A Logistic Regression Model of Determiner Omission in PPs

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Abstract

The realization of singular count nouns without an accompanying determiner inside a PP (determinerless PP, bare PP, Preposition-Noun Combination) has recently attracted some interest in computational linguistics. Yet, the relevant factors for determiner omission remain unclear, and conditions for determiner omission vary from language to language. We present a logistic regression model of determiner omission in German based on data obtained by applying annotation mining to a large, automatically and manually annotated corpus.

1 The problem and how to deal with it

Preposition-Noun Combinations (PNCs, sometimes called determinerless PPs or bare PPs) minimally consist of a preposition and a count noun in the singular that – despite requirements formulated elsewhere in the grammar of the respective language – appears without a determiner. The noun in a PNC can be extended through prenominal modification (1) and postnominal complementation (2). Still, a determiner is missing. The following examples are given from German.

(1) *auf parlamentarische Anfrage* (‘after being asked in parliament’), *mit beladenem Rucksack* (‘with loaded backpack’), *unter sanftier Androhung* (‘under gentle threat’)

(2) *Er wehrt sich gegen die Forderung nach Stilllegung einer Verbrennungsanlage.*

PNCs occur in a wide range of languages (Himmelmann, 1998); the conditions for determiner omission, however, have not been detected yet, and conditions applying to one language do not carry over to other languages. In addition, speakers only reluctantly judge the acceptability of newly coined PNCs, so that reliance to introspective judgments cannot be assumed.

For English, Stvan (1998) and Baldwin et al. (2006) have claimed that either the semantics of the preposition or of the noun play a major role in determining whether a singular count noun may appear without a determiner in a PNC. Stvan (1998) assumes that nouns determine the well-formedness of PNCs (3) if the denotation of the noun occurs in a particular semantic field, while Baldwin et al. (2006) assume that certain prepositions impose selection restrictions on their nominal complements that allow for determiner omission (4).

(3) *from school, at school, in jail, from jail, …*

(4) *by train, by plane, by bus, by pogo stick, by hydro-foil …*

Interestingly, Le Bruyn et al. (2009) have observed that basic assumptions of Stvan’s analysis do not apply to Dutch, French, or Norwegian. With regard to German, we observe that neither the pattern in (3) nor in (4) is productive. Constructions like (4) cannot be realized as PNCs in German, but require full PPs.

In the following, we propose an analysis of PNCs that combines corpus annotation, annotation mining (Chiarcos et al., 2008), and logistic regression modeling (Harrell, 2001). Annotation mining assumes that linguistically relevant generalizations can be derived in a bottom-up fashion from a suitably annotated corpus. Relevant hits in the corpus are mapped into a feature vector that serves as input for logistic regression.
classification. In the present case, the input consists of sentences containing either PNCs or PPs. Binary logistic regression suggests itself as a classification method since the problem of PNCs can be rephrased as the following question: Under which conditions can an otherwise obligatory determiner be omitted?

The majority of required annotations can be derived automatically, but there are no available systems for the automatic determination of preposition senses in German, so preposition sense annotation has to be carried out manually and requires a language-specific tagset for preposition senses.

While our initial analysis is based on German data, the general methodology can be applied to other languages, provided that corpora receive proper annotation.

2 Corpus annotation

2.1 General characteristics

The present analysis is based on a newspaper corpus of the Swiss-German newspaper *Neue Zürcher Zeitung* from 1993 to 1999, comprising approx. 230 million words. The annotation is based on an XML-stand-off format. MMAX2 (Müller and Strube, 2006) is used for manual annotation. Annotations are carried out both for PNCs and for full-fledged PPs. For each preposition, the following data is considered: PNCs, where N is a count noun; corresponding PPs with the same count noun; and PPs containing count nouns not appearing inside PNCs.

The following annotations are provided for each dataset in the corpus:

Lexical level: part-of-speech, inflectional morphology, derivational morphology of nouns, count/mass distinction of nouns, interpretation of nouns, interpretation of prepositions, noun compounding.

Syntactic level: mode of embedding of the phrase (adjunct or complement), syntactic dependents of the noun, modification of the noun.

Global level: Is the phrase contained in a headline, title, or quotation? Is the phrase idiomatic? Headlines, titles, and quotations are particularly prone to text truncation and PNCs occurring here might not be the result of syntactic operations. Similarly, idiomatic PNCs and PPs might follow combination rules that differ from the general modes of combination. Hence, the annotations may serve to exclude these cases from general classification.

