Methodologies for Aligning Pretrained Dialog Representations to Aspects of Human Judgments

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Contents

What is this about?

Dialog systems: Massive growth over the last few decades

Need good evaluation systems to develop

Problem: Human evaluation is too costly

Solution: Automatic evaluation

Apprehension: Do they correlate well with human judgements?

Resolve: Let's find out with some pretrained dialog representations

What has already been done?

BLEU[6], **ROUGE** [4], **METEOR**[12]: mostly syntactic

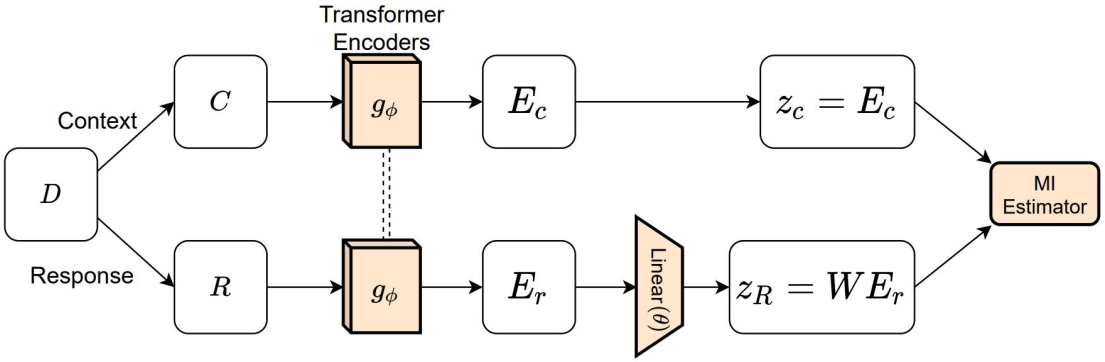
BLEURT[8], **BERTScore**[11]: Transformer based models[2, 5, 9] to calculate similarity

CTC[1] - Compression Transduction and Creation: family of unifying metrics

DMI[7] - Discourse Mutual Information: approximate MI between context and response

But why DMI + CTC?

Pre-training objective: approximate Mutual Information



CTC[1]: unifying perspective with its roots in information alignment

Question: Do they come “in phase” and enhance correlation?

Technicalities

Information Alignment: How well a aligns to b

$$align(a \rightarrow b) =< \alpha_1, \alpha_2, ..., \alpha_N >$$

Engagingness: Alignment of output with both input and context.

$$Engagingness(y, x, c) = sum(align(y \rightarrow [x, c]))$$

Groundedness: Alignment of output with context.

$$Groundedness(y, x, c) = sum(align(y \rightarrow, c))$$

Technicalities (contd)

