Interdisciplinary Approach to Emotion Detection from Text

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ABSTRACT Emotions not only influence most aspects of cognition and behavior, but also play a prominent role in interaction and communication between people. With current multidimensional research on emotions being vast and varied, all researchers of emotions, both psychologists and linguists alike, agree that emotions are at the core of understanding ourselves and others. As a primary vehicle of communication and interaction, language is the most convenient medium for approaching research on the topic of emotions. Not only is one of the main functions of language the emotive one, but the interplay of emotions and language occurs at all linguistic levels. Textual data, in particular, can be beneficial to emotion detection due to its syntactic and semantic information containing not only informative content, but emotional states as well. A general overview of the emotion models based on the research in psychology, as well as the major approaches to emotion detection from text found in linguistics, together with usage demonstration of emotion detection linguistic tools, will be given in this paper. Examples of useful applications – from psychologists analyzing session transcripts in search for any subtle emotions, over public opinion mining on social networks to the development of AI technology – will also be provided showing that emotion detection from text has an abundance of practical uses. As the methods for emotion detection from text become more accurate, uses and applications of emotion detection from text will become more numerous and diverse in the future.

KEYWORDS emotion detection, computational linguistics, psychology

1. INTRODUCTION

Current multi-dimensional research on EMOTIONS[1], being vast and varied (Ogarkova 2007), provides evidence for the ubiquity of emotion which influence extends to all aspects of cognition and behavior (Cacioppo and Gardner 1999). Not only do emotions have an important role in human intelligence, rational decision-making and social interaction (Quan and Ren 2014), but they also help in identifying attitudes, states, conditions or modes of a particular situation or circumstance (Haggag 2014).

Emotion and language are genuine and basic to human nature (Sarter 2012). They are interrelated in numerous ways and researchers from wide ranges of disciplines – from historians, anthropologists, sociologists, biologists to philosophers – are interested in questions arising from their relationship (Ogarkova 2007), while the interplay of the two has received increased attention in the fields of psychology and linguistics (Robinson and Altarriba 2014).

English is a prime example of a tool for emotion studies as "there are literally hundreds of words available to English-speakers to describe how they are feeling" (Hobbs and Gordon 2008, 29), with nouns and adjectives in particular (Ezhilarasi and Minu 2012). The sheer quantity of words that reference emotions in English shows that all words are able to potentially convey emotional meaning (Strapparava, Valitutti and Stock 2006) and the best way to approach emotion detection in language is through textual data, which does not only contain informative content, but it also, as Haggag (2014) points out, involves emotional states.

While emotion detection and analysis in general has been widely researched in neuroscience, psychology and behavior science, as "emotions are an important element of human nature" (Canales and Martínez-Barco 2014, 1), EMOTION DETECTION FROM TEXT[2] is a relatively new classification task. Nonetheless, it has attracted a growing attention of many researchers, especially in the field of computational linguistics, for its wide range of potentially useful applications (Agrawal and An 2012).

Therefore, the primary aim of this paper is to explore the concepts and methods behind emotion detection from text by providing an overview of the major psychological and linguistical theoretical frameworks involved in emotion detection from text.

The rest of the paper is organized as follows. In Section II, a literature survey of major theoretical approaches to emotions is presented. Section III provides a general overview of the emotion models based on research in psychology. An extensive review of relationship and interplay between language and emotion is presented in Section IV. Section V provides a general survey of the major linguistic methods to emotion detection from text along with a practical overview how they are utilized in research. Moreover, a wide range of applications of emotion detection from text is presented in Section VI. Finally, a conclusion is given and some future avenues of research work are predicted.

2. EMOTION THEORIES

The central point of emotion research is, of course, emotion, but defining what it is would prove to be a difficult task as there does not exist a clear definition (Izard 2010). Thus, "the determination of what an emotion is, is a notoriously difficult problem" (Ortony, Clore and Foss 1987, 342). As the aim of this paper is not to analyze the available definitions – for that consult Kleinginna and Kleinginna (1981) who have listed and analyzed 92 definitions of emotions – only the review of major theories of emotions, with their understanding what constitutes emotions, will be provided.

In *The Science of Emotion* (1996), Randolph Cornelius presents four major schools of emotion in psychology: Darwinian, Jamesian, cognitive and social constructivist. These four major theoretical perspectives study and look at emotions from somewhat different angles; however, all of them contribute to the understanding of different aspects of emotion and the way how we consequently approach emotion detection and recognition.

The central idea of the DARWINIAN PERSPECTIVE is the notion that "emotions are evolved phenomena with important survival functions that have been selected for because they have solved certain problems we have faced as a species" (Cornelius 2000, 3). The adaptive behavior, including facial expressions and states of readiness to respond, is regarded as central to what emotions are and this behavior may be considered universal. Therefore, emotions are FUNDAMENTAL, BASIC and PRIMARY (Cornelius 2000). This perspective focuses on the functions of emotions, while the following perspective is concerned with emotional experience.

The JAMESIAN PERSPECTIVE was inspired by William James' writings on emotion who maintained that "bodily changes follow directly from PERCEPTION of the exciting fact, and … our feeling of the same changes as they occur IS the emotion" (James 1884, 189–190). This perspective follows the idea that the experience of an emotion is a result of a "distinct bodily expression" (James 1884, 189), where the bodily expression or change is the emotion itself. Therefore, human body responds first and the experience of the bodily change constitutes what is called emotion, which is in turn differentiated by various bodily changes.

Among the four theoretical perspectives presented in this section, the COGNITIVE PERSPECTIVE is considered to be the dominant one (Cornelius 2000). The essence of this perspective lies in the notion that thought and emotion are inseparable (Arnold 1960) and the process of emotions is explained by the process of APPRAISAL – the process where events in the environment are judged or perceived. Magda Arnold (1960), the pioneer of this approach, argued that emotions are generated by judgments about the world and that an emotion always involves the assessment of how an object may harm or benefit a person. In essence, without appraisal there is no emotion and the type of emotion detected and recognized depends on the nature of appraisal as well. Elliott (1992) provides an overview of types of appraisals and emotion categories that stem from them. The overview is based on the works of Ortony, Clore and Collins (1988) and can be seen in Table 1.

Table 1. Emotion Categories Viewed from the Appraisal Perspective

Group	Specification	Category Label and Emotion Type
Well-Being	appraisal of a situation as an *event*	JOY: pleased about an *event* DISTRESS: displeased about an *event*
Fortunes-of-Others	presumed value of a situation as an *event* affecting another	HAPPY–FOR: pleased about an *event* desirable for another GLOATING: pleased about an *event* undesirable for another RESENTMENT: displeased about an *event* desirable for another JEALOUSY*: *resentment* over a desired mutually exclusive goal ENVY*: *resentment* over a desired non-exclusive goal SORRY–FOR: displeased about an *event* undesirable for another
Prospect-Based	appraisal of a situation as a prospective *event*	HOPE: pleased about a prospective desirable *event* FEAR: displeased about a prospective undesirable *event*
Confirmation	appraisal of a situation as confirming or disconfirming an expectation	SATISFACTION: pleased about a confirmed desirable *event* RELIEF: pleased about a disconfirmed undesirable *event* FEARS–CONFIRMED: displeased about a confirmed undesirable *event* DISAPPOINTMENT: displeased about a disconfirmed desirable *event*
Attribution	appraisal of a situation as an accountable *act* of some agent	PRIDE: approving of one's own *act* ADMIRATION: approving of another's *act* SHAME: disapproving of one's own *act* REPROACH: disapproving of another's *act*
Attraction	appraisal of a situation as containing an attractive or unattractive *object*	LIKING: finding an *object* appealing DISLIKING: finding an *object* unappealing
Well-Being / Attribution	compound emotions	GRATITUDE: admiration + joy ANGER: reproach + distress GRATIFICATION: pride + joy REMORSE: shame + distress
Attraction / Attribution	compound emotion extensions	LOVE: admiration + liking HATE: reproach + disliking

* Non-symmetric additions necessary for some stories.

