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Mensch IT

# DYME: A Dynamic Metric for Dialog Modeling Learned from Human Conversations


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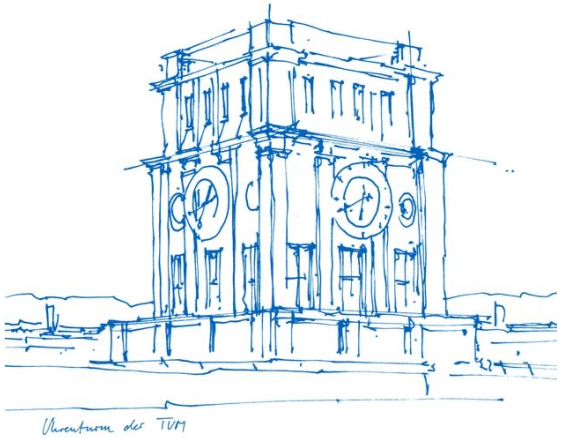
> Code and models on GitHub: https://github.com/florianvonunold/DYME



# Motivation

## Context

**Text-based chatbots**

- Chatbots are a natural way of human-machine interaction
- Practical applications
  - Business: customer service
  - Healthcare: nursing, virtual dietary advice
  - Education: virtual teaching

→ Interested in improving open-domain chatbots

# Motivation

## Goal

**Control data driven dialog generation to reflect human communication characteristics**

Assumption: Controlling chatbots‘ „behavior“ allows for more effective communication (human-machine interaction)

Control **maybe** particularly important for dialog generation: output text highly sensitive to given dialog situation

# Related Work

**Fine-tune dialog models with Reinforcement Learning** (Saleh et al., 2019; Xu, Wu, and Wu, 2018; Li et al., 2016)

- *Self-play / Self-talk*: two dialog models talk to each other to simulate conversations
- Optimize the model(s) w.r.t. certain reward functions (e.g., to get less repetitive models)
- Long-term influence of a generated utterance on the entire conversation is modeled
- Possibility to explore and move away from learned statistical dependencies

# Related Work

**Reward functions**

- Learn reward functions from human preferences
- Developer-defined reward functions
- Learn reward functions from dialog data

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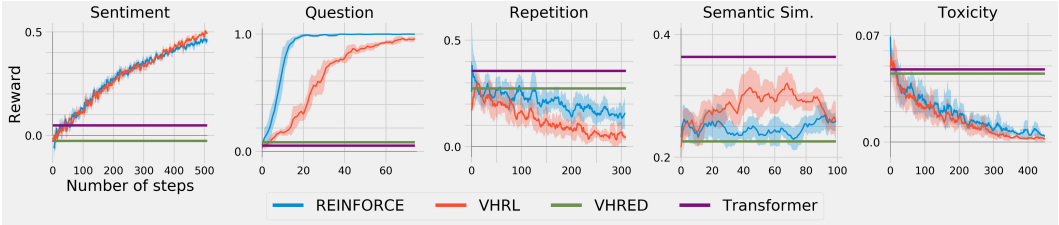
# Related Work

## Developer-defined reward functions

**Variational Hierarchical Reinforcement Learning (VHRL)** (Saleh et al., 2019)




[4]

Reward learning curves for the different metrics.

| Transformer | Sentiment | Question | Repetition | Semantic Sim. | Toxicity |
|---|---|---|---|---|---|
| [Usr]: hello!<br>[Bot]: i don't know.<br>[Usr]: how are you?<br>[Bot]: i don't know what that means. | [Usr]: hello!<br>[Bot]: i'm in my sunroom a lot and it's a great feeling!<br>[Usr]: sounds fun<br>[Bot]: i'm excited! | [Usr]: hi there!<br>[Bot]: what do you do for fun?<br>[Usr]: i read books<br>[Bot]: what do you like to do in your life? | [Usr]: how are you?<br>[Bot]: i'm a reservoir engineer<br>[Usr]: cool. i am still in college<br>[Bot]: today is my first day of vacation | [Usr]: i like to listen to ed sheeran<br>[Bot]: and what genre is it?<br>[Usr]: pop<br>[Bot]: any recommendations? | [Usr]: you're so stupid<br>[Bot]: you're cute<br>[Usr]: i hate you<br>[Bot]: but i don't know why |

[4]

Chat examples of the trained models after VHRL fine-tuning.

