



Discrete Geometries of Mathematics and Physics

# Mimetic spectral element method<sup>1</sup>

## Assignment #1

From 1D to higher dimensions

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*Note that we will restrict ourselves to no more than 2 dimensions in this series of assignments.*

### 1 Function spaces

In  $\mathbb{R}^2$ , consider a bounded domain  $\Omega$  that is contractible (its topology is same to a point, not to, for example, a doughnut) and has a smooth enough boundary  $\partial\Omega$  (means its smoothness is enough to carry on all derivatives in this series of assignments).

The space of square integrable functions in  $\Omega$  is the Sobolev space  $L^2(\Omega)$ ,

$$L^2(\Omega) = \{\varphi \mid \langle \varphi, \varphi \rangle_\Omega < +\infty\}.$$

We use  $\langle \cdot, \cdot \rangle_\Omega$  to denote a inner product. Namely, for any scalars  $a, b$  in  $\Omega$  and any vectors  $\mathbf{c}, \mathbf{d}$  in  $\Omega$ , we have

$$\langle a, b \rangle_\Omega = \int_\Omega ab \, d\Omega, \quad \langle \mathbf{c}, \mathbf{d} \rangle_\Omega = \int_\Omega \mathbf{c} \cdot \mathbf{d} \, d\Omega.$$

Some subspaces of  $L^2(\Omega)$  are

$$H(\text{curl}; \Omega) := \left\{ \omega \mid \omega \in L^2(\Omega), \nabla \times \omega \in [L^2(\Omega)]^2 \right\},$$

$$\mathbf{H}(\text{div}; \Omega) := \left\{ \mathbf{u} \mid \mathbf{u} \in [L^2(\Omega)]^2, \nabla \cdot \mathbf{u} \in L^2(\Omega) \right\},$$

$$H^1(\Omega) := \left\{ \phi \mid \phi \in L^2(\Omega), \nabla \phi \in [L^2(\Omega)]^2 \right\},$$

$$\mathbf{H}(\text{rot}; \Omega) := \left\{ \boldsymbol{\sigma} \mid \boldsymbol{\sigma} \in [L^2(\Omega)]^2, \nabla \times \boldsymbol{\sigma} \in L^2(\Omega) \right\}.$$

<sup>1</sup>[https://mathischeap.com/contents/teaching/advanced\\_numerical\\_methods/mimetic\\_spectral\\_element\\_method/main](https://mathischeap.com/contents/teaching/advanced_numerical_methods/mimetic_spectral_element_method/main)

They form two exact Hilbert complexes,

$$0 \longrightarrow H(\text{curl}; \Omega) \xrightarrow{\nabla \times} \mathbf{H}(\text{div}; \Omega) \xrightarrow{\nabla \cdot} L^2(\Omega) \longrightarrow 0,$$

$$0 \longrightarrow H^1(\Omega) \xrightarrow{\nabla} \mathbf{H}(\text{rot}; \Omega) \xrightarrow{\nabla \times} L^2(\Omega) \longrightarrow 0.$$

This means, for example, for any element  $\omega$  in  $H(\text{curl}; \Omega)$ ,  $\nabla \times \omega = \begin{bmatrix} \frac{\partial \omega}{\partial y} & -\frac{\partial \omega}{\partial x} \end{bmatrix}^T$  must be in  $\mathbf{H}(\text{div}; \Omega)$ . Similarly, you can understand other connections in these complexes. Note that at the continuous level,  $H(\text{curl}; \Omega)$  and  $H^1(\Omega)$  are the same space, and the operator  $\nabla \times$  on  $\omega \in H(\text{curl}; \Omega)$  is also called the perpendicular gradient. These spaces are all at the continuous level. Namely, they are infinite-dimensional. This is saying, for anyone of them, we cannot find a set of finite functions that forms a base for it. While the domain  $\Omega$  is a sub-domain of two-dimensional space  $\mathbb{R}^2$ . You should think carefully about the difference.

Apparently, we cannot solve something of infinite dimensions with our computers. This is why numerical methods need *discretization*. Different methods have their own ways for discretization. And the *mimetic spectral element method* decides to approximate these Sobolev spaces with the finite-dimensional (or discrete) *mimetic spectral element spaces* which are denoted by  $C(\Omega)$ ,  $\mathbf{D}(\Omega)$ ,  $G(\Omega)$ ,  $\mathbf{R}(\Omega)$ , and  $S(\Omega)$ . They are subspaces of the continuous spaces, i.e.

$$C(\Omega) \subset H(\text{curl}; \Omega), \quad \mathbf{D}(\Omega) \subset \mathbf{H}(\text{div}; \Omega), \quad G(\Omega) \subset H^1(\Omega), \quad \mathbf{R}(\Omega) \subset \mathbf{H}(\text{rot}; \Omega), \quad S(\Omega) \subset L^2(\Omega),$$

and also forms exact Hilbert complexes,

$$(1a) \quad 0 \longrightarrow C(\Omega) \xrightarrow{\nabla \times} \mathbf{D}(\Omega) \xrightarrow{\nabla \cdot} S(\Omega) \longrightarrow 0,$$

$$(1b) \quad 0 \longrightarrow G(\Omega) \xrightarrow{\nabla} \mathbf{R}(\Omega) \xrightarrow{\nabla \times} S(\Omega) \longrightarrow 0.$$

In this assignment, we will try to construct these discrete mimetic spectral element spaces.

## 2 Mimetic spectral element spaces

As we just introduced, a mimetic spectral element space is a discrete or finite-dimensional space. Recall what we have learned in linear algebra. If we can find a base for a mimetic spectral element space, we can express any element of it using the base and a set of expansion coefficients. Just like the space  $\mathbf{L}$  or  $\mathbf{E}$  in Assignment #0. Thus, the key of this assignment is constructing bases for the mimetic spectral element spaces.

