

UC Merced

Proceedings of the Annual Meeting of the Cognitive Science Society

Title

Predicting the Unexpected - Analysis and Modeling of the Denial of Expectation

Permalink

<https://escholarship.org/uc/item/7gx68315>

Journal

Proceedings of the Annual Meeting of the Cognitive Science Society, 46(0)

Author

Walch, Marie Christin

Publication Date

2024

Copyright Information

This work is made available under the terms of a Creative Commons Attribution License, available at <https://creativecommons.org/licenses/by/4.0/>

Peer reviewed

Predicting the Unexpected

Analysis and Modeling of the Denial of Expectation

Marie Christin Walch (marie.walch@germanistik.uni-hannover.de)

German Department, Leibniz University Hannover
Königsworther Platz 1, 30167 Hannover

Abstract

This paper explores the use of linguistic strategies, specifically discourse markers like 'but', to express contrasts between expectations and reality when faced with unexpected events. The study concentrates on Denial of Expectation (DofE), the most powerful form of contrast, which arises when the expected value based on background assumptions is not met. The main focus of this paper is to model DofE as a weighted homogeneous relationship between object properties. The aim is to predict DofE for numerical properties in specific contexts. I aim to address a gap in previous models by considering the role of context. This is achieved by analyzing contrastive sentences from German car and motorcycle reviews. The research presents the concept of expectation intervals for scalar properties. These intervals align with expectations and exceeding them triggers a potential contrast. The study incorporates causality, expected behavior, and a shift function in selecting contrastive pairs, transforming the conditions into an algorithm.

Keywords: contrast; computational and cognitive modeling; discourse analysis

Introduction

In our daily experiences, knowledge accumulation aids in comprehending our surroundings, resulting in established expectations. However, these may be disrupted by unexpected events. In response, linguistic strategies, particularly discourse markers (DMs) like "but," are employed to articulate contrasts between anticipated outcomes. A significant linguistic strategy involves inducing a Denial of Expectation (DofE), identified as the most potent form of contrast by Hobbs (1985). DofE occurs when background assumptions, rooted in domain knowledge, personal experience, or societal norms, are unmet or outright rejected. This study delves into the properties of DofE and its contextual behavior, aiming to model contrast as a weighted homogeneous relation between object properties. The objective is to predict DofE occurrences for numerical properties in specific contexts. Unlike previous models by Knott (2000) and Thomas and Matheson (2002), which focus on the cognitive process without considering context, this research scrutinizes conditions leading to DofE formation. Using DMs from a corpus of German car and motorcycle reviews, sentences were filtered and analyzed for distinctive features. Evaluated cars served as model objects with scalar properties. Assuming an expectation interval I_{exp} for scalar properties, a subset of all possible values based on world knowledge, values within I_{exp} align with expectations. Exceeding I_{exp} thresholds triggers potential contrasts. Based on the two factors, causality or correlation and the expected behavior, a candidate for a contrastive relation is determined from the set of object properties. Causality, de-

rived from the corpus and represented in a co-occurrence matrix, and a shift function reflecting anticipated property shifts, are considered. The conditions for selecting contrastive pairs were transformed into an algorithm. The model is applied to a database with technical specifications of 190 vehicles, providing domain knowledge for expected intervals. The algorithm identifies potential DofE cases in an examined database object, demonstrating the model's practical application.

Theoretical Background

There are several approaches to contrast analysis, among them are the classical and ambiguity approaches (Izutsu, 2008; Lakoff, 1971), the inferential contrast approach (Blakemore, 1989; Katriel & Dascal, 1984; Spender & Maier, 2009; Winter & Rimon, 1994), the formal contrast approach (Sæbø, 2019; Umbach, 2005), the question under discussion (QUD) approach (Jasinskaja, 2012). Traditional analyses rely on additional pragmatic processing to capture all uses of the DM *but*. The model presented here is based on a recent analysis by Bussière-Caraes (2022), which uses and complements the denial condition of the formal contrast approach to show how pragmatic processing is related to context. The argumentative use of *but* (as in *I ran fast but I missed the train.*) involves a weak rejection, which introduces new information to deny an objectionable inference (or defeasible rule) from the first conjunction (*Fast running leads to getting the train*). It also integrates the conversational question into the (enriched) background of an utterance and links the focus and background structure of an utterance to the information structure of the conversation in which it occurs (*A conversation about being late for work*).