Adapted from Elliott (1998) after Ortony, Clore and Collins (1988).

The SOCIAL CONSTRUCTIVIST PERSPECTIVE, also known as the CULTURAL PERSPECTIVE, views emotions as "social constructions, not biological givens" and as "improvisations, based on an individual's interpretation of the situation" (Averill 1980, 305). Emotions are therefore "cultural products that owe their meaning and coherence to learned social justice" (Cornelius 2000, 7). According to this perspective, culture provides the content of the appraisals that generate emotions making the content of appraisals cultural, while the process of appraisal remains to be a biological adaptation. "Recognition of the role of culture in specifying what we got emotional about and how we do it provides a powerful tool for understanding the larger social functions of emotions" (Cornelius 2000, 7). Culture in this case plays a central role in the organization, recognition and detection of emotions at a variety of levels.

Although being the youngest and the most diverse, the SOCIAL CONSTRUCTIVIST perspective is the most controversial of the four perspectives on emotion (Cornelius 2000) as it proposes that emotions are social constructs influenced by culture. This opens the door for the GREAT EMOTIONS DEBATE (Feldman Barrett, Lindquist and Gendron 2007) where the question of cross-cultural similarities and differences in emotions is raised (Shaver, Murdaya and Fraley 2001). The proponents of CROSS-CULTURAL SIMILARITIES have accumulated evidence for cross-cultural facial expressions of a certain emotion (e.g. Ekman 1999) and the dimensions underlying emotions (e.g. Russell 1980). Ortony and Turner (1990) collated a wide range of research on identification of universal emotions and a short theoretical overview of the emotion categories and basis for inclusion can be seen in Table 2. Arguments and evidence for CROSS-CULTURAL DIFFERENCES[3] have also been presented with different emotional expressions and display rules (e.g. Matsumoto et al. 1988) and emotion concepts[4] (e.g. Levy 1984) found in different cultures.

Table 2. A Selection of Lists of Universal Emotions

	Universal Emotions	Basis for Inclusion
Arnold (1960)	ANGER, AVERSION, COURAGE, DEJECTION, DESIRE, DESPAIR, FEAR, HATE, HOPE, LOVE, SADNESS	relation to action tendencies
Ekman, Friesen and Ellsworth (1982)	ANGER, DISGUST, FEAR, JOY, SADNESS, SURPRISE	universal facial expressions
Frijda (1986)*	DESIRE, HAPPINESS, INTEREST, SURPRISE, WONDER, SORROW	forms of action readiness
Gray (1982)	RAGE AND TERROR, ANXIETY, JOY	hardwired
Izard (1971)	ANGER, CONTEMPT, DISGUST, DISTRESS, FEAR, GUILT, INTEREST, JOY, SHAME, SURPRISE	hardwired
James (1884)	FEAR, GRIEF, LOVE, RAGE	bodily involvement
McDougall (1926)	ANGER, DISGUST, ELATION, FEAR, SUBJECTION, TENDER–EMOTION, WONDER	relation to instincts
Mowrer (1960)	PAIN, PLEASURE	unlearned emotional states
Oatley and Johnson-Laird (1987)	ANGER, DISGUST, ANXIETY, HAPPINESS, SADNESS	do not require propositional content
Panksepp (1982)	EXPECTANCY, FEAR, RAGE, PANIC	hardwired
Plutchik (1980)	ACCEPTANCE, ANGER, ANTICIPATION, DISGUST, JOY, FEAR, SADNESS, SURPRISE	relation to adaptive biological processes
Tomkins (1984)	ANGER, INTEREST, CONTEMPT, DISGUST, DISTRESS, FEAR, JOY, SHAME, SURPRISE	density of neural firing
Watson (1930)	FEAR, LOVE, RAGE	hardwired
Weiner and Graham (1984)	HAPPINESS, SADNESS	attribution independent

* Based on Ortony and Turner's (1990) personal communication, September 8, 1986.

Adapted from Ortony and Turner (1990, 316) who use the term 'basic emotions' in their paper; however, I chose to use the term 'universal emotions' in order to avoid the mix-up with the terminology used when describing the Darwinian perspective on emotions.

Both sides may provide compelling arguments for their stance, but the debate between the UNIVERSALIST and RELATIVISTS still continues and “there will never be a single, simple answer to the question of emotion universals versus particularities” (Shaver, Murdaya and Fraley 2001, 202). The general conclusion is that “both the biological foundation of and cultural influences on emotion have significant implications for human experience and behavior, and are worthy of intensive study. They should be considered complementary, not competing, approaches to a fascinating and complex topic” (Shiota and Keltner 2005, 35). In relation to language, one of the tentative conclusion of the ongoing debate is that regardless of the final outcome of the debate, the evidence provided from both sides indicates that “language is the most convenient channel for approaching research on the topic of emotion” (Argaman 2010, 90) and that “words are important, if not necessary, for emotion perception” (Fugate and Barrett 2014, 282), thus once again proving the existence of an inextricable link between linguistics and psychology in emotion studies.

3. EMOTION MODELS

A prerequisite to emotion detection research is choosing a suitable emotion model which contains information on how emotions are explained and described (Canales and Martínez-Barco 2014) and which at the same time stipulates the knowledge needed to appraise events (Binali, Wu and Potdar 2010) or, in this case, textual data. Therefore, a suitable emotion model needs to be selected with an appropriate emotion detection technique for the target text. Canales and Martínez-Barco (2014) note that although a number of approaches to emotion models exists in psychology, the two umbrella models that are most important and most often used in emotion detection from text are EMOTIONAL CATEGORIES and EMOTIONAL DIMENSIONS.

