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



HERIOT

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## Overview

Bayesian Networks are frequently used for detection of anomalies in the data and have been used to approximate deep learning methods.

#### Key Takeaways:

- Explainability
- Evaluation of explanations
- Dataset explaining BNs

#### The ExBAN Corpus (Explanations for BAyesian Networks)

collected in a two step process:

1. NL explanations were produced by human subjects

(84 participants)

- 2. 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 0
  - Clarity
- Automatic NLG Evaluation Metrics:
  - BLEU, ROUGE, METEOR, 0 **BERTScore & BLEURT**



**ExBAN Corpus** Scan the QR Code



**Diagram 1** 

earthquake the alarm will call John and Mary."

Ref: "In the event of either burglary or

MaryCalls

JohnCalls

#### **Results:** Correlation of Automatic Metrics with Human Evaluation

#### Informativeness

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*		

Clarity										
Diagram 1	Diagram 2	Diagram 3	All Diagrams							
0.25	0.09	0.34	0.24*							
0.24	0.15	0.41*	0.22							
0.01	0.10	0.31	0.14							
-0.01	0.09	0.18	0.10							
0.16	0.15	0.38	0.23							
0.17	0.13	0.30	0.21							
0.20	0.11	0.29	0.20							
0	0.24	0.46*	0.22							
0.21	0.09	0.33	0.21							
0.33	0.23	0.43*	0.33*							
0.26	0.22	0.53*	0.34*							
	Diagram 1 0.25 0.24 0.01 -0.01 0.16 0.17 0.20 0 0.21 <b>0.33</b> 0.26	Diagram 1 Diagram 2   0.25 0.09   0.24 0.15   0.01 0.10   -0.01 0.09   0.16 0.15   0.27 0.13   0.20 0.11   0 0.20   0.33 0.23   0.26 0.22	Diagram 1 Diagram 2 Diagram 3   0.25 0.09 0.34   0.24 0.15 0.41*   0.01 0.10 0.31   -0.01 0.09 0.18   0.16 0.15 0.38   0.17 0.13 0.30   0.20 0.11 0.29   0.21 0.09 0.33   0.33 0.23 0.43*							

Clarity

0

Significance of correlation: "\*" denotes p-values < 0.05

#### Word-overlap metrics, such as BLEU (B), METEOR (M) and ROUGE (R) .

- presented low correlation with human ratings 0
- they rely on word overlap and are not invariant to paraphrases 0
- 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.

B	. B2	2	B3	B4	SB	М	R1	R2	RL	BS	BRT	Inf.	Clar.
0.1	9 0.1	2	0	0	0.05	0.23	0.25	0.09	0.12	0.51	0.52	7	7

#### Sensors = Alarm = prevention or ALERT.

B1	B2	B3	B4	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
- The ExBAN corpus and this study will inform the development of NLG algorithms for NL explanations from graphical representations.