

Uncertainty quantification for hyperbolic PDEs

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Lituya Bay Mega Tsunami, Alaska, 1958

- ▶ Earthquake induced rockslide tsunami.
- ▶ **Highest recorded** wave run-up: 524 m !!!
- ▶ Widely studied.
- ▶ Simulation of [Asuncion, Castro, SM, Sukys, Sanchez, 2014](#):

What is needed I: The model

- ▶ Two-layer **Savage-Hutter** (**Shallow water**) model.

$$\left\{ \begin{array}{l} \frac{\partial h_1}{\partial t} + \frac{\partial q_1}{\partial x} = 0 \\ \frac{\partial q_1}{\partial t} + \frac{\partial}{\partial x} \left(\frac{q_1^2}{h_1} + \frac{g}{2} h_1^2 \right) + gh_1 \frac{\partial h_2}{\partial x} = gh_1 \frac{dH}{dx} + S_f + S_{b_1} \\ \frac{\partial h_2}{\partial t} + \frac{\partial q_2}{\partial x} = 0 \\ \frac{\partial q_2}{\partial t} + \frac{\partial}{\partial x} \left(\frac{q_2^2}{h_2} + \frac{g}{2} h_2^2 \right) + rgh_2 \frac{\partial h_1}{\partial x} = gh_2 \frac{dH}{dx} - rS_f + S_{b_2} + \tau. \end{array} \right. \quad (1)$$

- ▶ With

- ▶ **Coulomb friction**: $\tau = -g(1-r)h_2 \frac{q_2}{|q_2|} \tan(\delta_0)$,
- ▶ **Interlayer friction**: $S_f = c_f \frac{h_1 h_2}{h_2 + r h_1} (u_2 - u_1) |u_2 - u_1|$

What is needed II: The numerical scheme

- ▶ Savage-Hutter equations are **Non-conservative hyperbolic system**

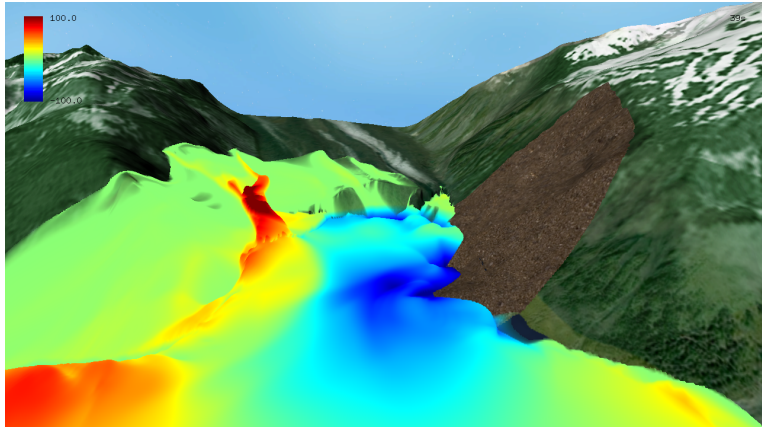
$$\mathbf{U}_t + \mathbf{A}(\mathbf{U})\mathbf{U}_x = 0.$$

- ▶ Specially designed **Path conservative finite volume scheme**
- ▶ Need to discretize **Non-conservative product** carefully.
- ▶ Optimized **GPU** implementation.

What is needed III: Inputs

- ▶ Initial data.
- ▶ Boundary conditions.
- ▶ Model parameters:
 - ▶ Acceleration due to gravity g .
 - ▶ Interlayer density ratio r
 - ▶ Bottom friction parameters $S_{b_{1,2}}$
 - ▶ Coulomb friction angle δ_0
 - ▶ Interlayer friction parameter c_f

Run-up at $T = 39s$



Critique of the simulation

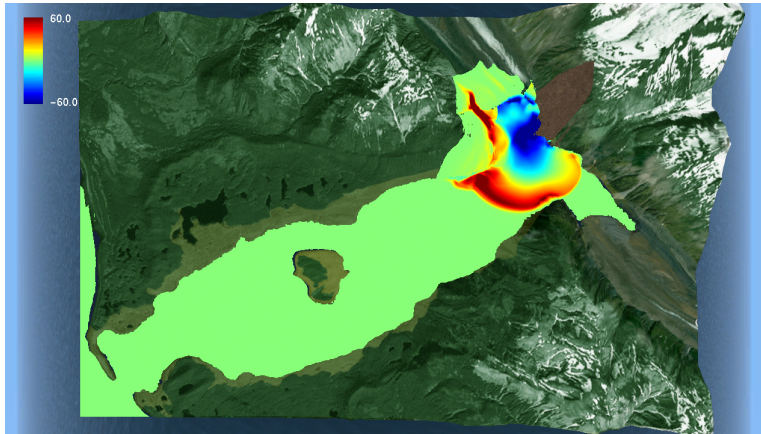
- ▶ Sources of **Errors**
 - ▶ **Modeling error**
 - Savage-Hutter is a good model (checked in the lab).
 - ▶ **Numerical (discretization) error.**
 - ▶ Good numerical scheme (Discretization error can be made as small as possible).
 - ▶ **Measurement (Data) errors:**
 - ▶ Rather low for initial data and boundary conditions.
 - ▶ **Unacceptably high** for r, c_f, δ_0 (even in the lab !!!)
 - ▶ Standard deviation is about 50 percent of mean !!!
- ▶ **High measurement error** \Rightarrow low trust in simulation ?

Generic situation in Science and Engineering

- ▶ **Mathematical modeling** of any physical/chemical/biological phenomena:
- ▶ **Model inputs:** are obtained by **Measurements:**
 - ▶ Initial conditions.
 - ▶ Boundary data.
 - ▶ Coefficients.
 - ▶ Parameters.
- ▶ **Measurements** are **Uncertain**.
- ▶ Uncertain **Inputs** \Rightarrow Uncertain **Solutions (Outputs)**.
- ▶ + Many models based on **Uncertain Dynamics** (high Model + Numerical error).

- ▶ **Uncertainty quantification** includes:
 - ▶ **Modeling** of uncertain inputs and dynamics.
 - ▶ Efficient **Computation** of the resulting output uncertainty.
 - ▶ **Interpretation** of the uncertain output.
 - ▶ Possible **Risk assessment** of the process.

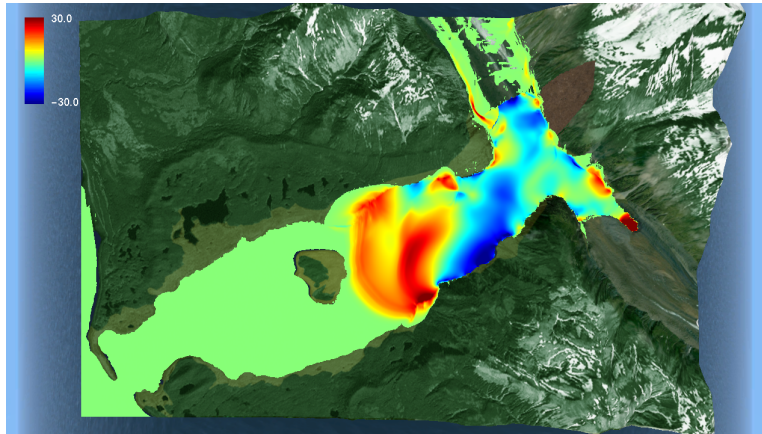
Run-up Mean at $T = 39s$



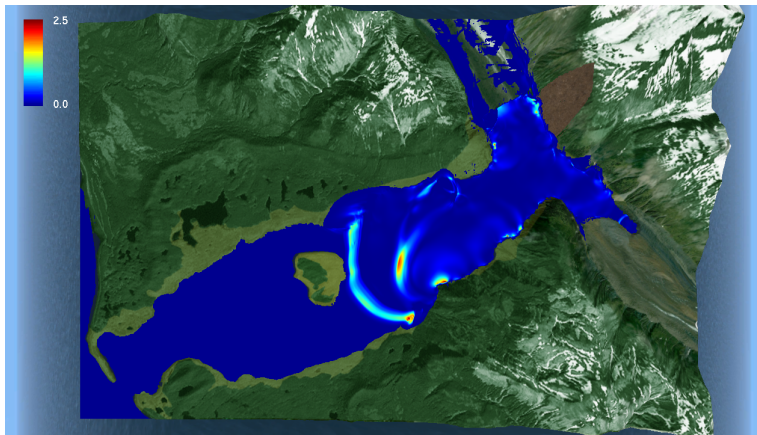
Run-up Variance at $T = 39s$



Run-up Mean at $T = 120s$



Run-up Variance at $T = 120s$



Aims and outline of mini course

- ▶ AIM: *To provide a brief overview of UQ for a specific class of PDEs (hyperbolic conservation laws) with a specific class of methods (Statistical sampling (Monte Carlo) methods).*
- ▶ Outline:
 - ▶ Brief introduction to Conservation laws.
 - ▶ High-resolution finite volume schemes
 - ▶ Modeling with Random fields
 - ▶ (Multi-level) Monte Carlo methods
 - ▶ Measure valued and statistical solutions
 - ▶ Massively parallel HPC implementation ?

Conservation laws

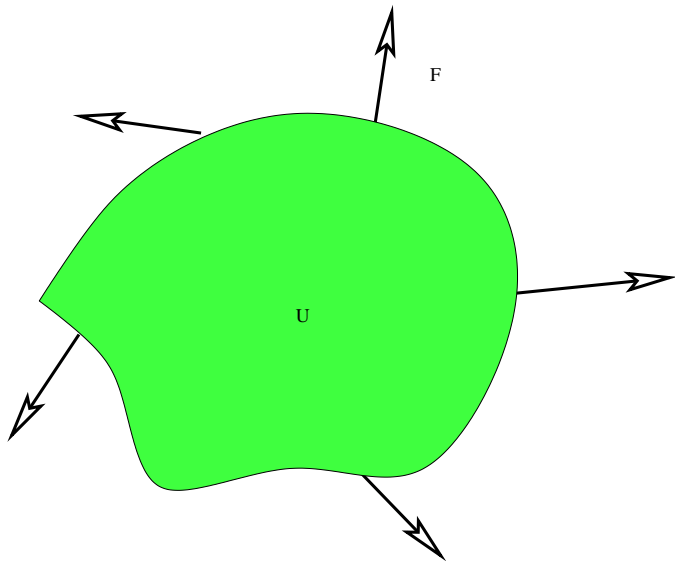
- ▶ Let D be a domain.
- ▶ Let \mathbf{U} be a quantity of interest.
- ▶ \mathbf{F} is flux across the boundary, then

$$\frac{d}{dt} \int_D \mathbf{U} dx = - \int_{\partial D} \mathbf{F} \cdot \mathbf{n} ds.$$

- ▶ Using divergence theorem gives,

$$\mathbf{U}_t + \operatorname{div}(\mathbf{F}(\mathbf{U})) = 0,$$

Conservation law



Example: Fluid dynamics

- ▶ Euler equations of Compressible fluid dynamics.
- ▶ Conservation of mass:

$$\rho_t + \operatorname{div}(\rho \mathbf{u}) = 0.$$

- ▶ Conservation of momentum:

$$(\rho \mathbf{u})_t + \operatorname{div}(\rho \mathbf{u} \otimes \mathbf{u} + p \mathcal{I}) = 0,$$

- ▶ Conservation of energy:

$$E_t + \operatorname{div}((E + p)\mathbf{u}) = 0.$$

- ▶ Equation of state (Ideal gas):

$$E = \frac{p}{\gamma - 1} + \frac{1}{2}\rho \mathbf{u}^2,$$

Euler equations

- ▶ Are a **system of conservation laws**:

$$\rho_t + \operatorname{div}(\rho \mathbf{u}) = 0,$$

$$(\rho \mathbf{u})_t + \operatorname{div}(\rho \mathbf{u} \otimes \mathbf{u} + p \mathcal{I}) = 0,$$

$$E_t + \operatorname{div}((E + p)\mathbf{u}) = 0.$$

- ▶ Other examples are
 - ▶ Shallow water equations (Meteorology).
 - ▶ MHD equations (Plasma physics).
 - ▶ Flows in porous media (Oil reservoirs).
 - ▶ Einstein equations (Relativity).
 - ▶ Many, many other applications.

Simplest Example: scalar conservation law

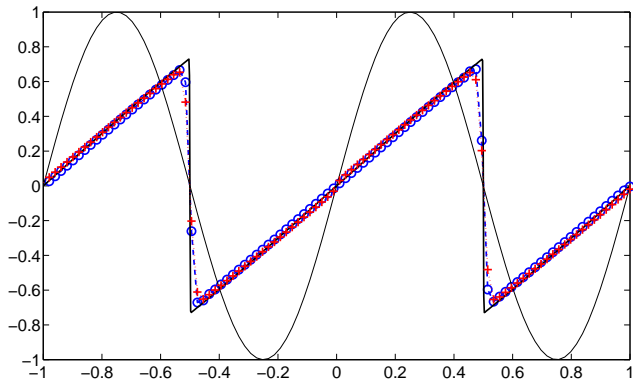
- ▶ In one dimension, equation of the form

$$u_t + (f(u))_x = 0,$$

- ▶ Solutions: Discontinuities for smooth initial data.
- ▶ **Shock formation**
- ▶ **Weak solutions**: for all test functions φ ,

$$\int_D \int_{\mathbb{R}_+} (u\varphi_t + f(u)\varphi_x) dx dt + \int_d u_0(x)\varphi(x, 0) dx = 0.$$

Non-linearity \Rightarrow Shocks



Entropy Solutions

- ▶ Weak solutions not necessarily unique.
- ▶ Have to be augmented by incorporating Physics – entropy criteria.
- ▶ **Entropy** should not decrease – 2nd law of thermodynamics.
- ▶ **Entropy solution**: For all $\varphi \geq 0 \in C_c^\infty(\mathbb{R} \times \mathbb{R}_+)$, we have

$$\int_D \int_{\mathbb{R}_+} (S(u)\varphi_t + Q(u)\varphi_x) dx dt + \int_D S(u_0)\varphi(x, 0) dx \geq 0$$

- ▶ Where the pair (S, Q) is the **entropy-entropy flux** pair satisfying,
 - ▶ S, Q are smooth with S convex.
 - ▶ $Q' = S'f'$
- ▶ Infinitely many entropies for scalar equations !!!
- ▶ **Entropy solutions** exist, are unique and stable in $L^1(D)$.

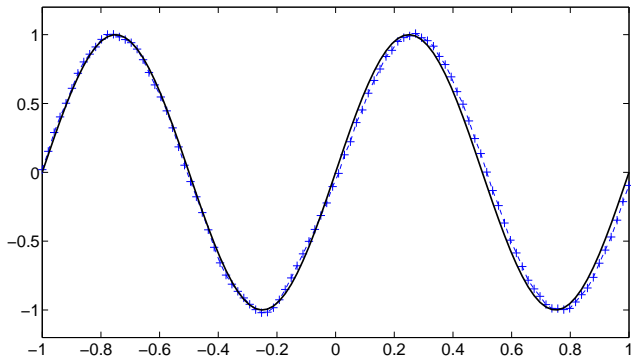
Numerical schemes: Linear advection

- ▶ Simplest example of scalar conservation law: $u_t + au_x = 0$
- ▶ Simplest **Finite difference** numerical scheme:
 - ▶ **Forward Euler** in time.
 - ▶ **Central difference** in space.
- ▶ Scheme is

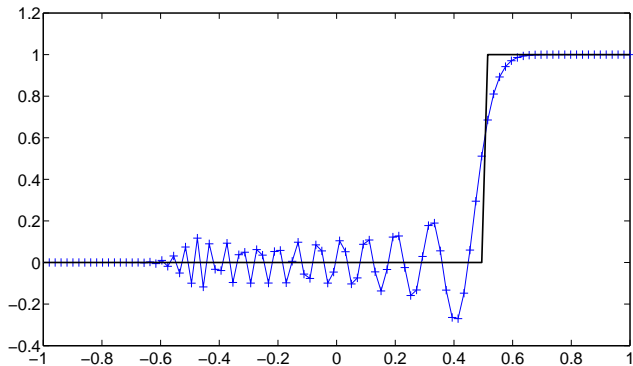
$$\frac{u_j^{n+1} - u_j^n}{\Delta t} + a \frac{u_{j+1}^n - u_{j-1}^n}{2\Delta x} = 0.$$

- ▶ **Unconditionally unstable**. Solutions blow up.
- ▶ Use Runge-Kutta (RK3) time integrator.

Linear Advection $a = 1$: Smooth solution



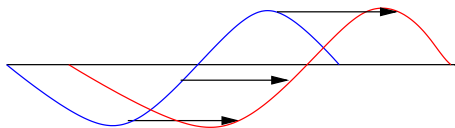
Linear Advection $a = 1$: Discontinuous solution



What goes wrong ?

- ▶ Exact solution (constant along **Characteristics**):

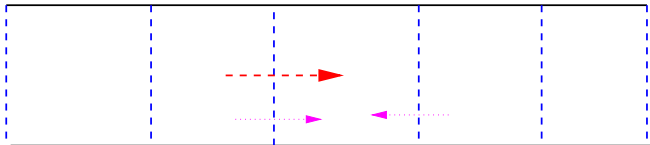
$$u(x, t) = u_0(x - at),$$



- ▶ **Hyperbolicity**:
 - ▶ Finite speed of information propagation.
 - ▶ Preferred directions of information propagation.
- ▶ Generalized to systems by considering **real eigenvalues of Jacobian matrix**

What goes wrong ?

- ▶ Taylor expansion no longer valid near **discontinuities**
- ▶ **Direction of propagation is incorrect !!!**.



- We need **Upwinding**.

Upwind finite difference scheme

- ▶ Form of the scheme,

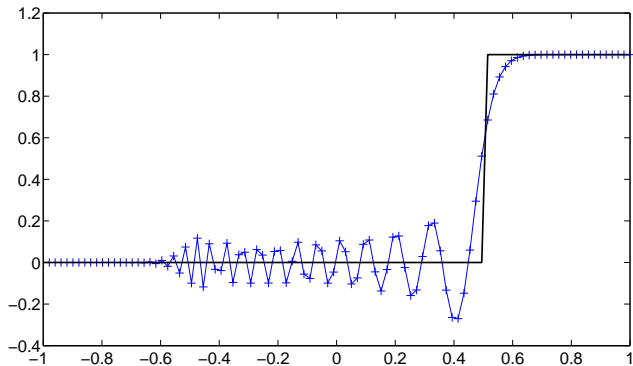
$$\frac{u_j^{n+1} - u_j^n}{\Delta t} + a \frac{u_j^n - u_{j-1}^n}{\Delta x} = 0.$$

- ▶ First order in space and time.
- ▶ Proved to **converge** as $\Delta x \rightarrow 0$ if **CFL** condition is satisfied,

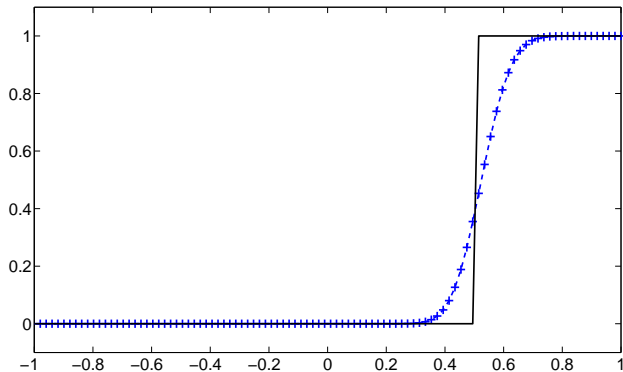
$$a \frac{\Delta t}{\Delta x} \leq 1.$$

- ▶ How to upwind for **nonlinear** equations ?

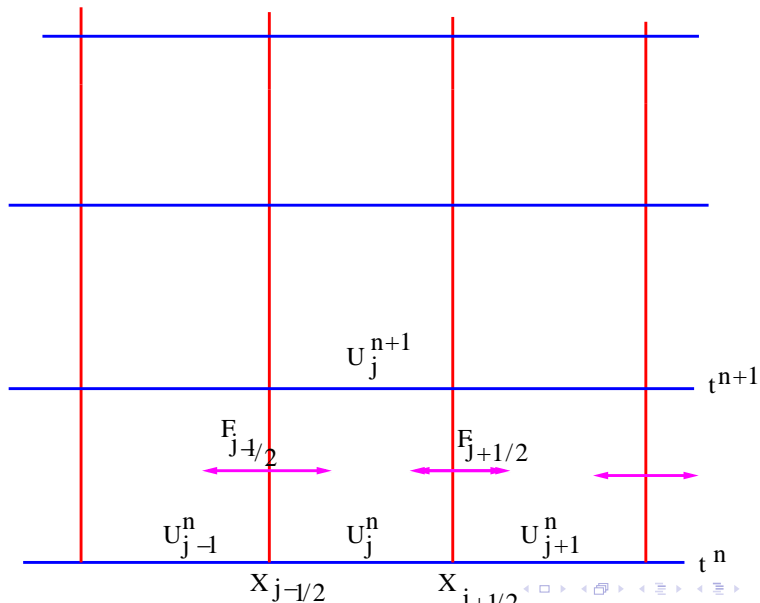
Linear Advection: Discontinuous solution



Linear Advection: Discontinuous solution



The grid



Finite Volume Schemes

- ▶ The domain is divided into cells (**control volumes**).
- ▶ Solutions may be discontinuous – methods based on **cell averages**:

$$u_j^0 = \frac{1}{\Delta x} \int_{x_{j-1/2}}^{x_{j+1/2}} u(0, x) dx$$

- ▶ Cell Average is evolved for each time step.
- ▶ Based on **conservation** inside each volume i.e

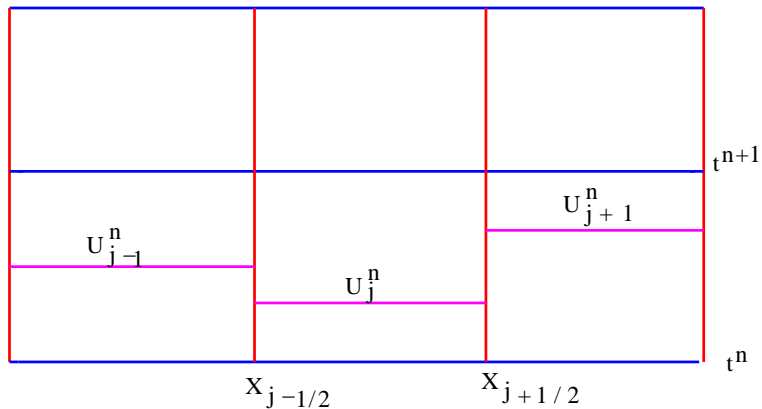
$$\frac{d}{dt} \int_{x_{j-1/2}}^{x_{j+1/2}} u^h(x, t) + \frac{1}{\Delta x} f(u^h(x_{j+1/2}+) - f(u^h(x_{j-1/2}-))) = 0$$

- ▶ How to define **interface fluxes** ?
- ▶ At the n th time level and each interface, we have Riemann problems with data,

$$u^h(x, t) = \begin{cases} u_j^n & x < x_{j+1/2} \\ u_{j+1} & x > x_{j+1/2} \end{cases}$$

- ▶ **Evolve** the solution exactly .
- ▶ Stop the evolution before neighboring waves interact.
- ▶ **Average** over each cell to obtain u_j^{n+1} .

Riemann Problems

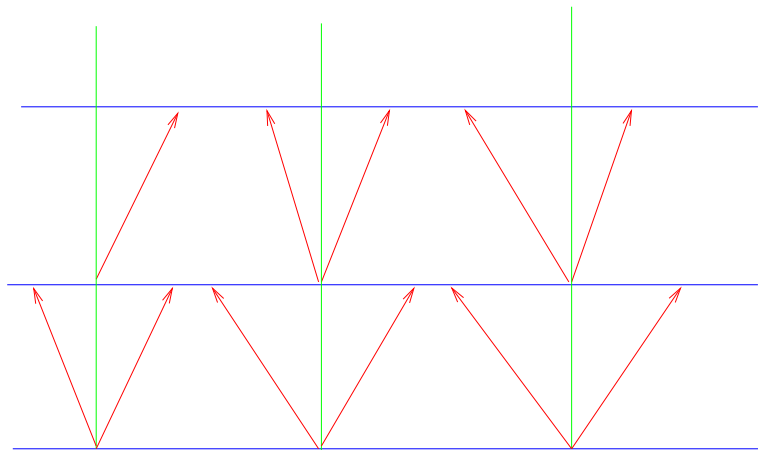


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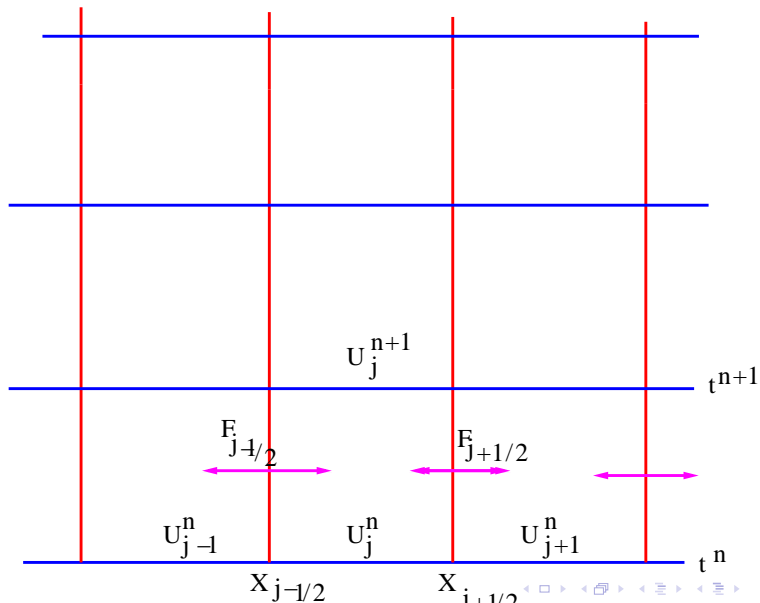
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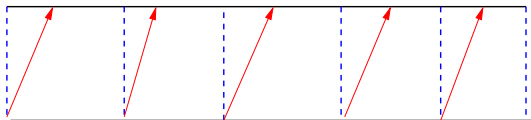
Riemann Problems



The grid



Linear Advection: Riemann solutions



- Form of the resulting scheme (**Upwind scheme**):

$$\frac{u_j^{n+1} - u_j^n}{\Delta t} + a \frac{u_j^n - u_{j-1}^n}{\Delta x} = 0.$$

Non-linear Equations: Explicit Formula for Godunov scheme

- ▶ The final scheme is of the form,

$$u_j^{n+1} = u_j^n - \frac{\Delta t}{\Delta x} (F(u_j^n, u_{j+1}^n) - F(u_{j-1}^n, u_j^n))$$

- ▶ Where the interface flux is given by,

$$F_{j+1/2} = F(u_j^n, u_{j+1}^n) = f(u^h(x_{j+1/2}))$$

- ▶ Even more explicit formula is given by,

$$F(a, b) = \begin{cases} \min_{\theta \in [a, b]} f(\theta), & \text{if } a \leq b \\ \max_{\theta \in [b, a]} f(\theta), & \text{if } a > b \end{cases}$$

Riemann Solvers (Contd..)

