Optimizing Selection of Assessment Solutions for Completing Information Extraction Results

Christina Feilmayr

Johannes Kepler University Linz, Institute of Application Oriented Knowledge Processing,
Altenberger Straße 69, 4040 Linz,
Austria

cfeilmayr@faw.jku.at

Abstract. Incomplete information produces serious consequences in information extraction: it increases costs and leads to problems in downstream processing. This work focuses on improving the completeness of extraction results by applying judiciously selected assessment methods to information extraction based on the principle of complementarity. Our recommendation model simplifies the selection of assessment methods which can overcome a specific incompleteness problem. This paper also focuses on the characterization of information extraction and assessment methods as well as on a rule-based approach that allows estimation of general processability, profitability in the complementarity approach, and the performance of an assessment method under evaluation.

Keywords. Information extraction, information quality, method selection, data and text mining.

Optimización de selección de soluciones de evaluación para completar los resultados de recuperación de información

Resumen. La información incompleta causa graves consecuencias en la extracción de la misma: aumenta los costos y propicia problemas para el procesamiento en cadena. El objetivo de este trabajo es presentar la mejora en los resultados de extracción con el fin de completarlos con métodos de evaluación juiciosamente selectos basados en el principio de complementariedad. El modelo propuesto simplifica la selección de los métodos de evaluación, los cuales pueden resolver un problema específico de información incompleta. Este artículo se enfoca también en la caracterización de la extracción de información y los métodos de evaluación con un enfoque basado en reglas que permita validar la capacidad de procesamiento general, la rentabilidad en el enfoque de complementariedad y el rendimiento de los métodos de evaluación.

Palabras clave. Extracción de información, calidad de información, selección del método, minería de datos y textos.

1 Introduction

1.1 Information Quality in Information Extraction

Low information quality is one of the reasons why information extraction (IE) initiatives fail. In particular, incomplete information has serious consequences: it increases the costs of IE on the one hand, and leads to problems in downstream processing on the other hand. This means that, if many template slot values are missing, the quality of information and models decreases proportionally. Consequently, IE domain analysis is strongly affected by missing values in template attributes (as a result of preprocessed IE tasks such as natural language processing), by missing descriptive context information, and by missing or incomplete constraints and conditions. Thus, information quality management is one of the greatest challenges in IE research.

Identification of incompleteness in information extraction. Quantifying incompleteness in the results of an IE system requires understanding both what the sources of these incompleteness errors are and how incompleteness is propagated through IE domain analysis. The first task in eliminating incompleteness is to confirm that the problem is in fact one of incompleteness. For this purpose,

several *completeness* measures (overall, template, attribute, instance, and value completeness) that closely follow Batini *et al*. [1] are automatically analyzed. However, incompleteness is not restricted to null values within templates; low *precision* and *balanced accuracy* values may also imply incompleteness, not at the instance-level but at the schema-level (e.g., in terms of missing or incomplete constraints and conditions), which equates to incomplete semantic information. Establishing an identification/typification module for IE refinement requires training on comparison of IE results with a given gold standard.

Characterization of incompleteness in information extraction. There are two definite cases of incompleteness: (i) if the completeness value (C) (and therefore also the precision value (P)) is 0, then the IE result deals with an *incomplete attribute-value pair*; (ii) if values of completeness (C) and precision (P) (or balanced accuracy, bA) are smaller than a user-defined threshold ($thres_C$, $thres_{PA}$) and the proportion of substitutions is higher than that of partially correct results, then *incomplete template semantics* (in terms of template conditions and constraints) is identified. The indefinite case occurs if completeness and precision are low, as in the previous case, but the proportion of partially correct results is higher than that of substitutions. For details concerning identifying and characterizing incompleteness in IE see [9].

1.2 Contribution

This research work focuses on improving the completeness of extraction results by applying judiciously selected assessment methods to IE within the *principle of complementarity*, an approach known from the field of information integration. Complementarity is defined as the combination of pieces of information from different sources, taking their respective levels of reliability into account [2]. For a detailed description of how the principle of complementarity is used in the context of this research work see [8]. A recommendation model simplifies the selection of assessment methods that are suited to overcome a specific incompleteness problem. In general, this recommendation model assists the IE system designer and contains the following information:

- human-readable information on the selected assessment method and its ability to integrate into an IE process in order to address a specific assessment category/task;
- a specification of the conditions under which integration of the assessment method can be achieved, possibly including prerequisites of the assessment method and its compatibility with preceding methods;
- a specification of the method's effects on the integration process and its data;
- an estimation of the assessment method's influence on completeness and accuracy.