In  $\mathbb{R}^2$ , we equip it with an orthogonal coordinate system  $(\xi, \eta)$  and consider a square domain  $\Omega_r := [-1, 1]^2$ . This domain is called the reference domain (or the reference element). We see that, along each axis,  $\Omega_r$  ranges from  $-1$  to  $1$ . So, we can apply the partition in Assignment #0 (see (1) there) to both axes,

$$(2) \quad -1 = \xi_0 < \xi_1 < \xi_2 < \cdots < \xi_N = 1,$$

$$(3) \quad -1 = \eta_0 < \eta_1 < \eta_2 < \cdots < \eta_N = 1,$$

where  $\xi_i = \eta_i$ ,  $i \in \{0, 1, \dots, N\}$ . Note that we do not have to use the same partition along both axes. However, to present the idea, using the same partition is a good choice. And also, it is usually the case in most scenarios.

With partitions (2) and (3), we can construct Lagrange polynomials and edges polynomials along  $\xi$ -axis and  $\eta$ -axis,

$$l^i(\xi), \quad i \in \{0, 1, \dots, N\},$$

$$e^i(\xi), \quad i \in \{1, 2, \dots, N\},$$

$$l^j(\eta), \quad j \in \{0, 1, \dots, N\},$$

$$e^j(\eta), \quad j \in \{1, 2, \dots, N\}.$$

These are one-dimensional polynomials. Using them, we construct two-dimensional polynomials as

$$\begin{aligned} 11^{ij}(\xi, \eta) &:= l^i(\xi)l^j(\eta), \quad i, j \in \{0, 1, \dots, N\}, \\ 1e^{ij}(\xi, \eta) &:= l^i(\xi)e^j(\eta), \quad i \in \{0, 1, \dots, N\}, j \in \{1, 2, \dots, N\}, \\ e1^{ij}(\xi, \eta) &:= e^i(\xi)l^j(\eta), \quad i \in \{1, 2, \dots, N\}, j \in \{0, 1, \dots, N\}, \\ ee^{ij}(\xi, \eta) &:= e^i(\xi)e^j(\eta), \quad i, j \in \{1, 2, \dots, N\}. \end{aligned}$$

From the one-dimensional Kronecker delta properties in Assignment#0, we can easily derive two-dimensional Kronecker delta properties,

$$\begin{aligned} (5a) \quad 11^{ij}(\xi_m, \eta_n) &= l^i(\xi_m)l^j(\eta_n) = \delta_{m,n}^{i,j}, \\ (5b) \quad 1e^{ij}(\xi_m, \eta_n) &= l^i(\xi_m) \int_{\eta_{n-1}}^{\eta_n} e^j(\eta) d\eta = \delta_{m,n}^{i,j}, \\ (5c) \quad e1^{ij}(\xi_m, \eta_n) &= l^j(\eta_n) \int_{\xi_{m-1}}^{\xi_m} e^i(\xi) d\xi = \delta_{m,n}^{i,j}, \\ (5d) \quad ee^{ij}(\xi_m, \eta_n) &= \int_{\xi_{m-1}}^{\xi_m} e^i(\xi) d\xi \int_{\eta_{n-1}}^{\eta_n} e^j(\eta) d\eta = \delta_{m,n}^{i,j}, \end{aligned}$$

where  $\delta_{m,n}^{i,j} = \begin{cases} 1, & \text{if } i = m, j = n \\ 0, & \text{else} \end{cases}$ . Then we can use them as basis functions of mimetic spectral element spaces in  $\Omega_r$ . In details, we have

$$\begin{aligned} (6a) \quad C(\Omega_r) &= G(\Omega_r) := \text{span} \left( \{ 11^{ij}(\xi, \eta) \mid i, j \in \{0, 1, \dots, N\} \} \right), \\ (6b) \quad \mathbf{D}(\Omega_r) &:= \left[ \begin{array}{l} \text{span} \left( \{ 1e^{ij}(\xi, \eta) \mid i \in \{0, 1, \dots, N\}, j \in \{1, 2, \dots, N\} \} \right) \\ \text{span} \left( \{ e1^{ij}(\xi, \eta) \mid i \in \{1, 2, \dots, N\}, j \in \{0, 1, \dots, N\} \} \right) \end{array} \right], \\ (6c) \quad \mathbf{R}(\Omega_r) &:= \left[ \begin{array}{l} \text{span} \left( \{ e1^{ij}(\xi, \eta) \mid i \in \{1, 2, \dots, N\}, j \in \{0, 1, \dots, N\} \} \right) \\ \text{span} \left( \{ 1e^{ij}(\xi, \eta) \mid i \in \{0, 1, \dots, N\}, j \in \{1, 2, \dots, N\} \} \right) \end{array} \right], \\ (6d) \quad S(\Omega_r) &:= \text{span} \left( \{ ee^{ij}(\xi, \eta) \mid i, j \in \{1, 2, \dots, N\} \} \right). \end{aligned}$$

