

A Study of Automatic Metrics for the Evaluation of Natural Language Explanations

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Overview

- Explanations are a core component of human interaction, e.g. robotics, deep learning
- Strong focus on evaluation methods, common practice for NLG researchers
- Can we adopt existing NLG Metrics?

The ExBAN Corpus

(Explanations for BAyesian Networks) collected in a two step process:

- 1. **NL explanations** were produced by human subjects
 - (84 participants)
- In a separate study, these explanations were rated on a 7-point Likert scale, in terms of Informativeness and Clarity (97 participants, 250 explanations)

NLG Evaluation Methods

- Human NLG Evaluation Metrics:
 - Informativeness
 - Clarity
 - Automatic NLG Evaluation Metrics:
 - BLEU, ROUGE, METEOR,
 BERTScore & BLEURT



ExBAN Corpus
Scan the QR Code

Burglary Alarm Alarm MaryCalls Diagram 1

Ref: "In the event of either burglary or earthquake the alarm will call John and Mary."

Results: Correlation of Automatic Metrics with Human Evaluation

Metric	Diagram 1	Diagram 2	Diagram 3	All Diagrams		
BLEU-1	0.27	0.25	0.41*	0.31*		
BLEU-2	0.24	0.27	0.44*	0.33*		
BLEU-3	0.15	0.23	0.39	0.26*		
BLEU-4	0.02	0.21	0.13	0.13		
SacreBleu	0.24	0.30	0.40*	0.30*		
METEOR	0.11	-0.04	0.16	0.09		
Rouge-1	0.27	0.24	0.41*	0.29*		
Rouge-2	0.11	0.29	0.48*	0.29*		
Rouge-L	0.29	0.28	0.34	0.29*		
BERTScore	0.37	0.21	0.52*	0.37*		
BLEURT	0.25	0.38	0.58*	0.39*		

Informativance

Metric	Diagram 1	Diagram 2	Diagram 3	All Diagram		
BLEU-1	0.25	0.09	0.34	0.24*		
BLEU-2	0.24	0.15	0.41*	0.22		
BLEU-3	0.01	0.10	0.31	0.14 0.10 0.23		
BLEU-4	-0.01	0.09	0.18			
SacreBleu	0.16	0.15	0.38			
METEOR	0.17	0.13	0.30	0.21		
Rouge-1	0.20	0.11	0.29	0.20		
Rouge-2	0	0.24	0.46*	0.22		
Rouge-L	0.21	0.09	0.33	0.21		
BERTScore	0.33	0.23	0.43*	0.33*		
BLEURT	0.26	0.22	0.53*	0.34*		

Clarity

- Word-overlap metrics, such as BLEU (B), METEOR (M) and ROUGE (R)
 - presented low correlation with human ratings
- o they rely on word overlap and are not invariant to paraphrases
- BERTScore (BS) and BLEURT (BRT)
 - produced higher correlation with human ratings than other metrics
 - seem to capture some relevant facts of explanations

Good and Bad Examples of Explanations

The **alarm** is triggered by a **burglary** or an **earthquake**.

B1	B2	В3	B4	SB	М	R1	R2	RL	BS	BRT	Inf.	Clar.
0.19	0.12	0	0	0.05	0.23	0.25	0.09	0.12	0.51	0.52	7	7

Sensors = Alarm = prevention or ALEF

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B1	B2	В3	В4	SB	М	R1	R2	RL	BS	BRT	Inf.	Clar.
0.06	0	0	0	0.01	0.04	0	0	0	0	0	1	1

- All metrics are reasonably good at capturing and evaluating the "Bad" examples of explanations
- BLEURT (BRT) is more sensitive to Informativeness and Clarity as it captures both "Good" and "Bad" examples of explanations.
 A larger study might be needed to show this empirically.

Conclusions & Future Work

- Finding accurate measures is challenging, particularly for explanations
- For future work, we plan to investigate the pragmatic and cognitive processes underlying explanations

from graphical representations.

 The ExBAN corpus and this study will inform the development of NLG algorithms for NL explanations