BUILDING AN EMOTION PROPOSITION STORE

SEBASTIAN RUDER

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ABSTRACT

Emotions and sentiment are an essential part of what makes us human. While psychology has tried to differentiate between certain emotions, past work on sentiment analysis has focused primarily on classifying sentiment as positive, negative, or neutral. In the following, I will use Plutchik's eight base emotions, i.e. anger, anticipation, joy, fear, surprise, disgust, sadness, and trust. I will collect patterns that are indicative of said emotions from a diverse set of sentiment resources. Using these patterns, I will extract emotion holders and causes from the Gigaword corpus using the Annotated Gigaword API. Distributional analyses of the extractions produce words that evoke certain emotions.

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1 INTRODUCTION

Categorizing sentences according to their sentiment (or opinion) is an important first step for many downstream applications for NLP such as dialogue systems [34], text-to-speech systems [4], media response analyses [35], and a host of others. Sentiment analysis is usually restricted to a polar classification: positive – negative with a non-sentiment-bearing neutral class. This binary classification falls short in light of the variety and multifacetedness of human emotions. Emotions are innate to humans, so much so that the inability to show emotions is considered a clear indicator of a societal outlier. They transcend cultures and facial expressions for basic emotions are identical even between cultures with no previous contact [11]. Recent work in sentiment analysis also includes the subtask of emotion analysis or emotion detection, which focuces on identifying emotions in text typically using a set of emotion categories suggested by psycholinguistic research (e.g. the 8 classes – joy, trust, fear, surprise, sadness, disgust, anger, anticipation – of Plutchik's wheel of emotions [32]) (cf. [24]). Identifying emotions in text can be beneficial in e.g., facilitating interaction with AI agents, helping companies understand people's feelings towards their products, assissting governments in recognizing growing anger or fear towards an event, preempting mass hysterias, or helping media companies understand people's emotional reaction towards controversial issues.

Emotion lexica have been pervasive in sentiment analysis and include true and tested ones like the General Inquirer [38]. Resources for emotion detection, however, are rare. In order to resolve this deficit, we will acquire a large number of propositions from a corpus, filter and generalize them (leveraging heuristics used by information extraction systems like KnowItAll/TextRunner and similar approaches) and store the resulting propositions in a proposition store. Distributional analysis of the component expressions will allow us to determine high-scoring single- vs. compound emotion-triggering expressions.

As many sentiment analysis applications have focused on news, with real-world use cases such as alerting traders and predicting the stock market [6] and as researchers have shown that domain-specific knowledge generally outperforms general-domain knowledge [3], we will use the Annotated Gigaword [27] corpus, which adds off-the-shelf annotations to the biggest static English news corpus in existence, for our endavour.

This method can also be applied to automatically extract a general-domain compositional emotion lexicon from the web (using a web mining approach as in [19]) as well as be extended to other special domain corpora, to learn about what the concepts and entities people love, hate, fear, or wish for, and where their emotions differ. In our proposition store, each entry contains information about an emotion holder, the emotion, and the cause of said emotion. We include modifiers and prepositional objects and the cause of the emotion can be either a nominal phrase or a clause.

As research in sentiment lexica has shown, linguistic triggers of emotions are diverse and can belong to different word classes: nouns like *disaster*, *prize*, or *crash*; adjectives like *mind-numbing*, *yucky*, or *moist*; and verbs like *cheat*, *praise*, or *betray* are all equally able to evoke certain emotions.

However, emotion (just as sentiment) is a compositional phenomenon. For instance, neither *prize* nor *go up* are by themselves emotion-triggering words; but compositional expressions such as *the prize went up* or *rising prizes* are prone to trigger emotions – which may be anger, fear or even joy (depending on the holder of emotion and the context).

Past research has shown that categorization of emotion is difficult (cf. [**?**]. Not only that, but also identifying the holder and the cause an emotion proves to be challenging (cf. [8]). Using clearly categorized linguistic cues that also clearly indicate the emotion holder and cause to automatically label emotion-triggering concepts and events thus seems a promising perspective for acquisition and categorization. In consequence we will select frequent and clearly emotion-indicating predicators such as *X be angry about NP / that S*, *X fears that S*, *X was surprised that S*, *X (absolutely) hates NP / S*, etc.

Using these patterns, we will be able to derive from a sentence such as "He was angry because prices had gone up" that *prices had gone up* is an event that triggers an emotion of anger in the subject of *be angry*. In this case, not a single part, but the full predication 'go_up(price)' is the trigger for the emotion. We can derive this from distributional properties of the harvested propositions in case the noun and the verb often appear jointly with the emotion, i.e. yield a high association score.

The structure of this thesis is as follows: In chapter 2 we will examine past research are relevant for our approach, including methods of emotion detection, psychologically-grounded models of emotion classification, and sentiment lexica. This serves the dual purpose of introducing key concepts of emotion detection and sentiment analysis as well as touching on some of the tools to be applied in our research.

In chapter 3, we will introduce premises that have shaped the compilation of the emotion-bearing patterns. We will give an overview of their sources and present the chosen corpus in more detail. We will detail the extraction steps as well as the chosen representation format.

Subsequently, in chapter 4, we will analyze and evaluate the results of the extractions.

Finally, we will summarize our findings and offer a conclusion.

2 FOUNDATIONS AND RELATED WORK

2.1 SENTIMENT ANALYSIS

Research on sentiment analysis has been vast and there are excellent summaries (cf. [28], [18], [20]). In the following, we will focus on work related to emotion detection, emotion verbs, and identifying the holder and the cause of an emotion. To avoid ambiguity, we will henceforth define sentiment as being positive or negative, while an emotion possesses more dimensions.

Past research in sentiment analysis tends to focus on explicit expressions of opinions. Deng et al. try to capture implicit attitudes by annotating benefactive/malefactive events. Their annotation scheme, however, raises some doubts, as some neutral events are still labeled as benefactive/malefactive, e.g. in *She bakes a cake*, *cake* is the object of the benefactive event.

Emotion clearly is a compositional phenomenon. However, while sentiment adheres to Montague's underlying *principle of compositionality*, with the notion of compositionality having been successfully applied in state-of-the-art approaches such as recursive neural tensor networks [36], which conceive the overall sentiment as a sum of the constituent polarities, compositionality for emotions is less clear: Two unemotive terms can – combined – evoke an emotion, e.g. "stock falls", "the blind sees", which doesn't lend itself to compositionality and can only be accurately predicted by making sense of the underlying world knowledge. Evidently, predicting emotion for events is harder than for nominal phrases, as modifiers contain a lot of meaningful information, e.g. "disgusting", "happy", "sad", etc. almost always propagate their respective emotion to the whole nominal phrase. Still, predicting sentiment for generic nominal phrases is not straightforward: Borth et al. are able to easily calculate the sentiment of adjective–noun pairs, such as *beautiful flower* or *disgusting food* based on compositionality; for emotion, however, they have to fall back on additional information taken from Flickr meta-data.

Lu et al. leverage such world knowledge to detect emotions on an event level, while we seek to identify concepts or entities that carry emotions themselves. Whereas we use association metrics derived from emotive contexts, their main insight is that the "*common mutual actions*" between two event participants are a major cue for detecting emotions. For instance, a snake in general performs undesirable actions towards a girl, which would give the event "a girl sees a snake" a negative emotion.

Given an event, they also account for active and passive. However, they don't match the patterns against an existing corpus as we do, but mine data from the web to generate mutual action histograms. They compare these to the histograms of a set of manually emotion-labeled events between reference pairs and return the emotion of the most similar histogram. However, they only identify positive, negative, or neutral emotions, omitting finer granularity.

Pantel and Pennacchiotti also automatically extract instances from the web using patterns. Their method starts off with a set of seed instances, from which they induce and then select new patterns. In contrast to most unsupervised approaches, they not only use *reliable* patterns (high precision, low recall), but also leverage generic patterns. They mitigate their imprecision by measuring pattern reliability based on the instantiations of the reliable patterns, which enables them to separate correct from incorrect instances.

While their approach is helpful for gathering knowledge to ontologize is-a and part-of relationships, the use of generic patterns for emotion detecion, which is already highly ambiguous, might introduce more noise and consequently rather damage than improve performance. Furthermore, the difficulty of finding seed instances that will generate reliable patterns is amplified for emotions: "I :: spiders", "I :: darkness", "I :: violence", and "I :: Bin Laden" might be promising seed instance to induce the pattern "X hate Y", they could also as easily be associated with "X am scared of Y", "X object to Y", etc; that is, while it is relatively straightforward to distill the essence of an is-a relationship via a set of seed instances, doing this for emotions is less easy and will invariably introduce a selection bias. Insofar, starting with a set of seed patterns and expanding them would be the prefered approach for emotion detection. We leave this for future work.

Fellbaum and Mathieu manually construct verb classes corresponding to the emotions surprise, fear, and annoyance and rank them by intensity of emotion by mining the lexical-semantic patterns "X (perhaps) even Y", "X, not to say Y", and "If not X then Y" from the web. Example 1 shows their ordering of *surprise* verbs.

astonish > surprise > amaze > astound > strike > stun > floor
> dumbfound > flabbergast > stupefy

(1)

Not only differentiating emotions but also identifying the perspective and the target of the emotion proves to be challenging. Das and Bandyopadhyay use VerbNet frames to identify the holder of an emotion. In linguistics, the agent or holder is the name of the thematic role of the participant of a situation that carries out an action. Consequently, the holder of an emotion is the agent experiencing the emotion. In contrast, the cause or stimulus of an emotion is the entity that prompts the emotional feeling. Semantic role labeling is the task in natural language processing that aims to identify the semantic arguments of the predicate and classify them into their specific roles.

Mohammad et al. frame the task of identifying the Experiencer, State, and Stimulus of an emotion as a classification task. As they train and use their classifier on a dataset of 2012 US presidential election tweets with annotations crowd-sourced to Amazon's Mechanical Turk [1], they are able to select the stimulus from a set of pre-chosen entities, which works for this narrow domain, but fails given an open set of potential stimuli.

While seed instances and patterns can be emotionally ambiguous, the micro-blogging platform Twitter provides a more salient indicator of emotions: hashtags. Mohammad Qadir and Riloff and both use hashtags to extract emotion-labeled tweets. While the former only use the emotions as hashtags, e.g. *#anger*, *#joy*, etc., the latter use a bootstrapping approach to learn new hashtags and hashtag patterns and harvest emotion phrases from these.

Balahur et al. in contrast don't use IE techniques but base their approach on their knowledge base EmotiNet. As their knowledge base is focused on the family domain, they only consider that domain, where their their approach outperforms an SVM algorithm trained on more data. They also remark that world knowledge is particularly valuable in cases where no emotion-bearing word, e.g. *happy* is present.

Both of the latter works consider verbs as essential indicators of emotions, with the associated emotion being also dependent on properties of the actor and the object. We on the other hand consider clearly emotion-bearing contexts, which enables us to identify concepts or entities that are intrinsically evokative of emotions.

2.2 MODELS OF EMOTION CLASSIFICATION

Psychologists have proposed a number of different theories for classifying emotions, e.g. distinguishing between instinctual and cognitive emotions. As emotions are inherently subjective, none has been universally accepted. Two classification theories have been frequently used by the research community: Ekman's and Plutchik's. Ekman proposes a theory with six basic emotions: anger, disgust, fear, joy, sadness, and surprise. According to Plutchik, there are two additional ones: anticipation and trust. He depicts them in a wheel, depicted in figure 1, where the intensity of the emotion increases with the proximity to the center, and organizes them in four opposing pairs: joy–sadness, trust–disgust, fear–anger, surprise–anticipation.

