Data mining experiments on the Angiotensin II-Antagonist in Paroxysmal Atrial Fibrillation (ANTIPAF-AFNET 2) trial: ‘exposing the invisible’

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Received 3 February 2016; accepted after revision 29 February 2016; online publish-ahead-of-print 11 October 2016

Aims
The aims of this study include (i) pursuing data-mining experiments on the Angiotensin II-Antagonist in Paroxysmal Atrial Fibrillation (ANTIPAF-AFNET 2) trial dataset containing atrial fibrillation (AF) burden scores of patients with many clinical parameters and (ii) revealing possible correlations between the estimated risk factors of AF and other clinical findings or measurements provided in the dataset.

Methods
Ranking Instances by Maximizing the Area under a Receiver Operating Characteristics (ROC) Curve (RIMARC) is used to determine the predictive weights ($P_w$) of baseline variables on the primary endpoint. Chi-square automatic interaction detector algorithm is performed for comparing the results of RIMARC. The primary endpoint of the ANTIPAF-AFNET 2 trial was the percentage of days with documented episodes of paroxysmal AF or with suspected persistent AF.

Results
By means of the RIMARC analysis algorithm, baseline SF-12 mental component score ($P_w = 0.3597$), age ($P_w = 0.2865$), blood urea nitrogen (BUN) ($P_w = 0.2719$), systolic blood pressure ($P_w = 0.2240$), and creatinine level ($P_w = 0.1570$) of the patients were found to be predictors of AF burden. Atrial fibrillation burden increases as baseline SF-12 mental component score gets lower; systolic blood pressure, BUN and creatinine levels become higher; and the patient gets older. The AF burden increased significantly at age >76.

Conclusions
With the ANTIPAF-AFNET 2 dataset, the present data-mining analyses suggest that a baseline SF-12 mental component score, age, systolic blood pressure, BUN, and creatinine level of the patients are predictors of AF burden. Additional studies are necessary to understand the distinct kidney-specific pathophysiological pathways that contribute to AF burden.

Keywords
Atrial fibrillation • Blood urea nitrogen • Creatinine • Data mining • Machine learning • RIMARC • SF-12

Introduction
Atrial fibrillation (AF) is the most common sustained arrhythmia. It is associated with relevant excess morbidity and mortality.1,2 So far, we are unable to prevent many of the severe complications associated with AF, despite antithrombotic therapy and management of concomitant heart disease.3–5 Specifically, the perceived benefit of rhythm control therapy by antiarrhythmic drugs appears to be offset by proarrhythmic side effects. Recently, Angiotensin II-Antagonist in Paroxysmal Atrial Fibrillation (ANTIPAF-AFNET 2) trial examined the hypothesis that blocking the angiotensin II type 1 receptor with olmesartan medoxomil reduces the incidence of episodes of AF in patients with paroxysmal AF during 12 months by 25% compared with standard medication without angiotensin receptor blocker (ARB) therapy in a prospective, randomized, placebo-controlled, double-blind trial.6 This trial revealed that 1 year of ARB therapy did not reduce the number of AF episodes in patients with documented paroxysmal AF without structural heart disease.

Data mining is the computational process that takes much of its inspiration and methods from the intersection of artificial intelligence and pattern recognition. It is a technique for discovering useful information and knowledge from large datasets. The goal of data mining is to extract patterns and relationships from the data, which can then be used to make predictions or decisions. In the context of the ANTIPAF-AFNET 2 trial, data mining was used to identify predictors of AF burden, with the aim of understanding the factors that contribute to AF and potentially informing future intervention strategies.
What’s new?

- Data-mining analyses of Angiotensin II-Antagonist in Paroxysmal Atrial Fibrillation (ANTIPAF-AFNET 2) trial dataset with Ranking Instances by Maximizing the Area under a Receiver Operating Characteristics Curve and chi-square automatic interaction detector algorithm suggest that:
  - AF burden increases as
    - § Baseline SF-12 mental component score gets lower
    - § Systolic blood pressure, BUN and creatinine levels become higher and the patient gets older
  - The AF burden increased significantly at age >76.

Data-mining experiments

To attain our aims on this dataset and extract patterns and relationships within, we pursued a data-mining approach with two different machine learning algorithms. First one is the RIMARC (Ranking Instances by Maximizing the Area under a Receiver Operating Characteristics (ROC) Curve) classification algorithm that was used to assign ‘predictive weights’ (having values between [0, 1]) to the baseline clinical parameters in determining the class label, i.e. AF burden. To calculate these predictive weights, RIMARC basically learns a ranking function over the instances by maximizing the area under the ROC curve, as this is a commonly accepted metric for assessing the accuracy of the results produced by a classifier. It comprises a method, MAD2C, that applies a discretization to the continuous (real-valued) parameters in the dataset and transforms them into categorical parameters with value ranges generating a maximal AUC. Thus, RIMARC algorithm starts by discretizing all the continuous (real-valued) parameters until the whole dataset is made up of categorical typed parameters. The emphasis laid on the robustness of RIMARC towards the missing values in a dataset is also attributed to the MAD2C method for discretizing the continuous (real-valued) parameters. As the result of a RIMARC execution, predictive weight for each parameter (now discretized) is calculated and respective value ranges are provided for an optimal AUC.

