learning and knowledge discovery to create automated, personalized hospital referral recommendations that take patient characteristics and preferences into consideration.

1.1. Introduction to the hospital referral problem

Hospital referral criteria usually come from research studies and personal experience. Many researchers have examined the relationship between outcomes of hospitals and various institutional characteristics. In particular, a large number of studies have related the volume of hospital surgical procedures to decreased in-hospital mortality [23,25,20,8].

Likewise, teaching hospitals have been shown in several studies to have lower in-hospital mortality [30,4]. Chen et al. [11] concluded that hospitals participating in the JCAHO survey process reported superior quality and outcomes. Elixhauser et al. [17] and others have reported that staffing affects quality. Among these institutional characteristics, the volume of patients or procedures is the most consistent predictor of in-hospital mortality and is broadly used as a hospital-selection criteria. Although the volume-outcome relationship holds for a number of complex surgeries, the magnitude of association varies across procedures [8,23]. Both "practice makes perfect" and "selective referral" appear to play a role in the volume-outcome relationship [26]. Usually, large institutions have favorable characteristics, such as technical sophistication and more staffing, and they are usually preferred for referral.

Although surgical volume is a strong predictor of outcomes, the usage of this indicator is sometimes criticized. Nallamothu et al. [33] explained three reasons that the quality of high-volume hospitals looks better than low-volume ones. First, low-volume hospitals may be less inclined to turn down high-risk cases. Second, large-volume hospitals attract more cases through physician referral or self-referral. Third, patients with opportunity and desire to be referred may be healthier because of several factors. These reasons can help to explain variations in the volume-outcome relationship. Many low-volume centers have very good performance, while some high-volume hospitals have poor performance because volume is an imperfect proxy measure of quality [16,26,8,23].

While many of these studies examine only one or two predictive variables, for practical usage, a good hospital referral decision should consider numerous factors, specifically including geography. Some medical situations are time-critical, and transportation time plays a very important role in outcomes. For patients living in rural and underserved areas, distance is often the most important concern when selecting a hospital. Even for nonemergency conditions, proximity is highly desirable. Therefore, several studies [9,15,16,33] have shown that patients often prefer local higher-risk hospitals over traveling to lower-risk hospitals. Geographic factors may influence the effect of institutional predictors. Ward et al. [41] indicated that the volume threshold suggested by The Leapfrog Group [22] does not perform well in a largely rural state. Other factors, such as a patient's physical condition, should also be considered. Glance et al. [21] stated that the risk reductions of high- and low-risk patients in different volume hospitals vary. If we considered the distance to an institution, the hospital referral recommendation for a healthier patient and a sicker patient can be dramatically different. A good hospital referral recommendation considers not only institutional but also patient factors, including the travel distance a patient can tolerate, and the patient's risk factors. Not surprisingly, it is challenging to give hospital-selection advice that considers these multiple complex and interdependent issues.

Some practical problems may arise if we consider only institutional factors. For example, should an acute myocardial infarction (AMI) patient go to a mid-size teaching hospital with JCAHO accreditation 20 miles away or a large-volume nonteaching hospital 40 miles away? The Leapfrog Group [22] suggested that a good hospital would have a procedure volume greater than 450 for coronary artery bypass graft (CABG) surgery. Should an 70-year-old AMI patient with congestive heart failure and diabetes who needs an emergency CABG choose a hospital with CABG procedure volume of 300, 30 miles away or another hospital with CABG procedure size of 450, 40 miles away? How about a younger and healthier patient who is not in an emergency situation but needs surgery? Obviously, the answers would be different for different people. It is hard to tell which hospital is better when we consider only institutional characteristics. The hospital referral problem is even more complex if we add other practical concerns, such as insurance coverage and estimated charge during a hospital stay.

From the perspective of knowledge management, the above research studies regarding identification of high quality institutional characteristics are called explicit knowledge [1]. Tacit knowledge, such as personal experience and working knowledge, plays an important role in health care settings. Experts can rely on it to derive solutions to their problems. Physicians refer a patient to a specific hospital considering the patient's physical condition and the travel distance involved. An experienced physician can choose the hospital that minimizes the patient's risk. Such a customized recommendation has a higher chance of being accepted by a patient.