2.2 Automatic annotation

The following tools are employed for automatic annotation: Regression Forest Tagger (Schmid and Laws, 2008) for POS tagging and morphological analysis (the tagger contains the SMOR component for morphological analysis, cf. Schmid, 2004), and Tree Tagger (Schmid, 1995) for chunk parsing.

To determine noun meanings, we make use of two resources. The first resource is GermanNet (Kunze and Lemnitzer, 2002), the German version of WordNet. We employ 23 top-level categories, and each noun is annotated with every top-level category it belongs to. Secondly, we use the computer lexicon HaGen-Lex (Hartmutpf et al., 2003), which offers specific sortal information derived from a formal ontology for each noun. Finally, we employ a classifier for the count/mass distinction. The classifier combines lexical statistics, expressed in terms of a decision tree classifier, with contextual information, which is handled by Naïve Bayes classification (cf. Stadtfeld 2010). The classification is based on the fine-grained distinctions first introduced in Allan (1980), but we employ a reduced set of five instead of eight classes. The classifier is type-based as it makes use of the relation between singular and plural realizations of noun lemmas, but takes the immediate context of the lemma into account.

Nouns are only assigned to a particular class if both classifiers come to the same result w.r.t. this class assignment. While this leads to some nouns being excluded from the count/mass distinction, the resulting classes show a high degree of precision.

2.3 Manual annotation of preposition senses

Prepositions are highly polysemous. What is more, the relation between a preposition and its senses has to be determined in a language-

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1 Nouns that are assigned to more than one top-level category are presumably homonymous or polysemous. We do not disambiguate the nouns. The reason is that individual features will be evaluated for their effect in a logistic model, and an ambiguous noun will receive a value in each feature. Hence, we can be sure that a significant semantic feature will be included in the classification.
specific manner. While the *Preposition Project* forms a basis for preposition sense annotation in English (cf. Litkowski and Hargraves 2005, 2007), little attention has been paid to specialized annotation schemata for preposition senses in German, which form the first prerequisite for a classification of preposition senses.

Based on four usage-based grammars and dictionaries of German (Duden 2002, Helbig and Buscha 2001, Durrell and Brée 1993, Schröder 1986), we have developed an annotation schema with a hierarchical structure, allowing for subtrees of preposition senses that require a fine-grained classification (such as TEMPORAL, SPATIAL, CAUSAL, and PRESENCE). For temporal and spatial interpretations, the annotation is further facilitated by the use of decision trees.  

Altogether, the annotation schema includes the following list of top-level categories: MODAL, CAUSAL, PRESENCE, SPATIAL, TEMPORAL, STATE, COMITATIVE, AGENT, REDUCTION/EXTENSION, PARTICIPATION, SUBORDINATION, RECIPIENT, AFFILIATION, CORRELATION/INTERACTION, TRANSGRESSION, ORDER, THEME, SUBSTITUTE, EXCHANGE, COMPARISON, RESTRICTIVE, COPULATIVE, ADVERBIAL, DISTRIBUTIVE, STATEMENT/OPTION, CENTRE OF REFERENCE, and REALISATION.

Based on an extension of the weighted kappa statistic we have reached an overall kappa value ($\kappa_w$) of 0.657 and values between 0.551 and 0.860 for individual features (cf. Müller et al. 2010a). Two properties of the annotation schema prohibit the application of a standard kappa statistic: First, the schema allows subsorts, and secondly, a preposition may receive more than one annotation if its sense cannot be fully disambiguated. The values reported in Müller et al. (2010) for maximal subtypes such as SPATIAL ($\kappa_w = 0.709$) and TEMPORAL ($\kappa_w = 0.860$) can be equated to aggregate values in standard kappa statistics.

In the models presented below, we employ top-level categories only and have aggregated more specific sense annotations.

### 3 Preparing logistic regression models for ohne (‘without’) and unter (‘under’, ‘below’)

The problem of PNCs, i.e. why a determiner is omitted in a construction which otherwise requires the realization of the determiner, can be rephrased as a problem for binary logistic regression and classification.

