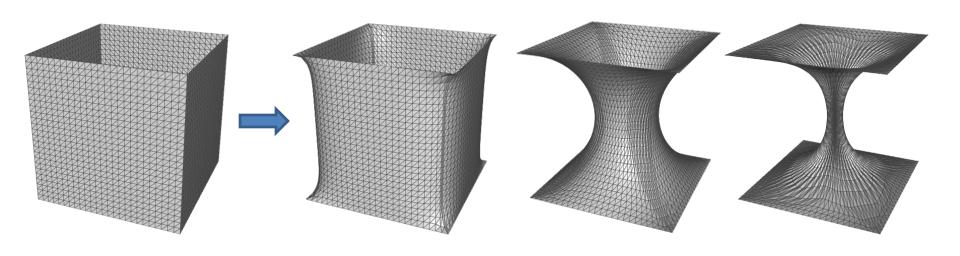
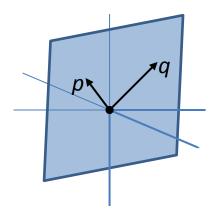


# Differential Geometry: Mean Curvature Flow



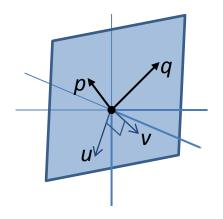
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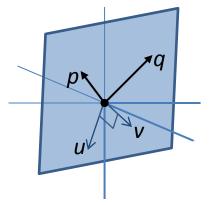
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- What if we want to v to have length  $\lambda$ ?



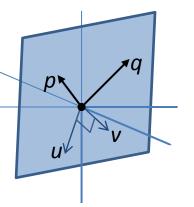
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If u and v are orthonormal, this is easy:

$$v = \lambda \frac{-bp + aq}{\sqrt{a^2 + b^2}}$$



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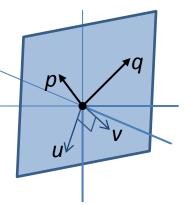
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If *u* and *v* are orthogonal, it's still easy:

$$v = \lambda \frac{-bp + aq}{\|-bp + aq\|} = \lambda \frac{-bp + aq}{\sqrt{b^2 \|p\|^2 + a^2 \|q\|^2}}$$



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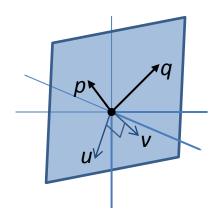
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- How can we find a vector v in the subspace that is perpendicular to u?
- What if we want to v to have length  $\lambda$ ? If u and v are orthonormal, this is easy. If u and v are orthogonal, it's still easy. What about for arbitrary p and q?

Given two (lin. ind.) vectors p, q in  $\mathbb{R}^n$ , we know that these vectors span a 2D subspace.

We can represent vectors in the 2D subspace by their coordinates with respect to p and q:

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This induces a new inner product on  $\mathbb{R}^2$  as:

$$\langle (a,b),(c,d) \rangle_{\{p,q\}} = \langle ap + bq, cp + dq \rangle$$
$$= ac \langle p, p \rangle + bd \langle q, q \rangle + (ad + bc) \langle p, q \rangle$$

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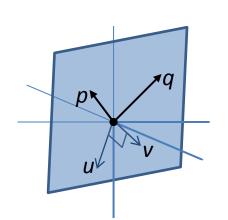
$$\langle (a,b),(c,d) \rangle_{\{p,q\}} = ac\langle p,p \rangle + bd\langle q,q \rangle + (ad+bc)\langle p,q \rangle$$

We can represent the induced inner-product by the symmetric (positive definite) matrix *M*:

$$M = \begin{pmatrix} \langle p, p \rangle & \langle p, q \rangle \\ \langle p, q \rangle & \langle q, q \rangle \end{pmatrix}$$

allowing us to represent the induced inner product as:

$$\langle (a,b),(c,d) \rangle_{\{p,q\}} = \begin{pmatrix} a & b \end{pmatrix} M \begin{pmatrix} c \\ d \end{pmatrix}$$