- ▶ Use **Approximate Riemann solvers** instead of full solution of the Riemann problem.
- ▶ Example: **Roe's** scheme based on **local linearization**.
- ▶ Flux given by

$$F^R(a, b) = \begin{cases} f(a) & \text{if } f'(av(a, b)) > 0 \\ f(b) & \text{if } f'(av(a, b)) < 0 \end{cases}$$

- ▶ Needs an entropy fix.
- ▶ Another Example: **Engquist-Osher** flux given by,

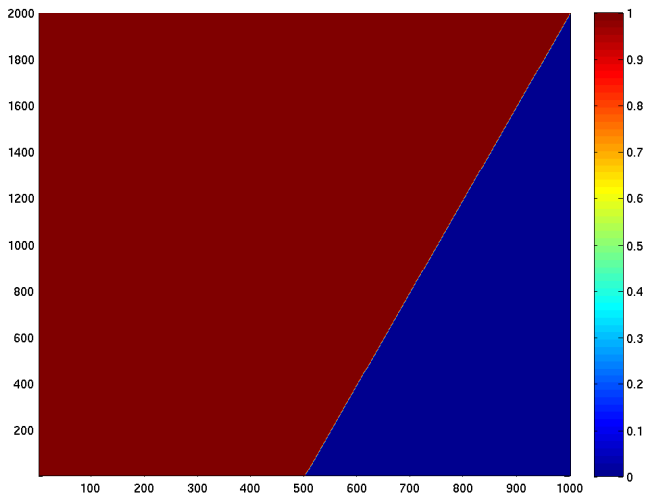
$$F^{EO}(a, b) = 0.5(f(a) + f(b)) - \int_a^b |f'(\xi)| d\xi$$

Convergence analysis

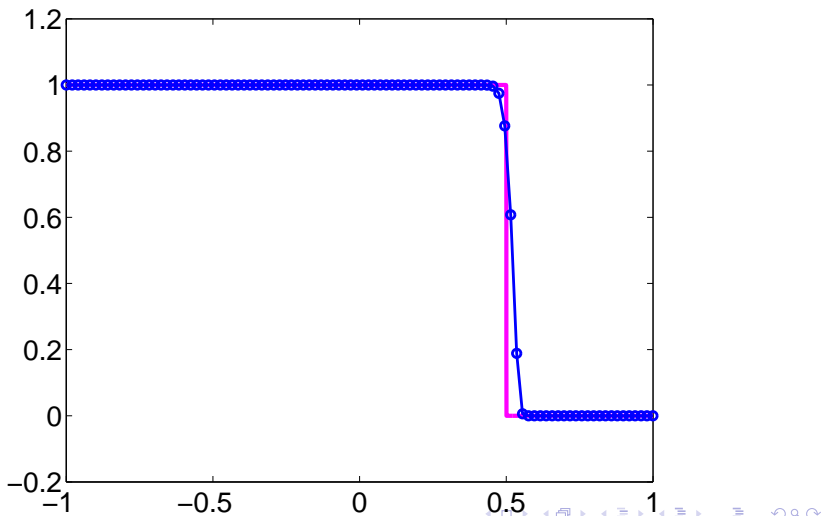
- ▶ Schemes are:
 - ▶ Formally **First-order accurate**.
 - ▶ **Conservative**: $\sum_j u_j^{n+1} = \sum_j u_j^n$.
 - ▶ **Consistent**: $F(a, a) = f(a)$
 - ▶ **Monotone**: if $u_j^n \leq v_j^n$ then $u_j^{n+1} \leq v_j^{n+1}$.
 - ▶ **Discrete L^1 contractive**: $\sum |u_j^{n+1} - u_j^n| \leq \sum |u_j^n - u_j^{n-1}|$
 - ▶ **TVD**: $\sum |u_{j+1}^{n+1} - u_j^{n+1}| \leq \sum |u_{j+1}^n - u_j^n|$
- ▶ Schemes **Converge** to the entropy solution as $\Delta x \rightarrow 0$.
- ▶ **Convergence rate**:

$$\|u - u^{\Delta x}\|_{L^\infty(\mathbb{R}_+, L^1(D))} \leq C(\Delta x)^{\frac{1}{2}}.$$

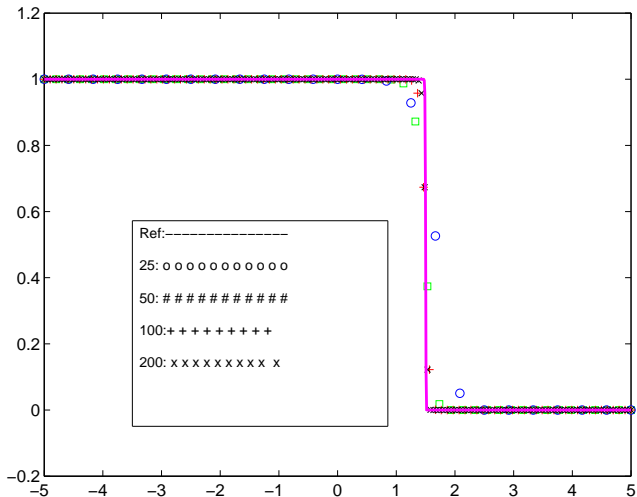
Num Ex:1, space time plot of u with Godunov scheme and $\Delta x = 0.01, CFL = 0.9$



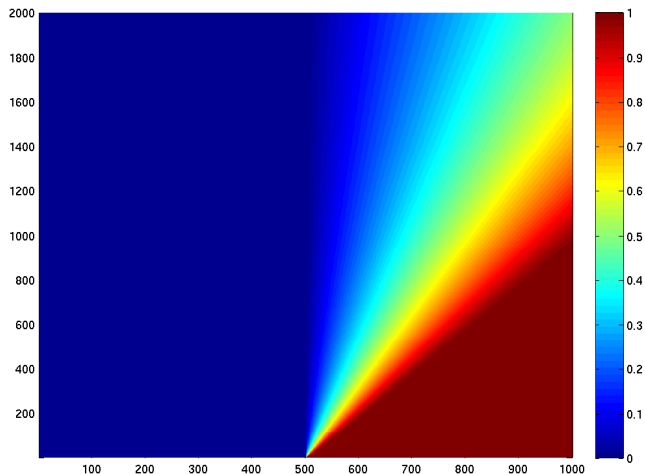
Num Ex:1, u at time $t = 3$ with Godunov scheme and $\Delta x = 0.01, CFL = 0.9$



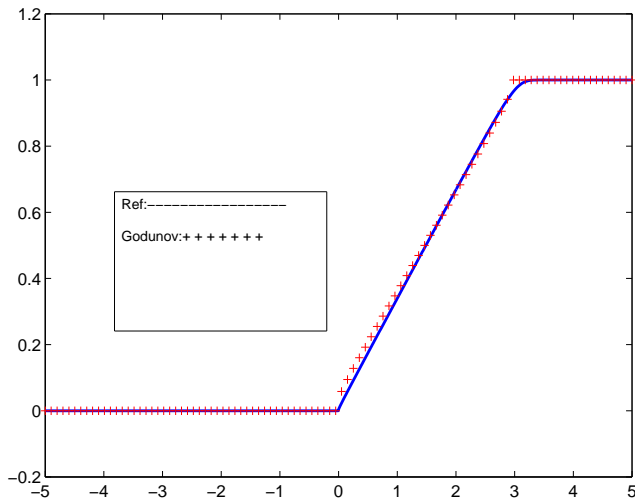
Effect of Mesh refinement on the Godunov scheme



Num Ex:2, space time plot of u with Godunov scheme and $\Delta x = 0.1, CFL = 0.9$



Num Ex:2, u at time $t = 3$ with Godunov scheme and $\Delta x = 0.01, CFL = 0.9$



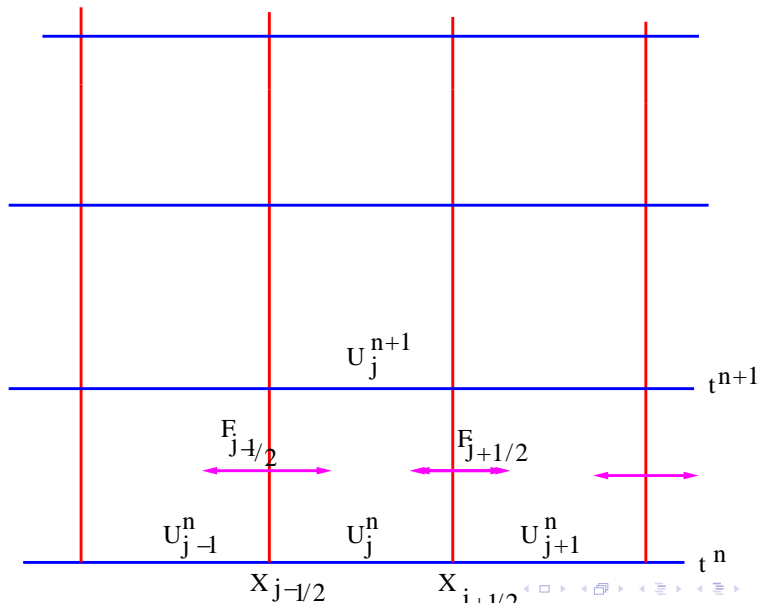
Systems of conservation laws

- ▶ Equations of the form,

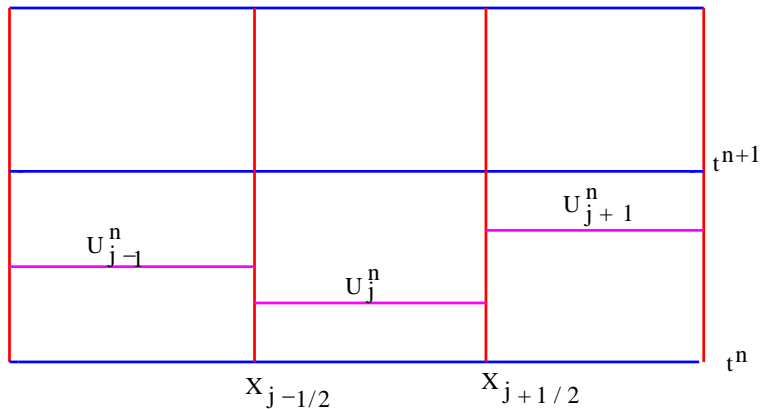
$$\mathbf{U}_t + (\mathbf{f}(\mathbf{U}))_x = 0,$$

- ▶ Where
 - ▶ \mathbf{U} : **Vector** of unknowns.
 - ▶ \mathbf{f} : **Flux vector**.
- ▶ Aim: Design numerical schemes to approximate systems.

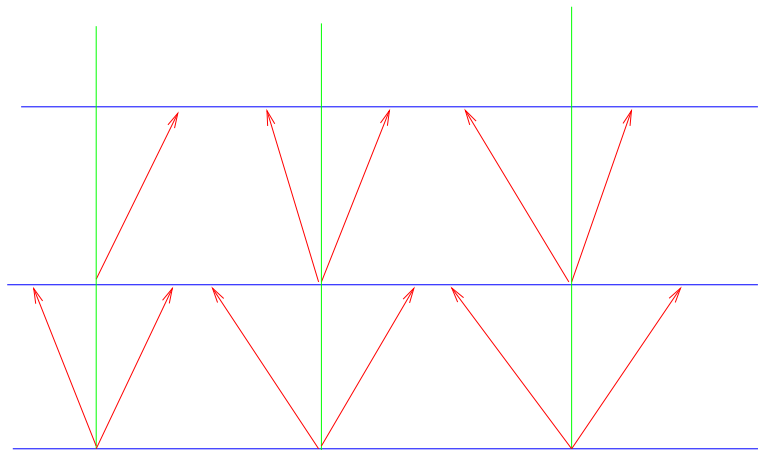
Finite volume grid



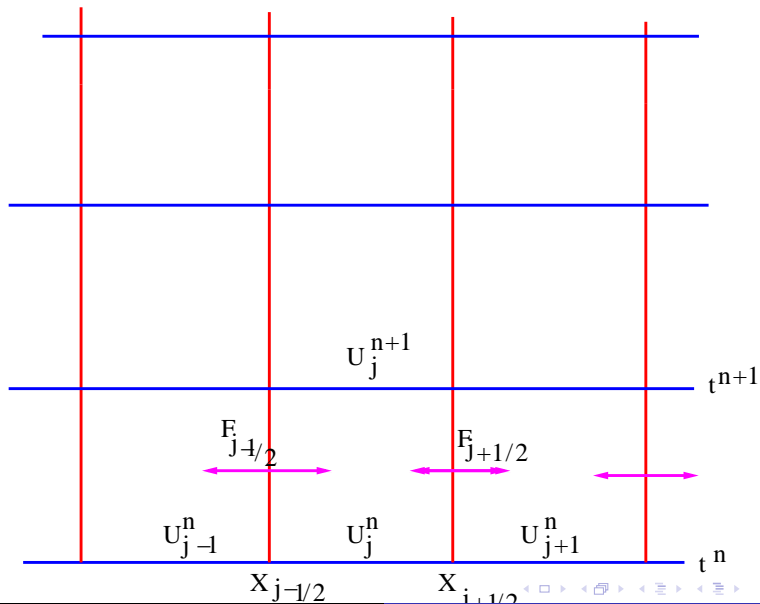
Riemann Problems



Riemann Problems



The grid



- ▶ Scheme of form:

$$\mathbf{U}_j^{n+1} = \mathbf{U}_j^n - \frac{\Delta t}{\Delta x} (\mathbf{F}(\mathbf{U}_j^n, \mathbf{U}_{j+1}^n) - \mathbf{F}(\mathbf{U}_{j-1}^n, \mathbf{U}_j^n))$$

- ▶ Interface flux:

$$\mathbf{F}_{j+1/2} = \mathbf{F}(\mathbf{U}_j^n, \mathbf{U}_{j+1}^n) = \mathbf{f}(\mathbf{U}^h(x_{j+1/2}))$$

- ▶ Exact Riemann solver: Extremely Difficult to obtain explicit formulas !!!

Wave structure

- ▶ Linearizing $\mathbf{U}_t + (\mathbf{f}(\mathbf{U}))_x = 0$, about a state

$$\mathbf{U}_t + A\mathbf{U}_x = 0,$$

- ▶ Wave structure consists of
 - ▶ (Real) **Eigenvalues** of A : wave speeds (**hyperbolicity**).
 - ▶ Eigenvectors: Jumps and states.
- ▶ Let $\{\lambda_i, r_i, l_i\}$ be the eigen-system of A , then,

$$\mathbf{U}_t + A\mathbf{U}_x = 0,$$

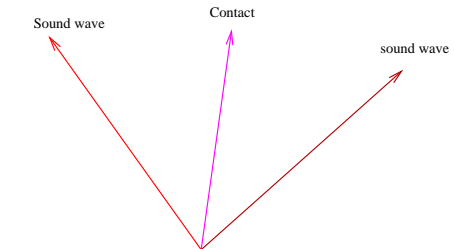
$$\mathbf{U}_t + R\Lambda R^{-1}\mathbf{U}_x = 0,$$

$$(R^{-1}\mathbf{U})_t + \Lambda(R^{-1}\mathbf{U})_x = 0,$$

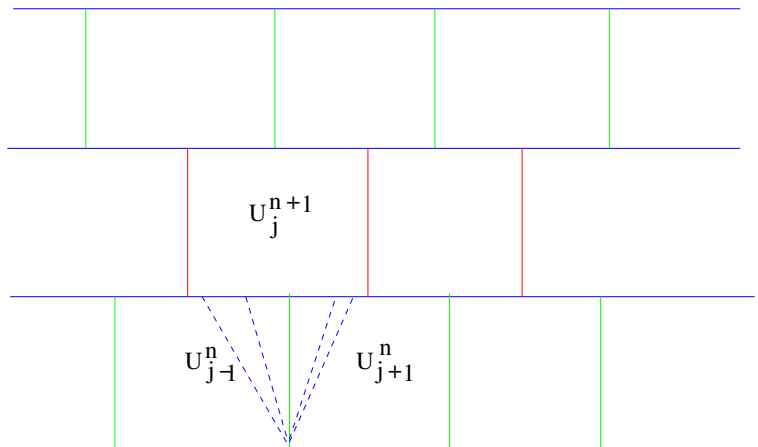
- ▶ System solved in terms of the **characteristic variables** $R^{-1}\mathbf{U}$

Riemann problem for Nonlinear system

- ▶ Consists of 3 possible families of Waves:
 - ▶ **Shocks** : Intersecting characteristics, Rankine-Hugoniot conditions.
 - ▶ **Rarefaction waves**: Lipschitz continuous, Self-Similar
 - ▶ **Contact discontinuity**: Parallel characteristics, linear waves.
- ▶ Example: Euler equations



Staggered Grid



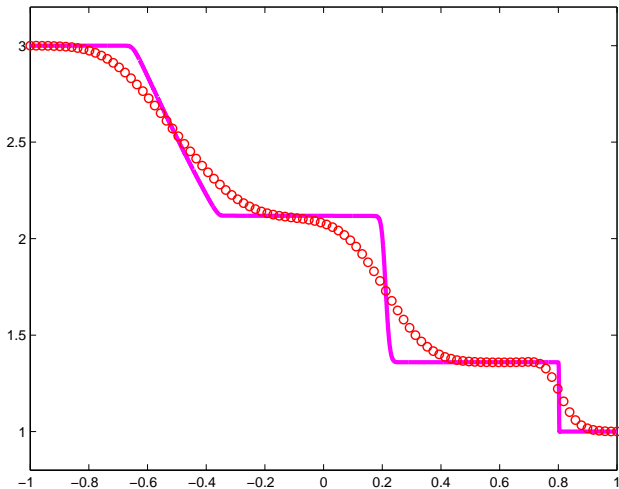
Central Schemes

- ▶ The grids at succeeding time levels are staggered with respect to each other.
- ▶ Riemann problems are solved at each interface but the averaging is over the entire Riemann fan.
- ▶ Simplest first order scheme is of the form,

$$\mathbf{U}_j^{n+1} = \frac{1}{2}(\mathbf{U}_{j-1}^n + \mathbf{U}_{j+1}^n) - \frac{\lambda}{2}(\mathbf{F}(\mathbf{U}_{j+1}^n) - \mathbf{F}(\mathbf{U}_{j-1}^n))$$

- ▶ Well known **Lax-Friedrichs** Scheme.
- ▶ No explicit details about the Riemann solution are required.

Sod Shock tube: ρ with LxF scheme (100 mesh points)



Linearized Solvers: Roe flux

- ▶ Based on quasi-linear form of the equation:

$$\mathbf{U}_t + A(\mathbf{U})\mathbf{U}_x = 0,$$

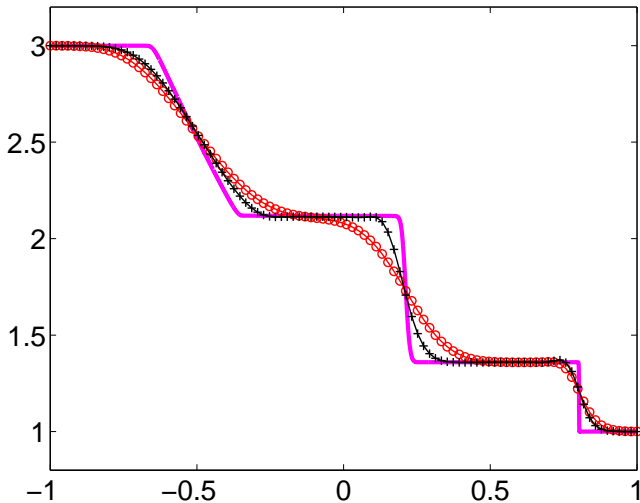
- ▶ Find a suitable state such that

$$\mathbf{F}(\mathbf{U}_r) - \mathbf{F}(\mathbf{U}_l) = A(\mathbf{U}_l, \mathbf{U}_r)(\mathbf{U}_r - \mathbf{U}_l),$$

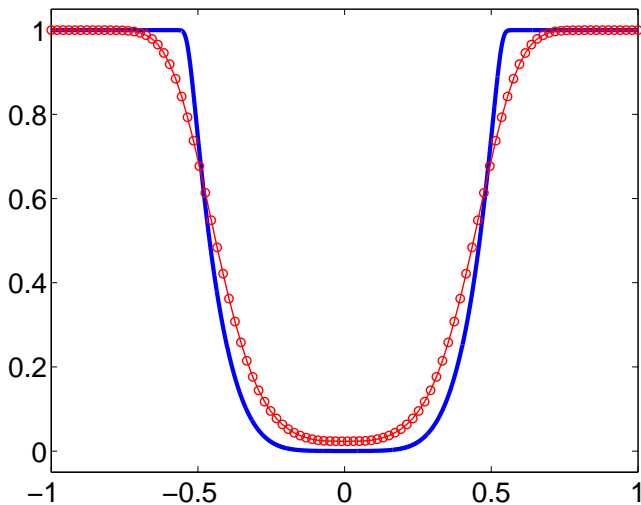
- ▶ $A(\mathbf{U}_l, \mathbf{U}_r)$ (Roe Matrix).
- ▶ Resulting scheme is

$$\mathbf{F}(\mathbf{U}_j, \mathbf{U}_{j+1}) = \frac{1}{2}(\mathbf{F}(\mathbf{U}_j) + \mathbf{F}(\mathbf{U}_{j+1})) - R_{j+1/2} |\Lambda|_{j+1/2} R_{j+1/2}^{-1} (\mathbf{U}_{j+1} - \mathbf{U}_j)$$

Sod shock tube: Roe vs LxF



Expansion problem: Roe vs. LxF



Non-linear solvers

- ▶ Roe solver: **Not positivity preserving**.
- ▶ Have to use non-linear **Hartex-Lax-vanLeer (HLL)** solvers.
- ▶ Approximate Riemann Problem with **two-waves**.
- ▶ **Conservation**:

$$\begin{aligned}\mathbf{F}(\mathbf{U}^*) - \mathbf{F}(\mathbf{U}_L) &= s_L(\mathbf{U}^* - \mathbf{U}_L), \\ \mathbf{F}(\mathbf{U}_R) - \mathbf{F}(\mathbf{U}^*) &= s_R(\mathbf{U}_R - \mathbf{U}^*),\end{aligned}$$

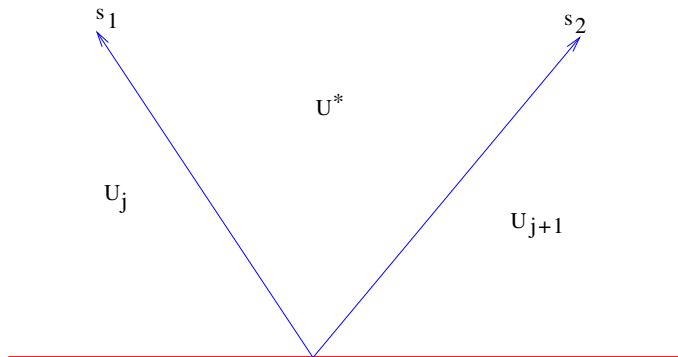
- ▶ Middle state:

$$\mathbf{u}^* = \frac{\mathbf{F}(\mathbf{U}_R) - \mathbf{F}(\mathbf{U}_L) - s_{j+1/2}^R \mathbf{U}_R + s_{j+1/2}^L \mathbf{U}_j}{s_{j+1/2}^L - s_{j+1/2}^R}$$

- ▶ Choice of wave speeds (**Einfeldt**)

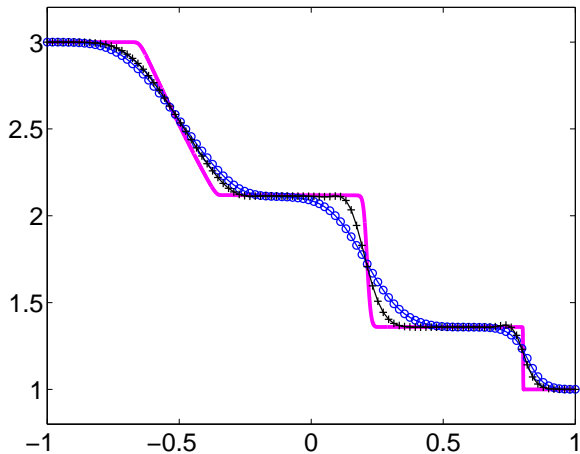
$$s_{j+1/2}^L = \min(\lambda_j^1, \lambda_{j+1/2}^1), \quad s_{j+1/2}^R = \max(\lambda_R^m, \lambda_{j+1/2}^m)$$

HLL 2-Wave solver

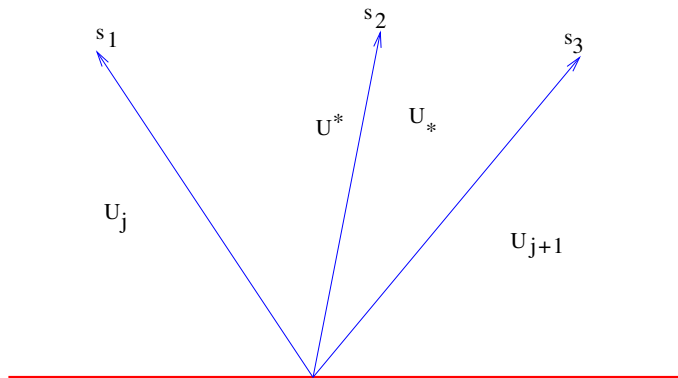


HLL 2 Wave Solver

Sod shock tube



HLL 3-Wave Solver



HLL 3-Wave Solver

- ▶ Two middle states: \mathbf{U}^* , \mathbf{U}_* .
- ▶ Conservation equations

$$\mathbf{F}(\mathbf{U}^*) - \mathbf{F}(\mathbf{U}_L) = s_L(\mathbf{U}^* - \mathbf{U}_L),$$

$$\mathbf{F}(\mathbf{U}_*) - \mathbf{F}(\mathbf{U}^*) = s_M(\mathbf{U}_* - \mathbf{U}^*),$$

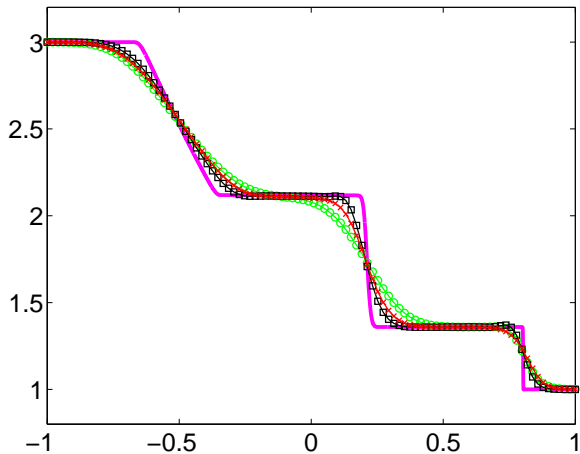
$$\mathbf{F}(\mathbf{U}_R) - \mathbf{F}(\mathbf{U}_L) = s_R(\mathbf{U}_R - \mathbf{U}_*),$$

- ▶ Middle speed $s_M = u_{L,R}^{\text{Roe}}$.
- ▶ Special properties:

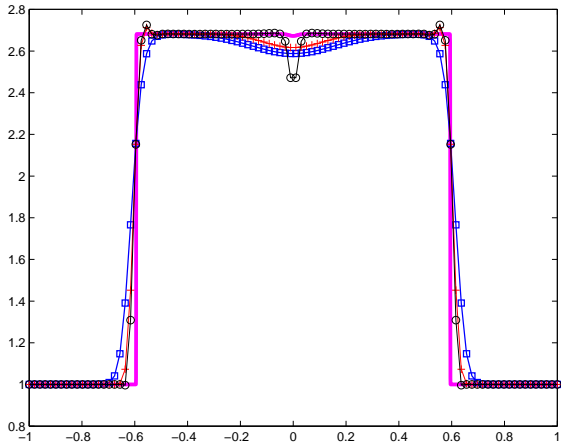
$$u_* = u^* = s_M, \quad p_* = p^*,$$

- ▶ Enables a unique solution.

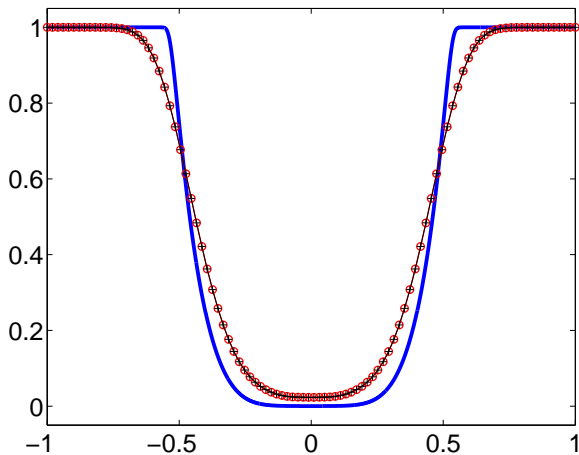
Sod shock tube



Double shocks



Expansion problem



Quality of Stable numerical approximation

- ▶ Key Indicator: **Order of Accuracy**.
- ▶ Consider the conservation law,

$$u_t + (f(u))_x = 0,$$

- ▶ Numerical scheme of the form,

$$v_j^{n+1} = H_{\Delta x}^{\Delta t}(\dots, v_{j-1}^n, v_j^n, v_{j+1}^n, \dots),$$

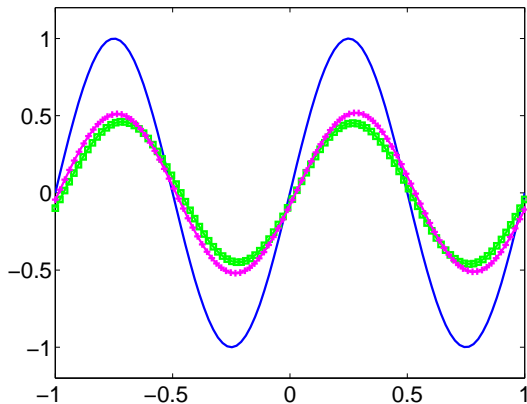
- ▶ Exact solution u , let $u(x_j, t^n) = u_j^n$, and

$$|u_j^{n+1} - H_{\Delta x}^{\Delta t}(\dots, u_{j-1}^n, u_j^n, u_{j+1}^n, \dots)| \leq C(\Delta x^p + \Delta t^q)$$

- ▶ The following orders of accuracy:
 - ▶ Spatial order: p ,
 - ▶ Temporal order: q ,

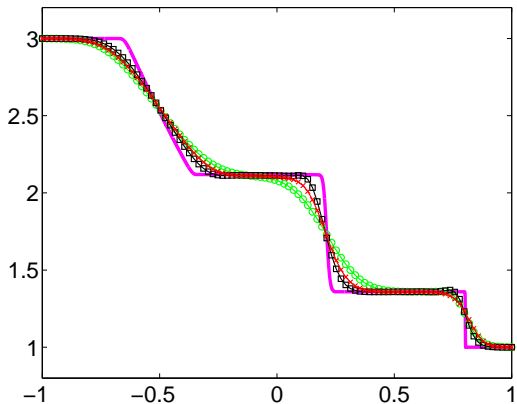
Order of accuracy: Example 1 (Linear advection)

- ▶ Upwind scheme is first-order accurate in both space and time !!!

