Linguistic Interpretation of Emotions for Affect Sensing from Text

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Abstract

Several approaches have already been employed to "sense" affective information from text, but none of those ever considered the cognitive and appraisal structure of individual emotions. Hence this paper aims at interpreting the cognitive theory of emotions known as the OCC emotion model, from a linguistic standpoint. The paper provides rules for the OCC emotion types for the task of sensing affective information from text. Since the OCC emotions are associated with several cognitive variables, we explain how the values could be assigned to those by analyzing and processing natural language components. Empirical results indicate that our system outperforms another state-of-the-art system.

1 Introduction and Motivation

While various conceptual models, computational methods, techniques, and tools are reported in (Shanahan et. al., 2006), we argue that the current work for sensing the affect communicated by text is incomplete and often gives inaccurate results. It is true that the assessment of affective content is inevitably subjective and subject to considerable disagreement. Yet the interest in sentiment or affect based text categorization is increasing with the large amount of text becoming available on the Internet. A brief discussion on available approaches is given in (Shaikh et. al., 2007a; Liu et. al., 2003). For example, keyword spotting, lexical affinity, statistical and hand crafted approaches target affective lexicons which are not sufficient to recognize affective information from text, because according to a linguistic survey (Pennebaker et. al., 2003), only 4% of words used in written texts carry affective content.

In this paper we consider the contextual-valenced based approached (i.e., SenseNet) as discussed by Shaikh et. al., (2007a, 2007b) and consider their SenseNet as the basis of our knowledgebase. For simplicity, we use the words 'sentiment' and 'opinion' synonymously and consider sentiment sensing as the prior task of "affect" or "emotion" sensing. The SenseNet can sense either positive or negative "sentiment", but it cannot classify different emotions. Therefore, this paper explains how the SenseNet can be employed to sense emotions from text. So the primary focus of this paper is to provide a set of rules for emotions characterized by the OCC (Ortony et. al., 1988) emotion model and discuss how the rules are implemented.

2 Affect Sensing from Text

2.1 Extending Valence Assignment Approach for Emotions Classification

For the task of affect sensing from text we should incorporate both commonsense knowledge and cognitive structure of emotions along with the semantic interpretation of the words used in a sentence. We have chosen the OCC model of emotions for this task. The rule-based definition of the OCC emotion types characterized by a rich set of linguistic tokens makes it appropriate to cope with the valence assignment approach for affect sensing from text.

2.2 Characterization of OCC Emotions

The OCC emotion types can be characterized by appropriate rules interplaying with several variables. There are two kinds of variables, namely,

emotion inducing variables (event, agent and object based variables) and emotion intensity variables. The event-based variables are calculated with respect to the event which is usually a verb-object pair found in the sentence. For example, the sentence, *John bought Mary an ice-cream*, gives an event as "buy, ice-cream". The variables are enlisted in Table 1. In general we call them "emotion variables".

Type	Variable Name
agent based	agent_fondness (*af*)
	cognitive_strength (*cs*)
object based	object_fondness (*of*)
	object_appealing (*oa*)
event based	self_reaction (*sr*)
	self_presumption (*sp*)
	other_presumption (*op*)
	prospect (*pros*)
	status (*stat*)
	unexpectedness (*unexp*)
	self_appraisal (*sa*)
	valenced_reaction (*vr*)
intensity	event_deservingness (*ed*)
	effort_of_action (*eoa*)
	expected_deviation (*edev*)
	event_familiarity (*ef*)

Table 1. OCC emotion variables

The OCC emotion model specifies 22 emotion types and 2 cognitive states. For example, OCC model literally defines "Happy-for" as "Pleased about a Desirable event for a Liked agent", and "Fear" as "Displeased about Negative Prospect of an Undesirable Unconfirmed event". Our goal is to represent these literal definitions by rules interplaying with the emotion variables so that the system can evaluate and get either a 'true' or 'false' value. For example, we have an input text *txt*, that has an agent *a*, associated with an event *e,* and we have a program entity *x* that detects emotion from *txt*. We can now represent the rule for "Happy-for" emotion as, *x* senses "Happy-for" if the following condition holds.
[Linguisitc_Token_found_for_HappyFor(txt) and *No_Negation_Found (txt)]* or [*vr* =True and *sr (e, txt)* = "Pleased" and *op*(*e, txt*) = "Desirable" and *af* (*x, txt*) = "Liked" and *cs* (a,*x*) = "Other"]

3 Implementation of the Rules

In this section, we first briefly discuss about the SenseNet and its different linguistic resources. Then we explain the 'emotion variables', their enumerated values and how the values are assigned to the respective variables.

