Automatic prediction of aspectual class of verbs in context

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Abstract
This paper describes a new approach to predicting the aspectual class of verbs in context, i.e., whether a verb is used in a stative or dynamic sense. We identify two challenging cases of this problem: when the verb is unseen in training data, and when the verb is ambiguous for aspectual class. A semi-supervised approach using linguistically-motivated features and a novel set of distributional features based on representative verb types allows us to predict classes accurately, even for unseen verbs. Many frequent verbs can be either stative or dynamic in different contexts, which has not been modeled by previous work; we use contextual features to resolve this ambiguity. In addition, we introduce two new datasets of clauses marked for aspectual class.

1 Introduction
In this work, we focus on the automatic prediction of whether a verb in context is used in a stative or in a dynamic sense, the most fundamental distinction in all taxonomies of aspectual class. The aspectual class of a discourse’s finite verbs is an important factor in conveying and interpreting temporal structure (Moens and Steedman, 1988; Dorr, 1992; Klavans and Chodorow, 1992); others are tense, grammatical aspect, mood and whether the utterance represents an event as completed. More accurate temporal information processing is expected to be beneficial for a variety of natural language processing tasks (Costa and Branco, 2012; UzZaman et al., 2013).

While most verbs have one predominant interpretation, others are more flexible for aspectual class and can occur as either stative (1) or dynamic (2) depending on the context. There are also cases that allow for both readings, such as (3).

(1) The liquid fills the container. (stative)
(2) The pool slowly filled with water. (dynamic)
(3) Your soul was made to be filled with God Himself. (both) (Brown corpus, religion)

Cases like (3) do not imply that there is a third class, but rather that two interpretations are available for the sentence, of which usually one will be chosen by a reader.

Following Siegel and McKeown (2000), we aim to automatically classify clauses for fundamental aspectual class, a function of the main verb and a select group of complements, which may differ per verb (Siegel and McKeown, 2000; Siegel, 1998b). This corresponds to the aspectual class of the clause’s main verb when ignoring any aspectual markers or transformations. For example, English sentences with perfect tense are usually considered to introduce states to the discourse (Smith, 1991; Katz, 2003), but we are interested in the aspectual class before this transformation takes place. The clause John has kissed Mary introduces a state, but the fundamental aspectual class of the ‘tenseless’ clause John kiss Mary is dynamic.

In contrast to Siegel and McKeown (2000), we do not conduct the task of predicting aspectual class solely at the type level, as such an approach ignores the minority class of ambiguous verbs. Instead we predict the aspectual class of verbs in the context of their arguments and modifiers. We show that this method works better than using only type-based features, especially for verbs with ambiguous aspectual class. In addition, we show that type-based features, including novel distributional features based on representative verbs, accurately predict predominant aspectual class for unseen verb types. Our work differs from prior work in that we treat the problem as a three-way classification task, predicting DYNAMIC, STATIVE or BOTH as the aspectual class of a verb in context.
2 Related work

Aspectual class is well treated in the linguistic literature (Vendler, 1957; Dowty, 1979; Smith, 1991, for example). Our notion of the stative/dynamic distinction corresponds to Bach’s (1986) distinction between states and non-states; to states versus occurrences (events and processes) according to Mourelatos (1978); and to Vendler’s (1957) distinction between states and the other three classes (activities, achievements, accomplishments).

Early studies on the computational modeling of aspectual class (Nakhimovsky, 1988; Passonneau, 1988; Brent, 1991; Klavans and Chodorow, 1992) laid foundations for a cluster of papers published over a decade ago (Siegel and McKeown, 2000; Siegel, 1998b; Siegel, 1998a). Since then, it has mostly been treated as a subtask within temporal reasoning, such as in efforts related to TimeBank (Pustejovsky et al., 2003) and the TempEval challenges (Verhagen et al., 2007; Verhagen et al., 2010; UzZaman et al., 2013), where top-performing systems (Jung and Stent, 2013; Bethard, 2013; Chambers, 2013) use corpus-based features, WordNet synsets, parse paths and features from typed dependencies to classify events as a joint task with determining the event’s span.

Costa and Branco (2012) explore the usefulness of a wider range of explicitly aspectual features for temporal relation classification.

Siegel and McKeown (2000) present the most extensive study of predicting aspectual class, which is the main inspiration for this work. While all of their linguistically motivated features (see section 4.1) are type-based, they train on and evaluate over labeled verbs in context. Their data set taken from medical discharge summaries comprises 1500 clauses containing main verbs other than be and have which are marked for aspectual class. Their model fails to outperform a baseline of memorizing the most frequent class of a verb type, and they present an experiment testing on unseen verbs. Siegel (1998a) investigates a classification method for the verb have in context; inspired by this work, our present work goes one step further and uses a larger set of instance-based contextual features to perform experiments on a set of 20 verbs. To the best of our knowledge, there is no previous work comprehensively addressing aspectual classification of verbs in context.

