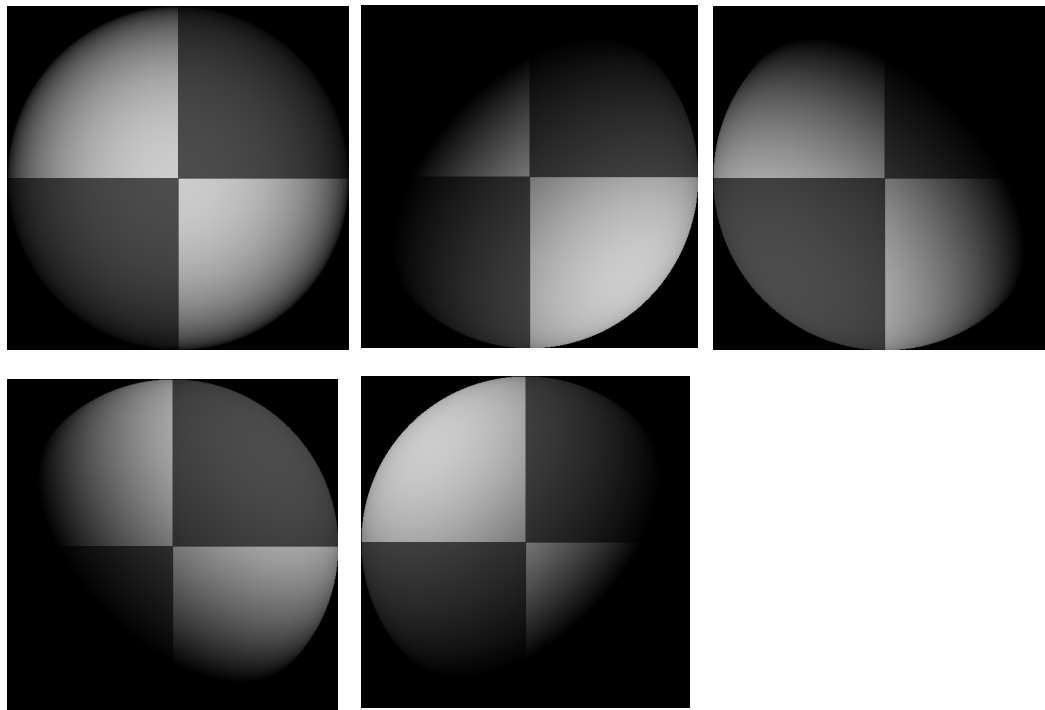


Photometric Stereo

- Shape from shading is hard! Consider an easier problem.
- Suppose that we have a number of known point sources, and we have successive pictures taken with each one used in turn.



Photometric Stereo

Thus combining the conditions given by each light, i , we get

$$\mathbf{i} = V\mathbf{g}$$

Where the i^{th} element of \mathbf{i} is $I_i(x,y)$ and the i^{th} row of V is V_i

Since \mathbf{g} has three elements, we need at least 3 lights.

If the number of lights is more than 3, then use least squares!

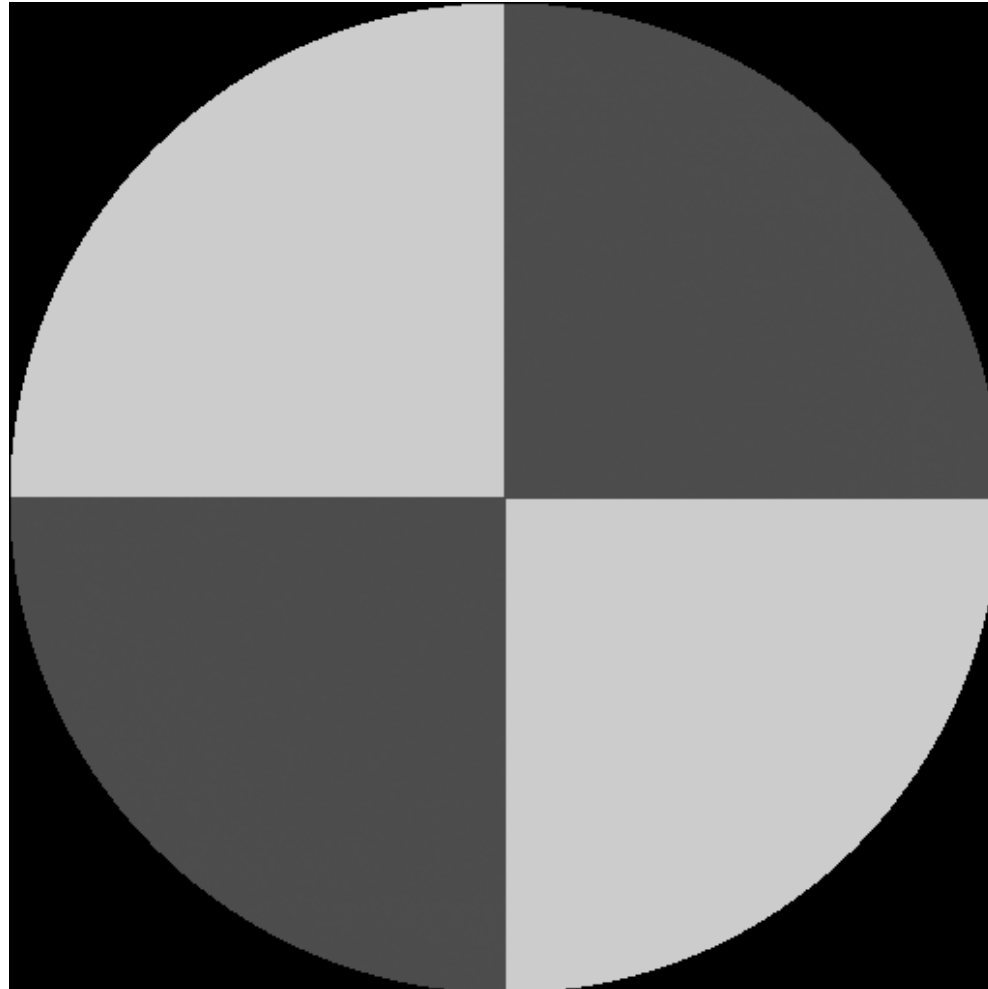
You should understand the construction of this problem.

