# An Introduction to Discontinuous Galerkin Methods

Module 3B: To Higher-Orders - Discrete System

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## **Numerical Quadrature (Gauss)**

- We now have a method for generating a robust arbitrary order solution approximation, but unlike before it isn't practical to analytically pre-calculate all the integrals.
- ▶ We can use a numerical quadrature technique to do this instead, able to integrate arbitrary functions
- $\triangleright$  If we call the interpolation of a function Inf then we assume that for a sufficiently accurate interpolation, we can use the interpolation of the function wherever we could use the function itself before. This is in general M-1 order accurate.

$$f \approx Inf = \sum_{i=0}^{M} f(x_i) L_i(x)$$
 (1)

$$\int f \approx \int Inf = \int \sum_{i=0}^{M} f(x_i) L_i(x) = \sum_{i=0}^{M} f(x_i) \int L_i(x) = \sum_{i=0}^{M} f(x_i) w_i$$

$$(2)$$

#### Hermite Interpolation (and quadrature)

- Recall: Hermite interpolation includes derivatives of interpolated function as well
- ▶ Consider a Hermite interpolation polynomial that includes first derivatives as well, the interpolation would be 2M-1 accurate. The quadrature using this polynomial would look like:

$$\int f \, dx \approx \sum_{i=0}^{M} f(x_i) w_i + \sum_{i=0}^{M} \left[ f'(x_i) \int (x - x_i) L_i^2(x) \, dx \right]$$
 (3)

▶ It turns out if we choose our quadrature/interpolation points to be the Legendre roots, the integral for the second term is zero. Thus no first derivative terms are needed for the Hermite quadrature, even though it is 2M-1 order accurate.

#### Truncation error/exact quadrature

- It is important to consider error sources from the approximation to the solution and integrals, these can affect convergence
- ► Three main error sources in quadrature: aliasing, truncation, and inexact quadrature
- ▶ Aliasing occurs if the function is not sampled frequently enough, it is assumed that the sol'n is sufficiently smooth and the discretization suitably fine to avoid this in most cases
- Truncation is unavoidable except where the exact function is of equal or lesser order than the interpolation/quadrature. Higher order terms present in the exact function are left off.
- ► Inexact quadrature occurs when the total polynomial order of the product of the interpolated functions undergoing quadrature exceeds the exactness of the quadrature. For Gauss-Legendre quadrature this isn't a problem for one and even two functions in the integrand. Each function is of order M-1 and the quadrature is exact for 2M-1, so the quadrature is able to exactly integrate the interpolation

#### **GL** Lagrange Orthogonality

- ► A final useful property of the Lagrange basis with Legendre interpolation points is orthogonality
- ▶ The product of two M-1 order Lagrange bases can be rearranged to be a Legendre poly of order M and a remainder polynomial of order M-2
- ▶ The remainder polynomial can be expressed as a linear combination of Legendre polys all of order < M, all are orthogonal to the order M Legendre, so

$$\int_{-1}^{1} L_i(x)L_j(x) dx = \delta_{ij}w_i \tag{4}$$

## **Local Mapping Function (Jacobian)**

- ▶ The domain of orthogonality for Legendre polynomials (and by extension GL Lagrange) is [-1,1]
- ▶ Elements may be arbitrary sizes though, we'd like to be able to transform  $x \in [x_L, x_R] \to X \in [-1, 1]$  by means of a mapping x = g(X) and it's inverse X = G(x)

$$x = g(X) = \frac{X+1}{2}\Delta x + x_L$$
 ,  $X = G(x) = \frac{2(x-x_L)}{\Delta x} + 1$  (5)

Applying a change of variables for the mapping

$$\int_{x_L}^{x_R} L_i(x) L_j(x) \, dx \to \int_{-1}^1 L_i(g(X)) L_j(g(X)) g' \, dX \tag{6}$$

•  $J=g'=\frac{\Delta x}{2}$  is called the determinant of the Jacobian matrix



#### Mass Matrix- Diagonalization

We have done what seems like quite a bit of tangential work, but it now pays off

$$\sum_{i=0}^{M} \frac{d\widetilde{q}_i}{dt} \int_k \psi_i(x)\phi_j(x) dx = \sum_{i=0}^{M} \frac{d\widetilde{q}_i}{dt} \int_I L_i(X)L_j(X) \frac{\Delta x}{2} dX$$
(7)

$$= \frac{\Delta x}{2} \sum_{i=0}^{M} \frac{dq_i}{dt} \delta_{ij} w_i = \frac{\Delta x}{2} q'_j w_j \quad \text{for all } j$$
 (8)

