18: Application Example OCR

Problem description and pipeline

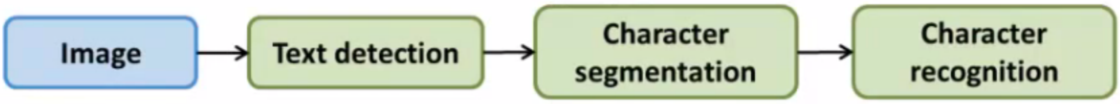
- Case study focused around photo OCR
- Three reasons to do this
  - 1) Look at how a **complex system** can be put together
  - 2) The idea of a machine learning **pipeline**
    - What to do next
    - How to do it
  - 3) Some more interesting ideas
    - Applying machine learning to tangible problems
    - **Artificial data synthesis**

What is the photo OCR problem?

- Photo OCR = photo optical character recognition
  - With growth of digital photography, lots of digital pictures
  - One idea which has interested many people is getting computers to understand those photos
  - The photo OCR problem is getting computers to read text in an image
    - Possible applications for this would include
      - Make searching easier (e.g. searching for photos based on words in them)
      - Car navigation
- OCR of documents is a comparatively easy problem
  - From photos it's really hard

OCR pipeline

- 1) Look through image and find text
- 2) Do character segmentation
- 3) Do character classification
- 4) *Optional* some may do spell check after this too
  - We're not focussing on such systems though



- **Pipelines** are common in machine learning
  - Separate modules which may each be a machine learning component or data processing component
- If you're designing a machine learning system, pipeline design is one of the most important questions
  - Performance of pipeline and each module often has a big impact on the overall performance a problem
  - You would often have different engineers working on each module
    - Offers a natural way to divide up the workload

Sliding window image analysis

- How do the individual models work?
- Here focus on a sliding windows classifier

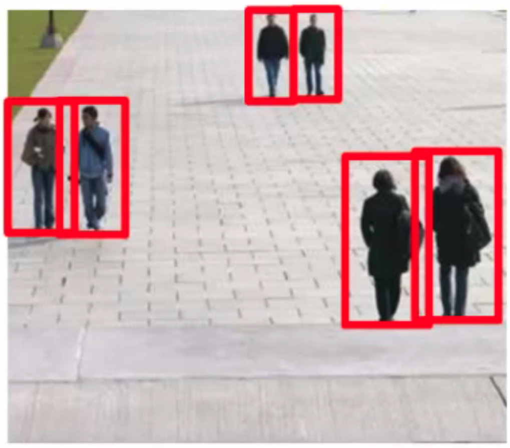
- As mentioned, stage 1 is **text detection**

  - Unusual problem in computer vision - different rectangles (which surround text) may have different aspect ratios (aspect ratio being height : width)
    - Text may be short (few words) or long (many words)
    - Tall or short font
    - Text might be straight on
    - Slanted

