18: Application Example OCR

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Problem description and pipeline

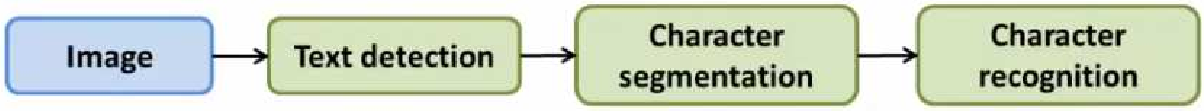
- Case study focused around photo OCR
- Three reasons to do this
    - 1) Look at how a **complex system** can be put together
    - 2) The idea of a machine learning **pipeline**
        - What to do next
        - How to do it
    - 3) Some more interesting ideas
        - Applying machine learning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

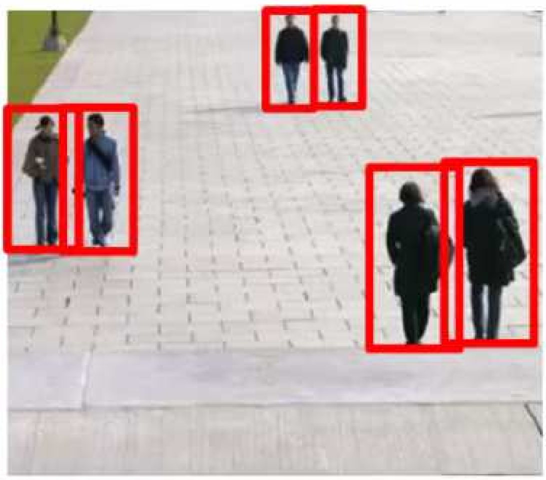
Sliding window image analysis

- 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

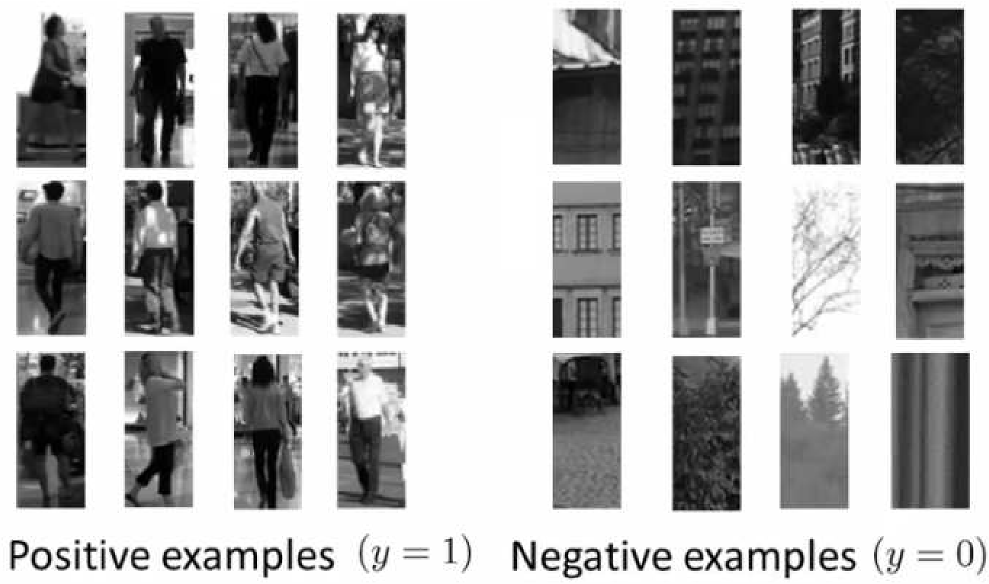
Pedestrian detection

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

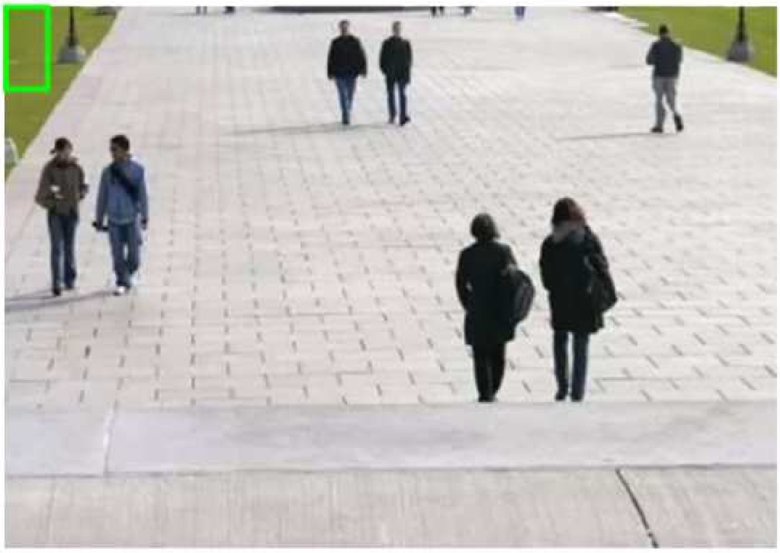


- This is a slightly simpler problem because the aspect ration remains pretty constant

