

Disagreement Detection

Milestone 1

Connor Capitolo, Max Li, Morris Reeves, Jiahui Tang



Harvard John A. Paulson
School of Engineering
and Applied Sciences



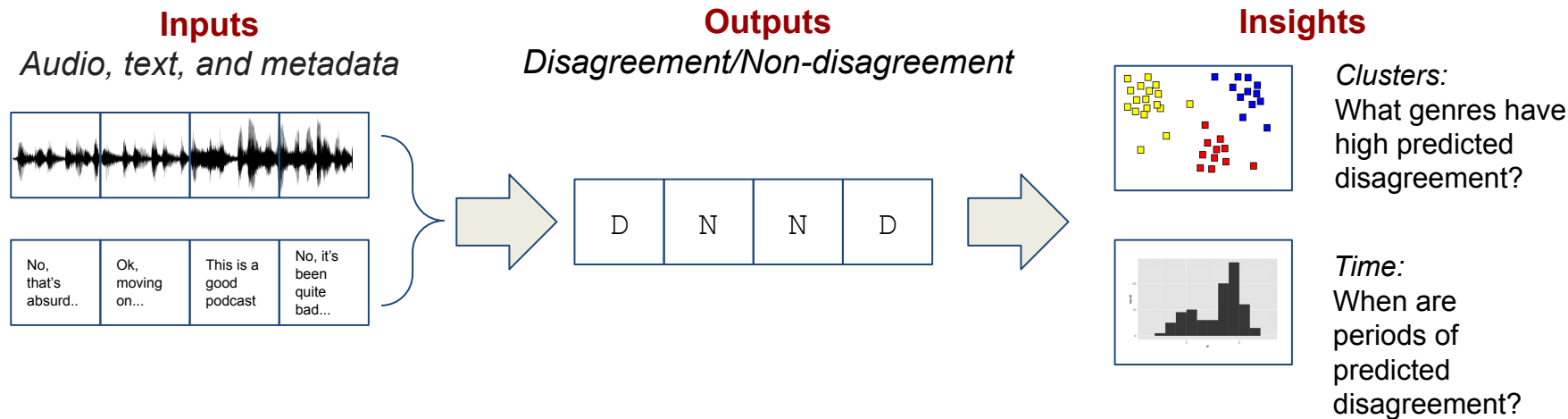
Overview

- Problem statement and scope of work
- Infrastructure and annotation progress
- Literature review and current ideas
- EDA:
 - Metadata
 - Audio
 - Text
- Next Steps
- Q&A



What are we trying to achieve?

Generate insights about disagreement based on Spotify podcast data



Why is disagreement detection in podcasts important & interesting?



