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Automatic Event-Level Textual Emotion Sensing Using Mutual Action Histogram between Entities

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Abstract

Automatic emotion sensing in textual data is crucial for the development of intelligent interfaces in many interactive computer applications. This paper describes a high-precision, knowledgebase-independent approach for automatic emotion sensing for the subjects of events embedded within sentences. The proposed approach is based on the probability distribution of common mutual actions between the subject and the object of an event. We have incorporated web-based text mining and semantic role labeling techniques, together with a number of reference entity pairs and hand-crafted emotion generation rules to realize an event emotion detection system. The evaluation outcome reveals a satisfactory result with about 85% accuracy for detecting the positive, negative and neutral emotions.

Keywords: emotion sensing, web text mining, semantic role labeling, affect recognition

1. Emotion sensing from textual data

Research on interface agents shows that a system's capacity for emotional interactions can makes the agents valuable [Bates 1994]. Aiming at enabling computers to express and to recognize emotions, emerging technological advances are inspiring the field of research on "affective computing" [Picard 1997]. Since many computer user interfaces today are textually-based, the automatic emotion recognition from textual data plays an important role in the design of intelligent user interfaces that are more natural and user-friendly.

In the past, many studies have been conducted to automatically detect a user's affective states from textual data. Some using "keyword-spotting" techniques [Elliott 1992], but the results are not satisfactory. Keyword-spotting approach apparently can't apply to sentences without clearly-defined affective keywords. A number of studies applied emotion theories to determine emotions of interactive agents in intelligent systems [Dyer 1987; Bartneck 2002]. In those approaches a variety of hand-crafted emotion models based on psychological theories (particularly those of Ortony, Clore, and Collins [Ortony et al. 1988]) were employed to specify how interactive events, agents and objects are appraised according to individual's goals, standards and attitudes. At this stage, emotion sensing based on an emotion theory, is

45 only applicable in interactive systems where the interactive events can be precisely
46 defined, enumerated and automatically detected. Because of the thorough nature of
47 this approach, its application in free-texts requires a detailed understanding and
48 analysis of the text which is rather beyond the reach of current natural language
49 processing techniques.

50
51 [Liu et al. 2003] reported an approach to detect sentence-level emotion based on a
52 large-scale common sense knowledgebase, ConceptNet. The approach uses real world
53 knowledge about the inherent affective nature of everyday situations (such as “getting
54 into a car accident”) to classify sentences into basic emotion categories. In the initial
55 stage, concepts in the ConceptNet with clearly defined affective keywords were
56 automatically annotated with desired basic emotion categories. Then the emotion for
57 other concepts with semantic relationships to the affectively annotated concepts are
58 assigned automatically based on certain emotion propagation models. The accuracy of
59 such emotion propagation process has not yet been investigated. In our opinion, the
60 restricted coverage of the concepts and relationships in ConceptNet seriously limits
61 the use of such approach in real life applications.

62
63 [Shaikh et al. 2007] recently developed a linguistic tool “SenseNet” to detect
64 polarity values of word, phrase, and sentence-level textual data. The approach uses
65 WordNet [Fellbaum 1998] as a linguistic corpus. Polarity values for adjectives and
66 adverbs in WordNet were manually annotated. The polarity of a verb is calculated via
67 some hand-crafted equations that count positive and negative senses from the
68 definitions in WordNet. The polarity of a noun is assigned based on the related verbs
69 obtained from relationships recorded in ConceptNet. For instance, “ticket” is
70 connected to the following verbs “allow”, “access”, “get”, “provide”, and “represent”
71 in ConceptNet. Thus the polarity of “ticket” is assigned as the average value of these
72 verbs. One major problem is that since the data in ConceptNet contains many
73 misspelled words, false concepts, and overly-specific data [Smith and Thomas 2004],
74 the correctness of polarity value of many concepts in SenseNet is questionable.
75 Moreover, SenseNet can only handle concepts existing in WordNet, so the concepts
76 not included in WordNet cannot be processed.

77
78 [Wu et al. 2006] recently proposed a novel approach for sentence-level emotion
79 detection based on the semantic labels (SLs) and attributes (ATTs) of entities of a
80 sentence. To distinguish the emotions “happy” and “unhappy”, the SLs are manually
81 classified into three categories, Active SLs (e.g. obtain, reach, lost, hinder), Negative
82 SLs (e.g. no, never), and Transitive SLs (e.g. finally, but, fortunately). ATTs of an
83 entity are automatically obtained by using WordNet as the lexical resource. For
84 example, in the sentence “I lost my money”, the emotion would be unhappy due to the
85 verb “lost” (an Active SL) and the attributes of “money” (such as wealth and
86 property). Wu carried out his work in two phases, training phase and testing phase. In

87 the training phase, a collection of sentences tagged with corresponding emotion states
88 are used as the training set. The SLs and ATTs of these sentences are automatically
89 extracted and then processed to obtain a variety of emotion associate rules (EARs)
90 that associate a particular emotion states with patterns of the SLs and ATTs. In the
91 testing phase, a target sentence is processed in the same manner to obtain its SLs and
92 ATTs before feeding into an emotion classifier. The emotion of the target sentence is
93 assigned based on the similarity comparison of the SLs and ATTs to the sets in the
94 EARs. An evaluation was conducted by using a small-scale corpus of a collection of
95 college students' daily conversations.

96
97 Consequently, the major issues of emotion sensing that might limit the
98 performance and applicability of this approach in wider contexts include: (1) the need
99 of affective-annotated sentences as training samples, and (2) the use of attributes
100 (ATTs) as the sentence-level emotion-invoking ingredients. First, the proposed
101 approach requires a sufficient large number of emotion-annotated sentences that are
102 not frequently available promptly within other domains. Furthermore, in many real
103 life situations, the "emotion-invoking" factors of an event may not always be possible
104 to be explicitly represented by the attributes (ATTs) of the event participants.
105 Emotions determined only with the attributes recorded in WordNet may often cause
106 erroneous results. For example, although a "rat" and a "squirrel" have quite a number
107 of similar or even identical attributes, rodent and mammal, as annotated in WordNet,
108 emotions evoked by both entities (the rat and the squirrel) are totally different. Even
109 worse, in real-life applications, event participants in a sentence often cover a
110 wide-spectrum of modern or domain-specific terms which may not be included in
111 formal lexical resources such as WordNet. For the example "Wii", the newest home
112 video game console released by Nintendo, which could often be mentioned in daily
113 conversations or news articles these days, is unfortunately not yet included in the
114 current version of WordNet. It is essential for a really universal and robust emotion
115 detection system to handle these situations.

