Towards the Unsupervised Acquisition of Implicit Semantic Roles

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Abstract

This paper describes a novel approach to find evidence for implicit semantic roles. Our data-driven models generalize over large amounts of *explicit* annotations only, in order to acquire information about implicit roles. We establish a generic background knowledge base of probablistic predicate-role co-occurrences in an unsupervised manner, and estimate thresholds which trigger the prediction of a missing role. Our approach outperforms the state-of-the-art in terms of recognition rate and offers a more flexible alternative to rule-based solutions which rely on costly, language and domain-specific lexica.

1 Introduction

In its classical form, an automated semantic role labeling (SRL) system (Gildea and Jurafsky, 2002) detects events (verbal or nominal predicates), together with their associated participants within the local context. Semantic roles are assigned to syntactic elements, such as A0 for the *agent* of an event, A1 for the patient (i.e. the entity which undergoes the action), etc.[1] The output of SRL systems have proven to offer a good approximation to a deeper semantic modeling of natural language. However, given its inherent complexity, recent efforts for improvement have tried to extend traditional SRL from the sentence-internal context to the *surrounding discourse*. As an illustration, consider the following biomedical example from Ruppenhofer et al. (2010).

> [$_{A0}$Twenty-two month old] with history of recurrent right middle lobe infiltrate. Increased [$_{A0}\varnothing$] cough, [$_{A0}\varnothing$] tachypnea, and [$_{A0}\varnothing$] work of breathing.

In the second sentence, a standard SRL system would ideally identify *cough*, *tachypnea* and *work of breathing* as nominal predicates. However, the A0 (experiencer/agent) role of these predicates is unfilled in the current sentence, and only explicitly realized in the preceding one (cf. *twenty-two month old*). Its identification is thus beyond the scope of the traditional parser, which is restricted to an isolated per-sentence analysis.

More precisely, the agent (argument) role of *cough*, for example, is non-overt or **implicit**, i.e. locally unexpressed in the second sentence and can only be resolved from the wider context. In general, many role realizations of this sort are suppressed on the surface level. These implicit roles are also called *null instantiations* (NIs) (Fillmore, 1986; Ruppenhofer, 2005) and have been extensively studied in the literature, cf. *zero anaphora* (Levinson, 1987; Hangyo et al., 2013).

The automated detection of such implicit roles (iSRL) and their fillers is a challenging task. Yet, if uncovered, NIs provide highly beneficial 'supplementary' information: These can in turn be incorporated into practical, downstream applications in the context of Natural Language Understanding, like text summarization, recognizing textual entailment or question answering.

Current issues in iSRL Corpus data with manually annotated implicit roles is extremely sparse and hard to obtain, and annotation efforts have emerged only recently; cf. Ruppenhofer et al. (2010), Gerber and Chai (2012), and also Feizabadi and Padó (2015) for an attempt to enlarge the number of annotation instances by combination of scarce resources. As a result, most state-of-the-art iSRL systems cannot be trained in a supervised setting and thus integrate custom, rule-based components to detect NIs. (We elaborate on related work in Section 2.) To this end, a predicate's overt roles are matched against a predefined predicate-

[1] For details on the PropBank labels used in our study, see Palmer et al. (2005).

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specific template. Informally, all roles found in the template but not in the text are regarded as null instantiations. Such pattern-based methods perform satisfactorily, yet there are drawbacks:
(1) They are inflexible and absolute according to their type, in that they assume that all candidate NIs are equally likely to be missing, which is unrealistic given the variety of different linguistic contexts in which predicates co-occur with their semantic roles.
(2) They are expensive in that they require handcrafted, idiosyncratic rules (Ruppenhofer et al., 2011) and rich background knowledge in the form of language-specific lexical resources, such as FrameNet (Baker et al., 1998), PropBank (Palmer et al., 2005) or NomBank (Meyers et al., 2004). Dictionaries providing information about each predicate and status of the individual roles (e.g., whether they can serve as implicit elements or not) are costly, and for most other languages not available to the same extent as for English.
(3) Most earlier studies heuristically restrict implicit arguments to *core* roles only,[2] but this is problematic as it ignores the fact that implicit non-core roles also provide valid and valuable information. Our approach remains agnostic regarding the role inventory, and can address both core and non-core arguments. Yet, in accordance with the limited evaluation data and in line with earlier literature, we had to restrict ourselves to evaluate NI predictions for core arguments only.