The purpose of this project is to build an expert system that can assist such a customized hospital-selection decision. An expert system is a computer program that can make inferences and give conclusions using the knowledge of specialists. A knowledge-based system (KBS) is an early and well-known type of expert system. The knowledge typically exists in the form of atomic facts about the domain of interest and rules for inferring new facts, but may also be in the form of graphs, trees, or networks. They are stored in a specific location called a knowledge base. The KBS uses an inference engine and the knowledge base to make inferences. MYCIN [38] was one of the earliest knowledge-based expert systems and can provide diagnosis and therapy recommendations. The knowledge in MYCIN is stored in the form of rules. These rules were derived from the knowledge of infectious disease experts. The process of transforming knowledge from human to machine is called knowledge acquisition, and is time- and labor-intensive [19]. In addition, maintaining the knowledge base is very difficult [42,13].

Case-based reasoning [43] is another technique for knowledge acquisition. This method does not require a knowledge base. Instead, all previously solved cases are stored in one place, called the case library, which is the knowledge source. Typically, a case comprises the problem, the solution, and the outcome. To obtain the solution for a new case, one simply finds the case with the most similar problem in the case library. The proposed solution is then the same as was observed in the retrieved case.

Machine learning methods are well known for knowledge discovery. They can help to elicit knowledge (explicit and tacit) [10,34] from data and generalize that knowledge to new, previously unseen cases. Machine learning methods have been successfully applied in several medical areas such as classification, diagnosis, and prognosis. In general, these methods can be classified as supervised or unsupervised learning methods. Supervised learning methods learn a function that maps features (the independent variables used to represent a case) to the corresponding labels (dependent variables, typically outcomes). The labeled samples for the unsupervised learning methods are not necessary because these methods cluster samples based on similarity of variables. In this project, we are only interested in supervised learning methods.

Supervised learning methods such as C4.5 [37] that learn patterns in the form of rules provide a partially automatic method for knowledge acquisition in traditional expert systems. However, much time and labor may still be required to construct and maintain the knowledge base. Other supervised learning methods induce patterns in the form of mathematical functions, which can be either linear or nonlinear. Knowledge is therefore encoded in these mathematical functions. They can be applied very successfully for their original design purpose, e.g., classification. However, methods for applying captured knowledge in other purposes are limited [5]. It is difficult to use the knowledge in a mathematical function to assist in an action decision, such as a customized hospital-selection decision.

This paper proposes a new method, called Prediction and Optimization-Based Decision Support System (PODSS) to extract knowledge in the form of the mathematical function from a classifier and apply optimization methods to use this knowledge source to solve the complex hospital referral problem. Similar to case-based reasoning, the knowledge source is data instead of a knowledge base. The difference is that the knowledge has been compiled in the form of mathematical functions. In addition, we obtain the action solution based on optimization methods instead of similarity.

1.2. An introduction to the PODSS algorithm

The purpose of the PODSS algorithm is to generate a suggested action that leads to a higher probability of the desired outcome. This type of problem can be found in many domains. Stock investors choose stocks carefully in order to maximize profit and minimize risk. Marketing managers design strategies to maximize their product sales under budgetary constraints. Experts are often consulted because they know how to maximize the probability of the desired results while considering multiple and sometimes competing factors. The proposed algorithm can simulate these experts by recommending actions that maximize the probability of the desired result.

There are many approaches that can help to understand factors (variables) that lead to a desired outcome. Careful use of regression techniques can allow us to determine the relative importance of variables by observing the sign and magnitude of coefficients (e.g., [2]). Sensitivity analysis provides a way to observe how sensitive a result is to variations in the variables of interest, thus determining the importance of these variables (e.g., [6]).

These methods can identify important factors for achieving a desired outcome. However, they cannot tell us what to do, how to do it, and how to resolve trade-offs among alternatives. For example, the above methods can identify which interventions are most likely to cure a disease, however, it usually takes an experienced doctor to know how to choose among alternative interventions, and how to tailor the intervention to the needs of a specific patient.

