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Final Report for Period Beginning 13-Jun-2016 and Ending 30-Nov-2022

Title: MURI: SCAN: Socio-Cultural Attitudinal Networks

Begin Performance Period: 13-Jun-2016

End Performance Period: 30-Nov-2022

Report Term: 0-Other

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STEM Degrees: 62

STEM Participants: 62

Major Goals: The major goals of this project are to:

- i) Understand the relationship between verbal and non-verbal methods of intra-group communication (e.g., via facial expressions, gestures, speech patterns) and dominance-deference, like-dislike, trust-distrust relationships between individuals within a group in a diverse cross-cultural setting.
 - ii) Develop methods to predict, from a given audio-video recording of group interaction, which pairs of people are dominant/deferential, like/dislike each other, trust/distrust each other.
 - iii) Develop methods to predict, from a given audio-video recording, who is being deceptive and when.
- Goal 1. Our first task is to develop a Cross Cultural Attitudinal Observatory (CCAO) to gather data that enabled the analysis of verbal and nonverbal behaviors related to expressions of dominance-deference, like-dislike, and trust-distrust between distinct cultures. A multiplayer in-person game will be created to elicit the behaviors of interest, capture attitudes, and record interactions. Individuals often rely on erroneous cues when judging others; the objective of this research is to explore reliable cues based on individual actions and networks of relationships. The following discusses steps taken to collect data including the creation of the game, attitudinal measurements, behavioral observations, lessons learned, and future plans.
- Goal 2. The second major project goal is to develop methods to monitor the heads, faces, limbs and upper torsos of each player to estimate their head and facial expressions, postures, gestures, and vocal features in accordance with TRC, DPT and IDT, with emphasis on like-dislike, dominance-deference and trust-distrust relationships.
- Goal 3. The third goal is to use the signals extracted in Goal 2 to automatically build a Socio-Cultural Attitudinal Network (SCAN). Specifically, for each pair (P1,P2) of players who participated in a game, this Thrust will develop methods to quantify, on a -1 to +1 continuous scale, how much P1 likes P2, how much P1 dominates P2, and how much P1 trusts P2.
- Goal 4. The fourth goal of the SCAN Project is to develop methods that use the verbal and non-verbal communication signals generated by Goal 2, together with the game data from Goal1, to identify which users are being deceptive, and identifying conditions on the features from Goal 1 that are predictive of when a person is being deceptive.

Accomplishments: The SCAN project made several huge advances in many directions:

- 1: Findings from deception in dyads cannot be readily generalized to deception in groups. It prompted the development of our version of the Resistance/Mafia game to study group deceptive interactions across cultures.
- 2: Accurate deception detection is best achieved by combining multimodal measurement with awareness of temporal changes in deceptive cues. Of these modalities, voice is better at producing accurate predictions than kinesic cues, but combinations of specific facial action units may produce the highest accuracy.
- 3: Network methods reveal collusion by deceivers in groups. Analysis of the speaking and gazing network patterns

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reveals that deceivers avoid eye contact with their allies. Less engaging deceivers are less successful in deceiving others.

4: The best model for deception detection combines verbal, vocal and visual cues. Multiple behavioral indicators achieved up to 90% accuracy in distinguishing truth from deception.

5: Deception detectors report relying on a small set of verbal and nonverbal cues to detect deception in group interaction. The top reported behavioral traits linked with distrust of other players include: (1) Acting in confusing or illogical ways; (2) Sounding overly confident in their role; (3) Talking an inappropriate amount; (4) Acting nervous; (5) Making extreme statements.

6: Because deceivers only deceive a fraction of the interaction time, we developed a novel method to account for the transitory nature of deception: detection via critical points. We demonstrate the effectiveness of the critical point approach by showing that, in the ten-second time periods after leader nomination and result announcement, deceivers and truth-tellers have a larger difference in the happiness and surprise emotions they display than over the entire group interaction.

7: Deception and deception detection processes are surprisingly similar across widely different cultures. Our data provide the strongest evidence to date for the universal cues hypothesis which predicts no cultural differences in deception across cultures.

8: To assess the generalizability of deception signals in groups, we developed a new experimental protocol: The Resume Experiment. Participants were assigned to groups of five and asked to complete several tasks as a team. Within each group, two participants were asked to act as a "spy" from a rival company. Both verbal and nonverbal cues of each participant were examined through textual analysis of transcripts and automatic detection of visual and vocal signals

9: Culture has limited effect on how dominance is expressed. Our analyses revealed that perceptions of dominance were remarkably consistent across culture.

10: Linguistic features may promote trustworthiness or signal deceptiveness. The proposed hypotheses were tested using conversational data.

11: Interactions between Deceivers and Non-Deceivers. Truth-tellers interact equally with everyone while deceivers interact more with truth-tellers.

12: Many nonverbal features are used by humans to detect dominance. The Mafia experiment we created investigated the effects of deception on relational communication, including dominance, during group interaction.

13: Nonverbal cues, besides signaling deception, signal the nature of the relationship between deceiver and deceived. These "relational messages" signal whether the deceiver is more assertive or subservient in relation to other group members, likes the others and wants to be trusted, is involved in the conversation rather than detached, feels composed or nervous in the others' presence, and conveys similarity to other group members.

14: Deceivers are most successful when establishing trust in combination with engaging in dominant communication. Those who fail to win others' trust and are regarded with suspicion are most likely to be deceptive. Deceivers are most successful when they temper their dominance and withhold being too assertive until the end of the discussion.

15: Vocal indicators are the most important variables indicating nervousness. Perceptions of nervousness increased as vocal animation decreased throughout the game.

16: Trust is a good proxy for identifying deceivers. We discovered that repeat phrases ratio, third person singular ratio, and third person plural ratio are positively associated with perceived trustworthiness, and present tense ratio is negatively associated with perceived trustworthiness.

17: Deception Prediction in Real-World Courtroom Videos. Using various classifiers, our automated system obtains an AUC of 0.877 when evaluated on subjects which were not part of the training set.

18: Predicting Deception in Groups, Attempt 1 – LiarOrNot. Our ADD framework was the first to capture long term deception in a group setting. We study deception in the well-known Resistance game. We achieve AUCs of over 0.70 in a fully automated setting.

19: Predicting Deception in Groups: Attention-based Facial Behavior Analytics. We analyzed the deceptive behavior of people from various countries and cultural orientations. The findings support the universal cues hypothesis.

20: A Network-based Model to Predict Deception. Our novel DeceptionRank approach, a PageRank based network model for predicting deception, outperforms other state-of-the-art approaches.

21: Predicting Deception in Groups: VG-GAN, Vision Transformer (ViT). Our results showed that encoding the input videos with a VQ-GAN resulted in 24% relative classification performance improvement compared to using the raw video frames as input to ViT.

22: Understanding Political Deception. Our POLLY (POLitical LYing) system builds upon past work by others to generate predictions for whether a politician is lying or not.

23: Predicting the Most Dominant Person in a Group. Our novel ensemble-based approach achieves 2.4% to 16.7% improvement in AUC compared to baselines on one dataset, and a gain of 0.6% to 8.8% in accuracy on the

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other.

24: Predicting Who is Looking at Who. We propose ICAF (Iterative Collective Attention Focus), a collective classification model to jointly learn the visual focus of attention of all people in multi-person discussions.

25: Relative Nervousness Prediction. Given a video of a group of interacting humans, we predict how nervous a person is.

26: Predicting Impressions of Subjects. Our novel Dyadic Impression Prediction System (DIPS) beats 8 baselines from the literature, yielding statistically significant improvements of 19.9-30.8% in AUC and 12.6-47.2% in F1-score.

27: Multimodal Persuasion Prediction. We solve two problems: the Debate Outcome Prediction (DOP) problem predicts who wins a debate while the Intensity of Persuasion Prediction (IPP) problem predicts the change in the number of votes before and after a speaker speaks.

28: Single End-to-End Prediction of Dominance, Nervousness, Deception. Our new TEDIC Framework is a neural network model that is uniformly good across different prediction tasks: detecting dominance, nervousness, deception

29: Hierarchical Temporal Networks. Our experiments show that methods using a hierarchical event structure as input outperform methods that use only sequential event input.

30: A Youtube interview dataset was analyzed for synchrony. We collected 178 mediated interviews between April 2020 to March 2021. Greater synchrony occurred in information-driven interviews compared to entertainment-driven interviews.

31: New Persuasion Dataset & Code. The dataset consists of video clips from the Chinese TV show Qipashuo.

32: New Global Political Deception Dataset. Our POLLY (Political Lying) dataset consists of 148 videos from 18 countries involving a total of 76 public figures.

33: New Contacts in a Workplace Dataset. We demonstrate that TEDIC is applicable to a wider range of social interaction networks than those obtained from the Resistance game.

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Training Opportunities: Students were trained via a number of mechanisms.

Summary: During this period, 47 PhD students, 6 postdoctoral fellows and 15 undergraduates were involved in this grant. They were active participants in the research and learned about image processing, speech processing, machine learning, as well as social science theories surrounding deception, and statistical modeling.

Research Training: For Stanford, 2 postdocs, one currently a faculty at Georgia Tech, another one became faculty at Purdue University in the fall of 2020. For Rutgers, 2 Webinars occurred on July 2020. For UMD/Northwestern/Dartmouth, one PhD student is now on the faculty at Georgia Tech, and other researchers now work at Amazon, Microsoft, Motorola, and Facebook. One postdoc is on the faculty of the College of Williams, one at the University of Louisville, and one is a Senior Research Associate at Northwestern.

Graduate student training: Grad students were involved in weekly meetings with their supervisors. In many cases, these grad students were participants in research meetings involving faculty from multiple universities. For Stanford, there were 3 graduate students, 1 visiting student between Stanford University and Dartmouth University. There were 5 grad students at the University of Arizona being trained. Three graduate students, Matt Giles and Mohemmad Hansia at UCSB and Vincent Denault at Universite de Montreal have assisted with this project.

Metzger and Dunbar both gave virtual guest lectures to graduate seminars at University of Arizona on the project.

Graduate Student Research visits: An important part of graduate training involves graduate students visiting research labs other than their own and participating substantively in joint research:

- i) PhD student Srijan Kumar from UMD spent time at Stanford and CMU as a student and later joined Stanford as a postdoc. This led to several joint papers between Stanford and UMD/Dartmouth researchers.
- ii) PhD student Chongyang Bai from Dartmouth spent 3 months in 2018 at Stanford University, resulting in 2 joint papers at IJCAI 2019.
- iii) PhD student Chongyang Bai from Dartmouth spent 3 months in 2019 at Stanford University, resulting in 2 joint papers.
- iv) PhD student Maks Bolonkin from Dartmouth spent 3 months at UMD, resulted in a paper that was presented at ICME 2019.

Undergraduate Student Training. For Rutgers, through course on ML and Computer CS 534 Vision this semester where students were taught developed Attention Methods. There are 7 students trained via the Deception Detection Project, there were 8 via the Fake News Project and there were 2 via the Critical Decision Point Analysis Project.

Government or Industry Training. For Dartmouth, this was done through the 2 Webinars in June and July 2020. For Rutgers, talks with Aberdeen Proving Grounds Researchers.

Faculty Training. There were also two workshops in October 2019: Walls, B., and Wang, X. OpenFace Processing and Video Data Collection Best Practices. Quantitative Methods in the Social Sciences workshop, University of California Santa Barbara, CA and Ken Fujiwara Analysis of Deception with Wavelets workshop, University of California Santa Barbara, CA

Workshops Organized. For Stanford, Workshops on Graph Learning at ICLR 2020, ICML 2020 and NeurIPS 2019.

Faculty visits from different SCAN institutions. Srijan Kumar from Stanford University organized the Fourth Workshop on Computational Methods in Online Misbehavior, on the sidelines of The Web Conference 2019.

Faculty Visits: Hosted Roberta Muchangwe from University of Zambia at UCSB for 1 month (06/05/19-07/07/19). She had meetings with the UCSB and Arizona research teams to help us analyze the Zambia cultural data. She presented to UCSB faculty and graduate students about Zambian culture.

V.S. Subrahmanian from Dartmouth visited Stanford in July 2018 and October 2018.

Multiple team meetings were held at UMD, University of Arizona.

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Results Dissemination: Results were disseminated to the external community via four mechanisms.

Book. A first book of its kind on computational models for the understanding and prediction, from video, of diverse phenomena such as deception, trust, dominance, deference, nervousness, like/dislike, and persuasion.

Subrahmanian, V.S., Burgoon, J.K. and Dunbar, N.E. eds., 2021. Detecting Trust and Deception in Group Interaction. Springer.

Summer Course. A one-summer course on the use of AI for advanced understanding and prediction of deception, trust, dominance, deference, nervousness, like/dislike, and persuasion was created and offered.

Keynotes and Invited Talk. The PIs delivered numerous invited talks and keynote talks are major conferences or venues.