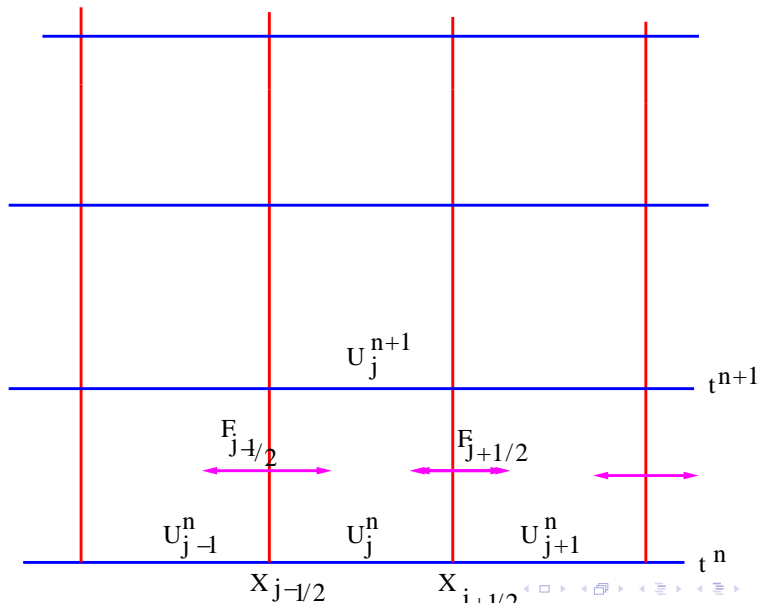


Order of accuracy: Example 2 (Euler Equations)

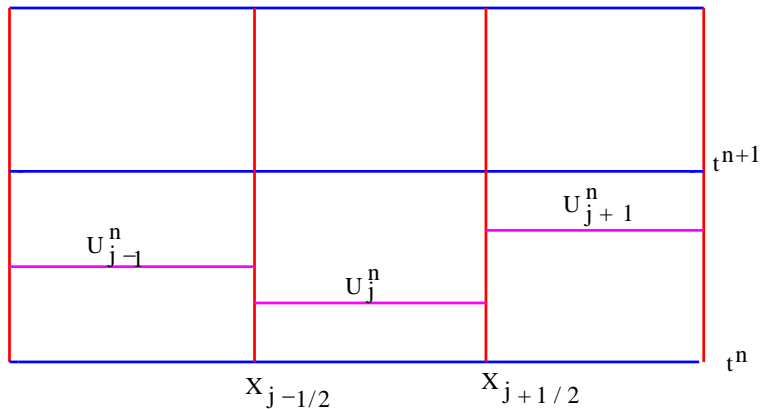
- ▶ **Riemann solvers** are **first-order** accurate in both space and time !!!



Finite volume grid



Riemann Problems

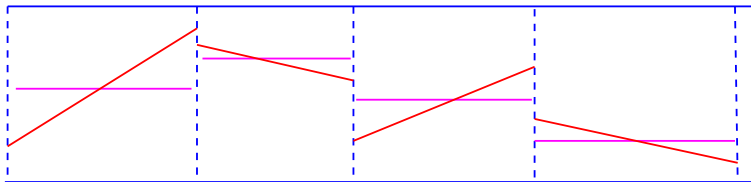


- ▶ Solution realized as: **Cell-averages**
- ▶ **Piecewise constants** in each cell.
- ▶ Replace **Piecewise constants** \mapsto **Piecewise linears** in each cell.
- ▶ Given cell-averages u_j , **reconstructed polynomial**:

$$p_j(x) = u_j + u_j'(x - x_j),$$

- ▶ For smooth solutions, $|p_j(x) - u(x)| \leq C\Delta x^2$,
- ▶ **Conservative** reconstruction.

Piecewise-linear Reconstruction



Resulting scheme for $\mathbf{U}_t + (\mathbf{F}(\mathbf{U}))_x = 0$

- ▶ Semi-discrete Godunov scheme based on **piecewise constants**:

$$\frac{d}{dt}(\mathbf{U}_j(t)) + \frac{1}{\Delta x}(\mathbf{F}(\mathbf{U}_j, \mathbf{U}_{j+1}) - \mathbf{F}(\mathbf{U}_{j-1}, \mathbf{U}_j))$$

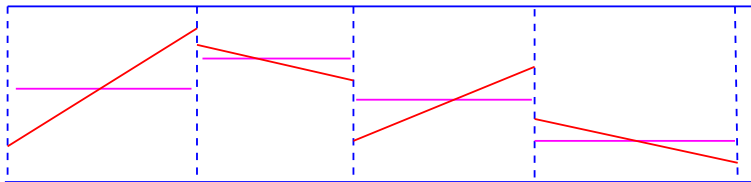
- ▶ Define edge values:

$$\mathbf{U}_j^+ = p_j(x_{j+1/2}), \mathbf{U}_j^- = p_j(x_{j-1/2}).$$

- ▶ Form of the **Second-order** scheme,

$$\frac{d}{dt}(\mathbf{U}_j(t)) + \frac{1}{\Delta x}(\mathbf{F}(\mathbf{U}_j^+, \mathbf{U}_{j+1}^-) - \mathbf{F}(\mathbf{U}_{j-1}^+, \mathbf{U}_j^-)) = 0.$$

Piecewise linear Reconstruction



Piecewise-linear Reconstruction

- ▶ Choice of Slopes:

- ▶ Backward:

$$U'_j = \frac{U_j - U_{j-1}}{\Delta x}$$

- ▶ Forward:

$$U'_j = \frac{U_{j+1} - U_j}{\Delta x}$$

- ▶ Central

$$U' = \frac{U_{j+1} - U_{j-1}}{\Delta x}$$

- ▶ Many, many other choices.

Choice of slope: Linear advection

- ▶ Choosing the Forward slope:

$$\frac{u_{j+1} - u_j}{\Delta x}$$

- ▶ Edge values,

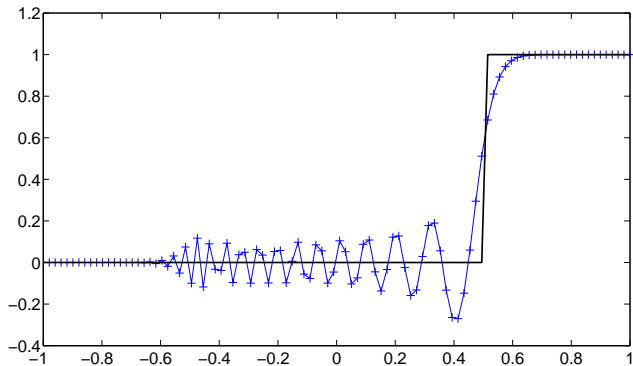
$$u_j^+ = \frac{u_j + u_{j+1}}{2}, u_j^- = \frac{u_{j+1}}{2} - \frac{3}{2}u_j,$$

- ▶ Second-order scheme is

$$\frac{d}{dt}u_j + \frac{u_{j+1} - u_{j-1}}{2\Delta x} = 0.$$

- ▶ Choice of slope is crucial.

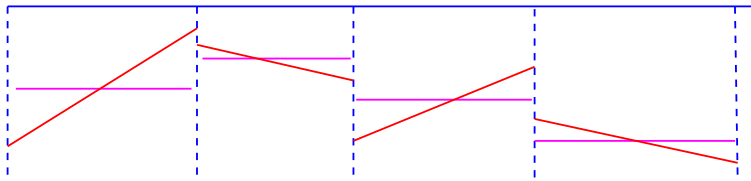
Linear Advection $a = 1$: Discontinuous solution



Clever choice of slopes

- ▶ We need **non-oscillatory** resolution of shocks.
- ▶ Reconstruction: Oscillatory for arbitrary choice of slopes.
- ▶ We need non-oscillatory reconstruction.
- ▶ Total variation: Indicator of oscillations.
- ▶ Require **TVD** piecewise linear reconstruction.

Piecewise linear reconstruction



TVD reconstruction

- ▶ Let $p_j(x) = \mathbf{U}_j + \mathbf{U}'_j(x - x_j)$
- ▶ Define,

$$(\mathbf{U}^{\Delta x}, p^{\Delta x}) = (\mathbf{U}_j, p_j(x)) \quad \text{if } x_{j-1/2} \leq x < x_{j+1/2},$$

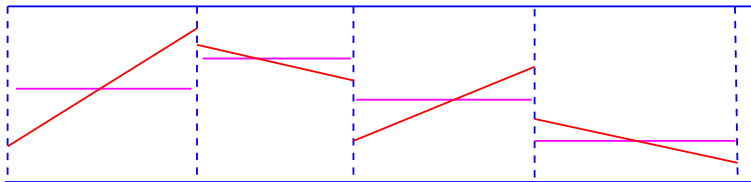
- ▶ Aim: Find slopes such that $TV(p^{\Delta x}) \leq TV(\mathbf{U}^{\Delta x})$.
- ▶ Solution: Use slope limiters: **Minmod limiter**:

$$u'_j = \text{minmod}\left\{\frac{\mathbf{U}_{j+1} - \mathbf{U}_j}{\Delta x}, \frac{\mathbf{U}_j - \mathbf{U}_{j-1}}{\Delta x}\right\}$$

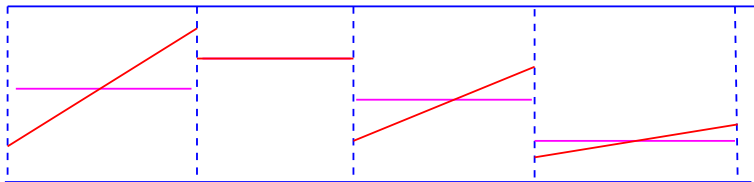
- ▶ Where

$$\text{minmod}\{a, b\} = \begin{cases} 0, & \text{if } \text{sgn}(a) \neq \text{sgn}(b), \\ \text{sgn}(a) \min\{|a|, |b|\}, & \text{otherwise,} \end{cases}$$

Piecewise linear Reconstructions



Minmod limiters



- ▶ MC limiter (Van Leer):

$$u'_j = M\left\{\frac{2(u_{j+1} - u_j)}{\Delta x}, \frac{u_{j+1} - u_{j-1}}{2\Delta x}, \frac{2(u_j - u_{j-1})}{\Delta x}\right\}$$

- ▶ Where

$$M\{a, b, c\} = \begin{cases} \operatorname{sgn}(a) \min\{|a|, |b|, |c|\}, & \text{if } \operatorname{sgn}(a) = \operatorname{sgn}(b) = \operatorname{sgn}(c) \\ 0, & \text{otherwise,} \end{cases}$$

- ▶ Superbee limiter:

Time integration

- ▶ Preceding schemes were semi-discrete.
- ▶ Can be time marched with Forward Euler.
- ▶ Second-order accuracy: Runge-Kutta methods
- ▶ Need to use second-order SSP RK methods.
- ▶ Developed by Gottlieb, Shu, Tadmor.

- ▶ Consider the following semi-discrete scheme,

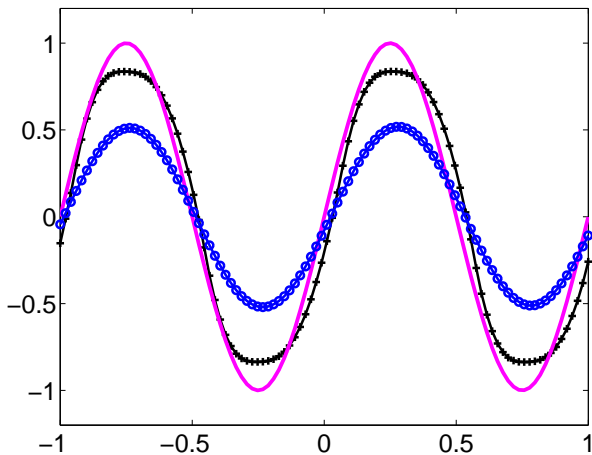
$$\frac{d}{dt}(u_j(t)) = H(u_{j-1}, u_j, u_{j+1}),$$

- ▶ SSP-RK2 is of the form,

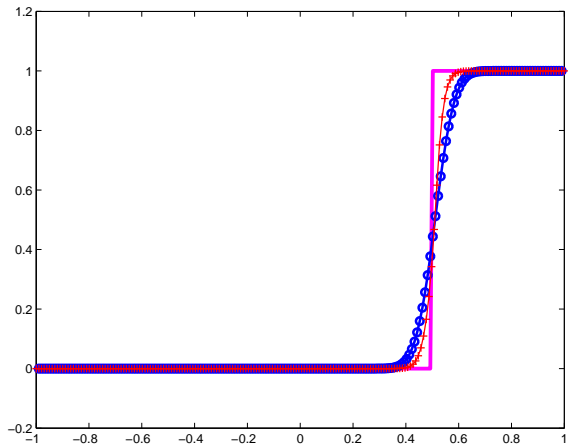
$$\begin{aligned}u_j^* &= u_j^n + \Delta t H(u_{j-1}^n, u_j^n, u_{j+1}^n), \\u_j^{**} &= u_j^* + \Delta t H(u_{j-1}^*, u_j^*, u_{j+1}^*), \\u_j^{n+1} &= \frac{1}{2}(u_j^n + u_j^{**}),\end{aligned}$$

- ▶ Time-integration is **second-order** accurate and **TVD**.

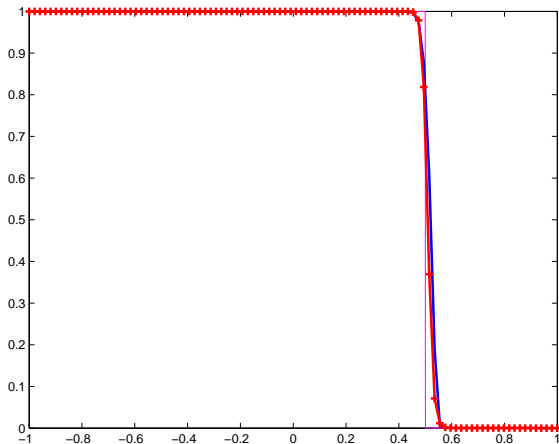
Linear advection: smooth solutions (comparison)



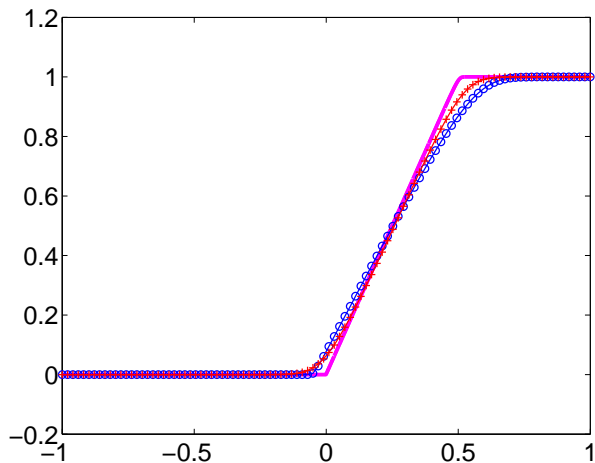
Linear advection: Discontinuities



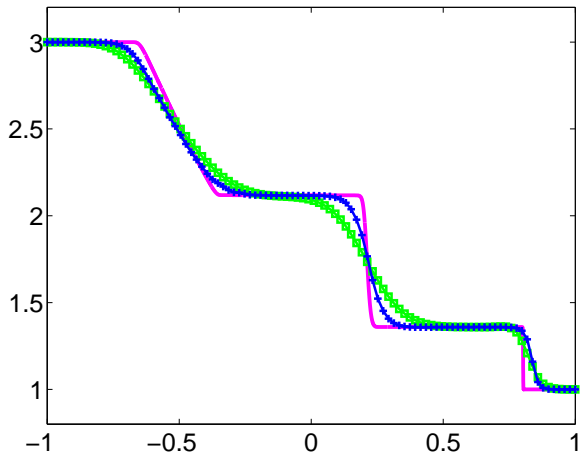
Burgers' equation: Shock



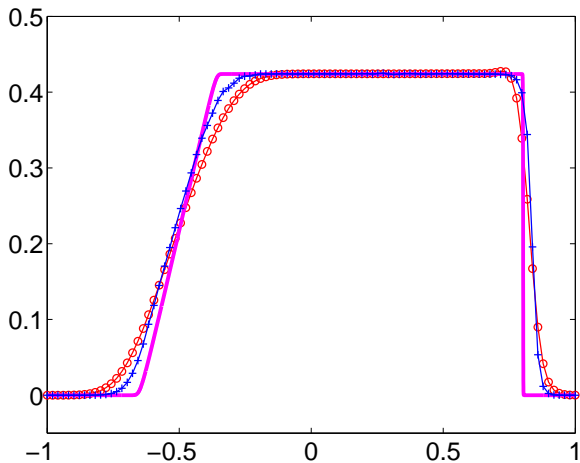
Burgers' equation: Rarefaction



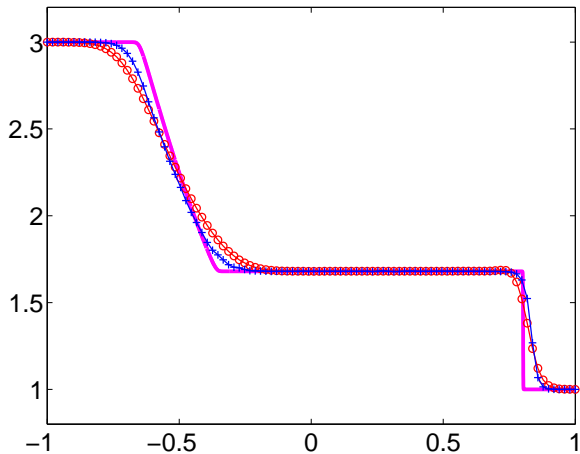
Sod shock tube ρ



Sod shock tube u



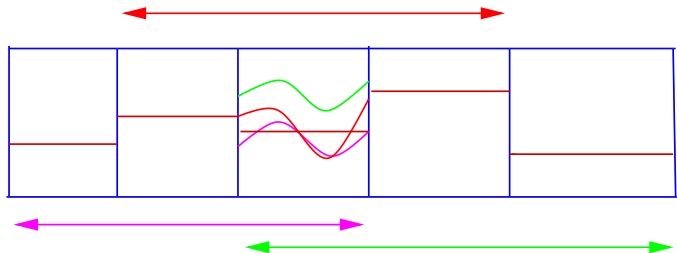
Sod shock tube p



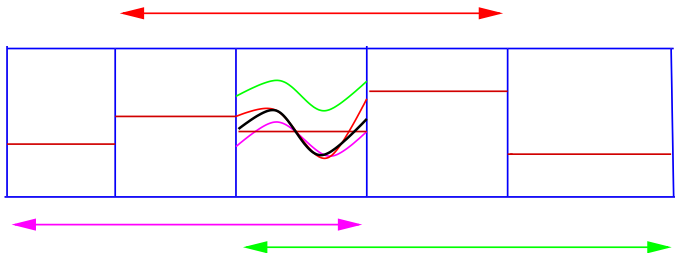
Even Higher-order schemes

- ▶ High-order **ENO** reconstructions Harten,Engquist,Osher, Chakravarty, 1985.
- ▶ High-order **WENO** reconstructions Shu,Osher 1989.
- ▶ High-order **SSP-RK** time-integration routines.

ENO reconstruction



WENO reconstruction



- ▶ Consider the following semi-discrete scheme,

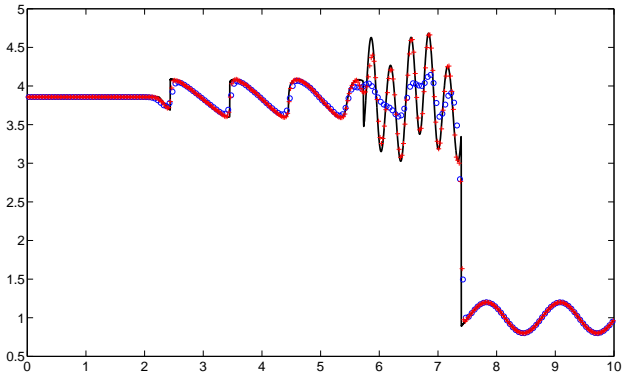
$$\frac{d}{dt}(U_j(t)) = \mathcal{L}(U_j),$$

$$U_j^* = u_j^n + \Delta t \mathcal{L}(U_j^n)$$

$$U_j^{**} = \frac{3}{4} U_j^n + \frac{1}{4} U_j^* + \frac{\Delta t}{4} \mathcal{L}(U_j^*)$$

$$U_j^{n+1} = \frac{1}{3} U_j^n + \frac{2}{3} U_j^{**} + \frac{2\Delta t}{3} \mathcal{L}(U_j^{**}).$$

Shock-Turbulence interaction for Euler equations: Minmod vs. WENO5



Finite volumes in multi-dimensions

- ▶ Consider a 2-D conservation law,

$$\mathbf{U}_t + \mathbf{F}(\mathbf{U})_x + \mathbf{G}(\mathbf{U})_y = 0.$$

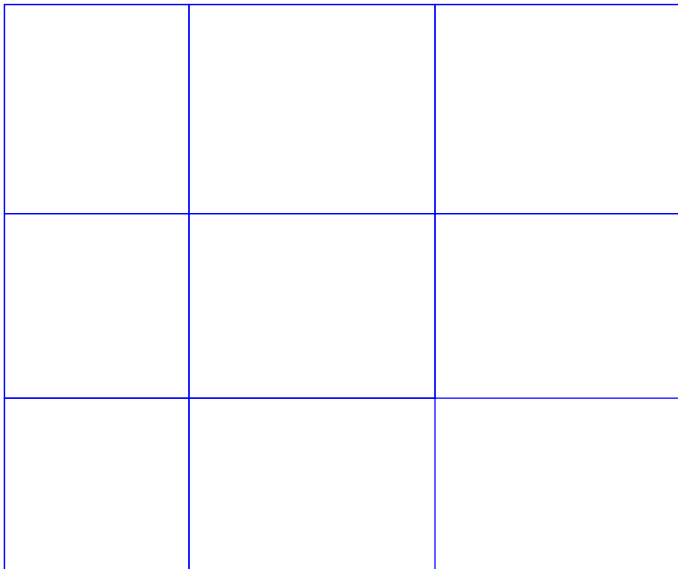
- ▶ The domain is divided into cells (**control volumes**).
- ▶ Consider a **Cartesian mesh**.
- ▶ Denote cell average as

$$\mathbf{U}_{i,j}(t) = \frac{1}{\Delta x \Delta y} \int_{x_{i-1/2}}^{x_{i+1/2}} \int_{y_{j-1/2}}^{y_{j+1/2}} \mathbf{U}(x, y, t) dx dy,$$

- ▶ Integrating the conservation law over each cell,

$$\begin{aligned} \frac{d}{dt} \mathbf{U}_{i,j} &= \int_{y_{j-1/2}}^{y_{j+1/2}} (\mathbf{F}(\mathbf{U}(x_{i+1/2}, y, t)) - \mathbf{F}(\mathbf{U}(x_{i-1/2}, y, t))) dy \\ &+ \int_{x_{i-1/2}}^{x_{i+1/2}} (\mathbf{G}(\mathbf{U}(x, y_{j+1/2}, t)) - \mathbf{G}(\mathbf{U}(x, y_{j-1/2}, t))) dx \end{aligned}$$

2-D Cartesian grid

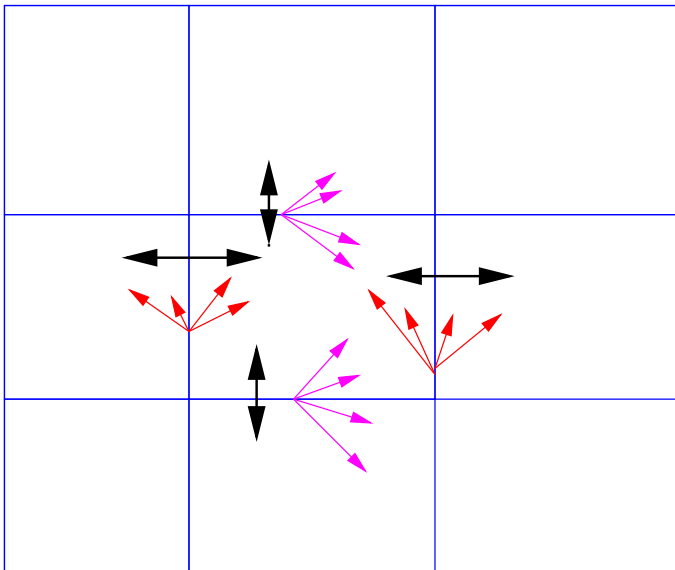


- ▶ Have to approximate **interface fluxes**.
- ▶ Solve **Riemann problems in the normal direction**
- ▶ Final form of the scheme,

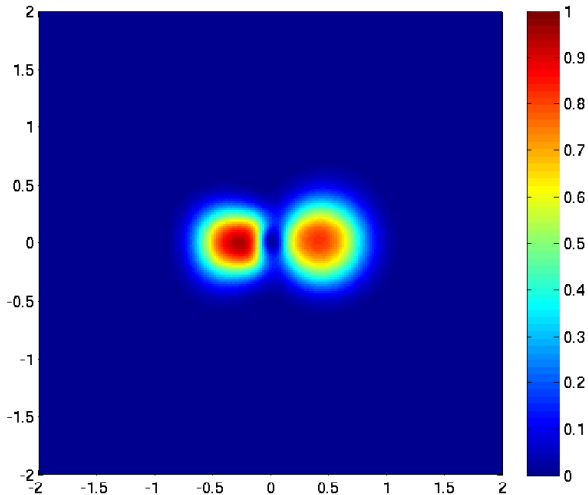
$$\begin{aligned} \frac{d}{dt} \mathbf{U}_{i,j} = & -\frac{1}{\Delta x} (\mathbf{F}(\mathbf{U}_{i,j}, \mathbf{u}_{i+1,j}) - \mathbf{F}(\mathbf{u}_{i-1,j}, \mathbf{u}_{i,j})) \\ & - \frac{1}{\Delta y} (\mathbf{G}(\mathbf{u}_{i,j}, \mathbf{u}_{i,j+1}) - \mathbf{G}(\mathbf{u}_{i,j-1}, \mathbf{u}_{i,j})), \end{aligned}$$

- ▶ **F, G** are numerical fluxes in x - and y - directions.
- ▶ Defined by **Exact or Approximate Riemann solvers in normal direction**.