The proposed algorithm is a decision tool that can provide suggestions by utilizing captured knowledge and optimizing the effectiveness of the chosen action. This algorithm can recommend an action decision based on multiple variables and the interactions among them. Fig. 1 illustrates the process of constructing and using this decision support tool. Examples with known outcomes are

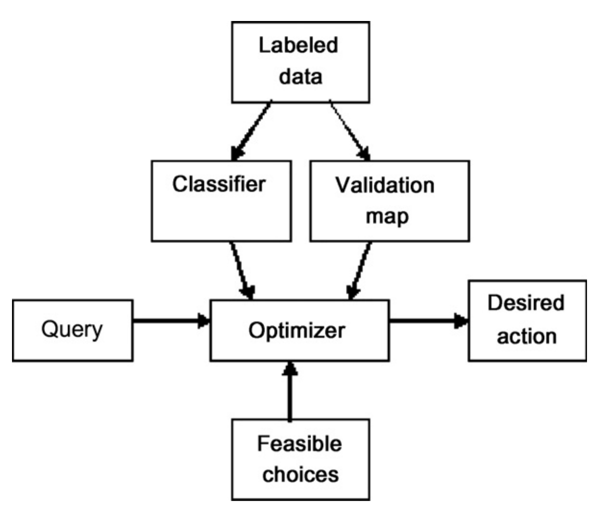

Fig. 1. The process to capture and apply knowledge.

used to capture knowledge in the form of a predictive model (classifier) and a validation map that estimates the probability of the desired outcome for any patient/action pair. A query will activate an optimization method which finds the best course of action using the captured knowledge, feasible choices, and information provided about the patient.

Communication between the decision support system and a user is required. The user provides information regarding a patient's characteristics and the maximal distance to a hospital that the patient can tolerate, and then the system can generate a customized hospital choice. This customized choice not only satisfies the given maximum tolerated distance but also identifies the hospital with the highest probability of the desired outcome. The maximum tolerated distance parameter should be decided by a patient and his/her doctor to ensure that the travel distance does not become a risk factor and is acceptable to the patient. For some healthier patients, this parameter value can be high. For an emergency case, this parameter must be very low.

Travel distance and survival probability are two important targets. The trade-off between different objectives can be addressed explicitly when the hospital choice decision is customized. In this study, the problem is first formulated as single-objective optimization, and can be solved by an exhaustive search because of the small solution space (only the number of hospitals). In this optimization, a query provides a patient's characteristics to the system, such as age, admission type, comorbidities, and the maximum tolerated distance. The optimization process will combine the provided information with the captured knowledge to generate a customized hospital selection. The objective of the knowledge extraction tool is to find a hospital with the highest survival probability under the constraint of the maximum tolerated distance to a hospital. If we also want to consider other issues in the hospital-selection decision, such as reduced likelihood of complications, then the problem is formulated as multi-objective optimization. We present the entire solution space to the user in an intuitive format, so that the relative importance among the targets can be decided by the user. Due to the small solution space, presenting the predicted outcomes of each hospital in an organized way to a user is more effective and efficient than having the system decide on a single optimal choice.

The rest of the article is organized as follows. In Section 2, we discuss how to capture knowledge, transform captured knowledge into an objective function, apply the captured knowledge, and use the algorithm in a hospital referral problem. We demonstrate both single- and multi-objective optimization examples. Section 3 discusses experimental results of these examples, and introduces an indirect evaluation method for determining the effectiveness of the method. Discussion of the computational experiments and possible extensions of this algorithm to other problems are included in Section 4.

2. Methods

There are a series of stages in the PODSS algorithm. As illustrated in Fig. 1, the algorithm relies on classifiers to capture knowledge. This step is the same as training a prediction model. Independent and dependent variables are required to train the model. The output score of the prediction model, which we convert to a probability, can be interpreted as the confidence level of the desired class prediction. The purpose of optimization is to maximize the confidence level of the desired class label.