We adopted Plutchik's emotion classification for the following reasons: (a) it is clearly founded in psychological research; (b) it is a

1 https://www.mturk.com/mturk/welcome

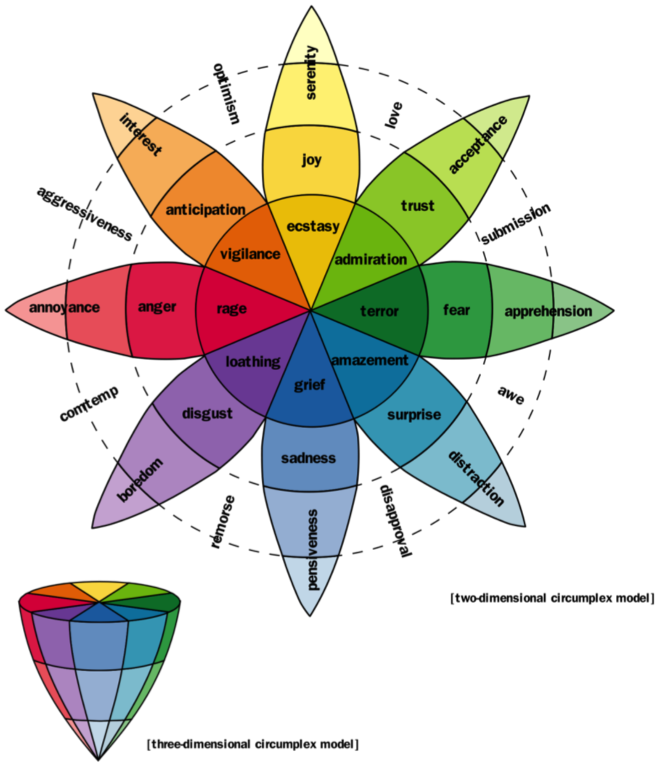

Figure 1: Plutchik's emotion wheel

superset of Ekman's six basic emotions; and (c) its use by other researchers (cf. [24], [7], [22]) increases the comparability and transferability of our work.

2.3 SENTIMENT LEXICA

Sentiment lexica have been pervasive in sentiment analysis. Their use has a long history. The General Inquirer [38], the first lexicon to our knowledge, was created in 1961. It contains 11,788 words labeled with 182 categories of word tags, including positive and negative sentiment and other affect categories. It was key in early experiments such as differentiating fake suicide notes from real ones, among others. Since then, it has been used for a plethora of other applications, particularly sentiment analysis, e.g. for contextualizing polarity [41], i.a.

WordNet-Affect [39] and SentiWordNet [12] are two more recent sentiment lexica built on top of the popular natural language processing resource WordNet [21]. WordNet is a lexical database that organizes nouns, verbs, and adjectives into *synsets* that pertain to underlying lexical concepts. WordNet-Affect annotates WordNet synsets representing affective concepts, whereas SentiWordNet assigns objectivity, positivity, and negativity scores to WordNet synsets.

The manual compilation of a sentiment lexicon can be a long and tedious process. Recently, researchers have looked for other methods:

Mohammad and Turney use crowd-sourcing to build a sentiment lexicon containing about 10,000 entries. They take their terms primarily from the *Macquarie Thesaurus*, as well as the General Inquirer and WordNet-Affect and crowd-source the annotations using Amazon Mechanical Turk. **?** follow the same approach to build the NRC Emotion Lexicon, containing about 14,000 word types, using *Roget's Thesaurus* instead of the *Macquarie Thesaurus*. They use it to quantitatively compare the emotion words in love and hate mail, as well as between genders.

Staiano and Guerini use a different form of crowd-sourced information to create a sentiment lexicion: `rappler.com` lets users vote on the mood of a news story. The authors initially build a document-by-emotion matrix, listing each story with the voting percentages for all eight moods, and term-by-document matrix using different frequency measures. Matrix-multiplication and normalization produces a final word-by-emotion matrix containing 37k entries.

3 PATTERN COMPILATION AND EXTRACTION

3.1 GUIDELINES

In this section, we present guidelines that we followed when collecting the emotion-bearing patterns in order to extract emotion holders and causes from the corpus. The guidelines are the following:

A. Avoidance of ambiguity

B. Extractability of emotion holder and cause

C. Diversity of causes

D. Storing of all meaningful information

3.1.1 *Avoidance of ambiguity*

A clear concern for the compilation of patterns is ambiguity: As emotions are ambiguous, many expressions can be indicative of more than one emotion, e.g. *anxious* can both refer to a state of eagerness or worry. Of 165 anger terms in WordNet-Affect, 53% have also been labeled with disgust. [24]

We seek to preempt this in two ways: (a) We only select expressions that are listed as pertaining to one emotion in one of our sources; and (b) measure agreement between three annotators on the selected expressions, choosing only those on which a majority agrees. We could have included multiple emotions for each pattern, but decided against it, as we wanted to focus

Furthermore, Fellbaum and Mathieu note that emotion verbs can overlap with cognition verbs: *shock* can evoke both a judgment or an emotion. We intend to overcome this issue by (a) selecting patterns whose dominant sense is emotive and (b) analyzing extracted propositions to retroactively patterns that lead to unemotive contexts.

Our overarching goal is the harvesting of emotion-evoking expressions. Insofar, we will avoid using complex sentence structures and omit error-prone concepts like proverbs, multiple embeddings, or idiosyncracies. Instead we focus on clear-cut cases and structures that can be easily disambiguated. In consequence, we will select expressions that are clearly emotion-bearing. Initial experiments have shown that part-of-speech labeling is important, as e.g. *trust* and *fear* can function both as verbs and nouns. Lemma representation is important on a representational level.

3.1.2 *Extractability of emotion holder and cause*

As we have outlined, we seek to show which expressions or entities are associated with or evoke certain emotions. Mohammad and Turney show that there is a slight distinction between *associated* and *evokes*, whereupon *associated* produces moderately higher agreement numbers between annotators when used in the annotation task description. As this agreement is not relevant for the annotation of our patterns, we will treat *associated* and *evokes* equivalently in the following.

In order to show association, we need to be able to extract both the holder and the cause of an emotion. Das and Bandyopadhyay have proven that automatically extracting the emotion holder for emotions can be difficult. Their syntax-based model using WordNet-Affect lists has an F-score of 66.98%. In order to create a reliable resource, our patterns need to be more accurate. Furthermore, they rely on manually annotated VerbNet frames, which would restrict us to VerbNet thereby greatling reducing both the size and consequently the dependability of our results.

We thus want to select patterns for which the emotion holder and the cause are both present. For instance, we would not like to choose simply *be happy* as a pattern since "I am happy" does not indicate the cause of happiness. *Be happy that* would be a more suitable pattern, as "I am happy that you came" provides more information as to the reason for the state of being happy. This leads us to mainly employ transitive constructions. Fellbaum and Mathieu only include Experiencer psych verbs in their emotion classes. In the transitive construction of these verbs, the subject refers to the cause, while the object expresses the experiencer, as depicted in 2a. Thus they include verbs like *scare* and *intimidate*, but exclude verbs like *fear*, whose subject in a transitive construction expresses the Experiencer, as in example 2b.

The dog frightens the man.
CAUSE EXPERIENCER (2a)

The man fears the dog.
EXPERIENCER CAUSE (2b)

We don't want to exclude verbs based on this property, since verbs in VerbNet's ADMIRE class – which encompasses *fear* and verbs with the same alternation behaviour – include other verbs like *abhor*, *deplore*, etc. that are clearly emotive. In order to adequately capture this property, we include a flag with each pattern that indicates if the order of subject–EXPERIENCER, object–CAUSE depicted in 2b is reversed.

As the Annotated Gigaword provides both annotations, we can extract information using both the dependency and the constituency structure.

3.1.3 *Diversity of causes*

If we only capture objects as causes, we will clearly miss out on a lot of variety that is inherent to emotions. Emotions can equally be evoked by a concept, entity, event, situation, or certain condition. Besides capturing nominal phrases, we thus also want to collect patterns that indicate emotions whose stimulus is an act, event, or condition encompassed in a sub-clause as can be seen in example 3.

I fear that my company will go bankrupt. (3)
EXPERIENCER CAUSE

The types of causes we thus expect are nominal phrases or subclauses. These are labeled as NP and S/SBAR respectively in phrase-structure grammars. Phrase-structure grammars are based on the constituency relation, which divides the most basic clause into subject (noun phrase NP) and predicate (verb phrase VP) and follows a one-to-one-or-more correspondence for each resulting clause. In the Penn Treebank tags – which is the tag set that is used by the Stanford parser in the Annotated Gigaword –, S is a simple declarative clause, SBAR is a declarative clause introduced by a subordinating conjunction, and NP is a noun phrase. If a predicate can occur with both a nominal phrase and a sub-clause, we will create a separate pattern for each cause type and add a flag indicating the type.

3.1.4 *Storing of all meaningful information*

Besides the emotion holder and cause, we want to extract all relevant information that might be useful for further analysis. Borth et al. clearly show that adjectives have significant emotive value by pairing positive or negative adjectives with neutral nouns to construct adjective-noun pairs. Thus we want to include any modifiers as well as any prepositional objects. Since we primarily are interested in what entities evoke certain emotions, we include a bag-of-words representation of the cause, in case additional tokens need to be considered.

3.2 PATTERN SOURCES

We make use of the selection of emotion lexica available as well as resources mentioned in previous works to collect emotion-bearing patterns. We use three categories of sources: (a) dictionaries and thesauri; (b) sentiment lexica as well as past research; and (c) general-purpose natural language processing (NLP) resources.

3.2.1 *Dictionaries and thesauri*

We use the emotion's definition in the Oxford English Dictionary to generate an initial list of emotions. The Oxford English Dictionary is widely acknowledged to be the most comprehensive and authoritative record of the English language, which makes it an apt starting point for our endeavour. We then use Merriam-Webster's Dictionary and Roget's Thesaurus – which was used to produce target terms by **?** – to retrieve synonyms for those verbs. As Roget's Thesaurus has a relevance ranking, we choose only those synonyms with the hightest relevance.

3.2.2 *Sentiment lexica and past research*

3.2.2.1 *Harvard General Inquirer*

The Harvard General Inquirer [38] contains a plethora of words ordered by categories, some of which are relevant to emotions: It contains 1045 positive words, with a subset tagged for indicating affiliation or supportiveness. It contains 1160 negative words, a subset of which is tagged for indicating an attitude or concern with hostility or aggressiveness. 168 words are tagged with PLEASURE indicating the enjoyment of a feeling; 254 PAIN words indicate suffering, lack of confidence, or commitment; 49 FEEL words describe particular feelings, including gratitude, apathy, and optimism; 166 AROUSAL words indicate excitation (aside from pleasures or pains); finally 311 EMOT words relate to different emotions such as *admiration*, *annoyance*, etc.

While the Inquirer has found use in a plethora of applications, it doesn't add a lot of value to our approach as it doesn't distinguish emotions on the finely granular level that we require for emotion detection.

3.2.2.2 *NRC Word-Emotion Association Lexicon*

As has already been mentioned, the NRC Word-Emotion Association Lexicon (also called EmoLex) was developed by **?** using crowdsourcing. While it also employs Plutchik's eight emotion classes, annotations can be very subtle and mirror underlying perception tendencies than what would be helpful in surfacing the holder and the cause of an emotion, as can be seen in example 4, where *abacus* is associated with the emotion trust. In consequence, we are not able to retrieve any clearly emotion-indicating patterns from it.

abacus trust 1 (4)

However, in the same vein, its entries, which evoke or are associated with emotions, are similar to the kind of entries that we would want to have in our proposition store. Insofar, we will use it for part of the evaluation of our proposition store in chapter 4.

3.2.2.3 *Emotion verb classes*

The manually constructed emotion verb classes by Fellbaum and Mathieu fulfil the requirements for our patterns: They clearly indicate an emotion and the emotion holder and cause can be extracted using the semantic roles.

We incorporate the following ten, five, and nine members respectively as emotion verbs for Plutchik's emotions surprise, fear, and anger, respectively, as anger is a degree of annoyance; for surprise: *astonish*, *surprise*, *amaze*, *astound*, *strike*, *stun*, *floor*, *dumbfound*, *flabbergast*, *stupefy*; for fear: *intimidate*, *scare*, *frighten*, *alarm*, *terrify*; for anger: *irk*, *nettle*, *irritate*, *annoy*, *anger*, *exasperate*, *infuriate*, *enrage*, *incense*.

3.2.2.4 *Adjectives*

As we have seen, linguistic triggers for emotions are diverse; not only verbs, but also adjectives are adt in capturing emotions. In WordNet, nouns and verbs are clustered in synsets and supersenses. Tsvetkov et al. induce supersenses for adjectives – taking GermaNet's guidelines[1] as inspiration – in order to create a taxonomy for adjectives.

