Promoting Reading Among Teens: Analyzing the Emotional Preferences of Teenage Readers

Joey Sherrill

Dennis Ng

Computer Science Department
Brigham Young University

sherr13@byu.edu

ng@compsci.byu.edu

1. Abstract

Reading is an invaluable skill for teenagers, with the National Institute of Child Health and Human Development (NICHD) claiming: "Reading is the single most important skill necessary for a happy, productive, and successful life." However, there is difficulty searching through large quantities of books trying to find one that is interesting and appealing enough to read. Depending on existing book recommender systems is not an answer to the problem, since most existing book recommender systems rely on previous reading data, reviews, or web traffic, but much of this data can be difficult or illegal to access for teenagers due to laws that protect the privacy of minors. Instead, we propose a novel technique of analyzing the emotional contents of a book and using them to compare the similarity of books and predict the likelihood a user will enjoy it based on their age. By using the NRC Emotion Intensity Lexicon (NRC-EIL), we construct an emotion vector that represents the book's ratio of emotions based on its description. By utilizing trends apparent in age groups regarding emotional preferences, we can create a recommender system to recommend books with relevant, age-appropriate emotional compositions and focuses. We further explore how to improve the accuracy of determining a book's emotions by analyzing the synonyms of non-emotional words as well as the different preferences of different age groups of teenagers, namely that 12-13 year olds prefer Joy and Surprise and dislike Sadness, Fear, and Anger, while older teenagers exhibit the opposite trend. We have also discovered that high-rated books were significantly different from low-rated books in terms of emotion composition across all age groups.

Keywords: Emotion Vector, Sentiment Analysis, preferences, books

2. Introduction

Reading is both an entertaining and educational hobby. There are many benefits for teenagers in reading books, including enhanced academic performance, social engagement and personal development (Howard, 2011; Garan, 2008), and enjoying the book one is reading is critical for getting the full benefits and being encouraged to read more (Wilhelm, 2016). Thus, creating a book recommender system for teenagers is very important to help them develop these skills. Most current book recommender systems are based solely on a user's former reading habits, perhaps including a small number of ratings or reviews (Alharthi 2018). However, this is very little data to work with, the data can be difficult to access in the first place, especially for minors, and determining how similar two books are to each other is also nontrivial. We also want to be able to recommend books for a reader with no knowledge of their reading background, basing our recommendations solely off of their age. There are trends among age groups in their reading preferences (Sturm, 2003). By more clearly defining and understanding what each age group is interested in reading, we can better inform and assist librarians, parents, teachers, and teen readers themselves in finding appealing and interesting books to read. The approach we consider in solving these problems is the creation of an emotion vector to represent the sentiment of a book.

The emotion vector measures eight emotions, which are the emotions included in the NRC-EIL based on the conclusions of past research defining them as elementary emotions (Plutchik, 1980; Mohammad, 2010). These eight emotions are Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise, Trust, and a catch-all ninth term Objective. The emotion vectors are constructed by analyzing a book's description, which we chose because it is much faster than analyzing the entire book while still containing enough information to accurately determine the emotional composition of a book. These vectors are created by using the NRC-EIL to assign each word in the book description with one or more of these emotions with varying intensity. If a word does not appear in the NRC-EIL, then we check if any synonyms appear in the NRC-EIL and substitute the synonym's values in place of the original word. If no synonyms are found in the NRC-EIL, then the word is assigned an Objective value of 1 (i.e. 100% Objective, 0% every other emotion). The emotion vector for a book description is the total sum of each of its word's emotion vectors, normalized to a unit vector.

Our work is heavily based on Batista (2020), who did a similar project working with children rather than teenagers. However, we have found that the preferences of teenagers are statistically significantly different from the preferences of children, and different age groups have noticeably different tastes in books' emotion vectors. Additionally, we also made several improvements over Batista's method, including the use of synset (see Section **4.5**) and a larger dataset.

3. Related Works

Several studies were found related to sentiment analysis specifically applied to books' contents, book reviews, and book descriptions (Srujan, 2018; Al-Smadi, 2015), however, none were found related to teenager's preferences in books in regard to emotion vectors or sentiment analysis. It is well known that children of different ages have different preferences in topics (Sturm, 2003), as well as different preferences in format (Kurata, 2017; Hussain, 2011; Milton 2020). However, our approach of analyzing the emotional contents of a book with a focus on teenagers is unique, as the most similar study to ours is Milton (2020), which focuses on children instead, and no other studies construct a similar emotion vector to ours.

There are a number of existing works on sentiment analysis. Kobayashi, Inui, and Matsumoto (2007) focus on extracting "opinion units" from user-written reviews. They define an opinion unit as a tuple containing an opinion holder, a subject, an aspect, and the evaluation. Their paper explores the methods for developing an algorithm to correctly parse these opinion units. However, opinion units only apply to part of our problem, that is, assessing the user's reviews to get a type of "target emotion vector," i.e. the user's preferred emotional composition of a book, to match to book descriptions. Kobayashi et al.'s work could be useful in extending our research and developing a book recommendation tool by combining the analysis of both user reviews and book descriptions. Kobayashi et. al based their algorithms on an already published software named BACT.

BACT was developed by Kudo & Matsumoto (2004) to improve upon "bag of word" models and better understand the meaning of semi-structured text, and to "automatically capture relevant structural information observed in text." It requires its input to be preformatted as an ordered tree. Unfortunately, BACT would not help quantify or classify book descriptions by using sentiment analysis because it is a machine learning tool that requires formatted input and test files. Even after training, it would likely still perform identically to the simple algorithm we used to prepare what would be BACT's test files, i.e. the emotion vectors constructed from a book's description.

Feldman (2013) and Liu (2010) are similar in their approach of separating sentences into "aspects." These aspects refer to parts of a product (i.e. a movie, book, comic, appliance, etc.) that the user had an opinion on. In the context of our project, an aspect of a book may be its characters, its pacing, or its humor. Again, these papers help with part of the problem, i.e. analyzing a user's review, but they are more focused on assessing a product's quality rather than calculating the emotional makeup of it.

Popescu and Etzioni (2005) describes a program they've developed known as OPINE, which analyzes the opinions that a user expresses about a given product based on the user's review of the product. Given a particular product and a corresponding set of reviews, OPINE outputs a set of product features, accompanied by a list of associated opinions, which are ranked based on the strength (how strongly the user feels about a feature) of each opinion. OPINE works in the opposite direction to BACT, so it determines the strengths of a product by compiling multiple user reviews. This could be useful in determining the strengths of a book (good characters, pacing, heartwarming ending, etc.) in addition to its emotional vector, but OPINE seems to not be open source, and Popescu and Etzioni do not indicate where the source code is archived, so we unfortunately cannot use it for our project.

There are hundreds of papers dealing with book recommendations, though none of them have the same approach as us. Milton et. al (2020) uses the NRC-EIL, among other methods, to determine trends in the enjoyability of a book for children. We explore this method in more depth and determine statistically significant differences between teenagers' age groups and their preferred books instead.

4. Our Emotion Trait Analysis Approach

The goal of analyzing a book's emotional composition from its description is to gauge the emotional contents of a book. We then analyze the trends apparent in books' emotional compositions to determine what types of books teenagers of different ages prefer. We can analyze a book's description by summing the emotion values of each word in the description according to the NRC-EIL. This approach yields accurate results and allows us to examine evident trends among age groups. More details are explained below.

Our work is a continuation of Batista (2020), taking their work on children's book ratings and expanding the age group to teenagers. We also improve on their work by implementing the python library synset, which allows us to check the NRC-EIL with a word's synonyms too, allowing us to essentially expand the NRC-EIL, lowering the number of words marked as Objective and increasing the accuracy of the book's emotion vector.

4.1 Processing A Book Description

We start by retrieving a book's description. We remove all stop words from the description - stop words are words necessary for grammar but which provide no inherent information, like "the," "a," "for," etc. We determine if a word is a stop word by using a combination of three python libraries: spacy, sklearn, and nltk. We combine the three lists of stop words to ensure we remove as many superfluous words as possible. We also clean the description of any latent HTML tags or similar junk data, replacing all non-letters with a space; we only care about the meaningful, emotional text. For each word in a book description, we check first if the word in its base form is located in the NRC-EIL. If it is, we add that word's emotion values to the book's total vector. If not, we repeat the process with the word's base noun form (i.e. "bats" → "bat") then its base verb form (i.e. "ran" or "running" → "run") then finally we use synset to check the first two "senses" of a word, which are defined below.

Synset effectively defines words in terms of what "sense" it gives from different definitions of the word, with the most common senses being listed first. For example, the word "Republic" is not in the NRC-EIL. The first sense that synset provides for "Republic" is "democracy.n.02," so we check other words that have that sense. First is "democracy," which also does not appear in the NRC-EIL, so we go to the next word, "republic." Note that currently, "republic" gets checked twice, which could be a potential source for optimization. The next word is "commonwealth," which does appear in the NRC-EIL, so we use its value for republic. Since we have found a word in the NRC-EIL, we stop searching through synset and continue running through the description. There is rarely a case where a word has more than one sense and none of the words given by the first sense are not in the NRC-EIL.

This way, we ensure that we check the most relevant and most common meanings of a word, running through several synonyms of each sense, checking those synonyms in the NRC-EIL and applying the first one that we find. If none of these methods found a match in the NRC-EIL, then we count the word as having an Objective score of 1.

4.2 Calculating an Emotion Vector

The dataset that we worked with was retrieved from Goodreads, which hosts a large collection of books and allows users to give feedback on them. The dataset includes book descriptions, the average rating of the book, and the average age of its readers. Each book appears only once in the dataset, so we had to work with these average scores rather than individual reviews. For example, the first entry in our database is the book "The Notebook" by Nicholas Sparks. It has an average rating of 4.1 and an average reader age of 16.8. The first few lines of the description reads:

> A man with a faded, well-worn notebook open in his lap. A woman experiencing a morning ritual she doesn't understand. Until he begins to read to her. The Notebook is an achingly tender story...

After removing the stop words, grammar, punctuation, and capitalization, we are left with the following list of words:

> man faded worn notebook open lap woman experiencing morning ritual understand begins read notebook achingly tender story...

By summing the emotion vectors of these words, along with the other words left in the description that are not listed above, we get the emotion vector for this book, shown below in Figure 1A. This is one of the emotion vectors that contributes to the average vector for very good (see section **4.4** for details on rating) books for 16-17 year olds, shown in Figure 1B.

