SCAN: Socio-Cultural Attitudinal Networks
Major Accomplishments to Date

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Joint work with many collaborators from the SCAN Team and Beyond.

Today’s Agenda

Time (EST)	Speaker	Title
12:00 - 13:15	V.S. Subrahmanian Dartmouth College	Main Contributions of the SCAN MURI
13:15 - 13:25		Break
13:25 – 13:50	Norah Dunbar, University of California Santa Barbara	Deception Detection: Social Science Research
13:50 - 14:15	Dimitris Metaxas, Rutgers University	Deception Detection: Predictive Computational Modeling
14:15- 14:25		Break
14:25 – 14:50	Judee Burgoon, University of Arizona	Dominance Analysis: Social Science Research
14:50 - 15:15	Jure Leskovec, Stanford University	Dominance Analysis: Predictive Computational Modeling
15:15 – 1525		Break
15:25 - 15:50	Miriam Metzger, University of California Santa Barbara	Cultural Analysis
15:50 – 16:00	V.S. Subrahmanian Dartmouth College	New Results: Like/Dislike and Nervousness Prediction
15:50-16:00	Jay Nunamaker, University of Arizona	New Results: Trust Prediction

All materials from today’s talks are available at: https://home.cs.dartmouth.edu/~mbolonkin/scan/register/review_session.html

Student Videos

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https://home.cs.dartmouth.edu/~mbolonkin/scan/register/review_session.html

Presenter	Organization	Title
Maksim Bolonkin	Dartmouth College	Automatic Long-Term Deception Detection in Group Interaction Videos
Maksim Bolonkin	Dartmouth College	Predicting Negative Impressions in Group Interaction Videos
Chongyang Bai	Dartmouth College	Predicting Dominance in Group Interaction Videos
Chongyang Bai	Dartmouth College	Predicting the Visual Focus of Attention in Multi-Person Discussion Videos
Chongyang Bai	Dartmouth College	M2P2: Multimodal Persuasion Prediction with Adaptive Fusion
Viney Regunath	Dartmouth College	Predicting Relative Nervousness from Group Interaction Videos
Anastasios Stathopoulos	Rutgers University	Deception Detection in Videos using Robust Facial Features
Pan Li	Stanford University	Dynamic Network Representation Learning
Yen-Yu Chang	Stanford University	F-FADE: Frequency Factorization for Anomaly Detection in Edge Streams
Yanbang Wang	Stanford University	TEDIC: Neural Modeling of Behavioral Patterns in Dynamic Social Interaction Network
Mohemmad Hansia	UCSB	Transcript Maagement
Yibei Chen	UCSB	Measuring Similarity -- Anna Karenina (Annak)
Lee Spitzley	University of Albany	Transcribing Speech in the SCAN Project
Xunyu Chen	University of Arizona	Deception Detection with Bag-of-Words Features
Xinran Wang	University of Arizona	Presenting Informational Stimuli and Using Nonverbal Behaviors to Detect Deception in Group Interaction
Saiying (Tina) Ge	University of Arizona	SCAN: Cultural Analyses. Effect of Culture on Verbal Behaviour During Deception
Bradley Walls	University of Arizona	Facial Analyses with Open Source Tools
Vincent Denault	University of Montreal	Qualitative Analysis for Deception Detection

SCAN Team

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SCAN Project Goals

Identify non-verbal behaviors and develop predictive models that enable us to better understand and predict

- **Dominance/deference relationships**
- **Trust/distrust relationships**
- **Like/dislike relationships**
- **Deception**

in group settings where multiple people interact with each other.

UNIVERSITY OF MARYLAND 1856 · ARIZONA · UCSB UNIVERSITY · RUTGERS · STANFORD UNIVERSITY · DARTMOUTH VOX CLAMANTIS IN DESERTO 1769

Potential SCAN Project Applications

Negotiations

Meetings

Interviews

Security Interviews

DoD Checkpoint

Sales Events

Talk Outline

Overview of the SCAN Project

- **How Humans Detect Deception and Dominance**
- How AI Algorithms Detect Deception and Dominance
- Other Major Contributions

Deception Detection

- Deception in Real-world Courtroom Videos
- Deception in Multi-Player Face to Face Games

Other Contributions

Programmatics

Accomplishment I: The SCAN Dataset

The world's **most extensive dataset** on human-human communications in a setting that is

- Multinational
- Multicultural
- Designed to elicit behaviors such as
  - Like/dislike
  - Trust/distrust
  - Dominance/deference
  - Deception
- 6 countries, 8 sites, almost 700 participants in all.
- Developed training manual and game software to support replicating our Resistance-style game

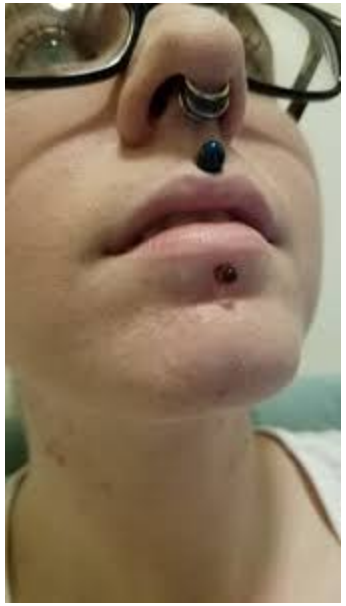
Accomplishment I: The SCAN Dataset

How Humans Detect Deception and Dominance

These results either study how humans use communication cues to detect deception and dominance, or how human-provided inputs in conjunction with statistical models can do so using the SCAN dataset.

Accomplishment II: Discovering the Cues used by Humans to Detect Deception

- Eye blinks
- Stretched lips, lips up
- Eyebrows – frown, raised
- Deceivers are more nervous over time
- Deceivers are less trusted over time
- Deceivers are less dominant
- Interaction with other Deceivers



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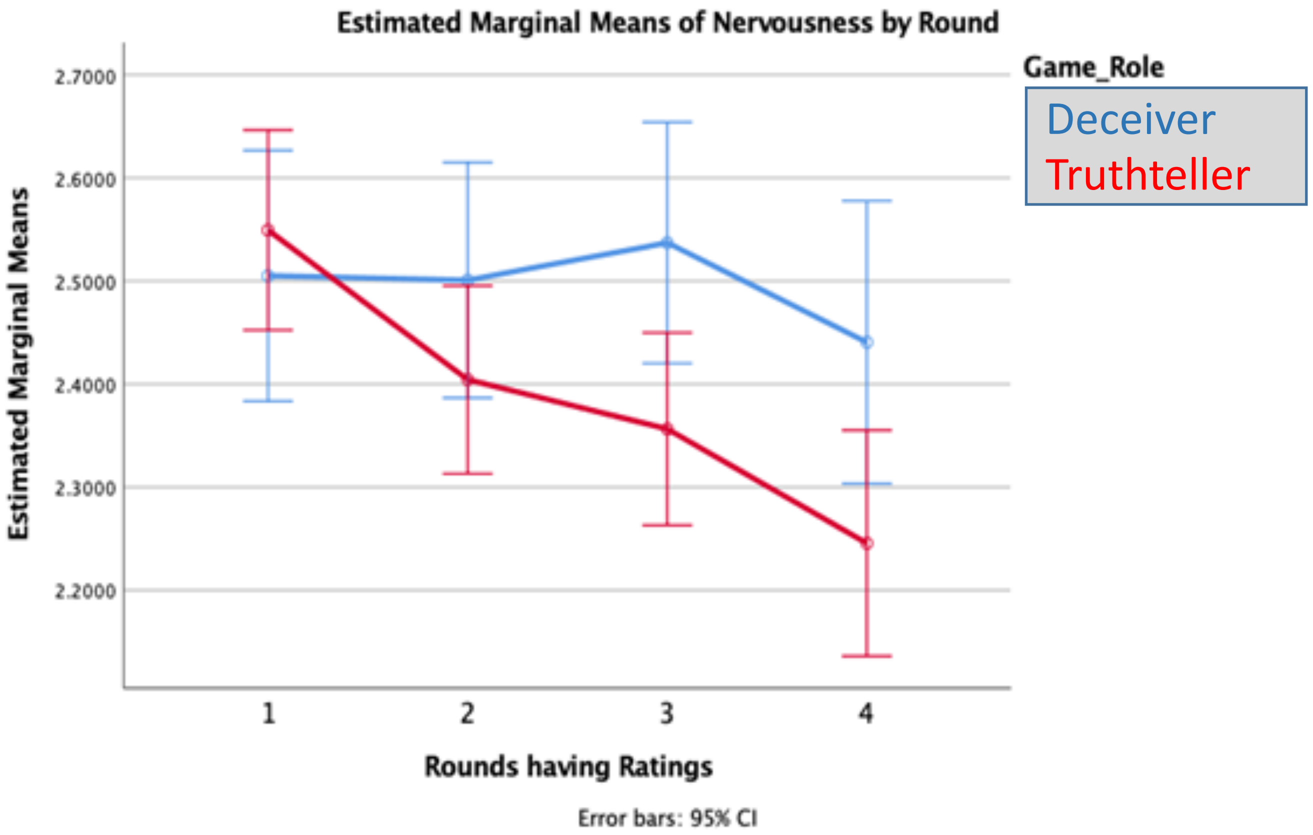

Accomplishment II: Discovering the Cues used by Humans to Detect Deception

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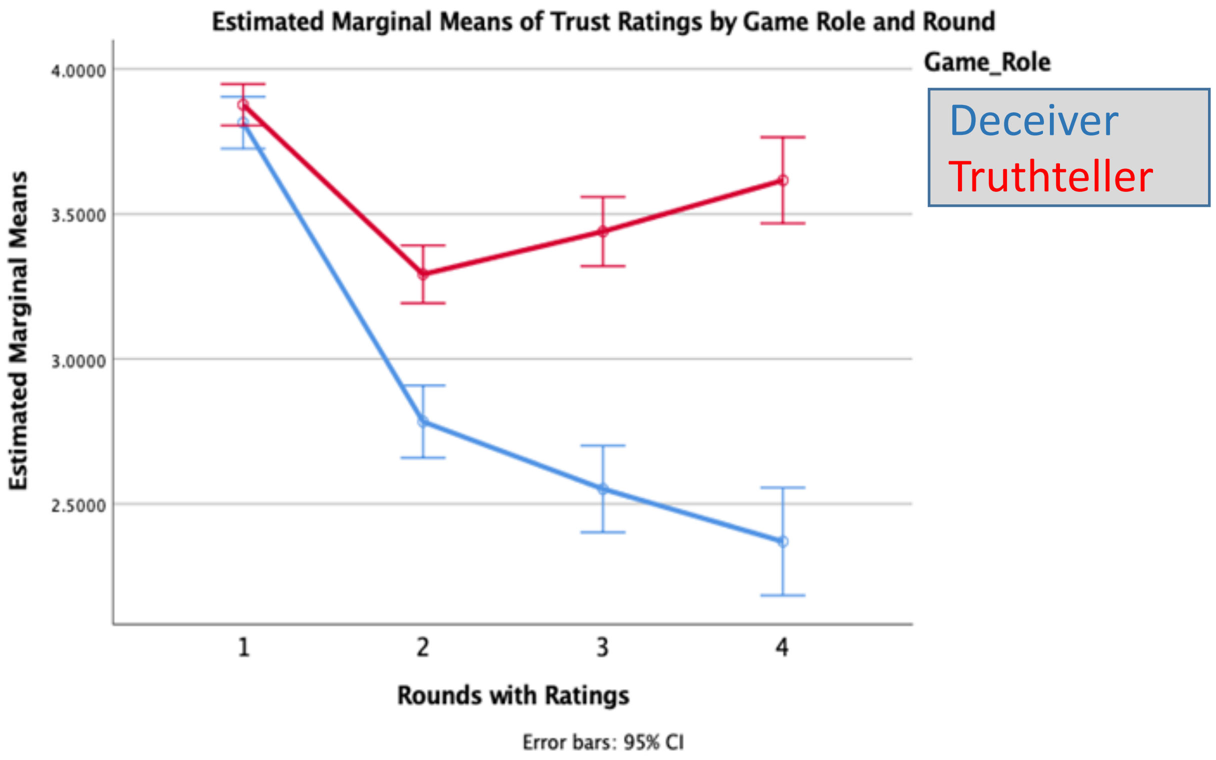
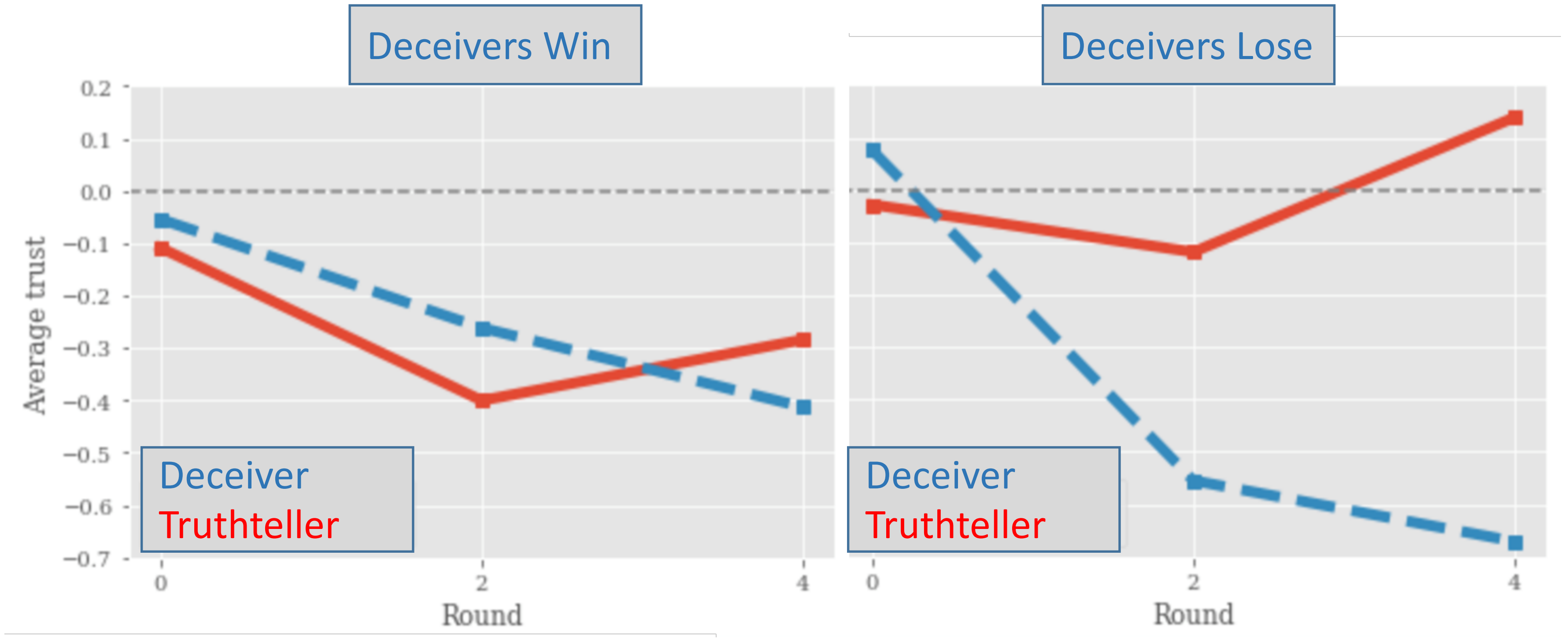
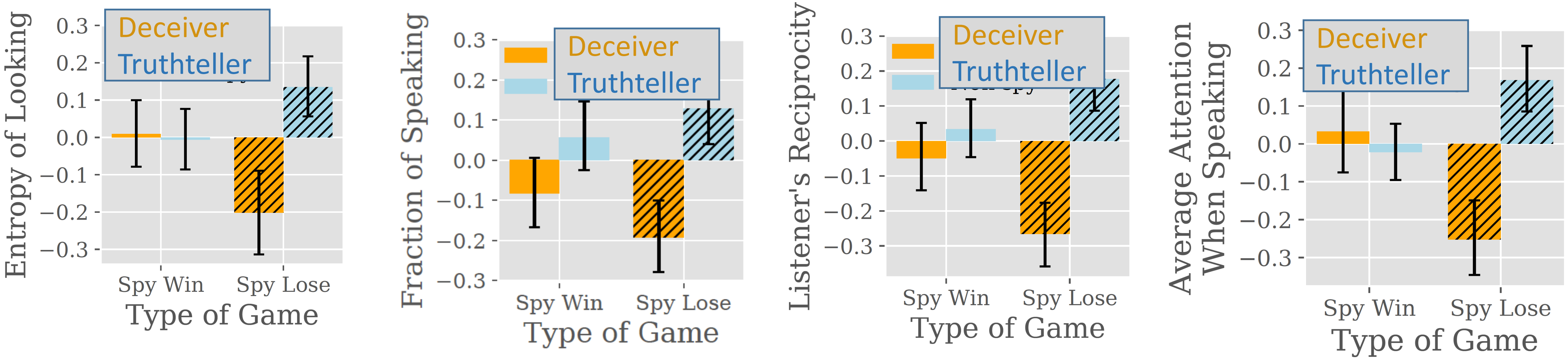


Accomplishment III: Deceivers are less trusted over time



Accomplishment IV: Signals of Deception from Looking and Speaking Networks

- Deceivers are indistinguishable from non-deceivers in games where deceivers win.
- Deceivers **speak less**, are **not listened to**, and **get less attention** in games where they lose.