- **Higher Retention**
- Improved Recommender
- Expand platform ecosystem



- **Better User Experience**
 - Tailored recommendations



podcast

- **Drive audience traffic + loyalty**
- Improve style or moderation



Infrastructure

Communication



Data/Code Storage



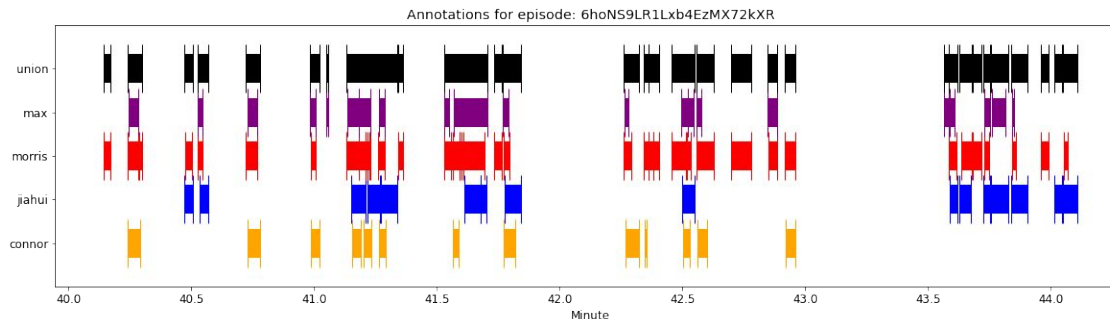
Packages



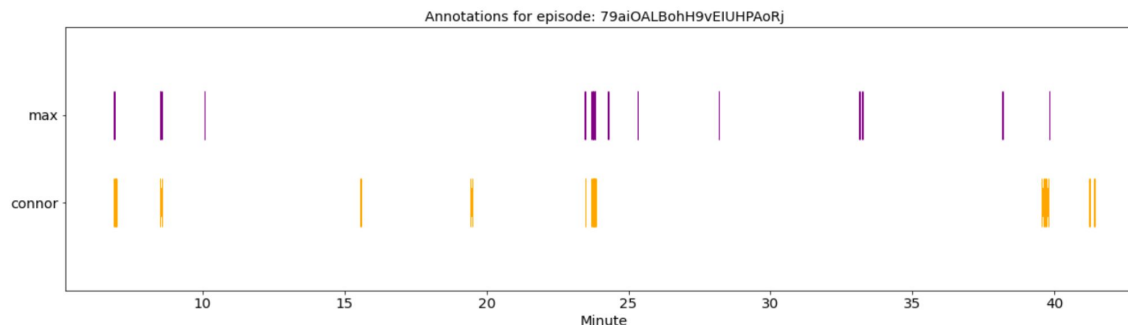
Annotation progress

- Working definition of disagreement: a speaker is **directly applying a contradiction or rejection** of another person's idea where it is **immediately perceptible** by the listener

Dog clip



Full episode



Literature

2. Primarily utterance-based granularity

	Xu et al. (2019)	Gokcen and de Marneffe (2015)	Wang and Cardie (2014)	Wang et al. (2011)	Hillard et al. (2003)
Disagreement definition or focus	Independent, differing stance-bearing utterances	Quote-response pairs; polarity or modality mismatch	Utterance or turn; "user's attitude"	Utterance; speaker rejects proposition by a first speaker	Spurt (no pauses > 0.5 second); audio and text-based cues
Model class	"RCN" (Reason Comparing Network): NN	Logistic regression (max entropy model, Stanford CoreNLP)	Isotonic CRF	Linear-chain CRF	Decision tree classifier
Features	Utterance pair (P, Q) Topic T	N-grams, speech acts, typed dependencies, etc.	Dependency relations, TFIDF, n-grams, etc.	Lexical features, prosodic features (pause, duration, speech rate, pitch)	Word-based features, prosodic features (pause, fundamental frequency (F0), etc.)
Performance	~0.58-0.73 macro F1	0.76 F1	0.51 F1	0.56 F1	0.53 - 0.58 Recall
Data	Text: tweets (SemEval-2016, stance labels)	Text: forum (Internet Argument corpus)	Text: forum (Wikipedia Discussions corpus)	Transcript + audio (Broadcast Conversations)	Transcript + audio (ICSI Meeting transcript corpus)

3. Performance is ~0.5 to 0.75 F1

1. Primarily text-based or highly structured data

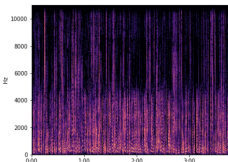


Harvard John A. Paulson
School of Engineering
and Applied Sciences

Project ideas

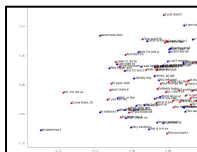
Current presentation

Audio featurization



- Prosodic features (e.g. pause, pitch, amplitude)
- Diarization

Transcript featurization

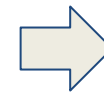


- Token-based embeddings
- Contextualized embeddings

Supervised modeling

Baseline

- Logistic regression

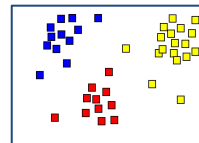


Sequential models

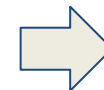
- RNN

Unsupervised modeling

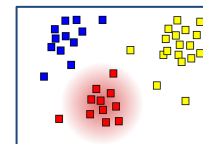
Audio + transcript clustering



- Join on timestamp
- Diarization-based segments



Similarity-based classification



- Based on distance to annotated disagreement examples



Metadata - Overview

105,360 episodes, 18,360 shows

- ~ 50k hours of audio
- > 600M words
- Jan 1, 2019 to March 1, 2020
- English language specific
- Professional + amateur creators

metadata



episode_title, author, category,
subcategory, show_name,
show_description, publisher, language,
episode_name,
episode_description,
duration