The contribution of this intermediate-stage Ph.D. research paper is threefold: (i) it proposes an approach to selecting optimal assessment methods for the complementarity approach; (ii) it characterizes IE methods and assessment methods; (iii) it defines feature mapping and IF-THEN rules in order to estimate a method's general processability, profitability in the complementarity approach, and finally its performance.

2 Recommendation Model

Given that no learning algorithm can systematically outperform all others ("No Free Lunch" theorem [18]), the model selection problem arises anew with each learning task. However, with the increasing number of learning methods available, exhausting experimentation is simply not feasible. There is a strong need for limiting the initial set of candidate algorithms on the basis of the given task.

The main aim of and motivation for the proposed recommendation model is to help IE system designers with exploring the space of valid integration[1] of assessment methods into an existing IE process, as it is difficult to define which of a set of methods is best suited. The key to

[1] Provided that a valid integration violates no fundamental constraints of its constituent techniques (e.g., an assessment method fulfills at least all criteria for being *processable* within the complementarity approach).

characterizing an integration procedure is to choose suitable features. This means identifying the characteristics of the selected IE methods in the context of the problem domain (incompleteness type and proximate assessment category) within which the problem at hand lies. Thus the question arises whether it is possible to model the relationship between these characteristics and properties of assessment methods that can improve overall performance. (Automatic) Guidance in model selection, model combination, and data transformation requires meta-knowledge which provides support in performing selection, combination and maybe transformation. Tackling the assessment method selection problem involves:

1. the availability of problem instances of varying complexity (evaluated IE results, determined assessment category and task(s)),
2. the existence of a large number of diverse assessment methods for tackling assessment tasks,
3. suitable properties to characterize IE methods and assessment methods, and
4. performance metrics (with respect to completeness) to evaluate the capacity for integration (assessment method in IE method).

Combining the features (3) with the performance metrics (4) across a large number of instances (1) using different algorithms (2) creates a comprehensive recommendation model that provides a set of meta-knowledge about algorithm performance.

Finally, the objective of the recommendation model is to derive rules of the form "*assessment method m_{AM} improves completeness of a single applied IE method m_{IE} that features specific meta-knowledge with a probability of x %*".

In general, the recommendation model must be subdivided into a domain-independent and a domain-dependent part. Currently, this work focuses only on the domain-independent part and therefore describes only domain-independent characteristics of IE and assessment methods in detail. Depending on whether an application domain already exists, the amount of available meta-knowledge varies. Assessment of the IE method itself depends firstly on the incompleteness type identified, and secondly on the category the assessment focuses on.

Identifying the assessment type. The assessment type determines whether the problem at hand is one of identifying pieces of information (tends to result in incomplete attribute-value pairs) or one of too imprecisely specified templates (results in incomplete template semantics). Thus, the incompleteness type determines the type of assessment. Templates that suffer from the former type of problem require assessment of attribute-value pairs, and templates that suffer from the latter type require assessment of semantics.

Identifying the assessment categories and tasks. Each incompleteness type requires a particular kind of assessment; hence, each assessment category corresponds to a specific problem that summarizes specific assessment tasks. In general, the problem defines the assessment method class and the method to be applied. Thus, assessment of attribute-value pairs requires *object identification*. Consideration of semantics leads to the categories: *object description*, *object reference,* and *object association*. Object description deals with using contextual information in order to describe several objects in detail. Object reference determines whether two objects are semantically related, and object association helps to identify and subsequently assess associations between existing concepts. A defined assessment task corresponds to a specific suggestion for improvement. An exemplary assessment task in the category *object description* is, for instance, the *generation of conditional collocations,* creating additional conditions in order to refine the value selection procedure in IE domain analysis and, consequently, to avoid substitution errors.