Now, elements in these spaces can be expressed as

$$\begin{aligned} (7a) \quad \omega_h &= \sum_{i=0}^N \sum_{j=0}^N \mathbf{w}_{ij} 11^{ij}(\xi, \eta), & \omega_h &\in C(\Omega_r) \text{ or } G(\Omega_r), \\ (7b) \quad \mathbf{u}_h &= \begin{bmatrix} u_h \\ v_h \end{bmatrix} = \begin{bmatrix} \sum_{i=0}^N \sum_{j=1}^N \mathbf{u}_{ij} 1e^{ij}(\xi, \eta) \\ \sum_{i=1}^N \sum_{j=0}^N \mathbf{v}_{ij} e1^{ij}(\xi, \eta) \end{bmatrix}, & \mathbf{u}_h &\in \mathbf{D}(\Omega_r), \\ (7c) \quad \boldsymbol{\sigma}_h &= \begin{bmatrix} \sigma_h \\ \tau_h \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^N \sum_{j=0}^N \mathbf{s}_{ij} e1^{ij}(\xi, \eta) \\ \sum_{i=0}^N \sum_{j=1}^N \mathbf{t}_{ij} 1e^{ij}(\xi, \eta) \end{bmatrix}, & \boldsymbol{\sigma}_h &\in \mathbf{R}(\Omega_r), \\ (7d) \quad \phi_h &= \sum_{i=1}^N \sum_{j=1}^N \mathbf{f}_{ij} ee^{ij}(\xi, \eta), & \phi_h &\in S(\Omega_r). \end{aligned}$$

Since the basis functions are two-dimensional polynomials, these elements are also polynomials. And because all basis functions are known, each set of expansion coefficient exclusively refers to one polynomial. For example, a particular set of expansion coefficients  $\{\mathbf{w}_{ij}\}^2$  one-to-one refers to an polynomial  $\omega_h$ . A particular set of expansion coefficients  $\{\mathbf{u}_{ij}\} \cup \{\mathbf{v}_{ij}\}$  one-to-one refers to an polynomial  $\mathbf{u}_h$ . This is why these expansion coefficients are also called *degrees of freedom (DoF's)*.

<sup>2</sup>A shortcut of  $\{\mathbf{w}_{ij} \mid i, j \in \{0, 1, \dots, N\}\}$  to simplify the notation. Same convention is used for other sets.

In fact, (7) reveals the *reconstructions* for mimetic spectral element spaces in  $\Omega_r$ .

The next important question is how to do *reductions* for these spaces. For  $\omega \in H(\text{curl}; \Omega_r)$  or  $H^1(\Omega_r)$ , to reduce  $\omega$  to  $\omega_h$ , we just need to evaluate  $\omega$  at the partition nodes to compute  $\mathbf{w}_{ij}$ , i.e.,

$$(8) \quad \mathbf{w}_{ij} = \omega(\xi_i, \eta_j).$$

For  $\mathbf{u} = \begin{bmatrix} u \\ v \end{bmatrix} \in H(\text{div}; \Omega_r)$ , the expansion coefficients of  $\mathbf{u}_h \in \mathbf{D}(\Omega_r)$  are computed through

$$(9a) \quad \mathbf{u}_{ij} = \int_{\eta_{j-1}}^{\eta_j} u(\xi_i, \eta) d\eta,$$

$$(9b) \quad \mathbf{v}_{ij} = \int_{\xi_{i-1}}^{\xi_i} v(\xi, \eta_j) d\xi.$$

For  $\boldsymbol{\sigma} = \begin{bmatrix} \sigma \\ \tau \end{bmatrix} \in H(\text{rot}; \Omega_r)$ , the expansion coefficients of  $\boldsymbol{\sigma}_h \in \mathbf{R}(\Omega_r)$  are computed through

$$(10a) \quad \mathbf{s}_{ij} = \int_{\xi_{i-1}}^{\xi_i} \sigma(\xi, \eta_j) d\xi,$$

$$(10b) \quad \mathbf{t}_{ij} = \int_{\eta_{j-1}}^{\eta_j} \tau(\xi_i, \eta) d\eta.$$

And for  $\phi \in S(\Omega_r)$ , the expansion coefficients of  $\phi_h \in S(\Omega_r)$  are

$$(11) \quad \mathbf{f}_{ij} = \int_{\xi_{i-1}}^{\xi_i} \int_{\eta_{j-1}}^{\eta_j} \phi(\xi, \eta) d\eta d\xi.$$

Clear, the idea of these reductions lies behind the Kronecker delta properties (5).

### Assignment 1.1.0: Projection for $\omega \in H(\text{curl}; \Omega_r)$ or $H^1(\Omega_r)$

You need to program two functions, the first one does the reduction and the second one does the reconstruction.

```

1  def CG_space_reduction(nodes, func):
2      """Reduce the function "func" to mimetic spectral element space C or G defined
3      over "nodes".
4
5      Parameters
6      -----
7      nodes : np.ndarray
8          The partition of the interval I. It should be a 1d array of shape (m, ).
9          For example, nodes = [-1, -0.8, -0.3, 0.3, 0.8, 1].
10     func :
11         The function to be reduced to the space.
12
13     Returns
14     -----
15     expansion_coefficients:
16         A 2d array of shape (m+1, m+1) that contains the expansion coefficients.
17
18     """
19
20 def CG_space_reconstruction(nodes, expansion_coefficients, xi, eta):
21     """Reconstruct the polynomial in the mimetic spectral element space C or G

```

```

20     over meshgrid of "xi" and "eta".
21
22     Parameters
23     -----
24     nodes : np.ndarray
25         The partition of the interval I. It should be a 1d array of shape (m, ).
26         For example, nodes = [-1, -0.8, -0.3, 0.3, 0.8, 1].
27     expansion_coefficients : np.ndarray
28         A 2d array of shape (m+1, m+1) that contains the expansion coefficients.
29     xi : np.ndarray
30         The coordinates we evaluate the polynomial along the first axis. It should
31         be a 1d array of shape (i, ). For example, xi = np.linspace(-1, 1, 100).
32         The polynomial will be evaluated on "np.meshgrid(xi, eta, indexing='ij')".
33     eta : np.ndarray
34         The coordinates we evaluate the polynomial along the second axis. It
35         should be a 1d array of shape (j, ). For example, eta = np.linspace(-1, 1,
36         100). The polynomial will be evaluated on "np.meshgrid(xi, eta,
37         indexing='ij')".
38
39     Returns
40     -----
41     reconstructed_values : np.ndarray
42         A 2d array of shape (i, j) that represents the reconstructed values at
43         "np.meshgrid(xi, eta, indexing='ij')".
44
45     """