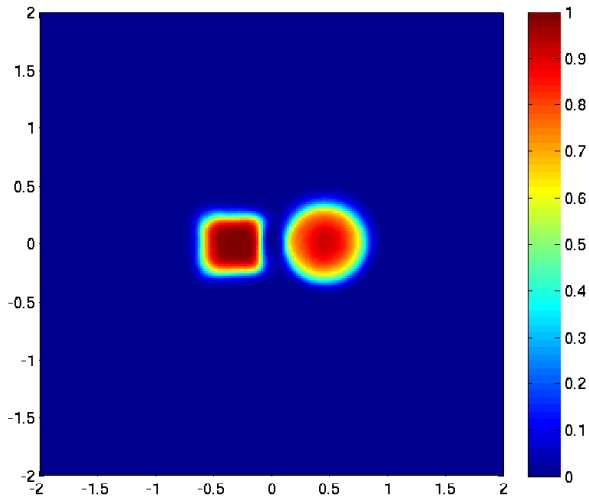
Normal Riemann problems



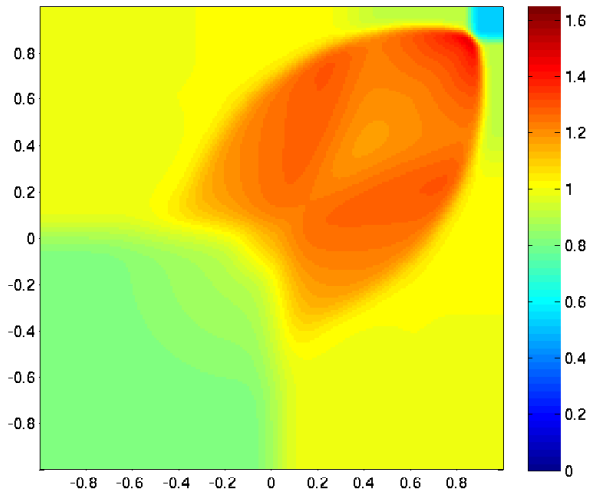
2 – D inhomogeneous advection with rotation: First order



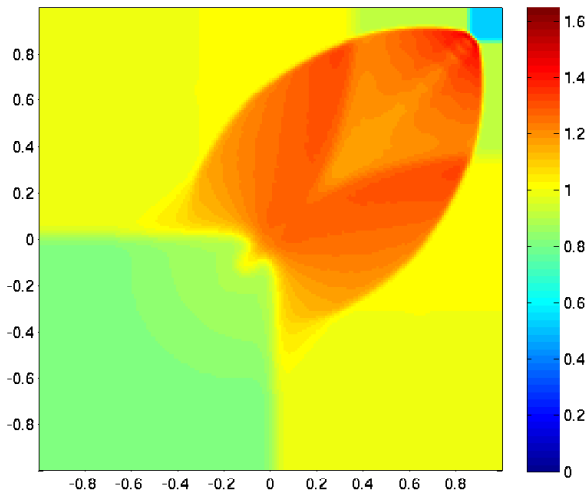
2 – D inhomogenous advection with rotation: Second order



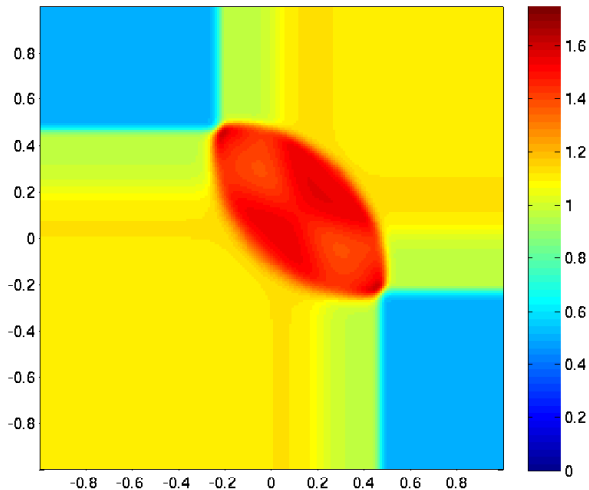
2 – D Euler: Mach vs. Regular reflection (First order)



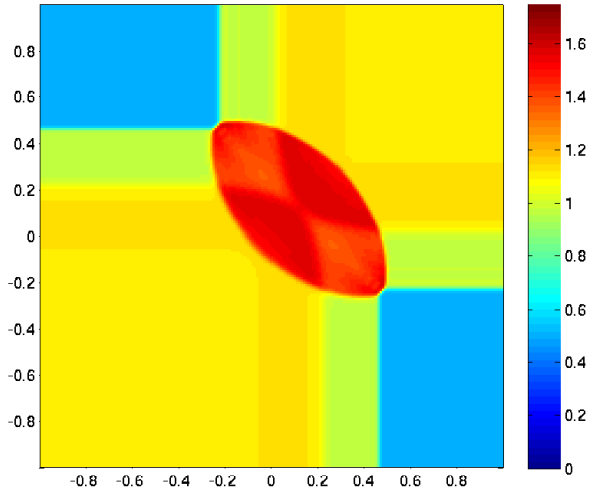
2 – D Euler: Mach vs. Regular reflection (Second order)



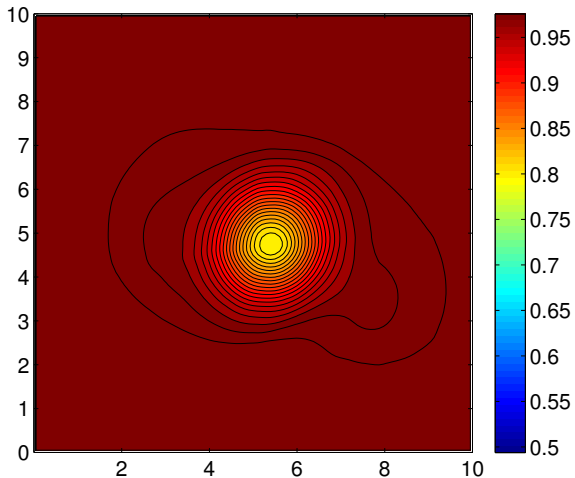
2 – D Euler: 2-Contact, 2-Rarefaction (First order)



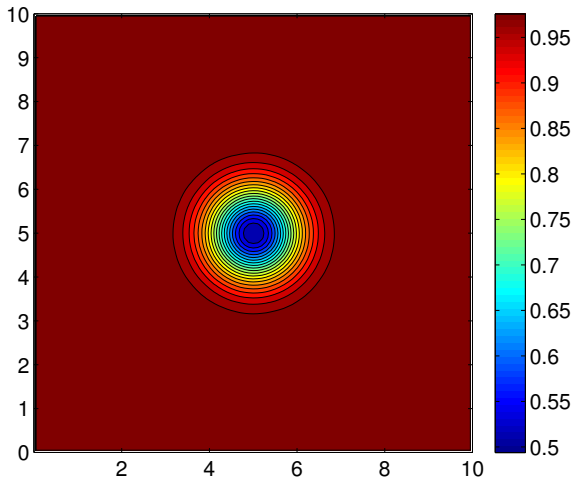
2 – D Euler: 2-Contact, 2-Rarefaction (Second order)



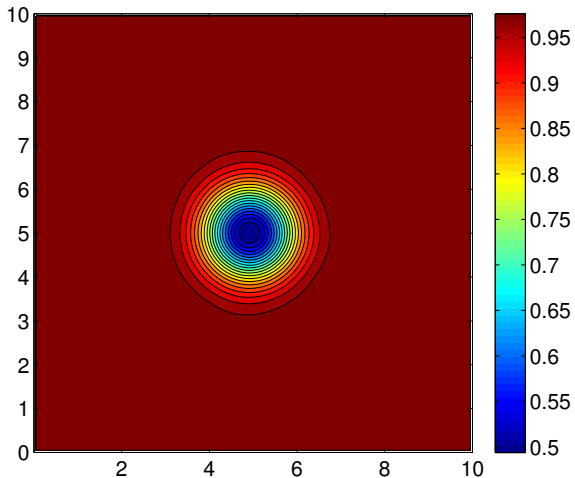
Advection of Euler vortex: TeCNO2



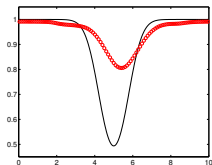
Advection of Euler vortex: TeCNO3



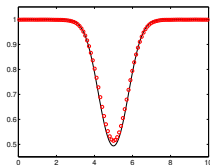
Advection of Euler vortex: TeCNO4



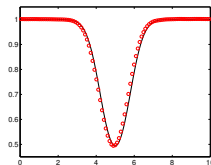
Advection of Euler vortex



(a) TeCNO2

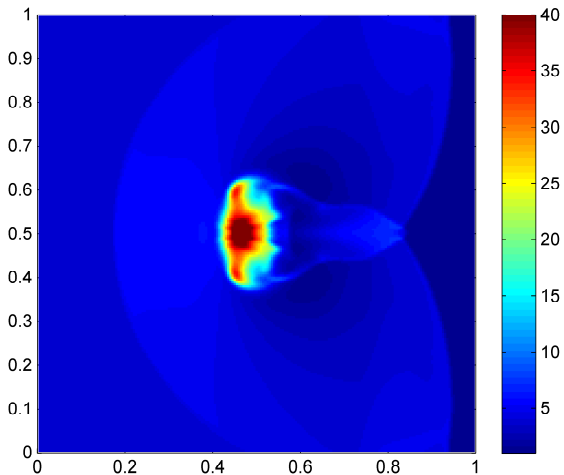


(b) TeCNO3

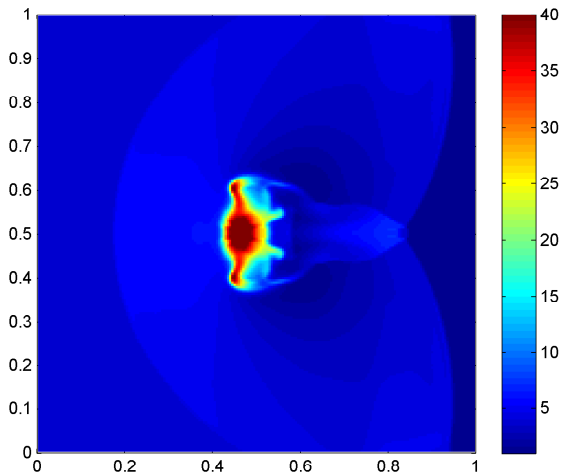


(c) TeCNO4

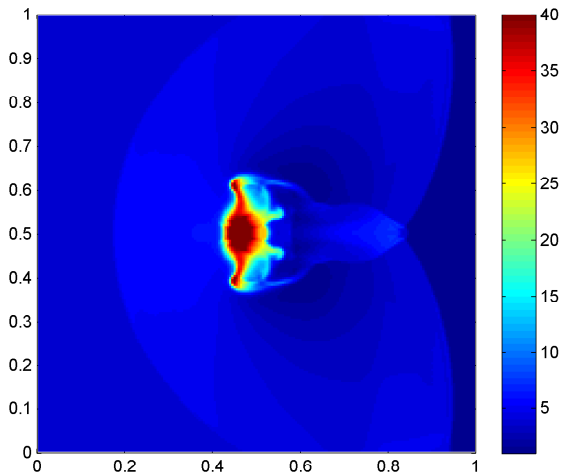
Euler: Cloud-Shock interaction: TeCNO2



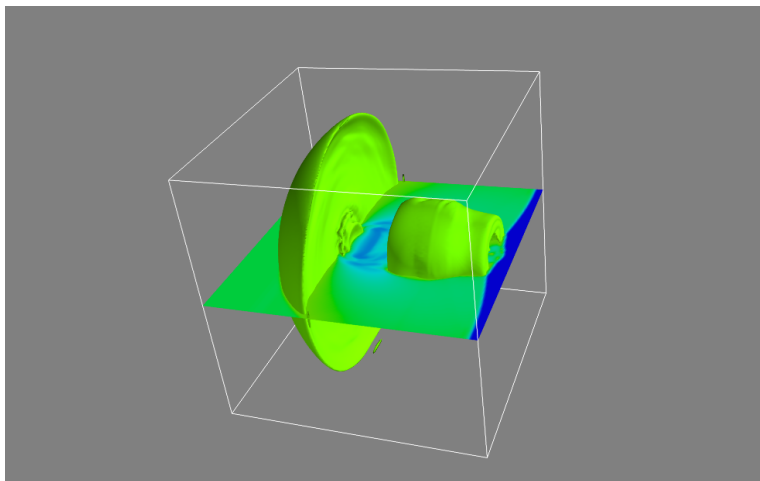
Euler: Cloud-Shock interaction: TeCNO3



Euler: Cloud-Shock interaction: TeCNO4



Euler: 3-D Cloud-Shock Interaction



Ideal MagnetoHydroDynamics (MHD) equations



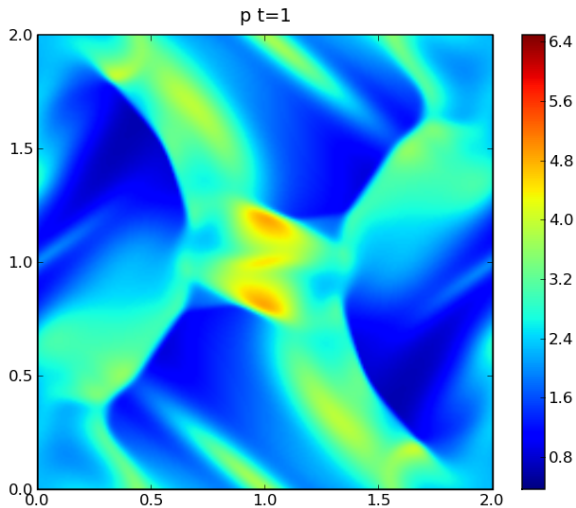
$$\begin{aligned}\rho_t + \operatorname{div}(\rho \mathbf{u}) &= 0, \\ (\rho \mathbf{u})_t + \operatorname{div}(\rho \mathbf{u} \otimes \mathbf{u} + (p + \frac{1}{2} |\mathbf{B}|^2) \mathbf{I} - \mathbf{B} \otimes \mathbf{B}) &= 0, \\ E_t + \operatorname{div}((E + p + \frac{1}{2} |\mathbf{B}|^2) \mathbf{u} - (\mathbf{u} \cdot \mathbf{B}) \mathbf{B}) &= 0, \\ \mathbf{B}_t + \operatorname{div}(\mathbf{u} \otimes \mathbf{B} - \mathbf{B} \otimes \mathbf{u}) &= 0, \\ \operatorname{div}(\mathbf{B}) &= 0.\end{aligned}$$

- ▶ Together with equation of state

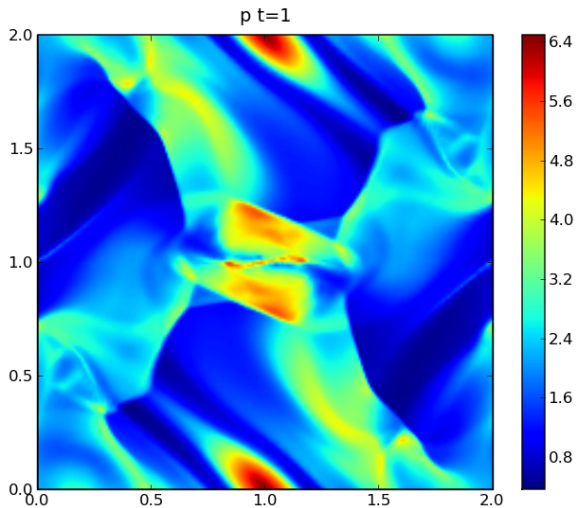
$$E = \frac{p}{\gamma - 1} + \frac{1}{2} \rho |\mathbf{u}|^2 + \frac{1}{2} |\mathbf{B}|^2,$$

- ▶ Usual form of MHD in practice.

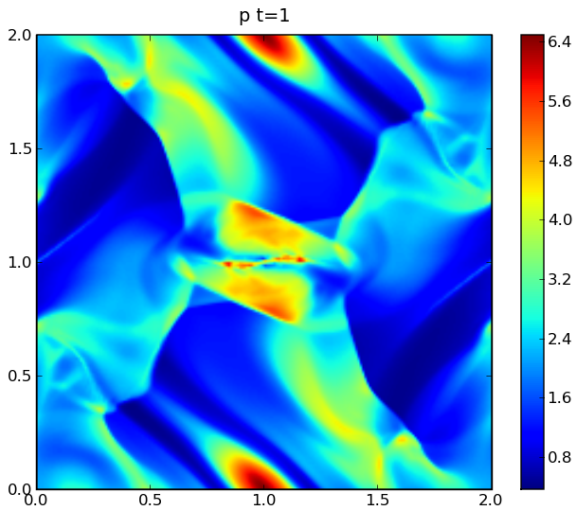
Orszag-Tang Vortex: Pressure (200×200 mesh) 1st Order



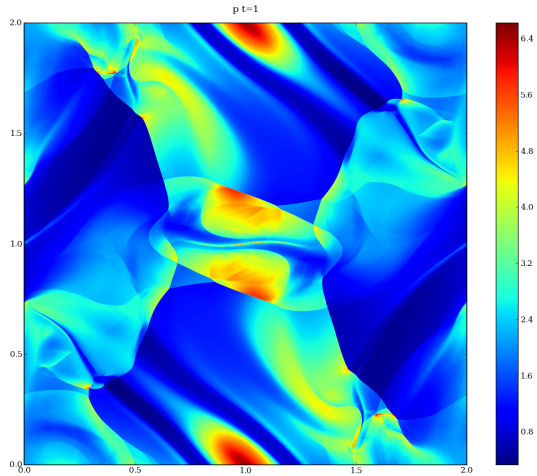
Orszag-Tang Vortex: Pressure (200×200 mesh) ENO



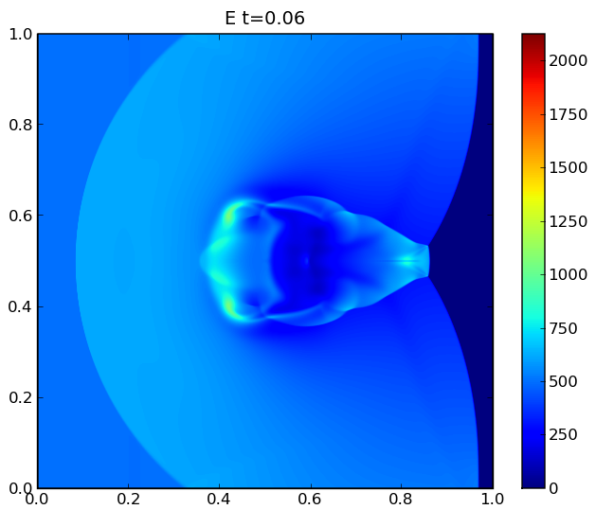
Orszag-Tang Vortex: Pressure (200×200 mesh) WENO



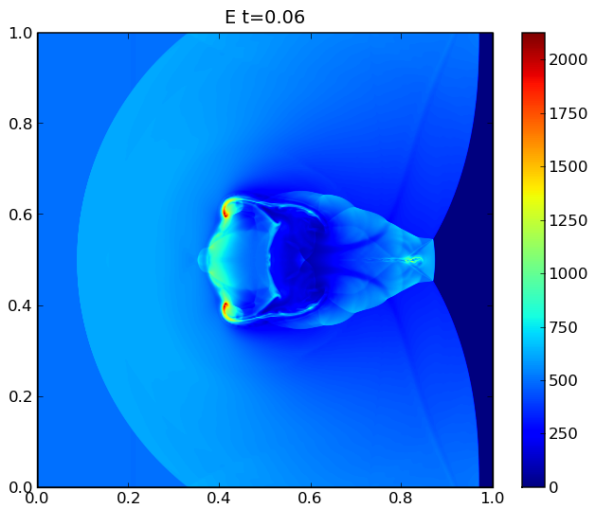
Highly resolved solution: WENO on 4000×4000 mesh



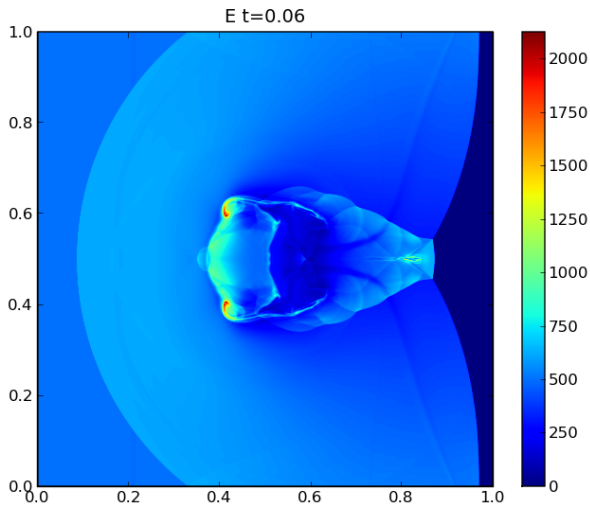
Cloud shock interaction: Energy (1600 \times 1600 mesh) 1st Order



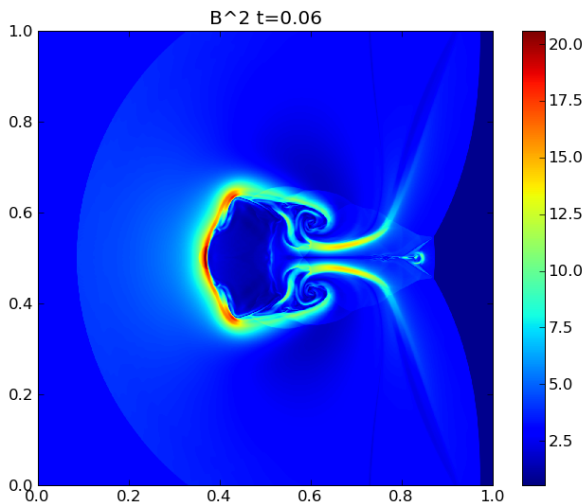
Cloud shock interaction: Energy (1600 \times 1600 mesh) ENO



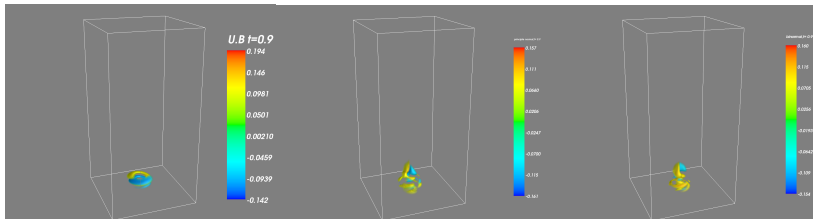
Cloud shock interaction : Energy (1600 \times 1600 mesh) WENO



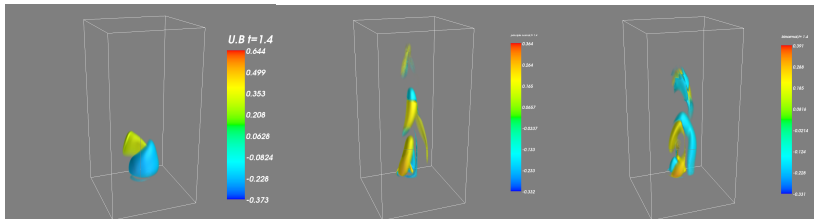
Cloud shock interaction : Magnetic pressure (4000×4000 mesh)



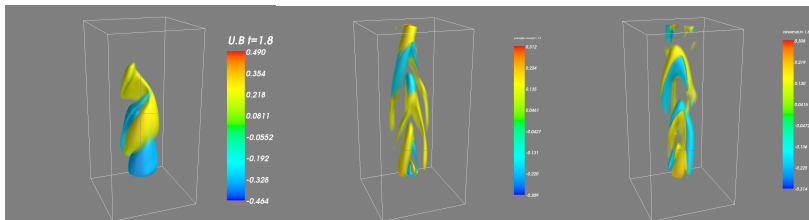
Alfven wave simulation: $T = 0.9$



Alfven wave simulation: $T = 1.4$



Alfven wave simulation: $T = 1.8$



$$\begin{aligned}\mathbf{U}_t + \operatorname{div}(\mathbf{F}(k(\mathbf{x}, t), \mathbf{U})) &= S(\mathbf{x}, t, \mathbf{U}), \\ \mathbf{U}(\mathbf{x}, 0) &= \mathbf{U}_0(\mathbf{x}), \\ \mathbf{U}|_{\partial D} &= \mathbf{U}_b(\mathbf{x}, t).\end{aligned}$$

- ▶ **Uncertainty** in determining:
 - ▶ Flux Coefficients (Equations of state, Material properties of porous media)
 - ▶ Initial data (Initial wave displacement in tsunamis)
 - ▶ Source terms (Bottom topography in shallow water waves)
 - ▶ Boundary data (Plasma circuit breakers)
- ▶ **UQ**: Given uncertainty in inputs \Rightarrow Compute uncertainty in the solution.

- ▶ How to model uncertainty in inputs ??
- ▶ Mathematical framework for uncertain solutions.
- ▶ Efficient numerical methods for UQ.

Modeling Input Uncertainty

- ▶ Use the **Probabilistic** framework a la **Kolmogorov**.
- ▶ Complete **Probability space**:
 - ▶ Ω (Set of **Outcomes**)
 - ▶ Σ (σ -algebra (field) of **Events**)
 - ▶ $\mathbb{P} : \Omega \mapsto [0, 1]$ with $\mathbb{P}(\Omega) = 1$ (**Probability measure**).

- ▶ Use **Random fields** to model **Uncertain**:
 - ▶ Initial data.
 - ▶ Boundary conditions.
 - ▶ Fluxes.
 - ▶ Sources.
- ▶ $(\Omega, \Sigma, \mathbb{P})$ is a complete **probability space**.
- ▶ **Random field** $\mathbf{U} : (\Omega, \Sigma) \mapsto (\mathcal{F}, \mathcal{B}(\mathcal{F}))$ **measurable**
- ▶ \mathcal{F} is a function space (separable Banach space) with **Borel σ -algebra** $\mathcal{B}(\mathcal{F})$
- ▶ For $\omega \in \Omega$, $\mathbf{U}(\omega) \in \mathcal{F}$.
- ▶ Example: Random initial data (**scalar conservation laws**):

$$u_0 : (\Omega, \Sigma) \mapsto (L^1(\mathbb{R}^d), \mathcal{B}(L^1(\mathbb{R}^d)))$$
$$u_0(\cdot, \omega) \in L^\infty(\mathbb{R}^d) \cap BV(\mathbb{R}^d), \mathbb{P} - a.s.$$

Representation of Random fields I: Parametric representation

- ▶ Random field represented by a finite number of **parameters** (Random Variables).
- ▶ Example I: Euler equations – Sod Shock tube – Uncertain initial **location + amplitude**:

$$\mathbf{u}_0(x, \omega) = \begin{cases} \mathbf{u}_l + \alpha(\omega) & \text{if } x \leq \beta(\omega), \\ \mathbf{u}_r & \text{if } x > \beta(\omega), \end{cases}$$

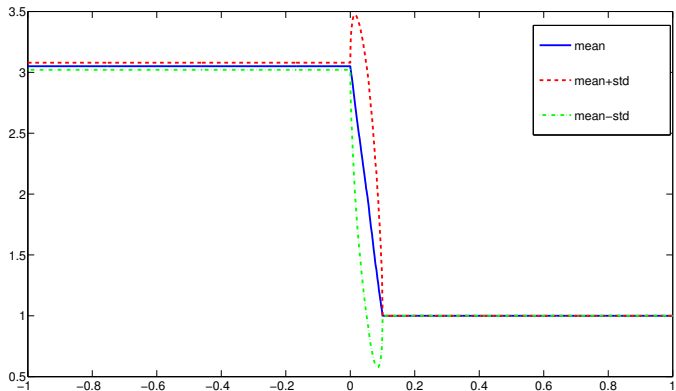
$$\alpha \sim 0.05\mathcal{U}[-1, 1]$$

$$\beta \sim 0.2\mathcal{U}[-1, 1]$$

- ▶ 2 **Uniformly distributed** random parameters.

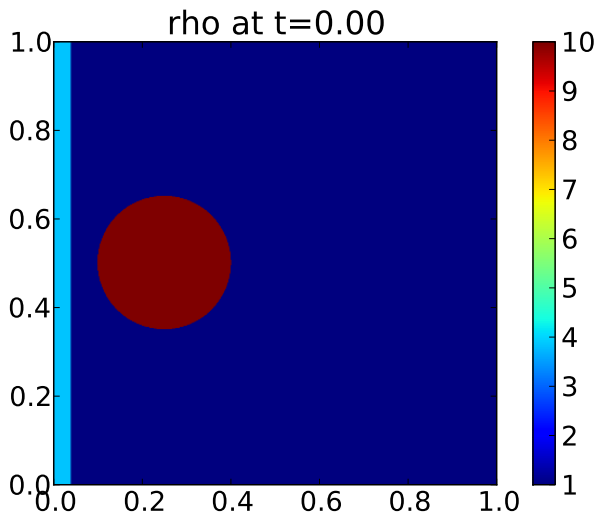
Euler equations – Sod Shock tube – Uncertain initial location + amplitude

- Mean \pm Standard deviation.



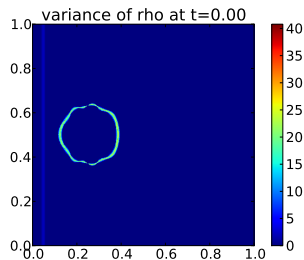
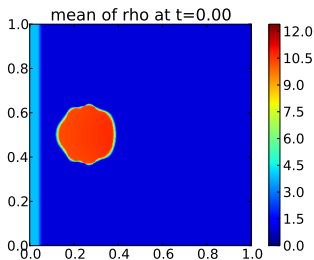
Ex II: Euler equations - Cloud shock interaction

- Deterministic **Initial data:**



Ex II: Euler equations - Cloud shock interaction

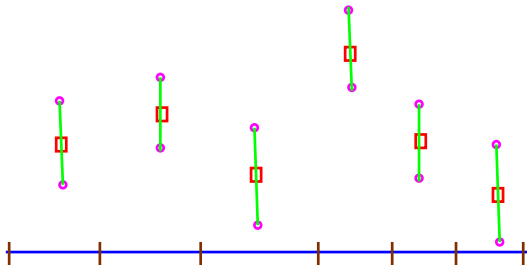
- Uncertain initial data in terms of 11 **uniformly distributed** parameters:



- Uncertainty in Shock location, amplitude, Bubble location, amplitude and geometry.

Ex III: Shallow water equations– bottom topography

- ▶ Real data bottom topography given by Digital Terrain Models.
- ▶ Typical representation:

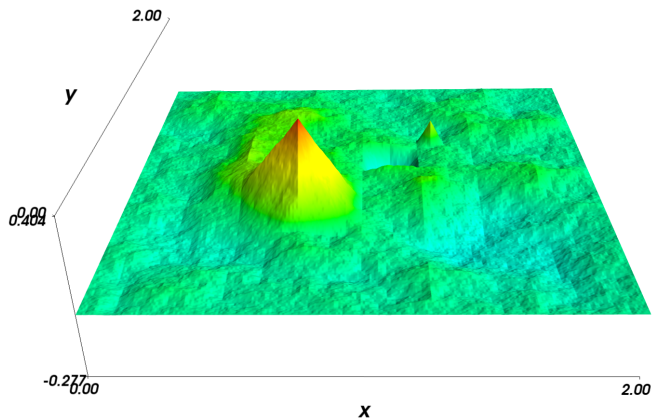


- ▶ Interpolation using hierarchical hat basis (SM, Schwab, Sukys, 2013)

Bottom topography: one sample (realization)

Hierarchical hat basis representation

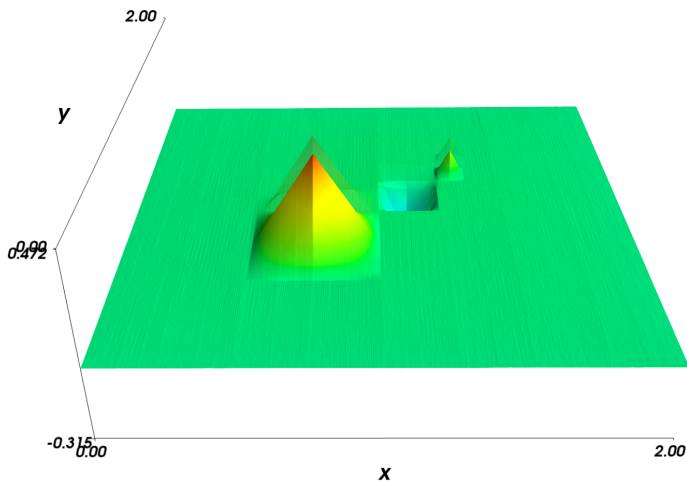
- 962 Random parameters !!!



