Last blocks:

Build an encoder and a decoder to:

Accept noisy image, produce clean version

By:

Constructing loss

Applying SGD to get minimal loss on training data

Using various tricks to get good behavior

New recipe, normal case

Procedure:

find many training pairs (image, normal)

adjust filters so that

Decode(Encode(image)) is close to normal

on average, over pairs

hope that this generalizes to new images

Result:

Single image normal predictor

Normal from depth

For training:

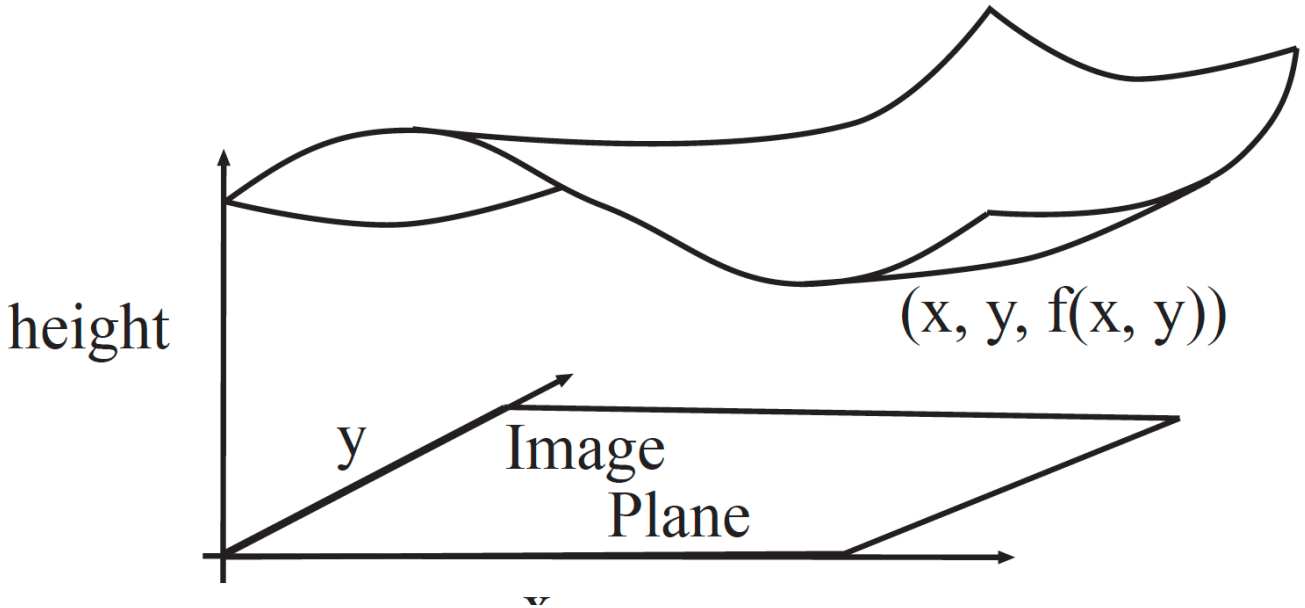
If you have depth data, fit a plane locally

use the plane's normal

Alternative:

geometric reasoning

Geometrical model (for now)



At (x, y) in image, depth is f(x, y)

We see a surface (x, y, f(x, y))

Normal from depth

illustrated in Figure 19.4 Now consider the vector from $(x, y, f(x, y)$ to $(x+\delta x, y, f(x+\delta x, y)$; as δx gets smaller, this vector will get shorter, but

$$\lim_{\delta x \to 0} \frac{1}{\delta x} \left(\delta_x, 0, f(x+\delta x, y) - f(x, y)\right)^T = \left(1, 0, \frac{\partial f}{\partial x}\right)^T$$

will be tangent to the surface if the derivative exists. Similarly,

$$\left(0, 1, \frac{\partial f}{\partial y}\right)^T$$

is tangent to the surface. Using the very widely established convention of writing

$$p = \frac{\partial f}{\partial x} \text{ and } q = \frac{\partial f}{\partial y}$$

the normal is

$$\frac{1}{\sqrt{1+p^2+q^2}} \left[-p, -q, 1\right]^T$$

(although you can flip the sign depending on whether you want the normal pointing from the surface to the camera or from the camera to the surface).

