So-Called Non-Subsective Adjectives

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Abstract

The interpretation of adjective-noun pairs plays a crucial role in tasks such as recognizing textual entailment. Formal semantics often places adjectives into a taxonomy which should dictate adjectives' entailment behavior when placed in adjective-noun compounds. However, we show experimentally that the behavior of *subsective* adjectives (e.g. *red*) versus *non-subsective* adjectives (e.g. *fake*) is not as cut and dry as often assumed. For example, inferences are not always symmetric: while *ID* is generally considered to be mutually exclusive with *fake ID*, *fake ID* is considered to entail *ID*. We discuss the implications of these findings for automated natural language understanding.

1 Introduction

Most adjectives are *subsective*, meaning that an instance of an adjective-noun phrase is an instance of the noun: a *red car* is a *car* and a *successful senator* is a *senator*. In contrast, adjective-noun phrases involving *non-subsective* adjectives, such as *imaginary* and *former* (Table 1), denote a set that is disjoint from the denotation of the nouns they modify: an *imaginary car* is not a *car* and a *former senator* is not a *senator*. Understanding whether or not adjectives are subsective is critical in any task involving natural language inference. For example, consider the below sentence pair from the Recognizing Textual Entailment (RTE) task (Giampiccolo et al., 2007):

1. (a) U.S. District Judge Leonie Brinkema accepted would-be hijacker Zacarias Moussaoui's guilty pleas . . .
   (b) Moussaoui participated in the Sept. 11 attacks.

Privative Non-Subsective (AN $\cap$ N = $\emptyset$)			
anti-	artificial	counterfeit	deputy
erstwhile	ex-	fabricated	fake
false	fictional	fictitious	former
hypothetical	imaginary	mock	mythical
onetime	past	phony	pseudo-
simulated	spurious	virtual	would-be
Plain Non-Subsective (AN $\not\subset$ N and AN $\cap$ N $\neq \emptyset$)			
alleged	apparent	arguable	assumed
believed	debatable	disputed	doubtful
dubious	erroneous	expected	faulty
future	historic	impossible	improbable
likely	mistaken	ostensible	plausible
possible	potential	predicted	presumed
probable	proposed	putative	questionable
seeming	so-called	supposed	suspicious
theoretical	uncertain	unlikely	unsuccessful

Table 1: 60 non-subsective adjectives from Nayak et al. (2014). Noun phrases involving non-subsective adjectives are assumed not to entail the head noun. E.g. *would-be hijacker* $\not\Rightarrow$ *hijacker*. (See Section 2 for definition of privative vs. plain).

In this example, recognizing that 1(a) does not entail 1(b) hinges on understanding that a *would-be hijacker* is not a *hijacker*.

The observation that adjective-nouns (ANs) involving non-subsective adjectives do not entail the underlying nouns (Ns) has led to the generalization that the deletion of non-subsective adjectives tends to result in contradictory utterances: *Moussaoui is a would-be hijacker* entails that it is not the case that *Moussaoui is a hijacker*. This generalization has prompted normative rules for the treatment of such adjectives in various NLP tasks. In information extraction, it is assumed that systems cannot extract useful rules from sentences containing non-subsective modifiers (Angeli et al., 2015), and in RTE, it is assumed that systems should uniformly penalize insertions and deletions of non-subsective adjectives (Amoia and Gardent, 2006).

