Detecting Deceptive Speech: Humans vs. Machines

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The Columbia Speech Lab



Deceptive Speech

- Deliberate choice to mislead
 - Without prior notification
 - To gain some *advantage* or to avoid some *penalty*
- *Not*:
 - Self-deception, delusion, pathological behavior
 - Theater
 - Falsehoods due to ignorance/error
- *Everyday (White) Lies* very hard to detect
- But *Serious Lies* may be easier to detect

Why would Serious Lies be easier to identify?

- Hypotheses in research and among practitioners:
 - Our *cognitive load* is increased when lying because we ...
 - Must keep story straight
 - Must remember what we **have** said and what we have *not* said
 - Our *fear of detection* is increased if...
 - We believe our target is difficult to fool
 - Stakes are high: serious rewards and/or punishments
- Makes it hard for us to control potential indicators of deception

But Humans very poor at Recognizing these Cues: Aamodt & Mitchell 2004 Meta-Study

()

Group	#Studies	#Subjects	Accuracy %	
Criminals	1	52	65.40	
Secret service	1	34	64.12	
Psychologists	4	508	61.56	
Judges	2	194	59.01	
Cops	8	511	55.16	
Federal officers	4	341	54.54	
Students	122	8,876	54.20	
Detectives	5	341	51.16	
Parole officers	1	32	40.42	

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Current Approaches to Deception Detection

- *'Automatic' methods* (polygraph, commercial products) no better than chance
- Train humans: John Reid & Associates
 - Behavioral Analysis: Interview/Interrogation no empirical support
 - Truth: I didn't take the money vs. Lie: I did not take the money (but non-native speakers rarely use contractions so....)
- *Laboratory studies*: Production and perception (facial expression, body posture/gesture, statement analysis, brain activation, odor,...)

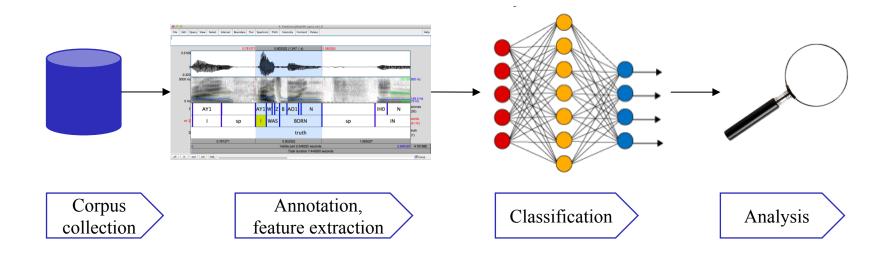
Our Approach

- Conduct *objective, experimentally verified* studies of spoken cues to deception *on large corpora* which predict better than *humans* or *polygraphs*
- Our method:
 - Collect speech data and extract *acoustic, prosodic*, and *lexical cues* automatically
 - Take *gender, ethnicity, and personality factors* into account as features in classification
 - Use *Machine Learning* techniques to train models to classify deceptive vs. non-deceptive speech

Questions We Hope to Answer

- Can we improve *human deception detection*
 - By providing new knowledge and training materials
 - By providing classifiers to aid in deception detection
- Can we *identify trust* in humans *and mistrust*
- Can we *control trust* in machines: an ethical question...
 - When robots and avatars should be trusted
 - When they should not...

Deception Detection from Text and Speech



Outline

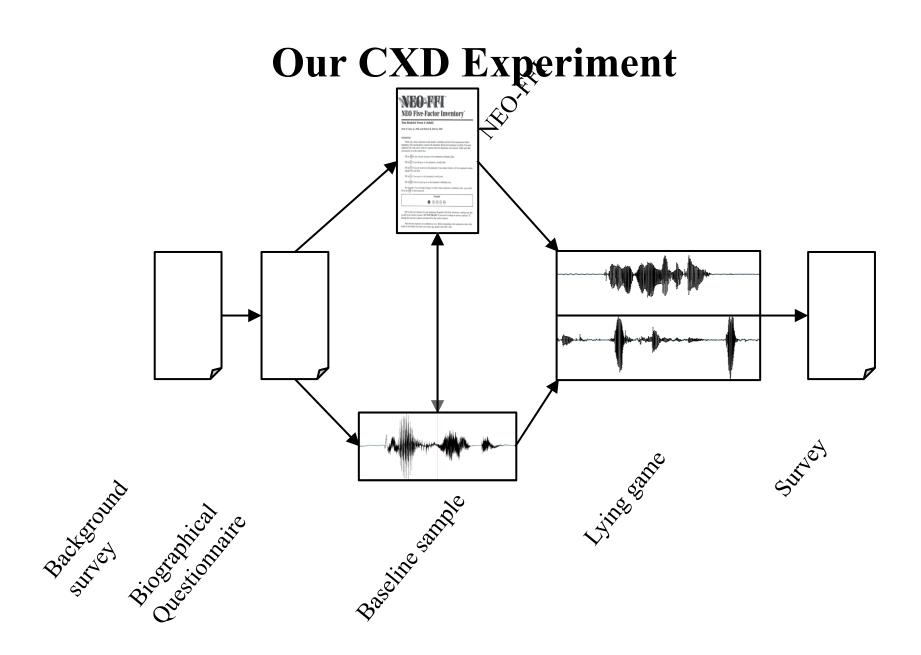
- Corpus collection
- Classification of deception from text and speech
- Individual differences in deceptive behavior
- New goal: Acoustic-prosodic indicators of trust