Accomplishment V: Linear Regression Model for Deception Detection

- A combination of **last round trust**, **second round trust**, **last round dominance** and **baseline dominance** yield the best predictive results.
- Can identify truthtellers at 81% accuracy, liars at 65% accuracy.

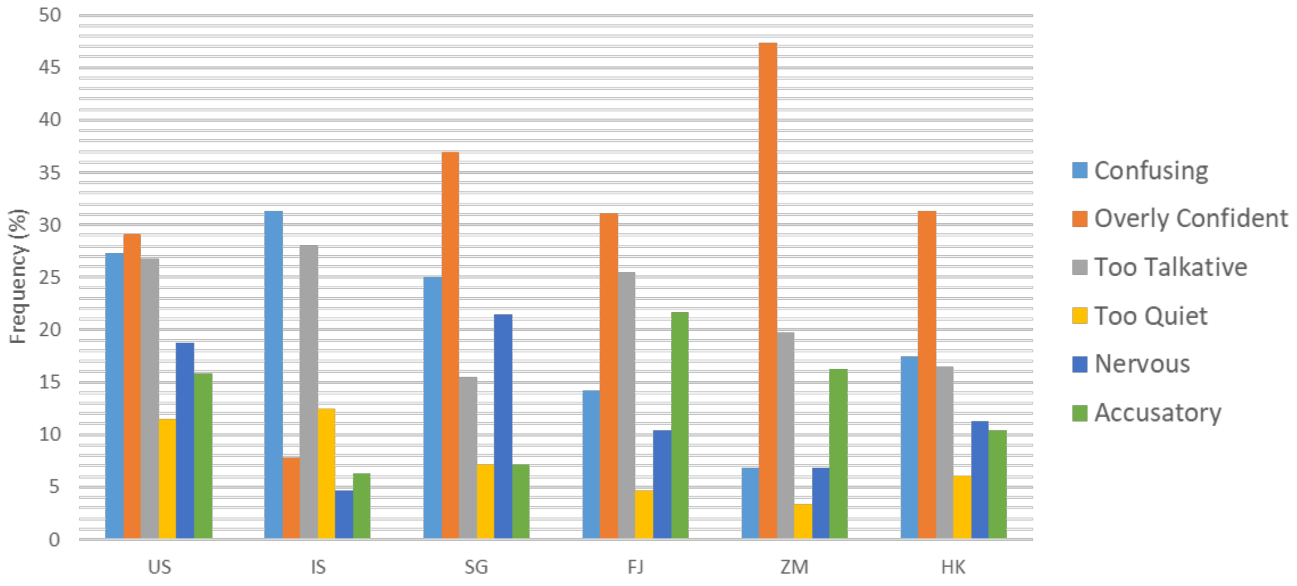
Discriminant Analysis of Relational Communication Dimensions as Discriminating between Deceivers and Truthteller, Test of Equality Between Means

	Wilks' Lambda	F	df1	df2	Sig.
Trust	.848	123.197	1	687	.000
Dominance	.964	25.505	1	687	.000
Arousal	.993	5.173	1	687	.023

Accomplishment VI: Discovering the Cues used by Humans to Detect Deception

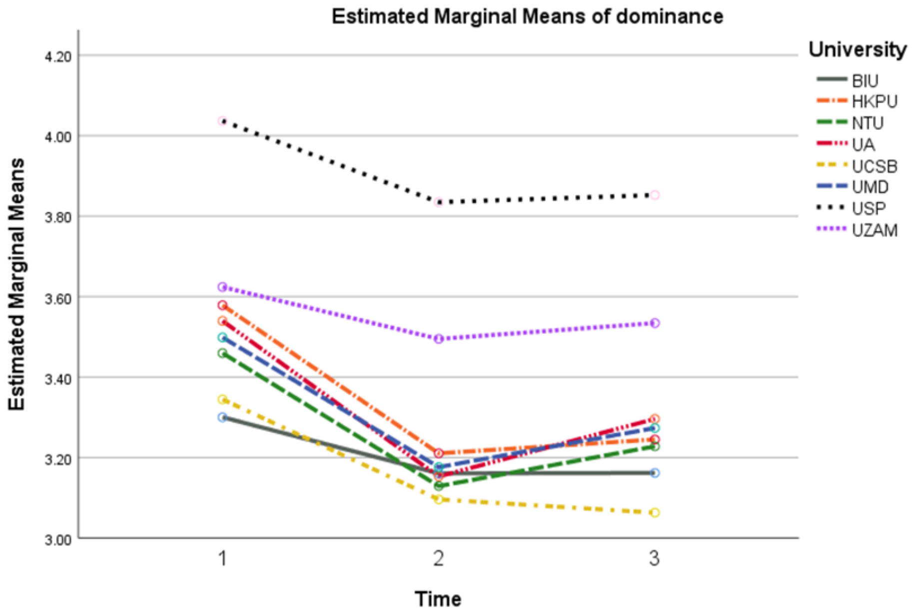
- Near **universal distrust for overly confident** statements
  - Less in Israel (horizontal individualist)
  - Most strong in Zambia (horizontal collectivist)
- More problematic to be **too talkative vs. too quiet** universally
- **Nervousness is more problematic in vertical societies** (US, SG, FJ, HK) than in horizontal ones
- **Confusion was perceived as less problematic** in the most highly collectivist societies (ZM, FJ, HK)

Key takeaway – Culture seems to matter



Accomplishment VII: Effect of Culture on Dominance

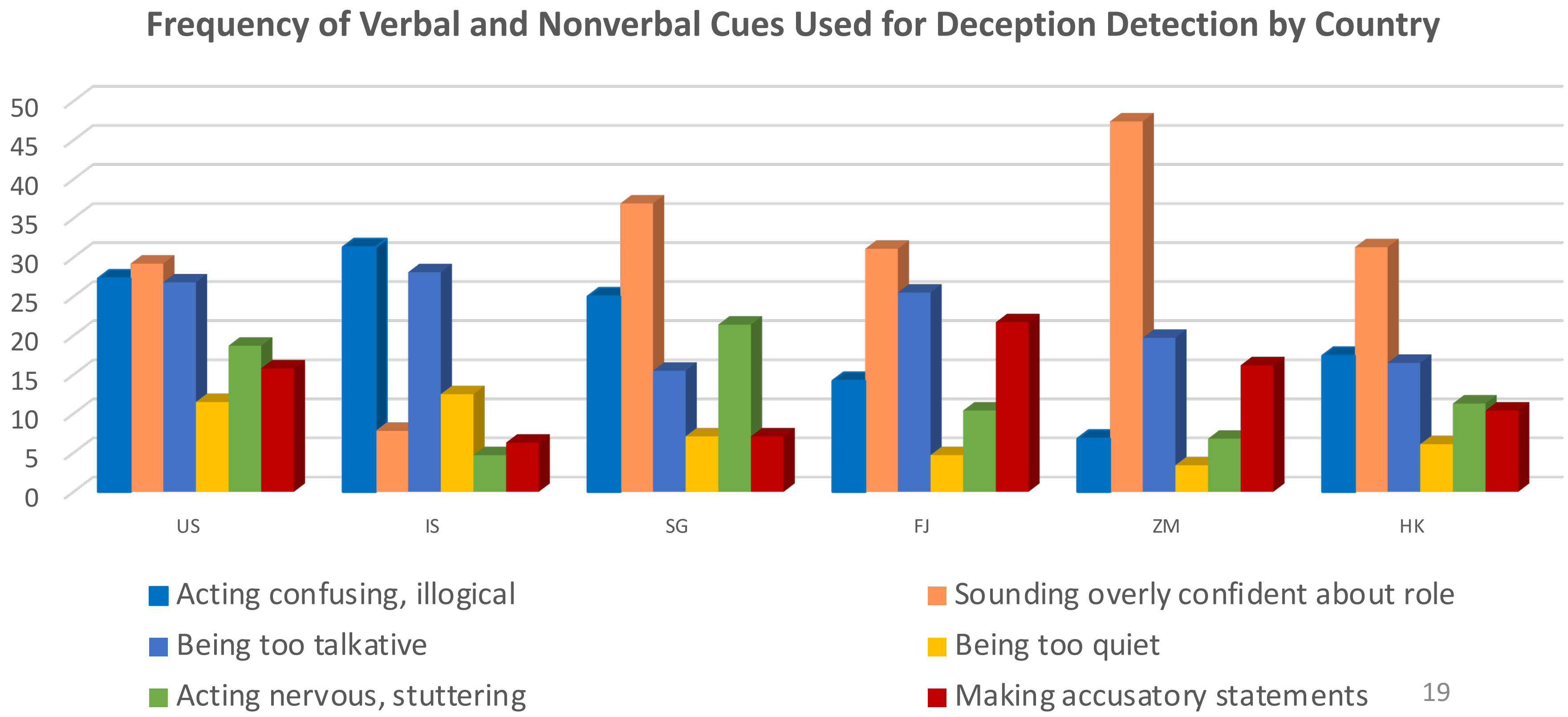
- Overall, dominance did not differ by location
- But, two locations stand out as different from the rest:
  - Fiji
  - Zambia
- Seen as more dominant than other locations



Accomplishment VII: How do Deception-Related Cues Vary by Culture?

Do the cues used to detect deception vary across cultures?

- Same cues used in the 6 countries
- but the cues are used with different frequencies in different cultures



Accomplishment VII: Culture and Accuracy in Deception Detection

Villagers' Deception Detection Accuracy Rates (Proportions) by Country

	Prop. of villagers winning game	Accuracy in detecting spies and villagers	True Positive rate (accurately detecting spies)	True Negative rate (accurately detecting villagers)
Singapore	.827	.730	.546	.840
Fiji	.424	.682	.413	.849
U.S.	.496	.676	.422	.846
Hong Kong	.803	.647	.295	.862
Zambia	.203	.636	.236	.866
Israel	.205	.620	.226	.867

Pearson correlations between cultural dimensions and deception detection accuracy

	Villagers winning game	Accuracy of detecting spies and villagers	True Positive rate (accurately detecting spies)	True Negative rate (accurately detecting villagers)
Horizontal Collectivism	.010	.064	.058	.041
Horizontal Individualism	.030	-.031	-.021	-.044
Vertical Collectivism	.038	**.100***	**.100***	.015
Vertical Individualism	**.136****	.092$^+$	**.101***	.050
Negative Face	.046	.076	.093$^+$	.009
Positive Face	-.017	.020	.020	-.015

Analyses controlled for prior game experience

Villagers win most in SG and HK:

- SG has highest overall accuracy and high true positive rate (best at detecting liars) but HK does not follow this same pattern
- True positive rate seems to be the most important factor in accuracy

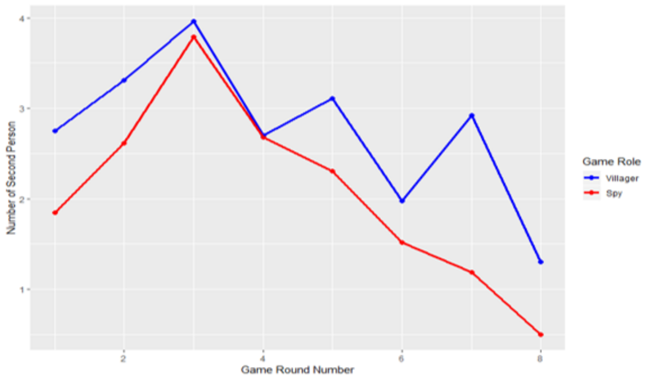
Culture matters in deception detection success:

- Cultural verticalism (competition and sacrifice for group) is associated with highest success in villagers' ability to accurately detect deception

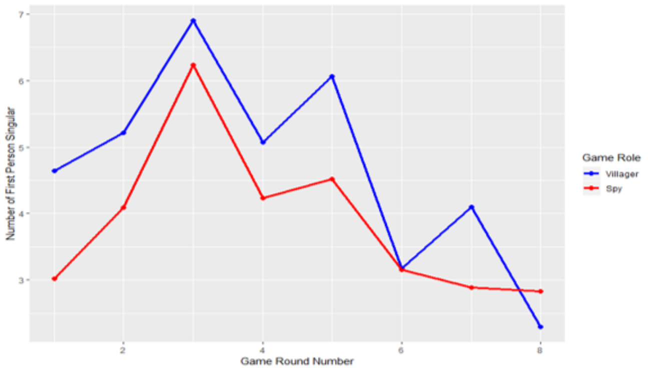
Culture seems to matter less than other factors => Need a deeper dive into this

Accomplishment VIII: Linguistic Analysis of Deceivers vs. Truth Tellers

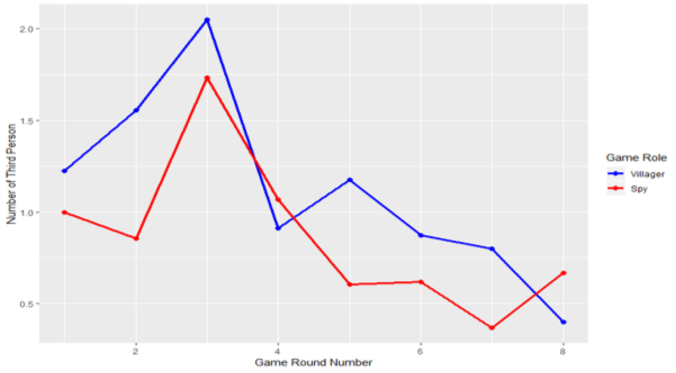
Number of Words



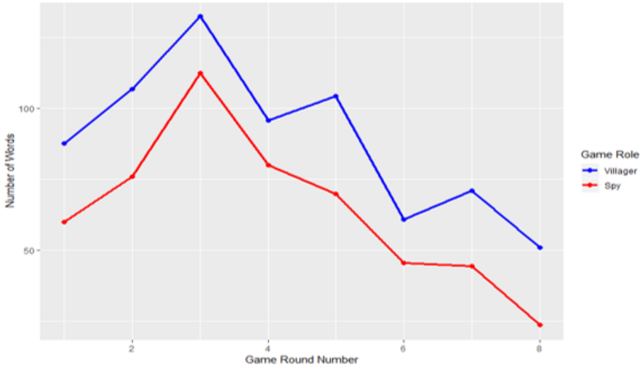
Number of First Person Singular Pronouns