Characteristics of expectation

Apart from its connection to context and world knowledge and its defeasibility (see e.g. Lagerwerf, 1998, Sanders, Spooren, & Noordman, 1992, Sweetser, 1990), our knowledge of how expectations are raised is limited. Although the source of a derivable contrast is enormously variable according to Schiffrin (1987), statements can be made about the origin of expectation from the DofE and the context in which it appears. As Leusen (2004) observed, the expectation must arise immediately. This phenomenon has been termed the **locality constraint**. However, the source of the defeasible rule itself can also be restricted. Although **causality** is the most common factor responsible for a DofE, its source can also potentially be a correlation, (non-monotonic) implication, or implicature (Robaldo & Milsakaki, 2014). Gärdenfors (1992) demonstrates that all expectations are de-

feasible, albeit to varying degrees. Therefore, expectations could be ranked based on their **level of defeasibility**. In a similar vein, the QUD approach utilizes the notion of argument strength. The concept of **domain affiliation** can be found as part of the ambiguity approach as well as in the formal approach in the broadest sense by linking the alternatives to the question. Fraser (2009) developed the concept further as semantically contrastive sets. To establish the sets or a superordinate QUD, the notion of similarity is explored in more detail in the following subsection.

Object Representation

In the given corpus, the relation DofE was mainly found in the comparison between properties of objects. Therefore, a formal method for comparing objects must be determined. The notion of similarity introduced by Smith (2020) was adopted and modified using concepts of distributive semantics (Firth, 1957) to represent objects as vectors of their (scalar) properties that also can be seen as such a set of contexts.

Definition 1 (Object). An object X can be represented by a vector \vec{X} containing all elements of its n -element property set as re-scaled values.

$$\vec{X} := \text{PROP}(\vec{X}) := \begin{pmatrix} \text{PROP}_1(X) \\ \vdots \\ \text{PROP}_n(X) \end{pmatrix}$$

In order to use the similarity function of Smith (2020) for modelling, it is necessary to define object classes. Similar to prototypes, these classes should contain the elementary properties that are typical for the object. These object classes can be classified as domains (Izutsu, 2008) or semantically contrastive sets (Fraser, 2006), which are outlined as follows.

Definition 2 (Object class). An object \vec{X}_i is considered an element of an object class \mathbb{X} only if it contains all n properties that are inherent to that class.

$$\mathbb{X} := \{\vec{X} | \forall i \in \{1, \dots, n\} : \text{PROP}_i(X) \in \text{PROP}(\mathbb{X})\}$$

Overview of the Corpus Analysis

The corpus (Hesse, 2020) is a collection of 40 car and motorcycle reviews from two German newspapers (FAZ and Welt). The articles are on average two pages long. The corpus is enhanced by a database of 190 vehicles (Allgemeiner Deutscher Automobil-Club, 2021). It is suitable for analysing the properties of the DofE in more detail because it contains a combination of objective technical specifications (propositional content) with subjective evaluation (expressive, evaluative content) often expressed through contrast. The evaluative content is based on the author's domain-specific experience and is naturally grounded in their subjective estimation. As experts, their approximation skills are over the average. Their domain knowledge is therefore represented by

the database of the ADAC e.V. ('General German Automobile Club'). The contrastive sentences were filtered out using their typical DMs and examined for distinctive features. The contrastive DM *aber* ('but') was the most frequent in the corpus (occurs with a frequency of 48,89 %).

Referentiality of the Contrastive Proposition

The following sentences are retrieved from the corpus and illustrate a contrast between features of the same object, the same feature of two different objects, or an object and a belonging prototype.

- (1) Das Triebwerk selbst ist als Einstiegsmotor mit 140 kW/190 PS allemal in Ordnung, doch weniger sollte es bei der rund 1,7 Tonnen schweren Mittelklasse-Limousine dann auch nicht sein.
'The power plant itself is an entry-level engine with 140 kW/190 hp, but it should not be less than that in a mid-size saloon weighing around 1.7 tonnes.'
- (2) Der Basispreis von 20.000 Eur ist absolut hoch und relativ niedrig. Allerdings kostet der scheidende Citigo-Benziner weniger als die Hälfte.
'The base price of 20,000 Eur is absolutely high and relatively low. However, the outgoing Citigo petrol engine costs less than half that.'
- (3) Erst bei flotter Autobahnfahrt - bei 130 Stundenkilometern wird abgerechnet - gehen die Verbrauchswerte Richtung 18 kWh. Aber das ist ja nicht die Domäne des Kleinen.
'Only when driving at high speed on the motorway - the speed limit is set at 130 kilometers per hour - do the consumption values approach 18 kWh. But that is not the domain of the small car.'