Identifying the assessment classes and methods. Since defined categories and their tasks differ in their aims, a variety of assessment methods is required. Methods are classified into four different categories: (i) *data mining functionalities,* which come from data mining classes, (ii) *general assessment method* class, which includes, for instance, methods for generating significant co-occurrences and/or collocations, (iii) *sorting/ordering* class, which provides methods for criteria-based and

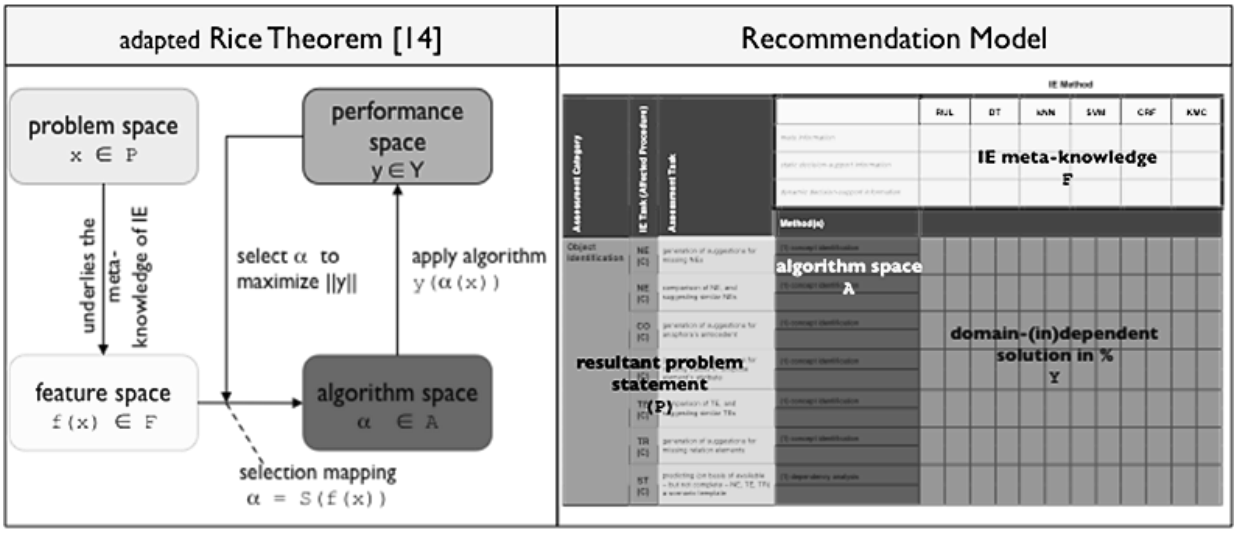

Fig. 1. Left: adapted schematic diagram of method selection; right: the resulting tabular representation of the proposed recommendation model

interestingness-based ordering and partial ordering, and (iv) *filtering/pruning class*, which includes methods for distance measuring, difference measuring, and duplication detection.

3 Approach to Designing the Recommendation Model

Designing the recommendation model requires a defined step-by-step approach that describes how to select, analyze, and finally, evaluate assessment methods in order to recommend only those algorithms that perform well for the recommendation model and thus also for the complementarity approach for IE refinement.

3.1 Assessment Method Selection

The assessment method selection can be traced back to the formal abstract model of Rice [14], which is applied to overcome an algorithm selection problem. This model is also often used in meta-learning, where automatic learning algorithms are applied to meta-data on machine learning experiments (properties of common machine learning methods) [4]. The algorithm selection problem can be stated formally as follows:

"For a given problem instance $x \in P$ with features $f(x) \in F$, find the selection mapping $S(f(x))$ into algorithm space *A* such that the selected algorithm $\alpha \in A$ maximizes the mapping performance $y(\alpha(x)) \in Y$" [14].

In the context of this research work, the Rice theorem was adapted to the following four model components:

- the problem space *P* (assessment category, assessment task), constrained by incompleteness type,
- the feature space *F* that contains measurable properties of IE methods (meta-knowledge about IE methods),
- the algorithm space *A* is the set of all algorithms considered for tackling the problem (i.e., all selected assessment methods from classes (i)-(iv)), and
- the mapping (or performance) space *Y* represents the mapping of a selected algorithm to a set of mapping performance metrics (mapping and IF-THEN rules).