One way to deal with shadows

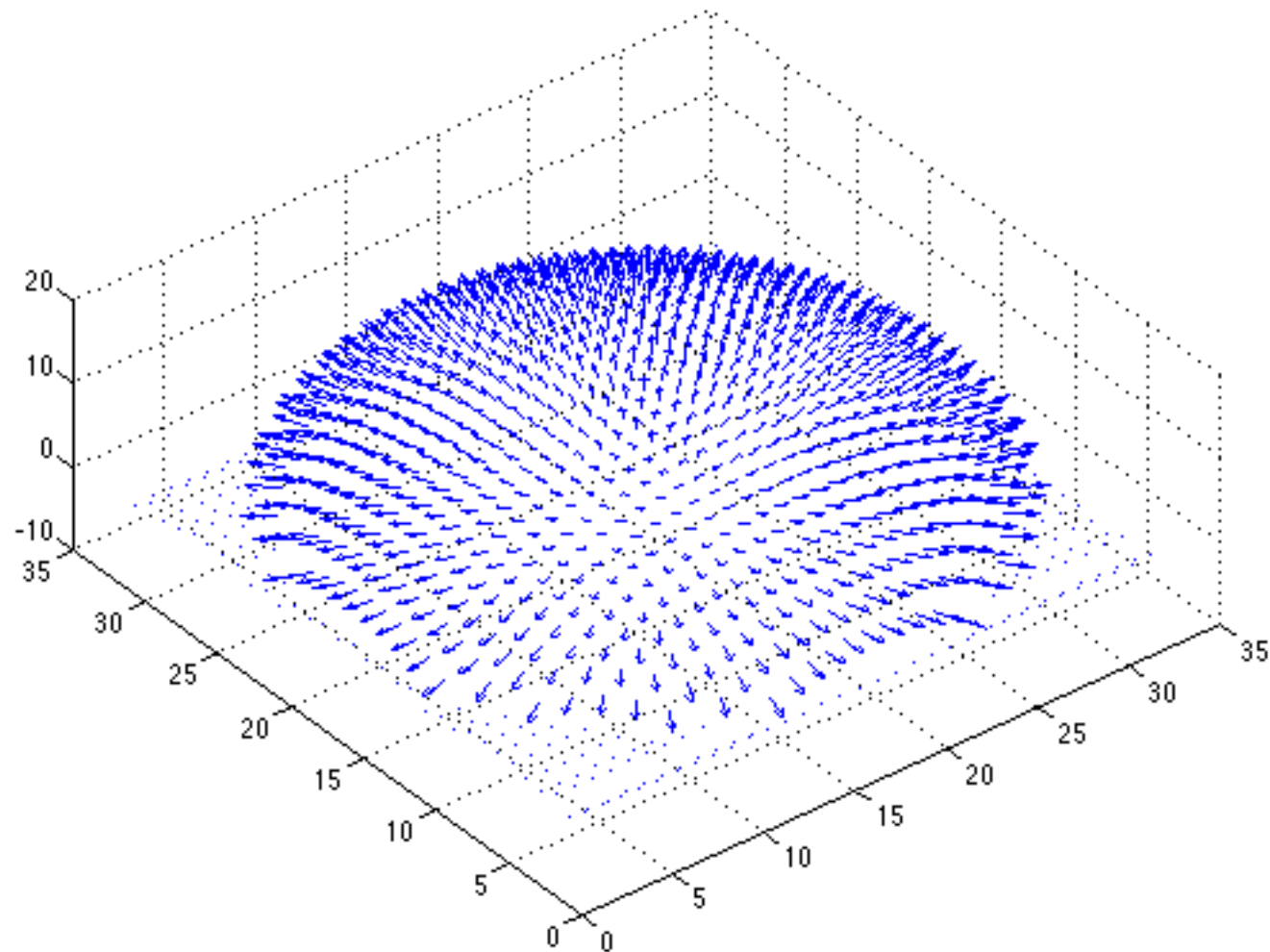
$$\begin{pmatrix} I_1^2(x,y) \\ I_2^2(x,y) \\ \vdots \\ I_n^2(x,y) \end{pmatrix} = \begin{pmatrix} I_1(x,y) & 0 & \dots & 0 \\ 0 & I_2(x,y) & \dots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ 0 & \vdots & 0 & I_n(x,y) \end{pmatrix} \begin{pmatrix} \mathbf{V}_1^T \\ \mathbf{V}_2^T \\ \vdots \\ \mathbf{V}_n^T \end{pmatrix} \mathbf{g}(x,y)$$

image intensity becomes squared
 shadow => 0
known light vectors
unknown

Recovered reflectance



Recovered normal field



From Normals to Shape

From \mathbf{g} we can get the normal $\hat{\mathbf{n}} = \frac{\mathbf{g}}{|\mathbf{g}|}$