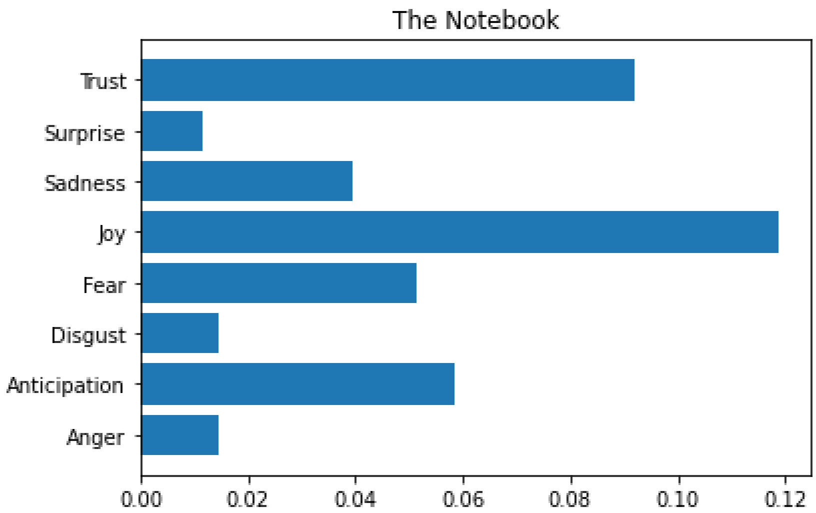

Figure 1A: the emotion vector of "The Notebook" by Nicholas Sparks

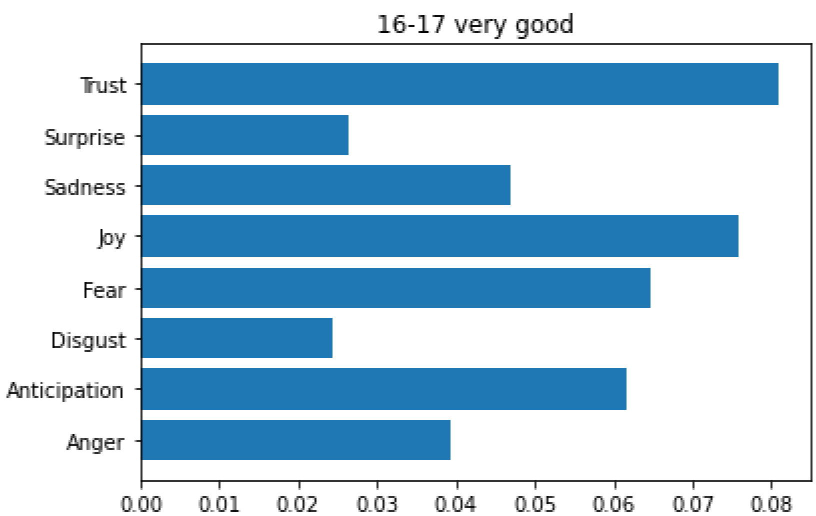

Figure 1B: the average vector for very good books for 16-17 year olds. Figure 1A contributes to the calculation of this average vector

4.3 Emotion Definitions

The eight emotions defined by the NRC-EIL (Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise, Trust) were based on previous work, namely that of Plutchik (1980), which defines these eight emotions as "primary emotion dimensions" (16). In other words, every emotion can be represented as a combination of these eight fundamental emotions. Plutchik also explains that these emotions can be thought of as pairs of opposites:

> Anger and fear are opposites in the sense that one implies attack and the other flight. Joy and sadness are opposites in the sense that one implies possession or gain while the other implies loss. Acceptance [trust] and disgust are opposites in the sense that one implies a

taking in, and the other implies an ejection, or riddance. Surprise and anticipation are opposites in the sense that one implies the unpredictable and the other implies the predictable. (16)

To get a sense for what the different emotion labels mean, Table 1 shows the highest-scoring words listed in the NRC-EIL for each emotion. In other words, these words capture the primary emotion dimensions most effectively. So, as indicated in Table 1, the most "Joyful" word is "happiest," and the most "Trustful" word is "trustfulness." Table 1 is meant to highlight the distinctions between these categories and assist the reader in gaining a better understanding of the emotions we focus on. Recall that any word not found in the NRC-EIL (as well as none of its synonyms) is given an Objective score of 1 when constructing the vectors:

Trust	**Surprise**	**Sadness**	**Joy**
truthfulness trusted trustworthy truth honor honest honesty trusting	surprise explode flabbergast explosion ambush explosive eruption shockingly	heartbreaking mourning tragic holocaust suicidal misery massacre euthanasia	happiest happiness bliss celebrating jubilant ecstatic elation beaming
Fear	**Disgust**	**Anticipation**	**Anger**
torture terrorist terrorism terrorists horrific suicidebombing kill homicidal	cannibalism mutilation incest molestation rape gonorrhea cannibal rot	excited anticipation excitement anticipate eagerness exciting expectant thrilling	outraged brutality hatred hateful terrorize infuriated violently furious

Table 1: highest-scoring words for each emotion in the NRC-EIL

Each word has a defined value in each emotion, which by default is zero. For example, the emotion vector of the word "death" is shown in Figure 2:

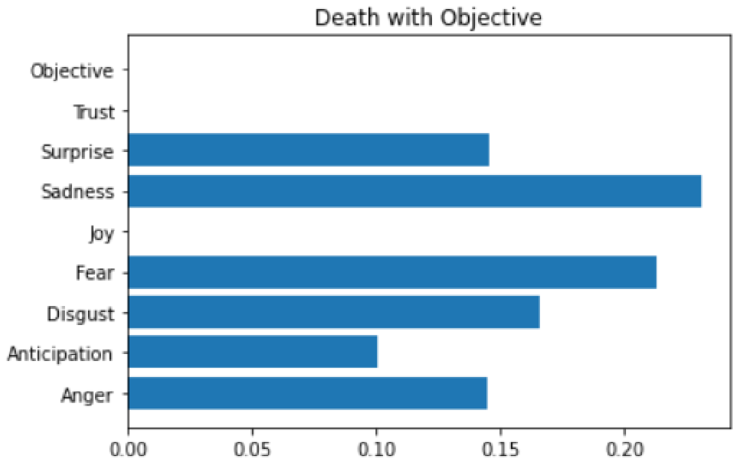

Figure 2: the emotion vector of the word "death"

For the word "death," values are defined for all emotions except Trust and Joy. Death's highest-scoring value, Sadness, is 0.915 while its lowest-scoring value, Anticipation, is 0.398. The reason why the axis labels on the chart are lower is because all of our vectors get normalized when we graph them. This makes it easier to compare books with different description lengths, which would otherwise have higher values of emotion by simply having more words.

For books, we use the book's description as a sample of the contents of the book. We sum the emotion vector of each word in the book's description to calculate the book's emotion vector. By focusing on only the book's description, we are able to calculate the emotion vector more quickly than iterating through the entire book, while still providing an accurate emotion vector for the book. Additionally, most publishers and online retailers do not give access to the contents of entire books due to copyright, so the book's description is useful for giving us access to what functions as a sample of the book's contents. For example, the book "The Things They Carried" by Tim O'Brien, a book detailing the author's experiences in the Vietnam War, has an emotional vector illustrated by Figure 3, which was calculated by the methods explained in section **4.1**.

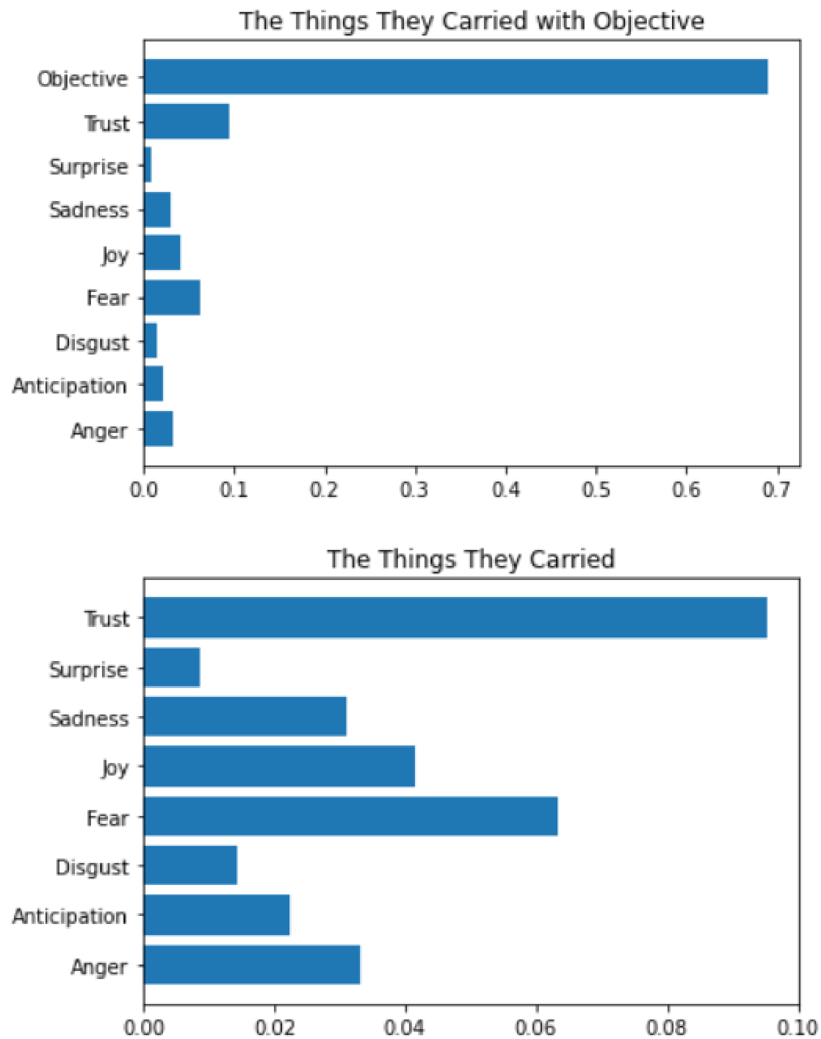

Figure 3: emotion vectors with and without Objective for the description of "The Things They Carried" by Tim O'Brien

Notice that because the 'Objective' category dominates the emotion vector, *we will be excluding it* from the other emotion vectors shown in this paper, since it carries very little useful information.

4.4 Partitioning Books by Average Ratings

We want to figure out the difference in emotional compositions between books that teenagers like and those they dislike. By doing so, we can determine what trends appear to make books more enjoyable. In order to determine how much readers enjoyed a book, we use the average ratings provided by the Goodreads dataset.