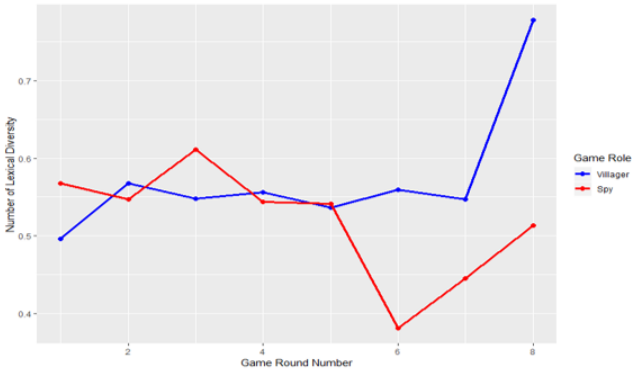
Number of Third Person Pronouns



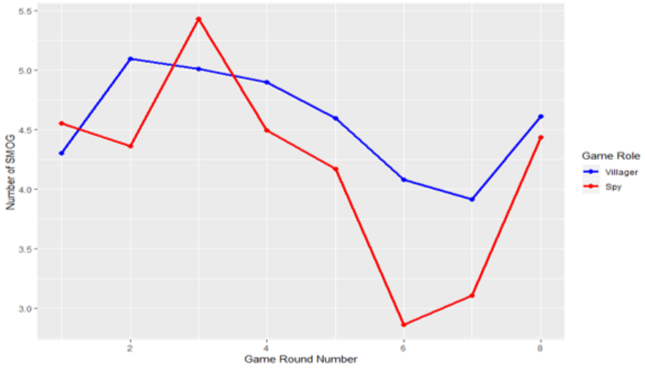
Number of Second Person Pronouns



Avg. Lexical Diversity

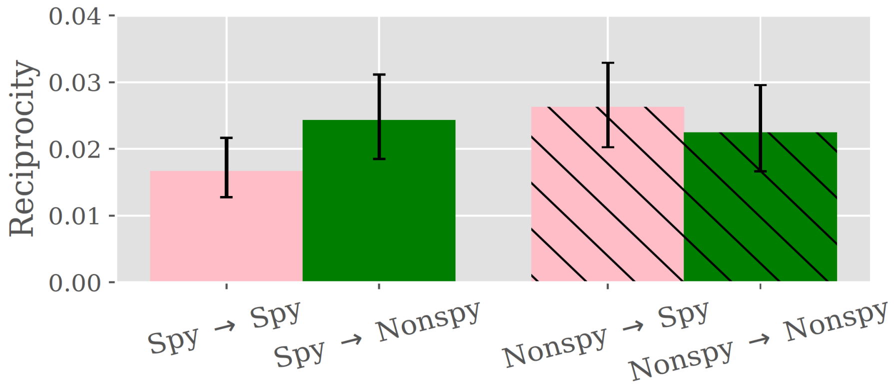


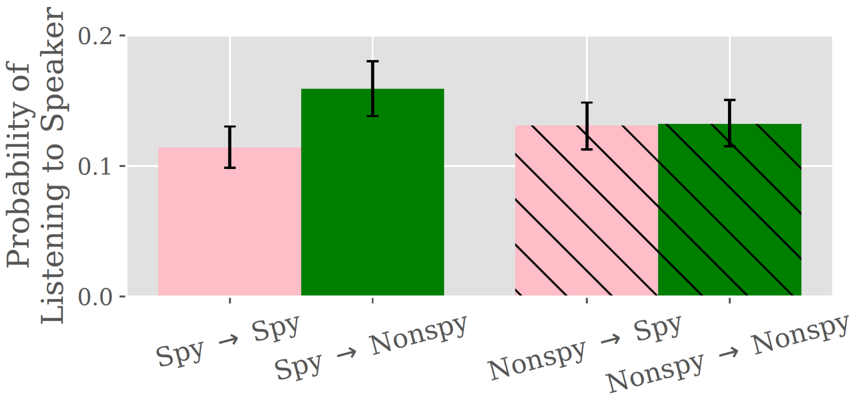
Avg. Comprehensibility (SMOG)



Accomplishment IX: Interactions between Deceivers and Non-Deceivers

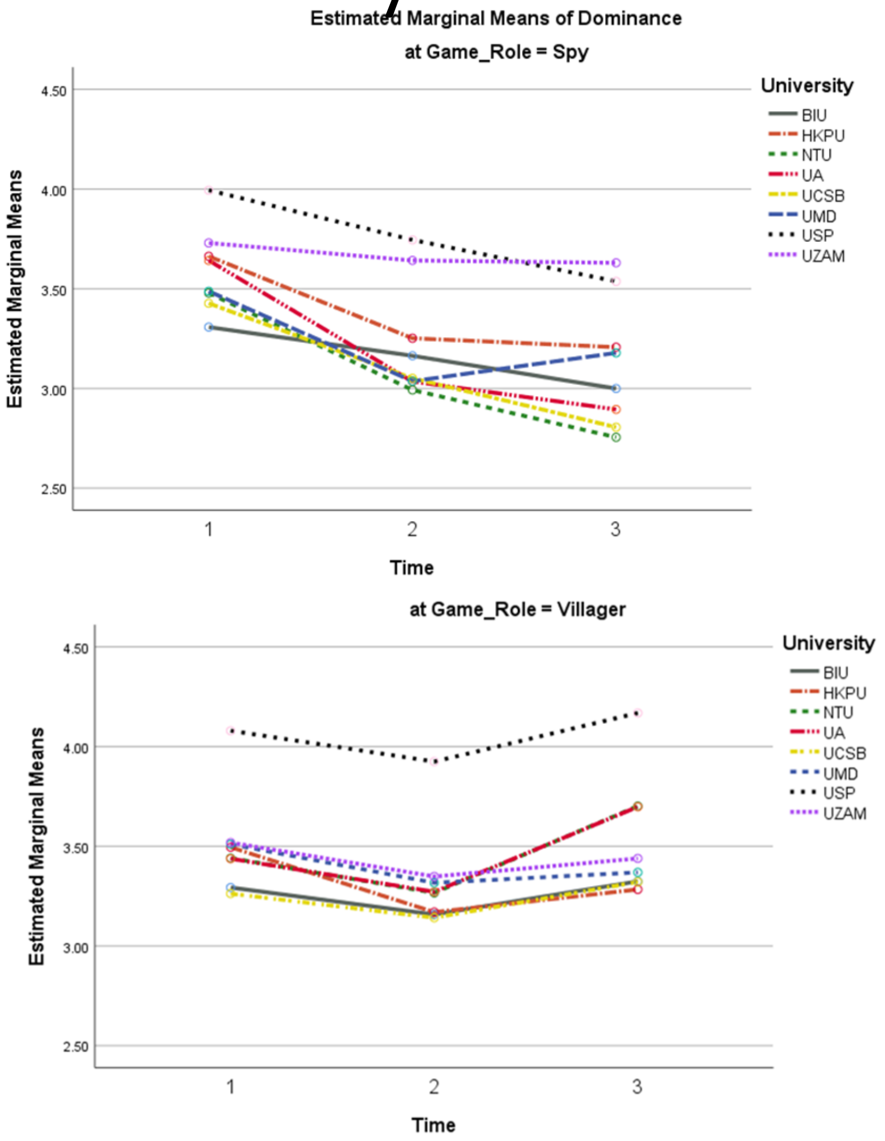
- Truth-tellers interact equally with everyone while deceivers interact more with truth-tellers.





Accomplishment X:Features Used by Humans to Detect Dominance

- Significant features
  - Mean pitch in final round
  - Variance of loudness
  - Mean voice quality
  - Variance in voice quality (harmonics to noise ratio)
  - Utterance length in words
- Deceivers diminish in dominance over time.
- But dominance and deception appear to be more culture sensitive – deceivers in Fiji and Zambia are more dominant. *Needs further investigation.*



Summary of Kinesic Indicators (Facial Expression) of Dominance

Characteristics of Dominance	Kinesic Cues of Dominance	Related Facial Action Units
Monopolizing / leadership	Lower brows Non-smiling mouths	FAU 4/14
Influential and self-confident	More talking	FAU 25 and other mouth related FAUs
Authoritative and avoiding uncertainty	Lower brows Non-smiling mouths	FAU 4/14
Animated and open, transparent with emotions	More happy/angry/disgusted expression Less fearful and sad expression Strong facial expressions	FAU 1/2/4/5/6/7/12/15/16/20/23/26

Summary of Voice Indicators of Dominance

Characteristics of Dominance	Cues of Dominance	Description of Cues
Monopolizing / leadership	Fundamental frequency Vocal energy	Lower/deeper pitch More pitch variability Larger amplitude
Influential and self-confident	Speech fluency	Few hesitations Short response latencies
Authoritative and avoiding uncertainty	Uncertainty	Few hesitations Short response latencies Rapid speaking rate
Animated and open, transparent with emotions	Vocal diversity	More pitch variability More change in jitter/shimmer/hoarseness

Summary of Linguistic Indicators of Dominance

Characteristics of Dominance	Cues of Dominance	Description of Cues
Monopolizing	Speech quantity	Talking often and talking for a longer duration
Influential and self-confident	Subjunctive phrases	A more definitive speech style and less use of subjunctive language
Authoritative and avoiding uncertainty	Uncertainty	Less hedging and fewer hesitations
Animated and open, transparent with emotions	Emotion	Greater exhibition of positive or negative emotions

Talk Outline

Overview of the SCAN Project

- How Humans Detect Deception and Dominance
- **How AI Algorithms Detect Deception and Dominance**
- Other Major Contributions

Deception Detection

- Deception in Real-world Courtroom Videos
- Deception in Multi-Player Face to Face Games

How AI Algorithms Detect Deception and Dominance

These results show how novel, state of the art AI algorithms to predict a host of factors linked to deception and dominance on the SCAN dataset in an end-to-end manner with no human involvement.

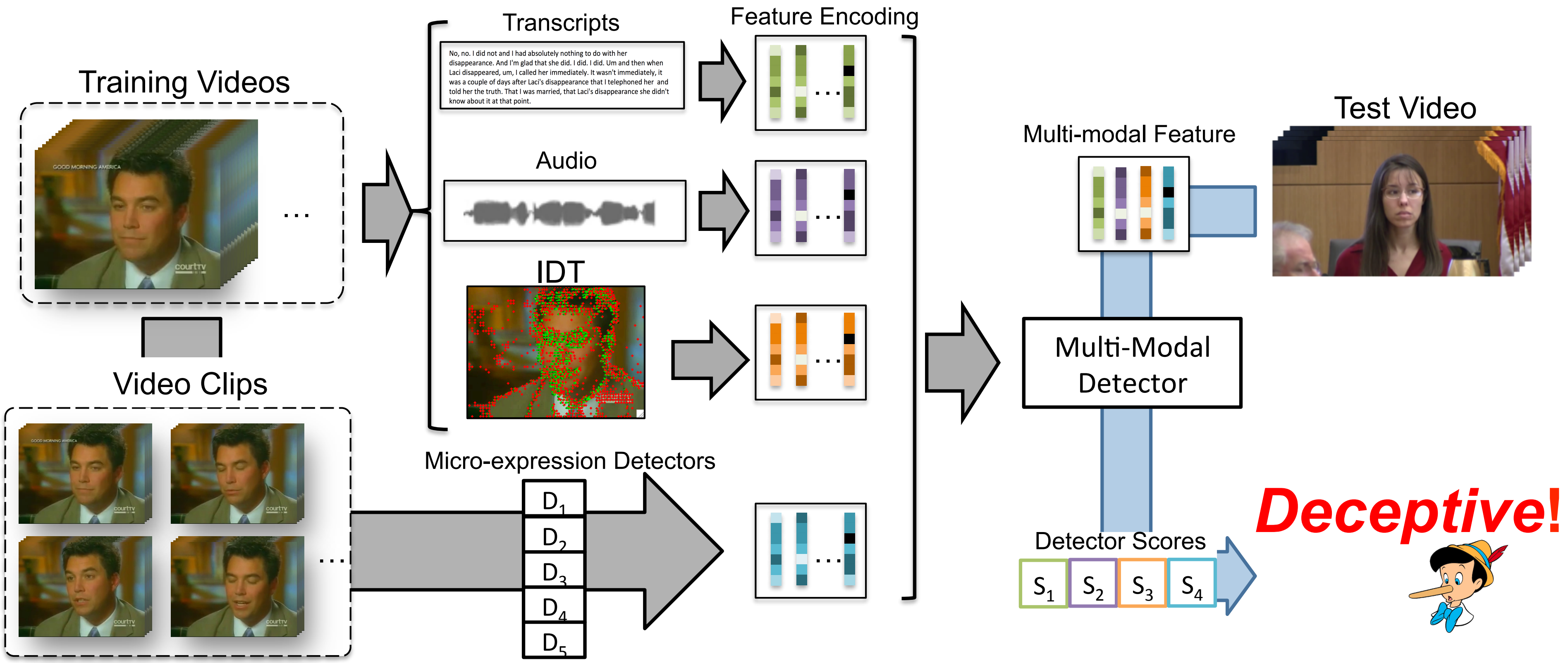
Contribution XI: Deception Prediction in Real-World Courtroom Videos

- Our automated multi-modal system considers visual, audio and verbal modalities.

- Show effectiveness of visual features incl. low-level motion features and high-level feature prediction scores of micro-expressions, and audio features, e.g. MFCC.
- Though the best past method uses human annotation, our *fully automated* system outperforms it by 5%. When combined with human annotations of micro-expressions, our AUC improves to 0.922 , 17% better.
- **We show that our automated DARE system is better than average**

DARE Demo
https://www.cs.dartmouth.edu/~mbolonkin/dare/demo/

Contribution XI: DARE Framework



DARE Demo
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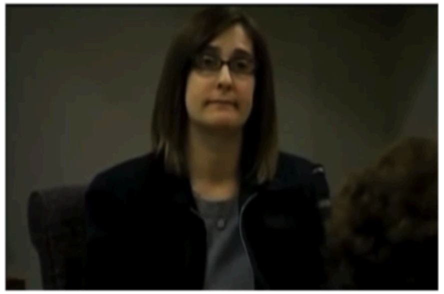
Contribution XI: Micro-Expressions

- We investigate 5 micro-expressions that are reported to be most effective among all micro-expressions in existing work.

