Tense Manages to Predict Implicative Behavior in Verbs

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Abstract

Implicative verbs (e.g. *manage*) entail their compliment clauses, while non-implicative verbs (e.g. *want*) do not. For example, while *managing to solve the problem* entails *solving the problem*, no such inference follows from *wanting to solve the problem*. Differentiating between implicative and non-implicative verbs is therefore an essential component of natural language understanding, relevant to applications such as textual entailment and summarization. We present a simple method for predicting implicativeness which exploits known constraints on the tense of implicative verbs and their compliments. We show that this yields an effective, data-driven way of capturing this nuanced property in verbs.

1 Overview

Understanding language requires the ability to perform basic inference– to make conclusions about what is likely true or false based on what is said. For example, given the sentence *She fixed the bug*, we should almost certainly infer that *the bug is fixed*. However, rather than stating plainly that *She fixed the bug*, one might instead say:

(1a) She **managed to fix** the bug before midnight.

(1b) She **happened to fix** the bug while refactoring.

In either case, the hearer should still infer that *the bug is fixed*. But it is not as easy as always inferring that embedded clauses are true. By changing only one word, these sentence no longer give a clear indication as to whether or not the bug has been fixed:

(2a) She **wanted to fix** the bug before midnight.

(2b) She **planned to fix** the bug while refactoring.

Implicative verbs, like those in (1), give rise to entailments, while non-implicative verbs, like those in (2), do not. It is therefore vital to natural language understanding to differentiate between clauses that are embedded under implicatives, which we can often infer to be either true or false, and those which are embedded under non-implicatives, for which such inferences cannot be made. In this paper, we exploit a known linguistic property of implicative verbs– that their compliment clause is constrained to be in the same tense as the main clause– in order to predict the tendency of verbs to behave implicatively. We show that our method almost perfectly separates non-implicatives from implicatives in a small hand-labeled dataset, and that it provides strong signal for predicting entailments in sentences involving implicative verbs.

2 Implicative Verbs

Some English verbs can take infinitival compliments, meaning they can appear in constructions of the form VB_1^* *to* VB_2, where VB_1^* is the "main" verb (which can be conjugated[1]) and VB_2 is the "compliment" verb (which is in infinitive form). Examples (1a)-(2b) illustrate verbs taking infinitive compliments.

Implicative verbs are a special subclass[2] of such verbs which give rise to entailments involving their

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[1] Here, * indicates that VB_1 can match any verb form, e.g. VB, VBD, VBP, etc. VB_2 can only match the base form VB.

[2] We note that *factive verbs* represent another special class of verbs which can take infinitival compliments. Unlike implica-

	Is the main verb negated?	Is the compliment entailed?	Example
Implicative	−	Yes	I managed to solve the problem. ⇒ I solved the problem.
Implicative	+	No	I did not manage to solve the problem. ⇒ I did not solve the problem.
Implicative	−	No	I failed to solve the problem. ⇒ I did not solve the problem.
Implicative	+	Yes	I did not fail to solve the problem. ⇒ I solved the problem.
Non-Impl.	−	Unknown	I wanted to solve the problem. ⇏ I solved the problem.
Non-Impl.	+	Unknown	I did not want to solve the problem. ⇏ I did not solve the problem.

Table 1: Implicative verbs give rise to entailments involving their compliment clauses. Non-implicatives entail neither the truth nor the falsity of their compliments, and thus the truth/falsity of the compliment is unaffected by negation of the main clause.

compliment clauses. Individual implicatives can differ in the entailments they generate: e.g. while *manage* entails the truth of its compliment, *fail* entails the falsity of its compliment (*failed to solve the problem ⇒ didn't solve the problem*). Despite these differences, however, implicatives represent a coherent class of verbs in that they permit some inference to be made about their compliments, and this inference is sensitive to the context (positive/negated) of the main clause. This contrasts with *non-implicative verbs*, like *want*, which do not permit any inference regarding their compliments, and for which the truth of the compliment is unaffected by negation in the main clause (Table 1).

The method described in this paper aims to separate implicatives from non-implicatives (*manage* vs. *want*), rather than to differentiate between types implicatives (*manage* vs. *fail*). Making this implicative/non-implicative distinction is a necessary first step toward handling inferences involving embedded clauses, and one that, to date, has only been performed using manually-constructed word lists (**?**; **?**).

2.1 Tense constraints on compliment clauses

?) observed that, in sentences involving implicatives, the tense of the main verb must necessarily match the tense of the compliment clause. For example, (3), in which the main clause and the compliment are both in the past tense, is acceptable but (4), in which the compliment is in the future, is clearly not. For non-implicatives, however, no such constraint exists: (6) is perfectly felicitous.