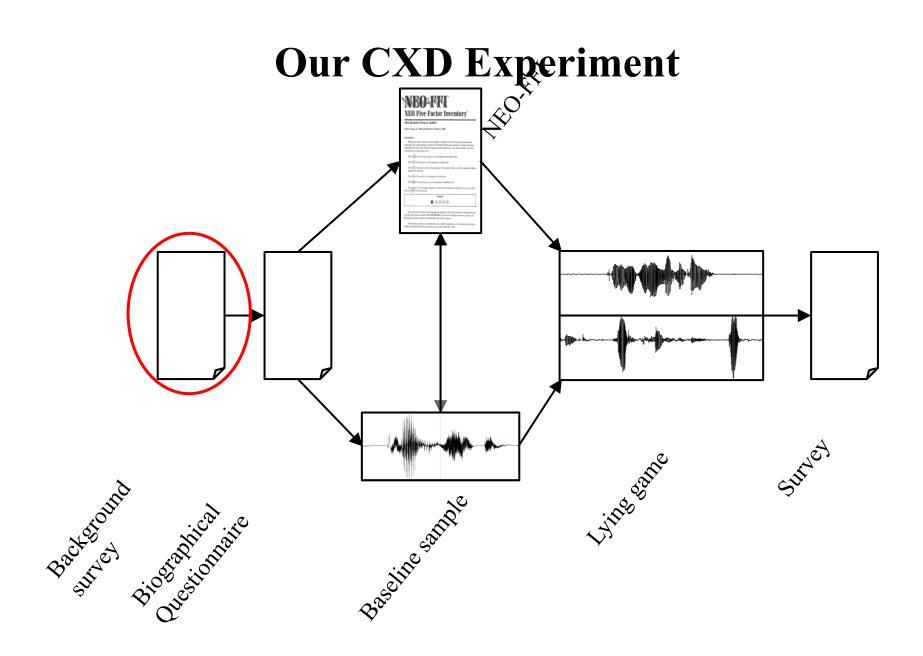
Columbia/SRI/Colorado Deception Corpus, 2003-5

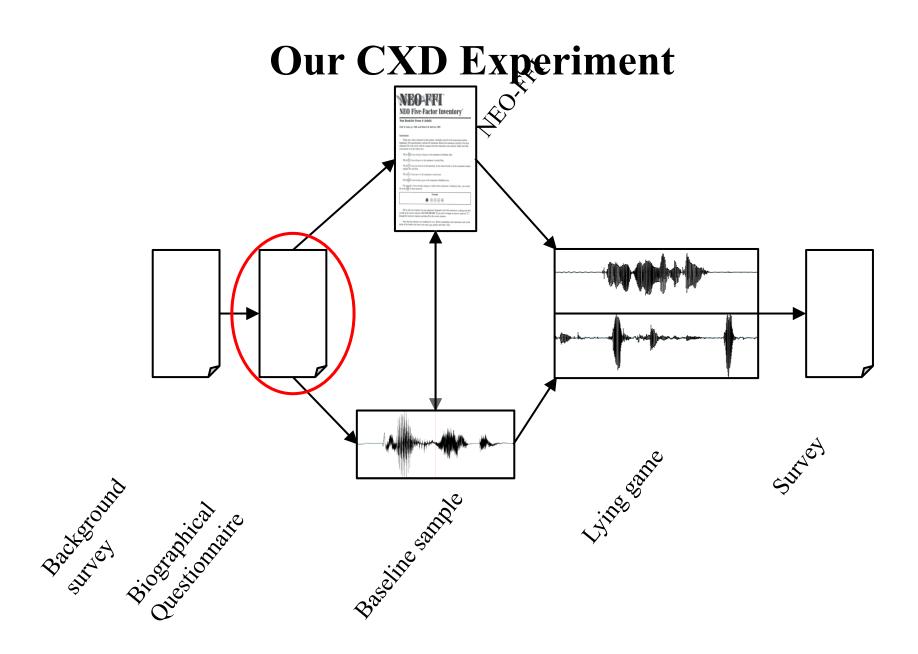
- *7h of speech* from 32 SAE-speaking subjects performing tasks and asked to lie about half
- *Lexical and acoustic-prosodic features* identified from psycholinguistic literature for classification
- Results
 - Classification accuracy (~70%) *significantly better than human performance* on our corpus
 - Considerable *individual differences* between speakers: Judges with certain *personality traits* performed better than our classifiers