In (1), two properties, the engine power and the weight of the entire vehicle, of the same object, the Volvo S60 T4, are compared. In contrast, (2) refers to the same property, the purchase price, but of two different objects, the Skoda Superb III and the Skoda Citigo. The third example (3) compares a specific object, the VW e-Up Facelift, and an associated prototype, a small car. These observations go along with Spooren (1989)'s statement that in the case of a denial, "two conjunctions refer to two aspects of an entity in the domain of discussion."

Polarity

The corpus analysis only identified contrasts that resulted in a change of polarity. For example, in (4), a contrast is made between the scalar properties of 'weight' (with a negative connotation) and 'speed' (with a positive connotation).

- (4) Der wuchtige Bentley Flying Spur ist kein Monument der Beharrung, sondern die schnellste Limousine der Welt.
'The massive Bentley Flying Spur is not a monument to perseverance, but the fastest limousine in the

world.’

- (5) The car consumes little fuel, although it has a lot of horsepower.

Nevertheless, it would be a misrepresentation to conclude that a contrast between a positively and a negatively evaluated statement is solely possible. This is demonstrated in example (5), where two positively connoted properties are juxtaposed.

Model Framework

There are two approaches so far that attempt to theoretically model the DofE. The approach by Knott (2000) focuses exclusively on monologues, while Thomas and Matheson (2002) addresses the prediction of DofE in dialogues. Both focus on the cognitive process associated with the DofE. Knott (2000) distinguishes between two uses of *but*: plan-based (including a temporal dimension) and expectation-based. For the latter, he provides an algorithm that can be summarized in four stages that include the posting of an epistemic goal by the agent, the defeasible rule by (deductive) reasoning, the testing of the rule, and the conclusion that the rule doesn’t match the perception of the agent. Both models closely adhere to the inferential approach (Blakemore, 1989; Katriel & Dascal, 1984; Spender & Maier, 2009; Winter & Rimon, 1994) and lack contextual references, as does the underlying theory. Furthermore, both approaches appear to be ineffective in processing sentences containing numeric or scalar expressions. This is because the negation of these expressions may result in the ambiguity of the functional right-hand side for the defeasible rule, as illustrated by example (6): Here, the consumption of more or less than 10 l leads to fulfillment.

- (6) A: The car drives 160 km/h maximum.
B: But it consumes 10 l per 100 km!
Rule: $\text{driving_160km/h}(X) \rightarrow \text{not_consuming_10l}(X)$

I aim to address context-boundedness and scalarity in the following framework by modeling the DofE based on the previously presented corpus and literature.

Relation Type

The previously described contrast type in evaluative texts can be defined as a relationship R between two property sets $\text{PROP}(X)$ and $\text{PROP}(Y)$ of the objects X and Y that belong to the same object class \mathbb{X} . As per the corpus findings, the discourse segments refer to various yet related features of one object, see (1), one feature of a second object, see (2), or a prototype (or object class), see (3). They all belong to the same domain and fulfill the conditions of domain affiliation and similarity. Building upon this, I introduce three (trivially irreflexive) types of contrastive relations that all belong to the same domain (a set of properties of an object class):

- (A) homogeneous relation (two PROP of X)
 $R_{ho} = \{(\text{PROP}_i(X), \text{PROP}_j(X)) \mid i \neq j\}$

- (B) heterogeneous relation (two different individuals X, Y)
 $R_{he1} = \{(\text{PROP}_i(X), \text{PROP}_j(Y)) \mid X, Y \in \mathbb{X} \wedge X \neq Y\}$

- (C) heterogeneous relation (X and an object class \mathbb{X})
 $R_{he2} = \{(\text{PROP}_i(X), \text{PROP}_j(\mathbb{X})) \mid X \in \mathbb{X}\}$

The diagram in Figure 1 compares the sets of properties of the same object.