E-based → D-based → R-based

Uses BERT-base or RoBERTa-large

No fine-tuning

$$\alpha_i = \max_{j \in [1,m]} sim(a_i, b_j)$$

Uses RoBERTa-large

Finetunes on weakly supervised data

$$\alpha_i = p(a_i|b)$$

Uses BERT-base

Finetunes on weakly supervised data

$$\alpha = \sum_i p(a_i|b)$$

Masking → Paraphrasing → Predicting

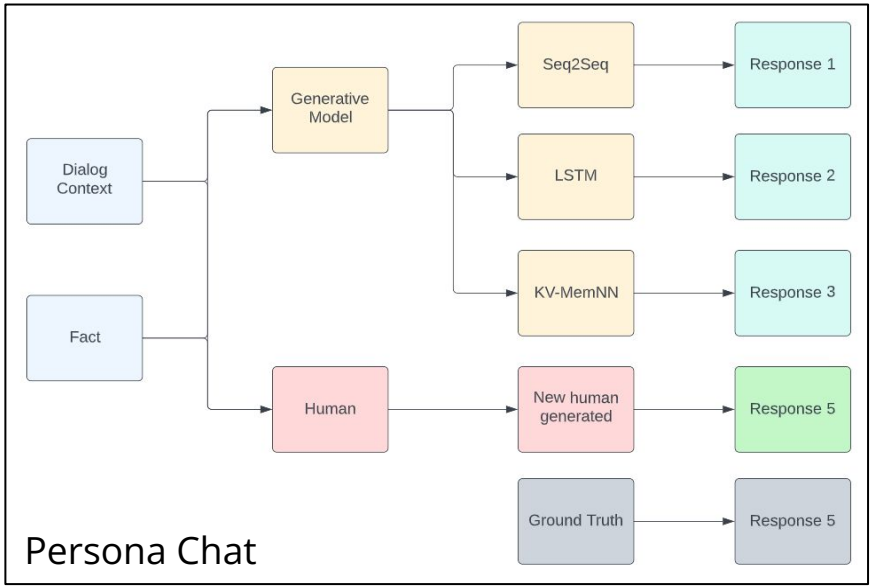
Weak supervision

Dataset

Persona chat[10, 13]: Chat in a way that's consistent with their personas.

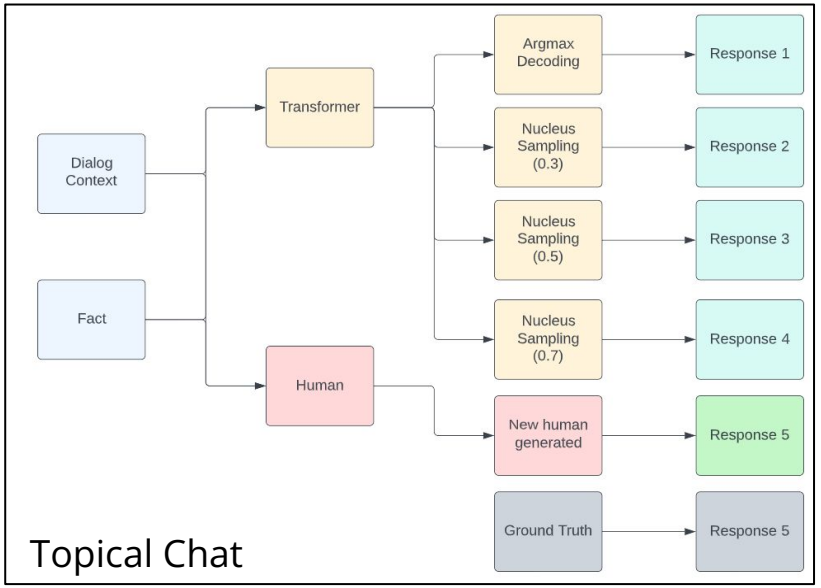
Topical Chat[3, 13]: Chat in a way that's grounded with the topic given.

$$60 * 5 = 300(c, r)pairs$$



Persona Chat

$$60 * 6 = 360(c, r)pairs$$



Topical Chat

Experiments

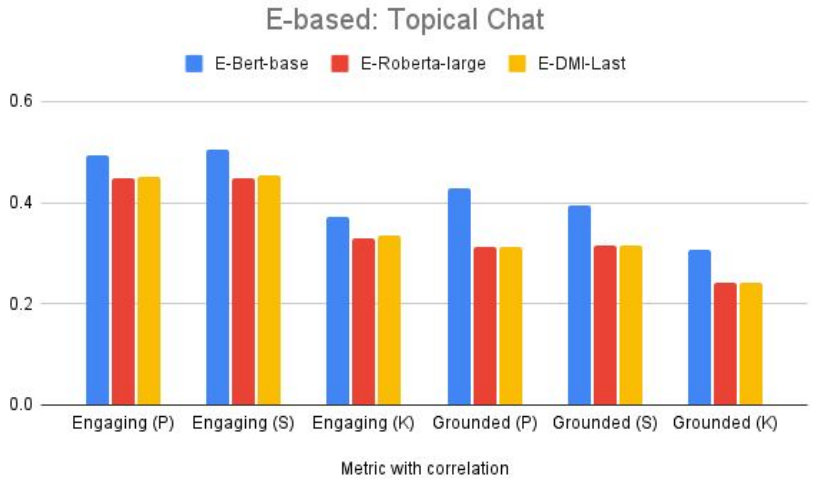
Expt 1: Reuse the pipelines, substitute with DMI