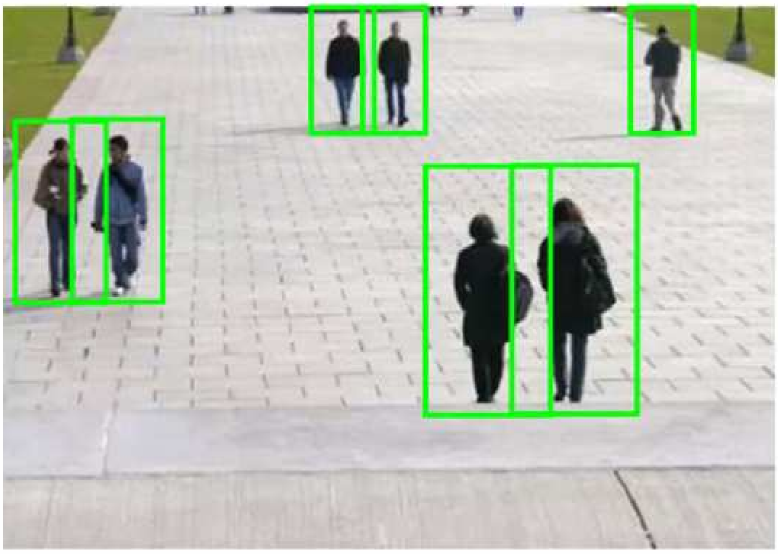
- Building our detection system
  - Have 82 x 36 aspect ratio
    - This is a typical aspect ratio for a standing human
  - Collect training set of positive and negative examples



  - 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

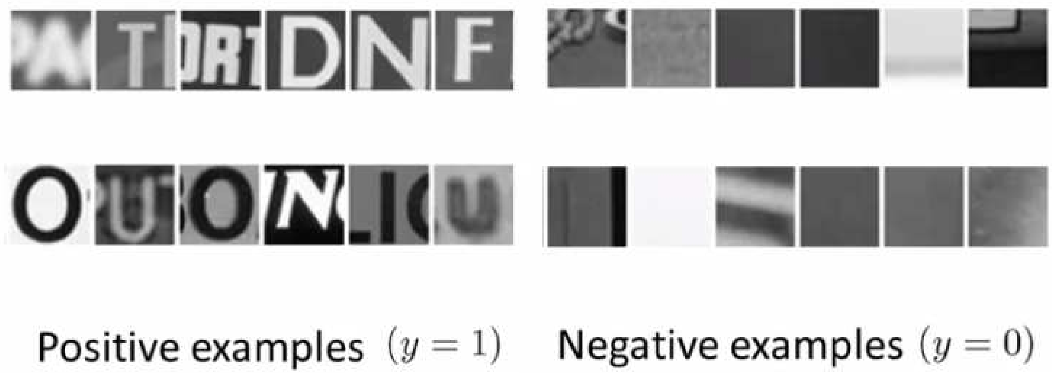


        - Run patch through classifier - hopefully in this example it will return y = 0
    - Next slide the rectangle over to the right a little bit and re-run
        - Then slide again
        - The amount you slide each rectangle over is a parameter called the step-size or stride
            - Could use 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

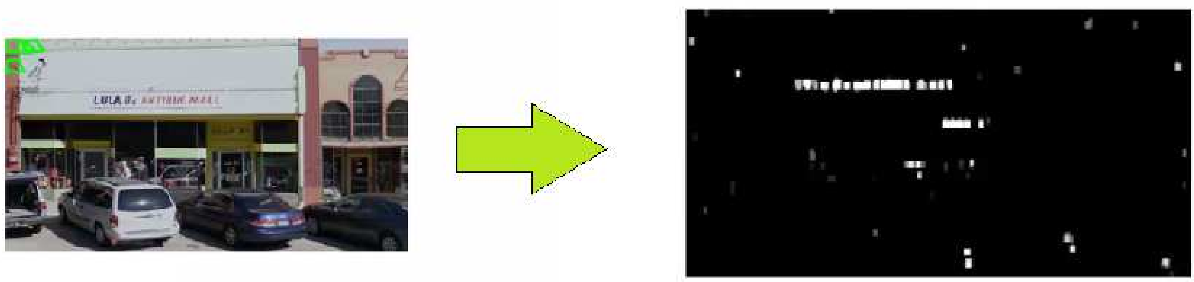


Text detection example

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



- 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



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    - 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

