Using Soft Constraints in Joint Inference for Clinical Concept Recognition

Prateek Jindal and **Dan Roth**
Dept. of Computer Science, UIUC
201 N. Goodwin Ave, Urbana, IL 61801, USA
{jindal2, danr}@illinois.edu

Abstract

This paper introduces IQPs (Integer Quadratic Programs) as a way to model joint inference for the task of concept recognition in clinical domain. IQPs make it possible to easily incorporate soft constraints in the optimization framework and still support exact global inference. We show that soft constraints give statistically significant performance improvements when compared to hard constraints.

1 Introduction

In this paper, we study the problem of concept recognition in the clinical domain. State-of-the-art approaches (de Bruijn et al., 2011; Patrick et al., 2011; Torii et al., 2011; Minard et al., 2011; Jiang et al., 2011; Xu et al., 2012; Roberts and Harabagiu, 2011) for concept recognition in clinical domain (Uzuner et al., 2011) use some sequence-prediction models like CRF (Lafferty et al., 2001), MEMM (McCallum et al., 2000) etc. These approaches are limited by the fact that they can model only local dependencies (most often, first-order models like linear chain CRFs are used to allow tractable inference).

Clinical narratives, unlike newswire data, provide a domain with significant knowledge that can be exploited systematically. Knowledge in this domain can be thought of as belonging to two categories: (1) *Background Knowledge* captured in medical ontologies like UMLS, MeSH and SNOMED CT and (2) *Discourse Knowledge* expressed in the fact that the narratives adhere to specific writing style. While the former can be used by generating more expressive knowledge-rich features, the latter is more interesting from our current perspective, since it provides global constraints on what *output* structures are likely and what are not. We exploit this structural knowledge in our global inference formulation.

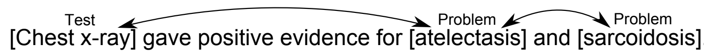
Integer Linear Programming (ILP) based approaches have been used for global inference in many works (Roth and Yih, 2007; Punyakanok et al., 2004; Marciniak and Strube, 2005; Bramsen et al., 2006; Barzilay and Lapata, 2006; Riedel and Clarke, 2006; Clarke and Lapata, 2008; Denis et al., 2007; Chang et al., 2011). However, in most of these works, researchers have focussed only on hard constraints while formulating the inference problem.

Formulating all the constraints as hard constraints is not always desirable because in many cases, constraints are not perfect. In this paper, we propose Integer Quadratic Programs (IQPs) as a way of formulating the inference problem. IQPs is a richer family of models than ILPs and it enables us to easily incorporate soft constraints into the inference procedure[1]. Our experimental results show that soft constraints indeed give much better performance than hard constraints.

2 Methodology

Task Description Input consists of clinical reports in free-text (unstructured) format. The task is: (1) to identify the boundaries of medical concepts and (2) to assign types to such concepts. Each concept can have 3 possible types, namely (1) Test, (2) Treatment and (3) Problem. We would refer to these three types by `TEST`, `TRE` and `PROB` in the following dis-

[1]It should be noted that it is possible to reduce IQPs to ILPs using variable substitution. However, resulting ILPs can be exponentially larger than original IQPs. Thus, IQPs provide a strict modeling advantage compared to ILPs.



(a) Example 1

(b) Example 2

Figure 1: This figure motivates the global inference procedure we used. For discussion, please refer to §2.

cussion.

Our Approach In the first step, we identify the concept boundaries using a CRF (with BIO encoding). Features used by CRF include the constituents given by MetaMap (Aronson and Lang, 2010), shallow parse constituents, surface form and part-of-speech of words in a window of size 3. We also use conjunctions of the features.

After finding concept boundaries, we determine the probability distribution for each concept over 4 possible types (`TEST`, `TRE`, `PROB` or `NULL`). These probability distributions are found using a multi-class SVM classifier (Chang and Lin, 2011). Features used for training this classifier include concept tokens, full text of concept, bi-grams, headword, suffixes of headword, capitalization pattern, shallow parse constituent, Metamap type of concept, MetaMap type of headword, occurrence of concept in MeSH and SNOMED CT, MeSH and SNOMED CT descriptors.