text
13GB



timestamp, speakers

audio
2TB



raw audio file

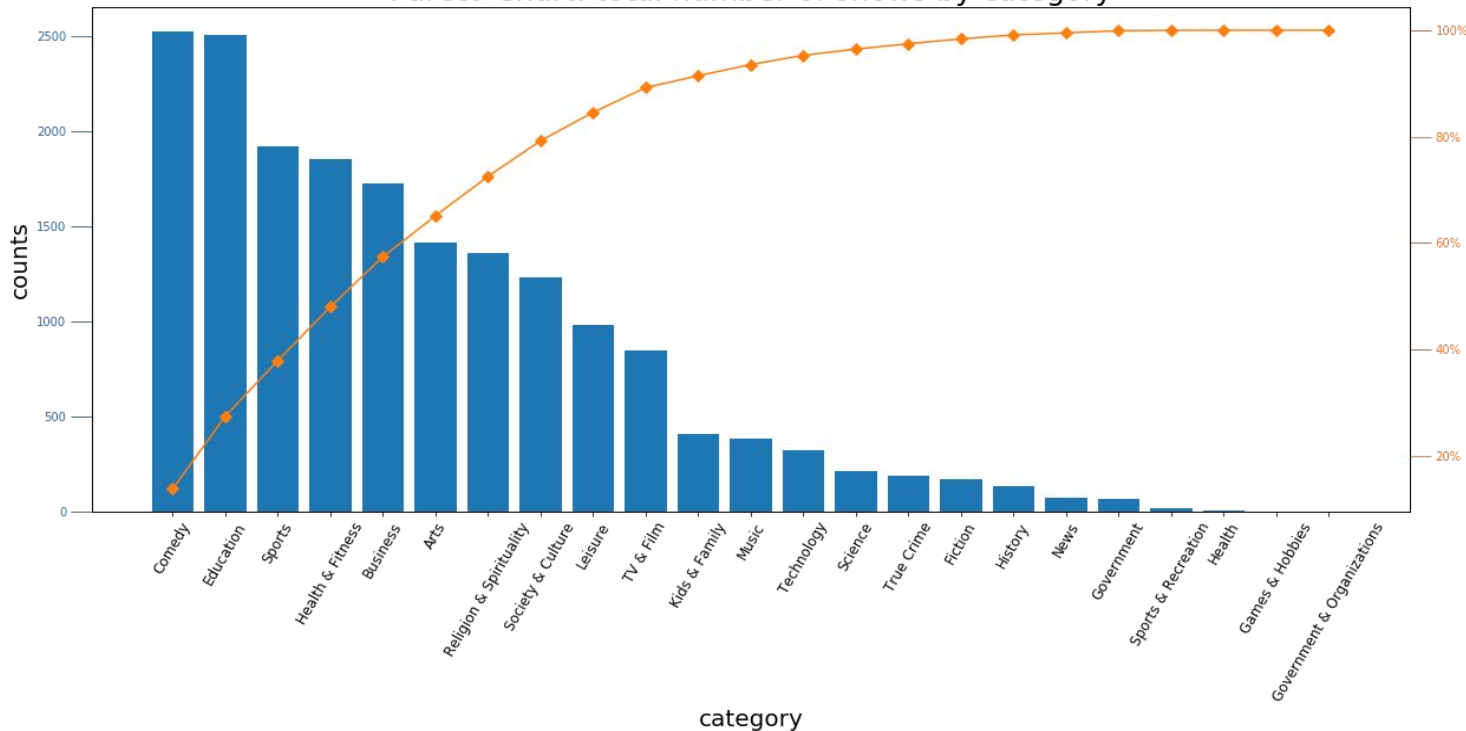
Dataset statistics

	min	average	max
minutes	<1	31.6	305.0