2.1. Dataset design

Our approach depends on the problem having two distinct types of independent variables. The first type is uncontrollable (unchangeable) variables. The values of these variables are given and cannot be changed. For example, patient variables such as demographic data, medical test results, diagnostic results, admission type, surgery status, comorbidity scores [14], and payment type are uncontrollable variables in this study. The second type is controllable (changeable) variables, whose values can be changed. The recommendation can be made based on these variables. In our application, each set of values of these variables describes a hospital. These hospital descriptive variables are owner type, hospital location, JCAHO accreditation, total number of surgical operations, AMI patient discharge volume, and the volume of CABG surgeries. Table 1 summarizes the variables used for classifier training. Variables 1–6 relate to the patient's characteristics and are uncontrollable; variables 7–13 relate to the hospital's characteristics and are controllable.

In the knowledge application stage, each type of variable plays a different role in the optimization process. The first set is constant and is provided by a user when querying. The solution variables comprise the second set. The

Table 1
Variables description

		Data type
1	Patient age	Numeric
2	Patient sex	Male, female
3	Patient race	White, other
4	Patient admission type	Emergency, urgent, elective
5	Patient comorbidity severity	Numeric
6	Patient payment type	Medicare, Blue Cross, Commercial, other
7	Hospital ownership type	Government owned or not
8	Hospital bed size	Numeric
9	Hospital metropolitan status	Numeric, from 0 to 6 based on population size
10	Hospital JCAHO status	JCAHO accreditation or not
11	Hospital surgery volume	Numeric, total surgical operations
12	Hospital discharge volume	Numeric
13	Hospital CABG volume	Numeric

optimal solution is the hospital with the most favorable descriptive variables that results in the highest optimum value (desired outcome with the highest probability). In a nonlinear model, the optimal solution may depend on the given uncontrollable variables due to variable interaction.

The 2004 State Inpatient Dataset (SID) for Iowa from the Agency for Healthcare Research and Quality (AHRQ) Healthcare Cost and Utilization Project (HCUP) [24] was used in our study. There are almost 360,000 discharge records in the SID. For this project we chose to build a hospital referral algorithm for patients with a principal diagnosis of acute myocardial infarction (AMI) with ICD-9-CM codes of 410.01 to 410.91.

We selected AMI for several reasons. First, it is relatively common and easy to identify in the datasets. Second, the outcomes of interest, including mortality, are also relatively common which facilitated model building. Third, AMI in-hospital mortality is being introduced by the Centers for Medicare and Medicaid Services as a required publicly reported performance indicator for all hospitals, thus the algorithm described here could find application in the near future. While we use AMI for this first demonstration, the algorithm can be easily modified to work with nearly any disease of interest where referral is an issue.

The SID can be linked to hospital descriptive data from the American Hospital Association (AHA) [3] by a hospital identification number. There are 116 nonfederal acute-care hospitals in Iowa. The SID contains zip codes for each patient and hospital, which permit the Euclidean distance between a patient and any hospital to be computed. The location (longitudinal and latitudinal) data were retrieved from http://www.brainyzip.com/. The distance estimation from MapQuest or Google Maps could be used to compute road distance estimation. Road distance estimation more accurately represents travel distance and is longer than Euclidean distance [27]. We choose the Euclidean distance estimation in our study because it was readily available for each patient/hospital pairing, whereby road distance estimation is not, and the difference between the two methods is relatively consistent in Midwestern states.

Four datasets were used in this study. The labels of the first three datasets are patients' in-hospital survival status, and the labels of the fourth dataset are hospital-acquired complication status. The complication labels are identified using ICD-9-CM codes of complication defined by Elixhauser and colleagues [18]. The first dataset includes all AMI patients whether surgery is performed or not. The second dataset is designed for AMI patients who do not have any surgery. In this dataset, patients with any surgical Diagnosis Related Groups (DRG) were excluded. The third dataset includes only AMI patients who have coronary artery bypass graft (CABG) surgeries (ICD-9 36.10 to 36.19). The last dataset contains the same patients as the third one but with a different label type. The data show only 12 hospitals in Iowa perform CABG surgeries. Thus, hospital selection is limited to these 12 hospitals in the third and fourth dataset. The size and percentage of the desired outcome label in each dataset are shown in Table 2.

Table 2
Description of four datasets

	Desired outcome (%)	Data size
All AMI	93.0	6599
Nonsurgery	93.4	5846
CABG	95.0	466
CABG–FFC	81.8	466

Desired outcome for the first three databases is survival and the last database is free from complications (FFC).

