Emotion Centric Content Classification

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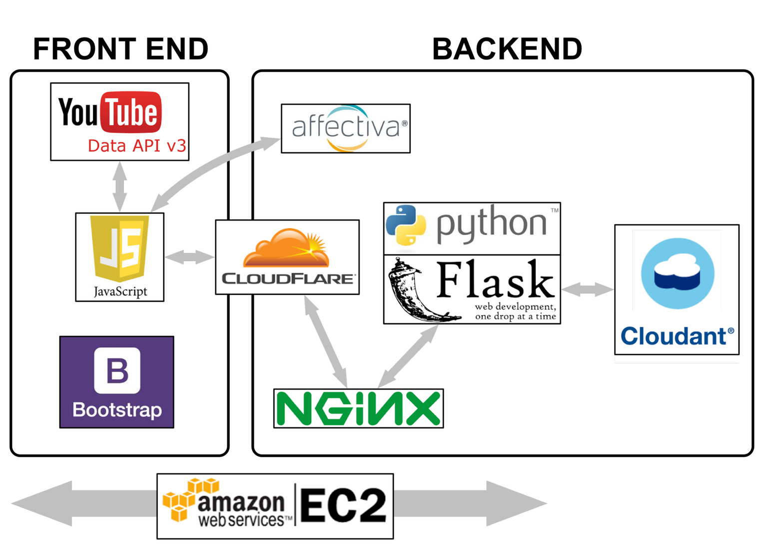
Introduction

Most recommendation systems fail to utilize the emotional response users have in relation to various pieces of content. These systems either assume content has an inherent emotional state independent of whoever is viewing it, or simply classify content in relation to clusters of users. These approaches fail to recognize the unique emotional relationships between users and content.

Figure 1 TrumpCat: Eliciting a variety of emotions

Architecture

We sought to further research into the classification of content along a emotional dimension by building a graph database consisting of user and content nodes, and edges capturing the emotional relationship. To accomplish this we setup a solution to capture data from users that was built using a variety of industry standard packages. Of particular note is the utilization of a cutting edge third party emotion detection API that allowed emotion classification of users facial expressions. This emotion classification data is aggregated every 5 seconds and posted to our NoSQL database (excluding images).



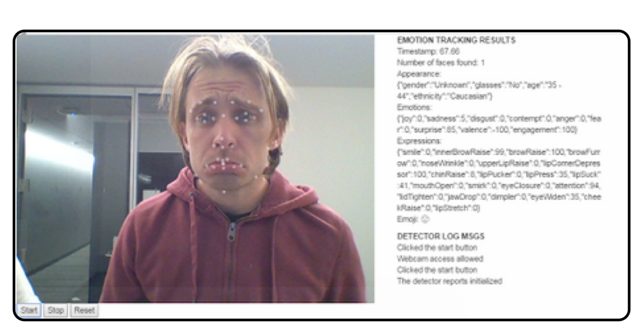


Figure 2a. Solution Architect

Figure 2b. Sample Response From Affectiva API

User Experience and Algorithm Design

A challenge of this project was designing a recommendation algorithm based on user data when we are actively designing the user interface and thus the data we are able to collect. We sought to balance complexity, users experience, and data quality. For example we recommend the top six videos to a user and in doing so we strike a balance between active learning and an engaging user experience.

