Automatic Medical Coding of Patient Records via Weighted Ridge Regression

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Abstract

In this paper, we apply weighted ridge regression to tackle the highly unbalanced data issue in automatic large-scale ICD-9 coding of medical patient records. Since most of the ICD-9 codes are unevenly represented in the medical records, a weighted scheme is employed to balance positive and negative examples. The weights turn out to be associated with the instance priors from a probabilistic interpretation, and an efficient EM algorithm is developed to automatically update both the weights and the regularization parameter. Experiments on a large-scale real patient database suggest that the weighted ridge regression outperforms the conventional ridge regression and linear support vector machines (SVM).

1. Introduction

Medical coding is best described as translation from the original language in the medical documentation about the diagnoses and procedures related to a patient into a series of code numbers that describe the diagnoses or procedures in a standard manner. Medical coding influences which medical services are paid, how much they should be paid and whether a person is considered a "risk" for insurance coverage. Medical coding is an essential activity that is required for reimbursement by all medical insurance providers. It drives the cash flow by which health care providers operate. Additionally, it supplies critical data for quality evaluation and statistical analysis.

There are several standardized systems for patient diagnosis coding, with ICD-9 (International Classification of Diseases, [9]) being the version currently in use. In most cases, an ICD-9 code is a real number consisting of a 2-3 digit disease category followed by a 1-2 decimal subcategory. For instance, the ICD-9 code of 428 represents Heart Failure (HF), with subcategories 428.0 (Congestive HF, Unspecified), 428.1 (Left HF), 428.2 (Systolic HF), 428.3 (Diastolic HF), 428.4 (Combined HF) and 428.9 (HF, Unspecified). There are more than 12,000 different ICD-9 diagnosis codes with a sophisticated hierarchy and interplay among exams, decision-making, and documenting the diagnosis.

The coding approach currently used in hospitals relies heavily on manual labeling performed by skilled and/or not so skilled personnel. This is not only a time consuming process, but also very error-prone given the large number of ICD-9 codes and patient records. Some studies (e.g., [2]) show that only $60\% \sim 80\%$ of the assigned ICD-9 codes reflect the exact patient medical diagnosis. Furthermore, variations in medical language usage can be found in different geographic locales, and the sophistication of the term usage also varies among different types of medical personnel. Therefore, an automatic medical coding system is of great importance and can not only speed up the whole process, but also improve the coding accuracy significantly.

Not much work has been done so far along this direction, partly because the patient records with ICD-9 labels are hard to get (due to HIPAA regulations), and also because of the extremely unbalanced training data for most of the codes (i.e., only very few records are labeled as positive examples). Earlier approaches to medical coding include rule-based engines [1, 10], automatic or semi-automatic methods [6, 8]. Several companies, such as CodeRite[1] and A-Life[2], provide semi-automatic solutions based on keywords in the disease name. However these approaches require significant human involvement after the keywords are spotted in the patient record.

In our previous work [7], we collected probably the largest set of patient records so far in the literature (with labeled ICD-9 codes), compared a few known classification methods on five of the most balanced ICD-9 codes, and developed a system that can automatically assign codes to a new patient record. In this paper, we propose a novel classification procedure based on weighted ridge regression, which is able to automatically learn both the weights and the regularization parameter. This algorithm is specifically designed to tackle the unbalanced training data problem, and

[1] http://coderitetraining.com/index.html
[2] http://www.alifemedical.com/

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is shown to improve the performance of 50 ICD-9 codes including both balanced problems and unbalanced problems.

The paper is organized as follows. We first review ridge regression and weighted ridge regression in Sec. 2, and then introduce their probabilistic interpretations with EM algorithms in Sec. 3. The experimental results are presented in Sec. 4, and finally Sec. 5 concludes the paper with some discussions as well as several ideas for future work.

