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The Author Perspective Model for Classifying Deontic Modality in Events

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Abstract

In this paper we present a generative model entitled the Author Perspective Model for the classification of deontic modality in event mentions. In the model modals, adverbials, and predicates associated with an event mention are generated by either a topic or author perspective where the author perspective is one of the three high level categories of deontic modality. We train the model with data gathered by a small set of seed phrases for each of the deontic modality categories. Our results show that we are able to classify the category of deontic modality with a micro-averaged F-Measure of 67.3%.

Introduction

Deontic modality informs the reader to an author's perception of the world, i.e. what the author thinks the world ought to be like. Such language is often employed as a means to persuade or manipulate others (Lillian 2008). Understanding an author's usage of deontic modality in regards to events and the way such cues are interpreted by others is crucial in both offensive and defensive psychological operations.

Events described using deontic modality are both irrealis and subjective in nature. They are irrealis in that the author is not presenting the event as having happened, i.e. is non-factual. They are subjective in that the deontic attributes of an event mention reveal not the author's knowledge about a factual event, but rather the author's desires, opinions, beliefs, and attitudes. As an example, let us examine the following sentence:

> The government ***ought to*** respond to the increasing terrorist threat posed by our under-protected borders.

From this example, we can deduce that the author believes the borders are under-protected and that this lack of adequate protection increases the threat of a terrorist action. Moreover, it can be seen that the author believes it is the government's duty to respond to the perceived increasing threat.

In English, deontic modality can be expressed through modal verbs (e.g. ought to), adverbials (e.g. hopefully), and other verbs (e.g. hope). Based on the work of Jespersen (1924) and Palmer (1986), we examine the three main sub-categories of deontic modality: *directive*, *commissive*, and *volitive*. Each of these three categories is further sub categorized as illustrated in Figure 1 (shown on the next page). Directive modality is concerned with one's ability, permission, or duty to perform some action or the requirement that others perform the action, e.g. "The government must not impair the rights of its citizens". There are six main sub-categories of directive modality: prohibitive, precative, permissive, obligative, imperative, and deliberative. Examples of each are as follows:

> The government must not impair the rights of its citizens. (Prohibitive)
> Will you answer the phone? (Precative)
> The ambassador may take his leave. (Permissive)
> The country ought to honor those lost. (Obligative)
> Explain yourself! (Imperative)
> Shall I start dinner? (Deliberative)

Commissive modality is used by a speaker to express his or her commitment through a promise or threat, e.g. "I will report to work by 9am." Finally, volitive modality expresses the author's hopes, wishes, or fears concerning some potential event. The sub-categories of volitive modality are desiderative (e.g. The terrorists want to bomb a major tourist attraction.) and optative (e.g. I wish the government would do something about the border.).

In this paper, we present a method for the identification and categorization of deontic modality using a generative model, which we call the Author Perspective Model (APM). In the APM the modals, adverbials, and predicates in event mentions are generated by a series of topics and author perspectives which represent the three main categories of deontic modality. The model is capable of running fully unsupervised. However, we utilize it in a semi-supervised fashion in order to guide the generative process. The semi-supervision is in the form of distant supervision, where we provide a small number of seed phrases per deontic category and gather a noisy labeled dataset to train the model over.

This paper will proceed as follows. First, we present background and related work. Then we detail the Author Perspective Model. We then present experimental results of the APM. Next, we give details of a case study where we use deontic modality identified utilizing the APM to profile au-

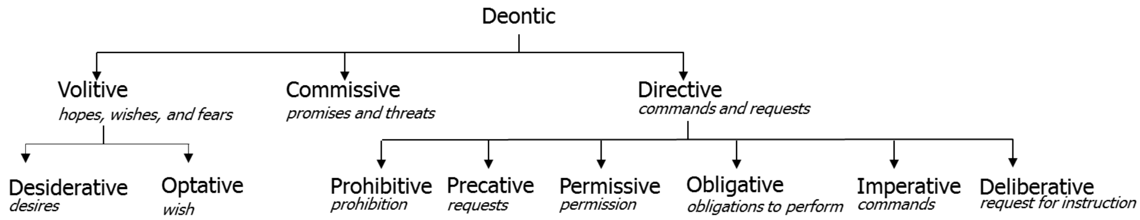

Figure 1: Categorization of deontic modality.

thors and groups. Finally, we give concluding remarks and discuss future research directions.