We partition the books in our dataset by their average ratings. Books are rated by users in the Goodread database on a scale of 0-5, with 5 being a perfect score. The Goodread database also includes book descriptions, which were used for our analysis (see section **4.1**), and it also combines individual user reviews into both an average rating and average age for a book. We consider the following categories for the average ratings:

	Min	Max
Very Good:	4	5
Medium:	2.5	4
Bad:	0	2.5

For each level of quality, we sample 100 books from each age 12-19, construct their emotion vector, then average all the emotion vectors together within the age group. We separate ratings into the age groups 12-13, 14-15, 16-17, and 18-19. So, for each age group, 200 sampled books are used to construct the average emotion vector. We graph the average emotional vector for each division of quality and age in Appendix I. Each dictionary can also be represented with more precision as a string, found in Appendix II. For example, the average *very good* book for 12-13 year olds is shown in Figure 4:

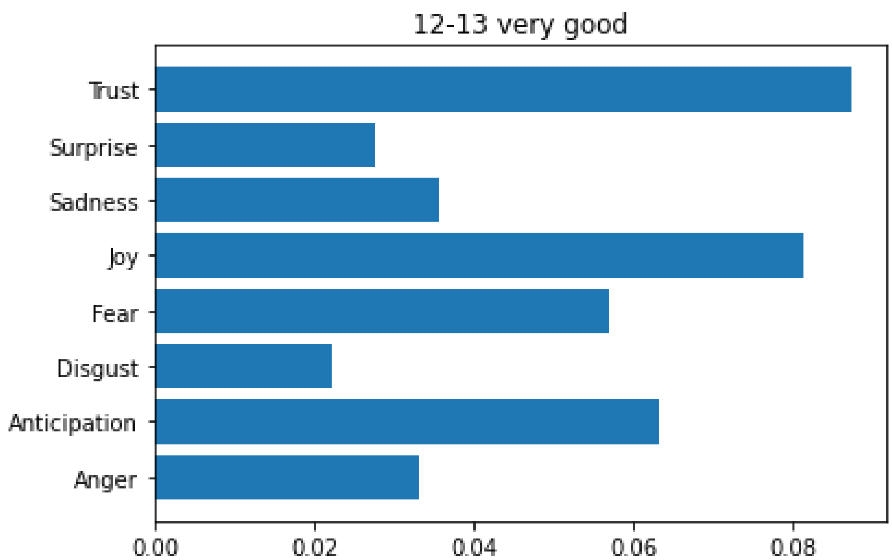

Figure 4: average emotion vector for books rated very good by 12-13 year olds

Figure 4 illustrates the fact that 12-13 year olds enjoy books that are high in Trust, Joy, and Anticipation, while having lower levels of Disgust. We can compare the average *very good* book to the average *bad* book as shown in Figure 5.

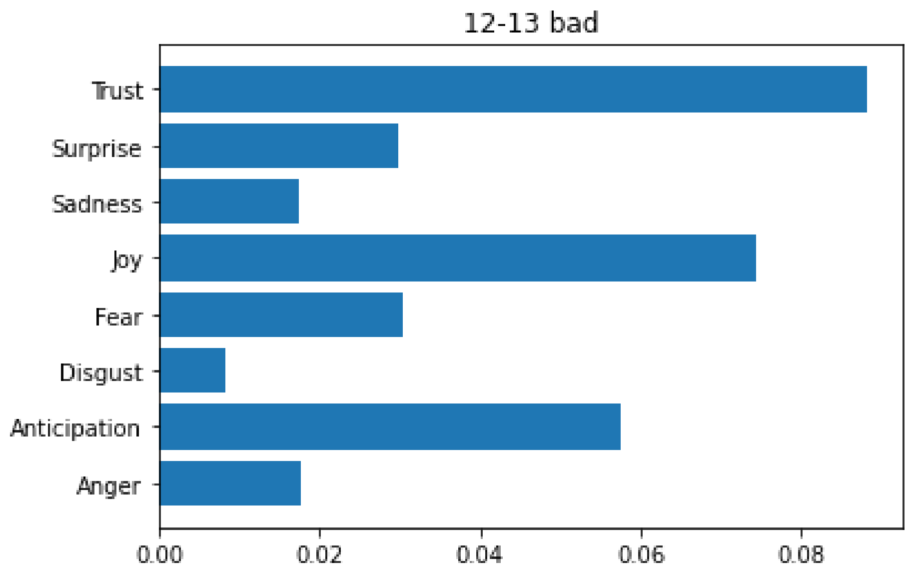

Figure 5: average emotion vector for books rated bad by 12-13 year olds

We see that *bad* books have similar, but fundamentally different emotional compositions to *very good* books. *Bad* books have much less sadness, an amount which is statistically significant (Table 7). They also have less Joy and Fear while having slightly more Surprise. These trends of *bad* books having lower values of most emotions than *very good* books suggest that 12-13 year olds dislike books that are lacking in emotion. We will see that this trend extends to all age groups, because we also compare the difference between the *very good* set and the *bad* set for each age group to determine if teenagers prefer certain emotions over others in their literature (Figure 6).

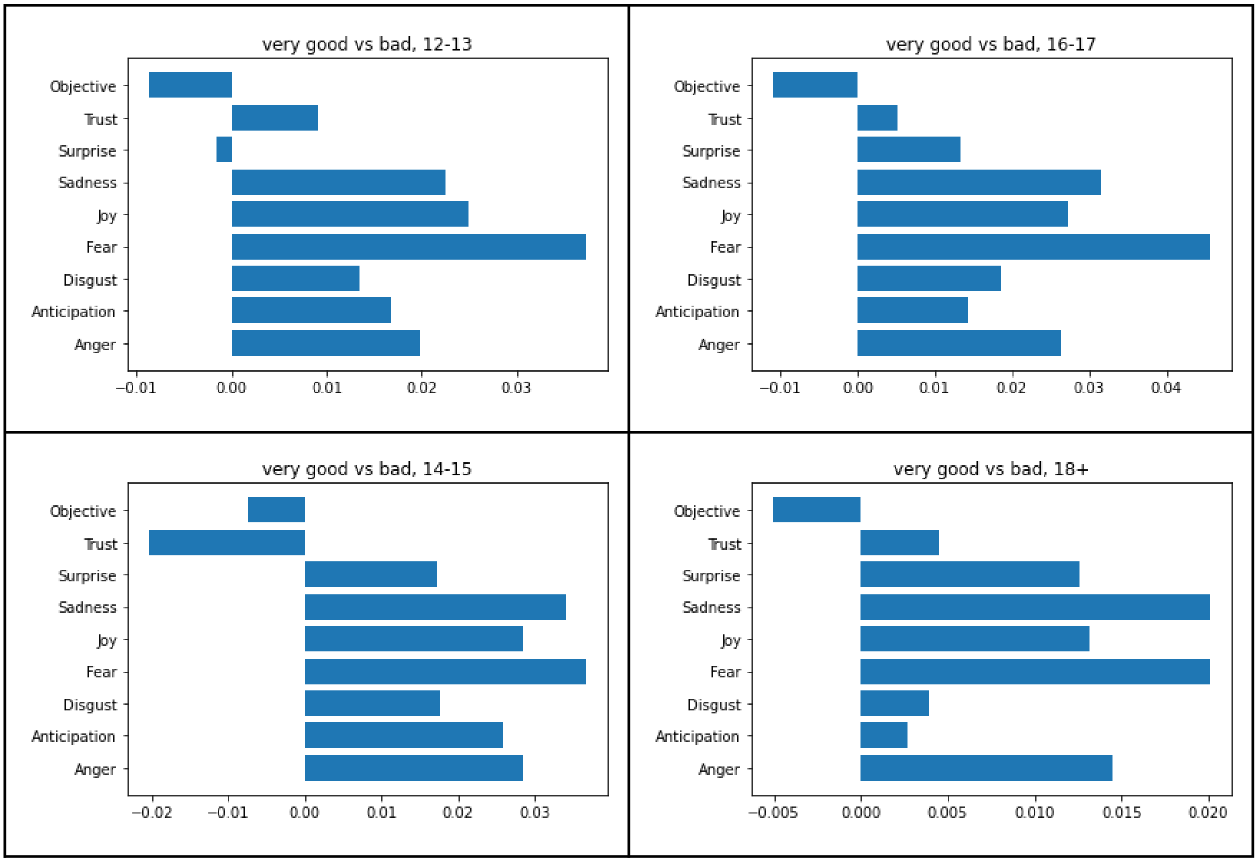

Figure 6: the difference between the average very good book and the average bad book's emotion vectors for each age group

Note that these graphs essentially display the result of the equation *veryGood - bad* for each age, as indicated in the graphs' titles. We can see that for all ages, Fear is the most significant indicator of whether a book will be more liked, with more Fear suggesting higher ratings. For teens 12-13, they prefer less Surprise, and more Sadness and Joy. 18-19 seem to be less affected by Anticipation and Disgust than 12-13. For each age group, Trust is among the lowest, meaning that *very good* and *bad* books have very similar amounts of Trust, so it does not work well as an indicator of a book's rating.

The negative Objective values for each age may be caused by worse books being described with more vocabulary not present in the NRC-EIL, such as authors' names ("rowling", "dahl", "steven", "king"), introducing characters or locations ("harry", "hogwarts", "paris", "maine"), or esoteric or difficult-to-categorize vocabulary ("hauntingly", "seven", "teenagers", "deep"), whereas *better* books are described with more expressive and emotionally charged vocabulary.

Table 7 shows which differences in emotion between *very good* and *bad* books are statistically significant. It was calculated using R, a programming language specialized for statistical analysis, and its built-in t.test function. The code used to produce these charts can be found on our github in the Evaluation folder, linked in section **4.5**. Cells highlighted green indicate statistical significance ($p < .05$).

	12-13 very good vs bad	14-15 very good vs bad	16-17 very good vs bad	18-19 very good vs bad
Anger	0.74106	2.28E-02	0.9977117	1.99E-01
Anticipation	0.2120763	0.006201215	0.2585912	0.2621973
Disgust	0.002878693	0.1311165	0.6660788	0.01224078
Fear	0.9346207	0.04576168	0.1183752	6.08E-02
Joy	0.2884206	0.457626	0.856244	0.7174294
Sadness	0.00116504	0.2434367	0.4398547	0.005975608
Surprise	0.9207632	0.02900242	0.9304403	0.002128576
Trust	0.4733924	0.05432569	0.9458534	0.1334071
Objective	0.2971554	0.05047257	0.3264709	0.006593198

Table 7: statistical significance of the difference between very good and bad books for each age group for each emotion

4.5 Reducing Objective Values by Comparing Synonyms

In order to improve the quality of the emotion vectors, we sought to reduce the amount of words that got marked as Objective, the default emotion for when the word was not included in the NRC-EIL. In order to do this, we utilized the python package synset, which allows us to get a word's synonyms, which we can search the NRC-EIL for in addition to the word itself. We ended up checking all of the synonyms in the first two "senses" provided by synset for each word. Note that because we potentially query the NRC-EIL for many more words, running the program with synset is slower than without, though, as we will see, it is more accurate and statistically significantly reduces the amount of Objective in the emotion vectors. Similarly, we can compare the *Very Good* emotion vectors with the *Bad*.