2. Weighted Ridge Regression

Ridge regression is a well-known linear regression method and has been proven to be effective for classification problems in the text mining domain. Suppose we have a sample set of pairs $(\mathbf{x}_i, y_i),\ i = 1, \cdots, N$, where $\mathbf{x}_i \in \mathbb{R}^d$ is the i-th feature vector and $y_i \in \{+1, -1\}$ is the corresponding label. Denote $\mathbf{X} \in \mathbb{R}^{N \times d}$ the feature matrix whose i-th row contains the features for the i-th data point, and $\mathbf{y}$ the label vector of N labels. The conventional linear ridge regression constructs a hyperplane-based function $\mathbf{w}^\top \mathbf{x}$ to approximate the output $\mathbf{y}$ by minimizing the following loss function [3]:

$$L_{\text{RR}}(\mathbf{w}) = \|\mathbf{y} - \mathbf{X}\mathbf{w}\|^2 + \lambda \|\mathbf{w}\|^2, \tag{1}$$

where $\|\cdot\|$ denotes the 2-norm of a vector and $\lambda > 0$ is the *regularization parameter*. Here the first term is the least square loss of the output, and second term is the regularization term which penalizes the $\mathbf{w}$ with high norm. λ here balances off the two terms. By zeroing the derivative of L with respect to $\mathbf{w}$, it is not difficult to see that ridge regression has a closed-form solution $\mathbf{w} = (\mathbf{X}^\top \mathbf{X} + \lambda \mathbf{I})^{-1} \mathbf{X}^\top \mathbf{y}$.

Traditional ridge regression sets equal weights to all the examples. When it is employed to solve classification problems (as is widely applied for text categorization), difficulties are encountered when the class distribution is highly unbalanced. For example, in our ICD-9 code database of 96,557 patient records, we only have 774 records assigned to the code 410.41 (which stands for "acute myocardial infarction of inferior wall"). Even if we misclassify all these patients, we may still have acceptable cost value in the classic ridge regression setting. Moreover, some examples can be very noisy due to contamination in the feature vectors or high uncertainty associated with the labels. It would be helpful to have different weights for different observations such that their costs of mislabeling are different.

This leads to the weighted ridge regression, which was studied decades ago [4]. Let $\alpha_i > 0$ be the weight for the i-th observation. The optimal set of hyperplane parameters $\mathbf{w}$ can be found by minimizing the following loss function:

$$\begin{aligned} L_{\text{WRR}}(\mathbf{w}) &= \sum_i \alpha_i (y_i - \mathbf{w}^\top \mathbf{x}_i)^2 + \lambda \|\mathbf{w}\|^2 \\ &= (\mathbf{y} - \mathbf{X}\mathbf{w})^\top \mathbf{A} (\mathbf{y} - \mathbf{X}\mathbf{w}) + \lambda \|\mathbf{w}\|^2, \end{aligned} \tag{2}$$

where $\mathbf{A}$ is a $N \times N$ diagonal matrix with its (i, i)-th entry being α_i. Correspondingly, the closed-form solution for the weighted ridge regression is:

$$\mathbf{w} = (\mathbf{X}^\top \mathbf{A} \mathbf{X} + \lambda \mathbf{I})^{-1} \mathbf{X}^\top \mathbf{A} \mathbf{y}.$$

3. Probabilistic Interpretations

The regularization parameter λ and weight matrix $\mathbf{A}$ are important for getting a good linear weight vector $\mathbf{w}$. They are mostly tuned via a cross-validation procedure, though there are some other ways of estimating λ in the ridge regression literature (see [4]). Here we present a probabilistic interpretation for these methods and derive a principled way of adapting these parameters.

3.1. Interpretation of Ridge Regression

Suppose the output y_i follows a Gaussian distribution with mean $\mathbf{w}^\top \mathbf{x}_i$ and variance σ^2, i.e., $y_i \sim \mathcal{N}(\mathbf{w}^\top \mathbf{x}_i, \sigma^2)$, and the weight vector $\mathbf{w}$ follows a Gaussian prior distribution: $\mathbf{w} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$. Then the negative log-posterior density of $\mathbf{w}$ is exactly the $L_{\text{RR}}(\mathbf{w})$ as defined in (1), with $\lambda = \sigma^2$. This interpretation is well-known in the literature (see [3]).

