the variance of the initial data  $f_0$ . Then as  $t \rightarrow \infty$ , it can be seen that the system forgets its initial data and tends towards a distribution with variance  $\sigma$ .

The equations on the moments have shown that the system indeed converges to a measure with mean  $\pm 1$  and variance  $\sigma$  however this is not sufficient to conclude that they are Gaussian. To do so requires closing equations on all the cumulants of the distribution. It can be shown that these vanish for all cumulants of order greater than three and so the system indeed converges towards the invariant measures found by solving the space-homogeneous PDE (6). This means that irrespective of initial data, we expect all particles to move on average in the same direction with the same velocity – a phenomenon known as unconditional flocking. The only exception is when the initial data has mean zero. In this case the system will converge to the Gaussian with mean zero, corresponding to disordered motion. +++not a great explanation+++

The dynamics of the space-homogeneous system have thus been fully characterised analytically. We will now turn our attention to the particle model in this case.

### 3.1.1 Particle System Dynamics

As the particle system approximates the McKean-Vlasov SDE, whose density solves the PDE (6), one would expect that it behaves in entirely the same way. This is in fact not the case, as we will now show. Consider the particle system (5) in the space-homogeneous case,

$$dv_t^{i,N} = G \left( \frac{1}{N} \sum_{j=1}^n v_t^{j,N} \right) dt - v_t^{i,N} dt + \sqrt{2\sigma} dW_t^i \quad (7)$$

It has been shown for the kinetic model that the invariant measures have mean zero and  $\pm 1$  when we consider a smoothed herding function. Here we will show that the space-homogeneous particle model only admits invariant measures with mean zero for any herding function satisfying the earlier requirements in Section 2, before finding analytic forms for the functions we will be using. First note that in the case of no interaction, that is  $G \equiv 0$ , the dynamics are governed by an Ornstein-Uhlenbeck process leading to a unique stationary distribution with mean zero. This is in agreement with the solution to the PDE under no interaction in Section 3. When  $G \neq 0$ , the invariant distribution still always has mean zero, unlike what we have seen for the space-homogeneous kinetic model. Given that we wish to find the behaviour of the mean velocity, it would be pertinent to find an equation

that it solves. To this end, let  $m_t = \frac{1}{N} \sum_{j=1}^N v_t^{j,N}$ . Summing the system across  $i$  gives an equation for  $m_t$ :

$$dm_t = [-m_t + G(m_t)] dt + \sqrt{2\sigma} dW_t$$

Let  $V(x) = \frac{x^2}{2} + \tilde{V}(x)$ , where  $-\tilde{V}'(x) = G(x)$  so that  $-V'(x) = -x + G(x)$ . The aim here is to find a function  $V$  such that the equation for  $m_t$  resembles the Langevin equation. The existence and uniqueness of the invariant measure will then follow from standard theory for the Langevin equation and its associated Fokker-Planck equation. Thus

$$dm_t = -V'(m_t) dt + \sqrt{2\sigma} dW_t. \quad (8)$$

By definition,  $\tilde{V}(x) = -\int_{-\infty}^x G(u) du$ . As  $G$  is bounded,  $\tilde{V}(x)$  grows at most linearly. This means  $V(x) \rightarrow \infty$  as  $|x| \rightarrow \infty$ ,  $V$  is a well-defined potential well and  $e^{-V(x)}$  is integrable. Hence (8) admits a unique invariant measure,  $\rho(x) = \mathcal{Z}^{-1} e^{-V(x)}$  with  $\mathcal{Z}$  a normalising constant.

What can we say about this invariant measure? Recall the only restrictions placed on  $G$  in Section 2 were firstly  $G$  must be odd, that is  $G(u) = -G(-u)$ , and secondly,

$$\begin{cases} G(u) > u & \text{if } 0 < u < 1, \\ G(u) < u & \text{if } u > 1. \end{cases}$$

If  $G$  is odd,  $\tilde{V}(x)$  is an even function, so  $V(x)$  is also an even function. Then the mean of the invariant distribution  $\rho$  is

$$\mathbb{E}_\rho[m] = \mathcal{Z}^{-1} \int_{\mathbb{R}} m e^{-V(m)} dm = 0,$$

as this is the integral of an odd function. The behaviour of the particle system is then fundamentally different to that of its corresponding kinetic model, despite weakly converging to the McKean-Vlasov SDE (4) whose density solves the PDE (6). This is in fact a well-known problem in the area of mean field equations +++cite+++.