Bottom topography: mean and standard deviation

Hierarchical hat basis representation

- 962 Random parameters !!!



Representation of random fields II: Karhunen-Loeve expansions

- ▶ **Bi-orthogonal decomposition** (a la **Fourier Series**).
- ▶ A prototypical example:
 - ▶ **Centered** random field $f : \Omega \mapsto L^2(D)$ with $\mathbb{E}(f) = 0$
 - ▶ **Covariance function**: $C \in L^2(D \times D)$ with

$$C_f(x, y) := \mathbb{E}(f(x, \omega)f(y, \omega)).$$

- ▶ **Covariance operator**: $K_C : L^2(D) \mapsto L^2(D)$:

$$K_{C_f}[g](x) = \int_D K_{C_f}(x, y)g(y)dy.$$

- ▶ K_C is a **Compact ++** operator !!!
- ▶ \Rightarrow possess orthonormal eigensystem (λ_k, f_k) over L^2

$$K_C[f_k] = \lambda_k f_k$$

Karhunen-Loeve expansions (Contd...)

- ▶ Hence, **Random field** f is

$$f(x, \omega) = \sum_{k=1}^{\infty} Z_k(\omega) f_k(x)$$

$$Z_k := \int_D f(x, \omega) f_k(x) dx$$

- ▶ Z_k 's are **Uncorrelated random variables** as

$$\mathbb{E}(Z_i Z_j) := \lambda_j \delta_{ij}.$$

- ▶ General form of **KL** expansion:

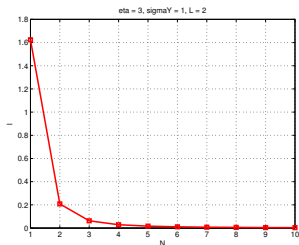
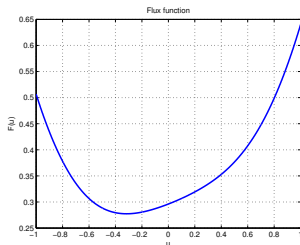
$$f = \bar{f} + \sum \sqrt{\lambda_k} Z_k g_k.$$

- ▶ Best L^2 truncated **N-term approximation** !!!
- ▶ **PCA**, **POD** are similar.

Ex I: Perturbed Burgers' flux

- ▶ Has the KL expansion:

$$f(\omega; u) = f(\mathbf{y}; \mathbf{u}) \Big|_{\mathbf{y}=\mathbf{Y}(\omega)} = \frac{u^2}{2} + \delta \left(\sum_{j \geq 1} \mathbf{y}_j \sqrt{\lambda_j} \Phi_j(\mathbf{u}) \right),$$



- ▶ Represented as a Gaussian process with exponential covariance: $C_Y(u_1, u_2) = \sigma_Y^2 e^{-|u_1 - u_2|/\eta}$, and

Ex II: Rock permeability for seismic imaging

- ▶ Seismic **Acoustic pulses** modeled by **Wave equation**:

$$p_{tt} + \operatorname{div}(\mathbf{c}\nabla p) = 0.$$

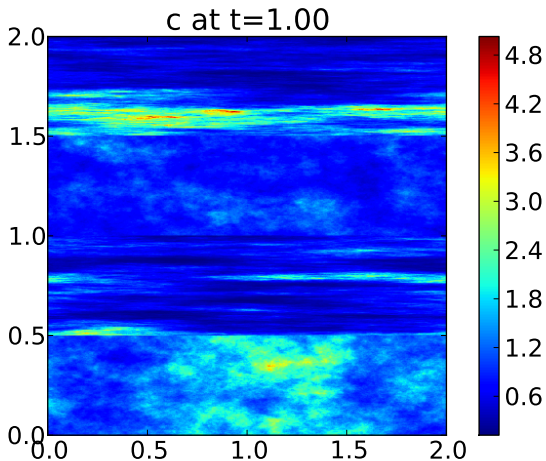
- ▶ Rewritten as a **linear system** of conservation laws.
- ▶ \mathbf{c} is the **rock permeability coefficient**
- ▶ **Highly uncertain** – modeled by a **log normal Gaussian random field**:

$$\log(\mathbf{c}(x, \omega)) := \log(\bar{\mathbf{c}}(x)) + \sum_{k=1}^{\infty} \sqrt{\lambda_k} Z_k(\omega) g_k(x).$$

- ▶ Many different **Covariance functions**.
- ▶ Need **Spectral FFT** + **Upscaling** for efficient generation.

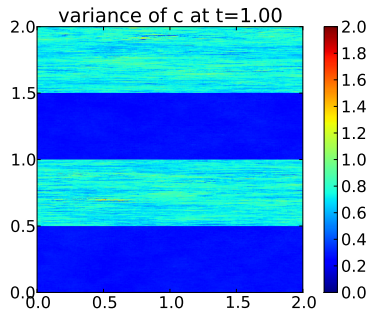
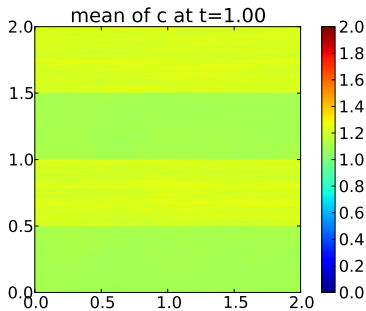
Ex II: 2-D log normal layered permeability field (sample)

- ≈ 1000 uncertain parameters !!!



Ex II: 2-D log normal layered permeability field (statistics)

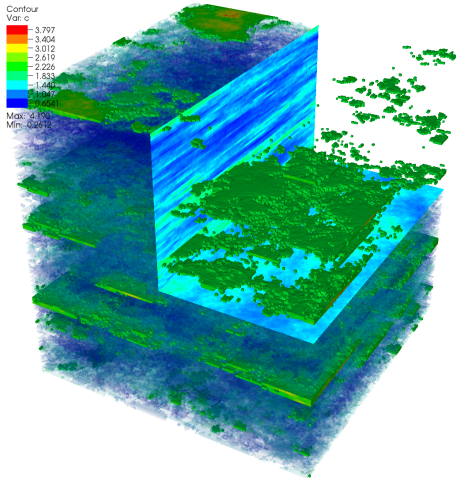
- ≈ 1000 uncertain parameters !!!



Ex II: 3-D log normal layered permeability field (sample)

- $\approx 10^6$ uncertain parameters !!!

DB: c at time 1



Mathematical framework (scalar case)

- ▶ **Random** scalar conservation laws:

$$\begin{aligned}u_t(x, t, \omega) + \operatorname{div}(f(\omega; u(x, t, \omega))) &= 0. \\u(x, 0, \omega) &= u_0(x, \omega).\end{aligned}$$

- ▶ with initial data and flux:

$$\begin{aligned}u_0 : (\Omega, \Sigma) &\mapsto (L^1(\mathbb{R}^d), \mathcal{B}(L^1(\mathbb{R}^d))) \\f : (\Omega, \Sigma) &\mapsto (C^1(\mathbb{R}^1; \mathbb{R}^d); \mathcal{B}(C^1(\mathbb{R}; \mathbb{R}^d)))\end{aligned}$$

Random entropy solution

- ▶ Solution is a **random field** that satisfies,
 - ▶ **Measurability:** $u : \Omega \times \omega \mapsto u(x, t; \omega)$ is measurable from (Ω, Σ) to $C((0, T); L^1(\mathbb{R}^d))$.
 - ▶ **Weak solution:** u satisfies the integral identity:

$$\int_{\mathbb{R}^d \times \mathbb{R}_+} (u(x, t, \omega) \varphi_t(x, t) + \langle f(\omega; u(x, t, \omega), \nabla \varphi(x, t)) \rangle) dx dt + \int_{\mathbb{R}^d} u(x, 0, \omega) \varphi(x, 0) dx = 0.$$

for \mathbb{P} -a.e $\omega \in \Omega$.

- ▶ **Entropy conditions:** satisfied for all entropy-entropy flux pairs and for \mathbb{P} -a.e $\omega \in \Omega$.

Well-posedness theorem: SM, Schwab, 2010, SM et al 2012.

- ▶ For sufficiently regular u_0 ,:
 - ▶ **Existence:** There exists a unique random entropy solution

$$u : \Omega \ni \omega \mapsto C_b(0, T; L^1(\mathbb{R}^d))$$

- ▶ **Construction:**

$$u(\cdot, t; \omega) = S(t)u_0(\cdot, \omega), \quad t > 0, \omega \in \Omega$$

- ▶ **Stability:** \mathbb{P} -a.s $\omega \in \Omega$,

$$\begin{aligned} \|u\|_{L^k(\Omega; C(0, T; L^1(\mathbb{R}^d)))} &\leq \|u_0\|_{L^k(\Omega; L^1(\mathbb{R}^d))}, \\ \|S(t)u_0(\cdot, \omega)\|_{(L^1 \cap L^\infty)(\mathbb{R}^d)} &\leq \|u_0(\cdot, \omega)\|_{(L^1 \cap L^\infty)(\mathbb{R}^d)} \\ TV(S(t)u_0(\cdot, \omega)) &\leq TV(u_0(\cdot, \omega)) \end{aligned}$$

Higher moments for random initial data

- ▶ Initial data satisfies,

$$u_0 \in L^r(\Omega; L^1(\mathbb{R}^d)).$$

- ▶ k -point correlation function

$$u(x_1, t_1; \omega) \otimes \cdots \otimes u(x_k, t_k; \omega) \in L^{r/k}(\Omega; L^1(\mathbb{R}^{kd})).$$

- ▶ k -th Moment:

$$\mathcal{M}^k u(t_1, \dots, t_k) := \mathbb{E}[u(\cdot, t_1; \omega) \otimes \cdots \otimes u(\cdot, t_k; \omega)] \in L^1(\mathbb{R}^{kd}).$$

- ▶ Stability:

$$\left\| \left(\mathcal{M}^k u \right) (t_1, \dots, t_k) \right\|_{L^1(\mathbb{R}^d)^{(k)}} \leq \|u_0\|_{L^r(\Omega; L^1(\mathbb{R}^d))}^r.$$

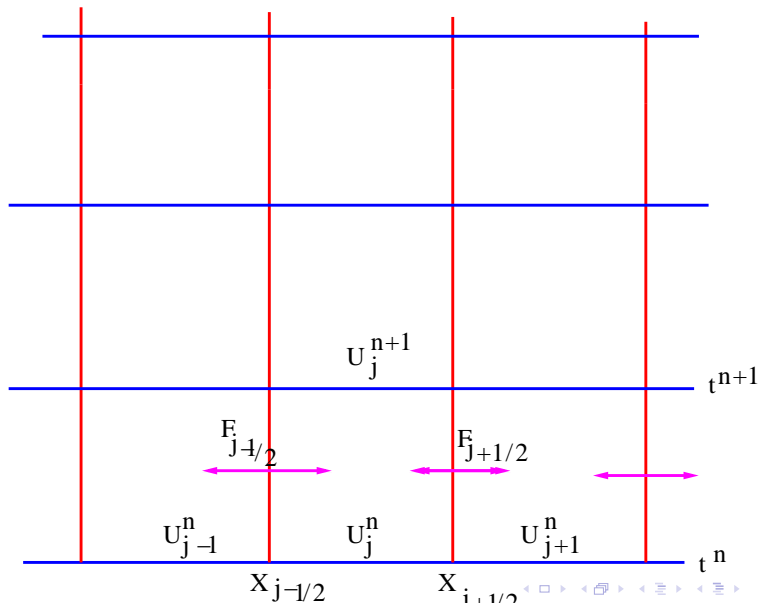
- ▶ Conservation law with **uncertain initial data**:

$$u_t(x, t, \omega) + \operatorname{div}(f(u(x, t, \omega))) = 0.$$

$$u(x, 0, \omega) = u_0(x, \omega).$$

- ▶ Discretization of Physical space-time.
- ▶ Standard **Finite volume method**

Finite volume Grid



- ▶ Of the form:

$$u_j^{n+1} - u_j^n + \frac{\Delta t}{\Delta x} (F_{j+1/2} - F_{j-1/2}) = 0$$

- ▶ Have the following **convergence rate**:

$$\|u(\cdot, t) - u_\tau(\cdot, t)\|_{L^1(\mathbb{R}^d)} \leq C \Delta x^5.$$

- ▶ **Work** estimate:

$$\text{Work}_\tau = \mathcal{O}(\Delta x^{-(d+1)}).$$

- ▶ **Accuracy vs. Work**:

$$\|u(\cdot, t) - u_\tau(\cdot, t)\|_{L^1(\mathbb{R}^d)} \leq C (\text{Work}_\tau)^{-\frac{5}{d+1}}.$$

- ▶ Random conservation law:

$$u_t(x, t, \omega) + \operatorname{div}(f(\omega; u(x, t, \omega))) = 0.$$

$$u(x, 0, \omega) = u_0(x, \omega).$$

- ▶ Need to discretize the **probability** space.
- ▶ Statistical sampling methods: **Monte Carlo (MC)** method.

- ▶ The MC algorithm:
 - ▶ Draw M i.i.d samples for the initial data and flux: $\{u_0^i, f^i\}_{1 \leq i \leq M}$.
 - ▶ For each sample: Solve conservation law by FVM to obtain u_τ^i .
 - ▶ Sample statistics:

$$\mathcal{M}^1 u(\cdot, t) \approx E_M[u_\tau(\cdot, t)] := \frac{1}{M} \sum_{i=1}^M u_\tau^i(\cdot, t).$$

$$\mathcal{M}^k u(t_1, \dots, t_k) := \frac{1}{M} \sum_{i=1}^M \underbrace{(u_\tau^i(\cdot, t_1) \otimes \dots \otimes u_\tau^i(\cdot, t_k))}_{k\text{-times}}.$$

- ▶ **Convergence:**

$$\|\mathbb{E}[u(\cdot, t)] - E_M[u_\tau(\cdot, t; \omega)]\|_{L^2(\Omega; L^1(\mathbb{R}^d))} \leq C_{\text{stat}} M^{-\frac{1}{2}} + C_{\text{st}} \Delta x^s.$$

- ▶ Number of samples: $M = \mathcal{O}(\Delta x)^{-2s}$.
- ▶ **Accuracy vs. Work:**

$$\|\mathbb{E}[u(\cdot, t)] - E_M[u_\tau(\cdot, t; \omega)]\|_{L^2(\Omega; L^1(\mathbb{R}^d))} \leq C(\text{Work}_\tau)^{-\frac{s}{d+1+2s}}.$$

- ▶ **Slow** convergence \Rightarrow **very high computational cost.**

Multi-level Monte Carlo (MLMC) FVM:

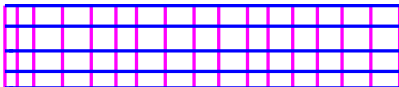
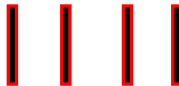
- ▶ **Heinrich** 1995: Quadrature.
- ▶ **Giles** 2002: Stochastic ODEs.
- ▶ **Barth, Schwab, Zollinger** 2010: Elliptic PDEs.

- ▶ **MLMCFVM** algorithm:
 - ▶ Different nested **levels** of resolution: l .
 - ▶ **Draw** M_l i.i.d samples for the initial data: $\{u_{l,0}^i\}_{1 \leq i \leq M_l}$.
 - ▶ For each draw: **Solve** conservation law by FVM to obtain $u_{l,\tau}^i$.
 - ▶ **Sample statistics**: with $u_{\tau,-1} = 0$,

$$\mathcal{M}^1 u(\cdot, t) \approx E^L[u(\cdot, t)] = \sum_{\ell=0}^L E_{M_\ell} [u_{\tau,\ell}(\cdot, t) - u_{\tau,\ell-1}(\cdot, t)]$$

$$\mathcal{M}^k u(t_1, \dots, t_k) := \sum_{\ell=0}^L E_{M_\ell} [u_{\tau,\ell}^{(k)}(\cdot, t) - u_{\tau,\ell-1}^{(k)}(\cdot, t)]$$

MLMCFVM



MESH Resolution

Number of samples

► **Convergence:**

$$\begin{aligned} \|\mathbb{E}[u(\cdot, t)] - E^L[u_\tau(\cdot, t, \omega)]\|_{L^2(\Omega; L^1(\mathbb{R}^d))} &\leq C_1 \Delta x_L^s + C_3 M_0^{-\frac{1}{2}} \\ &\quad + C_2 \left\{ \sum_{\ell=0}^L M_\ell^{-\frac{1}{2}} \Delta x_\ell^s \right\} \end{aligned}$$

► Level dependent number of samples: $M_l = \mathcal{O}\left(\frac{\Delta x_l^{2s}}{\Delta x_L^{2s}}\right)$

► **Accuracy vs. Work:** If $0 \leq s < (d+1)/2$,

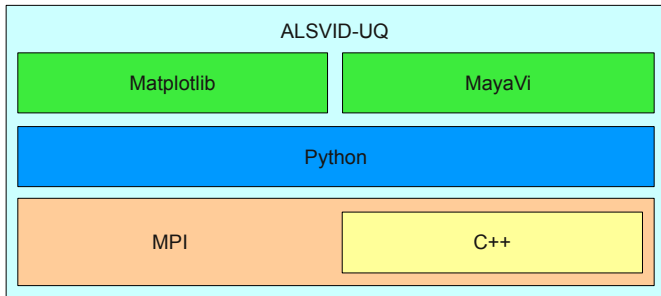
$$\|\mathbb{E}[u(\cdot, t)] - E^L[u_\tau(\cdot, t; \omega)]\|_{L^2(\Omega; L^1(\mathbb{R}^d))} \leq C(\text{Work})^{-\frac{s}{d+1}} \log(\text{Work})$$

► Same as the deterministic FVM !!!!!

► **Sparse tensor** higher moments computation with same efficiency.

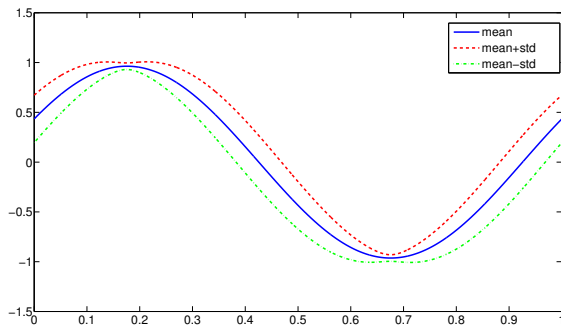
Implementation of MC methods

- ▶ Both MC and MLMC FVM are **non-intrusive**.
- ▶ Works with *any* spatio-temporal discretization.
- ▶ Interesting issues for **parallelization**.

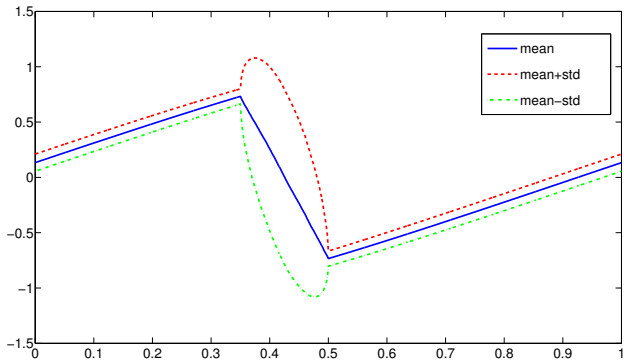


1-D Burgers' with uncertain initial phase

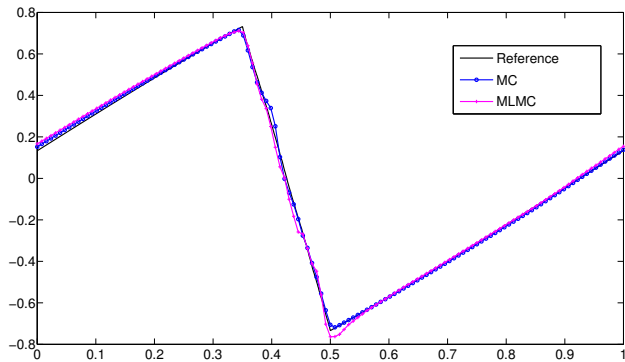
- 1 random parameter.



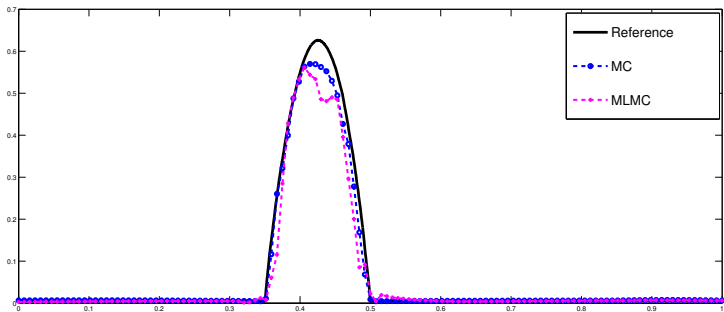
Mean \pm Standard deviation



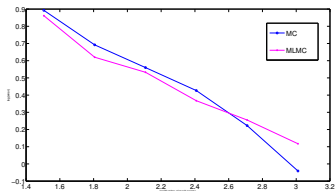
Mean: MC vs MLMC



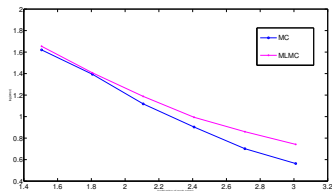
Variance: MC vs MLMC



$\log(\text{resolution})$ vs. $\log(\text{relative error})$

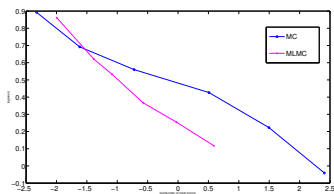


(d) mean

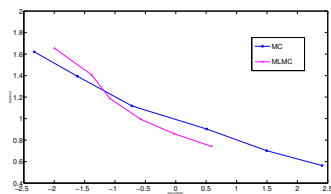


(e) variance

$\log(\text{runtime})$ vs. $\log(\text{relative error})$



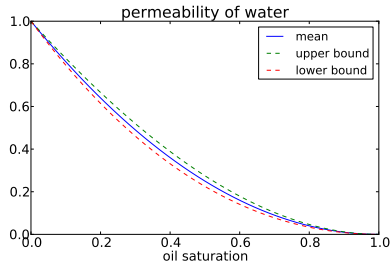
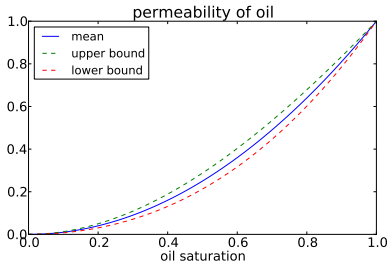
(f) mean



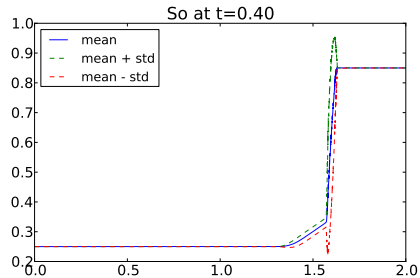
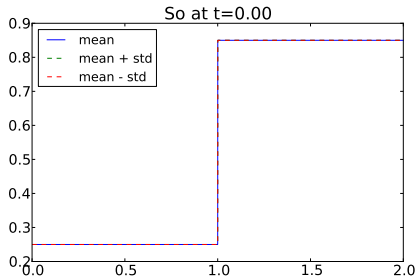
(g) variance

Buckley Leverette with uncertain relative permeabilities

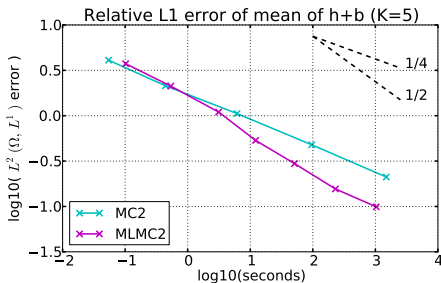
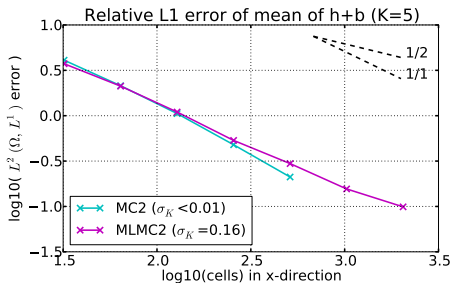
- 2 random parameters.



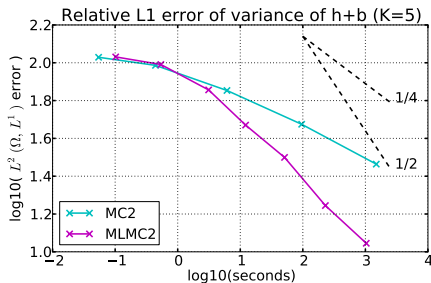
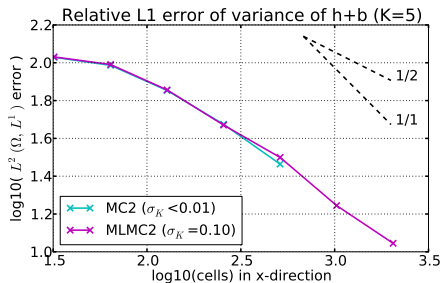
Buckley Leverette: mean \pm std of Water saturation



Buckley Leverette: convergence of mean



Buckley Leverette: convergence of variance



- ▶ **Random** linear systems of conservation laws:

$$\mathbf{U}_t(x, t, \omega) + \sum_{r=1}^d \frac{\partial}{\partial x_r} \left(\mathbf{A}_r(\mathbf{x}, \omega) \mathbf{U} \right) = 0.$$

$$\mathbf{U}(x, 0, \omega) = \mathbf{U}_0(x, \omega).$$

- ▶ with uncertain initial data and flux:

$$\mathbf{U}_0 : (\Omega, \Sigma) \mapsto (L^2(\mathbf{D}), \mathcal{B}(L^2(\mathbf{D})))$$

$$\mathbf{A}_r : (\Omega, \Sigma) \mapsto (C^1(\mathbf{D})^{m \times m}; \mathcal{B}(C^1(\mathbf{D})^{m \times m}))$$

Random Weak solution

- ▶ Solution is a **random field** that satisfies,
 - ▶ **Measurability:** $\mathbf{U} : \Omega \ni \omega \mapsto \mathbf{U}(x, t; \omega)$ is measurable from (Ω, Σ) to $C((0, T); L^2(\mathbf{D}))$.
 - ▶ **Weak solution:** \mathbf{U} satisfies the integral identity:

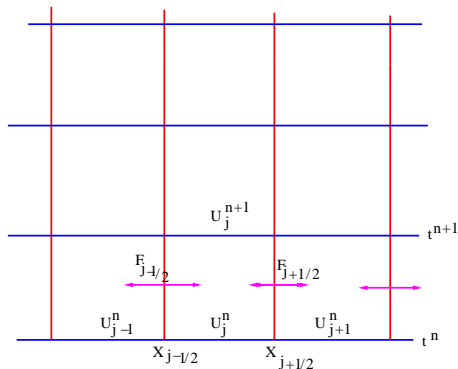
$$\int_{\mathbb{R}^d \times \mathbb{R}_+} \left(\mathbf{U} \cdot \varphi_t + \sum_{r=1}^d \mathbf{A}_r \mathbf{U} \cdot \frac{\partial}{\partial \mathbf{x}_r} \varphi \right) d\mathbf{x} dt + \int_{\mathbb{R}^d} \mathbf{U}_0 \cdot \varphi(t=0) d\mathbf{x} = 0.$$

for \mathbb{P} -a.e $\omega \in \Omega$.

- ▶ THM (SM, Schwab, Sukys 2014): Random weak solutions exist and are unique.

Schemes for Linear systems I: FVM

- ▶ Standard **Finite volume method** to discretize **Space-time**.