They build a weakly supervised classifier that labels adjective types (irrespective of context), which they train on a small set of seed examples, some of them translations of GermaNet. We take the 126 adjectives that pertain to FEELING and manually label them with Plutchik's eight emotion classes.

They also released 7511 WordNet adjectives tagged by their classifier with an adjective type vector. From these we derive the 920 adjectives that are labeled with the adjective type FEELING. As the classifier only has an accuracy of 54%, we receive many erroneous instances like *unknown*, *unreal*, etc. rendering this set of adjectives unusable for our purposes.

3.2.3 *General-purpose NLP resources*

The troika of resources, WordNet, VerbNet, and FrameNet, has seen frequent use in NLP applications leading us to investigate the use of the three for our purposes.

3.2.3.1 *VerbNet*

VerbNet [16] focuses on the syntax and semantics of verbs, clustering them in semantic groups pertaining to their occurrence in syntactic alternations. While it is helpful in identifying the holder and the cause

1 http://www.sfs.uni-tuebingen.de/lsd/adjectives.shtml

of an emotion via its frame annotations, it is inadequate in differentiating between different emotions, e.g. *fear* and *admire* are part of the same class. As many members of the *admire* class as can be seen in figure 2, e.g. *abhor*, *adore*, *deplore*, etc. are clearly emotion-indicating verbs, we adopt many of these, labeling them with the appropriate emotion.

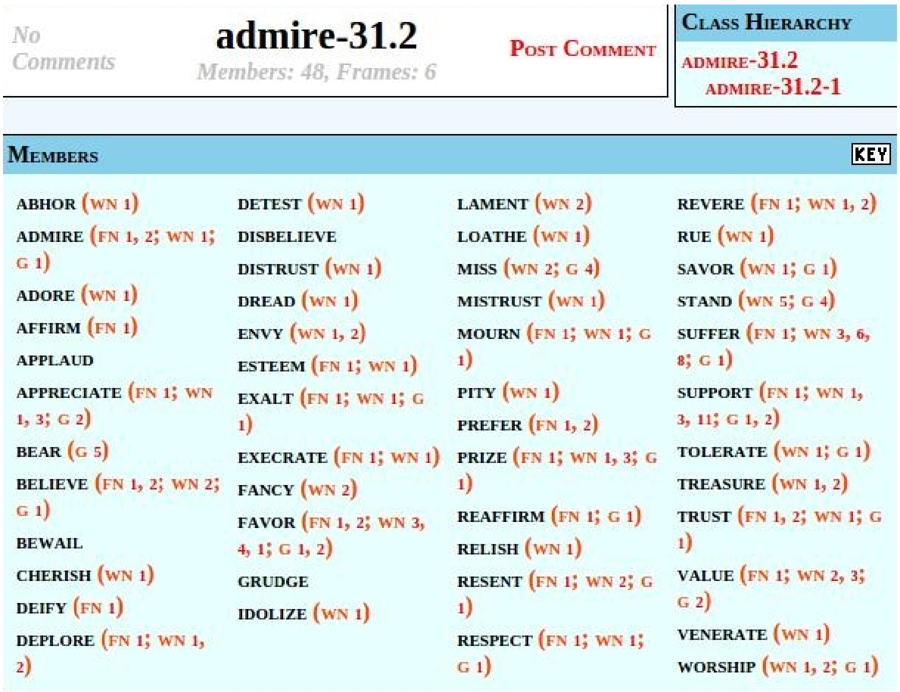

Figure 2: VerbNet's *admire* class

3.2.3.2 *FrameNet*

FrameNet [2] combines syntactic and semantic generalizations. Semantic frames represent the underlying meanings of the words, linking frame elements with their syntactic realizations.

In FrameNet emotions are conceptualized in the EMOTIONS frame, which describes an Experiencer in a particular emotional State that was provoked by a Stimulus. The frame EMOTIONS is used by ten other frames. Of these, we investigate more closely the DESIRING, EMOTION_ACTIVE, EMOTION_DIRECTED, and EXPERIENCER_OBJ frames.

In the DESIRING frame, the Experiencer desires that an Event occur. We derive 20 verbs from the DESIRING frame, all of whom we label with anticipation. In the EXPERIENCER_OBJ frame, some phenomenon (the Stimulus) provokes a particular emotion in the Experiencer. Experiencer and stimulus (cause) are core frame elements, making this frame ideal for our purposes. We derive 132 verbs from this frame. The EMOTION_ACTIVE frame is similar to EXPERIENCER_OBJ, but in this frame the verbs are more active. We derive 9 verbs from this frame.

Finally, the EMOTION_DIRECTED frame focuses on adjectives and nouns describing an Experiencer's emotional response to a Stimulus. We keep a few of these, convert some into verbs, and discard the rest, resulting in 12 verbs and adjectives from this frame.

Furthermore, EMOTIONS is inherited by the EMOTIONS_BY_STIMULUS frame that is in turn inherited by the ANNOYANCE, EMOTIONS_BY_POSSIBILITY, i.e. fear, EMOTIONS_OF_MENTAL_ACTIVITY, EMOTIONS_OF_SUCCESS_OR_FAILURE, JUST_FOUND_OUT, i.e. surprise, and OTHERS_SITUATION_AS_STIMULUS frames. While these frames all refer to emotions, we have obtained most of their lexical entries already from other sources and thus don't make use of them.

3.2.3.3 *WordNet*

WordNet [21] synsets by themselves don't contain any information about sentiment or emotion. As was previously mentioned, WordNet-Affect [39], an additional hierarchy of affective domain labels, annotates WordNet synsets representing affective concepts in the semi-automatically augmented WordNet Domains further with affective labels.

WordNet-Affect-1.1 only contains synsets that were tagged with the label EMO(TION) in the previous version and thus should serve our purposes. It further labels these synsets with a set of 279 distinct emotion categories, among them emotions such as *defeatism*, *self-depreciation*, *puppy-love*, etc. These categories are hierarchically connected via `is-a` relations, which we map to Plutchik's eight emotions.

Given the ID listed in the WordNet-Affect-1.1 synsets, we retrieve the respective WordNet-3.0 synset lemmas using NLTK toolkit [5] and the corresponding category. As WordNet focuses on nouns, adjectives, verbs, and adverbs are all listed with the noun that they are derived from. For these, we thus retrieve the category of the corresponding noun. This way, we produce 784 noun-, adjective-, verb-, and adverb synsets labeled with Plutchik's eight emotions. We investigate these and make use of the verb and adjective synonyms that indicate the emotion holder as well as the cause.

SentiWordNet [12], conversely, does not prove as helpful, as we require a finer granularity than the positivity, negativity, and subjectivity scores it assigns to WordNet synsets.

3.3 COMPILATION

To recapitulate, if a verb or an adjective has been listed in a source with an emotion, we adopt that emotion, given it is among Plutchik's eight emotion classes; if not, we manually label it. From these predications, we derive the pattern templates. We list the word in lemma form along with its emotion and Penn Treebank part-of-speech tags.

```
fear (?! not)(?! never)scare/VB[DGPZ]/[0-9]+ NP
fear (?<= )be/VB[PDGZ]/([0-9]+)(?! not)(?! never)(
    [a-z]+/RB/[0-9]+)? scare/VBN/[0-9]+ that/IN/[0-9]+ S
fear (?<= )be/VB[PDGZ]/([0-9]+)(?! not)(?! never)(
    [a-z]+/RB/[0-9]+)? scare/VBN/[0-9]+ by/IN/[0-9]+ NP
joy  (?! not)(?! never)be/VB[DGPZ]/[0-9]+(?! not)(?! never)(
    [a-z]+/RB/[0-9]+)? happy/JJ/[0-9]+ about/IN/[0-9]+ S
```

Figure 3: Regex patterns for *fear* and *be happy about*

As we stated before, we add two flags: the first one indicates if the cause of the emotion is an NP or an S. The second one specifies if the order of subject–EXPERIENCER, object–CAUSE is maintained. Two patterns can be found in 5: *scare* takes as direct object a nominal phrase, which takes the thematic role of the EXPERIENCER; *be scared happy about* refers to a clause, while its subject is the EXPERIENCER.

$$\begin{aligned}&\text{fear scare/Verb NP true}\\&\text{joy be/Verb RB happy/JJ about/IN S false}\end{aligned} \tag{5}$$

Subsequently, we convert the pattern templates into regular expression patterns. We allow adjectives to be with modified, but exclude negation. We add a regex to capture the index of a word to enable unambiguous retrieval. If the regular order specified by the second flag is reversed, e.g. for *annoy*, we generate additional regular expressions that capture the passive form. These are constructed with the prepositions *that* and *by* and take a clause and a nominal phrase as complement respectively. Following this approach, we generate three regular expression patterns for *scare* and one for *be happy about*, which can be viewed in 3.

3.4 CORPUS SELECTION

As our goal is to harvest as many emotion-evoking expressions as possible for a particular domain, we chose to use the English Gigaword corpus.

# tokens	**# documents**
4,032,686,000	9,876,086

Table 1: Number of tokens and documents for English Gigaword v.5

Not only is its latest addition, Gigaword v.5 [31], containing almost 10 million documents from seven news outlets, with a total of more than 4-billion words (cf. table 1), the largest static corpus of English news documents in existence; but also Napoles et al. recently made an annotated version of it available that facilitates processing. They provide the following pre-processing all of which we are using:

A. tokenized and segmented sentences,

B. Treebank-style constituent parse trees,

C. syntactic dependency trees,

D. named entities, and

E. in-document coreference chains.

The Annotated Gigaword has already been used for approximate search, e.g. to find relations similar to "X dived Y". As our patterns are of a similar format, it is ideal for our approach.

Genre and domain clearly play an important role in the context of emotions. Some genres are designed to elicit emotions, while others are geared to other functions. We expect that – as a collection of news corpora – Gigaword will be sparser in emotions than a collection of novels or fairy tales (cf. [22]) and its emotions will be of a different variety and towards a different set of concepts and entities.

3.5 EXTRACTION

We initially extracted emotion holder and cause by performing depth-first search on the Stanford constituency tree of a matched sentence and pruning the retrieved sub-tree. However, we chose to discard this approach as results were noisy and adapting to incongruencies of the sentence structure, e.g. exposed objects, leading adjuncts, etc. proved too error-prone. In consequence, we focused on extracting dependencies, which are less ambiguous and more clearly represent the emotion holder and cause relations that we are looking for.

We choose the Stanford collapsed dependencies, as these collapse dependencies like conjunctions or prepositional objects and thus make the extraction more straight-forward, e.g. a basic dependency like *prep*(cat, in) in 6 is collapsed to *prep*(cat, hat).

I saw a cat in a hat. *prep*(cat, in)
I saw a cat in a hat. *prep_in*(cat, hat) (6)

We extract the subject via the `nsubj` or `nsubjpass` relations and the direct object via the `dobj` relation. These relations can also be embedded in disjunctions or conjunctions, which we retrieve via the collapsed `conj_and`, `conj_or`, and `conj_but` dependencies[2] If the complement of the verb is a clause, we extract the S cause via the `ccomp`

2 The uncollapsed `cc` relation would increase the search depth by another relation.

or `xcomp` relations, which are clausal complements with and without their own subjects respectively. If the verb or the adjective appears with a preposition, e.g. *take pleasure in*, *be proud of*, we retrieve the complement via the `pcomp` (prepositional complement) or the `pobj` (prepositional object) relation respectively. If the verb modifies the subject, e.g. "a ruler loved by the people", we extract the subject via the `partmod` relation.[3].

In order to store all relevant information, we capture the following relations:

A. the modifiers of the noun:
   a) `nn` (noun compound modifier), e.g. `nn`(University-10, Harvard-9)
   b) `amod` (adjectival modifier)
   c) `num` (numeric modifier)[4]

B. the prepositional objects pertaining to the noun and the verb; collapsed prepositional objects consist of the preposition name prefixed with `prep_`, e.g. `prep_on`

We insert adjectival and numeric modifiers before the noun; we append prepositional objects prefixed by the preposition and separated by an underscore, if it is a noun, e.g. FOR:millionth_fan. We include prepositional objects modifying the predicate of a clause in a separate bag-of-words.

