

Can we do something cool with gradients already?

S. Avidan and A. Shamir

Seam Carving for Content-Aware Image Resizing

SIGGRAPH 2007

Paper: <http://www.win.tue.nl/~wstahw/edu/2IV05/seamcarving.pdf>

Simple Application: Seam Carving

- Imagine we want to rescale this by factor 2 in only one direction



Simple Application: Seam Carving

- Content-aware resizing



- Find path from top to bottom row with minimum gradient energy
- Remove (or replicate) those pixels

Simple Application: Seam Carving



Seam Carving

- A vertical seam \mathbf{s} is a list of column indices, one for each row, where each subsequent column differs by no more than one slot.
- Let G denote the image gradient magnitude. Optimal 8-connected path:

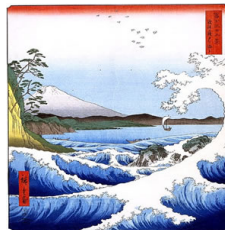
$$\mathbf{s}^* = \operatorname{argmin}_{\mathbf{s}} E(\mathbf{s}) = \operatorname{argmin}_{\mathbf{s}} \sum_{i=1}^n G(s_i)$$

- Can be computed via dynamic programming
- Compute the cumulative minimum energy for all possible connected seams at each entry (i, j) :

$$M(i, j) = G(i, j) + \min(M(i-1, j-1), M(i-1, j), M(i-1, j+1))$$

- Backtrack from min value in last row of M to pull out optimal seam path.

Seam Carving – Examples



Deep Learning Approaches



Project webpage: <http://www.wisdom.weizmann.ac.il/~vision/ingan/>

Edge Detection

State of The Art

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

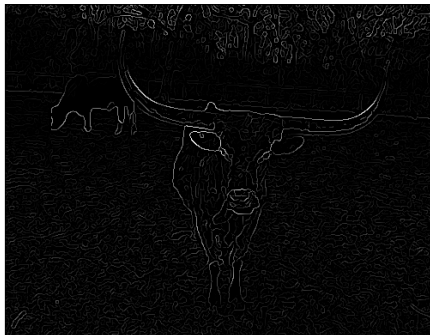


image gradients + NMS



Canny's edges

Testing the Canny Edge Detector

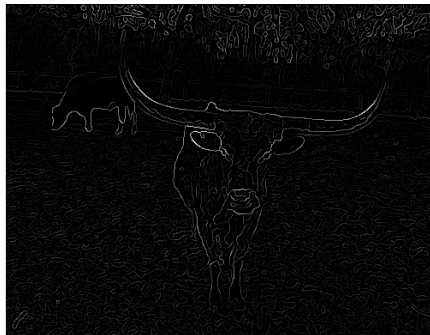


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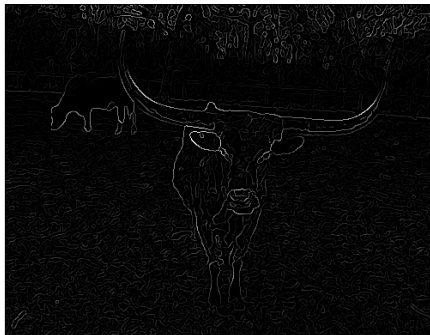


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Canny's edges

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

Annotate...

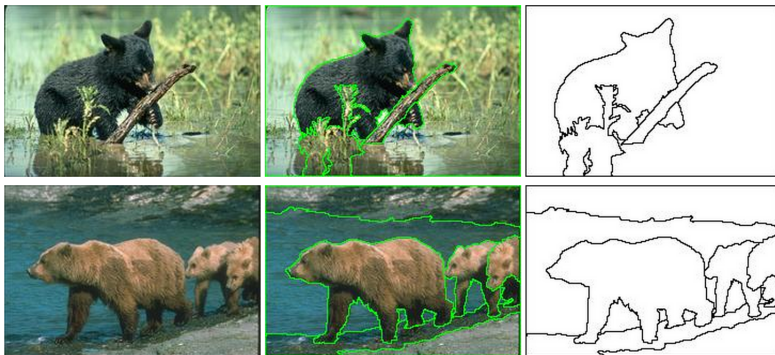
- Imagine someone goes and **annotates** which edges are **correct**
- ... and someone has:

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- ... and someone has:

The Berkeley Segmentation Dataset and Benchmark

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



... and do Machine Learning

- How can we make use of such data to **improve** our edge detector?