- 1) Keynote, New York State Cybersecurity Conference, June 2018 – Subrahmanian
 - 2) Invited talk at Google, July 2018 – Subrahmanian
 - 3) Invited series of lectures over one day, Netherlands Defense Academy, Netherlands, Sep 2018 – Subrahmanian
 - 4) Invited talk at Google, Oct 2018 – Subrahmanian
 - 5) Invited talk at the Foundation for the Defense of Democracies, Oct 2018 – Subrahmanian
 - 6) Plenary address, The World Academy of Sciences Annual Meeting, Nov 2018 - Subrahmanian
 - 7) Invited panelist, Launch of the NTU Institute for Technology & Humanities, Singapore, March 2019 – Subrahmanian
 - 8) Keynote: The Graduate Club, November 2018 – Nunamaker
 - 9) Invited Talk: Cognitive Science, University of Arizona, March 1, 2019 – Nunamaker
 - 10) Invited talk, Knowledge Extraction from Games workshop on the sidelines of the Thirty-Third AAAI Conference on Artificial Intelligence (AAAI-19), Kumar.
 - 11) Invited talk, International Workshop on Misinformation, Computational Fact-Checking and Credible Web on the sidelines of the ACM International Conference on World Wide Web (WWW-19) - Kumar.
 - 12) Keynote, WikiWorkshop on the sidelines of the ACM International Conference on World Wide Web (WWW), 2019 – Leskovec.
 - 13) Invited talk, University of Zurich, 2019 - Leskovec
 - 14) Distinguished Lecture, Network Science Institute, Northeastern University, 2019 - Leskovec
- Publications.** The PIs published numerous scientific publications in highly refereed conferences and archival journals
- [1] Bai, C., Bolonkin, M., Burgoon, J., Chen, C., Dunbar, N., Singh, B., and Subrahmanian, V.S., Automatic Long-Term Deception Detection in Group Interaction Videos. ICME'19
 - [2] Bai, C., Bolonkin, M., Kumar, S., Leskovec, J., Burgoon, J., Dunbar, N., and Subrahmanian, V.S., Predicting dominance in multi-person videos. To appear in IJCAI'19
 - [3] Bai, C., Kumar, S., Leskovec, J., Metzger, M., Nunamaker, J., Subrahmanian, V.S., Predicting the Visual Focus of Attention in Multi-person Discussion Videos. To appear in IJCAI'19
 - [4] Bai, C., Kumar, S., Leskovec, J., Metzger, M., Nunamaker, J. F., Subrahmanian, V. S. (accepted). Iterative Collective Classification for Visual Focus of Attention Prediction. International Joint Conference on Artificial Intelligence (IJCAI), August 2019.
 - [5] Bai, C., Bolonkin, M., Burgoon, J. K., Chen, Dunbar N, Regunath V, Subrahmanian V.S. , Predicting Relative Nervousness from Group Interaction Videos, submitted to ACM Multimedia 2020
 - [6] Bai C, Chen , Kumar S, Leskovec J, Subrahmanian V.S. , M2P2: Multimodal Persuasion Prediction using Adaptive Fusion, submitted to ACM Multimedia 2020
 - [7] Proudfoot, J., Jenkins, J. Valacich, J. and Nunamaker, J., "Slight of Hand: Identifying Concealed Information by Monitoring mouse Cursor Movement." To appear, Journal of the Association for Information Systems.
 - [8] Burgoon, J.K., Opinion: Microexpressions are not the best way to catch a liar. *Frontiers in Psychology*, 9, Sep 2018
 - [9] Burgoon, J. K., Separating the wheat from the chaff: Guidance from new technologies for detecting deception in the courtroom. *Frontiers in Psychology*, 9:774, Jan 2019
 - [10] Burgoon, J. K., Blair, J. P., Hamel, L. & Twyman, N. W. (2020). Factors that facilitate or impair kinesic and vocalic nonverbal behaviors during interpersonal deception. In A. Kosti? (Ed.), *Social Intelligence: The Adaptive Advantages of Nonverbal Communication*. Switzerland: Palgrave.
 - [11] Burgoon, J. K. (in press). Prelude: Relational communication and the link to deception. In V. S. Subrahmanian, J. K. Burgoon & N. E. Dunbar (Eds.), *Detecting Trust and Deception in Group Interaction*. New York, NY: Springer, 2020.
 - [12] Burgoon, J. K., Dunbar, N. E. & Jensen, M. (in press). An integrated spiral model of trust. In V. S. Subrahmanian, J. K. Burgoon & N. E. Dunbar (Eds.), *Detecting Trust and Deception in Group Interaction*. New York, NY: Springer, 2020.

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- [13] Burgoon, J. K., Metaxas, D. & Nunamaker, J. F. (in press). Cultural influence on deceptive communication. In V. S. Subramanian, J. K. Burgoon & N. E. Dunbar (Eds.), *Detecting Trust and Deception in Group Interaction*. New York, NY: Springer.
- [14] Denault, V., Plusquellec, P., Jupe, L. M., St-Yves, M., Dunbar, N. E., Hartwig, M., Sporer, S. L., Rioux-Turcotte, J., Jarry, J., Walsh, D., Otgaar, H., Viziteu, A., Talwar, V., Keatley, D. A., Blandón-Gitlin, I., Townson, C., Deslauriers-Varin, N., Lilienfeld, S. O., Patterson, M.L., Areh, I., Allan, A., Cameron, H.E., Boivin, R., ten Brinke, L., Masip, J., Bull, R., R., Cyr, M., Hope, L., Strömwall, L. A., Bennett, S., Al Menaiya, F., Leo, R. A., Vredeveltdt, A., Laforest, M., Honts, C. R., Manzanero, A. L., Mann, S., Geanhag, P.-A., Ask, K., Gabbert, F., Guay, J.-P., Coutant, A., Hancock, J., Manusov, V., Burgoon, J.K., Kleinaman, S. M., Wright, G., Landström, S., Freckelton, I., Vernham, Z., & van Koppen, P.J., *The analysis of nonverbal communication: the dangers of pseudoscience in security and justice contexts*. *Anuario de Psicología Jurídica*, 1-12, Apr 2019
- [15] Kumar, S., Zhang, X., Leskovec, J.. Predicting Embedding Trajectories in Temporal Interaction Networks. 25th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, 2019 [8] K. Xu, W. Hu, J. Leskovec, S. Jegelka, *How Powerful Are Graph Neural Networks?*. ICLR, 2019.
- [16] S. Kumar, X. Zhang, J. Leskovec. Predicting Dynamic Embedding Trajectory in Temporal Interaction Networks. ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD), 2019.
- [17] J. You, Y. Wang, A. Pal, P. Eksombatchai, C. Rosenberg, J. Leskovec. Hierarchical Temporal Convolutional Networks for Dynamic Recommender Systems. ACM International Conference on World Wide Web (WWW), 2019.
- [18] W. Hamilton, P. Bajaj, M. Zitnik, D. Jurafsky, J. Leskovec. Embedding Logical Queries on Knowledge Graphs. Neural Information Processing Systems (NeurIPS), 2018.
- [19] R. Ying, J. You, C. Morris, X. Ren, W. Hamilton, J. Leskovec. Hierarchical Graph Representation Learning with Differentiable Pooling. Neural Information Processing Systems (NeurIPS), 2018.
- [20] R. Ying, D. Bourgeois, J. You, M. Zitnik, J. Leskovec. GNNExplainer: Generating Explanations for Graph Neural Networks Neural Information Processing Systems (NeurIPS), 2019.
- [21] E. Ghalebi, B. Mirzasoleiman, R. Grosu, J. Leskovec. Dynamic Network Model from Partial Observations. Neural Information Processing Systems (NeurIPS), 2018.
- [22] J. You, R. Ying, X. Ren, W. L. Hamilton, J. Leskovec. GraphRNN: Generating Realistic Graphs with Deep Auto-regressive Models. International Conference on Machine Learning (ICML), 2018.
- [23] R. Ying, R. He, K. Chen, P. Eksombatchai, W. L. Hamilton, J. Leskovec. Graph Convolutional Neural Networks for Web-Scale Recommender Systems. ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD), 2018.
- [24] C. Donnat, M. Zitnik, D. Hallac, J. Leskovec. Learning Structural Node Embeddings via Diffusion Wavelets. ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD), 2018.
- [25] H. Yin, A. Benson, J. Leskovec. Higher-Order Clustering in Networks. Physical Review E 97 052306 (PRE), 2018.
- [26] J. Cheng, J. Kleinberg, J. Leskovec, D. Liben-Nowell, B. State, K. Subbian, L. Adamic. Do Diffusion Protocols Govern Cas

Honors and Awards: Runner up, Most Innovative Demo, 2019 International Joint Conference on Artificial Intelligence, Macao, Aug 2019.

Invited through American Institute of Medical and Biological Engineers to talk to congress and the senate towards increasing the NSF and the NIH budget with emphasis on AI, February 2020.

Outstanding Graduate Alumni Achievement Award, School of Communication, Illinois State University

Judee Burgoon was inducted into Hall of Fame, Arts & Sciences, Illinois State University

Most Prolific Author Award at HICSS for last 50 years. 102 papers written and accepted at HICSS over 50 years.

HICSS is attended by approximately 1200 national International Scholars Yearly. Over the years, Professor Nunamaker received ten "Best Paper of the Conference" awards.

The Distinguished Mechanical Engineer of the Year Award from the University of Pittsburgh - Professor Nunamaker.

V.S. Subrahmanian's paper "Hybrid Probabilistic Programs" with Alex Dekhtyar, published in Proc. 1997 Intl. Conf. on Logic Programming, Leuven, Belgium, July 8-12, 1997 was named the recipient of the "20 Year Test of Time Award" from the 2017 International Conference on Logic Programming, Melbourne, Australia, Aug 2017.

V.S. Subrahmanian was named an IEEE/Tencent Rhino Bird International Academic Expert, May 2017.

Runner Up for the Best Paper Award, 2017 World Wide Web Conference, Perth, Australia, April 2017. Joint work by UMD (Kumar, Subrahmanian) and Stanford teams.

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Protocol Activity Status:

Technology Transfer: Nothing to Report

PARTICIPANTS:

Participant Type: Faculty

Participant: V.S. Subrahmanian

Person Months Worked: 2.00

Project Contribution:

National Academy Member: N

Funding Support:

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Participant: Dimitris Metaxas

Person Months Worked: 2.00

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Project Contribution:

National Academy Member: N

Funding Support:

Participant Type: Faculty

Participant: Jay Leskovec

Person Months Worked: 1.00

Project Contribution:

National Academy Member: N

Funding Support:

Participant Type: Faculty

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SCAN: Socio-Cultural Attitudinal Network

Supplementary material for ARO Grant W911NF1610342

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What were the major goals and objectives of the project?

The major goals of this project are to:

- i) Understand the relationship between verbal and non-verbal methods of intra-group communication (e.g., via facial expressions, gestures, speech patterns) and dominance-deference, like-dislike, trust-distrust relationships between individuals within a group in a diverse cross-cultural setting.
- ii) Develop methods to predict, from a given audio-video recording of group interaction, which pairs of people are dominant/deferential, like/dislike each other, trust/distrust each other.
- iii) Develop methods to predict, from a given audio-video recording, who is being deceptive and when.

Goal 1. Our first task is to develop a Cross Cultural Attitudinal Observatory (CCAO) to gather data that enabled the analysis of verbal and nonverbal behaviors related to expressions of dominance-deference, like-dislike, and trust-distrust between distinct cultures. A multiplayer in-person game will be created to elicit the behaviors of interest, capture attitudes, and record interactions. Individuals often rely on erroneous cues when judging others; the objective of this research is to explore reliable cues based on individual actions and networks of relationships. The following discusses steps taken to collect data including the creation of the game, attitudinal measurements, behavioral observations, lessons learned, and future plans.

Goal 2. The second major project goal is to develop methods to monitor the heads, faces, limbs and upper torsos of each player to estimate their head and facial expressions, postures, gestures, and vocal features in accordance with TRC, DPT and IDT, with emphasis on like-dislike, dominance-deference and trust-distrust relationships.

Goal 3. The third goal is to use the signals extracted in Goal 2 to automatically build a Socio-Cultural Attitudinal Network (SCAN). Specifically, for each pair (P1,P2) of players who participated in a game, this Thrust will develop methods to quantify, on a -1 to +1 continuous scale, how much P1 likes P2, how much P1 dominates P2, and how much P1 trusts P2.

Goal 4. The fourth goal of the SCAN Project is to develop methods that use the verbal and non-verbal communication signals generated by Goal 2, together with the game data from Goal 1, to identify which users are being deceptive, and identifying conditions on the features from Goal 1 that are predictive of when a person is being deceptive.

What was accomplished towards achieving these goals?

The SCAN project made several huge advances in many directions.

Accomplishment 1: Findings from deception in dyads cannot be readily generalized to deception in groups.

Deception is defined as “the successful or unsuccessful deliberate attempt, without forewarning, to create in another a belief which the communicator considers to be untrue” (Vrij, 2008, p. 15). It is typically studied from a post positivist perspective, and usually focuses on dyadic interactions. This stands to reason considering how theoretical frameworks turn to deceiver-detector paradigms using experimental methods (Burgoon & Levine, 2010). Previous research suggests that deception in group interactions is more complex than in dyadic interactions (Hauch et al., 2016; Zhou et al., 2013). Yet, deception in group interactions is largely understudied, and guidance on how deception is enacted in such settings is limited (Vernham et al., 2016). As the number of group members increases, the process of identifying deceptive messages grows in complexity. This is likely due to a heightened sense of uncertainty among interactants (Burgoon, 2018), which can subsequently affect group performances (Booth-Butterfield et al., 1988), and a greater degree of interdependence among group members compared to dyadic interactions (Bonito & Staggs, 2018). In other words, deceptive group interactions increase the number of unknown variables group members must take into account (i.e., uncertainty) and the number of challenges they must overcome to achieve their goals (i.e., interdependence). They must also adjust their comments for multiple audience members rather than a single other. Groups also permit collusion and the formation of coalitions. Several other characteristics of deception in group interactions are overlooked. Our project was designed to overcome these gaps in the research literature in deception found in group interactions. It prompted the development of our version of the Resistance/Mafia game to study group deceptive interactions across cultures.

Accomplishment 2: Accurate deception detection is best achieved by combining multimodal measurement with awareness of temporal changes in deceptive cues.

Deception is embedded in impression management and persuasion. Deceivers strategically manage their body language as well as verbal expression. Nonverbally, deception cues include vocalic features such as pitch, loudness and fluency and kinesic emotional expressions from the face, head, torso, gestures and posture. Verbally, deception indicators include linguistic forms such as verb tense, pronoun use, amount of talk, diversity of language, and amount of hedging. Combinations of these result in greater accuracy in detecting deceivers. Of these modalities, *voice* is better at producing accurate predictions than kinesic cues, but combinations of specific facial action units may produce the highest accuracy. Multiple language features together can be powerful with and without considering voice. As important as the specific cues are their dynamic

character. Static depictions are misleading. Deceptive patterns change over time such that patterns evident at the beginning of interactions are not the same as those at the end.