116
117 As a first step for our endeavor towards a robust emotion sensing engine from
118 free-texts using web mining approaches, this study proposes a novel approach for
119 detecting emotion of an individual "event" embedded in English sentences such as "a
120 student failed in the examination", "a girl saw a diamond", "a cat was chased by a
121 dog", "a mouse encountered a cat", etc. We adopt the "*common mutual actions*"
122 between the event participants as the major cue to determine the event-level emotions.
123 In a real-life application when the emotions for free-text sentences are to be detected
124 automatically, the subject, verb, and object of an event embedded in a free-text
125 sentence can be obtained using Semantic Role Labeling (SRL) techniques. A general
126 overview of the state-of-the-art SRL techniques has been discussed fully in [Gildea
127 and Jurafsky 2002; Pradhan et al. 2003; Carreras and Marquez 2005]. Simply
128 speaking, in any sentence, a verb (predicate) dominates an event. The syntactic

129 arguments of a verb are usually associated with the participants of the event. A
130 “semantic role” is the relationship of a syntactic argument with the verb. One
131 commonly used scheme for specifying semantic roles is PropBank annotation [Dang
132 and Palmer 2005; Punyakanok et al. 2004; Punyakanok et al. 2005]. In PropBank
133 annotations, the arguments of a verb are labeled sequentially from ARG0 to ARG5,
134 where ARG0 is usually the subject of a transitive verb; ARG1 is a direct object, etc. A
135 variety of adjunctive arguments, such as ARGM-LOC for locatives, and ARGM-TMP
136 for temporal information, are also tagged. As an illustrative example, the set of
137 semantic roles for the sentence, “I saw a girl in the park this morning” based on the
138 PropBank style markup, can be presented as:

139
140 [ARG0 I] [Target saw] [ARG1 a girl] [ARGM-LOC in the park] [ARGM-TMP this morning]
141

142 SRL techniques can be applied to automatically identify the semantic roles of a
143 sentence. However, automatically tagging the semantic roles with high precision is
144 difficult since an event can often be referred to, by a variety of lexical items with
145 different syntactic realizations. In the literature survey, a number of studies have
146 proposed different methodologies for this purpose, such as [Gildea and Jurafsky 2002;
147 Pradhan et al. 2003; Koomen et al. 2005]. These methodologies have yielded quite
148 accurate results with about 80% precision on ARG0, ARG1, and 70% on
149 ARGM-LOC, ARGM-TMP [Carreras and Marquez 2005; Pradhan et al. 2004]. Given
150 the reasonable accuracy of current state-of-the-art SRL techniques, the automatically
151 parsing of subject, object, and verb in a free-text sentence for the emotion-sensing
152 applications is satisfactory.

153
154 In the following sections, the underlying principles of our approach will be
155 elaborated.

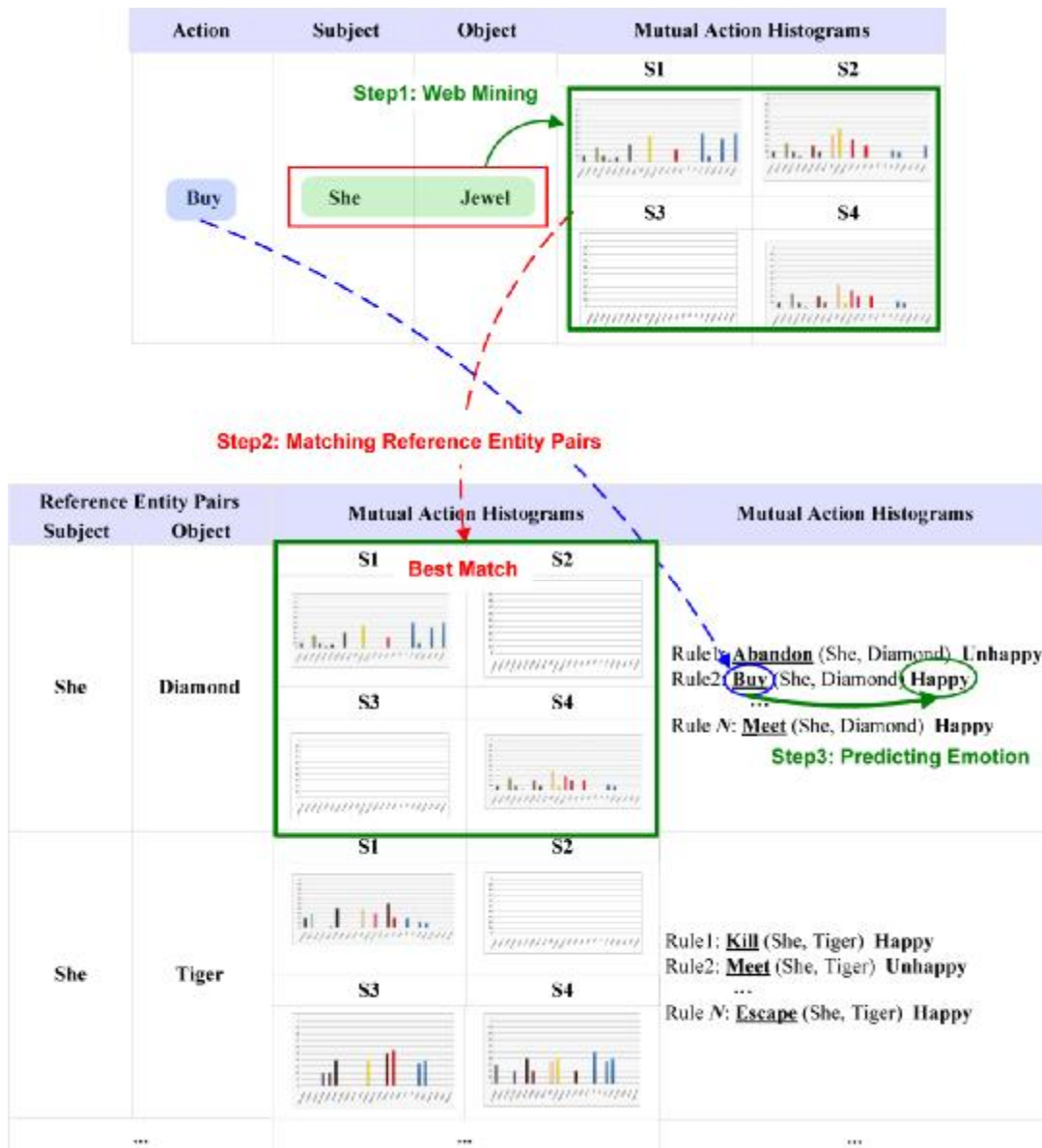
156 **2. Emotion sensing based on Mutual Action Histograms (MAHs)**

157 This section describes the underlying principles and detail processes of our
158 methodology for automatically sensing emotions of events embedded in textual
159 sentences. We first present here a typical scenario to illustrate the steps to achieve our
160 goal. In any English sentence, the verb of a sentence typically indicates a particular
161 “action” performed by one event participant to the other participant. For example, in
162 the sentence “The girl saw a viper snake”, the action is a “sighting action” with two
163 entities: “the girl” as the subject and “a viper snake” as the object. While we often
164 intuitively assume that the girl would often be terrified while meeting a viper snake,
165 but how can a computer understand this?

166
167 Let us investigate why a girl would usually be terrified when she sees a viper snake.
168 One way to reason is that the snake “usually” performs certain undesirable actions

169 (e.g. bite, paralyze, attack, or kill) but “seldom” performs desirable actions (e.g. love,
 170 feed, or supply) on a girl. Contrarily, a baby would usually be happy to see his/her
 171 mother since his/her mother “usually” perform desirable actions on the baby. The
 172 real-life probability distribution of such “mutual actions” between a subject and an
 173 object is termed as the “**Mutual Action Histogram (MAH)**” in this paper. In practice,
 174 knowing the MAH between the subject and the object in a specific event would allow
 175 a computer to reasonably guess the emotion invoked. For example, if the MAH
 176 between a vampire and a girl is close to that between a snake and a girl, the emotion
 177 of a girl when she saw a vampire should most likely similar to that of a girl when she
 178 saw a snake. As compared to the relevant work by [Wu et al. 2006], our approach
 179 adopts the mutual actions between the event participants instead of using their
 180 attributes as the features to determine the emotions.

