Chapter 12

Approaches for Automatically Tagging Affect: Steps Toward an Effective and Efficient Tool

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Abstract

The tagging of discourse is important not only for natural language processing research, but for many applications in the social sciences as well. This chapter describes an evaluation of a range of different tagging techniques to automatically determine the attitude of speakers in transcribed psychiatric dialogues. It presents results in a marriage-counseling domain that classifies the attitude and emotional commitment of the participants to a particular topic of discussion. It also gives results from the Switchboard Corpus to facilitate comparison for future work. Finally, it describes a new Java tool that learns attitude classifications using our techniques and provides a flexible, easy to use platform for tagging of texts.

Keywords: affect, automatic tagging, cats, stochastic affect, affect tool, psychological models.

1. Introduction

Detecting affect in written or spoken language has several potential benefits. First and most obvious, human-computer interaction can benefit by tailoring the computer's responses (or lack of) according to the affect detected in the human. A more natural and effective interaction will ensue. Conversely, if computers can detect affect, then they can also help humans understand the concept of affect itself. For example, by observing the changes in emotion and attitude in people conversing, psychologists can determine correct treatments for patients. Computers can aid this sort of study by allowing more data to be collected and analysed, leading to more reliable treatments and theories.

In this study, the data from psychologists at the University of Rochester is used to test their hypothesis that poor interactions between married couples in a time of stress, such as a major illness, can actually exacerbate the illness. The premise is that emotion and communication are important to mental and physical health and that there is a direct correlation between how well a couple copes with a serious illness and how well they interact to deal with it. Good interactions can lead to quicker recovery while poor interactions, such as disengagement during conversations, can at times exacerbate the illness. They tested this hypothesis by observing the engagement levels of conversation between married couples presented with a "what-if?" scenario of one of the participants having a major illness (Alzheimer's Disease). The participants are then asked to discuss how they would deal with the sickness. The transcriptions of the conversations were tagged with affect related codes to look for correlations between communication and marital satisfaction.

Hodson, Shields, and Rousseau (2003) have shown that this tagging operation is very useful in analyzing patients' interactions and providing assistance to them. However, tagging by hand can be extremely time consuming and tends to be unreliable, so automated tools that can quickly learn tagging schemes from small amounts of data would be very useful. This chapter describes the evaluation of several different tagging approaches with respect to their tagging accuracy, ranging from simple n-gram approaches with statistical models that are easy to learn and apply, to more complex information retrieval techniques that require significant computation to produce the models. The goal is to identify the most promising techniques to use in an automatic tagging tool. This tool will then be used to develop tagging models for new domains and to use these models to automatically tag new data in the domains.

The approaches in this chapter were evaluated on two corpora. The Rochester Marriage-Counseling Corpus (Shields, 1997) was used because it provides a rich dialogue between married couples, providing informal utterances that are tagged for the attitude each spouse has toward a particular topic. The conversations are frank, sometimes intense dialogues between people who have known each other for years. It is a unique domain that provides excellent data for analyzing attitude and affect in dialogue. The results were compared with the Switchboard Corpus (Godfrey, Holliman, and McDaniel, 1992) for the two-fold purpose of comparing our results to previous work and future approaches in determining dialogue attitude. The two corpora are ideal because they are meticulously hand-tagged and are relatively informal dialogues in which the attitude and affect of the participants is not repressed by a simulated experiment.

2. Background

Work in textual Affective Computing has spawned a myriad of approaches to identify the emotions expressed by a sentence or discourse. The earliest approaches involve searching a text for predetermined keywords and other cue phrases that convey strong emotion, thus tagging the sentence depending on which keywords (if any) it contains. While this method has the advantage of speed, it fails in sentences with negation and is limited by the list of keywords.

Boucouvalas and Ze (2002) found that a tagged dictionary can identify the basis of emotion in phrases and then use grammatical features to determine which of the words in the sentence carry some emotional weight. Its main advantage is that it has a scaled model of emotion, but has the drawback of having to create a tagged dictionary that encompasses the target domain.

Statistical methods have the advantage of being free from the pretagged list constraints but are dependent on having a large enough tagged corpus for training and, in some instances, do not fare well with tagging at the sentence level. Goertzel's Webmind (2000) project uses latent semantic analysis for affect classification in its domain. Wu (2002) uses transformation-based learning for tagging affect in chat-conversation analysis. The method works by automatically generating rules for tagging and then refining the rules by comparing them with a tagged corpus (ground truth) and iterating until no more improvements in the rules can be made.

One successful technique is used by Liu (2003); he created an affect tagger for email that uses a corpus of common-sense rules. The premise is that to successfully identify affect, one must take into account everyday knowledge (which for them was manually encoded) that would not be captured in statistical approaches.