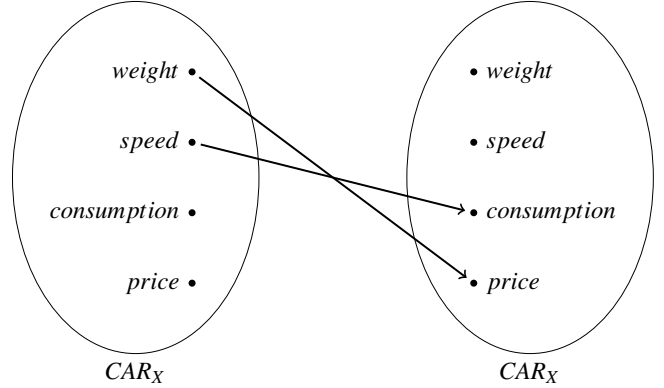


Figure 1: Homogeneous contrast relation R_{ho}

In the present data set, the most frequent relation was the homogeneous contrast relation R_{ho} (see A). Therefore, in what follows I focus on that relation. It contrasts the set of properties belonging to a single object, here CAR_X . No property of the same object can contrast with itself.

The relation is a subset of the Cartesian product of both property sets and is expressed in Figure 1 by the edges between properties.

In Figure (1): $R_{ho} = \{(weight, price), (speed, consumption)\}$

Expected Interval

It can be generally assumed that the interval encompassing all possible values for an object’s property is finite, and its boundaries should be set based on our knowledge of the world, expertise, and personal experience.

Definition 3 (Interval of all possible values). A set $I_{pos} = [x_{min}, x_{max}]$ contains all possible values for the property PROP of an object X according to the world knowledge, domain knowledge or/and personal experience of a speaker.

This interval I_{pos} should include a secondary interval as a subset relating to a property that speakers expect based on their world or domain knowledge and personal experiences. The interval is delimited by two (or at least one) threshold values, the exceeding of which triggers a contrastive relation.

Definition 4 (Interval of expected values). There is a subset $I_{exp} = [\theta_{min}, \theta_{max}] \subset I_{pos}$ containing all expected values for a property PROP according to the world knowledge, domain knowledge or/and personal experience of a speaker S .

An element contained in the interval I_{exp} should correspond to an ideal or typical value. The mean value \bar{x} of the scalar

property PROP_i of all objects within the class \mathbb{X} , of which X is a part, is most closely aligned with this ideal.

The interval is presented for property PROP_i of an object X in the event of the actual value x_i exceeding the interval expected by the speaker, see Figure 2.

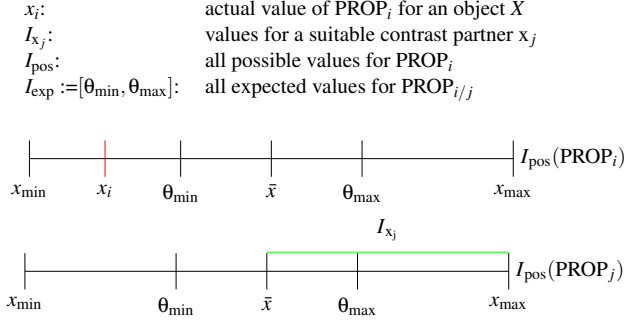


Figure 2: Intervals for two properties PROP_i and PROP_j of an object X

The depiction of intervals in Figure 2 is greatly simplified and not realistic. Both, the symmetry and existence of the two thresholds, θ_{\min} and θ_{\max} depend on the context and the natural and logical limits inherent in the property. For instance, the number of wheels is unequal 0 and must be an integer value. Furthermore, thresholds can be either categorical (like the number of doors), as in 2, or more likely continuous (like the speed of a car). However, a fixed boundary is required for the model.

Simply finding a property PROP_i that exceeds a threshold and triggers a contrast is insufficient. Additionally, it is necessary to identify the corresponding property, PROP_j , which will be set in contrast to PROP_i and deny a causal rule that connects them. The procedure is outlined in the subsequent sections.

Weighted Contrast

Examining natural language reveals selective expression of information guided by pragmatic rules, notably Grice's cooperative principle (Grice, 1967). In this context, not all potential contrasts are manifested in discourse due to the maxims of quantity and relevance. To address this, an idea by Gärdenfors (1992) is adopted - to order expectations. To closely emulate natural discourse, two functions are introduced: one for quantifying the weight of a property and another for assessing the strength of a contrast realization between two properties. The weight function, $w(x)$ quantifies the degree of unexpectedness. It is determined by the ratio between the distance of the actual value from the mean value of the property of all objects in the same class and the distance of this mean value to the I_{exp} threshold.