Often, the emotion holder and the cause of an emotion are expressed by pronouns, which by themselves only provide limited information and generalizability. For this reason, we leverage the Stanford coreference resolution annotations of the Annotated Gigaword replacing every mention with its most representative coreferent.

To further make our results more generalizable, we tag every named entity with its named entity tag, i.e. LOCATION, PERSON, and ORGANIZATION, replacing numbers with the NUMBER tag.

Finally, dependent on the argument order, we assign the subject and the object/clause to the EXPERIENCER or CAUSE respectively; we discard extractions where the cause still contains a pronoun, as we require our extractions to be as generalizable as possible.

3.6 REPRESENTATION FORMAT

The format we choose for the representation of our extractions can be seen in figure 4 (with tabs as delimiters).

In both examples, Japan is the emotion holder. In the first instance, the cause is a nominal phrase extracted via the `dobj` relation, while

3 As of the Stanford dependencies version 3.5.2, `partmod` has been generalized as a case of `vmod` (reduced non-finite verbal modifier)
4 `num` is converted to `nummod` as of version 3.5.2.

```
NYT_ENG_19960601.0010/1 trust rely on Japan/LOCATION economic
    clout     [its/PRP$, economic/JJ, clout/NN]
NYT_ENG_19960601.0010/9 anticipation expect Japanese    win
    right  [to/TO, win/VB, the/DT, right/NN, to/TO, host/VB,
    the/DT, tournament/NN]
```

Figure 4: Extractions with NP and S cause

in the second one, the cause is a clause extracted using the `xcomp` relation. We provide the following properties in ascending order of column index:

A. a unique identifier for each extraction created by concatenating the Annotated Gigaword document ID with the index of the sentence in that document;

B. the emotion;

C. the pattern that produced the extraction;

D. the emotion holder;

E. the NP cause of the emotion (can be empty);

F. the subject of the S cause of the emotion (can be empty);

G. the predicate of the S cause of the emotion (can be empty);

H. the direct object of the S cause of emotion (can be empty);

I. prepositional objects modifying the predicate of the S cause (can be empty); and

J. a bag-of-words representation of the cause, tagged with parts-of-speech.

As we also collect the full propositions, we can easily cross-reference extractions via the ID to extract collocations.

3.7 MEASURING ANNOTATION AGREEMENT

By also using the passive form when applicable, we arrive at 662 patterns for Plutchik's eight emotions. We run an initial extraction over a random sample of 2M sentences of the corpus. As we want to guarantee accuracy as well as recall, we retain patterns with an NP cause that appear at least ten times – as these are prevalent; we retain patterns with an S cause that appear at least once.

This leaves us with 180 active and passive patterns. In line with the difficulty of clearly differentiating between different emotions, emotion predicates can also be associated with more than one emotion

[24]. If one emotion is clearly dominant, we don't want to exclude them based on this property.

To select only those patterns that clearly pertain to only emotion, we let two additional annotators label the patterns with one of Plutchik's emotion. We also allow the annotators to label patterns with `none` in case a pattern doesn't indicate an emotion. We instruct them to label the patterns with a second choice if they think that more than one emotion applies. All three annotators are instructed to label the pattern with the degree of the assigned emotion to allow for an even finer measure of agreement.

We use Fleiss' kappa (κ) as a measure of inter-annotator agreement instead of the popular Cohen's κ, as Cohen's κ only measures agreement between two annotators. Our annotators have a Fleiss' κ of 0.65, which signifies substantial agreement according to Landis and Koch. This score is particularly significant given that κ usually declines as the number of categories increases. The different levels of agreement can be observed in table 2.

Fleiss' κ	Interpretation
0	poor agreement
0.00 - 0.20	slight agreement
0.21 - 0.40	fair agreement
0.41 - 0.60	moderate agreement
0.61 - 0.80	substantial agreement
0.81 - 1.00	almost perfect agreement

Table 2: Fleiss' κ values and their interpretations [17]

As can be seen in table 3, a substantial amount, 106 of 180 expressions have been labeled unanimously with the same emotion by all three annotators. Including the second choice only increases the number slightly.

Quite significantly, 39 expressions have been labeled with the same emotion as well as the same degree of emotion, which is a number

Annotated expressions	Number
with unanimous emotions	106
with unanimous emotions (including 2nd choice)	119
with majority emotions	163
with unanimous emotions + degree	39
with majority emotions + degree	131
Fleiss' κ	0.65

Table 3: Number of annotated expressions for different forms of agreement

much higher than chance[5] for what is essentially a 25-category classification problem (8 emotions · 3 degrees + 1 none). We finally select all patterns for which we observe a majority emotion agreement, i.e. at least two of three annotators assign the same emotion. These are 163 patterns. Their distributions across all emotions can be viewed in table 4.

Emotion	# of majority patterns
joy	31
trust	8
fear	22
surprise	16
sadness	18
disgust	14
anger	29
anticipation	25

Table 4: Number of patterns that have been labeled by the majority with the same emotion

All of the patterns can be viewed in appendix A in table 24. Anger is relatively evenly distributed across its degrees (annoyance $<$ anger $<$ rage) according to Plutchik's emotion wheel (cf. figure 1); anticipation is harder to grasp, having been assigned almost exclusively to annoyance (rather than interest or vigilance) by the majority; fear appears in all its degrees, slightly less in terror; joy patterns are mostly labeled as joy, with a few having been attributed to ecstasy and only one to serenity; disgust, sadness, surprise, and trust never appear in their weakest form, boredom, pensiveness, distraction, and acceptance respectively.

In general, the middle tier representing the general emotion class is prevalent among the patterns labeled by the majority, with a lot of emotions not appearing in their weakest degree due to selection bias as we tended to collect patterns that were clearly indicative of one emotion.

5 For chance, only $(\frac{1}{25})^2 \cdot 180 = 0.3$ of 180 expressions would be labeled with the same degree of emotion by all annotators.

4 ANALYSIS

4.1 EXTRACTION RESULTS

Matching the patterns against the whole annotated Gigaword corpus, we're able to retrieve 2,320,636 extractions. These extractions, however, contain many duplicates, e.g. the sentence "In 1997, with only three years as Texas governor, Bush raised a record-sized warchest that scared away several challengers and found himself at the top of polls of potential 2000 GOP candidates." occurs in the annotated Gigaword file APW_ENG_200011.XML.GZ 25 times in different documents.

After removing all extractions that stem from identical sentences, we arrive at 1,788,022 extractions. After an investigation of the results, we decided to remove extractions with the following patterns from the corpus as they may often refer to unemotive contexts in the news domain that are different from the ones we originally intended:

- *grate*: Although occasionally used emotively, *grate* is most often used in an unemotive context related to cooking.
- *depress*: As economics are a frequent topic, *depress* often refers to sales or prices rather than the mental state of persons.
- *aggravate*: In international politics, *aggravate* often relates to conditions instead of individuals.
- *rattle*: In politics, someone may *rattle off* an argument or an earthquake may *rattle* a city.
- *afflict*: An ailment often *afflicts* people.
- *inflame*: *Inflame* is often used metaphorically, i.e. *inflame* the bonfire of terrorism, the spirit of war, etc.

Excluding these patterns in their active and passive forms leaves us with 1,774,420 distinct extractions. Their emotion distribution is depicted in table 5, while the distribution of nominal phrases and clauses as causes can be viewed in table 6. As can be seen, anticipation makes up slightly more than half of all extractions, which is mainly due to *expect* being a very productive pattern, as depicted in table 8.

Due to space requirements, we display the top 10 patterns for each of the opposing emotion pairs, surprise–anticipation, joy–sadness, trust–disgust, and fear–anger, and discuss them briefly.

Analogous to social media data, which has been found to be predominantly happy [37] due to its subjectivity, neutral predicates are

Emotion	Frequency	% of total extractions	# of patterns with 10+ occurrences
anticipation	966,571	54.47	22
fear	249,103	14.04	20
joy	231,967	13.07	30
trust	89,217	5.03	6
anger	64,586	3.64	28
surprise	60,221	3.39	20
disgust	59,486	3.35	15
sadness	53,269	3.00	13
Total	1,774,420	100.00	154

Table 5: Frequencies of emotions in extractions

Emotion	# extractions with NP cause	# extractions with S cause
anticipation	407,738	558,833
joy	190,484	41,483
fear	82,116	166,987
trust	72,483	16,734
surprise	59,657	564
disgust	58,942	544
anger	57,379	7,207
sadness	26,064	27,205
Total	956,392	819,557

Table 6: Patterns with NP vs. S cause

prevalent given the idiosyncracies of the objective news domain. Consequently, anticipation as well as neutral predicates such as *expect*, *predict*, and *rely on* rank highly. Additionally, *enjoy* and *fear* are very productive, which seem to be the preferred ways to indicate the polar opposites of joy and fear. As is according to style conventions of newspaper and creative writing, passive forms play a subordinate role and are (except for trust, which had less than ten patterns) not found in the top ten patterns of any emotion. When we look at the distribution between NP causes and S causes between emotions in table 6, we see that – except for anticipation and fear – NP causes dominate and – in the cases of surprise, disgust, and anger – quite clearly. This is due to the prevalent use of the active form of Experiencer psych verbs such as *surprise*, *hate*, *provoke*, etc. which predominantly take a nominal phrase as their argument.

Pattern	Frequency
surprise	18,358
stun	16,211
shock	13,269
confuse	2,899
wow	2,003
confound	1,771
startle	1,680
baffle	1,169
puzzle	802
stagger	689
Total top 10	58,851
Total	60,221

Table 7: Top 10 surprise patterns

Pattern	Frequency
expect	490,640
predict	156,681
await	71,910
look forward to	59,884
prepare for	45,687
forecast	45,365
hope	28,277
anticipate	19,112
be hopeful	17,732
foresee	9,248
Total top 10	944,536
Total	966,571

Table 8: Top 10 anticipation patterns

Pattern	Freq
enjoy	131,102
be proud	21,842
be lucky	13,857
cheer	10,658
relish	5,590
impress	5,431
entertain	4,318
arouse	4,247
be satisfied	4,016
please	3,394
Total top 10	204,455
Total	231,967

Table 9: Top 10 joy patterns

Pattern	Freq
regret	24,395
mourn	7,948
be unhappy	6,120
be sad	5,071
disappoint	3,320
upset	2,439
grieve	1,317
pine for	1,064
agonize over	489
displease	423
Total top 10	52,586
Total	53,269

Table 10: Top 10 sadness patterns

4.2 DISTRIBUTIONAL ANALYSIS OF EMOTION HOLDER AND CAUSE

For the distributional analysis of the results, we first count the occurrences of all unigrams and bigrams respectively for the emotion holder, the NP cause, the S cause as well as the predicate of the S cause together with the subject and together with the object respectively. To guarantee maximum meaningfulness of the results, we treat prepositional objects as one unigram. We convert all ngrams to lowercase if they are not named entities; for named entities, we keep the

Pattern	Freq
rely on	50,480
count on	17,562
trust	14,749
reassure	5,384
take comfort in	620
charm	412
be charmed	7
be reassured	3
Total top 10	89,217
Total	89,217

Table 11: Top 10 trust patterns

Pattern	Freq
hate	22,804
shun	9,268
deplore	8,751
dislike	6,069
alienate	2,675
repel	2,054
despise	1,828
loathe	1,328
disdain	1,208
abhor	1,149
Total top 10	57,134
Total	59,486

Table 12: Top 10 disgust patterns

Pattern	Frequency
fear	155,968
be afraid	35,314
worry	25,361
be anxious	10,427
scare	6,704
be scared	3,340
be nervous	2,195
frighten	1,992
unnerve	1,573
dread	1,534
Total top 10	244,408
Total	249,103

Table 13: Top 10 fear patterns

Pattern	Frequency
provoke	16,528
be angry	6,808
bother	6,612
infuriate	5,316
harass	4,791
insult	3,534
frustrate	2,912
irritate	2,805
offend	2,482
fret	2,356
Total top 10	54,144
Total	64,586

Table 14: Top 10 anger patterns

NE tags in a shortened form for better readability; finally, we remove all stopwords.