- ▶ Under suitable assumptions on initial data + coefficients \mathbf{A}_r , FVM **Convergence rate**:

$$\|\mathbf{U} - \mathbf{U}^{\Delta x}\|_{L^2} \leq C\Delta x^s$$

Schemes for Linear systems II: MCFVM

- ▶ The MC algorithm:
 - ▶ Draw M i.i.d samples for the initial data and flux:
 $\{\mathbf{U}_0^i, \mathbf{A}_r^i\}_{1 \leq i \leq M}$.
 - ▶ For each sample: Solve linear system by FVM to obtain \mathbf{U}_τ^i .
 - ▶ Sample statistics:

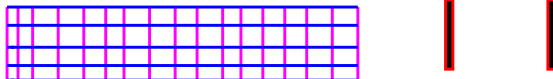
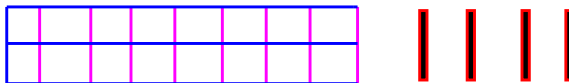
$$\mathbb{E}(\mathbf{U}(\cdot, t)) \approx E_M[\mathbf{U}_\tau(\cdot, t)] := \frac{1}{M} \sum_{i=1}^M \mathbf{U}_\tau^i(\cdot, t).$$

- ▶ Convergence (SM, Schwab, Sukys, 2014):

$$\|\mathbb{E}[\mathbf{U}(\cdot, t)] - E_M[\mathbf{U}_\tau(\cdot, t; \omega)]\|_{L^2(\Omega; L^2(\mathbf{D}))} \leq C_{\text{stat}} M^{-\frac{1}{2}} + C_{\text{st}} \Delta x^s.$$

- ▶ Slow convergence \Rightarrow very high computational cost.

Schemes for Linear systems III: MLMCFVM-SM, Schwab, Sukys 2014



MESH Resolution

Number of samples

► Convergence:

$$\begin{aligned} \|\mathbb{E}[\mathbf{U}(\cdot, t)] - E^L[\mathbf{U}_\tau(\cdot, t, \omega)]\|_{L^2(\Omega; L^2(\mathbb{R}^d))} &\leq C_1 \Delta x_L^s + C_3 M_0^{-\frac{1}{2}} \\ &+ C_2 \left\{ \sum_{\ell=0}^L M_\ell^{-\frac{1}{2}} \Delta x_\ell^s \right\} \end{aligned}$$

- Proper choice of $M_\ell \Rightarrow$ Same complexity as deterministic FVM !!!

Ex : Seismic imaging

- ▶ Seismic **Acoustic pulses** modeled by **Wave equation**:

$$p_{tt} + \operatorname{div}(\mathbf{c}\nabla p) = 0.$$

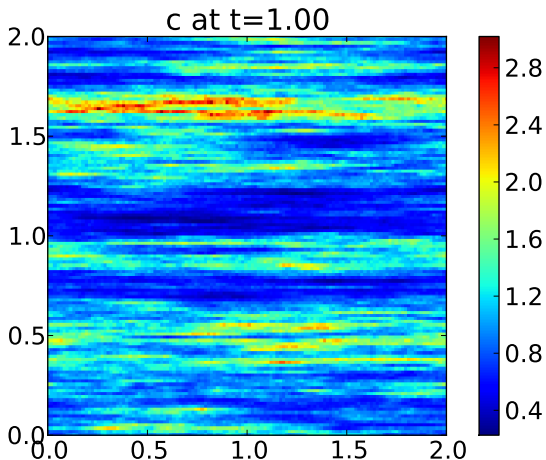
- ▶ Rewritten as a **linear system** of conservation laws.
- ▶ \mathbf{c} is the **rock permeability coefficient**
- ▶ **Highly uncertain** – modeled by a **log normal Gaussian random field**:

$$\log(\mathbf{c}(x, \omega)) := \log(\bar{\mathbf{c}}(x)) + \sum_{k=1}^{\infty} \sqrt{\lambda_k} Z_k(\omega) g_k(x).$$

- ▶ Many different **Covariance functions**.
- ▶ Need **Spectral FFT** + **Upscaling** for efficient generation.

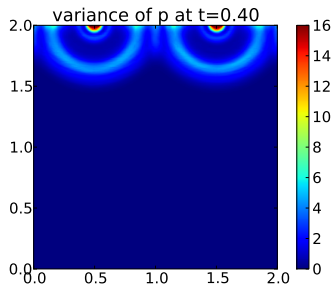
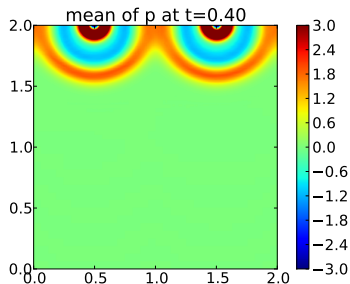
Ex : 2-D log normal layered permeability field (sample)

- ≈ 1000 uncertain parameters !!!



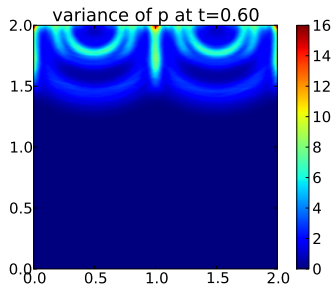
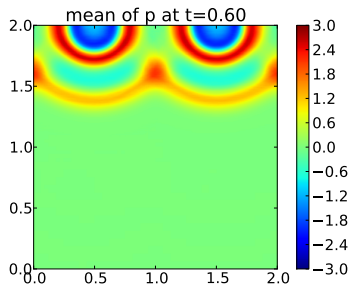
Ex : 2-D log normal layered permeability field $T = 0.4$

- ≈ 1000 uncertain parameters !!!



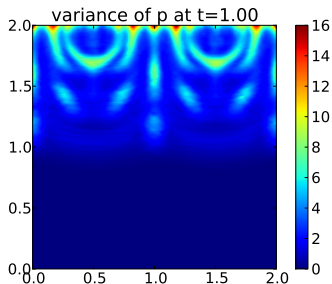
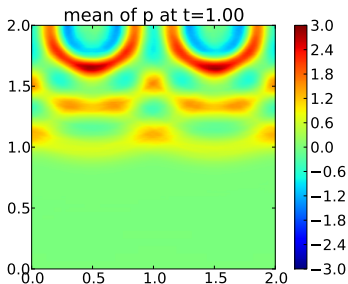
Ex : 2-D log normal layered permeability field $T = 0.6$

- ≈ 1000 uncertain parameters !!!



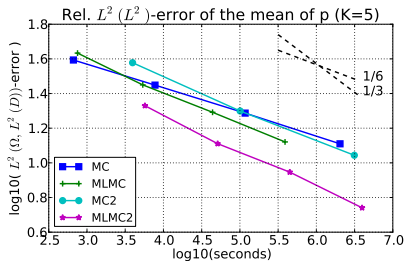
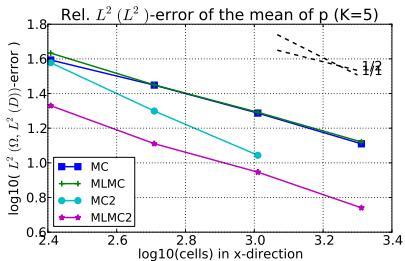
Ex : 2-D log normal layered permeability field $T = 1.0$

- ≈ 1000 uncertain parameters !!!



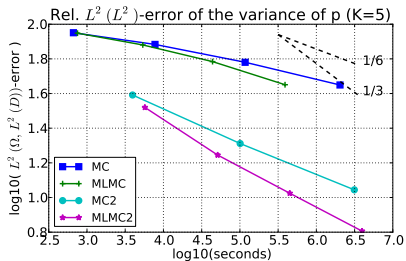
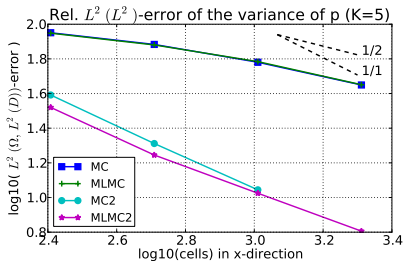
Convergence of mean

- ≈ 1000 uncertain parameters !!!



Convergence of variance

- ≈ 1000 uncertain parameters !!!



Ex II: 3-D log normal layered permeability field (sample)

- $\approx 10^6$ uncertain parameters !!!

DB: c at time 1

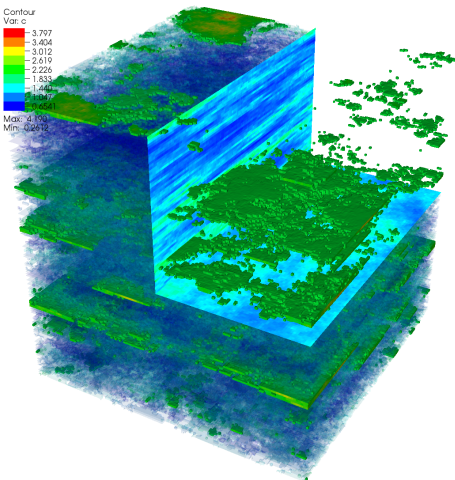
Contour

Var: c



Max: 4.100

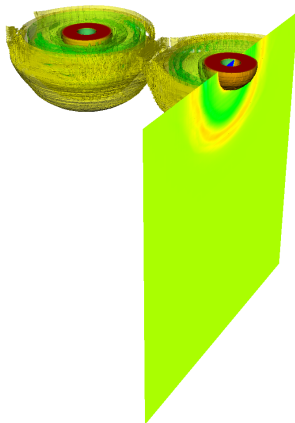
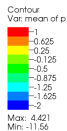
Min: -0.2512



Ex II: Mean at $T = 0.4$

- $\approx 10^6$ uncertain parameters !!!

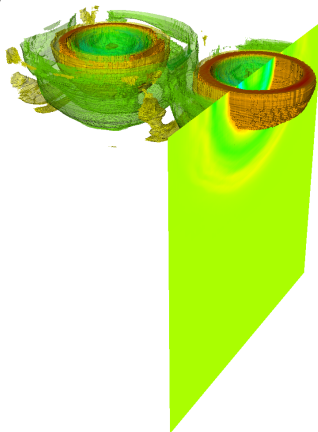
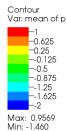
DB: mean of p at time 0.4



Ex II: Mean at $T = 0.6$

- $\approx 10^6$ uncertain parameters !!!

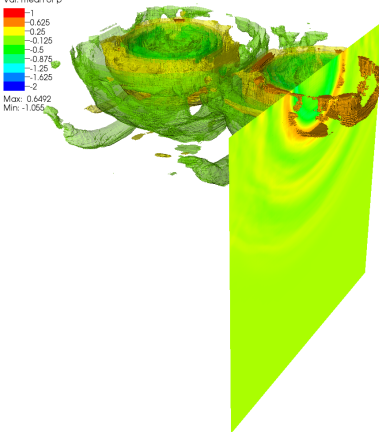
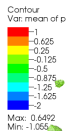
DB: mean of p at time 0.6



Ex II: Mean at $T = 1.0$

- $\approx 10^6$ uncertain parameters !!!

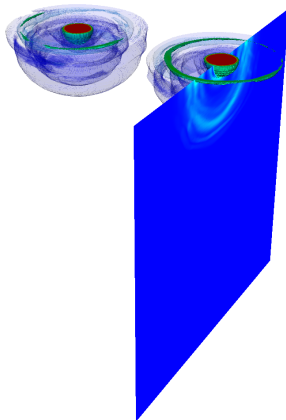
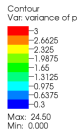
DB: mean of p at time 1



Ex II: Variance at $T = 0.4$

- $\approx 10^6$ uncertain parameters !!!

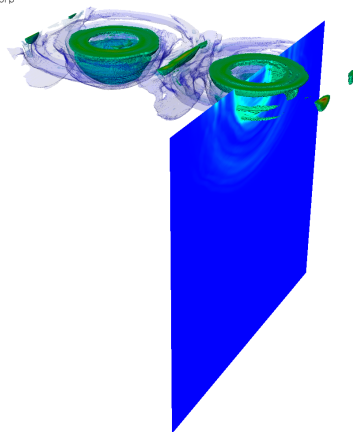
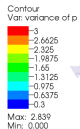
DB: variance of p at time 0.4



Ex II: Variance at $T = 0.6$

- $\approx 10^6$ uncertain parameters !!!

DB: variance of p at time 0.6



Ex II: Variance at $T = 1.0$

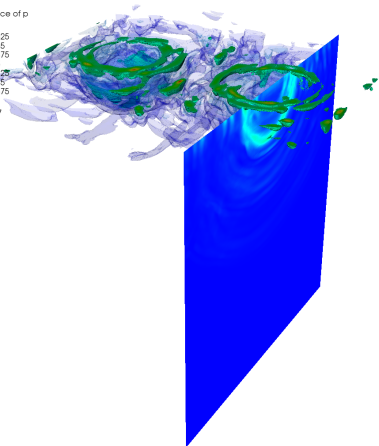
- $\approx 10^6$ uncertain parameters !!!

DB: variance of p at time 1

Contour
Var. variance of p



Max: 2.857
Min: 0.000



Non-Linear systems of conservation laws

- ▶ **Random** non-linear systems of conservation laws:

$$\mathbf{U}_t(x, t, \omega) + \operatorname{div}(\mathbf{F}(\omega, \mathbf{u}(x, t, \omega))) = 0.$$

$$\mathbf{U}(x, 0, \omega) = \mathbf{U}_0(x, \omega).$$

- ▶ with uncertain initial data and flux:

$$\mathbf{U}_0 : (\Omega, \Sigma) \mapsto (L^1(\mathbf{D})^m, \mathcal{B}((L^1(\mathbf{D}))^m))$$

$$\mathbf{F} : (\Omega, \Sigma) \mapsto (C^1(\mathbf{D})^m; \mathcal{B}(C^1(\mathbf{D})^m))$$

Random Entropy solution

- ▶ Solution is a **random field** that satisfies,
 - ▶ **Measurability:** $\mathbf{U} : \Omega \ni \omega \mapsto \mathbf{U}(x, t; \omega)$ is measurable from (Ω, Σ) to $(C((0, T); L^1(\mathbf{D})))^m$.
 - ▶ **Weak solution:** \mathbf{U} satisfies the integral identity:

$$\int_{\mathbb{R}^d \times \mathbb{R}_+} \left(\mathbf{U} \cdot \varphi_t + \sum_{r=1}^d \mathbf{F}_r(\mathbf{U}) \cdot \frac{\partial}{\partial \mathbf{x}_r} \varphi \right) d\mathbf{x} dt + \int_{\mathbb{R}^d} \mathbf{U}_0 \cdot \varphi(t=0) d\mathbf{x} = 0.$$

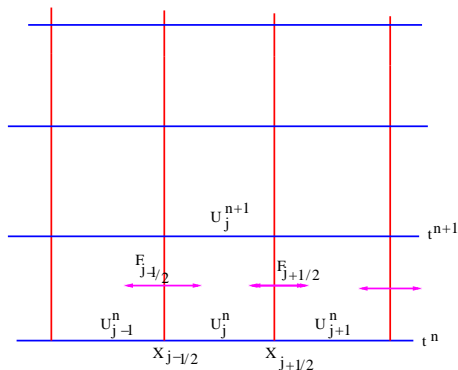
for \mathbb{P} -a.e $\omega \in \Omega$.

- ▶ **Entropy condition** to be satisfied \mathbb{P} a.s.

- ▶ **Deterministic problem:**
 - ▶ Wellposedness of 1-d + **small data** (Glimm, Bianchini-Bressan).
 - ▶ NO global existence results in multi-D.
 - ▶ **NON-UNIQUENESS** of entropy solutions in multi-D (DeLellis-Szekelyhidi).
- ▶ **Random entropy solutions**
 - ▶ NO Wellposedness results !!!

Schemes for Nonlinear systems I: FVM

- ▶ Standard **Finite volume method** to discretize **Space-time**.



- ▶ **NO rigorous convergence** results for any scheme !!!
- ▶ Can **Postulate Convergence rate** ??:

$$\|\mathbf{U} - \mathbf{U}^{\Delta x}\|_{L^1} \leq C\Delta x^s$$

Schemes for NonLinear systems II: MCFVM

- ▶ The MC algorithm:
 - ▶ Draw M i.i.d samples for the initial data and flux:
 $\{\mathbf{U}_0^i, \mathbf{A}_r^i\}_{1 \leq i \leq M}$.
 - ▶ For each sample: Solve linear system by FVM to obtain \mathbf{U}_τ^i .
 - ▶ Sample statistics:

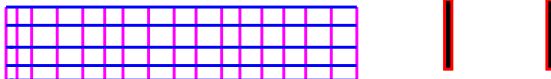
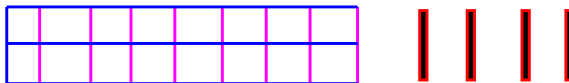
$$\mathbb{E}(\mathbf{U}(\cdot, t)) \approx E_M[\mathbf{U}_\tau(\cdot, t)] := \frac{1}{M} \sum_{i=1}^M \mathbf{U}_\tau^i(\cdot, t).$$

- ▶ Postulated Convergence:

$$\|\mathbb{E}[\mathbf{U}(\cdot, t)] - E_M[\mathbf{U}_\tau(\cdot, t; \omega)]\|_{L^2(\Omega; L^1(\mathbf{D}))} \leq C_{\text{stat}} M^{-\frac{1}{2}} + C_{\text{st}} \Delta x^s.$$

- ▶ Slow convergence \Rightarrow very high computational cost.

Schemes for NonLinear systems III: MLMCFVM-SM, Schwab, Sukys 2012



MESH Resolution

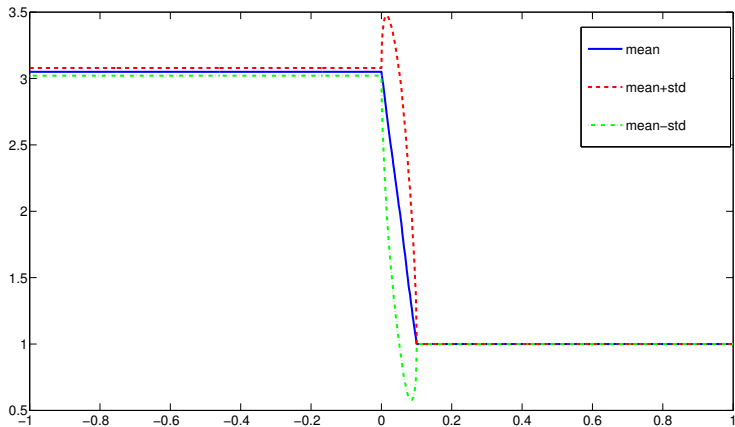
Number of samples

- ▶ Postulated Convergence:

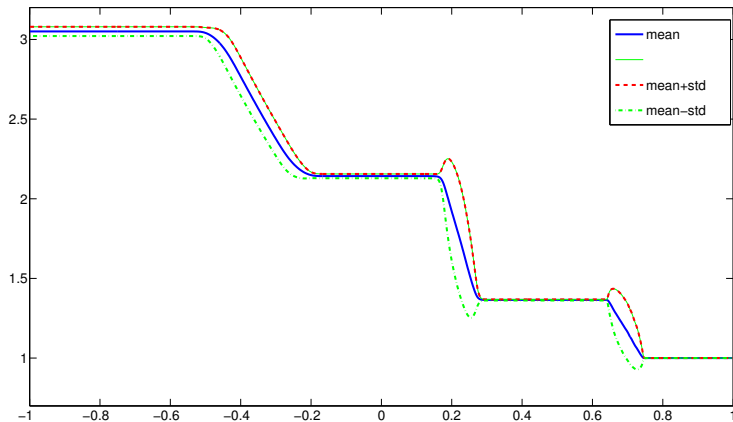
$$\begin{aligned} \|\mathbb{E}[\mathbf{U}(\cdot, t)] - E^L[\mathbf{U}_\tau(\cdot, t, \omega)]\|_{L^2(\Omega; L^1(\mathbb{R}^d))} &\leq C_1 \Delta x_L^s + C_3 M_0^{-\frac{1}{2}} \\ &+ C_2 \left\{ \sum_{\ell=0}^L M_\ell^{-\frac{1}{2}} \Delta x_\ell^s \right\} \end{aligned}$$

- ▶ Proper choice of $M_\ell \Rightarrow$ Same complexity as deterministic FVM !!!

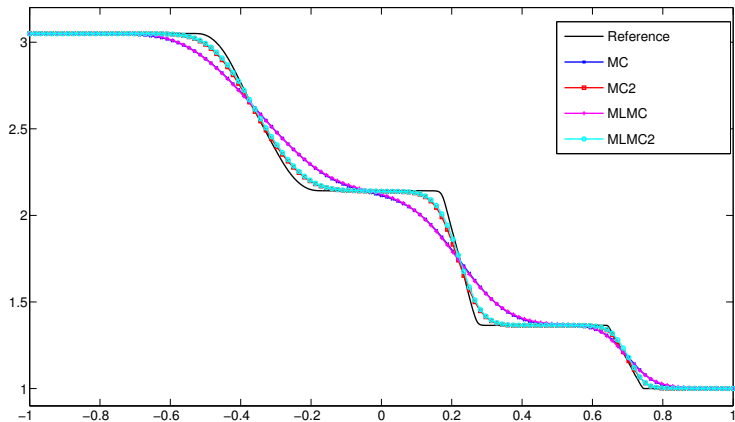
Euler equations with uncertain shock location and amplitude



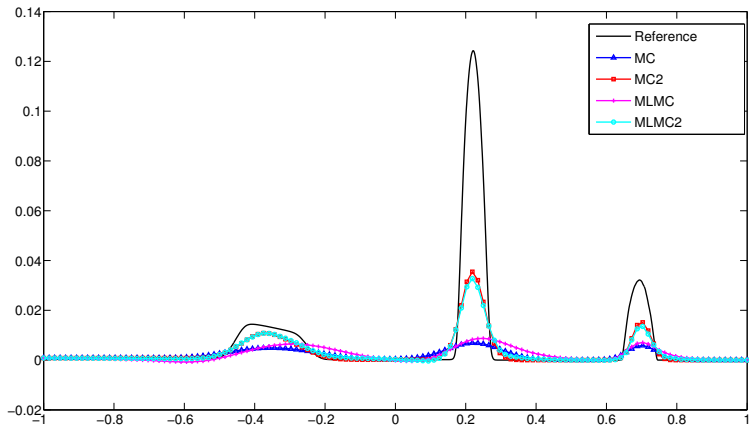
Mean \pm Standard deviation



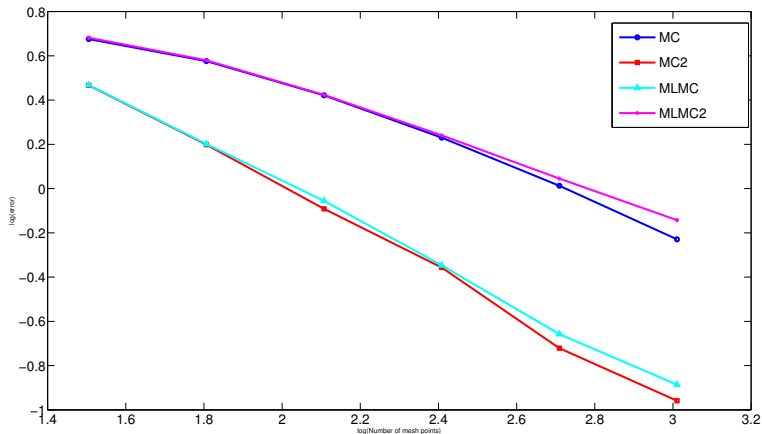
Mean: MC vs MLMC



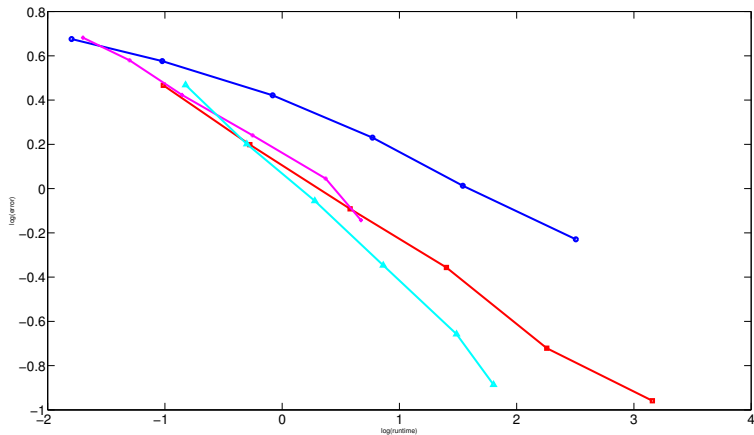
Variance: MC vs MLMC



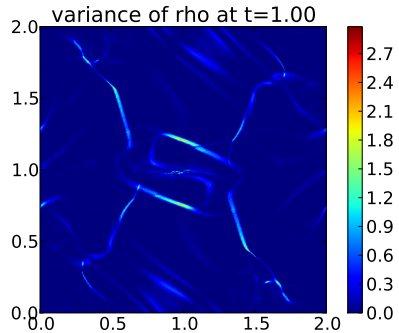
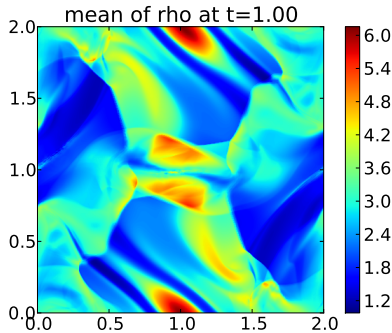
log(resolution) vs. log(relative error in mean)



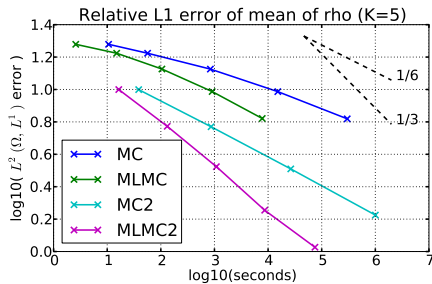
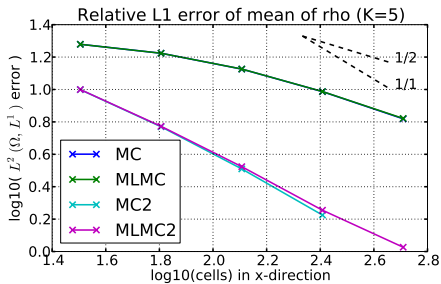
log(runtime) vs. log(relative error in mean)



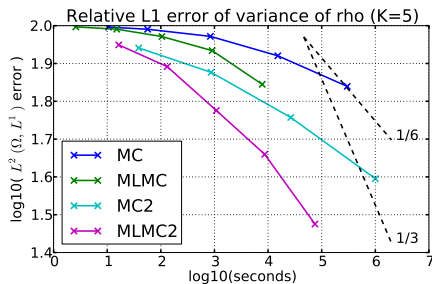
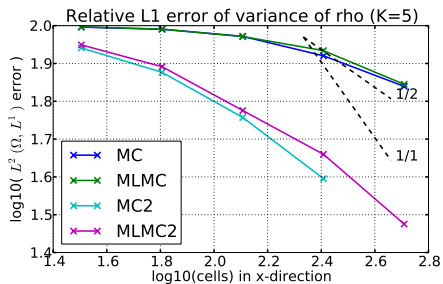
Uncertain Orszag-Tang vortex for MHD (2 Sources of uncertainty)



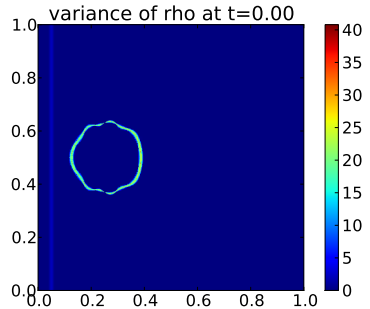
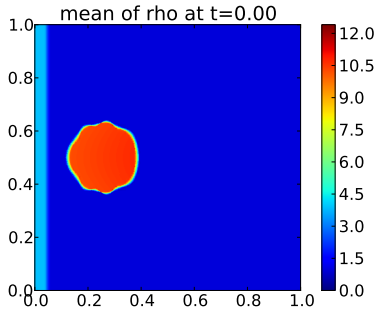
Uncertain Orszag-Tang vortex for MHD (Convergence of mean)



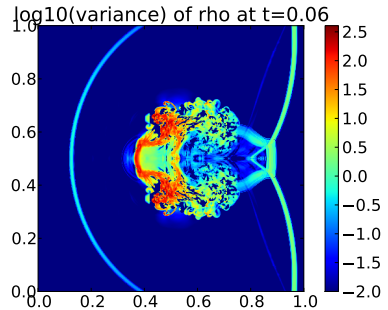
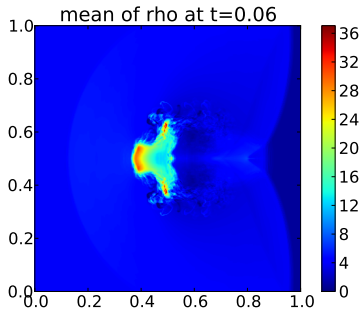
Uncertain Orszag-Tang vortex for MHD (Convergence of variance)



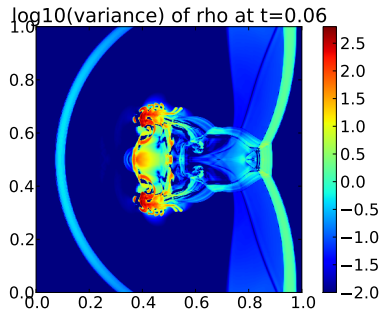
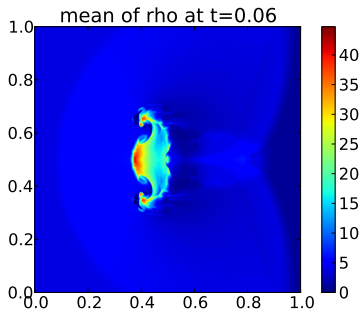
Euler: Cloud shock interaction with uncertain initial data (11 sources of uncertainty)



Euler: Cloud shock interaction with uncertain initial data (11 sources of uncertainty)

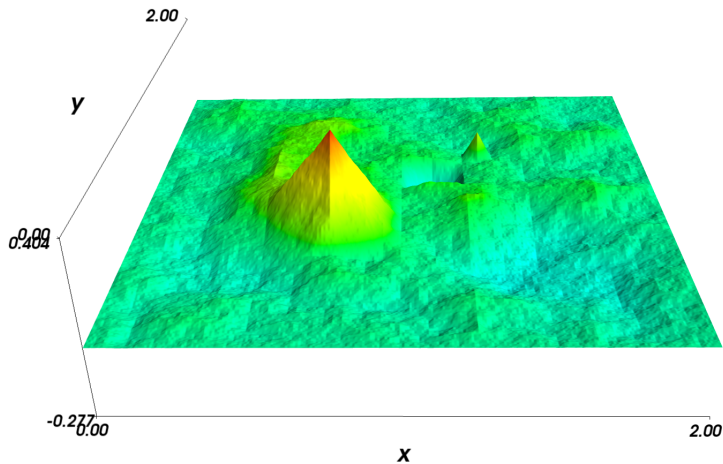


Euler: Cloud shock interaction with uncertain equations of state



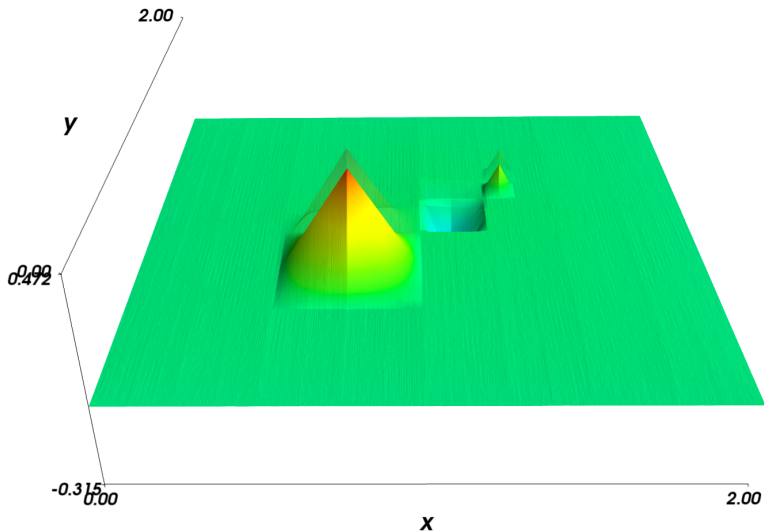
Bottom topography: one sample (realization)

Hierarchical hat basis representation



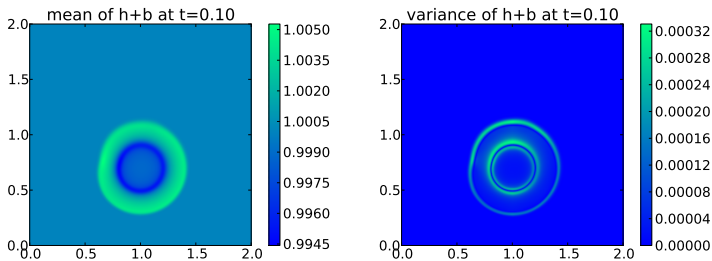
Bottom topography: mean and standard deviation

Hierarchical hat basis representation



MLMC solution for perturbation of a lake-at-rest

uncertain magnitude of the perturbation, hierarchical hat basis topography



$\approx 10^3$ -dimensional problem!