words	11	5,728	43,504

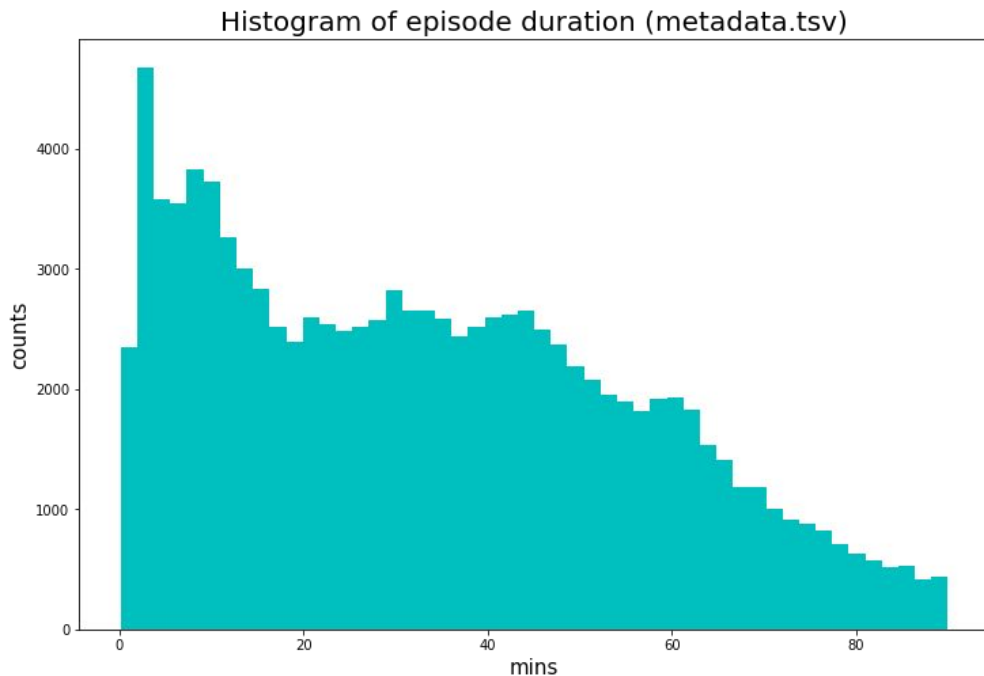


Metadata - genre

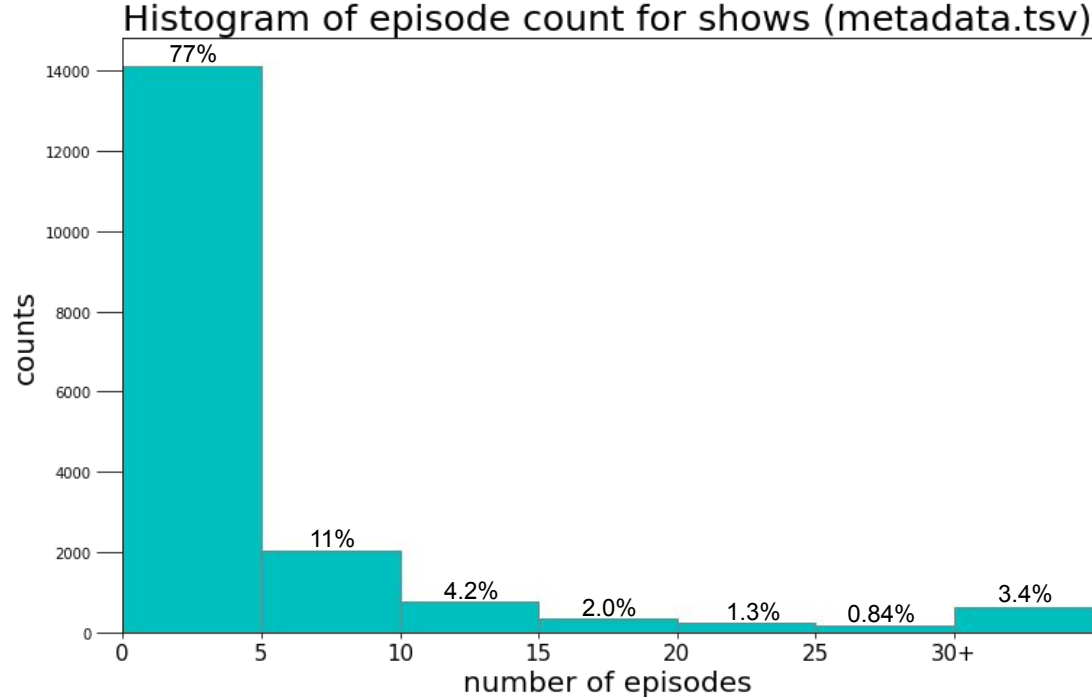
Pareto Chart: total number of shows by category