Dependent variables, such as survival status and complication status, are usually used to find the predictors of hospital quality. This study shows two types of expert system based on the number of desired targets. The first is called single-objective optimization, in which we use a classifier to find the relationship between independent variables and patients' survival status. Datasets 1, 2, and 3 are used in this study. The second is called multi-objective optimization. In addition to the survival status classifier, we add a second classifier for the complication status. The hospital-acquired complication is a very important concern to surgical patients, and the third and fourth datasets are used in this study.

2.2. Building a predictive model

Knowledge capturing in our model relies on supervised learning, which learns the relationship between independent and dependent variables. We used support vector machines (SVMs) [40] as the classifier to construct a separating surface between point sets of different classes. There are an infinite number of surfaces that can perform the separation. In order to generalize to unseen points well, the SVM classifier finds the separating surface with the greatest margin, or the distance from a point to the surface, during the training process.

Fig. 2 shows an example of a linear separating surface. In our example, the surface separates negative from positive cases, with the negative area to the left of the plane ($d(x) < 0$), and the positive region to the right ($d(x) > 0$). If a test case falls to the right of the separation surface, the predicted result will be positive. In general, there are some points that cannot be separated and are classified incorrectly. A high prediction score means a high probability that a patient will have the desired outcome. In other words, the confidence level of the desired outcome is high. On the other hand, if we can increase a data point's predictive score by changing certain independent variables (controllable), we may improve the probability to have the desired outcome. For example, the probability of point A^* corresponding to a positive outcome is higher than $A+$, and the probability of point $A+$ to be positive is higher than $A-$ (Fig. 2).

In many problems, linear surfaces are insufficiently flexible to separate the point sets well. Projecting the points to

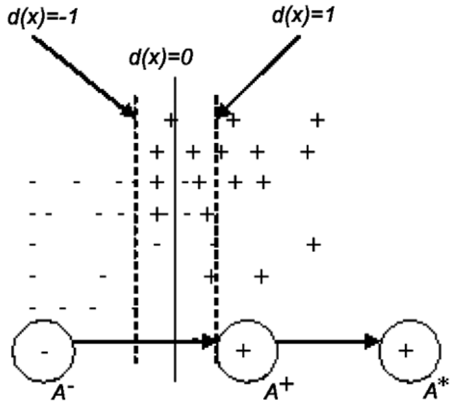

Fig. 2. Separating hyperplane with maximum margin created by a support vector machine. + and − represent the class of each data point. We assume + is the desired result (survival). The decision function, $d(x) = \sum_{i=1}^{n} y_i \alpha_i K(x, x_i) + b$, can decide the location of a point as the prediction result. We can improve the probability of a point being positive by improving the decision value, $d(x)$, of this point, for example, moving the point A− to A+ or A*.

a higher-dimensional space and building a linear surface in this space can solve this problem, but complicates the learning process. For example, consider a problem in which the input space has three dimensions x_1, x_2, and x_3. We could map them into a higher-dimensional feature space $x_1, x_2, x_3, x_1^2, x_1x_2, x_2x_3, x_1x_3, x_2^2, x_3^2 \ldots$ for model construction. SVMs use a kernel function, $K(x, x_i)$, to avoid the need to explicitly perform such a mapping. The radial basis function (RBF) kernel was used in our experiments.

Fig. 2 shows an example of a simple separating hyperplane, $d(x) = 0$, where $d(x) = \sum_{i=1}^{n} y_i \alpha_i K(x, x_i) + b$. α is a vector of the Lagrange multipliers, y is the class label, and b is the bias term. By using a nonlinear kernel function K, the separation can be performed in a high-dimensional space without explicitly performing the projection. SVMs have been shown to perform extremely well on a wide range of problems and are generally considered to be one of the best classification algorithms.

