	books	*kitchen appliances*
+	**Excellent** and **broad** survey of the development of civilization with all the punch of **high quality** fiction.	I was so **thrilled** when I unpack my processor. It is so **high quality** and **professional** in both looks and performance.
+	This is an **interesting** and **well researched** book.	**Energy saving** grill. My husband loves the burgers that I make from this grill. They are **lean** and **delicious**.
-	Whenever a new book by Philippa Gregory comes out, I buy it hoping to have the same experience, and lately have been sorely **disappointed**.	These knives are already showing spots of **rust** despite washing by hand and drying. Very **disappointed**.

Table 1: Positive (+) and negative (-) sentiment reviews in two different domains.

sentence	Excellent and broad survey of the development of civilization.
POS tags	Excellent/JJ and/CC broad/JJ survey/NN1 of/IO the/AT development/NN1 of/IO civilization/NN1
lexical elements (unigrams)	excellent, broad, survey, development, civilization
lexical elements (bigrams)	excellent+broad, broad+survey, survey+development, development+civilization
sentiment features (lemma)	excellent*P, broad*P, survey*P, excellent+broad*P, broad+survey*P
sentiment features (POS)	JJ*P, NN1*P, JJ+NN1*P

Table 2: Generating lexical elements and sentiment features from a positive review sentence.

3 Sentiment Sensitive Thesaurus

One solution to the feature mismatch problem outlined above is to use a thesaurus that groups different words that express the same sentiment. For example, if we know that both *excellent* and *delicious* are positive sentiment words, then we can use this knowledge to *expand* a feature vector that contains the word *delicious* using the word *excellent*, thereby reducing the mismatch between features in a test instance and a trained model. Below we describe a method to construct a sentiment sensitive thesaurus for feature expansion.

Given a labeled or an unlabeled review, we first split the review into individual sentences. We carry out part-of-speech (POS) tagging and lemmatization on each review sentence using the RASP system (Briscoe et al., 2006). Lemmatization reduces the data sparseness and has been shown to be effective in text classification tasks (Joachims, 1998). We then apply a simple word filter based on POS tags to select content words (nouns, verbs, adjectives, and adverbs). In particular, previous work has identified adjectives as good indicators of sentiment (Hatzivassiloglou and McKeown, 1997; Wiebe, 2000). Following previous work in cross-domain sentiment classification, we model a review as a bag of words. We select unigrams and bigrams from each sentence. For the remainder of this paper, we will refer to unigrams and bigrams collectively as *lexical elements*. Previous work on sentiment classification has shown that both unigrams and bigrams are useful for training a sentiment classifier (Blitzer et al., 2007). We note that it is possible to create lexical elements both from source domain labeled reviews as well as from unlabeled reviews in source and target domains.

Next, we represent each lexical element u using a set of features as follows. First, we select other lexical elements that co-occur with u in a review sentence as features. Second, from each source domain labeled review sentence in which u occurs, we create *sentiment features* by appending the label of the review to each lexical element we generate from that review. For example, consider the sentence selected from a positive review of a book shown in Table 2. In Table 2, we use the notation "*P" to indicate positive sentiment features and "*N" to indicate negative sentiment features. The example sentence shown in Table 2 is selected from a positively labeled review, and generates positive sentiment features as shown in Table 2. In addition to word-level sentiment features, we replace words with their POS tags to create