CS550: Machine Learning Survey Presentation

MULTIMODAL DECEPTION DETECTION

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Psychological Background

Deception is defined as an intentional attempt to mislead others[1]

Humans lie twice a day on average [2,3], high-stake lies may have heavy consequences[4].

Humans are hardly good at predicting deceit [5]. Methods such as polygraphs are impractical, biased, and can be fooled [6,7], which inspired learning-based approaches.

The driving mechanism behind automatic deceit detection is the leakage of behavioral cues to deception [8,9,10,11]. These cues are hard to create voluntarily and hardest to inhibit [12].

Multimodal deception detection - datasets

Datasets are either high-stakes but unconstrained or low-stakes and controlled.

Most influential high-stakes dataset is published in [13], consisting 60 truthful and 60 deceitful low-quality videos.

Example low-stakes dataset is Miami University deception detection database[14].

Common issues with most major benchmarks are the lack of data/subject, label bias, binary labels (truth/deceit), and poor video quality (resolution, framerate, etc.).

Multimodal deception detection - datasets

[14]

Figure 1: Sample screenshots showing facial displays and hand gestures from real-life trial clips. Starting at the top left-hand corner: deceptive trial with forward head movement (*Move forward*), deceptive trial with both hands movement (*Both hands*), deceptive trial with one hand movement (*Single hand*), truthful trial with raised eyebrows (*Eyebrows raising*), deceptive trial with scowl face (*Scowl*), and truthful trial with an up gaze (*Gaze up*).

Multimodal deception detection – facial analysis

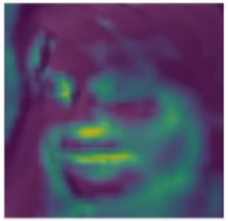
2D-3D facial reconstruction and facial analysis [15]

Attention mechanism for detecting salient face regions on deceit [16, 17]

Improved dense trajectories and facial microexpression prediction [18]

Multimodal deception detection – facial analysis

(a) An frame corresponding to the highest attention score for a deceptive video



(b) Visual cues are highlighted

(c) An frame corresponding to the highest attention score for a truth video

(d) Visual cues are highlighted

[16]

Multimodal deception detection – text analysis

Word n-grams (n-size strings)

Psycho-linguistic features (LIWC) [20]

Syntactical complexity/richness [1]

Word2Vec [21] representations

TF-IDF

Multimodal deception detection – text analysis

Category	*Examples*	*Words in category*
Total pronouns		116
Personal pronouns	I, them, her	70
1st person singular	I, me, mine	12
1st person plural	We, us, our	12
2nd person	You, your, thou	20
3rd person singular	She, her, him	17
3rd person plural	They, their, they'd	10
Impersonal pronouns	It, its, those	46
Articles	A, an, the	3
Verbs		314
Past tense	Went, ran	145
Present tense	Hear, take	169
Cognitive processes		730
Insight	Think, know	195
Causation	Because, effect	108
Discrepancy	Should, would	76
Tentative	Maybe, perhaps	155
Certainty	Always, never	83
Inhibition	Block, constrain	111
Inclusive	And, with, include	18
Exclusive	But, without	17

Sample categories from LIWC [23]

Multimodal deception detection – speech analysis

OpenSMILE [22]

Mel-frequency cepstral coefficients (MFCC)

Multimodal deception detection – network overview

Heavy focus on fusion

Formulated as a binary classification problem (truth/deceit)

Complex facial/textual analysis

Objective functions aim to maximize prediction accuracy

References

[1] B. M. DePaulo, J. J. Lindsay, B. E. Malone, L. Muhlenbruck, K. Charlton, and H. Cooper, "Cues to deception."Psychological bulletin, vol.129, no. 1, p. 74, 2003.

[2] – B. M. DePaulo, D. A. Kashy, S. E. Kirkendol, M. M. Wyer, and J. A. Epstein, "Lying in everyday life." Journal of personality and social Psychology , vol. 70, no. 5, p. 979, 1996.

[3] T. Hancock, J. Thom-Santelli, and T. Ritchie, "Deception and design: The impact of communication technology on lying behavior," in Proceedings of the SIGCHI conference on Human factors in computing systems. ACM, 2004, pp. 129–134.