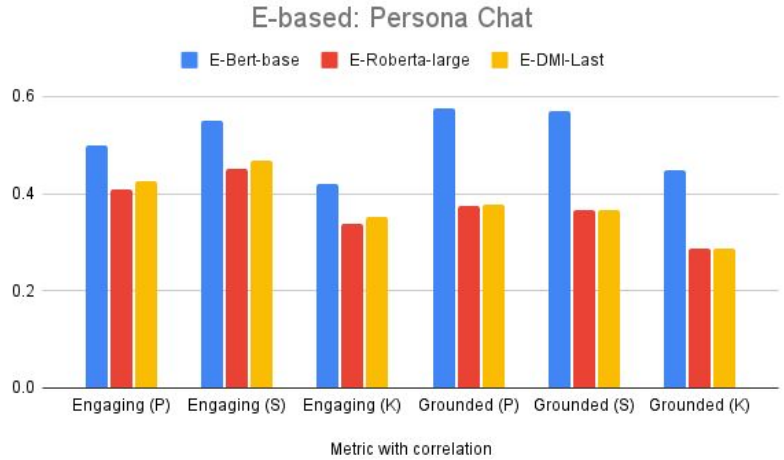
Expt 2: Explore a retrieval-based model

Expt 3: Explore representations from different layers (ablation)

Results: Embedding(E) based models

General trend: BERT > RoBERTa-base (DMI) > RoBERTa-large

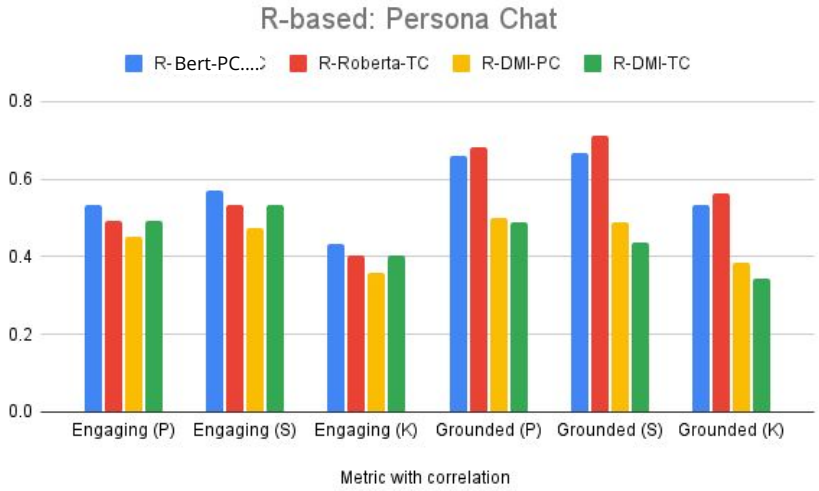


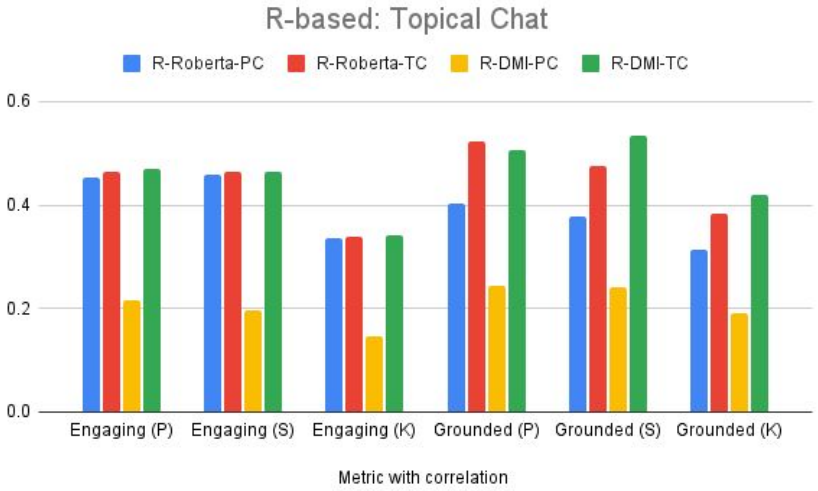


Possible reason for BERT > RoBERTa : Removal of **NSP** which assists NLI tasks

Results: Regression(R) based models

General trend: BERT > RoBERTa-base (DMI)