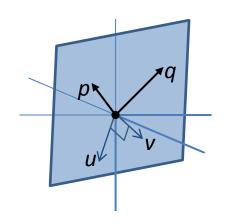
Math Review 
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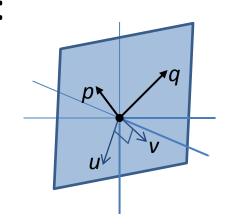
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Thus, if we set 
$$(c,d)=M^{-1}(-b,a)$$
, we get:
$$\langle (a,b),(c,d)\rangle_{\{p,q\}} = (a \quad b)M\begin{pmatrix} c\\d \end{pmatrix}$$

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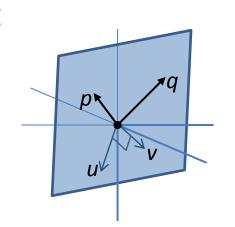
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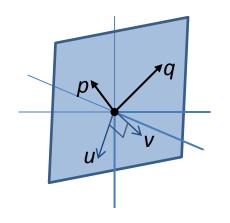
$$\langle (a,b),(c,d)\rangle_{\{p,q\}}=0$$

And, any scalar multiple  $M^{-1}(-\varepsilon b, \varepsilon a)$ will also be orthogonal.



So, if we would also like the vector (c,d) to have length  $\lambda$ , we can set:

$$\begin{pmatrix} c \\ d \end{pmatrix} = \lambda \frac{M^{-1} \begin{pmatrix} -b \\ a \end{pmatrix}}{ \left\| M^{-1} \begin{pmatrix} -b \\ a \end{pmatrix} \right\|_{\{p,q\}} }$$



Given a function  $F=(f_1,...,f_m):D\subset \mathbb{R}^n\to \mathbb{R}^m$ , the Dirichlet Energy is a measure of how much the function F changes over D:

$$E(F) = \int_{D} |dF(p)|^{2} dp = \sum_{i=1}^{m} \int_{D} |\nabla f_{i}(p)|^{2} dp$$

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Without constraints, the solution is trivially F=0.

#### **Challenge:**

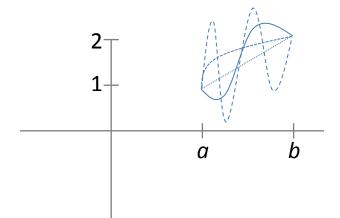
Given a domain  $D \subset \mathbb{R}^n$ , solve for the function  $F:D \to \mathbb{R}^m$  that satisfies the boundary constraints:

$$F(p) = C(p) \quad \forall p \in \partial D$$

and minimizes the Dirichlet Energy.

Example: 
$$E(F) = \int_{D} |dF(p)|^{2} dp = \sum_{i=1}^{m} \int_{D} |\nabla f_{i}(p)|^{2} dp$$

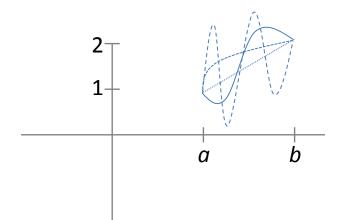
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That is, if *F* is linear.

#### Harmonic Functions

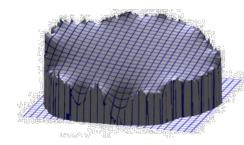
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## **Harmonic Functions**

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**Example (Image Cloning):** 

We copy the pattern into the target and then offset by the harmonic function f that interpolates the boundary differences.







Farbman et al. SIGGRAPH 2009

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Given a function G with zero values along the boundary, we can think of G as the offset values.

