



#### A Decision Tool Based on Mobile Sensing for Social Anxiety Disorder among University of Virginia (UVA) Students

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#### **Research and Working Experiences**

#### 07/2019 -- Present, Research Project on Glaucoma Detection using Color Fundus Images

Role: Team Member Supervisor: Postdoc Zhicheng Zhang, Stanford University

- Used Convolutional Neural Networks (CNN) and Grey Level Co-occurence Matrices (GLCM) to extract features, based on python cv2, skimage libraries
- Made evaluation of 3 machine learning algorithms in terms of image classification accuracy by sklearn

#### 09/2019 -- 06/2020, Research Project on Mobile Health, Measuring Anxiety Level in Social Interactions

Role: Team Member Supervisor: Prof. Mehdi Boukhechba, University of Virginia

- Collected data from Shimmer (ECG and GSR sensors), extracted time-series features from multimodal sensors to detect social anxiety level with Jupyter Notebook, Python 3
- Made comparison of machine learning algorithms to predict social anxiety interaction scale (SIAS) score change, such as Linear Regression, Support Vector Machine Regression, K-Nearest Neighbor, Gaussian Naive-Bayes, based on a system of loss functions, using python sklearn and keras libraries

#### 09/2019 -- 12/2019, Research Project on The Analysis and Improvement of Keppler Medical Device and Material Co. Ltd. Production System

#### Role: Team Member Supervisor: Prof. Cindy Chang, University of Virginia

- Applied of Production System Engineering Toolbox to do different manufacturing system analysis, like identification of bottleneck places and improvable places of this system
- Used Google Colab based on Python 3 to do opportunity window analysis to reallocate the workers

#### 01/2019 -- 05/2019, Research Report for the Heuristics of Arcade Game Design

- Searched all the literatures by myself, and did survey online
- Discovered the real art of designing arcade games in a comfortable rhythm, including a decent user interface, along with the reasonable difficulty and proper hints along with the game.

#### 03/2018 -- 07/2018, Hefei New Oriental English School

Role: Internship Student

- Used Excel to grade mock exams online, including SAT, ACT, TOEFL, AP and GRE; served as teaching assistants in English classes with size of 9 or smaller; wrote feedback for students.
- Enhanced my English reading, listening and oral communication skills.

#### 10/2016, Project of Video Technology and Cloud Computing, Chinese Academy of Sciences

- Completed the software for video dialogue forms all by myself, perfected various of expressions and voice communication function with teammates smoothly, created a decent user interface
- Independently wrote all the codes related to .json, learned to refer to the literature online for coding. completed the Python GUI programming and designed a GUI based chatting client, debugged all by myself.
- Did the investigation report about TS, PS, and PES with other members and presented the final report by myself





## **Topics Working On**

The current institution I am employed in: Zhejiang Lab

The current project I am working on:

- 1. The Deep Learning of EEG signals for epilepsy seizure detection (current working group)
- 2. The 3D game design about "Chronicles of the Earth"
- 3. Continuing on my current project and contribution 28005 "Identification of glaucoma using deep learning"



### Background





Electrocardiogram (ECG) Signals

Galvanic Skin Response (GSR) Signals

Social anxiety disorder:

an intense fear of being judged and scrutinized by others, beyond what would normally be expected in an overt situation

The purpose of study:

Selection of specific physiological and phychological features from ECG signals and GSR signals, build a model between these featuers and Social Interaction Anxiety Scores (SIAS)

A pilot study, including activity recognition (classification problem), score change prediction (regression problem), and treatment methods

### **Related Work**

Huang et. al. [1]:

- Feasibility study about a smartphone app tracking the GPS location data & brief questionnaires, reflecting students' moods and indicating SIAS scores
- Correlation and significance analysis, linear regression model

Kotsilieris [2]:

- The prediction of specific types of social anxiety disorders using machine learning techniques
- Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Networks (ANNs)

Gong et. al. [3]:

- 2-week study of 53 UVA undergraduates, questions about if behavioral patterns around social interactions vary across the social anxiety level with accelerometer, if these patterns depend on communication media or semantic locations
- Significant difference in these students' behaviors in terms of anxiety level and locations

Boukhechba et. al. [4]:

- Another pilot study in UVA, 20 students, heart rate and accelerometer data, interpretation bias of questionaires
- Correlation between them could be used to predict the changes in self-reported negative effect, the same pattern as the changes in interpretation bias and negative effect