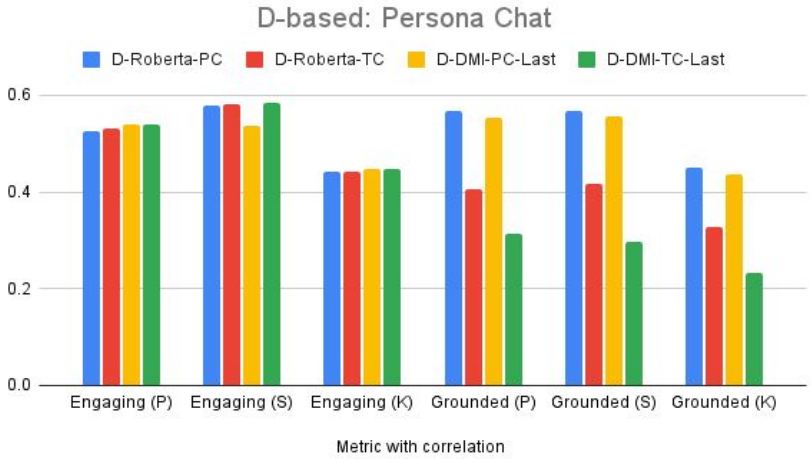


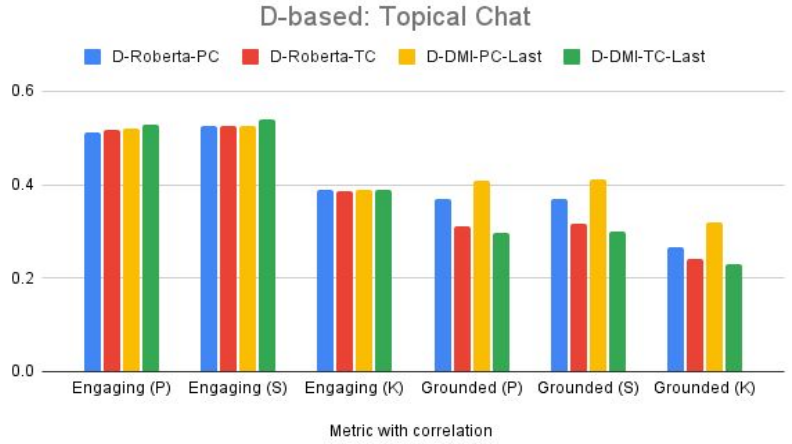
Possible reason for trend: Same as R-based analysis

Results: Discriminative(D) alignment models

Engagingness: RoBERTa-base (DMI) > RoBERTa-large

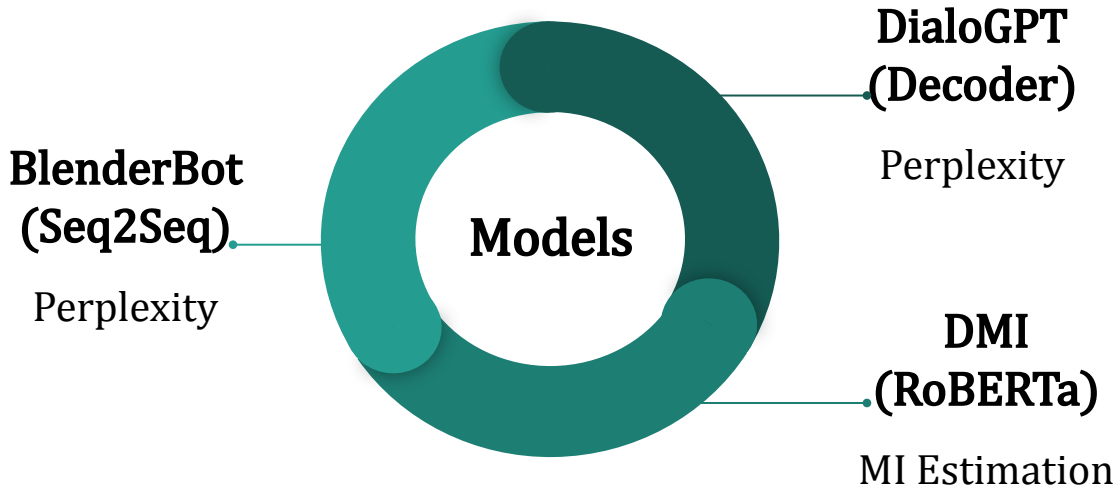
Groundedness: RoBERTa-large > RoBERTa-base (DMI)