Inference Procedure: The final assignment of types to concepts is determined by an inference procedure. The basic principle behind our inference procedure is: "*Types of concepts which appear close to one another are often closely related. For some concepts, type can be determined with more confidence. And relations between concepts' types guide the inference procedure to determine the types of other concepts.*" We will now explain it in more detail with the help of examples. Figure 1 shows two sentences in which the concepts are shown in brackets and correct (gold) types of concepts are shown above them.

First, consider first and second concepts in Figure 1a. These concepts follow the pattern: *[Concept1] gave positive evidence for [Concept2].* In clinical narratives, such a pattern strongly suggests that *Concept1* is of type `TEST` and *Concept2* is of type `PROB`. Table 1 shows more of such patterns. Next, consider different concepts in Figure 1b. All these concepts are separated by commas and hence, form a list. It is highly likely that such concepts should have the same type.

	Pattern
1	using [TRE] for [PROB]
2	[TEST] showed [PROB]
3	Patient presents with [PROB] status post [TRE]
4	use [TRE] to correct [PROB]
5	[TEST] to rule out [PROB]
6	Unfortunately, [TRE] has caused [PROB]

Table 1: Some patterns that were used in constraints.

3 Modeling Global Inference

Inference is done at the level of sentences. Suppose there are m concepts in a sentence. Each of the m concepts has to be assigned one of the following types: `TEST`, `TRE`, `PROB` or `NULL`. To represent this as an inference problem, we define the indicator variables $x_{i,j}$ where i takes values from 1 to m (corresponding to concepts) and j takes values from 1 to 4 (corresponding to 4 possible types). $p_{i,j}$ refers to the probability that i^{th} concept is of j^{th} type.

So, we can write the following optimization problem to find the optimal concept types:

$$max \sum_{i=1}^{m} \sum_{j=1}^{4} x_{i,j} \cdot p_{i,j} \tag{1}$$

$$\text{subject to} \sum_{j=1}^{4} x_{i,j} = 1 \qquad \forall i \tag{2}$$

$$x_{i,j} \in \{0, 1\} \qquad \forall i, j \tag{3}$$

The objective function in Equation (1) expresses the fact that we want to maximize the probability of assignment of concept types. Equation (2) enforces the constraint that each concept has a unique type. We would refer to these as **Type-1** constraints.

3.1 Constraints Used

In this subsection, we will describe two additional types of constraints (**Type-2** and **Type-3**) that were added to the optimization procedure described above. Whereas **Type-1** constraints described above were formulated as *hard constraints*, **Type-2** and **Type-3** constraints are formulated as *soft constraints*.

3.1.1 Type-2 Constraints

Certain constructs like comma, conjunction, etc. suggest that the 2 concepts appearing in them should have the same type. Figure 1b shows an example of such type of constraints. Suppose, there are n_2 such constraints. Also, assume that l^{th} constraint says that the concepts $\mathcal{R}_l$ and $\mathcal{S}_l$ should have the same type. Now, we define a variable w_l as follows:

$$w_l = \sum_{m=1}^{4} (x_{\mathcal{R}_l,m} - x_{\mathcal{S}_l,m})^2 \tag{4}$$

Now, if the concepts $\mathcal{R}_l$ and $\mathcal{S}_l$ have the same type, then w_l would be equal to 0. Also, if the concepts $\mathcal{R}_l$ and $\mathcal{S}_l$ don't have the same type, then w_l would be equal to 2. So, l^{th} constraint can be enforced by subtracting $(\rho_2 \cdot \frac{w_l}{2})$ from the objective function given by Equation (1). Thus, a penalty of ρ_2 would be enforced iff l^{th} constraint is violated.

3.1.2 Type-3 Constraints

Some short patterns suggest possible types for the concepts which appear in them. Each such pattern, thus, enforces constraint on the types of concepts which appear in them. Figure 1a shows an example of such type of constraints. Suppose there are n_3 such constraints. Also, assume that the k^{th} constraint says that the concept $\mathcal{A}_{1,k}$ should have the type $\mathcal{B}_{1,k}$ and that the concept $\mathcal{A}_{2,k}$ should have the type $\mathcal{B}_{2,k}$. Equivalently, k^{th} constraint says the following in boolean algebra notation: $(x_{\mathcal{A}_{1,k},\mathcal{B}_{1,k}} = 1) \wedge (x_{\mathcal{A}_{2,k},\mathcal{B}_{2,k}} = 1)$. For k^{th} constraint, we introduce one more variable $z_k \in \{0,1\}$ which satisfies the following condition:

$$z_k = 1 \Leftrightarrow x_{\mathcal{A}_{1,k},\mathcal{B}_{1,k}} \wedge x_{\mathcal{A}_{2,k},\mathcal{B}_{2,k}} \tag{5}$$