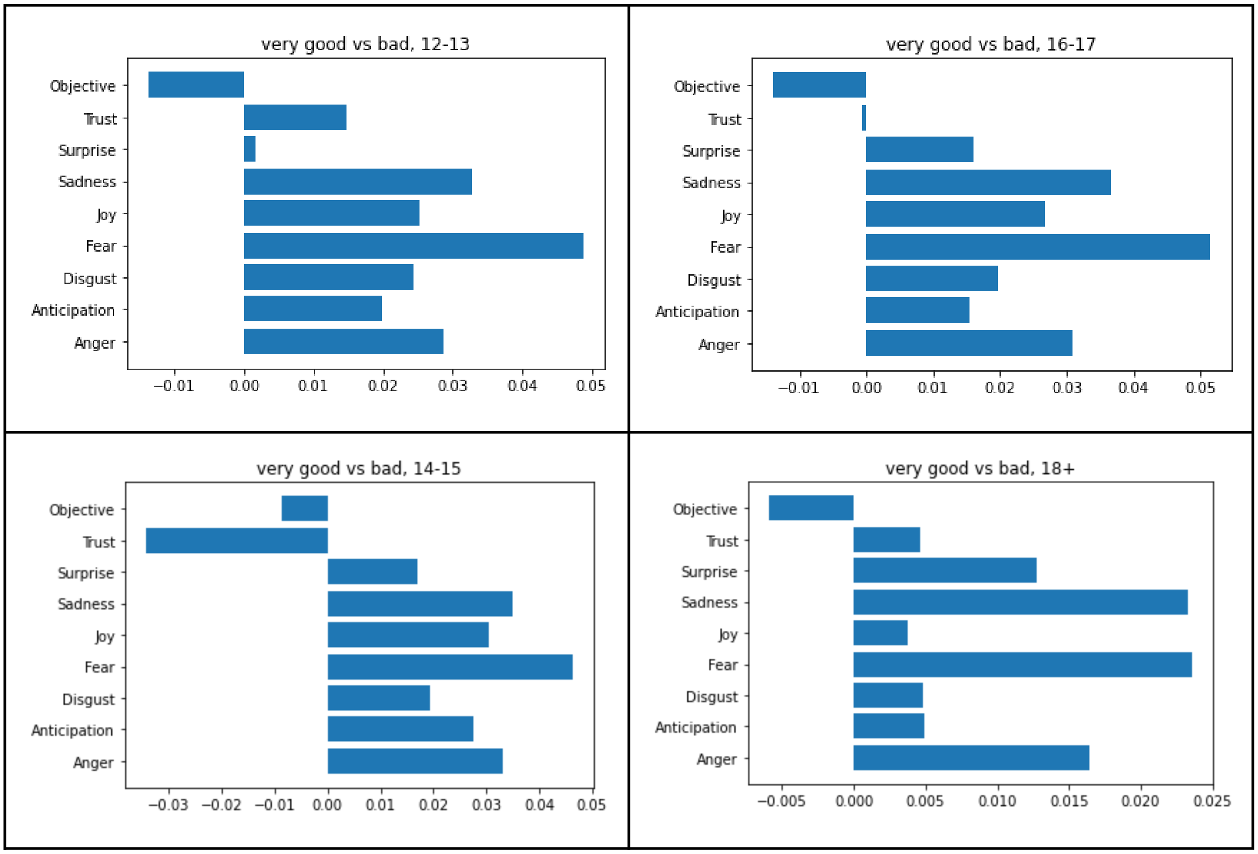

Table 8: the difference between the average Very Good book and the average Bad book's emotion vectors for each age group, with emotion vectors being calculated using synset

One difference that synset makes clearer is that 14-17 like books with less Trust. As before, the older groups can better handle books with more mature emotions like Fear and Anger. The 18-19 group is notable for liking books with a wider variety of emotions than younger age groups. 18-19 prefer books with more Sadness and Fear, but other emotions don't affect their opinion of a book very much. Note the horizontal axis labels that show how small the differences are in the 18-19 group when compared to the other groups. This implies that the emotion vector of a book's description may not be an accurate measure of how much a teenager older than 18 will enjoy a given book, though small trends are visible.

There is a statistically significant difference between creating the vectors without synset and with synset for almost every emotion ($p < .01$), as shown below in Table 9.

Anger	0.000629
Anticipation	0.0001825
Disgust	0.00276
Fear	0.004988
Joy	0.09231
Sadness	0.01133
Surprise	0.1829
Trust	0.0001945
Objective	**1.06E-05**

Table 9: statistical significant differences between vectors calculated with and without synset

For each age group besides 16-17, there is a statistically significant difference between *very good* and *bad* books for at least one emotion ($p < .05$), as shown in Table 7 above. For 12-13, those emotions are Disgust and Sadness. For 14-15, they are Anger, Anticipation, Fear, and Surprise. For 18-19, they are Disgust, Sadness, Surprise, and Objective. This means that these emotions are the most influential when deciding whether a book is *good* or *bad*. Likely, 12-13 year olds are more sensitive to Disgust and Sadness and dislike books that focus on those emotions. For older groups, Surprise may be influential because of their experience and desire to read new or novel ideas themes. There are general trends that can be observed in the emotion vectors of *very good* books when divided by *age* (Figure 10). An alternative representation of this data is found in Appendix I (Emotions of *Very Good* Books over Age Group).

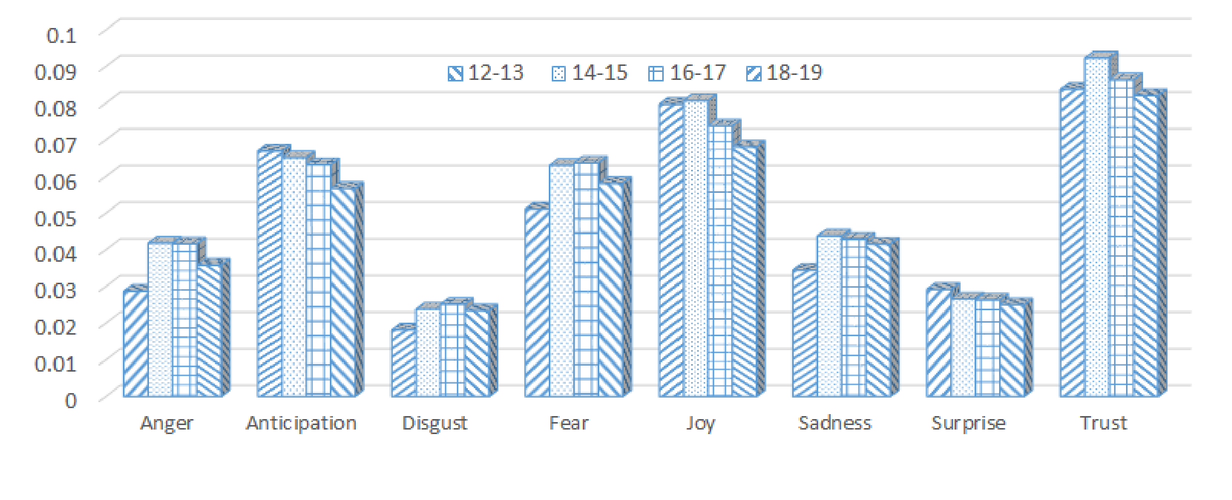

Figure 10: emotion of very good books by age group for each emotion

There is a similar relationship between Fear, Sadness, and Anger. This is likely because words that are in one of these categories often have values in the other two, such as the word "death" as shown in Figure 2. This trend shows these three emotions starting low in 12-13 year olds, rising for 14-15, then gradually declining. This exhibits younger teenager's aversions to these kinds of topics, whereas around 14, readers begin displaying interest in them, then interest in these emotions slowly decline, perhaps because older teenagers consider books that focus on them to be "edgy" or otherwise sacrificing meaningful storytelling in favor of shock value. Joy shows the opposite trend, starting high in 12-13, then quickly falling. Surprise similarly is highest among the youngest group.

We also find significant differences between different age groups' highly-rated books (Table 11). Each cell that indicates statistical significance ($p < .05$) is colored green. Notice that each green cell essentially communicates the fact that for two books with otherwise identical emotion vectors, but with different values for that cell's emotion (from the row header), will likely result in the two age groups (from the column header) giving different ratings for the two books.

	12-13 vs 14-15	12-13 vs 16-17	12-13 vs 18-19	14-15 vs 16-17	14-15 vs 18-19	16-17 vs 18-19
Anger	0.0293	0.1125	0.2314004	0.2296696	0.2419524	0.837907
Anticipation	0.3695	0.7946	0.01215974	0.3277576	9.12E-06	6.17E-06
Disgust	0.09787	0.2462	0.3734471	0.3310142	0.3900035	0.8938677
Fear	0.05266	0.2837	0.8251114	0.1602062	0.01636634	0.1030756
Joy	0.1769	0.1473	0.00976508	0.8869527	0.1259964	0.03916654
Sadness	0.01351	0.02025	0.1856107	0.582712	0.2102474	0.3244902
Surprise	0.7677	0.1383	0.05581075	0.00401542	0.00020563	0.09584255
Trust	0.4228	0.7976	0.08658959	0.4583065	0.2730633	0.07103579
Objective	0.07983	0.7019	0.02296486	0.1297992	0.00087301	0.01031348

Table 11: statistically significant differences between very good books for each age group comparison, separated by emotion. Green cells indicate statistical significance ($p < .05$)

4.6 Code

Our code was programmed in python and makes heavy use of the nltk and synset libraries. We used the NRC-EIL for associating words with emotions. We used the nltk lemmatizer to search for various forms of a word. We used synset (which was imported from nltk) to search for synonyms of a word, as explained in detail in section **4.5**. We excluded stop words from our analysis by using a combination of nltk, spacy, and sklearn, as mentioned in section **4.1**. Analysis and statistical significance tests were conducted using R.

