# Automatic Classification of Communicative Functions of Definiteness

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## Abstract

Definiteness expresses a constellation of semantic, pragmatic, and discourse properties—the communicative function—of an NP. We present a supervised classifier for English NPs that uses lexical, morphological, and syntactic features to predict an NP's communicative function in terms of a language-universal classification scheme. Our classifiers establish strong baselines for future work in this neglected area of computational semantic analysis. In addition, analysis of the features and learned parameters in the model provides insight into the grammaticalization of definiteness in English, not all of which is obvious a priori.

## 1  Introduction

Definiteness has been taken to associate morphosyntax of Noun Phrases (NPs) with aspects of their meaning, e.g. definite markers have prototypically been associated with identifiability (whether a referent for the NP can be identified by the discourse participants or not) (Lyons, 1999), together with other aspects such as inclusiveness (where the reference is made to the totality of objects or mass in the context) (Hawkins, 1978). While some morphosyntactic forms of definiteness are employed by all languages— namely, demonstratives, personal pronouns, and possessives—languages display a vast range of variation with respect to the form and meaning of definiteness. For example, while languages like English make use of definite and indefinite articles to distinguish between the discourse status of various entities (***the car*** vs. ***a car*** vs. *cars*), many other languages—including Czech, Indonesian, and Russian—do not have articles (although they do have demonstrative determiners). Sometimes definiteness is marked with affixes or clitics, as in Arabic. Sometimes it is expressed with other constructions, as in Chinese (a language without articles), where the existential construction can be used to express indefinite subjects and the *ba-* construction can be used to express definite direct objects (Chen, 2004).

Aside from this variation in the form of (in)definite NPs within and across languages, there is also variability in the mapping between semantic, pragmatic, and discourse functions of NPs and the (in)definites expressing these functions. We refer to these as *communicative functions* of definiteness, following Bhatia et al. (2014). Croft (2003, pp. 6–7) shows that even when two languages have access to the same morphosyntactic forms of definiteness, the conditions under which an NP is marked as definite or indefinite (or not at all) are language-specific. He illustrates this by contrasting English and French translations (both languages use definite as well as indefinite articles) such as:

(1)  He showed **extreme care**. (unmarked)
     Il montra **un soin extrême**. (indef.)

(2)  I love **artichokes** and asparagus. (unmarked)
     J'aime **les artichauts** et les asperges. (def.)

(3)  His brother became **a soldier**. (indef.)
     Son frère est devenu **soldat**. (unmarked)

A cross-linguistic classification of communicative functions should be able to characterize the aspects of meaning that account for the different patterns of definiteness marking exhibited in (1–3): e.g., that

- NONANAPHORA [−A,−B]  999
  - UNIQUE [+U]  287
    * UNIQUE_HEARER_OLD [+F,−G,+S]  251
      · UNIQUE_PHYSICAL_COPRESENCE [+R]  13
      · UNIQUE_LARGER_SITUATION [+R]  237
      · UNIQUE_PREDICATIVE_IDENTITY [+P]  1
    * UNIQUE_HEARER_NEW [−F]  36
  - NONUNIQUE [−U]  581
    * NONUNIQUE_HEARER_OLD [+F]  169
      · NONUNIQUE_PHYSICAL_COPRESENCE [−G,+R,+S]  39
      · NONUNIQUE_LARGER_SITUATION [−G,+R,+S]  117
      · NONUNIQUE_PREDICATIVE_IDENTITY [+P]  13
    * NONUNIQUE_HEARER_NEW_SPEC [−F,−G,+R,+S]  231
    * NONUNIQUE_NONSPEC [−G,−S]  181
  - GENERIC [+G,−R]  131
    * GENERIC_KIND_LEVEL  0
    * GENERIC_INDIVIDUAL_LEVEL  131

- ANAPHORA [+A]  1574
  - BASIC_ANAPHORA [−B,+F]  795
    * SAME_HEAD  556
    * DIFFERENT_HEAD  329
  - EXTENDED_ANAPHORA [+B]  779
    * BRIDGING_NOMINAL [−G,+R,+S]  43
    * BRIDGING_EVENT [+R,+S]  10
    * BRIDGING_RESTRICTIVE_MODIFIER [−G,+S]  614
    * BRIDGING_SUBTYPE_INSTANCE [−G]  0
    * BRIDGING_OTHER_CONTEXT [+F]  112
- MISCELLANEOUS [−R]  732
  - PLEONASTIC [−B,−P]  53
  - QUANTIFIED  248
  - PREDICATIVE_EQUATIVE_ROLE [−B,+P]  58
  - PART_OF_NONCOMPOSITIONAL_MWE  100
  - MEASURE_NONREFERENTIAL  125
  - OTHER_NONREFERENTIAL  148

|  | + | − | 0 |  | + | − | 0 |  | + | − | 0 |  | + | − | 0 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Anaphoric | 1574 | 999 | 732 | Generic | 131 | 1476 | 1698 | Predicative | 72 | 53 | 3180 | Specific | 1305 | 181 | 1819 |
| Bridging | 779 | 1905 | 621 | Familiar | 1327 | 267 | 1711 | Referential | 690 | 863 | 1752 | Unique | 287 | 581 | 2437 |