[4] L. ten Brinke and S. Porter, "Discovering deceit: Applying laboratory and field research in the search for truthful and deceptive behavior," in Applied issues in investigative interviewing, eyewitness memory, and credibility assessment. Springer, 2013, pp. 221–237.

[5] M. G. Aamodt and H. Custer, "Who can best catch a liar?" Forensic Examiner, vol. 15, no. 1, 2006.

[6] T. Gannon, A. R. Beech, and T. Ward, "Risk assessment and the polygraph," The Use of the Polygraph in Assessing, Treating and Supervising Sex Offenders: A Practitioner's Guide. Oxford: Wiley-Blackwell, pp. 129–154, 2009.

[7] A. Vrij, Detecting lies and deceit: The psychology of lying and implications for professional practice. Wiley, 2000.

[8] M. Abouelenien, V. Perez-Rosas, R. Mihalcea, and M. Burzo, "Deception detection using a multimodal approach," in Proceedings of the 16th International Conference on Multimodal Interaction. ACM, 2014, pp. 58–65.

[9] M. Hartwig and C. F. Bond Jr, "Lie detection from multiple cues: A meta-analysis," Applied Cognitive Psychology, vol. 28, no. 5, pp. 661-676, 2014.

[10] M. R. Morales, S. Scherer, and R. Levitan, "Openmm: An open-source multimodal feature extraction tool." in INTERSPEECH, 2017, pp. 3354–3358.

[11] K. Gopalan and S. Wenndt, "Speech analysis using modulation-based features for detecting deception," in 2007 15th International Conference on Digital Signal Processing. IEEE, 2007, pp. 619–622.

References

[12] C. Darwin and P. Prodger, The expression of the emotions in man and animals. Oxford University Press, USA, 1998.

[13] V. Perez-Rosas, M. Abouelenien, R. Mihalcea, and M. Burzo, “Deception detection using real-life trial data,” in Proceedings of the 2015 ACM on International Conference on Multimodal Interaction, ser. ICMI ’15. New York, NY, USA: ACM, 2015, pp. 59–66. [Online]. Available: http://doi.acm.org/10.1145/2818346.2820758

[14] E. P. Lloyd, J. C. Deska, K. Hugenberg, A. R. McConnell, B. T. Humphrey, and J. W. Kunstman, “Miami university deception detection database,” Behavior Research Methods, vol. 51, no. 1, pp. 429–439, Feb. 2019. [Online]. Available: https://doi.org/10.3758/s13428-018-1061-4

[15] M. Ngo, B. Mandira, S. F. Yilmaz, W. Heij, S. Karaoglu, H. Bouma, H. Dibeklioglu, and T. Gevers, “Deception detection by 2d-to-3d face reconstruction from videos,” CoRR, vol. Abs/1812.10558, 2018. [Online]. Available: http://arxiv.org/abs/1812.10558

[16] H. Karimi, “Interpretable multimodal deception detection in videos,” 10 2018, pp. 511–515.

[17] H. Karimi, J. Tang, and Y. Li, “Toward end-to-end deception detection in videos,” 2018 IEEE International Conference on Big Data (Big Data), pp. 1278–1283, 2018.

[18] Z. Wu, B. Singh, L. S. Davis, and V. S. Subrahmanian, “Deception detection in videos,” 2017.

[19] M. Ding, A. Zhao, Z. Lu, T. Xiang, and J.-R. Wen, “Face-focused cross-stream network for deception detection in videos,” 2018.

[20] J. W. Pennebaker and L. A. King, “Linguistic styles: Language use as an individual difference.” Journal of personality and social psychology, vol. 77, no. 6, p. 1296, 1999.

[21] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean, “Distributed representations of words and phrases and their compositionality,” in Advances in neural information processing systems , 2013, pp. 3111–3119.

[22] F. Eyben, M. Wollmer, and B. Schuller, “Opensmile: the munich versatile and fast open-source audio feature extractor,” in Proceedings of the 18th ACM international conference on Multimedia. ACM, 2010, pp. 1459–1462.

[23] B. Liang and D. L. Scammon, “We learn from each other: exploring interpersonal communications in online communities,” in International Conference on Web Based Communities and Social Media , vol. 20, 2017, p. 22.