```

### Assignment 1.1.1: Projection for $u \in H(\text{div}; \Omega_r)$

You need to program two functions, the first one does the reduction and the second one does the reconstruction.

```

1  def D_space_reduction(nodes, func):
2      """Reduce the function "func" to mimetic spectral element space D defined over
3      "nodes".
4
5      Parameters
6      -----
7      nodes : np.ndarray
8          The partition of the interval I. It should be a 1d array of shape (m, ).
9          For example, nodes = [-1, -0.8, -0.3, 0.3, 0.8, 1].
10     func :
11         The function to be reduced to the space.
12
13     Returns
14     -----
15     exp_coef_u:
16         A 2d array of shape (m+1, m) that contains the expansion coefficients for
17         the first component.
18     exp_coef_v:
19         A 2d array of shape (m, m+1) that contains the expansion coefficients for
20         the second component.
21
22     """
23
24     def D_space_reconstruction(nodes, exp_coef_u, exp_coef_v, xi, eta):

```

```

21     """Reconstruct the polynomial in the mimetic spectral element space C or G
    over meshgrid of "xi" and "eta".
22
23     Parameters
24     -----
25     nodes : np.ndarray
26         The partition of the interval I. It should be a 1d array of shape (m, ).
        For example, nodes = [-1, -0.8, -0.3, 0.3, 0.8, 1].
27     exp_coef_u : np.ndarray
28         A 2d array of shape (m+1, m) that contains the expansion coefficients of
        the first component.
29     exp_coef_v : np.ndarray
30         A 2d array of shape (m, m+1) that contains the expansion coefficients of
        the second component.
31     xi : np.ndarray
32         The coordinates we evaluate the polynomial along the first axis. It should
        be a 1d array of shape (i, ). For example, xi = np.linspace(-1, 1, 100).
        The polynomial will be evaluated on "np.meshgrid(xi, eta, indexing='ij')".
33     eta : np.ndarray
34         The coordinates we evaluate the polynomial along the second axis. It
        should be a 1d array of shape (j, ). For example, eta = np.linspace(-1, 1,
        100). The polynomial will be evaluated on "np.meshgrid(xi, eta,
        indexing='ij')".
35
36     Returns
37     -----
38     reconstructed_values_u : np.ndarray
39         A 2d array of shape (i, j) that represents the reconstructed values of the
        first component at "np.meshgrid(xi, eta, indexing='ij')".
40     reconstructed_values_v : np.ndarray
41         A 2d array of shape (i, j) that represents the reconstructed values of the
        second component at "np.meshgrid(xi, eta, indexing='ij')".
42
43     """

```

### Assignment 1.1.2: Projection for $\sigma \in H(\text{rot}; \Omega_r)$

You need to program two functions, the first one does the reduction and the second one does the reconstruction.

```

1  def R_space_reduction(nodes, func):
2      """Reduce the function "func" to mimetic spectral element space R defined over
        "nodes".
3
4      Parameters
5      -----
6      nodes : np.ndarray
7          The partition of the interval I. It should be a 1d array of shape (m, ). For
        example, nodes = [-1, -0.8, -0.3, 0.3, 0.8, 1].
8      func :
9          The function to be reduced to the space.
10
11     Returns
12     -----
13     exp_coef_s:
14         A 2d array of shape (m, m+1) that contains the expansion coefficients for

```

```

    the first component.
15  exp_coef_t:
16      A 2d array of shape (m+1, m) that contains the expansion coefficients for
    the second component.
17
18  """
19
20  def R_space_reconstruction(nodes, exp_coef_s, exp_coef_t, xi, eta):
21      """Reconstruct the polynomial in the mimetic spectral element space C or G
    over meshgrid of "xi" and "eta".
22
23      Parameters
24      -----
25      nodes : np.ndarray
26          The partition of the interval I. It should be a 1d array of shape (m, ).
    For example, nodes = [-1, -0.8, -0.3, 0.3, 0.8, 1].
27      exp_coef_s : np.ndarray
28          A 2d array of shape (m, m+1) that contains the expansion coefficients of
    the first component.
29      exp_coef_t : np.ndarray
30          A 2d array of shape (m+1, m) that contains the expansion coefficients of
    the second component.
31      xi : np.ndarray
32          The coordinates we evaluate the polynomial along the first axis. It should
    be a 1d array of shape (i, ). For example, xi = np.linspace(-1, 1, 100).
    The polynomial will be evaluated on "np.meshgrid(xi, eta, indexing='ij')".
33      eta : np.ndarray
34          The coordinates we evaluate the polynomial along the second axis. It
    should be a 1d array of shape (j, ). For example, eta = np.linspace(-1, 1,
    100). The polynomial will be evaluated on "np.meshgrid(xi, eta,
    indexing='ij')".
35
36      Returns
37      -----
38      reconstructed_values_s : np.ndarray
39          A 2d array of shape (i, j) that represents the reconstructed values of the
    first component at "np.meshgrid(xi, eta, indexing='ij')".
40      reconstructed_values_t : np.ndarray
41          A 2d array of shape (i, j) that represents the reconstructed values of the
    second component at "np.meshgrid(xi, eta, indexing='ij')".
42
43      """

```

### Assignment 1.1.3: Projection for $\phi \in S(\Omega_r)$

You need to program two functions, the first one does the reduction and the second one does the reconstruction.

```

1  def S_space_reduction(nodes, func):
2      """Reduce the function "func" to mimetic spectral element space S defined over
    "nodes".
3
4      Parameters
5      -----
6      nodes : np.ndarray
7          The partition of the interval I. It should be a 1d array of shape (m, ).