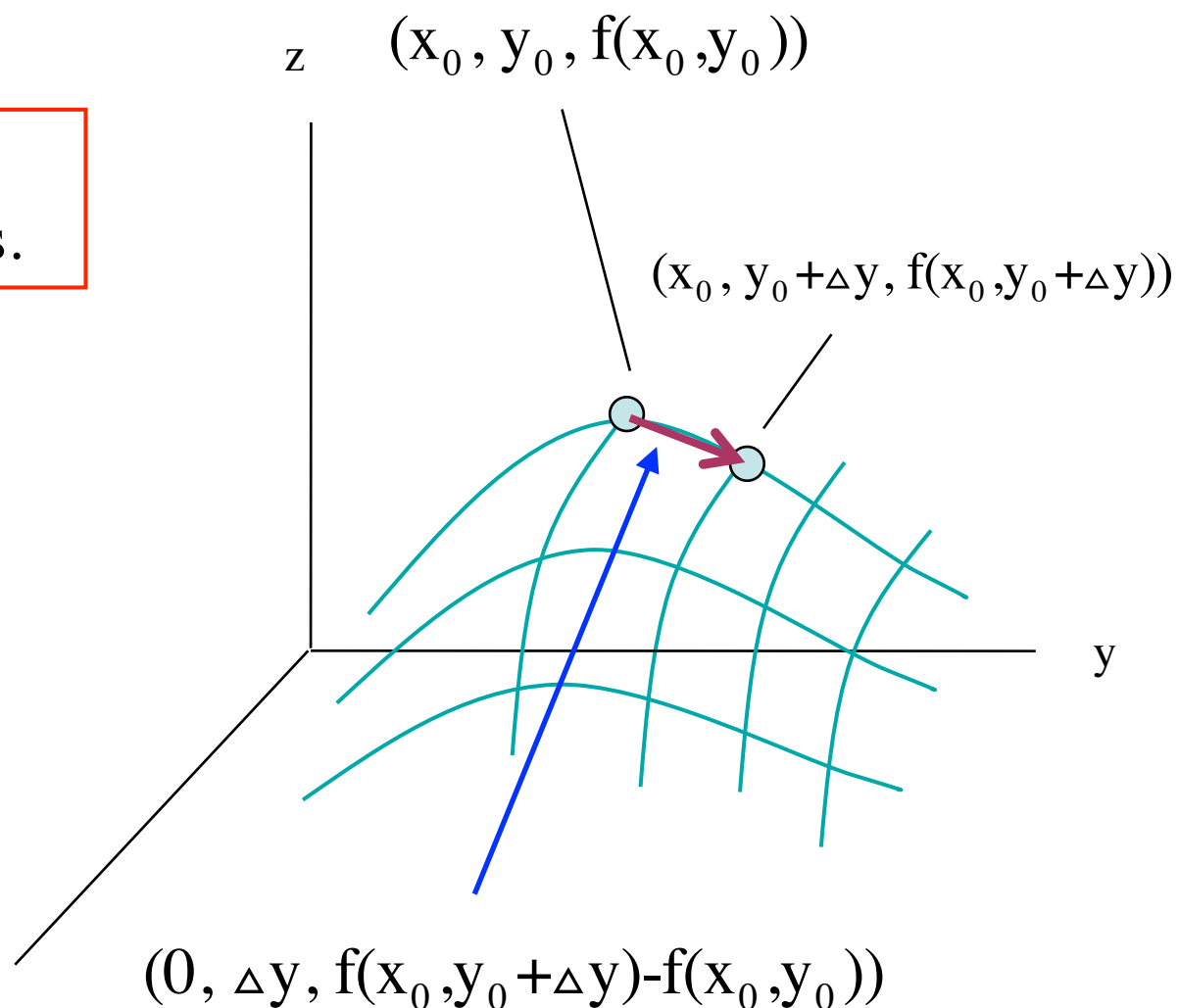
It is natural to represent surface as a depth map $(x, y, f(x, y))$

But what is the relationship between that and the normals?

From Normals to Shape

Given $(x, y, f(x,y))$, what is the surface normal direction?

Reminder why partial derivatives give tangents.

