Building an ASR Error Robust Spoken Virtual Patient System in a Highly Class-Imbalanced Scenario Without Speech Data

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Abstract

A Virtual Patient (VP) is a powerful tool for training medical students to take patient histories, where responding to a diverse set of spoken questions is essential to simulate natural conversations with a student. The performance of such a Spoken Language Understanding system (SLU) can be adversely affected by both the presence of Automatic Speech Recognition (ASR) errors in the test data and a high degree of class imbalance in the SLU training data. While these two issues have been addressed separately in prior work, we develop a novel two-step training methodology that tackles both these issues effectively in a single dialog agent. As it is difficult to collect spoken data from users without a functioning SLU system, our method does not rely on spoken data for training, rather we use an ASR error predictor to “speechify” the text data. Our method shows significant improvements over strong baselines on the VP intent classification task at various word error rate settings.

Index Terms: spoken language understanding,

1. Introduction

The Virtual Patient (VP) Spoken Dialog System (SDS) is a special-purpose conversation agent developed at The Ohio State University to train medical students to take patient histories [1–3]. VP is a simple question classification model where a student question is mapped into one of several canonical questions and a deterministic response is then generated. Like many traditional SDS, VP uses an upstream Automatic Speech Recognizer (ASR) and a downstream Spoken Language Understanding system (SLU) trained to understand text input. But the SLU component for such a system poses two main challenges.

The first challenge is the high degree of class-imbalance in the intent classification data. The VP dataset has 376 classes spanning over a training size of 11,584. This is done to cater to fine-grained user queries, ranging from the most frequent “How are you today?” to the most infrequent “Are you nervous?”. Given the small size of this dataset, it becomes difficult for a model to deal with the sparsity in class distribution.

The second challenge is to make the SLU component robust to ASR errors. A possible strategy is to collect speech data and use the ASR hypotheses for training the SLU [4], but it is not straightforward to collect speech data without a usable speech based VP. In the beginning, it is simpler to build a rule-based dialog agent like ChatScript [5] to interact with the user and collect typed data [1,2]. Once enough data is collected, a sophisticated neural model can be trained which is used to collect more data, making this a bootstrapping process. It is only after a reasonable SLU system can be deployed, that collection of spoken data from users becomes feasible. This results in a dataset with either zero or only limited speech.

Therefore, to build a robust dialog agent in a scenario like VP, we argue that the above challenges need to be addressed together. Prior studies have dealt with these two issues separately. To deal with class-imbalance in VP data, Jin et al. [6] combine a rule-based system with a neural model and show that the rule-based system helps improve performance on rare classes. Recently, a self-attention based RNN architecture [7] combined with a pairwise training approach [8] has shown significant improvements over previous work in class-imbalanced settings.

To build an ASR error robust SLU system, Ruan et al. [4] have proposed a loss function that uses both the ASR hypothesis and the gold text, but this technique assumes the availability of parallel speech and text data. In the VP domain, text-to-phonetic data augmentation has shown good performance on ASR transcripts [9]. Simulating ASR errors has also been shown to improve robustness in SLU [10,11].

We show that although previously proposed methods for building ASR error robustness give some performance boost in the VP domain, this improvement is constrained by a high degree of class imbalance. This work is a first step in building a single model that deals with these two issues in a unified way. In particular, we do not assume access to any speech data during training and utilize the recently proposed ASR error predictor [10] to simulate ASR errors and use these errors to train a neural model in a pairwise fashion as done by Sunder et al. [8]. The pairwise training helps with the class imbalance issue. We also introduce a novel fine-tuning step which uses the simulated ASR errors to reduce the gap between model performance on clean text and ASR hypothesis. Thus, our approach is a two-
Pretraining

![Diagram of pretraining process]

Fine tuning

![Diagram of fine tuning process]

Figure 2: Model overview. Solid arrows indicate forward propagation. Dashed arrows indicate backpropagation. The grey rectangles contain trainable parameters. The white rectangle has frozen parameters.

2. ASR Error Predictor

We use the recently proposed joint phonetic and word level error predictor model [10] for the purpose of translating true text (gold transcripts free from ASR errors) to recognized text (transcription hypotheses with hallucinated ASR errors). The architecture is based on a convolutional sequence to sequence framework [12] and consists of two encoders and one decoder. The first encoder takes a word sequence input corresponding to the true text, the second encoder takes the phoneme sequence input corresponding to the same, and the decoder produces predictions for the recognized word sequence. The encoders consist of 6 residual CNN layers each, and the decoder consists of 3 residual CNN layers that can each attend to both the encoders together. In order to encourage the decoder layers to attempt to attend to both encoders, an “encoder dropout” mechanism is used at train time when we randomly drop one of the two encoders with a certain probability during training. We pretrain the ASR error predictor and freeze it’s weights, not allowing the loss from the SLU model to backpropagate through it.