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tives, factives presuppose, rather than entail, their compliments. E.g. both *I was/was not glad to solve the problem* entail *I solved the problem*. We do not address factives here, as factives rarely take infinitival compliments: more often, they take "that" compliments (e.g. *know that, realize that*). Factives that do take infinitival compliments are mostly phrasal (e.g. *be glad to*).

(3) I <u>managed</u> to solve the problem <u>last night</u>.

(4) #I <u>managed</u> to solve the problem <u>tomorrow</u>.

(5) I <u>planned</u> to solve the problem <u>last night</u>.

(6) I <u>planned</u> to solve the problem <u>tomorrow</u>.

We exploit this property to predict *implicativeness*– whether the truth of a verb's compliment can be inferred– by observing the verb's usage in practice.

3 Method

We hypothesize that, given a large corpus, we should be able to distinguish implicative verbs from non-implicative verbs by observing how often the main verb tense agrees/disagrees with the tense of the compliment clause. Unfortunately, verbs in infinitival compliment clauses are not conjugated, and so are not necessarily marked for tense. We therefore use the Stanford Temporal Tagger (TT) (**?**) in order to identify time-referring expressions (e.g. *tomorrow* or *last night*) and resolve them to either past, present, or future tense.

We find all sentences containing VB_1^* *to* VB_2 constructions in the Annotated Gigaword corpus (**?**). We run the the TT over all of the sentences in order to identify time-referring expressions. We only consider sentences in which a time-referring expression appears and is in a direct dependency relationship with the compliment verb (VB_2). We provide the TT with the document publication dates,[3] which are used to resolve each time mention to a specific calendar date and time. We then map these time expressions coarsely to either past, present, or future tense by comparing the resolved time to the document creation time. Because of the fact that days

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[3]Provided as metadata in the Annotated Gigaword.

were often not resolved correctly, or at all, we eventually throw away sentences in which the compliment clause is labeled as present tense, as these are rarely true references to the present, and rather the result of incorrect time resolution, or implicit future references (e.g. *I am going to solve the problem today* implies the future as in *later today*, but this is not captured by the TT). We also assign the main clause to past, present, or future tense by using the fine-grained POS tag and a set of heuristics (for example, to check for modals).[4]

We assign a *tense agreement* score to each verb v as follows. Let S be the set of all VB_1^* *to* VB_2 constructions in which $VB_1^* == v$. Then tense agreement is simply $\frac{1}{|S|} \times |\{s \in S \mid$ compliment tense == main tense$\}|$, i.e. the fraction of constructions in S in which the tenses of the main and compliment clauses agree. We expect implicative verbs to occur mostly in agreeing constructions, and thus have high tense agreement, while non-implicatives may occur in both agreeing and non-agreeing constructions, and thus should have lower tense agreement. Note that while in theory, implicatives should never appear in non-agreeing constructions, the time annotation process is very imprecise, and thus we do not expect perfect results.

4 Evaluation

Recreating list from Karttunen (1971 ?) provides a short illustrative list of 7 known implicatives[5] and 8 non-implicatives (shown in Table 2). As a first evaluation, we test whether tense agreement can accurately separate the verbs in this list, such that the implicatives are assigned higher agreement scores than the non-implicatives. Table 2 shows that this is indeed the case. Tense agreement almost perfectly divides the list, with implicative verbs appearing above non-implicative verbs in all cases. The one exception is *decide* (reportedly non-implicative), which appears above *dare* (reportedly implicative). This error, however, seems understandable: while *decide* is not strictly implicative in

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[4]Full set of heuristics in supplementary material.

[5]The original list had 8 implicatives, but we omit *remember* since, in our data, it occurred almost exclusively with recurring time expressions, which we were not able to map to a specific date/time and thus tense, e.g. *consumers must remember to make payments every 14 days*.

the way *manage* is, it is often used as an implicative. E.g. the sentence *I decided to leave* would likely be taken to mean *I left*.

venture to	1.00	try to	0.42
forget to	0.80	agree to	0.34
manage to	0.79	promise to	0.22
bother to	0.61	want to	0.14
happen to	0.59	intend to	0.12
get to	0.52	plan to	0.10
decide to	0.45	hope to	0.03
dare to	0.44		

Table 2: Tense agreement scores for known implicatives (bold) and non-implicatives listed in **?**). Ranking by tense agreement almost perfectly divides the two classes.