Metadata - episode duration

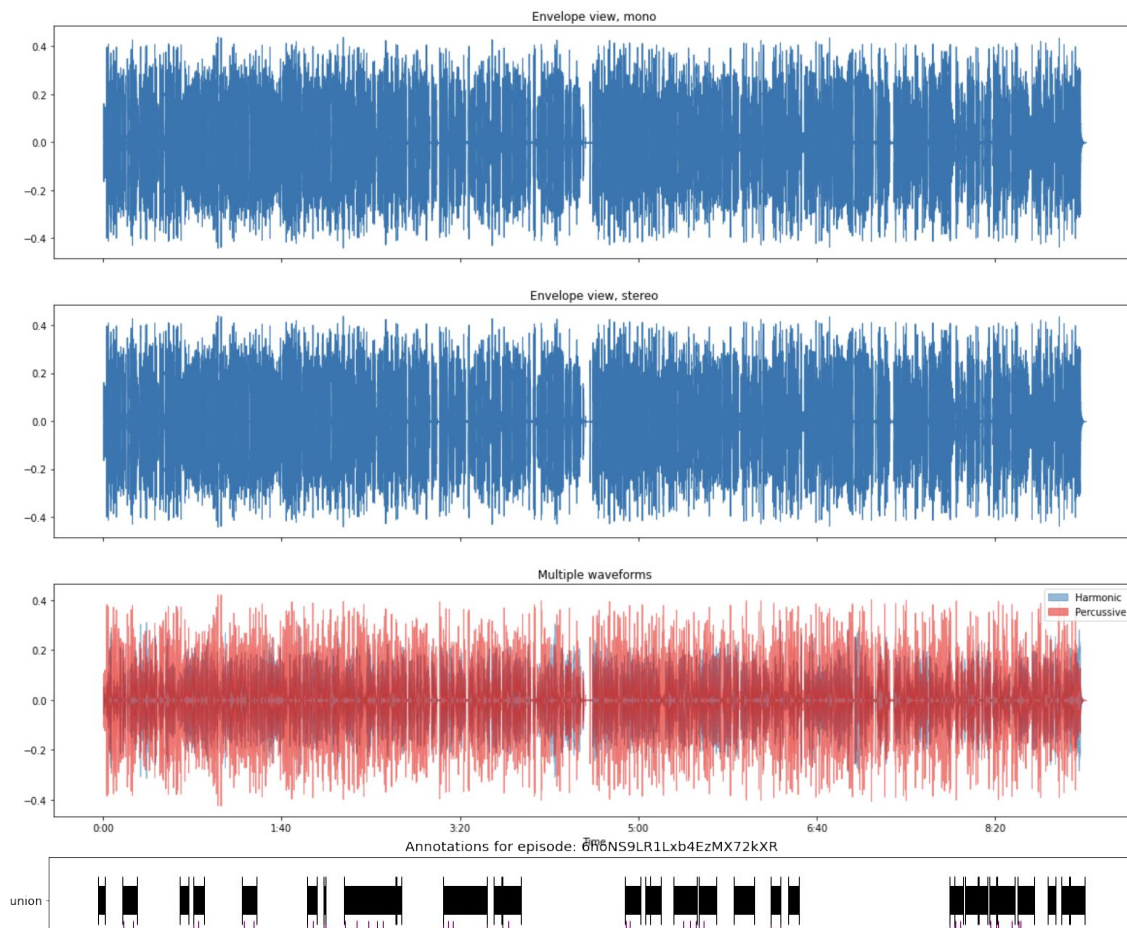


Metadata - number of episodes per show



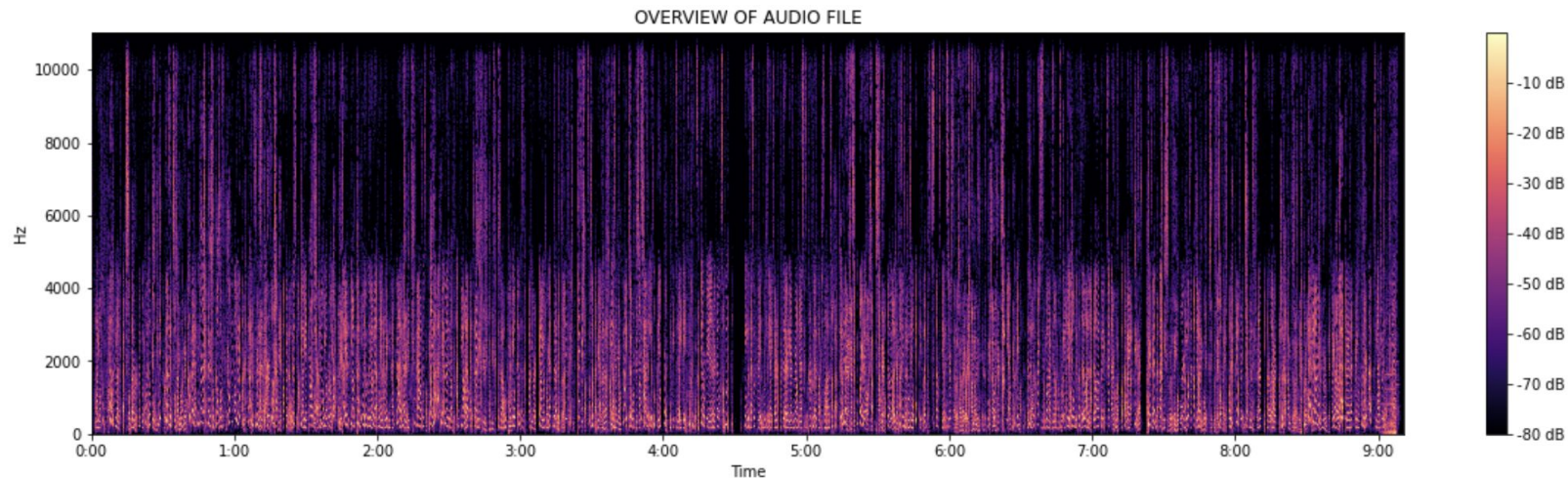
Audio - Librosa

- Librosa is a Python package for **music and audio** analysis.
- For **single annotated episode**
 - ~10min Annotated Episode w.r.t Dog
- WaveForm (amplitude envelope)