```

```

8         For example, nodes = [-1, -0.8, -0.3, 0.3, 0.8, 1].
9     func :
10         The function to be reduced to the space.
11
12     Returns
13     -----
14     expansion_coefficients:
15         A 2d array of shape (m, m) that contains the expansion coefficients.
16
17     """
18     def S_space_reconstruction(nodes, expansion_coefficients, xi, eta):
19         """Reconstruct the polynomial in the mimetic spectral element space C or G
20         over meshgrid of "xi" and "eta".
21
22         Parameters
23         -----
24         nodes : np.ndarray
25             The partition of the interval I. It should be a 1d array of shape (m, ).
26             For example, nodes = [-1, -0.8, -0.3, 0.3, 0.8, 1].
27         expansion_coefficients : np.ndarray
28             A 2d array of shape (m, m) that contains the expansion coefficients.
29         xi : np.ndarray
30             The coordinates we evaluate the polynomial along the first axis. It should
31             be a 1d array of shape (i, ). For example, xi = np.linspace(-1, 1, 100).
32             The polynomial will be evaluated on "np.meshgrid(xi, eta, indexing='ij')".
33         eta : np.ndarray
34             The coordinates we evaluate the polynomial along the second axis. It
35             should be a 1d array of shape (j, ). For example, eta = np.linspace(-1, 1,
36             100). The polynomial will be evaluated on "np.meshgrid(xi, eta,
37             indexing='ij')".
38
39         Returns
40         -----
41         reconstructed_values : np.ndarray
42             A 2d array of shape (i, j) that represents the reconstructed values at
43             "np.meshgrid(xi, eta, indexing='ij')".
44
45         """

```

### 3 Incidence matrices

So far, we have constructed mimetic spectral element spaces  $C(\Omega)$ ,  $G(\Omega)$ ,  $\mathbf{D}(\Omega)$ ,  $\mathbf{R}(\Omega)$ , and  $S(\Omega)$ , and know how to project functions into them. However, the key structure between them, i.e. the Hilbert complexes

$$\begin{aligned}
 0 &\longrightarrow C(\Omega) \xrightarrow{\nabla \times} \mathbf{D}(\Omega) \xrightarrow{\nabla \cdot} S(\Omega) \longrightarrow 0, \\
 0 &\longrightarrow G(\Omega) \xrightarrow{\nabla} \mathbf{R}(\Omega) \xrightarrow{\nabla \times} S(\Omega) \longrightarrow 0.
 \end{aligned}$$

is not addressed yet. Recall that, in Assignment #0, the connection between the Lagrange space and the edge space can be interpolated as the incidence matrix. Naturally, we look forward to a similar structure in two-dimensions.

We repeat that polynomials in the mimetic spectral element spaces have general formats as

$$\begin{aligned}\omega_h &= \sum_{i=0}^N \sum_{j=0}^N w_{ij} \mathbf{l}^{ij}(\xi, \eta), & \omega_h &\in C(\Omega_r) \text{ or } G(\Omega_r), \\ \mathbf{u}_h &= \begin{bmatrix} u_h \\ v_h \end{bmatrix} = \begin{bmatrix} \sum_{i=0}^N \sum_{j=1}^N u_{ij} \mathbf{l}^{ij}(\xi, \eta) \\ \sum_{i=1}^N \sum_{j=0}^N v_{ij} \mathbf{e}^{ij}(\xi, \eta) \end{bmatrix}, & \mathbf{u}_h &\in \mathbf{D}(\Omega_r), \\ \boldsymbol{\sigma}_h &= \begin{bmatrix} \sigma_h \\ \tau_h \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^N \sum_{j=0}^N s_{ij} \mathbf{e}^{ij}(\xi, \eta) \\ \sum_{i=0}^N \sum_{j=1}^N t_{ij} \mathbf{l}^{ij}(\xi, \eta) \end{bmatrix}, & \boldsymbol{\sigma}_h &\in \mathbf{R}(\Omega_r), \\ \phi_h &= \sum_{i=1}^N \sum_{j=1}^N f_{ij} \mathbf{e}^{ij}(\xi, \eta), & \phi_h &\in S(\Omega_r).\end{aligned}$$

In a geometric angle of view, the expansion coefficients represent degrees of freedom defined on points, edges, and faces, see Fig. 1.