All the code is included in the github repository at: https://github.com/PIReTship/StoryTime2.0

All the data we used can be found in the /Data folder on github. Likewise, tools for analysis and evaluation can be found in /Evaluation, including an R notebook, spreadsheets for organizing statistical significance, and a subsection of the Goodreads dataset with emotion vectors included, both with and without synset. The most-used code for our project can be found at /Sandbox/levesson/emotion_description/emotionItensity_Vector_with_objective.ipynb, which is a python notebook.

5. Conclusion

There are statistically significant differences in the emotion vectors of highly-rated books between age groups. There are also statistically significant differences in the emotion vectors of highly-rated books and low-rated books for each age group except 16-17. We found that overall, teenagers preferred books with more emotion in general. Additionally, several trends were observed between age groups, such as the correlation between Anger, Disgust, Fear, and Sadness for *very good* books, which began low for 12-13 year olds, then rose for 14-15 year olds, then slowly declined while remaining higher than the value for 12-13 year olds. Trust exhibits a similar trend, though Trust is consistently the highest-valued emotion among all age groups. Contrastly, Joy and Anticipation are highest among younger groups, and slowly decline over time. Surprise remains relatively constant over time, but does exhibit a slight downward trend.

Discovering these trends statistically allows for further research, both empirical and statistical. Implementing these findings in a functional book recommender is a natural continuation of our work, which would help teens find more emotionally appealing and interesting books than traditional recommender systems. For future work, researchers could attempt using synset in different ways, such as combining the emotion vectors of multiple synonyms rather than using just one as we do. Similarly, synset could be used to significantly expand the emotion lexicon with whichever protocol is decided upon. Expanding the emotion lexicon would make future calculations faster. Research could also analyze different age groups, considering which ages tend to have similar preferences. Additionally, other emotion lexicons could be created or utilized to expand the scope of this project to languages other than English. Also, an empirical study could be conducted to see how effective of a predictor an emotion vector is for a teenager's enjoyment of a book.

6. References

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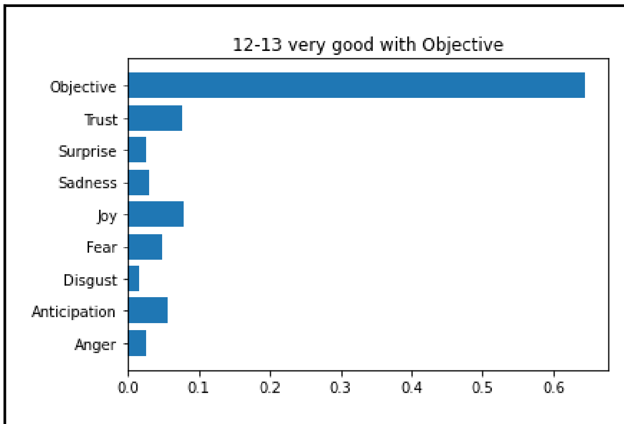
Appendix I

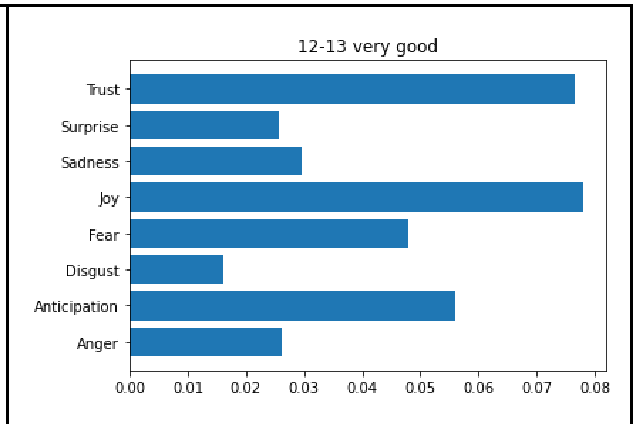
Without synset, All Graphs

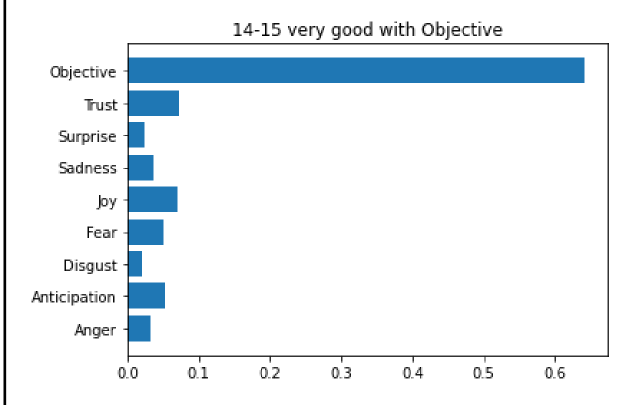
There are 24 graphs listed below, one for each combination of

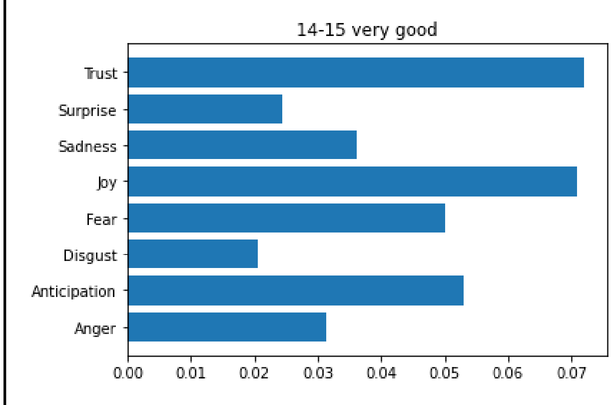
- Objective or No Objective
- Age Group (12-13, 14-15, 16-17, 18-19)
- Rating (Very Good, Medium, Bad)

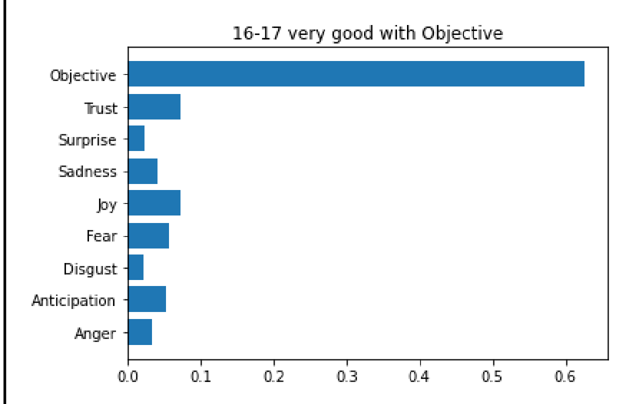
These graphs can be recreated precisely using the Dictionary Strings table located below, where each emotion's value is rounded to four or five decimal places.