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Figure 1. Illustrative diagram for the proposed approach.

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Based on the above analysis, it appears that the success of our approach for emotion detection would hinge on the ability of a computer to automatically retrieve the MAHs between two entities that participate in an event. While people may intuitively believe that MAHs between entities are difficult or impossible to obtain without extensive human annotations, we resort to web-based text mining that fortunately provide a convenient solution to achieve our goal. We introduce the overall flow diagram for our proposed emotion detection engine, as shown in Figure 1 below. First, in the training phase, we select a number of *entity pairs* (*subject-object*, e.g. girl-spider, girl-diamond, etc.) as the **Reference Entity Pairs (RE-Pairs)**. For each RE-Pair, the MAH is obtained using web-based text mining techniques. Then for each RE-Pair, possible emotion-invoking events that often occur between the two entities are enumerated and manually assigned with emotions to form a set of “Emotion Generation Rules” (**EGRs**). In the predicting (or testing) phase (emotion sensing stage), the subject and object of a target event, termed as the **Target Entity Pair (TE-Pair)**, in a sentence is automatically recognized using semantic role labeling techniques. The MAH of the TE-Pair is obtained using web-based text mining techniques to search and extract TE-Pair sentences from search engines. The emotion of the target event is assigned based on the EGRs of the RE-Pairs with best match on the MAHs to that of the TE-Pair. In the following, the underlying principles and detail operations of the proposed framework will be elaborated.

2.1. Web-based text mining for MAHs between entities

We apply web-based text mining techniques to retrieve mutual actions between two given entities. In the past, studies based on variations of text mining approaches have been investigated to retrieve different types of knowledge (e.g. [Gildea et al. 2006; Etzioni et al. 2005; Girju et al. 2006]). Given the vast amount of textual data available on the Web, we believe that the actions of two given entities described in web pages shall give a roughly normalized distribution of their common interactions. In the text mining approach, given a target event with two entities (the subject and target objects), the system analyzes the mutual actions between both entities by collecting large amount of emotion-invoking sentences from the Web. Therefore, hand-crafted “lexico-syntactic patterns” are generated and submitted to search engines for accumulating sentences from web pages within the search results. We borrow the glossary “lexico-syntactic patterns (LSPs)” from [Hearst 1992], in which a LSP indicates a particular semantic relationship between two entities.

In this paper, a set of effective lexico-syntactic patterns are formulated to describe emotion-invoking sentences. These sentences can be written either in “passive” or “active” style and the subject/target entities can be put in active/passive roles.

226 Consequently, given an Event (**E1**, **A**, **E2**), with an action **A** and two entities **E1** and
227 **E2**, four different styles of LSP sentences are automatically generated as followings:

228

229 Ÿ S1 (**E1-Active-E2**): (e.g., “She saw a snake.”)

230 Ÿ S2 (**E2-Passive-E1**): (e.g., “The snake was killed by her.”)

231 Ÿ S3 (**E2-Active-E1**): (e.g., “A snake bites her.”)

232 Ÿ S4 (**E1-Passive-E2**): (e.g., “She was bitten by a snake.”)

233 The following examples illustrate the process for obtaining the mutual actions
234 between two given entities. Considering an attempt to retrieve sentences that describe
235 the mutual actions between “female” and “snake”, typically intuitive syntactic
236 patterns can be applied to formulate following web queries:

237

238 Ÿ S1: “she * a snake”,

239 Ÿ S2: “snake was * by her”,

240 Ÿ S3: “snakes * her”, and

241 Ÿ S4: “she was * by the snake”.

242 In case there are insufficient collected sentences by using these primitive patterns,
243 it is possible to extend the patterns by considering variations of the verb tenses (e.g.
244 “she was * by the snake” in S4), plural forms (e.g. “snakes were * by her” in S2), and
245 articles (e.g. “she * the snake”). With these query strings, we typically accumulate a
246 large number of raw sentences from the snippets of web search results. To effectively
247 and efficiently compare the MAHs among entities pairs, the collected action verbs
248 will be categorized and normalized for estimating the MAHs of each writing styles
249 respectively.