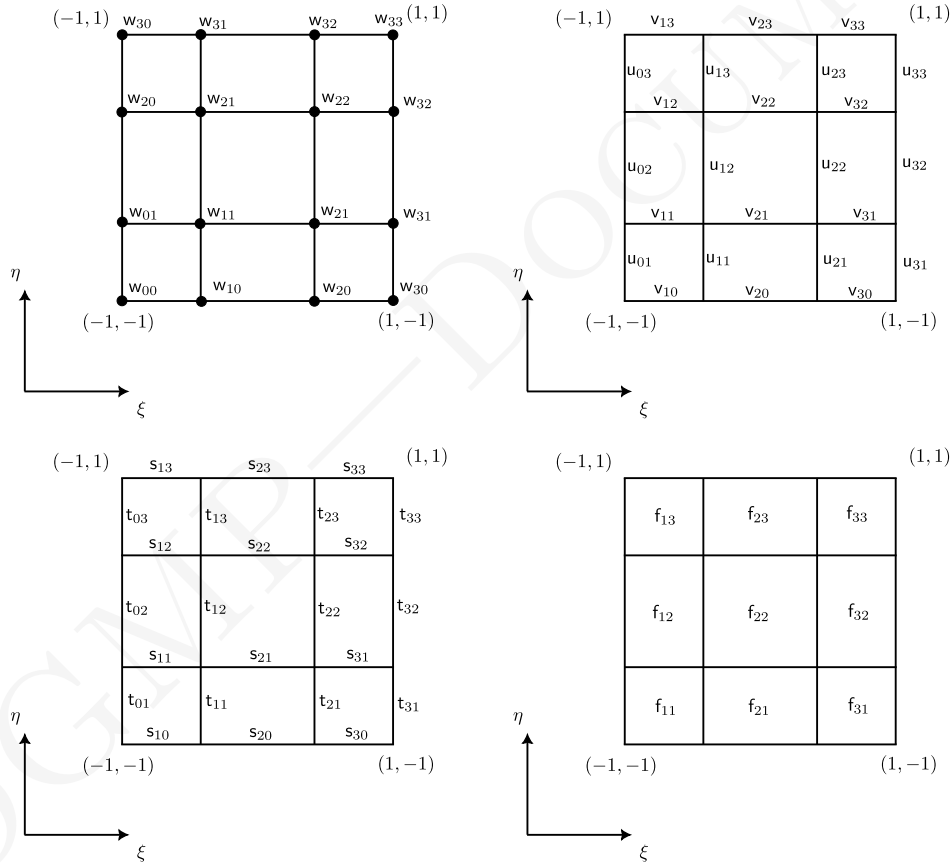


Fig. 1: Distributions of degrees of freedom in a geometric angle of view.

Assume that these polynomials are projections of  $\omega$ ,  $\mathbf{u}$ ,  $\boldsymbol{\sigma}$ , and  $\phi$  in corresponding spaces,

$$\omega_h = \pi(\omega), \quad \mathbf{u}_h = \pi(\mathbf{u}), \quad \boldsymbol{\sigma}_h = \pi(\boldsymbol{\sigma}), \quad \phi_h = \pi(\phi).$$

From the properties of Lagrange polynomials and edge polynomials, we can easily get the colusions in following subsections.

### 3.1 Incidence matrix $\mathbb{E}_C$

If  $\mathbf{u} = \nabla \times \omega$ , we must have  $\mathbf{u}_h = \nabla \times \omega_h$  and

$$(14) \quad \vec{\mathbf{u}} = \mathbb{E}_C \vec{\omega}.$$

The vectors are

$$\vec{\omega} = \begin{bmatrix} \mathbf{w}_1 \\ \mathbf{w}_2 \\ \vdots \\ \mathbf{w}_{(N+1)^2} \end{bmatrix}$$

where  $\mathbf{w}_{j \times (N+1) + i+1} = \mathbf{w}_{ij}, i, j \in \{0, 1, \dots, N\}$ , and

$$\vec{\mathbf{u}} = \begin{bmatrix} \mathbf{u}_1 \\ \mathbf{u}_2 \\ \vdots \\ \mathbf{u}_{(N+1) \times N} \\ \mathbf{v}_1 \\ \mathbf{v}_2 \\ \vdots \\ \mathbf{v}_{N \times (N+1)} \end{bmatrix}$$

where  $\mathbf{u}_{(j-1) \times (N+1) + i+1} = \mathbf{u}_{ij}, i \in \{0, 1, \dots, N\}, j \in \{1, 2, \dots, N\}$  and  $\mathbf{v}_{j \times N + i} = \mathbf{v}_{ij}, i \in \{1, 2, \dots, N\}, j \in \{0, 1, \dots, N\}$ . And the matrix  $\mathbb{E}_C$  is the incidence matrix who has  $2N \times (N+1)$  rows and  $(N+1)^2$  columns. It is a sparse matrix and the non-zero entries of it are

$$\begin{aligned} \mathbb{E}_C|_{(j-1) \times (N+1) + i+1, (j-1) \times (N+1) + i+1} &= -1, \quad i \in \{0, 1, \dots, N\}, j \in \{1, 2, \dots, N\}, \\ \mathbb{E}_C|_{(j-1) \times (N+1) + i+1, j \times (N+1) + i+1} &= 1, \quad i \in \{0, 1, \dots, N\}, j \in \{1, 2, \dots, N\}, \\ \mathbb{E}_C|_{N \times (N+1) + j \times N + i, j \times (N+1) + i} &= 1, \quad i \in \{1, 2, \dots, N\}, j \in \{0, 1, \dots, N\}, \\ \mathbb{E}_C|_{N \times (N+1) + j \times N + i, j \times (N+1) + i+1} &= -1, \quad i \in \{1, 2, \dots, N\}, j \in \{0, 1, \dots, N\}. \end{aligned}$$

See Fig. 2 for an illustration of the geometric representation for the incidence matrix  $\mathbb{E}_C$ .