One advantage of this interpretation is that one can optimize the regularization parameter $\lambda = \sigma^2$ by maximizing the marginal likelihood of the data, which is also called the evidence maximization (or the type-II likelihood):

$$\begin{aligned} \log P(\mathbf{y}|\sigma^2) = &- \frac{N}{2} \log 2\pi - \frac{1}{2} \log |\mathbf{X}\mathbf{X}^\top + \sigma^2 \mathbf{I}| \\ &- \frac{1}{2} \mathbf{y}^\top (\mathbf{X}\mathbf{X}^\top + \sigma^2 \mathbf{I})^{-1} \mathbf{y}. \end{aligned}$$

Alternatively, one can also derive an EM algorithm, taking $\mathbf{w}$ as the missing data and σ^2 the model parameter. In this approach, we estimate the posterior distribution of $\mathbf{w}$ in the E-step, which is a Gaussian $\mathcal{N}(\boldsymbol{\mu}_{\mathbf{w}}, \mathbf{C}_{\mathbf{w}})$, with

$$\begin{aligned} \boldsymbol{\mu}_{\mathbf{w}} &= (\mathbf{X}^\top \mathbf{X} + \sigma^2 \mathbf{I})^{-1} \mathbf{X}^\top \mathbf{y}, \\ \mathbf{C}_{\mathbf{w}} &= \sigma^2 (\mathbf{X}^\top \mathbf{X} + \sigma^2 \mathbf{I})^{-1}. \end{aligned}$$

Then in the M-step we maximize the "complete" log-likelihood with respect to σ^2, assuming the posterior of $\mathbf{w}$ as given in the E-step. This leads to the following update for σ^2:

$$\sigma^2 = \frac{1}{N} \left[\|\mathbf{y} - \mathbf{X}\mathbf{w}\|^2 + \text{tr}(\mathbf{X}\mathbf{C}_{\mathbf{w}}\mathbf{X}^\top) \right].$$

The final algorithm iterates the E-step and M-step until convergence. The posterior mean of $\mathbf{w}$ can be used to make predictions for test observations, and we can also report the variances of these predictions (by considering the posterior covariance of $\mathbf{w}$).

3.2. Interpretation of Weighted Ridge Regression

When the weights of the observations are not fixed as the same, there is also an interesting interpretation for weighted ridge regression. Instead of having a common variance term σ^2 for all the observations as in ridge regression, in weighted ridge regression we assume

$$y_i \sim \mathcal{N}\left(\mathbf{w}^\top \mathbf{x}_i, \frac{\sigma^2}{\alpha_i}\right), \tag{3}$$

which means if the weight of the i-th observation is high, the variance of the output is small. Here σ^2 is the common variance term shared by all the observations, and α_i is specific only to each observation i. With the same prior for $\mathbf{w}$, i.e., $\mathbf{w} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$, one can easily check that the negative log-posterior density of $\mathbf{w}$ is exactly the $L_{\text{WRR}}(\mathbf{w})$ as defined in (2), with $\lambda = \sigma^2$.

A similar EM algorithm can be derived to optimize σ^2 and α_i iteratively. In the E-step we have the estimated posterior of $\mathbf{w}$ as $\mathcal{N}(\boldsymbol{\mu}_\mathbf{w}, \mathbf{C}_\mathbf{w})$, with

$$\boldsymbol{\mu}_\mathbf{w} = (\mathbf{X}^\top \mathbf{A}\mathbf{X} + \sigma^2 \mathbf{I})^{-1} \mathbf{X}^\top \mathbf{A}\mathbf{y}, \tag{4}$$

$$\mathbf{C}_\mathbf{w} = \sigma^2 (\mathbf{X}^\top \mathbf{A}\mathbf{X} + \sigma^2 \mathbf{I})^{-1}. \tag{5}$$

Note how the weight matrix $\mathbf{A}$ influences the posterior mean and variance of $\mathbf{w}$. In (4) and (5), the contribution of each observation i depends on the weight α_i: it contributes more if the weight is higher (i.e., this is a good and important observation) and contributes less if the weight is smaller (i.e., it is a noisy observation).