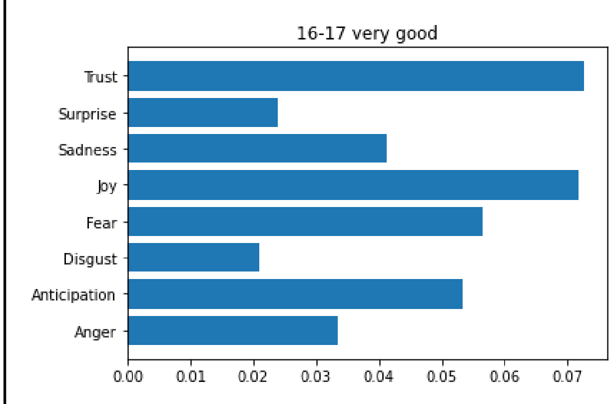


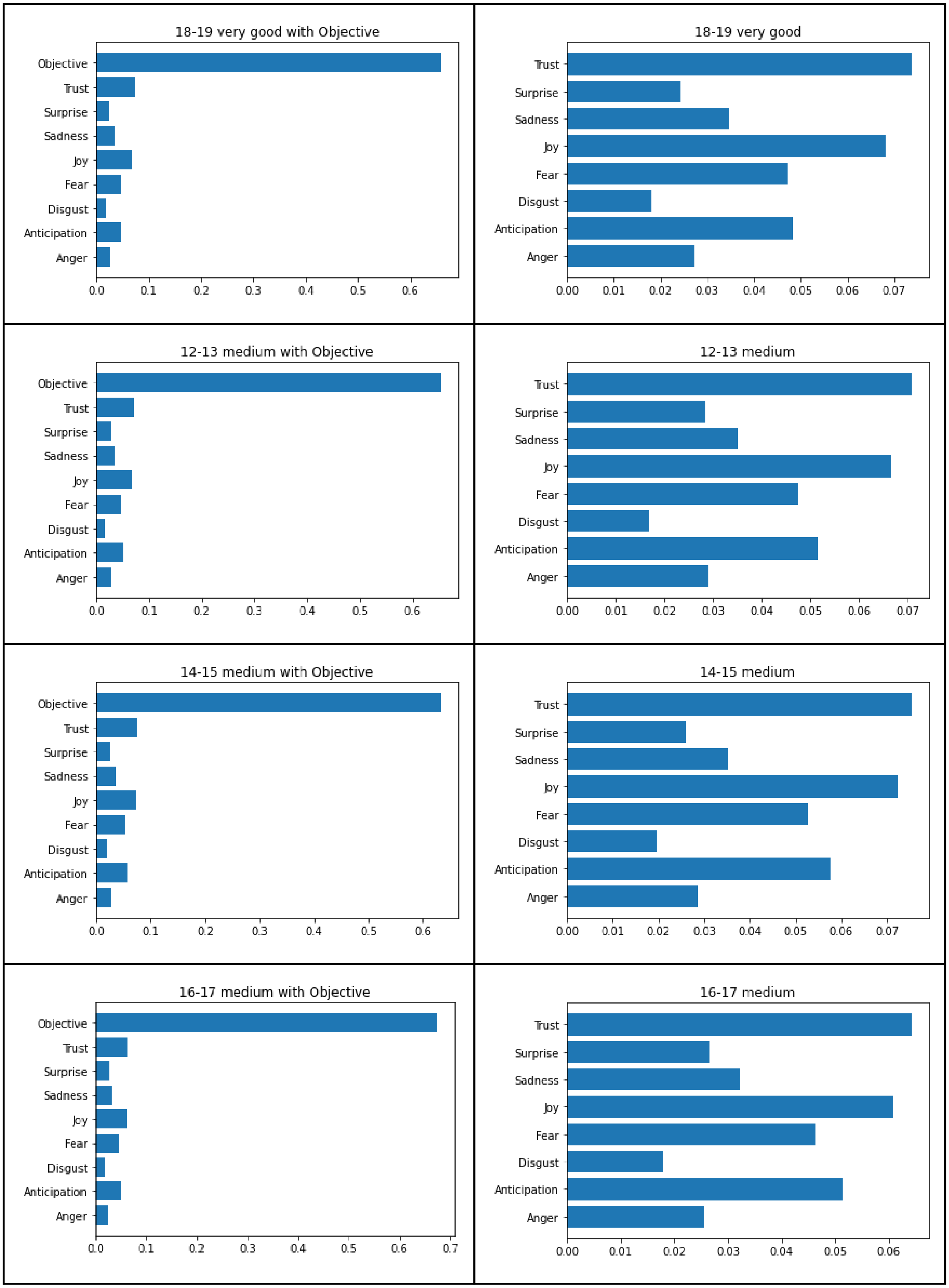











18-19 very good with Objective
Objective
Trust
Surprise
Sadness
Joy
Fear
Disgust
Anticipation
Anger
0.0 0.1 0.2 0.3 0.4 0.5 0.6
18-19 very good
Trust
Surprise
Sadness
Joy
Fear
Disgust
Anticipation
Anger
0.00 0.01 0.02 0.03 0.04 0.05 0.06 0.07
12-13 medium with Objective
Objective
Trust
Surprise
Sadness
Joy
Fear
Disgust
Anticipation
Anger
0.0 0.1 0.2 0.3 0.4 0.5 0.6
12-13 medium
Trust
Surprise
Sadness
Joy
Fear
Disgust
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14-15 medium with Objective
Objective
Trust
Surprise
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Joy
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Disgust
Anticipation
Anger
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14-15 medium
Trust
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0.00 0.01 0.02 0.03 0.04 0.05 0.06 0.07
16-17 medium with Objective
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16-17 medium
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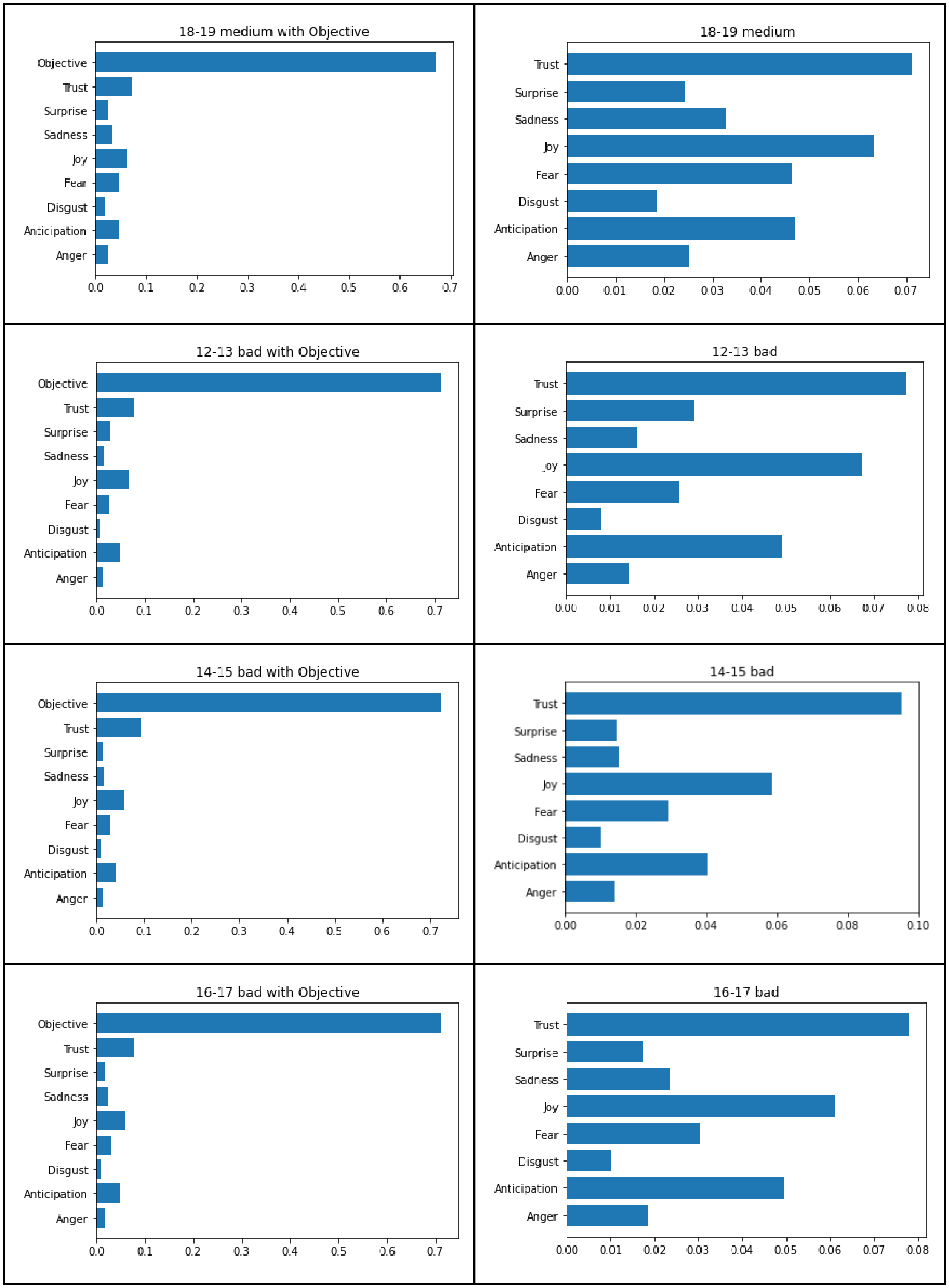
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18-19 medium
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12-13 bad with Objective
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14-15 bad
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16-17 bad with Objective
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16-17 bad
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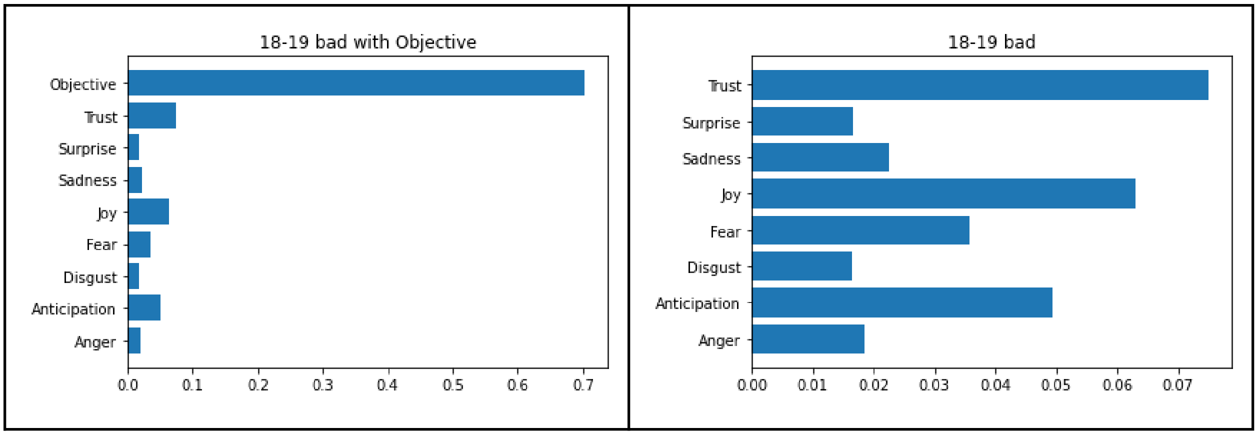
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18-19 bad
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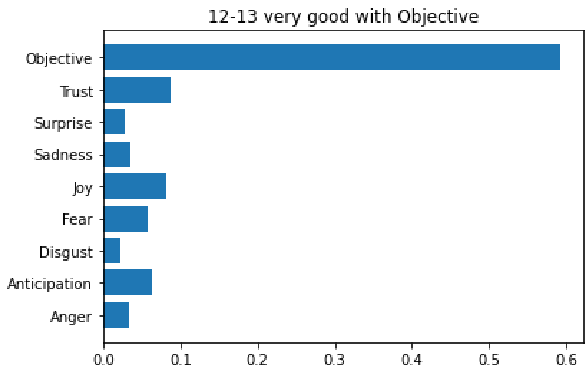
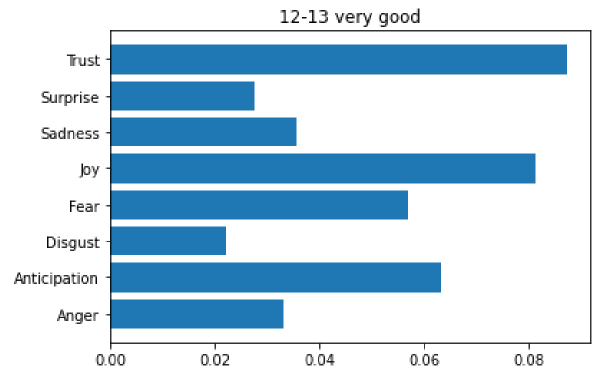
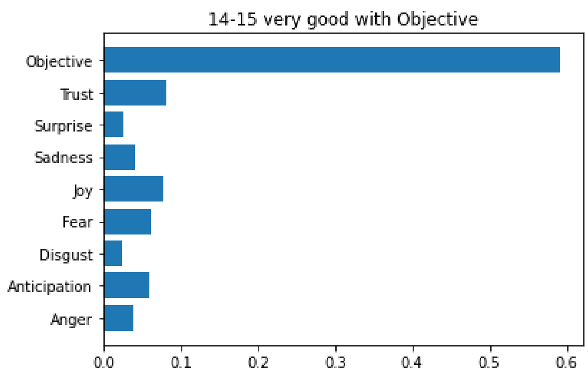
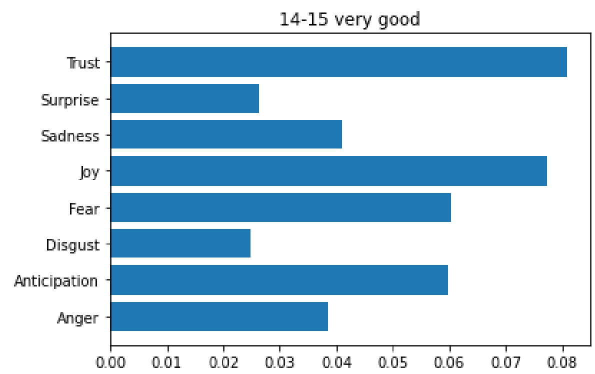
synset, All Graphs

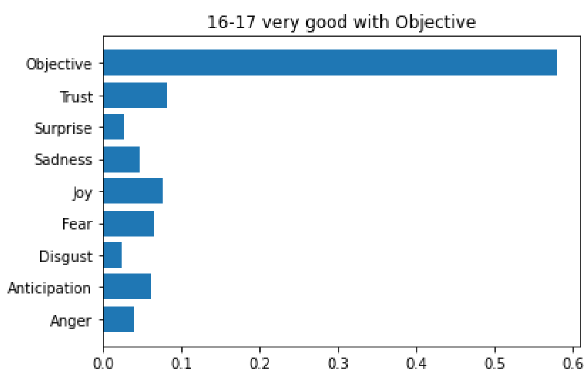
This table contains graphs with the same parameters as *Without synset, All Graphs*, but using synset.