 - Monophonic
 - Stereo
 - Harmonic + Percussive Components



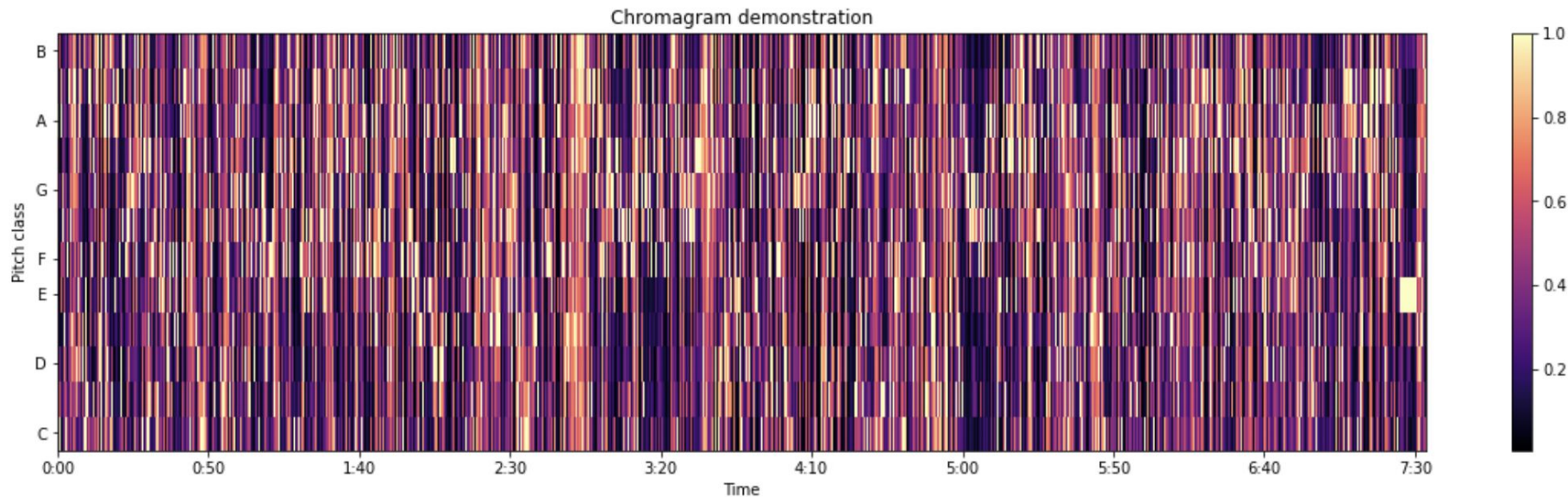
Spectrogram (Frequency)

It uses Short-time Fourier transform (STFT) to calculate signals in the **time-frequency(Hertz)** by computing discrete Fourier transforms over short overlapping windows



Chroma Plot (Pitch Class)