3 Data

Verb type seed sets Using the LCS Database (Dorr, 2001), we identify sets of verb types whose senses are only stative (188 verbs, e.g. belong, cost, possess), only dynamic (3760 verbs, e.g. alter, knock, resign), or mixed (215 verbs, e.g. fill, stand, take), following a procedure described by Dorr and Olsen (1997).

Asp-MASC The Asp-MASC corpus consists of 7875 clauses from the letters, news and jokes sections of MASC (Ide et al., 2010), each labeled by two annotators for the aspectual class of the main verb.\(^2\) Texts were segmented into clauses using SPADE (Soricut and Marcu, 2003) with some heuristic post-processing. We parse the corpus using the Stanford dependency parser (De Marneffe et al., 2006) and extract the main verb of each segment. We use 6161 clauses for the classification task, omitting clauses with have or be as the main verb and those where no main verb could be identified due to parsing errors (none). Table 1 shows inter-annotator agreement; Table 2 shows the confusion matrix for the two annotators. Our two annotators exhibit different preferences on the 598 cases where they disagree between DYNAMIC and STATIVE. Such differences in annotation prefer-

\(^1\)Direct comparison on their data is not possible; feature values for the verbs studied are available, but full texts and the English Slot Grammar parser (McCord, 1990) are not.

\(^2\)Corpus freely available from www.coli.uni-saarland.de/~afried.
Table 3: Asp-Ambig: confusion matrix for two annotators. Cohen’s $\kappa$ is 0.6.

|          | Dynamic | Static | Both |
|----------|---------|--------|------|
| Dynamic  | 1444    | 201    | 54   |
| Static   | 168     | 697    | 20   |
| Both     | 44      | 31     | 8    |

Table 4: LingInd feature set and examples for lexical items associated with each indicator.

| Feature                  | Values              | Example          |
|--------------------------|---------------------|------------------|
| part-of-speech tag of the verb | VB, VBG, VBN, ... | present, past, future |
| tense                     | true/false          | true/false       |
| progressive               | true/false          | true/false       |
| perfect                   | active/passive      | active/passive   |
| voice                     | WordNet lexname/POS |                  |
| grammatical dependents    |                     |                  |

Table 5: Instance-based (Inst) features

| Feature                  | Values              | Example          |
|--------------------------|---------------------|------------------|
| temporal-adverb          |                     | finally          |
| for-PP                   |                     | for an hour      |

4.2 Distributional Features (Dist)

We aim to leverage existing, possibly noisy sets of representative stative, dynamic or mixed verb types extracted from LCS (see section 3), making up for unseen verbs and noise by averaging over distributional similarities. Using an existing large distributional model (Thater et al., 2011) estimated over the set of Gigaword documents marked as stories, for each verb type, we build a syntactically informed vector representing the contexts in which the verb occurs. We compute three numeric feature values per verb type, which correspond to the average cosine similarities with the verb types in each of the three seed sets.

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3We thank the authors for providing us their code.
4.3 Instance-based features (Inst)

Table 5 shows our set of instance-based syntactic and semantic features. In contrast to the above described type-based features, these features do not rely on a background corpus, but are extracted from the clause being classified. Tense, progressive, perfect and voice are extracted from dependency parses as described above. For features encoding grammatical dependents, we focus on a subset of grammatical relations. The feature value is either the WordNet lexical filename (e.g. noun.person) of the given relation’s argument or its POS tag, if the former is not available. We simply use the most frequent sense for the dependent’s lemma. We also include features that indicate, if there are any, the particle of the verb and its prepositional dependents. For the sentence A little girl had just finished her first week of school, the instance-based feature values would include tense:past, subj:noun.person, dobj:noun.time or particle:none.

5 Experiments

The experiments presented in this section aim to evaluate the effectiveness of the feature sets described in the previous section, focusing on the challenging cases of verb types unseen in the training data and highly ambiguous verbs. The feature Lemma indicates that the verb’s lemma is used as an additional feature.

Experiment 1: SEEN verbs

The setting of our first experiment follows Siegel and McKeown (2000). Table 6 reports results for 10-fold cross-validation, with occurrences of all verbs distributed evenly over the folds. No feature combination significantly4 outperforms the baseline of simply memorizing the most frequent class of a verb type in the respective training folds.

Table 7: Experiment 2: UNSEEN verb types, Logistic regression, Asp-MASC. Baseline labels everything with the most frequent class in the training set (DYNAMIC). *Significantly4 different from line 1. †Significantly4 different from line 3.

Table 8: Experiment 3: ‘ONE- VS. MULTI-LABEL’ verbs, Asp-MASC. Baseline as in Table 6. *Indicates that result is significantly4 different from the respective baseline.

Experiment 2: UNSEEN verbs

This experiment shows a successful case of semi-supervised learning: while type-based feature values can be estimated from large corpora in an unsupervised way, some labeled training data is necessary to learn their best combination. This experiment specifically examines performance on verbs not seen in labeled training data. We use 10-fold cross validation but ensure that all occurrences of a verb type appear in the same fold: verb types in each test fold have not been seen in the respective training data, ruling out the Lemma feature. A Logistic regression classifier (Hall et al., 2009) works better here (using only numeric features), and we present results in Table 7. Both the LingInd and Dist features generalize across verb types, and their combination works best.

