Edge Detection Continued

Edge Detection

Idea: use machine learning!

P. Dollar and C. Zitnick

Structured Forests for Fast Edge Detection

ICCV 2013

Code:

`http://research.microsoft.com/en-us/downloads/389109f6-b4e8-404c-84bf-239f7cbf4e3d/default.aspx`

Testing the Canny Edge Detector

- Let's take this image
- Our goal (a few lectures from now) is to detect objects (cows here)

Testing the Canny Edge Detector

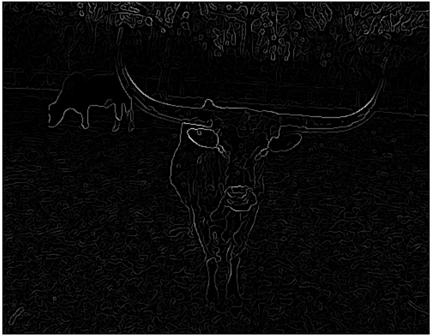
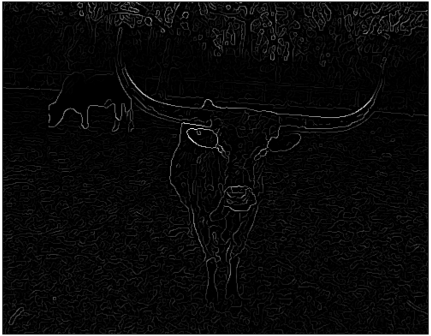


image gradients + NMS

Canny's edges

Testing the Canny Edge Detector



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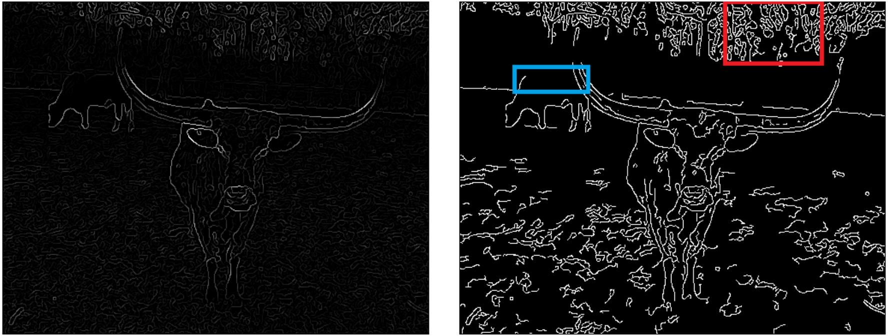

image gradients + NMS   Canny's edges

- Lots of "distractor" and missing edges
- Can we do better?

Annotate...

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- ... and someone has:
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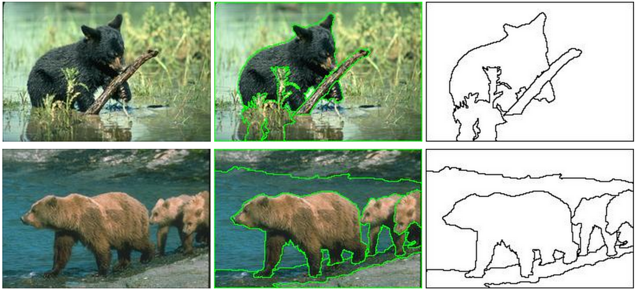
The Berkeley Segmentation Dataset and Benchmark

by D. Martin and C. Fowlkes and D. Tal and J. Malik



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- We can use Machine Learning techniques to:

Train classifiers!

- Please **learn what a classifier /classification is**
- In particular, learn what a **Support Vector Machine** (SVM) is (some links to tutorials are on the class webpage)
- With each week it's going to be more important to know about this
- You don't need to learn all the details / math, but to understand the concept enough to know what's going on

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Classification Problems

Let's think a bit:

- Problem: I want to predict whether it will snow in Oct. What should I do?