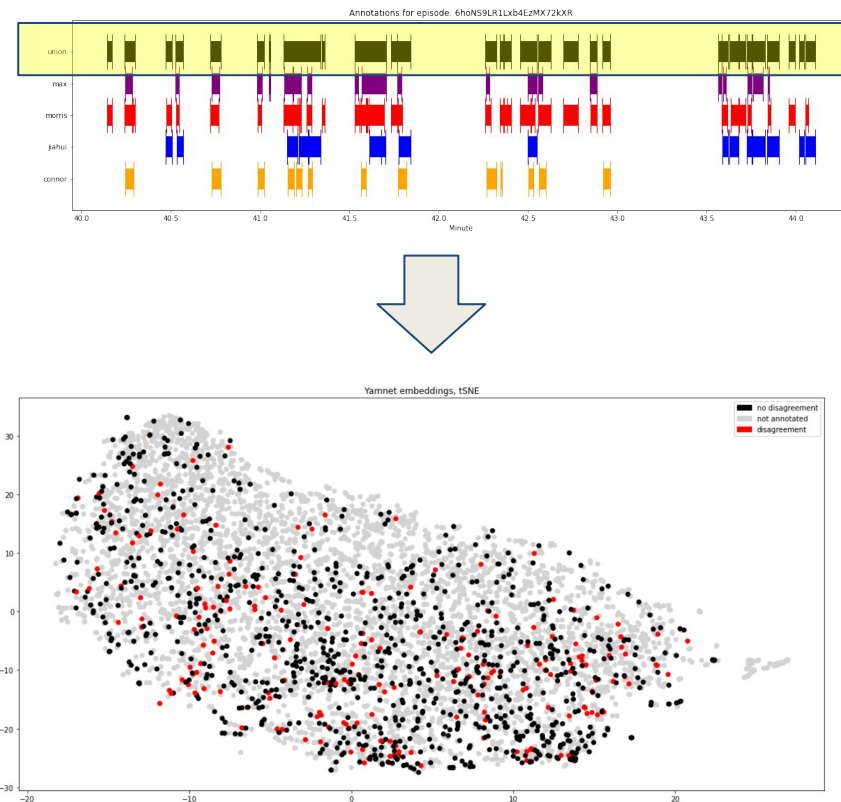
Chroma Plot gives information about Pitch Class Profile and its intensity, which is a powerful tool for analyzing music whose pitches can be meaningfully categorized



Audio - YAMNet

For single annotated episode...

- **Unioned** the disagreement annotations
- **YAMNet** - deep net that predicts 521 audio event classes (trained on AudioSet-YouTube corpus)
 - Mobilenet_v1 architecture
- Retrieved **Yamnet embedding** for episode:
 - Embeddings: 0.48 sec chunks, embedding dimension 1024
- Plotted tSNE of Yamnet embeddings vs. disagreement annotations



Text EDA Overview

- Creation of `Transcript` and `WordEmbeddingVectorizer` classes
 - Streamlined parsing of .json transcripts by using class instances
 - Allows flexibility in future swapping of text vectorization or episode discretization

```
gnews_vectorizer = WordEmbeddingVectorizer(embedding_dict = gnews_dict,  
                                           embedding_dim = 300,  
                                           lemmatize = False, remove_stopwords = True, n_token_filter = 10)
```

```
TRANSCRIPT_DIRECTORY = '../podcasts-no-audio-13GB/spotify-podcasts-2020/podcasts-transcripts/'  
EXAMPLE_JSON_FILEPATH = TRANSCRIPT_DIRECTORY + '4/9/show_49NxrBHUtto19pgLNAJkHY/6hoNS9LR1Lxb4EzMX72kXR.json'
```

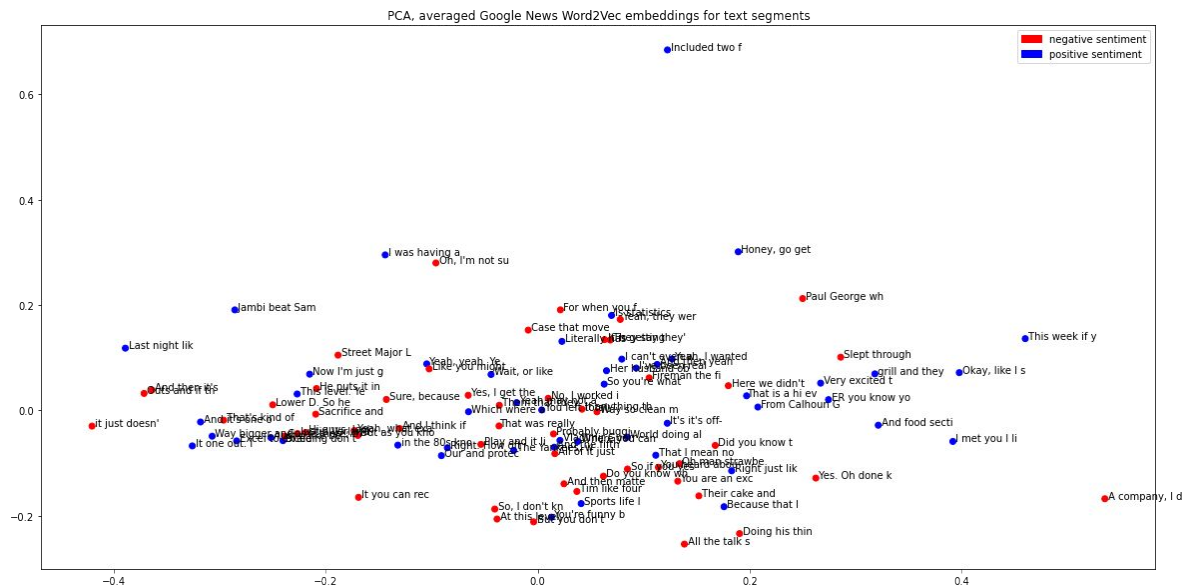
```
example_transcript = Transcript(EXAMPLE_JSON_FILEPATH, gnews_vectorizer, segment_definition = 'default')  
example_transcript.set_segment_vectors(gnews_vectorizer)  
example_transcript.set_sentiments(classifier)
```