Related Work

Modality and mood have been widely studied in the field of linguistics (Palmer 2001). Modality has been closely studied for the role it plays in regards to tense and aspect (Bybee, Perkins, and Pagliuca 1994) and for its use in discourse (Akatsuka and Clancy 1993; Bybee and Fleischman 1995; Clancy, Akatsuka, and Strauss 1997). In the field of Computational Linguistics modality as it relates to events was one of the areas of focus for the ACE (Automated Content Extraction) program (Doddington et al. 2004) and the resulting ACE corpus (Walker et al. 2006). In ACE, modality was defined as"asserted" and "other" with asserted modality relating to when the author or speaker references an event as a real occurrence. Modality was also the focus of a recent special issue in the Computational Linguistics journal (Morante and Sporleder 2012). In particular, a good deal of focus was given to the factuality and veridicality of events (de Marneffe, Manning, and Potts 2012; Sauri and Pustejovsky 2012) and negation (Baker et al. 2012; Velldal et al. 2012)

Deontic modality is closely related to speech acts, which are actions performed by individuals when making an utterance. Austin (1962) formalized the concept of speech acts by separating them into three classes: (1) *locutionary*, (2) *illocutionary*, and (3) *perlocutionary*. Locutionary acts the prosody, phonetics, and semantics of the utterance. Illocutionary acts are the intended functions of the utterances of the speaker. Perlocutionary acts are illocutionary acts that produce a certain effect in its addressee, e.g. scaring and insulting. Much of the work in speech acts has been focused on illocutionary acts due to the work of Searle (1969). In particular, two categories of illocutionary acts that Searle defines are directive and commissive which share the same definition as their modality counterparts.

Dialogue acts are specialized speech acts which include the internal structure, such as grounding and adjacency pairs, of a dialogue. There are a number of schemes for coding dialogue acts, such as DAMSL (Allen and Core 1997), VERBMOBIL (Jekat et al. 1995), and DIT++ (Bunt et al. 2010). The DAMSL coding scheme defines dialogue acts that are forward looking, which are extensions of speech acts, and which are backward looking, which relate the utterance to previous utterances. Frameworks like DIT++ have extended the typical coverage of dialogue acts to encompass a boarder set of acts, such as social obligations.

Recent work has examined social acts, which capture the socio-cognitive processes that act on individuals during communication. Social acts reflect the social intention of an utterance and serve a function to inform about an individual's social relationships. For example, in the statement "get me a cup of coffee", speech acts would focus on identifying the set of actions that would result from the utterance - presumably the target of the utterance physically going to get a cup of coffer for the speaker. In contrast, social acts focus on the social implicature of the statement, that the speaker is indicating their power over the target.

A number of recent approaches have examined the use of specialized social acts in the inference of social implicatures. Bracewell et al. (2011; 2012) examined a number of social acts for inferring whether two dialogue participants have a collegial relationship. Hassan et al. (2012) examined the detection of subgroups based on social acts around stance and attitude using signed social networks. Other research has focused on the annotation and identification of social acts. Tomlinson et al. (Tomlinson et al. 2012) examined the manifestation of a set of social acts in Arabic for inferring pursuits of power by participants. Bracewell et al. (2012) created an annotated corpus of *collegial* and *adversarial* social actions. Bender et al. (2011) created an annotated corpus of social acts relating to *authority claims* and *alignment moves* for determining authority and influence. Rosenthal and McKeown (2012) examined methods for identification of messages expressing opinionated claims.

The Author Perspective Model

The identification and categorization of deontic modality is done using a generative model in which the modals, adverbials, and predicates in event mentions are generated by a series of topics and author perspectives. Our model which is entitled the Author Perspective Model (APM) is inspired by the work of Huang and Mitchell (2006) in that we have a general topic, and provide means for feedback through making certain words "sticky" to a given author perspective. The model performs inference over event mentions identified as containing an instance of deontic modality. The graphical representation of the Author Perspective Model is shown in Figure 2.