The problem: Only qualitative studies showing the correlation, no study to select the best model No treatments for each subject

### Methods

- Members: 4 UVA undergraduates + 2 UVA graduates
- ♦ SIAS Score:
  - Score 1 to 5
  - 4 testing points: baseline/anticipatory/experiment/post-experiment, 3 score changes
  - 3 activities: solo video watching (video) /dyad conversation (no-eval) /dyad conversation with evaluation (eval)
- ECG data streams: accelerometer, gyroscope
- ◆ GSR data streams: skin conductance (subjects 3 and 4 do not have)
- sliding window algorithm: 2s, with the stride of 1s
- ♦ 34 features in total
- ◆ Questionaires: 3 to 13 questions in different testing points,





		Baselin	Baseline perdiod Anticipatory anxiety		Experience		Post-event		
Experience_type	Participant_id(s)	Start_time	End_time	Start_time	End_time	Start_time	End_time	Start_time	End_time
Solo Video	1	9:35:27 AM	9:36:41 AM	9:38:06 AM	9:42	9:42:36 AM	9:46:48 AM	9:47:25 AM	9:51:13 AM
Dyad No-eval	1	9:51:45 AM	9:53:21 AM	9:54:36 AM	9:58:15 AM	10:00:01 AM	10:05:39 AM	10:06:19 AM	10:10:46 AM
Dyad eval	1	10:17:05 AM	10:18:28 AM	10:21:56 AM	10:24:35 AM	10:27:15 AM	10:33:18 AM	10:33:51 AM	10:37:58 AM
Group eval	1								
Group No-eval	1								
Solo Video	2	9:31 AM	9:31	9:33	9:36:57 AM	9:38	9:44:45 AM	9:45:39 AM	9:49:06 AM
Dyad No-eval	2	9:50:23 AM	9:51:16 AM	9:54:40 AM	9:58:47 AM	10:00:01 AM	10:06:56 AM	10:07:36 AM	10:10:10 AM
Dyad eval	2	10:17:17 AM	10:18:16 AM	10:20:02 AM	10:24:20 AM	10:27:15 AM	10:33:29 AM	10:34:03 AM	10:37:58 AM
Group eval	2								
Group No-eval	2								
Solo Video	3	9:23:04 AM	9:24:13 AM	9:25:09 AM	9:27:25 AM	9:29:41 AM	9:35:19 AM	9:36:11 AM	9:40:52 AM
Dyad No-eval	3	9:41:18 AM	9:42:07 AM	9:44:08 AM	9:48:08 AM	9:49:04 AM	9:54:49 AM	9:56:51 AM	10:00:58 AM
Dyad eval	3	10:03:01 AM	10:03:54 AM	10:05:11 AM	10:09:13 AM		10:15:28 AM	10:17:56 AM	10:21:52 AM
Group eval	3								
Group No-eval	3								
Solo Video	4	Need to impute	Need to impute	Need to impute	9:27:30 AM	9:30:21 AM	9:32:15 AM	9:32:42 AM	9:34:17 AM
Dyad No-eval	4	9:38:02 AM	9:38:20 AM	9:40:06 AM	9:41:05 AM	9:49:04 AM	9:54:49 AM	9:57:06 AM	9:58:00 AM
Dyad eval	4	10:03:43 AM	10:04	10:06:35 AM	10:09:11 AM	10:11 AM	10:15	10:16:40 AM	10:19:36 AM
Group eval	4								
Group No-eval	4								
Solo Video	5	9:45:20 AM	9:45:49 AM	9:53:42 AM	9:59:04 AM	10:00:06 AM	10:03:19 AM	10:07:09 AM	10:11:08 AM
Dyad No-eval	5	10:19:22 AM	10:19:45 AM	10:25:39 AM	10:29:44 AM	10:31:09 AM	10:37:46 AM	10:38:52 AM	10:43:37 AM
Dyad eval	5	10:45:18 AM	10:45:40 AM	10:48:04 AM	10:50:49 AM	10:51:12 AM	10:57:05 AM	10:57:34 AM	11:00:41 AM
Group eval	5								
Group No-eval	5								
Solo Video	6	9:41:46 AM	9:43:11 AM	9:51:57 AM	9:56:03 AM	9:57:11 AM	10:02:13 AM	10:03:04 AM	10:07:39 AM
Dyad No-eval	6	10:19:22 AM	10:19:45 AM	10:25:39 AM	10:29:44 AM	10:31:09 AM	10:37:46 AM	10:38:52 AM	10:43:37 AM
Dyad eval	6	10:45:18 AM	10:45:40 AM	10:48:04 AM	10:50:49 AM	10:51:12 AM	10:57:05 AM	10:57:34 AM	11:00:41 AM
Group eval	6								
Group No-eval	6								