Our contribution We propose a novel, generic approach to infer information about implicit roles which does not rely on the availability of manually annotated gold data. Our focus is exclusively on *NI role identification*, i.e., per-predicate detection of the missing implicit semantic role(s) given their overtly expressed explicit role(s) (without finding filler elements) as we believe that it serves as a crucial preprocessing step and still bears great potential for improvement. We treat NI identification *separately* from the resolution of their fillers, also because not all NIs are resolvable from the context. In order to facilitate a more flexible mechanism, we propose to condition on the presence of other roles, and primarily argue that NI detection should be **probabilistic instead of rule-based**. More specifically, we predict implicit arguments using large corpora from which we build a background knowledge base of predicates, co-occurring (explicit) roles and their probabilities. With such a **memory-based** approach, we generalize over large quantities of explicit roles to find evidence for implicit information in a mildly supervised manner. Our proposed models are largely domain independent, include a sense distinction for predicates, and are not bound to a specific release of a hand-maintained dictionary. Our approach is portable across languages in that training data can be created using projected SRL annotations. Unlike most earlier approaches, we employ a generic role set which is based on PropBank/NomBank rather than FrameNet: The PropBank format comprises a relatively small role inventory which is better suited to obtain statistical generalizations than the great variety of highly specific FrameNet roles. While FrameNet roles seem to be more fine-grained, their greater number arises mostly from predicate-specific semantic roles, whose specific semantics can be recovered from PropBank annotations by pairing semantic roles with the predicate.

Yet another motivation of our work is related to the recent development of AMR parsing (Banarescu et al., 2013, Abstract Meaning Representation) which aims at modeling the semantic representation of a sentence while abstracting from syntactic idiosyncrasies. This particular appraoch makes extensive use of the PropBank-style framesets, as well, and would greatly benefit from the integration of information on implicit roles.

The paper is structured as follows: Section 2 outlines related work in which we exclusively focus on how previous research has handled the sole identification of NIs. Section 3 describes our approach to probabilistic NI detection; Section 4 presents two experiments and their evaluation in comparison with previous studies. Finally, we conclude our work in Section 5.

2 Related Work

In the context of the 2010 SemEval Shared Task on *Linking Events and Their Participants in Discourse*[3] on implicit argument resolution, Ruppenhofer et al. (2010) have released a data set of fiction novels with manual NI role annotations for diverse predicates. The data has been referred to

[2] *Core* roles are obligatory arguments of a predicate. Informally, *non-core* roles are optional arguments often realized as adjuncts or modifiers.

[3] http://semeval2.fbk.eu/semeval2.php

by various researchers in the community for direct or indirect evaluation of their results. The NIs in the data set are further subdivided into two categories: Definite NIs (DNIs) are locally unexpressed arguments which can be resolved to elements in the proceeding or following discourse; Indefinite NIs (INIs) are elements for which no antecedent can be identified in the surrounding context.[4] Also, the evaluation data comes in two flavors: a base format which is compliant with the FrameNet paradigm and a CoNLL-based PropBank format. Previous research has exclusively focused on the former.

Chen et al. (2010) present an extension of an existing FrameNet-style parser (SEMAFOR) to handle implicit elements in text. The identification of NIs is guided by the assumption that, whenever the traditional SRL parser returns the default label involved in a non-saturated analysis for a sentence, an implicit role has to be found in the context instead. Additional FrameNet-specific heuristics are employed in which, e.g., the presence of one particular role in a frame makes the identification of another implicit role redundant.[5]

Tonelli and Delmonte (2010, VENSES++) present a deep semantic approach to NI resolution whose system-specific output is mapped to FrameNet valency patterns. For the detection of NIs, they assume that these are always core arguments, i.e., non-omissible roles in the interaction with a specific predicate. It is unclear how different predicate senses are handled by their approach. Moreover, not all types of NIs can be detected, resulting in a low overall recall of identified NIs, also having drawbacks for nouns. Again using FrameNet-specific modeling assumptions, their work has been significantly refined in Tonelli and Delmonte (2011).