Accomplishment 3: Network methods reveal collusion by deceivers in groups.

Analysis of the speaking and gazing network patterns reveals that deceivers avoid eye contact with their allies. Less engaging deceivers are less successful in deceiving others. They look at fewer participants and are looked at less by others, and get less attention while speaking in the losing game. When analyzing the verbally expressed trust and distrust in the group, the regression results indicate that deceivers are less likely to receive endorsements and more likely to be perceived as distrustful. Additionally, deceivers are more cautious about expressing their trust to other participants because advocating for other deceivers could damage their reputations, while supporting other truth-tellers would not directly benefit the deceiver's team. Deceivers are most successful when they address less suspicion toward other participants in the group.

Accomplishment 4: The best model for deception detection combines verbal, vocal and visual cues.

In the SCAN project, linear regression analyses focused on three types of behavioral measures to predict deception: verbal, vocal and visual. Deceivers used many verbal "tells." They used language with more complexity. Their language included more adverbs, uncertainty and hedging, but fewer nouns and conjunctions. They used more dominant language, referred to themselves more often, and were less likely to offer suggestions and to promote a positive self-image. Vocally, deceivers' turns at talk became shorter than truth-tellers' as the interaction progressed. Visually, the most evident deception tells were lip stretching, blinking, fake smiles, and a number of specific facial movements. When combined, multiple behavioral indicators achieved up to 90% accuracy in distinguishing truth from deception. (The best combinatorial methods were linear discriminant analysis, logistic regression, and SVM.)

Accomplishment 5: Deception detectors report relying on a small set of verbal and nonverbal cues to detect deception in group interaction.

When asked what verbal and nonverbal cues detectors rely on to determine others' veracity, they typically formed five themes. The top reported behavioral traits linked with distrust of other players include: (1) *Acting in confusing or illogical ways*, such as engaging in nonsensical behavior or attempting to actively spread confusion amongst the players; (2) *Sounding overly confident* in their role, such as defiant denials (e.g., "I am not a spy!") or taking charge of and/or directing what other players should do in the game; (3) *Talking an inappropriate amount*, either too much or too little; (4) *Acting nervous*, both verbally such as stuttering or having many unnatural pauses in their speech, or nonverbally by showing a lack of confidence via their eye, face, or body movements; (5) *Making extreme statements* including accusing others as spies in an overly aggressive manner or being overly defensive themselves when challenged about

aspects of their behavior during the game. These themes are surprisingly consistent across locales and nationalities.

Accomplishment 6: Because deceivers only deceive a fraction of the interaction time, we developed a novel method to account for the transitory nature of deception: detection via critical points.

Critical points refer to the short time period when a novel and personally significant stimulus is presented to a target individual. The stimulus triggers different cognitive appraisals in deceivers and truth-tellers and thus enlarges their emotional and behavioral differences. Examples of critical points are leader nomination and result announcement. We demonstrate the effectiveness of the critical point approach by showing that, in the ten-second time periods after leader nomination and result announcement, deceivers and truth-tellers have a larger difference in the happiness and surprise emotions they display than over the entire group interaction. We further find that the stimulus type moderates deceivers' and truth-tellers' behavioral differences during critical points. When the stimulus is congruent with the truth-tellers' goal, deceivers display less intense facial action units, a more rigid face and head pose, and less positive emotions than the truth-tellers. The contrast generally shrinks or is even reversed if the stimulus is congruent with the deceivers' goal.

Accomplishment 7: Deception and deception detection processes are surprisingly similar across widely different cultures.

This study provides the most extensive data on cultural variations in deception and deception detection ever collected. Games were played in 6 countries across 4 continents. The data were analyzed using multiple ways of conceptualizing culture, including nationality, ethnicity, country of residence, and using psychometric cultural dimension scales (e.g., individualism collectivism, power distance). Cultural variations in deception and deception detection in the (a) self-report, (b) linguistic and vocalic, and (c) kinesic data were probed. Interestingly, few cultural differences emerged. While participants in all locations reported using similar cues to detect deception (see Accomplishment #5) players in the different locations used each of these cues with different frequency (e.g., sounding confident is used less frequently in Israel than in Zambia). A few vocalic (jitter, pitch) and linguistic (nouns, number of words) differences were found to distinguish truth-tellers from deceivers, but predictive power was small and these patterns were very specific to each location. No differences in facial action units (FAUs) were detected in deceivers from different cultures. Our data provide the strongest evidence to date for the *universal cues hypothesis* which predicts no cultural differences in deception across cultures. This perspective holds that because the evolutionary benefits of both deception and accurately detecting deception is the same for all humans, deceivers should act similarly across cultures and detectors should have evolved similarly to spot deceptive behavior.

Accomplishment 8: To assess the generalizability of deception signals in groups, we developed a new experimental protocol: The Resume Experiment.

Previous research has suggested that there is an interplay between dominant behavior and deception, depending on the context. Dunbar and colleagues (2014, 2021) reported that deceivers tend to enact more dominant behavior in dyadic settings and more submissive behavior in group settings. To better understand these differences, we designed a mock hiring experiment to tease out the nuances of dominant behavior in deceptive interactions. We were especially interested in the role of technology-mediated group interactions. Participants ($N = 109$) were assigned to groups of five and asked to complete several tasks as a team. Within each group, two participants were asked to act as a “spy” from a rival company. To simulate a realistic organizational scenario for deception, other participants were not informed of the existence of spies. The central task that each group had to complete was to assess five job candidates’ resumes and then discuss candidates’ qualification and interview performance together. Before the group discussion, each participant was asked to verbally present interview notes of one candidate to the group and two spies were given the notes of two least qualified candidates. All interview notes were only visible to the participant who presented them. After the discussion, participants were asked to vote for the best candidate for the job. The goal of the two spies was to persuade the group into choosing one of the two least qualified candidates. Both verbal and nonverbal cues of each participant were examined through textual analysis of transcripts and automatic detection of visual and vocal signals. To capture complex group dynamics and discover conversation patterns, we created a novel discourse analysis framework for charting speech acts in group discussions, abstracting content within each verbal turn into a set of entity transition sequences.

Accomplishment 9: Culture has limited effect on how dominance is expressed.

Previous research has demonstrated behaviors that communicate trustworthiness vary by culture. We were interested in the unique role that dominance played in perceptions of trustworthiness and if it varied based on the research site (as a proxy for culture). Dominant behavior may increase trust in individualistic culture but ensue suspicion in collectivistic cultures. Our analyses revealed, however, that dominance did not differ based on the research site. In fact, perceptions of dominance were remarkably consistent across culture. The one exception to this was at the University of the South Pacific in Fiji. Player-rated dominance scores that were significantly higher at this site compared to the other seven research sites. One notable finding related to the effects of culture on dominance was the unique contribution that the individual’s role in the game played in perceptions of how dominant their behavior was perceived. For instance, Villagers (i.e., truth-tellers) in Fiji were perceived as especially dominant compared to Spies (i.e., deceivers), whereas in Zambia, Spies were perceived as especially dominant compared to Villagers. This provides insight into how culture interacts with an individual’s role in the game (i.e., a communicator’s goal) during a deceptive group interaction.

Accomplishment 10: Linguistic features may promote trustworthiness or signal deceptiveness.

In answer to the question, Does language foster trust or indicate deception in the same social interaction, we analyzed the SCAN data. We hypothesized that language may evoke trust and also signal deception. The proposed hypotheses were tested using conversational data. A quantitative content analysis approach mapped free conversation to multiple verbal features that possibly indicate trust or deception. We found that the deceptive agents (spies) exhibited a lower level of verbal involvement, certainty, logicity, and immediacy. Their language conveyed more detachment, uncertainty, lack of logic and non-immediacy than that expressed by truth-tellers. On the other hand, agents who produced agreeable, cooperative, confident, and empathetic verbal messages contributed to an individual's perceived trustworthiness. This misalignment between the verbal cues to deception and the verbal factors that stimulate trust shed light on humans' unsatisfactory accuracy in deception detection tasks.

Accomplishment 11: Interactions between Deceivers and Non-Deceivers

Truth-tellers interact equally with everyone while deceivers interact more with truth-tellers.

Since deceivers know the role of all participants in the game, do they focus their attention on specific individuals? We found that deceivers look less at other deceivers. Since deceivers know the identity of non-deceivers, deceivers spend more time observing nondeceivers (and less time observing their fellow deceivers). Deceivers may also interact less with other deceivers to avoid 'guilt-by-association', i.e., getting caught in case the other deceivers are identified. We found that non-deceivers have a similar probability of listening to both deceptive and non-deceptive speakers. However, this is not the case for deceiver listeners. Deceivers have a lower probability of listening to other deceivers as compared to nondeceivers. This is possibly in order to avoid being suspected of supporting the deceiver. Surprisingly, we found that the verbal behavior between all pairs of participants is similar. This is in stark contrast to the previous two non-verbal findings. This shows that deceivers consciously adapt their verbal behavior to mimic non-deceivers, but not their nonverbal behavior. Since verbal behavior is noticed by everyone else, deceivers consciously do not exhibit any bias in verbal interaction with other participants to avoid getting caught. In summary, deceivers avoid non-verbal interactions with other deceivers.

Deception Detection in Group Video Conversations using Dynamic Interaction Networks. S. Kumar, C. Bai, V.S. Subramanian, J. Leskovec. AAAI International Conference on Weblogs and Social Media (ICWSM), 2021.

Accomplishment 12: Many nonverbal features are used by humans to detect dominance.

The Mafia experiment we created investigated the effects of deception on relational communication, including dominance, during group interaction. Participants in the experiment played a variant of the Mafia game in which they were divided into Spies and Villagers. The goal

of Villagers was to root out bad actors (Spies) through a series of missions. Spies had the goal of making missions fail, which required them to employ deception to keep their Spy identity secret. In addition, the Spies knew who the other Spies were in the game, giving them increased informational power compared to the Villagers. Spies might want to behave dominantly to ensure mission failures, but they also needed to do so surreptitiously so that the Villagers did not suspect them to be Spies right away. The results of the players ratings of one another during the game suggested that while Spies decreased their dominance over time, they did not change their strategy according to whether they were winning or losing. Comparisons across the locations showed that one location, the University of South Pacific (USP) in Fiji, had higher dominance ratings than any of the other locations and differed significantly from every other location ($p < .05$) at all three time periods. Fijian students also rated each other higher on the trust measure than the other locations. It appears that players at different locations used different dominance strategies according to their role. For example, while the Fiji players were perceived to be the most dominant, this was especially true when they were in the Villager role. In Zambia, however, it was Spies who were more likely to adopt a dominant role, according to their peers' perceptions. This suggests that the location of the data collection made an important difference in dominance ratings (especially for Fiji and Zambia compared to the other locations).

Accomplishment 13: Nonverbal cues, besides signaling deception, signal the nature of the relationship between deceiver and deceived.

These “relational messages” signal whether the deceiver is more assertive or subservient in relation to other group members, likes the others and wants to be trusted, is involved in the conversation rather than detached, feels composed or nervous in the others' presence, and conveys similarity to other group members. Because many behaviors can convey relational messages as well as be deceptive, it is important to distinguish indicators of relationship from indicators of deception. Aloofness or nervousness, for example, should not be mistaken for deception. Just as no single behavior signals deception, neither does it uniformly signal a relational message. Messages are more accurately interpreted from a multiplicity of signals.

Accomplishment 14: Deceivers are most successful when establishing trust in combination with engaging in dominant communication.

Predictive models analyzing the multimodal data from the SCAN project find that in decision-making groups, deceivers are most successful in escaping detection if they have established trust by the end of the discussion group or sooner. Although trust can build over time, it is especially important by the end of the discussion. Those who fail to win others' trust and are regarded with suspicion are most likely to be deceptive. Next most important is being dominant—assertive, influential, extroverted—in the beginning of the discussion and at its end. Impressions of one another are fluid among group members. A variety of variables showed that perceived dominance can be communicated by positive facial emotions, facial and vocal expressivity, and

louder voices. Eye contact and linguistic style matching also conveyed dominance. In addition, a greater amount of language production and a longer turn-at-talk duration also conveyed perceived dominance. Some of these behaviors are opposite of what deceivers do. Dominance can aid deceivers in successfully winning over others. But coming on too strong throughout the discussion is unwise. Deceivers are most successful when they temper their dominance and withhold being too assertive until the end of the discussion. Detecting deceivers can be improved by watching those who come on strong especially at the end.

Accomplishment 15: Vocal indicators are the most important variables indicating nervousness.

Cues indicating nervous behavior are an important component in deception research because people often assume that high-arousal is a sign of deceit—although there was previously limited empirical data to support this claim. We conceptualized nervousness as behavior that communicates a lack of composure and overall reticence throughout the group interaction. Nonverbal indicators of nervousness were associated with shorter turns-at-talk and more rigid body movement and facial animation. Although we did not find evidence of vocal pitch as an indicator of nervousness, there was a pattern of vocal channels being the key nonverbal indicator over time; namely, that perceptions of nervousness increased as vocal animation decreased throughout the game. This is likely because emotional indicators in the voice are more difficult to mask compared to facial expression and body movement. Finally, our analyses demonstrated that deceivers in group settings failed to show signs of composure *over time* compared to truth-tellers. In other words, it is important to be aware of how indicators of nervousness *change throughout* the social interaction. Truth-tellers may become increasingly relaxed throughout an interaction, whereas deceivers will remain hypervigilant.

Accomplishment 16: Trust is a good proxy for identifying deceivers.