Using boolean algebra, it is easy to show that Equation (5) can be reduced to a set of linear inequalities. Thus, we can incorporate the k^{th} constraint in the optimization problem by adding to it the constraint given by Equation (5) and by subtracting $(\rho_3(1 - z_k))$ from the objective function given by Equation (1). Thus, a penalty of ρ_3 is imposed iff k^{th} constraint is not satisfied ($z_k = 0$).

$$\begin{aligned} max \sum_{i=1}^{m}\sum_{j=1}^{4} x_{i,j} \cdot p_{i,j} - \sum_{k=1}^{n_3} \rho_3(1 - z_k) \\ - \sum_{l=1}^{n_2}\left(\rho_2 \cdot \frac{\sum_{m=1}^{4}(x_{\mathcal{R}_l,m} - x_{\mathcal{S}_l,m})^2}{2}\right) \end{aligned} \tag{6}$$

$$\text{subject to} \sum_{j=1}^{4} x_{i,j} = 1 \qquad \forall i \tag{7}$$

$$x_{i,j} \in \{0,1\} \qquad \forall i,j \tag{8}$$

$$z_k = 1 \Leftrightarrow x_{\mathcal{A}_{1,k},\mathcal{B}_{1,k}} \wedge x_{\mathcal{A}_{2,k},\mathcal{B}_{2,k}} \forall k \in \{1...n_3\} \tag{9}$$

Figure 2: Final Optimization Problem (an IQP)

3.2 Final Optimization Problem - An IQP

After incorporating all the constraints mentioned above, the final optimization problem (an IQP) is shown in Figure 2. We used Gurobi toolkit to solve such IQPs. In our case, it solves 76 IQPs per second on a quad-core server with Intel Xeon X5650 @ 2.67 GHz processors and 50 GB RAM.

4 Experiments and Results

4.1 Datasets and Evaluation Metrics

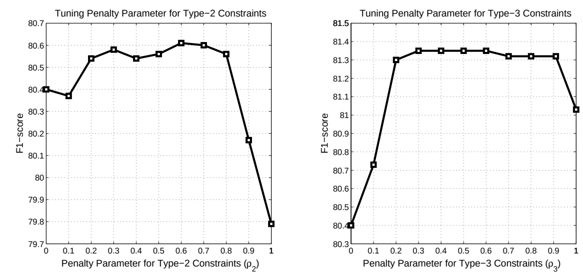
For our experiments, we used the datasets provided by i2b2/VA team as part of 2010 i2b2/VA shared task (Uzuner et al., 2011). The datasets used for shared task contained de-identied clinical reports from three medical institutions: Partners Healthcare (`PH`), Beth-Israel Deaconess Medical Center (`BIDMC`) and the University of Pittsburgh Medical Center (UPMC). UPMC data was divided into 2 sections, namely discharge (`UPMCD`) and progress notes (`UPMCP`). A total of 349 training reports and 477 test reports were made available to the participants. However, data which came from UPMC (more than 50% data) was not made available for public use. As a result, we had only 170 clinical reports for training and 256 clinical reports for testing. Table 3 shows the number of clinical reports made available by different institutions. The strikethrough text in this ta-

	B			BK			BC			BKC		
	P	**R**	**F1**	**P**	**R**	**F1**	**P**	**R**	**F1**	**P**	**R**	**F1**
TEST	92.4	79.4	85.4	91.9	80.2	85.7	92.7	79.6	85.7	92.1	80.4	**85.8**
TRE	92.1	73.6	81.8	92.0	79.5	85.3	92.3	76.8	83.8	92.0	80.2	**85.7**
PROB	83.6	83.6	83.6	88.9	83.7	86.3	85.9	83.8	84.8	89.6	83.9	**86.7**
OVERALL	88.4	79.4	83.6	90.7	81.4	85.8	89.6	80.5	84.8	91.0	81.7	**86.1**

Table 2: Our final system, **BKC**, consistently performed the best among all 4 systems (**B**, **BK**, **BC** and **BKC**).