Our approach differs from past approaches in two ways. First, it describes different statistical methods based on computing n-grams and individually tags sentences as opposed to tagging whole documents or paragraphs. The approaches are based on techniques that have been successful in another domain, discourse act tagging. Second, these approaches are incorporated into a tagging tool that a user interacts with to better tag a transcribed session.

3. Rochester Marriage-Counseling Corpus

The initial studies used a corpus of 45 annotated transcripts of conversations between married couples. These transcripts were provided by researchers from the Center for Future Health at the University of Rochester. At the start of each conversation, the moderator gave a husband and wife the task of discussing how they would cope if one of them developed Alzheimer's disease. Each transcript is broken into *thought units*, one or more sentences that represent how the speaker feels toward the topic. Each thought unit takes into account positive and negative words, comments on health, family, jobs, emotion, travel, sensitivity, detail, and many more. There are roughly two dozen tags, but the five major ones are given here:

- **GEN** verbal content towards illness is vague or generic. Discussion tends to be about outcomes. It can also can indicate that the speaker does not take ownership of emotions. (i.e. "It would be hard," "I think that it would be important.")
- **DTL** speaker's verbal content is distinct with regards to illness, emotions, dealing with death, etc. Speaker tends to describe the process rather than the outcome. (i.e. "It would be hard for me to see you so helpless," "I would take care of you.")
- **SAT** statements about the task; couple discusses what the task is and how to go about it. (i.e. "I thought I would be the caregiver.")
- **TNG** tangents; statements that are not related to the task. Thought unit contains no emotional content related to the central issues of the task. (i.e. talking about a friend with a disease.)
- **ACK** acknowledgments of the other speaker's comments. (i.e. "yeah" and "right")

The corpus contains a total of 14,390 unigrams and bigrams, of which 9,450 occur only once. There are 4,040 total thought units. The distribution of tags is as follows: GEN: 1964 (41.51%), ACK: 1075 (22.72%), DTL: 529 (11.18%), SAT: 337 (7.12%), TNG: 135 (2.85%).

4. Approaches to Tagging

We investigated two classes of approaches to automatic tagging. The first is based solely on building n-gram statistical models from training data. The second is a vector-based approach that builds sentence vectors from the n-grams in the training data.

4.1 N-gram Based Approaches

An n-gram approach tags a thought unit based on previously seen n-grams in the training data. The approach is motivated by the assumption that there are key phrases in each thought unit that identify which tag (emotion, attitude, etc.) should be used. Depending on the size of the n-grams being collected, a significant amount of word ordering can also be captured. However, n-gram models often lose many long range dependencies that extend beyond the n length of the n-gram.

The following approaches all use n-grams ranging from unigrams to 5-grams. Any n-gram that appears only once in the training corpus is considered sparse and is ignored. In addition, all unigrams, bigrams, and trigrams that appear only twice are thrown out. Due to the greater information content of the high n-grams, those that appeared twice are deemed helpful and are not ignored. The start of the thought unit was also considered a word (i.e. <*s*> *well* is a bigram in a sentence that begins with the word *well*).

4.1.1 Naive Approach

The Naive Approach to tagging the thought units is the most basic approach; it simply selects the *best* n-gram that appears.

$$P(tag_i \mid utt) = \max_{j,k} P(tag_i \mid ngram_{jk})$$

Where tag_i ranges over the set of available tags (GEN, DTL, SAT, TNG, ACK) and $ngram_{jk}$ is the *jth* n-gram of length *k* (*k*-gram) in the current thought unit *utt* of the test set. The example below illustrates how the naive approach would tag a sentence, showing the n-gram with the highest probability of each n-gram length.

Ex: I don’t want to be chained to a wall

N-Gram Size (tag)	Top N-gram	Probability
1: (GEN)	don’t	0.665
2: (GEN)	to a	0.692
3: (GEN)	<s> I don’t	0.524
4: (DTL)	don’t want to be	0.833
5: (DTL)	I don’t want to be	1.00

The highest n-gram is *I don’t want to be* with 1.00 probability, indicating that this phrase always appeared with the DTL tag in the training set. Therefore, the unit is tagged DTL.

4.1.2 Weighted Approach

The Weighted Approach builds upon the Naive by assuming that higher n-grams provide more reliable information and that the sum of all n-gram probabilities will give a broader estimation. Each n-gram that appears in the given thought unit is multiplied by a weight assigned to the length of the n-gram. In more detail, the probability of a thought unit being tagged is:

$$P(tag_i \mid utt) = \sum_{k=0}^{m}((\max_j P(tag_i \mid ngram_{jk}))*weight_k)$$

Where *m* is the length of the longest n-gram (m=5 in this study) and again, *ngram$_{jk}$* is the *jth* n-gram of length *k*. *weight$_k$* is the weight of an n-gram of length *k*. We will refer to the weights 0.4, 0.4, 0.5, 0.8, 0.8 (i.e. unigrams and bigrams are weighted 0.4, trigrams are 0.5, etc.) whenever the Weighted Approach is used. Many different weights can be assigned, each between 0 and 1 to try and obtain better results. However, the improvement is both minimal and approximately the same no matter which weights are chosen (as long as the longer n-grams are weighted more than unigrams and bigrams).