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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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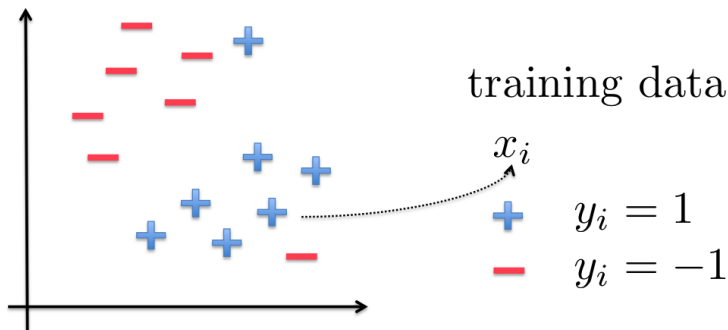
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- We are ready for math

Classification – a Disney edition (pictures only)

- Each data point \mathbf{x} lives in a n -dimensional space, $\mathbf{x} \in \mathbb{R}^n$
- We have many data points \mathbf{x}_i , and for each we have a **label**, y_i
- A label y_i can be either 1 (positive example – correct edge in our case), or -1 (negative example – wrong edge in our case)



Classification – a Disney edition (pictures only)

Let's think a bit:

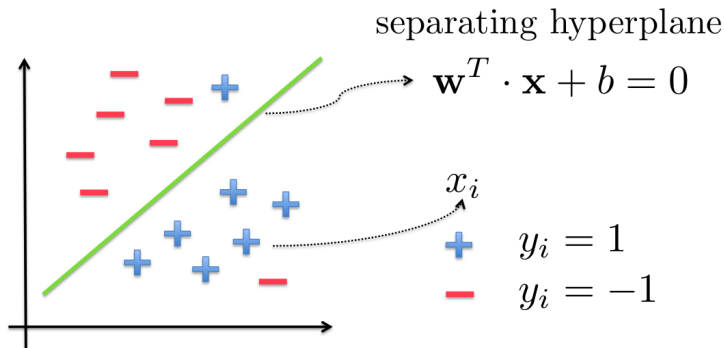
- Problem: I want to predict whether it will snow tomorrow. What should I do?

Classification – a Disney edition (pictures only)

Let's think a bit:

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

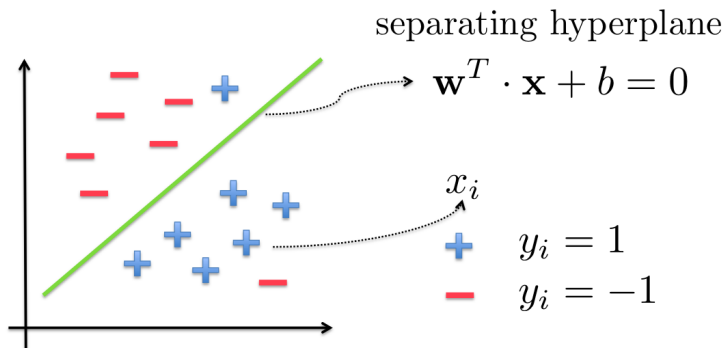
Classification – a Disney edition (pictures only)



- We define a **model**, for example a linear function:

$$f(\mathbf{x}; \mathbf{w}) = \mathbf{w}^T \mathbf{x} + b$$

Classification – a Disney edition (pictures only)



At **training** time:

Finding **weights** \mathbf{w} so that positive and negative examples are optimally separated

Classification – a Disney edition (pictures only)

Training:

- We typically have an objective or **loss function** that measures how well our model fits the data:

$$\text{loss}(\{\mathbf{x}, y\}_i; \mathbf{w})$$

- A very simple loss function is:

$$\text{loss}(\{\mathbf{x}, y\}_i; \mathbf{w}) = \sum_{i=1}^N (f(\mathbf{x}_i; \mathbf{w}) - y_i)^2$$

but this one is typically not well suited for classification (why?). Better loss functions: cross-entropy loss, hinge loss (used for SVMs), etc

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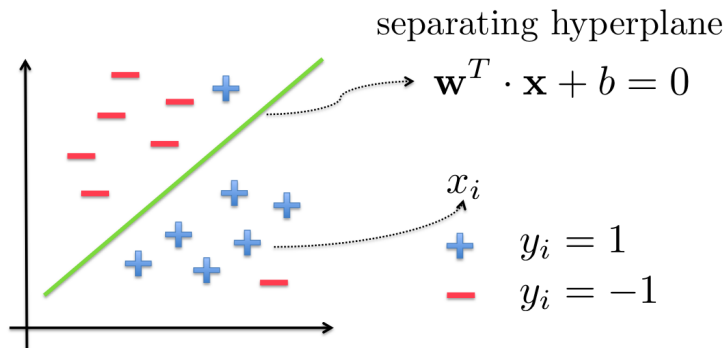
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- We are trying to find:

$$\min_{\mathbf{w}} \text{loss}(\{\mathbf{x}, y\}_i; \mathbf{w})$$

Classification – a Disney edition (pictures only)