	PH	BIDMC	~~UPMCD~~	~~UPMCP~~
Train	97	73	~~98~~	~~81~~
Test	133	123	~~102~~	~~119~~

Table 3: Dataset Characteristics



(a) Type-2 Constraints **(b)** Type-3 Constraints

Figure 3: These figures show the result of tuning the penalty parameters (ρ_2 and ρ_3) for soft constraints.

ble indicates that the data was not made available for public use and hence, we couldn't use it. We used about 20% of the training data as a development set. For evaluation, we report precision, recall and F1 scores.

4.2 Results

In this section, we would refer to following 4 systems: (1) *Baseline* (**B**), (2) *Baseline + Knowledge* (**BK**), (3) *Baseline + Constraints* (**BC**) and (4) *Baseline + Knowledge + Constraints* (**BKC**). Please note that the difference between **B** and **BK** systems is that the **B** system (unlike **BK** system) doesn't use features derived from domain-specific knowledge sources (namely MetaMap, UMLS, MeSH and SNOMED CT) for training the classifiers. Both **B** and **BK** systems do not use the inference procedure. **BKC** system uses all the features and also the inference procedure. In addition to these 4 systems, we would refer to another system, namely, **BKC-HARD**. This is similar to **BKC** system. However, it sets $\rho_2 = \rho_3 = 1$ which effectively turns **Type-2** and **Type-3** constraints into hard constraints by imposing very high penalty.

4.2.1 Importance of Soft Constraints

Figures 3a and 3b show the effect of varying the penalties (ρ_2 and ρ_3) for **Type-2** and **Type-3** constraints respectively. These figures show the F1-score of **BKC** system on the development set. Penalty of 0 means that the constraint is not active. As we increase the penalty, the constraint becomes stronger. As the penalty becomes 1, the constraint becomes hard in the sense that final assignments must respect the constraint.

We observe from Figures 3a and 3b that for **Type-2** and **Type-3** constraints, global maxima is attained at $\rho_2 = 0.6$ and $\rho_3 = 0.3$ respectively.

Hard vs Soft Constraints Table 4 compares the performance of **BKC-HARD** system with that of **BKC** system. First 3 rows in this table show the performance of both systems for the individual categories (TEST, TRE and PROB). Fourth row shows the overall score of both systems. **BKC** system outperformed **BKC-HARD** system on all the categories by statistically significant differences at $p = 0.05$ according to Bootstrap Resampling Test (Koehn, 2004). For the OVERALL category, **BKC** system improved over **BKC-HARD** system by $(86.1 - 85.1 =)1.0$ F1 points.

4.2.2 Comparing with state-of-the-art baseline

In 2010 i2b2/VA shared task, majority of top systems were CRF-based models. So, we decided to use CRF as our baseline. Table 2 compares the performance of 4 systems: **B**, **BK**, **BC** and **BKC**. As pointed out before, our **BK** system uses all the knowledge-based features and is very similar to the

	BKC-HARD	**BKC**
TEST	84.7	**85.8**
TRE	84.7	**85.7**
PROB	85.6	**86.7**
OVERALL	85.1	**86.1**

Table 4: Soft constraints **(BKC)** consistently perform much better than hard constraints **(BKC-HARD)**.

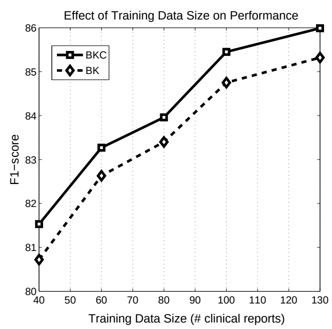


Figure 4: This figure shows the effect of training data size on performance of concept recognition.

top-performing systems in i2b2 challenge. We see from Table 2 that **BKC** system consistently performed the best for individual as well as overall categories[2]. This result is statistically significant at $p = 0.05$ according to Bootstrap Resampling Test (Koehn, 2004). It is also to be noted that **BC** system performed significantly better than **B** system for all the categories. Thus, the constraints are helpful even in the absence of knowledge-based features. Since we report results on publicly available datasets, the future works would be able to compare their results with ours.

4.2.3 Effect of training data size

In Figure 4, we report the overall F1-score on a part of the development set as we vary the size of training data from 40 documents to 130 documents. We notice that the performance increases steadily as more and more training data is provided. This suggests that if we could train on full training data as was made available during challenge, the final scores could be much higher. We also notice from the figure that **BKC** system consistently performs better than state-of-the-art **BK** system as we vary the size of training data. This shows that the joint inference procedure designed by us is very robust.

