# **Item Removal Detection for Retail Environments by using Neural Networks**

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**Abstract**

*Inspired by the recent success of Recurrent Neural Networks (RNN) and Convolutional Neural Network (CNN) in classification, localization, and segmentation, we propose a neural network application in item removal detection for retail environments. Different Amazon Go which relies on both sensor fusion, and deep learning algorithms, we focus on only use only deep to enable customers to explore and shop more efficiently. Unlike traditional image classification, the input into our network is a steam of video while the output is the prediction of class of removed items as well as number of removed items. We will implement popular video classification algorithm, compare the performance, and explore method to enhance the prediction result. Specifically, C3D, two stream convolutional networks, long term recurrent convolutional network will be implemented. Eventually, we will explore the pros and cons of each networks and try to find the best network to solve this item removal detection problem.*

# Introduction

# Related work

So far, Convolutional Neural Networks (CNNs) [1] have outperform most other algorithms in understanding image contents and shows the state-of-the-art performance in image classification, localization, segmentation, detection, and so on [2] [3] [4] [5] [6] [7]. Under these condition, CNNs is power enough to extract image feature [8].

However, currently there is not a single video classification benchmark that perform at the same level of current image data set. First, compare to images, videos are significantly harder to annotate. It takes large amount of time to collect large enough of data to feed CNNs. Second, videos have more dense information compared to image and it is much hard to classify. Last but not least, each frame of the video has temporal and spatial relationship.

Currently, there are three major approach to solve video classification problems: C3D, Long-term Recurrent Convolutional Networks, two-steam Convolutional Networks.

C3D stands for deep 3-dimentionsal convolutional networks (3D ConvNet) [9]. Different from image CNNs which apples a 2D convolutional networks, C3D simply stack each frame of video together into 3D space and apply a 3D convolutional filter in all intermediate hidden layers and some fully connected layers at the end.

Two-steam convolutional networks incorporate spatial and temporal networks [10]. Unlike C3D which feed stacked images which is extracted from video, Two-steam convolution networks combine both spatial stream convent from single frame and temporal steam convent from multi-frame optical flow. The result from both CNNs will be concatenated together and feed into fully connected layer eventually. Another two steams approach is also developed for large-scale video classification by using a context steam that learns features on low-resolution frames and a high-resolution fovea steam that only operates on the middle portion of the frames [11]

Inspired by RNNs which are widely used in natural language processing (NLP) [12], Long-term recurrent convolutional networks are also developed for visual recognition and description [13]. Different from CNNs, RNNs use LSTM structure. At each time step, it feeds in both the hidden information from last time step as well as one frame from the video.

# Methods

We first use pre-trained model from tensorflow for video classification dataset.

We first implement the C3D because it is easy to implement by only adding a depth direction for 3D convolution. Convolutional layer dimension was finely tune to 3x3x3 which give the best performance. Stochastic gradient decent is use to only update the parameters for the last fully connected layer while keeping the hidden layer parameters fix. Random search is used for find the best regularization to prevent overfitting.

Second, we are planning to implement two-steam by using two-stream architecture for video recognition. Similarly, we will use pretrained model. We will form two steam convolutional networks for spatial steam from single frame and temporal steam from multi frame optical flow. Eventually, two frame results will be either concatenated together through fully connected layer and apply stochastic gradient decent the minimize the softmax loss function.

Third, we will implement Long-term recurrent convolutional networks. Each RNN layer will use LSTM structure to prevent gradient explosion as well as gradient vanishing. Similarly to CNNs case, hidden layer RNNs will from pre-trained model and we will fine turn the fully connected layer parameter from our training data set.

# Dataset and features

# Experiments/Results/Discussion

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