[4] Figure and Table taken from (Saleh et al., 2019)

# Related Work

## Developer-defined reward functions

**Variational Hierarchical Reinforcement Learning (VHRL)** (Saleh et al., 2019)

$reward_{VHRL} = 0.15 * sentiment + 0.25 * question + 0.5 * repetition + 0.05 * similarity + 0.05 * toxicity$

According to the reward, every utterance at any given position in a dialog should adhere to these static, developer-defined metrics

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According to the reward, every utterance at any given position in a dialog should adhere to these static, developer-defined metrics

→ **Not necessarily valid**

**Example dialog**

[Speaker 1]: Hey!

[Speaker 2]: Hi, how are you?

[Speaker 1]: Fine, and you?

[Speaker 2]: I think about how sad it is that I‘ve not yet been able to meet you in person... ← suitable utterance will receive lower reward

→ Possible problem: **static rewards**

# Contributions

1. Analysis of metric dynamics in written human conversations → Metrics in human dialogs are dynamic.

2. **DYME**: A **DY**namic **ME**tric for Dialog Modeling Learned from Human Conversations → A dynamic metric can be learned from dialog data.

# Experiments and Results

1. Analysis of metric dynamics in written human conversations

2. **DYME**: A **DY**namic **ME**tric for Dialog Modeling Learned from Human Conversations

# Experiments and Results

## Analysis of metric dynamics in written human conversations

**Metric:** any function that computes a real-valued number for a given utterance in a two-speaker, multi-turn conversation

**Used metrics**

- Adapted Reward Function Metrics[5]
  - Question, repetition, …
- New Empathy-Based Metrics[6]
  - Emotional reaction, interpretation & exploration

**Used datasets**: human-written, multi-turn, two-speaker, open-domain dialogs

- DailyDialog (Li et al., 2017)
- EmpatheticDialogues (Rashkin et al., 2019)

[5] Adapted versions of the reward functions in (Saleh et al., 2019)

[6] Following the EPITOME framework of expressed empathy (Sharma et al., 2020)

# Experiments and Results

## Analysis of metric dynamics in written human conversations

| | |
|---|---|
| $u_1$ | did you ever buy food from the snack stands near our hotel ? |
| $u_2$ | yes , several times . |
| $u_3$ | how do you like them ? |
| $u_4$ | not bad . |
| $u_5$ | i always have the temptation to eat something there . |
| $u_6$ | then , why did n't you do that ? |
| $u_7$ | i do n't know how much we can trust them . do you have any ideas ? |
| $u_8$ | some of them , i think , are not good . |
| $u_9$ | it does n't taste good ? |
| $u_{10}$ | no , i mean some of them are not clean enough . |
| $u_{11}$ | that 's my greatest concern . but how can you tell which one is clean ? |
| $u_{12}$ | i judge by appearances . |
| $u_{13}$ | i got it . i think it 's worth trying . |
| $u_{14}$ | it certainly is . |
| $u_{15}$ | i 'd like to try some kebab , roasted squid , and many different appealing things . |
| $u_{16}$ | do n't try everything at one time , please . |
| $u_{17}$ | i see . thank you . |

A sample dialog from DailyDialog (Li et al., 2017) of length 17.

# Experiments and Results

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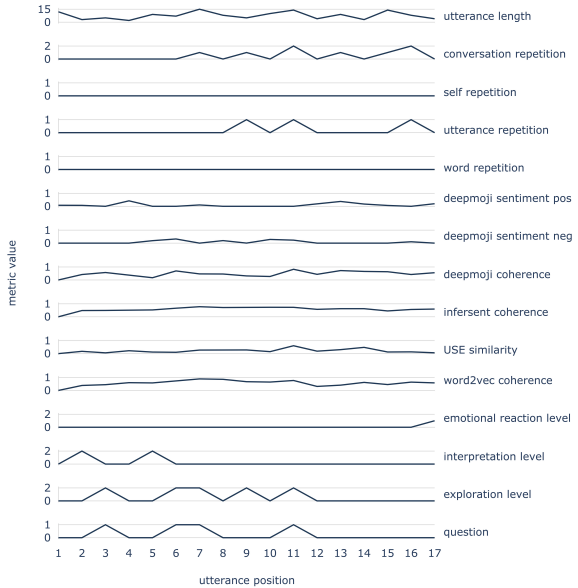
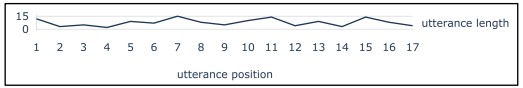



The metric progress within the sample dialog.