We built a predictive model using independent variables of patients' characteristics (or uncontrollable variables), x_{1i} $i \in$ patients, and their chosen hospitals' descriptive features (or controllable variables), $x_{2\bar{j}} j \in$ hospitals, to predict whether or not a patient will survive (or be free from complication) during a hospital stay. Note that we use the notation $\bar{j}$ to indicate the index of the hospital actually chosen by the particular patient. After training, the decision function is represented as $d(x_1 \cup x_2)$. As in Fig. 2, the value of d can decide the confidence level of the desired outcome. Our goal is to increase this confidence level.

2.3. Extracting recommendation information

In this problem, we assume that the only way to improve a patient's expected outcome is to change hospitals, and hence, change the values of x_2. Optimization methods provide a scientific way to improve the confidence level to the desired outcome and find the values of x_2. The decision function can naturally become the source of the objective function, since we want to maximize the confidence that the desired outcome occurs.

The idea of using optimization is intuitive. In real life, the probability of survival in different hospitals for the same patient will vary. After training, a classifier can estimate the score of survival or freedom-from-complication (FFC) for a query patient in each hospital by an evaluation function. A good hospital will result in a higher predictive score, so the evaluation function value will be higher. In other words, the optimization method can help to identify such a hospital. The mathematical model can represent the hospital referral scenario in real life, since a high quality institution can prevent medical error and increase the chance of survival (or FFC). The survival function optimization is formulated as follows:

$$\begin{aligned} &\underset{x_{2j}}{\text{maximize}} && d(x_1 \cup x_{2j}) \\ &\text{subject to} && \text{dist}(j, x) \leqslant DL \\ & && x_{2j} \in X_2 \end{aligned} \tag{1}$$

where x_1 is the characteristic variables of the query patient, and x_{2j} is the set of descriptive variables describing the hospital j. $\text{dist}(j, x)$ is the Euclidean distance from the patient to the hospital j. DL is the maximum tolerated traveling distance parameter given by the user.

The purpose of the optimization process is to find the hospital $\hat{j}$ with the most favorable descriptive features $x_{2\hat{j}}$, such that the objective function $d(x_1 \cup x_{2\hat{j}})$ is the maximum. Although a high quality hospital can improve a patient's survival probability, the effect is sometimes limited. The physical condition, x_1, of each patient is different, and is a more important factor in deciding the survival probability. There are three possible situations when patients change their original chosen hospital to the referred one:

1. Patients may move from predicted negative to less negative (less predicted probability of death).
2. Patients may move from predicted negative to positive (predicted death to predicted survival).
3. Patients may move from predicted positive to more positive (increasing the probability of the prediction of survival).

We note that in the general case that the problem in Eq. (1) might be formulated as a linear, nonlinear, or mixed integer problem to reflect the nature of the variables x_2. These methods can construct the characteristic of a "perfect" hospital. However, in our application this approach makes no sense, since such a hospital does not necessarily exist. To maintain feasibility, the optimization should not create the value of x_{2j}. Instead, we should evaluate the value of $d(x_1 \cup x_{2j})$ from all hospitals j within the distance limit, and find one with the highest value of d. Due to the small search space in the hospital referral problem, exhaustive search of the possible hospitals is fast enough to examine the evaluation function value in each hospital j within the given distance limit.

To demonstrate the flexibility of our mathematical formulation, we move the distance constraint into the objective function. In the multi-objective optimization formulation

$$\begin{aligned} &\underset{x_{2j}}{\text{maximize}} \quad D(x) = (d_1(x), d_2(x), -d_3(x)) \\ &\text{subject to} \quad x_{2j} \in X_2 \end{aligned} \tag{2}$$

$x = x_1 \cup x_{2j}$, d_1 represents the survival decision function, d_2 represents the FFC decision function, and d_3 is the Euclidean distance function, which is the same as $\text{dist}(j, x)$. The goal in this formulation is to optimize the three desired objectives. These objectives can be combined in several ways, such as additive, multiplicative, and multi-linear forms [28]. Each objective should be assigned a weight when combining. The relative importance (weight) of each objective can be decided based on a user's consideration. In order to give customized decision support, the system should not decide the balance of weight for the user.

For this problem, we present the individualized solution space to the query patient rather than determine a single choice for the patient. With sufficient information and visual presentation, a patient can decide his/her best solution easily. The solution space contains information of the query patient's survival probability, the FFC probability, and the distance to each hospital.