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$$= 2\sum_{i=1}^{m} \int_{D} \langle \nabla f_{i}(p), \nabla g_{i}(p) \rangle dp = -2\sum_{i=1}^{m} \int_{D} \Delta f_{i}(p) g_{i}(p) dp$$

Thus, the function is a local extremum of the Dirichlet energy if:

$$0 = \int_{D} \Delta f_{i}(p) g_{i}(p) dp$$

 $0 = \int_{D} \Delta f_{i}(p)g_{i}(p)dp$  for every coordinate offset function  $g_{i}$ .

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for every coordinate offset function  $g_i$ .

That is, *F* is optimal if it satisfies the boundary condition and has the property that the Laplacian of the coordinate functions are 0.

Additionally, since the "change in direction G" is the inner-product of G with the Laplacian of F:

$$\lim_{\varepsilon \to 0} \frac{E(F + \varepsilon G) - E(F)}{\varepsilon} = -2\sum_{i=1}^{m} \int_{D} \Delta f_{i}(p) g_{i}(p) dp$$

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#### **Laplacian Smoothing:**

This means that if we start with an arbitrary function *F*, we can minimize the energy by stepping in the direction opposite the Laplacian:

$$f_i \leftarrow f_i - \varepsilon \Delta f_i$$

# Dirichlet Energy and Laplacians

Formally, the Laplacian of f at a point p is defined as the sum of second partial derivatives:

$$\Delta f = \frac{\partial^2 f}{\partial x_1^2} + \dots + \frac{\partial^2 f}{\partial x_n^2}$$

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Informally, the Laplacian measures how different the value of f at p is from the average value of the neighbors.

### Dirichlet Energy

One can extend the notion of Dirichlet Energy to a regular surface *S*, to obtain an anologous formulation:

$$\lim_{\varepsilon \to 0} \frac{E(F + \varepsilon G) - E(F)}{\varepsilon} = -2\sum_{i=1}^{m} \int_{S} \Delta_{S} f_{i}(p) g_{i}(p) dp$$

Where  $\Delta_S$  is the analog of the Laplacian defined over S, called the Laplace-Beltrami operator.

### Dirichlet Energy

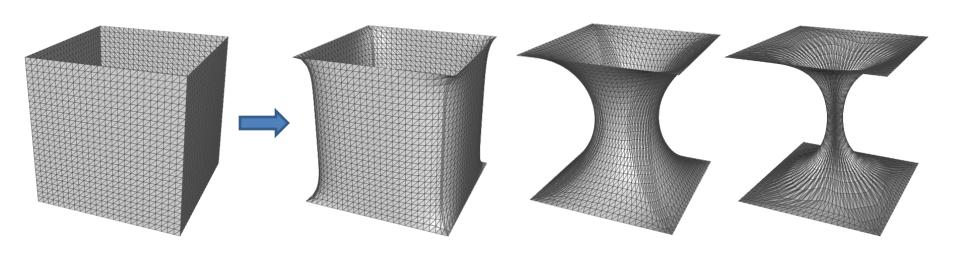
On a surface *S*, if one considers the embedding function:

$$F(x, y, z) = (x, y, z)$$

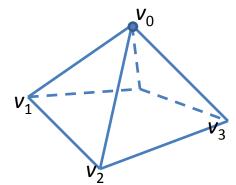
the Dirichlet Energy becomes twice the area, and the Laplacian is equal to the normal, scaled by the mean curvature.

#### Mean Curvature Flow

Thus, if we offset points on the surface in the direction of the negative mean curvature, we evolve the surface towards a smoother surface with smaller surface area.



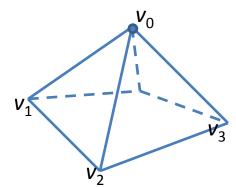
Given a triangle mesh (*V*,*E*,*F*), how should we define the Laplacian?



The Laplacian should be a linear operator that takes a function defined on the mesh vertices and returns a function defined on the vertices.

