Montague semantics and modifier consistency measurement in neural language models

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Abstract
In recent years, distributional language representation models have demonstrated great practical success. At the same time, the need for interpretability has elicited questions on their intrinsic properties and capabilities. Crucially, distributional models are often inconsistent when dealing with compositional phenomena in natural language, which has significant implications for their safety and fairness. Despite this, most current research on compositionality is directed towards improving their performance on similarity tasks only. This work takes a different approach, and proposes a methodology for measuring compositional behavior in contemporary language models. Specifically, we focus on adjectival modifier phenomena in adjective-noun phrases. We introduce three novel tests of compositional behavior inspired by Montague semantics. Our experimental results indicate that current neural language models behave according to the expected linguistic theories to a limited extent only. This raises the question of whether these language models are not able to capture the semantic properties we evaluated, or whether linguistic theories from Montagovian tradition would not match the expected capabilities of distributional models.

1 Introduction
Distributional semantics and neural language models have been a dominant approach in language representation models for nearly a decade since the emergence of deep learning methods (Lenci et al., 2022). This is due to the consistent achievements in terms of the state-of-the-art performance in various downstream NLP tasks and the progressive increase of their parameter size and complexity. Interest in the properties of these models and their relationships with semantic formalisms is older than their rise to mainstream use (Baroni and Zamparelli, 2010). However, the recent demand for models delivering safety guarantees and better inference control has highlighted its importance (Floridi and Chiriatti, 2020).

Indeed, understanding the intrinsic linguistic and semantic properties of distributional neural language models can provide important insight on their capabilities and limitations. From a purely distributional perspective, studies have been conducted on analysing the concept drift (Sommerauer and Fokkens, 2019) and biases (Bhardwaj et al., 2021) of such models. On a linguistic front, attempts at mapping vector representations to dictionary senses and lexical features have yielded promising results (Pilehvar andNavigli, 2015; Carvalho and Nguyen, 2017). Similarly, works that probed for the presence of linguistic features in sentence-level representations revealed a wide array of syntactic information captured (Miaschi and Dell’Orletta, 2020; Ferreira et al., 2021).

However, one issue that has been underexplored from a linguistic standpoint is compositionality and their associated set-theoretic (Montagovian) concepts, where efforts have been directed towards improving performance of the representations on similarity tasks (see Section 5), without attempting to relate the linguistic principles involved with compositional properties observed.

This work proposes to fill this research gap, electing the modifier phenomena as a starting point for the analysis of compositional properties in language models, and adopting text embeddings as proxies of concept denotations. In this way, we can test the manifestation of compositional properties in adjective phrase denotations, such as intersectivity, as a function of the consistency of geometric properties in the embedding space, in the form of metamorphic relations. The hypothesis of proxying denotations through embeddings has been implicitly used for the “vector analogy” tasks (e.g., king − man + woman = queen), but is used here explicitly to test denotation properties in the embedding space.
Similarly, the concept of metamorphic relation has recently waded its way from the field of software engineering (Chen et al., 2018) to machine learning and natural language processing (Belinkov and Bisk, 2018; Manino et al., 2022). There, it brings the promise of formally defining the expected behavior of a learning-based model and rigorously testing whether it holds in practice without the need for ground-truth labels. Popular applications of behavioral testing usually focus on plain substitutions of similar words (e.g., robustness to synonym replacement) (Jia et al., 2019), or semantic opposition (e.g., changing the gender of nouns) (Ma et al., 2020). However, efforts have been made to extend this framework to higher-level linguistic properties such as systematicity and transitivity (Manino et al., 2022). The present work continues this line of research by grounding the concept of metamorphic relation onto the linguistic tradition of formal semantics.

**Hypothesis [embedding-denotation analogy]:** Assume that the modifier phenomena is described by a Set representation/Montague semantics compositional model. We expect a large language model, which at the limit captures the distributional properties of an infinite corpus of utterances, to show empirical evidence of the formal properties of the modifier phenomena.

**Research Questions:** In this paper, we restrict our inquiry to adjective modifiers and contemporary neural language models. In this setting, we can pose the following research questions:

**RQ1.** Adjective-noun composition is described in Montague semantics as a function mapping elements between two sets $A \rightarrow P$ corresponding to the properties satisfied by the individuals referred by each set (denotation). Can we expect to observe a correspondence of these theoretical linguistic properties in neural language models that operate on dense vector spaces?

**RQ2.** Existing neural language models are limited by their choices of the learning process (objective functions) and the language data available for model training. To what degree can we observe evidence of the compositional effect of adjective modifiers? Do contextual models differ from non-contextual ones in this regard?