2.4. Building a validation map

The SVM scores are not probabilities. Although we can improve the predictive score by recommending a hospital to the query patient, we still want to understand how much the survival probability can be improved. The validation method is also a problem. The dataset recorded historical events of patients' characteristics, the hospital they chose, and the outcomes. We have no way to know if sending those patients to the recommended hospitals would have changed their results. However, we can observe the distribution of predictive scores corresponding to survival by learning the relationship between class labels and predictive scores (Eq. (3)). Platt's calibration method [36] provides a computational solution to this problem. This method provides an approach to map SVM scores, d, into probabilities, p, through a sigmoid function

$$P(y = +1|d) = \frac{1}{1 + \exp(Ad(x) + B)} \tag{3}$$

The parameters A and B are found from the negative log likelihood of the data, which is a cross-entropy error function

$$\underset{A,B}{\text{minimize}} \quad \sum_i t_i \log(p_i) + (1 - t_i)\log(1 - p_i) \tag{4}$$

where $p_i = 1/(1 + \exp(Ad(x_i) + B))$ and

$$t_i = \begin{cases} \frac{N_+ + 1}{N_+ + 2}, & \text{if } y_i = +1 \\ \frac{1}{N_- + 2}, & \text{if } y_i = -1 \end{cases}$$

We used a variation of Platt's method [32] which avoids numerical difficulties to build a smooth mapping from the SVM score to a posterior probability of survival. Niculescu-Mizil and Caruana [35] tested several classifiers using Platt's calibration and isotonic regression [44] and indicate that SVM is one of the best methods to predict probabilities after calibration.

Using the calibration function we can construct a validation map based on the relationship between scores and probabilities. Fig. 3 shows the validation maps for the four datasets. The predicted survival probability of a patient in each hospital can be found on this map. For example, in the all-AMI-patients experiment (Fig. 3a), the predicted survival probability of a patient may improve about 5% if the query patient's predictive score improves from 0 to 1 by switching to the recommended hospital.

Fig. 4 shows pseudocode for the PODSS algorithm in knowledge capturing. Figs. 5 and 6 show the algorithms for single- and multi-objective optimization, respectively. The main purpose of the knowledge capturing (training) is to learn a decision function and probability transfer function from the data. In other words, knowledge is stored in these functions. In the single-objective optimization, given the query patient's characteristic variables and the maximum tolerated distance, the optimization will find the hospital with the highest survival probability satisfying the distance constraint. In the multi-objective optimization, a patient does not need to give the maximum tolerated distance. Instead, the algorithm will give information including the survival probability, the freedom-from-complication probability, and the distance to each hospital.

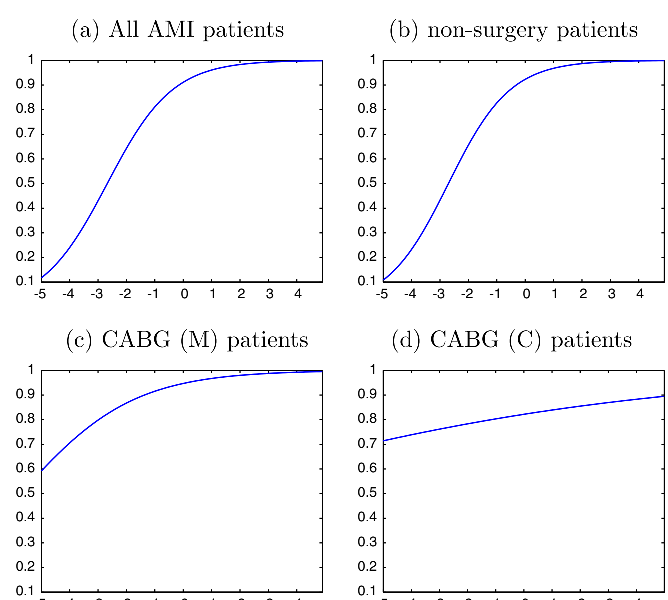

Fig. 3. The validation maps of (a) all AMI, (b) nonsurgery, (c) CABG (mortality), and (d) CABG (complication) patients.