Classification Problems

Let's think a bit:

- Problem: I want to predict whether some kid will grow over 2 meters when he grows up

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- We are ready for math

Classification Examples

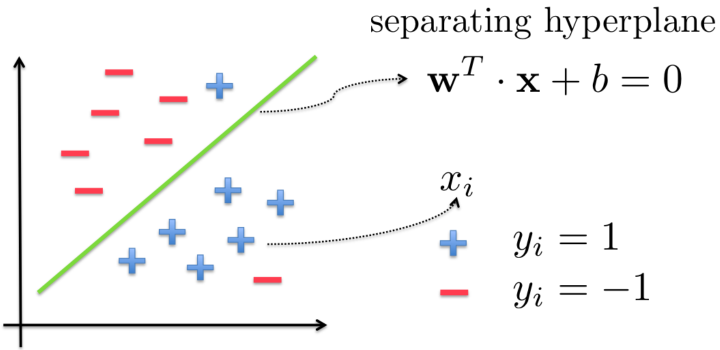
- Each data point **x** lives in a n-dimensional space, $x \in \mathbb{R}^n$
- For example, an n pixel image becomes a length n vector
- Or image is compressed into two features: object size, colour

Source: Wikipedia

Classification Examples

- Each data point $\mathbf{x}$ lives in a n-dimensional space, $x \in \mathbb{R}^n$
- For example, an n pixel image becomes a length n vector
- A better idea might be to compress (project) into two features: object size, colour
- We have a bunch of data points $\mathbf{x}_i$, and for each we have a **label**, y_i
- A label y_i can be either 1 (positive example – penny in our case), or -1 (negative example – loonie in our case)

Classification Problems)



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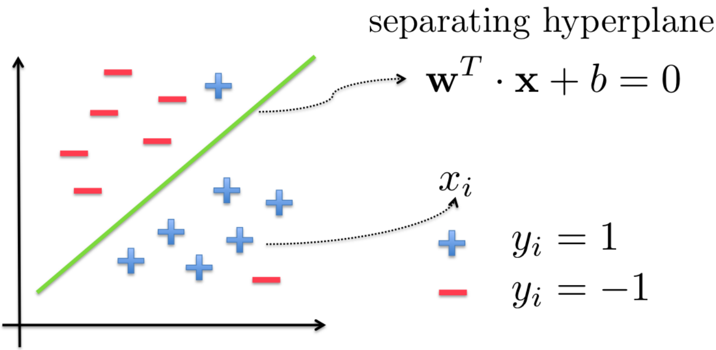
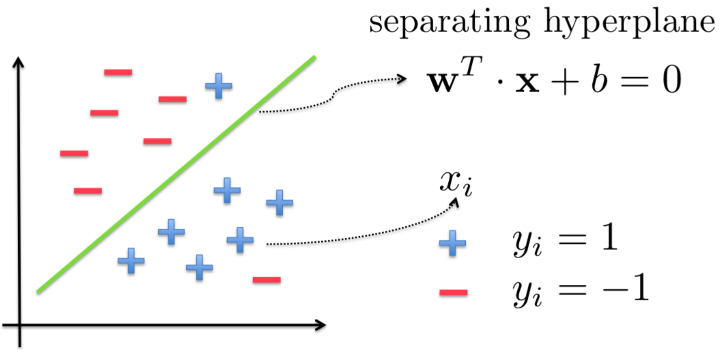


At training time:

Finding **weights w** so that positive and negative examples are optimally separated

Classification Problems)



At test time:

$\mathbf{w}^T \cdot \mathbf{x} + b > 0 \rightarrow \mathbf{x}$ is a positive example

$\mathbf{w}^T \cdot \mathbf{x} + b < 0 \rightarrow \mathbf{x}$ is a negative example

Training an Edge Detector

- How should we do this?

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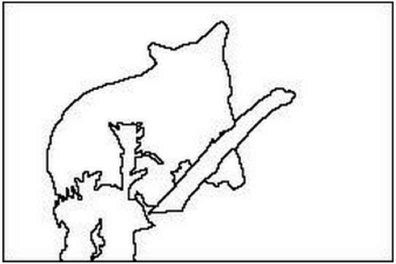
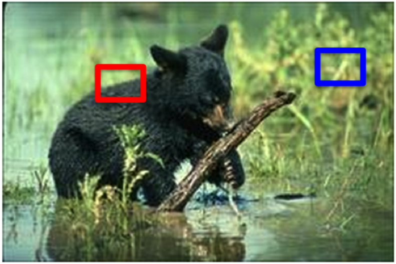
image