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

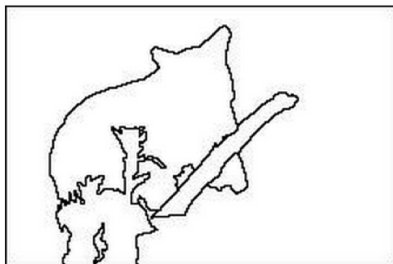
- How should we do this?

Training an Edge Detector

- How should we do this?



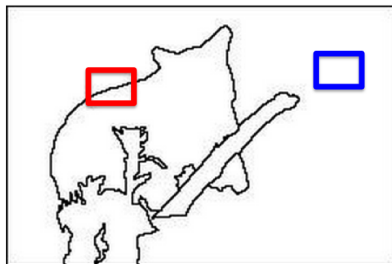
image



annotation

Training an Edge Detector

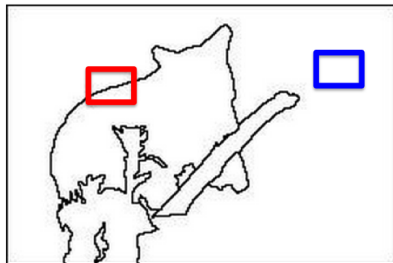
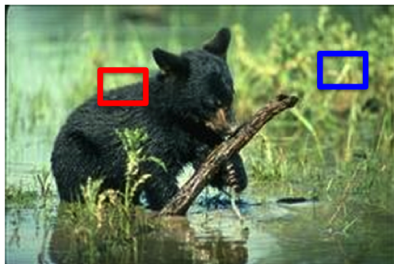
- We extract lots of image patches



We call each such crop an image patch

Training an Edge Detector

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



→ edge

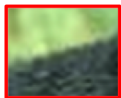


→ no edge

} 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 \mathbf{P}) to represent each one with a vector (representing measurements about the patch) \mathbf{x} . The simplest possibility in our case would be to just vectorize an image patch. Any problems with this?

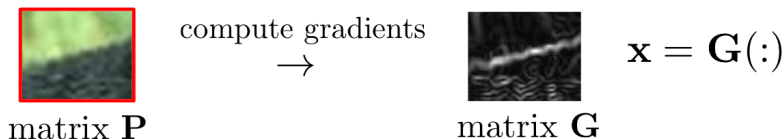


$$\rightarrow \mathbf{x} = \mathbf{P}(:)$$

matrix \mathbf{P}

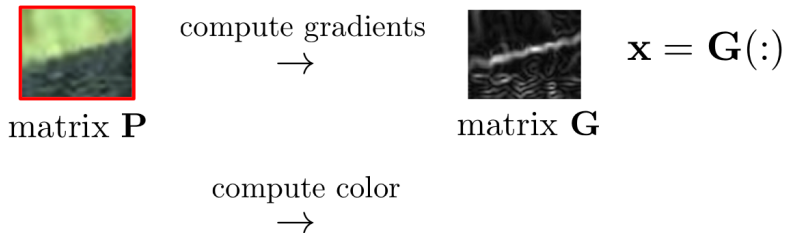
Training an Edge Detector

- 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



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.