# Experiments and Results

## Analysis of metric dynamics in written human conversations




Dialog 1

σ: Intra-dialog metric standard deviation

μ: Metric mean across the positions in the dialog

Coefficient of Variation (CV): CV = σ / μ

# Experiments and Results

## Analysis of metric dynamics in written human conversations


Dialog 1

Dialog 2

Dialog n

σ: Average intra-dialog metric standard deviation

μ : Average metric mean across the positions in the dialog

Coefficient of Variation (CV): $CV_{l,m} = \sigma / \mu$

# Experiments and Results

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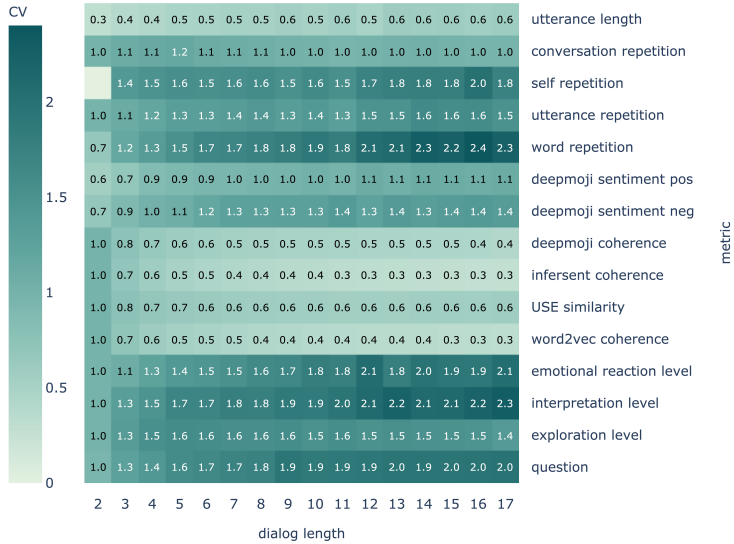
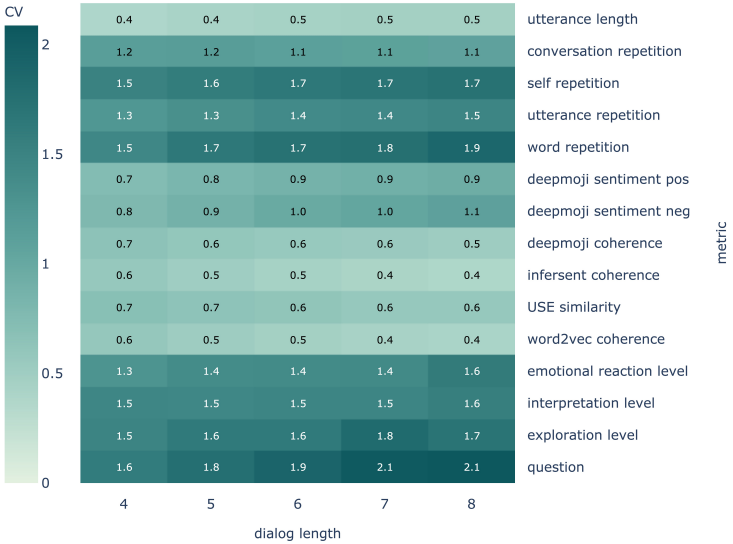


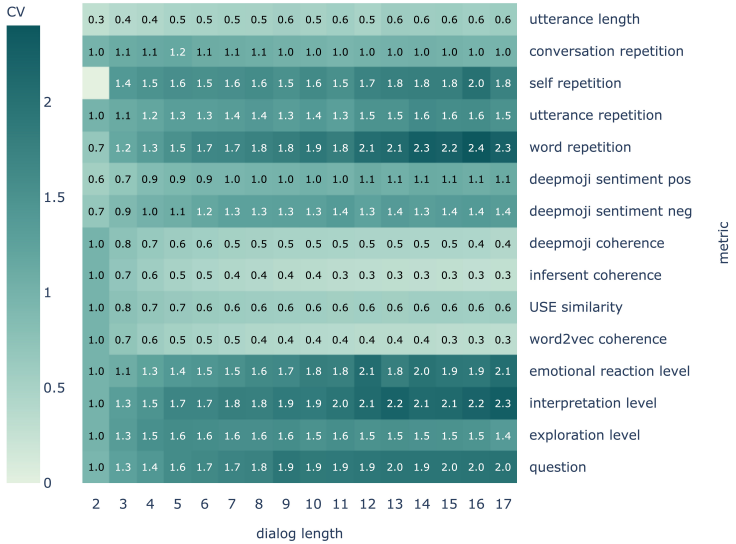

Heatmap of $CV_{l,m}$, the average variability of metric m within all dialogs of length l, for all dialog lengths and all metrics in the dialogs in DailyDialog.