250

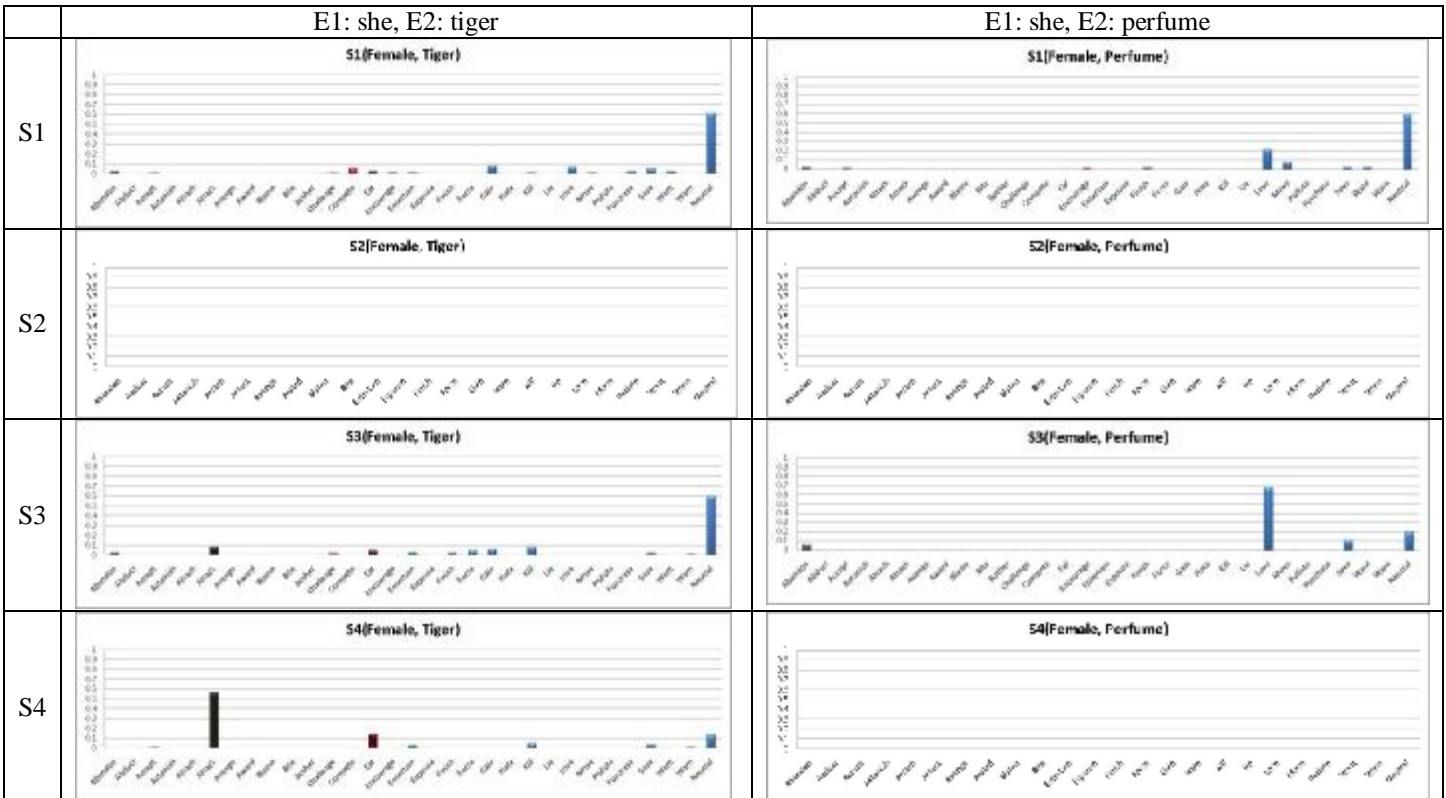
251 **2.1.1. Verb categorization**

252

253 In practice, the matching for the MAHs between the TE-Pair and RE-Pair are based
254 on a coarse-grained verb categorization. We collected about 800 popular verbs from
255 Yahoo! Online Dictionary¹. Given an entity pair of an event, semantically similar
256 verbs typically invoke a similar emotion to the subject. Thus, these collected verbs are
257 first categorized into 87 groups of synonyms (refer to Appendix 1). Within these verb
258 groups, we manually determine whether a given verb group is “*emotion-invoking*” or
259 not. If a verb of a given event often causes a certain emotion to the subject or object, it
260 is considered as emotion-invoking. For example, if **E1** frequently “attacks” **E2**, it is

¹ <http://tw.dictionary.yahoo.com/>

261 naturally that **E1** is an unpleasant object to **E2** and thus “attack” is considered as an
 262 emotion-invoking verb. These emotion-invoking verbs are used as the main features
 263 to predict the emotion of the subject or object of an event. Based on this principle, 30
 264 emotion-invoking verb groups are manually selected by experts, including abandon,
 265 abduct, accept, astonish, attach, attack, avenge, award, blame, bite, bother, challenge,
 266 compete, eat, encourage, entertain, espouse, finish, force, gain, hate, kill, lie, move,
 267 pollute, purchase, save, want and warn. Verbs other than those identified as
 268 emotion-invoking verbs are grouped as “neutral” verbs. Consequently, experts
 269 manually assign 800 verbs into 31 verb groups.
 270



271 Figure 2: Mutual Action Histograms for two entity pairs.

272
 273 For each sentence style, among all the sentences extracted from crawled pages, we
 274 count all frequencies based on verbs appearing within the 31 verb groups. Thus, the
 275 4-style histogram is specialized into four 31-group histograms, S1 – S4. In each style
 276 histogram, each bin is normalized by the total occurrences of 31 verb groups; the
 277 histogram therefore presents the probability distribution of 31 verb groups in the style
 278 template. Figure 2 shows the histograms of two examples entity pairs: (she, tiger) and
 279 (she, perfume). Notably, a female frequently “loves” perfume (S3) but is frequently
 280 “attacked” by a tiger (S4). Overall, both cases have significantly different histograms.
 281

282 Following research issue is finding the best matching between the MAHs of a TE-Pair
283 with the RE-pairs so that the query emotion can be predicted by applying the best
284 matching on MAHs.

285 286 **2.2. Reference Entity Pairs (RE-Pairs) with Emotion Generation Rules (EGRs)**

287
288 We select a number of RE-Pairs appearing in daily emotional events and manually
289 assign emotions to those events to form a set of EGRs. The MAHs between RE-Pairs
290 are obtained by using the web-based text mining approach described above.
291 Obviously, the interaction between two entities of a RE-Pair is widely described in
292 web pages so that the MAH would reliably represent the un-biased distribution of
293 mutual actions between them. To widely cover different emotion-invoking scenarios,
294 the RE-Pair set needs to take care of all the emotion categories for the training
295 performance. Also, all actions defined in the verb groups should be considered.
296 However, given a RE-Pair, only few actions are used to describe the events of the
297 RE-Pair. That is many actions are zero-frequency in the RE-Pair’s MAHs as we can
298 see in Figure 2. Consequently for each RE-Pair, a set of EGRs are manually
299 constructed for all verb groups, in which zero-frequency verbs are labeled as “N/A”.
300 Appendix 2 gives a list of EGRs for an example RE-Pair, “she” and “diamond ring”.
301 Rule 1 says that the emotion of a female when she “abandons” a diamond ring is
302 typically unhappy. Rule 4 says a female is typically happy when she “accepts” a
303 diamond ring.

304 305 **2.3. Matching MAHs among RE-Pairs**

306
307 In the emotion recognition stage, the emotion of the subject in a target event is
308 assigned based on the similarity comparison between the MAHs of the TE-Pair (i.e.
309 the event participants) with those of the RE-Pairs. The emotion of the subject in a
310 target event is based on the RE-Pairs with the most similar MAH to that of the
311 TE-Pair. For instance, given the target event, “a girl meets a wolf”, the MAH that a
312 wolf frequently acts on a girl is similar to that of the RE-Pair, “female” and “snake”.
313 The emotion of the girl is inferred as “unhappy” according to the “meet” EGRs of the
314 RE-Pair, “female” and “snake.”

315
316 Conventionally, comparisons of histograms can be achieved by using “Mean
317 Square Error (MSE)” or “KL divergence” algorithms [Kullback and Leibler 1951].
318 We applied the MSE approach in this study since it is more computational efficient.
319 Let the 4-style 31-verb histograms of a TE-Pair be $H_T = \{t_i : i = 1 \dots 124\}$, and the 4-tyle
320 histograms of a RE-Pair be $H_R = \{r_i : i = 1 \dots 124\}$. The L_I distance is adopted to
321 compute the dissimilarity between the 4-style histograms of the TE-Pair and the

322 4-style histograms of the RE-Pairs. L_1 distance has been used to compare histograms
323 in many applications, such as image retrieval [Rubner et al. 2000]. The L_1 distance
324 between two histograms is defined as:

$$325 \quad d_{L_1}(H_T, H_R) = \sum_i |t_i - r_i|.$$

327
328 The RE-Pair with the minimum L_1 distance to the TE-Pair is considered to have the
329 most similar relationship between entities as the target event. For example, the entity
330 pair (*she, purse*) is matched to (*she, diamond*) with minimum L_1 distance. It is
331 apparent that two entity pairs have a similar emotion relationship, while (*she, purse*)
332 and (*she, snake*) have a larger distance in the entity-relationship space. After matching
333 the target pair to one RE-pair, the emotion of the subject in a target event is inferred
334 from the EGRs of the matched RE-Pair.

335 336 337 **3. Evaluations**

338
339 To evaluate the performance of the proposed methodology we have conducted the
340 following evaluation experiments. First, a number of entity pairs, covering “pleasant”,
341 “unpleasant”, and “neutral” objects, are selected as RE-Pairs. MAHs of RE-Pairs are
342 automatically measured based on the web text mining approach that analyzes
343 sentences from large amount of web pages. Then, three researchers label each
344 sentence with one of three emotional categories: “positive (happy)”, “negative
345 (unhappy)”, and “neutral”. These data form the training set of the system.

346
347 The testing data are also collected from sentences that describe daily events. These
348 testing data are labeled by the manpower different from the training data to reserve
349 the objectivity of evaluation. Details of training, testing, evaluation and observation
350 processes are illustrated in the following sections.

351 **3.1 The Training Phase**

352 In the training phase, the subject “she” and following objects touched in the daily
353 life are selected to form 11 RE-Pairs.

354
355 **Y** Pleasant objects: diamond ring, purse, new dress, prince;

356 **Y** Unpleasant objects: tiger, thief, spider, bug;

357 **Y** Neutral objects: table, tissue, book.