The behaviour of the particle system here is not wholly unexpected – the change in velocity is inherently random. To see how this affects the invariant measure, first recall the case when  $G \equiv 0$ , in which the particle system is the Ornstein-Uhlenbeck process and the kinetic model is its corresponding Fokker-Planck equation (2). Here, the particle moves in a potential well with a parabolic shape with a minima at zero. When  $G \neq 0$ , the particles move within a double-well potential. For the choices of the herding function described here, this well will have minima at -1, 0 and 1<sup>a</sup>. Moving deterministically, as the evolution described by the kinetic model is, the particles must settle in one of the two wells leading to a system with mean 1, 0 or -1. Under random movement however, there is a chance that the Wiener process forces the particle to jump over the potential barrier and into the other well. If this happens to enough particles, the remaining particles will also make the jump due to the effect of the herding function. We thus expect, for a finite number of particles, the motion to switch randomly between having average velocity positive one and negative one leading to the invariant measure having mean zero. This switching of mean velocity is known as metastability – the Gaussian invariant measures for the PDE are only metastable in the particle model. We emphasise again that the dynamics under the kinetic model are fully deterministic and as such no switch of stability is possible. +++Dynkin's formula? Calc on exp time to switch?+++

<sup>a</sup>This is not quite true for any sigmoid  $G$  in which  $\alpha$  is not large enough.

Figure 2: Particles in wells. Parabolic (OU) and Double Well showing jump between

	Herding Function	Invariant Measure
Step	$\frac{1+\text{sgn}(u)}{2}$	+++not correct, not double well or normalised+++ $\exp\left(\frac{ v }{2}\right)$
Smooth	$\frac{\arctan(u)}{\arctan(1)}$	$\frac{1}{(v^2+1)^{\frac{2}{\pi}}} \exp\left(-\frac{v^2}{2} + \frac{4}{\pi} v \arctan(v)\right)$
Sigmoid	$\frac{2}{1+e^{-\alpha u}} - 1$	$\mathcal{Z}^{-1}(e^{\alpha v} + 1)^{\frac{2}{\alpha}} \exp\left(-\frac{v^2}{2} - v\right)$

Table 1: Normalised densities for the space-homogeneous particle model (7) with different herding functions

The method used above to characterise the mean of the distribution gives all that is required to calculate closed forms of the invariant measure. Table 1 gives expressions for the three herding functions given in Section 2.

+++Convergence to invariant measure? Depends on metastability, rate of switching between wells  
+++

Figure 3: Potential Wells +++distributions?+++ for the invariant measure of the space-homogeneous particle system for various herding functions

+++Full particle model invariant measure?+++

In the space-homogeneous case, the analysis above gives a full picture of the dynamics of both the particle model and the kinetic model. However, the full system (1) is much harder to analyse. It can be shown that the invariant measures for (6) are also invariant, however it cannot be shown that they are the only ones. In particular, it can not be expressed in a gradient form like it could be in the space-homogeneous case. The aim now is to exploit our understanding of the space-homogeneous case to develop robust numerical techniques to learn more about the full system.

## 4 Numerical Methods

The analysis presented so far has been able to fully characterise the behaviour of the space-homogeneous kinetic model. However, it is unable to describe the dynamics of the full space-inhomogeneous model. It has been shown that the space-homogeneous model possesses only three invariant measures and converges to one of them dependent on the sign of the mean of the initial data. The full model also has these invariant measures, however it is not proven whether these are all of them or not. That is, the full model may have stationary distributions which are not homogeneous in space. By utilising numerical methods, we can relax some of the restrictions which the analysis requires. The goal is to show that for some choice of initial data and interaction function, the

particle system will have a stationary distribution that isn't uniform in space. At its most basic, this could be two clusters of particles moving on the same direction diametrically opposite each other. The system will still converge in velocity to the values predicted by the homogeneous model, but spatial heterogeneity will remain. While this may be the case for the particle system, we conjecture that such behaviour will not occur in the kinetic model.

The aim is to be able to accurately simulate the dynamics of both the space-inhomogeneous PDE +++ref+++ and the corresponding interacting particle system. The latter is relatively simple to simulate using techniques for SDEs. However, we have shown analytically that the particle system does not have the same invariant measures as the continuum model, or indeed its McKean-Vlasov equation. The kinetic model is more difficult as it contains both advective and diffusive terms. We begin this section with a presentation of numerical methods for SDEs before reviewing methods for advection-type and diffusion-type equations, following the treatment of Hundsdorfer and Verwer [3] as well as Morton and Meyers [4].

Mirroring the approach in the analysis, we will develop the techniques required first for the space-homogeneous system with no interaction, before adding further levels of complexity. Doing so allows the rigorous testing of any schemes developed as analytic solutions are available. Throughout this section it is recommended to follow along with the supplementary Jupyter notebook available at:

<https://github.com/Tom271/Whales> +++Change name+++

Every figure within this report was produced using the notebook and its accompanying source code.