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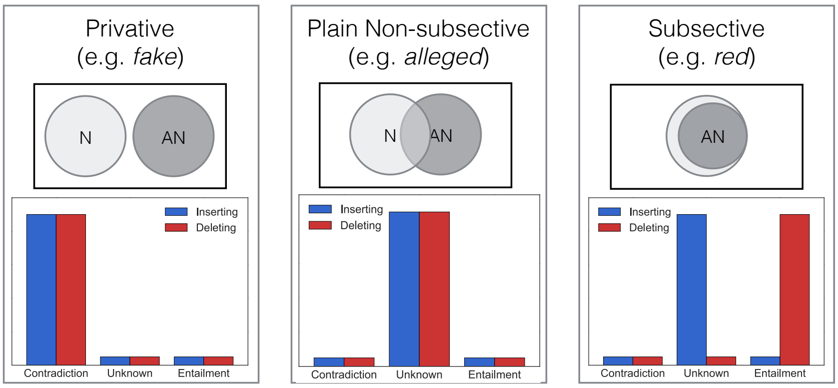


Figure 1: Three main classes of adjectives. If their entailment behavior is consistent with their theoretical definitions, we would expect our annotations (Section 3) to produce the insertion (blue) and deletion (red) patterns shown by the bar graphs. Bars (left to right) represent CONTRADICTION, UNKNOWN, and ENTAILMENT

While these generalizations are intuitive, there is little experimental evidence to support them. In this paper, we collect human judgements of the validity of inferences following from the insertion and deletion of various classes of adjectives and analyze the results. Our findings suggest that, in practice, most sentences involving non-subsective ANs can be safely generalized to statements about the N. That is, non-subsective adjectives often behave like normal, subsective adjectives. On further analysis, we reveal that, when adjectives do behave non-subsectively, they often exhibit asymmetric entailment behavior in which insertion leads to contradictions (*ID* $\Rightarrow$ $\neg$ *fake ID*) but deletion leads to entailments (*fake ID* $\Rightarrow$ *ID*). We present anecdotal evidence for how the entailment associated with inserting/deleting a non-subsective adjective depends on the salient properties of the noun phrase under discussion, rather than on the adjective itself.

2 Background and Related Work

Classes of Adjectives. Adjectives are commonly classified taxonomically as either subsective or non-subsective (Kamp and Partee, 1995). Subsective adjectives are adjectives which pick out a subset of the set denoted by the unmodified noun; that is, AN $\subset$ N[1]. For non-subsective adjectives, in contrast, the AN cannot be guaranteed to be a subset of N. For example, *clever* is subsective, and so a *clever thief* is always a *thief*. However, *alleged* is non-subsective, so there are many possible worlds in which an *alleged thief* is not in fact a *thief*. Of course, there may also be many possible worlds in which the *alleged thief* is a *thief*, but the word *alleged*, being non-subsective, does not guarantee this to hold.

Non-subsective adjectives can be further divided into two classes: *privative* and *plain*. Sets denoted by privative ANs are completely disjoint from the set denoted by the head N (AN $\cap$ N = $\emptyset$), and this mutual exclusivity is encoded in the meaning of the A itself. For example, *fake* is considered to be a quintessential privative adjective since, given the usual definition of *fake*, a *fake ID* can not actually be an *ID*. For plain non-subsective adjectives, there may be worlds in which the AN is and N, and worlds in which the AN is not an N: neither inference is guaranteed by the meaning of the A. As mentioned above, *alleged* is quintessentially plain non-subsective since, for example, an *alleged thief* may or may not be an actual *thief*. In short, we can summarize the classes of adjectives in the following way: subsective adjectives entail the nouns they modify, privative adjectives contradict the nouns they modify, and plain non-subsective adjectives are compatible with (but do not entail) the nouns they modify. Figure 1 depicts these distinctions.

While the hierarchical classification of adjectives described above is widely accepted and often applied in NLP tasks (Amoia and Gardent, 2006; Amoia and Gardent, 2007; Boleda et al., 2012; McCrae et al., 2014), it is not undisputed. Some linguists take the position that in fact privative ad-

[1]We use the notation N and AN to refer both the the natural language expression itself (e.g. *red car*) as well as its denotation, e.g. $\{x|x \textit{ is a red car}\}$.

jectives are simply another type of subsective adjective (Partee, 2003; McNally and Boleda, 2004; Abdullah and Frost, 2005; Partee, 2007). Advocates of this theory argue that the denotation of the noun should be expanded to include both the properties captured by the privative adjectives as well as those captured by the subsective adjectives. This expanded denotation can explain the acceptability of the sentence *Is that gun real or fake?*, which is difficult to analyze if *gun* entails *¬fake gun*. More recent theoretical work argues that common nouns have a "dual semantic structure" and that non-subsective adjectives modify part of this meaning (e.g. the functional features of the noun) without modifying the extension of the noun (Del Pinal, 2015). Such an analysis can explain how we can understand a *fake gun* as having many, but not all, of the properties of a *gun*.