3. SLU Model

The SLU model consists of an encoder and a classifier. The encoder is a bidirectional GRU [13] with a self-attention mechanism [14] which converts the GloVe embedding matrix of an utterance text to a vector representation. This vector is fed to a 3-layer fully connected classifier MLP with tanh activations.

To deal with class-imbalance in the VP dataset, we use the recently proposed contrastive loss and interpolation based pairwise training framework [8] to train the above model. We also utilize the pretrained ASR error predictor to inject errors into the training input for the SLU model (section 3.2). Further, fine tuning of the above trained model is done to bring the predictions on the ASR text closer to the corresponding clean text (section 3.3). The overview of our model is given in figure 2.

3.1. Pairwise Training Framework

Given the dataset \( \{(x_i, y_i)\}_{i=1}^n \), where \( x_i \) is an utterance text and \( y_i \) its label, pairs of training instances are created. Each such instance is denoted as \( (x_i, x_j, y_i, y_j) \). The encoder converts the GloVe representation of \( x_i \) to \( r_i \) and \( x_j \) to \( r_j \). Then, a contrastive loss is computed as,

\[
L_{con} = \frac{1}{2} \gamma_{pair} \left( \max(0, D - m_{pos}) \right)^2 + \frac{1}{2} \left( 1 - \gamma_{pair} \right) \left( \max(0, m_{neg} - D) \right)^2
\]

Here, \( D \) is the euclidean distance between \( \frac{r_i}{\|r_i\|_2} \) and \( \frac{r_j}{\|r_j\|_2} \). \( \gamma_{pair} \) is 1 if \( y_i = y_j \) and 0 otherwise. \( m_{pos} \) and \( m_{neg} \) are positive and negative margins set to 0.8 and 1.2 respectively.

The contrastive loss only trains the encoder. To train the classifier, the mixup strategy is used. A mixed representation of a paired training instance is created by interpolating between their encoded representation \( r_i \) and \( r_j \). The same is done to the one-hot representation of the labels (\( y_i \) and \( y_j \)). This creates a new training instance \( (r_{mix}, y_{mix}) \) as,

\[
\begin{align*}
r_{mix} &= \lambda r_i + (1 - \lambda) r_j \\
y_{mix} &= \lambda y_i + (1 - \lambda) y_j
\end{align*}
\]

\( \lambda \) is sampled from \( \lambda \sim \text{Beta}(\alpha, \alpha) \), where \( \alpha \) is a hyperparameter. The representation \( r_{mix} \) is fed to the classifier to get an output distribution \( p(y|x_i, x_j) \). A mixup loss is computed as a KL-divergence term,

\[
L_{mix} = K L(y_{mix}, p(y|x_i, x_j))
\]

The final loss for training the utterance classification model is,

\[
L_1 = \beta L_{con} + (1 - \beta) L_{mix}
\]

Here, \( \beta \in [0, 1] \) is tuned on the development set.

3.2. Hallucination of ASR Errors

The pairwise training framework helps to deal with the high class imbalance issue effectively. But during inference, we also
expect performance degradation due to the presence of ASR errors. To tackle this issue, we utilize the pretrained ASR error predictor. During pairwise training, for a paired training instance \((x_i, x_j)\), we sample pseudo speech recognized alternatives for \(x_i\) and \(x_j\) using the ASR error predictor. These alternatives are used as the replacement for the original training example with a probability \(\epsilon\) (a hyperparameter). This strategy has shown effectiveness in dealing with ASR errors in downstream tasks \([9, 10]\) and is called the “hallucination” strategy.

3.3. Fine Tuning

After the utterance classification model is trained using the above methods, we try to bring the model predictions on errorful text and gold text closer by using a loss function proposed by Ruan et al. \([4]\). We compute the cross-entropy losses on clean text \((x_i)\) and a corresponding errorful text \((\tilde{x}_i)\). The errorful text \((\tilde{x}_i)\) is the ASR hypothesis when available and sampled from the ASR error predictor otherwise. We also add to this the KL-divergence loss on model predictions for both. Formally, 

\[
L_2 = CE(x_i, y) + \eta(CE(\tilde{x}_i, y) + KL(p(y|x_i), p(y|\tilde{x}_i))
\]

Here, 

\[
CE(\cdot, \cdot) = -\log p(y|\cdot)
\]

and \(\eta \in \{0.1, 1.0, 10.0\}\) is a hyperparameter tuned on the development set.