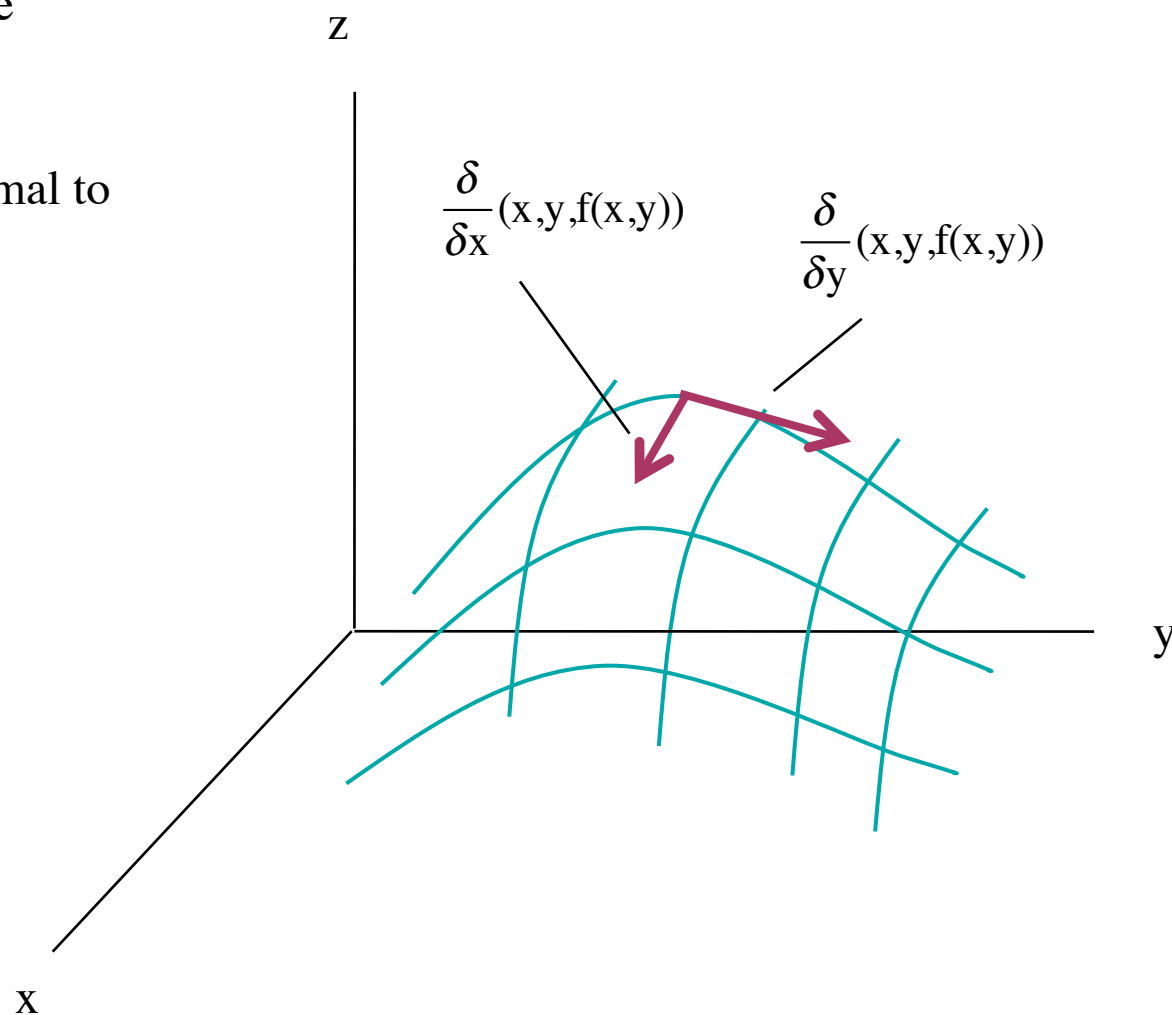


$$\underset{x}{(0, \Delta y, f(x_0, y_0 + \Delta y) - f(x_0, y_0))} = \Delta y * (0, 1, \frac{f(x_0, y_0 + \Delta y) - f(x_0, y_0)}{\Delta y})$$

approximately parallel to $(0, 1, \frac{\partial f}{\partial y})$

The partials in x and y give us two tangents which are vectors in the plane touching the surface.

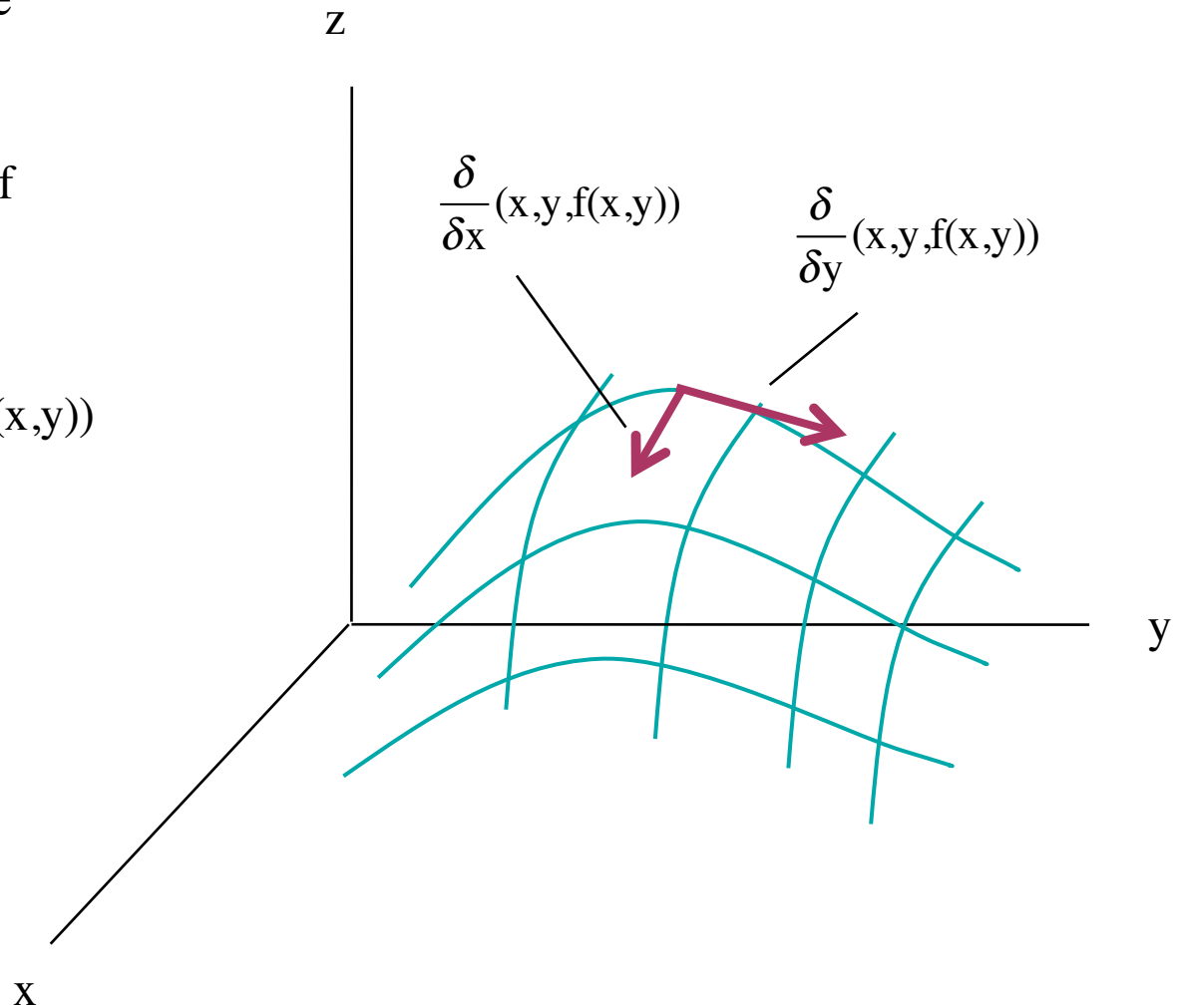
So, we want a vector that is normal to both of them.