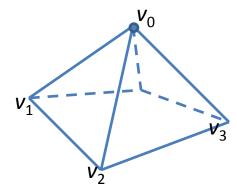
So if there are |V| vertices on the mesh, it can be represented by a |V|x|V| matrix.

$$g_i = \sum_{v_i \in V} L_{ij} f_j$$



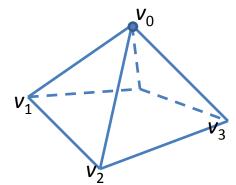
#### • Sparse:

Since we are only interested in the average value at neighboring vertices, distant vertices should not effect the value.



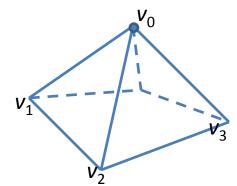
- Sparse
- Positivity:

When averaging of the neighbors' values, we want to use non-negative linear combinations.



- Sparse
- Positivity
- Symmetry:

As in the continuous case, we want the matrix to be symmetric PSD.



- Sparse
- Positivity
- Symmetry
- Linear Precision:

If the mesh lives in a plane and the function values are obtained by sampling a linear function, the Laplacian of the function should be zero.

- Sparse
- Positivity
- Symmetry
- Linear Precision
- Convergence:

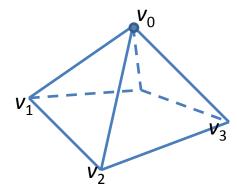
The discrete Laplacian should converge to the smooth Laplacian under mesh refinement.

- Sparse
- Positivity
- Symmetry
- Linear Precision
- Convergence

[Wardetzky et al. 2007] Show that though it is desirable, it is not actually possible to satisfy all of these properties simultaneously.

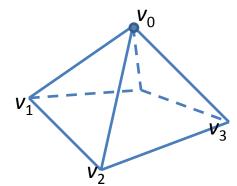
Note that since the Laplacian measures the difference between a vertex and the average values of its neighbors, we expect that is equal to zero on constant functions, so:

$$L_{ii} = -\sum_{v_j \in V | i \neq j} L_{ij}$$



Additionally, if the Laplacian is supported in the 1-ring of a vertex, so that averaging is only performed over immediate neighbors:

$$g_i = L_{ii} f_i + \sum_{v_j \in Nbr(v_i)} L_{ij} f_j$$

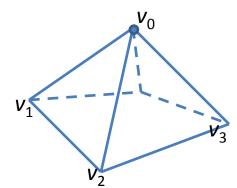


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then we can think of the Laplacian as weights associated to the (directed) edges of a graph:

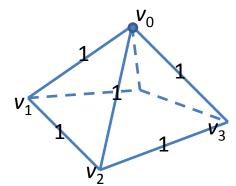
$$g_i = \sum_{v_j \in Nbr(v_i)} L_{ij} (f_j - f_i)$$



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#### Some Possibilities

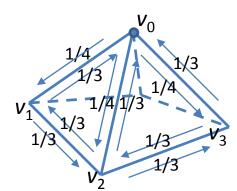
• Tutte Laplacian:  $L_{ij}=1$ 



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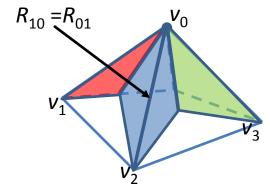
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- Graph Laplacian:  $L_{ij}=1/\text{valence}(v_i)$



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#### Some Possibilities

- Tutte Laplacian:  $L_{ii}=1$
- Graph Laplacian:  $L_{ij}=1/\text{valence}(v_i)$
- Area-Weighted Laplacian:  $L_{ij} = R_{ij}$

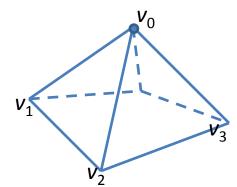


$$g_i = \sum_{v_j \in Nbr(v_i)} L_{ij} (f_j - f_i)$$

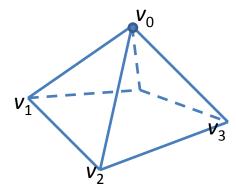
#### Some Possibilities

- Tutte Laplacian:  $L_{ii}=1$
- Graph Laplacian:  $L_{ij}=1/\text{valence}(v_i)$
- Area-Weighted Laplacian:  $L_{ij} = R_{ij}$

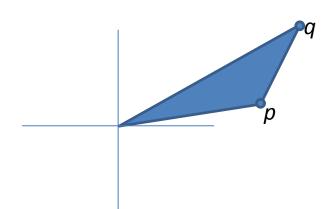
Which one should we choose?