Figure 1 shows an adapted schematic diagram of the algorithm selection model, originally

proposed in [14]. The objective of this diagram is to find a mapping *S* from the meta-data <P, A, Y, F>. Hence, the approach to identifying *best-suited* assessment methods can be formulated as follows:

1. Evaluating meta-knowledge about the IE method and properties of the assessment method.
2. Checking the *processability* of the assessment method.
3. Calculating profitability of the assessment method.
4. Quantifying the performance of the assessment method in each assessment task.
5. Selecting the best assessment method with the best performance value for the recommendation model at hand.

Deriving suitable meta-knowledge about IE methods and identifying properties of assessment methods in order to characterize both constitutes the main challenge.

3.2 Meta-Knowledge within the Recommendation Model

The meta-knowledge of the recommendation model is composed of meta-knowledge about the IE method and *properties of assessment methods* (PAM). In detail, the former is subdivided into *meta-information* (MI, composed of label, applicable to IE task, type of output, measures and parameter used), *static-decision-support information* (SDSI, domain-independent), and *dynamic-decision-support information* (DDSI, domain-dependent). SDSI, DDSI, and PAM are also composed of several features.

In general, there are two different approaches to IE and assessment method characterization, namely (i) domain-dependent dataset characterization and (ii) mainly domain-independent algorithm-/model-based characterization. The former provides quantitative measures such as *general features* (GF), *statistical features* (SF), and *information-theoretical features* (ITF). The latter approach results in objective measures, termed *algorithm-profiling features* (APF), and in subjective measures, termed *experience-based features* (EBF).

Castiello *et al.* [5] define the dataset characteristics (i.e., the general, statistical, and information-theoretic features) as follows:

- **general features (GF)** include general information related to the dataset and provide measures for determining the complexity and the size of the underlying problem. General features provide information about the number of positive examples in the dataset, number of features, or number of output values.
- **statistical features (SF)** make use of standard statistical measures to describe the numerical properties of data distribution. An exemplary statistical feature is the degree of correlation between the features themselves and the target concept.
- **information-theoretic features (ITF)** are based mainly on information theory and provide features, such as average class entropy or entropy of features.

Algorithm-based or model-based characteristics deliver information about the learning algorithm, including its strengths and weaknesses, its constraints in application, its scalability, its tolerance of noise and incompleteness. In contrast to [4], this type of characteristic need not be acquired by analyzing a specially designed dataset. Most of the feature values are studied in several experiments and are reported in publications:

- **algorithm-profiling features (APF)** describe qualitative terms that form the area of expertise of a learning algorithm. Examples of algorithm-profiling features are data/model, processable data type(s).
- **experience-based features (EBF)** are characteristics whose values were studied in various experiments and then reported. Examples of such features are specific parameter settings, or – compared to other datasets – differently applied components (e.g., distance function, kernel function).

Meta-Knowledge about Information Extraction Methods. This kind of meta-

Table 1. Excerpt of representative features of an IE method's SSD information

Class	Feature Label	Description
APF	`feature selection`	method performs a feature selection approach
APF	`feature type`	set of features the IE method works with
APF	`number of used features`	number of features used for learning
APF	`produces data/model`	kind of data the algorithm works with (output)
APF	`output type`	(intermediate) results of the algorithm
EBF	`IDS influence`	influence of imbalanced dataset on IE performance
EBF	`overfitting avoidance`	approach applied to avoid overfitting

knowledge covers, as it was previously mentioned, IE method meta-information and static-/dynamic-decision-support information. SDSI of an IE method is mainly composed of APF and EBF; DDSI consists of many dataset characteristics, such as GF, SF, ITF, but also EBF of the algorithm-based characterization approach. Table 1 lists representative features of SDS information about IE methods.

Properties of assessment methods. The properties of assessment methods are composed mainly of APF and EBF. In addition, some properties must be present to ensure processability in the context of the complementarity approach, while others are profitable and thus necessary for good performance in the integration scenario. Processable features provide information about an assessment method's processable data type(s), the kind of data to which it can be applied, or its ability to handle a particular assessment category. Processable features are subdivided into pre- and post-conditions. The

Table 2. Representative features of assessment methods. The last column in the table represents the feature's individual weight in %, that is, the ratio the feature contributes to an assessment method's processable, profitable, and performance status