Despite their good performance in the overall task, Silberer and Frank (2012, S&F) give a rather vague explanation regarding NI identification in text. Using a FrameNet API, the authors restrict their analysis only to the core roles by excluding "conceptually redundant" roles without further elaboration.

Laparra and Rigau (2013) propose a deterministic algorithm to detect NIs on grounds of discourse coherence: It predicts an NI for a predicate if the corresponding role has been explicitly realized for the same predicate in the preceding discourse but is currently unfilled. Their approach is promising but ignorant of INIs.

Earlier, Laparra and Rigau (2012, L&R) introduce a statistical approach to identifying NIs similar to ours in that they rely on frequencies from overt arguments to predict implicit arguments. For each predicate template (frame), their algorithm computes all Frame Element patterns, i.e., all co-occurring overt roles and their frequencies. For NI identification a given predicate and its overtly expressed roles are matched against the most frequent pattern not violated by the explicit arguments. Roles of the pattern which are not overtly expressed in the text are predicted as missing NIs. Even though their approach outperforms all previous results in terms of NI detection, Laparra and Rigau (2012) only estimate the *raw* frequencies from a very limited training corpus, raising the question whether all patterns are actually sufficiently robust. Also, the authors disregard all the valuable less frequent patterns and limit their analysis to only a subtype of NI instances which are resolvable from the context.

Finally, Gerber and Chai (2012) describe a supervised model for implicit argument resolution on the NomBank corpus which—unlike the previous literature—follows the PropBank annotation format. However, NI detection is still done by dictionary lookup, and the analysis is limited to only a small set of predicates with only one unambiguous sense. Again limiting NIs to only core roles, the authors empirically demonstrate that this simplification accounts for 8% of the overall error rate of their system.

3 Experimental Setup

3.1 Memory-Based Learning

Memory-based learning for NLP (Daelemans and van den Bosch, 2009) is a lazy learning technique which keeps a record of training instances in the form of a background knowledge base (BKB). Classification compares new items directly to the stored items in the BKB via a distance metric. In semantics, the method has been applied by, e.g., Peñas and Hovy (2010) for semantic enrichment, and Chiarcos (2012) to infer (implicit markers for) discourse relations. Here, we adopt its methodology to identify null-instantiated argument roles in text. More precisely, we setup a BKB of probablistic predicate-role co-occurrences and estimate

[4]The average F-score annotator agreement for frame assignments is about .75 (Ruppenhofer et al., 2010).

[5]Cf. *CoreSet* and *Exludes* relationship in FrameNet.

thresholds which serve as a trigger for the prediction of an implicit role (a slight modification of the distance metric). We elaborate on this methodology in Section 4.

3.2 Data & Preprocessing

We train our model on a subset of the *WaCkypedia_EN*[6] corpus (Baroni et al., 2009). The data set provides a 2008 Wikipedia dump from which we extracted $\frac{1}{5}$ of the complete corpus ($\approx$ 10 million sentences which are tokenized already). We applied the MATE[7] parser (Björkelund et al., 2009) for the automatic detection of semantic roles to the portion of the Wikipedia dump annotating it with SRL information. MATE has been used in previous research on implicit elements in text (Roth and Frank, 2013) and provides semantic roles with a sense disambiguation for both verbal and nominal predicates. The resulting output is based on the PropBank format.

