

Listening to Oral History: Emotion Annotation and Recognition in the ACT UP Oral History Project

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The "deep dark secret" of oral history, is that nobody spends much time listening to or watching recorded and collected interview documents.

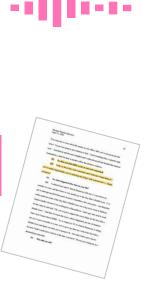
Michael Frisch

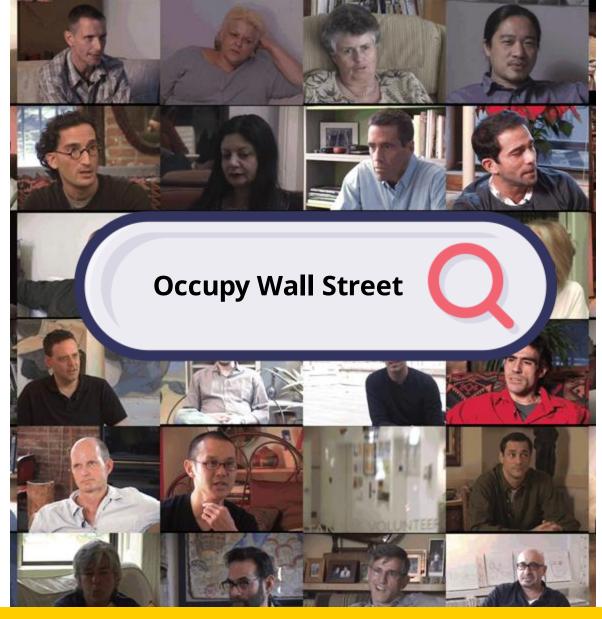


Computational techniques have brought new insights to the field of oral history, with methods such as:

Automatic Speech Recognition and

Natural Language Processing.







The interview process is "a performance in search of a text".

Reading only the interview transcriptions results in missing the performance itself.





Michael Petrelis Interview April 21, 2003

"You want me to worry about the smoke in your office, after you've news? I'm just not going to pay attention to that. I need something i now." And then he and the nurse laughed and I collected myself and examination, a little bit later in another office that did have windows.

SS: So, then you had AIDS, as far as you were concerned.

MP: Yeah, as far as they were concerned, and I went into a huge thing of – you've made a big mistake, you've mixed up my biopsy with someone else's – denial, you know?

SS: So, what happened after that, in your life?

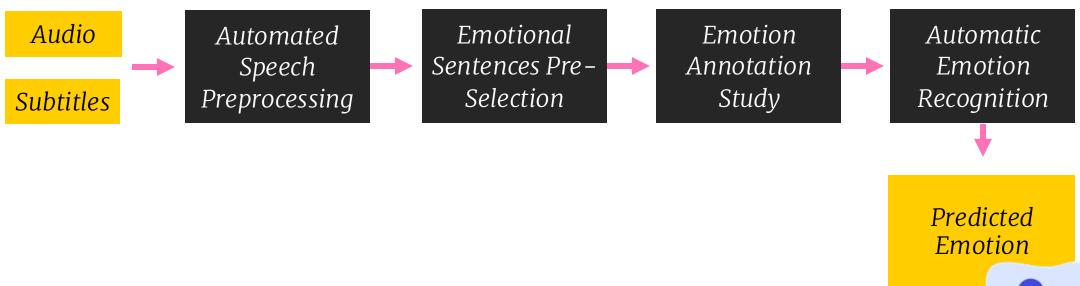
MP: I calmed down and N. Patrick Hennessey tells me, I've got about six months to a year, and that I have to very quickly go to the Gay Men's Health Crisis. I've got to interrupt myself at this point, because I remember a few years prior – one thing that