Several other studies abandon the attempt to organize adjectives taxonomically, and instead focus on the properties of the modified noun. Nayak et al. (2014) categorize non-subsective adjectives in terms of the proportion of properties that are shared between the N and the AN and Pustejovsky (2013) focus on syntactic cues about exactly which properties are shared. Bakhshandh and Allen (2015) analyze adjectives by observing that, e.g., *red* modifies `color` while *tall* modifies `size`. In Section 5, we discuss the potential benefits of pursuing these property-based analyses in relation to our experimental findings.

Recognizing Textual Entailment. We analyze adjectives within the context of the task of Recognizing Textual Entailment (RTE) (Dagan et al., 2006). The RTE task is defined as: given two natural language utterances, a premise p and a hypothesis h, would a typical human reading p likely conclude that h is true? We consider the RTE task as a three-way classification: ENTAILMENT, CONTRADICTION, or UNKNOWN (meaning p neither entails nor contradicts h).

3 Experimental Design

Our goal is to analyze how non-subsective adjectives effect the inferences that can be made about natural language. We begin with the set of 60 non-subsective adjectives identified by Nayak et al. (2014), which we split into plain non-subsective and privative adjectives (Table 1).[2] We search through the Annotated Gigaword corpus (Napoles et al., 2012) for occurrences of each adjective in the list, restricting to cases in which the adjective appears as an adjective modifier of (is in an *amod* dependency relation with) a common noun (NN). For each adjective, we choose 10 sentences such that the adjective modifies a different noun in each. As a control, we take a small sample 100 ANs chosen randomly from our corpus. We expect these to contain almost entirely subsective adjectives.

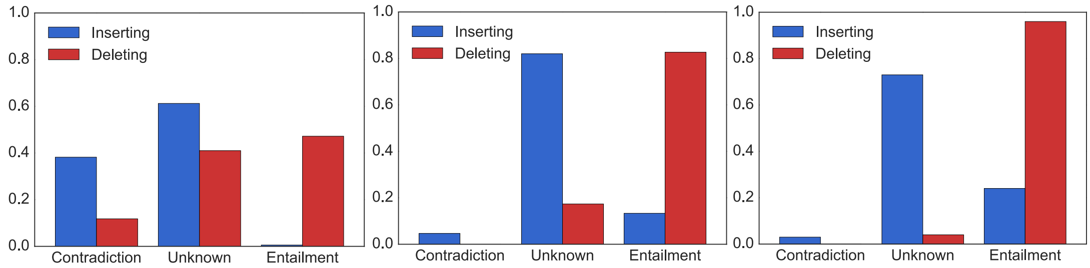
For each selected sentence s, we generate s' by deleting the non-subsective adjective from s. We then construct two RTE problems, one in which $p = s$ and $h = s'$ (the *deletion* direction), and one in which $p = s'$ and $h = s$ (the *insertion* direction). For each RTE problem, we ask annotators to indicate on a 5-point scale how likely it is that p entails h, where a score of -2 indicates definite contradiction and a score of 2 indicates definite entailment. We use Amazon Mechanical Turk, requiring annotators to pass a qualification test of simple RTE problems before participating. We solicit 5 annotators per p/h pair, taking the majority answer as truth. Workers show moderate agreement on the 5-way classification ($\kappa = 0.44$).