3.3 Model Generation

We build a probablistic model from annotated predicate-role co-occurrences as follows:

1. For every sentence, record all distinct predicate instances and their associated roles.
2. For every predicate instance, sort the role labels lexicographically (not the role fillers), disregarding their sequential order. (We thus obtain a normalized template of role co-occurrences for each frame instantiation.)
3. Compute the frequencies for all templates associated with the same predicate.
4. By relative frequency estimation, derive all conditional probabilities of the form:

$$P(r|R, \textsc{predicate})$$

with $\mathcal{R}$ being the role inventory of the SRL parser, $R \subseteq \mathcal{R}$ a (sub)set of explicitly realized semantic roles, and $r \in \mathcal{R} \setminus R$ an arbitrary semantic role. When we try to gather information on null instantiated roles, r is typically an unrealized role label. The PREDICATE consists of the lemma of the corresponding verb or noun, followed by sense number (predicates are sense-disambiguated) and its part of speech (V/N), e.g., PLAY.01.N.

[6]http://wacky.sslmit.unibo.it/doku.php?id=corpora
[7]http://code.google.com/p/mate-tools/

Paradigm		#Roles Overt	DNI	INI	#Overt / #DNI+#INI
Train	FrameNet	2,526	303	277	4.36
	PropBank	1,027	125	101	4.52
Test	FrameNet	3,141	349	361	4.42
	PropBank	1,332	167	85	5.28

Table 1: Label distribution of the SemEval 2010 data set for overt and null instantiated arguments for both the FrameNet (all roles and parts of speech) and the PropBank version (only core roles for nouns and verbs).

3.4 Annotated Data

In accordance with previous iSRL studies, we evaluate our model on the SemEval data set (Ruppenhofer et al., 2010). However, to the best of our knowledge, this is the first study to focus on the PropBank version of this data set. It has been derived semi-automatically from the FrameNet base format using hand-crafted mapping rules (as part of the data set) for both verbs and nouns. For example, a conversion for the predicate *fear* in FrameNet's EXPERIENCER_FOCUS frame is defined as *fear.01* (its first sense) with the roles EXPERIENCER and CONTENT mapped to PropBank labels A0 and A1, respectively. In accordance with the mapping patterns, the resulting distribution of NIs varies slightly from the base format. Table 1 shows the label distribution of overt roles, DNIs, INIs for both the FrameNet and PropBank versions, respectively. Some information is lost while the general proportions remain similar to the base format. This is also due to the fact that for some parts of speech (e.g., for adjectives) no mappings are defined, even though some of them are annotated with NI information in the FrameNet version. Moreover, mapping rules exist *only for core roles* A0-A4 (agent, patient, ...). As a consequence, we restrict our analysis to these five (unique) roles, even though our models described in this work incorporate probabilistic information for *all possible roles* in $\mathcal{R}$, i.e., A0-A4, but also for *non-core* (modifier) roles, such as AM-TEMP (temporal), AM-LOC (location), etc.

4 Experiments

4.1 Experiment 1

Usually, a predicate occurs with an arbitrary number of overt arguments, and similarly the number of missing NIs varies, too. In this experiment, we introduce different data-driven variants to predict the correct set of null instantiations for any given

NI Pattern	Freq	NI Pattern	Freq
-	706	A0 A2	7
A1	86	A1 A2	6
A0	51	A3	5
A2	35	A1 A4	3
A4	18	A0 A1 A2	1
A0 A1	11		

Table 2: The 929 NI role patterns from the test set sorted by their number of occurrence. Most of the predicates are saturated and do not seek an implicit argument. Only one predicate instance has three implicit roles.

predicate and its associated explicit roles. Specifically, to tackle the problem, we take the SemEval train and test split (744 vs. 929 unrestricted frame instances of the form: any combination of overt roles vs. any combination of NI roles per predicate). In this setting, we do not draw a distinction between DNIs and INIs, but treat them generally as NIs. Table 2 shows the distribution of the different NI role patterns in the test data.

4.1.1 Task Description

Given a predicate and its overtly expressed arguments (ranging from any combination of A0 to A4 or none), predict the correct set of null instantiations (which can also be empty or contain up to five different implicit elements).