359 For each RE-Pair, the web text mining processes of generating the MAHs
360 (124-dimensions: four styles of 31 verb groups) and emotion generation rules (EGRs)
361 of the RE-Pair are summarize as followings:

362 ¶ The general web crawler collects emotion-invoking web pages by submitting
363 queries (e.g. “she * diamond ring”) to search engines and following links within
364 search results to crawl more pages, as described in section 2.1.

365 ¶ According to these collected web pages, each sentence is extracted and parsed by
366 the SRL tool to identify the objects and verbs of the event. We use the publicly
367 available SRL tool, ASSERT [Pradhan et al. 2004], to perform the task. Although
368 only the query “she * diamond ring” was issued to the search engine, more
369 RE-Pairs are also collected after the SRL parsing process. For example, other
370 emotion-invoking sentences with subject “she” and verb group “buy” contain
371 objects, such as “chicken nuggets”, “i-pod”, “ps2”, etc. These novel objects will
372 be considered as testing objects in the testing phase.

373 ¶ Based on the RE-Pair (e.g. she and diamond ring) and 31 verb groups, the
374 statistical information is used to generate the MAH of the RE-Pair as shown in the
375 aforementioned Figure 2.

376 ¶ Then, the emotions of events corresponding to the RE-Pair and 31 verb groups are
377 manually labeled as: happy, unhappy, neutral, or N/A, as shown in Appendix 2.
378 The RE-Pair and one verb group determine the emotion of the event forms the
379 emotion generation rule (EGR). For example, the RE-Pair (*she, diamond ring*)
380 with EGRs corresponding to “actions” was manually labeled as shown in
381 Appendix 2. The rule 1 presents the knowledge: (*she, diamond ring*) AND
382 “abandon” imply the “unhappy” emotion. The rule 4 indicates: (*she, diamond ring*)
383 AND “accept” imply “happy”. The rule 2 is labeled as “N/A” since people seldom
384 describe (*she, diamond ring*) AND “abduct” in the same event. Each EGR is
385 determined based on an agreement reached by three researchers.

386 Consequently, the EGR set consists of 341 rules associated to the emotions of all
387 events generated from 11 RE-Pairs and 31 verb groups.

389 3.2 The Testing Phase

390
391 In the testing phase (or predicting phase), using “she” as the subject, various objects
392 and verbs (actions) that a female widely encounters in her daily life are selected to be
393 TE-Pairs (roughly 120 or so). By randomly combining verbs with the TE-Pairs, we

efficiently generated thousands sentences as candidate events of the testing set. For example, sentences about daily life, such as “she saw a car accident”, “she plays a Wii”, “she buys a hamburger”, etc. are automatically generated as events in this way. Obviously, the authors have manually precluded various unreasonable events (e.g. “she drinks a computer”) for the experiment. Consequently, 600 sentences with equal-distribution on three emotion categories (roughly labeled by the authors) are employed in the evaluation experiment, as shown in Table 1.

Table 1: number of sentences for evaluation

Emotion Categories	Positive	Negative	Neutral
# of composed sentences (events)	200	200	200

To objectively evaluate the testing result, the testing events are labeled by the manpower different from that of the training set. We recruit 10 graduate students (mostly graduate students majoring in computer science) to assess these 600 events. Every assessor is requested to judge the emotion for each of the six hundred events as one of the “Positive”, “Negative”, and “Neutral” emotions. The ground-truth emotion of an event is determined by the majority voting from the answers of assessors. Among the 600 events, 529 events receive more than 5 consistent votes (the half of votes) among the 10 assessors, in which the 529 events include 184/175/170 positive/negative/neutral sentences. Human assessors do not reach consistent emotion judgments on many events, such as “she changes her dress” and “she rides a bicycle”. Only 161 events receive more than 9 consistent votes among the 10 assessors. This implies that there is a certain degree of inconsistency (uncertainty) in the emotional evaluations.

The testing set is shown in Appendix 3. The web mining system automatically generates lexico-syntactic patterns based on the subject “she” with those objects and verbs listed in Appendix 3. Then, the same crawling and analyzing processes are applied to these events for measuring MAHs of TE-Pairs. Given the MAH of a TE-Pair, the matching process illustrated in section 2.3 is applied to find the best matched MAH from the RE-Pair set. The EGRs (rule set) of the matched RE-Pair is triggered by the action (verb) of the event, the emotion of the event is therefore predicted based on the emotion category labeled in the fired EGR.

3.3 Experiment Results

The performance of the proposed emotion detection system is measured by the precision of correct predictions. Based on the events and emotions labeled in section 3.2, the ground-truth testing sets are dynamically determined based on the threshold of majority votes reached by assessors. Accordingly, the precision rate is defined as:

$$precision = \frac{\# \text{ of correctly answered events by system}}{\# \text{ of events with the majority vote } > n}$$

The evaluation results are shown in Table 2. For the case with the threshold of majority vote ($n > 5$), the precision rate is about 77.5%. As the threshold n increases, the precision rate also increases accordingly. The highest precision rate 90.0% is achieved at $n = 9$. This indicates that the system is able to correctly predict emotions of events that human assessors tend to have consistent opinions on those emotions. In general, the system achieves a high precision rate 85% by averaging all cases of majority votes ($n = 5 - 9$).

Table 2: Evaluation results of the proposed emotion detection system

Majority votes (n)	# of Sentences	Positive	Negative	Neutral	Precision	# of sentences (correct)	Positive (correct)	Negative (correct)	Neutral (correct)
5	529	184	175	170	77.5%	410	130	146	134
6	380	141	115	124	81.0%	308	98	102	108
7	303	103	102	98	87.1%	264	79	92	93
8	183	54	66	63	88.5%	162	40	61	61
9	161	46	57	58	90.0%	145	35	53	57

3.4 Observations

Based on the web text mining approach, many events with novel object nouns are correctly predicted. For example, tested sentences with the lexical-syntactic pattern “she bought a * yesterday” are correctly predicted for novel objects, such as “Wii”, “i-Phone”, “i-Pod”, “PS2”, “Mercedes S600”, “Rolex”, etc. Those novel nouns are usually found in daily conversations but absent in the dictionary or the common sense knowledgebase so that emotions of sentences contain novel nouns are hard to be identified by knowledge-based approaches. Consequently, the web text mining method is adaptive to the rapidly changed web environment.

In previous emotion-detection systems, some wrong predictions are raised from modifiers (e.g. adjective “luxury” or adverb adjective “pretty good”) that are often used to modify noun phrases of TE-Pair objects within general sentences. Apparently, the modifier may change the meaning of a noun phrase so that the emotion of the sentence is also influenced. For instance, two opposite sentences “she bought a nice car” and “she bought a broken car” are decorated with opposite modifiers “nice” and “broken”, respectively. Therefore, for the same object “car” and verb “buy”, both sentences are labeled with positive and negative emotions, respectively. The advantage of the proposed methodology is that a modifier to the noun phrase can be completely identified as an object so that “nice car” or “broken car” are individually processed by the web mining approach and are correctly matched with MAHs of RE-Pairs. For example, the S1 template of the TE-Pair (*she, nice car*) shows female usually loves/purchases a nice car and dominates the matching process toward to the

467 RE-Pair (*she, purse*). Similarly, the TE-Pair (*she, broken car*) is matched with the
468 RE-Pair (*she, thief*) since the S1 template of (*she, broken car*) presents female usually
469 abandons/dislikes a broken car as that of (*she, thief*).