• We've reduced the full mass matrix into a diagonal mass matrix with all other terms zero, compared to Module 2 solver case the mass matrix is trivially invertible. We have:  $\frac{\Delta x}{2}\mathbf{q'M}$  where  $\mathbf{M}_{jj}=w_j$ 

#### Log differentiation

- lacktriangle We can get a closed form expression for  $L_j'(x)$  in the stiffness term by using logarithmic differentiation
- ▶ The main idea is that in general f'/f = ln(f) so applying this to our Lagrange basis

$$L'_{j}(x) = L_{j} \sum_{r=0, r \neq j}^{N} \frac{1}{x - x_{r}}$$
 (9)

- using our previous function code for "Lag(x)" we can get a general expression dLag= @(x,nv) Lag(x,nv).\*sum(1./bsxfun(@minus,x,nn(nv,:,:)),3)
- We need a more involved method for evaluation at the interp points (see dLagrange.m)

#### **Stiffness Integral**

We now have a routine for calculating  $L_j'$ , and suitable quadrature; we can evaluate the stiffness integral

$$\int_{k} \sum_{i=0}^{M} \left[ c\widetilde{q}_{i} \psi_{i}(x) \right] \phi_{j}'(x) dx = \sum_{i=0}^{M} c\widetilde{q}_{i} \int_{I} L_{i}(X) L_{j}'(X) dX$$
(10)

- ightharpoonup No Jacobian term from the mapping. The derivative in the integrand produces a complementary 1/J that cancels due to the change of variables.
- No tricks to be had for reducing the stiffness matrix, it is a full matrix. We have:  $c{f K}_{ji} \stackrel{\sim}{{f q}}$

#### Numerical Flux (Extrapolated)

- One downside of using Gauss-Legendre points is there are no points on the boundary
- ▶ It is easy to calculate the boundary solution values from the solution interpolation at the left end (same idea for the right)

$$\widetilde{q}(x_L) = \sum_{i=0}^{M} \widetilde{q}_i L_i(x_L)$$
(11)

- ▶ Call  $L_i(x_L) = L_{iL}$ , the vector notation is then  $\overset{\sim}{q}_L = \mathbf{L}_{iL}^T \overset{\sim}{\mathbf{q}}$
- lacksquare So that our numerical flux vector is  $\hat{\mathbf{f}} = c(q_R^k \mathbf{L}_{jR} q_R^{k-1} \mathbf{L}_{jL})$
- ► Lobatto alternative gives boundary points, but would make the mass matrix a full matrix. Inversion is likely more expensive than interpolation

#### **Assembly of System**

 We can now combine the mass, stiffness, and numerical flux terms

$$\frac{\Delta x}{2} \mathbf{q}' \mathbf{M} + \hat{\mathbf{f}} - c \mathbf{K}_{ji} \overset{\sim}{\mathbf{q}} = 0$$
 (12)

▶ solving for q'

$$\widetilde{\mathbf{q}}' = \frac{2}{\Delta x} (c\mathbf{K}_{ji} \widetilde{\mathbf{q}} - \mathbf{\hat{f}}) \mathbf{M}^{-1}$$
(13)

it is also possible to represent it componentwise easily thanks to the diagonal mass matrix

$$\widetilde{q}_{j}' = \frac{2}{w_{j} \Delta x} (c \mathbf{K}_{j} - \widetilde{\mathbf{q}} - \widehat{f}_{j})$$
(14)

#### **RK4 Time discretization**

▶ Compared to the simple linear DG solver, we'd like to use a higher order time discretization, Runge-Kutta 4th order: RK4. We can express as a function:  $\overset{\sim}{\mathbf{q}}'(\overset{\sim}{\mathbf{q}})$  from our discrete system. RK4 consists of 4 trial steps:

$$k_{1} = \widetilde{\mathbf{q}}'(\widetilde{\mathbf{q}}) \Delta t$$

$$k_{2} = \widetilde{\mathbf{q}}'(\widetilde{\mathbf{q}} + \frac{k_{1}}{2}) \Delta t$$

$$k_{3} = \widetilde{\mathbf{q}}'(\widetilde{\mathbf{q}} + \frac{k_{2}}{2}) \Delta t$$

$$k_{4} = \widetilde{\mathbf{q}}'(\widetilde{\mathbf{q}} + k_{3}) \Delta t$$

$$\mathbf{q}(t+1) = \mathbf{q} + \frac{k_{1}}{6} + \frac{k_{2}}{3} + \frac{k_{3}}{3} + \frac{k_{4}}{6}$$

#### Investigate p-Convergence

- ► How does the p-convergence rate compare with h-convergence?
- ▶ Does the smoothness of the initial sol'n seem to effect the rate of convergence? (e.g. sin(x) vs gaussian curve)
- Does h or p refinement seem to be more efficient?