4.1.2 Predicting Null Instantiations

We distinguish two main types of classifiers: *supervised classifiers* are directly obtained from NI annotations in the SemEval training data, *mildly supervised classifiers* instead use only information about (automatically obtained) explicitly realized semantic roles in a given corpus, *hybrid classifiers* combine both sources of information. We estimated all parameters optimizing F-measure on the train section of the SemEval data set. Their performance is evaluated on its test section. We aim to demonstrate that mildly supervised classifiers are capable of predicting implicit roles, and to study whether NI annotations can be used to improve their performance.

Baseline: Given the diversity of possible patterns, it is hard to decide how a suitable and competitive baseline should be defined: predicting the majority class means not to predict anything. So, instead, we predict implicit argument roles randomly, but in a way that emulates their frequency distribution in the SemEval data (cf. Tab. 2), i.e., predict no NIs with a probability of 76.0% (706/929), A1 with 38.6% (86/929), etc. The baseline scores are averaged over 100 runs of this random 'classifier', further referred to as A.

Supervised classifier: Supervised classifiers, as understood here, are classifiers that use the information obtained from manual NI annotations. We set up *two* predictors B_1 and B_2 tuned on the SemEval training set: B_1 is obtained by counting for each predicate its *most frequent NI role pattern*. For instance, for *seem.02*—once annotated with implicit A1, but twice without implicit arguments—B_1 would predict an empty set of NIs. B_2 is similar to B_1 but conditions NI role patterns not only on the predicate, but also on its explicit arguments.[8] For prediction, these classifiers consult the most frequent NI pattern observed for a predicate (B_2: plus its overt arguments). If a test predicate is unknown (i.e., not present in the training data), we predict the majority class (empty set) for NI.

Mildly supervised classifier: Mildly supervised classifiers do not take any NI annotation into account. Instead, they rely on explicitly realized semantic roles observed in a corpus, but use explicit NI annotations only to estimate prediction thresholds. In what follows, we present eight parameter-based classification algorithms for our model trained on 10 million sentences.

We define prediction for classifier $\mathbf{C}_0$ as follows: Given a predicate PREDICATE, the role inventory $\mathcal{R} = \{A0..A4\}$, its (possibly empty) set of overt roles $R \subseteq \mathcal{R}$ and a fixed, predicate-independent threshold t_0. We start by optimizing threshold t_0 on all predicate instances with *no* given overt argument. If there is *no* overt role and an unrealized role $n_i \in \mathcal{R}$ for which it is true that $P(n_i|\text{PREDICATE}) > t_0$, then predict n_i as an implicit role. If there is an overt role $o_j \in R$ and an unrealized role $n_i \in \mathcal{R} \setminus R$ for which it is true that $P(n_i|o_j,\text{PREDICATE}) > t_0$, then predict n_i as an implicit role. Note that C_0 requires that this condition to hold for *one* o_j, not all explicit arguments of the predicate instance (logical disjunction).

We refine this classifier by introducing an additional parameter that accounts for the group of overtly realized frames with exactly *one* overt argument, i.e., $\mathbf{C}_1$ predicts n_i if $P(n_i|o_j,\text{PREDICATE}) > t_1$; for all other configu-

[8]Specifically, we extract finer-grained patterns, e.g., *evening.01*[A1] → {}=2, {A2}=3, where a predicate is associated with its overt role(s) (left side of the arrow). The corresponding implicit role patterns and their number of occurrence is shown to the right.

Classifier	A	B_1	B_2	C_0	C_1	C_2	C_3	C_4	$C_{4_{n,v}}$	$C_{4_{n,v,B1}}$	$C_{4_{n,v,B2}}$
Precision	*0.149*	0.848	**0.853**	*0.368*	*0.378*	0.398	0.400	0.400	0.423	0.561	0.582
Recall	*0.075*	*0.155*	*0.206*	**0.861**	0.851	0.837	0.837	0.837	0.782	0.615	0.814
F_1 Score	*0.100*	*0.262*	*0.332*	*0.516*	*0.523*	*0.540*	*0.541*	*0.541*	*0.549*	0.589	**0.679**

Table 3: Precision, recall and F_1 scores for all classifiers introduced in Experiment 2. Scores are compared row-wise to the best-performing classifier $C_{4_{n,v,B2}}$. A significant improvement over a cell entry with $p < .05$ is indicated in *italics*.

rations the procedure is the same as in C_0, i.e., the threshold t_0 is applied.