## 4.1 Particle Systems

Simulating particle systems requires the numerical solution of coupled SDEs. The standard method for this is the Euler-Maruyama (EM) method, which can be seen as the stochastic analogue of Euler's method. Our motivating example here will be the Ornstein-Uhlenbeck process<sup>b</sup>.

$$dx_t = -x_t dt + \sigma dW_t \quad (9)$$

This is exactly the same evolution as that which drives the space-homogeneous particle system (7), with no interaction between particles, and so provides the ideal starting point. It describes the motion of a damped particle moving randomly within a potential well as illustrated in Section 3.1.1. Applying the EM method to the above equation gives:

$$x_{n+1} = x_n - x_n \Delta t + \sqrt{2\sigma \Delta t} Z_n,$$

where  $Z_n$  is a standard normal random variable. This discretisation is very quick to compute, and has strong order  $\frac{1}{2}$  [2]. This gives us a method of finding the stationary distribution: simulate many particles for a long time. Eventually, the density of the particles will be approximately the stationary distribution of the system. In this case it is in fact not even necessary to simulate many particles – if the system is allowed to evolve for long enough, one particle will suffice as there is no interaction between particles and the scheme is ergodic. The particle system will be an excellent metric by

<sup>b</sup>This is also the overdamped Langevin equation

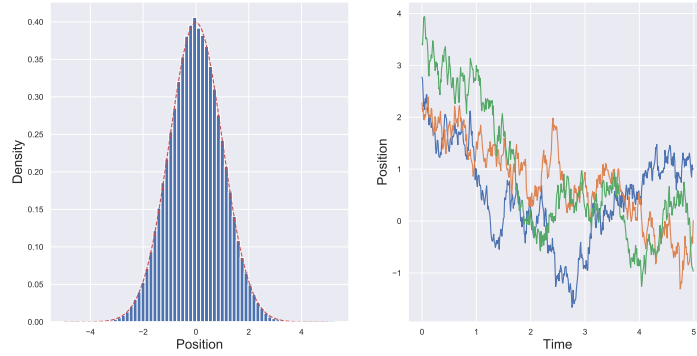


Figure 4: Histogram of positions of 1000 particles after 100s with  $\sigma = 1$ , and positions of 5 particles over time. +++conv in moments?+++

which to test the schemes developed for the continuum models. One drawback however will be the presence of only one invariant measure, as was shown analytically in Sec 3.1.1 and will be shown numerically in +++ref+++.

## 4.2 Diffusion Equations

As a prototypical example of a diffusion equation, consider the heat equation in one dimension given by

$$\begin{cases} \partial_t u(t, x) = \sigma \partial_{xx} u(t, x), & \sigma > 0 \\ u(0, x) = u_0(x), & t \in \mathbb{R}^+, x \in \mathbb{R}, \end{cases} \quad (10)$$

To solve this numerically, we must truncate the domain in both time and space. To do this, a region is chosen where we expect most of the mass to be throughout the time of interest. Here, we truncate to  $x \in [-L, L]$ ,  $t \in [0, T]$  for some  $L > 0$  and a finite time horizon  $T$ . Doing so requires a boundary condition to be enforced. A natural choice for this equation is a zero Dirichlet condition,  $u(t, L) = u(t, -L) = 0$ . As long as  $L$  is chosen large enough, the heat which spreads beyond this limit is negligible – this will however be a source of error. To mitigate this, one could compare the difference between analytic solutions (where available) on the full real line and the truncated domain, then choosing  $L$  accordingly. In general, boundary conditions are determined by the phenomenon being modelled. The problem geometry may naturally suggest conditions, or they may be enforced by numerical constraints as in this case. We must also discretise in space and time, to create a mesh covering  $[0, T] \times [-L, L]$ . Let  $\{x_j\}_{j=0}^J$  partition the space equally such that  $x_0 = -L$ ,  $x_J = L$  and  $x_j - x_{j-1} = \Delta x$  for all  $j$ . Similarly, let  $\{t_n\}_{n=0}^N$  partition  $[0, T]$  in such a way that  $t_0 = 0$ ,  $t_N = T$  and  $t_n - t_{n-1} = \Delta t$ . The parameters  $\Delta x, \Delta t$  are the space step and time step respectively. We thus have a discretised description of the continuum that we can implement.