We generate unigrams for the following strings:

A. The emotion holder

B. The NP cause

C. The whole S cause

We generate bigrams for the above as well as the following strings:

A. The subject of the S cause concatenated with its predicate

B. The predicate of the S cause concatenated with its object

In both of the latter, the predicate is always part of the bigram. The counts of number of unigrams and bigrams for the different configurations can be found in 15. We have unigram counts around 2m, while bigram counts range around 1m, except for the predicate + direct object configuration.

Ngram type	**# unigrams**	**# bigrams**
Subj + Pred (S cause)	0	921,337
NP cause	1,856,712	915,122
Pred + Dobj (S cause)	0	168,013
S cause	2,307,214	1,490,232
Emotion holder	2,809,796	1,279,699

Table 15: Number of unigrams and bigrams for different emotion holder / cause configurations

We use two association metrics that have been used frequently in sentiment analysis: pointwise mutual information (PMI) and chi-square.

4.2.1 *PMI*

PMI models the mutual information between two expressions. It was derived from information theory. The PMI for two expressions x and y is defined as the ratio of their joint probability and the product of their individidual probabilities:

$$pmi(x;y) = log\frac{p(x,y)}{p(x)p(y)}$$

with $p(x,y) = \frac{f(x;y)}{N}$ and $p(x)p(y) = \frac{f(x)f(y)}{N^2}$, where $f(x)$ is the frequency of x in the corpus.

x and y are associated with each other, if their PMI is greater than 0 – with their association strength increasing with the PMI score; they are negatively associated if their PMI is less than 0. In our case, x is the emotion and y is a unigram or bigram that occurs with the emotion.

The regular PMI measure has one issue in that if y occurs just once with emotion x and with no other emotion, $p(x,y) = p(y)$, which reduces the above equation to $pmi(x;y) = log\frac{1}{p(x)}$, which is independent of the ngram y as it is just the probability of emotion x.

Mohammad simply ignore ngrams that ignore less than five times, which, however, only unsatisfactorily mitigates the issue. Instead, in order to penalize such low-frequency observations, we use a simple discounting method that has been described by Pantel and Ravichandran and already put to you use by Gerber and Chai. Multiplying the numinator with the discount factor produces the following term:

$$\frac{f(x;y)}{N} \cdot \frac{f(x;y)}{f(x;y)+1}$$

If the ngram occurs very rarely, the discount factor will be small, reducing the PMI score. We apply a similar discount to the denominator, which reduces to the n-gram frequency divided by the n-gram frequency + 1, as the ngram would always occur less often than the associated emotion category:

$$\frac{f(x)f(y)}{N^2 \frac{min(f(x),f(y)}{min(f(x),f(y)+1}} = \frac{f(x)f(y)}{N^2 \frac{f(y)}{f(y)+1}}$$

If the ngram is rarely observed, $\frac{f(y)}{f(y)+1}$ is small, making the denominator large, which reduces the PMI score. In general, the discount factor reduces the PMI score for ngrams that are very infrequent ($f(y)$ close to 1) and minimally impacts all other PMI scores – which is exactly the behaviour that we want.

Another common variant of the PMI measure is the normalized PMI score, which restricts the PMI value to the interval $[-1, +1]$, where -1 signifies no joint occurrence, 0 is independence, and +1 represents complete co-occurrence. We have experimentally applied this, but found that it negates the effect of the introduced discount, which led us to decide against its use.

4.2.2 *Chi-square*

Chi-square (χ^2) is another common measure. Let n be the number of all documents, i.e. extractions, $p(x|y)$ be the conditional probability of emotion x occurring with ngram y, $P(x)$ be the fraction of extractions containing emotion x, and $F(y)$ be the fraction of extractions containing ngram y, which we define as follows:

$$p(x|y) = \frac{p(x;y)}{p(y)}$$

$$P(x) = \frac{f(x)}{n}$$

$$F(y) = \frac{f(y)}{n}$$

With these, the χ^2 metric between emotion x and ngram y is defined as [1]:

$$\chi^2 = \frac{n \cdot F(y)^2 \cdot (p(x|y) - P(x))^2}{F(y) \cdot (1 - F(y)) \cdot P(x) \cdot (1 - P(x))}$$

χ^2 and PMI are two different ways of measuring how well a term and a category correlate. χ^2 in contrast to PMI is a normalized value, making it more comparable across the same category. χ^2, however, doesn't penalize infrequent terms, which the discounted PMI score does. We compare the results of the PMI and χ^2 metrics for an initial set of results and then proceed with the metric that yields the better performance.

4.2.3 *PMI vs. chi-square*

We clearly want to be able to compare values not only among the different types of unigrams and bigrams that we extract. If we compare the PMI values of top bigrams in the NP cause of different emotions, we find that their range lends itself to easy comparison, with the top 10,000 bigrams of each emotion falling in an interval between 3.40 (sadness) and 0.16 (surprise) as depicted in figure 5.

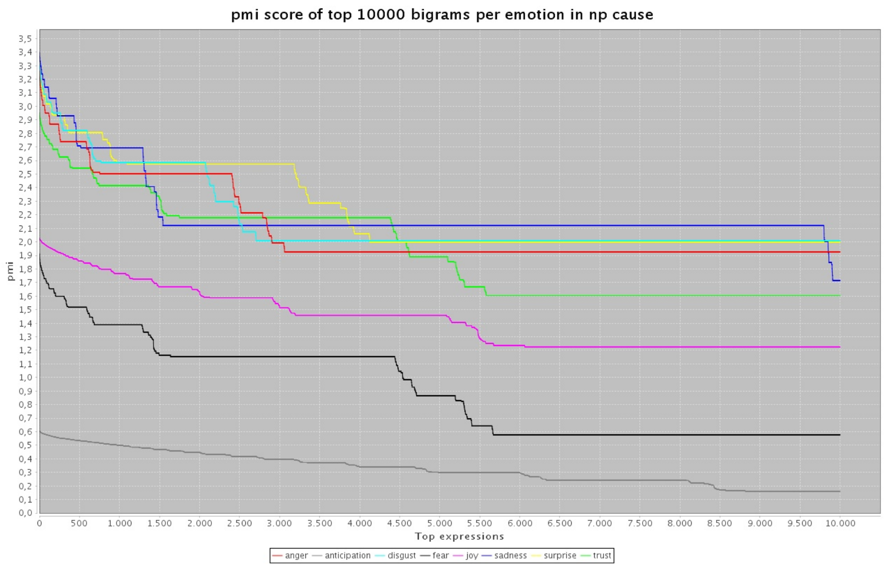

Figure 5: PMI values for the top 10,000 bigrams for each emotion

Conversely, χ^2 values, whose distribution ranges from 9,426 (sadness) to 73.68 (fear) for the top 100 bigrams of each emotion, as can be seen in figure 6 renders comparison of χ^2 values across emotions moot.

Comparing the top 10 NP cause bigrams of sadness, the emotion with the top-ranked bigram for each measure, in table 16 shows that both measures produce sensible candidates. Among χ^2 sadness bigrams, the theme of *loss* is prevalent, while among PMI bigrams *death* dominates. PMI bigrams are also grouped much more closely, while

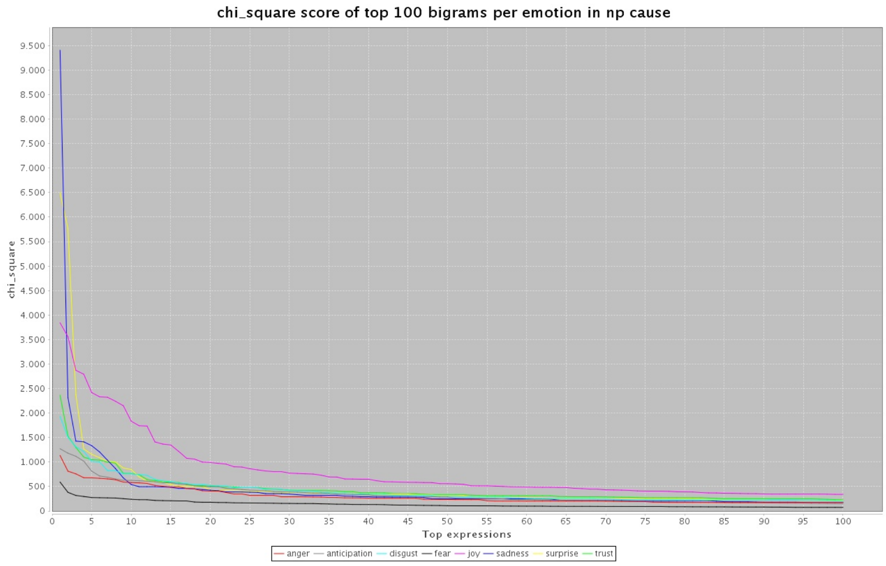

Figure 6: χ^2 values for the top 100 bigrams

the huge gap between the first and second χ^2 candidate isn't plausibly justifiable.

χ^2 **bigram**	χ^2 **value**	**PMI bigram**	**PMI value**
loss of:life	9426.09	death of:NUM	3.40
loss of:innocent_life	2317.45	quake victim	3.37
tragic loss	1430.38	death of:wife	3.37
loss of:civilian_life	1416.05	loss of:man	3.37
civilian casualty	1303.09	tragic loss	3.36
death of:NUM	1208.49	death of:father	3.36
death of:NUM_people	1038.87	death of:NUM_people	3.34
NUM victim	870.43	death of:relative	3.33
unfortunate incident	677.81	loss of:friend	3.33
choice of:word	516.71	innocent victim	3.33

Table 16: Comparison of χ^2 and PMI values for the top 10 sadness NP cause bigrams

In light of the lack of comparability across emotions and the semantically injustifiable huge differences for the same emotion with the χ^2 measure and given length constraints, we choose to proceed with further analyses using the PMI metric.

4.2.4 *Bigrams vs. unigrams*

Having seen the top 10 NP cause sadness bigrams, when we take a look at the corresponding unigrams in table 17, we find that, while a lot of them are plausible, units like *to:embassy*, *of:grandson*, or *of:Princess_Diana/PERS* are totally inconsequential without the relevant context. Note that *uday* – actually Uday Hussein – was erroneously tagged as VBP.

Unigram	**PMI score**
inconvenience	3.43
misunderstanding	3.42
passing	3.32
to:embassy	3.32
slay	3.28
of:grandson	3.27
assassinate	3.27
of:Princess_Diana/PERS	3.25
error	3.25
uday	3.24

Table 17: Top 10 NP cause sadness unigrams

In order to avoid errors in further analyses, we focus on bigrams instead of unigrams, as they are more meaningful without context.

4.2.5 *Ambiguous concepts*

Before investigating individual emotions, we take a look at the most ambiguous bigrams, those who have the highest PMI score summed across all emotions. The top 20 NP cause bigrams are displayed in 18, with each emotion's portion of the overall PMI score depicted in percent. The same information is displayed in absolute PMI scores for the top 50 bigrams in figures 7 and 8 across emotions and sentiment respectively. Interestingly, anticipation and fear don't appear among the most ambiguous bigrams.

Named entities like state leaders and states are among the most polarizing concepts. Even regarding these political powers, PMI scores of the neutral anticipation – essentially the most common emotion in politics – are negative, emphasizing the genericity and vagueness of Plutchik's anticipation and underlining why it isn't used in other classifications [10].