As above, the same example sentence is given here to illustrate this approach. The top GEN and DTL n-grams are shown.

Ex:I don’t want to be chained to a wall

N-Gram Size (tag)	Top N-gram	Probability
1: (GEN)	don’t	0.665
1: (DTL)	want	0.452
2: (GEN)	to a	0.692
2: (DTL)	want to	0.443
3: (GEN)	<s> I don’t	0.524
3: (DTL)	I don’t want	0.592
4: (GEN)	I don’t want to	0.27
4: (DTL)	don’t want to be	0.833
5: (GEN)	<s> I don’t want to	0.25
5: (DTL)	I don’t want to be	1.00

GEN sum (w/weights) 1.255
DTL sum (w/weights) 2.086

Ignoring the other possible tags in this example, it is easy to see that DTL gains ground in the higher probabilities, 0.833 for the 4-gram and 1.00 for the 5-gram. DTL’s final sum of the n-gram weighted probabilities is clearly higher and the sentence is correctly tagged DTL.

The added weights do not differ much from the Naive Approach in this example, but one of the many cases where it does differ can be seen in the utterance, “*and really decide if there were places we wanted.”* The Naive Approach pulls out the unigram *really* as the highest single probability and tags it GEN. However, the Weighted Approach sums the max of each n-gram for the tags and DTL wins because *decide if there* has a higher probability than GEN’s top trigram. Trigrams are weighted higher than the lower n-grams where GEN is considered more likely, so the Weighted Approach chooses DTL while the naive approach would incorrectly choose GEN.

4.1.3 Lengths Approach

The Lengths Approach also builds upon the Naive Approach by adding the lengths of each thought unit as a type of weight (much like the Weighted Approach) to compute the maximum n-gram probabilities. During training with the training set, the number of words are counted in each tag's thought units. By calculating the average utterance length for each tag and its corresponding standard deviation, the length weight for each new thought unit in the test corpus can be obtained.

$$lenWeight_{ts} = \frac{e^{(-(n_s - n_t)^2)/(2*dev_t^2)}}{\sqrt{2\pi} * dev_t}$$

Where n_s is the number of words in utterance *s*, n_t is the average word length for the tag *t*, and dev_t is the length standard deviation for tag *t*. The length weights from our example sentence of nine words are as follows:

GEN	DTL	ACK	SAT	TNG
0.0396	0.0228	0.0004	0.0613	0.0354

The above table shows that the weights are relatively equal except for the ACK and SAT tags. Acknowledgment phrases tend to be very short and concise, one or two words long, so this low weight for a sentence of nine words is consistent with the motivation for this approach. Once these tag weights are computed, we choose our tag by the following:

$$P(tag_i \mid utt) = (\max_{j,k} P(tag_i \mid ngram_{jk})) * lenWeight_{im}$$

Where *m* is the word length of *utt*. Below shows how this method influences our example utterance. Again, only the top n-gram for each is shown.

Ex: I don't want to be chained to a wall

1: (GEN) don't	.665 * .0396 =	.026
2: (GEN) to a	.692 * .0396 =	.027
3: (GEN) <s> I don't	.592 * .0396 =	.021
4: (DTL) don't want to be	.833 * .0228 =	.019
5: (DTL) I don't want to be	1.00 * .0228 =	.023

The highest weighted n-gram is now the bigram, *to a*, with 0.027 final probability. The length weight effectively changes the Naive Approach's result to GEN. The majority of cases where the Lengths Approach differs the most can be found in ACK thought units. For example, the utterance *I don't either* should be tagged ACK, but none of the three words are strong indicators of the ACK tag and the training set does not contain this trigram. However, the length weight of ACK is 0.174 while the nearest tag, GEN, is 0.029. The Naive Approach normally considers this sentence three times more likely to be GEN than ACK. However, the length weight takes the short length of this utterance and correctly weights the ACK probability higher than GEN.

4.1.4 Weights with Lengths Approach

After finding only minor improvements over both the Weighted and Lengths approaches, we combined the two together. The example above is continued here by recalling the results of the Weighted Approach followed by the addition of the lengths weight:

GEN	sum (w/weights)	1.255
DTL	sum (w/weights)	2.086
GEN	weight/length	1.255 * 0.0396 = 0.0497
DTL	weight/length	2.086 * 0.0228 = 0.0476

Adding the length weight to this example reverses the Weighted Approach's DTL tag to a GEN tag. This occurs because DTL utterances typically are very long, while GEN utterances are very often under 10 words long (as is our example).