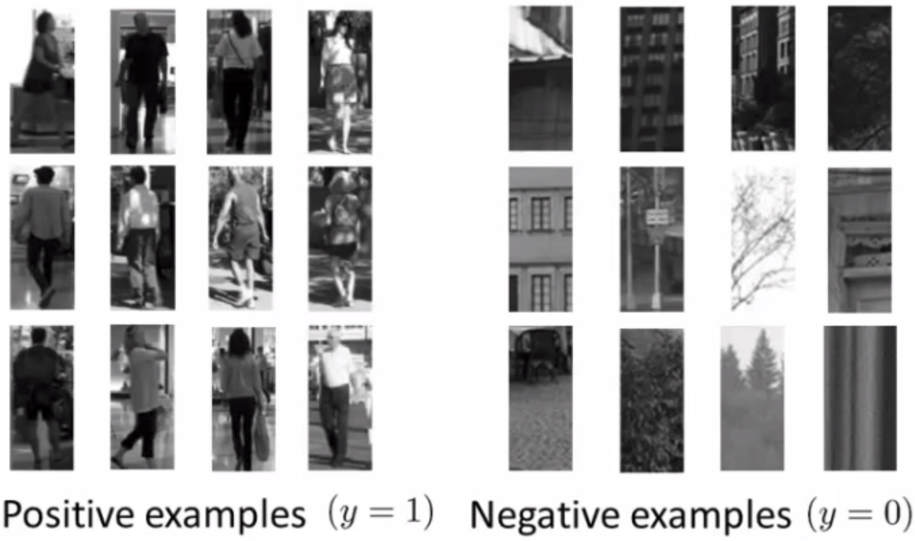
- Let's start with a simpler example

Pedestrian detection

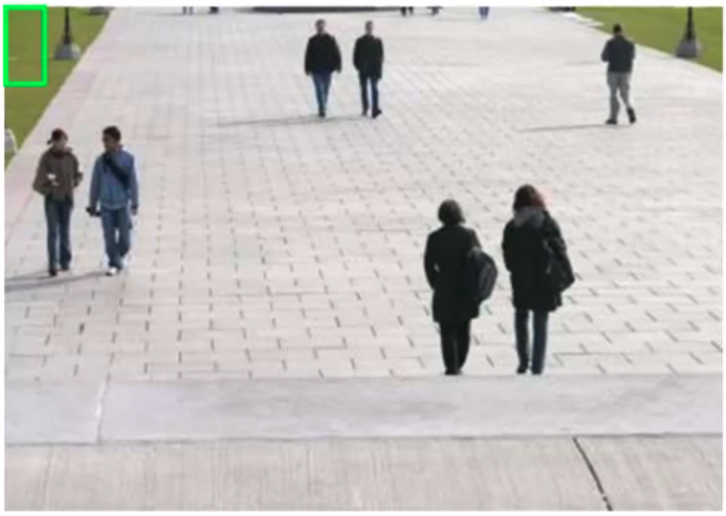
- Want to take an image and find pedestrians in the image



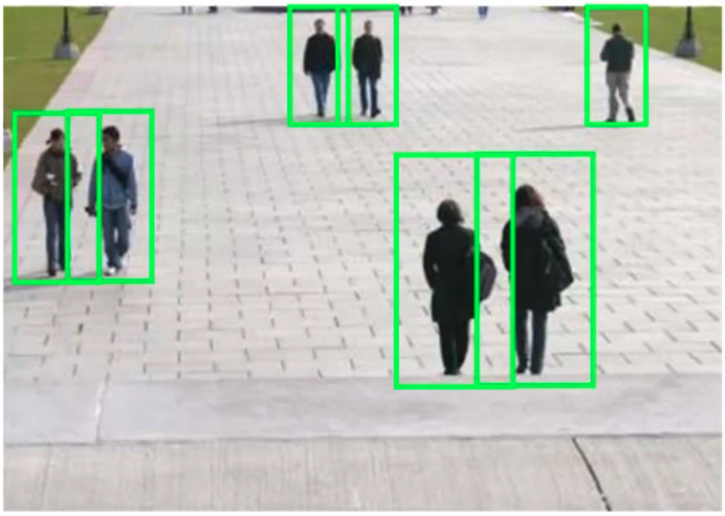
- This is a slightly simpler problem because the aspect ration remains pretty constant
- Building our detection system
  - Have 82 x 36 aspect ratio
    - This is a typical aspect ratio for a standing human
  - Collect training set of positive and negative examples



  - Could have 1000 - 10 000 training examples
  - Train a neural network to take an image and classify that image as pedestrian or not
    - Gives you a way to train your system
- Now we have a new image - how do we find pedestrians in it?
  - Start by taking a rectangular 82 x 36 patch in the image



    - Run patch through classifier - hopefully in this example it will return y = 0
  - Next slide the rectangle over to the right a little bit and re-run
    - Then slide again
    - The amount you slide each rectangle over is a parameter called the step-size or stride
      - Could use 1 pixel
        - Best, but computationally expensive
      - More commonly 5-8 pixels used
    - So, keep stepping rectangle along all the way to the right
      - Eventually get to the end
    - Then move back to the left hand side but step down a bit too
    - Repeat until you've covered the whole image
  - Now, we initially started with quite a small rectangle
    - So now we can take a larger image patch (of the same aspect ratio)
    - Each time we process the image patch, we're resizing the larger patch to a smaller image, then running that smaller image through the classifier
  - Hopefully, by changing the patch size and rastering repeatedly across the image, you eventually recognize all the pedestrians in the picture

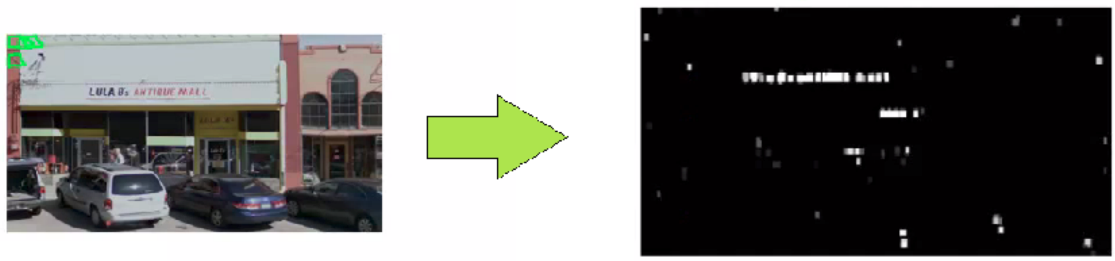


Text detection example

- Like pedestrian detection, we generate a labeled training set with
  - Positive examples (some kind of text)
  - Negative examples (not text)

