Behavioral AI: Modeling Patient Behavioral Dynamics in Alcoholism/Narcotics Therapy

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Abstract

Advances in human-centered machine learning and offer new applications in healthcare including psychotherapy. Motivational interviewing, a specific type of therapy uses a coding scheme to characterize spoken utterances with either a skill used by a counselor, or the behavior evoked in their patient. Presented is a series of experiments which explore and evaluate the predicitve correlation between what was said and will be said.

Preliminaries

- **Session** - a collection of utterances that are labeled with MISC codes and speaker identification.
- **Turn** - an entire section of speech that is said by a single person. Each time the speaker changes so does the turn
- **Utterance** - a segment of speech which represents a complete thought or idea. A turn can be comprised of many utterances. MISC is assigned on a per utterance basis.
- **Patient Codes**:
  - POS - a postitive label indicates a **"change talk"** utterance, *i.e.* patient references behavior change from their alcoholic/narcotic tendencies
  - NEG - a negative label indicates a **"sustain talk"** utterance, *i.e.* patient inidicates willingness to continue their behavior
  - NEU - a neutral label corresponds with a neutral utterance which points in neither direction.

The analysis performed is on a data set consisting of 450+ sessions , with over 68K+ turns taken.

Results

Session Level

- Correlation is observed in session level analysis
- Implies therapist does have an influence on patient behavior

Turn Level

- Therapist input does not seem to be as effective "in-situ" in predicting patient output.
- Demonstrates that initial disposition and latent parameters are more meaningful for prediction

Further analysis required to examine how therapist input can affect the progression of the patient's output response.

Session Level Analysis

We begin by first constructing therapist and patient vector pairs that represent the distribution of a particular sessions MISC codes.

Patient Codes		
POS	NEG	NEU
10.59%	8.53%	80.88%

Table 1

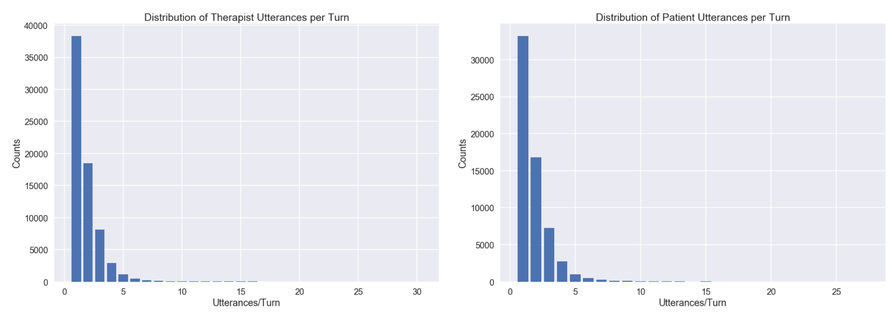


Figure 1

Table 1 shows the average patient codes distribution (for training). This is used as a predictive baseline and compared against a simple linear neural network with softmax activation

Figure 1 shows the distribution of utterances per turn, we can see that most turns are only one utterance long, however a fair amount of turns contain multiple utterances.

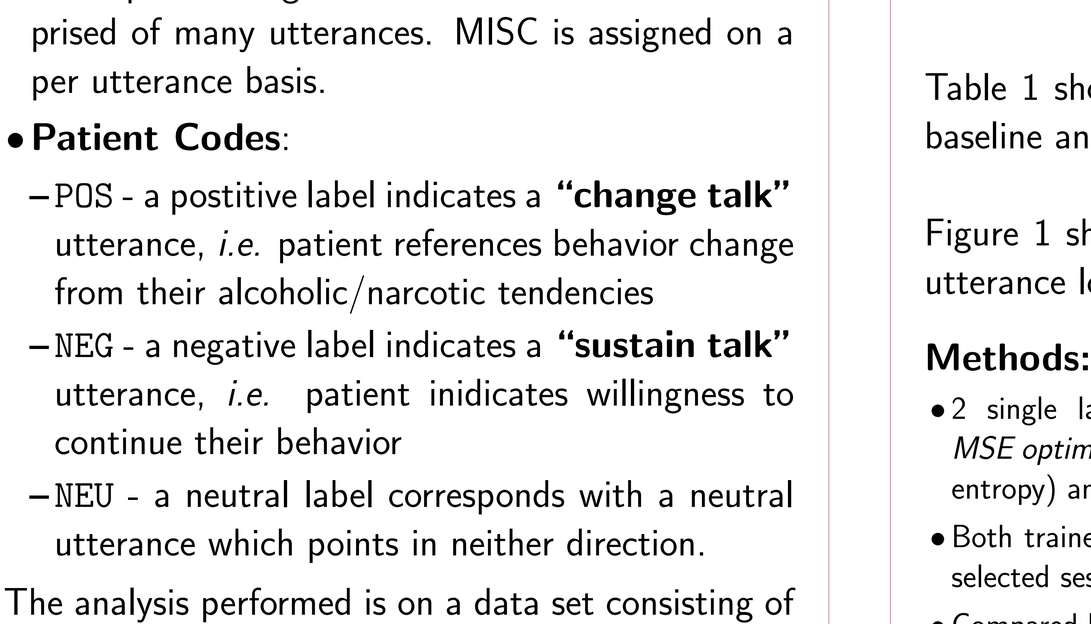
Methods:

- 2 single layer neural networks, *KL optim* and *MSE optim*, were trained for KL-Divergence (cross-entropy) and Mean Squeared Error respectively
- Both trained on the same set of 90% of randomly selected sessions
- Compared KL and MSE loss of trained models with average vector on unseen sessions

Model	MSE Loss	MSE % Change	KLD Loss	KLD % Change
Average	0.0151	N/A	0.0967	N/A
MSE optim	0.0122	19.05%	0.0809	16.34%
KL optim	0.0122	19.18%	0.0802	17.00%

Table 2

Turn Level Analysis



Approaches:

- **Isolated vs Contextualized** - compare using only the previous single turn to predict the current, compared to using a vector averaged all preceding turns
- **Windowed vs Complete Context** - using an average vector over a sliding window of preceding turns instead of entire preceding conversation. Also compared training without class weights and then normalizing by the prior distribution versus using the inverse of the prior as weights to scale training penalties by class.
- **Multilabel training** - instead of using distributional perspective, solve a multi-label classificiation problem.
- **Therapist/Patient Seperation** - use only therapist codes (average over a window) and seperately only patient vectore (average over a a window) to predict the next patient turn codes