4.1.5 Analytical Approach

Many of the ACK utterances were found to be mis-tagged as GEN by the above approaches. Most of these were grounding utterances that repeated some of what was said in the previous utterance. For example, the second utterance below is mis-tagged:

B - so then you check that your tire is not flat
A - check the tire

This is a typical example of grounding where speaker A repeats a portion of B's last utterance in order to indicate understanding. Instead of adding another weight to our already growing list on the Naive Approach, a new model can be created that takes repeated words and the length of the two utterances into account (the repeated phrase is usually shorter than the original).

$$\begin{aligned}&P(w_1 \mid T) * P(w_2 \mid T) * \ldots * P(w_n \mid T) * \\ &P(R_{w_1} \mid O_{w_1}, L, L_p, T) * \ldots * P(R_{w_n} \mid O_{w_n}, L, L_p, T) * \\ &P(L \mid T) * P(T)\end{aligned}$$

Where w_i is a unigram in the utterance and $0 \leq \mathrm{i} < \mathrm{n}$ where n is the length of the utterance, O_{wi} is a unigram occurring in the previous utterance, R_{wi} is the repeated unigram (i.e. the unigram appeared in this utterance as well, L is the length of the current utterance, and L_p is the length of the previous utterance. The third line of the equation is the length weight brought over from the Lengths Approach. Due to the obvious sparseness of the data for such an ambitious statistic, we put each unigram in one of four buckets according to its number of occurrences in the training data (5, 30, 100, infinity). The sentence lengths are thrown into only two buckets (2, 100000). Since most acknowledgements are two or less words in length, this statistic should help find the majority of them while the repeated unigrams will find the rest.

This method produced worse results than the Naive Approach. Other bucket sizes were experimented with, but none significantly altered the result. This may be a direct result from the frequency of tags GEN and ACK. These two tags make up 64% of the 5 tags that occur in the corpus and the probability *P(L|T)* heavily favors one of the two tags (ACK dominates short sentences and GEN dominates the rest). Unfortunately, it seems to pull down the overall results when it is a factor in any calculation.

4.2 Information Retrieval-Based Approaches

Two vector-based methods for automatically tagging the utterances in the marriage corpus are discussed in this section. The first method is based on the Chu-Carroll and Carpenter routing system (1999). The second method dispenses with matrix construction of exemplar vectors and compares test sentences against a database of sentences.

4.2.1 Chu-Carroll and Carpenter

Chu-Carroll and Carpenter's domain is a financial call center with 23 possible caller destinations. The algorithm to route callers to the appropriate destination is summarized here. First, the caller's voice request is sent to a parser and a routing module. If the module generates only one destination, then the call is routed to that department. If more than one destination is generated, the system tries to generate a disambiguation query. If such a query cannot be generated, then the call defaults to a human operator (calls are also sent to human operators if the routing module does not generate a destination). When the clarifying query is generated, the algorithm is repeated with the caller's disambiguating response to the query.

The routing module is the most important part of the system. It consists of a database of a large collection of documents (previous calls) where each document is a vector in n-dimensional space. A query is a sentence transformed into a single vector and compared to each document (or destination) in the database. The document most similar to the query vector is the final destination.

Creation of the database of documents consists of the following training process; each word of the input is filtered morphologically, stop-words are removed, and all unigrams, bigrams and trigrams are extracted. The database or term-document matrix is an *M x N* matrix where *M* is the number of salient terms and *N* is the number of destinations. $A_{t,d}$ is the number of times term *t* occurs in calls to destination *d*. This matrix is then normalized for n-grams:

$$B_{t,d} = \frac{A_{t,d}}{\sqrt{\sum_{1 \le e \le n} A_{t,e}^2}}$$

A second normalizing metric, inverse document frequency (IDF), is also employed to lower the weight of a term that occurs in many documents since it is not a good indicator of any destination:

$$IDF(t) = \log_2 \frac{n}{d(t)}$$

where *n* is the number of documents in the corpus and *d(t)* is the number of documents containing term *t*. Each entry in the matrix thus becomes:

$$C_{t,d} = IDF(t) \times B_{t,d}$$

Query matching consists of transforming the input call to a vector in the same manner as above. A cosine distance metric is then used to compare this vector against the *n* destinations in the matrix.