Normal from depth

Notice that derivatives => noise problems => smoothing

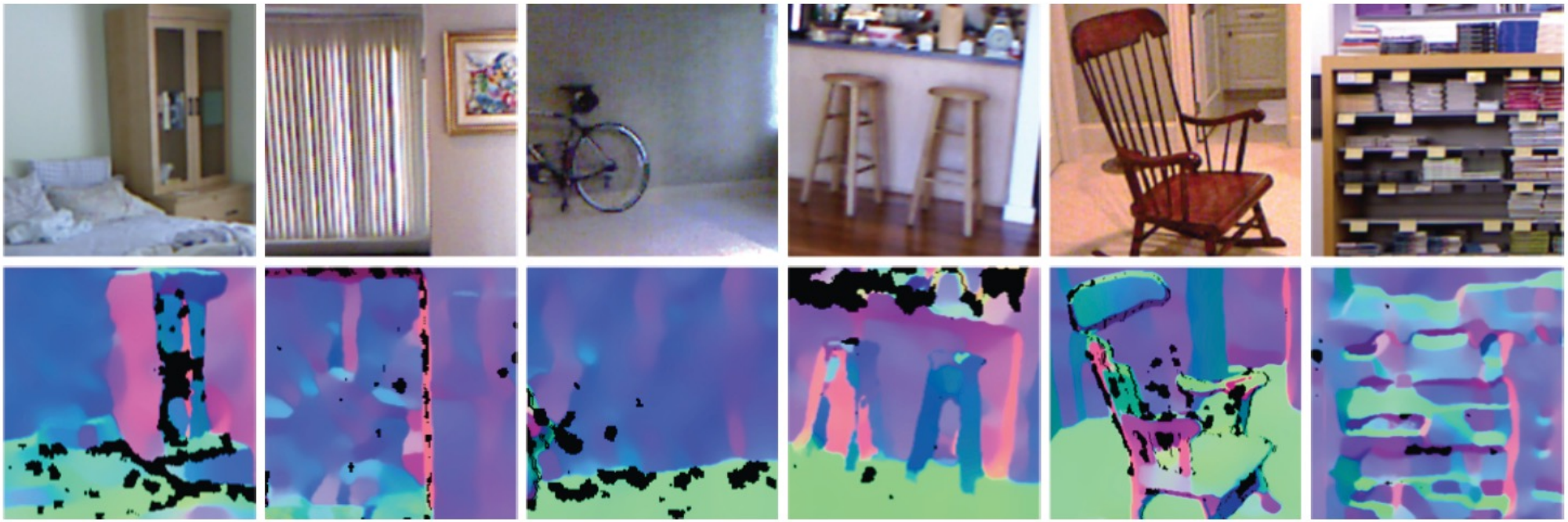
Notice also that there is noise in measured depths

(property of depth cameras)

Image and depth

Data example from NYUV2

Normal estimates from depth data can be shaky



Loss – building in a confidence score

Normal predictors require care, because the ground truth predicted from depth images can present problems (Figure 19.4). Pushing the normal predictor to reduce prediction error at locations where the ground truth isn't reliable can cause training problems. However, there are manageable procedures to estimate where the ground truth is right (Figure 19.6). Predictions can be notably improved by incorporating such an estimate. Write κ_i for an estimate of predicted normal uncertainty at pixel i, where κ_i is larger when the predictor is more certain. Write μ_i for the predicted value of the normal at i and $\mathbf{n}_i$ for the ground truth normal at i. Then

$$\mathcal{L}(\kappa_i, \mu_i, \mathbf{n}_i) = -\log\left(1+\kappa_i^2\right) + \log\left(1+\exp\left(-\kappa_i \pi\right)\right) + \kappa_i \text{acos} \mu_i \mathbf{n}_i$$

is a loss that encourages the network to reveal when the prediction is uncertain but also encourages the prediction to be like the ground truth.

Rough story

$$\mathcal{L}(\kappa_i, \mu_i, \mathbf{n}_i) = -\log\left(1+\kappa_i^2\right) + \log\left(1+\exp\left(-\kappa_i \pi\right)\right) + \kappa_i \text{acos}\mu_i \mathbf{n}_i$$