3.1 SenseNet

Semantic Parser. The SenseNet has implemented a semantic parser using Machinese Syntax (Connexor Oy, 2005) that produces XML-formatted syntactic output for an input text. For example, the sentence, *"My mother presented me a nice wrist watch on my birthday and made delicious pancakes."*, the output of the semantic parser is shown in Table 2.

Triplet Output of Semantic Parser	
Triplet 1	[[*'Subject Name:'*, 'mother', *'Subject Type:'*, 'Person', *'Subject Attrib:'*, ['PRON PERS GEN SG1:i']], [*'Action Name:'*, 'present', *'Action Status:'*, 'Past ', *'Action Attrib:'*, ['time: my birthday', 'Dependency: and']], [*'Object Name:'*, 'watch', *'Object Type:'*, 'N NOM SG', *'Object Attrib:'*, ['Determiner: a', 'A ABS: nice', 'N NOM SG: wrist', 'Goal: i']]]
Triplet 2	[[*'Subject Name:'*, 'mother', *'Subject Type:'*, 'Person', *'Subject Attrib:'*, []], [*'Action Name:'*, 'make', *'Action Status:'*, 'Past ', *'Action Attrib:'*, []], [*'Object Name:'*, 'pancake', *'Object Type:'*, 'N NOM PL', *'Object Attrib:'*, ['A ABS: delicious']]]

Table2. Semantic Verb-Frames outputted by Semantic Parser

Semantic parser outputs each semantic verb-frame of a sentence as a triplet of "subject, verb, and object". Hence, one obtains multiple triplets if the parser encounters multiple verbs in a sentence. In our case, we consider each triplet to indicate an event encoding the information about "who is doing what and how". Therefore, the output given in Table 2 has two events, which are dependent to each other as indicated by 'dependency' keyword in the action attribute of Triplet 1.

Valenced Output. SenseNet is the implementation of contextual valence based approach that deals with semantic relationships of the words in a sentence and assign contextual-valence using a set of rules and prior-valence of the words. It outputs a numerical value ranging from -15 to +15 flagged as the 'sentence-valence' for each input sentence.

For examples, SenseNet outputs -11.158 and +10.973 for the inputs, *"The attack killed three innocent civilians."* and *"It is difficult to take bad photo with this camera.",* respectively. These values indicate a numerical measure of negative or positive sentiments carried by the sentences.

Scored-list of Action, Adjective, and Adverb. SenseNet has initially assigned prior-valence to 928 verbs, 948 adjectives and 144 adverbs by manual investigations of eight judges where the inter-agreement among the judges are reported as reliable (i.e., the Kappa value is 0.914). The judges have manually counted the number of positive and negative senses of each word of a selected list according to the contextual explanations of each sense found in WordNet 2.1. A database of words with prior-valence assigned using Equations (1) to (3) is developed and scores are stored in the scale of -5 to 5.

Prior-Valence = Average (((Positive-Sense Count – Negative-Sense Count)/Total Sense Count) * 5.0) (1)

Prospect Polarity = if (Positive-Sense Count > Negative-Sense Count) then 1 else -1 (2)

Prospective Valence = Average(max(Positive-Sense Count, Negative-Sense Count)/Total Sense Count) * 5.0*Prospect Polarity)

Praiseworthy Valence = Average (Prior-Valence + Prospective Valence) (3)

Scored-list of Nouns. SenseNet does an automatic approach to assign prior-valence to nouns by employing ConceptNet (Liu and Singh, 2004). A value between -5 to 5 is assigned as the valence for an unrated noun or concept as follows. To assign a prior-valence to a concept, the system collects all semantically connected entities that ConceptNet returns for the input concept. For example, to get the prior-valence for the noun 'rocket', the system failed to find it in the existing knowledgebase, but from the action list of the concept the system returned the value 4.112 by averaging the scores of the verbs 'carry (4.438)', 'contain (4.167)', 'fly (3.036)', 'launch (5.00)' and 'go (3.917)'.

3.2 Assigning Values to the Emotion Variables

According to the OCC model, the values for the variables self_presumption (*sp*) and self_reaction (*sr*) are "Desirable" or "Undesirable", and "Pleased" or "Displeased" respectively. For example, for the events *"buy ice-cream"*, *"present wrist watch"*, *"kill innocent civilians"* referred in the example sentences   SenseNet returns contextual valence as +7.832, +8.817 and -8.458, respectively. According to SenseNet scoring system the valence range for an event (i.e., verb, object pair) is ±10. Thereby we decide that for an event if the valence is positive (i.e., "buy ice-cream"), *sp* and *sr* are set as "Desirable" and "Pleased", and in the case of negative valence (i.e., "Kill innocent civilian") *sp* and *sr* are set to "Undesirable" and "Displeased", respectively.