EMOTIONAL CATEGORIES are based on distinct emotional classes or labels (Canales and Martínez-Barco 2014). This model assumes that there are

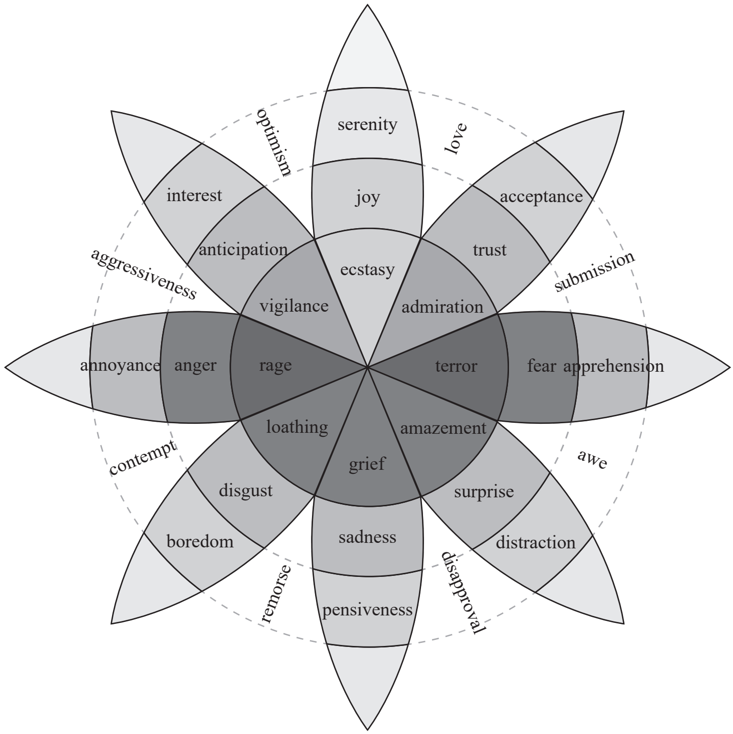

Figure 1. Bipolar Model

discrete emotional categories, i.e. a certain emotion has its own unique linguistic label, with Ekman's (1999) and Plutchik's (1982) models being the most known examples of emotional categories. According to Ekman's (1999) research on universal facial expressions, six basic emotions were discovered and identified: ANGER, DISGUST, FEAR, HAPPINESS, SADNESS, and SURPRISE. Plutchik's (1982) model was created in relation to adaptive biological processes reflected in his psycho-evolutionary theory of emotion which included 8 primary bipolar emotions – JOY-SADNESS, ANGER-FEAR, TRUST-DISGUST, SURPRISE-ANTICIPATION – with the ability to combine one with another to form different emotions, e.g. ANTICIPATION and JOY may be combined into OPTIMISM (Figure 1).

Table 3. Categorization of Emotions

Primary Emotion	Secondary Emotion	Tertiary Emotions
LOVE	AFFECTION	ADORATION, AFFECTION, LOVE, FONDNESS, LIKING, ATTRACTION, CARING, TENDERNESS, COMPASSION, SENTIMENTALITY
	LUST	AROUSAL, DESIRE, LUST, PASSION, INFATUATION
	LONGING	LONGING
JOY	CHEERFULNESS	AMUSEMENT, BLISS, CHEERFULNESS, GAIETY, GLEE, JOLLINESS, JOVIALITY, JOY, DELIGHT, ENJOYMENT, GLADNESS, HAPPINESS, JUBILATION, ELATION, SATISFACTION, ECSTASY, EUPHORIA
	ZEST	ENTHUSIASM, ZEAL, ZEST, EXCITEMENT, THRILL, EXHILARATION
	CONTENTMENT	CONTENTMENT, PLEASURE
	PRIDE	PRIDE, TRIUMPH
	OPTIMISM	EAGERNESS, HOPE, OPTIMISM
	ENTHRALLMENT	ENTHRALLMENT, RAPTURE
	RELIEF	RELIEF
SURPRISE	SURPRISE	AMAZEMENT, SURPRISE, ASTONISHMENT
ANGER	IRRITATION	AGGRAVATION, IRRITATION, AGITATION, ANNOYANCE, GROUCHINESS, GRUMPINESS
	EXASPERATION	EXASPERATION, FRUSTRATION
	RAGE	ANGER, RAGE, OUTRAGE, FURY, WRATH, HOSTILITY, FEROCITY, BITTERNESS, HATE, LOATHING, SCORN, SPITE, VENGEFULNESS, DISLIKE, RESENTMENT
	DISGUST	DISGUST, REVULSION, CONTEMPT
	ENVY	ENVY, JEALOUSY
	TORMENT	TORMENT
SADNESS	SUFFERING	AGONY, SUFFERING, HURT, ANGUISH
	SADNESS	DEPRESSION, DESPAIR, HOPELESSNESS, GLOOM, GLUMNESS, SADNESS, UNHAPPINESS, GRIEF, SORROW, WOE, MISERY, MELANCHOLY
	DISAPPOINTMENT	DISMAY, DISAPPOINTMENT, DISPLEASURE
	SHAME	GUILT, SHAME, REGRET, REMORSE
	NEGLECT	ALIENATION, ISOLATION, NEGLECT, LONELINESS, REJECTION, HOMESICKNESS, DEFEAT, DEJECTION, INSECURITY, EMBARRASSMENT, HUMILIATION, INSULT
	SYMPATHY	PITY, SYMPATHY
FEAR	HORROR	ALARM, SHOCK, FEAR, FRIGHT, HORROR, TERROR, PANIC, HYSTERIA, MORTIFICATION
	NERVOUSNESS	ANXIETY, NERVOUSNESS, TENSENESS, UNEASINESS, APPREHENSION, WORRY, DISTRESS, DREAD

Adapted from Shaver et al. (1987, 1067).

Another model constituting of primary emotions merging and forming secondary and tertiary is provided by Shaver et al. (1987) which can be seen in Table 3. Although simpler and familiar when conducting emotion detection research, the drawback of emotional categories is contained in the notion that they may not cover all emotions adequately and may not correlate to a certain emotional state as they are limited in scope – a specific set of linguistic labels can only be used to identify a specific set of emotions.

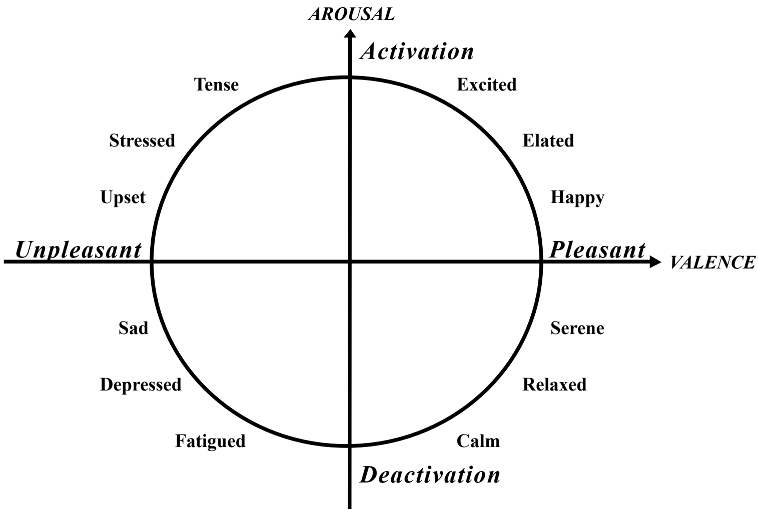

Figure 2. Circumplex Model

EMOTIONAL DIMENSIONS reflect the notion that emotions are combinations of several psychological dimensions where each emotion occupies a location in a dimensional form (Canales and Martínez-Barco 2014). Representatives of this emotional dimensions include Russell's (1980) CIRCUMPLEX and Mehrabian's (1996) PLEASURE-AROUSAL-DOMINANCE (PAD) model of emotions. Russell's (1980) model suggests that emotions are distributed in a two-dimensional circular space, as shown in Figure 2. The horizontal VALENCE dimension indicates how much pleasant or unpleasant an emotion is, while the vertical AROUSAL dimension differentiates activation and deactivation states of an emotion.