Classifiers $\mathbf{C}_2$, $\mathbf{C}_3$ and $\mathbf{C}_4$ extend C_1 accordingly and introduce additional thresholds t_2, t_3, t_4 for the respective number of overt arguments. For example, $\mathbf{C}_3$ predicts n_i if $P(n_i|o_{j_1}, o_{j_2}, o_{j_3},\text{PREDICATE}) > t_3$, for configurations with less arguments, it relies on C_2, etc. Our general intuition here is to see whether the increasing number of specialized parameters for increasingly marginal groups of frames is justified by the improvements we achieve in this way.

A final classifier $\mathbf{C}_{4_{n,v}}$ extends C_4 by distinguishing verbal and nominal predicates, yielding a total of ten parameters $t_{0_n}..t_{4_n}, t_{0_v}..t_{0_n}$.

Hybrid classifier: To explore to what extent explicit NI annotations improve the classification results, we combine the best-performing and most elaborate mildly supervised classifier $C_{4_{n,v}}$ with the supervised classifiers B_1 and B_2: For predicates encountered in the training data, $\mathbf{C}_{4_{n,v,B_1}}$ (resp., $\mathbf{C}_{4_{n,v,B_2}}$) uses B_1 (resp., B_2) to predict the most frequent pattern observed for the predicate; for unknown predicates, apply the threshold-based procedure of $C_{4_{n,v}}$.

4.1.3 Results & Evaluation

Table 3 contains the evaluation scores for the individual parameter-based classifiers. All classifiers demonstrate significant improvements over the random baseline. Also the mildly supervised classifiers outperform the supervised algorithms in terms of F_1 score and recall. However, detecting NIs by the supervised classifiers is very accurate in terms of high precision. Classifier B_2 outperforms B_1 as a result of directly incorporating additional information about the overt arguments.

Concerning our parameter-based classifiers, the main observations are: First, the overall performance (F_1 score) increases from C_0 to C_4 (yet not significantly). Secondly, with more parameters, recall decreases while precision increases. We can observe, however, that improvements from C_2 to C_4 are marginal, at best, due to the sparsity of predicates with two or more overt arguments. Similar problems related to data sparsity have been reported in Chen et al. (2010). Results for C_3 and C_4 are identical, as no predicate with more than three overt arguments occurred in the test data. Encoding the distinction between verbal and nominal predicates into the classifier again slightly increases the performance.

A combination of the high-precision supervised classifiers and the best performing mildly supervised algorithm yields a significant boost in performance (Tab. 3, last two columns). In Table 4, we report the performance of our best classifier $C_{4_{n,v,B2}}$ with detailed label scores.

Roles	A0	A1	A2	A3	A4
# Labels	70	107	49	5	21
Precision	0.675	0.578	0.432	0.400	0.791
Recall	0.800	0.897	0.653	0.400	0.905
F_1 Score	0.732	0.703	0.520	0.400	0.844

Table 4: Evaluation of $C_{4_{n,v,B2}}$ for all 252 implicit roles.

Summarizing our results, Experiment 1 has shown that combining supervised and mildly supervised strategies to NI detection achieves the best results on the SemEval test set. Concerning the mildly supervised, parameter-based classifiers, it has proven beneficial to incorporate a maximum of available information on overtly expressed arguments in order to determine implicit roles.

4.2 Experiment 2

A second experiment focuses on the comparison with previous research in which DNI and INI predictions are separately evaluated. In our setting, however, we regard this evaluation as artificial as DNI/INI classification could alternatively be decided depending on distance and availability of potential antecedents, a problem we would like to address in subsequent experiments.