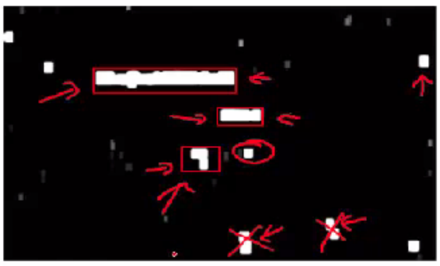
Positive examples $(y = 1)$ Negative examples $(y = 0)$

- Having trained the classifier we apply it to an image
    - So, run a sliding window classifier at a fixed rectangle size
    - If you do that end up with something like this



- White region show where text detection system thinks text is
    - Different shades of gray correspond to probability associated with how sure the classifier is the section contains text
        - Black - no text
        - White - text
    - For text detection, we want to draw rectangles around all the regions where there is text in the image
- Take classifier output and apply an **expansion algorithm**
    - Takes each of white regions and expands it
    - How do we implement this
        - Say, for every pixel, is it within some distance of a white pixel?
        - If yes then colour it white

- Look at connected white regions in the image above
    - Draw rectangles around those which make sense as text (i.e. tall thin boxes don't make sense)

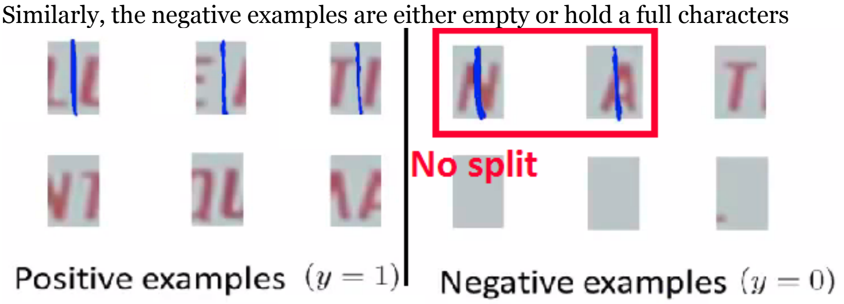


- This example misses a piece of text on the door because the aspect ratio is wrong
    - Very hard to read

Stage two is character segmentation

- Use supervised learning algorithm

- Look in a defined image patch and decide, is there a split between two characters?
    - So, for example, our first training data item below looks like there is such a split
    - Similarly, the negative examples are either empty or hold a full characters



- We train a classifier to try and classify between positive and negative examples
    - Run that classifier on the regions detected as containing text in the previous section
- Use a 1-dimensional sliding window to move along text regions
    - Does each window snapshot look like the split between two characters?
        - If yes insert a split
        - If not move on
    - So we have something that looks like this

Character classification

- Standard OCR, where you apply standard supervised learning which takes an input and identify which character we decide it is

    - Multi-class characterization problem

Getting lots of data: Artificial data synthesis

- We've seen over and over that one of the most reliable ways to get a high performance machine learning system is to take a low bias algorithm and train on a massive data set
    - Where do we get so much data from
    - In ML artifice data synthesis
        - Doesn't apply to every problem
        - If it applies to your problem can be a great way to generate loads of data
- Two main principles

    - 1) Creating data from scratch
    - 2) If we already have a small labeled training set can we amplify it into a larger training set

Character recognition as an example of data synthesis

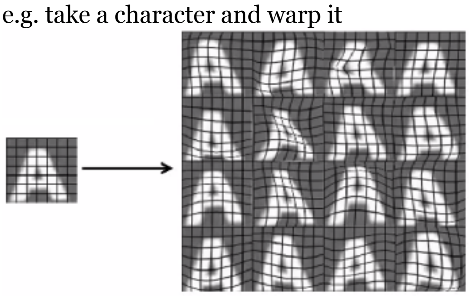
- If we go and collect a large labeled data set will look like this
    - Goal is to take an image patch and have the system recognize the character
    - Treat the images as gray-scale (makes it a bit easer)

Real data

- How can we amplify this
    - Modern computers often have a big font library
    - If you go to websites, huge free font libraries
    - For more training data, take characters from different fonts, paste these characters again random backgrounds
- After some work, can build a synthetic training set

Synthetic data

- - Random background
    - Maybe some blurring/distortion filters
    - Takes thought and work to make it look realistic
        - If you do a sloppy job this won't help!
        - So unlimited supply of training examples
    - This is an example of creating new data from scratch
- Other way is to introduce distortion into existing data
    - e.g. take a character and warp it