**Figure 1:** CFD (Communicative Functions of Definiteness) annotation scheme, with frequencies in the corpus. Internal (non-leaf) labels are in bold; these are not annotated or predicted. +/− values are shown for ternary attributes Anaphoric, Bridging, Familiar, Generic, Predicative, Referential, Specific, and Unique; these are inherited from supercategories, but otherwise default to 0. Thus, for example, the full attribute specification for UNIQUE_PHYSICAL_COPRESENCE is $[−A,−B,+F,−G,0P,+R,+S,+U]$. Counts for these attributes are shown in the table at bottom.

(2) concerns a generic class of entities while (3) concerns a role filled by an individual. For more on communicative functions, see §2.

This paper develops supervised classifiers to predict communicative function labels for English NPs using lexical, morphological, and syntactic features. The contribution of our work is in both the output of the classifiers and the models themselves (features and weights). Each classifier predicts communicative function labels that capture aspects of discourse-newness, uniqueness, specificity, and so forth. Such functions are useful in a variety of language processing applications. For example, they should usually be preserved in translation, even when the grammatical mechanisms for expressing them are different. The communicative function labels also represent the discourse status of entities, making them relevant for entity tracking, knowledge base construction, and information extraction.

Our log-linear model is a form-meaning mapping that relates syntactic, lexical, and morphological features to properties of communicative functions. The learned weights of this model can, e.g., generate plausible hypotheses regarding the form-meaning relationship which can then be tested rigorously through controlled experiments. This hypothesis generation is linguistically significant as it indicates new grammatical mechanisms beyond the obvious *a* and *the* articles that are used for expressing definiteness in English.

To build our models, we leverage a cross-lingual definiteness annotation scheme (§2) and annotated English corpus (§3) developed in prior work (Bhatia et al., 2014). The classifiers, §4, are supervised models with features that combine lexical and morphosyntactic information and the prespecified attributes or groupings of the communicative function labels (such as Anaphoric, Bridging, Specific in fig. 1) to predict leaf labels (the non-bold faced labels in fig. 1); the evaluation measures (§5) include one that exploits these label groupings to award partial credit according to relatedness. §6 presents experiments comparing several models and discussing their strengths and weaknesses; computational work and applications related to definiteness are addressed in §7.

## 2 Annotation scheme

The literature on definiteness describes functions such as uniqueness, familiarity, identifiability, anaphoricity, specificity, and referentiality (Birner and Ward, 1994; Condoravdi, 1992; Evans, 1977, 1980; Gundel et al., 1988, 1993; Heim, 1990; Kadmon, 1987, 1990; Lyons, 1999; Prince, 1992; Roberts, 2003; Russell, 1905, *inter alia*) as being related to definiteness. Reductionist approaches to definiteness

try to define it in terms of one or two of the aforementioned communicative functions. For example, Roberts (2003) proposes that the combination of uniqueness and a presupposition of familiarity underlie all definite descriptions. However, possessive definite descriptions (*John's daughter*) and the weak definites (*the son of Queen Juliana of the Netherlands*) are neither unique nor necessarily familiar to the listener before they are spoken. In contrast to the reductionist approaches are approaches to grammaticalization (Hopper and Traugott, 2003) in which grammar develops over time in such a way that each grammatical construction has some prototypical communicative functions, but may also have many non-prototypical communicative functions. The scheme we are adopting for this work—the annotation scheme for Communicative Functions of Definiteness (CFD) as described in Bhatia et al. (2014)— assumes that there may be multiple functions to definiteness. CFD is based on a combination of these functions and is summarized in fig. 1. It was developed by annotating texts in two languages (English and Hindi) for four different genres—namely TED talks, a presidential inaugural speech, news articles, and fictional narratives—keeping in mind the communicative functions that have been associated with definiteness in the linguistic literature.

CFD is hierarchically organized. This hierarchical organization serves to reduce the number of decisions that an annotator needs to make for speed and consistency. We now highlight some of the major distinctions in the hierarchy.