Disclaimer. This design does not directly test the taxonomic properties of non-subsective ANs. Rather than asking "Is this instance of AN an instance of N?" we ask "Is this statement that is true of AN also true of N?" While these are not the same question, theories based on the former question often lead to overly-cautious approaches to answering the latter question. For example, in information extraction, the assumption is often made that sentences with non-subsective modifiers cannot be used to extract facts about the head N (Angeli et al., 2015). We focus on the latter question, which is arguably more practically relevant for NLP, and accept that this prevents us from commenting on the underlying taxonomic relations between AN and N.

4 Results

Expectations. Based on the theoretical adjective classes described in Section 2, we expect that both the insertion and the deletion of privative adjectives from a sentence should result in judgments of CONTRADICTION: i.e. it should be the case that *fake ID* $\Rightarrow \neg$ *ID* and *ID* $\Rightarrow \neg$ *fake ID*. Similarly, we expect plain non-subsective adjectives

[2] The division of these 60 adjectives into privative/plain is based on our own understanding of the literature, not on Nayak et al. (2014).



(a) Privative (b) Plain Non-Sub. (c) Subsective

Figure 2: Observed entailment judgements for insertion (blue) and deletion (red) of adjectives. Compare to expected distributions in Figure 1.

to receive labels of UNKNOWN in both directions. We expect the subsective adjectives to receive labels of ENTAILMENT in the deletion direction (*red car* ⇒ *car*) and labels of UNKNOWN in the insertion direction (*car* $\not\Rightarrow$ *red car*). Figure 1 depicts these expected distributions.

Observations. The observed entailment patterns for insertion and deletion of non-subsective adjectives are shown in Figure 2. Our control sample of subsective adjectives (Figure 2c) largely produced the expected results, with 96% of deletions producing ENTAILMENTs and 73% of insertions producing UNKNOWNs.[3] The entailment patterns produced by the non-subsective adjectives, however, did not match our predictions. The plain non-subsective adjectives (e.g. *alleged*) behave nearly identically to how we expect regular, subsective adjectives to behave (Figure 2b). That is, in 80% of cases, deleting the plain non-subsective adjective was judged to produce ENTAILMENT, rather than the expected UNKNOWN. The examples in Table 2 shed some light onto why this is the case. Often, the differences between N and AN are not relevant to the main point of the utterance. For example, while an *expected surge in unemployment* is not a *surge in unemployment*, a policy that deals with an *expected surge* deals with a *surge*.

The privative adjectives (e.g. *fake*) also fail to match the predicted distribution. While insertions often produce the expected CONTRADICTIONs, deletions produce a surprising number of ENTAILMENTS (Figure 2a). Such a pattern does not fit into any of the adjective classes from Figure 1. While some ANs (e.g. *counterfeit money*) behave in the prototypically privative way, others

[3] A full discussion of the 27% of insertions that deviated from the expected behavior is given in Pavlick and Callison-Burch (2016).

(1)	Swiss officials on Friday said they've launched an investigation into Urs Tinner's **alleged role**.
(2)	To deal with an **expected surge** in unemployment, the plan includes a huge temporary jobs program.
(3)	They kept it close for a half and had a **theoretical chance** come the third quarter.

Table 2: Contrary to expectations, the deletion of plain non-subsective adjectives often preserves the (plausible) truth in a model. E.g. *alleged role* $\not\Rightarrow$ *role*, but *investigation into alleged role* ⇒ *investigation into role*.

(e.g. *mythical beast*) have the property in which N⇒¬AN, but AN⇒N (Figure 3). Table 3 provides some telling examples of how this AN⇒N inference, in the case of privative adjectives, often depends less on the adjective itself, and more on properties of the modified noun that are at issue in the given context. For example, in Table 3 Example 2(a), a *mock debate* probably contains enough of the relevant properties (namely, arguments) that it can entail *debate*, while in Example 2(b), a *mock execution* lacks the single most important property (the death of the executee) and so cannot entail *execution*. (Note that, from Example 3(b), it appears the jury is still out on whether *leaps in artificial intelligence* entail *leaps in intelligence*...)