1) Frown

2) Eyebrows Raised



3) Lip Corner Up

4) Lips Protruded

5) Head side turn

Contribution XI: DARE Experiments

- We evaluate four individual features, as well as their different combinations, using several classifiers to test the robustness

Features	L-SVM	K-SVM	NB	DT	RF	LR	Adaboost
IDT	0.7731	0.6374	0.5984	0.5895	0.5567	0.6425	0.6591
MicroExpression	0.7502	0.7540	0.7629	0.7269	0.8064	0.7398	0.7507
Transcript	0.6457	0.4667	0.6625	0.5251	0.6172	0.5643	0.6416
MFCC	0.7694	0.8171	0.6726	0.4369	0.7393	0.6683	0.6900
IDT+MicroExpression	0.8347	0.7540	0.7629	0.7687	0.8184	0.7419	0.7507
IDT+MicroExpression+Transcripts	0.8347	0.7540	0.7776	0.7777	0.8184	0.7419	0.7507
IDT+MicroExpression+MFCC	0.8596	0.8233	0.7629	0.7687	0.8477	0.7894	0.7899
All Modalities	**0.8773**	0.8233	0.7776	0.7777	0.8477	0.7894	0.7899

Table 1: Deception Detection results using different feature and classifier combinations. First 4 rows are results of independent features. Last 4 rows are late fusion results of multi-modal features.

Features	L-SVM	K-SVM	NB	DT	RF	LR	Adaboost
GTMicroExpression	0.7964	0.8102	0.8325	0.7731	0.8151	0.8275	0.8270
GTMicroExpression+IDT	0.8456	0.8137	0.8468	0.7834	0.8205	0.8988	0.8270
GTMicroExpression+IDT+Transcript	0.8594	0.8137	0.8923	0.8074	0.8205	0.8988	0.8270
GTMicroExpression+IDT+MFCC	0.8969	0.9002	0.8668	0.7834	0.8319	0.9221	0.8320
GTMicroExpression+All Modalities	0.9065	0.9002	0.8905	0.8074	0.8731	**0.9221**	0.8321

Table 2: Deception Detection results with Ground Truth micro-expression features and other feature modalities.

Accomplishment XII: Predicting Deception in Groups, 1st Attempt

- DARE (AAAI 2018) was able to predict deception in court-room settings with AUC of 0.877.
- But long term deception in a much more free environment is harder to detect
- A fully automated system (LiarOrNot) for predicting long- term deception in videos
- A new class of histogram-based features
- A novel "meta-feature" called LiarRank that builds on the basic features
- An ensemble based prediction model
- Achieves an **AUC of 0.705** in predicting the role of a player in the game
- AUC for prediction by humans is 0.583

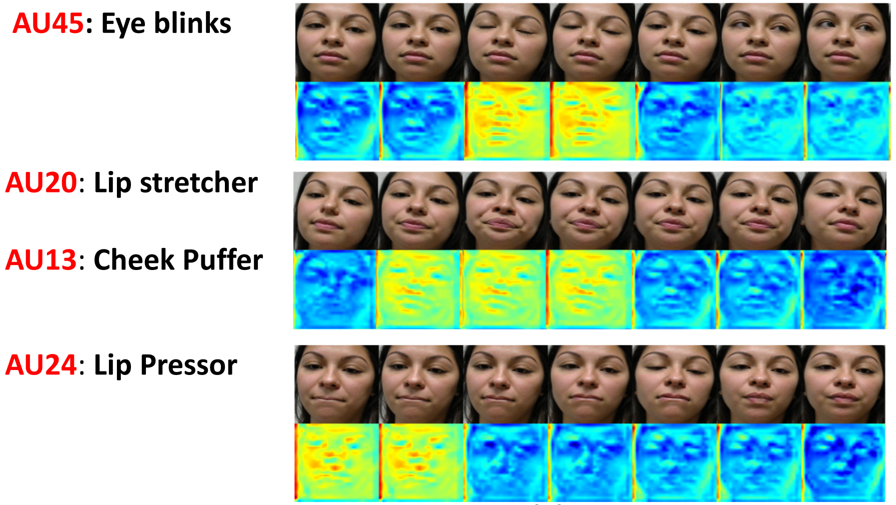
LiarOrNot Demo: https://home.cs.dartmouth.edu/~mbolonkin/scan/demo/

Accomplishment XIII: Predicting Deception in Groups, Attention-Based Facial Behavior Analytics

- Attention technique discovers the important **spatial and temporal** information on the face for deceiver/truth-teller detection
- Quantitative results liar vs. truth-teller: model trained with attention-based sampling (giving more weight to the video data with higher attention probabilities) **achieves ~4% higher accuracy** than conventional training
- Qualitative results on the fact that our attention NN is capable of discovering cues for deceivers, which are related to what is known from communication theory for deception.

Accomplishment XIV: Predicting Deception in Groups, Attention-Based Facial Behavior Analytics

- We show that players exhibiting some Facial Action Units (AUs:13,20,24,45 are more likely to be classified as deceivers.
- According to the communication theory:
  - AUs 20 and 45 are related to deception, which is consistent to our expectation that deceivers are more willing to lie, but not always.
  - AU 20 = stretched lips
  - AU 45 = eye blinks
- Our approach can detect small facial movements related to deception like **eye blinking** in the top row, and detect the **fake smile** (bottom) so as to correctly classify the type of player's role.



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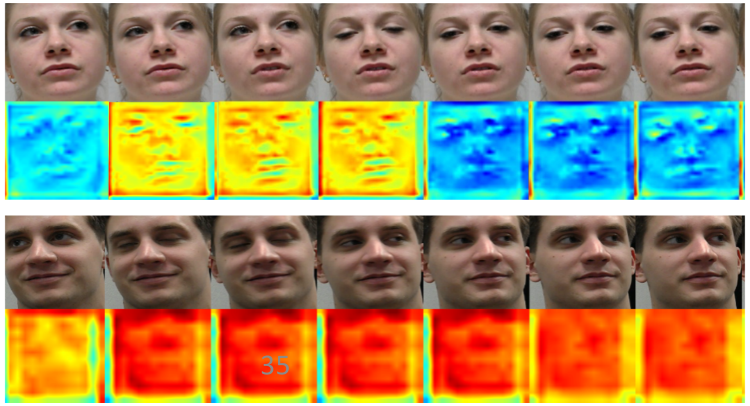
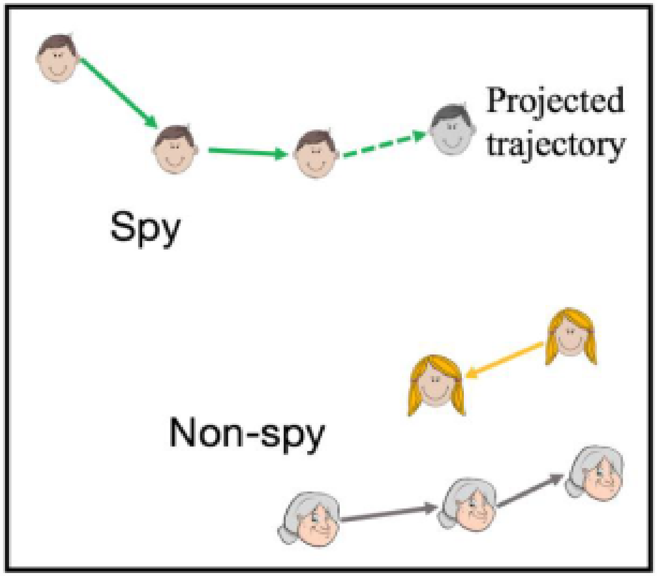
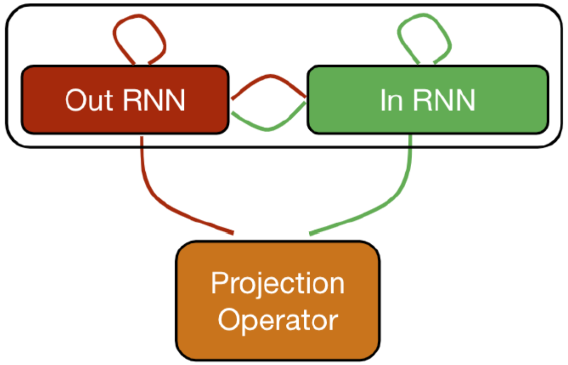

(b)

Accomplishment XV: Predicting Deception with Graph Convolution Models

- To predict deception, we used interaction networks to train
  - A Temporal Graph Convolutional Network model,
  - a Belief Propagation Model (on the negative network),
  - A Deep Temporal Model that uses Dynamic Embeddings
- Tested and evaluated all models on deception prediction in the context of the SCAN game.
- Current AUC is 0.73 using one minute of video





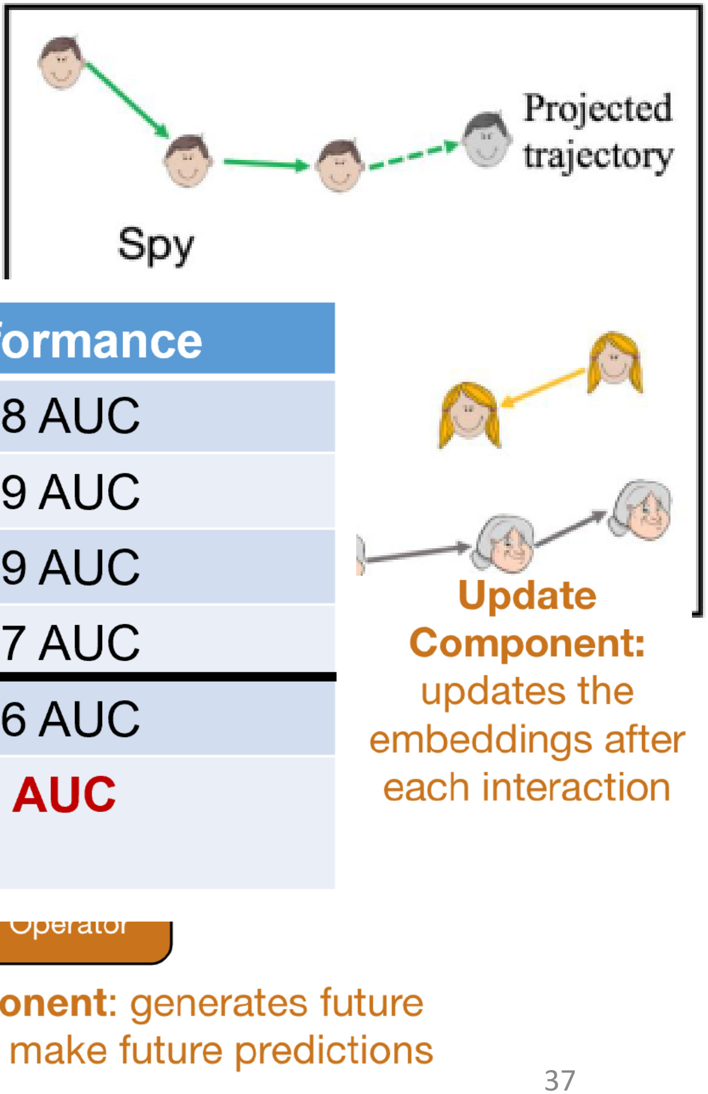
Update Component: updates the embeddings after each interaction

Project Component: generates future embeddings to make future predictions

Accomplishment XV: Predicting Deception with Graph Convolution Model

- To predict deception, we used interaction networks to train
  - A Te Netv
  - a Bel nega
  - A De Dyna
- •Testec on dece context
- •Currer minute

	Method	Performance
Baselines	Emotion	0.538 AUC
	Head and eye movement	0.549 AUC
	Facial action unit	0.569 AUC
	Late fusion	0.587 AUC
Our new models	Graph convolution network model	0.596 AUC
	Belief propagation on negative network	**0.73 AUC**



Accomplishment XVI: Predicting the Most Dominant Person in a Group

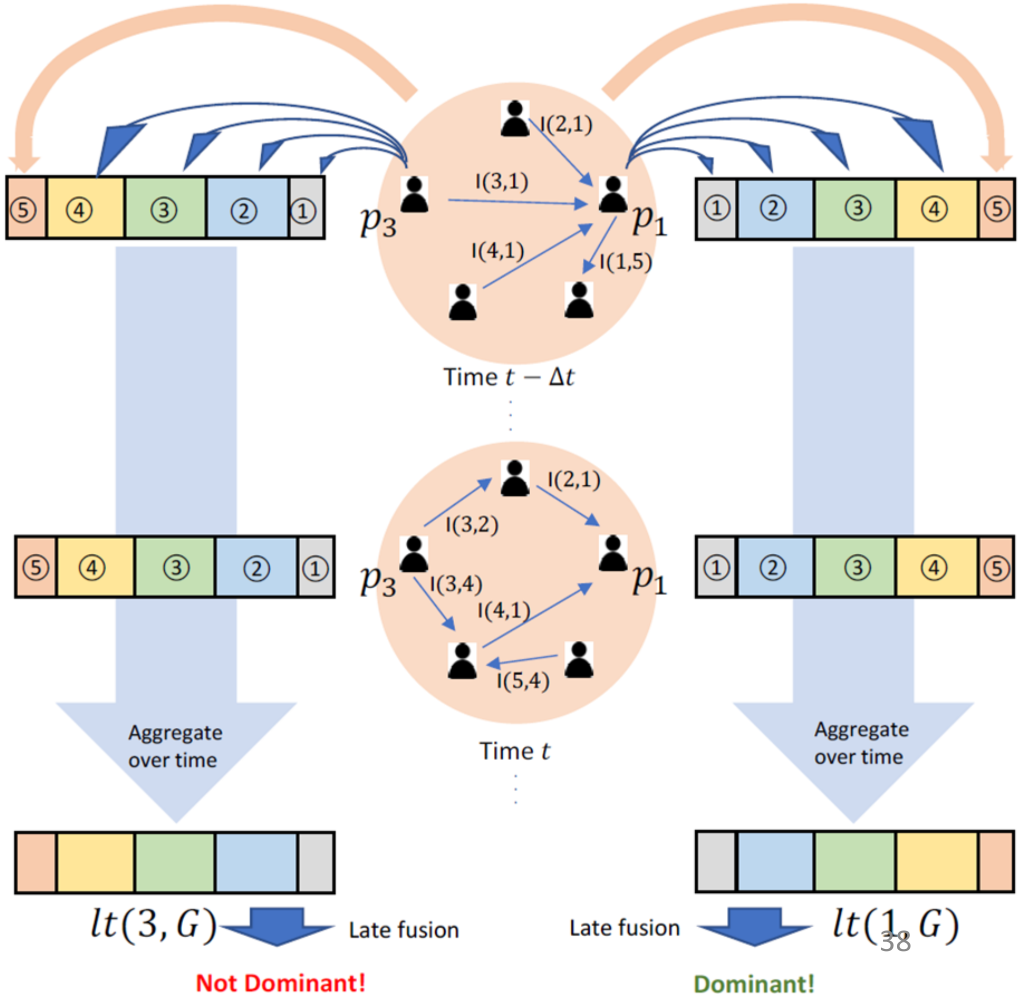
Features:
1. Speaking probability
2. Facial Action Units
3. Emotions
4. Audio features (MFCC)
5. Dominance Rank feature (new!)

Aggregation:
1. Fisher Vector
2. Histograms

Ensemble:

$$S = \sum_{i=1}^{5} \alpha_i S_i ,$$

where S_i are scores for individual feature types.