In the M-step, we have (recall that $\mathbf{A}(i,i) = \alpha_i$)

$$\sigma^2 = \frac{1}{N}\left[(\mathbf{y} - \mathbf{X}\mathbf{w})^\top \mathbf{A}(\mathbf{y} - \mathbf{X}\mathbf{w}) + \operatorname{tr}(\mathbf{X}\mathbf{C}_\mathbf{w}\mathbf{X}^\top \mathbf{A})\right],$$

$$\alpha_i = \frac{\sigma^2}{(y_i - \mathbf{w}^\top \mathbf{x}_i)^2 + \mathbf{x}_i^\top \mathbf{C}_\mathbf{w} \mathbf{x}_i}. \tag{6}$$

Since the scales of σ^2 and $\mathbf{A}$ are inter-dependent (i.e., only the ratio σ^2/α_i is of interest), one might need to normalize $\mathbf{A}$ such that $\operatorname{tr}(\mathbf{A}) = 1$ after each update. Note that (6) provides one way to update the weights in a *reweighted least square* scheme, in which not only the residual but also a covariance term should be considered.

It is seen from the EM algorithm that the weight matrix $\mathbf{A}$ does not need to be a diagonal matrix in general. A non-diagonal $\mathbf{A}$ essentially assumes that the N outputs for these N observations are not i.i.d. sampled, i.e., $\mathbf{y} \sim \mathcal{N}(\mathbf{X}\mathbf{w}, \sigma^2 \mathbf{A}^{-1})$. In the case of ICD-9 code classification, this is useful when one observation (i.e., one record) is only for one visit of a certain patient, and doctors need to consider the records from multiple visits (i.e., multiple observations) to make one decision (i.e., output).

In practice, however, it is not always good to update the weight matrix $\mathbf{A}$ in this way, especially when we have a large number of observations. Overfitting is very likely to occur in this situation. One can constrain the matrix $\mathbf{A}$ even further, in order to reduce the number of free parameters, by assuming some observations share a common weight. One popular choice is to assume all the positive observations share one weight α_+, and all the negative ones share α_-. The updates in this case will be

$$\alpha_+ = \frac{1}{N_+} \sum_{\{i|y_i=+1\}} \frac{\sigma^2}{(y_i - \mathbf{w}^\top \mathbf{x}_i)^2 + \mathbf{x}_i^\top \mathbf{C}_\mathbf{w} \mathbf{x}_i},$$

$$\alpha_- = \frac{1}{N_-} \sum_{\{i|y_i=-1\}} \frac{\sigma^2}{(y_i - \mathbf{w}^\top \mathbf{x}_i)^2 + \mathbf{x}_i^\top \mathbf{C}_\mathbf{w} \mathbf{x}_i},$$

where N_+ and N_- are the numbers of positive and negative examples, respectively. One might also normalize such that $\alpha_+ + \alpha_- = 1$.

The EM update for the α_+ and α_- might not necessarily optimize the F1 or AUC (Area Under ROC Curve) measures because it only minimizes the regularized least square of classification errors. Therefore, we use the validation set to select optimal α_+ and α_- such that maximize the F1 in the experiments. Finally we iterate the E-step and M-step until convergence. As before we can use $\boldsymbol{\mu}_\mathbf{w}$ to make predictions for new observations.

4. Experiments

In this section, we describe the experimental setup and compare results using weighted ridge regression with the canonical ridge regression and linear SVM.