The values for other_presumption (*op*) could be set "Desirable" or "Undesirable". For the sentence *"A terrorist escaped from the Jail"*, the value for *op* (for the event *"escape from jail")* is presumably "Desirable" for the agent "terrorist" but it gets "Undesirable" and "Displeased" for *sp* and *sr* because of negative valence (i.e., -6.715) of the event. From SenseNet we get the valence for terrorist as -3.620. Thus in this case we set *op* as "Desirable" because of having a negative valenced event associated with a negative valenced agent. Similarly we have the following simple rules to assign the values to *op*.

- If a positive valenced event is associated with a positive valenced agent, *op* is set "Desirable". e.g., *the Teacher was awarded the best-teacher award.* [(teacher, +4.167) , (award best-teacher award, +8.741)]
- If a negative valenced event is associated with a positive valenced agent, *op* is set "Undesirable". e.g., *the employee was sacked from the job.* [(employee, +3.445), (sack from job, -6.981)]
- If a positive valenced event is associated with a negative valenced agent, *op* is set "Undesirable". e.g., *the criminal was punished for the crime*. [(criminal,-3.095), (punish for crime, +5.591)]

In this context and in accordance to the OCC model, the value for cognitive_strength (*cs*) indicates how closely the computer program considers selfness. This value is set as "Self" if the agent described in the text is a first person (i.e., I or We); otherwise it is set as "Other". For the sentence, *"I wish I could win the lottery."*, *cs* is set "Self", but for the sentence, *"Susan won the million dollar lottery."*, *cs* is set "Other".

According to the OCC model, prospect of an event involves a conscious expectation that it will

occur in the future, and the value for the variable prospect (*pros*) can be either "Positive" or "Negative". In the aforementioned equation (2), SenseNet considers either the positive or negative sense-count (whichever is the maximum for a verb) to calculate "prospective valence" with the notion of semantic orientation towards optimistic-pessimistic scale. In order to assign *pros* value to an event we also consider the 'prospective valence' of the verb instead of 'prior-valence' of that verb. Thus "positive" or "negative" is assigned according to a certain threshold (i.e., ±3.5) for "positive" or "negative" valence obtained for that event. For example, the events *"admit into university", "kill innocent people", "do it",* SenseNet returns +9.375, -8.728, +2.921, respectively and according to this valence, *pros* of the events is set to "positive", "negative" and "null", respectively.

The variable status (*stat*) has the values like: "Unconfirmed", "Confirmed" and "Disconfirmed". We decide if the tense of the verb is present or future, the value is set to "Unconfirmed" (e.g., *I am trying to solve it.*); and if it is past or modal without a negation, *stat* is set "Confirmed" (e.g., *I succeeded.*), but with a negation, *stat* is set "Disconfirmed" (e.g., *I did not succeed.*).

If the valence of the agent/object is positive, "Liked" is set to the variables agent_fondness (*af*) and object_fondness (*of*) variables, otherwise "Not-liked" is set. For example, for the sentences, *"The hero appeared to save the girl."*, and *"A terrorist escaped from the Jail"*, *af* for "hero" and "terrorist" is set to "Liked" and "Not-Liked" because of positive and negative valence. Similarly, *of* is set "Liked" and "Not-Liked" for "girl" and "Jail" respectively.

The value for self_appraisal (*sa*) can be either "Praiseworthy" or "Blameworthy". In the aforementioned equation (3) SenseNet takes the average of "Prior Valence" and "Prospective Valence" of a verb with the notion of average semantic orientation of the verb from both good-bad and optimistic-pessimistic perspective. Like assigning *pros* value to an event we consider the "praiseworthy valence" of the verb to assign value to *sa*. Thereby for the same events discussed above to explain *pros* assignment, the value for *sa* is set "Praiseworthy", "Blameworthy" and "null", respectively.