# Experiments and Results

## Analysis of metric dynamics in written human conversations




Heatmap of $CV_{l,m}$, the average variability of metric m within all dialogs of length l, for all dialog lengths and all metrics in the dialogs in EmpatheticDialogues.

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1. Analysis of metric dynamics in written human conversations → Metrics in human dialogs are dynamic

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# Experiments and Results

DYME: A DYnamic MEtric for Dialog Modeling Learned from Human Conversations

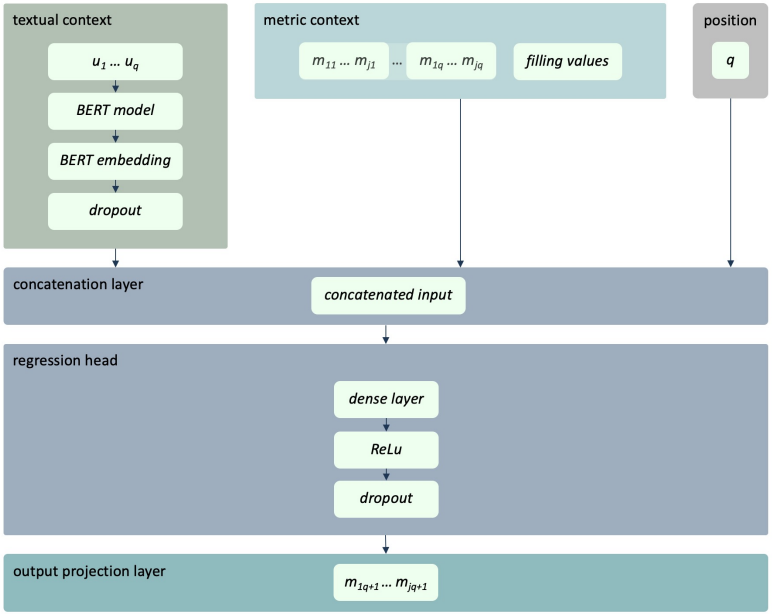
**Task**

- Given a dialog history (textual and metric context) predict the values of all metrics for the next utterance
- Multi-label regression

# Experiments and Results

DYME: A DYnamic MEtric for Dialog Modeling Learned from Human Conversations

**Approach: DYME – A dynamic metric**



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## Approach: DYME – A dynamic metric

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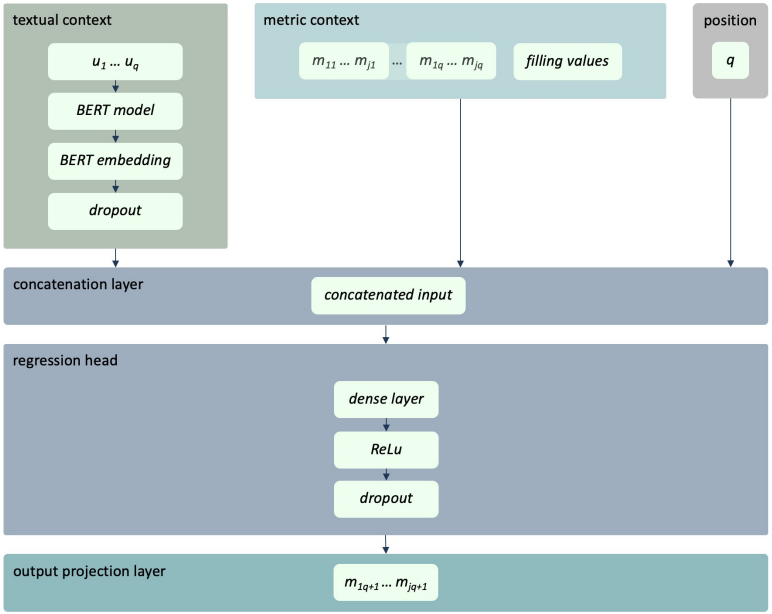