4.2.2 Method 1: Routing-Based Method

A modified version of Chu-Carroll and Carpenter's algorithm was also analyzed; it is described here. Stop-word filtering is not done, so some common stop words such as "hmmm" or "uh" are included in the list of n-grams. A 2-gram model is used, so the term extraction phase generates all unigrams and bigrams. The same weighting principles and IDF metrics are employed for the matrix construction phase. The modification to the algorithm is the introduction of the entropy (amount of disorder) of each term. If a term is found in several documents then it exhibits low entropy, or a low amount of disorder. On the other hand, terms such as *yeah* or *right*, which appear in several tags, are bad exemplars and should be pruned from the database given their entropy. The following formula for determining the entropy of a term was used:

$$entropy(t) = -\sum_{1\le e\le n} \frac{A_{t,e}}{\sum_{1\le f\le n} A_{t,f}} \times \frac{\log A_{t,e}}{\sum_{1\le f\le n} A_{t,f}}$$

A pruning threshold must be determined in order to use entropy to eliminate unhelpful terms. In the marriage-counseling corpus, the maximum entropy for any term was 2.9. The testing algorithm was repeated starting with this cutoff value and decrementing by 0.1 for each new test. Figure 1 shows how this method would assign the DTL tag to the sentence, *I don't want to be chained to a wall*. After the matrix of canonical vectors is created, the test sentence (in vector form) is compared to each of the vectors. The one that is closest to our example thought unit is DTL, if only by a small margin over GEN. Hence it is selected, correctly, as the tag. It should be noted that figure 1 is purely conceptual. In reality, the cosine test is done over an n-dimensional space (as opposed to 2) where n in this test is 38,636.

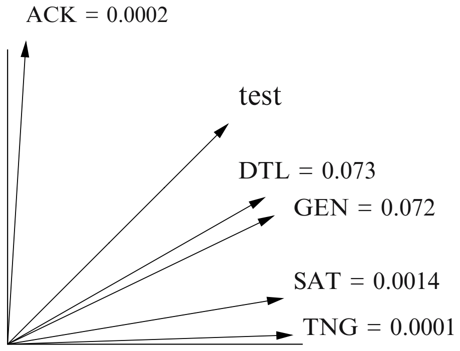


Figure 1. IR Method 1 Results of Test Sentence (not to scale)

Length	GEN	ACK	TNG	DTL	SAT
1-2	218	991	10	13	42
3-4	389	140	26	29	68
5-6	400	49	31	68	55
7-8	312	20	15	72	63
Over	1107	19	54	426	126

Figure 2. Distribution of the lengths of thought units for each tag.

In addition, we created two more vectors to raise the tagging accuracy: sentence length and repetition. The intuition behind the former is that tags tend to be correlated with sentences of a certain length. For example, ACK utterances are usually one or two words in length because most of them are phrases such as “yeah” or “yeah ok.” On the other hand, tags that tend to communicate more, such as DTL, would have longer sentences. The distribution can be seen in figure 2. Additional vectors are added to the matrix for each sentence length and the frequencies above are encoded in these vectors using the normalization schemes. During the test phase, the length of the test sentence is included in its vector representation.

The intuition behind the repetition metric is that ACK’s can be better modeled by taking into account repeated words from the previous thought unit. If key words are repeated then it is likely that the second speaker used those words to signal a backchannel. Repetition, or percent overlap, is calculated by dividing the number of n-grams in the intersection of the current and previous utterance by the number of current utterance n-grams. A “bin” system is used as was done in the sentence length metric, making new tags of 0% repetition, 1- 25%, 26-50%, 51-75%, 76-100% and 100% overlap. All unigrams are thrown out under the assumption that they won’t add any useful information since higher order n-grams are better predictors. Keeping them results in a 1% drop in performance.

4.2.3 Method 2: Direct Comparison of Sentence Vectors

The Direct Comparison method directly compares a test vector to a database. Unlike the Chu-Carroll and Carpenter algorithm, there is no construction of n-grams and normalizing of data.

Each thought unit is converted to a vector in which the index of the vector is a term. The cosine test is again used to determine similarity, but here it is used somewhat differently. Every other vector in the database is compared with our test vector. The ten highest cosine scores (highest similarities) are kept and used to calculate the best tag. First, each of the ten thought units’ tags are normalized to 100%, so if a thought unit had multiple tags and tag counts of ((GEN 2) (DTL 1)), the result would be (GEN 66.67%) and (DTL 33.33%). Next, these percents are normalized by multiplying by the respective cosine score and dividing by the sum of all ten cosine scores. This makes vectors that are very close to the test vector more significant (weighting). Finally, each tag is summed across the ten thought units and the one with the highest sum is returned as the most likely tag. Using the same test example, the top five sentences selected using this method are shown in figure 3. Weighting the tags appropriately, the scores are: DTL = 0.3741, SAT = 0.2169, GEN = 0.2045, TNG = 0.2044, ACK = 0. Thus, DTL is correctly selected.