Accomplishment XVI: Predicting the Most Dominant Person in a Group: The DELF algorithms

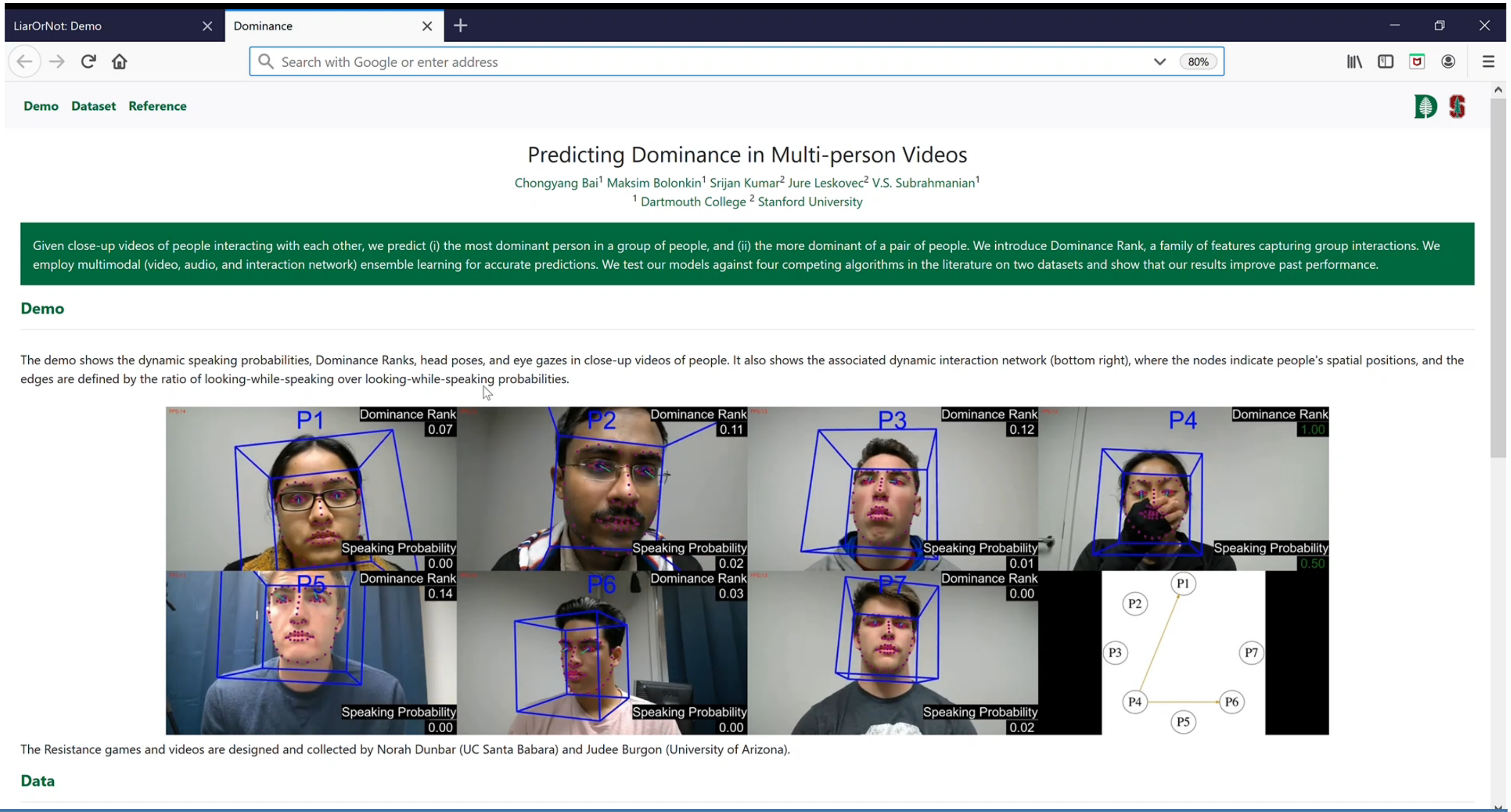
	MPD-All			MDP-Distinct			PDP-All			PDP-Distinct		
Features	**AUC**	**FPR**	**Acc.**	**AUC**	**FPR**	**Acc.**	**AUC**	**FPR**	**Acc.**	**AUC**	**FPR**	**Acc.**
DELF	**0.791**	0.027	0.769	**0.894**	0.021	0.889	**0.874**	0.281	0.792	**0.949**	0.189	0.876
DR (LS/LL, 1 sec) + FV	0.754	0.056	0.761	0.855	0.017	0.89	0.77	0.281	0.694	0.832	0.235	0.741
DR (LS/LL, 1 sec) + Hist.	0.754	0.252	0.711	0.836	0.209	0.868	0.788	0.314	0.724	0.861	0.392	0.768
DR (LS/LL, 5 sec) + FV	**0.773**	0.064	0.761	**0.861**	0.167	0.868	0.771	0.328	0.695	0.835	0.28	0.74
DR (LS/LL, 5 sec) + Hist.	0.770	0.252	0.720	0.844	0.179	0.879	0.793	0.441	0.709	0.861	0.347	0.788
Speaking + FV	0.741	0.279	0.689	0.838	0.030	0.875	**0.853**	0.261	0.762	**0.92**	0.179	0.825
Speaking + Hist.	0.756	0.066	0.770	0.821	0.150	0.879	0.847	0.258	0.778	0.91	0.164	0.860
Baseline (speak.)	0.738	0.103	0.730	0.769	0.200	0.879	0.800	0.274	0.738	0.893	0.198	0.845
Baseline (comb.)	0.767	0.252	0.716	0.764	0.214	0.879	0.828	0.290	0.759	0.906	0.168	0.863

Also predicting the more dominant person in a group of two people

Accomplishment XVI: Predicting the Most Dominant Person in a Group: The GDP algorithms

Feature	Classif.	AUC	FPR	Acc.
		MDP-All		
Speaking + FV	MLP	0.809	0.219	0.745
Speaking + FV	RF	**0.817**	0.133	0.770
DR (LS/LL, 5sec) + FV	MLP	0.783	0.222	0.733
DR (LS/LL, 5sec) + Hist.	MLP	0.772	0.157	0.746
		MDP-Distinct		
Speaking + FV	MLP	**0.936**	0.048	0.917
Speaking + FV	RF	0.902	0.088	0.849
DR (LS/LL, 5sec) + FV	RF	0.878	0.071	0.878
DR (LS/LL, 5sec) + FV	MLP	0.850	0.065	0.889

Accomplishment XVI: DELF/GDP Dominance Prediction System



Dominance Prediction Demo: http://home.cs.dartmouth.edu/~cy/dom/

Accomplishment XVI: Predicting Dominance on Related Datasets, Cooperative Environment

Key question: Does Dominance Rank work for datasets that already exist with a similar goal of predicting dominance?

- Swiss group developed the ELEA dataset in which participants were assigned a winter survival task and were asked to elect a leader.

- Difference with SCAN dataset: task is cooperative, everyone wants to survive.

- **Dominance Rank based Features yielded the best results.**

[Okada *et al.*, 2018]	58.82	64.71
[Aran and Gatica-Perez, 2013]	65.69	59.80
[Okada *et al.*, 2015]	67.65	68.63
DR (LS/LL) + FV (ours)	**76.47**	67.65
DR (LS/LL) + Hist. (ours)	74.51	**71.57**
Human scores	68.63	—

Predicting Pairwise Dominance

Dominance Rank based Features Outperform Humans

Accomplishment XVII: Key Factors Linked to Dominance Prediction

- Used ablation testing to identify which features' exclusion led to the greatest drop in AUC.
- Dominance Rank Features dominate for Most Dominant Player Prediction
- Audio Features dominate for Pairwise Dominance Prediction
- FAU features AU15, AU20, AU25 all significant
  - AU 15 = lip corner depressor
  - AU20 = lip stretcher
  - AU 25 = lips parted

Excluded Feature	**AUC**
MDP-All	
All features present	0.790
FAU (AU15, AU20, AU25)	0.790
MFCC	0.775
DR (LS/LL, 5sec) + FV	**0.757**
Emotions (Angry, Surprised, Calm)	0.772
Speaking+Hist.	0.775
MDP-Distinct	
All features present	0.894
FAU (AU05, AU14, AU20)	0.888
MFCC	0.890
DR (LS/LL, 5sec) + FV	**0.849**
Emotions (Angry, Confused)	0.891
Speaking+FV	0.884
PDP-All	
All features present	0.874
FAU (AU15, AU20, AU25)	0.824
MFCC	0.867
DR (LS/LL, 5sec) + Hist.	0.866
Emotions (Smile, Angry, Surprised)	0.866
Speaking+ FV	**0.816**
PDP-Distinct	
All features present	0.949
FAU (AU14, AU15, AU25)	0.948
MFCC	**0.921**
DR (LS/LL, 1sec) + Hist.	0.934
Emotions (Happy, Angry, Calm)	0.945
Speaking + FV	0.949

Accomplishment XII: Key Factors Linked to Dominance Prediction

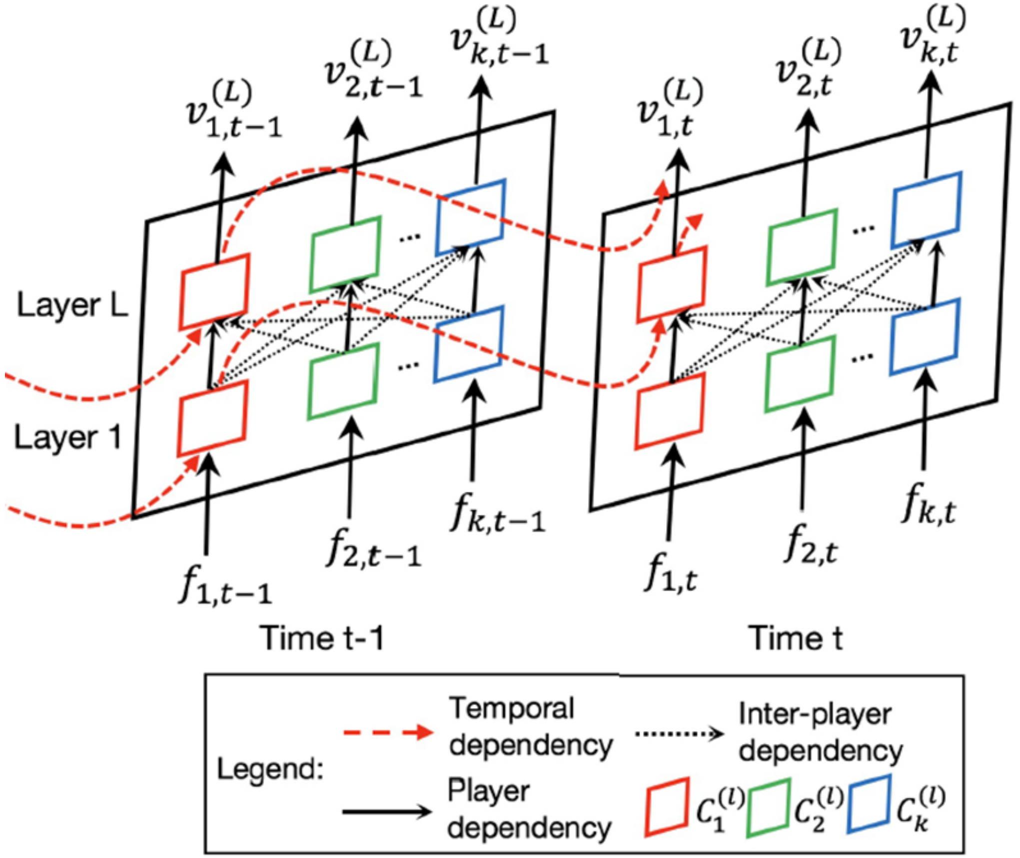
FAU features AU15, AU20, AU25 all significant

- Lip corner depressor
- Lip stretcher
- Lips part

Sample FAU images from: https://www.cs.cmu.edu/~face/facs.htm

Accomplishment XVII: Predicting Who is Looking at Who

- Raw features at time *t-1* or *t* are at the bottom
- Novel collective classification algorithm used at each time point to capture player-player dependencies.
- Novel temporal dependency metric used to capture dependency on solution at time *t-1* to predict solution at time *t*

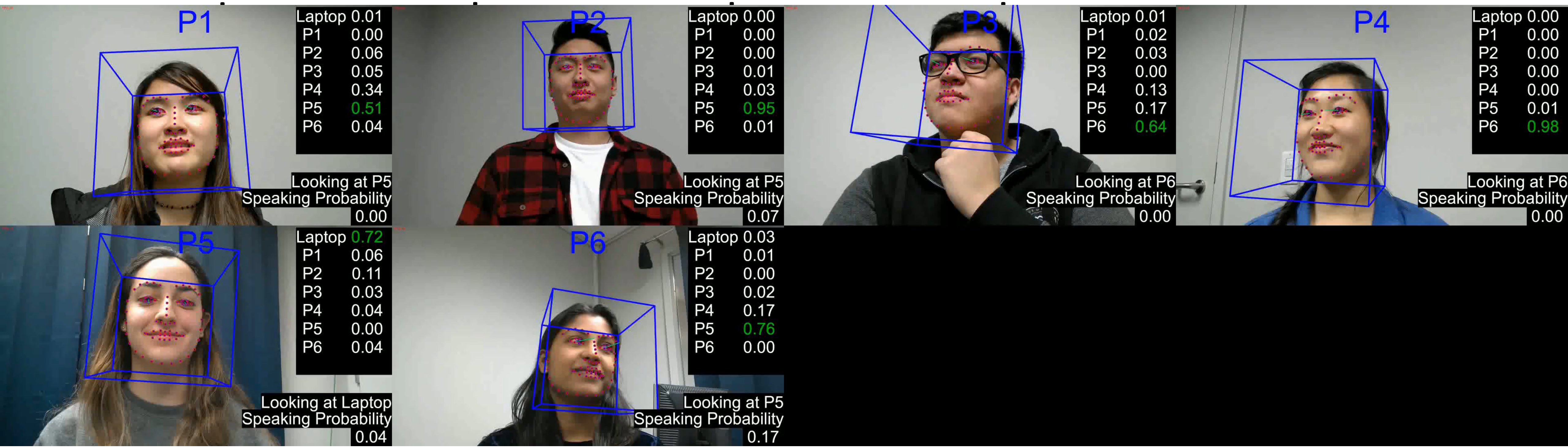


Accomplishment XIX: Building Out Who is Looking at Who Network

- Developed ICAF (Iterative Collective Attention Focus) algorithm and system
- Predictive accuracy is over 60% for the best algorithm compared to a baseline of 11-16% for random guessing.
- ICAF automatically generates networks! For each game
  - Weighted network measures the probability score of looking at another player
  - Binary network has edges with the highest probability of looking at another player

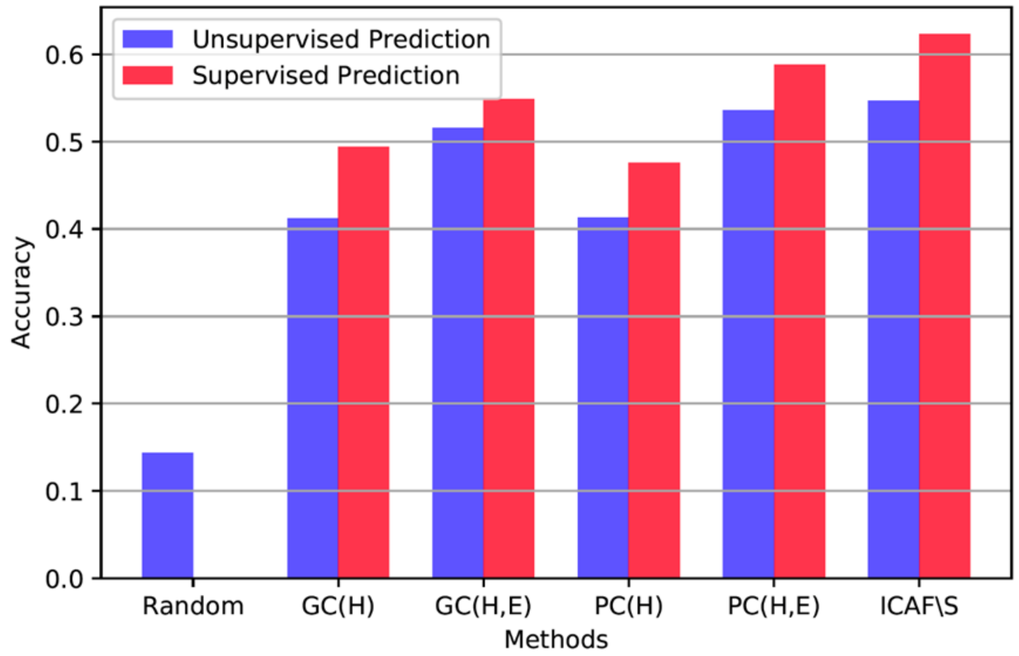
Dataset statistics	
Number of networks	62
Number of nodes	451
Number of edges	3,126,993
Average number of edges per network	50,435
Total temporal length	142,005 seconds
Average temporal length per network	2,290 seconds

Accomplishment XIX: ICAF System



Accomplishment XIX: Predicting Who is Looking at Who

- Developed ICAF (Iterative Collective Attention Focus) algorithm and system
- Predictive accuracy is over 60% for the best algorithm compared to a baseline of 11-16% for random guessing.