Unlike previous work, we use this only as a fine-tuning criterion and do not assume access to real ASR transcripts.

3.4. Inference

At test time, we combine a 1-nearest-neighbor search with the classifier’s prediction \([8]\). We cache the encoder representations for all utterances in the training set along with their 4 closest ASR alternatives in the euclidean space from the error predictor.

Given a test instance \(x_{i\text{test}}\), we first encode it using the encoder and then perform a 1-nearest-neighbor search\([4]\) on the cached training set. Thus, we get a closest distance score for each class. We convert this into a class distribution \(p_{nn}(y|x_{i\text{test}})\) by first inverting the distance scores, z-score normalization and then taking a softmax. The pre-softmax output of the classifier is also z-score normalized before passing to the softmax which gives the class distribution \(p(y|x_{i\text{test}})\). The final prediction is computed as,

\[
p_{\text{final}}(y|x_{i\text{test}}) = \gamma p_{nn}(y|x_{i\text{test}}) + (1 - \gamma) p(y|x_{i\text{test}})
\]

\(\gamma \in [0, 1]\) is tuned on the development set.

4. Experimental setup

4.1. Virtual Patient Dialog Data

The Virtual Patient data is a dataset of conversations between a medical student and a patient (a virtual agent) experiencing back pain. Each student utterance is classified to one of 376 possible classes and each class has a fixed agent response. The total size of the train, dev and test set is 11384, 1635 and 5016 student utterances respectively. This is a highly class imbalanced dataset as evident from the data distribution in figure 3.

The data was collected in a bootstrapping manner wherein some initial (typed) conversations were collected using a rule based agent (ChatScript \([5]\)) and after a neural model was trained using this data, spoken data was collected by deploying this model. Thus, 6711 utterances in the training set were typed and the rest were spoken. The spoken utterances were transcribed manually and by a cloud based ASR system. We make sure that all the data in the dev and test set is spoken data.

4.2. Data for Training the ASR Error Predictor

Our cloud based ASR system used at test-time didn’t offer publicly available error characterization data, and we had cost and rate limit constraints on how much data we could collect, so for our training set we used characterization data available from an unrelated but homegrown ASR system’s transcriptions of the Fisher corpus used for a prior version of the error predictor \([17]\). This resulted in a set of 1.8 million odd pairs of true text and recognized text used for training the error predictor. In order to finetune our errors to our test-time scenario, we used a randomly selected subset of 100k utterances from the Fisher corpus that we passed through the cloud based ASR system. In the experiments where some real ASR data from the Virtual Patient project was assumed available, the pairs of manual transcripts and cloud ASR transcripts for the spoken portion of the train set were added to the finetuning subset.

4.3. Training details

For the error predictor, we train with a Nesterov accelerated gradient descent optimizer \([18]\) for 60 epochs with a learning rate of 0.1 and a momentum of 0.99 on the training data from the homegrown ASR system, followed by 15 additional epochs on the finetuning data from the cloud based ASR system.

We train the SLU model using early stopping with a patience of 6 epochs. We use the Adam optimizer \([19]\) with learning rate of \(1 e^{-3}\) for pairwise training and \(8 e^{-5}\) for fine-tuning. We add a dropout of 50% for every layer in the neural network.

Figure 3: Distribution of classes in the training set of VP. Over 70% of the data belongs to the first quintile of classes

5. Results and Discussion

The results are shown in table 4. To test the effectiveness of our model in noisy acoustic conditions or a possible domain mismatch for an off-the-shelf ASR \([20]\), we show results when the test data has errors from 3 different ASR systems. Training is done in two scenarios: a) no real ASR hypotheses is used, i.e. all utterances in train were either typed text or manual transcriptions; b) the available ASR hypotheses is present in train. When present, these hypotheses come from a fixed ASR (system 1). This is a deployment setting where it is not feasible to re-train the SLU with new hypotheses if the upstream ASR changes. We use 4 prior studies as our baselines:

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1. We use the FAISS toolkit for efficient search \([16]\) (https://github.com/facebookresearch/faiss)
Table 1: Accuracy/Macro-F1 scores using different training methods. Italic numbers indicate the oracle performance, i.e., when no errors are present. Bold numbers indicate best performance in the corresponding column; classification is either with softmax classifier (*) or combined softmax/nearest neighbor (†). (2), (3) were proposed specifically to help with ASR errors. (4) was proposed to help with class-imbalance. (5), (6) and (7) are variants of our proposal that help with both these issues. Results averaged over 10 runs.