5 Discussion and Related Work

Joint inference approaches which incorporate declarative knowledge in statistical models have been widely used in last few years to solve IE tasks. Some of the representative models for joint inference include posterior regularization (PR) (Ganchev et al., 2010), generalized expectations (GE) (Mann and McCallum, 2007; Mann and McCallum, 2008), constraint-driven learning (CoDL) (Chang et al., 2007), methods based on integer programs (Roth and Yih, 2004), gibbs sampling (Finkel et al., 2005) and recently the methods that are based on dual-decomposition (Reichart and Barzilay, 2012). Among these approaches, PR, GE and CoDL were proposed for semi-supervised setting. However, in this paper, we are considering a fully supervised scenario.

Roth and Yih (2004) suggested the use of integer programs to model joint inference in a fully supervised setting. Their approach is most closely related to ours. However, they used only hard constraints in their inference formulation. Chang et al. (Chang et al., 2012) recently used soft constraints in Constrained Conditional Models. However, unlike us, they performed approximate inference using beam search. In this paper, we showed that it is possible to do exact inference efficiently even while using soft constraints.

Conclusion

This paper presented a global inference strategy (using IQP) for concept recognition which allows us to model structural knowledge of the clinical domain as soft constraints in the optimization framework. Our results showed that soft constraints are much more effective than hard constraints.

Acknowledgments

This research was supported by Grant HHS 90TR0003/01 and by the IARPA FUSE Program via Department of Interior National Business Center contract number D11PC2015. Its contents are solely the responsibility of the authors and do not necessarily represent the official views of the HHS, IARPA, DoI/NBC or the US government.

[2]Please note that the results reported in Table 2 can not be directly compared with those reported in the challenge because we had only a fraction of the original training and testing data.

References

A.R. Aronson and F.M. Lang. 2010. An overview of metamap: historical perspective and recent advances. *Journal of the American Medical Informatics Association*, 17(3):229.

R. Barzilay and M. Lapata. 2006. Aggregation via set partitioning for natural language generation. In *Proceedings of HLT-NAACL*, pages 359–366. ACL.

P. Bramsen, P. Deshpande, Y.K. Lee, and R. Barzilay. 2006. Inducing temporal graphs. In *Proceedings of the 2006 Conference on Empirical Methods in Natural Language Processing*, pages 189–198. Association for Computational Linguistics.

Chih-Chung Chang and Chih-Jen Lin. 2011. LIBSVM: A library for support vector machines. *ACM Transactions on Intelligent Systems and Technology*, 2:27:1–27:27. Software available at `http://www.csie.ntu.edu.tw/~cjlin/libsvm`.

Ming-Wei Chang, Lev Ratinov, and Dan Roth. 2007. Guiding semi-supervision with constraint-driven learning. *Urbana*, 51:61801.

K.-W. Chang, R. Samdani, A. Rozovskaya, N. Rizzolo, M. Sammons, and D. Roth. 2011. Inference protocols for coreference resolution. In *CoNLL Shared Task*, pages 40–44, Portland, Oregon, USA. Association for Computational Linguistics.

Ming-Wei Chang, Lev Ratinov, and Dan Roth. 2012. Structured learning with constrained conditional models. *Machine learning*, pages 1–33.

J. Clarke and M. Lapata. 2008. Global inference for sentence compression: An integer linear programming approach. *Journal of Artificial Intelligence Research*, 31(1):399–429.

B. de Bruijn, C. Cherry, S. Kiritchenko, J. Martin, and X. Zhu. 2011. Machine-learned solutions for three stages of clinical information extraction: the state of the art at i2b2 2010. *Journal of the American Medical Informatics Association*, 18(5):557–562.

P. Denis, J. Baldridge, et al. 2007. Joint determination of anaphoricity and coreference resolution using integer programming. In *Proceedings of NAACL HLT*, pages 236–243.

J.R. Finkel, T. Grenager, and C. Manning. 2005. Incorporating non-local information into information extraction systems by gibbs sampling. In *Proceedings of the 43rd Annual Meeting on Association for Computational Linguistics*, pages 363–370. Association for Computational Linguistics.