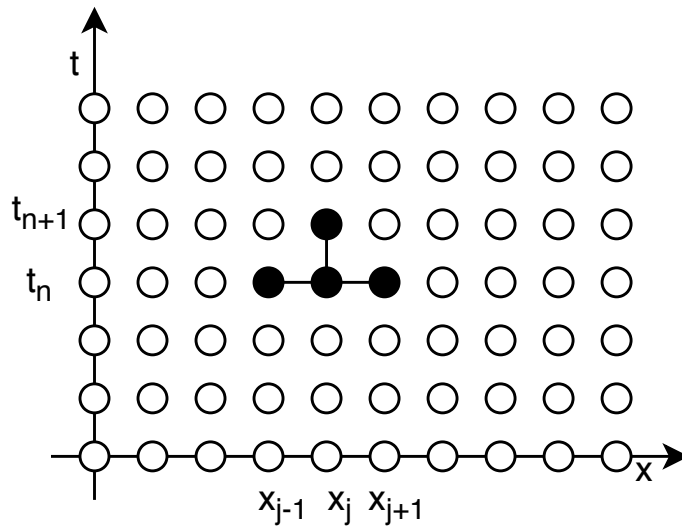


Figure 5

### Forward Time Centred Space

The aim is to solve the equation approximately on this grid. We shall denote approximate solutions by capital letters, that is  $u(x_j, t_n) \approx U_j^n$ . How can we approximate the solution? We must approximate each term in the equation separately. First the time derivative, or transient term can be approximated using the definition of the derivative. Recall

$$\frac{du}{dt} = \lim_{\Delta t \rightarrow 0} \frac{u(t + \Delta t) - u(t)}{\Delta t}.$$

We can then approximate the time derivative for fixed  $x$  by simply taking  $\Delta t$  small. Doing so leads to the forward difference approximation

$$\partial_t u(t_n, x_j) \approx \frac{U_j^{n+1} - U_j^n}{\Delta t}.$$

Now for the diffusion term, the most obvious approximation is to apply the forward difference scheme twice.

$$\begin{aligned} \partial_{xx} u(t_n, x_j) &\approx \partial_x \left( \frac{U_{j+1}^n - U_j^n}{\Delta x} \right) \\ &= \left( \frac{\partial_x U_{j+1}^n - \partial_x U_j^n}{\Delta x} \right) \\ &\approx \frac{U_{j+1}^n - 2U_j^n + U_{j-1}^n}{(\Delta x)^2} \end{aligned}$$

This is sufficient to give a first approximation to (10).

$$\frac{U_j^{n+1} - U_j^n}{\Delta t} = \sigma \frac{U_{j+1}^n - 2U_j^n + U_{j-1}^n}{(\Delta x)^2} \quad (11)$$

$$U_j^{n+1} = U_j^n + \frac{\sigma \Delta t}{(\Delta x)^2} [U_{j+1}^n - 2U_j^n + U_{j-1}^n] \quad (12)$$

This is the Forward Time Centred Space (FTCS) method, a fully explicit scheme which means that we can write the next time step solely in terms of known values. We now have a method for approximating the true solution. When developing any numerical scheme, three properties need to be considered: stability, consistency and convergence. These concepts will be developed further below. Heuristically, a scheme is unstable if certain mesh spacings cause rapid growth in solutions – a blow-up. A method is consistent if the error it makes in each step tends to zero as the size of the step tends to zero. Finally, a scheme is convergent if the approximate solution tends towards the true solution for any point in space and time.

The heat equation (10) can be solved by separation of variables, giving the solution as a Fourier series. If the initial data is a single Fourier mode, the solution is

$$u(t, x) = e^{-\sigma(2\pi k)^2 t} \varphi_k(x), \quad \varphi_k(x) = e^{2\pi i k x} \text{ for } k \in \mathbb{Z}.$$

If we assume our approximate solution is a Fourier mode, a criterion for stability will emerge.

$$U_j^n = \lambda^n e^{ik(j\Delta x)}, \quad k \in \mathbb{Z} \quad (13)$$

$$\implies U_j^{n+1} = \lambda U_j^n, \quad U_{j\pm 1}^n = e^{\pm ik\Delta x} U_j^n \quad (14)$$

Clearly if  $|\lambda| > 1$ , the solution will be unstable. Substituting this into the finite difference scheme (11) gives

$$\lambda = 1 - 4\mu \sin^2\left(\frac{k\Delta x}{2}\right), \quad \text{with } \mu = \frac{\sigma \Delta t}{(\Delta x)^2}, \quad (15)$$

and so,

$$U_j^n = \left(1 - 4\mu \sin^2\left(\frac{k\Delta x}{2}\right)\right)^n e^{ikj\Delta x}.$$

Looking at (13), as  $n \rightarrow \infty$ , the numerical solution will grow unless  $|\lambda| \leq 1$ . If  $|\lambda| \leq 1$ , the solution will decay with higher modes being damped quicker. This is what we expect from our analytic knowledge of the heat equation. The restriction on the mesh spacing thus arises from (15),

$$-1 \leq \lambda \leq 1 \implies \mu = \frac{\sigma \Delta t}{(\Delta x)^2} \leq \frac{1}{2}$$

This is not ideal: if more accuracy is required in the solution we can refine the space mesh, however in doing so the time step must also be shortened to maintain stability and the computational effort quickly increases.