In the smooth case, we know that if the value of the function at vertex v is the position of v, then the Laplacian of the function at v should be the area gradient.

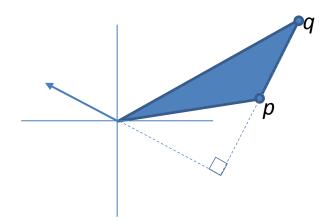


Given a triangle (0,p,q) what direction should we move the vertex at the origin in order to maximally increase the area?

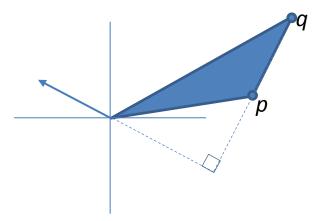


Given a triangle (0,p,q) what direction should we move the vertex at the origin in order to maximally increase the area?

The area of the triangle is half the base times the height. So if we set pq to be the base, we want to move in the perpendicular direction.

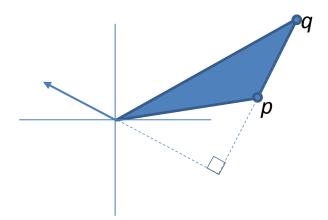


If we take a step of size  $\epsilon$  in this direction, how will the area change?



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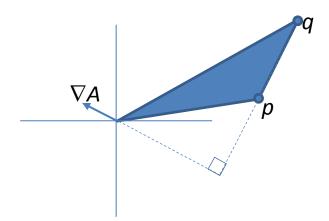
The base remains |p-q| and the height becomes  $(height+\varepsilon)$ , so the change is  $(\varepsilon x|p-q|)/2$ .



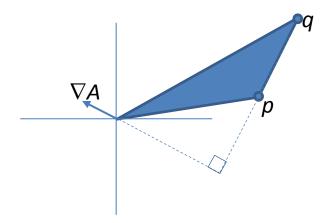
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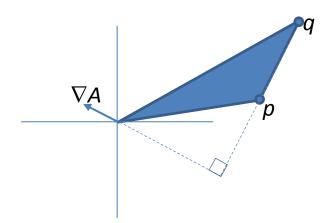
Thus, the gradient is the vector perpendicular to p-q with length equal to |p-q|/2.



Given vectors p and q, what is the vector that is perpendicular to p-q and with length |p-q|/2?



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Given vectors p and q, what is the vector that is perpendicular to p-q and with length |p-q|/2? With respect to the basis  $\{p,q\}$ , the coefficients of p-q are (1,-1). So we need the coefficients (c,d) such that:

$$\binom{1}{-1}^T M \binom{c}{d} = 0 \quad \text{and} \quad$$

$$\begin{pmatrix} 1 \\ -1 \end{pmatrix}^T M \begin{pmatrix} c \\ d \end{pmatrix} = 0 \quad \text{and} \quad \begin{pmatrix} c \\ d \end{pmatrix}^T M \begin{pmatrix} c \\ d \end{pmatrix} = \frac{1}{4} \begin{pmatrix} 1 \\ -1 \end{pmatrix}^T M \begin{pmatrix} 1 \\ -1 \end{pmatrix}_{q}$$

where:

$$M = \begin{pmatrix} \langle p, p \rangle & \langle p, q \rangle \\ \langle p, q \rangle & \langle q, q \rangle \end{pmatrix}$$