At the highest level, the distinction is made between **Anaphora**, **Nonanaphora**, and **Miscellaneous** functions of an NP (the annotatable unit). **Anaphora** and **Nonanaphora** respectively describe whether an entity is old or new in the discourse; the **Miscellaneous** function is mainly assigned to various kinds of nonreferential NPs.

The **Anaphora** category has two subcategories: **Basic_Anaphora** and **Extended_Anaphora**. **Basic_Anaphora** applies to NPs referring to entities that have been mentioned before. **Extended_Anaphora** applies to any NP whose referent has not been mentioned itself, but is evoked by a previously mentioned entity. For example, after mentioning a wedding, *the bride*, *the groom*, and *the cake* are considered to be **Extended_Anaphora**.

Within the **Nonanaphora** category, a first distinction is made between **Unique**, **Nonunique**, and **Generic**. The **Unique** function applies to NPs whose referent becomes unique in a context for any of several reasons. For example, *Obama* can safely be considered unique in contemporary political discourse in the United States. The function **Nonunique** applies to NPs that start out with multiple possible referents and that may or may not become identifiable in a speech situation. For example, *a little riding hood of red velvet* in fig. 2 could be annotated with the label **Nonunique**. Finally, **Generic** NPs refer to classes or types of entities rather than specific entities. For example, *Dinosaurs* in *Dinosaurs are extinct.* is a **Generic** NP.

Another important distinction CFD makes is between **Hearer_Old** for references to entities that are familiar to the hearer (e.g., if they are physically present in the speech situation), versus **Hearer_New** for nonfamiliar references. This distinction cuts across the two subparts of the hierarchy, **Anaphora** and **Nonanaphora**; thus, labels marking **Hearer_Old** or **Hearer_New** also encode other distinctions (e.g., **Unique_Hearer_Old**, **Unique_Hearer_New**, **Nonunique_Hearer_Old**). For further details on the annotation scheme, see fig. 1 and Bhatia et al. (2014).

Because the ordering of distinctions determines the tree structure of the hierarchy, the same communicative functions could have been organized in a superficially different way. In fact, Komen (2013) has proposed a hierarchy with similar leaf nodes, but different internal structure. Since it is possible that some natural groupings of labels are not reflected in the hierarchy we used, we also decompose each label into fundamental communicative functions, which we call *attributes*. Each label type is associated with values for attributes <u>A</u>naphoric, <u>B</u>ridging, <u>F</u>amiliar, <u>G</u>eneric, <u>P</u>redicative, <u>R</u>eferential, <u>S</u>pecific, and <u>U</u>nique. These attributes can have values of +, −, or 0, as shown in fig. 1. For instance, with the <u>A</u>naphoric attribute, a value of + applies to labels that can never mark NPs new to the discourse, − applies to labels that can *only* apply if the NP is new in the discourse, and 0 applies to labels such as **Pleonastic** (where anaphoricity is not applicable because there is no discourse referent).

*Once upon a time there was a dear little girl who was loved by everyone who looked at her, but most of all by her grandmother, and there was nothing that she would not have given to the child.*

Once  <u>she</u>  gave  <u>her</u>  a little riding hood of  <u>red velvet</u>  , which suited  <u>her</u>  so well that
    Same_Head    Different_Head        Other_Nonreferential        Same_Head
                Nonunique_Hearer_New_Spec

    <u>she</u>  would never wear anything else; so  <u>she</u>  was always called 'Little Red Riding Hood.'
Same_Head          Quantified    Same_Head        Unique_Hearer_New

**Figure 2:** An annotated sentence from "Little Red Riding Hood." The previous sentence is shown for context.

## 3 Data

We use the English definiteness corpus of Bhatia et al. (2014), which consists of texts from multiple genres annotated with the scheme described in §2.[1] The 17 documents consist of prepared speeches (TED talks and a presidential address), published news articles, and fictional narratives. The TED data predominates (75% of the corpus);[2] the presidential speech represents about 16%, fictional narratives 5%, and news articles 4%. All told, the corpus contains 13,860 words (868 sentences), with 3,422 NPs (the annotatable units). Bhatia et al. (2014) report high inter-annotator agreement, estimating Cohen's $\kappa = 0.89$ within the TED genre as well as for all genres.

Figure 2 is an excerpt from the "Little Red Riding Hood" annotated with the CFD scheme.