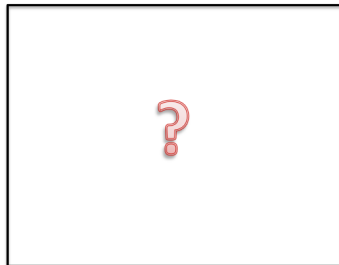


Using an Edge Detector

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



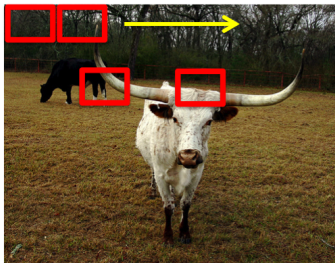
image



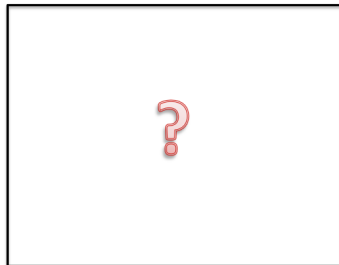
prediction

Using an Edge Detector

- We extract all image patches



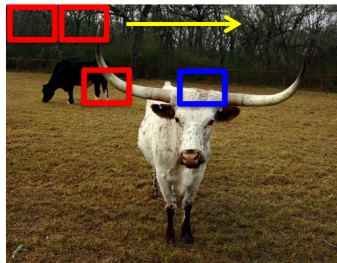
image



prediction

Using an Edge Detector

- We extract all image patches
- Extract features and use our trained classifier



image



prediction



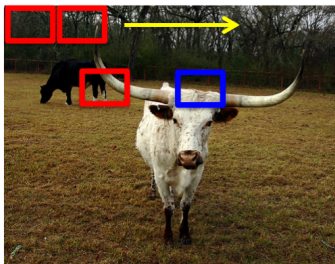
classify



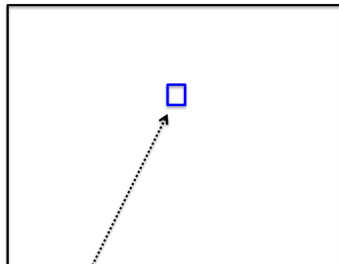
e.g. $\text{score} = \mathbf{w}^T \mathbf{x} + b$

Using an Edge Detector

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



image



prediction



classify
→

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

Comparisons: Canny vs Structured Edge Detector



image



image gradients



gradients + NMS



"edginess score"



score + NMS

Comparisons: Canny vs Structured Edge Detector



image



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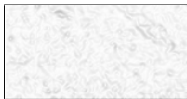


image gradient



"edginess" score



"edginess" score



score + NMS

Comparisons: Canny vs Structured Edge Detector



image

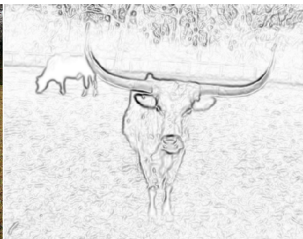
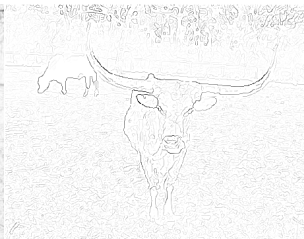
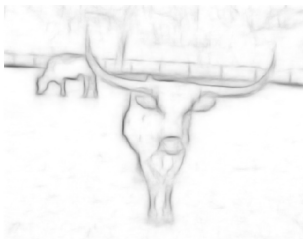


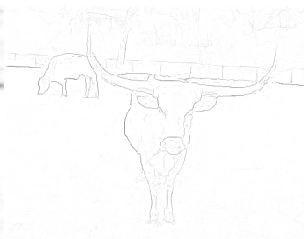
image gradients



gradients + NMS



"edginess" score



score + NMS

Comparisons: Canny vs Structured Edge Detector



image



image gradients



gradients + NMS



"edgeness" score



score + NMS

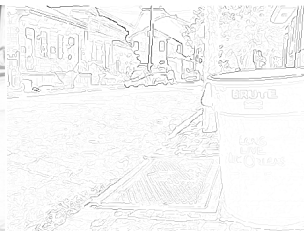
Comparisons: Canny vs Structured Edge Detector