To satisfy the perpendicularity condition, the coefficients (c,d) must be:

$$\begin{pmatrix} c \\ d \end{pmatrix} = M^{-1} \begin{pmatrix} \varepsilon \\ \varepsilon \end{pmatrix} = \frac{\varepsilon}{\langle p, p \rangle \langle q, q \rangle - \langle p, q \rangle^2} \begin{pmatrix} \langle q - p, q \rangle \\ \langle p - q, p \rangle \end{pmatrix}$$

for some value of  $\varepsilon$ .

$$M = \begin{pmatrix} \langle p, p \rangle & \langle p, q \rangle \\ \langle p, q \rangle & \langle q, q \rangle \end{pmatrix} \qquad M^{-1} = \frac{1}{\langle p, p \rangle \langle q, q \rangle - \langle p, q \rangle^2} \begin{pmatrix} \langle q, q \rangle & -\langle p, q \rangle \\ -\langle p, q \rangle & \langle p, p \rangle \end{pmatrix}$$

To satisfy the condition on the length, note that:

$$\begin{pmatrix} 1 \\ -1 \end{pmatrix}^{T} M \begin{pmatrix} 1 \\ -1 \end{pmatrix} = \langle p, p \rangle + \langle q, q \rangle - 2\langle p, q \rangle$$

and

$$\begin{pmatrix} c \\ d \end{pmatrix}^{T} M \begin{pmatrix} c \\ d \end{pmatrix} = \begin{pmatrix} \varepsilon \\ \varepsilon \end{pmatrix}^{T} M^{-1} \begin{pmatrix} \varepsilon \\ \varepsilon \end{pmatrix} = \varepsilon^{2} \frac{\langle p, p \rangle + \langle q, q \rangle - 2\langle p, q \rangle}{\langle p, p \rangle \langle q, q \rangle - \langle p, q \rangle^{2}}$$

$$M = \begin{pmatrix} \langle p, p \rangle & \langle p, q \rangle \\ \langle p, q \rangle & \langle q, q \rangle \end{pmatrix} \qquad M^{-1} = \frac{1}{\langle p, p \rangle \langle q, q \rangle - \langle p, q \rangle^2} \begin{pmatrix} \langle q, q \rangle & -\langle p, q \rangle \\ -\langle p, q \rangle & \langle p, p \rangle \end{pmatrix}$$

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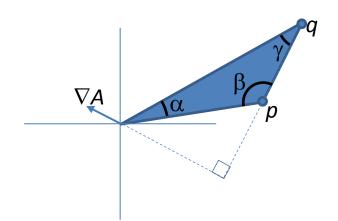
which gives:

$$\varepsilon = \frac{\sqrt{\langle p, p \rangle \langle q, q \rangle - \langle p, q \rangle^2}}{2}$$

$$M = \begin{pmatrix} \langle p, p \rangle & \langle p, q \rangle \\ \langle p, q \rangle & \langle q, q \rangle \end{pmatrix} \qquad M^{-1} = \frac{1}{\langle p, p \rangle \langle q, q \rangle - \langle p, q \rangle^2} \begin{pmatrix} \langle q, q \rangle & -\langle p, q \rangle \\ -\langle p, q \rangle & \langle p, p \rangle \end{pmatrix}$$

$$\varepsilon = \frac{\sqrt{\langle p, p \rangle \langle q, q \rangle - \langle p, q \rangle^2}}{2}$$

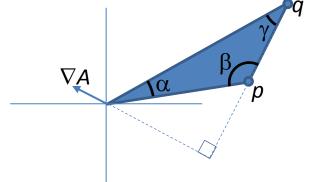
$$\binom{c}{d} = \frac{1}{2} \frac{1}{\sqrt{\langle p, p \rangle \langle q, q \rangle - \langle p, q \rangle^2}} \binom{\langle q - p, q \rangle}{\langle p - q, p \rangle}$$