### Methods



The activity recognition model selection: Bandom Forest Classifier (BEC), Gaussian Naiv

Random Forest Classifier (RFC), Gaussian Naive Bayes (GNB), Decision Trees (DT), k-Nearest Neighbors (kNN)

The treatments: Exposure (EXP) [5], Social Skills Training (SST) [6] based on Virtual Reality (VR), Selection Serotonin Reuptake Inhibitors (SSRIs) [7]

Prediction of the score changes: Linear Regression (LR), Least Absolute Shrinkage and Selection Operator (LASSO), ElasticNet Regression

The loss function: RMSE

### Results



TABLE I THE ACCURACY OF ACTIVITY RECOGNITION WITH INDIVIDUAL ECG

Algo	ECG						
Act	Total	0	1	2			
kNN	45.22	66.96	69.12	68.32			
NBC	10.83	28.78	34.28	31.36			
DT	62.85	87.37	80.54	80.27			
RFC	68.43	88.40	84.76	85.09			

TABLE III THE ACCURACY OF ACTIVITY RECOGNITION WITH INDIVIDUAL PPG

Algo	PPG						
Act	Total	0	1	2			
kNN	18.02	33.73	43.01	40.44			
NBC	16.16	26.33	37.53	43.89			
DT	27.22	45.26	46.84	43.26			
RFC	28.30	45.86	47.12	46.08			

TABLE II THE ACCURACY OF ACTIVITY RECOGNITION WITH INDIVIDUAL GSR

ſ	Algo	GSR						
Ì	Act	Total	0	1	2			
Ì	kNN	34.28	48.45	59.86	53.57			
Ì	NBC	20.20	36.56	38.23	42.55			
Ì	DT	51.38	75.92	72.65	57.92			
ľ	RFC	55.36	76.51	76.32	66.15			

RFC: the best accuracy in both ECG and GSR features classification. PPG: very low accuracy, discarded

### Results

#### TABLE V THE ACCURACY OF ACTIVITY RECOGNITION WITH COMBINED ECG AND GSR FEATURES

Algo	Cor	combined ECG and GSR					
Act	Total	0	1	2			
kNN	45.22	66.96	69.12	68.32			
NBC	10.97	28.63	34.38	31.37			
DT	85.04	93.24	94.28	84.78			
RFC	90.09	95.88	96.32	91.61			

#### TABLE VI THE ACCURACY OF ACTIVITY RECOGNITION WITH 18 ECG FEATURES FOR SUBJECT 3 AND 4

Algo	Combined ECG and GS					
Act	Total	0	1	2		
kNN	49.74	71.15	75.56	80.69		
NBC	14.96	32.41	44.81	37.07		
DT	77.87	85.37	91.11	83.40		
RFC	87.85	87.75	95.93	92.27		



- To the best utilization of data:
- 14 ECG features, and 5 GSR features for subjects 1,2,5 and 6
- > 18 ECG features for subjects 3 and 4
- The combination of ECG and GSR features: RFC best accuracy, over 90%
- A little bit lower accuracy with only ECG features

### Results

Participant	Activity	Baseline	Anticipatory	Experience	Post	B-A	A-E	E-P
1	0	2.667	2.923	2.077	1.714	0.256	-0.846	-0.363
1	1	1.667	2.846	2.923	2.143	1.179	0.077	-0.78
1	2	1	3.077	2.923	2.286	2.077	-0.154	-0.637
2	0	3	3	1.923	2	0	-1.077	0.077
2	1	2	2.846	2.769	2.857	0.846	-0.077	0.088
2	2	2.333	3.154	2	3	0.821	-1.154	1
3	0	3.667	2.692	2.231	2.286	-0.975	-0.461	0.055
3	1	2.667	3	2.308	1.571	0.333	-0.692	-0.737
3	2	2.333	2.538	2.846	2.714	0.205	0.308	-0.132
4	0	2	3.077	3.077	3.143	1.077	0	0.066
4	1	3	3.308	3.538	3	0.308	0.23	-0.538
4	2	1.333	2.692	3	2.413	1.359	0.308	-0.587
5	0	3	3.308	2.769	2.571	0.308	-0.539	-0.198
5	1	3.333	2.615	1.846	2.571	-0.718	-0.769	0.725
5	2	3.333	3.154	2	2	-0.179	-1.154	0
6	0	3	1.615	1.077	1	-1.385	-0.538	-0.077
6	1	2.667	2	1.923	1	-0.667	-0.077	-0.923
6	2	1	1.923	1.923	1	0.923	0	-0.923