Mehrabian's PAD model (1996) is a three-dimensional model, as seen in Figure 3. The emotions are presented in the three-dimensional space[5] based on how pleasant or unpleasant (PLEASURE), how energized or soporific (AROUSAL), and how dominant versus submissive (DOMINANCE) they are. Although emotional dimensions are able to capture subtle emotion concepts that differ only slightly, they may not provide clear-cut linguistic labels like the emotional categories do.

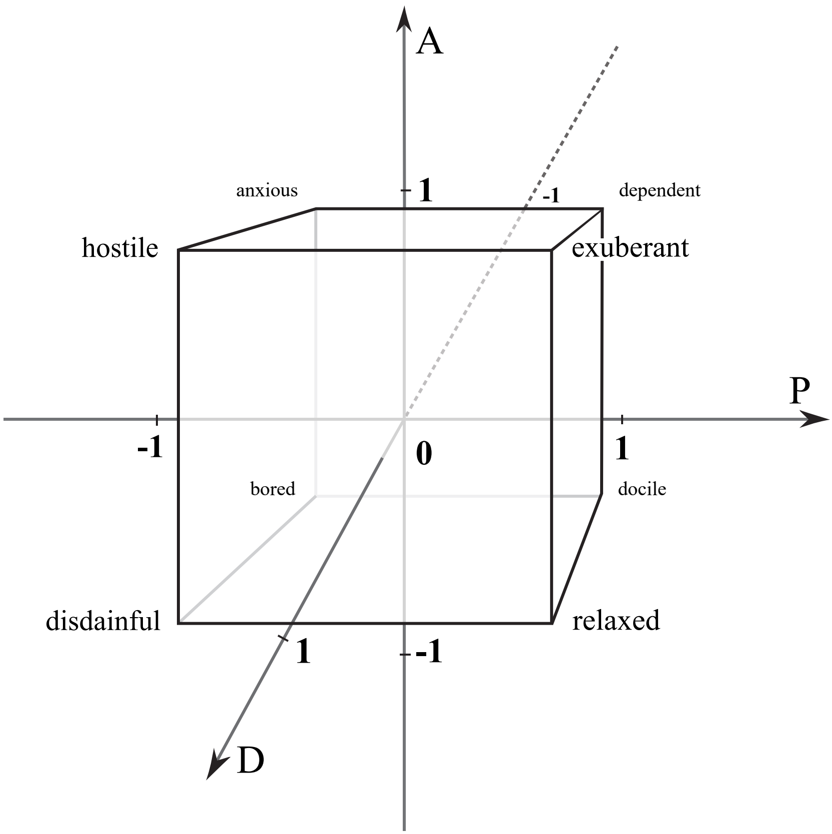

Figure 3. PAD Model

Neither of the two umbrella models of emotions is better than the other, and the selection of an emotion model depends on the textual data and the set of emotions we want to detect. Depending on the research goal, the researcher may opt for one of the emotional categories model if they want to clearly identify a specific emotion, or they will choose an emotional dimensions model when measuring a specific dimension such as pleasure or dominance. Examples of utilizing methods based on both major umbrella emotion models will be demonstrated in a later section.

4. EMOTION AND LANGUAGE

Emotions are not linguistic, but primarily psychological constructs; however, “the most convenient nonphenomenological access we have to them is through language” (Ortony, Closer and Foss 1987, 342). The existing research on emotions and language, ranging from the study of the metaphorical power of emotions (Lakoff and Johnson 1980; Kövecses 2000) to exploring language as context for the perception of emotion (Feldman Barrett, Lindquist and Gendron 2007) and even proposing a special language to describe emotions (Wierzbicka 1999), indicates that “language may run deeper in emotions than either laypeople or researchers previously thought” (Lindquist, MacCormack and Shablack 2015, 1).

	REFERENTIAL	
EMOTIVE	**POETIC** **PHATIC**	**CONATIVE**
	METALINGUAL	

Figure 4. Functions of Language

In his well-known article *Linguistics and Poetics*, Roman Jakobson (1960) explores the relationship between language and the world. He lists six primary functions of language (Figure 4) and states that although the basic function of language is referential and cognitive, the emotive function cannot be ignored as it produces a direct expression of the speaker’s attitude towards what they are speaking about and tends to produce an impression of a certain emotion. Jakobson (1960, 73) further illustrates the emotive function:

> The purely emotive stratum in language is presented by the interjections. They differ from the means of referential language both by their sound pattern (peculiar sound sequences or even sounds elsewhere unusual) and by their syntactic role (they are not components but equivalents of sentences). "Tut! Tut! said McGinty"; the complete utterance of Conan Doyle's character consists of two suction clicks. The emotive function, laid bare in the interjections, flavors to some extent all our utterances, on their phonic, grammatical, and lexical level.

Although Jakobson (1960) lists only interjections as one example of when the emotive function is expressed, "nearly every dimension of every language at least potentially encodes emotion" (Wilce 2009, 3). To explore if emotion can interact with language at many levels of structure – from the sound patterns of a language to its lexicon and grammar, and beyond how it appears in conversation and discourse – Majid (2012) analyzed research results from diverse subfields across the language sciences – including cognitive linguistics, psycholinguistics, linguistic anthropology, and conversation analysis. In his review he demonstrated that "emotion is, indeed, relevant to every dimension of language – from phonology to lexicon, grammar to discourse – emotional expression is finely tuned to language-specific structures" (Majid 2012, 441) proving once again that "emotion is in some sense indexed in and through almost every dimension of language" (Wilce 2009, 14).

Language can additionally be analyzed in terms of its role in different theories of emotion (Fugate and Barrett 2014). For example, language is viewed as independent of emotion in the Darwinian perspective, while in the social constructivist perspective it is culture's language that reflects the emotion experience and perception. Next, emotion words in the Jamesian perspective are constitutive of emotion generation and perception while, according to the cognitive perspective, they constrain categories in which appraisals are placed. For practitioners, such as psychotherapists in general and psychoanalysts in particular, language is a bridge to understanding the patient's soul, especially the unconscious part of the soul (Freud 1958).

The reasoning behind is based on the notion that "language is the most convenient channel for approaching research on the topic of emotions" (Argaman 2010, 90) and that it also helps constitute emotion by cohering sensations into specific perceptions of emotion categories (Lindquist, Satpute and Gendron 2015, 99). Moreover, "emotion words are the best way to reflect the emotional experience … [and] the most natural way to externally express the inner emotional world" (Argaman 2010, 90). Furthermore, the research results show that words in particular, do not only convey information about internal states, attitudes, beliefs, social contexts, elicitors, motivations, values, behaviors, and many other referents (Shiota and Keltner 2005), but they also "construct and stabilize human mental emotional categories" (Jablonka, Ginsburg and Dor 2012, 2157). Moreover, language makes it much easier to manipulate emotions for both aggressive and cooperative ends (Jablonka, Ginsburg and Dor 2012), showing that language is not only a descriptor of emotions, but an inducer and manipulator as well. When writing about the perception of language in relation to emotion, Bamberg (1997, 309–310) notes:

> If language is conceived of as merely representing (in the sense of 'mirroring') the world of emotions and/or people's conceptualizations and understandings of the emotions, language offers an immediate access. ... If language, however, is conceived of in one or another way as contributing to how emotions are understood, or even, to what emotions "are", the relationship is not direct, but mediated.