If normals associated with similar patches are similar

k can be big

If they're not

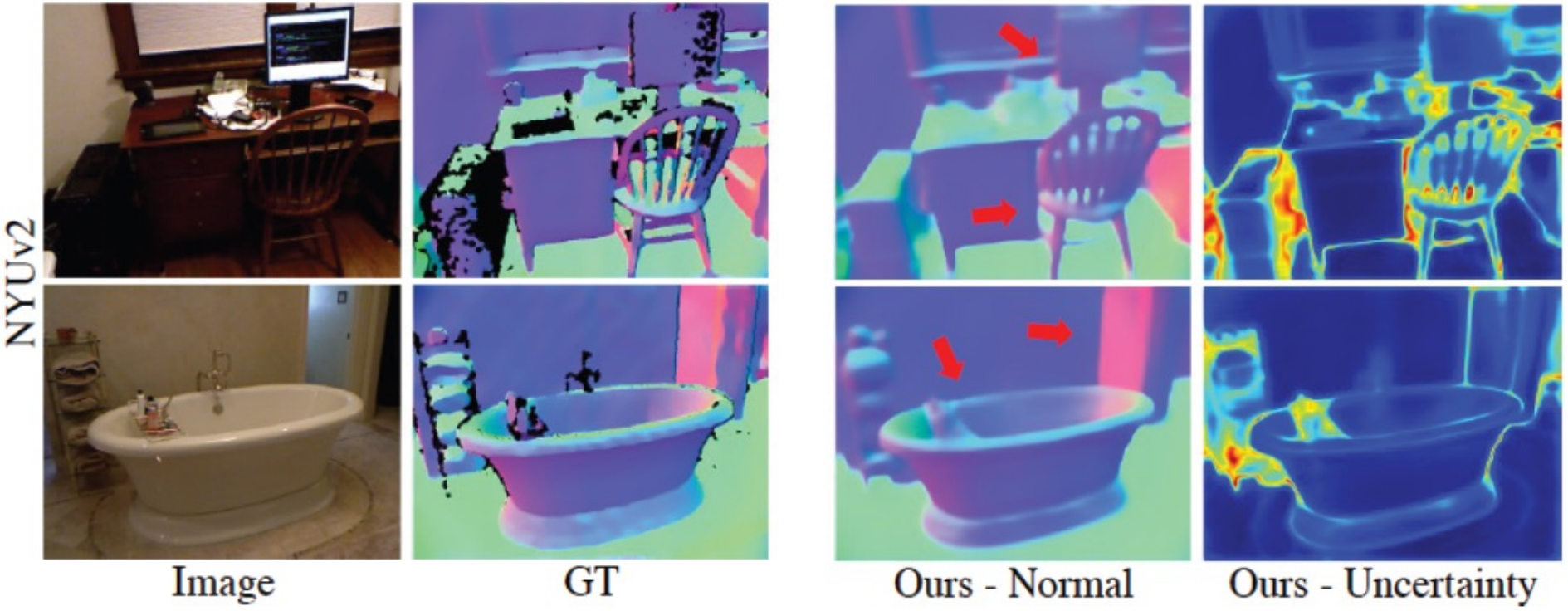
k must be small

Result: you can estimate k

What normal predictors predict

What comes out of a normal predictor is usually not the normal. Write $(n_x, n_y, n_z)^T$ for the components of the unit normal. Most normal predictors report $(1/2)(n_x + 1, n_y + 1, n_z + 1)^T$, which has the advantage of being in the range $[0, 1]$. If you don't know this, using the normal predictor can be difficult.

Normal predictors work really well too



Evaluating normal predictors

Accuracy in normal predictors is usually evaluated using mean and median of the angle between true and predicted normals, and the percentage of normals where that angle is below some set of thresholds (typically 11.25^o, 22.5^o and 30^o).

SOTA

25%, and a frame rate of between 5 and 90 FPS. For normal predictors, you could expect to see mean angular errors of 15^o to 30^o, depending on model and dataset.

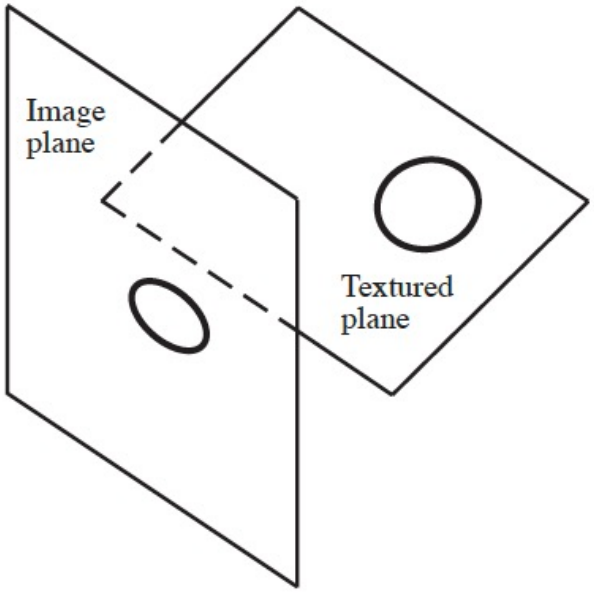
Why does all this work? I

- The depth and normal at a pixel is usually rather similar to the depth and normal at neighboring pixels. Further, large changes in depth and normal are usually signalled by edges.
- Depth maps aren't all that complicated. Scenes tend to have fairly stylized depth maps, so, for example, rooms are boxes with other boxes in them, and so on. Further, many depth regions are roughly either inclined planes, cylinders or spheres.
- Surface textures and shading offer cues to the orientation of a surface and so to the normal. Shading cues are discussed in Section 15.10. Texture cues are

Why does all this work? II

Texture deformations are a cue to normals

(archaic term: shape from texture)



Depth and normal are linked

You can predict normal from depth

You can predict depth from normal (next slide)

Idea:

- train depth and normal predictors together
  - with a consistency loss
- improvements manifest

Depth from normal

If you have a normal estimate that is good enough you can estimate depth up to a constant of integration. Assume the normal predictor predicts a unit normal at each location $\mathbf{x} = (x, y)^T$. Write $[n_x(\mathbf{x}), n_y(\mathbf{x}), n_z(\mathbf{x})]^T$ for that normal. Now

$$\frac{-n_x(\mathbf{x})}{n_z(\mathbf{x})} = \frac{\partial z(\mathbf{x})}{\partial x} = p(\mathbf{x}) \text{ and } \frac{-n_y(\mathbf{x})}{n_z(\mathbf{x})} = \frac{\partial z(\mathbf{x})}{\partial y} = q(\mathbf{x})$$

so you should be able to recover the depth map up to a missing constant by integration. This requires some care, because the estimates of the normal might not be exactly right. Recall that

$$\frac{\partial p}{\partial y} = \frac{\partial q}{\partial x}$$

a condition often referred to as *integrability*. An algorithm appears below. Better