4.1. Data Collection and Preprocessing

The diagnosis coding task is a very complex classification problem also in that the concept of a document is not very well defined. First, for every patient in the medical database there are one or more visits to one or more hospitals – in our experiments we focus on data from only one hospital [7]. During each hospital visit, patients undergo several examinations, treatments and procedures, as well as evaluations. For most of these events, documents in electronic format are authored by different people with different qualifications (e.g., physician, nurse, etc). Each of these documents inserted in the patient database represents an event in the patient's hospital stay: e.g., radiology note, personal physician note, lab test, etc. The number of documents varies from 1 to more than 200 per patient. For the purpose of this paper we limit the number of notes to 200. Because of all of these elements, the patient data will be very unbalanced in the number of medical notes per patient visit. In this work we combine the notes for each patient visit to create a hospital visit profile that we define to be

Table 1. Statistics of the 50 ICD-9 codes

ICD-9	Freq	Description
786.50	0.446	Chest pain
414.00	0.262	Coronary atherosclerosis of unspecified type of vessel, native or graft
401.9	0.246	Unspecified hypertension
272.4	0.163	Unspecified hyperlipidemia
786.09	0.157	Other dyspnea & respiratory abnormalities
⋮	⋮	⋮
410.9	0.021	AMI: Unspecified site
427.32	0.018	Atrial flutter
410.71	0.014	AMI: Subendocardial infarction
423.9	0.013	Unspecified disease of pericardium
410.41	0.008	AMI: Other inferior wall

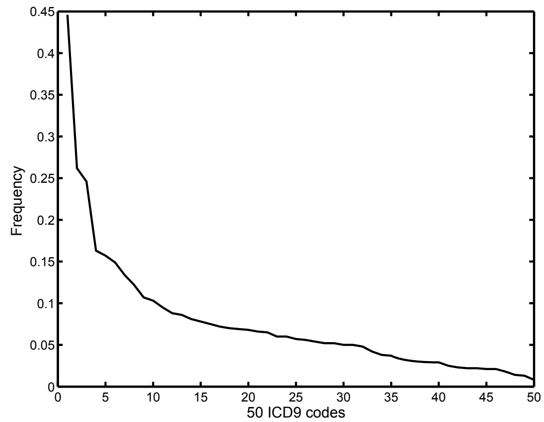

Figure 1. Frequency of the 50 ICD-9 codes

an individual document. The corpus extracted from the patient database contains diagnostic codes for each individual patient visit, and therefore for each of our documents.

Very often, a previous doctor's note is copied and parts of it are modified as the patient visit progresses. This means that a document may contain redundant data that was not intended to provide additional information. During preprocessing, we eliminate redundancy at a paragraph level throughout each document, then perform tokenization and split each paragraph into sentences using a combination of uni-gram frequency and constraint-based approach. Tokens then go through a process of number and pronoun class smoothing, during which all numbers are replaced with a meta token and all person pronouns are replaced with another meta token. After that the uni-gram features with an occurrence frequency greater than or equal to 10 are extracted, which amounts to 29,063. Finally, a feature selection step is performed for each ICD-9 code using the χ^2 strategy (see, [11] for details), and the top 1,500 features with the highest χ^2 values were selected to make up the feature vector. To account for the various document lengths, as the last step we normalize each document to have unit Euclidean norm.

Our corpus consists of 96,557 visit-level documents after the consolidation, and 2,618 distinct ICD-9 codes associated with these visits. In this experiment we pick up the 50 most frequently appearing codes, some of which are listed in Table 1 with frequencies (i.e., the percentage of positive examples over all documents) and descriptions, in the order of decreasing frequency. Fig. 1 plots the percentage for each of 50 codes. The figure clearly shows that around 80% of 50 codes have less than 10% of instances over the entire corpus, which attests the unbalance of ICD-9 codes. We then randomly split the visits into training, validation, and test sets which contain 70%, 15%, and 15% of the corpus respectively. We train binary classifiers for each individual diagnostic code (label), use the validation set to adjust the parameters, and then test on the unseen test set. The training set consists of 67,745 patient visits, which is probably the largest training set so far in the ICD-9 coding literature. This corpus is real-world — a corpus built on an actual patient database, and ICD-9 codes assigned by professionals — making these experiments more realistic compared to previous work, such as the medical text dataset used in the very recent Computation Medicine Center competition[3] which uses overall 2,216 sub-paragraph level documents.