Cosine Score	Tag	Sentence
0.6396	SAT	Are we supposed to get them?
0.6030	GEN	That sounds good
0.6030	TNG	That’s due to my throat
0.5583	DTL	But if I said to you I don’t want to be Ruth and I don’t want to get anywhere close to being Ruth, that I would expect that you would respect my wishes
0.5449	DTL	If it were me, I’d want to be a guinea pig to try things

Figure 3. IR Method 2 results of test sentences

5. Evaluations

The different methods discussed in this paper were evaluated based on a six-fold cross validation of their percent accuracy. In regards to the Marriage-Counseling Corpus, the corpus is divided into six equal portions and cross validation was used (train on five, test on the remaining one) to extract the final tagging accuracy percentage for each approach. All six combinations of the validation were tested and the average of the six is used as the final percentage.

5.1 N-Gram Based Approaches

The five n-gram approaches performed relatively the same on the marriage corpus. The results are given in figure 4. The Weighted Approach performed the best, scoring almost one percent above the Naive Approach and more so above the others. The Naive, which simply takes the n-gram with the highest probability, performed better than the other added metrics.

5.1.1 IR Method 1

Several instantiations of the modified Chu-Carroll and Carpenter algorithm were evaluated by toggling these pruning methods:

- **Prune-1:** terms that occur only once are pruned
- **Entropy:** the above entropy method is used
- **IDF:** terms are pruned using IDF

To determine which values were best, all six combinations of the three pruning methods were tested. The X's in figure 5 denote which pruning method was used.

The results in figure 5 show that only using the entropy model (with or without terms that occur only once) offers roughly a 4% advantage over the IDF method. The top two combinations of models (using entropy with/without Prune-1) were then run on the entire corpus with the model eliminating values that occur only once. This resulted in an average of 66.16% over the 6 cross-validation sets, while the model not using Prune-1 averaged 65.69%.

Using the best instantiation (Prune-1 and Entropy) from the first six tests, new n-grams for sentence length were made: sentences less than 2, of length 3 or 4, of length 5 or 6, and so forth so the final new n-gram was sentences 10 words or longer. Only a marginal increase in performance was found at 66.76%.

Naïve	Weighted	Lengths	Weight w/Length	Analytical
66.80%	67.43%	64.35%	66.02%	66.60%

Figure 4. Percent correct comparison of the five n-gram approaches for the UR Marriage Corpus.

Prune-1	Entropy	IDF	Accuracy
X	X		66.16%
	X		65.69%
			65.17%
X	X	X	61.56%
	X	X	61.40%
X		X	61.37%

Figure 5. IR Method 1 results

5.1.2 IR Method 2

The result (using cross-validation as in Method 1 and the best instantiation: Prune-1 and Entropy, but no IDF) is an overall average of 63.16%, slightly lower than Method 1. See figure 6.

Prune-1	Entropy	IDF	Accuracy
	X	N/A	63.10%
X	X	N/A	65.25%

Figure 6. IR Method 2 results

Metric	Accuracy
Sentence Length	66.76%
Repetition: No Unigrams	66.39%
Repetition: All N-grams	65.59%

Figure 7. IR Extension Metrics

6. Discussion

Of the two vector approaches, the Routing-Based Method achieved the best result with almost a 1% improvement over the Direct Method. Both approaches did best when Prune-1 and Entropy were factored in. Pruning terms that appeared only once helped in most cases (except for IDF, adding Prune-1 lowered the score); this intuitively makes sense. Words with only one occurrence do not convey accurate information and tend to bring the accuracy down. The entropy factor also improved performance, adding 1.5% to IDF and almost 2% to the combination of Prune-1 and IDF. When Prune-1 and entropy were combined, they resulted in the highest Routing-Based and Direct Method results. However, with a score of 66.16%, the Routing-Based Prune-1 and Entropy scored almost 1% over the Direct's 65.25%.

The N-Gram Approaches proved to be much more versatile than was initially thought. The Naive Approach does surprisingly well, scoring a half percentage higher than the best Routing-Based method, 66.80%. Several additions to the Naive were tried to improve performance, but nothing significantly improved the results. Giving the n-grams different weights produced the most accurate results with a 6-fold cross validation score of 67.43%. Putting the lengths of the thought units into consideration actually hurt the results in the marriage corpus. The Analytical Approach looks the most promising since it seems to capture the length of utterances and repeated words more precisely than the Naive Approach; however, the Analytical performs relatively the same as the Naive, scoring just 0.2% lower.

The Weighted Approach performed the best on the marriage corpus out of all the methods discussed in this chapter. This result goes against intuition and shows us that a simple n-gram comparison between the training set and the testing set performs as well and even better than the more complicated vector based approaches. Further, adding different weights to the Naive often hurts and very rarely improves the performance. Choosing the most indicative n-gram for the correct tag produces the most accurate results.