The model assumes that each word (modal, adverb, or verb) in an event mention is generated either by a topic (Z) or an author perspective (P). We define author perspective as being related to the desires, hopes, and fears, i.e. deontic

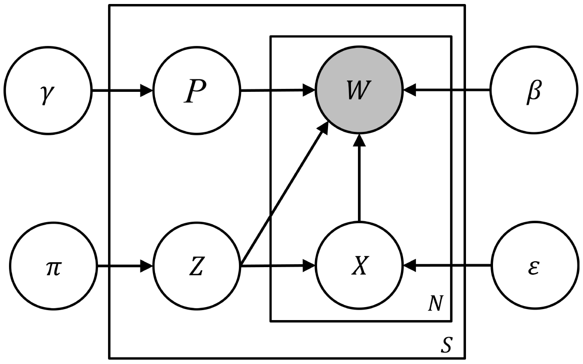

Figure 2: Graphical representation of the Author Perspective Model.

modality, expressed by the author in the communication. We define a topic as general content being transmitted through the communication and for which the author's perspective may be focused. A switching variable (X) is used to determine whether the word is a topic word or a perspective word. The switching variable is used during inference to determine the likelihood that a word (modal, adverb, or verb) is representing deontic modality or is general content (i.e. a topic).

More formally, given a corpus C of E event mentions $C = e_1, e_2, \cdots, e_E$ where e_i is represented as a vector of words $\{w_{ij}; j \in 1, 2, \cdots, n_i\}$ made up of the modals, adverbs, and predicates. We use the notation z_i to represent the value of the hidden topic variable Z, p_i to represent the value of the hidden author perspective variable P, and x_i to represent the value of the hidden variable X associated with an observed word w_i. The corpus likelihood of C given our model θ is defined as:

$$\begin{aligned} P(C|\theta) = \textstyle\prod_{i=1}^{E} \sum_{z_i=1}^{|Z|} P(z_i) \sum_{l_i=1}^{|P|} P(p_i) \\ \textstyle\prod_{j=1}^{n_i} [P(x_{ij} = 1|z_i) P(w_{ij}|z_i) \\ + P(x_{ij} = 0|z_i) P(w_{ij}|p_i)] \end{aligned} \tag{1}$$

Rewriting the probability in terms of the model parameters results in the following:

$$\begin{aligned} P(C|\theta) = \textstyle\prod_{i=1}^{E} \sum_{z_i=1}^{|Z|} \pi_i \sum_{l_i=1}^{|P|} \gamma_i \\ \textstyle\prod_{j=1}^{n_i} [\epsilon \beta_{z_i w_{ij}} + (1-\epsilon) \beta_{p_i w_{ij}}] \end{aligned} \tag{2}$$

We can solve the equation using the expectation maximization (EM) algorithm (Dempster, Laird, and Rubin 1977). EM is a standard algorithm for determining the parameters of a model where the calculation of the parameters depends on latent, or hidden, variables. EM works in an alternating fashion by first calculating the expected values (the E step) of the parameters and then maximizing (the M step) the likelihood of the values calculated in the E step.

The E Step for the APM is as follows:

$$\begin{aligned} &\phi_i^t(z) \equiv P(z_i = z | e_k \theta^t) \\ &= \frac{\pi_z^t \prod_{j=1}^{n_i} \sum_{m=1}^{|P|} \left[\epsilon_z^t \beta_{z w_{ij}}^t + (1-\epsilon_z^t) \beta_{m w_{ij}}\right]}{\sum_{k=1}^{|Z|} \pi_k^t \prod_{j=1}^{n_i} \sum_{m=1}^{|P|} \left[\epsilon_k^t \beta_{k w_{ij}}^t + (1-\epsilon_k^t) \beta_{m w_{ij}}\right]} \end{aligned} \tag{3}$$