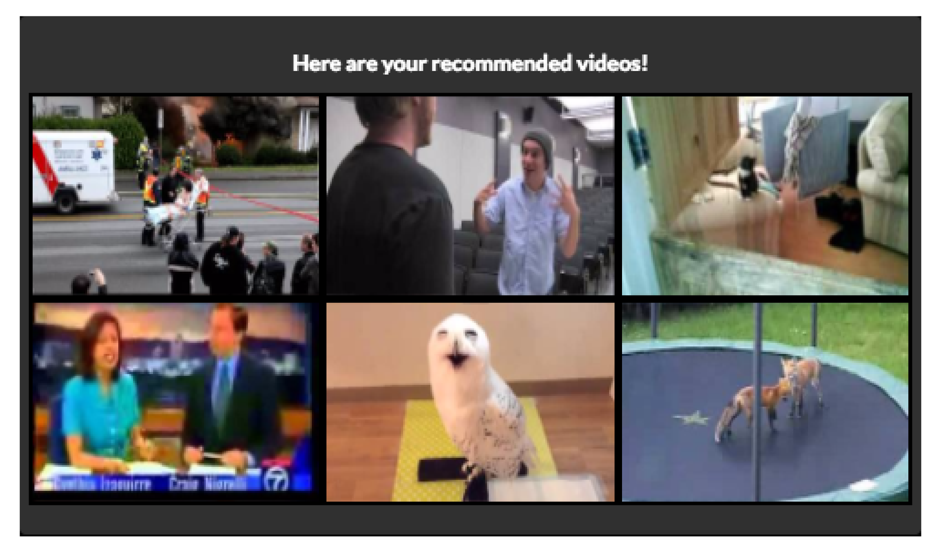


Figure 3 User Recommendation Selection Box

Impact Analysis

By intelligently choosing which content to show a given user(s) we can drastically cut down on the amount of data required to build an accurate model. Because the data we get back from Affectiva is so rich our "target emotional response" is undefined. We chose to implement an active learning strategy called impact analysis which is ambivalent to the choice of the optimization target or algorithm.

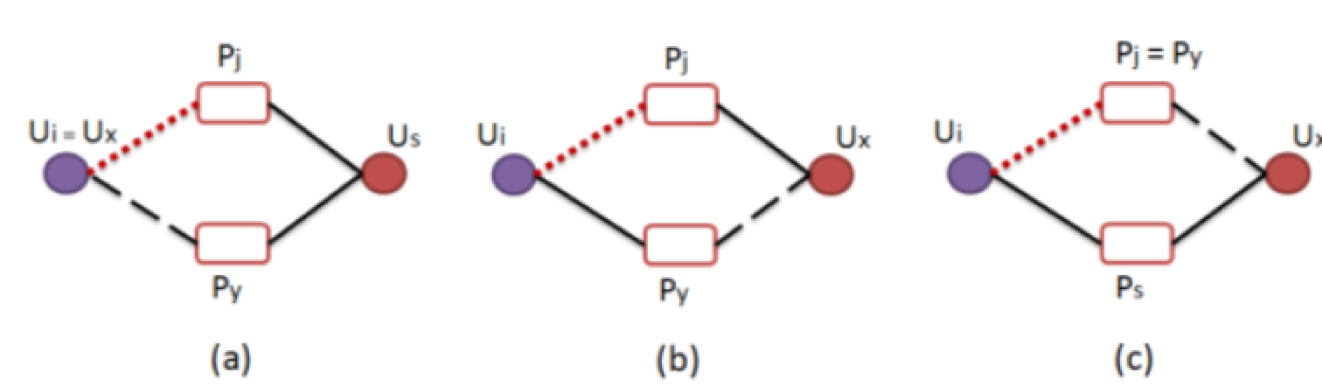


Figure 4 Four-node path

The key insight behind the algorithm is that in order to make a recommendation for a user there must be a four-node path that goes through the user in question (Figure 4). The more of these four-node paths there are the more accurate recommendations you will be able to make.

This strategy naturally lead to a diverse set of user-item pairs that will allow us to make useful predictions regardless of the choice of the target function.

