Automated Lip Reading using Deep Reinforcement Learning

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1. Introduction

Lip reading, also known as audio-visual recognition, has been considered as a solution for speech recognition tasks, especially when the audio is corrupted or when the conversation happened in noisy environments. It can also be an extremely helpful tool for people who are hearing-impaired to communicate through video calls. This task, however, is challenging, due to factors such as the variances in the inputs (facial features, skin colors, speaking speeds, etc.) and the one-to-many relationships between viseme and phoneme (Chung et al., 2016; Garg et al., 2017). This project aims to tackle lip reading by modeling an agent that is capable of learning the features by interacting with the environment using reinforcement learning methodology.

Task Description: Given a video of a speaker with no audio file and no hidden facial features (especially the lip region), the system transcribes lip movements into text.

2. Related Works

Most of the works done in lip reading focused on using either variations of Hidden Markov Model (Rekik et al., 2015; Gergen et al., 2016) or deep neural network models (Krizhevsky et al., 2012; Simonyan and Zisserman, 2015; Garg et al., 2017). Chung et al. developed a *Watch, Listen, Attend and Spell* network which utilises a novel dual attention mechanism in addition to LSTM networks. Deep reinforcement learning, on the other hands, is becoming more popular, especially for tasks concerning language generation (Young et al., 2018). Razanto et al. applied reinforcement learning to train RNN-based models for several sequence generation tasks, i.e. text summarization, machine translation and image captioning. The ultimate goal of an automated lip reading system is to generate text from lips movement; thus, it fits into the tasks where deep reinforcement learning can be applied.

3. Methods

3.1. Dataset

For this project, I proposed using two datasets, the GRID dataset (available at http://spandh.dcs.shef.ac.uk/gridcorpus/) and the BBC-Oxford LWR dataset (available at http://www.robots.ox.ac.uk/~vgg/data/lip_reading_sentences/). The two datasets are similar in the way that both are designed for learning lip reading at sentence level, instead of just words

and utterances. Each dataset consists of videos with visible facial features and annotated text transcriptions of the content.

3.2. Video Processing and Image Encoder

The video is first separated into still frames (images). For both the LWR and GRID dataset, I will crop the image so that it focused on the lips region only. There are two approaches for this: i. Use a face-detection module in OpenCV, and ii. Use the dlib library to detect the mouth region. I have implemented both and decided to go with the second approach since it gave more accurate results. Each (lip-region) image is then passed into the ConvNet architecture - in this case, a VGG-16 model using pre-trained weights, which outputs the vector representation encoding the features of mouth region.

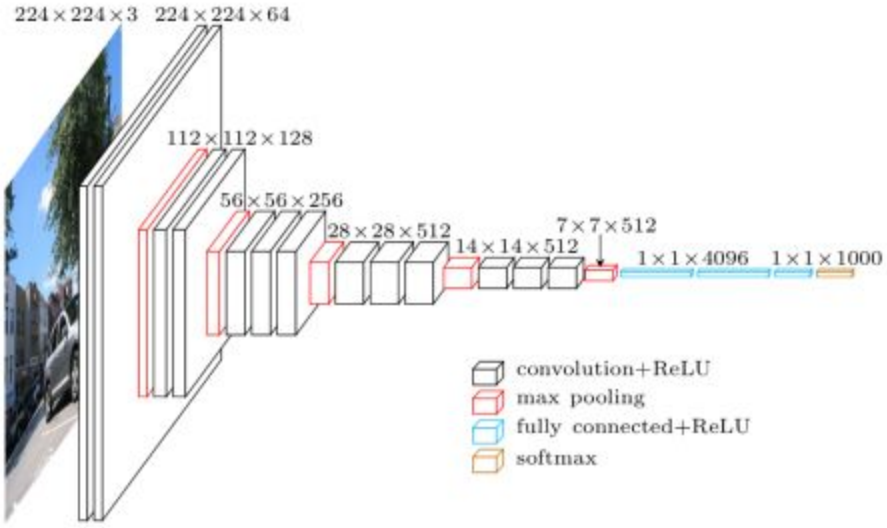

Figure 1. VGG-16 model for Image Encoder (with 13 convolutional layers followed by 3 fully-connected layers). Image Credits: https://blog.heuritech.com/2016/02/29/a-brief-report-of-the-heuritech-deep-learning-meetup-5/