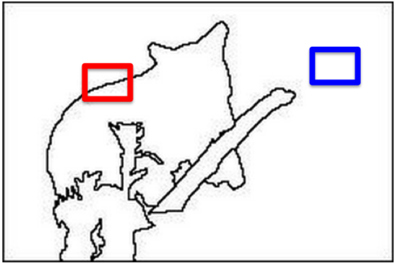


annotation

Training an Edge Detector

- We extract lots of image patches

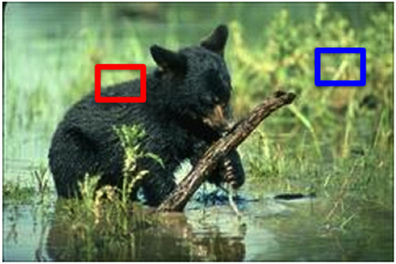


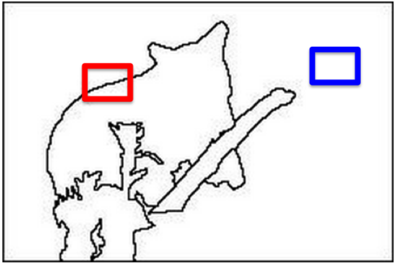


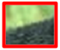
We call each such crop an **image patch**

Training an Edge Detector

- We extract lots of image patches
- These are our training data





 $\rightarrow$ edge

 $\rightarrow$ no edge

} our training data

Training an Edge Detector

- We extract lots of image patches
- These are our training data
- We need to do something with each of our data samples (image patches **P**) to represent each one with a vector (representing measurements about the patch) **x**. The simplest possibility in our case would be to just vectorize an image patch. Any problems with this?

matrix $\mathbf{P}$

$$\rightarrow \quad \mathbf{x} = \mathbf{P}(:)$$

Training an Edge Detector

- We extract lots of image patches
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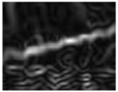
- This works better: Extract meaningful **image features** such as gradients, a color histogram, etc, representing each patch

matrix $\mathbf{P}$

$\xrightarrow{\text{compute gradients}}$



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Training an Edge Detector

- We extract lots of image patches
- These are our training data
- This works better: Extract meaningful **image features** such as gradients, a color histogram, etc, representing each patch
- Image features are mappings from images (or patches) to other (vector) meaningful representations.

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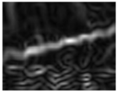

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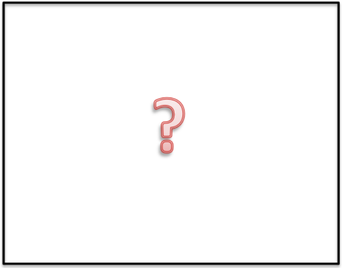
$\xrightarrow{\text{compute color}}$

- Once trained, **how can we use** our new edge detector?

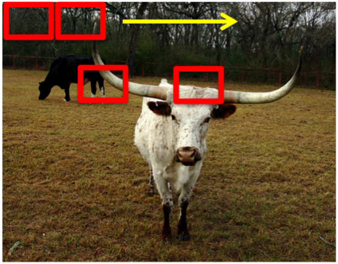

image



prediction

Using an Edge Detector

- We extract all (overlapping) image patches



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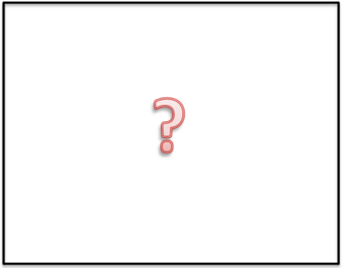

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Using an Edge Detector

- We extract all (overlapping) image patches
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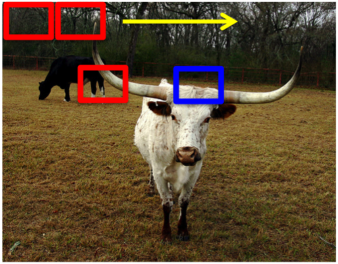

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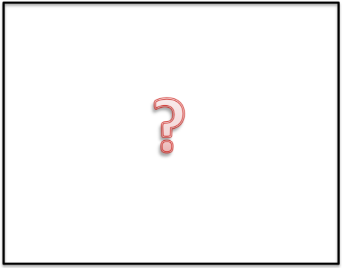
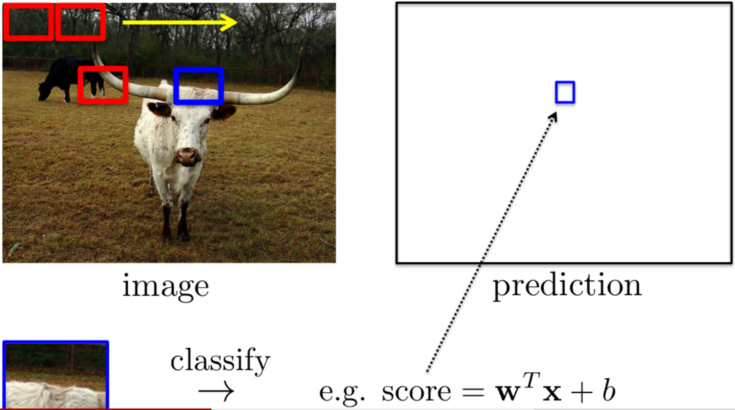


prediction

$$\xrightarrow{\text{classify}} \qquad \text{e.g. score} = \mathbf{w}^T\mathbf{x} + b$$