## 4 Classification framework

To model the relationship between the grammar of definiteness and its communicative functions in a data-driven fashion, we work within the supervised framework of feature-rich discriminative classification, treating the functional categories from §2 as output labels *y* and various lexical, morphological, and syntactic characteristics of the language as features of the input *x*. Specifically, we learn two kinds of probabilistic models. The first is a log-linear model similar to multiclass logistic regression, but deviating in that logistic regression treats each output label (response) as atomic, whereas we decompose each into *attributes* based on their linguistic definitions, enabling commonalities between related labels to be recognized. Each weight in the model corresponds to a feature that mediates between *percepts* (characteristics of the input NP) and attributes (characteristics of the label). This is aimed at attaining better predictive accuracy as well as feature weights that better describe the form–function interactions we are interested in recovering. We also train a random forest model on the hypothesis that it would allow us to sacrifice interpretability of the learned parameters for predictive accuracy.

Our setup is formalized below, where we discuss the mathematical models and linguistically motivated features.

### 4.1 Models

We experiment with two classification methods: a log-linear model and a nonlinear tree-based ensemble model. Due to their consistency and interpretability, linear models are a valuable tool for quantifying and analyzing the effects of individual features. Non-linear models, while less interpretable, often outperform logistic regression (Perlich et al., 2003), and thus could be desirable when the predictions are needed for a downstream task.

#### 4.1.1 Log-linear model

At test time, we model the probability of communicative function label *y* conditional on an NP *x* as follows:

$$p_{\boldsymbol{\theta}}(y|x) = \log \frac{\exp \boldsymbol{\theta}^{\top} \mathbf{f}(x,y)}{\sum_{y' \in \mathcal{Y}} \exp \boldsymbol{\theta}^{\top} \mathbf{f}(x,y')} \tag{1}$$

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[1]The data can be obtained from `http://www.cs.cmu.edu/~ytsvetko/definiteness_corpus`.

[2]The TED talks are from a large parallel corpus obtained from `http://www.ted.com/talks/`.

where $\boldsymbol{\theta} \in \mathbb{R}^d$ is a vector of parameters (feature weights), and $\mathbf{f} : \mathcal{X} \times \mathcal{Y} \to \mathbb{R}^d$ is the feature function over input–label pairs. The feature function is defined as follows:

$$\mathbf{f}(x,y) = \boldsymbol{\phi}(x) \times \tilde{\boldsymbol{\omega}}(y) \tag{2}$$

where the percept function $\boldsymbol{\phi} : \mathcal{X} \to \mathbb{R}^c$ produces a vector of real-valued characteristics of the input, and the attribute function $\tilde{\boldsymbol{\omega}} : \mathcal{Y} \to \{0,1\}^a$ encodes characteristics of each label. There is a feature for every percept–attribute pairing: so $d = c \cdot a$ and $f_{(i-1)a+j}(x,y) = \phi_i(x)\tilde{\omega}_j(y), 1 \leq i \leq c, 1 \leq j \leq a$.[3] The contents of the percept and attribute functions are detailed in §4.2 and §4.3 respectively.

For prediction, having learned weights $\hat{\boldsymbol{\theta}}$ we use the Bayes-optimal decision rule for minimizing misclassification error, selecting the $y$ that maximizes this probability:

$$\hat{y} \leftarrow \arg\max_{y \in \mathcal{Y}} p_{\hat{\boldsymbol{\theta}}}(y|x) \tag{3}$$

Training optimizes $\hat{\boldsymbol{\theta}}$ so as to maximize a convex $L_2$-regularized[4] learning objective over the training data $\mathcal{D}$:

$$\hat{\boldsymbol{\theta}} = \arg\max_{\boldsymbol{\theta}} -\lambda \|\boldsymbol{\theta}\|_2^2 + \sum_{\langle x,y \rangle \in \mathcal{D}} \log \frac{\exp \boldsymbol{\theta}^\top \mathbf{f}(x,y)}{\sum_{y' \in \mathcal{Y}} \exp\left(\boldsymbol{\theta}^\top \mathbf{f}(x,y')\right)} \tag{4}$$

With $\tilde{\boldsymbol{\omega}}(y) = $ *the identity of the label*, this reduces to standard logistic regression.

### 4.1.2 Non-linear model

We employ a random forest classifier (Breiman, 2001), an ensemble of decision tree classifiers learned from many independent subsamples of the training data. Given an input, each tree classifier assigns a probability to each label; those probabilities are averaged to compute the probability distribution across the ensemble.

An important property of the random forests, in addition to being an effective tool in prediction, is their immunity to overfitting: as the number of trees increases, they produce a limiting value of the generalization error.[5] Thus, no hyperparameter tuning is required. Random forests are known to be robust to sparse data and to label imbalance (Chen et al., 2004), both of which are challenges with the definiteness dataset.

## 4.2 Percepts

The characteristics of the input that are incorporated in the model, which we call *percepts* to distinguish them from model features linking inputs to outputs,[6] are intended to capture the aspects of English morphosyntax that may be relevant to the communicative functions of definiteness.