Kuzman Ganchev, Joao Graça, Jennifer Gillenwater, and Ben Taskar. 2010. Posterior regularization for structured latent variable models. *The Journal of Machine Learning Research*, 11:2001–2049.

M. Jiang, Y. Chen, M. Liu, S.T. Rosenbloom, S. Mani, J.C. Denny, and H. Xu. 2011. A study of machine-learning-based approaches to extract clinical entities and their assertions from discharge summaries. *J Am Med Info Assoc*, 18(5):601–606.

P. Koehn. 2004. Statistical significance tests for machine translation evaluation. In *Proceedings of EMNLP*, volume 4, pages 388–395.

John D. Lafferty, Andrew McCallum, and Fernando C. N. Pereira. 2001. Conditional random fields: Probabilistic models for segmenting and labeling sequence data. In *Proceedings of the Eighteenth International Conference on Machine Learning*, ICML '01, pages 282–289, San Francisco, CA, USA. Morgan Kaufmann Publishers Inc.

Gideon S Mann and Andrew McCallum. 2007. Simple, robust, scalable semi-supervised learning via expectation regularization. In *Proceedings of the 24th international conference on Machine learning*, pages 593–600. ACM.

Gideon Mann and Andrew McCallum. 2008. Generalized expectation criteria for semi-supervised learning of conditional random fields. In *Proc. ACL*, pages 870–878.

T. Marciniak and M. Strube. 2005. Beyond the pipeline: Discrete optimization in nlp. In *Proceedings of the Ninth Conference on Computational Natural Language Learning*, pages 136–143. Association for Computational Linguistics.

A. McCallum, D. Freitag, and F. Pereira. 2000. Maximum entropy markov models for information extraction and segmentation. In *Proceedings of the Seventeenth International Conference on Machine Learning*, pages 591–598.

A.L. Minard, A.L. Ligozat, A.B. Abacha, D. Bernhard, B. Cartoni, L. Deléger, B. Grau, S. Rosset, P. Zweigenbaum, and C. Grouin. 2011. Hybrid methods for improving information access in clinical documents: Concept, assertion, and relation identification. *J Am Med Info Assoc*, 18(5):588–593.

J.D. Patrick, D.H.M. Nguyen, Y. Wang, and M. Li. 2011. A knowledge discovery and reuse pipeline for information extraction in clinical notes. *Journal of the American Medical Informatics Association*, 18(5):574–579.

V. Punyakanok, D. Roth, W. Yih, and D. Zimak. 2004. Semantic role labeling via integer linear programming inference. In *Proceedings of the 20th international conference on Computational Linguistics*, page 1346. Association for Computational Linguistics.

Roi Reichart and Regina Barzilay. 2012. Multi event extraction guided by global constraints. In *Proceedings of the 2012 Conference of the North American Chapter of the Association for Computational Linguistics:*

Human Language Technologies, pages 70–79. Association for Computational Linguistics.

S. Riedel and J. Clarke. 2006. Incremental integer linear programming for non-projective dependency parsing. In *Proceedings of the 2006 Conference on Empirical Methods in Natural Language Processing*, pages 129–137. Association for Computational Linguistics.

K. Roberts and S.M. Harabagiu. 2011. A flexible framework for deriving assertions from electronic medical records. *Journal of the American Medical Informatics Association*, 18(5):568–573.

D. Roth and W. Yih. 2004. A linear programming formulation for global inference in natural language tasks. In *CoNLL*, pages 1–8. Association for Computational Linguistics.

D. Roth and W. Yih. 2007. Global inference for entity and relation identification via a linear programming formulation. *Introduction to Statistical Relational Learning*, pages 553–580.

M. Torii, K. Wagholikar, and H. Liu. 2011. Using machine learning for concept extraction on clinical documents from multiple data sources. *Journal of the American Medical Informatics Association*, 18(5):580–587.

O. Uzuner, B.R. South, S. Shen, and S.L. DuVall. 2011. 2010 i2b2/va challenge on concepts, assertions, and relations in clinical text. *Journal of American Medical Informatics Association*.

Y. Xu, K. Hong, J. Tsujii, I. Eric, and C. Chang. 2012. Feature engineering combined with machine learning and rule-based methods for structured information extraction from narrative clinical discharge summaries. *Journal of the American Medical Informatics Association*, 19(5):824–832.