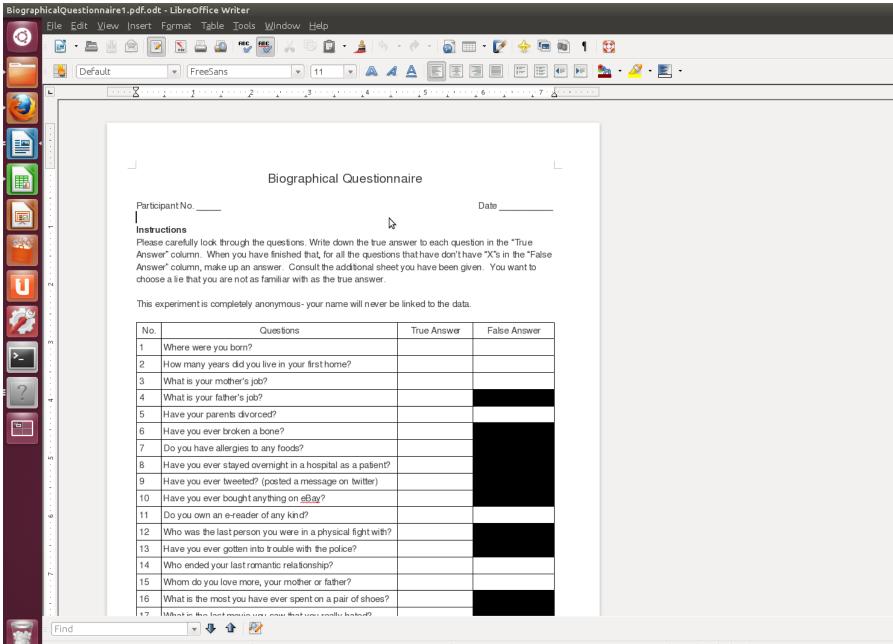
Columbia X-cultural Deception Corpus (2011--)

- New questions to ask:
 - Can *personality factors* help in predicting individual differences in deception?
 - Can people who detect lies better also lie more successfully?
 - Do *differences in gender and native language* influence deceptive behavior? Judgment of deception?
- *New study*: Pair native speakers of Standard American English with Mandarin Chinese speakers, speaking English, interviewing each other