While binary logistic regression does not prohibit moncausal explanations, typical models for binary logistic regression employ more than one factor, and the value of the coefficients models the relative influence of the individual factors. Logistic regression thus does not only help to identify factors for determiner omission, but also reveals the interplay of multiple licensing conditions – thus possibly accounting for the relative difficulty to distinguish acceptable from unacceptable PNCs.

We are aiming at a description of PNCs in German for the 22 prepositions listed in (5).

(5) *an, auf, bei, dank, durch, für, gegen, gemäß, hinter, in, mit, mittels, nach, neben, ohne, seit, über, um, unter, vor, während, wegen*

These prepositions have been chosen on the basis of the following two assumptions: a) they appear in PNCs and PPs, and b) their ‘typical’ object is an NP.

We present logistic regression models of determiner realization for two prepositions: ohne (‘without’) and unter (‘under’, ‘below’). The first preposition, *ohne*, is the only preposition that appears more often in PNCs than in PPs. The second preposition, *unter*, belongs to the class of highly polysemous prepositions. In fact, it is the preposition with the second largest number of senses (10 senses), only surpassed by *mit* (‘with’) (11 senses), which however appears much more often than *unter* in the corpus and thus requires further annotation. The following table summarizes the distribution of PNCs and PPs for both prepositions, after tokens that had been annotated as belonging to *headlines, quotations, telegram style sentences*, or as being idiomatic were excluded from the data. With regard to the first group (headlines etc.), the elimination mostly applies to PNCs, but among the PPs we found many idiomatic expressions and fixed phrases, which have also been excluded from modeling.

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2 The schema does not directly distinguish between local and directional senses, but makes use of cross-classification to deal with the distinction. Cf. Müller et al. (2010b).
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and the interpretation of the noun.
Features starting with DEP signify syntactic
arguments of the noun (DEP-S a sentential compo-
ment, DEP-NP an NP complement, etc.); the feature ADIA signifies the presence of one or
more modifying adjectives; the feature COM-
ound indicates whether the noun in question is
a compound. The feature GOVERNED indicates
whether a noun or a verb governs the phrase.
The feature NOMINALIZATION provides informa-
tion about the derivational structure of
noun, in particular it indicates whether a noun is
derived from a verb by use of the suffix -ung.
Features starting with GN are GermaNet top-
level categories, features starting with HL are
HaGenLex ontological sorts; both describe the
interpretation of the noun.
The statistical modeling started with the as-
sumption that each feature is relevant, so that an
initial feature set of 92 features was considered.
Feature elimination took place through fast
backwards elimination (Lawless and Singhal,
1978) and manual inspection. The results of fast
backwards elimination were not followed
blindly. Following Harrell’s (2001:56) sugges-
tion, we have kept factors despite their low
significance levels. In most cases, however, man-
ual inspection and fast backwards elimination
suggested the same results. The resulting mod-
els were subjected to bootstrap validation to
identify possible overfitting (cf. section 5.1).

\begin{table}[h]
\centering
\begin{tabular}{|l|c|c|c|}
\hline
Preposition & $\Sigma$ & PP & PNC \\
\hline
ohne & 3,750 & 591 & 3,159 \\
unter & 5,181 & 4,334 & 857 \\
\hline
\end{tabular}
\caption{Data Distribution of PNCs and PPs}
\end{table}

The value DET = no is taken to be the default
value in the following models. As a conse-
quence, negative values for coefficients indicate
rising probability for an omission of a deter-
miner, while positive coefficients shift odds in
favor of a realization of the determiner.

4 Logistic models for the omission of a
determiner with ohne and unter

The logistic regression models developed for
the prepositions ohne and unter make use of 13
and 22 features, respectively. In each case, we
have started with a full model fit (Harrell,
2001:58f.), evaluated the full model and elimi-
nated factors through manual inspection and fast
backwards elimination. The coefficients for the
models for ohne and unter are reported in tables
2 and 3.