After preprocessing the text with a dependency parser and coreference resolver, which is described in §6.1, we extract several kinds of percepts for each NP.

### 4.2.1 Basic

**Words of interest.** These are the *head* within the NP, all of its *dependents*, and its *governor* (external to the NP). We are also interested in the *attached verb*, which is the first verb one encounters when traversing the dependency path upward from the head. For each of these words, we have separate percepts capturing: the token, the part-of-speech (POS) tag, the lemma, the dependency relation, and (for the head only) a binary indicator of plurality (determined from the POS tag). As there may be multiple dependents, we have additional features specific to the first and the last one. Moreover, to better capture tense, aspect and modality, we collect the attached verb's *auxiliaries*. We also make note of the negative particle (with dependency label *neg*) if it is a dependent of the verb.

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[3]Chahuneau et al. (2013) use a similar parametrization for their model of morphological inflection.

[4]As is standard practice with these models, bias parameters (which capture the overall frequency of percepts/attributes) are excluded from regularization.

[5]See Theorem 1.2 in Breiman (2001) for details.

[6]See §4.1

**Structural.** The structural percepts are: the *path length* from the head up to the root, and to the attached verb. We also have percepts for the number of dependents, and the number of dependency relations that link non-neighbors. Integer values were binarized with thresholding.

**Positional.** These percepts are the *token length* of the NP, the NP's *location* in the sentence (first or second half), and the *attached verb's position* relative to the head (left or right). 12 additional percept templates record the POS and lemma of the left and right neighbors of the head, governor, and attached verb.

### 4.2.2 Contextual NPs

When extracting features for a given NP (call it the "target"), we also consider NPs in the following relationship with the target NP: its *immediate parent*, which is the smallest NP whose span fully subsumes that of the target; the *immediate child*, which is the largest NP subsumed within the target; the *immediate precedent* and *immediate successor* within the sentence; and the *nearest preceding coreferent mention*.

For each of these related NPs, we include all of their basic percepts conjoined with the nature of the relation to the target.

### 4.3 Attributes

As noted above, though CFD labels are organized into a tree hierarchy, there are actually several dimensions of commonality that suggest different groupings. These attributes are encoded as ternary characteristics; for each label (including internal labels), every one of the 8 attributes is assigned a value of +, −, or 0 (refer to fig. 1). In light of sparse data, we design features to exploit these similarities via the attribute vector function

$$\boldsymbol{\omega}(y) = [y, A(y), B(y), F(y), G(y), P(y), R(y), S(y), U(y)]^\top \tag{5}$$

where $A : \mathcal{Y} \to \{+, -, 0\}$ returns the value for Anaphoric, $B(y)$ for Bridging, etc. The identity of the label is also included in the vector so that different labels are always recognized as different by the attribute function. The categorical components of this vector are then binarized to form $\tilde{\boldsymbol{\omega}}(y)$; however, instead of a binary component that fires for the 0 value of each ternary attribute, there is a component that fires for *any* value of the attribute—a sort of bias term. The weights assigned to features incorporating + or − attribute values, then, are easily interpreted as deviations relative to the bias.

## 5  Evaluation

The following measures are used to evaluate our predictor against the gold standard for the held-out evaluation (dev or test) set $\mathcal{E}$:

• **Exact Match:** This accuracy measure gives credit only where the predicted and gold labels are identical.

• **By leaf label:** We also compute precision and recall of each leaf label to determine which categories are reliably predicted.

• **Soft Match:** This accuracy measure gives partial credit where the predicted and gold labels are related. It is computed as the proportion of attributes-plus-full-label whose (categorical) values match: $|\boldsymbol{\omega}(y) \cap \boldsymbol{\omega}(y')|/9$.

## 6  Experiments

### 6.1  Experimental Setup

**Data splits.** The annotated corpus of Bhatia et al. (2014) (§3) contains 17 documents in 3 genres: 13 prepared speeches (mostly TED talks),[7] 2 newspaper articles, and 2 fictional narratives. We arbitrarily choose some documents to hold out from each genre; the resulting test set consists of 2 TED talks ("Alisa_News", "RobertHammond_park"), 1 newspaper article ("crime1_iPad_E"), and 1 narrative ("Little Red Riding Hood"). The test set then contains 19,28 tokens (111 sentences), in which there are 511 annotated NPs; while the training set contains 2,911 NPs among 11,932 tokens (757 sentences).