$$w(x_i) := \frac{d(\bar{x}, x_i)}{d(\bar{x}, \theta_{\min/\max})}$$

Only properties $\text{PROP}_i(x_i)$ with weights greater than 1 are potential contrast candidates (otherwise expected). The weight of a property increases with the deviation of its actual value from the mean value relative to the size of the expectation interval. If multiple properties could trigger a contrast, they can be ranked according to their weight, and the weaker ones can be excluded. However, this analysis is incomplete as the causal complex (Hobbs, Stickel, Appelt, & Martin, 1993) of an event (here property) can include several others. To evaluate the importance of contrast, it is necessary to consider not only the weight of the unexpected property but also its contrastive partner. Therefore, a further function is required to map the intensity or power of the contrast relationship as the product of the weights of the two contrasting properties $< x_i, x_j >$.

$$\text{pow}(< x_i, x_j >) := w(x_i)w(x_j)$$

Thus, both properties' weights can be incorporated to rank the pairs based on their strength. A contrast pair $< x_i, x_j >_c$ is stronger than a second contrast pair $< x_k, x_l >$ if:

$$\text{pow}(< x_i, x_j >) \succ \text{pow}(< x_k, x_l >)$$

To update the adjacency matrix with property weights and enable later analysis of contrast pairs, a diagonal matrix, D_X , is created. The diagonal entries of D_X correspond to the weights, $w(x_i)$, of the respective property, PROP_i . The updated adjacency matrix, A^* , is obtained by multiplying D_X on both sides of A . To update the adjacency matrix with property weights and enable subsequent analysis of contrast pairs, a diagonal matrix D_X is created with the weights $w(x_i)$ of the respective property PROP_i on the diagonal. The updated adjacency matrix A^* is obtained by multiplying D_X from both sides of A .

$$A^*(< X, X >) := D_X A_{n,n} D_X, \text{ with } D_X := \text{diag}(w(x_1), w(x_2), \dots, w(x_n))$$

The updated adjacency matrix, A^* , maps the weights of two properties onto each other. Each entry, a_{ij} , in the matrix represents the contrast's strength between PROP_i and PROP_j . The following adjacency matrix, A^* , is updated for an object with three properties. The entries on the diagonal remain unchanged 0.

$$A_{3,3}^* = \begin{pmatrix} 0 & \text{pow}(< x_1, x_2 >) & \text{pow}(< x_1, x_3 >) \\ \text{pow}(< x_2, x_1 >) & 0 & \text{pow}(< x_2, x_3 >) \\ \text{pow}(< x_3, x_1 >) & \text{pow}(< x_3, x_2 >) & 0 \end{pmatrix}$$

In this case, it is assumed that if the hypothetical speaker wanted to express a single contrastive relation, they would choose the deviation perceived as stronger: " x_2 but x_1 ".

Definition 5 (Shift function). A property PROP_j has the potential to condition another property PROP_i of the elements belonging to class \mathbb{X} if its increase results in a corresponding change of PROP_i . I will describe this change as an asynchronous shift if PROP_i decreases, and as a synchronous shift if it increases. With \mathbb{X} defined as above:

$I_{exp}(\text{PROP}_i(X)) := [\theta_1, \theta_2]$ we define $\mathbb{Y} := \{\bar{Y} | \bar{Y} \in \mathbb{X} \wedge \exists j \in \{1, \dots, n\} : \text{PROP}_j(Y) > \theta_2\}$ and

$$\bar{x}_i = \frac{\sum_{X \in \mathbb{X}} \text{PROP}_i(X)}{|\mathbb{X}|}, \quad \bar{y}_i = \frac{\sum_{Y \in \mathbb{Y}} \text{PROP}_i(Y)}{|\mathbb{Y}|}$$

$$\text{shift}(\text{PROP}_i, \text{PROP}_j) := \text{sgn}(\bar{x}_i - \bar{y}_i) = \begin{cases} -1, & \text{asynchronous shift}(\uparrow\downarrow, \downarrow\uparrow) \\ 1, & \text{synchronous shift}(\uparrow\uparrow, \downarrow\downarrow) \end{cases}$$

The advantage of this solution is its independence with regard to the positive or negative evaluation of a property and its connection to causality.

Update of the Adjacency Matrix

Algorithm 1 computes edge weights in the adjacency matrix, which are based on the object's properties. It considers the average property values of a given object class to determine the strength of the contrast. The weight of the contrastive connections between an object properties can be read from the resulting matrix A^* . This algorithm calculates the weights of the existing edges in the adjacency (co-occurrence) matrix based on the properties of the objects. It takes into account the average values of the properties of an object class to reflect the strength of the contrast. The updated matrix A^* reflects these weighted contrastive links between objects.