\begin{table}[h]
\centering
\begin{tabular}{|l|c|c|c|c|}
\hline
 & Coef. & S.E. & Wald Z & p \\
\hline
INTERCEPT & -2.4024 & 0.1109 & -21.66 & 0.000 \\
OMINAL. & -1.3579 & 0.1870 & -7.26 & 0.000 \\
ADIA & 1.1360 & 0.1188 & 9.57 & 0.000 \\
CAUSAL & 1.2063 & 0.1302 & 9.26 & 0.000 \\
COMITAT. & 2.2821 & 0.5201 & 4.39 & 0.000 \\
PARTICIP. & 3.4027 & 0.4895 & 6.95 & 0.000 \\
PRESENCE & -0.7780 & 0.1463 & -5.32 & 0.000 \\
DEP-S & 5.0797 & 1.0542 & 4.82 & 0.000 \\
DEP-NP & 2.9752 & 0.1718 & 17.32 & 0.000 \\
DEP-PP & 2.1978 & 0.1487 & 14.78 & 0.000 \\
GN-RELAT. & -1.0292 & 0.4072 & -2.53 & 0.011 \\
GN-ATTR. & -1.3528 & 0.3038 & -4.45 & 0.000 \\
GN-EVENT & -0.8431 & 0.1431 & -5.89 & 0.000 \\
GN-Arte & -0.4117 & 0.1564 & -2.63 & 0.008 \\
\hline
\end{tabular}
\caption{Coefficients for a logistic regression
model of determiner omission with ohne.}
\end{table}

\footnote{In the following tables, S.E. stands for standard error
Wald Z reports the Z-score of the Wald statistic, which is
determined by divided the value of the coefficient through
its standard error. The squared Wald Z statistic is $\chi^2$-
distributed and thus indicates the goodness of fit for the
coefficients of the model.}
Table 4. Coefficients for a logistic model of determiner omission with *unter*.

| Coef. | S.E. | Wald Z | p   |
|-------|------|--------|-----|
| INTERCEPT | -0.4379 | 0.1657 | -2.64 | 0.008 |
| NOMINAL | -0.8346 | 0.2259 | -3.70 | 0.000 |
| ADJA | -1.0177 | 0.1432 | -7.11 | 0.000 |
| COMPOUND | 2.1719 | 0.2538 | 8.56 | 0.000 |
| GOVERNED | 1.9894 | 0.3017 | 6.59 | 0.000 |
| SPATIAL | 2.3237 | 0.2044 | 11.37 | 0.000 |
| CAUSAL | 1.3047 | 0.2272 | 5.74 | 0.000 |
| SUBORD. | 3.0529 | 0.2559 | 11.93 | 0.000 |
| ORDER | 3.4228 | 0.1861 | 18.40 | 0.000 |
| TRANSGR. | 4.4186 | 0.3677 | 12.02 | 0.000 |
| DEP-S | 8.4717 | 4.0734 | 2.08 | 0.037 |
| DEP-NP | 0.8551 | 0.1436 | 5.95 | 0.000 |
| DEP-PP | 0.3043 | 0.2170 | 1.40 | 0.161 |
| GN-GROUP | 0.5241 | 0.2563 | 2.04 | 0.041 |
| GN-COMM. | -0.9149 | 0.1443 | -6.34 | 0.000 |
| GN-LOC. | 2.2704 | 0.6208 | 3.66 | 0.000 |
| GN-REL. | -2.1161 | 0.6022 | -3.51 | 0.000 |
| GN-Poss. | -0.8482 | 0.3665 | -2.31 | 0.021 |
| GN-ATTR. | -2.2847 | 0.2741 | -8.33 | 0.000 |
| GN-ARTE. | 0.4169 | 0.1601 | 2.60 | 0.009 |
| GN-HUM. | 1.8870 | 0.4999 | 3.77 | 0.000 |
| HL-AD | -1.0253 | 0.1888 | -5.43 | 0.000 |
| HL-AS | -1.4214 | 0.3804 | -3.74 | 0.000 |

Table 3. Coefficients for a logistic model of determiner omission with *unter*.

General measures of the two models are reported in table 4. Somers’ $D_{xy}$ describes the proportion of observations, for which the model provides an appropriate class probability. $D_{xy}$ can be derived from $C$, the corresponding receiver operating characteristic curve area, since $D_{xy} = 2 \times (C - 0.5)$. Model L.R. (likelihood ratio) indicates the improvement reached by including the predictors. Degrees of freedom (d.f.) have been omitted from table 4, as they correspond to the number of predictors, i.e. 12 in the case of *ohne* and 23 in the case of *unter*. The high figures for Somers’ $D_{xy}$ are reassuring.

| Model L.R. | p | C | $D_{xy}$ |
|------------|---|---|----------|
| ohne | 1,063.5 | 0 | 0.876 | 0.753 |
| unter | 2,245.6 | 0 | 0.937 | 0.874 |

Table 4. Model Quality.