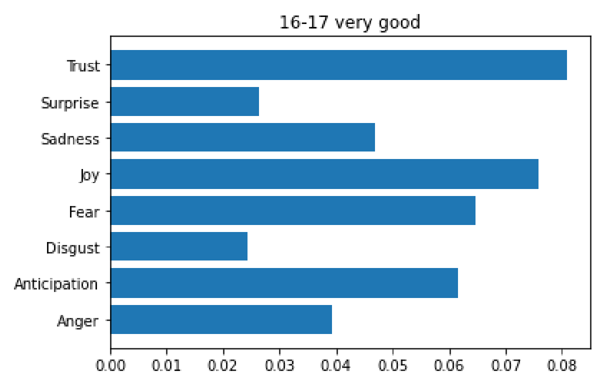


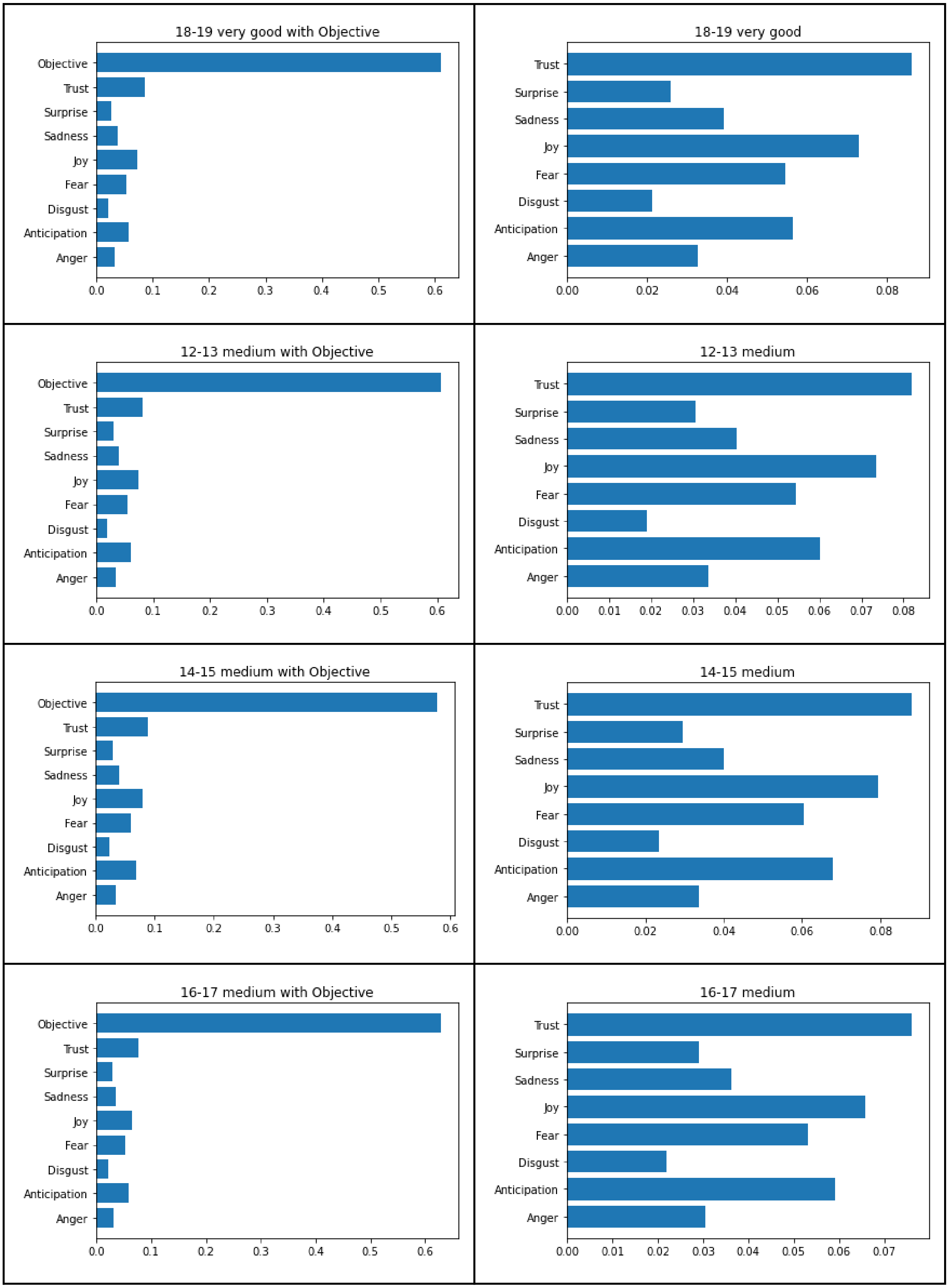











18-19 very good with Objective
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18-19 very good
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16-17 medium with Objective
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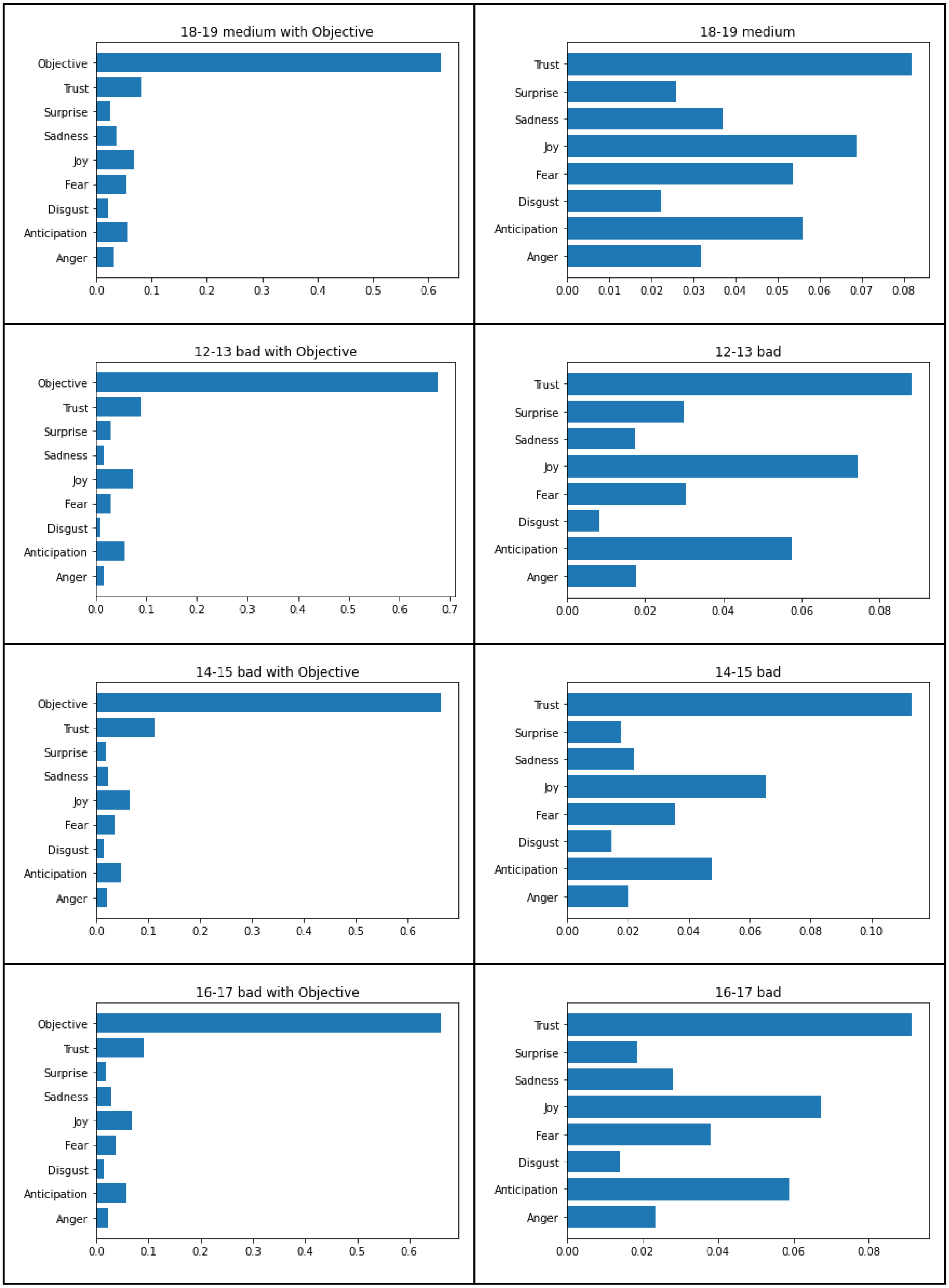
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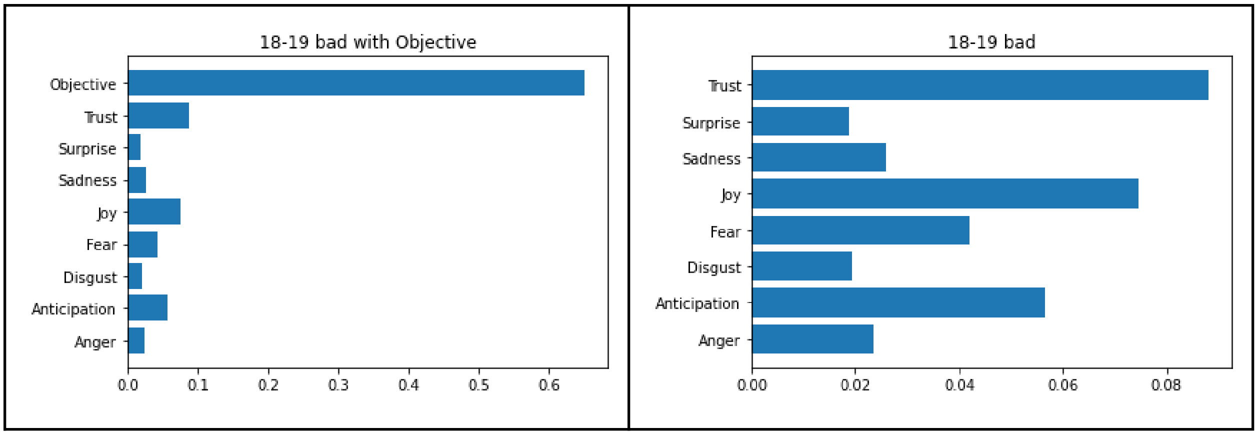
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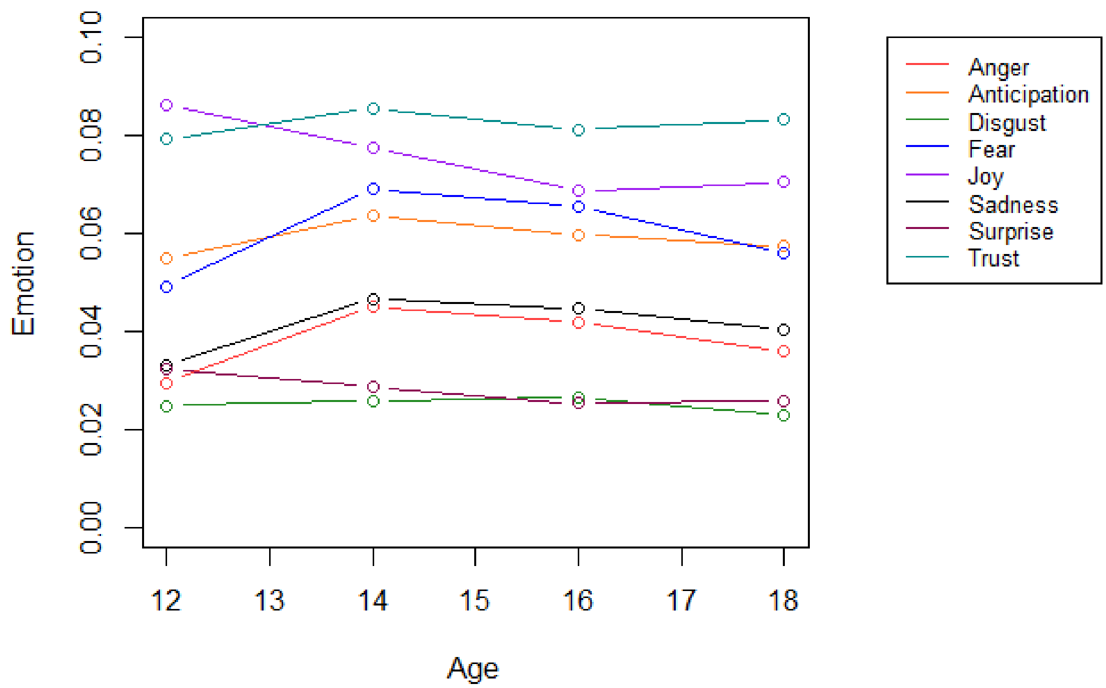
Emotions of Very Good Books over Age Group