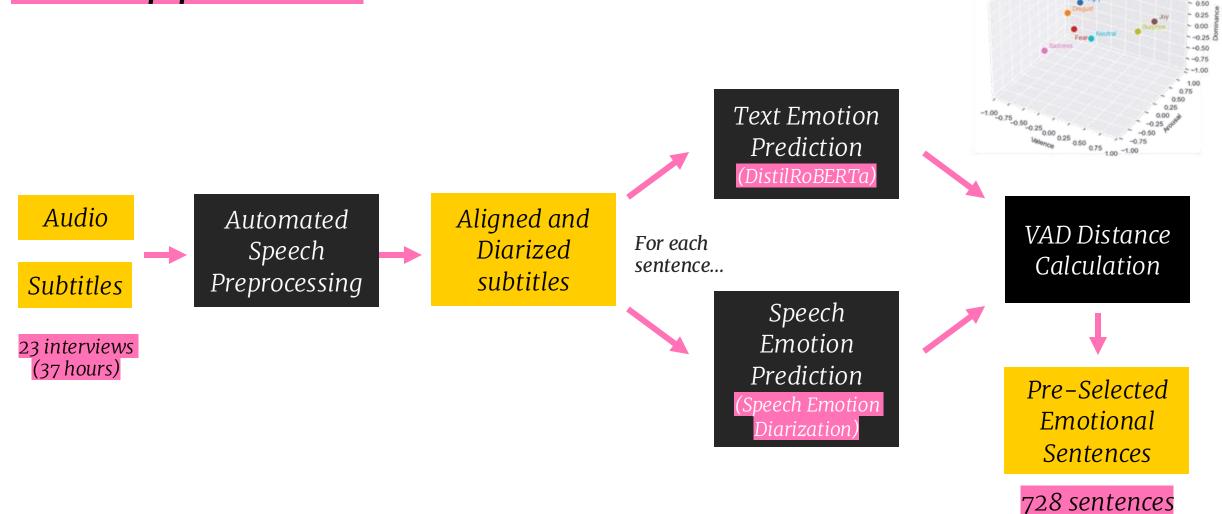
Our approach – Overview







Our approach – Sentence Pre-Selection





Our approach – Sentence Pre-Selection



Neutral

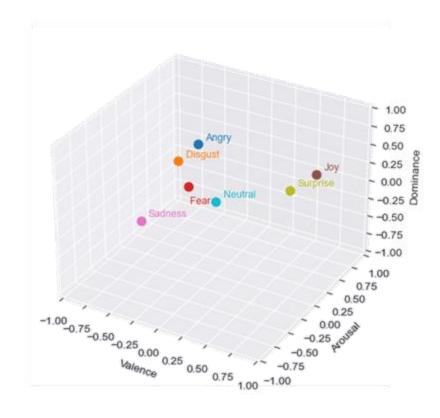
Нарру

5 sec

10 Sec

Well, my grandmother gets all upset and says, you know, "Oh, this is some Mafia-controlled baby beauty contest!".

Anger



 $distance(\frac{paralinguistics}{paralinguistics}) =$

 $distance(\frac{neutral}{neutral}, \frac{anger}{neutral} + distance(\frac{happy}{neutral}, \frac{t_{happy}}{neutral}) * t_{happy}$



Our approach – Emotion Annotation Study (Trial 1)

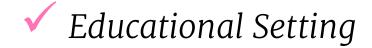


Speech Emotion
Annotation

"The whole art world, the trajectory of the art world, the marketplace, everything, it was frightening."

Text Emotion
Annotation

"Combination of anger and sadness but overall just blehhhh" (paralinguistics)



- ✓ 32 annotators
- √ 3 to 4 annotators per sentence (per modality)
- Annotations based on common sense

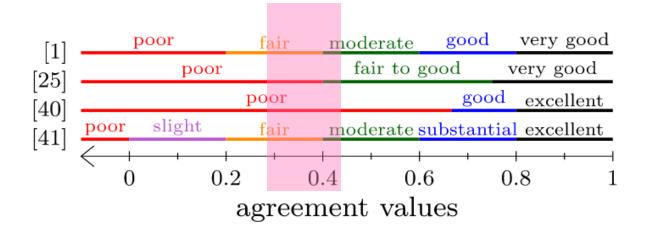
Emotions: 6 Ekman basic emotions (happy, sad, angry, fear, disgust, surprise) + neutral



Our approach – Emotion Annotation Study (Trial 1)

Krippendorff's alpha:

- Linguistics: 0.42
- Paralinguistics: 0.31



Challenge #1: There are different interpretations for the Krippendorff's alpha making it challenging to interpret results consistently



Our approach – Emotion Annotation Study

Let's consider that "qood" corresponds to κ or $\alpha > 0.67$.

J Multimodal User Interfaces (2014) 8:17-28 DOI 10.1007/s12193-013-0129-9

ORIGINAL PAPER

Inter-rater reliability for emotion ann interaction: comparison and methodo

A Multimodal, Multilabel Approach to Recognize **Emotions in Oral History Interviews**

Anargh Viswanath*, Michael Gref[†], Teena Hassan[‡] and Christoph Schmidt[§] *Digital Linguistics Lab Rielefeld University Rielefeld Germany

Ingo Siegert · Ronald Böck

Table 6 Overview and the IRR for the 405

Challenge 2: Subjective annotation tasks are difficult!

