



Model Order Reduction of Rarefied Gases Using Neural Networks

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Outline

Introduction

The BGK-Model

Sod's shock tube

Proper Orthogonal Decomposotion (POD)

Neural Networks

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Governing equations

- The Boltzmann equation approximated by Q the BGK operator as a source term with

$$\partial_t f + v \partial_x f = \frac{1}{\tau} (M_t - f) \tag{1}$$

- The equilibrium solution is a Maxwellian distribution M_f with

$$M_{f} = \frac{\rho(x,t)}{(2\pi RT(x,t))^{\frac{3}{2}}} \exp(-\frac{(v-u(x,t))^{2}}{2RT(x,t)})$$
 (2)

– The duration to evolve into equilibrium is given by the relaxation time au with

$$\tau^{-1} = \frac{\rho(x, t)T^{1-\nu}(x, t)}{Kn} \tag{3}$$

- The rarefaction level is defined over the Knudsen number **Kn** with

$$Kn = \frac{\lambda}{I} \tag{4}$$



¹PhysRev.94.511.





Knudsen number

- Solution is f(x, v, t) in 1D and $f(x, y, v_x, v_y, t)$ in 2D and $f(x, y, z, v_x, v_y, v_z, t)$ in 3D

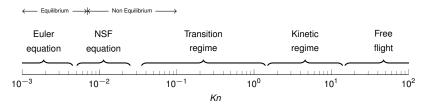


Figure: Partitioning of *Kn*, the Knudsen number, into levels of rarefaction.

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²NumaKUL.



Discretization in space and velocity space in 1D

- Space and time discretization considering a uniform grid i.e.
 - $x_i = i\Delta x$ and $i \in \mathbb{Z}$, $v_k = k\Delta v$ and $k \in \mathbb{Z}$, $t^i = i\Delta t$ and $t \in \mathbb{N}$,
- is leading from the full PDE to a set of ODE's in time

$$\partial_t f_{j,k} = -(v_k)_1 D_x f_{j,k}(t) + \frac{1}{\tau} (M_{f_{j,k}}(t) - f_{j,k}(t)).$$
 (5)

- KJ first-order differential equations need to be evaluated when K and J are the number of gridpoints in space and velocity space.
- In 3D there are K^3J^3 first-order differential equations.
- The discretization in velocity space requires the computation of the moments of f.





Moments/ Expected values of f

- By multiplying the collision invariants $\Phi(v) = [1, v, \frac{1}{2}v^2]$ with f and integrating in velocity space v the moments are obtained.
- The first moment/ the Density is

$$\rho(x,t) = \int f \, \mathrm{d}v \,, \tag{6}$$

- the second moment/ the Momentum is

$$\rho(x,t)u(x,t) = \int vf \, dv \,, \tag{7}$$

- the third moment/ the kinetic Energy is

$$E(x,t) = \int \frac{1}{2} v^2 f \, \mathrm{d}v \,. \tag{8}$$







Moments/ Expected values of f

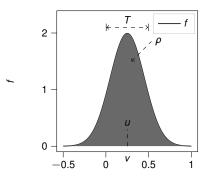


Figure: Illustration of the linkage between the macroscopic quantities of the gas flow and the distribution function f.







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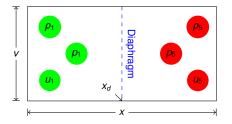


Figure: Problem setup of Sod's shock tube for the BGK model in 1D.

- Test case for numerical schemes solving
- non-linear hyperbolic conservation laws in gas dynamics (Gary A. Sod in 1978)
- Idea:
 - Solve problem analytically (Rankine-Hugoniot jump conditions)
 - Solve problem numerically
 - Compare resolution of discontinuities







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ToDo

- ToDo schreiben
- ToDo abarbeiten