If we ignore named entities, expressions that are associated with violence such as *shooting death* and *hostage crisis* or that may potentially be deployed controversially such as *police officer*, *security guard*, and *Russian troops* possess the highest aggregated scores. Trust is placed in the *Russian troops* e.g. by "Tajikistan 's hard-line government", which relied on them in 1998 "to guard the Afghan border against incursions by guerillas and smugglers" (`APW_ENG_19980116.0782/13`. The capability to showcase the development of such emotive trends over

Bigram	anger	disgust	joy	sadness	surprise	trust
former president	21.09	28.12	0.79	20.74	25.46	3.81
prime minister	28.50	11.05	0.00	2.71	31.20	26.53
shoot death	27.55	20.80	0.00	31.05	20.60	0.00
United/LOC States/LOC	19.35	34.57	0.00	0.00	25.77	20.31
hostage crisis	29.78	22.87	0.00	24.69	22.66	0.00
president Chen/PERS	41.25	32.82	0.00	0.00	19.22	6.72
president Clinton/PERS	27.69	32.52	1.43	11.26	13.96	13.16
Tony/PERS Blair/PERS	21.51	28.01	0.00	0.00	25.61	24.87
police officer	34.97	18.29	0.00	2.19	34.56	9.99
president George/PERS	21.21	25.61	1.68	0.00	26.18	25.32
Israeli/LOC prime	30.29	0.00	0.00	12.08	37.24	20.39
Boris/PERS Yeltsin/PERS	0.00	19.69	0.00	13.78	43.14	23.39
security guard	16.49	42.61	0.00	0.00	18.10	22.79
russian troops	14.11	33.98	0.00	0.00	26.94	24.98
minister Tony/PERS	25.29	23.48	0.00	0.00	23.27	27.96
president Jacques/PERS	36.64	15.50	0.00	21.97	9.19	16.69
Rudolph/PERS Giuliani/PERS	30.31	32.14	0.00	0.00	37.54	0.00
W./PERS Bush/PERS	14.72	30.69	4.48	1.38	25.89	22.84
Saudi/LOC Arabia/LOC	25.35	0.00	0.00	9.31	38.51	26.83

Table 18: Emotion distribution in % of top 20 NP cause bigrams with highest aggregated PMI score; *fear* and *anticipation* have 0 PMI for all instances

time thus presents an interesting research opportunity and will produce further insights on how public opinion on certain concepts fares. Date information can be easily extracted from the extraction ID; as an investigation of the temporal aspect would significantly inflate the scope of this project, we will leave it for future work.

Interestingly, even among such potentially violent concepts as the ones mentioned above, PMI scores for fear are still negative. Conversely, the top 10 NP cause bigrams that have the highest fear PMI scores (cf. A, table 25) all spread fear on a national level, while the above mentioned concepts would be condemned by the general public rather than scare it.

Finally, considering the two expressions ranked as the most ambiguous, *former president* and *prime minister*, both of them can refer to leader of states that are objects of a diversity of emotions, e.g. "South Korea's former president Roh" (`AFP_ENG_20090528.0118/7`) is mourned by thousands, while Washington loathes "two (corrupt) former presidents (of Nicaragua)" (`APW_ENG_20051205.0005/5`). Even former leader's decisions may still evoke expressions of anger or surprise, but the media will be more cautious with signs of the stronger disgust for current as for former leaders. Furthermore, the degree of anteriority implied by *former president* is linked to sadness, whereas support will rather be given to a current leader.

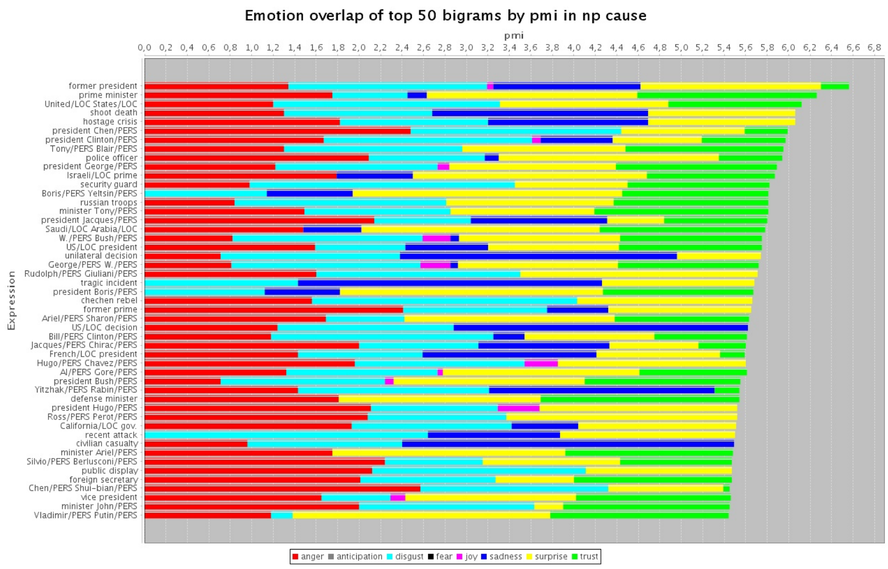

Figure 7: Overlap across emotions for the top 50 PMI NP cause bigrams

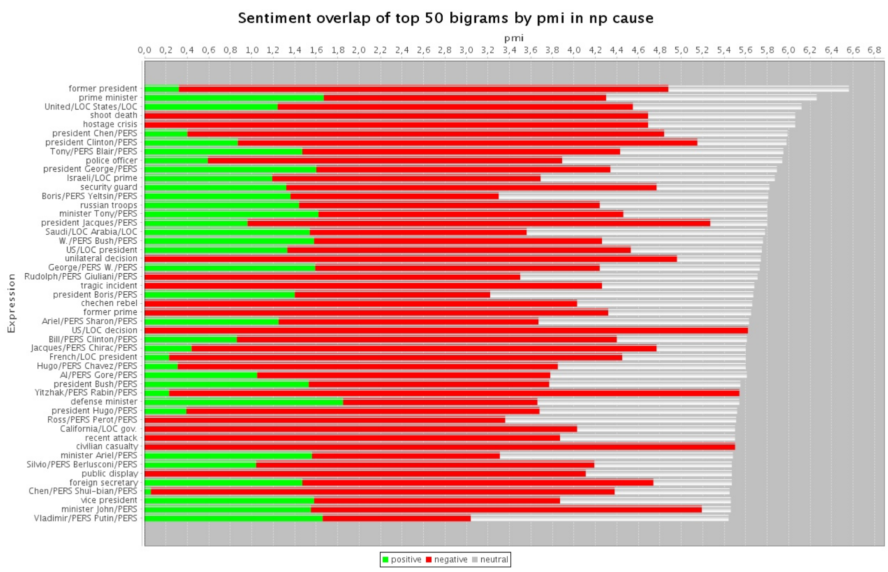

Figure 8: Overlap across sentiment for the top 50 PMI NP cause bigrams

Considering the entirety of ambiguous expressions displayed in 7, we observe that degrees of anger (*red*), disgust (*cyan*), and surprise (*yellow*) are present in almost all concepts. Trust (*green*) frequently appears as well, sadness (*blue*) less often, although more dominantly if it does, while joy (*magenta*) is hardly visible. All in all, negative sentiment (*red*) prevails as seen in 8.

Emotion	Sentiment	Emotion	Sentiment
anticipation	neutral	anger	negative
surprise	neutral	fear	negative
joy	positive	disgust	negative
trust	positive	sadness	negative

Table 19: Mapping of emotions to sentiment

4.2.6 *Emotion holder vs. cause configurations*

We have previously mentioned the NRC Word-Emotion Association Lexicon [**?**] (EmoLex). We weren't able to use it for our collection of patterns; we will, though, utilize it in order to partially validate association with an emotion for our concepts. We will initially compare the overlap of the different configurations of bigrams at hand with EmoLex to evaluate which bigrams we will examine more closely in our subsequent human-annotated evaluation.

We will compare at this point bigrams from (a) the emotion holder, (b) the NP cause, (c) the S cause subject and predicate, and (d) the S cause predicate and object . As the predicate of the complement is the most meaningful part in a clausal cause, it is always present in the two latter bigrams. We initially calculate the PMI scores for all emotions for all bigram configurations, excluding all bigrams that contain a named entity as these are not present in EmoLex. In order to allow a We select the top 30 bigrams per emotion per configuration and calculate a ternary overlap with EmoLex: As EmoLex only contains unigrams, we assign `NA` (*grey*) if none of the unigrams of the bigram appears in EmoLex; if one of them appears in EmoLex with the respective emotion, we assign `TRUE` (*green*); otherwise we assign `FALSE`. As EmoLex also contains a label for *positive* and *negative*, we also calculate the sentiment overlap by mapping our emotions to its sentiment (see table 19) and checking if it appears with the respective sentiment in EmoLex as above.

We show the results in tables 20, 21, 22, and 23. We include 9 exemplarily to visualize the values in table 23. Sentiment columns for anticipation and surprise only contain `NA` as EmoLex doesn't contain a *negative* label. All numbers are given as percentage of the top 30 bigrams that were chosen for each emotion respectively. Note that percentages for `TRUE` equal precision. As our *gold standard* for this evaluation, EmoLex, contains 14,000 terms and we only select the 30 bigrams for this evaluation, we don't provide recall nor F-score as they wouldn't add additional insights.

As we've outlined before, emotion is a compositional phenomenon. Thus, this evaluation employing comparison on an unigram-level may only serve as a guideline that will inform further investigation.

Overlap	anger		anticipation		disgust		fear	
	Emo	*Sen*	*Emo*	*Sen*	*Emo*	*Sen*	*Emo*	*Sen*
TRUE	46,67	50,00	10,00	0,00	6,67	53,33	10,00	20,00
NA	6,67	6,67	50,00	100,00	20,00	20,00	20,00	20,00
FALSE	46,67	43,33	40,00	0,00	73,33	26,67	70,00	60,00
Overlap	**joy**		**sadness**		**surprise**		**trust**	
	Emo	*Sen*	*Emo*	*Sen*	*Emo*	*Sen*	*Emo*	*Sen*
TRUE	3,33	30,00	3,33	6,67	0,00	0,00	13,33	10,00
NA	20,00	20,00	46,67	46,67	16,67	100,00	30,00	30,00
FALSE	76,67	50,00	50,00	46,67	83,33	0,00	56,67	60,00

Table 20: Overlap of the top PMI emotion holder bigrams with EmoLex in %

Overlap	anger		anticipation		disgust		fear	
	Emo	*Sen*	*Emo*	*Sen*	*Emo*	*Sen*	*Emo*	*Sen*
TRUE	3,33	23,33	33,33	0,00	6,67	13,33	23,33	23,33
NA	16,67	16,67	3,33	100,00	50,00	50,00	36,67	36,67
FALSE	80,00	60,00	63,33	0,00	43,33	36,67	40,00	40,00
Overlap	**joy**		**sadness**		**surprise**		**trust**	
	Emo	*Sen*	*Emo*	*Sen*	*Emo*	*Sen*	*Emo*	*Sen*
TRUE	20,00	36,67	23,33	33,33	3,33	0,00	23,33	36,67
NA	30,00	30,00	6,67	6,67	30,00	100,00	23,33	23,33
FALSE	50,00	33,33	70,00	60,00	66,67	0,00	53,33	40,00

Table 21: Overlap of the top PMI S cause subject + predicate bigrams with EmoLex in %

Another thing to remark is that due to data sparseness for S causes of surprise, disgust, and anger (see table 6), we PMI will frequently not be able to determine reliable candidates, particularly regarding direct objects, which are only present in a subset of the instances.

As can be seen in table 20, emotion holder bigrams frequently are not associated with the emotion in EmoLex. This does not surprise, as the experiencer doesn't generally presuppose an emotion, in contrast to the cause of the emotion. The superior precision for anger is due to the fact that *provoke*, the most productive anger pattern, in news frequently refers to inanimate concepts that are – in fact – associated with anger, such as *international outcry*, *angry response*, or *international outrage*.