Those group members who are viewed as the least trustworthy are likely deceiving. Perceived trustworthiness is best measured by combining individuals' multimodal behavioral features (e.g., linguistic and vocalic behaviors) and historic actions in group communication (e.g., the number of times the individual is a successful group leader). When historic actions are not available, linguistic and vocalic behaviors can be used to approximate perceived trustworthiness at an accuracy level similar to using historic actions alone. We identify the four most important linguistic features for predicting perceived trustworthiness. Specifically, repeat phrases ratio, third person singular ratio, and third person plural ratio are positively associated with perceived trustworthiness, and present tense ratio is negatively associated with perceived trustworthiness. We also find a few vocalic features related to mel-frequency cepstral coefficients (MFCCs) and line spectral pair frequencies (LSPs) are important predictors of perceived trustworthiness.

Accomplishment 17: Deception Prediction in Real-World Courtroom Videos

We develop a system for covert automated deception detection using information available in a video. We study the importance of different modalities like vision, audio and text for this task. On the vision side, our system uses classifiers trained on low level video features which predict human microexpressions. We show that predictions of high-level microexpressions can be used as features for deception prediction. Surprisingly, IDT (Improved Dense Trajectory) features which have been widely used for action recognition, are also very good at predicting deception in videos. We fuse the score of classifiers trained on IDT features and high-level microexpressions to improve performance. MFCC (Mel-frequency Cepstral Coefficients) features from the audio domain also provide a significant boost in performance, while information from transcripts is not very beneficial for our system. Using various classifiers, our automated system obtains an AUC of 0.877 (10-fold cross-validation) when evaluated on subjects which were not part of the training set. Even though state-of-the-art methods use human annotations of micro-expressions for deception detection, our fully automated approach outperforms them by 5%. When combined with human annotations of micro-expressions, our AUC improves to 0.922. We also present results of a user-study to analyze how well do average humans perform on this task, what modalities they use for deception detection and how they perform if only one modality is accessible.

Wu, Z., Singh, B., Davis, L. and Subrahmanian, V., 2018, April. Deception detection in videos. In *Proceedings of the AAAI conference on artificial intelligence* (Vol. 32, No. 1).

Accomplishment 18: Predicting Deception in Groups, Attempt 1 – LiarOrNot

Most work on automated deception detection (ADD) in video has two restrictions: (i) it focuses on a video of one person, and (ii) it focuses on a single act of deception in a one or two minute video. Our ADD framework was the first to capture long term deception in a group setting. We study deception in the well-known Resistance game (like Mafia and Werewolf) which consists of 5-8 players of whom 2-3 are spies. Spies are deceptive throughout the game (typically 30-65 minutes) to keep their identity hidden. We develop an ensemble predictive model to identify spies in Resistance videos. We show that features from low-level and high-level video analysis are insufficient, but when combined with a new class of features that we call LiarRank, produce the best results. We achieve AUCs of over 0.70 in a fully automated setting.

Bai, C., Bolonkin, M., Burgoon, J., Chen, C., Dunbar, N., Singh, B., Subrahmanian, V.S. and Wu, Z., 2019, July. Automatic long-term deception detection in group interaction videos. In *2019 IEEE International Conference on Multimedia and Expo (ICME)* (pp. 1600-1605). IEEE.

Accomplishment 19: Predicting Deception in Groups: Attention-based Facial Behavior Analytics.

We developed a method for detecting deception in videos based on facial micro-expressions (measured by Facial Action Unit presences and intensities). We also developed an attention-based framework that detects the key frames of a video that includes deceptive behavior. With the attention methods we developed for this project, we analyzed the deceptive behavior of people from various countries and cultural orientations. The findings support the universal cues hypothesis. Lip Stretching, blinking and fake smile are FAUs that our models discovered are important when a clip contains a deceptive act. However, our analysis did not suggest statistically significant differences in the prediction accuracy of our models trained on data sourced from different cultures. Furthermore, there were no noticeable differences in the FAUs across people from different countries. There were differences in the intensity of the FAUs.

Wang, L., Bai, C., Bolonkin, M., Burgoon, J.K., Dunbar, N.E., Subrahmanian, V.S. and Metaxas, D., 2021. Attention-based facial behavior analytics in social communication. In *Detecting Trust and Deception in Group Interaction* (pp. 123-137). Springer, Cham.

Accomplishment 20: A Network-based Model to Predict Deception

Our novel DeceptionRank approach, a PageRank based network model for predicting deception, outperforms other state-of-the-art approaches.

Our novel method called DeceptionRank can detect deceivers even from very short (one minute) video snippets. It utilizes the notion of Negative Dynamic Interaction Networks (or NDINs) that captures when two participants avoid interacting with one another. DeceptionRank derives NDINs from the original interaction networks — two nodes are linked with an edge if their corresponding participants do not interact. Our method initializes the prior deception scores of each node through a novel process which normalizes and aggregates the verbal and non-verbal behaviors of nodes. It then iteratively runs PageRank on and aggregates scores from the set of negative dynamic interaction networks. This generates a deception score for each node. We show that DeceptionRank outperforms the state-of-the-art computer vision, graph embedding, and ensemble methods by over 20.9% AUROC in detecting deceivers. Moreover, we show that DeceptionRank is consistently the best performing method across different lengths of video segments and regardless of the final outcome of the game.

Deception Detection in Group Video Conversations using Dynamic Interaction Networks. S. Kumar, C. Bai, V.S. Subramanian, J. Leskovec. AAAI International Conference on Weblogs and Social Media (ICWSM), 2021.

Accomplishment 21: Predicting Deception in Groups: VG-GAN, Vision Transformer (ViT).

We developed a framework for deception prediction based on recent success of VQ-GAN and ViT models. In particular, we developed a VQ-GAN model to compress the input frames of a given video to a more relevant lower-dimensional dimensional representation. Then, we trained a

Vision Transformer (ViT) model for deception detection. Our results showed that encoding the input videos with a VQ-GAN resulted in 24% relative classification performance improvement compared to using the raw video frames as input to ViT.

Accomplishment 22: Understanding Political Deception

Politicians lie. Frequently. Depending on the country they are from, politicians may lie more frequently on some topics than others. We develop the novel concept of a tripartite “VAT” graph (Video-Article-Topic) with three types of nodes: videos (with a politician featured in each), news articles that mention the politician, and topics discussed in the videos or articles. We develop several novel types of audio and video deception scores for each audio/video, as well as a topic deception score and an edge deception score for each edge in the graph. Our POLLY (POLitical LYing) system builds upon past work by others to generate predictions for whether a politician is lying or not. We test POLLY on a novel dataset (which will be made publicly available upon publication of this paper) consisting of 146 videos and 6337 news articles involving 73 politicians from 18 countries from all major continents. We show that POLLY achieves AUC and F1 scores over 77%, beating out several baselines. We further show that POLLY is robust to translation errors made by Google Translate.

Bai, C., Bolonkin, M., Regunath, V. and Subrahmanian, V.S., 2022, November. POLLY: A Multimodal Cross-Cultural Context-Sensitive Framework to Predict Political Lying from Videos. In *Proceedings of the 2022 International Conference on Multimodal Interaction* (pp. 520-530).

Accomplishment 23: Predicting the Most Dominant Person in a Group

We consider the problems of predicting (i) the most dominant person in a group of people, and (ii) the more dominant of a pair of people, from videos depicting group interactions. We introduce a novel family of variables called Dominance Rank. We combine features not previously used for dominance prediction (e.g., facial action units, emotions), with a novel ensemble-based approach to solve these two problems. We test our models against four competing algorithms in the literature on two datasets and show that our results improve past performance. We show 2.4% to 16.7% improvement in AUC compared to baselines on one dataset, and a gain of 0.6% to 8.8% in accuracy on the other. Ablation testing shows that Dominance Rank features play a key role.

Bai, C., Bolonkin, M., Kumar, S., Leskovec, J., Burgoon, J.K., Dunbar, N.E. and Subrahmanian, V.S., 2019, January. Predicting dominance in multi-person videos. In *IJCAI* (pp. 4643-4650).

Accomplishment 24: Predicting Who is Looking at Who

Visual focus of attention in multi-person discussions is a crucial nonverbal indicator in tasks such as inter-personal relation inference, speech transcription, and deception detection. However, predicting the focus of attention remains a challenge because the focus changes rapidly, the discussions are highly dynamic, and the people’s behaviors are inter-dependent. We propose ICAF (Iterative Collective Attention Focus), a collective classification model to jointly learn the visual focus of attention of all people. Every person is modeled using a separate classifier. ICAF models the people collectively—the predictions of all other people’s classifiers are used as inputs to each person’s classifier. This explicitly incorporates interdependencies between all people’s behaviors. We evaluate ICAF on a novel dataset of 5 videos (35 people, 109 minutes, 7604 labels in all) of the popular Resistance game and a widely-studied meeting dataset with supervised prediction. ICAF outperforms the strongest baseline by 1%–5% accuracy in predicting the people’s visual focus of attention. Further, we propose a lightly supervised technique to train models in the absence of training labels. We show that light-supervised ICAF performs similar to the supervised ICAF, thus showing its effectiveness and generality to previously unseen videos.

Bai, C., Kumar, S., Leskovec, J., Metzger, M., Nunamaker Jr, J.F. and Subrahmanian, V.S., 2019, August. Predicting the Visual Focus of Attention in Multi-Person Discussion Videos. In *IJCAI* (pp. 4504-4510).

Accomplishment 25: Relative Nervousness Prediction

Given a video of a group of interacting humans, we solve three problems:

(i) The Pairwise Nervousness Prediction (PNP) problem predicts if person A is more nervous than B even if the ground truth nervousness ratings for A and B are very close. (ii) The PNP-Distinct problem predicts if A is more nervous than B when the ground truth nervousness ratings for A and B differ by at least 1 on a 5 point scale. (iii) The Nervousness Change Prediction (NCP) problem predicts if A's nervousness rating increases or decreases compared to his previous rating in the same video.

Compared to past work based on facial expressions, action units (FAUs), and movements, we make two new contributions: (i) We develop two new classes of features based on the interactions that A and B have with others. As social science theory suggests that A might be more nervous than B if B is more dominant, we define a new class of features called audio and video nervousness scores (NSs). NSs use dominance and gaze (who is looking at who) relationships, and speaker (who is speaking) information. (ii) We develop a novel Facial Expression Graph Convolution Network (FEGCN) together with an ensemble prediction architecture.

We show that: (i) either NSs or FEGCN generate the best AUC in head-to-head comparisons with seven past baselines, (ii) an ensemble that merges NSs and FEGCN beats the 7 baselines on

both F1-score and AUC, and (iii) our learned FEGCN identifies faces and landmarks that are highly relevant for nervousness prediction.

Accomplishment 26: Predicting Impressions of Subjects

We consider the problem of predicting the impression that one subject has of another in a video clip showing a group of interacting people. Our novel Dyadic Impression Prediction System (DIPS) contains 2 major innovations. First, we develop a novel method to align the facial expressions of subjects P1 and P2 as well as account for the temporal delay that might be involved in P1 reacting to P2's facial expressions. Second, we propose the concept of a multilayered stochastic network for impression prediction on top of which we build a novel Temporal Delayed Network graph neural network architecture. Our overall DIPS architecture predicts six dependent variables relating to the impression P1 has of P2. Our experiments show that DIPS beats 8 baselines from the literature, yielding statistically significant improvements of 19.9-30.8% in AUC and 12.6-47.2% in F1-score. We further conduct ablation studies showing that our novel features contribute to the overall quality of the predictions made by DIPS.

Bai, C., Bolonkin, M., Regunath, V. and Subrahmanian, V.S., 2022. DIPS: A Dyadic Impression Prediction System for Group Interaction Videos. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*.

Accomplishment 27: Multimodal Persuasion Prediction

Identifying persuasive speakers in an adversarial environment is a critical task. In a national election, politicians would like to have persuasive speakers campaign on their behalf. When a company faces adverse publicity, they would like to engage persuasive advocates for their position in the presence of adversaries who are critical of them. Debates represent a common platform for these forms of adversarial persuasion. This paper solves two problems: the Debate Outcome Prediction (DOP) problem predicts who wins a debate while the Intensity of Persuasion Prediction (IPP) problem predicts the change in the number of votes before and after a speaker speaks. Though DOP has been previously studied, we are the first to study IPP. Past studies on DOP fail to leverage two important aspects of multimodal data: 1) multiple modalities are often semantically aligned, and 2) different modalities may provide diverse information for prediction. Our M2P2 (Multimodal Persuasion Prediction) framework is the first to use multimodal (acoustic, visual, language) data to solve the IPP problem. To leverage the alignment of different modalities while maintaining the diversity of the cues they provide, M2P2 devises a novel adaptive fusion learning framework which fuses embeddings obtained from two modules – an alignment module that extracts shared information between modalities and a heterogeneity module that learns the weights of different modalities with guidance from three separately trained unimodal reference models. We test M2P2 on the popular IQ2US dataset designed for DOP. We also introduce a new dataset called QPS (from Qipashuo, a popular Chinese debate TV show) for IPP. M2P2 significantly outperforms 4 recent baselines on both datasets.

Bai C, Chen H, Kumar S, Leskovec J, Subrahmanian VS. M2p2: Multimodal persuasion prediction using adaptive fusion. *IEEE Transactions on Multimedia*. 2021 Dec 9.

Accomplishment 28: Single End-to-End Prediction of Dominance, Nervousness, Deception

Our new TEDIC Framework, is a neural network model that is uniformly good across different prediction tasks: detecting dominance, nervousness, deception, etc.