No matter how the relationship between language and emotion is viewed, there is a general consensus that "emotion is not confined to the outskirts of linguistic civilization but pervades its core" (Wilce 2009, 3) at the same time recognizing "the impossibility of exploring other people's emotions without keeping language in focus: both as an object and as a tool of study" (Enfield and Wierzbicka 2002, 2).

5. LINGUISTIC RESOURCES FOR EMOTION DETECTION

As explored in the previous section, text, in addition to informative, contains attitudinal, and more specifically, emotional content (Ovesdotter Alm, Roth and Sproat 2005). The language – words, phrases and sentence structures in particular – people use in their daily lives can reveal important aspects of their social and psychological worlds. Emotions are at the core of understanding ourselves and others (Gill et al. 2008) making them "a key semantic component of human communication" (Calix et al. 2010, 544) and interaction. Therefore, emotion detection from text aims not only to infer the underlying emotions influencing the author by studying their input texts (Binali, Wu and Potdar 2010), but it also allows researchers to "reliably and quickly assess features of what people say as well as subtleties in their linguistic styles" (Pennebaker, Mehl and Niederhoffer 2003, 547).

Advancements in textual analysis have allowed the area of emotion detection to become a recent interest in computational linguistics (Mulcrone 2012). In this branch of linguistics, emotion detection from text does not only enhance our experience with technologies (Gill et al. 2008), but it also provides many applications in fields where there is a need to understand and interpret emotions exists (Binali, Wu and Potdar 2010). The possible applications will be discussed in one of the later sections of this paper, while in the next section, the use of computational linguistic tools to derive emotional features will be explored.

5.1. EMOTION DETECTION FROM TEXT: ANALYTICAL APPROACHES

Emotion detection from text is done primarily utilizing the following analytical approaches: KEYWORD-BASED, LEARNING-BASED and HYBRID-BASED (Haggag, Fathy and Elhaggar 2015). These methods use features primarily selected from syntactic – n-grams, POS tags, phrase patterns, etc. – and semantic – e.g. synonym sets – data to detect emotions (Binali, Wu and Potdar 2010). In this section, a brief description of them based on

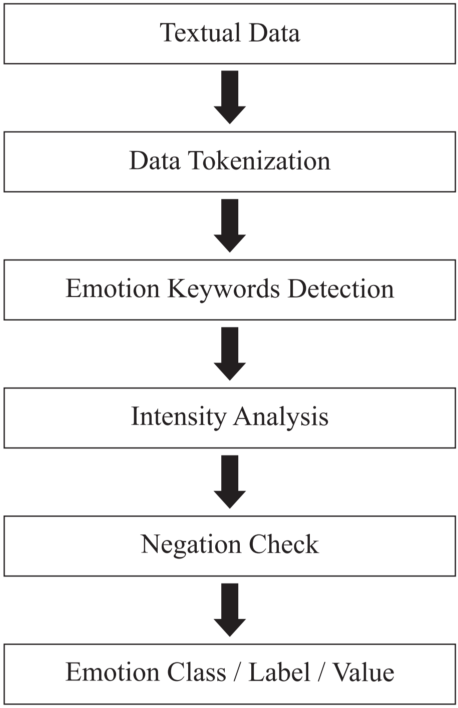

Figure 5. Keyword-based Approach

Haggag, Fathy and Elhaggar's (2015, 240–241) work, including their limitations[6], will be provided.

Keyword-based approach relies on the presence of keywords and involves pre-processing with a parser and emotion dictionary containing emotional value of words (Figure 5). In order to classify emotions, emotional keywords are searched from input text, making this approach intuitive, straight forward and easy to implement and use. However, classification methods based on only keywords suffer from the ambiguity in the keyword definitions – a word may have different meanings according to usage and context, the lack of linguistic information and the incapability of recognizing emotions within sentences not containing emotional keywords.

Learning-based approach uses a trained classifier to categorize input text into emotion classes by using keywords as features. It is easier and faster to adapt to domain changes since it can quickly learn new features from corpora by supplying a large training set to a machine learning algorithm for building a classification model. However, acquiring large corpora may not always be feasible and the major drawback of this approach is that it leads to blurred boundaries between emotion classes.

Hybrid-based approach consists of a combination of the keyword-based and learning-based methods, in addition to information from different sciences like psychology. The advantages of this approach are that it can yield higher accuracy results from training a combination of classifiers and, adding knowledge-rich linguistic information from dictionaries and thesauri, it will offset the high cost involved in using human indexers for information retrieval tasks and minimize complexities encountered while integrating different lexical resources.

5.2. EMOTION DETECTION FROM TEXT: A DEMONSTRATION

For this demonstration, analytical tools written in Python, "a popular [programming] language for machine learning, scientific, statistical, mathematical, and other types of specialized computing" (opensource.com n.d.) including emotion detection from text, will be used. Python is ideal for novice researchers and anyone interested in researching emotions as it is freely distributable and open sourced, available without charge for all major platforms. Moreover, this interpreted, object-oriented, high-level programming language with dynamic semantics supports modules and packages, which in turn encourages program modularity and code reuse (Python Software Foundation n.d.). Python's wide range of applications can be illustrated by millions of developers who use it to perform tasks ranging from image manipulation, scientific calculations and data mining to powering some of the world's most complex applications and websites such as Google's search engine, YouTube and Instagram (Love n.d.;

opensource.com n.d.; Python Software Foundation n.d.). Thus, the advantages of this interpreted, object-oriented, high-level programming language with dynamic semantics for emotion detection from text can be summarized as threefold (Love n.d.):

a) Python's easy-to-learn syntax, which closely resembles the English language using words like 'not' and 'in', makes it simple and easy to learn, while at the same time it emphasizes readability and reduces the cost of program maintenance;
b) being developed in the late 1980s by Guido van Rossum and named after Monty Python, Python contains a plethora of written code and due to its open source nature, a large portion of it, including various modules and packages, has been made public providing resources for developers to (re)use and build upon;
c) as an open source and modular language, Python has user groups and developer communities everywhere, thus providing continuous support and feedback.

A search for emotion detection projects written in Python on GitHub[7] reveals an existence of thriving community of developers interested in this topic[8]. For the purpose of this demonstration, the code repository TEXT ANALYSIS[9] which includes a set of analytical tools for emotion detection from text in the form of Python scripts[10] will be used. It combines not only emotion, but also sentiment[11], subjectivity, orientation, and color keyword data in performing textual analysis, not only showing that textual data contains plethora of information to analyze, but also providing analytical tools for the aforementioned data. Its core data set is comprised of five lexicons – NRC Word-Emotion Association Lexicon, NRC Word-Colour Association Lexicon, Opinion Lexicon, Subjectivity Lexicon, Harvard General Inquirer.