Class	Feature Label	Description	%
pre-conditions for the flag *processable*			**42**
APF	`KDD phase`	restricts algorithms that can be applied	4
APF	`processable IE task`	IE tasks the assessment method works with	7
APF	`processable data type(s)`	data type(s) the method works with	10
APF	`processable data format(s)`	– granularity of input the method can work with – kind of data the algorithm works with (input) – set of available parameter(s) of the algorithm	21
post-conditions for the flag *processable*			**11**
APF	`task`	task required to achieve the assessment goal	4
APF	`produces data/model`	maps task to output	7
features for the flag *profitable*			**47**
APF	`goal of assessment method`	kind of assessment in order to complete IE results (i.e., description, identification)	7
APF	`resilience`	sensitivity to or tolerance of an algorithm to data characteristics	9
APF	`practicability`	interpretability of the learned model; degree of automatic handling	4
APF	`positive effects on completeness`	characteristics of algorithms that have positive side-effects on completing IE results	8
EBF	`assessment task(s)`	in order to overcome incompleteness	13
EBF	`components`	kind of components the algorithm works with	6

Table 3. Exemplary mapping rules for asserting that an assessment method is processable

IE Meta-Knowledge		Property of Assessment Method
dataset-independent: `feature type`	=	`processable data type*`
IE output type (MI_`output`)	=	`processable data format(s)*` data/models used, parameters

** if feature types are not in agreement, remedial transformation of data is required.*

former must be fulfilled in order for the method to be applicable, and the latter determine the conditions that must hold true after the method has been applied. Profitable properties give insight into the ability of an assessment method to overcome incompleteness. Table 2 describes individual features that constitute the flags *processable* and *profitable*.

3.3 Identification of Optimal Assessment Methods

Meta-information and features of SDSI are mapped to properties of the *processable* class in order to determine whether (intermediate) IE results are suitable as input to the selected assessment method. If all (selected) features of the IE method accord with the property values of the assessment method, then the assessment method can be deemed processable and can be further analyzed (in terms of profitability; cf. assessment method selection approach step (2)). Examples of such mapping rules are shown in Table 3.

Checking features for *profitability* primarily serves to analyze to what extent assessment methods overcome the shortcomings of IE methods and ultimately improve the completeness of IE results. The higher the profitability value, the more suitable the assessment method for the complementarity approach (cf. assessment method selection approach step (3)). For example, if the IE method is unsuitable for imbalanced datasets and the

Table 4. Exemplary IF-THEN rules for asserting that an assessment method is *profitable*

IE Meta-Knowledge		Property of Assessment Method	Profitable value
`IDS influence == high`	∧	`resilience ≥ 2`	value + [6,9]* %
`¬overfitting avoidance`	∧	`resilience ≥ 3`	value + [7,9]* %
`P := nec. assessment task`	∧	`∃ c ∈ components: P(c)`	value + 6%

** Final weight of feature depends on individual weighting of the assessment method's property.*

assessment method offers high resilience, then the assessment method is given extra points and may outperform another (higher-scoring) method in its dedicated assessment method class. Table 4 presents some exemplary IF-THEN rules:

The notion of good performance in a given assessment category/task is typically defined in relative terms. The approach to quantifying performance of an integration scenario follows that proposed in [3] by Brazdil *et al*., who defined a range relative to the performance of the best algorithm in that assessment category/task. All the algorithms with a mismatch rate of mapping performance within this range are considered to *perform well* (cf. assessment method selection approach step (4)). This range can be defined as follows (1):

$$\left[mm_{\min}, mm_{\min} + \sqrt{\frac{mm_{\min}(1-mn_{\min})}{n}} \right], \qquad (1)$$

where mm_{min} are the mismatches (in percent) of the best-performing algorithm, and n is the number of analyzed algorithms applied to one assessment task. For example, let us assume that the mismatch rate of the best-performing algorithm is 21% (mm_{min} = 0,21) and the number of algorithms analyzed for the task is 3 (n=3), then

$$\left[0.21, 0.21 + \sqrt{\frac{0.21(1-0.21)}{3}} \right] = [0.21, 0.27]$$

which results in an interval from 0.21 to 0.27. In this example, an algorithm whose mismatches are between 21 and 27 % percent is classified as performing well. Since a method must achieve 60% in order to be classified as *processable*, the overall percentage of an assessment method that *performs well* must reach at least 73% (the best achieve 79%). Assessment methods that are in this interval are recommended for the complementarity approach (and are considered in the recommendation model; cf. assessment method selection approach step (5)).