To quantify the local truncation error,  $R$ , of the scheme, we substitute the exact solution  $u(t, x)$  in to

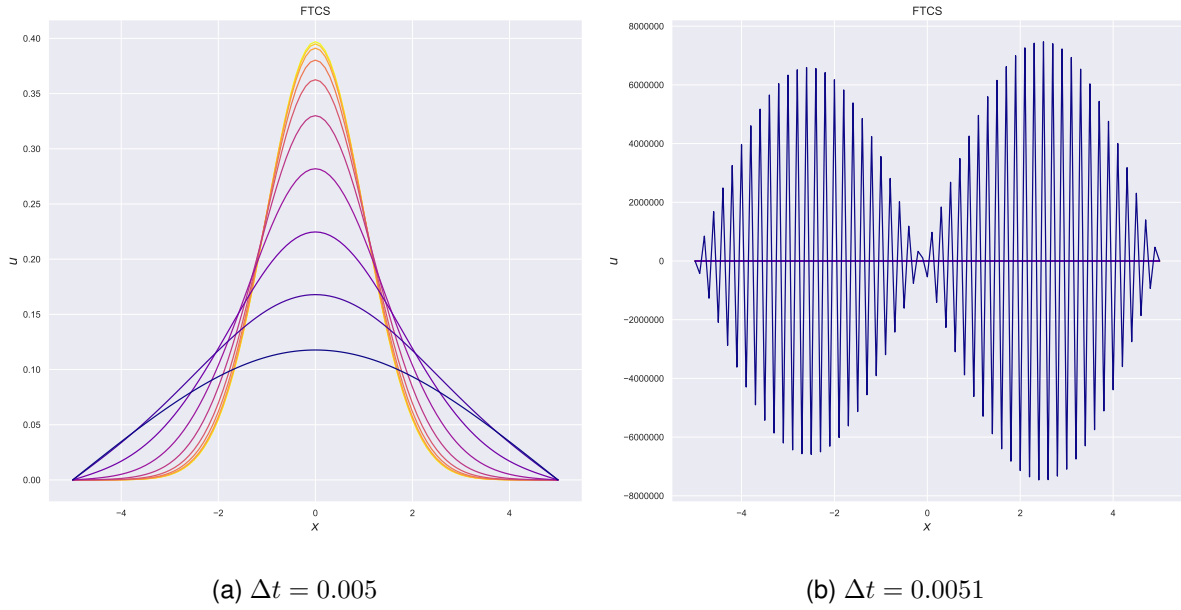


Figure 6: Using the FTCS scheme to solve the heat equation (10) on  $[-5, 5] \times [-1, 1]$  with  $\sigma = 1$ ,  $\Delta x = 0.1$  with a Gaussian initial profile.

the discretisation and perform a Taylor expansion around  $x = j\Delta x$  and  $t = n\Delta t$ .

$$\begin{aligned}
 u_j^{n+1} &= u_j^n + \Delta t \partial_t u_j^n + \frac{1}{2}(\Delta t)^2 \partial_{tt} u_j^n + \mathcal{O}(\Delta t^3) \\
 \implies R_j^n &= \partial_t u_j^n - \partial_{xx} u_j^n + \frac{1}{2}(\Delta t)^2 \partial_{tt} u_j^n + \mathcal{O}(\Delta x^2) + \mathcal{O}(\Delta t^3) \\
 \implies R_j^n &= \mathcal{O}(\Delta t) + \mathcal{O}(\Delta x^2).
 \end{aligned}$$

So the explicit scheme (11) is first order in time and second order in space.

Of these two results, the stability condition is the greater concern. In the next section we look to new methods to remove any restrictions on the mesh spacing, whilst maintaining (or improving) the truncation error.

## Backward Time Centred Space

### Theta Method

To overcome the restriction in mesh spacing, one can use an implicit method, that is one where the solution depends on future time steps as well as the current. A method of this form is not as easy to solve, but as we will show here, has better accuracy and is unconditionally stable. The implicit Euler scheme appears the same as the explicit scheme above however here we calculate the spatial derivative at the future time step in place of the current one as follows:

$$\frac{U_j^{n+1} - U_j^n}{\Delta t} = \sigma \frac{U_{j+1}^{n+1} - 2U_j^{n+1} + U_{j-1}^{n+1}}{(\Delta x)^2}$$



