Depression Detection

- Week 9

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Internship Period: Jan – July 2024

Undergraduate 4th year

Duration of the presentation: ~7 minutes

Agenda

1. **Analysis of Dataset Consolidation Methods**
2. **Data Augmentation**
    1. Methodology per the paper
    2. Results on Yuxin's code
3. **Insights from paper - Depression Predictions Language Based Dynamics**
4. **Linguistic Analysis of the Transcripts**
5. **Tentative plan for next week**

Analysis of Dataset Consolidation Methods

Table 1: Statistics of Word Counts in different versions of the transcript

	Mean	Std Dev	Min	Max
Complete Transcripts	1484.66	812.66	168	4710
Topic (Q) based	334.70	208.78	79	1465
Emotional	739.15	456.20	71	2509

Table 2: Statistics of Sentence Counts in different versions of the transcript

	Mean	Std Dev	Min	Max
Complete Transcripts	172.44	75.07	43	387
Topic (Q) based	11.27	3.11	6	21
Emotional	58.08	25.63	17	156

Data Augmentation

[1] Context-aware Deep Learning for Multi-modal Depression Detection (Lam et al, 2019) | Paper | Code

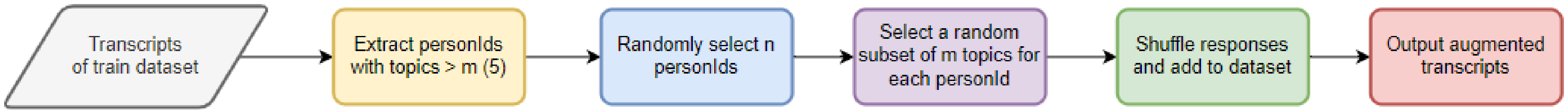

Fig 1: Method followed for data augmentation in line with [1]

Table 3: Dataset distribution after Augmenting

	Train	Dev	Test	Total
Original	107	35	47	189
Augment	307	35	47	389

Table 4: Results on Yuxin's code

	Precision	Recall	F1	Accuracy
Transcripts	0.63	0.67	0.65	0.66
Question based	0.62	0.64	0.63	0.62
Augmented	0.70	0.58	0.63	0.67

Insights from paper - Language Based Dynamics

Table 5: Definition of metrics used to predict depression [2]

Name	Definition	Operationalization	Conceptual overlap
Variability	The amplitude of an individual's emotion. This is time-unstructured, referring to the "general dispersion" of scores.	Within-person SD (*iSD*)	Variance
Instability	The amplitude of moment-to-moment changes in emotion. This is time-structured, where higher scores indicate greater variance and less positively correlated between observations.	Mean squared successive difference	Variance, time-dependency
Inertia	How well a previous emotional state predicts the next emotional state. This is time-structured, where greater correlation coefficient indicates increased temporal dependency between observations.	Autocorrelation coefficient	Time-dependency

$$p(category) = \sum_{word \in category} p(word) = \frac{\sum_{word \in category} count(word)}{N\_words} \quad [1]$$

$$iSD = \sqrt{\frac{\sum_i s_i^2}{n-1}} \quad [2]$$

$$MSSD = \frac{\sum_{i=1}^{n-1} (x_{i+1} - x_i)^2}{n-1} \quad [3]$$

$$\text{time-adjusted } MSSD = \frac{median(\Delta t)}{(n-1)} \sum_{i=1}^{n-1} \frac{(x_{i+1} - x_i)^2}{(t_{i+1} - t_i)} \quad [4]$$

Fig 2: Formulas for metrics [2]

[2] Predicting Depression From Language-Based Emotion Dynamics: Longitudinal Analysis of Facebook and Twitter Status Updates (Seabrook et al, 2018) | Paper

Insights from paper - Language Based Dynamics

Table 6: Results on experimentation by [2]

