DERP: An Evaluation Metric for Dialogue Systems

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Introduction

- Current automatic metrics for dialogue eval correlate poorly with human judgement (Serban et. al., How NOT to Evaluate your dialogue system)
- Obtaining human scores time consuming and costly
- Automatic metric which shows good correlation with human judgement invaluable
 -> learn it from data
- Hypothesis: discriminatory model easier to learn than generative dialogue system
- Need tuples of the form < context , gold_response , alternate_response , human_score > : impossible to collect a large number of these
- IDEA: automatically discover such tuples and train a model on this

Reddit Corpora

- Working with 2 data dumps of Reddit
 - o 30Gbs, 53M comments from 1 month
 - 200Gbs (Compressed), all Reddit

Pruning Rules

- Empty/Deleted comments
- Top level comments with no children
- Comments with URLs
- Comments with subreddit mentions
- Comments with Length <= 3
- Reply comments with Length > 40
- Comments common across multiple contexts

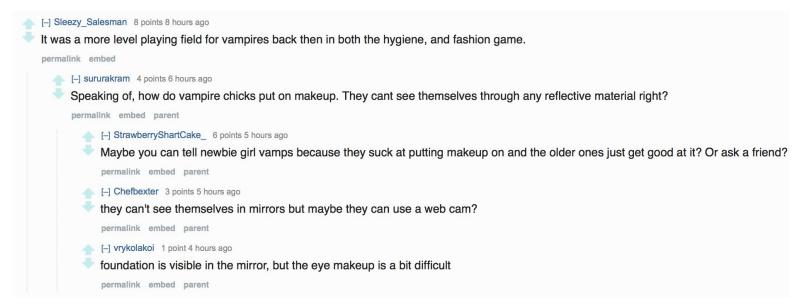
ARCtx Dataset

- Find alternate responses to the same context by matching contexts of 2 separate conversations
- Skip-thoughts sentences vectors for matching contexts



ARCmt Dataset

- Comments on Reddits can get more replies
- We can hunt for alternate comments to any comment to build the dataset



Example:

< It was a more...right?, Maybe you can ... friend?, they can't ... web cam?, 1>

Label Noise in ARCmt Dataset

- Manually checked 200 positive examples and 100 negative examples generated
- 90% negative examples are correct
- 80% positive examples are correct
- **TODO:** ways to deal with label noise? Better pruning? Is it even needed given the sheer amount of data

Baseline Models

- Word-overlap based metrics
 - BLEU
 - ROUGE
- Embedding based metrics
 - Distance between skip-thought vectors of responses
 - Tfidf vectors for context and responses followed by logistic regression
 - Skip-thoughts followed by logistic regression

Our Models

- Tfidf vectors for context and LSTM encodings of responses followed dense layer
- LSTM encodings for context and responses followed dense layer
- 2 Attention weighted representations of the context by attending using either response
- HRED model for encoding context with either response

Results

Data Stats

Training Size6M

Validation Size240K

Testing Size300K

Accuracy

• BLEU score : 54%

• Tfidf with Logistic Regression: 67%

Skip-thoughts : <Training>