**Contributions:** We propose a methodology for measuring the presence of compositional behaviour in contemporary neural language models related to adjectival modifier phenomena in adjective-noun phrases, from a Montagovian formalism perspective. Our methodology translates a set-based formal semantic theory into metamorphic relations in embedding spaces based on the cosine distance between embeddings (RQ1). Our results show that current neural language models do not behave consistently according to the linguistic theories with regard to the evaluated intersective property. In fact, there is no statistically significant difference between different adjective categories: the empirical behaviour we observe tends to be intersective across all inputs and language models (RQ2). On the other hand, the differences between adjective categories are noticeable in single adjective interactions, indicating that such differences are encoded in individual word representations, but they do not transfer generally in the expected way to the compositions (RQ2). This raises the question of whether current language models are not capable of capturing the evaluated semantic properties of language on limited context, or whether linguistic theories from Montagovian tradition would not match expected capabilities of distributional models.

The remainder of this paper is organized as follows: Section 2 explains the linguistic grounding of this work in more detail, Section 3 discusses our methodology, Section 4 reports our experimental setup and discusses its findings, Section 5 presents the broader landscape of related works, and finally Section 6 summarizes our contribution and concludes with some final remarks.

## 2 The modifier phenomena

Of all linguistic phenomena arising from the composition of meaning of two or more words, modification, and in particular the application of adjectives, has been the subject of extensive study (Dixon et al., 2004; Morzycki, 2016).

### 2.1 Modification semantics

From a linguistic standpoint, modification does not constitute a single grammatical phenomenon, being a term for expressions that do not fit into either the predicate or argument categories. In fact, modification characterizes both a family of (internal) lexical semantic characteristics and of (external) distributional ones (Morzycki, 2016). For the purpose of our study, we narrow down the definition of modifiers to a set of compositional principles regarding intensional interpretations from a Montagovian formalism, with adjective phrases being
Adjectives can be classified according to their effect on the denotations they modify. E.g. “alleged criminal” denotes a set of individuals whose inclusion in the set of criminals is dubious or undefined, while “former president” denotes a set of individuals that are not presidents anymore.

- **Plain non-subsective:** describes a set that may or may not be a subset of the noun denotation it modifies, depending on the context or the adjective itself. E.g. “alleged criminal” denotes a set of individuals whose inclusion in the set of criminals is dubious or undefined, while “former president” denotes a set of individuals that are not presidents anymore.

- **Ambiguous:** can be applied to any of the previous categories, depending on the context and the modified noun. E.g. “big” is intersective in the phrase “big truck” and subsective non-intersective in the phrase “big fool”.

Section 3.1 contains a further formalization of these adjective types and their related properties.

### 2.3 Distributional questions

Hanging fundamentally on the distributional hypothesis, distributional models are primarily optimised for capturing statistical co-occurrence relations (syntagmatic and paradigmatic relations) at scale. As a result, distributional models naturally excel at computing measures of semantic relatedness and semantic similarity between any given pair of terms in a corpus. However, their ability at capturing more structured compositional behaviour is unclear.

Efforts at building distributional models that exhibit compositional behaviour by construction has been made in the past (Clark and Pulman, 2007; Mitchell and Lapata, 2008; Guevara, 2010). Unfortunately, these efforts predate the advent of state-of-the-art self-supervised language models, and cannot compete with their performance. In fact, recent language models have tackled composition in more implicit ways, with state-of-the-art approaches being trained on multiple objectives such as masked word prediction, sentence-level similarity and entailment functions (Reimers and Gurevych, 2019; San, 2019; Ni et al., 2022).

This raises the question of whether the representations obtained in this way could be employed as proxies for word and phrase denotations. If this is the case, then any term comparisons made in the embedding spaces would represent an equivalent operation between denotations (e.g., subset inclusion). Conversely, set theoretical properties on denotations could be interpreted as geometrical
properties of the embedding space (e.g., vector distance constraints). This understanding lies at the foundation of the methodology presented hereon.

3 Methodology

Our methodology is centred around the hypothesis that neural embeddings should correctly approximate the linguistic denotation of the input phrases. In this light, we propose three different metamorphic tests to check whether neural models satisfy such hypothesis.

3.1 Set-based phrase denotations

In general, we say that a noun $n$ can be modified by an adjective $a$ to form an adjective-noun phrase $p = an$. The denotation of $p$ can be represented as a set, and depends on the type of the adjective $a$ (see Section 2). More specifically, we divide the adjectives into two main categories: intersective and non-intersective. Here, the non-intersective category includes both subsective and non-subsective adjectives.

