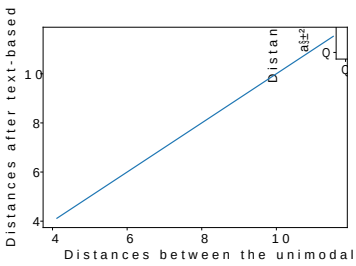
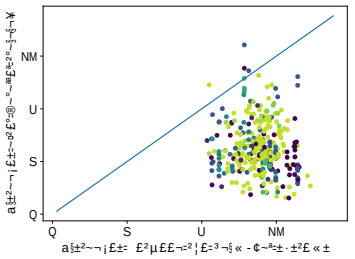


(a) Speech after text



(b) Speech after parallel

Fig. 3: Distance comparison between text and speech embeddings before and after multiview training (each point represents an utterance)

sufficient amount of speech data, the unimodal speech-only training achieves above 60% accuracy. Our observations from the first experiments still hold for this case, i.e. text-based pretraining of the classifier and then learning the speech encoder ("Speech after text") helps improving the performance and in the very low-resource case (less than 30 hours), additional fine-tuning (Speech after parallel) with the parallel data helps further increasing the accuracy.

In Table 2, we report the true text and ASR-text based testing of the multiview model for the second set of experiments performed on ASR-based speech embeddings. In terms of the results, the major difference between the previous experiment and the current one is that here, speech-only results approach to the true text based performance and they are significantly better than ASR-text based testing. This shows that we can achieve better performance than an ASR+NLP system with speech-only training when ASR-based speech embeddings are used.

When we compare "NP speech" and "Speech after parallel" setups, for the low-resource case, we get between 5-20% relative improvement in accuracy after fine-tuning with parallel data. The largest gain is observed when we have 10 hours of non-parallel speech data (0.516 to 0.620). Although the relative improvements are not as large as the first experiments, the absolute accuracies are much better in this case. If we compare ASR text-based testing to the speech-only testing case, we achieve about 15% improvement in accuracy (roughly from 0.55 to 0.63).

5. CONCLUSIONS

In this work, we have proposed a technique to train SLU task with non-parallel speech and text data, using speech-only dialog act recognition as an example. We showed how classification accuracy can be improved using non-parallel data. To handle the lack of parallel data, we proposed a multiview approach that consists of two branches each of which contains an encoder and a classifier. By sharing the classifier between two branches, we constrain the encodings from text and speech to be similar. One of the main advantages of this architecture is that it allows testing the system in a unimodal fashion. In our experiments on the SWDA corpus, we showed that text-based pretraining of the classifier in the multiview system helps improving speech-only classification accuracy (up to 32%) and also that additional fine-tuning on parallel data helps further (up to 40%) in the cases where we have less than 30 hours of speech. Since the text branch uses BERT features from a pretrained model, we also experimented with the case where the speech features come from a pretrained ASR model. In these experiments, speech accuracy approached to that of the text and also performed significantly better than ASR-text based testing of the text branch (up to 15%).

Dialog act classification is highly context dependent, as similar words can imply different acts depending on the history of the conversation. Therefore, one future goal is to incorporate context information into training. Another direction could be to investigate other multiview learning techniques such as deep canonical correlation analysis in this framework.

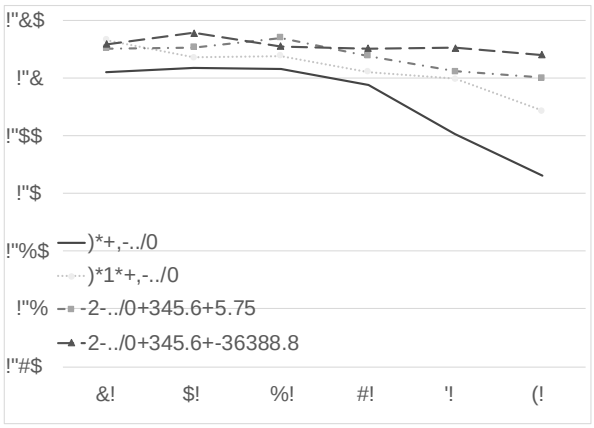


Fig. 4: Classification accuracy versus the amount of non-parallel (NP) speech data when inputs are ASR based embeddings

Table 2: Amount of non-parallel data (hr) to pretrain the branches and the accuracy of the text-only, speech-only and ASR-text based testing of the multiview model for the ASR embedding-based setup

Training condition (in hr)			Test Accuracy		
Text	Speech	Parallel	Text	Speech	ASR-text
60	60	14.5	0.677	0.630	0.549
70	50	14.5	0.688	0.640	0.549
80	40	14.5	0.672	0.628	0.535
90	30	14.5	0.681	0.626	0.558
100	20	14.5	0.682	0.627	0.556
110	10	14.5	0.672	0.620	0.543

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