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[7]We have combined the TED talks and presidential speech genres since both involved prepared speeches.

| Condition | $|\boldsymbol{\theta}|$ | $\lambda$ | Exact Match Acc. | Soft Match Acc. |
|---|---|---|---|---|
| Majority baseline | — | — | 12.1 | 47.8 |
| Log-linear classifier, attributes only | 473,064 | 100 | 38.7 | 77.1 |
| Log-linear classifier, labels only | 413,931 | 100 | 40.8 | 73.6 |
| Full log-linear classifier (labels + attributes) | 926,417 | 100 | 43.7 | **78.2** |
| Random forest classifier | 20,363 | — | **49.7** | 77.5 |

**Table 1:** Classifiers and baseline, as measured on the test set. The first two columns give the number of parameters and the tuned regularization hyperparameter, respectively; the third and fourth columns give accuracies as percentages; the best in each column is bolded.

| Leaf label | No. of Instances | Prec. | Recall | $F_1$ |
|---|---|---|---|---|
| Nonunique_Predicative_Identity | 10 | — | 0 | — |
| Pleonastic | 44 | 100 | 78 | 88 |
| Nonunique_Nonspec | 173 | 9 | 25 | 13 |
| Other_Nonreferential | 134 | 39 | 36 | 37 |
| Nonunique_Larger_situation | 97 | 29 | 25 | 27 |
| Bridging_Other_Context | 96 | 33 | 6 | 11 |
| Same_Head | 452 | 41 | 41 | 41 |
| Unique_Hearer_New | 26 | — | 0 | — |
| Quantified | 213 | 57 | 57 | 57 |
| Different_Head | 271 | 32 | 33 | 32 |
| Bridging_Nominal | 33 | 33 | 10 | 15 |
| Measure_Nonreferential | 98 | 88 | 26 | 40 |
| Part_of_Noncompositional_MWE | 88 | 20 | 17 | 18 |
| Bridging_Restrictive_Modifier | 552 | 58 | 84 | 68 |
| Nonunique_Hearer_New_Spec | 190 | 36 | 46 | 40 |
| Predicative_Nonidentity | 57 | 0 | 0 | — |
| Unique_Larger_situation | 97 | 52 | 58 | 55 |
| Generic_Individual_Level | 113 | 14 | 11 | 13 |
| Bridging_Event | 9 | — | 0 | — |
| Nonunique_Physical_Copresence | 36 | 0 | 0 | — |

**Table 2:** Leaf Precision, Recall and F1 as percentages. The number of instances in the first column are from the training set.

**Preprocessing.** Automatic dependency parses and coreference information were obtained with the parser and coreference resolution system in Stanford CoreNLP v. 3.3.0 (Socher et al., 2013; Recasens et al., 2013) for use in features (§4.2). Syntactic features were extracted from the Basic dependencies output by the parser. To evaluate the performance of Stanford system on our data, we manually inspected the dependencies for a subset of sentences from our corpus (using texts from TED talks and fictional narratives genres) and recorded the errors. We found that about 70% of the sentences had all correct dependencies, and only about 0.04% of the total dependencies were incorrect for our data.

Throughout our experiments (training as well as testing), we use the gold NP boundaries identified by the human annotators. The automatic dependency parses are used to extract percepts for each gold NP. If there is a conflict between the gold NP boundaries and the parsed NP boundaries, to avoid extracting misleading percepts, we assign a default value.

**Learning.** The log-linear model variants are trained with an in-house implementation of supervised learning with $L_2$-regularized AdaGrad (Duchi et al., 2011). Hyperparameters are tuned on a development set formed by holding out every tenth instance from the training set (test set experiments use the full training set): the power of 10 giving the highest Soft Match accuracy was chosen for $\lambda$.[8] The Python `scikit-learn` toolkit (Pedregosa et al., 2011) was used for the random forest classifier.[9]

## 6.2 Results

Measurements of overall classification performance appear in table 1. While far from perfect, our classifiers achieve promising accuracy levels given the small size of the training data and the number of labels in the annotation scheme. The random forest classifier is the most accurate in Exact Match measure,

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[8] Preliminary experiments with cross-validation on the training data showed that the value of $\lambda$ was stable across folds.

[9] Because it is a randomized algorithm, the results may vary slightly between runs; however, a cross-validation experiment on the training data found very little variance in accuracy.

likely due to the robustness of that technique under conditions where the data are small and the frequencies of individual labels are imbalanced. In Soft Match measure, our attribute-aware log-linear models perform very well. The most successful of the log-linear models is the richest model, which combines the fine-grained communicative function labels with higher-level attributes of those labels. But notably the attribute-only model, which breaks down the semantic labels into combination of attributes, does not fall much behind and performs almost as well as the random forest classifier in Soft Match. This is encouraging because it suggests that the model has correctly exploited known linguistic generalizations to account for the grammaticalization of definiteness in English.