On the one hand, if $a$ is an intersective adjective, then the denotation of $p$ is simply the intersection of the denotations of $a$ and $n$. For example, the intersective phrase $p = \text{Canadian writer}$ is associated with the following Montague denotations (intensions):

$$n(x) = \lambda x. [\text{writer}(x)]$$

$$a(x) = \lambda x. [\text{Canadian}(x)]$$

$$p(x) = \lambda x. [a(x) \land n(x)]$$

and corresponding sets (extensions):

$$N \equiv \{ x \mid n(x) = \top \}$$

$$A \equiv \{ x \mid a(x) = \top \}$$

$$P \equiv A \land N$$

where $P \subseteq N$ and $P \subseteq A$.

On the other hand, if $a$ is a non-intersective adjective, then the denotation of $p$ involves functions over sets. For example, the phrase $p = \text{skilled writer}$ requires the following Montague denotations:

$$a(n, x) = \lambda n. \lambda x. [\text{skilled}(n(x), x)]$$

$$p(x) = \lambda x. [a(W, x)]$$

where function $a$ can discriminate whether $x$ is a skilled writer, but has no concept of “skillfulness” in general. Accordingly, the corresponding sets (extensions) are:

$$P \equiv A \equiv \{ x \mid p(x) = \top \} \subseteq N$$

Note that in the intersective case (see Equation 1) the set $P$ is included in both $A$ and $N$, whereas in the non-intersective case (see Equation 2) this is not the case. As a result, if we could measure the distance between these three sets for a generic adjective-noun phrase $p = an$, then we should be able to identify the type of the adjective $a$. Figure 2 illustrates this concept of relations between sets.

3.2 Embedding-denotation analogy

Thus, our core hypothesis is the following. If the phrase embedding correctly represents its denotation, we should observe some analogous inclusion relations between them. Since embeddings are defined in vector space, the inclusion relations must be replaced with another appropriate measure (e.g., cosine, Euclidean). This hypothesis motivates the following tests.

3.3 Testing intersectivity (single phrase)

Assume $p = t_1 t_2 \ldots t_k$ is an adjective-noun phrase containing one or more adjectives. If all adjectives were intersective, the corresponding set relations $P \subseteq T_i$ would be satisfied (see Section 3.1). In contrast, any two individual terms $t_j, t_k$ are generally unrelated, yielding $T_j \nsubseteq T_k$. We hypothesise that set inclusion translates into shorter distances between embedding, which leads us to the following test of intersectivity:

$$I_{m,p} \equiv d(\text{emb}_m(p), \text{emb}_m(t_j)) \leq d(\text{emb}_m(t_j), \text{emb}_m(t_k))$$

$$\forall i, j, k; \ j < k$$

where $t_{i..h}$ is a term of the phrase $p$ and $\text{emb}_m$ is the embedding function for model $m$. We define...
We propose to test for non-subsectivity by looking where

with a
Canadian surgeon
when

where

value of Equation 6 should approach 1.0 when all
embedding of
p
do not. Consequently, we hypothesise that the
P
and noun set
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be an adjective-noun phrase with associated set
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noun when combined in a phrase. Let

at the relative change caused by an adjective to a
noun when combined in a phrase. Let

where

are both Canadian. In contrast, a
skilful writer
are not similar as there is
Canadian writer, Canadian surgeon
skilful writer, skillful surgeon
where

Canadian is an intersective adjective and
skilful is not. For example:

d(Canadian writer, Canadian surgeon)
≤ d(skillful writer, skillful surgeon)

where

II_{m,\{p\}} = d(emb_{m}(p_{a_{1}n_{1}}), emb_{m}(p_{a_{1}n_{2}}))
\leq d(emb_{m}(p_{a_{2}n_{1}}), emb_{m}(p_{a_{2}n_{2}}))

when

a_{1}
is intersective and
a_{2}
is not. For example:

d(Canadian writer, Canadian surgeon)
≤ d(skillful writer, skillful surgeon)

where

Canadian
is an intersective adjective and
skilful
is not. This is because we expect a
Canadian writer
to have something in common with a
Canadian surgeon,i.e., the fact that they
are both Canadian. In contrast, a
skillful writer
and
skillful surgeon
are not similar as there is
minimal overlap between their skills.

As for Equation 4, we call the consistency of
m:

E_{m,L}\{II_{m,\{p\}} = \top\}, \quad \{p\} \sim L^{2}

where

\{p\} \equiv \{a_{1}n_{1}, a_{1}n_{2}, a_{2}n_{1}, a_{2}n_{2}\}

The value of Equation 6 should approach 1.0 when all
a_{1}
is intersective and all
a_{2}
is not.

3.5 Testing non-subsectivity

We propose to test for non-subsectivity by looking at the relative change caused by an adjective to a
noun when combined in a phrase. Let
p = an
be an adjective-noun phrase with associated set
P
and noun set
N
. Subsective composition guarantees
P \subseteq N
, whereas non-subsective composition does not. Consequently, we hypothesise that the
embedding of
p
is closer to
n
when
a
is subsective.