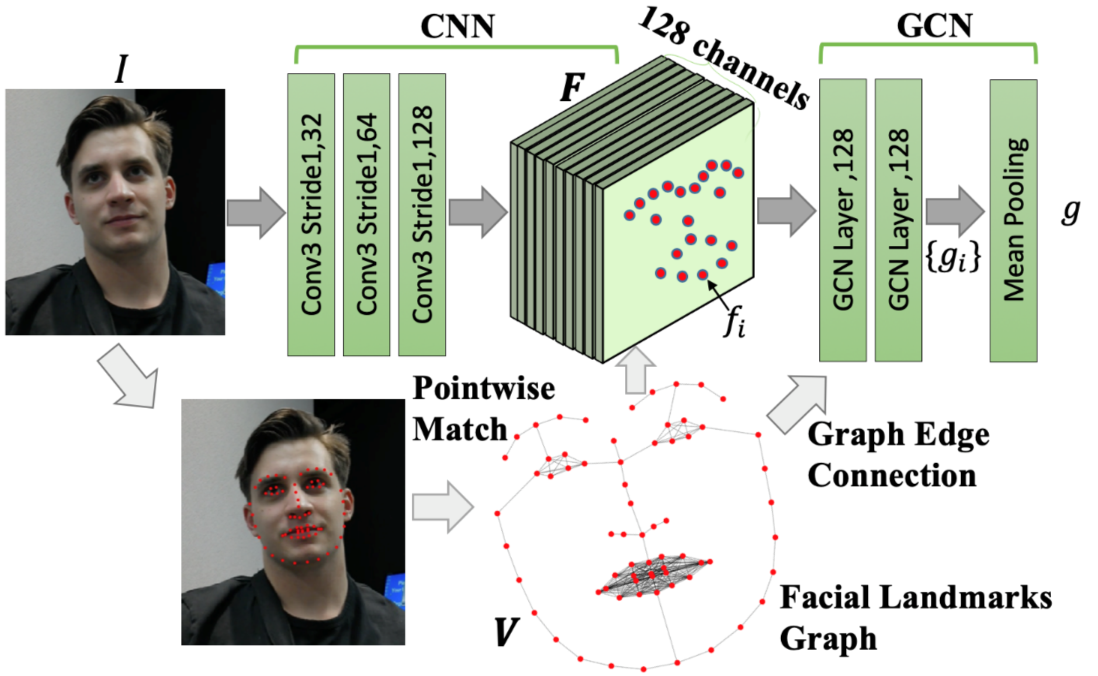
Accomplishment XX:
Relative Nervousness Prediction

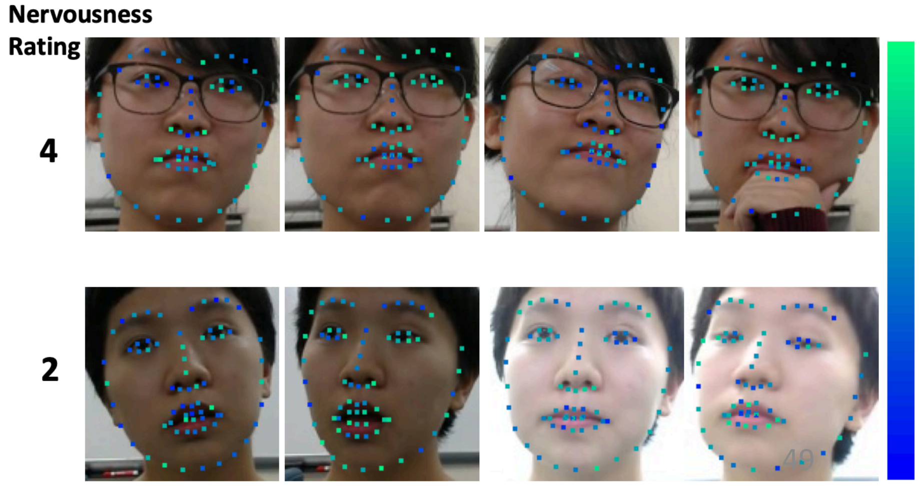
- Tasks considered:
  - Pairwise Nervousness Prediction (PNP)
  - PNP-Distinct
  - Nervousness Change Prediction (NCP)
- Combine positive/negative emotions toward speaker and relative dominance of speaker with listeners to generate nervousness scores.
- Audio and Visual Nervousness Scores

$$NS_t(v) = \alpha NS_{pos,t}(v) + (1-\alpha) NS_{neg\ t}(v)$$

- Facial Emotion-oriented Graph Convolutional Network (FE-GCN)

	The Resistance PNP	The Resistance PNP-Distinct	The Resistance NCP	ELEA PNP
ANS	0.635	0.723	**0.724**	0.623
VNS	0.668	**0.765**	0.667	0.760
FE-GCN	**0.681**	0.744	0.634	**0.802**





Accomplishment XX: Predicting Impressions of Subjects

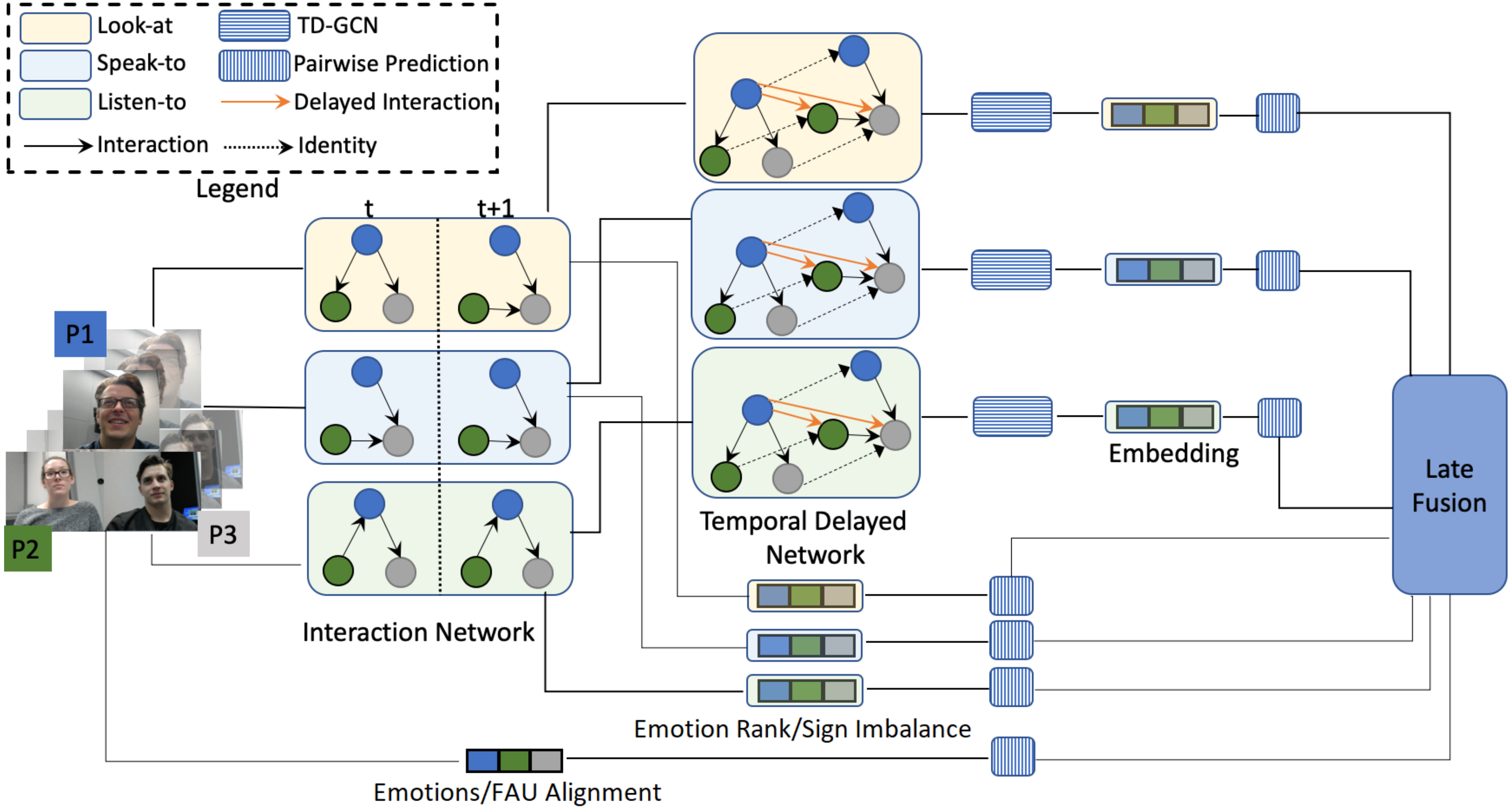
Participants score each other on several variables on a 7-point scale:

Question #	Variables in the survey.
Q1	Very cold : Very warm
Q2	Very negative : Very positive
Q3	Very unpleasant : Very pleasant
Q4	Very unfriendly : Very friendly
Q5	Very unlikable : Very likable
Q6	Very unsociable : Very sociable

Our task: **for a pair or participants predict whether participant A will give participant B a low score on given variable.**

Accomplishment XXI: Predicting Impressions of Subjects

1. Emotion Rank
2. Sign Imbalance
3. Alignment Features
4. Temporal Delayed Network



Accomplishment XXI: Predicting Impressions of Subjects

$$\underbrace{ES(e, p_i, p_j, G_I, \tau)}_{\text{Emotion score}} = \frac{1}{|\tau|} \sum_t \underbrace{v_t(p_i, e)}_{\text{Emotion intensity}} \cdot \underbrace{w(p_{i,t}, p_{i,t})}_{\text{Interaction probability}}$$

Emotion Rank

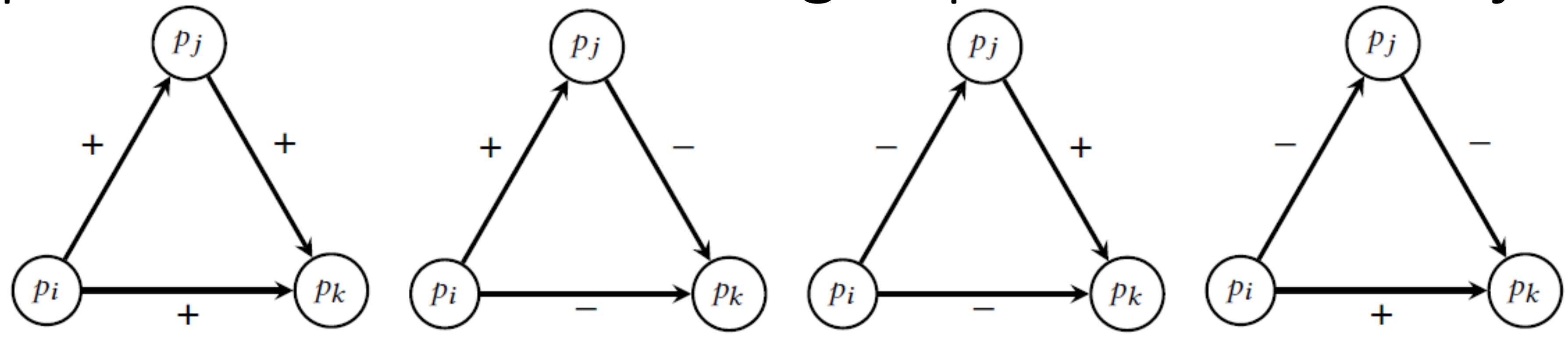
How p_i feels towards p_j

How other players feel towards p_j

How p_i feels towards other players

$$ER_f(p_i, p_j, G_I, \tau) = \alpha_0 + \alpha_1 f(EV(p_i, p_j, G_I, \tau)) + \alpha_2 \sum_{k \neq i,j} \frac{ER_f(p_k, p_j, G_I, \tau) \cdot f(EV(p_k, p_j, G_I, \tau))}{out(p_k)} + \alpha_3 \sum_{k \neq i,j} \left\{ \frac{ER_f(p_i, p_k, G_I, \tau) \cdot f(EV(p_i, p_k, G_I, \tau))}{out(p_i)} \cdot \frac{ER_f(p_k, p_j, G_I, \tau) \cdot f(EV(p_k, p_j, G_I, \tau))}{out(p_k)} \right\}$$