NRC Word-Emotion Association Lexicon, also known as EmoLex (Mohammad and Turney 2010; Mohammad and Turney 2013), contains a list of 14,182 words and their associations with eight emotions – anger, fear, anticipation, trust, surprise, sadness, joy, and disgust – and two sentiments – negative and positive. Each word is assigned a value of 0 or 1 for each of the aforementioned eight emotions and two sentiments, with 0 indicating that the target word has no association with a specific emotion or sentiment category and 1 indicating an association. NRC Word-Colour Association Lexicon (Mohammad 2011a; Mohammad 2011b) is comprised of around 14,000 unique words and the colors – white, black, red, green, yellow, blue, brown, pink, purple, orange and grey – they are most associated with. Opinion Lexicon, also known as Sentiment Lexicon (Hu and Liu 2004; Liu, Hu and Cheng 2005), is a list containing 2006 positive and 4782 negative English words. Subjectivity Lexicon (Riloff and Wiebe 2003; Wilson, Wiebe and Hoffmann 2005) is a list of 8222 words containing subjectivity clues – clues that are subjective in most contexts are considered strongly subjective, and those that may only have certain subjective usages are considered weakly subjective. Harvard General Inquirer (Stone and Hunt 1963; Stone et al. 1966) is a lexicon attaching syntactic, semantic, and pragmatic information to 11,788 words labeled with 182 categories of word tags, including positive and negative sentiment.

The aforementioned lexicons were parsed and compiled into a single unified lexicon[12] containing textual data forming word categories listed in Table 4. The code repository used provides an additional Python script that allows inclusion of other data source, primarily lexicons, which in turn allows additional modification to the categories used when performing textual analysis. However, as the aim of this demonstration is to make readers of this paper somewhat familiar with the possibilities of using Python in research on emotion detection from text, the Unified Lexicon that is by default included in the code repository will not be modified in any way and only the results in the emotion and sentiment category will be presented and briefly commented upon.

Table 4. Unified Lexicon Data

Words Total	Words with Sentiment	Words with Subjectivity	Words with Orientation	Words with Color
14,852	10,916 (73.5%)	6,886 (46.4%)	2,192 (14.8%)	5,404 (36.4%)

The set of textual data for analyses is comprised of different types of texts reflecting different stages of evolution of the English language. Lewis Carroll's novels *Alice's Adventures in Wonderland* (1865) and *Through the Looking-Glass* (1872) reflect the English literature of the 19th century, J.K. Rowling's series of *Harry Potter* books (1997; 1998; 1999; 2000; 2003; 2005; 2007) is written for the masses and filled with neologisms, a selection of Edgar Allan Poe's poems (1827; 1830; 1845; 1849a; 1849b) was chosen to examine the importance of the structural element of the text in emotion detection, David Bowie's song lyrics (1969; 1971a; 1971b; 1977; 1972a; 1972b; 1974; 1980; 1983a; 1983b) were analyzed to see whether lyrics isolated from the instrumental part and the vocal abilities of the singer convey the same emotion, and tweets by TV host Ellen Degeneres, actor Ryan Reynolds and YouTube creator Shane Dawson were studied as they contain numerous pragmatic markers and often resort to plays on words to elicit a reaction or emotion.

Using a built-in Python script, the text was beforehand parsed into discrete words in lowercase separated by spaces with punctuation removed. Subsequently the textual data was analyzed using another Python script and values, according to the categories at hand – emotion, color, orientation, sentiment, subjectivity, chapter (optional) – were assigned to words. The data itself was saved as a comma-separated values (CSV). Finally, additional Python script was used to compute the median category value of the target text categories and save the results as a JavaScript Object Notation (JSON) file. Each item in the output file represents a group of words, with numbers between 0 and 1 representing the relative weight of that particular category value (Figure 6). Moreover, the JSON file was further converted to a more reading-friendly Excel format as seen in Tables 5–10.

```
[
  {
        “chapter”: 1,
        “emotion”: [
                0.262, // anger
                0.071, // fear
                0.119, // anticipation
                0.643, // trust
                0.071, // surprise
                0.143, // sadness
                0.071, // joy
                0.143 // disgust
],
        “orientation”: [
                0.712, // active
                0.613 // passive
],
        “sentiment”: [
                0.657, // positive
                0.657 // negative
],
        “color”: [
                0.045, // white
                0.136, // black
                0.227, // red
                0.136, // green
                0.023, // yellow
                0.045, // blue
                0.251, // brown
                0.023, // pink
                0.023, // purple
                0.023, // orange
                0.068 // grey
],
        “subjectivity”: [
                0.681, // weak
                0.473 // strong
]
  }
]
```


Figure 6. Example of JSON Output File

Table 5. Results for *Alice's Adventures in Wonderland*

Chapter	*Emotion*								*Sentiment*	
	ANGER	FEAR	ANTICIPATION	TRUST	SURPRISE	SADNESS	JOY	DISGUST	POSITIVE	NEGATIVE
1	0.574	0.396	0.117	0.679	0.021	0.114	0.075	0.156	0.506	0.683
2	0.607	0.498	0.195	0.354	0.057	0.177	0.147	0.171	0.496	0.788
3	0.294	0.147	0.216	0.234	0.084	0.060	0.105	0.069	0.471	0.554
4	0.595	0.336	0.147	0.408	0.027	0.486	0.174	0.150	0.680	0.967
5	0.351	0.234	0.156	0.628	0.003	0.159	0.090	0.351	0.630	0.681
6	0.342	0.607	0.222	0.474	0.027	0.081	0.201	0.153	0.698	1.000
7	0.423	0.150	0.228	0.246	0.063	0.357	0.120	0.150	0.780	0.730
8	0.508	0.700	0.216	0.405	0.057	0.126	0.123	0.360	0.540	0.831
9	0.694	0.126	0.168	0.324	0.027	0.048	0.171	0.658	0.621	0.802
10	0.306	0.375	0.279	0.288	0.018	0.216	0.153	0.114	0.425	0.808
11	0.312	0.270	0.261	0.282	0.051	0.027	0.120	0.072	0.511	0.636
12	1.000	0.258	0.159	0.402	0.015	0.123	0.174	0.432	0.472	0.847

Table 6. Results for *Through the Looking-Glass*

Chapter	*Emotion*								*Sentiment*	
	ANGER	FEAR	ANTICIPATION	TRUST	SURPRISE	SADNESS	JOY	DISGUST	POSITIVE	NEGATIVE
1	0.355	0.688	0.327	0.413	0.015	0.186	0.236	0.173	0.581	0.755
2	0.613	0.145	0.156	0.314	0.195	0.067	0.149	0.076	0.425	0.625
3	0.524	0.286	0.301	0.353	0.084	0.143	0.128	0.182	0.532	0.642
4	0.429	0.392	0.158	0.489	0.032	0.084	0.104	0.160	0.502	0.658
5	0.868	0.182	0.351	0.517	0.206	0.290	0.104	0.113	0.552	0.672
6	0.753	0.260	0.299	0.329	0.028	0.327	0.190	0.048	0.505	0.709
7	0.424	0.126	0.212	0.455	0.009	0.277	0.154	0.351	0.403	0.634
8	0.760	0.452	0.459	0.312	0.011	0.221	0.286	0.180	0.714	0.824
9	1.000	0.385	0.199	0.671	0.004	0.320	0.100	0.374	0.710	1.000
10	0.009	0.004	0	0.004	0	0	0	0.004	0.006	0.019
11	0.004	0.002	0	0.002	0	0	0	0	0	0.002
12	0.442	0.268	0.160	0.465	0.032	0.158	0.255	0.182	0.633	0.794