TABLE VII THE RMSE OF PREDICTION ABOUT SCORE CHANGE FOR SUBJECTS 1,2,5 AND 6

Subjects	LR	LASSO	ElasticNet
1,2,5,6	0.672265	0.672277	0.672271
3,4	0.475057	0.475072	0.475065

- Similar performance in three models
- Our final decision:

$$\blacktriangleright$$
 a<sup>\*</sup><sub>1</sub> = EXP for eval

$$a_2^* = SSRIs$$
 for eval

$$\succ$$
 a<sup>\*</sup><sub>3</sub> = EXP for no-eval

- $\blacktriangleright$  a<sup>\*</sup><sub>4</sub> = EXP for eval
- $\blacktriangleright$  a<sup>\*</sup><sub>5</sub> = SSRIs for no-eval
- $\blacktriangleright$  a<sup>\*</sup><sub>6</sub> = EXP for eval

### Limitations and Future Work



Main problems

- > Too small sample size (30 participants at least)
- Further work in data analysis part, especially signal processing (working on it now)
- > More factors, such as demographics of students

Virtual Reality (VR) can give us some aids:

- Virtual Reality Exposure (VRE) system to track eye contact avoidance [8]
- > VRE therapy: might be at least equally effective as in vivo exposure [9]
- > Higher complexity, larger number of people and more precise ways [10]

### References



[1] Y. Huang et. al., Assessing Social Anxiety using GPS Trajectories and Point-Of-Interest Data, Ubicomp' 16, 2016, Sep.12-16, 898-903.

[2] T. Kotsilieris, E. Pintelas, I.E. Livieris and P. Pintelas, Reviewing Machine Learning Techniques for Predicting Anxiety Disorders, Technical Report, No. TR18-01.

[3] M. Boukehechba et. al., "Physiological Changes over the Course of Cognitive Bias Modification for Social Anxiety", 2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI), 4-7 March 2018,Las Vegas, Nevada, USA, pp. 422-425.

[4] M. Boukhechba et. al., "Monitoring mental health and social interactions of college students using smartphones", Smart Health 9-10 2018, pp. 192-203, ISSN 2352-6483, https://doi.org/10.1016/j.smhl.2018.07.005.

[5] J. A. Scheurich, D. C. Beidel, and M. Vanrycheghem, "Exposure Ther- apy for Social Anxiety Disorder in People Who Stutter: An Exploratory Multiple Baseline Design", Journal of Fluency Disorders 2019, Vol. 59, pp.21-32. DOI: https://doi.org/10.1016/j.jfludis.2018.12.001.

### References



[6] P. J. Olivares-Olivares, P. F. Ortiz-Gonzalez and J. Olivares, "Role of social skills training in adolescents with social anxiety disorder", International Journal of Clinical and Health Psychology 2019, Vol. 19, pp. 41-48.

[7] Harvard Mental Health Letter, Treating Social Anxiety Disorder, March 2010.

[8] H. Grillon, F. Riquier, B. Herbelin, and D. Thalmann, "Virtual reality as therapeutic tool in the confines of social anxiety disorder treatment", Int J Disabil Human Dev 2006, Vol. 5, No. 3.

[9] S.M.Edwardset.al.," VirtualRealityExposureTherapyforSocialAnx- iety Disorder: A Randomized Controlled Trial", Journal of Consulting and Clinical Psychology, 2013, Vol. 81, No. 5, pp. 751–760.

[10] S. Bouchard et. al., "Virtual reality compared with in vivo exposure in the treatment of social anxiety disorder: a three-arm randomised controlled trial", The British Journal of Psychiatry 2017, Vol. 210, pp. 276–283.



# Any questions?