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$$\begin{pmatrix} c \\ d \end{pmatrix} = \frac{1}{2} \frac{1}{\sqrt{\langle p, p \rangle \langle q, q \rangle - \langle p, q \rangle^2}} \begin{pmatrix} \langle q - p, q \rangle \\ \langle p - q, p \rangle \end{pmatrix}$$

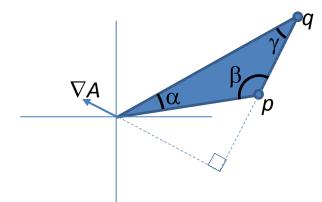
$$= \frac{1}{2} \frac{1}{\sqrt{\|p\|^2 \|q\|^2 - \|p\|^2 \|q\|^2 \cos^2 \alpha}} \begin{pmatrix} \langle q - p, q \rangle \\ \langle p - q, p \rangle \end{pmatrix}$$



$$\varepsilon = \frac{\sqrt{\langle p, p \rangle \langle q, q \rangle - \langle p, q \rangle^2}}{2}$$

$$\begin{pmatrix} c \\ d \end{pmatrix} = \frac{1}{2} \frac{1}{\sqrt{\|p\|^2 \|q\|^2 - \|p\|^2 \|q\|^2 \cos^2 \alpha}} \begin{pmatrix} \langle q - p, q \rangle \\ \langle p - q, p \rangle \end{pmatrix}$$

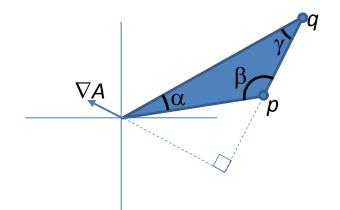
$$= \frac{1}{2} \frac{1}{\|p\| \|q\| \sin \alpha} \begin{pmatrix} \langle q - p, q \rangle \\ \langle p - q, p \rangle \end{pmatrix}$$



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$$\begin{pmatrix} c \\ d \end{pmatrix} = \frac{1}{2} \frac{1}{\|p\| \|q\| \sin \alpha} \begin{pmatrix} \langle q - p, q \rangle \\ \langle p - q, p \rangle \end{pmatrix}$$

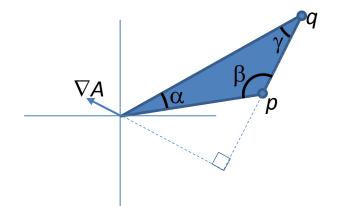
$$= \frac{1}{2} \frac{1}{\|p\| \|q\| \sin \alpha} \begin{pmatrix} \|q - p\| \|q\| \cos \gamma \\ \|q - p\| \|p\| \cos \beta \end{pmatrix}$$



$$\varepsilon = \frac{\sqrt{\langle p, p \rangle \langle q, q \rangle - \langle p, q \rangle^2}}{2}$$

$$\begin{pmatrix} c \\ d \end{pmatrix} = \frac{1}{2} \frac{1}{\|p\| \|q\| \sin \alpha} \begin{pmatrix} \|q - p\| \|q\| \cos \gamma \\ \|q - p\| \|p\| \cos \beta \end{pmatrix}$$

$$= \frac{1}{2} \begin{pmatrix} \frac{\|q - p\| \|q\| \cos \gamma}{\|p\| \|q\| \sin \alpha} & \frac{\|q - p\| \|p\| \cos \beta}{\|p\| \|q\| \sin \alpha} \end{pmatrix}^{T}$$



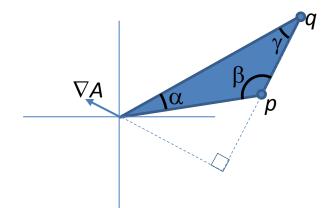
$$\varepsilon = \frac{\sqrt{\langle p, p \rangle \langle q, q \rangle - \langle p, q \rangle^2}}{2}$$

$$\begin{pmatrix} c \\ d \end{pmatrix} = \frac{1}{2} \left( \frac{\|q - p\| \|q\| \cos \gamma}{\|p\| \|q\| \sin \alpha} \right)^{T}$$