Predicting entailment Our interest is not in distinguishing implicatives from non-implicatives for its own sake, but rather to predict, based on the main verb, whether the truth of the compliment can be inferred. We therefore conduct a second evaluation to assess how well tense agreement predicts this entailment property. We design our evaluation following the recognizing textual entailment (RTE) task (**?**), in which two sentences are given, a premise p and a hypothesis h, and the goal is to determine whether p reasonably entails h. To construct our p/h pairs, we take all the verbs extracted in Section 3 which appear in at least 50 tense-labeled sentences. For each of these verbs, we choose 3 random sentences in which the verb appears as VB_1^* in a VB_1^* *to* VB_2 construction.[6] From each sentence, we extract the compliment clause by deleting VB_1^* *to* from the sentence, and conjugating VB_2 to match the tense of VB_1^*. We then use the original sentence as p and the extracted compliment as h: e.g. a p/h pair might look like *I get to interact with fellow professors/I interact with fellow professors*. We ask 5 independent annotators on Amazon Mechanical Turk to read each p and then determine whether h is true, false, or unclear given p.[7] We take the majority answer as the true label. We expect that implicative verbs should lead to judgements which are decidedly true or false while non-implicatives should lead to mostly judgements of unclear.

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[6]These sentences can come from anywhere in the Gigaword corpus, they are not required to contain time expressions.

[7]Full annotation guidelines in supplementary material.

(**0.14**) UFJ **wants to merge** with Mitsubishi, a combination that'd surpass Citigroup as the world's biggest bank. $\not\Rightarrow$ The merger of Japanese Banks creates the world's biggest bank.
(**0.55**) After graduating, Gallager **chose to accept** a full scholarship to play football for Temple University. $\Rightarrow$ Gallager attended Temple University.
(**0.68**) Wilkins **was allowed to leave** in 1987 to join French outfit Paris Saint-Germain. $\Rightarrow$ Wilkins departed Milan in 1987.

Table 3: Examples from the RTE3 dataset (**?**) which require recognizing implicative behavior, even in verbs that are not implicative by definition. The tendency of certain verbs (e.g. *be allowed*) to behave as *de facto* implicatives is captured surprisingly well by the tense agreement score (shown in parentheses).

Figure 1 shows that these expectations hold. When a verb with low tense agreement appeared as the main verb of a sentence, the truth of the compliment could only be inferred 30% of the time. When a verb with high tense agreement appeared as the main verb, the truth of the compliment could be inferred 91% of the time. This difference is significant at $p < 0.01$. That is, tense agreement provides a strong signal for identifying non-implicative verbs, and thus can help systems avoid false-positive entailment judgements, e.g. incorrectly inferring that *wanting to merge $\Rightarrow$ merging*.
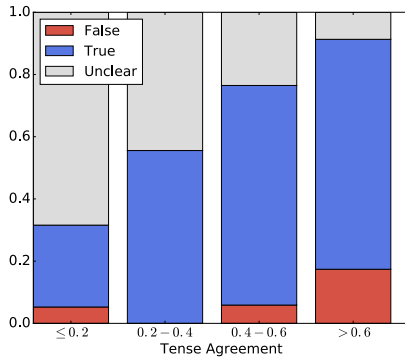

Figure 1: Whether or not compliment is entailed for main verbs with varying levels of tense agreement. Verbs with high tense agreement yield more definitive judgments (true/false). Each bar represents aggregated judgements over approx. 20 verbs.

Interestingly, tense agreement accurately models verbs that are not implicative by definition, but which nonetheless tend to behave implicatively in practice. For example, our method finds high tense agreement for *choose to* and *be allowed to*, which are often used to communicate, albeit indirectly, that their compliments did in fact happen. To convince ourselves that treating such verbs as implicatives makes sense in practice, we manually look through the RTE3 dataset (**?**) for examples containing high-scoring verbs according to our method. Table 3

shows some example inferences that hinge precisely on recognizing these types of *de facto* implicatives.

5   Discussion and Related Work

Language understanding tasks such as RTE (**?**; **?**) and bias detection (**?**) have been shown to require knowledge of implicative verbs, but such knowledge has previously come from manually-built word lists rather than from data. **?**) and **?**) describe automatic systems to handle implicatives, but require hand-crafted rules for each unique verb that is handled. The tense agreement method we present offers a starting point for acquiring such rules from data, and is well-suited for incorporating into statistical systems. The clear next step is to explore similar data-driven means for learning the specific behaviors of individual implicative verbs, which has been well-studied from a theoretical perspective (**?**; **?**; **?**; **?**). Another interesting extension concerns the role of tense in word representations. While currently, tense is rarely built directly into distributional representations of words (**?**; **?**), our results suggest it may offer important insights into the semantics of individual words. We leave this question as a direction for future work.

6   Conclusion

Differentiating between implicative and non-implicative verbs is important for discriminating inferences that can and cannot be made in natural language. We have presented a data-driven method that captures the implicative tendencies of verbs by exploiting the tense relationship between the verb and its compliment clauses. This method effectively separates known implicatives from known non-implicatives, and, more importantly, provides good predictive signal in an entailment recognition task.

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