Using an Edge Detector

- We extract all (overlapping) image patches
- Extract features and use our trained classifier
- Place the predicted value (score) in the output matrix at the center pixel



Comparisons: Canny vs Structured Edge Detector

image

image gradients

gradients + NMS

“edgeness score”

score + NMS

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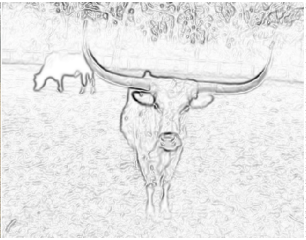

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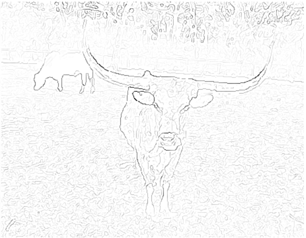
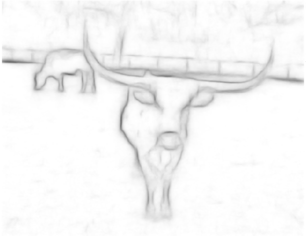
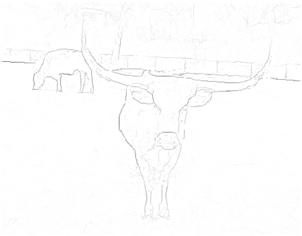


gradients + NMS



“edgeness” score



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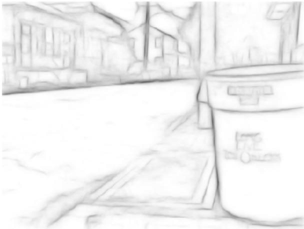

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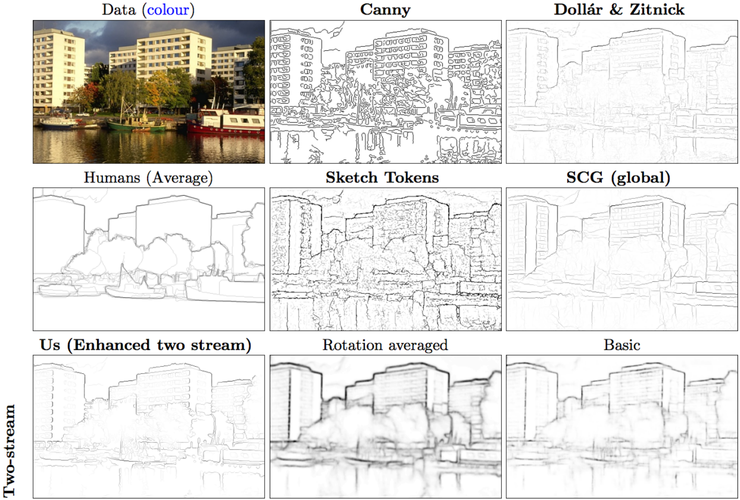
Deep Approach

- You can use more fancy classifiers (e.g., Neural Networks)



[Kivien, Williams, Hees. Visual Boundary Prediction: A Deep Neural Prediction Network and Quality Dissection. AISTATS'2014]