Algorithm 1: Update of the adjacency matrix with the weight function $w(x_i)$

Input : $A_{n,n}, X_{k,n}$ with $k \in [0, \dots, n-1]$
Output: Updated adjacency matrix A^*
 Let $A_{n,n}^*$ be a new matrix with
 $A^*[i, i] := 0 \forall i = [0, \dots, n-1]$;
for $i = 0$ **to** $n-1$ **do**
 for $j = 0$ **to** $n-1$ **do**
 if $A[i][j] \neq 0$ **then**
 $A^*[i][j] := \frac{d(\text{mean}(X_i), x_i)}{\sigma(X_i)} \cdot \frac{d(\text{mean}(X_j), x_j)}{\sigma(X_j)}$;
 end
end
end
return A^* ;

Algorithm: Search for contrast pairs

The purpose of this algorithm is to search for a contrast pair $\langle x_i, x_j \rangle$ where x_i represents the unexpected value that triggers the contrast. Algorithm 2 takes as input the updated adjacency matrix $A_{n,n}^*$, an object vector \vec{x} , and a database with the thresholds of I_{exp} for every property of the corresponding object class. A list $L_{3,n}$ is initialized to store the property indices and the power of the contrast as three-element entries. In a loop, the object vector is traversed and searched for property values that potentially trigger a contrast. If a candidate x_i is found, the i -th row of the adjacency matrix is iterated and

Algorithm 2: Update A^* - Search for contrast pairs

$\langle x_i, x_j \rangle$

Input : $A_{n,n}^*, \vec{x}, I_{exp}$ for the object class/group
Output: Updated matrix A^*
 Initialization of a list $L_{3,n}$, a three-element array
 $\text{temp} := [0, 0, 0]$ and $k := 0$;
for $i = 0$ **to** $n-1$ **do**
 if $x_i \notin I_{exp}(X_i)$ **then**
 for $j = 0$ **to** $n-1$ **do**
 if $A^*[i][j] > \text{temp}[0]$ &
 $\text{shift}(x[i], x[j]) == \text{sgn}(d(x[i], x[j]))$ **then**
 $\text{temp}[0] := k$;
 $\text{temp}[1] := i$;
 $\text{temp}[2] := j$;
 end
 end
 $L := \text{insertSort}(L, \text{temp})$;
 $k := k + 1$;
 $\text{temp} := [0, 0, 0]$;
 end
end
return $L[0] - L[3]$;

the conditions described above are checked. Only if these are fulfilled and the contrast with x_j is stronger than that of a previously found candidate cached in temp , it is replaced. The pairs found are sorted into a mental list L and the three "strongest" pairs are returned at the end.

Result

The Peugeot 208 was selected as an example object from the database to apply the model. To set up the adjacency matrix and to examine the nine properties for co-occurrence, all 198 contrastive sentences found in the corpus were examined extracting both contrasted properties. That contrast could have been explicit or implicit. The co-occurrence network shown here translates the adjacency matrix into a directed graph (see Figure 3) and displays all dependencies assumed as causal (or at least correlated) between the PROP_i . Simply aligned edges are to be read such that the property from which the arrow originates provides the context for the property into which the arrow terminates. Edges with arrows at both ends are equivalent to a mutual relevance relation between the two properties. Given the speaker's high level of domain knowledge and the classification of the Peugeot as a small car in the database, it is necessary that the referencing object class only includes other small cars that share a high degree of similarity with the object. Table 1 lists the expectation intervals of the (re-scaled) properties for the object class 'small car'. The mean values of all properties in this class from the car database were employed to calculate their upper and lower limits, with the standard deviation being added to or subtracted from these.