The same data as Figure 10 in section 4.5, but represented as a line chart to be more succinct.



Appendix II

Side-by-side Dictionary Strings

This table contains 24 emotion vectors in string form, one for each age group and rating, and for both with and without using synset to calculate them, with each value rounded down to four or five decimal places. This table is useful for anyone wanting to recreate our data or test their code. Note that values are rounded down to four or five decimal places. Also note that each vector calculated with synset has a lower Objective value than its corresponding vector without synset, which indicates the success found with using synset to check synonyms of words that were not in the NRC-EIL.

	Without synset	**With synset**
Very Good	{'12-13': {'Anger': 0.0260, 'Anticipation': 0.0559, 'Disgust': 0.01604, 'Fear': 0.0478, 'Joy': 0.0780, 'Sadness': 0.0296, 'Surprise': 0.02557, 'Trust': 0.0764, 'Objective': 0.6443}, '14-15': {'Anger': 0.0313, 'Anticipation': 0.0530, 'Disgust': 0.0205, 'Fear': 0.05007, 'Joy': 0.0709, 'Sadness': 0.03603, 'Surprise': 0.02435, 'Trust': 0.0719, 'Objective': 0.6417}, '16-17': {'Anger': 0.033, 'Anticipation': 0.0533, 'Disgust': 0.0209, 'Fear': 0.0564, 'Joy': 0.071, 'Sadness': 0.0411, 'Surprise': 0.0239, 'Trust': 0.0726,	{'12-13': {'Anger': 0.0332, 'Anticipation': 0.0631, 'Disgust': 0.02222, 'Fear': 0.0569, 'Joy': 0.0813, 'Sadness': 0.0356, 'Surprise': 0.0275, 'Trust': 0.0874, 'Objective': 0.5925}, '14-15': {'Anger': 0.0384, 'Anticipation': 0.0596, 'Disgust': 0.02481, 'Fear': 0.06017, 'Joy': 0.0773, 'Sadness': 0.04101, 'Surprise': 0.02624, 'Trust': 0.0807, 'Objective': 0.5914}, '16-17': {'Anger': 0.0393, 'Anticipation': 0.0616, 'Disgust': 0.0243, 'Fear': 0.0646, 'Joy': 0.0759, 'Sadness': 0.0470, 'Surprise': 0.0263, 'Trust': 0.0809,

	'Objective': 0.6263}, '18-19': {'Anger': 0.02735, 'Anticipation': 0.0483, 'Disgust': 0.0181, 'Fear': 0.0471, 'Joy': 0.068, 'Sadness': 0.0346, 'Surprise': 0.02422, 'Trust': 0.0737, 'Objective': 0.6582}}	'Objective': 0.579}, '18-19': {'Anger': 0.03258, 'Anticipation': 0.05649, 'Disgust': 0.02123, 'Fear': 0.05449, 'Joy': 0.0727, 'Sadness': 0.03914, 'Surprise': 0.02581, 'Trust': 0.0861, 'Objective': 0.6113}}

Medium	{'12-13': {'Anger': 0.02918, 'Anticipation': 0.05155, 'Disgust': 0.01689, 'Fear': 0.0475, 'Joy': 0.0666, 'Sadness': 0.0350, 'Surprise': 0.02837, 'Trust': 0.0708, 'Objective': 0.6538}, '14-15': {'Anger': 0.028, 'Anticipation': 0.05761, 'Disgust': 0.0196, 'Fear': 0.05270, 'Joy': 0.0723, 'Sadness': 0.0351, 'Surprise': 0.0258, 'Trust': 0.0753, 'Objective': 0.6327}, '16-17': {'Anger': 0.02564, 'Anticipation': 0.05136, 'Disgust': 0.01792, 'Fear': 0.0464, 'Joy': 0.06082, 'Sadness': 0.0322, 'Surprise': 0.02666, 'Trust': 0.0642, 'Objective': 0.6746}, '18-19': {'Anger': 0.0252, 'Anticipation': 0.0469, 'Disgust': 0.01856, 'Fear': 0.0464, 'Joy': 0.063, 'Sadness': 0.0328, 'Surprise': 0.02429, 'Trust': 0.0711, 'Objective': 0.6711}}	{'12-13': {'Anger': 0.0337, 'Anticipation': 0.0601, 'Disgust': 0.01901, 'Fear': 0.05440, 'Joy': 0.0733, 'Sadness': 0.0404, 'Surprise': 0.03065, 'Trust': 0.0819, 'Objective': 0.6063}, '14-15': {'Anger': 0.0335, 'Anticipation': 0.0678, 'Disgust': 0.02341, 'Fear': 0.0604, 'Joy': 0.0793, 'Sadness': 0.0401, 'Surprise': 0.0294, 'Trust': 0.0880, 'Objective': 0.5776}, '16-17': {'Anger': 0.03045, 'Anticipation': 0.05905, 'Disgust': 0.0219, 'Fear': 0.0530, 'Joy': 0.065, 'Sadness': 0.03618, 'Surprise': 0.02902, 'Trust': 0.076, 'Objective': 0.628}, '18-19': {'Anger': 0.03172, 'Anticipation': 0.0560, 'Disgust': 0.02224, 'Fear': 0.0536, 'Joy': 0.0687, 'Sadness': 0.03685, 'Surprise': 0.02594, 'Trust': 0.0818, 'Objective': 0.6229}}

Bad	{'12-13': {'Anger': 0.01425, 'Anticipation': 0.04917, 'Disgust': 0.00787, 'Fear': 0.02559, 'Joy': 0.0674, 'Sadness': 0.01615, 'Surprise': 0.0291, 'Trust': 0.0773, 'Objective': 0.7129}, '14-15': {'Anger': 0.01411, 'Anticipation': 0.0403, 'Disgust': 0.01003, 'Fear': 0.02914, 'Joy': 0.05844, 'Sadness': 0.0152, 'Surprise': 0.01453, 'Trust': 0.0953, 'Objective': 0.7227}, '16-17': {'Anger': 0.01853, 'Anticipation': 0.0495, 'Disgust': 0.01024, 'Fear': 0.0304, 'Joy': 0.0610, 'Sadness': 0.02351, 'Surprise': 0.01728, 'Trust': 0.077, 'Objective': 0.7115}, '18-19': {'Anger': 0.01868, 'Anticipation': 0.0494, 'Disgust': 0.01640, 'Fear': 0.03572, 'Joy': 0.0630, 'Sadness': 0.02254, 'Surprise': 0.01674, 'Trust': 0.0750, 'Objective': 0.7024}}	{'12-13': {'Anger': 0.01765, 'Anticipation': 0.0574, 'Disgust': 0.00816, 'Fear': 0.03041, 'Joy': 0.0742, 'Sadness': 0.01744, 'Surprise': 0.0299, 'Trust': 0.0881, 'Objective': 0.676}, '14-15': {'Anger': 0.0202, 'Anticipation': 0.04756, 'Disgust': 0.01451, 'Fear': 0.0354, 'Joy': 0.0653, 'Sadness': 0.02188, 'Surprise': 0.01766, 'Trust': 0.113, 'Objective': 0.6641}, '16-17': {'Anger': 0.02333, 'Anticipation': 0.0588, 'Disgust': 0.01410, 'Fear': 0.03796, 'Joy': 0.0673, 'Sadness': 0.0281, 'Surprise': 0.01870, 'Trust': 0.091, 'Objective': 0.6603}, '18-19': {'Anger': 0.0235, 'Anticipation': 0.0565, 'Disgust': 0.01925, 'Fear': 0.04201, 'Joy': 0.0745, 'Sadness': 0.025, 'Surprise': 0.01884, 'Trust': 0.0880, 'Objective': 0.6512}}