### 4.1 The model for *ohne*

Starting with the model in table 2, we can identify several groups of factors:

The first group comprises the interpretation of the preposition. The group discriminates between determiner omission and realization. The semantic features CAUSAL, COMITATIVE, and PARTICIPATION show positive coefficients, suggesting that prepositions receiving the aforementioned interpretations tend to favor an ‘ordinary’ NP including a determiner. The interpretation PRESENCE, on the other hand, shows a negative coefficient and thus suggests the omission of a determiner. There are further senses of *ohne*, which do not have a significant effect on determiner omission/realization.

Turning to the representation of syntactic argument structure of the noun, we find that the coefficients of DEP-S, DEP-NP, and DEP-PP receive positive values throughout. The presence of syntactic complements thus shifts odds in favor of determiner realization. There is a strong preference against determiner omission with DEP-S, and somewhat weaker values for DEP-NP and DEP-PP, respectively. A comparison of interpretation and complement realization offers a general assessment of PNCs. As *ohne* and *unter* share only a few senses, we do not necessarily expect that the discerning senses relevant for a realization of a PNC with *ohne* carry over to *unter*; but we do expect that features pertaining to the syntactic structure of the nominal complement play a role not only for *ohne*, but for *unter* (or for prepositions admitting PNCs in general) as well. And this prediction is actually borne out in the model for *unter*. The model thus already offers interesting insights not only w.r.t. the realization conditions of PNCs and PPs headed by *ohne*, but for broader analyses of PNCs as well.

We will return to the role and value of the features ADJA and NOMINALIZATION in section 4.3.

The last group comprises the semantic characteristics of nouns derived from GermaNet. If a noun is classified as belonging to the relevant GermaNet top-level categories, determiner omission is favored.
4.2 The model for unter

A first glance at the model for unter shows that it requires a larger set of predictors than the model for ohne. In part, this is due to the higher degree of polysemy of unter: with more senses, we expect more semantic predictors to enter the discrimination. In addition, a wider range of senses also allows for a wider range of selection restrictions, and hence for a larger number of different sortal specifications for selected nouns. The higher complexity of the model, however, should not conceal a peculiarity of this model that casts serious doubt on the idea that PNCs are monocausally licensed by particular senses of a preposition: the model selects five senses from the ten top level interpretations of unter; but the coefficients are unsigned. Thus, the model indicates that the senses SPATIAL, CAUSAL, SUBORDINATION, ORDER, and TRANSgression block the omission of a determiner. What we do not find are senses that favor the omission of a determiner.

The features DEp-S, DEp-NP, and DEp-PP again favor the realization of a determiner. A comparison of the coefficient of DEp-S to the coefficients of DEp-NP and DEp-PP shows, however, that the presence of a sentential complement has a strong influence on determiner realization, while NP- and PP-complements may still occur in PNCs, as their coefficients are relatively low (also in comparison to the coefficients of these values for ohne).

In more general terms, we suspect a general mechanism relating sentential complementation to the realization of the determiner, a topic to be addressed in future research.

It should also be noted that the external syntactic realization of the phrase plays a role for unter. The feature GOVERNED did not play a role for ohne, but suggests the realization of a determiner for unter. The reason might be that few verbs or nouns govern the preposition ohne. Prepositional objects headed by unter, however, are more common. Prepositional objects headed by ohne make up only 1.2% of the occurrences of ohne in the present corpus, while the share of prepositional objects headed by unter is three times larger: 3.6%.

Finally, we note that a variety of sortal classifications for nouns suggest either an omission or realization of the determiner, supporting the assumption that in addition to the preposition’s meaning, the meaning of the noun plays a role. GermaNet top-level categories were already discriminating in the model for ohne; but the model for unter also makes use of HaGenLex sortal categories (HL-AD and HL-AS). The predictors stand for dynamic and static concepts that both receive an abstract interpretation. Their inclusion is particularly interesting, as it is sometimes claimed (e.g. Bale and Barner, 2009) that ‘abstract’ nouns are never to be classified as count nouns.

4.3 General assessment of the models

Both models show that the realization of syntactic complements, of sentential complements in particular, seems to impede determiner omission. That syntactic complexity does not seem to play a role per se, can be deduced from the coefficients for the factor ADIA: While ADIA favors determiner realization with ohne, it prohibits determiner realization with unter.