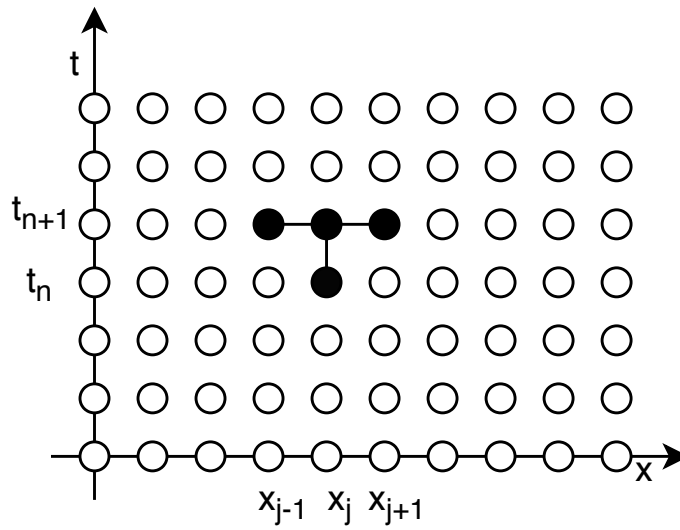


Figure 7

The Crank-Nicolson scheme involves taking the average of the implicit and explicit schemes outlined so far:

$$\frac{U_j^{n+1} - U_j^n}{\Delta t} = \frac{\sigma}{2} \left( \frac{U_{j+1}^{n+1} - 2U_j^{n+1} + U_{j-1}^{n+1}}{(\Delta x)^2} + \frac{U_{j+1}^n - 2U_j^n + U_{j-1}^n}{(\Delta x)^2} \right)$$

Rearranging this equation so that all unknown quantities (future time steps) are on the left hand side gives,

$$-\frac{\mu}{2}U_{j-1}^{n+1} + (1 + \mu)U_j^{n+1} - \frac{\mu}{2}U_{j+1}^{n+1} = U_j^n + \frac{\mu}{2}(U_{j+1}^n - 2U_j^n + U_{j-1}^n),$$

where  $\mu = \frac{\sigma \Delta t}{(\Delta x)^2}$ . This is a tridiagonal system and can be reduced to an upper triangular matrix and solved using the Thomas algorithm<sup>c</sup>. Doing so removes the costly requirement of inverting a matrix.

As for the stability of such a method, by applying the method seen for the fully-explicit scheme, one obtains

$$\lambda = \frac{1 - 2\mu \sin^2\left(\frac{k\Delta x}{2}\right)}{1 + 2\mu \sin^2\left(\frac{k\Delta x}{2}\right)}.$$

Here  $|\lambda| \not\geq 1$ , so the method is unconditionally stable. We can also apply the same method as before to find the truncation error. Doing so gives that the Crank-Nicolson scheme is second-order in both time and space.