Accordingly, we can test for non-subsectivity with the following metamorphic relation:

NI_{m,p} = d(emb_{m}(p), emb_{m}(a))
\leq d(emb_{m}(p), emb_{m}(n))

and the corresponding consistency metric:

E_{m,L}\{NI_{m,p} = \top\}, \quad p \sim L

where
L
is the same language as in Equation 4.

4 Experimentation and discussion

4.1 Experimental setup

To perform the tests introduced in Section 3, we need the following components: a measure of distance
\(d\) in embedding space, a set of adjective-noun phrases covering all adjective types (the input data), and the language models to be tested. In all our experiments we use the cosine distance, the input phrases and the language models described below.

4.1.1 Data collection

We consider adjective categories based on
Morzycki (2016)
and
Pavlick and Callison-Burch (2016)
, where the latter provides a further subdivision of non-subsective adjectives. We select the examples in
Morzycki (2016)
for the sets of subsective adjectives, and we use the dataset in
Pavlick and Callison-Burch, 2016
for the collection of non-subsective adjectives, totaling 61 adjectives. At the same time, we choose a set of 12 nouns covering both concrete and abstract concepts to form adjective/noun phrases.

The adjective and nouns lists were reviewed by each of the authors. While most adjective categorisations were left unchanged, we included an “ambiguous” category to house those adjectives that had ambiguous meaning within our phrase set. The complete list of categorised adjectives is included as supplementary material (Appendix A).

4.1.2 Phrase Generation

The phrases were generated by using a regular language defined by the expression
(‘adj’) + ‘noun’, where
adj
and
noun
are taken from the lists of adjectives and nouns respectively. More formally,\nadj = (wild|red|...)\nand
noun = (student|dog|...). All the phrases up to 3 words were generated: e.g. “wild dog” and “square assumed law”. The final dataset contains 44652 phrases.\footnote{https://bit.ly/3bSaxi}
For reasons of space, we introduce a shorthand notation for the two types of phrases we generate: we write AN (respectively, AAN) to denote a phrase composed of a single adjective followed by a noun (respectively, two adjectives followed by a noun). With slight abuse of notation, we also use AN and AAN to refer to the set interpretation (denotation) of a phrase rather than the phrase itself.

4.1.3 Encoding Strategy & Language Models

As we investigate emergent compositional behaviour, we selected models that provide a single sentence representation rather than a sequence of token representations. Most often than not, these are variants of state-of-the-art transformer-based model. However, they are further trained to generate composed vector representations which are more informative than, for example, mean pooling of token representations. More specifically, we consider sentence-BERT (Reimers and Gurevych, 2019), and sentence-based adaptations of models such as DistilRoBERTa (San, 2019), T5 (Ni et al., 2022), MiniLM (Wang et al., 2020), DPR (Karpukhin et al., 2020) and LaBSE (Feng et al., 2022).

For comparison, we also run the experiments on non-contextual language models trained on a purely distributional objective. In particular, we use mean-pooled representations of the Word2Vec (Mikolov et al., 2013) and Glove (Pennington et al., 2014) models. These models provide a useful baseline to compare the aforementioned contextual models against.

4.2 Results and discussion

4.2.1 Intersectivity experiment (single phrase)

Our first metamorphic property from Section 3.3 requires that the embedding of an adjective-noun phrase lies closer to each term than the distance between any pair of terms. At first glance, the results in Table 1 indicate that all the models satisfy this property to a large degree, at least on AN phrases. Interestingly, there is no perceptible differences between adjective categories.

If we interpret the metric in Equation 4 as indicative of intersective behaviour, we would have to conclude that the models are treating all adjectives intersectively. Alternatively, we could argue that the cosine distance measures the semantic similarity between embeddings, and this choice is poorly reflective of the set-theoretic distance implied by the denotations. However, when we consider the results on phrases with two adjectives (AAN format), the scores tend to get lower. This is especially true when both adjectives are not intersective (more details available on Appendix B).