We developed a neural network-based model, temporal network-diffusion convolutional networks (TEDIC), to learn node representations of dynamic social interaction networks in a general manner, which fit into various node-level prediction tasks. The first part of TEDIC is network diffusion of node attributes that naturally captures the interweaving between highly dynamic node attributes and interactions. The second part of TEDIC is a temporal convolutional network (TCN) accompanied with set pooling to aggregate representations of nodes over a long time span. Due to the locality of temporal convolution kernels, TCN is able to extract patterns from interactions with various durations as these interactions may appear alternatively across multiple consecutive snapshots, and set-pooling is useful to collect subtle patterns scattered over a long-time span. Moreover, TEDIC is end-to-end trainable, and therefore provides an opportunity for social scientists to automatically process dynamic social interactions and obtain insights from the data simultaneously. TEDIC significantly outperforms previous baselines over four different node-level prediction tasks, including identification of people's dominance, nervousness, lying behavior, as well as underlying community, on five different real social interaction networks. We further analyze TEDIC's explaining power and broader societal implication and found that direct interactions (e.g. looking, speaking) among individuals may be more informative for dominance and nervousness detection, while signals of avoiding direct interactions are strongly informative for deception detection. We also found that the difference between the quantified attributes of one individual and those of his/her interacted neighbors is a stronger signal to indicate his/her dominance and nervousness, when compared with his/her own attributes. We also showed that TEDIC remains least biased to people from different regions despite its strong classification power on given tasks.

TEDIC: Neural Modeling of Behavioral Patterns in Dynamic Social Interaction Networks. Y. Wang, P. Li, C. Bai, J. Leskovec. ACM International Conference on World Wide Web (WWW), 2021.

Accomplishment 29: Hierarchical Temporal Networks

A general deep learning framework to build hierarchical graphs from temporal data.

We developed a novel approach for handling temporal, event-based data. Our key insight is that we consider past events and potential future events not as a linear sequence, but as a hierarchical event structure. Each event is represented by a graph. Nodes in each event graph are connected to related nodes in other event graphs. At the lowest level of the hierarchy are Level 0 events. Each

input event creates one Level 0 event. Additionally, we add edges between consecutive input events, connecting related nodes. Our approach constructs events at level n from events at level $n-1$ in a hierarchical and incremental fashion. Connections are created between related nodes across events at the same or different levels of hierarchy. In this way, a sequence of input events is organized in a hierarchical event structure, which can be used for a wide range of downstream tasks, such as predicting future events, identifying missing events, performing temporal counterfactual reasoning, and improving interpretability of events. Our experiments show that methods using a hierarchical event structure as input outperform methods that use only sequential event input.

Accomplishment 30: A Youtube interview dataset was analyzed for synchrony.

We collected 178 mediated interviews (116 from the US, 2 from the UK, 60 from Japan) mainly from YouTube between April 2020 to March 2021.³ Each interview was between 1 to 69 minutes long (Median = 9 minutes and 50 seconds) and had only one interview host and one interview guest on the screen. Additionally, the interview must have been conducted using video conferencing technology in which each person was on the split-screen looking at the camera for most of the interview. Research assistants who were blind to the study's hypotheses coded each video for the type of interview (i.e., informative or entertainment) depending on the social attributes of the guest. For example, the interview was coded as an information-driven interview when the guest was an expert or professional such as a government official, medical doctor, or scientist. Conversely, if the guest was an artist, athlete, comedian, etc., the interview was coded as an entertainment-driven interview. All the videos were coded as either information-driven or entertainment-driven interviews. The US and UK videos were classified by American RAs, and Japanese videos were categorized by a Japanese RA. Since only one Japanese RA could be employed, one of the authors (Japanese) independently classified the data in advance, and the results were compared with the classification of Japanese RA, which was 100% matched. The gender of each interactant was also coded. The results (in press in *Journal of Nonverbal Behavior*, Fujiwara et al. 2022), suggest that the synchrony phenomenon was captured as it occurred outside the laboratory because it was advantageous to use a mediated format that ensured a fixed-angle camera and front-facing subjects. Throughout the interview, both interactants coordinated their facial displays and beyond the chance level, which varied according to the communication goals set for specific interviews. More specifically, greater synchrony occurred in information-driven interviews compared to entertainment-driven interviews.

Accomplishment 31: New Persuasion Dataset & Code

We developed a novel dataset consisting of video clips from the Chinese TV show Qipashuo. In this dataset, audience members vote on a topic. A speaker is persuasive if s/he increases the number of people supporting his/her position on a given debate topic. The degree of persuasion

of that speaker can also be measured in terms of the increase in number of audience votes toward his/her position. The figure below shows a sample of the show as well as the analysis by our M2P2 system for multimodal persuasion prediction.



In order to facilitate future research, both our data and our code have been publicly released at <https://snap.stanford.edu/persuasion/>.

Accomplishment 32: New Global Political Deception Dataset

Can we predict if a politician is lying or not, based on a video of the speaker, text transcripts of the speech (which are usually easily available from TV news channels), as well as background news articles prior to the speech. Our POLLY (Political Lying) dataset consists of 148 videos from 18 countries involving a total of 76 public figures. It can be downloaded from Dropbox [here](#).

Accomplishment 33: New Contacts in a Workplace Dataset

Inferring a department identity from a dataset of 92 people in an office building over 2 weeks

We demonstrate that TEDIC is applicable to a wider range of social interaction networks than those obtained from the Resistance game. In particular, we showed that TEDIC works when the dynamics is less vibrant and the time range is relatively short by using the CIAW dataset, which is a dynamic network built from 92 people's timestamped proximities (of up to 1.2 meters) in a workplace over 20 days. The task is to infer one's department identity based on the dynamic network. We observed that our model can still perform well in this very different scenario, though the accuracy gain to the strongest baseline is comparatively marginal. TEDIC can also be applied to other real-world dynamic systems with similar properties as the social interaction networks. For example, the financial network among traders and companies in the stock market are usually high-frequency with strong local dynamic patterns and interweaving influence among nodes. TEDIC components can be easily adapted for node prediction tasks over such networks such as fraudulence detection. It could be used to forecast the conditions of traffic nodes such as nextday flow volume and/or congestion level. In computing systems, communications between

different softwares also share similar properties. Therefore, we can adapt TEDIC for the malware detection task in software communication networks.

TEDIC: Neural Modeling of Behavioral Patterns in Dynamic Social Interaction Networks. Y. Wang, P. Li, C. Bai, J. Leskovec. ACM International Conference on World Wide Web (WWW), 2021.

Technology Transfer

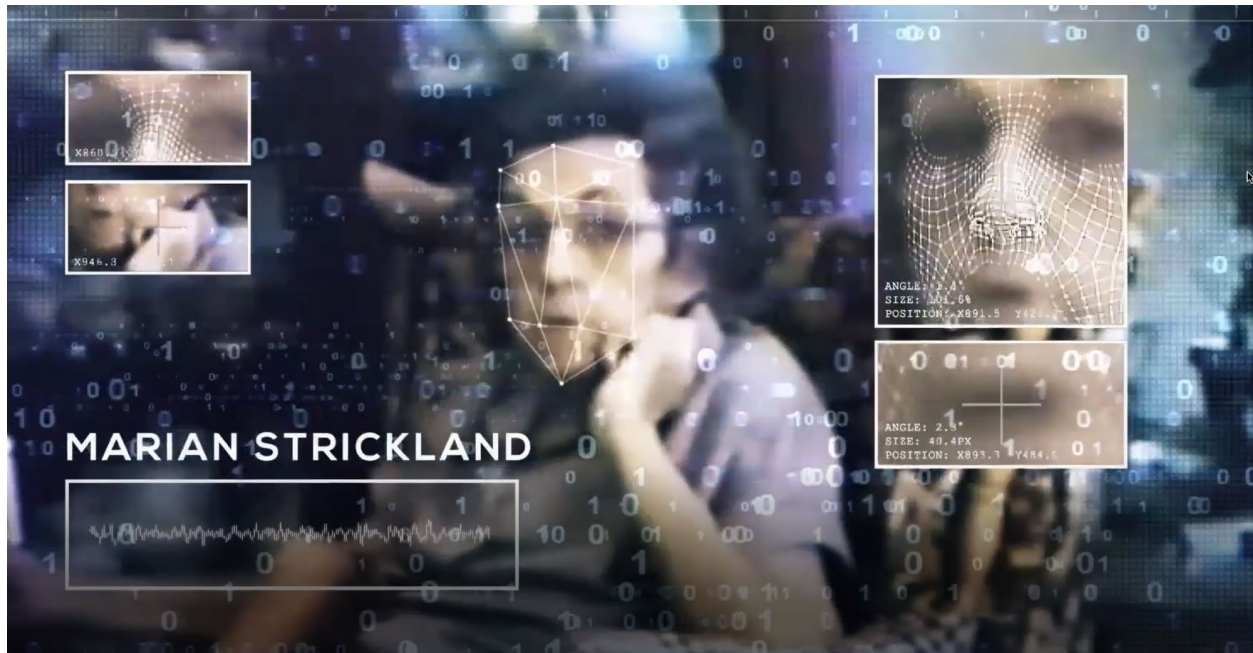
Roswell: The Final Verdict 6-Episode TV Show on Discovery Plus

As part of the 75th anniversary of the 1947 incident in Roswell, NM, October Films Inc. (UK) licensed the application of technology developed at Dartmouth under the SCAN project to predict whether a person is telling the truth or lying.

The producers of the show sent the SCAN PIs a list of video clips of witness testimony. These witnesses were no longer alive. The testimony was run through the LiarOrNOt engine developed under the SCAN project. Each video was assessed with the probability of whether the witness was being honest or not.

The LiarOrNot deception detection technology developed as part of this MURI grant was used in every single episode of the 6-episode series. The producers of the show used the results of LiarOrNot to assess the veracity of the technology. Two screenshots from the show are provided below.





CourtScribes

CourtScribes Inc., a major player in the recording and transcription of courtroom and legal proceedings (e.g. depositions) has applied the technology described in the LiarOrNot paper and independently implemented it for use in the market. The resulting program is undergoing trials and would likely be deployed for various markets, e.g. to tell lawyers deposing a witness about questions where the deponent's answer might be false.

Other Transitions

- *Stanford transitioned some of their work on JODIE to Reddit and Wikipedia.*
- *Stanford's work on graph neural networks has been released as open source in PyG, one of the most popular libraries for graph neural networks with over 100K monthly downloads.*
- *Dartmouth's methods for automated analysis of facial expressions were used by ARL to analyze facial expressions in videos of drivers and passengers in cars as part of an ongoing ARL effort. Dartmouth's code developed under this MURI was run on ARL data and shipped back.*
- *A number of the data and software code generated by Dartmouth & Stanford has been publicly released.*

What opportunities for training and professional development did the project provide?

Students were trained via a number of mechanisms.

Summary: During this period, 47 PhD students, 6 postdoctoral fellows and 15 undergraduate students were involved in this grant. They were active participants in the research and learned about image processing, speech processing, machine learning, as well as social science theories surrounding deception, and statistical modeling.

Graduate student training: Grad students were involved in weekly meetings with their supervisors. In many cases, these grad students were participants in research meetings involving faculty from multiple universities.

Graduate Student Research visits: An important part of graduate training involves graduate students visiting research labs other than their own and participating substantively in joint research.

- i) PhD student Chongyang Bai from Dartmouth spent 3 months in 2018 at Stanford University, resulting in 2 joint papers at IJCAI 2019.
- ii) PhD student Chongyang Bai from Dartmouth spent 3 months in 2019 at Stanford University, resulting in 2 joint papers.
- iii) PhD student Maks Bolonkin from Dartmouth spent 3 months at UMD, resulted in a paper that was presented at ICME 2019.

Faculty training: A visitor from Zambia (one of the research sites) has spent one month at UCSB.

Workshop: Srijan Kumar from Stanford University organized a workshop The Fourth Workshop on Computational Methods in Online Misbehavior, on the sidelines of The Web Conference 2019.

Faculty Visits: V.S. Subrahmanian from Dartmouth visited Stanford in July 2018 and October 2018.

How were the results disseminated to communities of interest?

Results were disseminated to the external community via four mechanisms.

- 1) A first book of its kind on computational models for the understanding and prediction, from video, of diverse phenomena such as deception, trust, dominance, deference, nervousness, like/dislike, and persuasion.
- 2) A one-summer course on the use of AI for advanced understanding and prediction of deception, trust, dominance, deference, nervousness, like/dislike, and persuasion was created and offered.

- 3) The PIs delivered numerous invited talks and keynote talks at major conferences or venues.
- 4) The PIs published numerous scientific publications in highly refereed conferences and archival journals

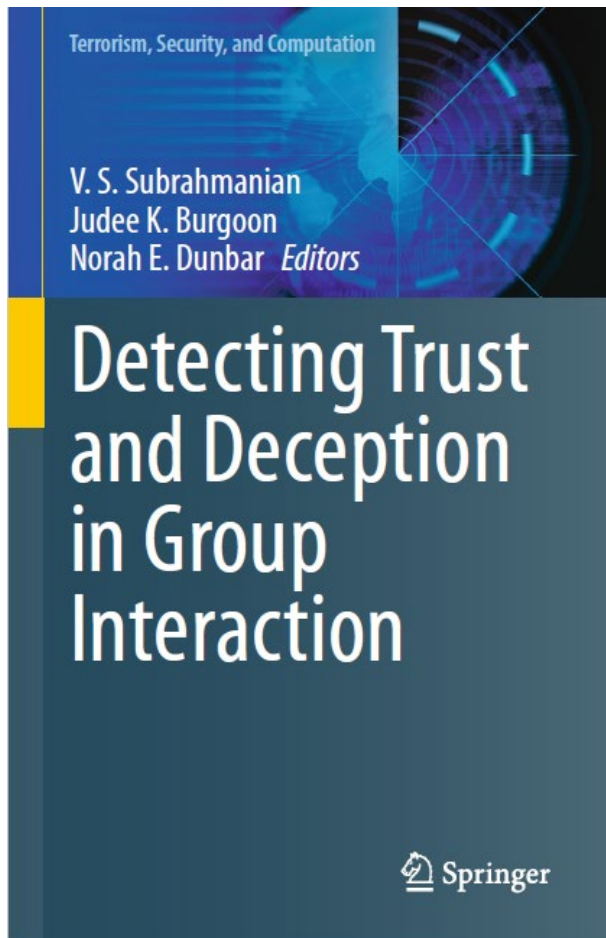
We summarize each below.