The low values for anger and disgust in table 21 are generally due to data sparseness. EmoLex only inadequately captures the objects of anticipation that are most prominent in news stories: While *grow* of

Overlap	anger		anticipation		disgust		fear	
	Emo	*Sen*	*Emo*	*Sen*	*Emo*	*Sen*	*Emo*	*Sen*
TRUE	16,67	40,00	3,33	0,00	10,00	33,33	33,33	33,33
NA	6,67	6,67	0,00	100,00	10,00	10,00	13,33	13,33
FALSE	76,67	53,33	96,67	0,00	80,00	56,67	53,33	53,33
Overlap	**joy**		**sadness**		**surprise**		**trust**	
	Emo	*Sen*	*Emo*	*Sen*	*Emo*	*Sen*	*Emo*	*Sen*
TRUE	3,33	23,33	30,00	40,00	3,33	0,00	23,33	40,00
NA	3,33	3,33	3,33	3,33	0,00	100,00	3,33	3,33
FALSE	93,33	73,33	66,67	56,67	96,67	0,00	73,33	56,67

Table 22: Overlap of the top PMI S cause predicate + object bigrams with EmoLex in %

gross grow appears in EmoLex, synonyms like *rise* or *expand* do not. A lot of fear is either due to viruses or war. While *flu* and *disease* are associated with fear in EmoLex, *virus* is just associated with negative. EmoLex captures bigrams such as *flu mutate* or *war destabilize*, but does not account for equally fearful ones such as *h5n1 mutate*, *virus mutate*, *strain mutate*, or *bird mutate*. Sports-based joy programs such as *team achieve* or *player accomplish* are captured by EmoLex, while others that are only joyful because of their compositionality, e.g. *nobody hurt*, *nobody kill(ed)*. Furthermore, our approach captures a lot of terms that are very relevant in politics, such as *condition stabilise*. A lot of combinations of subjects and predicates are context-dependent. *Situation occur* or *position arise* might be neutral, positive, or negative, but are associated with sadness in the news domain. Suprise bigrams derived from the S cause and predicate are very ambiguous, due to the neutrality of surprise. Bigrams like *settlement allow* or *anyone object* depend on the context more than anything else to elicit surprise. Trust bigrams usually refer to the actions of political leaders or powers such as *democrats handle*, *democrats deal*, or *political contribute*. While a few of these are contained in EmoLex, most of them express a partisan trust.

A combination of a predicate and its object is more adequate in evoking a sentiment. While a few unigrams such as *deny* in *deny honor* are contained in EmoLex, other objects of anger such as *kill teenager*, *refuse plea*, or *molest boy* are not expressed. Some of the highest-ranked bigrams are very context-dependent. For instance, *offer aid* is only a source of anger if is offered virtually unconditionally to Pyongyang. Even though many bigrams could be correctly considered as source of anticipation, e.g. *rise percent*, *increase percent*, *fall percent*, *reach dollar*, this economics-based anticipation is not captured by EmoLex. Due to data sparseness, we only have a few disgust bigrams, which are very

Overlap	anger		anticipation		disgust		fear	
	Emo	*Sen*	*Emo*	*Sen*	*Emo*	*Sen*	*Emo*	*Sen*
TRUE	6,67	16,67	13,33	0,00	16,67	43,33	60,00	60,00
NA	33,33	33,33	6,67	100,00	13,33	13,33	16,67	16,67
FALSE	60,00	50,00	80,00	0,00	70,00	43,33	23,33	23,33
Overlap	**joy**		**sadness**		**surprise**		**trust**	
	Emo	*Sen*	*Emo*	*Sen*	*Emo*	*Sen*	*Emo*	*Sen*
TRUE	33,33	73,33	83,33	86,67	16,67	0,00	33,33	46,67
NA	3,33	3,33	0,00	0,00	50,00	100,00	6,67	6,67
FALSE	63,33	23,33	16,67	13,33	33,33	0,00	60,00	46,67

Table 23: Overlap of the top PMI NP cause bigrams with EmoLex in %

context-dependent. Some fear bigrams like *destabilize region*. *upset balance*, or *engulf region* are not expressed in EmoLex, while others like *trigger pandemic* or *spark violence* are, mostly during their frightening object. Furthermore, others such as *spark (arms) race* or *use (nuclear) program* showcase that more relevant information is needed to satisfactorily determine the relevant emotion without context. Joy bigrams have a very low precision, as unigrams like *survive* in *survive appeal*, *survive attempt*; *escape* in *escape card*, *escape injury*; or *win* in *win set* or *win decision* are not associated with joy in EmoLex, even though they would be a source of joy in the respective bigrams. Sadness achieves a higher precision, as bigrams like *light candle*, *announce death*, or *leave friend* are labeled correctly. Others, like *wear skirt* are culturally sensitive. Surprise bigrams are highly ambiguous: While *terminate agent*, *include flaw*, *know scientist*, *exclude mortgage*, or *support opposed* might surprise the respective parties, they are not labeled as such in EmoLex. The trust bigrams reduce to trusting someone with a certain action, often to *handle* a *problem*, an *issue*, a *matter*, *security*, etc. These are not captured in EmoLex.

A lot of high-ranked bigrams derived from the NP cause can't be identified just using

For NP cause bigrams in figure 9, we generally receive the highest overlap

4.3 EVALUATION

[33] use a

In order to validate our results, we select the top 20 bigrams per emotion for the NP cause and the concatenated predicate and object of the S cause and hand them over for annotation. We match every

Include all three values for each emotion in Plutchik's wheel.

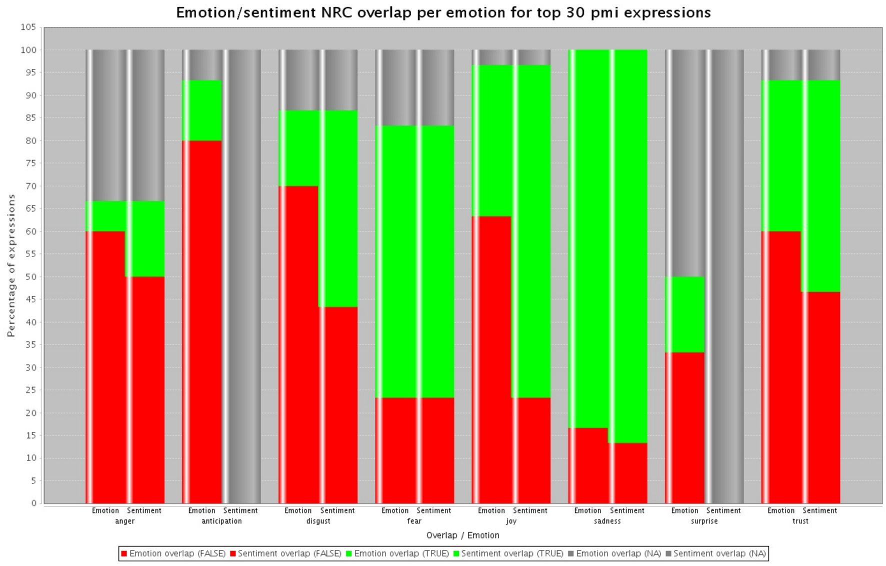

Figure 9: Emotion and sentiment overlap of NP cause bigrams with the NRC Emotion Lexicon

Does this concept or entity evoke or is it associated with the following emotion? Yes/No.

If no, does it evoke or is it associated with the emotion in the following sentence? Yes/No.

Even though

For the annotation, we exclude all named entities from the ngrams, since their evoked emotion is mostly dependent on the context.

Observe that 22.5% of the target terms strongly evoke at least one of the eight basic emotions.

- two interesting aspects related to this: 1: find frequent and unambiguous trigger contexts so that from these we can find indications on what are secondary emotion words in their scope (complements) 2: (which we did not choose as primary step to take if I recall correctly) is to acquire a wider variation of emotion indicating words. This we could still do in a second step.

5 CHAPTER TITLE

5.1 TOPIC MODELING, WORD CLOUDS

LDA introduction

[15] use supervised LDA.

Interesting article here: http://nbviewer.ipython.org/gist/benjamincohen1/d7caaa3d07bbb89cd39a

Anette: When I looked at the sentence examples, and also the cut-down predicates of the embedded sentences, I was wondering whether extracting verb argument structures from the acquired propositions is the right way to go. Maybe it will be possible with a better filtering technique (getting more data - and there should be enough - but cleaning it by better filters). But we could, in a first step, also use the bare embedded material and apply topic modeling to them. This would mean we induce topics for embedded contexts that are pre-labelled with the embedding emotion indicating predicates. This way, we should be able to induce topics that reflect these emotions, and more filtering could be applied then, to sharpen these contexts or topics in better ways. This is related to the work I did with Matthias Hartung [**?**]. It's a kind of distant supervision for inducing semantically constrained LDA topics.

But also using some association statistics for detecting collocations could be a first step to see what we can get out of these contexts.

- Possibly more interesting to investigate nature/clarity of Plutchik's emotion classes in contrast to a pure pos/neg/neutral classification.

[37] evaluate on SemEval 2007 task on 'Affective Text' evaluate topic modeling on it

5.2 OUTLOOK

temporal precedence PMI score

evaluate with depechemood unigrams?

Pattern expansion and ontologization as in [29]

Investigate compositionality further

A

APPENDIX A

A.1 TERMS RETRIEVED FROM EMOTION SOURCES

A.1.1 *Oxford English Dictionary emotion definitions*

- Joy: *A vivid emotion of pleasure arising from a sense of well-being or satisfaction; the feeling or state of being highly pleased or delighted; exultation of spirit; gladness, delight.*
- Trust: *Confidence in or reliance on some quality or attribute of a person or thing, or the truth of a statement. Const. in (of, on, upon, to, unto).*
- Fear: *The emotion of pain or uneasiness caused by the sense of impending danger, or by the prospect of some possible evil.*
- Surprise: *The feeling or mental state, akin to astonishment and wonder, caused by an unexpected occurrence or circumstance.* first sense is act of surprise, military act, etc.
- Sadness: *The condition or quality of being sad (Of a person, or his or her feelings, disposition, etc.: feeling sorrow; sorrowful, mournful, heavy-hearted.).* Obsolete senses precede it.
- Disgust: *Strong repugnance, aversion, or repulsion excited by that which is loathsome or offensive, as a foul smell, disagreeable person or action, disappointed ambition, etc.; profound instinctive dislike or dissatisfaction.*
- Anger: *The active feeling provoked against the agent; passion, rage; wrath, ire, hot displeasure.*
- Anticipation: *The action of looking forward to, expectation.*

A.1.2 *Merriam-Webster's*

anger: enrage, incense, inflame (also enflame), infuriate, ire, madden, outrage, rankle, rile, roil, steam up, tick off fear: bother, fear, fret, fuss, stew, stress, sweat, trouble joy (rejoice): crow, delight, exuberate, glory, jubilate, joy, kvell, rejoice, triumph sadness (sadden): bum (out), burden, dash, deject, get down, oppress, sadden, weigh down anticipation (anticipate): anticipate, await, hope (for), watch (for) disgust: gross out, nauseate, put off, repel, repulse, revolt, sicken, turn off

A.1.3 *Roget's Thesaurus*

anticipate: expect, predict, assume, await, count on, forecast, foresee, prepare for, see anger: aggravate, annoy, antagonize, arouse, displease, embitter, enrage, exacerbate, exasperate, excite, incense, inflame, infuriate, irritate, offend, outrage, provoke, rankle, rile fear: feel alarmed, be scared off, anticipate, avoid, dread, expect, foresee, shun, suspect, worry joy: exult, revel, make happy, delight, amuse, attract, charm, cheer, enchant, enrapture, entertain, fascinate, gratify, please, rejoice, satisfy, thrill, wow sadness (sadden): discourage, dishearten, dispirit, grieve disgust: bother, disenchant, displease, disturb, insult, irk, nauseate, offend, outrage, revolt, shock, sicken, turn off, upset surprise: astonish, amaze, astound, awe, bewilder, confound, confuse, dazzle, disconcert, dismay, dumbfound, flabbergast, overwhelm, perplex, rattle, shock, startle, stun, unsettle trust: count on, depend on, look to

A.1.4 *FrameNet*

fear lexical units that create this frame afraid.a, apprehension.n, dread.n, fear.n, freaked.a, frightened.a, $live_in_fear$.v, nervous.a, scared.a, terrified.a, terror.n

trust lexical units: believe.v, credence.n, credulous.a, faith.n, gullible.a, reliability.n, reliable.a, trust.n, trust.v, trustworthy.a

$cause_emotion$ lexical units: affront.n, affront.v, $call_names$.v, concern.v, insult.n, insult.v, offend.v, offense.n, offensive.a