+++table summary of all methods (error order, stability) CN == Goldilocks.+++

<sup>c</sup>This is also known as the tridiagonal matrix algorithm

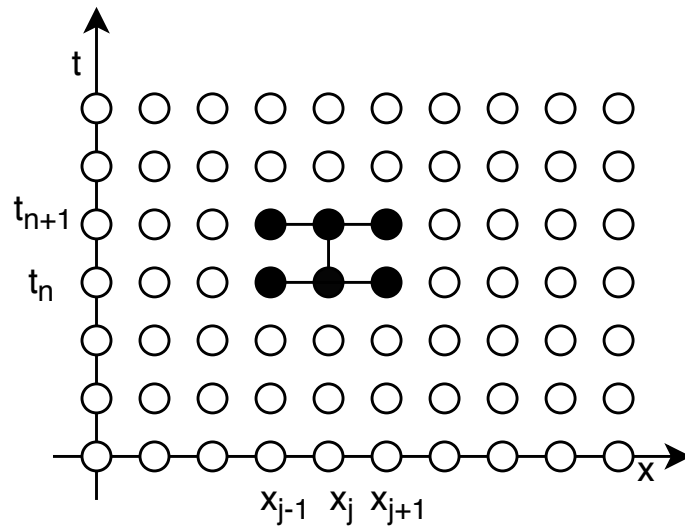


Figure 8

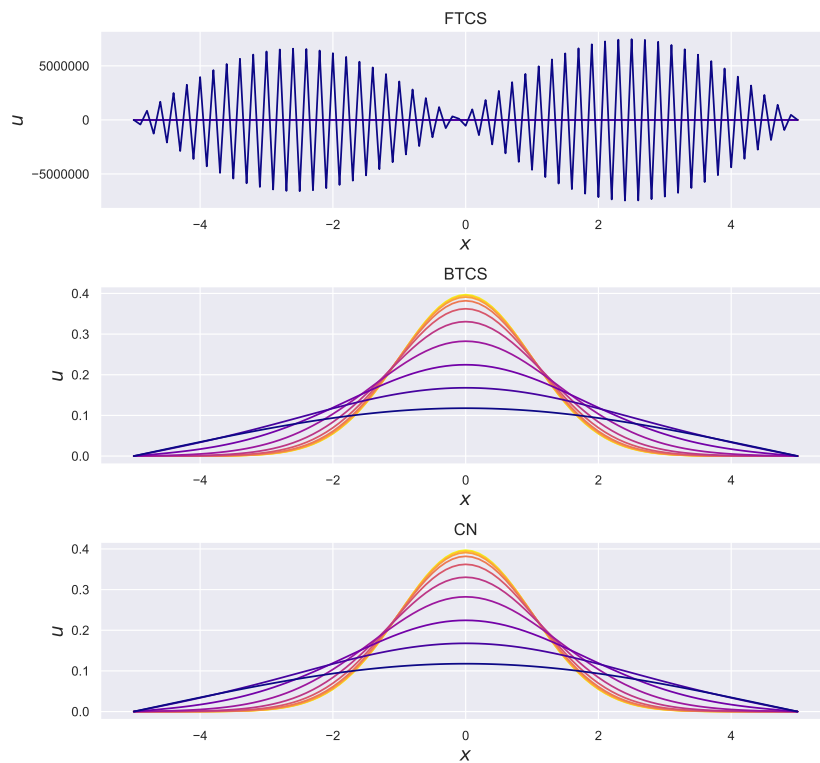


Figure 9: Solving the heat equation as in Figure 6 using FTCS, BTCS and CN respectively. The implicit solvers remain stable regardless of step size.

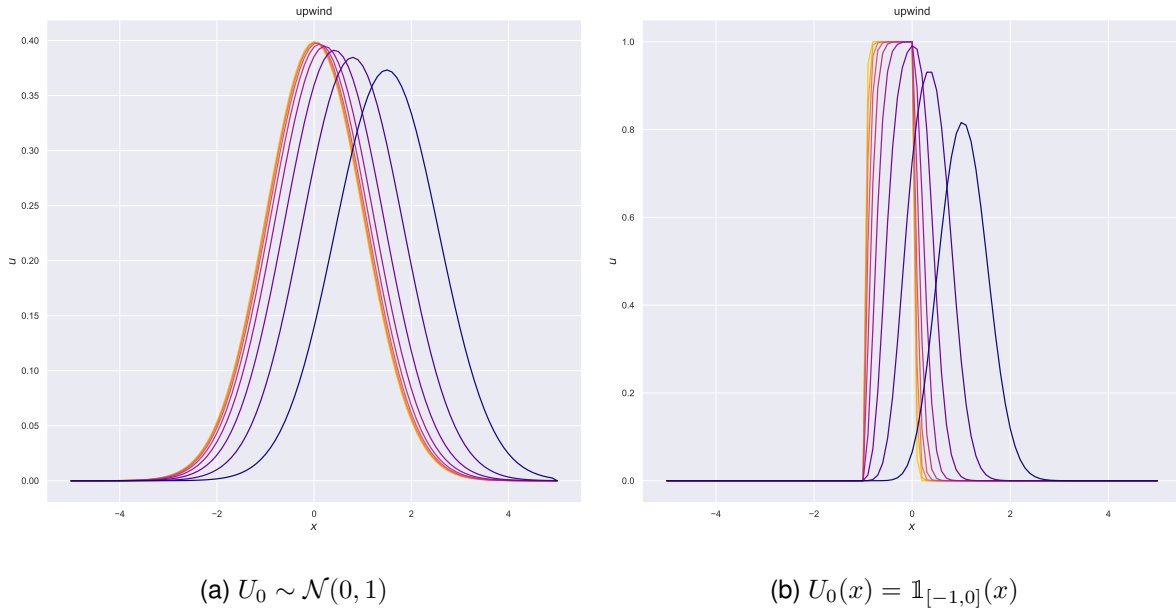


Figure 10: Solving equation (16) with the upwind scheme. Even with very smooth initial data, dispersive effects can be severe.

### 4.3 Advection Equations

Our prototypical example in this case will be the one-way wave equation,

$$\begin{cases} \partial_t u(t, x) + a \partial_x u(t, x) = 0, \\ u(0, x) = u_0(x), \end{cases} \quad t \in \mathbb{R}^+, x \in \mathbb{R}. \quad (16)$$

Using the same discretisation as for the time derivative in the diffusion equation, yields the first order upwind scheme,

$$\frac{U_j^{n+1} - U_j^n}{\Delta t} = \begin{cases} a \frac{U_{j+1}^n - U_j^n}{\Delta x} & \text{if } a > 0 \\ a \frac{U_j^n - U_{j-1}^n}{\Delta x} & \text{if } a < 0 \end{cases}$$

If the sign of  $a$  is not taken into account, the scheme is unstable. For further details see [3]. +++Error, modified equation showing dispersion, CFL CONDITION +++