Evaluation

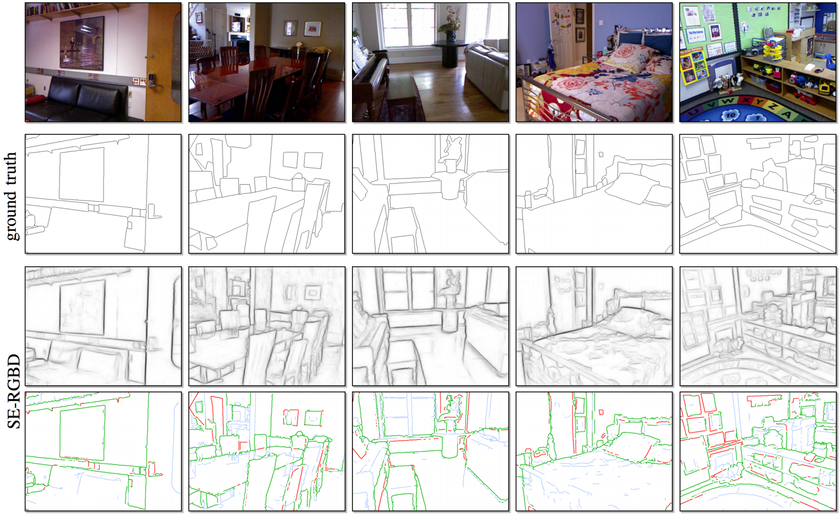
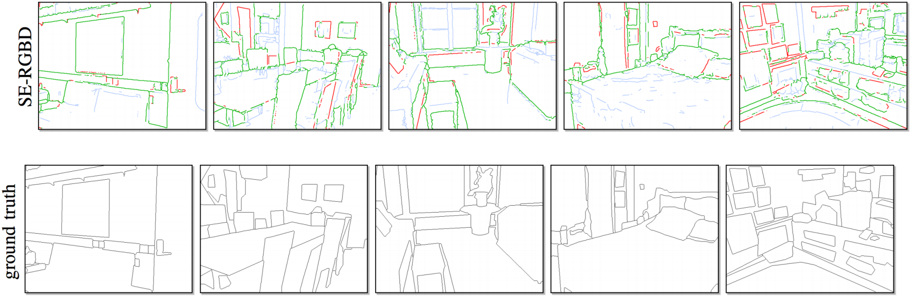


Figure: green=correct, blue=wrong, red=missing, green+blue=output edges

Evaluation

- **Recall:** How many of all **annotated** edges we got correct (best is 1)
- **Precision** How many of all **output** edges we got correct (best is 1)

$$\textbf{Recall} = \frac{\#\text{ of green (correct edges)}}{\#\text{ of all edges in ground-truth (second Row)}}$$



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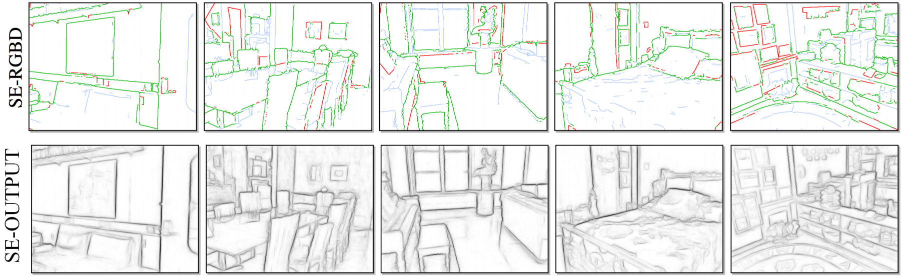

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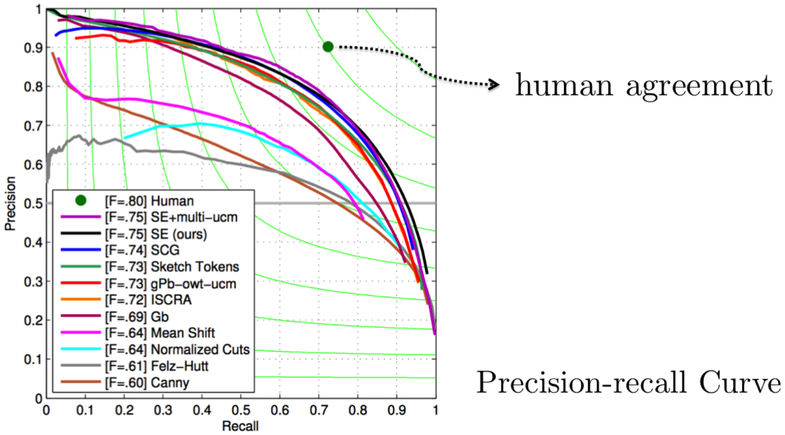

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- In this case, the method seems to work better for finding object boundaries (edges) than finding text boundaries. Any idea **why**?
- What would you do if you wanted to detect text (e.g., licence plates)?
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- What would you do if you wanted to detect text (e.g., licence plates)?
- **Think about your problem**, don't just use code as a black box
- **Great news:** This type of approach can also be used to detect objects (cars, cows, people, etc)! More about it later in class