The role of morphological derivation through –ung, as represented by the factor NOMINALIZATION, is the same in both models: derived nominals shift odds in favor of determiner omission. While the derivational structure might be considered a formal property of the construction, it might also reflect an underlying denotational distinction between events and objects, which has to be clarified in future work.

It is a striking feature of the model for unter that we do not find interpretational features of the preposition unter that favor determiner omission. Taken together with the other factors in the two models presented, the analysis suggests a picture rather different from the (more or less) monocular analyses of Stvan (1998) and Baldwin et al. (2006). With regard to unter a model in the sense of Baldwin et al. (2006) could only provide negative rules of the form “if P does not mean this, its nominal complement may be realized without a determiner”, but such a model would lead to less precision than the multicausal model presented here.

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4 One could argue against the inclusion of the coefficient for DEp-PP altogether, as it does not seem to be significant (p > 0.05) in the first place. However, we have followed Harrell’s (2001) advice that blind exclusion of seemingly insignificant factors may not lead to model improvement. In fact, models for unter including Dep-PP outperform models excluding this feature.
5 Validation of the models

5.1 Bootstrap validation

Logistic regression models may suffer from overfitting the data. We have thus carried out a bootstrap validation of both models and applied penalized maximum likelihood estimation (Harrell, 2001) to the models. The results of the initial (non-penalized) models are reported in Table 5 and Table 6, where we report values for \( D_{xy} \) and the average maximal error of the model. Bootstrap validation makes use of sampling with replacement. The training samples for evaluation thus may contain certain instances many times, but some original data will never be sampled and can thus be used for testing the models. Bootstrap validation is carried out 200 times, the results being averaged. The overfitting of the models is determined by the optimism derived from the bootstrap evaluation.

|       | \( D_{xy} \) | \( E_{\text{max}} \) |
|-------|------------|-----------------|
| Original Index | 0.7525 | 0.0000 |
| Training | 0.7578 | 0.0000 |
| Test | 0.7497 | 0.0123 |
| Optimism | 0.0080 | 0.0123 |
| Corrected Index | 0.7445 | 0.0123 |

Table 5. Bootstrap validation of model for ohne.\(^5\)

|       | \( D_{xy} \) | \( E_{\text{max}} \) |
|-------|------------|-----------------|
| Original Index | 0.8736 | 0.0000 |
| Training | 0.8744 | 0.0000 |
| Test | 0.8692 | 0.0055 |
| Optimism | 0.0052 | 0.0055 |
| Corrected Index | 0.8684 | 0.0055 |

Table 7. Bootstrap validation of penalized model for ohne.

Penalized maximum likelihood estimation (Harrell, 2001:207) for both models resulted in penalties of 0.3 and 0.8, respectively, based on Akaike’s AIC. The updated models have again been bootstrap validated, resulting in the improved values presented in table 7 and table 8.

5 \( E_{\text{max}} \) is the maximal error determined in average over the bootstrap runs.

5.2 Representing the influence of factors in a nomogram

The respective influence of individual factors can be read of a nomogram (Banks, 1985) derived from the models presented above (we make use of a tabular presentation for reasons of legibility). The nomogram for ohne consists of the tables 9 and 10. Table 9 lists the individual scores for the factors in the model for ohne, were 0 indicates that the pertinent property is not present and 1 indicates that the property is present. Table 10 maps the sum to probability of determiner omission.

| Predictor | 0 | 1 |
|-----------|---|---|
| NOMINALIZATION | 27 | 0 |
| ADJIA | 0 | 22 |
| CAUSAL | 0 | 24 |
| COMITATIVE | 0 | 45 |
| PARTICIPATIVE | 0 | 67 |
| PRESENCE | 15 | 0 |
| DEP-S | 0 | 100 |
| DEP-NP | 0 | 59 |
| DEP-PP | 0 | 43 |
| GN-RELATION | 20 | 0 |
| GN-ATTRIBUTE | 27 | 0 |
| GN-EVENT | 17 | 0 |
| GN-ARTEFACT | 8 | 0 |

Table 9. Nomogram: individual scores of predictors for ohne.
the probability of article realization. While this is a speculation, based on the models presented here, it might very well be that this dependency reflects a deeper referential requirement.

In developing further models for prepositions, we expect that the realization of a complement of the noun will establish itself as a common factor, but this has to await further research and model development.

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