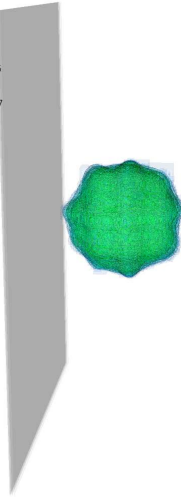
3D Euler– Initial Mean

DB: mean of rho at time 0

Contour
Var: mean of rho

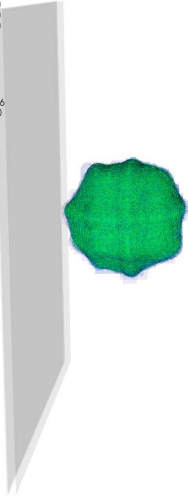
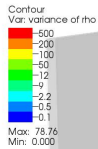


Max: 16.17
Min: 0.000



3D Euler– Initial Variance

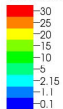
DB: variance of rho at time 0



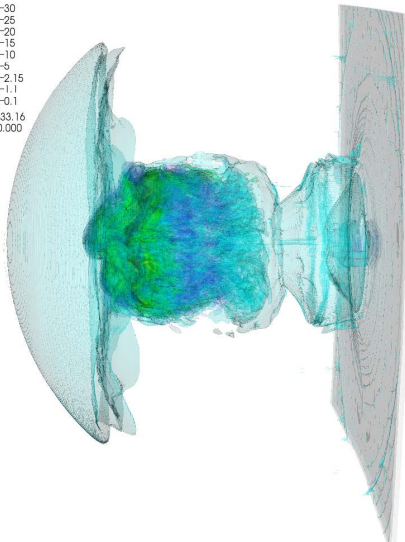
3D Euler- Mean

DB: mean of rho at time 0.06

Contour
Var: mean of rho



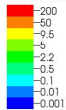
Max: 33.16
Min: 0.000



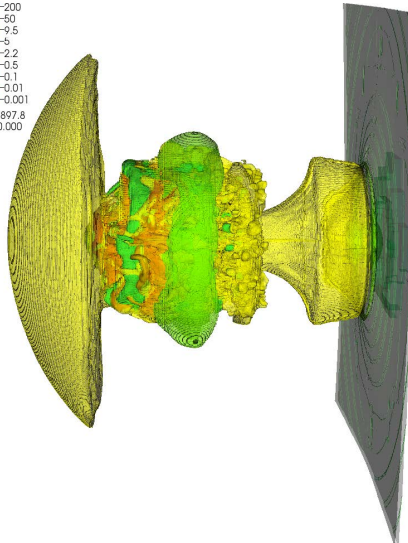
3D Euler– Variance

DB: variance of rho at time 0.06

Contour
Var: variance of rho



Max: 897.8
Min: 0.000



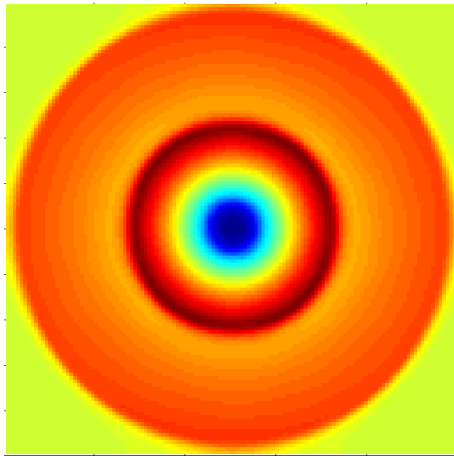
- ▶ **Convergence** of both **MC** + **MLMCFVM** relies on:
- ▶ **Postulated convergence** of FVM:

$$\|\mathbf{U} - \mathbf{U}^{\Delta x}\|_{L^p} \leq C \Delta x^s$$

- ▶ for some s, p .
- ▶ Widely expected to hold !!!
- ▶ Is this **TRUE** ?

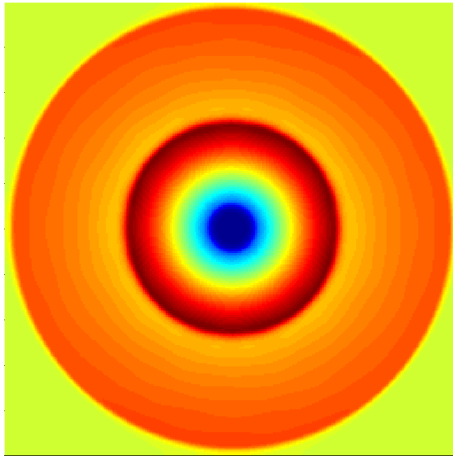
Numerical convergence Example 1: 2-D Radial shock tube

128^2 grid



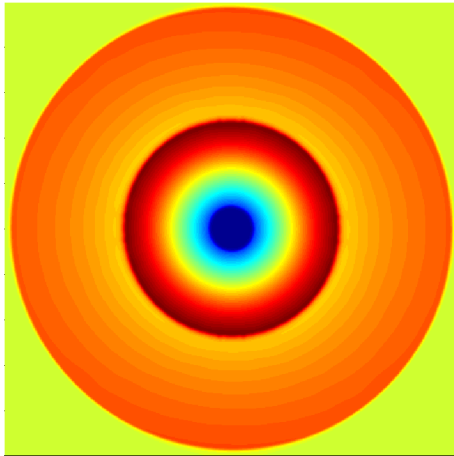
Numerical convergence Example 1: 2-D Radial shock tube

256² grid

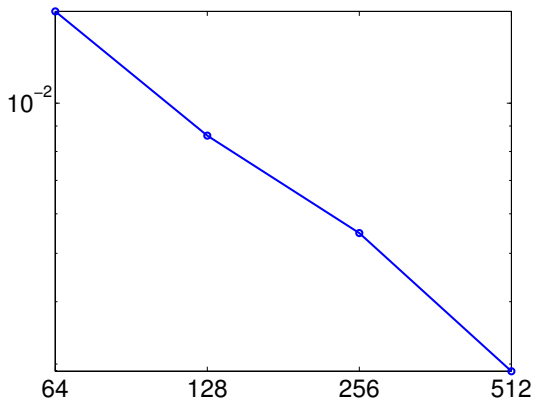


Numerical convergence Example 1: 2-D Radial shock tube

512² grid



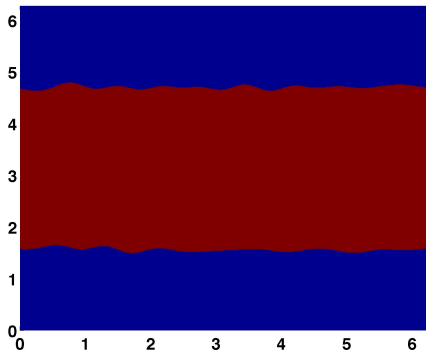
L^1 Error vs mesh resolution Example 1: 2-D Radial shock tube



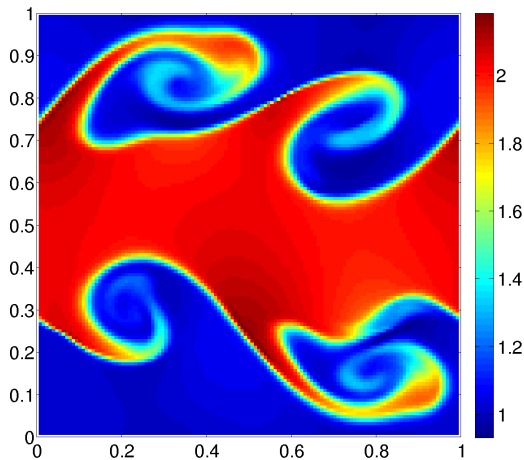
- Suggests L^1 convergence of approximate solutions to **Entropy solutions**

Ex II: Kelvin-Helmholtz problem: Compressible Euler equations

- Finite volume TeCNO3 simulation of Fjordholm, Käpelli, SM, Tadmor, 2014.

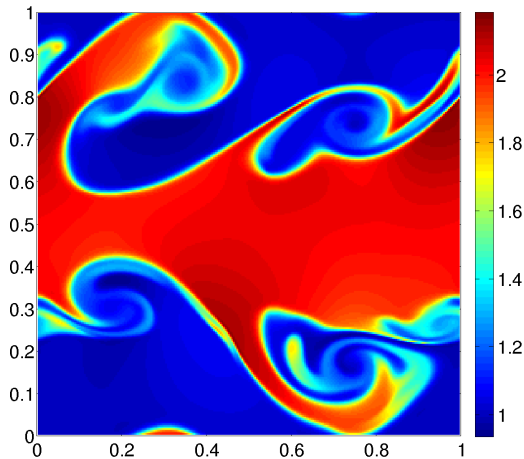


Numerical convergence: 2-D Kelvin-Helmholtz problem 128^2 grid ($T = 2$)



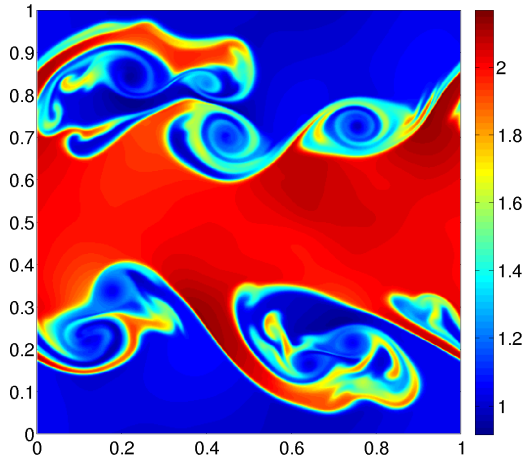
Numerical convergence: 2-D Kelvin-Helmholtz problem

256^2 grid $T = 2$



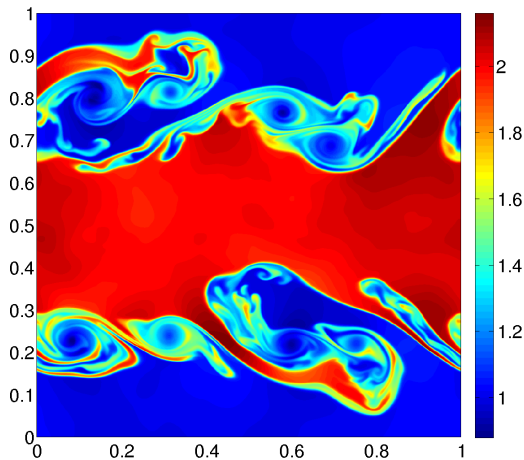
Numerical convergence: 2-D Kelvin-Helmholtz instability

512² grid $T = 2$

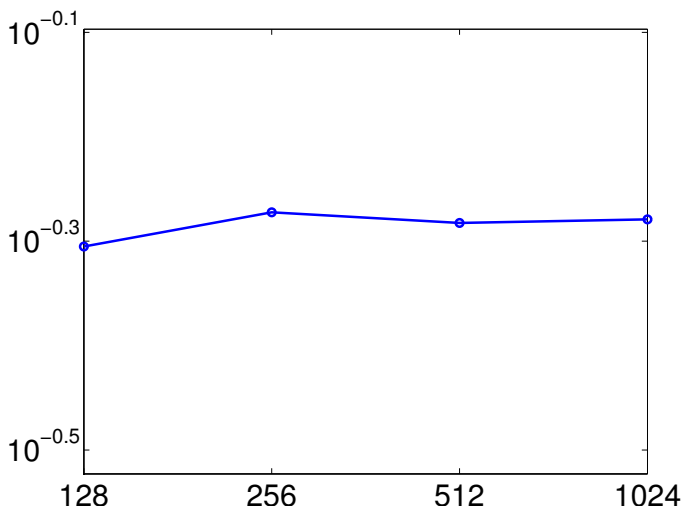


Numerical convergence: 2-D Kelvin-Helmholtz instability

1024^2 grid $T = 2$



L^1 Error vs mesh resolution: 2-D Kelvin-Helmholtz instability $T = 2$



Problem : Lack of convergence

- ▶ Suggests **Lack of convergence** to any function.
- ▶ Refining resolution reveals more **small scale** phenomena.
- ▶ Many Other examples like **Richtmeyer-Meshkov** problem.
- ▶ Generic to **Unstable** and **Turbulent** flows.
- ▶ Similar behavior for all numerical schemes.

- ▶ MC-MLMC UQ methods assume **Convergence** of FVM !!!
- ▶ **NO observed convergence** of any numerical scheme in multi-D (in general).
- ▶ Linked to
 - ▶ Lack of **Global existence** results for **Entropy solutions** of deterministic problem.
 - ▶ **NON-uniqueness** of entropy solutions !!!
- ▶ \Rightarrow Lack of **Well-posedness** of **Random entropy solutions**
- ▶ Search for a different **Solution framework**

Entropy measure valued solutions

- ▶ Pioneered by DiPerna (early to mid 80's).
- ▶ Contributions from Majda, Murat, Tartar.
- ▶ Solutions are Young measures i.e, space-time parametrized probability measures $\nu_{x,t}$.
- ▶ With action:

$$\langle g, \nu_{x,t} \rangle := \int_P g(\lambda) d\nu_{x,t}(\lambda)$$

- ▶ Characterizes weak limits of sequences of bounded functions.
- ▶ MVS assigns a probability distribution (likely value) for a.e point in space-time (one-point statistics)

Generalized Cauchy problem for $\mathbf{U}_t + \mathbf{F}(\mathbf{U})_x = 0$

$$\begin{aligned}\langle ID, \nu \rangle_t + \langle \mathbf{F}, \nu \rangle_x &= 0, \quad \text{in } \mathcal{D}'(D) \\ \nu_{x,0} &= \sigma_x, \quad \text{a.e } x \in \mathbb{R}.\end{aligned}$$

- ▶ **EMVS** satisfies:
 - ▶ Weak solution.
 - ▶ Entropy condition: $\langle S, \nu \rangle_t + \langle \mathbf{Q}, \nu \rangle_x \leq 0$
 - ▶ Initial data (**DiPerna**)

$$\lim_{t \rightarrow 0^+} \int_{\mathbb{R}} \varphi(x) \langle ID, \nu_{x,t} \rangle dx = \int_{\mathbb{R}} \varphi(x) \langle ID, \sigma_x \rangle dx$$

- ▶ σ_x models **Uncertainty** in initial data (EMVS is an **UQ** framework).
- ▶ Efficient **Computation** of EMVS: **Algorithm** designed by Fjordholm, Käppeli, SM, Tadmor (**FKMT**), 2014.

Step 1: Preparation of initial data

- ▶ Let $\{\Omega, \Sigma, \mathcal{P}\}$ be a complete probability space.
- ▶ Find **random field** $\mathbf{U}_0 : \Omega \mapsto L^1(\mathbb{R}) \cap L^\infty(\mathbb{R})$, such that:
- ▶ σ_x be the **LAW** of the random field \mathbf{U}_0 i.e, for all Borel subsets $\bar{D} \subset \mathbb{R}^m$:

$$\sigma_x(\bar{D}) := \mathcal{P}(\{\omega \in \Omega : \mathbf{U}_0(\omega, x) \in \bar{D}\}),$$

Step 2: Numerical approximations

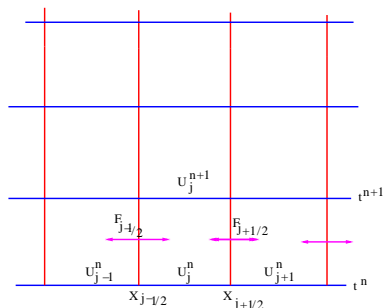
- ▶ **Standard** semi-discrete finite volume scheme:

$$\frac{d}{dt} \mathbf{U}_j^{\Delta x}(t) + \frac{1}{\Delta x} (\mathbf{F}_{j+1/2} - \mathbf{F}_{j-1/2}) = 0$$

$$\mathbf{U}_j^{\Delta x}(0, \omega) = \mathbf{U}_0(x_j, \omega)$$

$$\mathbf{U}^{\Delta x}|_{[x_{j-1/2}, x_{j+1/2})} = \mathbf{U}_j^{\Delta x}.$$

- ▶ On the grid:



Step 3: Abstract Convergence criteria, Fjordholm, Käppeli, SM, Tadmor 2014

- ▶ Let $\nu_{x,t}^{\Delta x}$ be the law of the random field $\mathbf{U}^{\Delta x}$
- ▶ Thrm: $\nu_{x,t}^{\Delta x}$ is a young measure on phase space.

Step 3: Abstract Convergence criteria, (Contd..)

- ▶ L^∞ bounds:

$$\|\mathbf{U}^{\Delta x}\|_{L^\infty} \leq C, \quad \text{a.e } \omega$$

- ▶ Discrete entropy inequality:

$$\frac{d}{dt} S(\mathbf{U}_j(t)) + \frac{1}{\Delta x} (Q_{j+1/2} - Q_{j-1/2}) \leq 0$$

- ▶ Weak BV bounds (for a.e. ω):

$$\int_0^T \sum_j |\mathbf{U}_{j+1} - \mathbf{U}_j|^{p+1} dt \leq C.$$

- Thrm: Then, $\nu^{\Delta x} \rightharpoonup \nu$ (EMVS of the system).

Convergent schemes

- ▶ Schemes satisfy **Discrete entropy inequality** + **Weak BV** bound:
 - ▶ TeCNO schemes (**Fjordholm, SM, Tadmor** 2012).
 - ▶ Space-time DG schemes (**Hiltebrand, SM**, 2013).
- ▶ Assumption of L^∞ bound.
- ▶ Relaxed in (**Fjordholm, SM** 2014) with **Generalized young measures**.
- ▶ Numerical schemes satisfy L^2 bounds (**Entropy estimate**).

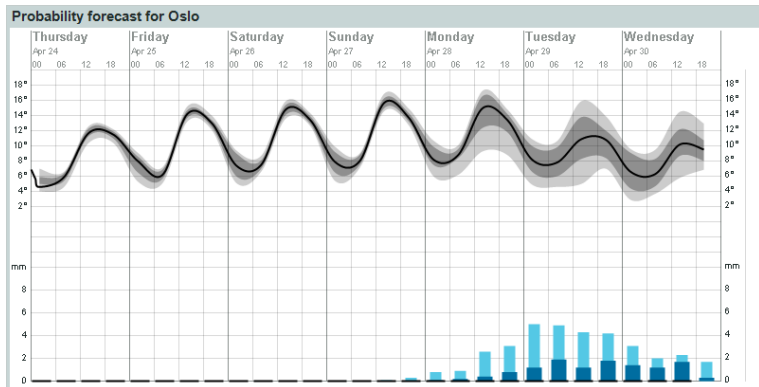
Computing the EMVS

- ▶ **Narrow convergence** \Rightarrow as $\Delta x \rightarrow 0$, convergence of

$$\int_{D_t} \psi(x, t) \langle g, \nu_{x,t}^{\Delta x} \rangle dx dt \rightarrow \int_{D_t} \psi(x, t) \langle g, \nu_{x,t} \rangle dx dt$$

- ▶ Sense of convergence: **Statistics of functionals of interest**
- ▶ Precisely the outputs of **measurement**
- ▶ Typical observables:
 - ▶ $g(\lambda) = \lambda$ (**Mean**).
 - ▶ $g(\lambda) = \lambda \otimes \lambda$ (**Variance**).

Typical measurements: Weather

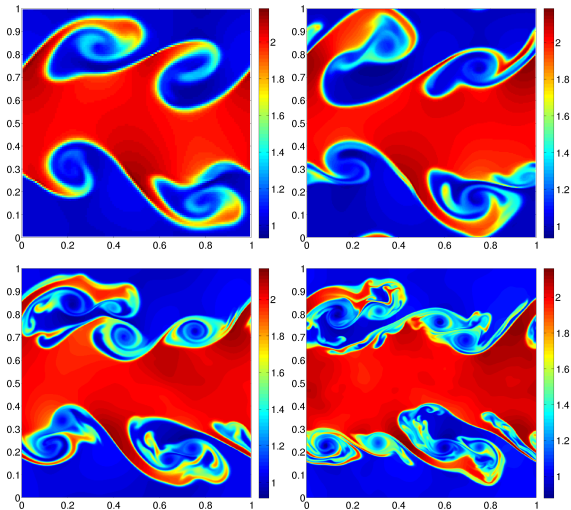


- ▶ We need to compute:

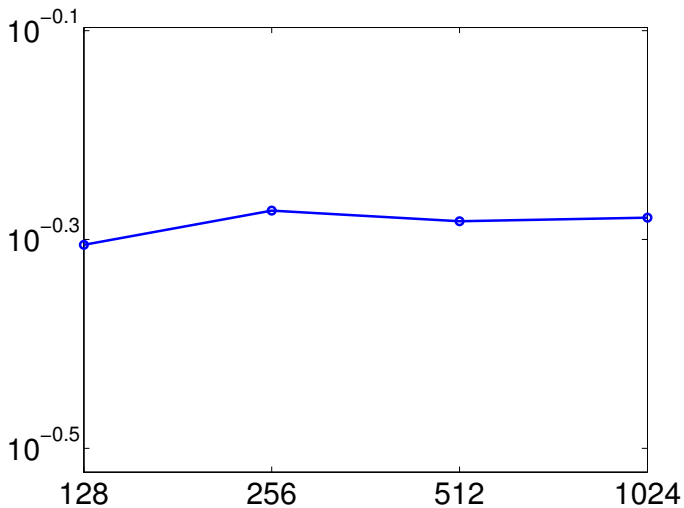
$$\begin{aligned}\langle g, \nu_{x,t}^{\Delta x} \rangle &= \int_{\mathcal{P}} g(\lambda) d\nu_{x,t}^{\Delta x}(\lambda) \\ &= \int_{\Omega} g(\mathbf{U}^{\Delta x}(x, t, \omega)) d\mathcal{P}(\omega) \quad (\text{Definition of law}) \\ &\approx \frac{1}{M} \sum_{1 \leq i \leq M} g(\mathbf{U}_i^{\Delta x}(x, t)) \quad (\text{MC approximation}).\end{aligned}$$

- ▶ $\mathbf{U}_i^{\Delta x}$ are M i.i.d samples
- ▶ Convergence proof as $M \rightarrow \infty$ ([Fjordholm, Käppeli, SM, Tadmor, 2014](#)).