### 4.4 Finite Volume Schemes

In Section 3, equations were closed on the moments of the distribution. From this, we know that  $\dot{M}_0 = 0$ , that is mass is conserved. This suggests that numerical schemes designed to conserve mass would be ideal for solving this system. One such method is a finite volume scheme, a generalisation of finite difference methods. First, we write the system in conservative form. This is an equation of the form  $\partial_u = \partial_x(a(x)u)$ . For the space homogenous model (6), this corresponds to

$$\partial_t f_t = \partial_v [(v - G(\langle w \rangle_{f_t})) f_t + \sigma \partial_v f_t]. \quad (17)$$

Using the same discretisation as in Section 4, we further introduce auxiliary points  $v_{j\pm\frac{1}{2}} = \frac{1}{2}(v_{j\pm 1} + v_j)$ . Then within any cell (or volume),  $\Omega_j = [v_{j-\frac{1}{2}}, v_{j+\frac{1}{2}}]$ , we can calculate the average.

$$\bar{f}_t(v_j) = \frac{1}{\Delta v} \int_{\Omega_j} f_t(v) dv = f_t(v_j) + \frac{1}{24(\Delta v)^2} \partial_{vv} f_t(v_j)$$

Furthermore, the change in the average density within the cell is equal to difference of the mass lost through either side of the volume, that is,

$$\Delta v \frac{d\bar{f}_t(v_j)}{dt} = a(v_{j-\frac{1}{2}}) f_t(v_{j-\frac{1}{2}}) - a(v_{j+\frac{1}{2}}) f_t(v_{j+\frac{1}{2}}),$$

where  $a(v) = [(v - G(\langle w \rangle_{f_t(v)})) f_t + \sigma \partial_v f_t(v)]$ . This can then be approximated using a finite volume scheme:

$$\frac{F_j^{n+1} - F_j^n}{\Delta t} = \frac{1}{\Delta v} [a(v_{j-\frac{1}{2}}) F_{j-\frac{1}{2}}^n - a(v_{j+\frac{1}{2}}) F_{j+\frac{1}{2}}^n]$$

This is the first-order upwind scheme in conservative (flux) form. As in the previous upwind scheme, the choice of spatial points at which to evaluate depends on the sign of the advection term. That is,

$$a(v_{j+\frac{1}{2}}) F_{j+\frac{1}{2}}^n = a^+(v_{j+\frac{1}{2}}) F_j^n + a^-(v_{j+\frac{1}{2}}) F_{j+1}^n,$$

where  $a^+ = \max(a, 0)$ ,  $a^- = \min(a, 0)$ . This scheme is still order 1, however it provides the ideal setting for developing higher order schemes. +++show agreement with FD, particle, show symmetry in error+++

## 5 Applying the Numerical Scheme

We now have enough techniques to begin solving the kinetic model. Consider the space-homogeneous evolution given by (6), that is

$$\partial_t f_t(v) = \partial_v v f_t(v) - \partial_v G(\langle w \rangle_{f_t}) f_t(v) + \sigma \partial_{vv} f_t(v). \quad (18)$$

Using the methods developed in the previous section, we are now able to solve this system numerically. As when solving the heat equation, a zero boundary condition shall be enforced. This is valid as we know that the stationary distributions are Gaussian and centred at  $-1, 0, +1$ . The boundary  $L$  can then be chosen depending on the the diffusion so that almost no mass is contained beyond the boundary. For example if  $\sigma = 1$ , the mass contained beyond  $L = 5$  is of the order  $10^{-5}$ .

Simpson's rule will be used as a quick way to approximate the integral within the herding coefficient. To differentiate between the integral and its approximation, we write  $\langle w \rangle_{F^n}$ . Below is the scheme when both the herding coefficient and the velocity are positive, using a finite difference scheme with a CN discretisation for the diffusive term and an upwind method for the damping and herding terms.

$$\begin{aligned} \frac{F_j^{n+1} - F_j^n}{\Delta t} = & -G(\langle w \rangle_{F^n}) \left[ \frac{F_{j+1}^n - F_j^n}{\Delta v} \right] + \left[ \frac{v_j F_j^n - v_{j-1} F_{j-1}^n}{\Delta v} \right] \\ & + \frac{\sigma}{2} \left[ \frac{F_{j+1}^{n+1} - 2F_j^{n+1} + F_{j-1}^{n+1}}{(\Delta v)^2} + \frac{F_{j+1}^n - 2F_j^n + F_{j-1}^n}{(\Delta v)^2} \right] \end{aligned}$$

+++Pictures, moments converging, error (in moments too?) in particular, mass loss? -¿ compare conservative methods i.e. fin vol +++

## 5.1 Space Heterogeneous

+++ phi = 1 still, moving in space. Animations/diagrams showing Leb in space. +++

## 6 Discussion + Conclusion

+++ future add other phi, recalc M +++

## References

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## A Thomas Algorithm