6.1 Switchboard Corpus Evaluation

6.1.1 Switchboard Data Set

To further determine the effectiveness of a tagging system, it is necessary to compare it to other methods on a common corpus. The Stolcke et al. modified Switchboard Corpus of spontaneous human-to-human telephone speech (Godfrey, Holliman, and McDaniel, 1992) from the Linguistic Data Consortium was chosen for this purpose. Unlike the Marriage-Counseling data set, the Switchboard set is composed of conversations of random topics as opposed to planned task-oriented ones. In addition, the data set has a much richer tagging set, being composed of 42 Dialog Acts (DA's) that are the Switchboard's version of thought unit tags. The five most prominent tags, which comprise 78% of the corpus, are (and their percentage of the corpus): Statement (36%), Backchannel/Acknowledgement (19%), Opinion (13%), Abandoned/Uninterruptible (6%), Agreement/Accept (5%). The tagged corpus consists of 205,000 utterances and 1.4 million words making it significantly larger than any other similarly tagged corpora.

6.1.2 Evaluation Method and Results

After splitting the Switchboard Corpus into six subsets as was done with the Marriage Corpus, a six fold cross-validation test was run. All the results are averages over the six combinations of training on five subsets and testing on one.

Figure 8 shows the results of the vector-based approaches on the Switchboard Corpus. The base model uses the original Chu-Carroll and Carpenter formalism of pruning entries that occur once and using IDF. The second method adds the entropy metric. The following approaches incorporate sentence length and word repetition as n-grams in the vector. As in the Marriage-Counseling corpus, these improve accuracy slightly. The Direct Approach performs significantly better than it did in the other corpus, mostly due to the fact there is more data to compare with.

Figure 9 shows the results of the five n-gram approaches described in section 4.1. The performance is similar to that on the Marriage Corpus (figure 4), but the Analytical Approach experiences a drop of 7.8%. This can be attributed to an even denser clustering of tags in the Switchboard corpus, where the three most frequent tags appear 71% of the time in the corpus. The length probability in the Analytical Approach favors them greatly (so it is often used instead of the correct tag). It can be seen, however, that the Weighted with Lengths Approach out-performs the other approaches. It correctly tags 1.6% more than the closest approach, breaking 70%.

Base Model	Entropy & IDF	Repeated Words	Length	Repeated & Length	Direct Approach
58.42%	57.26%	60.93%	60.92%	60.93%	63.53%

Figure 8. Percent Correct in the Information Retrieval Approaches for the Switchboard Corpus

Naïve	Weighted	Lengths	Weight w/Length	Analytical
68.41%	68.77%	69.01%	70.08%	61.40%

Figure 9. Percent Correct comparison of the five n-gram approaches for the Switchboard Corpus

7. CATS Tool

The culmination of this research has led to the development of a first version of an easy to use tool that is based off of the Naive Approach. Written in Java for multi-platform portability, this automated tagging system (CATS) employs the Lengths Approach, but uses only unigrams and bigrams. One of the main concerns during development of CATS was the hardware limitation that exists for a helpful tool. The methods discussed in this chapter require intensive computing resources and would be too slow to be of use to a human user. However, it was found that the Naive Approach performs as well as the vector-based approaches yet requires much less computing power. In addition, using just unigrams and bigrams performs almost as well as including the higher order n-grams. This is most likely the result of sparse data, but sparse data is usually the norm for untagged corpora. As a result, CATS employs a unigram-bigram Naive Approach with length weights. Computing time is acceptable and the results are comparable.

The program's main goal is ease of use for the researcher. As can be seen in figure 10, the main tagging attributes (case #, speaker, tag, text) are contained in separate windows to keep a clean workspace. Features such as auto-completion, tag flexibility, model customization, and others make the program both a text editor and an automated tagger. One can build a naive method model off of data by loading any text file with thought units and tags into the CATS program. A simple click of the button builds the model. To tag new text based off of this model, a new file of thought units (without tags obviously) can be loaded and automatically tagged with another click of the mouse.

CATS splits the new thought units into unigrams and bigrams and draws its tags using the naive length weighted approach discussed in this paper. A certainty percentage, the tagger's assessment of its tag choices, is given with each tag as well. The percent is based off of the second highest tag choice for the thought unit (high / (high + 2nd high) x 100). Low certainty measurements are colored red to bring the researcher's attention to a potentially incorrect tag.