Another observation relates to the differences in model architectures. Improvements over the BERT architecture, both using knowledge distillation (DistilRoBERTa, MiniLM) or text-to-text encoder-decoders (T5), show a more pronounced intersective effect than base sBERT. This effect may indicate a correlation between the degree of information compression and intersective behaviour. Additionally, with the exception of sBERT, the models using [CLS] token representation (DPR, LaBSE) for the sentence embeddings demonstrate

| Models   | S-I  | S-NI | NS-Pl | NS-Pr | A   |
|----------|------|------|-------|-------|-----|
| sBERT    | 0.95 | 0.97 | 0.99  | 1.0   | 0.97|
| DistilRoBERTa | 1.0 | 1.0 | 1.0   | 1.0   | 1.0 |
| T5       | 1.0  | 1.0  | 1.0   | 1.0   | 1.0 |
| DPR      | 1.0  | 1.0  | 0.98  | 1.0   | 1.0 |
| Labse    | 1.0  | 1.0  | 1.0   | 1.0   | 1.0 |
| MiniLM   | 1.0  | 1.0  | 1.0   | 1.0   | 1.0 |
| Glove    | 1.0  | 1.0  | 1.0   | 1.0   | 1.0 |
| Word2Vec | 1.0  | 1.0  | 1.0   | 1.0   | 1.0 |

Table 1: Consistency scores of the intersective property in Equation 4, for single adjective-noun phrases (AN format). We use the following shorthand notation in the columns: Ambiguous (A), Subsective-Intersective (S-I), Subsective Non-Intersective (S-NI), Plain Non-Subsective (NS-Pl), Privative Non-Subsective (NS-Pr).

| Models   | Adjective Type Pair |
|----------|---------------------|
|          | (S-I, S-I)          |
|          | (S-NI, S-I)         |
|          | (NS-Pl, S-I)        |
|          | (NS-Pr, S-I)        |
|          | (A, S-I)            |
| sBERT    | 0.794 0.735 0.774 0.849 0.765 |
| DistilRoBERTa | 0.981 0.963 0.958 0.975 0.982 |
| T5       | 0.996 0.990 0.993 0.998 1.0   |
| DPR      | 0.825 0.817 0.773 0.844 0.836 |
| Labse    | 0.920 0.934 0.953 0.914 0.967 |
| MiniLM   | 0.980 0.944 0.976 0.992 0.972 |
| Glove    | 1.0 1.0 1.0 0.939 1.0   |
| Word2Vec | 0.997 1.0 0.969 0.940 1.0   |

Table 2: Consistency scores of the intersective property in Equation 4, for adjective-noun phrases with two adjectives (AAN format). Same notation as Table 1. Results for all type combinations are included as supplementary material (Appendix B).
4.2.2 Intersectivity experiment (phrase pair)

Our second metamorphic property from Section 3.4 completes the picture on intersectivity. The property requires adjective-noun phrases that share the same intersective adjective to be closer to each other than phrases with non-intersective ones. Table 3 reports the results of our experiments, which suggest the presence of an intersectivity hierarchy for each language model. For example, sBERT would sort adjectives according to the following order (from more intersective to less intersective): S–I > S–NI > NS–Pl > NS–Pr > A.

4.2.3 Non-subsectivity experiment

Our third metamorphic relation from Section 3.5 requires the adjective to “pull” the embedding of the whole phrase closer to them than the associated noun. This is a reasonable requirement because non-subsective adjectives completely change the meaning of the noun, rather than just specializing it. Our final experiment allows us to test whether this is indeed the behaviour of contemporary language models.

The results are in Table 4. More specifically, sBERT behaves as expected: intersective adjectives display a much higher consistency for the tested property, while non-subsective ones are all much lower. This effect also manifests in the non-contextual models Glove and Word2Vec, perhaps to an even more pronounced degree.

At the same time, the contextual models DistilRoBERTa and T5 differ from sBERT in their treatment of privative non-subsective adjectives, with the consistency score being much closer to that of intersective adjectives. In these cases, the differences between the intersective score and other adjective type scores are much less pronounced, perhaps indicating that this phenomenon is not as strongly modelled by these models.

A case of particular interest is the ambiguously typed adjectives (dependent on the represented word sense): we see that the models do not always seem to agree on the chosen sense. The numerical behaviour hints at whether the model is more likely to choose intersective or non-intersective senses of adjectives such as “old”.

Thus, while adjective type differences display relatively low compositional effects on broad intersectivity in the evaluated models, the effects are noticeable in single adjective interactions. This phenomenon indicates that such differences are encoded in individual word representations, but they do not transfer generally in the expected way to the compositions. Unexpectedly, this is also true for subjective non-intersective adjectives, even in the non-contextual models. This is an indication that such adjective representations carry a stronger signal than the others.

5 Related work

Before the advent of self-supervised language models, much work has gone into constructing formally-motivated vector representations. To this end, Clark and Pulman (2007) employs tensor product operations composition, while (Clark et al., 2008) complements the previous approach with pregroup se-
mantics. Similarly, Mitchell and Lapata (2008) employs vector sums and products, whereas Guevara (2010), Guevara (2011) and Baroni and Zamparelli (2010) model composition as a learnable function of two vectors. In the same vein, Paperno et al. (2014) proposes a generalised representation of composition functions.