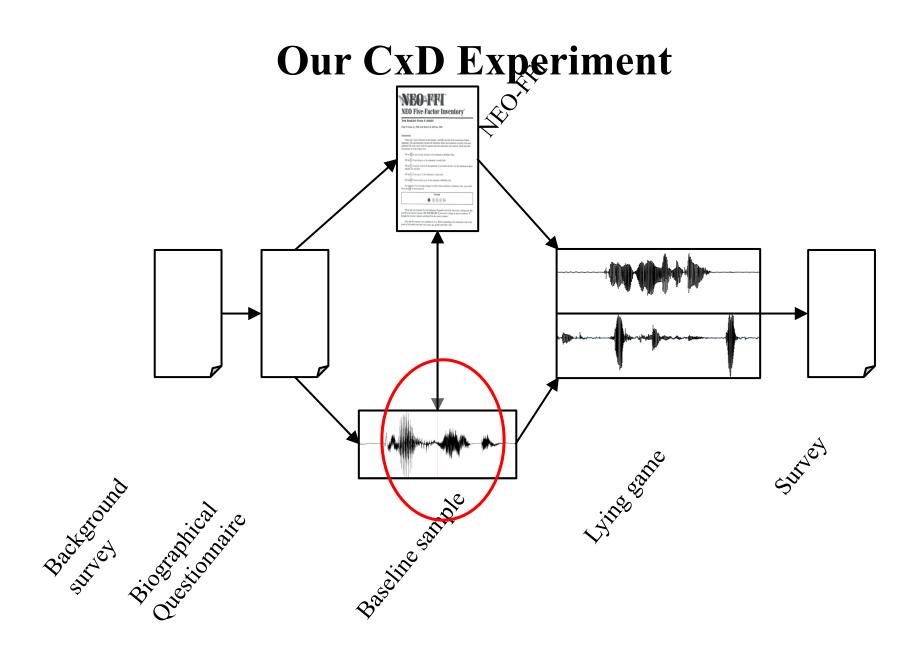


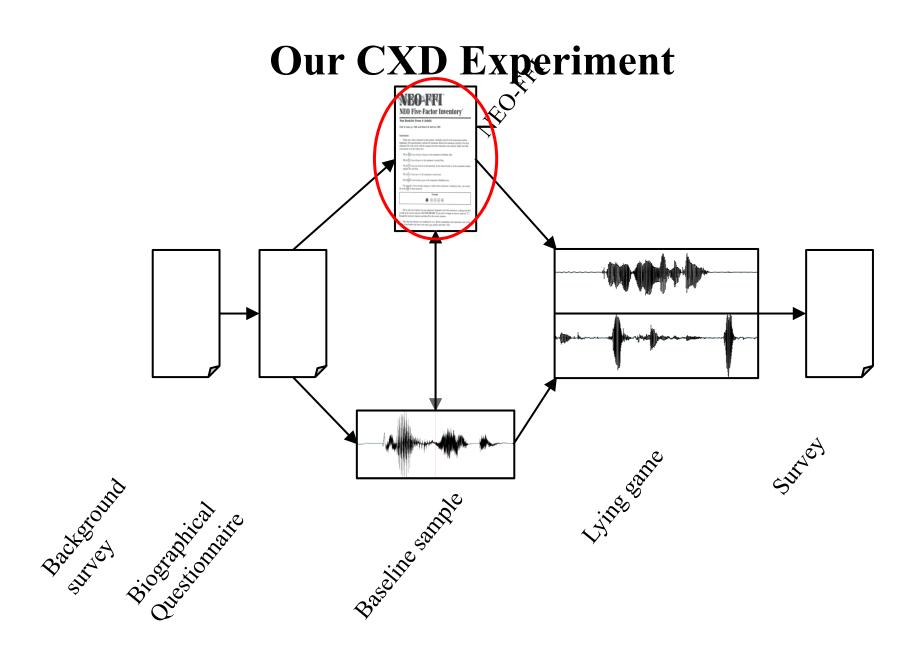




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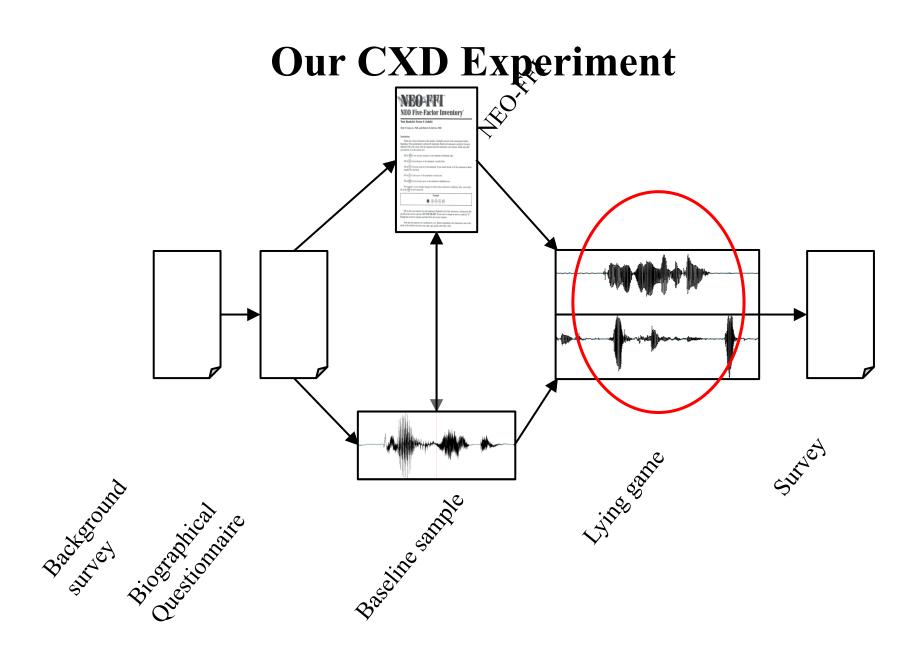
Default





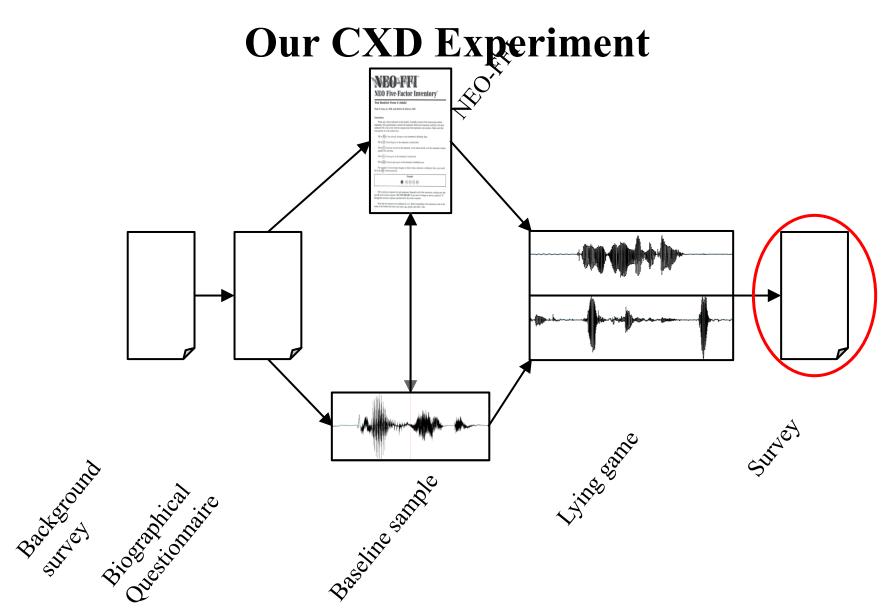
The Big Five NEO-FFI (Costa & McCrae, 1992)