Accomplishment XXI: Predicting Impressions of Subjects

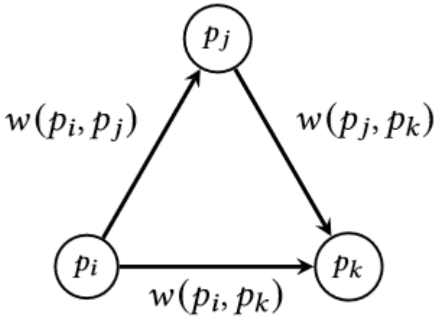


Friend of my friend is my friend

Enemy of my friend is my enemy

Friend of my enemy is my enemy

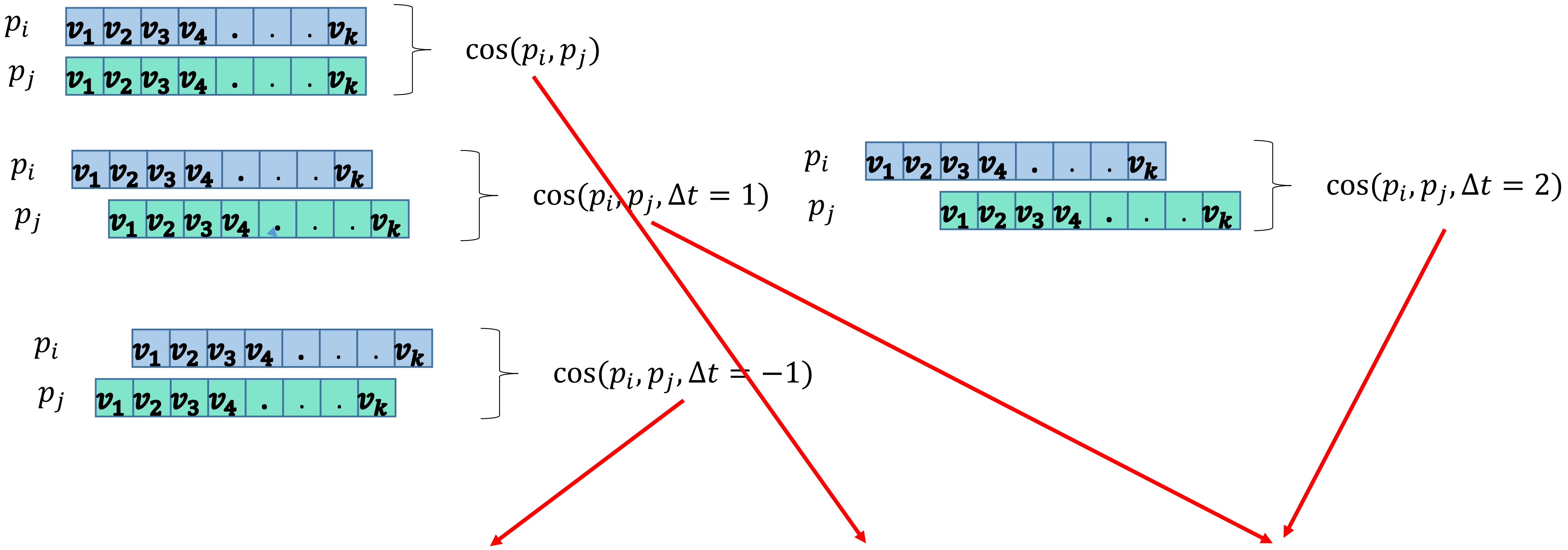
Enemy of my enemy is my friend



$$SI(p_i, G_I, \tau) = \frac{1}{N} \sum_{p_j, p_k \in V, i \neq j \neq k} |w(p_i, p_j) \cdot w(p_j, p_k) - w(p_i, p_k)|,$$

Measure of sign imbalance

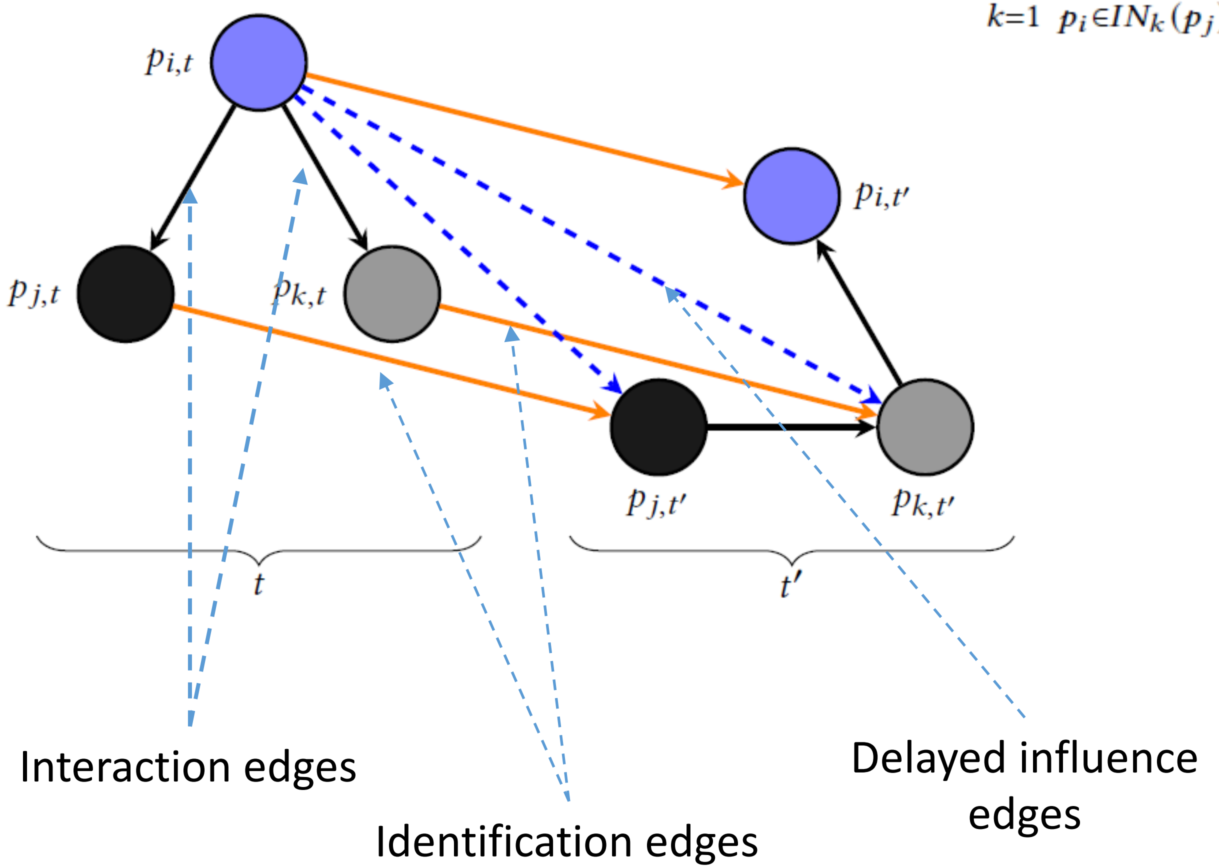
Accomplishment XXI: Predicting Impressions of Subjects



$$AL(p_i, p_j, e) = [\cos(\mathbf{P}_{-\Delta t}(p_i, e), \mathbf{P}(p_j, e)), \ldots, \cos(\mathbf{P}(p_i, e), \mathbf{P}(p_j, e)), \ldots, \cos(\mathbf{P}_{+\Delta t}(p_j, e), \mathbf{P}(p_i, e))]$$

Measures alignment between emotion vectors of p_i, p_j over time

Accomplishment XXI: Predicting Impressions of Subjects



$$\tilde{x}_{p_j} = \sum_{k=1}^{3}\Big(\sum_{p_i \in IN_k(p_j)} c(p_i, p_j) w_k(p_i, p_j) f_k(x_{p_j}) + \sum_{p_i \in OUT_k(p_j)} c(p_j, p_i) w_k(p_i, p_j) f_k(p_j)\Big),$$

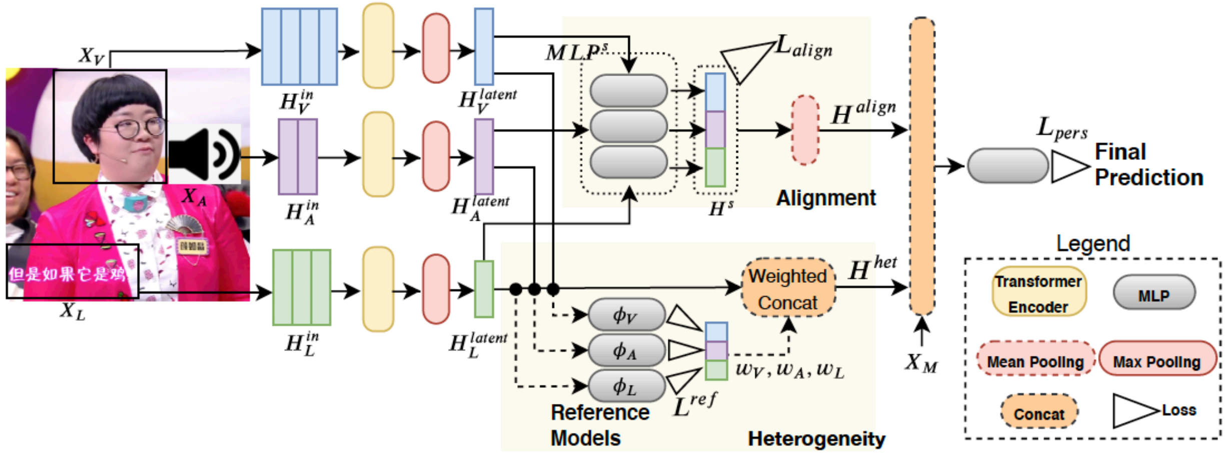
$$w_k(p_i, p_j) = attn(f_k(x_{p_i}), f_k(x_{p_j})),$$

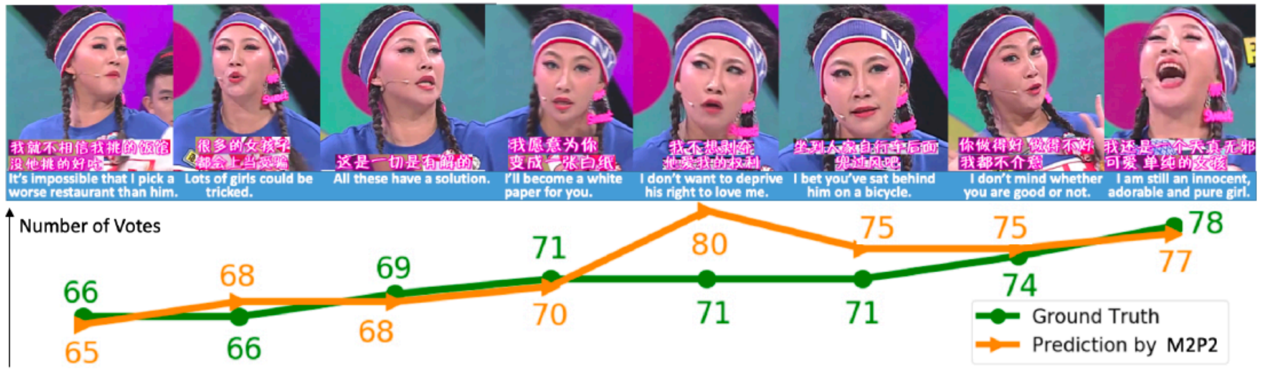
$$attn(x_1, x_2) = \frac{exp(LeakyReLU(a^T[x_1 || x_2]))}{\sum_{x_2} exp(LeakyReLU(a^T[x_1 || x_2]))},$$

Builds out a novel construct called a Temporally Delayed Graph Convolutional Network (TD-GCN).

Accomplishment XXII: Multimodal Persuasion Prediction

- **M2P2 architecture.**
  - Audio, face and language sequences are extracted from a video clip and fed to extract primary input embeddings X.
  - Each of embeddings is fed to a Transformer encoder and max pooling to the latent embeddings H^{latent}.
  - The latent embeddings are fed to the **alignment** and **heterogeneity** modules to generate the embeddings H^{align} and H^{het}.
  - Concatenate H^{align} and H^{het} and the debate meta-data X_M, and feed to an MLP for persuasiveness prediction.
  - H^{latent} interact with two procedures alternately:
    - Optimize the alignment loss L_{align} and persuasiveness loss L_{pers}
    - Learn weights through 3 reference models ϕ.
- **Real-time prediction of debate persuasiveness** using M2P2. The debate is from a Chinese debate TV show, Qipashuo. M2P2 closely predicts the ground truth number of votes.
- **Experiments on two tasks**
  - Debate outcome prediction (DOP)
  - Intensity of persuasion prediction (IPP)





Methods	Acc. on DOP	MSE on IPP
Brilman et al.[1]	0.614	0.016
Nojavanasghari et al.[2]	0.615	0.016
Santos et al. [3]	0.598	0.02
M2P2	0.635	0.012

Accomplishment XXII: Multimodal Persuasion Prediction

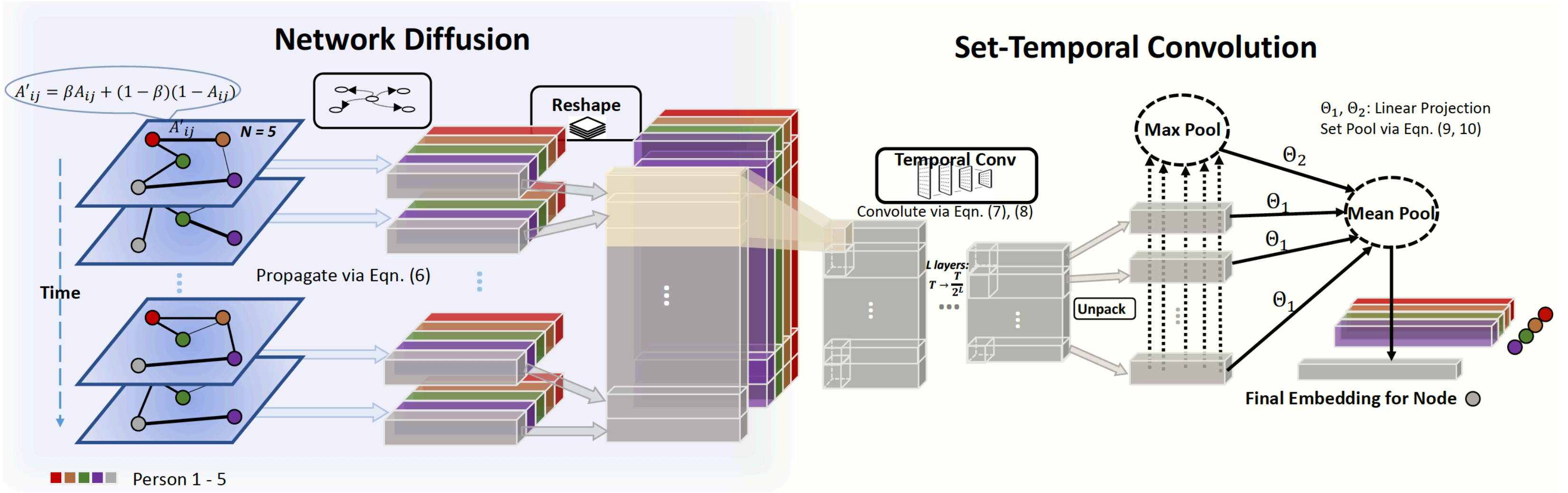
- Debate Outcome Prediction (DOP) - Binary classification
- Intensity Persuasion Prediction (IPP) – Regression in scale [0,1]

Method	DOP(Accuracy)	IPP(MSE)
Brilman et al. 2015	0.614	0.016
Nojavanasghari et al. 2016	0.615	0.016
Santos et al. 2018	0.598	0.020
M2P2	**0.635 ($p < 0.05$)**	**0.012 ($p < 0.01$)**

[Brilman et al., 2015] A multimodal predictive model of successful debaters or how i learned to sway votes.
[Nojavanasghari et al., 2016] Deep multimodal fusion for persuasiveness prediction.
[Santos et al., 2018] Multimodal prediction of the audience's impression in political debates.