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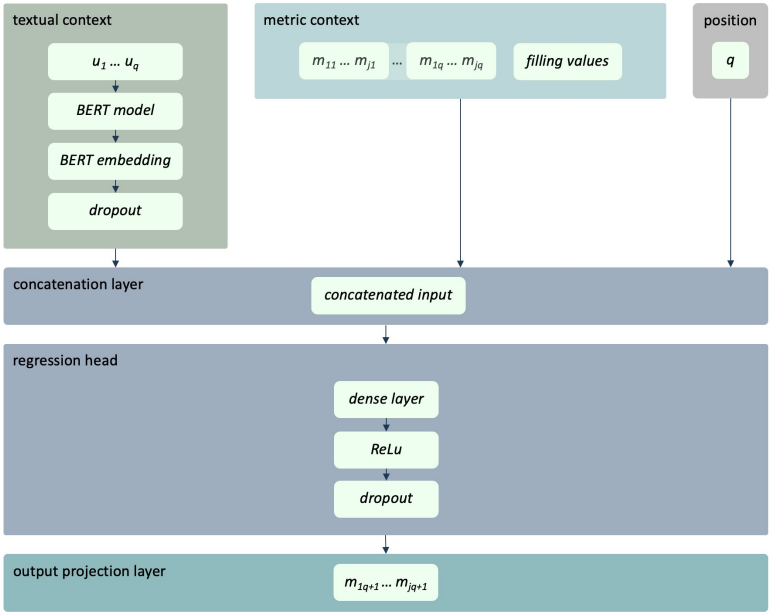

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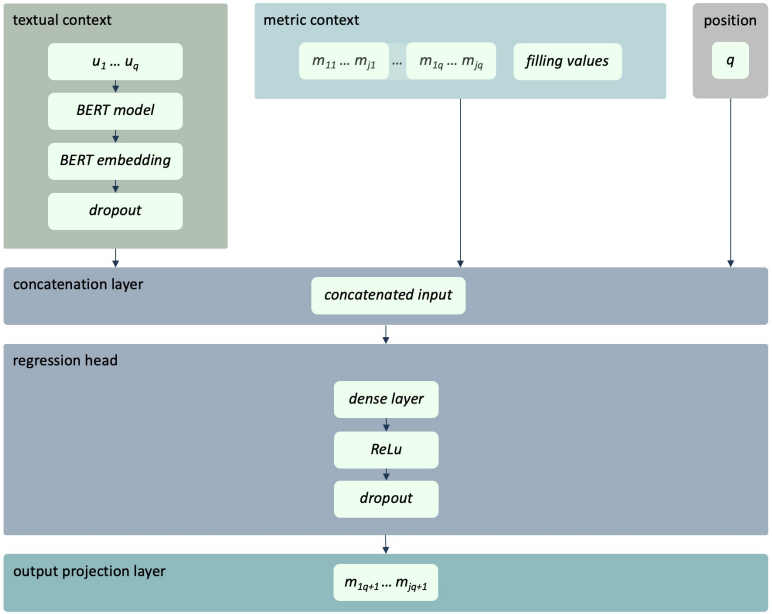