- Openness to Experience: "I have a lot of intellectual curiosity."
- **Conscientiousness:** "I strive for excellence in everything I do."
- Extraversion: "I like to have a lot of people around me."
- Neuroticism: "I often feel inferior to others."
- Agreeableness: "I would rather cooperate with others than compete with them."



Our CXD Experiment





Motivation and Scoring

- Monetary motivation
 - Success for interviewer:
 - Add \$1 for every correct judgment, truth or lie
 - Lose \$1 for every incorrect judgement
 - Success for interviewee:
 - Add \$1 for every lie interviewer thinks is true
 - Lose \$1 for every lie interviewers thinks is a lie
- *Good liars tell the truth as much as possible* when lying, so how do we know what's true or false for follow-up questions?
 - Interviewees press T/F keys after every phrase

Columbia X-Cultural Deception (CXD) Corpus

- 340 subjects, balanced by gender and native language (American English, Mandarin Chinese):122 hours of speech
- *Crowdsourced transcription*, speech alignment
 TF keypress alignment
- Segmented into
 - Inter-pausal units (IPUs)
 - Speaker turns
 - Question/answer sequences (Q/A and Q/A+ follow-up)

"Where were you born?"

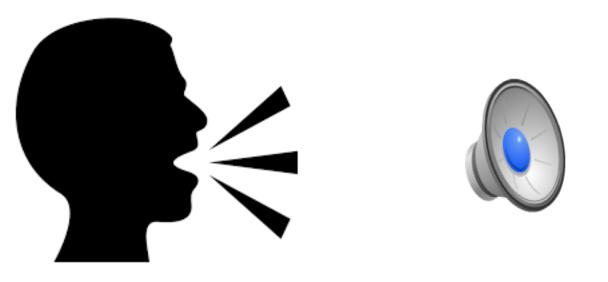


True or False?

"Where were you born?"



"What is the most you have ever spent on a pair of shoes?"



True or False?

"What is the most you have ever spent on a pair of shoes?"



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Features We Extract

- Currently:
 - Text-based: n-grams, psycholinguistic,
 Linguistic Inquiry and Word Count (LIWC)
 (Pennybaker et al), word embeddings (GloVe trained on 2B tweets)
 - Speech-based: openSMILE IS09 (386)
 - Gender, native language
 - Five personality dimensions (NEO-FFI)
- *Next*: Syntactic features (complexity) and all combined

Corpus Segmentation

- Inter-pausal unit (IPU)
- Turn
- **Question-level** (first answer, first+follow-up answers)

Unit	Interview ee	Interview er	Total	Avg. length (sec)	Avg. #	words
IPU	111,479	81,536	193,015	1.4	4.5	
Turn	43,706	41,753	85,459	4.7	12.4	
Q-level	7,418	7,418	14,836	one chnk 3.2 20.9	one 7.9	chnk 56.5

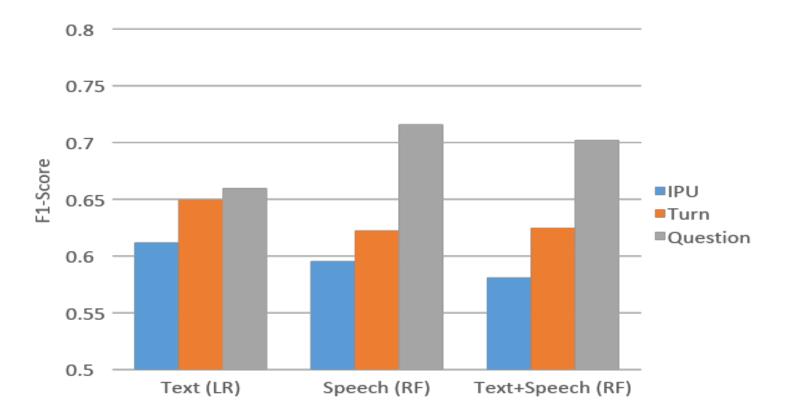
- What are the best classification models?
- What are the optimal segmentation units?
- Which feature sets are most useful?