Table 7. Results for *Harry Potter* Book Series

Book	*Emotion*								*Sentiment*	
	ANGER	FEAR	ANTICIPATION	TRUST	SURPRISE	SADNESS	JOY	DISGUST	POSITIVE	NEGATIVE
1	0.547	0.273	0.205	0.351	0.046	0.142	0.149	0.213	0.450	0.648
2	0.513	0.196	0.202	0.411	0.052	0.123	0.128	0.162	0.542	0.704
3	0.473	0.195	0.177	0.307	0.031	0.093	0.107	0.169	0.437	0.634
4	0.457	0.194	0.173	0.249	0.018	0.105	0.107	0.136	0.421	0.623
5	0.635	0.289	0.264	0.448	0.032	0.131	0.162	0.226	0.533	0.747
6	0.543	0.311	0.261	0.451	0.032	0.190	0.184	0.238	0.552	0.736
7	0.474	0.221	0.198	0.367	0.038	0.125	0.120	0.161	0.453	0.649

(1) Harry Potter and the Sorcerer's Stone
(2) Harry Potter and the Chamber of Secrets
(3) Harry Potter and the Prisoner of Azkaban
(4) Harry Potter and the Goblet of Fire
(5) Harry Potter and the Order of the Phoenix
(6) Harry Potter and the Half-Blood Prince
(7) Harry Potter and the Deathly Hallows

Table 8. Results for Edgar Allan Poe Poems

Poem	*Emotion*								*Sentiment*	
	ANGER	FEAR	ANTICIPATION	TRUST	SURPRISE	SADNESS	JOY	DISGUST	POSITIVE	NEGATIVE
The Raven	1.000	0.260	0.410	0.940	0.040	0.670	0.180	0.400	0.862	1.000
Annabel Lee	0.110	0.110	0.020	0.120	0	0.040	0.040	0.080	0.182	0.234
A Dream Within a Dream	0.130	0.060	0.030	0.100	0	0.010	0.010	0.100	0.098	0.146
Alone	0.200	0.050	0.020	0.110	0	0.080	0.020	0.180	0.084	0.190
Eldorado	0.100	0.060	0.010	0.040	0.010	0.030	0.010	0.030	0.044	0.119

Table 9. Results for Twitter Posts

Tweet	*Emotion*								*Sentiment*	
	ANGER	FEAR	ANTICIPATION	TRUST	SURPRISE	SADNESS	JOY	DISGUST	POSITIVE	NEGATIVE
1	0.500	0.333	0	0.167	0	0	0	0.167	0.054	0.432
2	0.500	0.333	0	0.500	0	0	0	0.167	0.054	0.432
3	0.500	0.500	0	0.333	0	0	0	0.167	0.054	0.514
4	0.667	0.333	0	0.333	0	0	0	0	0.054	0.514
5	0.667	0.333	0	0.333	0	0	0	0.167	0.135	0.622
6	0.333	0.167	0	0.333	0	0	0	0	0.054	0.270

(1) I wish everyone in that category could have won. Congratulations, @EdSheeran! So sorry I asked you to pet sit tonight. #GRAMMYs
(Ellen Degeneres, 28 January 2018, source: https://twitter.com/TheEllenShow)
(2) Portia bought baby carrots to give to trick-or-treaters. On the bright side, we'll probably never be out of toilet paper again. #HallowEllen
(Ellen Degeneres, 1 November 2012, source: https://twitter.com/TheEllenShow)
(3) People in LA are deathly afraid of gluten. I swear to god, you could rob a liquor store in this city with a bagel.
(Ryan Reynolds, 7 January 2017, source: https://twitter.com/VancityReynolds)
(4) No matter which kids book I read to my screaming baby on an airplane, the moral of the story is always something about a vasectomy.
(Ryan Reynolds, 7 August 2016, source: https://twitter.com/VancityReynolds)
(5) if u guys have any other title ideas for today's video let me know! i was trying to think of one that summed up the video but it was really hard hahaha
(Shane Dawson, 11 April 2018, source: https://twitter.com/shanedawson)
(6) omg. i just opened twitter and saw what happened. please everyone at hq stay safe :((
(Shane Dawson, 10 January 2018, source: https://twitter.com/shanedawson)

Table 10. Results for David Bowie Song Lyrics

Song	*Emotion*								*Sentiment*	
	ANGER	FEAR	ANTICIPATION	TRUST	SURPRISE	SADNESS	JOY	DISGUST	POSITIVE	NEGATIVE
1	0.262	0.071	0.119	0.643	0.071	0.143	0.071	0.143	0.657	0.657
2	0.310	0.143	0.143	0.095	0.024	0.143	0.071	0.119	0.636	0.804
3	1.000	0.143	0.071	0.357	0.095	0.190	0.119	0.071	0.594	1.000
4	0.595	0.405	0.024	0.095	0	0.071	0.143	0.524	0.462	0.979
5	0.524	0.357	0.167	0.190	0.190	0.286	0.167	0.119	0.608	0.888
6	0.405	0.190	0.071	0.143	0.119	0.095	0.095	0.167	0.385	0.734
7	0.524	0.048	0.143	0.310	0	0.143	0.071	0.190	0.559	0.825
8	0.405	0.238	0.095	0.476	0.024	0.095	0.143	0.286	0.510	0.832
9	0.429	0.190	0.095	0.048	0.119	0.429	0.048	0.143	0.350	0.972
10	0.214	0.238	0	0.071	0.048	0.190	0	0.095	0.147	0.559

(1) Space Oddity
(2) Changes
(3) Life on Mars
(4) Heroes
(5) Starman
(6) Ziggy Stardust
(7) Rebel Rebel
(8) Ashes to Ashes
(9) Let’s Dance
(10) Modern Love

Since the intention of this section was to demonstrate how one can perform research on emotion detection from text, an in-depth analysis of the results is not provided. However, some remarks were made.

The findings reflect the limitations of using the keyword-based approach mentioned in the previous section. Calculating values exclusively of the annotated words found in emotion lexicons is a major drawback for emotion detection from certain types of text, as can be seen with Carroll's (1865; 1872) and Rowling's (1997; 1998; 1999; 2000; 2003; 2005; 2007) novels. Although primarily written for children, these books, as the results indicate, are filled with anger and fear and generally provide a negative sentiment. However, as readers acquainted with them know, that is not the case. The analysis of Poe's (1827; 1830; 1845; 1849a; 1849b) works also suffers from a similar ailment – the emotion that is achieved through line and verse structure, rhyme and rhythm is lost when parsing the text into discrete words separated by space with punctuation removed. Twitter posts reveal that the use of pragmatic markers such as ":)" or "hahaha" plays a significant role in emotion expression and perception, something, alongside sarcasm being a component a humor as well, is not taken into account by the analytical tools used in this demonstration. Finally, David Bowie's song lyrics reveal, especially with *Let's Dance* (1983a), that words that are repeated, often in choruses, may contribute to achieving a higher score in a certain category, although the song, when lyrics and the instrumental part are combined, conveys another emotion. All the above-mentioned factors form an intrinsic connection in emotion perception, evoking and detection.