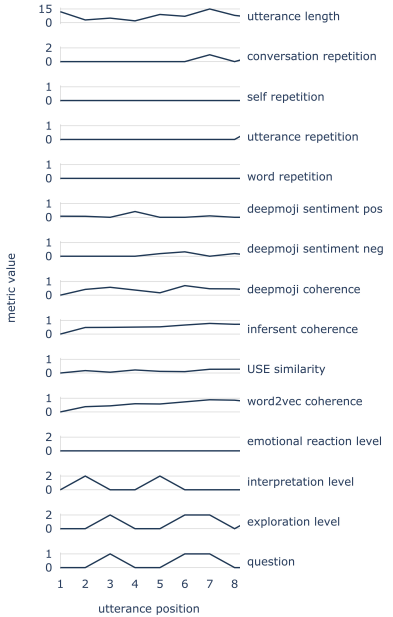

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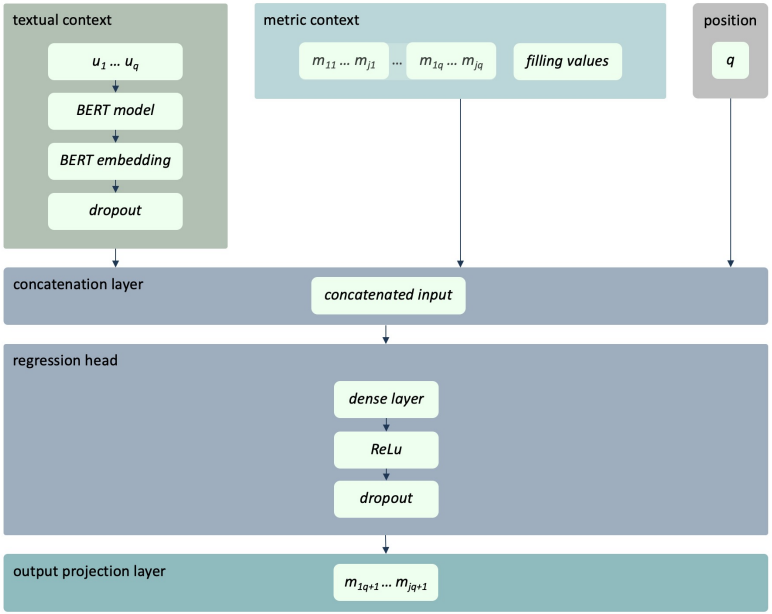


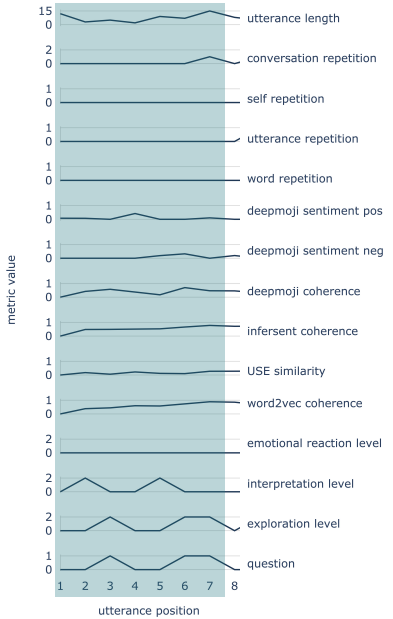

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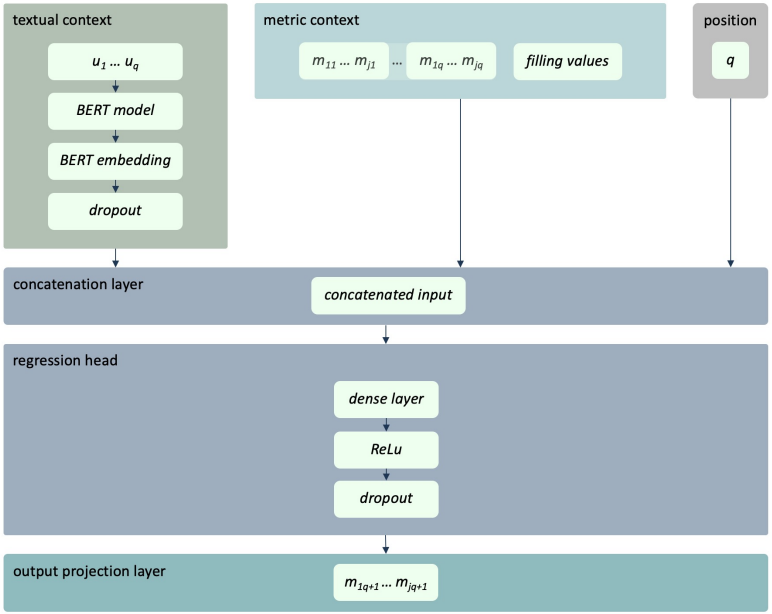


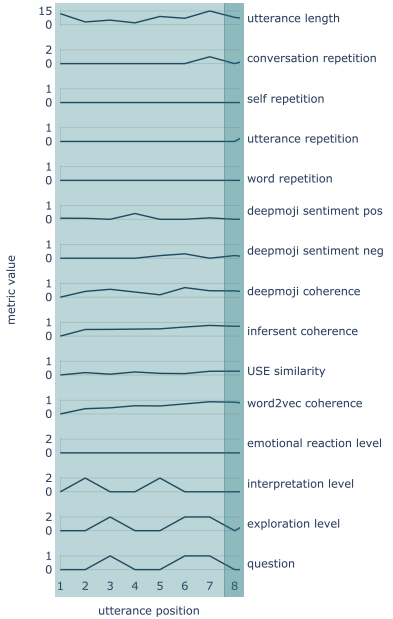

# Experiments and Results

DYME: A DYnamic MEtric for Dialog Modeling Learned from Human Conversations

**Training**

- Supervised Learning
- DailyDialog and EmpatheticDialogues (80% training, 10% validation, 10% testing)
- Learning objective: minimize the average Mean Squared Error (MSE) between the predicted metric values $\hat{y}$ and the ground truth metric values $y$ across all metrics

