Project 1: The State Classification Challenge

Introduction:

Object recognition for coarse estimation of the object type has achieved human-like accuracy. However, for robotics, recognizing object type alone is usually not sufficient. When perform a manipulation tasks, a robot would need to know if the desired outcome of the manipulation has been reached or not. This would require fine-grained object state recognition. It is especially important for robotic cooking.

Robotic cook is very useful especially for seniors and people with severe physical disabilities. Since cooking involves many manipulation tasks that requires physical interaction, such as cutting, it is still very challenging for a robot to perform those tasks in a general kitchen setting [1]. It is well-known that robotic cooking faces tremendous challenges in basic physically-interactive manipulations [2-4] and task-oriented grasping [5-11]. However, the semantic flow of the cooking process has not been fully explored [28].

To perform a cooking task, a robot would need to know not only the cooking process such as a recipe, but also the innate relationship between cooking utensils and food ingredients [12,13]. Once the innate relationship between objects are leaned, it could be used to help robots to recognize the right object and carry out the correct manipulation motions [14].

To learn those relationships, instructional cooking videos on YouTube and many cooking sites could be automatically process to extract the relationships between cooking utensils and food ingredients along with cooking actions [15]. The learned knowledge of cooking is represented by a functional object-oriented network (FOON) [16, 17]. Different from other knowledge representations for service robots [18], FOON connects objects/states and motions.

Object state plays an important role in FOON as it does in cooking. For example, a robot should recognize if an onion is a full onion or a half onion since the robot needs to grasp the onion differently. The robot should also recognize if the onion is a peeled onion or an unpeeled one since the processing steps would be different for the two cases.

An initial state recognition for cooking has been carried out in a small scale [19,29]. In the paper, objects and ingredients in cooking videos were explored and the most frequent objects were analyzed. The paper summarized and examined 11 states from the most frequent cooking objects. A dataset of images containing those objects and their states was created [20].

The state recognition could be tackled using many different convolutional neural networks. In [19], A Resnet [21] based deep model was used and initialized with Imagenet weights and trained on the dataset of 11 classes. VGG nets [22], GoogleNet [23], Inception V3 [24] have also been used.

State recognition is related to captions for images and videos. In [25] Yao et al. use attributes and their interactions with deep networks to provide captions. Other work such as [26], and [27] perform multi-label classification on a single image using RNN- and CNN-based deep architectures. Although these papers provide various labels for an image, they do not consider states of objects as another label for the image.

1) Project Goal:

In this project students will be designing a deep convolutional neural network to classify an image of a cooking object to one of its states. For example given an image of a *"sliced tomato" or "sliced bread"*, the network should give as output *"sliced"*.

2) Project Dataset:

The dataset contains 17 cooking objects (chicken/turkey, beef/pork, tomato, onion, bread, pepper, cheese, strawberry, ...) with 11 different states (whole, julienne, sliced, chopped, grated, paste, floured, peeled, juice, mixed, other). This dataset contains 9309 images. The dataset can be downloaded from https://drive.google.com/file/d/1HU0Z3X3OltW8oUlW_Kkqsz_6kA_ma2tX/view. For more information about the dataset we refer the students to https://arxiv.org/abs/1805.06956/.

Other food-related datasets:
http://pic2recipe.csail.mit.edu/
http://www.ivl.disco.unimib.it/activities/food-recognition/

3) Project Description:

Part 1 Data Annotation (20 pts):

The data annotation includes one batch of approximately 200 frames (images). You will be assigned one (or two) objects with a google drive link which contains a directory of frames (images). You have to annotate all frames containing the objects assigned to you. To annotate you need to create a bounding box around the object (e.g. potato) in the frame and also specify the state (e.g. sliced) of that object. You should do this for every frame that contains the assigned object. After annotation you should dump the results into PASCAL VOC format. For annotation you need to create an account in the cvat.ai website. A video has been uploaded to canvas that explains how to create an account in cvat.org, how to create a task, how to annotate and finally how to dump the results. You need to create a zip file from the dumped annotations files and upload it on canvas. After annotations are done, each student will be given a random set of videos from other students to check for annotation errors. Students could lose points for poor annotation.

The dataset assigned to you will be email to you by the TA.

Part 1 submission
- You should submit all labels of the frames (15 pts)
- You will evaluate other student's labels and provide corrections (5 pts)

Part 2 Neural network design and training (50 pts):

A sample Python code for training a neural network for state classification will be given to you. You should build upon the code and create your own convolutional neural network. A data set will be provided to you for training and validation. You should split the data given to you into train and validation data and use train data for training your model. You should validate your model during and after training with your validation data. You should add convolutional layers, pooling layers and test various deep learning techniques to improve your results as much as possible. Failure to add various layers will result in a deduction of your points. ***The code should be implemented in Python. You can Tensorflow but no other programming language or platform is acceptable.*** We will test your code on unpublished test data and report the results to you 2 days after your submission. If you substantially change the code or have your own implementation of the model, you have to provide instructions on how to run your code and also help files (readme.txt and requirements.txt if needed) and a test script to run on the test portion of the dataset. If your program is not easily test-able on the test set, you will loss 10 pts.

Part 2 Submission:
- Training code (30 pts)
- Testing script of the train model. It should include loading a dataset and provide outputs. (5 pts)
- Training and validation results

Part 3 Improvement and comparison (30 pts)

To improve your neural network's performance, you should perform at least the follow techniques:

- data augmentation (6 pts)
- different drop rates (4 pts)
- batch normalization (5 pts)
- use Inception module (5 pts)
- use residual connections (5 pts)

The remain 5 pts is based on your model's classification accuracy of on unpublished test data.

Your submission should include
- Source code for training the best model
- Your best trained model and a architecture drawing of the model

- Test script load your best trained model so that we can test it on the test data
- Figures showing the performance differences using the required techniques

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