This section was not intended to criticize available tools as inadequate for emotion research, but to point out their limitations and offer suggestions for improving them. For example, including lexicons such as NRC Hashtag Emotion Lexicon (Mohammad 2012; Mohammad and Kiritchenko 2015) to the Unified Lexicon will yield much more accurate results when analyzing tweets, while the usage of Whissell Dictionary of Affect in Language (Whissell and Whissell 2000; Whissell 2009) may be more appropriate for the detection of emotion in song lyrics.

Taking context, structure of the text and its purpose into account, that is, combining multiple approaches, minimizing limitations and mitigating drawbacks by utilizing multilevel approach, will result in building more accurate tools and contribute to a more precise emotion detection from text. The first step is to get yourself acquainted with such tools with Python being just one of them. As more accurate methods bring more accurate results, this will in turn allow not only more theoretical, but also everyday applications as well. The next section is concerned with exactly such applications.

6. APPLICATIONS OF EMOTION DETECTION FROM TEXT

As illustrated in the previous sections, emotion detection research studies have been conducted in regards to emotions expressed through different mediums and observed in the changes of physiological state, facial expressions, prosody and text; however, there is a relative scarcity of research in emotion detection from text in comparison to the other areas of emotion detection (Binali, Wu and Potdar 2010). Nevertheless, emotion detection and analysis of emotional categories from text has attracted the attention of many researchers in computational linguistics because of its widespread applications[13].

Emotion detection from text has a great number of important applications, with the prime one being the capability to gather the overall emotion of a specific text. These applications range from sentiment analysis to opinion mining, market analysis and developing natural language interfaces such as e-learning environments or educational games (Haggag, Fathy and Elhaggar 2015). Furthermore, it can also increase human-computer interaction by instructing the computer how to provide an accommodating form of interaction with the user depending on the user's emotional state (Shelke 2014). Emotion detection from text can help psychologists infer people's emotions based on the text that they write, which they can use to predict their state of mind (Binali, Wu and Potdar 2010, 172); moreover, it can be applied to suicide prevention or it can measure the well-being of a community (Canales and Martínez-Barco (2014).

Some of the proposed applications also include the ability to search based on emotions; the ability to study how emotional expression changes over time, between genders, or between ethnic groups (Shelke 2014).

With current methods of emotion detection from texts it is possible to approach its applicability with interesting results, as illustrated in the previous paragraph. As these methods become more accurate over time, their use in natural language applications will likely become even more ubiquitous opening exciting applicative perspectives for the future (Mohammad 2015).

7. CONCLUSION

As Jakobson (1960, 72) writes, "language must be investigated in all the variety of its functions." In this paper, the emotive function that allows the interplay of language and emotions at all levels – from sound patterns, lexicon and grammar to conversation and discourse – proving that "all speaking and writing is inherently emotional to a greater or lesser extent" (Wilce 2009, 3) was explored. Emotions, as the literature survey has shown, are important as they not only influence most aspects of cognition and behavior, but also play a prominent role in the interaction and communication between people. To understand emotions is to understand ourselves and others.

This paper has vividly shown the existence of the undeniably strong and important link between language and emotion. The interplay of the two occurs at all linguistic levels, and to study emotions, to detect them in particular, is unconceivable without taking language into account. As a primary vehicle of communication and interaction, language is and will remain the most convenient medium for approaching research on the topic of emotions. The textual data, in particular, can be beneficial to emotion detection due to its syntactic and semantic information containing emotional states along with the informative content. As the methods for emotion detection from text become more accurate, its uses and applications will become more numerous and diverse as time goes by. The future for emotion detection from text looks bright.

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NOTES

[1] In this paper the term “emotion” will be used following the convention and tradition that emerged in English-speaking scientific literature. For the in-depth analysis of applicability of this term in cross-cultural studies see Wierzbicka (1999, 25–26).

[2] In this paper “emotion detection from text” is used to refer to the task of automatically determining feelings from text, in other words, automatically determining valence, emotions, and other affectual states from text.

[3] An experiment conducted by Gendron et al. (2014) provides some arguments against culturally universal emotions. The experiment was conducted with Namibian tribal members who had to sort photos of six people making six facial expressions of basic emotions according to Ekman (1999). This did not result in six neat piles of images, but instead the tribal members created a multitude of piles, with some images appearing in more than one. The experiment was repeated in the USA with more unanimity in the sorting providing evidence against the emotion universals.

[4] Examples of cross-cultural differences in emotion concepts can be observed with concepts such as Korean *han* – the state of feeling sad and hopeful at the same time, German *schadenfreude* – the state of feeling pleasure derived by someone from another person’s misfortune, or Danish *hygge* – the state of feeling cozy and comfortable conviviality that engenders a feeling of contentment or well-being.

[5] The space occupied by the PAD model might be divided into eight sub-spaces, that are named after extreme emotions represented by the extreme points of a scale (Mehrabian, 1996):

EXUBERANT (+P +A +D) VS. BORED (-P -A -D);
DEPENDENT (+P +A -D) VS. DISDAINFUL (-P -A +D);
RELAXED (+P -A +D) VS. ANXIOUS (-P +A -D);
DOCILE (+P -A -D) VS. HOSTILE (-P +A +D).

[6] For an extensive review of limitations found in emotion detection from text, consult Mohammad (2016, 204–206).

[7] GitHub is an online repository service that stores source code of projects written in a variety of different programming languages, Python included, that are publicly available for anyone to download and use. For more information visit https://github.com/.

[8] As of December 15, 2017, there are 31 Python code repositories available for projects related to ‘emotion detection’, 53 to ‘emotion text’, 92 to ‘emotion recognition’ and 137 to ‘emotion’ in general.

[9] The entire code repository, including analytical tools and guidelines how to use them for textual analysis, can be found at https://github.com/beefoo/text-analysis.

[10] A Python script is a series of commands written in Python within a file that is capable of being executed in order to perform a certain task.

[11] Sentiment refers to a general opinion, and sentiment analysis focuses on classifying the polarity of the given textual data – i.e. whether the expressed opinion from text is positive, negative or neutral.

[12] Lexicons listed in this demonstration are used for non-commercial purposes. They are freely available for research uses. Some restrictions may apply. Consult with the respective authors for further details.

[13] For an extensive review of applications of emotion detection from text, including public health, politics, brand management, education, emotion tracking in social media, detecting personality traits, understanding gender differences, literary analysis and visualizing emotions, consult Mohammad (2015, 202–203).

FIGURES

[1] Adapted from Kamińska, Sapiński and Pelikant (2014, 453) after Plutchik (1982).

[2] Adapted from Valenza, Lanata and Scilingo (2011, 238) after Russell (1980).

[3] Adapted from Kołakowska et al. (2015) after Mehrabian (1996).

[4] Adapted from Jakobson (1960, 357).

[5] Adapted from Chopade (2015, 410).

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