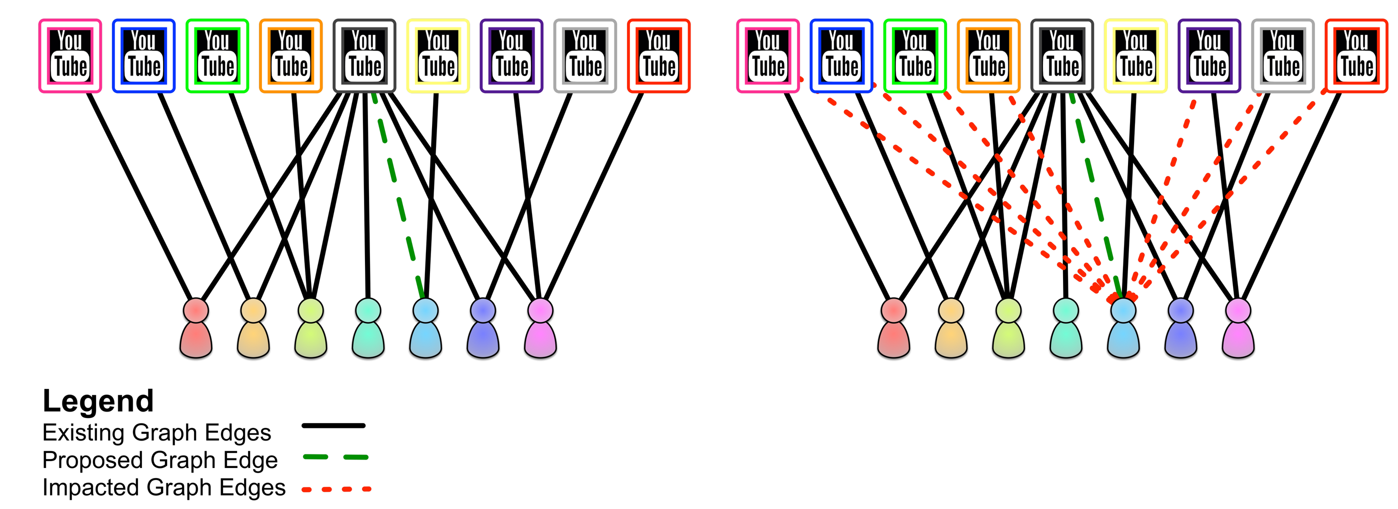
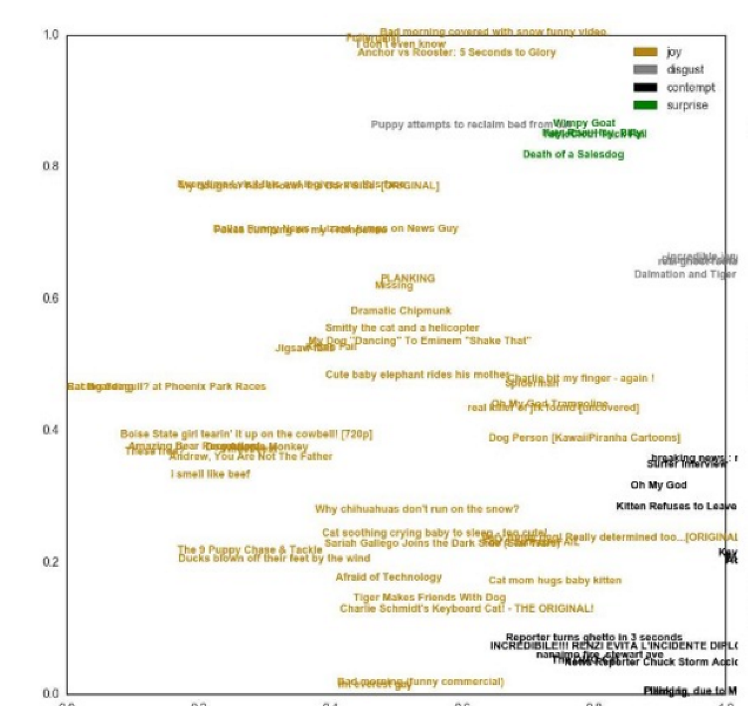


Figure 5. Bipartite User-Video Graph

Results

We are able to create general categories of videos in terms of the (most common) emotions they elicit as well as analyze the variation amongst each of the viewers across individual videos.



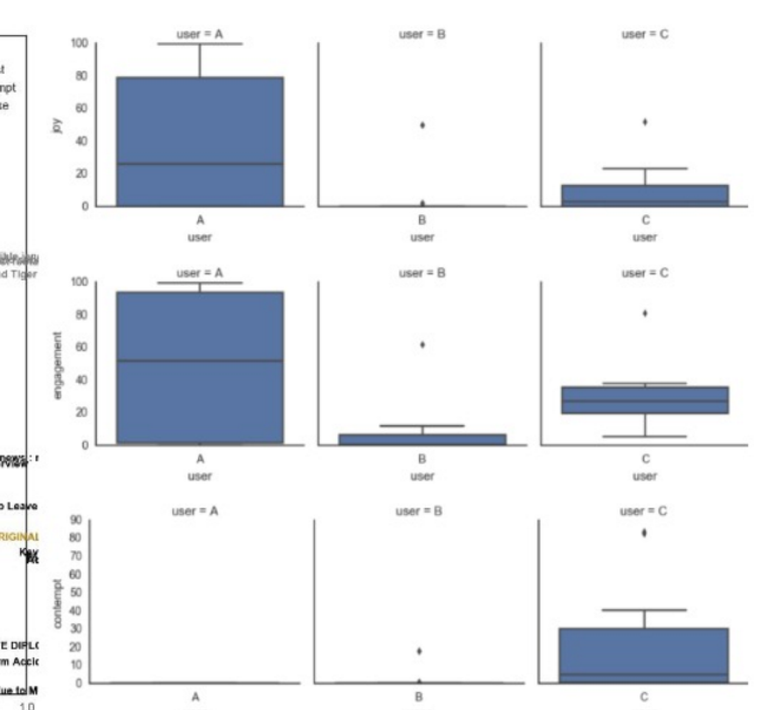


Figure 6a. Video Classification

Figure 6b. Diverse User Reaction so a Single Piece of Content

Future Work

- Users Contribute to Content
- User picks what emotions they want to feel
- Diversify content (text, audio)
- Connect to social media
- See how friends reacted to the same content