- EDA:
 - Pretrained sentiment models on segments
 - Averaged (fixed) word embeddings



Text EDA: Sentiment

- Averaged word vectors vs. sentiment
- Exploration 1: **Sentiment and word embeddings** (for single podcast episode)



Text EDA: Baseline Model

- Baseline cosine similarity model for disagreement detection:
- Implemented as method of `Transcript` class

Cosine similarity threshold

```
example_transcript.get_disagreement_cosine("No, I completely disagree with you.", 0.7)
```

(array([" Doing his thing. There were Michael Jordan was just coming up there weren't there weren't many things to do that. You actually went and played outside. It was yeah, it was a different time. I feel like if people like it now of kids like i t now is because they play Big play the score I think so not there's not a lot of or you know their families obsessed with i t, you know, I don't know. **No, I think that's I think that's true.** But I think the biggest problem that baseball has is that they don't have a villain because I think every I mean you have",

" If anything that is like not slightly Gary, you know that I'm right they keep a dog in this little tiny ass apartm ent. They **never take it for walks** because they're alone and can't find a boyfriend. It's not the dog's fault. You're a fucki ng loser. **That is not first of all,** are you are you saying? That's what I am. No, you're just laughing because he knows it's true. No, it's just the most ridiculous tape.",

" You are an exception. Most people get animals for selfish reasons. It's not an exception though. I'm just an avera ge normal person. Like I'm not an exceptionally not. Oh my gosh. I'm talking you up, but you're talking other women down and **I totally disagree** with them not talking them Dad. I'm telling the truth. No, I don't think that just like first of all you do get a dog because you want company. That's the only that's why people like what everybody gets dogs.",

" Because that loud say what you're feeling is **there's two of us.** Yes, but when there was just one of us, which ther e was for many years of his life right out of his mind. **Oh get over yourself.** I love that. You think that you just add so mu ch. I like that. You just can never admit that I'm right because that's not right you there's parts of it that truth is yo u're the one that own the dog so you don't want to see the other side. I said, I don't want to see what I've seen definitely got a dog because I wanted",

" Did you know that happened? I heard that yeah, that's your to 2019 Mets season in a nutshell can wean you put peop le in the memoriam who are totally alive since I know I've how do you screw that up? That is eight easy Google search on bas eball-reference very very simple. I mean, obviously we know if we know anything about the Mets is that they don't do their r esearch. No, it's my clearly when it comes to scouting or",

```
dtype='<U642'),  
array([[ 539.8,  569.6],  
       [2443.4, 2471.1],  
       [2532.2, 2560.9],  
       [2604.8, 2634. ],  
       [2716.2, 2743.9]]),  
array([0.70385551, 0.70334772, 0.72889266, 0.70259684, 0.70927119]))
```

[Start, end]
timestamps

Cosine similarity
scores



Next steps

- Text-audio data join
 - Clustering on combination of text and audio features
- Smarter discretization of transcript and audio
 - e.g. pyannotate-audio diarization
- Scaling up to audio corpus and text corpus
 - Active learning
- Further disagreement annotations and refinement
- Baseline model and evaluation





Harvard John A. Paulson
School of Engineering
and Applied Sciences

WHERE
SCIENCE
AND
ENGINEERING
CONVERGE

Q&A



Harvard John A. Paulson
School of Engineering
and Applied Sciences

WHERE
SCIENCE
AND
ENGINEERING
CONVERGE

Thank You