4 Application Scenario

The application scenario "*curriculum vitae analysis"* described in this section is a case of semantic incompleteness. It illustrates (i) how the incompleteness type can be detected, (ii) how it is measured, (iii) which IE procedures (value selection, class assignment, mapping, matching) are affected, and (iv) which assessment method must be selected for the task in order to overcome the incompleteness.

The general aim is to extract personal information from a given CV corpus (1.000 documents). Personal information comprises a person's name, address, birth date, highest education level, and latest position (job). Amongst other errors, there is a substitution error in the highest education level label. Figure 2 shows the document context (size of context window = 4), the correct content of the highest education template slot, the extracted value, and the measured evaluation values (overall completeness C, which subsumes template and instance completeness, precision P, and the label of the IE error).

Table 5. Exemplary recommendation for the template slot `highest education level`

IE Task	Assessment Category	Affected Procedure	Assessment Method	%
EDU (TE)	object description	value selection	method class (ii): statistical methods *identification of co-occurrences*	89

The fact that this is a semantic incompleteness problem is shown by the zero precision value (P = 0, $\text{thres}_{PA} = 0.7$) of the slot value extracted, which indicates a substitution error (SUB). Hence, this slot requires semantic assessment. By using the recommendation model, the assessment category and task can be further restricted. Completing the `highest education level` slot therefore requires an additional object description, and thus a more detailed description of slot constraints, in order to improve value selection and to avoid a resulting substitution error. In this context, methods that identify significant co-occurrences are considered to perform very well and are taken forward to assist the rule-based IE system in the complementarity approach. Table 5 shows the recommendation based on IE method applied, incompleteness error, and required assessment.

5 Background

Background work related to the subject of this paper can be considered under two headings: (i) general approaches to method selection (borrowed from meta-learning research) and (ii)

Slot	Document Context	Correct Answer of Document	IE Result	Evaluation Values, Label
TE EDU:label	of Linz, Subject **Computer Science** September, 2005 Graduation	Computer Science	Master of Science	C = 1, P = 0 SUB

Fig. 2. Substitution error in template slot `highest education level`

approaches to analyzing and evaluating methods. Detailed knowledge of the features corresponding to an IE method's meta-knowledge and properties of assessment methods was drawn mainly from meta-learning research, most notably from research publications by the major figures in this field, including Brazdil *et al.* [4] (author of comprehensive work on meta-learning), Castiello *et al.* [5], Hilario *et al.* [11], and Giraud-Carrier [10]. Castiello *et al.* [5] identified the most important dataset characteristics and thus defined significant meta-features that discriminate between different learning tasks. In addition, they proposed guidelines for selecting the most informative meta-features. Hilario *et al.* [11] devised a way of using information about algorithms independently of datasets. A combination of meta-features describing algorithms and datasets is possible due to the application of a case-based reasoning approach.

Furthermore, research in meta-learning that assists data analysis in KDD processes [13, 15], [16, 17] was considered. Serban *et al*. [15] provided a comprehensive survey of prominent research results (systems, background knowledge, and significant meta-features) of the Intelligent Discovery Assistants (IDAs). In [13], workflow-templates were designed which help the user on the basis of defined meta-features to structure and handle the data mining workflow.
Meta-features for IE methods, and especially for assessment methods, also come from ontology-assisted method selection approaches applied and also for meta-learning and their ontologies, such as KDDONTO [7], DMO [12], and the DL ontology proposed by [6].

6 Future Work

The foundation for the recommendation model has been laid, including the selection of IE methods for consideration and relevant assessment methods that are generally applicable to tackling incompleteness. Hence, the first step of the method selection approach has been accomplished; meta-information and static-decision-support information about IE methods has been assembled, and values of assessment method properties have been determined. The steps (2) to (5) of the assessment method selection approach (i.e., verification of assessment method, processability, profitability, and performance) are currently being examined.

In the last third of this project, specific assessment methods will be chosen (using the recommendation model) for given incompleteness scenarios. Under consideration of both static- and dynamic-decision-support information, the methods will be tested for their effectiveness in the complementarity approach. Thus, the difference between domain-dependent and domain-independent recommendation will become apparent. The application domain is –as proposed in Section 4– the extraction of personal data from curricula vitae written mostly in German.