- What are the best classification models?
 - Statistical machine learning Logistic Regression, SVM, Random Forest
 - Neural networks DNN, LSTM, hybrid system
- What are the optimal segmentation units?
- Which feature sets are most useful?

- What are the best classification models?
- What are the optimal segmentation units? –Inter-Pausal Unit (IPU), speaker turns, Q/A, Q/A+follow-up As
- Which feature sets are most useful?

- What are the best classification models?
- What are the optimal segmentation units?
- Which feature types are most useful?
 - -Text-based: n-grams, psycholinguistic-based, LIWC, GloVe word embeddings trained on 2B tweets
 - -Individual difference features: gender, native language, personality
 - -Speech-based: openSMILE IS09 acousticprosodic features (e.g. f0, intensity, speaking rate, VQ)

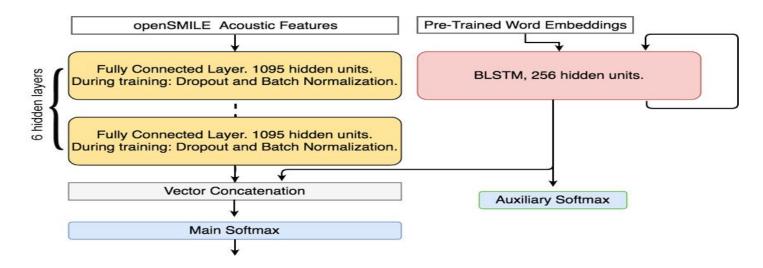
Segmentation – Longer is Better: IPU, Turn, Question



Mendels, Levitan et al. 2017, "Hybrid acoustic lexical deep learning approach for deception detection "

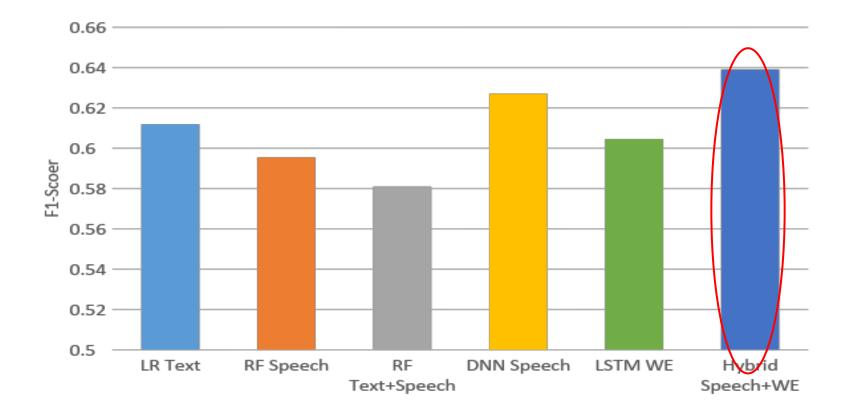
Deep Learning Approaches

- BLSTM-lexical
- DNN-openSMILE
- Hybrid: BLSTM-lexical + DNN-openSMILE



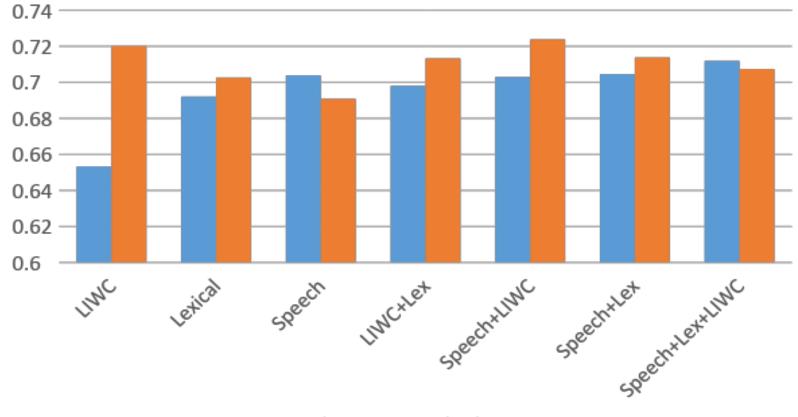
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IPU Classification: Hybrid is Better



Mendels, Levitan et al. 2017, "Hybrid acoustic lexical deep learning approach for deception detection "