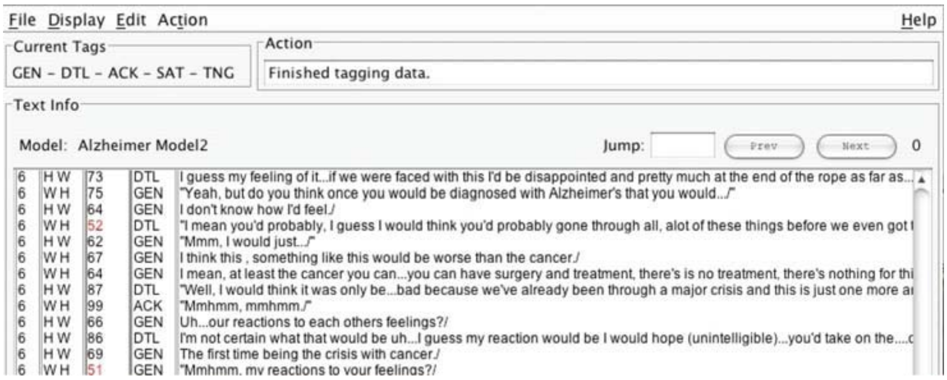
Currently, there is no program that can train on data with a click of the mouse and instantly build a statistical model based on the given tags. Tagging new data is completed in seconds with CATS, saving the researcher weeks or even months of work. We have worked closely with the Center for Future Health and have received good feedback on the interface and ease of use of the tool. Preliminary results have even been seen of 80 to 90% accuracy (based on smaller tag sets than the one discussed in this paper) with this tool when there is enough data to train on.

The fields of anthropology, linguistics, and psychology frequently employ several undergraduates and graduates to tag speech dialogues for information content. The process is extremely tedious and can take months. However, a tool like CATS has the potential to cut the process down to a few seconds. Once an initial dataset of adequate size is tagged, CATS trains itself on the data and is able to accurately and quickly tag new data. We feel that the tool is a good first step at automating the time intensive task of tagging text for the research community.

7.1 Future Tools

CATS fails in many aspects to fulfill the need of a fully functional tagging tool, both in its graphical interface and in its results. Although the results haven't been found scientifically, there are reports that making a list of *high importance* words and using them to tag utterances is more effective than the automated approaches. If a given utterance contains a word in this list, it is tagged as the list specifies. These lists must be created by hand.

The n-gram models discussed above should take into account high importance words, but these anecdotes show that users are often distrustful of black box tools and require other options to manipulate the models themselves. Also, n-gram models only represent relations between adjacent words, losing the correspondence between words on opposite sides of an utterance or paragraph. It may be that the high importance list captures more of these relations than n-gram and vector based approaches are able. Also, when data is too sparse to train on, automatic tools need fallback methods such as word lists to be effective. More work is needed to build larger and more general models that are robust enough to be used in an automated tagging tool.



Current Tags: GEN - DTL - ACK - SAT - TNG

Action: Finished tagging data.

Text Info

Model: Alzheimer Model2

Jump:

6	H W	73	DTL	I guess my feeling of it...if we were faced with this I'd be disappointed and pretty much at the end of the rope as far as...
6	W H	75	GEN	"Yeah, but do you think once you would be diagnosed with Alzheimer's that you would.../"
6	H W	64	GEN	I don't know how I'd feel./
6	W H	52	DTL	"I mean you'd probably, I guess I would think you'd probably gone through all, alot of these things before we even got t
6	H W	62	GEN	"Mmm, I would just.../"
6	W H	67	GEN	I think this , something like this would be worse than the cancer./
6	W H	64	GEN	I mean, at least the cancer you can...you can have surgery and treatment, there's is no treatment, there's nothing for thi
6	H W	87	DTL	"Well, I would think it was only be...bad because we've already been through a major crisis and this is just one more ar
6	W H	99	ACK	"Mmhmm, mmhmm./"
6	H W	66	GEN	Uh...our reactions to each others feelings?/
6	H W	86	DTL	I'm not certain what that would be uh...I guess my reaction would be I would hope (unintelligible)...you'd take on the....c
6	H W	69	GEN	The first time being the crisis with cancer./
6	W H	51	GEN	"Mmhmm, my reactions to your feelings?/

Figure 10. CATS tags data and gives a certainty measure to its left. Low certainty tags can be glanced over by the researcher to assure correctness.

8. Related Work

Stolcke (2000) developed a dialogue model that is "based on treating the discourse structure of a conversation of a hidden Markov model and the individual dialogue acts are modeled via a dialogue act n-gram." Whereas word n-grams form the basis of analysis for both metrics discussed in this paper, word n-grams are part of a set of methods used to implement the statistical dialogue grammar. Decision trees and neural nets are also used. In addition, while our methods only look at written text, Stolcke et al. have models that integrate prosody and speech.

Their model fared about the same as the Lengths and Weights metric, tagging 71% correctly. In comparison, their study of human annotators had human annotation scoring 84% and a baseline of 35%.

9. Conclusion

This chapter has described several vector and n-gram based approaches to automatically tagging text. It describes a new domain involving married couples in which its approaches perform reasonably well, but without much variation from each other. The computationally expensive vector based approaches for recognizing the emotional content of a speaker is outperformed by much more simple n-gram approaches. It has also described a platform independent tagging tool that can be employed by researchers to learn tagging patterns and automatically tag large corpora of dialogues or written text. Finally, the approaches in this chapter have shown to perform similarly on the Switchboard Corpus and have provided scores for others to compare future work on automatic tagging.

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