At the same time, existing studies cover a wide range of modifier phenomena: adjective-noun (AN) compositions (Boleda et al., 2013), verb-argument composition (Lenci, 2011), determiner-noun (DP) phrases (Bernardi et al., 2013), recursive adjectival modifications (Vecchi et al., 2013), reverse adjectival composition for phrase generation (Dinu and Baroni, 2014), pointwise mutual information (PMI) analysis over AN compositions (Paperno and Baroni, 2016), morpheme representation (Marelli and Baroni, 2015) and metaphorical sense modeling (Lazaridou et al., 2013; Gutierrez et al., 2016).

More recently, syntax-aware composition of dependency tree nodes is comprehensively addressed by Weir et al. (2016), with empirical results tying previous approaches together. This work is complemented by Gamallo (2021) using contextual representations from transformer models. Finally, Purver et al. (2021) proposes a dynamic syntax framework for unambiguous composition of sentences through incremental semantic parsing, which was evaluated with non-contextual representations.

After the advent of contextual transformer-based representation, the interest has shifted into testing for specific compositional behaviours. The majority of existing works on metamorphic testing of language models focus on checking simple behavioural rules at scale (Belinkov and Bisk, 2018). This procedure is sometimes referred to as behavioural testing, as in (Ribeiro et al., 2020).

For example, Ma et al. (2020) investigate fairness-related behaviours by measuring the model robustness to changes in the gender of nouns or addition of population-specific adjectives. Similarly, Sun and Zhou (2018) focus on multi-language machine translation and compare direct translations to multi-hop ones. Likewise, Tu et al. (2021) test the robustness of question-answer systems to changes in the given text. Finally, Manino et al. (2022) define higher-order metamorphic relations that simultaneously mutate multiple base inputs. Thanks to this, they can test the systematicity and transitivity of language models.

Our work centers on behavioural testing for an embedding-denotation analogy, attempting to address concerns (in the fresh context of contextual transformer-based representations) such as the limitation stated in (Kartsaklis, 2014): that compositions may describe spurious relations which result from expressiveness limitations, rather than modelling theoretical compositional behaviour.

6 Conclusion

In this paper, we presented a methodology for measuring the presence and consistency of compositional behaviour in existing language models (LMs), comprising a set of tests for consistency of metamorphic relations associated to adjectival modifier phenomena in adjective-noun phrases, from a Montagovian formalism perspective. Our approach can provide important insight on LMs capabilities and limitations beyond semantic relatedness/similarity, helping to shape expectations on their use in applications with higher safety/criticality/fairness requirements. Although the tests are limited in scope, they can be applied to any language embedding.

Our empirical evaluation results indicate that current neural language models do not behave consistently according to expected behavior from the formalisms, with regard to the evaluated intersecutive property, raising the question of whether current language models, given limited context, are not capable of capturing the evaluated semantic properties of language, or whether linguistic theories from Montagovian tradition are not matching the expected capabilities of distributional models.

On the other hand, the results also show that conforming adjective type differences are encoded by the LMs at word level, which motivates further examination on compositional capabilities of state-of-the-art LMs. Future work also includes expanding the scope of the tests to other linguistic properties and an investigation on the effect of measured consistency on relevant downstream tasks (e.g., Natural Language Inference).

Limitations

Having been designed as a set of measurements for quasi-symbolic analogy, the presented approach is not intended to demonstrate or prove the properties of the distributional models but rather to verify compliance to particular “desirable” behaviours.
Furthermore, while the Montagovian perspective of compositionality is highly relevant from the symbolic and verification standpoints, other theoretical frameworks can present different constraints regarding word and phrase interpretations and are worthy of exploration.

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List of adjectives and nouns

**Subsective (Intersective):** wild, red, Canadian, depressed, square, seasonal, flamboyant, vigorous, loud, orange, shy

**Subsective (Non-Intersective):** skilful, powerful, particular, extreme, rare, unexpected

**Plain Non-Subsective:** former, alleged, apparent, arguable, assumed, believed, disputed, doubtful, erroneous, expected, faulty, future, historic, impossible, improbable, likely, ostensible, plausible, potential, proposed, putative, questionable, so-called, suspicious, theoretical, uncertain, unsuccessful

**Privative Non-Subsective:** artificial, counterfeit, deputy, ex-, fabricated, fictional, hypothetical, imaginary, mock, mythical, past, phony, spurious, virtual

**Ambiguous:** old, small, big

**Nouns:** student, dog, potato, story, king, person, chair, occurrence, law, problem, disaster, statement

Table 5 shows the adjective type composition and definitions for the denotations.