| WER in test set | Some real data from ASR system 1 in train set? | Helps with | Training | Accuracy/Macro-F1 (in %) |
|-----------------|-----------------------------------------------|-------------|----------|-------------------------|
|                 |                                               |             |          | 0% | 8.9% (ASR system 1) | 12.5% (ASR system 2) | 41.1% (ASR system 3) |
| None (baseline) | 1× cross-entropy [7]                           | (1)         |          | 79.7/59.8 | 78.0/57.8 | 73.1/56.6 | 77.0/57.4 | 65.6/45.8 | 66.7/47.3 |
| ASR Errors      | 2× cross-entropy w/ hallucination [10]     | (2)         |          | -           | 78.3/58.3 | 79.5/59.0 | 77.4/58.0 | 77.8/57.8 | 67.9/48.6 | 65.7/48.5 |
| Class-Imbalance | 3× $\mathcal{L}_2$ only [4]                | (3)         |          | -           | 78.6/58.6 | 79.4/59.8 | 77.5/58.0 | 77.4/58.5 | 67.9/48.8 | 67.2/47.7 |
| Both            | 4× pairwise only [8]                          | (4)         |          | 80.6/65.7 | 79.0/63.7 | 79.7/64.5 | 77.4/61.7 | 77.3/62.0 | 66.9/50.4 | 67.0/50.7 |
|                 | 5× pairwise w/ hallucination                 | (5)         |          | -           | 79.3/64.3 | 79.0/64.8 | 77.9/62.7 | 77.6/62.2 | 67.9/52.0 | 67.1/51.2 |
|                 | 6× pairwise + fine tune with $\mathcal{L}_2$ | (6)         |          | -           | 79.0/64.5 | 80.2/64.6 | 77.9/62.2 | 77.3/62.3 | 67.6/50.9 | 68.3/51.6 |
|                 | 7× pairwise w/ hallucination + fine tune with $\mathcal{L}_2$ | (7)       |          | -           | 79.9/65.1 | 80.4/65.1 | 78.4/63.1 | 78.3/62.8 | 68.5/52.4 | 68.5/52.0 |

(1) cross-entropy [7]. A self-attention GRU trained with cross-entropy loss for classification.
(2) cross-entropy w/ hallucination [10] Same as 1., except the input training instance is randomly replaced (with probability $\epsilon$) by an errorful alternative sampled from the error predictor.
(3) $\mathcal{L}_2$ only [4] The fine-tuning objective in section 3.3 is used as the only criterion without any pretraining step.
(4) pairwise only [8] The pairwise training described in section 3.1 is used without any hallucination or fine-tuning.
(5) pairwise + fine tune with $\mathcal{L}_2$ Pairwise training is used along with error hallucination. No fine-tuning is done.
(6) pairwise + fine tune with $\mathcal{L}_2$ Pairwise training is used without error hallucination but fine tuning with $\mathcal{L}_2$ is done.
(7) pairwise w/ hallucination + fine tune with $\mathcal{L}_2$ All the components are combined.

We now fine tune a model with $\mathcal{L}_2$, pretrained using pairwise training without hallucination. This gives us a mean improvement of 0.7% in accuracy and 0.5% in F1-score ((4) → (6)). This validates the fine tuning criterion.

We see the best performance across all settings when we combine all the techniques (row (7)). This improvement is on accuracy and F1 both, which shows that we have successfully combined the ability of pairwise training to handle class imbalance with effective strategies to deal with ASR errors.

Note that our technique leads to significant improvements even when the off-the-shelf ASR system does not perform well. With higher WERs, the performance is better without any real ASR data than with it. This may be because the real ASR data present in the training set does not have the same type of errors seen at test time. This shows the need for SLU models to not rely on static ASR data during training. Our approach of using an error predictor model is a step in this direction.

### Ablation Study
To assess the effect of fine-tuning with ASR errors, we perform an ablation study by setting $\eta = 0$ in $\mathcal{L}_2$ (table 2). This study is performed in the case when there are no real ASR hypothesis in the training set and the test set has a WER of 8.9%. The fact that we notice a performance degradation when $\eta = 0$ indicates that the errors generated by the ASR error predictor carry useful information about the real-world error. However, we believe that there is scope for more improvements in the fine-tuning stage by exploring better ways to distill more knowledge from clean text to ASR text [21].

### 6. Conclusion
In this paper, we explored methods to tackle the problem of class-imbalance and ASR errors together for SLU in a special-purpose, low-resource SDS. We introduced a training method that effectively combines a pairwise training framework with a simple fine-tuning criteria to achieve significant improvements over strong baselines. Our technique assumes that there are no real ASR transcripts available during training and thus uses a pretrained ASR error predictor to simulate ASR errors. Future work should explore ways to distill knowledge from clean text to ASR text directly during pairwise training.

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