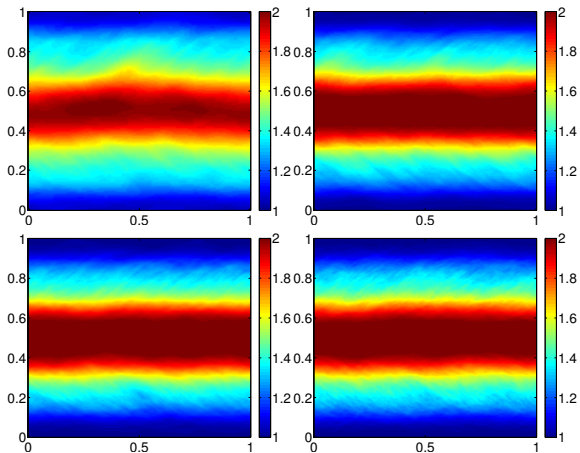
KH (Sample): Density at different resolutions



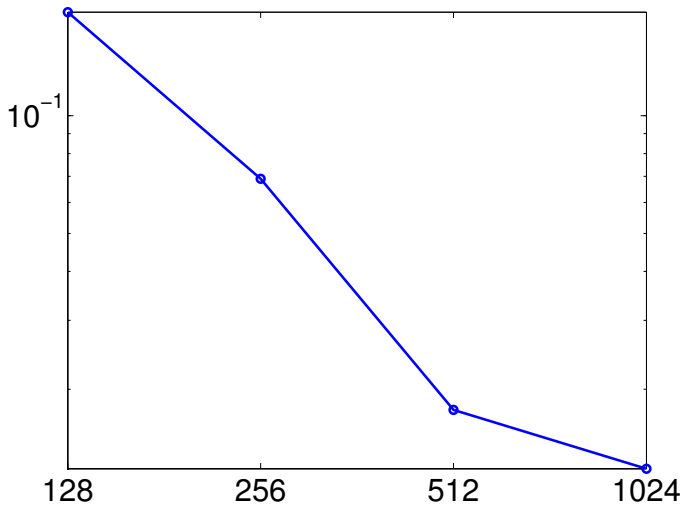
Cauchy rates $\|\mathbf{U}^{\Delta x} - \mathbf{U}^{\Delta x/2}\|_{L^1}$



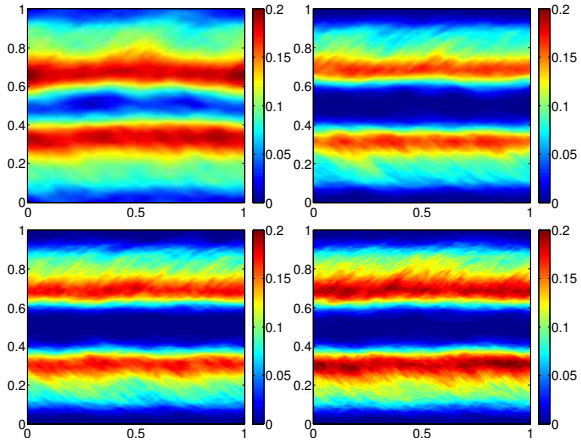
KH mean on different meshes (200 samples)



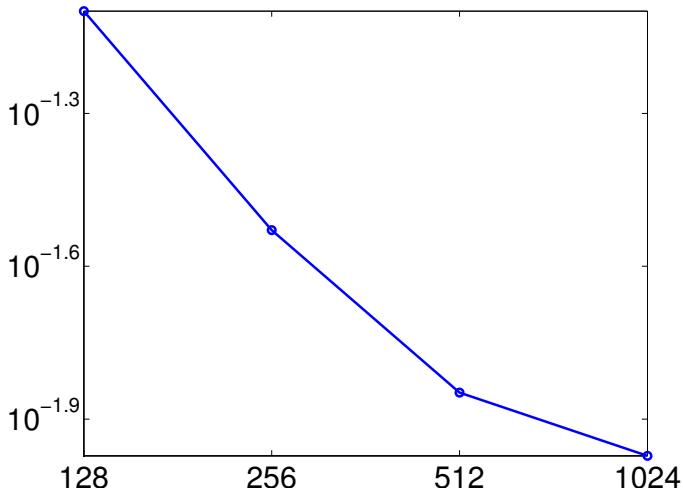
Mean: Cauchy rates $\|\mathbf{U}^{\Delta x} - \mathbf{U}^{\Delta x/2}\|_{L^1}$



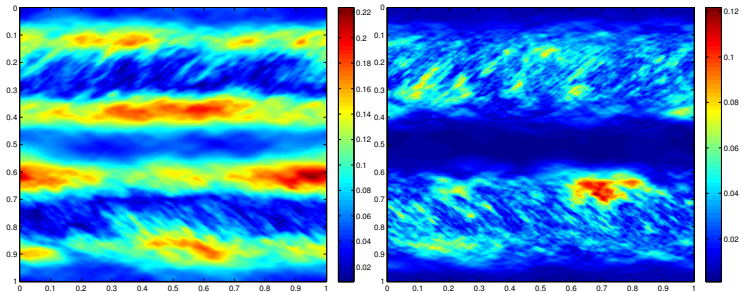
KH variance on different meshes (200 samples)



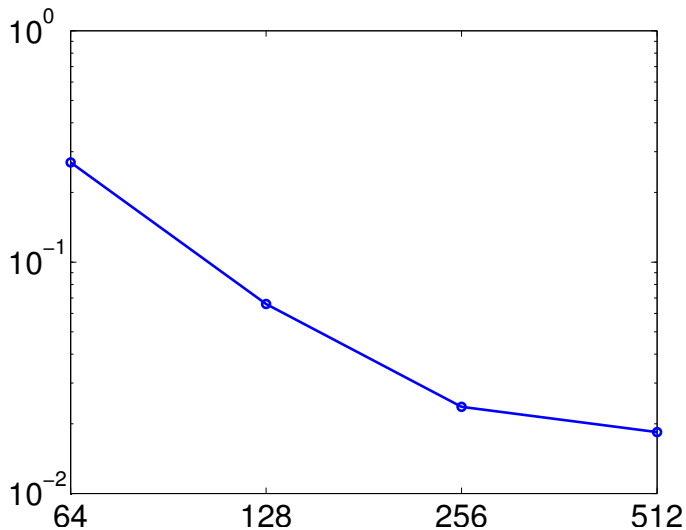
Variance: Cauchy rates $\|\mathbf{U}^{\Delta x} - \mathbf{U}^{\Delta x/2}\|_{L^1}$



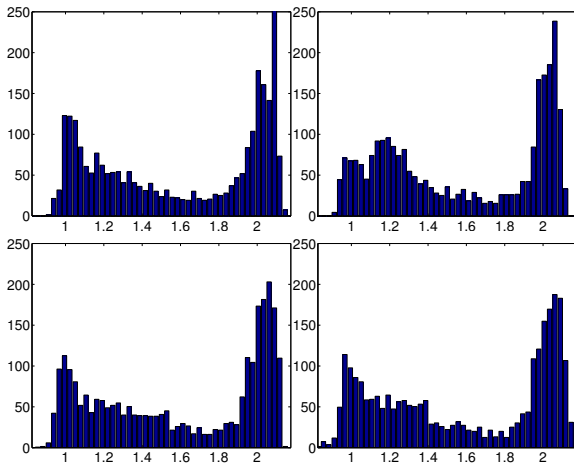
Wasserstein distances $\mathcal{W}_1(\nu^{\Delta x}, \nu^{\Delta x/2})$ for different resolutions



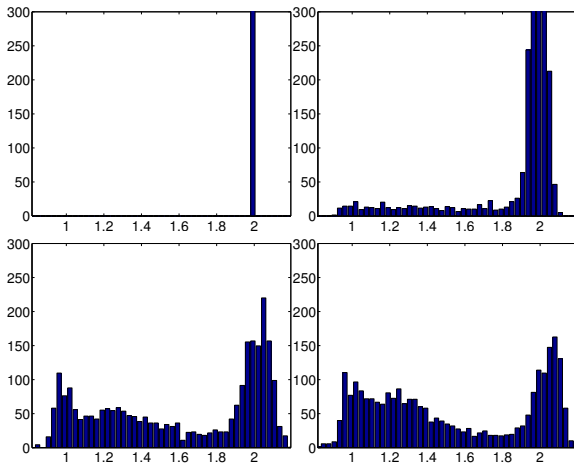
Cauchy rates in $L^1(\mathcal{W}_1)$



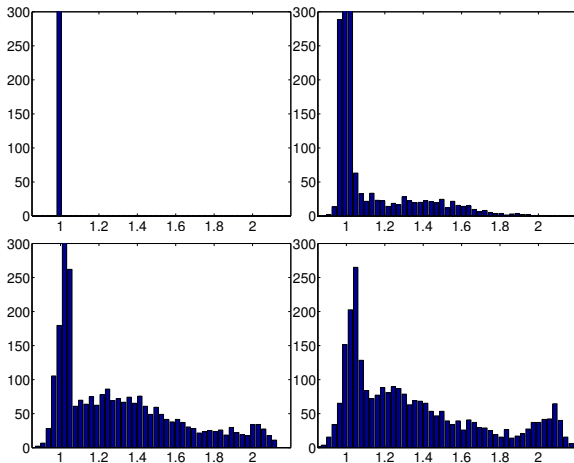
Convergence of PDFs



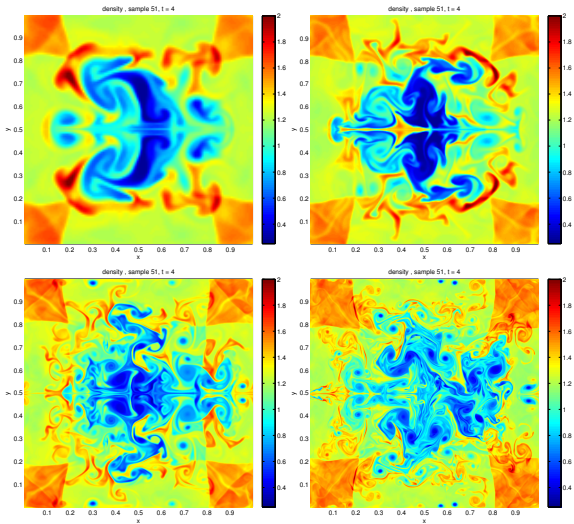
Atomic initial measure \Rightarrow Non-atomic young measure



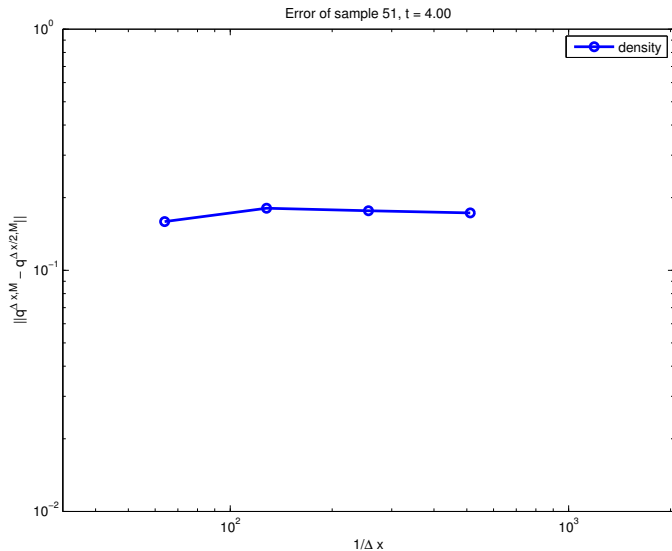
Atomic initial measure \Rightarrow Non-atomic young measure



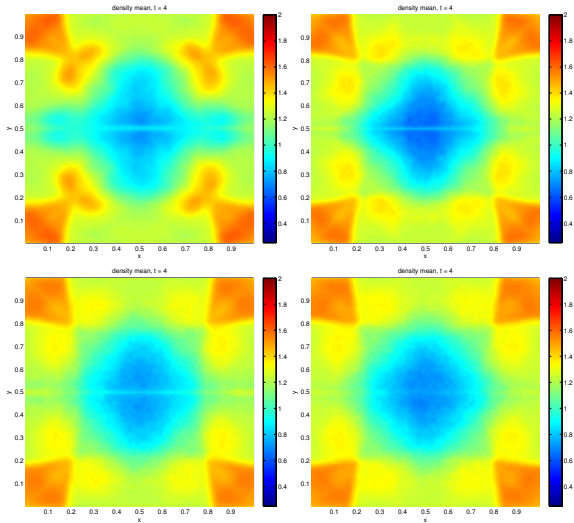
Richtmeyer Meshkov (Sample): Density



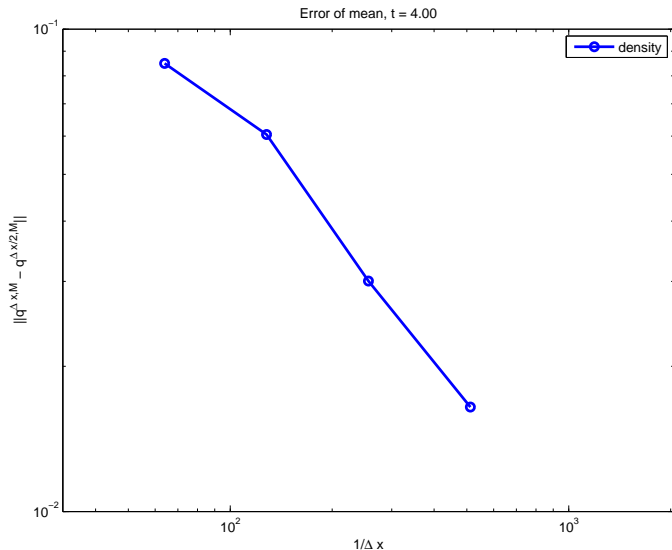
Cauchy rates $\|\mathbf{U}^{\Delta x} - \mathbf{U}^{\Delta x/2}\|_{L^1}$



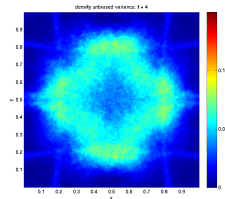
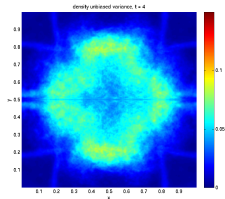
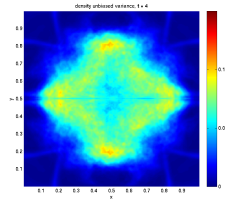
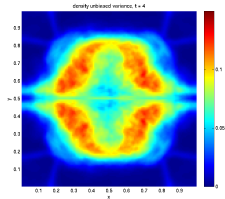
RM mean on different mean meshes (200 samples)



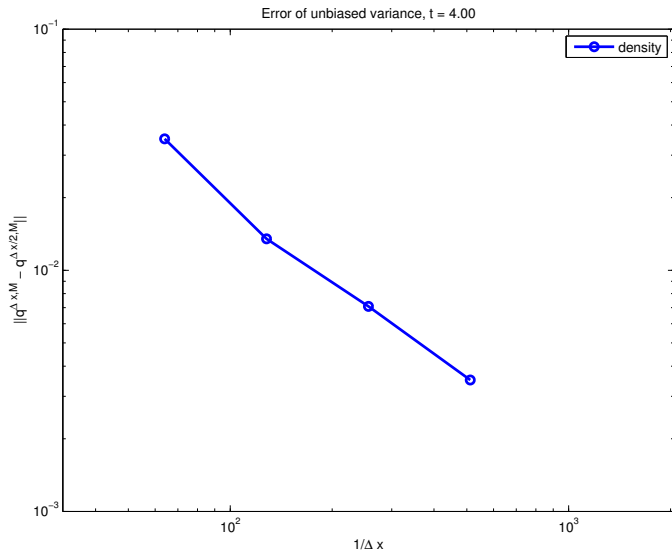
Mean: Cauchy rates $\|\mathbf{U}^{\Delta x} - \mathbf{U}^{\Delta x/2}\|_{L^1}$



RM variance on different meshes (200 samples)



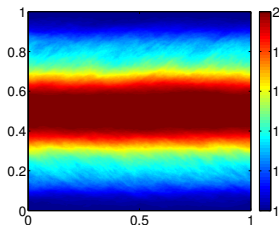
Variance: Cauchy rates $\|\mathbf{U}^{\Delta x} - \mathbf{U}^{\Delta x/2}\|_{L^1}$



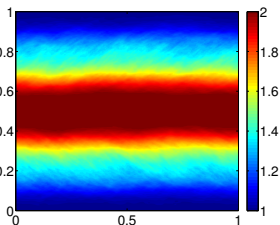
MVS Issues I: Uniqueness (stability) ?

- ▶ A generic admissible (entropy) MVS is **Not unique**.
- ▶ Similar construction a la **DeLellis, Szekelyhidi**.
- ▶ However, computed MVS seems to **very stable** wrt
 - ▶ Different numerical schemes.
 - ▶ Different types of initial perturbations.

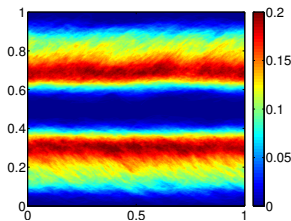
Stability vis a vis different numerical schemes



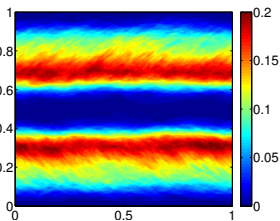
(h) Mean, TeCNO3



(i) Mean, FISH

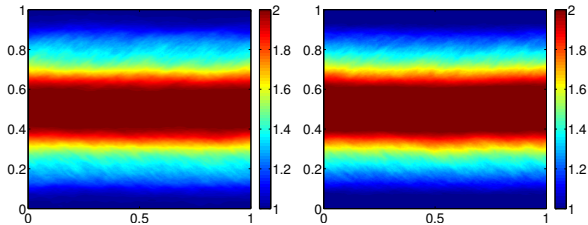


(j) Variance, TeCNO3



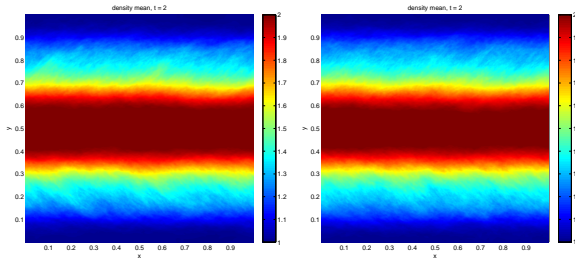
(k) Variance, FISH

Stability vis a vis different types of perturbations: Mean



(l) Phase

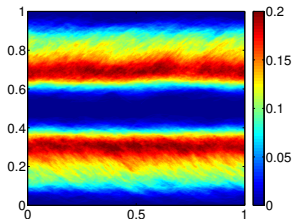
(m) Amplitude



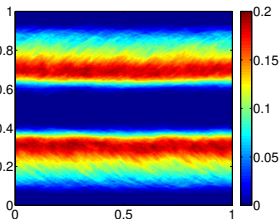
(n) Uniform

(o) Normal

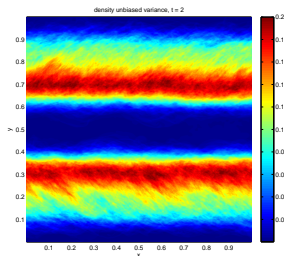
Stability vis a vis different types of perturbations: Variance



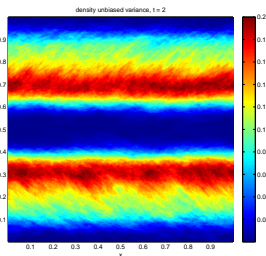
(p) Phase



(q) Amplitude



(r) Uniform



(s) Normal

Stability of MVS ?

- ▶ Numerical experiments suggest that computed solution is stable !!
- ▶ Additional **selection criteria** for the computed solution ?

MVS as a UQ framework

- ▶ MVS is an **UQ framework** for **Uncertain initial data + coefficients**.
- ▶ MV Cauchy problem:

$$\begin{aligned}\langle ID, \nu \rangle_t + \operatorname{div} \langle \mathbf{F}, \nu \rangle &= 0, \quad \text{in } \mathcal{D}'(D) \\ \nu_{x,0} &= \sigma_x, \quad \text{a.e } x \in \mathbb{R}.\end{aligned}$$

- ▶ Initial **Young measure** σ_x represents **1-pt statistics**.
 - ▶ **1-pt statistics** evolved by MVS $\nu_{x,t}$.
 - ▶ DOESNOT account for **Spatial correlations** in initial data or solutions !!!
- ▶ **Spatially independent** initial data \Rightarrow **Spatially correlated** solutions !!!

Statistical solutions

- ▶ Developed by [Fjordholm, Lanthaler, SM, 2015](#).
- ▶ Statistical solution $\mu \in \text{Prob}(L^p(D))$ i.e, **probability measure** on a function space.
- ▶ THM: Completely characterized by all k -point **correlation measures**.

$$\mu_t \iff \left\{ \begin{array}{l} \nu_{x,t}^1 \\ \nu_{x_1,x_2,t}^2 \\ \dots \\ \nu_{x_1,x_2,\dots,x_k,t}^k \\ \dots \end{array} \right.$$

- ▶ Identification through **Cylindrical test functions**.

Statistical solutions (Contd)

- ▶ **Infinite dimensional Liouville** equation characterized by,

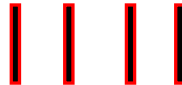
$$\partial_t \langle \nu_{x_1, x_2, \dots, x_k, t}^k, \xi_1 \xi_2 \dots \xi_k \rangle + \sum_{i=1}^k \partial_{x_i} \langle \nu_{x_1, x_2, \dots, x_k, t}^k, \xi_1 \xi_2 \dots \mathbf{F}(\xi_i) \dots \xi_k \rangle = 0, \quad \forall k \in \mathbb{N}$$

- ▶ + Suitable **Entropy conditions**.
- ▶ **Fjordholm, Lanthaler, SM, 2015** show:
 - ▶ **Existence** of statistical solutions.
 - ▶ **Approximation** of statistical solutions using the **FKMT** algorithm !!!
- ▶ Promising description of **Turbulent flows**.
- ▶ **UQ framework** that accounts for correlations.
- ▶ Uniqueness of statistical solutions is very much open.

- ▶ Phase space integrals by **Monte Carlo** (MC) sampling:

$$\langle g, \nu_{x,t}^{\Delta x} \rangle \approx \frac{1}{M} \sum_{1 \leq i \leq M} g(\mathbf{u}_i^{\Delta x}(x, t)).$$

- ▶ MC converges at rate $\mathcal{O}\left(\frac{1}{\sqrt{M}}\right)$
- ▶ **Slow convergence** \Rightarrow **Extreme computational cost.**
- ▶ Possible solution: **Multi-level Monte Carlo (MLMC)** methods.



MESH Resolution

Number of samples

MLMC-FKMT algorithm: Lye, SM, in preparation

- ▶ Different nested **levels** of resolution: l .
- ▶ **Draw** M_l i.i.d samples for the initial random field:
 $\{\mathbf{U}_{l,0}^i\}_{1 \leq i \leq M_l}$.
- ▶ For each draw: **Solve** conservation law by numerical scheme to obtain $\mathbf{U}_{\tau,l}^i$.
- ▶ **Sample statistics**: with $u_{\tau,-1} = 0$,

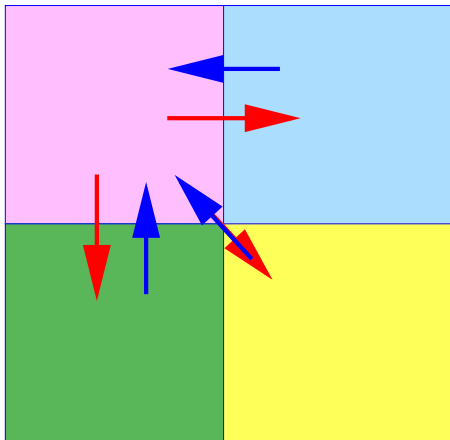
$$\langle g, \nu_{x,t}^\tau \rangle = \sum_{l=0}^L \sum_{i=1}^{M_l} \frac{1}{M_l} \left(g(\mathbf{U}_i^{\tau,l}(x,t)) - g(\mathbf{U}_i^{\tau,l-1}(x,t)) \right)$$

- ▶ Convergence of ν^τ to EMVS.
- ▶ Complexity estimate + Numerical experiments – Work in progress !!!

- ▶ **Online computation** of variance !!
- ▶ A **Good Pseudo-random number generator** !!
 - ▶ **WELL**-series of pseudo random number generators:
 - ▶ We used WELL512a:
 - ▶ buffer size: 16
 - ▶ period length: $2^{512} - 1$
 - ▶ very good equidistribution
 - ▶ fast: takes 33 sec for 10^9 draws

Parallel implementation I

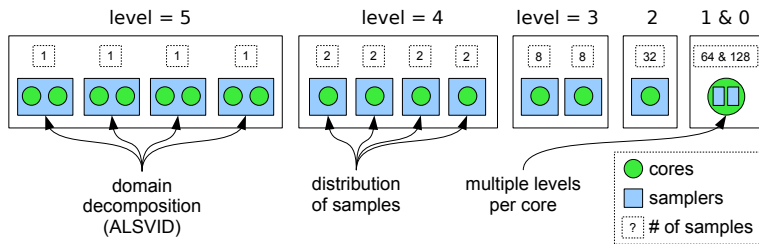
- ▶ Domain decomposition for the FMV solver.



- ▶ Use MPI for message passing between processors.

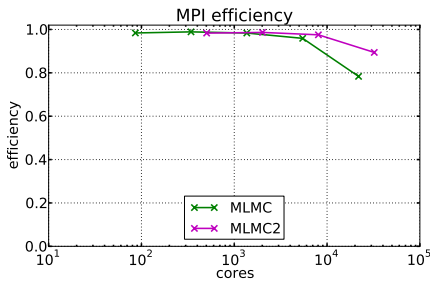
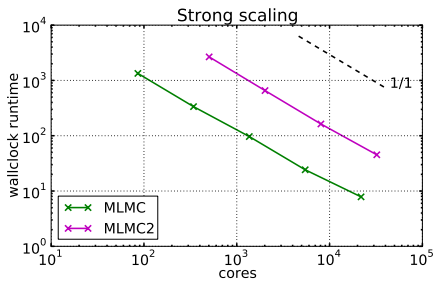
Parallel implementation II

- ▶ **Static load balancing procedure** for MLMC – SM, Schwab, Sukys 2012.



- ▶ A **Dynamic load balancing** version – Sukys, 2013.

Strong scaling atleast upto 50000 processors



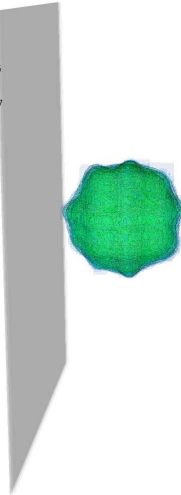
3D Euler– Initial Mean

DB: mean of rho at time 0

Contour
Var: mean of rho

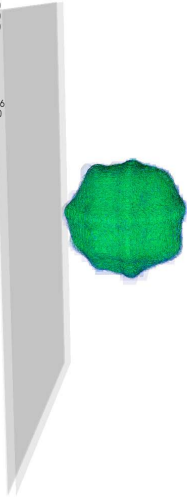
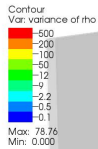


Max: 16.17
Min: 0.000



3D Euler– Initial Variance

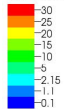
DB: variance of rho at time 0



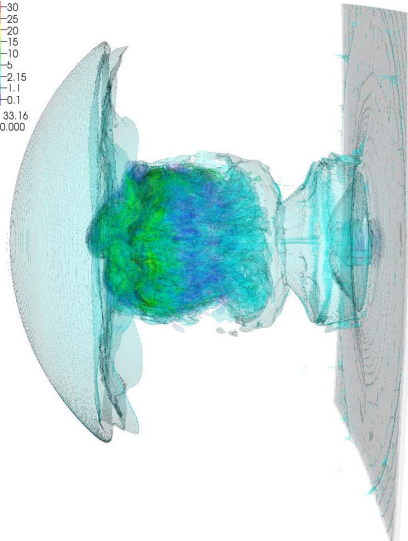
3D Euler– Mean (Cost: 5 hours on 50000 processors)

DB: mean of rho at time 0.06

Contour
Var: mean of rho



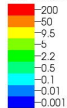
Max: 33.16
Min: 0.000



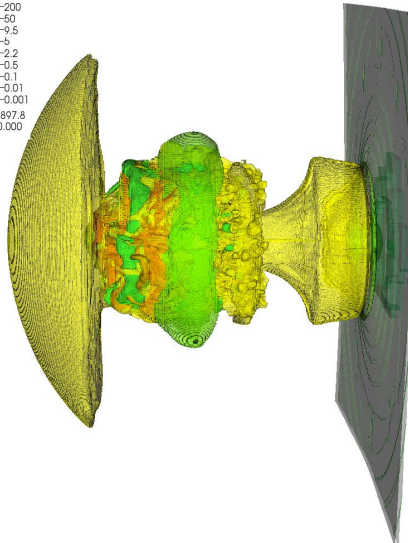
3D Euler– Variance (Cost: 5 hours on 50000 processors)

DB: variance of rho at time 0.06

Contour
Var: variance of rho



Max: 897.8
Min: 0.000



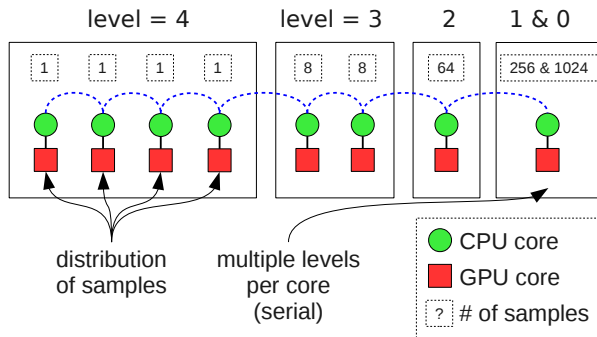
Emerging massively parallel HPC architectures: Piz Daint (CSCS, Switzerland)

- ▶ **Hybrid** CRAYXC30 machine. (6-th in **Top500**)
- ▶ 5272 compute nodes (115000 cores)
- ▶ Each nodes consists of Intel Xeon E5-2670 (**CPU**) and NVIDIA TESLA 20 X (**GPU**) !!!
- ▶ Peak performance: 7.78 petaflops.

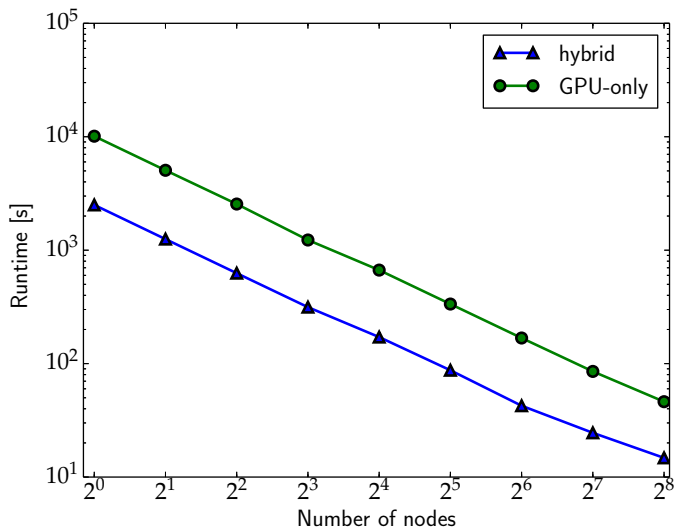


Hybrid MLMC

- ▶ Based on **Dynamic load allocation** algorithm (Grosheintz, SM, Sukys, forthcoming).
 - ▶ **Master-Slave** type load distributor.
 - ▶ **CPU** fast for coarse resolution but **GPU** fast for fine resolution.



Hybrid MLMC is efficient



- ▶ Modeling of uncertain inputs + solutions:
 - ▶ Random fields (Scalar conservation laws, linear systems)
 - ▶ Young measures (Nonlinear systems)
- ▶ Computation of Uncertainty:
 - ▶ MC (slow but robust)
 - ▶ MLMC (fast)
- ▶ Massively parallel implementation on hybrid architectures.

MLMCFVM: Advantages over Stochastic Galerkin and Collocation methods (if they work)

- ▶ Ability to handle **very large dimensions**.
- ▶ **low regularity** requirements:
 - ▶ SGL and SCL methods need **high** regularity wrt stochastic variables.
 - ▶ For non-linear hyperbolic systems: Discontinuities in stochastic variables.
- ▶ Totally **Non-intrusive** and readily parallelizable.