5 Discussion

The results presented suggest a few important patterns for NLP systems. First, that while a non-subsective AN might not be an instance of the N (taxonomically speaking), statements that are true of an AN are often true of the N as well. This is relevant for IE and QA systems, and is likely to become more important as NLP systems focus more on "micro reading" tasks (Nakashole and Mitchell, 2014), where facts must be inferred from single documents or sentences, rather than by exploiting

(1a)	ENTAIL.	Flawed **counterfeit software** can corrupt the information entrusted to it.
(1b)	CONTRA.	Pharmacists in Algodones denied selling **counterfeit medicine** in their stores.
(2a)	ENTAIL.	He also took part in a **mock debate** Sunday.
(2b)	CONTRA.	Investigation leader said the prisoner had been subjected to a **mock execution**.
(3a)	ENTAIL.	The plants were grown under **artificial light** and the whole operation was computerised.
(3b)	UNKNOWN	Thrun predicted that leaps in **artificial intelligence** would lead to driverless cars on the roads by 2030.

Table 3: Entailment judgements for the *deletion* of various privative adjectives from a sentence. Whether or not deletion results in CONTRADICTION depends on which properties of the noun are most relevant.

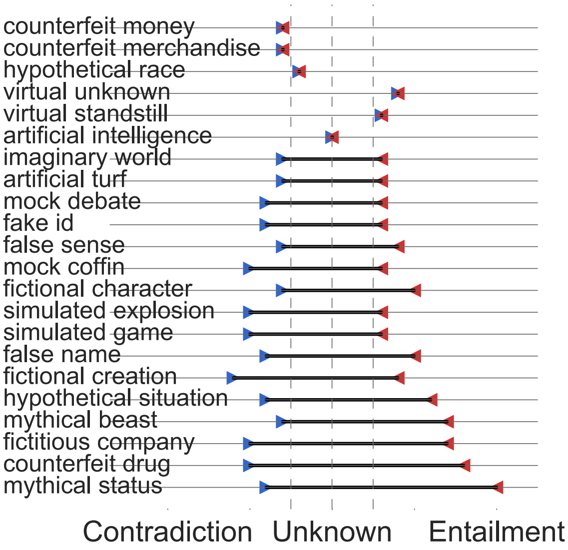


Figure 3: Entailments scores for insertion (blue) and deletion (red) for various ANs. E.g. the bottom line says that *status* $\Rightarrow \neg$ *mythical status* (insertion produces CONTRADICTION), but *mythical status* $\Rightarrow$ *status* (deletion produces ENTAILMENT).

the massive redundancy of the web. Second, the asymmetric entailments associated with privative adjectives suggests that the contradictions generated by privative adjectives may not be due to a strict denotational contradiction, but rather based on implicature: i.e. if an *ID* is in fact *fake*, the speaker is obligated to say so, and thus, when *ID* appears unmodified, it is fair to assume it is not a *fake ID*. Testing this hypothesis is left for future research. Finally, the examples in Tables 2 and 3 seem to favor a properties-oriented analysis of adjective semantics, rather than the taxonomic analysis often used. Nayak et al. (2014)'s attempt to characterize adjectives in terms of the number of properties the AN shares with N is a step in the right direction, but it seems that what is relevant is not *how many* properties are shared, but rather *which* properties are shared, and which properties are at issue in the given context.

6 Conclusion

We present experimental results on textual inferences involving non-subsective adjectives. We show that, contrary to expectations, the deletion of non-subsective adjectives from a sentence does not necessarily result in non-entailment. Thus, in applications such as information extraction, it is often possible to extract true facts about the N from sentences involving a non-subsective AN. Our data suggests that inferences involving non-subsective adjectives require more than strict reasoning about denotations, and that a treatment of non-subsective adjectives based on the properties of the AN, rather than its taxonomic relation to the N, is likely to yield useful insights.

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