**B Full experimental results**

Tables 6 and 7 present the complete results of the set distance experiments for single phrases and phrase pairs, respectively (Section 4.2.1). Table 8 presents the complete results for the phrase-word distance experiment (Section 4.2.3).
| Adjective Type                      | Set-Theoretic Definition | Examples  | # of Adjectives |
|------------------------------------|--------------------------|-----------|-----------------|
| Subsective (Intersective)          | $A N \subseteq N$ and $A N \subseteq A$ | Red, Wild | 11              |
| Subsective (Non-Intersective)      | $A N \subseteq N$ and $A N \nsubseteq A$ | Skilful, Rare | 6              |
| Non-Subsective (Plain)             | $A N \nsubseteq N$ and $A N \cap N \neq \emptyset$ | Alleged, Disputed | 27            |
| Non-Subsective (Privative)         | $A N \cap N = \emptyset$ | Fake, Imaginary | 14            |
| Ambiguous                          | Contextually, one of the above | Old, Big | 3              |

Table 5: Adjective type composition for the vocabulary.

| Models      | Adjective Type Pair | (S-I, S-I) | (S-NI, S-I) | (NS-Pl, S-I) | (NS-Pr, S-I) | (A, S-I) | (S-I, S-NI) | (S-NI, S-NI) | (NS-Pl, S-NI) | (NS-Pr, S-NI) |
|-------------|---------------------|-----------|------------|-------------|-------------|----------|------------|-------------|-------------|-------------|
| BERT        | (S-I, S-I)          | 0.7939    | 0.7348     | 0.7741      | 0.8495      | 0.7651   | 0.7525     | 0.5694      | 0.7494      | 0.8253      |
| DistilRoBERTa | (S-NI, S-I)      | 0.9810    | 0.9633     | 0.9576      | 0.9751      | 0.9823   | 0.9507     | 0.9305      | 0.8868      | 0.8918      |
| T5          | (NS-Pl, S-I)       | 0.9962    | 0.9898     | 0.9935      | 0.9978      | 1.0      | 0.9734     | 0.9694      | 0.9454      | 0.9375      |
| DPR         | (NS-Pr, S-I)       | 0.8249    | 0.8169     | 0.7730      | 0.8441      | 0.8358   | 0.8257     | 0.8000      | 0.7232      | 0.8055      |
| LaBSE       | (NS-Pl, S-NI)      | 0.9204    | 0.9343     | 0.9534      | 0.9139      | 0.9671   | 0.9431     | 0.9555      | 0.9295      | 0.9394      |
| MiniLM      | (NS-Pr, S-NI)      | 0.9803    | 0.9444     | 0.9764      | 0.9924      | 0.9722   | 0.9217     | 0.8805      | 0.9022      | 0.9037      |
| Glove       | (A, S-I)           | 1.0       | 1.0        | 1.0         | 0.9393      | 1.0      | 1.0        | 1.0         | 0.9414      | 0.9394      |
| Word2Vec    | (A, S-NI)          | 0.9969    | 1.0        | 0.9691      | 0.9404      | 1.0      | 1.0        | 1.0         | 0.9686      | 0.9394      |
| BERT        | (S-I, NS-Pl)       | 0.7175    | 0.7875     | 0.7247      | 0.6635      | 0.7605   | 0.7860     | 0.8463      | 0.8244      | 0.7497      |
| DistilRoBERTa | (NS-Pr, NS-Pl)    | 0.9537    | 0.9430     | 0.9002      | 0.8520      | 0.8992   | 0.9372     | 0.9816      | 0.9573      | 0.9309      |
| T5          | (NS-Pr, NS-Pr)     | 0.9722    | 0.9946     | 0.9742      | 0.9392      | 0.9600   | 0.9825     | 0.9972      | 0.9751      | 0.9594      |
| DPR         | (NS-Pr, NS-Pr)     | 0.9074    | 0.7567     | 0.7011      | 0.6255      | 0.7352   | 0.8034     | 0.8814      | 0.8660      | 0.7768      |
| LaBSE       | (NS-Pr, NS-Pr)     | 0.9814    | 0.9584     | 0.9274      | 0.8360      | 0.8858   | 0.9588     | 0.8874      | 0.9176      | 0.8536      |
| MiniLM      | (NS-Pr, NS-Pr)     | 0.9398    | 0.9725     | 0.9130      | 0.9102      | 0.9433   | 0.9393     | 0.9880      | 0.9196      | 0.9488      |
| Glove       | (A, S-I)           | 1.0       | 1.0        | 1.0         | 0.9992      | 0.9442   | 1.0        | 0.9393      | 0.9414      | 0.9442      |
| Word2Vec    | (A, S-NI)          | 1.0       | 0.9691     | 0.9404      | 0.9394      | 1.0      | 0.9691     | 0.9404      | 0.9394      | 0.9122      |
| BERT        | (NS-Pr, NS-Pr)     | 0.8021    | 0.8015     | 0.7752      | 0.6898      | 0.7880   | 0.8412     | 0.8194      |              |             |
| DistilRoBERTa | (NS-Pr, A)        | 0.9523    | 0.9841     | 0.9949      | 0.9953      | 0.9845   | 0.9920     | 1.0         |              |             |
| T5          | (NS-Pr, A)         | 0.9317    | 0.9861     | 0.9949      | 0.9953      | 0.9835   | 0.9900     | 1.0         |              |             |
| DPR         | (NS-Pr, A)         | 0.8942    | 0.8769     | 0.8560      | 0.8935      | 0.7993   | 0.8234     | 0.875       |              |             |
| LaBSE       | (NS-Pr, A)         | 0.6483    | 0.9166     | 0.9848      | 0.9861      | 0.9701   | 0.9523     | 1.0         |              |             |
| MiniLM      | (NS-Pr, A)         | 0.9565    | 0.9464     | 0.9747      | 0.9675      | 0.9619   | 0.9742     | 0.8888      |              |             |
| Glove       | (A, A)             | 0.8873    | 0.9345     | 1.0         | 1.0         | 1.0      | 0.9345     | 1.0         |              |             |
| Word2Vec    | (A, A)             | 0.8736    | 0.9404     | 1.0         | 1.0         | 0.9691   | 0.9404     | 1.0         |              |             |