Table 2 reports the precision and recall of each leaf label predicted. Certain leaf labels are found to be easier for the classifier to predict, e.g. the communicative function label Pleonastic has a high F1 score. This is expected as the Ploenastic CFD for English is quite regular. The percept "POS is EX" fires very consistently for NPs which are gold annotated with Pleonastic CFD label in English. The classifier found predictions for certain CFD labels, such as Bridging_Event, Bridging_Nominal and Nonunique_Nonspecific, to be hard due to the fact that there were not enough training instances for the classifier to learn the generalizations corresponding to these CFDs. Bridging_Other_Context was hard to predict as this was a category which referred not to the entities previously mentioned but to the whole speech event. There seem to be no clear morphosyntactic percepts associated with this CFD, hence to train a classifier to predict this category label, we need more complex percepts involving complex semantic and discourse information. This is also applicable to the confusion between the Same_Head and Different_Head since both of these labels share all the semantic attributes used in this study.

Figure 3 lists 10 features that received the highest positive weights in the full model for the + and − values of the Specific attribute. This is a feature of log-linear models that we can take advantage of since these models make feature weights available which can provide useful insights into the model's behavior. Indeed looking at these feature weights, our prior knowledge about definites and indefinites is confirmed. The definite article, possessives (PRP$), proper nouns (NNP), and the second person pronoun are all associated with specific NPs, while the indefinite article is associated with nonspecific NPs. The model also seems to have picked up on the less obvious but well-attested tendency of objects to be nonspecific (Aissen, 2003).

In addition to confirming known grammaticalization patterns of definiteness, we can mine the highly-weighted features for new hypotheses: here the model thinks that objects of "from" are especially likely to be specific, see figs. 3 and 4, and that NPs with comparative adjectives (JJR) are especially likely to be nonspecific, as in fig. 3. For another example in fig. 3, *Num. of dependents, dependent's POS: 1,PRP$* has higher weight than, say *Num. of dependents, dependent's POS: 2,PRP$*. This observation can lead us to formulate a hypothesis that in English the NPs which have possessive pronouns immediately preceding the head are more likely to be specific than the NPs which have intervening words between the possessive pronoun and the head. Similarly, looking at another example in fig. 4, the following two percepts fire for the NP "the United States of America", viz. Last dependent's POS: NNP, and first dependent's lemma: the, we may hypothesize that these percepts are indicators of specificity. Thus this methodology allows us to generate hypotheses, however, each of these hypotheses may not hold true under further investigation. This is due to the fact that the feature weights the classifier generates may be due to a number of reasons: either these weights indeed reflect the inherent association with specificity, or they may be a result of the frequency for that pattern observed in our corpus. Whether these are general trends, or just an artifact of the sentences that happened to be in the training data, will require further investigation, ideally with additional datasets and more rigorous hypothesis testing.

Finally, we can remove features to test their impact on predictive performance. Notably, in experiments ablating features indicating articles—the most obvious exponents of definiteness in English—we see a decrease in performance, but not a drastic one. This suggests that the expression of communicative functions of definiteness is in fact much richer than morphological definiteness.

**Errors.** Several labels are unattested or virtually unattested in the training data, so the models unsurprisingly fail to predict them correctly at test time. SAME_HEAD and DIFFERENT_HEAD, though both common, are confused quite frequently. Whether the previous coreferent mention has the same

**Percepts**

| +Specific | | −Specific | |
|---|---|---|---|
| First dependent's POS | PRP$ | First dependent's lemma | a |
| Head's left neighbor's POS | PRP$ | Last dependent's lemma | a |
| Last dependent's lemma | you | Num. of dependents, dependent's lemma | 1,a |
| Num. of dependents, dependent's lemma | 1,you | Head's left neighbor's POS | JJR |
| Num. of dependents, dependent's POS | 1,PRP$ | Last dependent's POS | JJR |
| Governor's right neighbor's POS | PRP$ | Num. of dependents, dependent's lemma | 2,a |
| Last dependent's POS | NNP | First dependent's lemma | new |
| Last dependent's POS | PRP$ | Last dependent's lemma | new |
| First dependent's lemma | the | Num. of dependents, dependent's POS | 2,JJR |
| Governor's lemma | from | Governor's left neighbor's POS | VB |

**Figure 3:** Percepts receiving highest positive weights in association with attribute values.

| Example | Relevant percepts from fig. 3 | CFD annotation |
|---|---|---|
| This is just for *the United States of America*. | Last dependent's POS: NNP, first dependent's lemma: the | Unique_Larger_situation |
| We were driving from *our home in Nashville* to a little farm we have 50 miles east of Nashville — driving ourselves. | First dependent's POS: PRP$, head's left neighbor's POS: PRP$, governor's right neighbor's POS:PRP$, governor's lemma: from | Bridging_restrictiveModifier |