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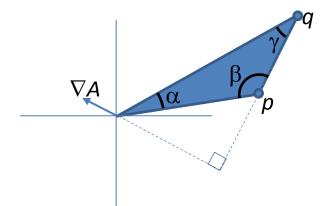


$$\varepsilon = \frac{\sqrt{\langle p, p \rangle \langle q, q \rangle - \langle p, q \rangle^2}}{2}$$

$$\binom{c}{d} = \frac{1}{2} \left( \frac{\|q - p\| \cos \gamma}{\|p\| \sin \alpha} \quad \frac{\|q - p\| \cos \beta}{\|q\| \sin \alpha} \right)^{T}$$

$$= \frac{1}{2} \left( \frac{\|q - p\| \cos \gamma}{\|p\|} \frac{\|p\|}{\|q - p\| \sin \gamma} \frac{\|q - p\| \cos \beta}{\|q\|} \frac{\|q\|}{\|q - p\| \sin \beta} \right)^{T}$$

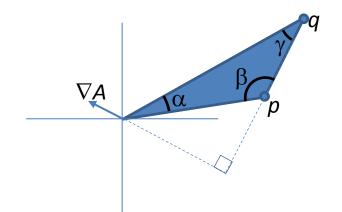
$$\frac{\|q-p\|\cos\beta}{\|q\|} \frac{\|q\|}{\|q-p\|\sin\beta}$$



$$\varepsilon = \frac{\sqrt{\langle p, p \rangle \langle q, q \rangle - \langle p, q \rangle^2}}{2}$$

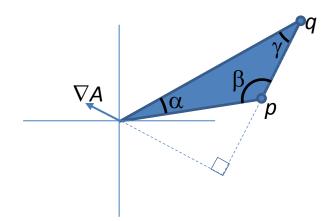
$$\begin{pmatrix} c \\ d \end{pmatrix} = \frac{1}{2} \left( \frac{\|q - p\| \cos \gamma}{\|p\|} \frac{\|p\|}{\|q - p\| \sin \gamma} \frac{\|q - p\| \cos \beta}{\|q\|} \frac{\|q\|}{\|q - p\| \sin \beta} \right)^{T}$$

$$= \frac{1}{2} \left( \frac{\cos \gamma}{\sin \gamma} \frac{\cos \beta}{\sin \beta} \right)^{T} = \frac{1}{2} \begin{pmatrix} \cot \gamma \\ \cot \beta \end{pmatrix}$$



Thus, the vector that is perpendicular to p-q with length |p-q|/2 is the vector:

$$\frac{1}{2}(\cot(\beta)p + \cot(\gamma)q)$$

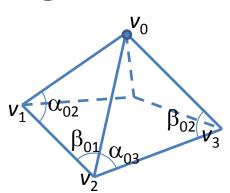


Thus, the vector that is perpendicular to p-q with length |p-q|/2 is the vector:

$$\frac{1}{2}(\cot(\beta)p + \cot(\gamma)q)$$

so the area gradient at vertex  $v_i$  can be obtained by iterating over the edges adjacent to  $v_i$  and summing using the cotans of opposite angles:

$$\frac{\partial A}{\partial v_i} = \frac{1}{2} \sum_{v_j \in Nbr(v_i)}^{k} \left( v_i - v_j \right) \left( \cot \left( \alpha_{ij} \right) + \cot \left( \beta_{ij} \right) \right)$$



This leads to the cotangent-weight Laplacian:

$$L_{ij} = \begin{cases} \frac{1}{2} \left( \cot(\alpha_{ij}) + \cot(\beta_{ij}) \right) & \text{if } i \neq j \text{ and } v_j \in \text{Nbr}(v_i) \\ -\sum_{v_k \in \text{Nbr}(v_i)} L_{ik} & \text{if } i = j \\ 0 & \text{otherwise} \end{cases}$$