470
471 According to the experiment results, the highest precision rate is 90.0% with the
472 threshold of majority vote 9, i.e. 90% assessors have the same emotion judgment. In
473 this test, there are 11, 4 and 1 sentences mismatched with manually labeled emotion
474 categories of “positive”, “negative” and “neutral”, respectively. Some of the
475 incorrectly predicted sentences are depicted below and observations of these error
476 predictions are also discussed for seeking further improvements.

477
478 The problems of wrong predictions result largely from the *polysemy* entities that
479 have multiple senses corresponding to different emotion interpretations. For instance,
480 the TE-Pairs (*she, jaguar*) and (*she, giant*) do not match with the correct (or relevant)
481 RE-Pairs, because “jaguar” and “giant” are usually regarded as the famous brands that
482 produce vehicles and bikes, respectively. So assessors labeled both entities as
483 “Happy”. However, “jaguar” is a panther and often performs several unpleasant
484 actions (e.g. *attack, kill*, etc.). After analyzing from web pages, MAHs of both
485 TE-Pairs tend to clarify general meanings so that the system inferred the “negative”
486 emotion of “she meets a jaguar” from that of “she meets a tiger”.

487
488 As for the semantic problem about the subject “she”, females generally have
489 positive feeling to objects “chocolate”, “rabbit” and “puppy”; assessors therefore tend
490 to label sentences with TE-Pairs (*she, chocolate*), (*she, rabbit*), and (*she, puppy*) as
491 positive emotions. However, S4 templates of the MAHs show that females are usually
492 bitten and attacked by those objects. S1 and S2 templates represent that females do
493 not often perform “love”, “purchase” and other “pleasant” actions on those objects.
494 Therefore, these TE-Pairs tend to match with “negative” RE-Pairs and result in wrong
495 predictions.

496 3.5 Context-sensitive problems vs. Emotion sensing

497 Based on the aforementioned observations, incorrectly predicted sentences are
498 resulted from “polysemy entities” and “semantic problems”. Both situations can be
499 concluded as “context-sensitive problems”. For example, in many retrieved web pages,
500 extracted sentences contain the polysemy entities “jaguar” and “giant” also frequently
501 contain nearby sentences describing about “animals” and “adventures”, respectively.
502 As for the semantic problem, web page sentences mention “chocolate” are frequently
503 relevant to party or politic events, such as “people are attacked by chocolates” in
504 parties or politic activities. Many web pages also mention that puppies (or rabbit)

505 probably attack (or bite) people during the playing activities. Therefore, the system
506 collected these kinds of sentences for TE-Pairs (*she, chocolate*), (*she, rabbit*), and
507 (*she, puppy*) and mined MAHs that are dominated by S4 templates. Consequently,
508 these TE-Pairs are matched with RE-Pairs like (*she, tiger*) or (*she, snake*) and are
509 predicted as “negative” emotions.

510

511 According to these observations, we conclude that emotions of sentences are
512 context-sensitive. However, the context-sensitive problem is not considered in the
513 tested sentences since each sentence is individually applied without nearby sentences.
514 Generally speaking, emotion sensing applications should be domain-dependent so that
515 the domain background knowledge facilitates the prediction of emotion. For example,
516 applying the system to chatbot (chat robot) applications will obtain better performance
517 of emotion sensing since previous typed sentences can be use to detect the
518 background domain of the current chitchat, such as “animals”, “adventures”, or
519 “parties”. Therefore, domain-knowledge and the proposed emotion sensing system
520 will be integrated to improve the system performance for various applications in the
521 future.

522

523 **4. Conclusions and future works**

524 This paper proposes an event-level textual emotion detecting approach based on the
525 common action distribution between event participants. Based on 11 RE-Pairs
526 associated with 31 verb groups, sentences (parsed by the SRL tool) are collected from
527 web search engines and manually labeled with emotions, Positive, Negative or
528 Neutral. The web-based text mining approach is applied to collect and analyze large
529 amount of event sentences as training and testing data. No need of any large-scale
530 lexical sources or knowledgebase, the proposed system works well on predicting the
531 emotion of a sentence, even the sentence contains entities or verbs that are absent in
532 the knowledgebase or database. Experiment results indicate that the proposed system
533 achieves a relative high precision about 85% in par with past studies. Also, the system
534 is adaptive to the dynamic Web environment that novel name entities are frequently
535 created in web pages.

536

537 As we concluded that the emotion sensing problem is context-sensitive, the future
538 work is toward to applying the system to domain-dependent applications like chatbot.
539 Based on the current result, improving the system for sensing more complicated
540 sentences or emotions is the future research issue. In [Soong et al. 2001], machine
541 learning techniques are applied to handle complicated sentences or paragraphs where
542 many events are often intermingled together. For example, the sentence “I saw a
543 snake chasing a frog” is simple but contains more than one event. Based on the

544 emotion theory [Ortony et al. 1988], the emotion of a sentence is influenced by all
545 participants contained in the sentence. As for sensing more complicated emotions, to
546 enhance the usability of the system, the proposed method should be able to precisely
547 sensing more emotional categories, such as big-six emotions [Ekman 1993], including
548 Happy, Sadness, Fear, Anger, Disgust and Surprise. Those emotions are widely used
549 in human-computer interactive applications.