4.2. Variation of Performance With Respect To α

First we present a simple test to validate the proposed method. A fixed α is assigned to the training examples with positive labels, and $(1-\alpha)$ to the ones with negative labels respectively. Hence we have a convex combination weighting on the training examples by varying α between 0 and 1. When $\alpha = 0.5$, the weighted ridge regression reduces to the conventional ridge regression. Therefore variations of different performance measures with respect to α indicate the performance of the proposed method.

We randomly split the training data into 100 folds, each time pick 99 folds as training examples for a given α, and evaluate the performance of trained model on the remaining 1 fold original samples. Two representative ICD-9 codes, 250.00 and 401.9, are shown in Fig. 2. Code 250.00 (diabetes mellitus) only appears 4,811 times out of overall 96,557 data samples in the whole corpus, while code 401.9 (unspecified hypertension) has 23,720 instances. We plot the mean values of F1 and AUC measures out of 100 Monte Carlo simulations as functions of weight α with error bars being the standard deviations. These figures clearly show the effects of different weighting on the performance of weighted ridge regression in terms of F1 and AUC. As the weighted ridge regression assigns more weight on the

[3] See http://www.computationalmedicine.org/challenge/index.php for details of the competition and the results.

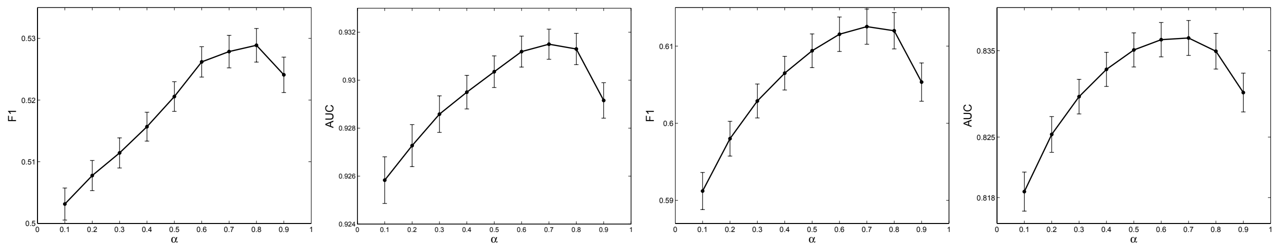

Figure 2. Variations of F1 and AUC w.r.t. α for the codes 250.00 (left two) and 401.9 (right two)

training examples with positive labels, the performance improves. However, over-weighting might deteriorate the results. An optimal α can be selected depending on the performance measure we choose. By selecting an optimal α, the weighted ridge regression outperforms the conventional un-weighted ridge regression ($\alpha = 0.5$ in the figures).

4.3. Results

We present the classification results on 50 ICD-9 codes with the proposed method, the canonical ridge regression and linear SVM here. The comparison measures are given by the precision, recall, F1 and AUC. The precision, recall and F1 measures are standard criteria in text classification. The AUC criterion offers an overall performance for a classifier. We use SVM light toolkit [5] with a linear kernel and default regularization parameter. In the experiment, we set the cost factor as the number of negative training examples over the positive one. Table 2 shows the experiment results over all 50 ICD-9 codes for SVM, the canonical ridge regression and the weighted ridge regression. The order of the codes is sorted by the frequency of codes with the most frequent ones on the top. We highlight the maximum values over 3 methods for the F1 and AUC measures. As the data becomes more and more unbalanced, the performance of SVM deteriorates even though we have set the cost factor accordingly. The weighted ridge regression achieves better results over the canonical one. For some codes with extreme unbalance, significant improvements can be seen in the table. For example, weighted ridge regression improves 9% in F1 over the canonical one for the code 410.41, which is the most infrequent code in the corpus. These results suggest that our method outperforms canonical ridge regression and SVM for unbalanced ICD-9 code classification.