3.3. Reinforcement Learning Methods

In order to use a reinforcement learning method to solve this task, it is important to cast the problem in the reinforcement learning framework (Sutton and Barto, 1998). The components of a reinforcement learning task are an agent, an environment, a set of actions and policies, and a reward. In this framework, the lip reading model acts as an agent, which interacts with the external environment (the input vectors encoding lips region). By interacting with the environment, the agent learns the best policy (model's parameters) by picking an optimal action (refers to predicting the next word in the sequence at each time step) that maximizes the reward. In order to promote lip reading at sentence level, a reward is only given when the whole sentence is output.

3.3.1 Deep Q-Network (Value-based RL)

Deep Q-network (Mnih et al., 2015), is a method that combines reinforcement learning with deep neural network. In *Human-level control through deep reinforcement learning,* Mnih et al. used the deep convolutional network to exploit the local spatial correlations presented in the classical Atari 2600 game. For this project, instead of using convolutional network, I will replace it with the recurrent neural network with LSTMs to perform sequence level training in text. In addition, I will also implemented Experience Replay, which allows the network to train itself using stored memories from its experiences, and the second 'target' network (to compute the the target Q-values during each update.)

Word Error Rate, a common evaluational metric in tasks concerning language generation, will be used to measure the performance of the network.

3.3.2 Policy Gradient

(Ranzato et al., 2016 section 3.2.1 did a terrific job on explaining this. I will just summarize the main point.) The reward function is BLEU (bilingual evaluation understudy) which is very popular metrics for tasks like machine translation or language generation in general. "During training we choose actions according to the current policy and only observe a reward at the end of the sequence … by comparing the sequence of actions from the current policy against the optimal action sequence." In other words, we want to minimize the loss function:

$$L_\theta = -R(w_1, ..., w_T) \times log\, P(w_{t+1} \mid \theta)$$

One problem with this method is that for a large output space (e.g. words in vocabulary), the method is very unstable. Solution: Add a baseline. The loss function now becomes:

$$L_\theta = -(R(w_1, ..., w_T) - \overline{r_{t+1}}) \times log\, P(w_{t+1} \mid \theta)$$

With $\overline{r_{t+1}}$ being the average reward at time t + 1. There are many ways to determine this number. In this project, I will use estimate this baseline using a linear regression model. (The parameters of this model are trained by minimizing the mean squared error $\|\overline{r_t} - R\|$. The purpose of this baseline is to either "encourage a word choice w_{t+1} if R > $\overline{r_{t+1}}$ or discourage it if R < $\overline{r_{t+1}}$.

3.3.3 Asynchronous Actor-Critic Agents (A3C)

(to be updated)

3.4. API for pre-trained network

Since I want my lip reading system to be integrated into video call and/or lip reading applications, I will build a streaming API for the network pre-trained using the BBC-Oxford LWR dataset.

4. Project Timeline

Date	Tasks	Status
04/12	Proposal draft submitted to Ursula via GitHub (https://github.com/DungLe13/CS-4161/blob/master/Project/Proposal.pdf) Implementation of video processing and image encoder	Completed
04/19	**Milestone 1**: Completion of video processing and image encoder (GRID corpus is processed)	Completed
04/26	Update proposal to reflect the actual code Implementation of Policy Gradient method	
05/03		
05/10	Update proposal on Asynchronous Actor-Critic Agents Implementation of Deep Q-Network	
05/17		
05/24	Implementation of Asynchronous Actor-Critic Agents	
05/31		

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