The value of object_appealing (*oa*) indicates whether an object is "Attractive" or "Unattractive". In order to assign a value to *oa*, we deal with two scores (i.e., object valence, and familiarity valence) having the following heuristic. "Attractive" is set if the object has a positive valence with a familiarity valence less than a certain threshold. Reversely "Unattractive" is set if the object has a negative valence with a familiarity valence above a certain threshold. The familiarity valence is obtained from the ConceptNet by calculating the percentage of nodes (out of 300,000 concept-nodes) linking to and from the given object/concept. For example, the familiarity valence for "restaurant", "thief" and "diamond ring" is 0.242%, 0.120% and 0.013%, respectively. Heuristically we kept the threshold 0.10% to signal familiarity and unfamiliarity of an object. Thus "diamond ring" and "thief" gets "Attractive" and "Unattractive" set for *oa,* but "restaurant" gets 'null' accordingly.

The value for valenced_reaction (*vr*) is set either "True" or "False" in order to initiate further analysis to sense emotions or decide the sentence(s) as expressing a neutral emotion. We consider *vr* to be "True" if the 'sentence-valence' returned by SenseNet is either above than 3.5 or less than -3.5. For example, *"I go."*, doesn't lead to further processing (i.e., sentence-valence is +3.250) but *"I go to gym everyday."*, leads to classify emotion because of the sentence-valence +7.351 obtained from SenseNet. The value to the variable unexpectedness (*unexp*) is set "true" if there is a linguistic token to represent suddenness (e.g., abruptly, suddenly, swiftly etc.) in the input sentence, otherwise "false" is set. We have a list of such tokens to indicate suddenness.

OCC model has several variables to signify emotional intensity. For example, the value for the intensity variable event_deservingness (*ed*) is set "High" for an event having a higher positive valence (i.e., above +7.0) or "Low" for higher negative one (i.e., less than -7.0). If an action is qualified with an adverb (e.g., *He worked very hard*) or target object qualified with an adjective (e.g., *I am looking for a quiet place*) without a negation, the value for effort_of_action (*eoa*) is set "Obvious", otherwise "Not-Obvious". Another variable called expected_deviation (*edev*) indicates the difference between the event and its actor. For example, in the sentence *"The police caught the criminal finally."*, the actor "police" and the event "catch criminal" don't deviate because the action is presumably expected by the actor. We set the value for *edev* to "Low" if ConceptNet can find any se-

mantic relationship between the actor and event; otherwise "High" is set. For example, for sentence *"the student invented the theory."*, *edev* is set "High" because ConceptNet doesn't return any relationship between "student" and "invent". The values "Common" or "Uncommon" are set for event_familiarity (*ef*) according to the familiarity valence obtained from ConceptNet for the input event as discussed before.

4.3 The rules for the OCC Emotion Types

In section 2.2 we briefly illustrated how a rule for the OCC defined emotion (e.g., happy-for) is characterized. Now using the same notion we enlist the rules for the OCC model defined emotion types. Although in *txt* there might be multiple *e* described and we also deal with such cases to get the resultant emotion types from *txt*, but we don't discuss that in the scope of this paper and describe the simple cases. Thus, the rules for emotion types are given considering an event *e*, for example, the program *x* senses 'Joy' for *e* if following condition is true:

[Linguisitc_Token_found_for_Joy(txt) and *No_Negation_Found (txt)]* or [*vr*= true and *sr*= "Pleased" and *sp*= "Desirable" and *cs*= "Self"] (i.e., literally joy means being 'pleased about a desirable event'.) Since we have the token words for each emotion types, we omit the first condition in the subsequent rules for space limitations. The rules for the emotion are listed as following and due to space limitations we are not providing the rules for all the emotions.

- if (*vr*= true and *sr*= "Pleased" and *pros*= "Positive" and *sp*= "Desirable" and *status*= "Unconfirmed"), "hope" is true.
- if (*vr*= true and *sr* = "Displeased" and *pros*= "Negative" and *sp*= "Undesirable" and *status*="Unconfirmed"), "fear" is true.
- if (*vr*= true and *sr* = "Pleased" and *pros*= "Negative" and *sp*= "Undesirable" and *status*= "Disconfirmed"), "relief" is true.
- if (*vr*= true and *sr* = "Displeased" and *pros*= "Positive" and *sp*= "Desirable" and *status*= "Disconfirmed"), "disappointment" is true.
- if (*vr*= true and *sr*= "Displeased" and *sa*= "Blameworthy" and *sp*= "Undesirable" and *cs*="Self"), "shame" is true.

- if (*vr*= true and *sp*= "Desirable" and *sr*= "Pleased" and *of*= "Liked" and *oa*= "Attractive"), "love" is true.
- if (*vr*= true and *sp*= "Undesirable" and *sr*= "Displeased" and *of*= "Not-Liked" and *oa*= "Unattractive"), "hate" is true.