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Group	Verbs
1	Abandon (cease, discard, terminate, discontinue, stop, halt, escape, restrain, quit, forsake, leave)
2	Abduct (kidnap, hijack)
3	Abound (teem, swarm, flourish, overflow)
4	Accept (allow, permit, admit, recognize, adopt, agree, approve, accede, obey)
5	Access (entry, approach)
6	Addict (affect)
7	Aim (try, intend, attempt, attend, direct, point)
8	Ask (question, inquire, query, interrogate, request, beg, solicit, demand, plead, consult)
9	Astonish (surprise, amaze, astound, shock)
10	Attach (affix, tack, append, adhere)
11	Attack (hurt, beset, hit, cuff, assail, bombard, kick, strike, swat, punch, assault, maul)
12	Avenge (revenge, retaliate, requite, punish, repay, retort)
13	Award (reward, prize, medal, trophy, grant, gift, bestow)
14	Banish (exile, deport, outlaw)
15	Bark (yelp, yip, yap, bay, woof, ululate, bowwow, snap, hoot)
16	Bear (tolerate, yield, endure)
17	Begin (start, commence)
18	Bite (pierce, nip)
19	Blame (berate, accuse, impeach, reprehend, decry, condemn, denounce, charge, indict)
20	Bother (disturb, annoy, irritate)
21	Challenge (confront, question, dispute, counteract, defy, doubt, dare, suspect, protest, gage, controvert, mistrust, withdraw, struggle)
22	Change (alter, vary, deviate, substitute, replace, modify, convert, shift, switch, transfer, turn, exchange, transform)
23	Clarify (explain, refine, simplify, illuminate, illustrate, expound, specify, purify, define, interpret, unfold)
24	Classify (organize, categorize, sort, catalog, assort, grade, file, rank, collocate)
25	Collect (gather, assemble, accumulate)
26	Compete (contest, rival, contend, fight, strive)
27	Conduct (manage, direct, guide, control, govern, captain, command, instruct, steer)
28	Congratulate (bless, compliment, flatter, commend, praise)
29	Conquer (prevail, overtake, vanquish, defeat, overcome, rout, overpower)
30	Contain (include, hold, comprise, involve, enclose)
31	Cooperate (coact, coordinate, conspire)
32	Compare (correlate, parallel)
33	Create (build, make, manufacture, fabricate, develop, form, compose, shape, devise, invent, originate)
34	Dance (dance, rock, reel, twirl, caper, step, swing, prance, disco, hop, gambol, romp, leap, wiggle, wriggle)
35	Decrease (decline, decelerate, detract, devalue, dilute, weaken, thin, diminish, deduct, deteriorate, demote, degrade, reduce, lower, debase, abase, cheapen, devalue)
36	Deliver (consign, convey, transport, transmit, send, dispatch, forward, pass)
37	Determine (decide, judge)
38	Devote (devote, consecrate, hallow)
39	Die (decease, perish, expire)
40	Disguise (conceal, hide, camouflage, misrepresent)
41	Ease (facilitate, relieve, help, comfort, relax, loosen, aid, lighten, assuage, allay, release)
42	Eat (dine, chew, swallow, feed, graze, devour, nibble, gobble, gulp)
43	Emphasize (stress, punctuate, accent, mark, intensify, highlight, underscore, accentuate,)
44	Encourage (support, urge, sponsor, promote, cheer, inspire, boost, excite, arouse, awaken, wake, kindle, pique, provoke, actuate, rouse, arise, aspire)
45	Entertain (play, amuse, delight, titillate, tickle, please, show)
46	Espouse (espouse, betroth)
47	Evaluate (value, assess, compute, count, account, calculate, gauge, rate, measure, criticize, weigh, reckon, appraise, approximate)
48	Evolve (breed, develop, diffuse, grow,)
49	Examine (inspect, observe, study, review, investigate, scrutinize, diagnose)
50	Expect (anticipate, await, hope)
51	Express (tell, present, describe, allege, announce, declare, acquaint, articulate, aver, inform, mean, signify, connote, perform, talk, assert, pronounce, confide, denote, detail, elaborate, display, show, speak, appear, say, show)
52	Fall (immerse, drop, plunge, swoop, sink)
53	Find (discover, detect, excavate, dredge, dig, unearth, dissect, learn, ascertain, locate)
54	Finish (accomplish, fulfill, complete, consummate, end, terminate, conclude, cease, stop)
55	Force (compel, pressure, compress, confine, bend, constrict, tighten, lessen, press, push, brake, quell, choke, coerce, oblige, motivate, propel)
56	Forget (disregard, overlook, ignore, pretermit, neglect)
57	Frustrate (dampen, dishearten, depress, despair, discourage, dissuade, dismay, thwart)

58	Gain (earn, secure, obtain, acquire, receive, get)
59	Go (run, walk)
60	Greet (welcome, invite)
61	Group (flock, sort, classify, organize, arrange, assemble, cluster, gather)
62	Grow (breed, develop, diffuse, disseminate, grow, evolve, mature, raise)
63	Guarantee (affirm, guarantee, assure, convince, pledge, insure, satisfy, vow, vouch, ensure, promise, attest, certify, depose, testify, confirm, verify, validate, authenticate, corroborate, substantiate, warrant, evidence, endorse, prove, cite, commit)
64	Hate (dislike, despise, abominate, aggravate, infuriate, anger, grumble, complain, argue, quarrel, detest, disapprove, disfavor, oppose, object, disparage, belittle, underestimate, dispute, dissatisfy, displease, exacerbate, envenom, embitter)
65	Hide (hide, cover, conceal, blanket, bury)
66	Increase (enlarge, extend, expand, augment, multiply, advance, raise, add, annex, amplify, greaten, widen, broaden, lengthen, elongate, prolong, prolongate, protract, dilate, ascend, deepen, strengthen, reinforce, redouble, heighten, rise, mount, rocket)
67	Kill (destroy, kill, slay, slaughter, murder)
68	Lean (bend, lean, slope, slant, incline, rest)
69	Lie (beguile, lie, betray, deceive, misdirect, misinform, fool, delude, hoax, dupe, chisel, defraud, disbelieve, discredit, distrust, fib, falsify)
70	Live (exist, dwell, inhabit)
71	Love (like, enjoy, cherish, treasure, adore, admire, appreciate, relish, fancy, idolize)
72	Marry (marry, wed)
73	Meet (encounter, join, see, incorporate, unite, connect, converge, confront)
74	Move (lift, carry, send, throw, push, pull)
75	Name (label, title, term, tag, identify)
76	Open (launch, expose, uncover, disclose, disclose)
77	Plan (propose, design, plot, arrange, program, patch, project, scheme)
78	Pollute (defile, contaminate, infect, taint, tarnish, foul, poison, alloy, smoke, deteriorate, mess, demoralize, spoil)
79	Prepare (equip, concoct, provide, ready)
80	Purchase (buy, shop, purchase, order, market)
81	Put (place, fix, lay, set, deposit, arrange, spread)
82	Remove (avert, delete, erase, cancel, obliterate, denude, disappear, disband, remove, withdraw, extract, eject, expel, oust, evacuate, eradicate, dethrone, unseat, scatter, dislodge, dismantle, dispel, replace, displace)
83	Ride (cruise, drive, journey)
84	Save (preserve, keep, guard, maintain, store, reserve, scrimp, conserve)
85	Want (wish, crave, need, require, covet, desire, fancy, demand, ambition)
86	Warn (threaten, intimidate, bulldoze, alert, admonish, menace, browbeat, terrorize, thunder, horrify, scare, frighten, appall, deter, bully, fear, startle, terrify)
87	Worry (concern, care)

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Appendix 2: Emotion rules for the reference entity pair with “she” as the subject and “diamond ring” as the object.

1	Abandon	Unhappy
2	Abduct	N/A
3	Abound	N/A
4	Accept	Happy
5	Access	Happy
6	Addict	Happy
7	Aim	N/A
8	Ask	Neutral
9	Astonish	Happy
10	Attach	Happy
11	Attack	Unhappy
12	Avenge	N/A
13	Award	Happy
14	Banish	N/A
15	Bark	Unhappy
16	Bear	N/A
17	Begin	N/A
18	Bite	Unhappy
19	Blame	Unhappy
20	Bother	N/A
21	Challenge	N/A
22	Change	Happy
23	Clarify	Happy
24	Classify	Happy
25	Collect	Happy
26	Conduct	N/A
27	Compete	Unhappy
28	Congratulate	N/A
29	Conquer	N/A
30	Contain	Happy
31	Cooperate	N/A
32	Compare	Neutral
33	Create	Happy
34	Dance	N/A
35	Decrease	Unhappy
36	Deliver	Neutral
37	Determine	Neutral
38	Devote	N/A
39	Die	Unhappy
40	Disguise	N/A
41	Ease	N/A
42	Eat	Unhappy
43	Emphasize	Happy
44	Encourage	N/A

45	Entertain	Happy
46	Espouse	Happy
47	Evaluate	Neutral
48	Evolve	Happy
49	Examine	Neutral
50	Expect	Happy
51	Express	Happy
52	Fall	Unhappy
53	Find	Happy
54	Finish	Unhappy
55	Force	Unhappy
56	Forget	Unhappy
57	Frustrate	N/A
58	Gain	Happy
59	Go	N/A
60	Greet	Happy
61	Group	Happy
62	Grow	N/A
63	Shout	Unhappy
64	Guarantee	N/A
65	Hate	Unhappy
66	Hide	Unhappy
67	Kill	Unhappy
68	Lean	Happy
69	Lie	N/A
70	Live	N/A
71	Love	Happy
72	Marry	N/A
73	Meet	Happy
74	Move	Neutral
75	Name	Neutral
76	Open	Happy
77	Plan	N/A
78	Pollute	Unhappy
79	Prepare	Happy
80	Purchase	Happy
81	Put	Happy
82	Remove	Unhappy
83	Ride	Neutral
84	Save	Happy
85	Want	Happy
86	Warn	N/A
87	Worry	Unhappy

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Appendix 3: A list of tested events with the majority vote $n > 9$.