5. Conclusions

In this paper we investigated the use of the weighted ridge regression algorithm to perform classification of unbalanced ICD-9 codes on a population of patients seen at a hospital. Contrary to the conventional approach of selecting the regularization parameter by cross validation, we automatically update this parameter through an EM algorithm. This approach speeds up the computation for the large scale ICD-9 codes database. The weights assigned to different examples can also be updated through the same scheme. Our experiments show the weighted ridge regression improves the performance when compared to canonical ridge regression and SVMs in terms of F1 measure and AUC score. Several interesting directions for future work include exploiting correlations between different ICD-9 codes of the same patient and testing the methods described above on data coming from a previously unseen hospital.

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Table 2. Comparison on the 50 ICD-9 code classification, with bold numbers indicating highest values over 3 methods for F1 and AUC measures.

ICD-9	SVM				Ridge Regression				Weighted Ridge Regression			
Code	Prec	Rec	F1	AUC	Prec	Rec	F1	AUC	Prec	Rec	F1	AUC
786.50	0.702	0.760	0.730	**0.827**	0.636	0.831	0.721	0.815	0.643	0.851	**0.733**	0.825
414.00	0.751	0.830	0.789	**0.930**	0.790	0.779	0.785	0.924	0.789	0.795	**0.792**	**0.930**
401.9	0.506	0.851	0.635	0.859	0.582	0.689	0.631	0.850	0.600	0.703	**0.647**	**0.861**
272.4	0.478	0.830	0.607	0.904	0.565	0.694	0.623	0.897	0.568	0.716	**0.634**	**0.905**
786.09	0.119	0.853	0.208	0.573	0.452	0.586	0.510	0.811	0.446	0.608	**0.514**	**0.820**
786.59	0.302	0.763	0.432	**0.792**	0.306	0.698	0.426	0.776	0.325	0.691	**0.442**	0.791
427.31	0.623	0.837	0.714	0.945	0.721	0.766	0.743	0.940	0.708	0.784	**0.744**	**0.945**
414.01	0.484	0.899	0.629	**0.948**	0.693	0.664	0.678	0.943	0.678	0.691	**0.685**	0.945
V71.7	0.199	0.628	0.302	0.721	0.251	0.442	0.320	0.714	0.235	0.521	**0.324**	**0.724**
428.0	0.436	0.783	0.560	0.910	0.633	0.609	0.621	0.907	0.616	0.640	**0.628**	**0.912**
429.2	0.345	0.807	0.483	0.902	0.504	0.551	0.527	0.889	0.543	0.534	**0.539**	**0.903**
794.39	0.326	0.825	0.468	**0.901**	0.424	0.644	0.511	0.890	0.477	0.560	**0.515**	0.897
429.3	0.212	0.714	0.326	0.807	0.279	0.515	0.362	0.801	0.285	0.539	**0.373**	**0.813**
424.0	0.249	0.740	0.372	0.857	0.370	0.552	0.443	0.846	0.425	0.493	**0.456**	**0.861**
425.4	0.539	0.840	0.657	0.947	0.797	0.644	0.712	0.945	0.746	0.703	**0.724**	**0.951**
413.9	0.269	0.765	0.398	0.867	0.484	0.502	0.493	0.868	0.481	0.535	**0.507**	**0.871**
780.2	0.272	0.702	0.392	0.848	0.523	0.490	**0.506**	0.849	0.575	0.452	**0.506**	**0.853**
414.9	0.283	0.823	0.421	0.906	0.430	0.597	0.500	0.893	0.493	0.561	**0.525**	**0.907**