Book

Many of the results of the SCAN MURI Grant have been summarized in the following book:

Subrahmanian, V.S., Burgoon, J.K. and Dunbar, N.E. eds., 2021. *Detecting Trust and Deception in Group Interaction*. Springer.

This book will serve as a handy reference for future research on trust and deception detection in groups of humans who are interacting with one another.



Summer Course

The SCAN MURI PIs developed a series of lectures during the summer of 2020 highlighting the main results of the research. The materials (slides plus video) are accessible from: <https://cs.dartmouth.edu/~mbolonkin/scan/press-stats.html>

Summer 2020 Webinar Series			
Register			
Date	Time (EST)	Speaker	Title
June 4	15:00 - 16:30	Dr. Purush Iyer US ARO V.S. Subrahmanian Dartmouth College	Introduction to the SCAN Project and Deception Detection from Online Videos Video Slides
June 10	16:00 - 17:00	Judee Burgoon University of Arizona	A Novel Approach to Investigating Deception during Group Interaction Video Slides
June 15	12:00 - 13:00	Norah Dunbar UCSB	Persuasive Deception and Dyadic Power Theory Video Slides
June 22	15:00 - 16:00	Jure Leskovec Stanford University	Dynamic Embeddings of Temporal Interaction Networks Video Slides
June 29	15:00 - 15:40	Pan Li Stanford University	An Interpretable Representation Learning Framework for Dynamic Social Networks Video Slides
July 13	15:00 - 16:00	Chongyang Bai Dartmouth College	Dominance Detection in Group Interaction Videos Video Slides
July 20	16:00 - 17:00	Dimitris Metaxas Rutgers University	Detection and Tracking of Humans and Faces using Machine Learning Video Slides
July 27	16:00 - 17:00	Dimitris Metaxas Rutgers University	Video-based Deception Detection and Corresponding Feature Discovery Video Slides
August 11	14:00 - 15:00	Jay F. Nunamaker, Jr University of Arizona	Going the Last Mile for SCAN Transition Video Slides-1 Slides-2
August 18	13:00 - 14:00	Miriam Metzger UCSB	International Data Collection using Human Subjects: Logistics and Challenges Video Slides

Keynotes and Invited Talks

- 1) Keynote, New York State Cybersecurity Conference, June 2018 – Subrahmanian
- 2) Invited talk at Google, July 2018 – Subrahmanian
- 3) Invited series of lectures over one day, Netherlands Defense Academy, Netherlands, Sep 2018 – Subrahmanian
- 4) Invited talk at Google, Oct 2018 – Subrahmanian
- 5) Invited talk at the Foundation for the Defense of Democracies, Oct 2018 – Subrahmanian
- 6) Plenary address, The World Academy of Sciences Annual Meeting, Nov 2018 - Subrahmanian
- 7) Invited panelist, Launch of the NTU Institute for Technology & Humanities, Singapore, March 2019 – Subrahmanian
- 8) Keynote: The Graduate Club, November 2018 – Nunamaker
- 9) Invited Talk: Cognitive Science, University of Arizona, March 1, 2019 – Nunamaker
- 10) Invited talk, Knowledge Extraction from Games workshop on the sidelines of the Thirty-Third AAAI Conference on Artificial Intelligence (AAAI-19), Kumar.

- 11) Invited talk, International Workshop on Misinformation, Computational Fact-Checking and Credible Web on the sidelines of the ACM International Conference on World Wide Web (WWW-19) - Kumar.
- 12) Keynote, WikiWorkshop on the sidelines of the ACM International Conference on World Wide Web (WWW), 2019 – Leskovec.
- 13) Invited talk, University of Zurich, 2019 - Leskovec
- 14) Distinguished Lecture, Network Science Institute, Northeastern University, 2019 – Leskovec
- 15) Invited Talk, IEEE Hyderabad Chapter, May 2020.
- 16) Invited Talk, University of Rome Italy, May 2020
- 17) Invited Talk, AAAS/Elsevier/SenseAboutScience talk on “AI: Pros & Cons” at the AAAS Annual Conference, Feb 2020, Seattle, WA.
- 18) Invited Dinner Speaker, AAAS/Elsevier Dinner Speaker on Strengths & Weaknesses of Data Science, Feb 2020, Seattle, WA.
- 19) Invited Talk, Institute for Information Infrastructure Protection (I3P) Webinar, Feb 2020.
- 20) Invited Talk at Google, Feb 2020
- 21) Invited Speaker to brief the President and other top executives of Samsung Electronics, Nov 2019.
- 22) Invited Speaker, 2019 Digital Meet, Padua, Italy, Oct 2019.
- 23) Invited Tutorial, 2019 Intl. Summer School on Machine Learning & Cybersecurity, Padua, Italy Sep 2019.
- 24) Keynote Speaker, 8th International Workshop on Parallel and Distributed Computing for Large-Scale Machine Learning and Big Data Analytics (ParLearning 2019), in conjunction with the 25th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD 2019), Anchorage, Alaska, Aug 2019.
- 25) MIDAS, University of Michigan, Nov 18 2019
- 26) MIT Machine Learning seminar, Nov 7 2019
- 27) UCLA Machine Learning seminar, Nov 1 2019
- 28) Chan Zuckerberg BioHub, October 17 2019
- 29) Keynote International Conference on Statistical Language and Speech Processing, October 14 2019
- 30) Amazon Distinguished Speaker Series, Sept 27 2019
- 31) KDD Time Series workshop, Aug 6 2019
- 32) KDD DL day keynote, Aug 5 2019
- 33) KDD Deep Learning for Graphs Keynote, Aug 5 2019
- 34) International Conference on Computer Science and Education (ICCSE, Toronto August, 20, 2020) Title: Scalable and Explainable Analytics for Computer Vision and Medical Applications
- 35) Computer Science and Engineering, University of Nebraska – Lincoln, January 18, 2020
- 36) Chinese University of Hong Kong, Shenzhen, October 16, 2019

- 37) Google Research, SFO, September 6, 2019
- 38) Judee Burgoon lecture on the Good, the Bad and the Ugly of Deception, Illinois State University Hall of Fame Convocation[Sept. 2019]
- 39) Judee Burgoon lecture on Deception and Cognitive Science, Cognitive Science Seminar, Institute for Intelligent System, University of Memphis, October [Oct. 2019]
- 40) Spitzley, L. A., Pentland, S. J., Dorn, B., Walls B., Burgoon J. K. (2019). Using multimodal data to infer group dynamics in an adversarial group game. Presented to the IEEE International Carnahan Conference on Security Technology (ICCST), Montreal, October. [Oct. 2019]
- 41) Wang, X., Burgoon, J. K., Nunamaker, J. F. Presenting Informational Stimuli to Distinguish Deceivers from Truth-tellers in Group Interaction. Invited presentation at the Credibility Assessment and Screening Technologies Symposium at the Hawaii International Conference on System Sciences, Wailea, HI. [Jan. 2020]
- 42) Chen, X., Burgoon, J. K., Nunamaker J. F. Behavioral Analysis at Decision Points in Adversarial Group Interaction. Invited presentation at the Credibility Assessment and Screening Technologies Symposium at the Hawaii International Conference on System Sciences, Wailea, HI. [Jan. 2020]
- 43) Ge, S., Burgoon, J. K., Nunamaker, J. F. Cultural Influence on Linguistic Behaviors during Deceptive Communication. Invited presentation at the Credibility Assessment and Screening Technologies Symposium at the Hawaii International Conference on System Sciences, Wailea, HI. [Jan. 2020]
- 44) Pentland, S. J., Spitzley, L. A., Chen X., Wang X., Burgoon, J. K., Nunamaker J. F. Behavioral Indicators of Dominance in an Adversarial Group Negotiation Game. Invited presentation at the Credibility Assessment and Screening Technologies Symposium at the Hawaii International Conference on System Sciences, Wailea, HI. [Jan. 2020]
- 45) Spitzley, L. A., Analyzing Face-to-Face Multicultural Group Communication with Computational Linguistics and Vocalics: Procedures, Results and Implications for Future Research Indicators. Presented at University at Albany School of Business Faculty Research Seminar, Albany, NY. [February 2020]
- 46) Stathopoulos, A., Han, L., Dunbar, N., Burgoon, J. K., & Metaxas, D. (2020, November). Deception Detection using Facial Cues. Future Technologies Conference (FTC 2020), Vancouver, BC.

Publications

- [1] Bai, C., Bolonkin, M., Burgoon, J., Chen, C., Dunbar, N., Singh, B., and Subrahmanian, V.S., Automatic Long-Term Deception Detection in Group Interaction Videos. ICME'19
- [2] Bai, C., Bolonkin, M., Kumar, S., Leskovec, J., Burgoon, J., Dunbar, N., and Subrahmanian, V.S., Predicting dominance in multi-person videos. To appear in IJCAI'19

- [3] Bai, C., Kumar, S., Leskovec, J., Metzger, M., Nunamaker, J., Subrahmanian, V.S., Predicting the Visual Focus of Attention in Multi-person Discussion Videos. To appear in IJCAI'19
- [4] Bai, C., Kumar, S., Leskovec, J., Metzger, M., Nunamaker, J. F., Subrahmanian, V. S. (accepted). Iterative Collective Classification for Visual Focus of Attention Prediction. International Joint Conference on Artificial Intelligence (IJCAI), August 2019.
- [5] Bai, C., Bolonkin, M., Burgoon, J. K., Chen, Dunbar N, Regunath V, Subrahmanian V.S. , Predicting Relative Nervousness from Group Interaction Videos, submitted to ACM Multimedia 2020
- [6] Bai C, Chen , Kumar S, Leskovec J, Subrahmanian V.S. , M2P2: Multimodal Persuasion Prediction using Adaptive Fusion, submitted to ACM Multimedia 2020
- [7] Proudfoot, J., Jenkins, J. Valacich, J. and Nunamaker, J., "Slight of Hand: Identifying Concealed Information by Monitoring mouse Cursor Movement." To appear, Journal of the Association for Information Systems.
- [8] Burgoon, J.K., Opinion: Microexpressions are not the best way to catch a liar. *Frontiers in Psychology*, 9, Sep 2018
- [9] Burgoon, J. K., Separating the wheat from the chaff: Guidance from new technologies for detecting deception in the courtroom. *Frontiers in Psychology*, 9:774, Jan 2019
- [10] Burgoon, J. K., Blair, J. P., Hamel, L. & Twyman, N. W. (2020). Factors that facilitate or impair kinesic and vocalic nonverbal behaviors during interpersonal deception. In A. Kostić (Ed.), *Social Intelligence: The Adaptive Advantages of Nonverbal Communication*. Switzerland: Palgrave.
- [11] Burgoon, J. K. (in press). Prelude: Relational communication and the link to deception. In V. S. Subramanian, J. K. Burgoon & N. E. Dunbar (Eds.), *Detecting Trust and Deception in Group Interaction*. New York, NY: Springer, 2020.
- [12] Burgoon, J. K., Dunbar, N. E. & Jensen, M. (in press). An integrated spiral model of trust. In V. S. Subramanian, J. K. Burgoon & N. E. Dunbar (Eds.), *Detecting Trust and Deception in Group Interaction*. New York, NY: Springer, 2020.
- [13] Burgoon, J. K., Metaxas, D. & Nunamaker, J. F. (in press). Cultural influence on deceptive communication. In V. S. Subramanian, J. K. Burgoon & N. E. Dunbar (Eds.), *Detecting Trust and Deception in Group Interaction*. New York, NY: Springer.
- [14] Denault, V., Plusquellec, P., Jupe, L. M., St-Yves, M., Dunbar, N. E., Hartwig, M., Sporer, S. L., Rioux-Turcotte, J., Jarry, J., Walsh, D., Otgaar, H., Viziteu, A., Talwar, V., Keatley, D. A., Blandón-Gitlin, I., Townson, C., Deslauriers-Varin, N., Lilienfeld, S. O., Patterson,

M.L., Areh, I., Allan, A., Cameron, H.E., Boivin, R., ten Brinke, L., Masip, J., Bull, R., R., Cyr, M., Hope, L., Strömwall, L. A., Bennett, S., Al Menaiya, F., Leo, R. A., Vredeveltdt, A., Laforest, M., Honts, C. R., Manzanero, A. L., Mann, S., Geanhag, P.-A., Ask, K., Gabbert, F., Guay, J.-P., Coutant, A., Hancock, J., Manusov, V., Burgoon, J.K., Kleinaman, S. M., Wright, G., Landström, S., Freckelton, I., Vernham, Z., & van Koppen, P.J., The analysis of nonverbal communication: the dangers of pseudoscience in security and justice contexts. *Anuario de Psicología Jurídica*, 1-12, Apr 2019

- [15] Kumar, S., Zhang, X., Leskovec, J.. Predicting Embedding Trajectories in Temporal Interaction Networks. 25th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, 2019 [8] K. Xu, W. Hu, J. Leskovec, S. Jegelka, How Powerful Are Graph Neural Networks?. ICLR, 2019.
- [16] S. Kumar, X. Zhang, J. Leskovec. Predicting Dynamic Embedding Trajectory in Temporal Interaction Networks. ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD), 2019.
- [17] J. You, Y. Wang, A. Pal, P. Eksombatchai, C. Rosenberg, J. Leskovec. Hierarchical Temporal Convolutional Networks for Dynamic Recommender Systems. ACM International Conference on World Wide Web (WWW), 2019.
- [18] W. Hamilton, P. Bajaj, M. Zitnik, D. Jurafsky, J. Leskovec. Embedding Logical Queries on Knowledge Graphs. Neural Information Processing Systems (NeurIPS), 2018.
- [19] R. Ying, J. You, C. Morris, X. Ren, W. Hamilton, J. Leskovec. Hierarchical Graph Representation Learning with Differentiable Pooling. Neural Information Processing Systems (NeurIPS), 2018.
- [20] R. Ying, D. Bourgeois, J. You, M. Zitnik, J. Leskovec. GNNExplainer: Generating Explanations for Graph Neural Networks Neural Information Processing Systems (NeurIPS), 2019.
- [21] E. Ghalebi, B. Mirzasoleiman, R. Grosu, J. Leskovec. Dynamic Network Model from Partial Observations. Neural Information Processing Systems (NeurIPS), 2018.
- [22] J. You, R. Ying, X. Ren, W. L. Hamilton, J. Leskovec. GraphRNN: Generating Realistic Graphs with Deep Auto-regressive Models. International Conference on Machine Learning (ICML), 2018.
- [23] R. Ying, R. He, K. Chen, P. Eksombatchai, W. L. Hamilton, J. Leskovec. Graph Convolutional Neural Networks for Web-Scale Recommender Systems. ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD), 2018.