Question-Level Random Forest; Context is Better





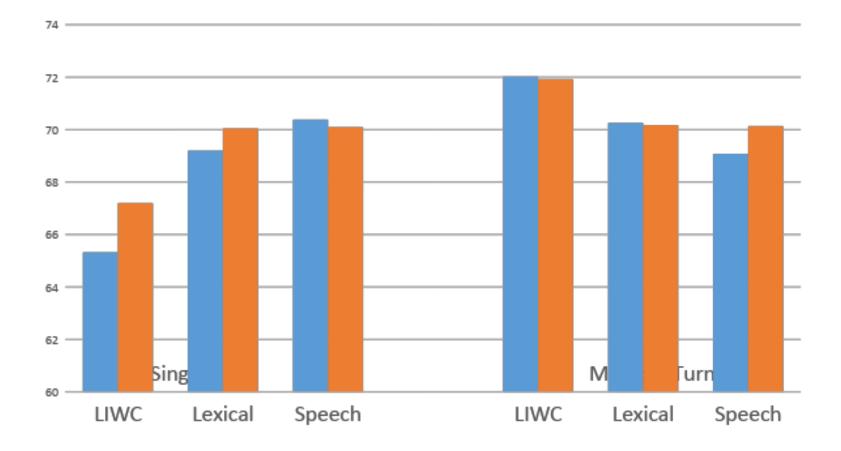
Analysis – Acoustic Features

Feature	t	р	sig
Duration	-0.63	0.53	
Pitch Max	4.37	1.28E-05	*
Pitch Mean	0.56	0.58	
Intensity Max	3.45	0.0006	*
Intensity Mean	1.33	0.18	
Speaking Rate	-1.69	0.09	
Jitter (f0 var.)	-1.31	0.19	
Shimmer (Ampl var.)	-1.39	0.17	
NHR	0.35	0.73	

Analysis – Lexical Features

Truth	Lies	Neutral
Negation	Clout	Laughter
Function words	Informal	Comparison
Certain	Word count	Anger
Cognitive processes	Words per second	Power
	Past tense	Present tense
	Specificity	Future tense
	Hedges	Complexity
	Imagery	
	3 rd person pronouns	

Classification with Gender and Native Language: 1st Answer and Chunks: Personal Info Helps with Less Context



Results for Classification

- Deception classification experiments
 - >.72 F1-Score when using question segmentation to predict lies
 - Note that human interviewers' F1 is 0.43
 - **Deep learning** approaches for IPU segmentation probably most promising route in future
 - Many more features to examine together

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- Individual differences in deceptive behavior and detection of deception
- Acoustic-prosodic indicators of trust

Some Individual Differences

- *Extroversion* is correlated with success at deception, for **English male** speakers
- *Native English speakers* perform better at deception when paired with a **native Chinese** interviewer



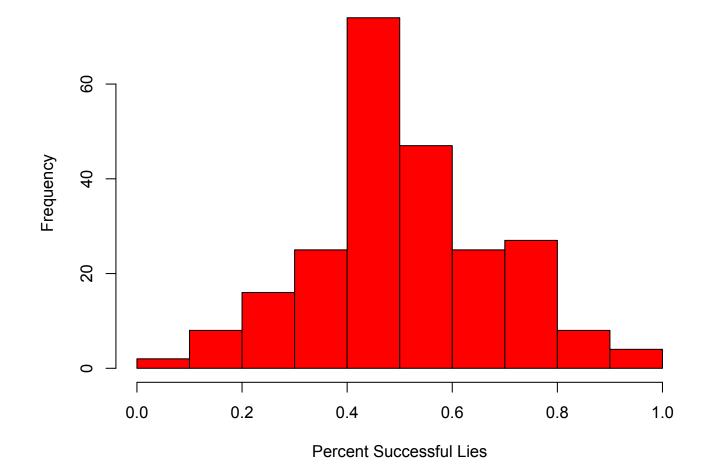


Individual Differences in Deception and Truth-telling

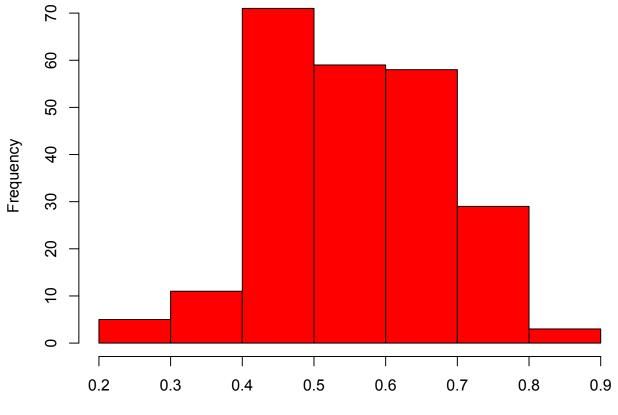
Male	Female	English	Chinese
Positive emotion (T)	Jitter (T)	Intensity mean (F)	Speaking rate (T)
Interrogative s (F)	Perceptual process (F)	<mark>Swear</mark> (F)	Certainty (T)
	Future tense (F)		Feel (F)
			Causation (F)

Levitan et al. 2018, "Linguistic indicators of deception and perceived deception in spoken dialogue"

Differences in Deceptive Ability: How well did interviewees lie?



Differences in Deception Detection: How well did interviewers judge deception?