$$\begin{aligned} &\psi_i^t(p) \equiv P(p_i = p | e_i \theta^t) \\ &= \frac{\gamma_l^t \prod_{j=1}^{n_i} \sum_{k=1}^{|Z|} \left[\epsilon_k^t \beta_{k w_{ij}}^t + (1-\epsilon_k^t) \beta_{l w_{ij}}\right]}{\sum_{m=1}^{|L|} \gamma_l^t \prod_{j=1}^{n_i} \sum_{k=1}^{|Z|} \left[\epsilon_k^t \beta_{k w_{ij}}^t + (1-\epsilon_z^t) \beta_{m w_{ij}}\right]} \end{aligned} \tag{4}$$

$$\begin{aligned} &\rho_i^t(z) \equiv P(x_{ij} = 1 \mid z_i = z, w_{ij}; \theta^t) \\ &= \frac{\epsilon_z^t \beta_{z w_{ij}}^t}{\epsilon_z^t \beta_{z w_{ij}}^t + \sum_{m=1}^{|P|} (1-\epsilon_z^t) \beta_{m w_{ij}}^t} \end{aligned} \tag{5}$$

where ϕ is the probability of a topic given the event mention, ψ is the probability of an author perspective given the event mention, and ρ is the probability that the word is generated by a topic. In this manner, the APM determines the strength of the deontic modality in the given event mention by updating ψ and ϕ which relate to the likelihood that the event mention contains an expression of deontic modality or is non-deontic. This is important as the data feed to the APM is noisy and will contain sentences that do not have deontic modality present.

The M Step for the Author Perspective Model uses the expected values (results of the E-Step) to maximize the probability of the corpus given the model. The M-Step is calculated as follows:

$$\pi_z^{t+1} = \frac{\sum_{i=1}^{E} \phi_i^t(z)}{E} \tag{6}$$

$$\gamma_p^{t+1} = \frac{\sum_{i=1}^{E} \gamma_i^t(p)}{E} \tag{7}$$

$$\epsilon_z^{t+1} = \frac{\sum_{i=1}^{E} \phi_i^t(z) \sum_{j=1}^{n_i} \rho_{ij}^t(z)}{\sum_{i=1}^{E} \phi_i^t(z) \cdot n_i} \tag{8}$$

$$\beta_{zv}^{t+1} = \frac{\sum_{i=1}^{E} \phi_i^t(z) \sum_{j=1}^{n_i} \delta(w_{ij} = v) \rho_{ij}^t(z)}{\sum_{i=1}^{S} \phi_i^t(z) \sum_{j=1}^{n_i} \rho_{ij}^t(z)} \tag{9}$$

$$\beta_{lv}^{t+1} = \frac{\sum_{i=1}^{E} \sum_{k=1}^{|Z|} \phi_i^t(k) \sum_{j=1}^{n_i} \delta(w_{ij} = v) \rho_{ij}^t(k)}{\sum_{i=1}^{E} \sum_{k=1}^{|Z|} \phi_i^t(k) \sum_{j=1}^{n_i} \rho_{ij}^t(k)} \tag{10}$$

The Z and P variables represent clusters of words (modals, adverbs, and verbs). The Z clusters represent topics found in the corpus whereas the P clusters are made up of words that are manifestations of a particular author perspective, i.e. type of deontic modality.

The model as described now is fully unsupervised and capable of learning sets of cue words for the categories of deontic modality. In order to guide the generative process into finding manifestations of specific categories of deontic modality we add supervision. Supervision is incorporated in two ways. First, a set of seed phrases are used to construct a noisy set of training data. Second, using the noisy training data a second set of seeds are learned and fixed to author perspectives, i.e. we inform the model that certain phrases are always generated by a specific author perspective. This second set of seed phrases are "sticky" in that they have a constant probability of 1.0 with the category for which they are a manifestation.