Table 6: Satisfaction score (consistency) for the set distance property (Equation 4), for noun phrases with pairs of adjectives of the indicated types (AAN format). We use the following shorthand notation in the table columns: A: Ambiguous, S-I: Subsective-Intersective, S-NI: Subsective Non-Intersective, NS-Pl: Plain Non-Subsective, NS-Pr: Privative Non-Subsective
### Table 7: Satisfaction score (consistency) for the set distance property across adjective phrase pairs (Equation 5), for noun phrases with pairs of adjectives of the indicated types (AN format). We use the following shorthand notation in the table columns: A: Ambiguous, S-I: Subsective-Intersective, S-NI: Subsective Non-Intersective, NS-Pl: Plain Non-Subsective, NS-Pr: Privative Non-Subsective

| Models       | Adjective Type Pair       |                          |                          |                          |                          |                          |
|--------------|----------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
|              | (S-I, S-I)                 | (S-I, S-NI)              | (S-I, NS-Pl)             | (S-I, NS-Pr)             | (S-NI, S-NI)             | (S-NI, NS-Pl)             |
| BERT         | 0.5000                     | 0.7561                   | 0.7549                   | 0.7883                   | 0.6382                   | 0.5000                   |
| DistilRoBERTa| 0.5000                     | 0.7594                   | 0.7006                   | 0.5545                   | 0.7700                   | 0.5000                   |
| T5           | 0.5000                     | 0.6641                   | 0.6300                   | 0.5409                   | 0.7550                   | 0.5000                   |
| DPR          | 0.5000                     | 0.3728                   | 0.3944                   | 0.4504                   | 0.6454                   | 0.5000                   |
| LaBSE        | 0.5000                     | 0.4252                   | 0.3386                   | 0.5268                   | 0.3316                   | 0.5000                   |
| MiniLM       | 0.5000                     | 0.7048                   | 0.7275                   | 0.5197                   | 0.8909                   | 0.5000                   |

### Table 8: Non-subsectivity experiment, reporting satisfaction score (consistency) for the property in equation 7, as its expectation for the phrase dataset (Equation 8).

| Models       | Subsective (Intersective) | Subsective (Non-Intersective) | Non-Subsective (Plain) | Non-Subsective (Privative) | Ambiguous |
|--------------|----------------------------|-------------------------------|------------------------|---------------------------|-----------|
| BERT         | 0.8030                     | 0.5000                        | 0.4907                 | 0.5833                    | 0.7777    |
| DistilRoBERTa| 0.7424                     | 0.5000                        | 0.5432                 | 0.7380                    | 0.3333    |
| T5           | 0.6818                     | 0.5416                        | 0.5864                 | 0.6547                    | 0.4166    |
| DPR          | 0.4772                     | 0.3750                        | 0.4907                 | 0.5595                    | 0.3611    |
| LaBSE        | 0.3560                     | 0.3055                        | 0.5123                 | 0.3273                    | 0.1944    |
| MiniLM       | 0.6136                     | 0.4861                        | 0.4320                 | 0.6785                    | 0.1111    |
| Glove        | 0.6060                     | 0.2222                        | 0.2191                 | 0.3214                    | 0.2777    |
| Word2Vec     | 0.5530                     | 0.2083                        | 0.3364                 | 0.4940                    | 0.0        |