The partials in x and y give us two tangents which are vectors in the plane touching the surface.

To get a vector normal to both of them, take their cross product.

$$\hat{\mathbf{n}} \propto \frac{\partial}{\partial x}(x,y,f(x,y)) \times \frac{\partial}{\partial y}(x,y,f(x,y))$$



Reminder about cross product

$$A = (a_1, a_2, a_3) \quad B = (b_1, b_2, b_3)$$

$$\text{Then } A \times B = (a_2 b_3 - a_3 b_2, a_3 b_1 - a_1 b_3, a_1 b_2 - a_2 b_1)$$

$$A \times B \perp A \quad \text{and} \quad A \times B \perp B$$

In right hand coordinates: A, B , and $A \times B$ form a right hand system.

$$\text{Algebraically, } A \times B \cdot A = 0 \quad \text{and} \quad A \times B \cdot B = 0 \quad (\text{check!})$$

$$|A \times B| = |A||B|\sin\theta$$

From Normals to Shape

Given $(x, y, f(x,y))$, what is the surface normal direction?

Method one (cross product)

$$\hat{\mathbf{n}} \propto \frac{\delta}{\delta x}(x,y,f(x,y)) \times \frac{\delta}{\delta y}(x,y,f(x,y))$$

(If you are on the surface the partial with respect to x gives the direction in 3D if you try to go in the x direction. Ditto for y . The normal is perpendicular to these two directions).

From Normals to Shape

$$\hat{\mathbf{n}} \propto \frac{\partial}{\partial x}(x, y, f(x, y)) \times \frac{\partial}{\partial y}(x, y, f(x, y))$$

$$= (1, 0, f_x) \times (0, 1, f_y)$$

$$= (-f_x, -f_y, 1)$$

$$\text{using } A \times B = (a_2b_3 - a_3b_2, a_3b_1 - a_1b_3, a_1b_2 - a_2b_1)$$

From Normals to Shape

Given $(x, y, f(x, y))$, what is the surface normal direction?

Method two (level curves)

Given a surface, S , specified by $g(x, y, z) = 0$

$\nabla g(x, y, z)$ is normal to S

So, find $g(x, y, z)$ such that $g(x, y, z) = 0$ is our surface

$$g(x, y, z) = z - f(x, y)$$

From Normals to Shape

Given $(x, y, f(x,y))$, what is the surface normal direction?

Method two (level curves)

$$g(x,y,z) = z - f(x,y)$$

$$\nabla g(x,y,z) = (-f_x, -f_y, 1)$$

From Normals to Shape

Either way, $\mathbf{n} = \rho \hat{\mathbf{n}} \propto (-f_x, -f_y, 1)$

From \mathbf{n} we can get the albedo (it is $\|\mathbf{n}\|$)

Note that we have two vectors that are parallel. We do not know the relative scale, but the ratios of components cancel out the scale. So,

$$\frac{n_x}{n_z} = \frac{-f_x}{1} \quad \text{and} \quad \frac{n_y}{n_z} = \frac{-f_y}{1}$$