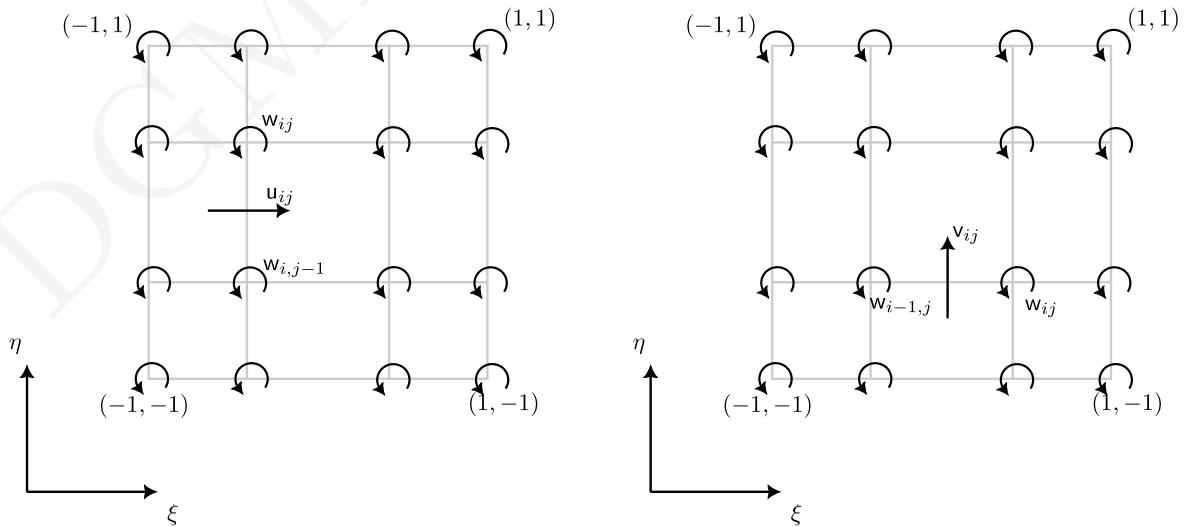


Fig. 2: An illustration of the geometric representation for the incidence matrix  $\mathbb{E}_C$ .

### 3.2 Incidence matrix $\mathbb{E}_G$

If  $\sigma = \nabla \omega$ , we must have  $\sigma_h = \nabla \omega_h$  and

$$(15) \quad \vec{\sigma} = \mathbb{E}_G \vec{\omega}.$$

The vector  $\vec{\sigma}$  is

$$\vec{\sigma} = \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_{(N+1) \times N} \\ t_1 \\ t_2 \\ \vdots \\ t_{N \times (N+1)} \end{bmatrix}$$

where  $s_{j \times N+i} = s_{ij}$ ,  $i \in \{1, 2, \dots, N\}$ ,  $j \in \{0, 1, \dots, N\}$  and  $t_{(j-1) \times (N+1)+i+1} = t_{ij}$ ,  $i \in \{0, 1, \dots, N\}$ ,  $j \in \{1, 2, \dots, N\}$ . And the matrix  $\mathbb{E}_G$  is the incidence matrix who has  $2N \times (N+1)$  rows and  $(N+1)^2$  columns. It is a sparse matrix and the non-zero entries of it are

$$\mathbb{E}_G|_{j \times N+i, j \times (N+1)+i} = -1, \quad i \in \{1, 2, \dots, N\}, j \in \{0, 1, \dots, N\},$$

$$\mathbb{E}_G|_{j \times N+i, j \times (N+1)+i+1} = 1, \quad i \in \{1, 2, \dots, N\}, j \in \{0, 1, \dots, N\},$$

$$\mathbb{E}_G|_{N \times (N+1)+(j-1) \times (N+1)+i+1, (j-1) \times (N+1)+i+1} = -1, \quad i \in \{0, 1, \dots, N\}, j \in \{1, 2, \dots, N\},$$

$$\mathbb{E}_G|_{N \times (N+1)+(j-1) \times (N+1)+i+1, j \times (N+1)+i+1} = 1, \quad i \in \{0, 1, \dots, N\}, j \in \{1, 2, \dots, N\}.$$

See Fig. 3 for an illustration of the geometric representation for the incidence matrix  $\mathbb{E}_G$ .

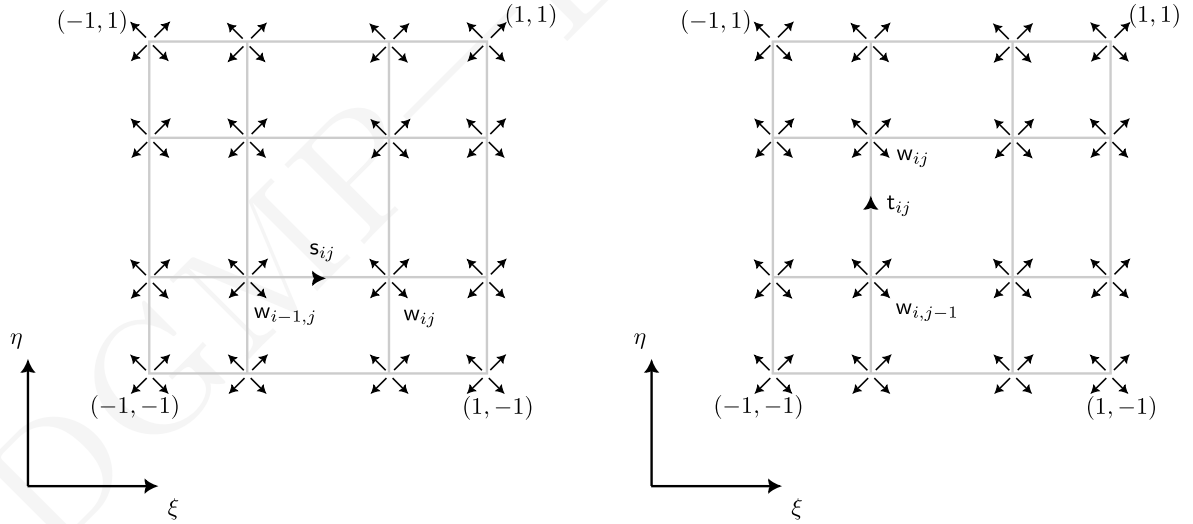


Fig. 3: An illustration of the geometric representation for the incidence matrix  $\mathbb{E}_G$ .