Verb	Object	Subjective	System	Verb	Object	Subjective	System
get	chocolate	Happy	Unhappy	lose	scholarship	Unhappy	Unhappy
award	chocolate	Happy	Unhappy	reduce	scholarship	Unhappy	Unhappy
order	puppy	Happy	Unhappy	discard	skirt	Unhappy	Unhappy
see	puppy	Happy	Unhappy	discard	vaio	Unhappy	Unhappy
buy	rabbit	Happy	Unhappy	misplace	vaio	Unhappy	Unhappy
receive	dessert	Happy	Happy	lean	cobra	Unhappy	Unhappy
receive	diamond	Happy	Happy	hate	crocodile	Unhappy	Unhappy
see	diamond	Happy	Happy	see	ghost	Unhappy	Happy
get	wii	Happy	Happy	meet	ghost	Unhappy	Happy
receive	golden ring	Happy	Happy	meet	snake	Unhappy	Unhappy
receive	iphone	Happy	Happy	find	snake	Unhappy	Unhappy
get	jewel	Happy	Happy	detect	vampire	Unhappy	Unhappy
receive	jewel	Happy	Happy	see	vampire	Unhappy	Unhappy
award	luxury yacht	Happy	Happy	meet	vampire	Unhappy	Unhappy
buy	luxury yacht	Happy	Happy	look	vicious	Unhappy	Unhappy
purchase	miniskirt	Happy	Happy	see	vicious	Unhappy	Unhappy
wish	ipod nano	Happy	Happy	meet	vicious	Unhappy	Unhappy
see	new camera	Happy	Happy	hate	centipede	Unhappy	Unhappy
reward	new house	Happy	Happy	detect	centipede	Unhappy	Unhappy
desire	new scooter	Happy	Happy	look	rattlesnake	Unhappy	Unhappy
accept	perfume	Happy	Happy	see	rattlesnake	Unhappy	Unhappy
wear	perfume	Happy	Happy	see	zombie	Unhappy	Unhappy
buy	perfume	Happy	Happy	look	zombie	Unhappy	Unhappy
receive	prada	Happy	Happy	find	gang	Unhappy	Happy
desire	prada	Happy	Happy	see	demon	Unhappy	Unhappy
award	prize	Happy	Unhappy	see	rat	Unhappy	Unhappy
accept	prize	Happy	Unhappy	find	rat	Unhappy	Unhappy
accept	ps2	Happy	Happy	lean	rat	Unhappy	Unhappy
get	ps2	Happy	Happy	detect	bobcat	Unhappy	Happy
receive	rolex	Happy	Happy	meet	villain	Unhappy	Unhappy
purchase	rolex	Happy	Happy	see	villain	Unhappy	Unhappy
get	scholarship	Happy	Happy	eat	apple	Neutral	Neutral
receive	scholarship	Happy	Happy	change	hair	Neutral	Neutral
award	tivo	Happy	Happy	express	hair	Neutral	Neutral
buy	tivo	Happy	Happy	show	hair	Neutral	Neutral
join	tour	Happy	Unhappy	find	desk	Neutral	Neutral
wish	tour	Happy	Unhappy	receive	desk	Neutral	Neutral
see	vaio	Happy	Happy	purchase	door	Neutral	Neutral
desire	watch	Happy	Happy	See	Wine	Neutral	Neutral
buy	watch	Happy	Happy	award	window	Neutral	Neutral
punch	robber	Happy	Happy	receive	window	Neutral	Neutral
kill	malady	Happy	Unhappy	receive	coin	Neutral	Neutral
shoot	malady	Happy	Unhappy	Get	coin	Neutral	Neutral
kill	rat	Happy	Happy	receive	spoon	Neutral	Neutral
kick	rat	Happy	Happy	award	spoon	Neutral	Neutral
attack	rat	Happy	Happy	award	toothbrush	Neutral	Neutral
lose	benz	Unhappy	Unhappy	accept	toothbrush	Neutral	Neutral
destroy	benz	Unhappy	Unhappy	get	soap	Neutral	Neutral
break	bikini	Unhappy	Unhappy	award	soap	Neutral	Neutral
shatter	bikini	Unhappy	Unhappy	receive	soap	Neutral	Neutral
lose	bonus	Unhappy	Unhappy	see	fork	Neutral	Neutral
abandon	bonus	Unhappy	Unhappy	get	fork	Neutral	Neutral
destroy	iphone	Unhappy	Unhappy	receive	fork	Neutral	Neutral
break	iphone	Unhappy	Unhappy	receive	curtain	Neutral	Neutral
abandon	jewel	Unhappy	Unhappy	receive	wheat	Neutral	Neutral
lose	jewel	Unhappy	Unhappy	purchase	wheat	Neutral	Neutral
lose	lv	Unhappy	Unhappy	open	document	Neutral	Neutral
shatter	lv	Unhappy	Unhappy	touch	hair	Neutral	Neutral
dislike	miniskirt	Unhappy	Unhappy	close	envelope	Neutral	Neutral
lose	miniskirt	Unhappy	Unhappy	accept	envelope	Neutral	Neutral
destroy	ipod nano	Unhappy	Unhappy	cut	hair	Neutral	Neutral
break	new scooter	Unhappy	Unhappy	lose	cotton tag	Neutral	Unhappy
shatter	new scooter	Unhappy	Unhappy	open	envelope	Neutral	Neutral
lose	newborn baby	Unhappy	Unhappy	receive	envelope	Neutral	Neutral
abandon	newborn baby	Unhappy	Unhappy	buy	envelope	Neutral	Neutral
break	prada	Unhappy	Unhappy	get	envelope	Neutral	Neutral

abandon	prada	Unhappy	Unhappy	see	desk	Neutral	Neutral
lose	prize	Unhappy	Unhappy	award	desk	Neutral	Neutral
kill	prize	Unhappy	Unhappy	take	toothbrush	Neutral	Neutral
reduce	prize	Unhappy	Unhappy	eat	wheat	Neutral	Neutral
shatter	rolex	Unhappy	Unhappy	buy	wheat	Neutral	Neutral
dislike	rolex	Unhappy	Unhappy	order	wheat	Neutral	Neutral
open	door	Neutral	Neutral	touch	window	Neutral	Neutral
receive	door	Neutral	Neutral	get	window	Neutral	Neutral
see	wheat	Neutral	Neutral	find	window	Neutral	Neutral
get	chair	Neutral	Neutral	get	desk	Neutral	Neutral
receive	chair	Neutral	Neutral	find	toothbrush	Neutral	Neutral
receive	shop	Neutral	Neutral	touch	desk	Neutral	Neutral
arrive	train station	Neutral	Neutral	buy	toothbrush	Neutral	Neutral
look	train station	Neutral	Neutral	purchase	toothbrush	Neutral	Neutral
meet	train station	Neutral	Neutral				

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