Rearranging a bit, $f_x = -\frac{n_x}{n_z}$ and $f_y = -\frac{n_y}{n_z}$

From Normals to Shape

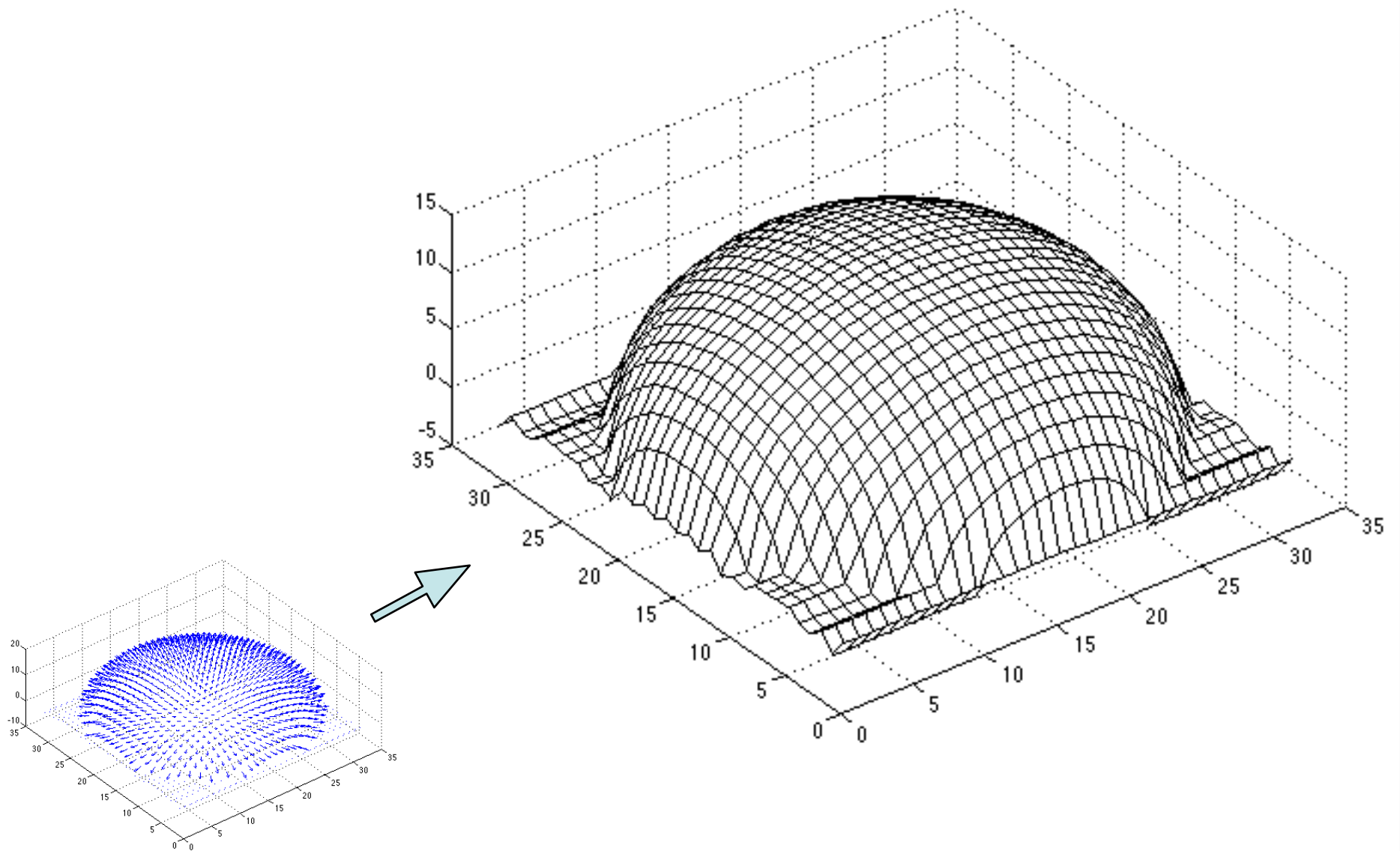
So, if we have the normals, we can estimate the derivatives of $f(x,y)$

Minor point for those who have vector calculus: If we assume that f_x and f_y are the derivatives of a differentiable function, $f(x,y)$ we can further check (or constrain) that $f_{xy} = f_{yx}$.

We can recover the surface height at any point by integration along some path. For example, if we declare the origin to be at height C , and go along the x axis, then parallel to the y axis:

$$f(x,y) = \int_0^x f_x(x',0)dx' + \int_0^y f_y(x,y')dy' + C$$

Surface recovered by integration



Color

Color is a sensation

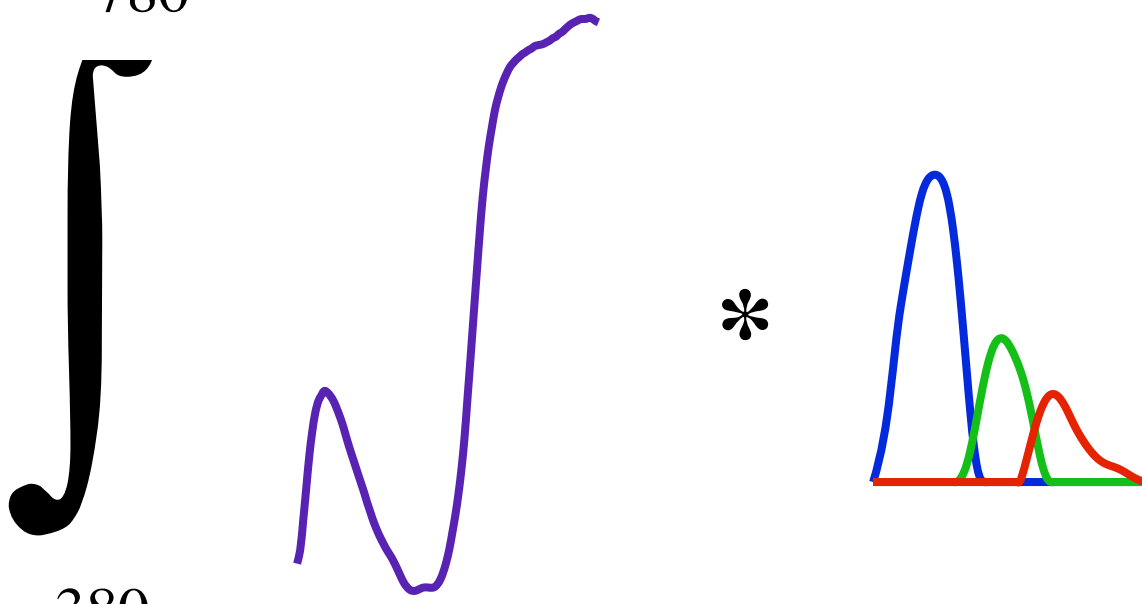
Usually there is light involved, and usually there is a relationship between the world and the colors you see