Accomplishment XXIII: Representation Learning Framework for Dynamic Social Interaction Networks

- Temporal Network-Diffusion Convolution Networks (TN-DCN)
  - Network Diffusion
    - Weighted combination of both network (interaction) and complement network (avoid interaction)
    - Multi-hop diffusion for node features
  - Set-Temporal Convolution
    - Aggregate the node features over time via 1D convolutions
    - Max-pooling and mean-pooling over time to get the final embedding for each node.
    - The node embeddings can be used to learn various tasks



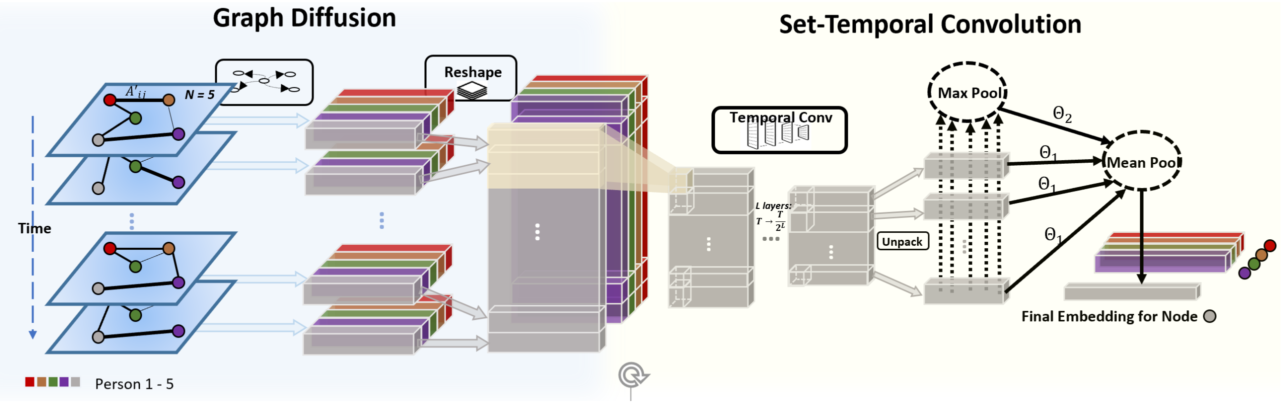
Comparison of performance on on RESISTANCE (first three) and CIAW(last one)

	Dominance Identification		Deception Detection		Nervousness Detection		Community Detection	
	Method	Performance	Method	Performance*	Method	Performance	Method	Perform.
Baselines	MKL [6]	0.879	FAU [12]	0.608	LR.	0.493	WD-GCN [27]	0.813
	DELF [4]	0.889	TGCN-L†[26]	0.550	RF.	0.678	CD-GCN [27]	0.819
	GDP-MLP [4]	0.917	LiarOrNot [3]	0.665	GCN-LSTM [39]	0.702	GCN-LSTM [39]	0.601
	GDP-RF [4]	0.878	ADD [46]	0.632	Facial Cues [16]	0.733	EvolveGCN[32]	0.893
Ours	-	**0.923** (±0.009)	-	**0.689** (±0.021)	-	**0.769** (±0.023)	-	**0.929** (±0.011)

Accomplishment XXIV: Single End-to-End Prediction of Dominance and Deception

TEDIC Framework

- A neural network model that is **uniformly good** across different prediction tasks:
  - *Detecting dominance, nervousness, deception, etc.*
- With other desirable features:
  - **Self-explaining power**: automatically learn certain social insights
  - **Fairness:** judge people from different places equally
  - **General Applicability**: can be applied to dynamic social networks of various natures *(e.g. proximity-based one from body sensors)*



Combines

1. Graph diffusion in order to refine node features in each network snapshot
2. Set-temporal convolution in order to aggregate the refined node features over time

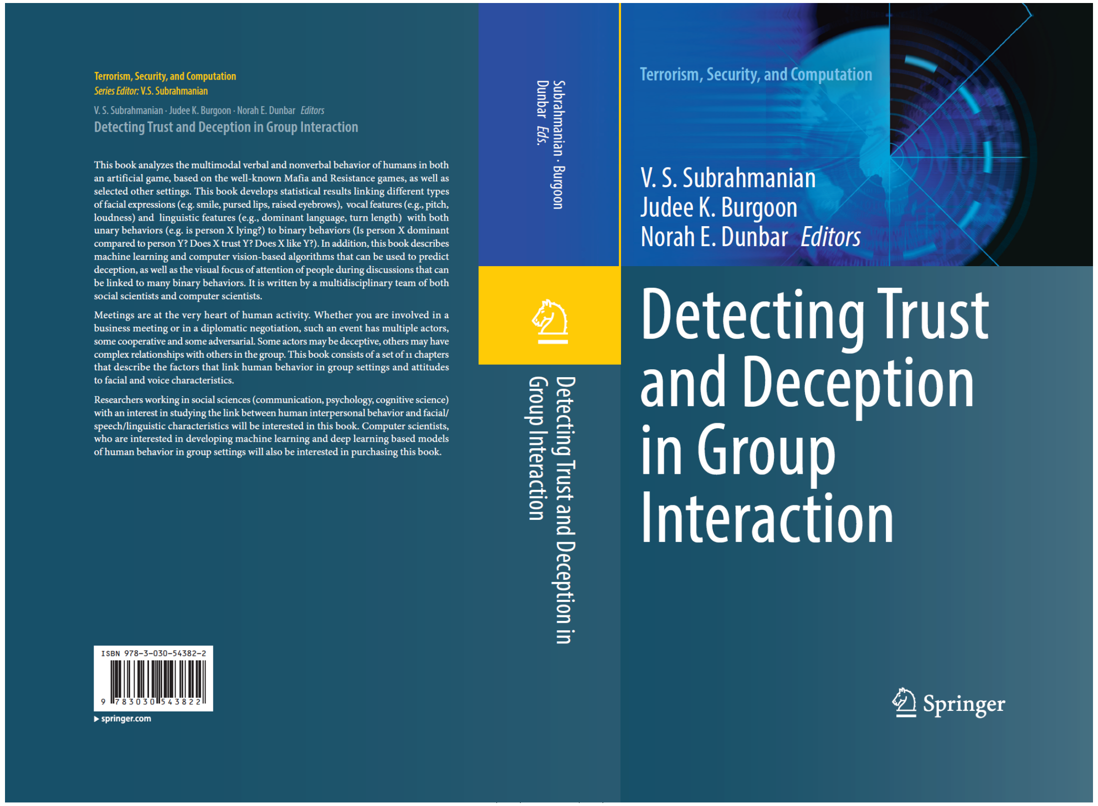
Accomplishment XXIV: Single End-to-End Prediction of Dominance and Deception

Method		Dominance (R)	Dominance (E)	Deception	Nervousness
Knowledge-based	Top-1 Method	0.918±0.013	0.769±0.019	0.668±0.021	0.733±0.022
	Top-2 Method	0.887±0.015	0.677±N/A	0.638±0.016	0.729±0.015
Dyn. GNNs	CD-GCN[30]	0.687±0.042	0.794±0.022	0.673±0.018	0.534±0.084
	GCRN[39]	0.587±0.096	0.795±0.032	0.643±0.045	0.336±0.104
	EvolveGCN[34]	0.602±0.061	0.739±0.077	0.623±0.042	0.397±0.099
Proposed	TEDIC	**0.923**±0.009	**0.815**±0.019	**0.689**±0.012	**0.769**±0.023

Table 2: Accuracy of detecting dominance, deception and nervousness. Mean Accuracy ± 95% confidence interval is reported.

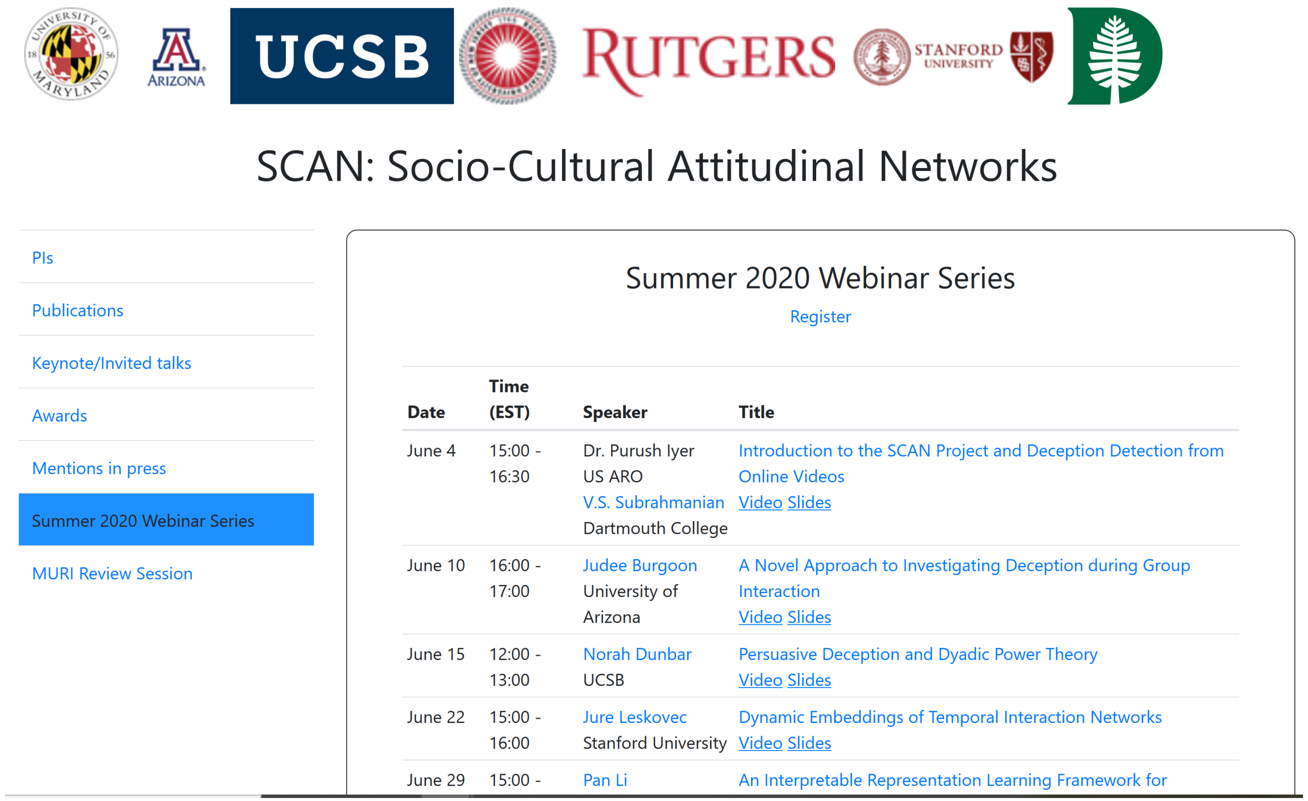
Programmatics

Summary of the Project’s Results to Date



https://tinyurl.com/y5vpaas3

Tentative Release date: Jan 3 2021



SCAN: Socio-Cultural Attitudinal Networks

- PIs
- Publications
- Keynote/Invited talks
- Awards
- Mentions in press
- Summer 2020 Webinar Series
- MURI Review Session

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 -	Pan Li	An Interpretable Representation Learning Framework for

https://home.cs.dartmouth.edu/~mbolonkin/scan/webinars/webinar_info.html

Publications

- 1 research monograph (scheduled Jan 3 2021) summarizing the main findings of the MURI research to date.
- Over 70 jointly authored papers in top venues such as
  - CVPR
  - ICML
  - WWW
  - IJCAI
  - AAAI
  - KDD

Awards & Honors

1. Best Paper Award,
2. Best Paper Award,
3. Google ASPIRE Award, Dec 2019
4. Runner up, Most Innovative Demo, 2019 International Joint Conference on Artificial Intelligence, Macao, Aug 2019.
5. "20 Year Test of Time Award" from the 2017 International Conference on Logic Programming, Melbourne, Australia, Aug 2017.
6. Named an IEEE/Tencent Rhino Bird International Academic Expert, May 2017.
7. Runner Up for the Best Paper Award, 2017 World Wide Web Conference, Perth, Australia, April 2017.

Major Invited Talks/Keynotes Delivered Since the Start of the MURI

- Over 100 invited/keynote talks during the past 4 years.
- Invited Talks to:
  - Government: US Army Science Board
  - Industry: ADP, Amazon, Boeing, Google
  - CEO Briefings: Capital One Bank, Samsung USA
  - Other: United Nations Security Council, UNISSIG Conference, World Science Forum
  - Academia: Numerous talks at top academic conferences

Tech Transition

- Ran driving videos through Dartmouth software for ARL (POC: Jean Vettel) for a project on memory retention while distracted.
- Dartmouth is negotiating with a TV documentary production company for use of our deception detection software in programs that they produce.
- Our deception work discovered 127 instances of review fraud in online platforms (out of a total of 150 discovered).

Today's Agenda

Time (EST)	Speaker	Title
12:00 - 13:15	V.S. Subrahmanian Dartmouth College	Main Contributions of the SCAN MURI
13:15 - 13:25		Break
13:25 – 13:50	Norah Dunbar, University of California Santa Barbara	Deception Detection: Social Science Research
13:50 - 14:15	Dimitris Metaxas, Rutgers University	Deception Detection: Predictive Computational Modeling
14:15- 14:25		Break
14:25 – 14:50	Judee Burgoon, University of Arizona	Dominance Analysis: Social Science Research
14:50 - 15:15	Jure Leskovec, Stanford University	Dominance Analysis: Predictive Computational Modeling
15:15 – 1525		Break
15:25 - 15:50	Miriam Metzger, University of California Santa Barbara	Cultural Analysis
15:50 – 16:00	V.S. Subrahmanian Dartmouth College	New Results: Like/Dislike and Nervousness Prediction
15:50-16:00	Jay Nunamaker, University of Arizona	New Results: Trust Prediction

All materials from today's talks are available at: https://home.cs.dartmouth.edu/~mbolonkin/scan/register/review_session.html

Student Videos

All materials from today's talks are available at
https://home.cs.dartmouth.edu/~mbolonkin/scan/register/review_session.html

Presenter	Organization	Title
Maksim Bolonkin	Dartmouth College	Automatic Long-Term Deception Detection in Group Interaction Videos
Maksim Bolonkin	Dartmouth College	Predicting Negative Impressions in Group Interaction Videos
Chongyang Bai	Dartmouth College	Predicting Dominance in Group Interaction Videos
Chongyang Bai	Dartmouth College	Predicting the Visual Focus of Attention in Multi-Person Discussion Videos
Chongyang Bai	Dartmouth College	M2P2: Multimodal Persuasion Prediction with Adaptive Fusion
Viney Regunath	Dartmouth College	Predicting Relative Nervousness from Group Interaction Videos
Anastasios Stathopoulos	Rutgers University	Deception Detection in Videos using Robust Facial Features
Pan Li	Stanford University	Dynamic Network Representation Learning
Yen-Yu Chang	Stanford University	F-FADE: Frequency Factorization for Anomaly Detection in Edge Streams
Yanbang Wang	Stanford University	TEDIC: Neural Modeling of Behavioral Patterns in Dynamic Social Interaction Network
Mohemmad Hansia	UCSB	Transcript Maagement
Yibei Chen	UCSB	Measuring Similarity -- Anna Karenina (Annak)
Lee Spitzley	University of Albany	Transcribing Speech in the SCAN Project
Xunyu Chen	University of Arizona	Deception Detection with Bag-of-Words Features
Xinran Wang	University of Arizona	Presenting Informational Stimuli and Using Nonverbal Behaviors to Detect Deception in Group Interaction
Saiying (Tina) Ge	University of Arizona	SCAN: Cultural Analyses. Effect of Culture on Verbal Behaviour During Deception
Bradley Walls	University of Arizona	Facial Analyses with Open Source Tools
Vincent Denault	University of Montreal	Qualitative Analysis for Deception Detection

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