- - - 16 new examples
        - Allows you amplify existing training set
    - This, again, takes though and insight in terms of deciding how to amplify

Another example: speech recognition

- Learn from audio clip - what were the words
    - Have a labeled training example
    - Introduce audio distortions into the examples
- So only took one example
    - Created lots of new ones!
- When introducing distortion, they should be reasonable relative to the issues your classifier may encounter

Getting more data

- Before creating new data, make sure you have a low bias classifier

- Plot learning curve
- If not a low bias classifier increase number of features
  - Then create large artificial training set
- Very important question: How much work would it be to get 10x data as we currently have?
  - Often the answer is, "Not that hard"
  - This is often a huge way to improve an algorithm
  - Good question to ask yourself or ask the team
- How many minutes/hours does it take to get a certain number of examples
  - Say we have 1000 examples
  - 10 seconds to label an example
  - So we need another 9000 - 90000 seconds
  - Comes to a few days (25 hours!)
- Crowd sourcing is also a good way to get data
  - Risk or reliability issues
  - Cost
  - Example
    - E.g. Amazon mechanical turks

Ceiling analysis: What part of the pipeline to work on next

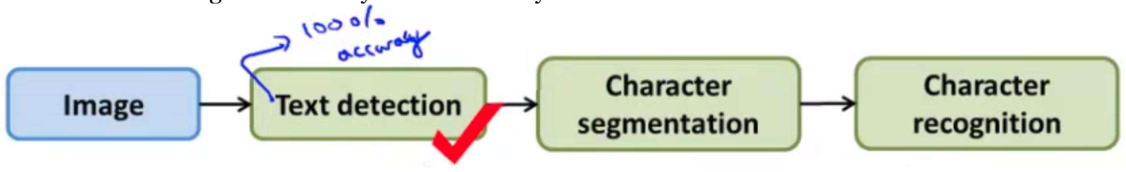
- Through the course repeatedly said one of the most valuable resources is developer time
  - Pick the right thing for you and your team to work on
  - Avoid spending a lot of time to realize the work was pointless in terms of enhancing performance

Photo OCR pipeline

- Three modules
  - Each one could have a small team on it
  - Where should you allocate resources?
- Good to have a single real number as an evaluation metric
  - So, character accuracy for this example
  - Find that our test set has 72% accuracy

Ceiling analysis on our pipeline

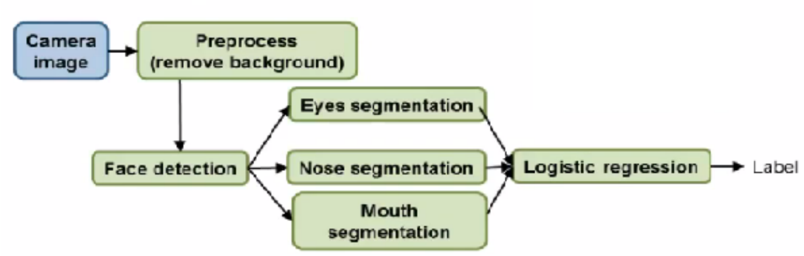
- We go to the first module
  - Mess around with the test set - manually tell the algorithm where the text is
  - Simulate if your text detection system was 100% accurate
    - So we're feeding the character segmentation module with 100% accurate data now
  - How does this change the accuracy of the overall system



  - Accuracy goes up to 89%
- Next do the same for the character segmentation
  - Accuracy goes up to 90% now
- Finally doe the same for character recognition
  - Goes up to 100%
- Having done this we can qualitatively show what the upside to improving each module would be
  - Perfect text detection improves accuracy by 17%!
    - Would bring the biggest gain if we could improve
  - Perfect character segmentation would improve it by 1%
    - Not worth working on
  - Perfect character recognition would improve it by 10%
    - Might be worth working on, depends if it looks easy or not
- The "ceiling" is that each module has a ceiling by which making it perfect would improve the system overall

Other example - face recognition

- NB this is not how it's done in practice



  - Probably more complicated than is used in practice
- How would you do ceiling analysis for this
  - Overall system is 85%
  - Perfect background -> 85.1%
    - Not a crucial step
  - + Perfect face detection -> 91%
    - Most important module to focus on
  - + Perfect eyes ->95%
  - + Perfect Nose -> 96%
  - + Perfect Mouth -> 97%
  - + Perfect logistic regression -> 100%
- Cautionary tale
  - Two engineers spent 18 months improving background pre-processing
    - Turns out had no impact on overall performance
    - Could have saved three years of man power if they'd done ceiling analysis