785.1	0.340	0.764	0.470	0.896	0.498	0.583	0.537	0.891	0.499	0.583	**0.537**	**0.895**
786.05	0.151	0.657	0.246	0.763	0.252	0.332	0.287	0.765	0.223	0.441	**0.296**	**0.771**
424.1	0.249	0.742	0.373	0.880	0.538	0.514	0.526	0.869	0.569	0.508	**0.537**	**0.885**
411.1	0.228	0.815	0.357	0.883	0.429	0.445	0.437	0.880	0.417	0.476	**0.444**	**0.890**
785.9	0.207	0.730	0.323	**0.857**	0.385	0.433	0.408	0.842	0.404	0.432	**0.418**	0.850
427.89	0.267	0.760	0.395	0.889	0.471	0.541	0.504	0.890	0.479	0.542	**0.509**	**0.895**
272.0	0.225	0.775	0.349	0.887	0.542	0.392	0.455	0.872	0.451	0.499	**0.474**	**0.890**
396.3	0.229	0.635	0.336	0.849	0.325	0.362	0.343	0.836	0.314	0.475	**0.378**	**0.850**
427.9	0.142	0.662	0.234	0.800	0.174	0.514	0.260	0.785	0.203	0.453	**0.281**	**0.801**
V45.01	0.640	0.926	0.757	**0.981**	0.816	0.842	0.829	0.973	0.816	0.849	**0.832**	0.973
729.5	0.155	0.619	0.248	0.799	0.393	0.388	**0.391**	0.790	0.383	0.398	**0.391**	**0.802**
397.0	0.144	0.642	0.235	0.797	0.216	0.278	0.243	0.786	0.220	0.346	**0.269**	**0.798**
250.00	0.315	0.849	0.459	0.932	0.413	0.668	0.511	0.934	0.435	0.647	**0.520**	**0.934**
V45.81	0.345	0.887	0.497	0.959	0.545	0.684	0.607	0.952	0.557	0.706	**0.623**	**0.960**
433.10	0.246	0.804	0.376	0.914	0.602	0.584	0.593	0.908	0.615	0.615	**0.615**	**0.916**
V53.31	0.527	0.927	0.672	**0.977**	0.716	0.774	0.744	0.968	0.700	0.807	**0.750**	0.970
780.4	0.099	0.654	0.173	0.786	0.209	0.366	0.266	0.789	0.221	0.356	**0.272**	**0.797**
443.9	0.212	0.804	0.335	0.918	0.686	0.428	0.527	0.922	0.671	0.444	**0.534**	**0.927**
780.79	0.081	0.613	0.143	0.768	0.199	0.189	0.194	0.767	0.144	0.341	**0.203**	**0.780**
785.0	0.111	0.696	0.191	0.831	0.231	0.296	0.260	0.813	0.266	0.289	**0.277**	**0.834**
427.1	0.210	0.758	0.329	0.920	0.632	0.519	**0.570**	0.914	0.632	0.519	**0.570**	**0.927**
794.31	0.080	0.585	0.141	0.772	0.160	0.273	0.201	0.765	0.176	0.268	**0.212**	**0.775**
416.0	0.088	0.658	0.155	0.820	0.217	0.285	0.246	0.821	0.259	0.235	**0.246**	**0.836**
412	0.116	0.746	0.201	0.870	0.225	0.403	0.289	0.878	0.234	0.427	**0.302**	**0.887**
428.22	0.264	0.862	0.404	0.978	0.582	0.594	0.588	0.978	0.579	0.641	**0.608**	**0.982**
496	0.137	0.742	0.231	0.900	0.274	0.544	0.364	0.903	0.291	0.588	**0.389**	**0.913**
785.2	0.082	0.540	0.142	0.793	0.166	0.339	0.223	0.790	0.180	0.304	**0.226**	**0.803**
410.9	0.127	0.703	0.215	0.891	0.261	0.419	0.321	0.897	0.290	0.434	**0.348**	**0.905**
427.32	0.132	0.734	0.224	0.913	0.424	0.582	0.491	0.911	0.434	0.566	**0.491**	**0.918**
410.71	0.085	0.574	0.148	**0.881**	0.167	0.384	0.233	0.877	0.175	0.374	**0.239**	0.878
423.9	0.089	0.603	0.155	0.860	0.328	0.364	0.345	0.856	0.349	0.364	**0.356**	**0.865**
410.41	0.146	0.529	0.229	**0.910**	0.141	0.286	0.188	0.899	0.266	0.286	**0.275**	0.908