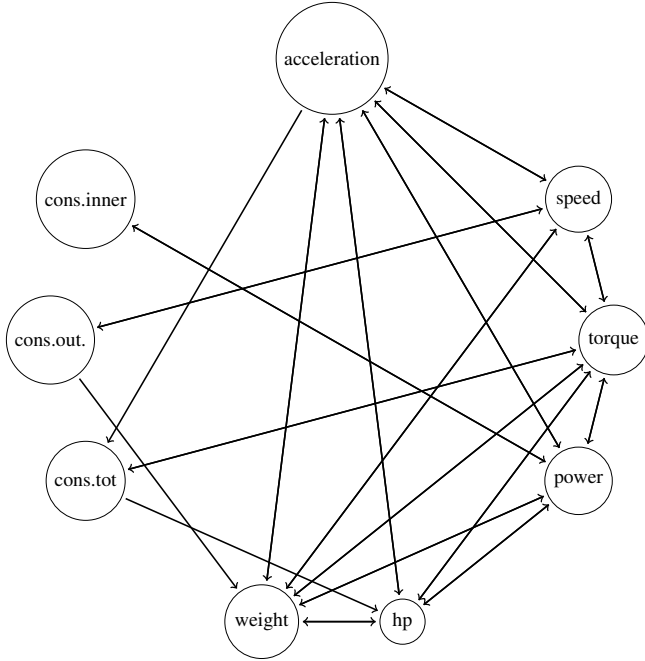


Figure 3: Co-occurrence network

<i>PROP</i>	SMALL CAR			
	\bar{x}	θ_1	θ_2	P_{208}^{\rightarrow}
hp	0.413	0.14	0.676	0.235
PowerMax	0.634	0.394	0.873	0.763
Torque	0.428	0.227	0.628	0.375
Weight	0.546	0.362	0.73	0.435
Acceleration	0.375	0.156	0.594	0.333
ConsumptionCity	0.523	0.318	0.727	0.364
ConsumptionHighway	0.563	0.375	0.75	0.344
ConsumptionTotal	0.568	0.378	0.73	0.351
SpeedMax	0.435	0.204	0.676	0.537

Table 1: Comparison of P_{208}^{\rightarrow} and the object class *SMALL*

Assuming the hypothetical speaker is aware of causalities or correlations between the properties, the possible contrast partners among the co-occurring *PROP* are identified in the next step. To achieve this, the row of the weighted adjacency matrix that corresponds to the property triggering the contrast is passed through. If the j -th entry is non-zero, the shift function is applied.

shift (-/+)	torque	speed	weight	hp	$PROP_{i..n}$
consH	0	-0.51(+)	0.71(+)	0	0 ... 0
consT	0.31(+)	0	0	0.74(+)	0 ... 0

Table 2: Results for the object P_{208}^{\rightarrow}

Table 2 presents a subset of rows from the weighted adjacency matrix corresponding to the contrast candidates (in blue) identified in Table 1. The outcomes of the shift function are denoted within brackets, with a positive sign indicat-

ing synchronous shifts (depicted in blue) and a negative sign denoting asynchronous shifts (depicted in red). For the property *consumption total* no suitable partner for a contrastive relationship was found. However, a partner is found for *consumption highway*. The *speed* is above average for the class and contradicts the defeasible rule that a fast car should normally have higher consumption. Since no other candidates were found, the mental list contains only one element that can be realised. The hypothetical speaker would choose an appropriate discourse marker in the last step and utter the sentence following the syntactic rule “Although p q”:

- (7) Although the Peugeot 208 reaches a relatively high top speed of 188 km/h, it consumes little gasoline on the highway.

Conclusion

Following the modified denial condition by Bussière-Caraes (2022), the model selects a trigger for the contrast based on unexpectedness and corresponds to a weak rejection in the given context. This context is created by constructing domain knowledge of the hypothetical speaker and a superordinated QUD (*Should the reader buy this car?*) the speaker wants to answer. Furthermore, the model integrates findings from the literature review and the corpus study by incorporating domain affiliation, causality, and the order of expectations of the DofE. The consideration of domain affiliation in contrasting entities involves studying scalar properties of similar objects within classes. The challenge lies in capturing not only all object properties but also their most significant features. Using the available database, an object class (small cars) was constructed to predict expectation deviations. These object classes can also be seen as prototypes, with their properties dependent on the speaker’s experience (expert vs. layperson). An experimental approach could aid in their construction. The model should be equally applicable to non-numeric scalar properties, assuming they can be categorized as scalar. The corpus analysis has thus far overlooked the distinction between sources of the DofE when examining contrastive relationships between properties. However, it is unclear whether the speaker is always aware of the underlying source, so this distinction may be unnecessary. An experimental production study focussing on the speaker’s perspective could be well suited for an extended test and adaptation of the model.

Acknowledgments

Many thanks to all those involved in the QUD Gen Project for providing data, especially Dr Anton Benz and Dr Christoph Hesse. I would also like to thank Dr Berit Gehrke and Prof Manfred Krifka for their invaluable support and supervision.