image



image gradients



gradients + NMS



image gradient



"edginess" score



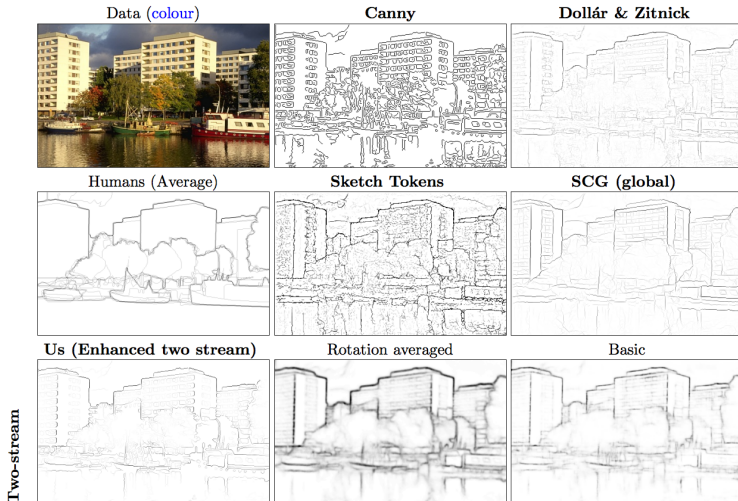
"edginess" score



score + NMS

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

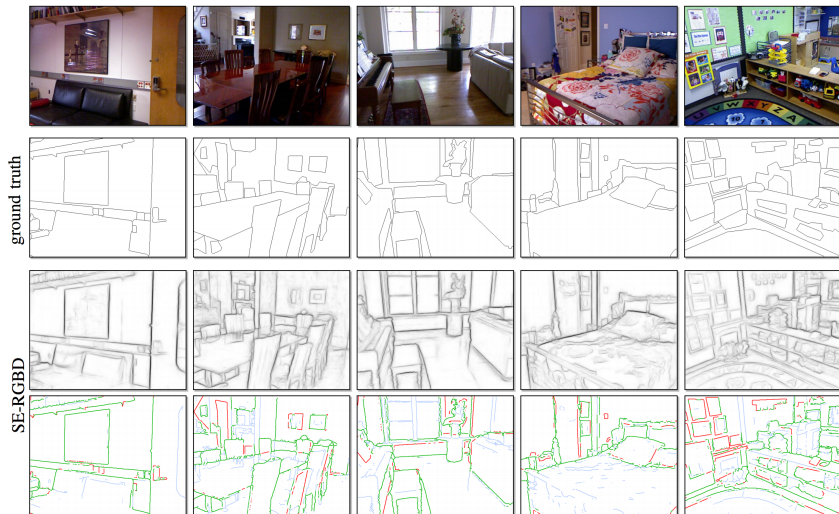
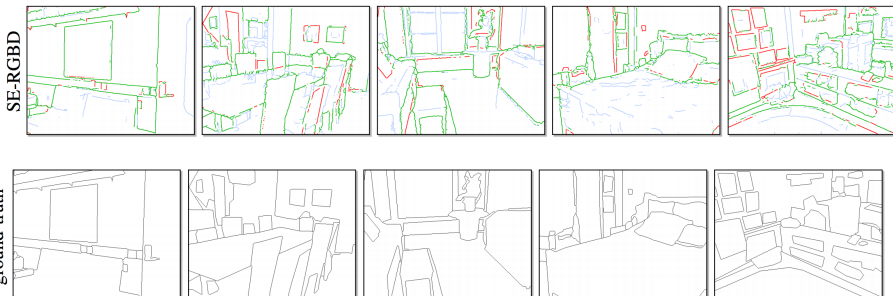


Figure: green=correct, blue=wrong, red=missing, green+blue=output edges

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)

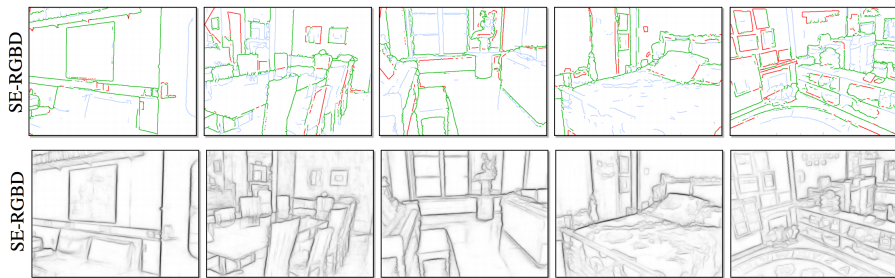
$$\text{Recall} = \frac{\# \text{ of green (correct edges)}}{\# \text{ of all edges in ground-truth (second picture)}}$$



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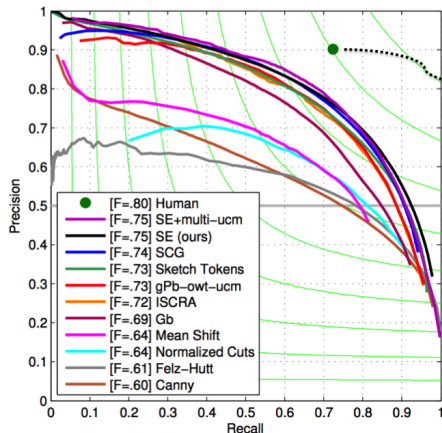
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human agreement

Precision-recall Curve

- **Trained detectors** (typically) perform better (true for all applications)
- 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)?
- **Think about your problem**, don't just use code as a black box

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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