	Interaction type	1V10
Set 1	Random	Au
Set 2		Vio
Set 3		Au

Categories: sadness, helpless joy, surprise, confusion, ange emotion.

Emotions	Fleiss' Kappa $(\kappa)\uparrow$
Happy	0.49
Sad	0.44
Anger	0.31
Surprise	0.10
Disgust	0.30
Fear	0.33

Emotions	HdG		CMU-MOSEAS	
	AUC	balAcc	AUC	balAcc
Happy	0.78	0.72	0.70	0.66
Sad	0.63	0.61	0.74	0.68
Anger	0.76	0.72	0.80	0.77
Surprise	0.81	0.75	0.60	0.59
Disgust	0.77	0.74	0.66	0.64
Fear	0.67	0.64	0.64	0.62
Overall*	0.74	0.70	0.69	0.66

^{*}Mean average of all six emotions

Mess! ork for Building **iotated Corpus**

lercq, Veronique Hoste

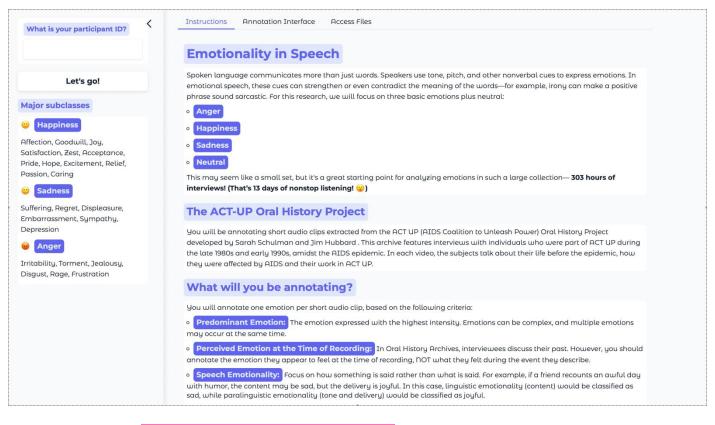
Ghent University lgium te}@ugent.be

		1	
	iess	0,315	
Optimism		0,438	
Pity		0,597	
Pride		0,524	
Rejection		0,357	
Relief		nan	
Remorse		0,602	
Sadness		0,678	
Suffering		0,442	
Surprise		0,079	
Torment		0,01	

emotion category.



Our approach – Emotion Annotation Study (Trial 2)



- Online Setting
- √ 18 annotators



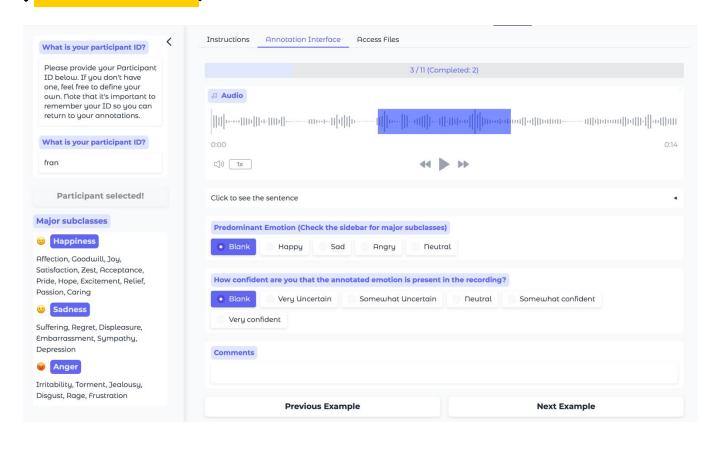
- 2 annotators per sentence
- Context before and after the target sentence
- Extensive instructions

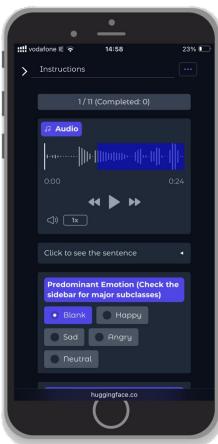
Emotions: happy, sad, angry and neutral

Open-source annotation tool developed for Trial 2



Our approach – Emotion Annotation Study (Trial 2)





Try it out!