System	NI recall	DNI/INI interpret. prec relative	absolute
L&P	0.66	-	-
SEMAFOR	0.63	0.55	0.35
S&F	0.58	0.70	**0.40**
T&D	0.54	**0.75**	**0.40**
VENSES++	0.08	0.64	0.05
This Paper	**0.81**	0.57	0.36

Table 5: Recognition rate (recall) for all NIs, relative (based on correctly recognized) and absolute precision scores comparing the different state-of-the-art systems to our best-performing classifier $C4_{n,v,B2}$.

System	Type	Precision	Recall	F_1 Score
T&D	DNI	0.39	0.43	0.41
	INI	**0.46**	0.38	**0.42**
SEMAFOR	DNI	**0.57**	0.03	0.06
	INI	0.20	**0.61**	0.30
This paper	DNI	0.43	**0.44**	**0.43**
	INI	0.24	0.51	0.32
L&R	DNI	**0.50**	0.66	**0.57**
This paper	DNI	0.41	**0.86**	0.55

Table 6: INI vs. DNI classification compared to previous works (upper part). Silberer and Frank (2012) do not report individual NI type scores. L&R focus only on DNI detection. Our results on this subtask are shown in the last column.

4.2.1 Task Description

For every predicate, predict the set of null instantiations as in Exp. 1. Then, classify every predicted NI as DNI or INI.

4.2.2 Predicting Null Instantiations

We take the best-performing classifier $C4_{n,v,B2}$ from Exp. 1. Following Tonelli and Delmonte (2011), we then employ a rule-based classifier $\mathbf{C}_{\text{DNI,INI}}$ to separate predicted NIs into DNIs or INIs: (a) predict INI for predicates with part of speech VBN/VBG (e.g., in passive voice); (b) predict the majority class according to DNI/INI frequencies for the predicate in the SemEval training set; (c) predict DNI if DNI/INI frequencies are equal or the predicate is missing in the SemEval training data.

4.2.3 Results

Incorporating $C_{\text{DNI,INI}}$ into the best performing NI classifier from Experiment 1 outperforms current state-of-the-art systems in terms of NI recall (Table 5) but has drawbacks in DNI/INI classification.[9]

A closer look at the individual NI types (upper part of Table 6) reveals that, overall, the performance of our predictor is competitive regarding the accuracies by the systems reported by Tonelli and Delmonte (2011, T&D) and Chen et al. (2010, SEMAFOR). More specifically, there is no single best performing system. The T&D system is generally powerful in predicting INIs, SEMAFOR has high recall and high precision for both, while we outperform the others on DNI analysis. Clearly, the best results are obtained by Laparra and Rigau (2012, L&R). However, they only report accuracies for the identification of DNIs, as INIs are beyond their scope. The last row of Table 6 gives the scores of our tool when we substitute $C_{\text{DNI,INI}}$ by predicting the majority class (DNI). Outperforming all other systems, we are able to detect 86% of all DNIs in the test set with an F_1 score only marginally worse than L&R.

5 Summary and Outlook

We have presented a novel, statistical method to infer evidence for implicit roles from their explicit realizations in large amounts of automatically annotated SRL data. Despite its simplicity, we demonstrated the suitability of our approach: Even though our results do not outperform the state-of-the-art in F_1 score, they are still highly competitive. Our models are best in the overall recognition rate, however, still suffer in precision of the respective null instantiated arguments.

Thus, directions for future research should consider integrating additional contextual features and would benefit from the *complete* role inventory of our models (including non-core/modifier roles). Regarding this extended setting, we would like to experiment with other machine learning approaches, as well, in order to assess whether the accuracy of the detected NIs can be increased.

In addition, we plan to extend the memory-based strategy described in this paper to NI *resolution* (on top their detection), and in this context, also re-address the DNI/INI classification problem.

We conclude that—especially when annotated training data is sparse—memory-based approaches to implicit role detection seem highly promising and offer an alternative solution to static rule- or template-based methods with a much greater degree of flexibility.

[9]Note that our scores are not directly comparable as none of the other systems report precision scores for their pattern-based NI detection modules and our evaluation is based on the PropBank version of the data set whose label distribution, contrasting DNIs and INIs, is different from the FrameNet format (DNI majority class: 66.3% vs. 50.8%).

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