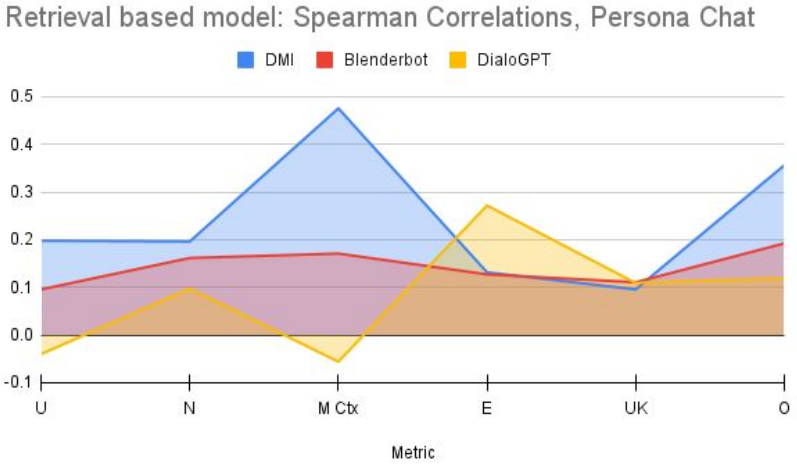


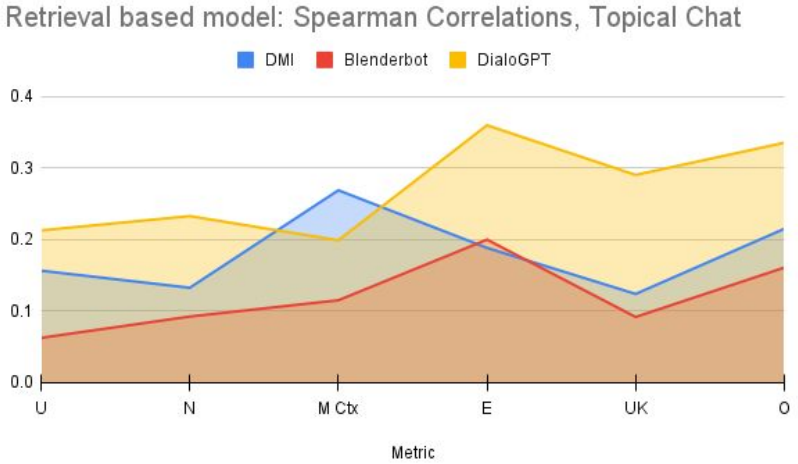
Possible explanation: The D-model formulation aligns with DMI pretraining

Experiment II: Retrieval based comparison



Results





Persona: DMI does better on most cases apart from uses knowledge
Topical: DialoGPT beats other models in all cases apart from maintains context
Overall: DMI always scores well in maintains context aspect

Layer-wise analysis

Layer	PC-Engaging	PC-Grounded	TC-Engaging	TC-Grounded
E-DMI-Last	0.4241	0.3777	0.452	0.3131
E-DMI-2L	0.424	0.3801	0.4521	0.3132
E-DMI-3L	0.4256	0.3853	0.4533	0.3142
E-DMI-4L	0.4266	**0.391**	0.4522	**0.3169**
E-DMI-5L	**0.4267**	0.3856	**0.4525**	0.3133
E-DMI-6L	0.4259	0.3851	0.4508	0.31
E-DMI-7L	0.4254	0.3869	0.4513	0.3118
E-DMI-8L	0.4228	0.3907	0.4494	0.3146
E-DMI-9L	0.4217	0.392	0.4491	0.3143
E-DMI-10L	0.4179	0.3904	0.4448	0.3101

Note: Here L means Last; E-DMI-3L refers to representations harnessed from the 3rd last layer

Inference: 4th and 5th layers lead to best correlation!

Conclusion and Future Work

We beat their performance for the D-based model (engagingness).

We find promising results from the retrieval based model.

We get motivated to explore the application of BERT in DMI

We then use values from intermediate layers for fine-tuning.

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THANK YOU!

Questions?