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References

1. **Batini, C. & Scannapieca, M. (2010).** *Data Quality: Concepts, Methodologies and Techniques,* (Softcover reprint of hardcover 1st ed. 2006). Berlin; New York: Springer.
2. **Bloch, I., Hunter, A., et al. (2001).** Fusion: General Concepts and Characteristics. *International Journal of Intelligent Systems*, 16(10), 1107–1134.
3. **Brazdil, P.B. & Henery, R.J. (1994).** Analysis of Results. *Machine Learning, Neural and Statistical Classification*, (175–212), New York: Ellis Horwood.
4. **Brazdil, P., Giraud-Carrier, C., Soares, C., & Vilalta, R. (2009).** *Meta-Learning: Applications to Data Mining*. Berlin: Springer.
5. **Castiello, C., Castellano, G., & Fanelli, A.M. (2005).** Meta-Data: Characterization of Input Features for Meta-Learning. *Modeling Decisions for Artificial Intelligence. Lecture Notes in Computer Science*, 3558, 457–468.
6. **Charest, M. & Delisle, S. (2006).** Ontology-Guided Intelligent Data Mining Assistance: Combining Declarative and Procedural Knowledge. *10th International Conference on*

Artificial Intelligence and Soft Computing, Palma de Mallorca, Spain, 9–14.

7. **Diamantini, C., Potena, D., & Storti, E. (2009).** KDDONTO: An Ontology for Discovery and Composition of KDD Algorithms. *Third Generation Data Mining: Towards Service-Oriented Knowledge Discovery (SoKD'09)*, Bled, Slovenia, 13–24.
8. **Feilmayr, C. (2012).** Tackling Incompleteness in Information Extraction - A Complementarity Approach. *The Semantic Web: Research and Applications. Lecture Notes in Computer Science,* 7295, 808–812.
9. **Feilmayr, C. (2012).** Characterization and Resolution of Incompleteness in (World-Wide-Web) Information Extraction. *23rd International Workshop on Database and Expert Systems Applications*, Vienna, Austria, 241–245.
10. **Giraud-Carrier, C. (2008).** Meta-Learning – A Tutorial, Technical Report for Tutorial on 7th International Conference on Machine Learning and Applications (ICMLA).
11. **Hilario, M. & Kalousis, A. (2001).** Fusion of Meta-Knowledge and Meta-Data for Case-based Model Selection. *Principles and Practice of Knowledge Discovery. Lecture Notes in Computer Science,* 2168, 180–191.
12. **Hilario, M., Kalousis, A., Nguyen, P., & Woznica, A. (2009).** A Data Mining Ontology for Algorithm Selection and Meta-Mining. *Third Generation Data Mining: Towards Service-Oriented Knowledge Discovery (SoKD'09)*, Bled, Slovenia, 76–87.
13. **Kietz, J.U., Serban, F., Bernstein, A., & Fischer, S. (2010).** Data Mining Workflow Templates for Intelligent Discovery Assistance and Auto-Experimentation. *Third-Generation Data Mining: Towards Service-oriented Knowledge Discovery (SoKD-10),* Barcelona, Spain, 1–12**.**
14. **Rice, J.R. (1976).** The Algorithm Selection Problem. *Advances in Computation*, 15, 65–118.
15. **Serban, F., Vanschoren, J., Kietz, J.U., & Bernstein, A. (2013).** A Survey of Intelligent Assistants for Data Analysis. *ACM Computing Surveys*, 45(3).
16. **Smith-Miles, K.A. (2008).** Cross-Disciplinary Perspectives on Meta-Learning for Algorithm Selection. *ACM Computing Surveys*, 41(1), Article 6.
17. **Vilalta, R., Giraud-Carrier, C., Brazdil, P., & Soares, C. (2004).** Using Meta-Learning to Support Data-Mining. *International Journal of Computer Science & Applications*, 1(1), 31–45.
18. **Wolpert, D.H. (1996).** The Lack of a Priori Distinction between Learning Algorithms. *Neural Computation*, 8(7), 1341–1390.

Christina Feilmayr is a Ph.D. student at the Institute of Application Oriented Knowledge Processing. Her Ph.D. thesis is related to completing information extraction results via data/text mining methods.

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