Your brain has a big effect on the colors you see

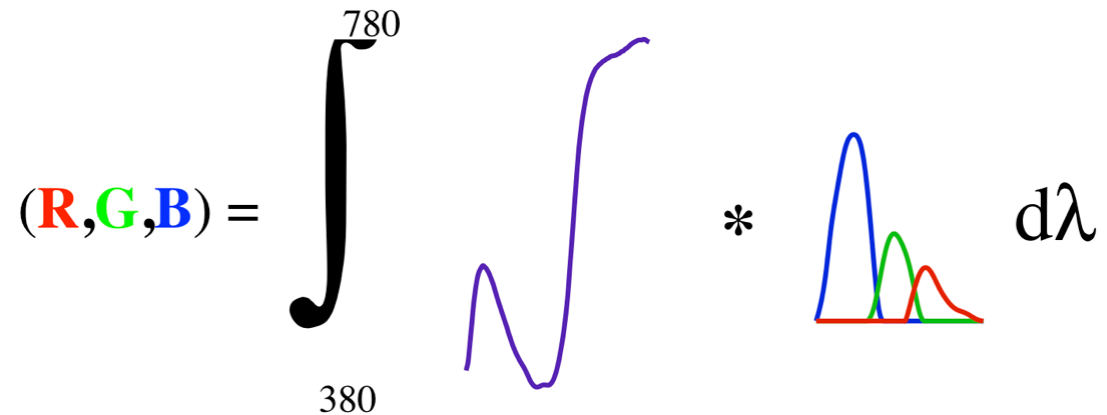
We will focus on what colors mean to a camera which is **much simpler**

Color for a camera (R,G,B) is a very limited sampling of spectral light energy (why three values?)

Recall Image Formation (Spectral)

$$(\mathbf{R}, \mathbf{G}, \mathbf{B}) = \int_{380}^{780} \text{Spectral Response} * \text{Light Spectrum} d\lambda$$


The diagram illustrates the spectral integration process for image formation. It shows a large integral symbol with the limits 380 and 780. To the right of the integral is a purple curve representing the spectral response of a sensor. This is followed by an asterisk (*) indicating convolution or multiplication. To the right of the asterisk are three overlapping curves in blue, green, and red, representing the spectral power distributions of the light sources. The entire expression is followed by $d\lambda$.

$$(\mathbf{R}, \mathbf{G}, \mathbf{B}) = \int_{380}^{780} \text{[Spectrum]} * \text{[Sensitivity Curves]} d\lambda$$


Alternative notation $C_k = \int L(\lambda) R^{(k)}(\lambda) d\lambda$

Discrete version: $\mathbf{C} = \mathbf{R} \cdot \mathbf{L}$

where \mathbf{L} is the light spectra as a column vector

\mathbf{R} has the sensor sensitivities as rows

\mathbf{C} is the camera responses as a column vector

From previous slide

$$\mathbf{C} = \mathbf{R} * \mathbf{L}$$

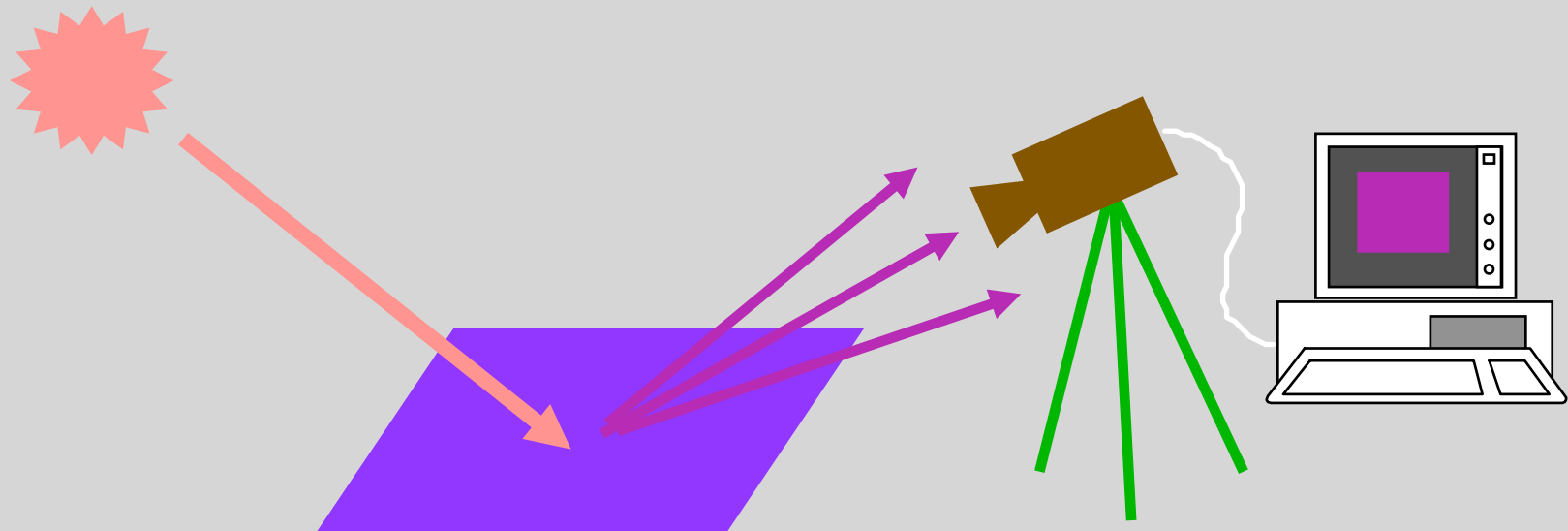
\mathbf{R} is **not** full rank (typical values are 3 by 101 or 3 by 31)

First key observation is that you cannot recover \mathbf{L} from \mathbf{C}
(\mathbf{L} is spectra, \mathbf{C} is RGB)

Second observation---many spectra can have the same RGB.
These are metamers (the spectra are a metameric match).