Experimentation

To seed the APM we manually constructed a set of bigrams (two word phrases) for each of the three deontic categories. On average each category had 75 bigrams which included automatically generated conjugations and related forms. Using the bigrams we extracted sentences from the Blog06 corpus (Macdonald, Ounis, and Soboroff 2007). From the sentences we extracted all event mentions and all tokens with a modal, adverb, or verb part-of-speech attached via a depedency relation. We filtered the event mentions using a classifier that determined if the modality of the event mention was "ASSERTED" or "OTHER" as defined by ACE.

The classifier we used was a maximum entropy model which utilized a total of 36 features including, words around the trigger, the presence and distance of modal words, part of speech, dependency relations, presence of temporal arguments, sentence construction, polarity, genericity, tense, and even the output of a rule based modality classifier. Event mentions were only keep if the classified modality was OTHER. In total, about 1 million event mentions were extracted from the corpus. The extracted event mentions were then used as the training corpus from which the APM learned the likelihood that a word (modal, adverb, or verb) belonged to a topic or author perspective (deontic modality).

Using the training corpus, we automatically extracted a second set of seeds that we assigned as "sticky" to the author perspectives. We determined these second set of seeds using a log-likelihood test which is calculated as:

$$D = -2ln\frac{L(\theta_0)}{L(\theta_1)} \tag{11}$$

where $L(\theta_0)$ is the likelihood of the null model, i.e. a word represents a manifestation of a particular author perspective and $L(\theta_1)$ is the likelihood of the alternate model, i.e. the word does not represent a manifestation of an author perspective. We chose the top 10 phrases per author perspective.

To test the system, we manually constructed a test set of 150 event mentions, 50 per deontic category, from a political debate forum that was not a part of the Blog06 corpus. A political debate forum was chosen as it has rich and varying expressions of deontic modality. The baseline performance (randomly selecting one of the three categories) on our dataset is 33% F-measure. Table 1 lists the results for the Author Perspective Model on the test set.

	Precision	Recall	F-measure
Commissive	0.614	0.686	0.648
Directive	0.673	0.660	0.667
Volitive	0.750	0.673	0.710
MICRO	0.673	0.673	0.673

Table 1: Results of the APM model.

As can be seen in Table 1 the Author Perspective Model doubled the F-measure over the baseline. All three of the categories performed well ranging in F-measure from 0.648 for Commissive to 0.710 for Volitive. In contrast, while not directly comparable scores for speech acts associated with directive modality, e.g. request, instruct, etc., have seen scores ranging from 0.61 to 0.81 (Kang, Ko, and Seo 2013; Petukhova and Bunt 2011). Scores for speech acts related to commisive modality, e.g. promise, have scores ranging from 0.48 (Qadir and Riloff 2011) to 0.71 (Kang, Ko, and Seo 2013) F-Measure.

Case Study: Iranian Elections

As a proof-of-concept, we analyzed English language tweets around the Iranian elections in 2013. We focused on the leadership of Iran, the eventual winner, and individuals supportive of the reform and mainstream political groups. In particular, we collected tweets for the Supreme Ayatollah Ali Khamenei (2,460 in total), ex-President Mahmoud Ahmadinejad (832 in total), and current President Hassan Rouhani (1,335 in total). Additionally, we collected and aggregated tweets for other individuals into "Reform" (30,755 in total) and "Mainstream" (21,193 in total) political groups.

We employed the Author Perspective Model to identify the three categories of deontic modality and "no deontic modality" for each leader/group. We then filtered the tweets to only those in which there was an expression of deontic modality. This filtering facilitates examination of the difference in usage of the three categories of deontic modality between the leaders and political groups. Table 2 lists a breakdown of the percentage of tweets (rates of usage) for each category of deontic modality for those tweets with a manifestation of deontic modality.

	Commissive	Directive	Volative
Khamenei	21.7%	41.8%	36.5%
Ahmadinejad	24.0%	25.3%	50.7%
Rouhani	23.6%	41.9%	34.5%
Reform	21.8%	25.1%	53.1%
Mainstream	20.9%	21.8%	57.2%

Table 2: Results of the APM model.