A.2 MAJORITY PATTERNS

Emotion	**Pattern**
anger	harass
anger	offend
anger	irk
anger	frustrate
anger_1	be irate that
anger_1	outrage
anger_1	inflame
anger_1	infuriate
anger_1	be incense that
anger_1	enrage
anger_2	scorn
anger_2	torment

anger_2	be angry at
anger_2	vex
anger_2	be angry that
anger_2	be angry with
anger_2	afflict
anger_2	insult
anger_2	aggravate
anger_2	be angry about
anger_2	fret about
anger_2	rankle
anger_2	provoke
anger_3	bother
anger_3	irritate
anger_3	grate
anger_3	annoy
anger_3	sting
anger_3	disturb
anticipation	yearn for
anticipation	predict that
anticipation	ache for
anticipation	be intent on
anticipation	intrigue
anticipation_2	aspire
anticipation_2	be hopeful that
anticipation_2	expect
anticipation_2	anticipate
anticipation_2	covet
anticipation_2	aspire to
anticipation_2	crave
anticipation_2	foresee
anticipation_2	hunger for
anticipation_2	predict
anticipation_2	prepare for
anticipation_2	long for
anticipation_2	await
anticipation_2	forecast that
anticipation_2	hope for
anticipation_2	expect that

anticipation_2	be eager for
anticipation_2	look forward to
anticipation_2	forecast
anticipation_3	be curious about
disgust	horrify
disgust	shun
disgust_1	abhor
disgust_1	loathe
disgust_1	despise
disgust_1	hate
disgust_1	deplore
disgust_1	disdain
disgust_2	dislike
disgust_2	shame
disgust_2	be ashamed of
disgust_2	alienate
disgust_2	repel
disgust_2	disgust
fear	be afraid of
fear	unnerve
fear	rattle
fear	dread
fear_1	terrify
fear_1	be terrify that
fear_2	be frightened that
fear_2	be scared that
fear_2	fear that
fear_2	frighten
fear_2	fear
fear_2	intimidate
fear_2	spook
fear_2	be scared of
fear_2	scare
fear_2	be afraid that
fear_3	concern
fear_3	be anxious that
fear_3	be anxious about
fear_3	be apprehensive about

fear_3	worry
fear_3	be nervous about
joy	be enthusiastic about
joy	comfort
joy	fulfill
joy	desire
joy_1	thrill
joy_1	be elate that
joy_1	rejoice
joy_1	be ecstatic that
joy_1	be thrill that
joy_1	relish
joy_2	entertain
joy_2	excite
joy_2	enjoy that
joy_2	impress
joy_2	satisfy
joy_2	delight
joy_2	be mad about
joy_2	take pleasure in
joy_2	enjoy
joy_2	arouse
joy_2	be happy about
joy_2	please
joy_2	be lucky that
joy_2	cheer
joy_2	soothe
joy_2	captivate
joy_2	be proud of
joy_2	be satisfy that
joy_2	amuse
joy_2	savor
joy_3	calm
sadness	devastate
sadness	agonize over
sadness	regret that
sadness	pine for
sadness	worry about

sadness	be sad that
sadness	depress
sadness	regret
sadness_1	mourn that
sadness_1	grieve that
sadness_1	mourn
sadness_2	be unhappy that
sadness_2	upset
sadness_2	displease
sadness_2	be disappoint that
sadness_2	be unhappy about
sadness_2	be sadden that
sadness_2	disappoint
surprise	boggle
surprise	baffle
surprise	puzzle
surprise_1	be stun that
surprise_1	confound
surprise_1	stagger
surprise_1	stun
surprise_1	amaze
surprise_1	be bewilder that
surprise_1	be amaze that
surprise_1	wow
surprise_1	shock
surprise_2	surprise
surprise_2	startle
surprise_2	be flabbergast that
surprise_2	confuse
trust	charm
trust	be reassure that
trust_1	rely on
trust_2	trust
trust_2	take comfort in
trust_2	count on
trust_2	trust that
trust_2	reassure

Table 24: Patterns and their emotion/degree assigned by the majority

Bigram	PMI score
government reprisal	1.91
attack by:ethnic_albanian	1.90
possible reprisal	1.88
political backlash	1.87
long-term effect	1.87
reprisal attack	1.87
reprisal for:genocide	1.85
unintended consequence	1.85
new crackdown	1.84
government retribution	1.83

Table 25: Top 10 NP cause bigrams with highest fear PMI score

BIBLIOGRAPHY

[1] Charu C Aggarwal and ChengXiang Zhai. *Mining text data*. Springer Science & Business Media, 2012.

[2] Collin F Baker, Charles J Fillmore, and John B Lowe. The berkeley framenet project. In *Proceedings of the 17th international conference on Computational linguistics-Volume 1*, pages 86–90. Association for Computational Linguistics, 1998.

[3] Alexandra Balahur, Jesús M Hermida, and Andrés Montoyo. Detecting implicit expressions of emotion in text: A comparative analysis. *Decision Support Systems*, 53(4):742–753, 2012.

[4] Jerome R Bellegarda. Emotion analysis using latent affective folding and embedding. In *Proceedings of the NAACL HLT 2010 workshop on computational approaches to analysis and generation of emotion in text*, pages 1–9. Association for Computational Linguistics, 2010.

[5] Steven Bird. NLTK: the natural language toolkit. In *Proceedings of the COLING/ACL on Interactive presentation sessions*, pages 69–72. Association for Computational Linguistics, 2006.

[6] Johan Bollen, Huina Mao, and Xiaojun Zeng. Twitter mood predicts the stock market. *Journal of Computational Science*, 2(1):1–8, 2011.

[7] Damian Borth, Rongrong Ji, Tao Chen, Thomas Breuel, and Shih-Fu Chang. Large-scale visual sentiment ontology and detectors using adjective noun pairs. In *Proceedings of the 21st ACM international conference on Multimedia*, pages 223–232. ACM, 2013.

[8] Dipankar Das and Sivaji Bandyopadhyay. Emotion holder for emotional verbs–the role of subject and syntax. In *Computational Linguistics and Intelligent Text Processing*, pages 385–393. Springer, 2010.

[9] Lingjia Deng, Yoonjung Choi, and Janyce Wiebe. Benefactive/-malefactive event and writer attitude annotation. In *ACL (2)*, pages 120–125, 2013.

[10] Paul Ekman. An argument for basic emotions. *Cognition & emotion*, 6(3-4):169–200, 1992.

[11] Paul Ekman and Wallace V Friesen. *Unmasking the face: A guide to recognizing emotions from facial clues*. Ishk, 2003.

[12] Andrea Esuli and Fabrizio Sebastiani. Sentiwordnet: A publicly available lexical resource for opinion mining. In *Proceedings of LREC*, volume 6, pages 417–422. Citeseer, 2006.

[13] Christiane Fellbaum and Yvette Yannick Mathieu. A corpus-based construction of emotion verb scales. *Linguistic Approaches to Emotions in Context*, 241:99, 2014.

[14] Matthew Gerber and Joyce Y Chai. Semantic role labeling of implicit arguments for nominal predicates. *Computational Linguistics*, 38(4):755–798, 2012.

[15] Matthias Hartung and Anette Frank. Exploring supervised [lda] models for assigning attributes to adjective-noun phrases. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*, pages 540–551. Association for Computational Linguistics, 2011.

[16] Karin Kipper-Schuler. *A Broad-Coverage Comprehensive Verb Lexicon*. PhD thesis, Computer and Information Science Dept., University of Pennsylvania, Philadelphia, PA, 2005.

[17] J Richard Landis and Gary G Koch. An application of hierarchical kappa-type statistics in the assessment of majority agreement among multiple observers. *Biometrics*, pages 363–374, 1977.

[18] Bing Liu. Sentiment analysis and opinion mining. *Synthesis Lectures on Human Language Technologies*, 5(1):1–167, 2012.

[19] Cheng-Yu Lu, Shian-Hua Lin, Jen-Chang Liu, Samuel Cruz-Lara, and Jen-Shin Hong. Automatic event-level textual emotion sensing using mutual action histogram between entities. *Expert systems with applications*, 37(2):1643–1653, 2010.

[20] Walaa Medhat, Ahmed Hassan, and Hoda Korashy. Sentiment analysis algorithms and applications: A survey. *Ain Shams Engineering Journal*, 5(4):1093–1113, 2014.

[21] George A Miller. Wordnet: a lexical database for english. *Communications of the ACM*, 38(11):39–41, 1995.

[22] Saif Mohammad. From once upon a time to happily ever after: Tracking emotions in novels and fairy tales. In *Proceedings of the 5th ACL-HLT Workshop on Language Technology for Cultural Heritage, Social Sciences, and Humanities*, pages 105–114. Association for Computational Linguistics, 2011.

[23] Saif M Mohammad. # emotional tweets. In *Proceedings of the First Joint Conference on Lexical and Computational Semantics-Volume 1: Proceedings of the main conference and the shared task, and Volume 2:*

Proceedings of the Sixth International Workshop on Semantic Evaluation, pages 246–255. Association for Computational Linguistics, 2012.

[24] Saif M Mohammad and Peter D Turney. Crowdsourcing a word-emotion association lexicon. *Computational Intelligence*, 29(3):436–465, 2013.

[25] Saif M Mohammad and Tony Wenda Yang. Tracking sentiment in mail: how genders differ on emotional axes. In *Proceedings of the 2nd Workshop on Computational Approaches to Subjectivity and Sentiment Analysis (ACL-HLT 2011*, pages 70–79, 2011.

[26] Saif M Mohammad, Xiaodan Zhu, and Joel Martin. Semantic role labeling of emotions in tweets. 2013.

[27] Courtney Napoles, Matthew Gormley, and Benjamin Van Durme. Annotated gigaword. In *Proceedings of the Joint Workshop on Automatic Knowledge Base Construction and Web-scale Knowledge Extraction*, pages 95–100. Association for Computational Linguistics, 2012.

[28] Bo Pang and Lillian Lee. Opinion mining and sentiment analysis. *Foundations and trends in information retrieval*, 2(1-2):1–135, 2008.

[29] Patrick Pantel and Marco Pennacchiotti. Automatically harvesting and ontologizing semantic relations. *Ontology learning and population: Bridging the gap between text and knowledge*, pages 171–198, 2008.

[30] Patrick Pantel and Deepak Ravichandran. Automatically labeling semantic classes. In *HLT-NAACL*, volume 4, pages 321–328, 2004.

[31] Robert Parker, David Graff, Junbo Kong, Ke Chen, and Kazuaki Maeda. English gigaword fifth edition. 2011.

[32] Robert Plutchik. A general psychoevolutionary theory of emotion. *Theories of emotion*, 1, 1980.

[33] Ashequl Qadir and Ellen Riloff. Learning emotion indicators from tweets: Hashtags, hashtag patterns, and phrases.

[34] Niklas Ravaja, Timo Saari, Marko Turpeinen, Jari Laarni, Mikko Salminen, and Matias Kivikangas. Spatial presence and emotions during video game playing: Does it matter with whom you play? *Presence: Teleoperators and Virtual Environments*, 15(4): 381–392, 2006.

[35] Thomas Scholz and Stefan Conrad. Opinion mining in newspaper articles by entropy-based word connections. In *EMNLP*, pages 1828–1839, 2013.

[36] Richard Socher, Alex Perelygin, Jean Y Wu, Jason Chuang, Christopher D Manning, Andrew Y Ng, and Christopher Potts. Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1631–1642. Citeseer, 2013.

[37] Jacopo Staiano and Marco Guerini. DepecheMood: a lexicon for emotion analysis from crowd-annotated news. *arXiv preprint arXiv:1405.1605*, 2014.

[38] Philip J Stone and Earl B Hunt. A computer approach to content analysis: studies using the [g]eneral [i]nquirer system. In *Proceedings of the May 21-23, 1963, spring joint computer conference*, pages 241–256. ACM, 1963.

[39] Carlo Strapparava and Alessandro Valitutti. WordNet Affect: an affective extension of WordNet. In *LREC*, volume 4, pages 1083–1086, 2004.

[40] Yulia Tsvetkov, Nathan Schneider, Dirk Hovy, Archna Bhatia, Manaal Faruqui, and Chris Dyer. Augmenting English adjective senses with supersenses. In *Proc. of LREC*, 2014.

[41] Theresa Wilson, Janyce Wiebe, and Paul Hoffmann. Recognizing contextual polarity in phrase-level sentiment analysis. In *Proceedings of the conference on human language technology and empirical methods in natural language processing*, pages 347–354. Association for Computational Linguistics, 2005.