**Figure 4:** Sentences from our corpus to illustrate Percepts fired and the corresponding CFD annotations.

or different head is a simple distinction for humans; low model accuracy is likely due to errors propagated from coreference resolution. This problem is so frequent that merging these two categories and retraining the random forest model improves Exact Match accuracy by 8% absolute and Soft Match accuracy by 5% absolute. Another common confusion is between the highly frequent category UNIQUE_LARGER_SITUATION and the rarer category UNIQUE_HEARER_NEW; the latter is supposed to occur only for the first occurrence of a proper name referring to a entity that is not already part of the knowledge of the larger community. In other words, this distinction requires world knowledge about well-known entities, which could perhaps be mined from the Web or other sources.

## 7 Related Work

Because semantic/pragmatic analysis of referring expressions is important for many NLP tasks, a computational model of the communicative functions of definiteness has the potential to leverage diverse lexical and grammatical cues to facilitate deeper inferences about the meaning of linguistic input. We have used a coreference resolution system to extract features for modeling definiteness, but an alternative would be to predict definiteness functions as input to (or jointly with) the coreference task. Applications such as information extraction and dialogue processing could be expected to benefit not only from coreference information, but also from some of the semantic distinctions made in our framework, including specificity and genericity.

Better computational processing of definiteness in different languages stands to help machine translation systems. It has been noted that machine translation systems face problems when the source and the target language use different grammatical strategies to express the same information (Stymne, 2009; Tsvetkov et al., 2013). Previous work on machine translation has attempted to deal with this in terms of either (a) preprocessing the source language to make it look more like the target language (Collins et al., 2005; Habash, 2007; Nießen and Ney, 2000; Stymne, 2009, *inter alia*); or (b) post-processing the machine translation output to match the target language, (e.g., Popović et al., 2006). Attempts have also been made to use syntax on the source and/or the target sides to capture the syntactic differences between languages (Liu et al., 2006; Yamada and Knight, 2002; Zhang et al., 2007). Automated prediction of (in)definite articles has been found beneficial in a variety of applications, including postediting of MT output (Knight and Chander, 1994), text generation (Elhadad, 1993; Minnen et al., 2000), and identification and correction of ESL errors (Han et al., 2006; Rozovskaya and Roth, 2010). More recently, Tsvetkov et al. (2013) trained a classifier to predict where English articles might plausibly be added or

removed in a phrase, and used this classifier to improve the quality of statistical machine translation.

While definiteness morpheme prediction has been thoroughly studied in computational linguistics, studies on additional, more complex aspects of definiteness are limited. Reiter and Frank (2010) exploit linguistically-motivated features in a supervised approach to distinguish between generic and specific NPs. Hendrickx et al. (2011) investigated the extent to which a coreference resolution system can resolve the bridging relations. To the best of our knowledge, no studies have been conducted on automatic prediction of semantic and pragmatic communicative functions of definiteness more broadly.

Our work is related to research in linguistics on the modeling of syntactic constructions such as dative shift and the expression of possession with "of" or "'s". Bresnan and Ford (2010) used logistic regression with semantic features to predict syntactic constructions. Although we are doing the opposite (using syntactic features to predict semantic categories), we share the assumption that reductionist approaches (as mentioned earlier) are not able to capture all the nuances of a linguistic phenomenon. Following Hopper and Traugott (2003) we observe that grammaticalization is accompanied by *function drift*, resulting in multiple communicative functions for each grammatical construction. Other attempts have also been made to capture, using classifiers, (propositional as well as non propositional) aspects of meaning that have been grammaticalized, e.g. see Reichart and Rappoport (2010) for tense sense disambiguation, Prabhakaran et al. (2012) for modality tagging, and Srikumar and Roth (2013) for semantics expressed by prepositions.

## 8    Conclusion

We have presented a data-driven approach to modeling the relationship between universal communicative functions associated with (in)definiteness and their lexical/grammatical realization in a particular language. Our feature-rich classifiers can give insights into this relationship as well as predict communicative functions for the benefit of NLP systems. Exploiting the higher-level semantic attributes, our log-linear classifier compares favorably to the random forest classifier in Soft Match accuracy. Further improvements to the classifier may come from additional features or better preprocessing. This work has focused on English, but in future work we plan to build similar models for other languages—including languages without articles, under the hypothesis that such languages will rely on other, subtler devices to encode many of the functions of definiteness.

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