Reducing the Pain of Parking using Machine Learning.

Intent

The search for parking spots adds to the tedium of commuting; current means of expediting search, such as occupancy level billboards outside parking lots, do not offer sufficiently specific information for the purpose of finding a spot quickly. We desire to enhance the specificity of occupancy information available to users through a machine learning-driven application[1]. Namely, we aspire to establish the following workflow:

User requests for spot-wise occupancy status through the application,
↓
picture of lot taken by a standard CCTV or dedicated camera,
and transmitted to associated *cloud-based deep-learning model*,
↓
spots in picture classified as empty or occupied by model,
↓
picture deleted, and user sent spatially-accurate abstraction of spot-wise occupancy.

Choice of Machine Learning Tool

The deep-learning model aforementioned refers to a convolutional neural network (CNN). CNNs are a class of artificial neural networks, which are statistical models that are designed to fit complex nonlinear hypotheses to data and improve them iteratively and automatically. CNNs in particular are currently state-of-the-art in computer vision-related tasks; our task is one of binary image classification.

Before a CNN is ready for use in ascertaining the occupancy of a parking lot from its picture, it must be trained to do so. This training process requires a large number of *training examples* – namely, different pictures of the parkling lot which each have their spot-wise occupancy manually labelled. During the training process, the CNN will learn what aspects of the picture of a spot imply it is occupied or empty through relating the images to their labels. This training process can take several hours or days, depending on the number of training examples at hand.

After training, the CNN will be able to create predictions with an estimable level of accuracy. Per-image prediction is almost instantaneous.

Partial Proof of Concept

A large dataset concerning two parking lots, PKLot, is publicly available. The lots are pictured below[2]. The dataset contains about 700,000 images of spots between the two lots, taken over a month. It is robust in the sense that it contains images from a wide range of light and weather conditions.

[1] In this document, an individual parking space is referred to as a parking *spot*, and spots constitute a parking *lot*.

[2] Almeida, P., Oliveira, L. S., Silva Jr, E., Britto Jr, A., Koerich, A., (2015). PKLot's two parking lots. [image] Available at: https://web.inf.ufpr.br/vri/databases/parking-lot-database/ [Accessed 26 Feb. 2018].

Parking1a

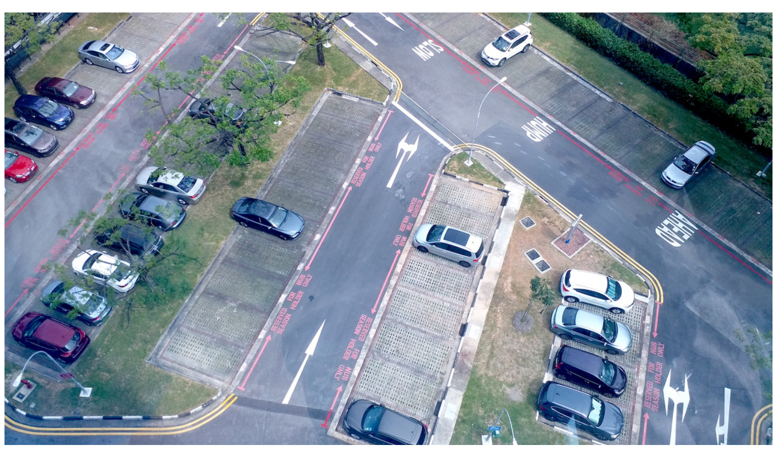
Parking1b

Parking2

We created a CNN for each of these parking lots, and achieved prediction accuracies of 99+%, which translated to the misclassification of about 300 spots in requesting for the prediction of the state of about 175,000. It is therefore without question that CNNs are apt tools for this task. It will be fruitful to understand how this success can be replicated in the local context, where we have control over collection of data.

Data Collection: Obtaining Images of the Parking Lot

We intend to use an Arduino Yun (an inexpensive microcontroller board with WiFi support), connected to a 720p USB webcam and a 64 GB microSD card to capture pictures of our selected lot: we will perch the device at a vantage point overlooking the parking lot adjacent to Block S17. The following is an image from this point, taken at 720p.



Some context of the vantage's location:

Images will be taken by the device at five minute intervals for most of the working day, for four weeks. They will be wirelessly transmitted to a private DropBox account, and will also be encrypted and stored in the attached microSD card for backup purposes.

When the observational period is over, all images will be downloaded and then deleted from the microSD card and DropBox account. Before further use, they will be processed:

(An aside) privacy concerns regarding identifiable features of licence plates and persons. Given the resolution of the camera, and the distance and angle of the vantage from the lot, little has to be done to obscure such features. Therefore it will be sufficient to apply a light blur to images before storage:

Training the CNN, on the Cloud.

Training and configuration of CNNs will be done online on Floydhub, which means that we will ultimately be storing all collected image data on a private repository on the cloud. These images will stay there until this project culminates, likely in August 2018. There are a number of reasons for these choices:

1. Great computing power is available on the cloud inexpensively; it will save us many hours in training.
2. Training multiple configurations of the same CNN concurrently is possible – on a personal computer, it is not. Again, time will be saved.
3. Working on the cloud allows all involved in the project to collaborate seamlessly, and is the norm in industry.
4. Moving development to the cloud will better prepare us for what is below.

Responding to User Requests, on the Cloud.

Tools like Amazon's Amazon Web Services (AWS) allow us to put a CNN on the cloud for prediction purposes. They offer serverless services that can scale dynamically in capacity in response to demand, and are only billed per user request. Our application intends to harness this tool in its back-end.

Conclusion

Increasing the resolution of information available to those seeking a parking spot is not the only implication of this project, especially given that NUS' parking lots are organized appropriately for demand. Rather, we see this project as a capability-building exercise; a segue into greater problems that can be addressed by machine learning – either by us or those who take reference to our experiences in the future.
How would you like me to name-drop OSHE's bus request here? Will need you to talk about them earlier first.