- [24] C. Donnat, M. Zitnik, D. Hallac, J. Leskovec. Learning Structural Node Embeddings via Diffusion Wavelets. ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD), 2018.
- [25] H. Yin, A. Benson, J. Leskovec. Higher-Order Clustering in Networks. Physical Review E 97 052306 (PRE), 2018.
- [26] J. Cheng, J. Kleinberg, J. Leskovec, D. Liben-Nowell, B. State, K. Subbian, L. Adamic. Do Diffusion Protocols Govern Cascade Growth? AAAI International Conference on Weblogs and Social Media (ICWSM), 2018.
- [27] S. Kumar, W. Hamilton, J. Leskovec, D. Jurafsky. Community Interaction and Conflict on the Web. ACM International Conference on World Wide Web (WWW), 2018.
- [28] T. Kurashima, T. Althoff, J. Leskovec. Modeling Interdependent and Periodic Real-World Action Sequences. ACM International Conference on World Wide Web (WWW), 2018.
- [29] Z. Lin, T. Althoff, J. Leskovec. I'll Be Back: On the Multiple Lives of Users of a Mobile Activity Tracking Application. ACM International Conference on World Wide Web (WWW), 2018.
- [30] E. Pierson, T. Althoff, J. Leskovec. Modeling Individual Cyclic Variation in Human Behavior. ACM International Conference on World Wide Web (WWW), 2018.
- [31] Wang, L., Yu, X., Bourlai, T., & Metaxas, D. N. (2019). A coupled encoder–decoder network for joint face detection and landmark localization. *Image and Vision Computing*, 87, 37-46.
- [32] Wang, L., Bai C., Bolonkin, M., Burgoon J. K., Dunbar N. E., Subrahmanian, V. S., Metaxas, D. N. (2019). “Attention-based Facial Behavior Analytics in Social Communication”. In British Machine Vision Conference (BMVC).
- [33] Wang, L., Wu, Z., Karanam S., Peng, K. C., Singh, R. V., Liu, B., Metaxas, D. N. (2019). “Sharpen focus: Learning with attention separability and consistency.” In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*.
- [34] Tian, Y., Peng, X., Zhao, L., Zhang, S., & Metaxas, D. N. (2018). CR-GAN: learning complete representations for multi-view generation. arXiv preprint arXiv:1806.11191.
- [35] C. Coleman, C. Yeh, S. Mussmann, B. Mirzasoleiman, P. Bailis, P. Liang, J. Leskovec, M. Zaharia. Selection Via Proxy: Efficient Data Selection For Deep Learning. International Conference on Learning Representations (ICLR), 2020.
- [36] Daniels, Z. A., Frank. L. D., Menart, C. J., Raymer, M., Hitzler, P.. "A framework for explainable deep neural models using external knowledge graphs." In *Proc. SPIE 11413*,

- [37] Dorn, B. et al. (in press). A system for multi-person, multi-modal data collection in behavioral informatics. In V. S. Subramanian, J. K. Burgoon & N. E. Dunbar (Eds.), *Detecting Trust and Deception in Group Interaction*. New York, NY: Springer.
- [38] Ebesu Hubbard, A. S. & Burgoon, J. K. (2019). Nonverbal communication. In M. Salwen & D. W. Stacks (Eds.), *An integrated approach to communication theory and research*, 3e (pp. 333-346). Mahwah, NJ: LEA.
- [39] Ford, B., Dunbar, N. E., Dorn, B., Giles, M., Metzger, M., & Subrahmanian, V.S. "Deception in Groups: How dyadic theories can predict deception and its detection in group contexts." Paper presented to the National Communication Association, 2018.
- [40] Ford, B. R., Dorn, B., Hansia, M., Dunbar, N. E., Giles, M., Metzger, M., Burgoon, J. K., Subrahmanian, V. S. (2019, January). *Fight vs Flight: Dominance strategies of groups of deceivers*. Paper presented to the 52nd Hawaii International Conference on System Sciences, Wailea, HI.
- [41] Han, L., Stathopoulos, A., Xue, T., Metaxas, D. N. (2020). "Unbiased Auxiliary Classifier GANs with MINE". In *IEEE Conference on Computer Vision and Pattern Recognition Workshop (CVPRW)*.
- [42] Han, L., Zou, Y., Gao, R., Wang, L., Metaxas, D. N. (2019). "Unsupervised Domain Adaptation via Calibrating Uncertainties". *IEEE Conference on Computer Vision and Pattern Recognition Workshop (CVPRW)*.
- [43] Han, L., Gao, R., Kim, M., Tao, X., Liu, B., Metaxas, D. N. (2020). "Robust Conditional GAN from Uncertainty-Aware Pairwise Comparisons". *34th AAAI Conference on Artificial Intelligence (AAAI)*.
- [44] H. Ren, W. Hu, J. Leskovec. Query2box: Reasoning Over Knowledge Graphs In Vector Space Using Box Embeddings. International Conference on Learning Representations (ICLR), 2020.
- [45] Helquist, J., Wiers, K. & Burgoon, J. K. (in press). Detection of deception in task groups. In V. S. Subramanian, J. K. Burgoon & N. E. Dunbar (Eds.), *Detecting Trust and Deception in Group Interaction*. New York, NY: Springer.
- [46] H. Wang, F. Zhang, M. Zhang, J. Leskovec, M. Zhao, W. Li, Z. Wang. Knowledge-aware Graph Neural Networks with Label Smoothness Regularization for Recommender Systems. ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD), 2019.

- [47] J. You, H. Wu, C. Barrett, R. Ramanujan, J. Leskovec. G2SAT: Learning to Generate SAT Formulas. Neural Information Processing Systems (NeurIPS), 2019.
- [48] I. Chami, R. Ying, C. Re, J. Leskovec. Hyperbolic Graph Convolutional Neural Networks. Neural Information Processing Systems (NeurIPS), 2019.
- [49] Nunamaker, J. F., Jr., Burgoon, J. K. & Giboney, J. S. (in press). On systems designed to detect deception, fraud and malicious intent and insider threat. *Journal of Management Information Systems*.
- [50] Stathopoulos, A., Han, L., Dunbar, N., Burgoon, J. K., Metaxas, D. N. (2020). "Deception Detection using Facial Cues". In *Future Technologies Conference (FTC)*.
- [51] Spitzley, L., Pentland, S., Dorn, B., Walls, B. & Burgoon, J. K. Using multimodal data to infer group dynamics in an adversarial group game. Paper submitted to the *IEEE International Carnahan Conference on Security Technology (ICCST)*, 2018.
- [52] Spitzley L. A. et al. (in press). Behavioral Indicators of Dominance in an Adversarial Group Negotiation Game. In V. S. Subramanian, J. K. Burgoon & N. E. Dunbar (Eds.), *Detecting Trust and Deception in Group Interaction*. New York, NY: Springer.
- [53] Subrahmanian, V.S., Burgoon, J. K. & Dunbar, N. E. (Eds.) (2020). *Detecting trust and deception in group interaction*. New York, NY: Springer.
- [54] Matt Giles, Mohemmad Hansia, Miriam Metzger, Norah E. Dunbar, The Impact of Culture in Deception and Deception Detection. In V. S. Subramanian, J. K. Burgoon & N. E. Dunbar (Eds.), *Detecting Trust and Deception in Group Interaction*. New York, NY: Springer, 2020.
- [55] Norah E. Dunbar, Bradley Dorn, Mohemmad Hansia, Becky Ford, Matt Giles, Miriam Metzger, Judee K. Burgoon, Jay F. Nunamaker, V.S. Subrahmanian, Dominance in Groups: How Dyadic Power Theory Can Apply to Group Discussions. In V. S. Subrahmanian, J. K. Burgoon & N. E. Dunbar (Eds.), *Detecting Trust and Deception in Group Interaction*. New York, NY: Springer, 2020.
- [56] Joel Helquist, Karl Wiers, Judee K. Burgoon, Effects of Modality Interactivity and Deception Communication Quality and Task Performance. In V. S. Subrahmanian, J. K. Burgoon & N. E. Dunbar (Eds.), *Detecting Trust and Deception in Group Interaction*. New York, NY: Springer, 2020.
- [57] Lee Spitzley, Incremental Information Disclosure in Qualitative Financial Reporting: Differences between Fraudulent and Non-Fraudulent Companies. In V. S. Subrahmanian, J. K. Burgoon & N. E. Dunbar (Eds.), *Detecting Trust and Deception in Group Interaction*. New York, NY: Springer, 2020.

- [58] C. Kang, S. Kraus, C. Molinaro, F. Spezzano, and V.S. Subrahmanian. Diffusion Centrality in Social Networks, *Artificial Intelligence*, Vol. 239, pages 70-96, July 2016.
- [59] V.S. Subrahmanian and S. Kumar. Predicting Human Behavior: The Next Frontiers, *Science*, Vol. 355 (6324), p. 489. This is a one page invited essay.
- [60] Z. Wu, B. Singh, L. Davis and V.S. Subrahmanian. Deception Detection in Videos, *Proc. AAAI 2018*, Feb 2018, acceptance rate: 24.55%.
- [61] S. Kumar, B. Hooi, M. Kumar, D. Makhija, C. Faloutsos, and V.S. Subrahmanian. Rev2: Fraudulent User Prediction in Rating Platforms, *Proc. 11th ACM Conf. on Web Search & Data Mining (WSDM)*, Los Angeles, Feb 2018. Acceptance rate: 16.15%.
- [62] T. Chakraborty, D. Chandhok, and V.S. Subrahmanian. MC3: A Multi-Class Consensus Classification Framework, *Proc. 2017 Pacific-Asia Knowledge Discovery & Data Mining Conference (PAKDD-2017)*, Jeju, South Korea, Springer, May 2017. Regular presentation paper. Acceptance rate: 28.2%
- [63] S. Kumar, J. Cheng, J. Leskovec, and V.S. Subrahmanian. An Army of Me: Sockpuppets in Online Discussion Communities, *Proc. 26th International Conference on the World Wide Web (WWW 2017)*, Perth, Australia, April 2017. Received Best Paper Honorable Mention (will be public only at the end of WWW 2017). Acceptance rate: 17%.
- [64] S. Kumar, F. Spezzano, V.S. Subrahmanian and C. Faloutsos. Edge Weight Prediction in Weighted Signed Networks, *Proc. 2016 IEEE International Conference on Data Mining (ICDM 2016)*, Barcelona, Spain, Dec 2016. Acceptance rate for regular papers: 8.5%.
- [65] T. Chakraborty, N. Park, and V.S. Subrahmanian. Ensemble-Based Algorithms to Detect Disjoint and Overlapping Communities in Networks, *Proc. 2016 IEEE/ACM Conf. on Advances in Social Network Analysis and Mining*, San Francisco, Aug 2016. Acceptance rate: 13.61%. Runner up for best paper award.
- [66] S. Kumar, E. Serra, F. Spezzano, and V.S. Subrahmanian. Metric Logic Program Explanations for Complex Separator Functions, *Proc. 2016 Intl. Conf. on Scalable Uncertainty Management*, Nice, Sep 2016.
- [67] E. Serra, F. Spezzano, and V.S. Subrahmanian. ChoiceGAPs: Competitive Diffusion as a Massive Multi-Player Game in Social Networks, *Proc. 2016 Intl. Conf. on Scalable Uncertainty Management*, Nice, Sep 2016.
- [68] T. Althoff, R. Sosis, J. L. Hicks, A. C. King, S. L. Delp, J. Leskovec. Large-scale physical activity data reveal worldwide activity inequality. *Nature*, 547.7663, 2017.

- [69] W. Hamilton, J. Zhang, C. Danescu-Niculescu-Mizil, D. Jurafsky, J. Leskovec. Loyalty in Online Communities. AAAI International Conference on Weblogs and Social Media (ICWSM), 2017.
- [70] J. Zhang, W. Hamilton, C. Danescu-Niculescu-Mizil, D. Jurafsky, J. Leskovec. Community Identity and User Engagement in a Multi-Community Landscape. AAAI International Conference on Weblogs and Social Media (ICWSM), 2017.
- [71] J. Cheng, M. Bernstein, C. Danescu-Niculescu-Mizil, J. Leskovec. Anyone Can Become a Troll: Causes of Trolling Behavior in Online Discussions. Computer-Supported Cooperative Work and Social Computing (CSCW), 2017. Best paper award.
- [72] D. Hallac, S. Vare, S. Boyd, J. Leskovec. Toeplitz Inverse Covariance-Based Clustering of Multivariate Time Series Data. ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD), 2017. Best paper runner-up.
- [73] L. Zhao, X. Peng , Y. Tian, M. Kappadia, D. Metaxas Learning to Forecast and Refine Residual Motion for Image-to-Video Generation, ECCV 2018.
<https://arxiv.org/abs/1807.09951>
- [74] B Liu, XT Yuan, L Wang, Q Liu, D. Metaxas. Dual iterative hard thresholding: From non-convex sparse minimization to non-smooth concave maximization, ICML 2017.
- [75] X Peng, Z Tang, F Yang, RS Feris, D Metaxas. Jointly optimize data augmentation and network training: Adversarial data augmentation in human pose estimation. IEEE CVPR 2018
- [76] X Peng, S Zhang, Y Yu, DN Metaxas. Toward personalized modeling: Incremental and ensemble alignment for sequential faces in the wild. International Journal of Computer Vision 126 (2-4), 184-197, 2018
- [77] X Peng, RS Feris, X Wang, DN Metaxas. RED-Net: A Recurrent Encoder–Decoder Network for Video-Based Face Alignment. International Journal of Computer Vision 126 (10), 1103—1119, 2018
- [78] Dunbar, N. E., Metaxas, D., Buck, R. W., Burgoon, J. K., Kumar, S., Subrahmanian, V. S., Fujiwara, K. (2018, November). Culture, biology and nonverbal behavior: Can new technologies detect elusive relationships? Competitive panel presented to the National Communication Association annual meeting, Salt Lake City, UT.
- [79] Schuller, B., Steidl, Batliner, A., Hirschberg, J., Burgoon, J. K., Coutinho, A. (2016) The INTERSPEECH 2016 Computational Paralinguistics Challenge: Deception & Sincerity.