The OCC model has four complex emotions namely, "gratification", "remorse", "gratitude" and "anger". For example:

- If both "joy" and "pride" are true, "gratification" is also true.
- If both "distress" and "reproach" are true, "anger" is also true.

The cognitive states "Shock" (i.e.; unpleasant surprise) and "Surprise" (i.e., pleasant surprise) are ruled as; If both "distress" and *unexp* are true, "shock" is true. (e.g., The bad news came unexpectedly.). Similarly, if both "joy" and *unexp* are true, "surprise" is true. (e.g., I suddenly met my school friend in Tokyo.)

Like Liu et al. (2003), we also believe that a statement may contain more than one type of emotions. In our case, the 22 emotion types and two cognitive states are grouped into seven groups, namely, well-being emotion, fortune of other emotion, prospect based emotion, cognitive state, attribution emotion, attraction emotion, and compound emotion. Hence an input sentence may contain one of the emotion types from each group. For example, the sentence *"I suddenly got to know that my paper won the best paper award."*, outputs the following emotions: {Joy, Satisfaction, Surprise, Pride, Gratification}.The sentence *"She failed to pass the entrance examination."*, outputs {Distress, Sorry-for, Disappointment, Reproach, Anger} emotion types. In order to reduce the number of emotions, we consider the intensity variables. For the first set of emotions, we can reduce it to {Satisfaction, Surprise, Pride} because "Joy" doesn't have any intensity variables and the intensity variables *ed* and *edev* are set to "High" in this case.

4   Test and Evaluation

The similar system like ours is Liu's system (Liu et. al., 2003). It is a rule based system, and it seems to be the best performing system for sentence-level affect sensing that senses happy, fearful, sad, angry, disgust, and surprise emotions. On the practical side, it is freely available on the Internet. Ex-

ample input and output are enlisted to given an idea about the outputs of the two systems.

Input: I avoided the accident luckily.

Liu's output: fearful(26%),happy (18%), angry (12%),sad(8%),surprised(7%),disgusted (0%)

Ours output: valence: +11.453; [joy, pride, relief, surprise, gratification]

Input: Susan bought a lottery ticket and she was lucky to win the million dollar lottery.

Liu's output: sad(21%), happy(18%), fearful (13%),angry(11%),disgusted(0%),surprised (0%)

Ours: valence: +12.533; [happy-for, satisfaction, admiration, love]

We evaluated our system to assess the accuracy of sentence-level affect sensing when compared to human-ranked scores (as "gold standard") for 200 sentences assessed by two systems. The sentences were collected from Internet based sources for reviews of products, movies, and news. In order to conduct system's performance and acceptance test we have two systems X (i.e., Liu's System) and Y (i.e., our system). The judges were not told about the characteristics of any of the systems. Each judge receives the output from both X and Y for each input sentence and can accept either both outputs or anyone of the two or reject both. Thus %X means the percentage of the number of acceptances received by X in terms of accuracy of output. Similarly %Y, %XY, and %!XY indicate the percentage of acceptances received by the system Y, both the systems and neither of the two systems respectively. For example, for the input sentence *"She is extremely generous, but not very tolerant with people who don't agree with her.",* among the 5 judges 3 accepted the output of Y, 2 accepted the output of X. Since the majority of the judges accepted Y, vote for this sentence was counter for Y. Thus the vote for each sentence is counted. Outcome of our experiment is reported below while the valence range to classify a neutral sentence is considered ±3.5 for the SenseNet upon which system Y is built.

System Y received 16.069% more acceptances than that of X, which indicates that the output of Y is more acceptable and accurate than that of X. Though the test was conducted with a small group of judges with relatively small input size, but the experiment result (i.e., 82% accuracy with an average precision 76.49%, recall 81.04% and F-score 78% for classifying positive, negative and neutral classes using the same dataset) for sentiment sens-

ing reported by SenseNet, provides an optimistic believe that the result would not vary even the survey is conducted with larger group of judges. Table 3 summarizes the experimental result for 200 sentences.

Data-Set of 200 Sentences			
%X	%Y	%XY	%!XY
20.344	36.413	24.283	18.96

Table 3. Experimental Result

5 Conclusion

In order to perform more testing and usability study, we plan to implement a web-based user interface where any user can input a chunk of text and get outputs from the both systems mentioned above. Thereby we can get user's acceptance test in terms of accuracy of output. Next we plan to perform the task of affect sensing using online resources (e.g., blogs, reviews, etc.).

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