(This is the essence of color reproduction)

(R,G,B) depends on the light, the surface, and the camera

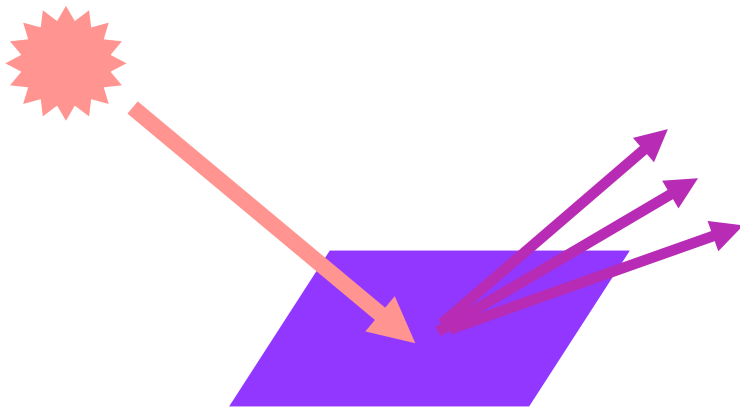


Spectral reflectance

We define spectral reflectance by

$$S(\lambda) = \frac{L(\lambda)}{E(\lambda)} \quad \text{where } E(\lambda) \text{ is incoming and } L(\lambda) \text{ is outgoing}$$

$$\text{So } L(\lambda) = E(\lambda)S(\lambda)$$



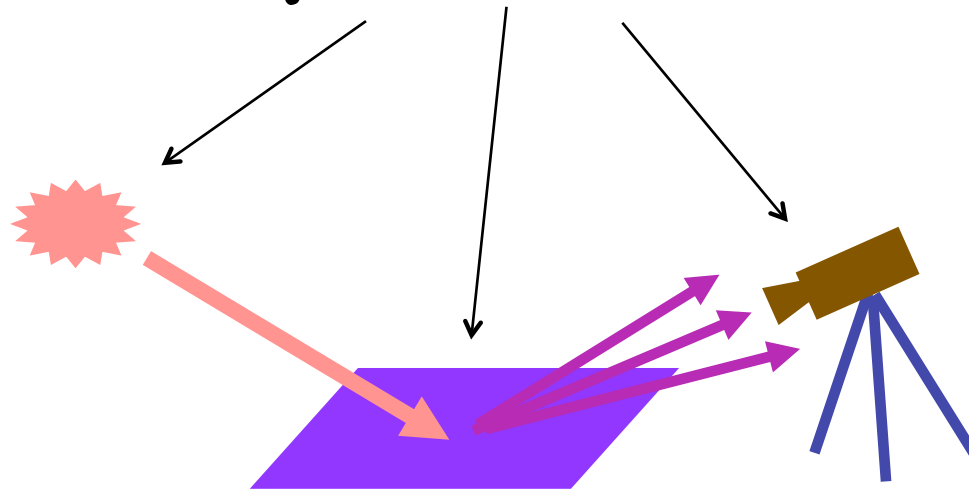
Recalling the BDRF, we know S is function of incoming and outgoing angles. Here we are assuming a particular pair of angles.

Spectral reflectance

$$L(\lambda) = E(\lambda)S(\lambda) \quad (\text{previous slide})$$

Recall $C_k = \int L(\lambda) R^{(k)}(\lambda) d\lambda$

Now, $C_k = \int E(\lambda) S(\lambda) R^{(k)}(\lambda) d\lambda$

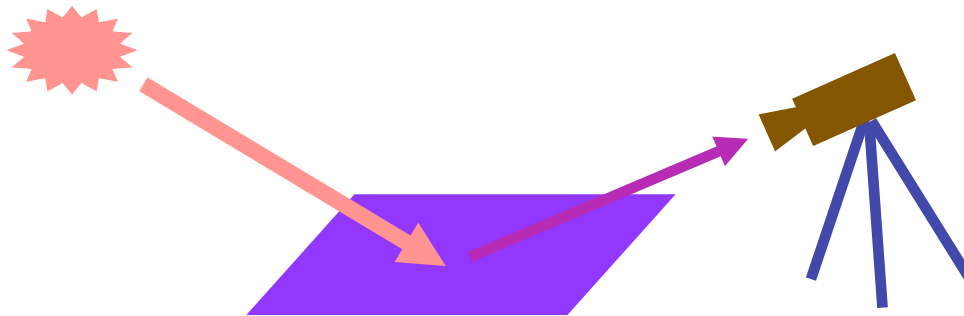


Color imaging summary

To get the color at a pixel, which is a particular outgoing direction with respect to the surface the pixel sees, we can add up the contributions of light rays reaching the surface.

For each contribution we have $E(\lambda)$ and $S(\lambda)$ and we can assume we know $R^{(k)}(\lambda)$.

We get the value of each channel by $C_k = \int E(\lambda)S(\lambda)R^{(k)}(\lambda)d\lambda$



Imaging system

$$\text{In } C_k = \int E(\lambda)S(\lambda)R^{(k)}(\lambda)d\lambda$$

$L(\lambda) = E(\lambda)S(\lambda)$ is about the world

The integration of $L(\lambda)$ against the sensitivity functions is a property of the **imaging** system.

This is a good model for cameras, and for human color matching experiments.

However, notice the implicit assumption that every pixel behaves the same.

Human Color Constancy Demo