- [80] Elkins, A., Proudfoot, J., Twyman, N., Burgoon, J. K., Nunamaker, J. F. (2016). Embodied Conversational Agent-based Deception Detection. INTELLISYS 2016, London.
- [81] Burgoon, J. K., Dunbar, N. E. & Giles, H. (2017). Interaction coordination and adaptation. In A. Vinciarelli, M. Pantic, N Magnenat-Thalmann, & J. K. Burgoon (Eds.), Social signal processing (pp. 78-96). Cambridge, UK: Cambridge University Press.
- [82] Burgoon, J. K., Metaxas, D., Bourlai, T. & Elkins, A. (2017). Social signals of deception and dishonesty. In A. Vinciarelli, M. Pantic, N Magnenat-Thalmann, & J. K. Burgoon (Eds.), Social signal processing (pp. 404-428). Cambridge, UK: Cambridge University Press.
- [83] Burgoon, J. K., Dunbar, N. E. & Elkins, A. (2017). Analyzing video and audio nonverbal dynamics: Kinesics, proxemics, haptics and vocalics. In A. VanLear and D. J. Canary (Eds.), Sourcebook: Researching Communication Interaction Behavior. Thousand Oaks, CA: SAGE.
- [84] Burgoon, J. K. & Dunbar, N. E. (2018). Coding nonverbal behavior. In E. Brauner, M. Boos & M. Kolbe (Eds.) (2018). The Cambridge Handbook of Group Interaction (pp. 104-120). Cambridge, UK: Cambridge University Press.
- [85] Pentland, S. J., Twyman, N. W., Burgoon, J. K., Nunamaker, J. F., and Diller, C. B. R. (2017). A Video-Based Screening System for Automated Risk Assessment Using Nuanced Facial Features, *Journal of Management Information Systems* (34:4), Routledge, pp. 970–993. <https://doi.org/10.1080/07421222.2017.1393304>
- [86] Twyman, N. W., Pentland, S. J., and Spitzley L. (2018). Deception Detection in Online Automated Job Interviews. International Conference on HCI in Business, Government, and Organizations. Las Vegas, NV.
- [87] Spitzley, L. A. (2018). Manager-analyst interactions in fraudulent earnings calls. 13th Annual Symposium on Information Assurance (ASIA '18). June 5-6, 2018. Albany, NY
- [88] Twyman, N. W., Pentland, S. J., Spitzley, L. A. (in press). Design principles for signal detection in modern job application systems: Identifying fabricated qualifications. *Journal of Management Information Systems*.
- [89] W. Hu, B. Liu, J. Gomes, M. Zitnik, P. Liang, V. Pande, J. Leskovec. Strategies For Pre-training Graph Neural Networks International Conference on Learning Representations (ICLR), 2020.
- [90] Zhao, L., Peng, X., Chen, Y., Kapadia, M., Metaxas, D.N. (2020). “Knowledge as Priors: Cross-Modal Knowledge Generalization for Datasets without Superior Knowledge”. In

What do you plan to do during the next reporting period to accomplish the goals and objectives?

Not applicable as this is the final report for this grant.

Honors: What honors or awards were received under this project in this reporting period?

1. Inaugural Natalie Cone Speaker Series, Deception and its Detection: the Good, the Bad, the Ugly, UCLA, April (Burgoon)
2. Outstanding Graduate Alumni Achievement Award, School of Communication, Illinois State University (Burgoon)
3. Inducted into Illinois State University College of Arts & Sciences Hall of Fame (Burgoon)
4. Speaker, Cognitive Neurosciences Seminar Series lecture on deception, Institute for Intelligent Systems University of Memphis, October. (Burgoon)
5. Address to Hall of Fame convocation, Arts & Sciences. Illinois State UniversityMost Prolific Author Award at HICSS for last 50 years. 102 papers written and accepted at HICSS over 50 years. HICSS is attended by approximately 1200 national International Scholars Yearly. Over the years, Professor Nunamaker received ten "Best Paper of the Conference" awards. (Nunamaker)
6. The Distinguished Mechanical Engineer of the Year Award from the University of Pittsburgh (Nunamaker).
7. Top paper award for the Japan-U.S. Communication Association, National Communication Association (NCA), November, 2022. (Dunbar)
8. Elected Fellow of the International Communication Association, May 2021. (Dunbar)
9. Co-Winner John Garrison Memorial Award for the best applied manuscript from the Interpersonal Division of the International Communication Association, 2021. (Dunbar)
10. Faculty co-author on Best Student-led Paper Award at Future Technologies Conference (FTC), 2020. (Dunbar)
11. Top Four Papers, Interpersonal Communication Division of the National Communication Association (NCA), November, 2016. (Dunbar)
12. IEEE ICDM Research Contributions Award, 2019 (Leskovec)
13. Cheriton Faculty Scholar in the School of Engineering, Stanford University, 2017 (Leskovec)

14. Best application paper award, ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD), 2021 (Leskovec)
15. 10-year test of time award, Intl. Conf. on Knowledge Discovery & Data Mining, 2019 (Leskovec)
16. Best paper award, ACM Intl. Conf. on Computer-Supported Cooperative Work and Social Computing (CSCW), 2017 (Leskovec)
17. Best research paper runner-up award, ACM Intl. Conf. on Knowledge Discovery and Data Mining (KDD), 2017 (Leskovec)
18. Best student paper runner-up award, ACM Intl. Conf. on Knowledge Discovery and
19. Data Mining (KDD), 2017 (Leskovec)
20. Best paper award honorable mention, ACM Intl. Conf. on World Wide Web, 2017 (Leskovec)
21. 10-year test of time award, Intl. Conf. on Knowledge Discovery & Data Mining, 2016 (Leskovec)
22. 10-year test of time award, Pacific-Asia Conf. on Knowledge Discovery & Data Mining, 2016 (Leskovec)
23. Best Paper Award for “Active Scene Classification via Dynamically Learning Prototypical Views”, Zachary A. Daniels and Dimitris Metaxas, DDDAS2020 Conference
24. Best Student Paper Award for “Deception Detection in Videos using Robust Facial Features”, Anastasis Stathopoulos, Ligong Han, Norah Dunbar, Judee Burgoon, Dimitris Metaxas, FTC 2020
25. Elected Fellow of the International Communication Association (Metzger)
26. Invited Talk, United Nations, Nov/Dec 2016.
27. 20-year Test of Time Award, 2017 Intl. Conf. on Logic Programming, Leuven, Belgium. (Subrahmanian)
28. *Named an IEEE/Tencent Rhino Bird International Academic Expert*, May 2017. (Subrahmanian)
29. *Runner Up for the Best Paper Award*, 2017 World Wide Web Conference, Perth, Australia, April 2017. (Subrahmanian)
30. *Named to the IEEE Golden Core*, 2022 (Subrahmanian)
31. *Named a Fellow of the Asia-Pacific AI Association* (Subrahmanian)
32. Keynote Address, TCS TACTiCS regional conference for North America - Latin America, Nov 2022. (Subrahmanian)
33. Keynote Address, Wells Fargo Confluence conference, Dec 2021. (Subrahmanian)
34. Keynote Speaker, 18th International Conference on Security and Cryptography (SECRYPT 2021), July 2021. (Subrahmanian)
35. Keynote Speaker, UnitedHealth Group Healthcare Technology Advisory Council, June 30, 2021. (Subrahmanian)
36. Keynote Speaker, Working Group on Children Recruited by Terrorist and Violent Extremist Groups (“CRTG”) Live Briefing, April 29 2021. (Subrahmanian)

37. Keynote Speaker, 1st International Conference on Autonomous Intelligent Cyber-defence Agents, Paris France (but via Zoom), March 2021. (Subrahmanian)
38. Keynote Speaker, 8th International Workshop on Parallel and Distributed Computing for Large-Scale Machine Learning and Big Data Analytics (ParLearning 2019), in conjunction with the 25th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD 2019), Anchorage, Alaska, Aug 2019. (Subrahmanian)
39. Keynote Speaker, 17th International Conference on Practical Applications of Agents and Multi-Agent Systems, Avila, Spain, June 2019. (Subrahmanian)
40. Keynote Speaker, 14th International Conference on Information Systems Security, Bangalore, India, Dec. 2018. (Subrahmanian)
41. Plenary Speaker, The World Academy of Science General Meeting, Trieste, Italy, Nov 2018. (Subrahmanian)
42. Keynote Speaker, 2018 New York State Cybersecurity Conference, Albany, NY, June 2018. (Subrahmanian)
43. Keynote Speaker, ADCOM-2016, Advanced Computing and Communications Society, Bangalore, India, Sep 2016. (Subrahmanian)

Participants

First Name	Last Name	University	Type
Anastasios	Stathopoulos	Rutgers	Grad Student
Becky	Ford	UC-Santa Barbara	Grad student & postdoc
Bharat	Singh	UMD	Grad Student
Bia	Kinder	UCSB	Undergraduate
Bo	Liu	Rutgers	Grad Student
Bradley	Dorn	U. Arizona	Grad student
Bradley	Walls	U. Arizona	Grad Student
Chaowei	Tan	Rutgers	Student
Chiara	Pulice	Dartmouth	Postdoc
Chongyang	Bai	Dartmouth	Grad student
Christopher	Yeh	Stanford	Grad student
Dimitris	Metaxas	Rutgers	Faculty
Ellie	Tran	UCSB	Undergraduate

Haipeng	Chen	Dartmouth	Postdoc
Han	Zhang	Rutgers	Grad Student
Hui	Qu	Rutgers	Grad Student
Jay	Nunamaker	U of Arizona	Faculty
Jingjing	Liu	Rutgers	Grad Student
Jingru	Yi	Rutgers	Grad Student
Josie	Reece	UCSB	Undergraduate
Judee	Burgoon	U of Arizona	Faculty
Jure	Leskovec	Stanford	Faculty
Karissa	Macleod	UCSB	Undergraduate
Kelsey	Bernard	UCSB	Undergraduate
Lee	Splitzley	U. Arizona	Grad student
Lezi	Wang	Rutgers	Grad Student
Ligong	Han	Rutgers	Grad Student
Long	Zhao	Rutgers	Grad student
Maksim	Bolonkin	Dartmouth	Grad student
Mark	Dilsizian	Rutgers	Grad Student
Matt	Giles	UC-Santa Barbara	Grad student
Melissa	Lindberg	UCSB	Undergraduate
Miriam	Metzger	UC-Santa Barbara	Faculty
Mohemmad	Hansia	UCSB	Grad
Morgan	Fraiyo	UCSB	Undergraduate
Nadine	Karmalawy	UCSB	Undergraduate
Norah	Dunbar	UC-Santa Barbara	Faculty
Pan	Li	Stanford	Grad student
Pengxiang	Wu	Rutgers	Grad Student
Qi	Chang	Rutgers	Grad student
Qiaoying	Huang	Rutgers	Grad Student
Rebecca	Wang	U of Arizona	Grad

Reema	Moussa	UCSB	Undergraduate
Riddhi	Panchal	UCSB	Undergraduate
Rok	Sosic	Stanford	Postdoc
Roberta	Muchangwe	University of Zambia	Faculty
Rushin	Gindra	Rutgers	Grad
Sagar	Honnungar	Stanford	Grad student
Saiying	Ge	University of Arizona	Grad
Sam	Rasmussen	UCSB	Undergraduate
Sami	Resnick	UCSB	Undergraduate
Sharon	Paglieri	UCSB	Undergraduate
Shu	Wang	Rutgers	Grad student
Srijan	Kumar	Stanford	Postdoc
Stacey	Hall	UCSB	Undergraduate
Steven	Pentland	U. Arizona	Grad student
Tina	Ge	U of Arizona	Grad
Vera	Lin	Stanford	Grad
Vincent	Denault	Universite de Montreal	Graduate
Viney	Regunath	Dartmouth	Undergrad
V.S.	Subrahmanian	Dartmouth	Faculty
Xi	Peng	Rutgers	Grad student
Xiang	Yu	Rutgers	Grad Student
Xinran	Wang	U of Arizona	Grad
Xunyu	Chen	U of Arizona	Grad
Yan	Zhu	Rutgers	Grad Student
Yanbang	Wang	Stanford	Grad
Yang	Yu	Rutgers	Grad Student
Yanhai	Xiong	Dartmouth	Postdoc
Yu	Tian	Rutgers	Grad Student
Yuxiao	Chen	Rutgers	Grad

Zachary	Daniels	Rutgers	Grad (graduated)
Zhe	Wu	UMD	Grad student
Zhennan	Yan	Rutgers	Grad Student
Zhiqiang	Tang	Rutgers	Grad student