Experiment 3: ONE- VS. MULTI-LABEL verbs

For this experiment, we compute results separately for one-label verbs (those for which all instances in Asp-MASC have the same label) and
for multi-label verbs (instances have differing labels in Asp-MASC). We expect one-label verbs to have a strong predominant aspectual class, and multi-label verbs to be more flexible. Otherwise, the experimental setup is as in experiment 1. Results appear in Table 8. In each case, the linguistic indicator features again perform on par with the baseline. For multi-label verbs, the feature combination Lemma+LingInd+Inst leads to significant\(^4\) improvement of \(2\%\) gain in accuracy over the baseline; Table 9 reports detailed class statistics and reveals a gain in F-measure of 3 points over the baseline. To sum up, Inst features are essential for classifying multi-label verbs, and the LingInd features provide some useful prior. These results motivate the need for an instance-based approach.

### Experiment 4: Instance-based classification

For verbs with ambiguous aspectual class, type-based classification is not sufficient, as this approach selects a dominant sense for any given verb and then always assigns that. Therefore we propose handling ambiguous verbs separately. As Asp-MASC contains only few instances of each of the ambiguous verbs, we turn to the Asp-Ambug dataset. We perform a Leave-One-Out (LOO) cross validation evaluation, with results reported in Table 10.\(^5\) Using the Inst features alone (not shown in Table 10) results in a micro-average accuracy of only 58.1\%: these features are only useful when combined with the feature Lemma. For classifying verbs whose most frequent class occurs less than 56\% of the time, Lemma+Inst features are essential. Whether or not performance is improved by adding LingInd/Dist features, with their bias towards one aspectual class, depends on the verb type. It is an open research question which verb types should be treated in which way.

| SYSTEM | CLASS | ACC. | P | R | F |
|--------|-------|------|---|---|---|
| baseline | micro-avg. | 78.9 | 0.75 | 0.79 | 0.76 |
| LingInd | DYNAMIC | 0.84 | 0.95 | 0.89 | |
| +Inst |STATIVE | 0.76 | 0.69 | 0.72 | |
| +Lemma | BOTH | 0.51 | 0.24 | 0.33 | |
| micro-avg. | 80.9* | 0.78 | 0.81 | 0.79 | |

Table 9: Experiment 3: ‘Multi-label’, precision, recall and F-measure, detailed class statistics for the best-performing system from Table 8.

### Table 10: Experiment 4: Instance-based Classification

| VERB | # of INST. | MAJORITY CLASS\(^5\) | Inst +Lemma | Inst +LingInd | Inst +LingInd +Dist |
|------|-----------|----------------------|-------------|---------------|---------------------|
| feel | 128       | 96.1 STAT            | 93.0        | 93.8          |
| say  | 138       | 94.9 DYN             | 93.5        | 93.5          |
| make | 136       | 91.9 DYN             | 91.2        | 91.2          |
| come | 133       | 88.0 DYN             | 87.2        | 87.2          |
| take | 137       | 85.4 DYN             | 85.4        | 85.4          |
| meet | 130       | 83.9 DYN             | 86.2        | 87.7          |
| stand| 130       | 80.0 STAT            | 79.2        | 83.1          |
| find | 137       | 74.5 DYN             | 69.3        | 68.8          |
| accept| 134      | 70.9 DYN             | 64.9        | 65.7          |
| hold | 134       | 56.0 BOTH            | 43.3        | 49.3          |
| carry | 136      | 55.9 DYN             | 55.9        | 58.1          |
| look | 138       | 55.8 DYN             | 72.5        | 74.6          |
| show | 133       | 54.9 DYN             | 69.2        | 68.4          |
| appear | 136     | 52.2 STAT            | 64.7        | 61.0          |
| follow | 122    | 51.6 BOTH            | 69.7        | 65.6          |
| consider | 138  | 50.7 DYN             | 61.6        | 70.3          |
| cover | 123       | 50.4 STAT            | 46.3        | 54.5          |
| fill | 134       | 47.8 DYN             | 66.4        | 62.7          |
| bear | 135       | 47.4 DYN             | 70.4        | 67.4          |
| allow | 135       | 37.8 DYN             | 48.9        | 51.9          |
| micro-avg. | 2667 | 66.3 | 71.0* | 72.0* |

Table 10: Experiment 4: Instance-based Classification. Accuracy (in \%) on Asp-Ambug. *Differs significantly\(^4\) from the majority class baseline.

### 6 Discussion and conclusions

We have described a new, context-aware approach to automatically predicting aspectual class, including a new set of distributional features. We have also introduced two new data sets of clauses labeled for aspectual class. Our experiments show that in any setting where labeled training data is available, improvement over the most frequent class baseline can only be reached by integrating instance-based features, though type-based features (LingInd, Dist) may provide useful priors for some verbs and successfully predict predominant aspectual class for unseen verb types. In order to arrive at a globally well-performing system, we envision a multi-stage approach, treating verbs differently according to whether training data is available and whether or not the verb’s aspectual class distribution is highly skewed.

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