The usage rates by themselves show difference, but are not as informative as comparing the differences in the rate of usage between groups. Therefore, we next examined the difference in usage rates of the three categories of deontic modality between the leaders and political groups. We determined if the difference was statistical significant by calculating the log-likelihood using G. The G is commonly used when comparing differences in frequencies across two sets of data, e.g. words usage in two different corpora. Table 3 illustrates the differences between the leaders of Iran and the reform and mainstream political groups (bolded numbers with "*" represent a significant difference at $p < 0.05$).

As can be seen in Table 3 there were no significant differences in the usage of commissive modality (i.e. expressions of commitment as a promise or threat) between any of the individuals or groups. However, of possible interest is that

Commissive	Khamenei	Ahmadinejad	Rouhani	Reform	Mainstream
Khamenei	-	-2.24%	-1.91%	-0.05%	0.80%
Ahmadinejad	2.24%	-	0.33%	2.20%	3.05%
Rouhani	1.91%	-0.33%	-	1.87%	2.72%
Reform	0.05%	-2.20%	-1.87%	-	0.85%
Mainstream	-0.80%	-3.05%	-2.72%	-0.85%	-
Directive	Khamenei	Ahmadinejad	Rouhani	Reform	Mainstream
Khamenei	-	16.46%*	-0.06%	16.67%*	19.97%*
Ahmadinejad	-16.46%*	-	-16.51%*	0.22%	3.51%
Rouhani	0.06%	16.51%*	-	16.73%*	20.02%*
Reform	-16.67%*	-0.22%	-16.73%*	-	3.30%
Mainstream	-18.60%*	-3.51%	-20.02%*	-3.30%	-
Volitive	Khamenei	Ahmadinejad	Rouhani	Reform	Mainstream
Khamenei	-	-14.21%*	-1.97%	-16.63%*	-20.77%*
Ahmadinejad	14.21%*	-	16.18%*	-2.42%	-6.56%
Rouhani	1.97%	-16.18%*	-	-18.60%*	-22.74%*
Reform	16.63%*	2.42%	18.60%*	-	-4.14%*
Mainstream	20.77%*	6.56%	22.74%*	4.14%*	-

Table 3: Differences in usage for (a) commisive , (b) directive, and (c) volitive modality between Iranian leaders and the mainstream and reform political groups in Iran. Significant differences at $p < 0.05$ are indicated with an "*".

the tweets by the reform and mainstream had on average higher rates of commissive modality. The usage of directive (i.e. commands in which the author is requiring some degree of conformity by the audience) and volitive modality (i.e. expressions of desires, wishes or fears) did have a number of significant differences. The current and eventual Iranian leadership (Khamenei and Rouhani) had significantly increased usages of directive modality and asignificantly decreased usage of volitive modality compared to ex-President Ahmadinejad and the two political groups. Interestingly, Khamenei and Rouhani did not have a significant difference in their usage of deontic modality (across all three categories). While the exact reason for this would require an Iranian culture export, it does seem to suggest that a leader in Iran must be in command and eliminate uncertainty (e.g. hopes and fears).

Conclusion

In this paper we presented the Author Perspective Model for the identification and categorization of deontic modality. The APM is a generative model in which modals, adverbials, and predicates associated with an event mention are generated by either a topic or author perspective where the author perspective is one of the three high level categories of deontic modality. We trained the model with noisy data gathered by a small set of seed phrases for each of the deontic modality categories. Our results showed that we were reliably able to classify the category of deontic modality with a micro-averaged F-Measure of 67.3%.

In addition, we presented a case study around the Iranian elections where we used deontic modality to compare and contrast individuals and groups. We found that there were interesting differences between those in and those out of power. While just scratching the surface, this analysis showed potential for using deontic modality for understanding the social relationships between individuals and groups.

Thus far we have reported numbers for identifying the three major categories of deontic modality. In the future, we will examine delving into the more fine grained categories of deontic modality as illustrated Figure 1. Additionally, we will focus on improving the performance of the APM by constructing a development set with which we will tune the APM's parameters. The development set will be created by identifying the deontic modality for sentences using the APM and then having a human manually verify the result. In this way, we should be able to quickly construct a sufficiently sized development set.

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