Our approach – Emotion Annotation Study (Trial 2)

Participants' Annotations

Emotions

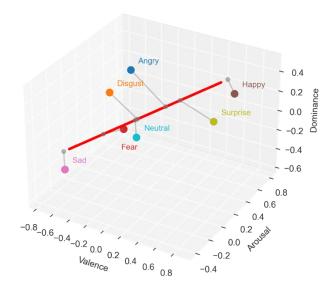
Happy, Sad, Angry, Neutral

Confidence

Very uncertain → Very confident Nominal Krippendorff's α

Proposed Weighted (Ordinal) Krippendorff's α

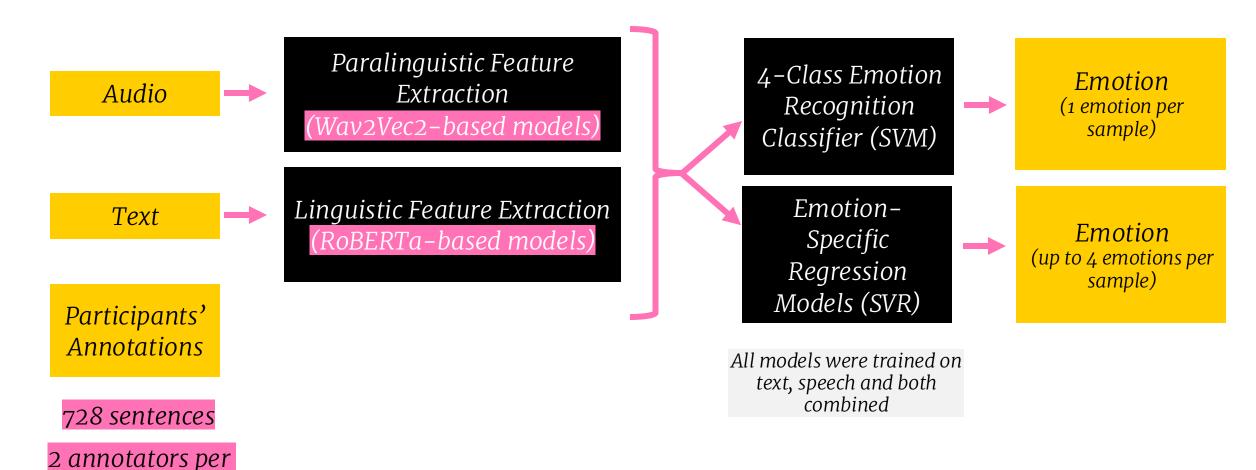
Correlation between confidence and agreement



Visualization of emotion coordinates in the VAD space with the 1st PCA direction.



Our approach – Emotion Recognition





sample

Our approach – Emotion Recognition





Annotator 1

I am <mark>very confident sadness</mark> is present in this example.

"And I felt scared, you know, because even inside the city hall, they're gunning us down."

I am somewhat uncertain happiness is present in this example.

"The high pitch in the word "scared" makes me feel like he's happy saying it, which is why I used "happy" — it sounds like he's relieved while saying it."





Our approach – Emotion Recognition

4-Class Emotion Recognition Classifier

Sample 1.1



Audio

Sad

Sample 1.2



Audio

Нарру

Each annotation is seen as an independent sample for both training and testing.

4 Emotion-Specific Regression Models

Sample 1 (Happy, Sad, Angry, Neutral)



(1, 1, 0, 0) or weighted for confidence (2, 5, 0, 0)

Annotations are combined into a single ground truth label.

The threshold for emotion binarization defined iteratively during cross-validation.



Insights – Emotion Annotation Study

Participants'
Annotations

Nominal α

Nominal α (Trial 2) \approx 0.30 Ordinal α (Trial 2) \approx 0.40

Emotions

Happy, Sad, Angry, Neutral Ordinal α

Trial 2 has a lower stardard deviation for α , suggesting more consistent agreement across annotator pairs.

Confidence

Very uncertain → Very confident confidence vs agreement Confidence positively correlated with agreement (r = 0.20, p < 1e-14)



Insights – Emotion Recognition

4-Class Emotion
Recognition
Classifier

EmotionSpecific
Regression
Models

Emotion
(1 emotion per sample)

Emotion(up to 4 emotions per sample)

Speech > Text for emotion recognition

Best model: F1 ≈ 0.66 (emotion-specific regression, paralinguistic modality)

Comparable to state-of-the-art for emotion prediction in Oral History
Archives

All models were trained on text, speech and both combined



Conclusion and Future Work

Tools show strong potential for analyzing emotion in OHA

Towards listening at scale: new ways to engage archives

Next: deep learning for ambiguity + full ACT UP archive





Sharing science, shaping tomorrow

Contact:

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GitHub:

github.com/franciscapessanha/ emotion-annotation-with-gradio

