

model to identify potential opinion relations in all sentences, and then the associations between opinion targets and opinion words are estimated.

- 2) **Candidate confidence estimation:** Based on these associations, we exploit a graph-based algorithm to compute the confidence of each opinion target candidate. Then the candidates with higher confidence scores are extracted as opinion targets.

3.2 Mining associations between opinion targets and opinion words using Word-based Translation Model

This component is to identify potential opinion relations in sentences and estimate associations between opinion targets and opinion words. We assume opinion targets and opinion words respectively to be nouns/noun phrases and adjectives, which have been widely adopted in previous work (Hu et al., 2004; Ding et al., 2008; Wang et al., 2008; Qiu et al., 2011). Thus, our aim is to find potential opinion relations between nouns/noun phrases and adjectives in sentences, and calculate the associations between them. As mentioned in the first section, we formulate opinion relation identification as a word alignment task. We employ the word-based translation model (Brown et al. 1993) to perform monolingual word alignment, which has been widely used in many tasks, such as collocation extraction (Liu et al., 2009), question retrieval (Zhou et al., 2011) and so on. In our method, every sentence is replicated to generate a parallel corpus, and we apply the bilingual word alignment algorithm to the monolingual scenario to align a noun/noun phrase with its modifier.

Given a sentence with n words $S = \{w_1, w_2, \dots, w_n\}$, the word alignment $A = \{(i, a_i) | i \in [1, n]\}$ can be obtained by maximizing the word alignment probability of the sentence as follows.

$$\hat{A} = \arg \max_A P(A | S) \quad (1)$$

where (i, a_i) means that a noun/noun phrase at position i is aligned with an adjective at position a_i . If we directly use this alignment model to our task, a noun/noun phrase may align with the irrelevant

words other than adjectives, like prepositions or conjunctions and so on. Thus, in the alignment procedure, we introduce some constraints: 1) nouns/noun phrases (adjectives) must be aligned with adjectives (nouns/noun phrases) or null words; 2) other words can only align with themselves.

Totally, we employ the following 3 WTMs (IBM 1~3) to identify opinion relations.

$$\begin{aligned} P_{IBM-1}(A | S) &\propto \prod_{j=1}^n t(w_j | w_{a_j}) \\ P_{IBM-2}(A | S) &\propto \prod_{j=1}^n t(w_j | w_{a_j}) d(j | a_j, n) \\ P_{IBM-3}(A | S) &\propto \prod_{i=1}^n n(\phi_i | w_i) \prod_{j=1}^n t(w_j | w_{a_j}) d(j | a_j, n) \end{aligned} \quad (2)$$

There are three main factors: $t(w_j | w_{a_j})$, $d(j | a_j, n)$ and $n(\phi_i | w_i)$, which respectively models different information.

1) $t(w_j | w_{a_j})$ models the co-occurrence information of two words in corpora. If an adjective co-occurs with a noun/noun phrase frequently in the reviews, this adjective has high association with this noun/noun phrase. For example, in reviews of cell phone, “big” often co-occurs with “phone’s size”, so “big” has high association with “phone’s size”.

2) $d(j | a_j, l)$ models word position information, which describes the probability of a word in position a_j aligned with a word in position j .

3) $n(\phi_i | w_i)$ models the fertility of words, which describe the ability of a word for “one-to-many” alignment. ϕ_i denotes the number of words that are aligned with w_i . For example, “Iphone4 has amazing screen and software”. In this sentence, “amazing” is used to modify two words: “screen” and “software”. So ϕ equals to 2 for “amazing”.

Therefore, in Eq. (2), $P_{IBM-1}(A | S)$ only models word co-occurrence information. $P_{IBM-2}(A | S)$ additionally employs word position information. Besides these two information, $P_{IBM-3}(A | S)$ considers the ability of a word for “one-to-many” alignment. In the following experiments section, we will discuss the performance difference among these models in detail. Moreover, these models