$$loss(y, \hat{y}) = \frac{1}{j} \sum_{i=1}^{j} (y_i - \hat{y}_i)^2$$

# Experiments and Results

DYME: A DYnamic MEtric for Dialog Modeling Learned from Human Conversations

**Baseline**

- Moving average baseline
- Uses the per-metric average of the given metric context as prediction for the next utterance position
- Does not make use of the textual context at all
- **Would achieve perfect accuracy if metrics were static**

# Experiments and Results

DYME: A DYnamic MEtric for Dialog Modeling Learned from Human Conversations

**Results** (Average RMSE on test dataset)

| | |
|---|---|
| Baseline: | 0.2326 |
| DYME: | 0.1845 |

→ Absolute improvement: 4.81%
→ Relative improvement: 20.68%

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**Results** (Average RMSE on test dataset)

Baseline: 0.2326
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→ Absolute improvement: 4.81%
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| Metric | DYME | Baseline | Absolute improvement over baseline | Relative improvement over baseline (in %) |
|---|---|---|---|---|
| Word2Vec coherence | 0.1237 | 0.2575 | 0.1338 | 51,96 |
| Infersent coherence | 0.1086 | 0.2232 | 0.1146 | 51,34 |
| Deepmoji coherence | 0.2114 | 0.2879 | 0.0765 | 26,57 |
| Question | 0.2121 | 0.2804 | 0.0683 | 24,36 |
| USE similarity | 0.1552 | 0.2002 | 0.0450 | 22,48 |
| Exploration level | 0.3048 | 0.3599 | 0.0551 | 15,31 |
| Emotional reaction level | 0.2621 | 0.3059 | 0.0438 | 14,32 |
| Interpretation level | 0.3370 | 0.3791 | 0.0421 | 11,11 |
| Word repetition | 0.0600 | 0.0671 | 0.0071 | 10,58 |
| Conversation repetition | 0.0781 | 0.0854 | 0.0073 | 8,55 |
| Deepmoji sentiment | 0.1568 | 0.1700 | 0.0041 | 7,76 |
| Self repetition | 0.1068 | 0.1149 | 0.0081 | 7,05 |
| Utterance repetition | 0.0954 | 0.1020 | 0.0066 | 6,47 |
| Utterance length | 0.1039 | 0.0954 | -0.0085 | -8,91 |

Average prediction errors (average RMSE) across all positions for each metric in descending order of the improvement of DYME over the baseline. The reported value for a metric m describes the model's average prediction error across all positions when predicting the value of metric m.

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**Results** (Average RMSE on test dataset)

Baseline: 0.2326
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| Position | DYME | Baseline | Absolute improvement over baseline | Relative improvement over baseline (in %) |
|---|---|---|---|---|
| 1 | 0.1523 | 0.3192 | 0.1669 | 52.29 |
| 2 | 0.1619 | 0.2490 | 0.0871 | 34.98 |
| 3 | 0.1905 | 0.2381 | 0.0476 | 19.99 |
| 4 | 0.1792 | 0.2223 | 0.0431 | 19.39 |
| 5 | 0.1703 | 0.2081 | 0.0378 | 18.16 |
| 6 | 0.1792 | 0.2049 | 0.0257 | 12.54 |
| 7 | 0.1700 | 0.1992 | 0.0292 | 14.66 |

Average prediction errors (average RMSE) across all metrics at each prediction position in ascending order of the position. The reported value for a prediction position q describes the model's average prediction error across all metrics when predicting for utterance position q+1, given the input context up to utterance position q.

# Conclusion

1. Metrics in human dialogs are dynamic.

2. A dynamic metric can be learned from dialog data.
   We propose **DYME**: A **DY**namic **ME**tric for Dialog Modeling Learned from Human Conversations.

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Thank you!

> Slides, code and models on GitHub: https://github.com/florianvonunold/DYME