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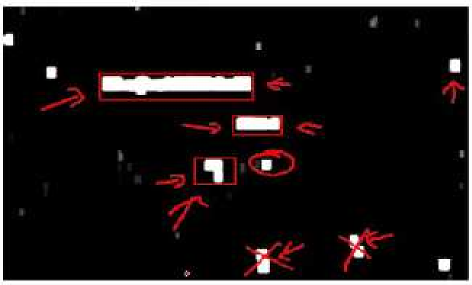
    - Look at connected white regions in the image above
        - Draw rectangles around those which make sense as text (i.e. tall thin boxes don't make sense)



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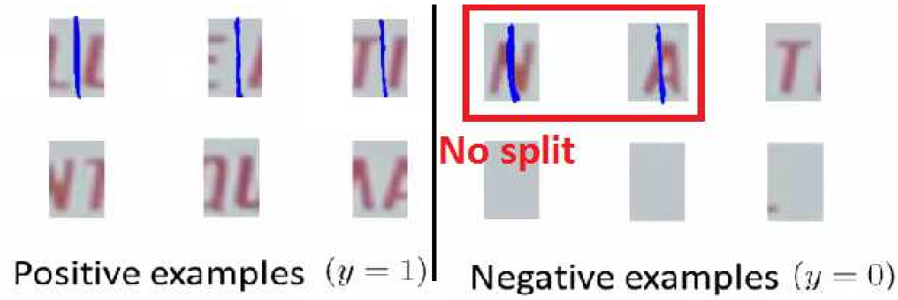
    - This example misses a piece of text on the door because the aspect ratio is wrong
        - Very hard to read

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 we can do artificial data synthesis
    - This doesn't apply to every problem
    - If it applies to your problem, it 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

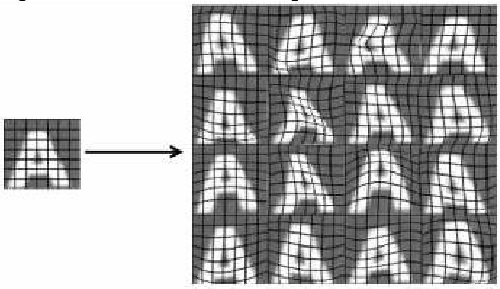
- If we go and collect a large labeled data set will look like this
  - The goal is to take an image patch and have the system recognize the character
  - Let's treat the images as gray-scale (makes it a bit easer)

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

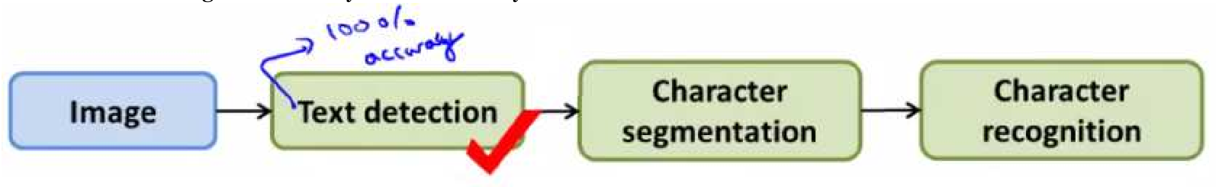
- Through the course repeatedly said one of the most valuable resources is developer time
    - Pick the right thing for you and your team to work on
    - Avoid spending a lot of time to realize the work was pointless in terms of enhancing performance

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

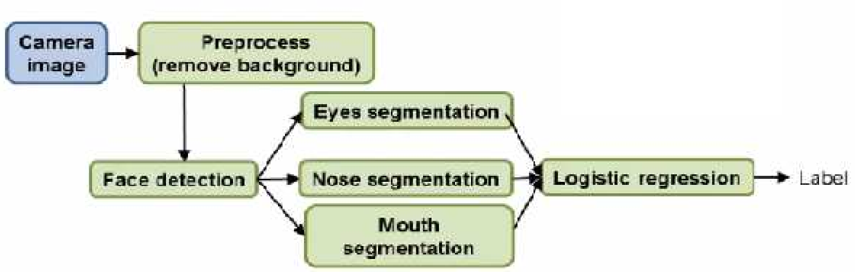
- We go to the first module
    - Mess around with the test set - manually tell the algorithm where the text is
    - Simulate if your text detection system was 100% accurate
        - So we're feeding the character segmentation module with 100% accurate data now
    - How does this change the accuracy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