Variable	Facebook			Twitter		
	Range	Mean (SD)	Median (IQR[a])	Range	Mean (SD)	Median (IQR)
Depression severity (PHQ-9[b])	1-22	11.48 (6.38)	10 (5.5-17)	0-26	9.80 (6.81)	9 (4-14)
Status update frequency						
Recording period (days)[c]	22-356	170.69 (116.05)	134 (54-290)	9-365	145.61 (124.97)	74.00 (33.50-272.00)
Status updates per day	0.03-1.72	0.03 (0.36)	0.16 (0.07-0.51)	0.03-4.56	0.79 (1.09)	0.40 (0.09-0.90)
Interval difference (min) between status updates[d]	661-34827	8446.65 (8724.25)	3818.00 (1877.75-13522.75)	4.0-28428.5	3939.79 (6616.84)	1037 (206.25-4571.25)
Positive emotion words						
Average proportion	0.02-0.57	0.10 (0.10)	0.08 (0.05-0.11)	0.01-0.14	0.07 (0.03)	0.08 (0.05-0.09)
Variability (*iSD*)[e]	0.04-0.47	0.13 (0.09)	0.10 (0.07-0.16)	0.03-0.17	0.07 (0.03)	0.08 (0.05-0.09)
Instability (time-adjusted MSSD)[f]	0.003-11.54	1.14 (2.94)	0.11 (0.02-0.47)	0.0002-26.80	1.49 (4.40)	0.12 (0.02-0.83)
Negative emotion words						
Average proportion	0.00-0.17	0.04 (0.04)	0.02 (0.01-0.05)	0.01-0.26	0.09 (0.06)	0.09 (0.04-0.12)
Variability (*iSD*[e])	0.00-0.31	0.07 (0.08)	0.03 (0.02-0.09)	0.02-0.14	0.08 (0.03)	0.08 (0.06-0.11)
Instability (time-adjusted MSSD[f])	0.00-1.23	0.11 (0.24)	0.01 (0.002-0.14)	0.0006-37.99	1.31 (5.43)	0.15 (0.03-0.49)

[2] Predicting Depression From Language-Based Emotion Dynamics: Longitudinal Analysis of Facebook and Twitter Status Updates (Seabrook et al, 2018) | Paper

Relevant Insights:

- Negative emotion word instability was associated with depression severity
- Average of negative and positive word usage was not associated with depression

Linguistic Analysis of the Transcripts

Table 7: The mean/std dev for linguistic features in the topic (Q) based dataset

	pronoun	absolutist	laugh	um	sniffle	sigh	depressive	negative	positive
Non-depressed	19.17/ 12.98	6.31/ 7.27	3.63/ 5.76	18.17/ 16.86	0.30/ 1.98	2.18/ 4.32	1.32/ 3.47	32.58/ 13.05	64.96/ 27.41
depressed	20.55/ 12.29	7.52/ 6.12	5.24/ 7.68	17.50/ 15.70	0.00/ 0.00	2.34/ 4.30	2.61/ 4.23	34.94/ 13.20	49.84/ 16.96

Table 8: The mean/std dev for linguistic features in the emotional based transcript

	pronoun	absolutist	laugh	um	sniffle	sigh	depressive	negative	positive
Non-depressed	26.61/ 10.94	7.87/ 5.64	3.87/ 5.64	13.16/ 12.88	0.14/ 0.76	1.10/ 2.31	1.16/ 1.81	19.51/ 7.65	63.83/ 15.58
depressed	28.88/ 12.27	8.89/ 5.38	4.41/ 4.43	10.67/ 11.62	0.27/ 0.88	1.76/ 3.43	2.08/ 2.67	20.95/ 8.10	61.16/ 16.30

[3] What reveals about depression level? The role of multimodal features at the level of interview questions (Shat et al, 2020) | Paper | Code

Value = (count/num_of_words) * 1000

Tentative Plan

Plan for next week

1. Reading more statistics-based literature
2. Beginning to write in line with a literature review
3. Building and iteratively improving upon a model

Relevant Links

1. Overall project plan and timeline: Link
2. Analysis and notes from relevant papers: Link
3. GitHub documenting everyone's presentations and codes: Link

End