### 3.3 Incidence matrix $\mathbb{E}_D$

If  $\phi = \nabla \cdot \mathbf{u}$ , we must have  $\phi_h = \nabla \cdot \mathbf{u}_h$  and

$$(16) \quad \vec{\phi} = \mathbb{E}_D \vec{\mathbf{u}}.$$

The vector  $\vec{\phi}$  is

$$\vec{\phi} = \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_{N^2} \end{bmatrix}$$

where  $f_{(j-1) \times N + i} = w_{ij}$ ,  $i, j \in \{1, 2, \dots, N\}$ . The matrix  $\mathbb{E}_D$  is the incidence matrix who has  $N^2$  rows and  $2N \times (N + 1)$  columns. It is a sparse matrix and the non-zero entries of it are

$$\begin{aligned} \mathbb{E}_D|_{(j-1) \times N + i, (j-1) \times (N+1) + i} &= -1, \quad i, j \in \{1, 2, \dots, N\}, \\ \mathbb{E}_D|_{(j-1) \times N + i, (j-1) \times (N+1) + i + 1} &= 1, \quad i, j \in \{1, 2, \dots, N\}, \\ \mathbb{E}_D|_{(j-1) \times N + i, N \times (N+1) + (j-1) \times N + i} &= -1, \quad i, j \in \{1, 2, \dots, N\}, \\ \mathbb{E}_D|_{(j-1) \times N + i, N \times (N+1) + j \times N + i} &= 1, \quad i, j \in \{1, 2, \dots, N\}. \end{aligned}$$

See Fig. 4 for an illustration of the geometric representation for the incidence matrix  $\mathbb{E}_D$ .

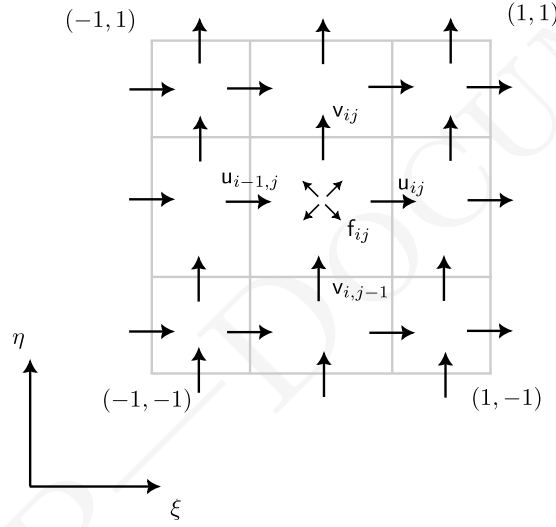


Fig. 4: An illustration of the geometric representation for the incidence matrix  $\mathbb{E}_D$ .

### 3.4 Incidence matrix $\mathbb{E}_R$

If  $\phi = \nabla \times \sigma$ , we must have  $\phi_h = \nabla \times \sigma_h$  and

$$(17) \quad \vec{\phi} = \mathbb{E}_R \vec{\sigma}.$$

The matrix  $\mathbb{E}_R$  is the incidence matrix who has  $N^2$  rows and  $2N \times (N + 1)$  columns. It is a sparse matrix and the non-zero entries of it are

$$\begin{aligned} \mathbb{E}_R|_{(j-1) \times N + i, N \times (N+1) + (j-1) \times (N+1) + i} &= -1, \quad i, j \in \{1, 2, \dots, N\}, \\ \mathbb{E}_R|_{(j-1) \times N + i, N \times (N+1) + (j-1) \times (N+1) + i + 1} &= 1, \quad i, j \in \{1, 2, \dots, N\}, \\ \mathbb{E}_R|_{(j-1) \times N + i, (j-1) \times N + i} &= 1, \quad i, j \in \{1, 2, \dots, N\}, \\ \mathbb{E}_R|_{(j-1) \times N + i, j \times N + i} &= -1, \quad i, j \in \{1, 2, \dots, N\}. \end{aligned}$$

See Fig. 5 for an illustration of the geometric representation for the incidence matrix  $\mathbb{E}_R$ .

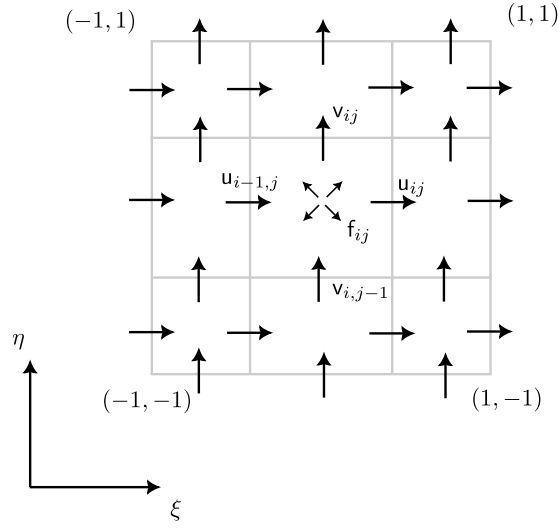


Fig. 5: An illustration of the geometric representation for the incidence matrix  $\mathbb{E}_R$ .

#### Assignment 1.2.0: Incidence matrix $\mathbb{E}_C$

You need to program a function to compute the incidence matrix  $\mathbb{E}_C$ . Then you can play with the incidence matrix to verify (14).

#### Assignment 1.2.1: Incidence matrix $\mathbb{E}_G$

You need to program a function to compute the incidence matrix  $\mathbb{E}_G$ . Then you can play with the incidence matrix to verify (15).

#### Assignment 1.2.2: Incidence matrix $\mathbb{E}_D$

You need to program a function to compute the incidence matrix  $\mathbb{E}_D$ . Then you can play with the incidence matrix to verify (16).

#### Assignment 1.2.3: Incidence matrix $\mathbb{E}_R$

You need to program a function to compute the incidence matrix  $\mathbb{E}_R$ . Then you can play with the incidence matrix to verify (17).

## 4 Three dimensions

In this series of assignments, we will not go to three dimensions. But the approach is similar. Read [1, Chapter 2] for the details.

## References

- [1] Y. Zhang, Mimetic Spectral Element Method and Extensions toward Higher Computational Efficiency (2022).