Percent Correct Judgments

Results

- There are gender and cultural/native language differences in deceptive behavior
- There are differences in ability to deceive and in ability to detect deception
- Understanding these differences can improve deception classification by machines and perhaps by humans...

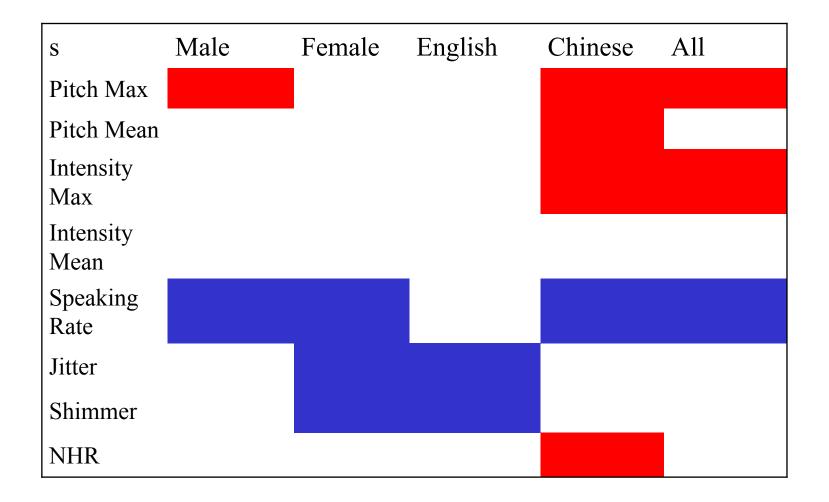
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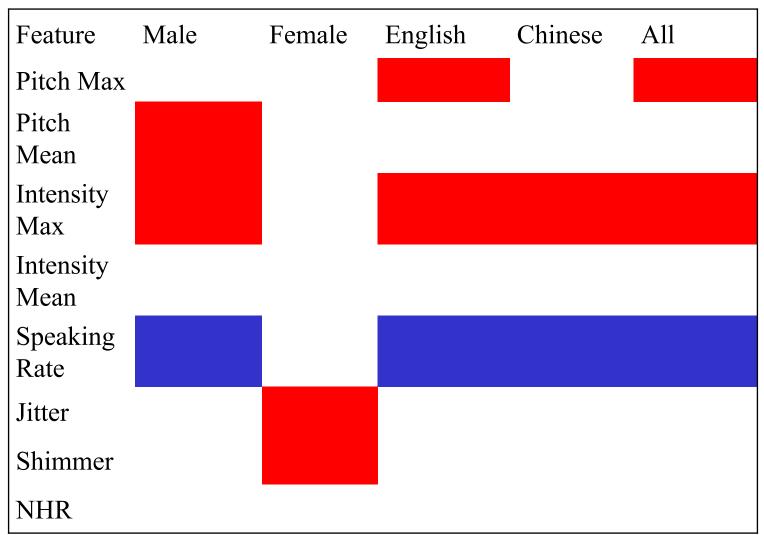
Features of Perceived Lies and Truth

Feature	t	p	sig
Pitch Max	2.35	0.02	*
Pitch Mean	1.65	0.1	
Intensity Max	2.625	0.009	*
Intensity Mean	-0.785	0.43	
Speaking Rate	-3.785	0.0002	*
Jitter	-1.815	0.07	
Shimmer	-1.905	0.06	
NHR	0.58	0.56	

Group-Specific "Trust" Indicators: Speakers: Native Language Matters



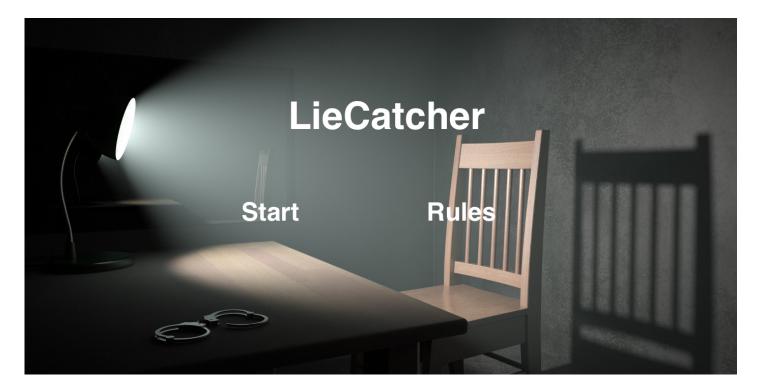
Group-specific "Trust" Indicators for Interview*ers***: Gender Matters**



What's Next?

- *Classifiers* to detect trustworthy voices and *TTS systems* to create them
- Even better deception classifiers
- Tools to train humans in deception detection
- A *fun game*...

Games with a Purpose



Levitan et al. 2018, "LieCatcher: Game framework for collecting human judgments of deceptive speech"



TRUE or FALSE?







TRUE or FALSE?





Thank you!