References

- Allgemeiner Deutscher Automobil-Club. (2021). Retrieved from <https://github.com/MMLangner/qudgensystem> (Last accessed 01 February 2023)
- Blakemore, D. (1989). Denial and contrast: A relevance theoretic analysis of "but". *Linguistics and Philosophy*, 12(1), 15–37.
- Bussière-Caraes, L. (2022). *No means no!: Speech acts in conflict* (Doctoral dissertation). Institute for Logic, Language and Computation, Universiteit van Amsterdam.
- Firth, J. (1957). A synopsis of linguistic theory, 1930-1955. *Studies in linguistic analysis*, 10–32.
- Fraser, B. (2006). Towards a theory of discourse markers. *Approaches to Discourse Particles*, 189-204.
- Fraser, B. (2009). An account of discourse markers. *International Review of Pragmatics*, 1, 293-320.
- Grice, H. P. (1967). Logic and conversation. In P. Grice (Ed.), *Studies in the way of words*. Harvard University Press.
- Gärdenfors, P. (1992). The role of expectations in reasoning. In *Proceedings of the international conference logic at work* (p. 1-16).
- Hesse, C. (2020). *question-under-discussion*. Retrieved from <https://github.com/christoph-hesse> (Last accessed 01 February 2023)
- Hobbs, J. R. (1985). On the coherence and structure of discourse. In *Journal of language and social psychology* (p. 213-232).
- Hobbs, J. R., Stickel, M. E., Appelt, D. E., & Martin, P. (1993). Interpretation as abduction. *Artificial Intelligence*, 63(1), 69-142.
- Izutsu, M. N. (2008). Contrast, concessive, and corrective: Toward a comprehensive study of opposition relations. *Journal of Pragmatics*, 40(4), 646-675.
- Jasinskaja, K. (2012). Correction by adversative and additive markers. *Lingua*, 122(15), 1899-1918.
- Katriel, T., & Dascal, M. (1984). What do indicating devices indicate? *Philosophy & Rhetoric*, 17(1), 1–15.
- Knott, A. (2000). An algorithmic framework for specifying the semantics of discourse relations. *Computational Intelligence*, 16, 501-510.
- Lagerwerf, L. (1998). *Causal connectives have presuppositions. effects on coherence and discourse structure* (Doctoral dissertation). LOT (Netherlands graduate School of Linguistics).
- Lakoff, R. (1971). If's, and's and but's about conjunction. In *Studies in linguistic semantics*. Irvington: Charles J. Fillmore and D. Terence Langendoen.
- Leusen, N. (2004). Incompatibility in context: A diagnosis of correction. *Journal of Semantics*, 21, 415-415.
- Robaldo, L., & Miltsakaki, E. (2014). Corpus-driven semantics of concession: Where do expectations come from? *Dialogue and Discourse*, 5, 1-36.
- Sæbø, K. J. (2019). Presupposition and contrast: German 'aber' as a topic particle. In *Proceedings of sinn und bedeutung* (p. 257–271).
- Sanders, T., Spooren, W., & Noordman, L. (1992). Toward a taxonomy of coherence relations. *Discourse Processes*, 15, 1-35.
- Schiffrin, D. (1987). *Discourse markers*. Cambridge: Cambridge University Press.
- Smith, R. (2020). Simulative plurality and the nature of alternatives. *Semantics and Pragmatics*, 13, 15:1-44.
- Spenader, J., & Maier, E. (2009). Contrast as denial in multi-dimensional semantics. *Journal of Pragmatics*, 41, 1707-1726.
- Spooren, W. (1989). *Some aspects of the form and interpretation of global contrastive coherence relations* (Doctoral dissertation). Nijmegen University, Nijmegen.
- Sweetser, E. (1990). From etymology to pragmatics: Metaphorical and cultural aspects of semantic structure. In *Cambridge studies in linguistics*. Cambridge: Cambridge University Press.
- Thomas, K., & Matheson, C. (2002). Modelling denial of expectation in dialogue: Issues in interpretation and generation. In *Proceedings of the 6th annual computational linguistics united kingdom research colloquium: Cluk-6*.
- Umbach, C. (2005). Contrast and information structure: A focus-based analysis of but. *Linguistics*, 43(1), 207–232.
- Winter, Y., & Rimon, M. (1994, 11). Contrast and implication in natural language. *Journal of Semantics*, 11(4), 365-406.