In this study, the class variable is AF burden and baseline variables are all other baseline clinical parameters that affect AF burden. The primary endpoint of the study was the percentage of days with documented episodes of paroxysmal AF or with suspected persistent or permanent AF. The AF burden was calculated as the number of days with paroxysmal AF or with preceding documentation of suspected persistent AF (up to a maximum of 365 days) divided by the number of measurement days, that is, days in follow-up with at least one readable tele-ECG recording (up to a maximum 365 days). Regarding these, AF burden is a valid choice for the class variable to be used in our experiments. Apart from AF burden, the ANTIPAF-AFNET 2 dataset contains 23 baseline clinical parameters for a total of 425 patients. The clinical parameters are shown in Table 1. To build a classifier model, a categorical class variable is needed indicating a discriminative condition over the instances; therefore, we applied a thresholding that assigns the two categories of ‘Normal’ (N) and ‘Patient’ (P) for each sample based on their corresponding AF burden values. The AF burden score <0.10 is set as N and >0.10 is set as P. Following this class label discretization, RIMARC algorithm is applied to assign predictive weights to each clinical parameter for determining the AF burden of a patient.

In this dataset, clinical parameters have an overall missing value rate of ~23%. To compare RIMARC results with the widely used decision tree classification method, we must choose a technique that is also robust to
missing values like RIMARC. In the CHAID (Chi-Square Automatic Interaction Detector) decision tree classification algorithm within which a chi-square test is used to build the tree, missing values are treated as a set of separate predictor category. Unlike many other decision tree classification approaches generating binary node splits, CHAID generates multi-node split decision nodes with categorization of continuous (real-valued) parameters. Similar to the way RIMARC acts, the algorithm first generates the ‘best’ set of parameter categories performing chi-square tests using all non-missing values from the dataset. Next, not to disregard missing valued instances, it identifies the category that is most similar to the ‘missing’ category in hand. Finally, it decides whether to merge the missing category with its most similar category or to keep the missing category as a separate category. While building its decision tree with multiple node splits, CHAID executes a pre-pruning approach that ensures the elimination of any redundant nodes. A node is made to split further down only when a significance criterion is fulfilled and thus the incident of overfitting is prevented from happening right from the start. The output of a CHAID decision tree can also be interpreted as a rule base effectively leading an instance towards a prediction through the divided categories for each parameter defining the dataset.

Table 1  Baseline clinical parameters in the analysis

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>Ischemic heart disease (Y/N)</td>
</tr>
<tr>
<td>Gender (F/M)</td>
<td>Diabetes mellitus (Y/N)</td>
</tr>
<tr>
<td>SF-12 physical component score</td>
<td>Aspirin (Y/N)</td>
</tr>
<tr>
<td>SF-12 mental component score</td>
<td>Verapamil (Y/N)</td>
</tr>
<tr>
<td>Systolic blood pressure (mmHg)</td>
<td>Diltiazem (Y/N)</td>
</tr>
<tr>
<td>Diastolic blood pressure (mmHg)</td>
<td>Statin (Y/N)</td>
</tr>
<tr>
<td>Left ventricular ejection fraction (%)</td>
<td>Diuretic (Y/N)</td>
</tr>
<tr>
<td>Blood urea nitrogen (mg/dL)</td>
<td>Tri-tetracyclic antidepressant (Y/N)</td>
</tr>
<tr>
<td>Creatinine (mg/dL)</td>
<td>Oral anticoagulants (Y/N)</td>
</tr>
<tr>
<td>Glomerular filtration rate</td>
<td>Dihydropyridin (Y/N)</td>
</tr>
<tr>
<td>Hypertension (Y/N)</td>
<td>Nitrates (Y/N)</td>
</tr>
<tr>
<td>NYHA Class IV (Y/N)</td>
<td></td>
</tr>
</tbody>
</table>

Table 2  RIMARC based predictive weights ($P_w$) of the parameters on atrial fibrillation burden

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$P_w$</th>
<th>Parameter</th>
<th>$P_w$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline SF-12 mental component score</td>
<td>0.3597</td>
<td>Aspirin</td>
<td>0.0418</td>
</tr>
<tr>
<td>Age</td>
<td>0.2865</td>
<td>Diuretic</td>
<td>0.0367</td>
</tr>
<tr>
<td>Blood urea nitrogen (mg/dL)</td>
<td>0.2719</td>
<td>Ischaemic heart disease</td>
<td>0.0358</td>
</tr>
<tr>
<td>Systolic blood pressure (mmHg)</td>
<td>0.2240</td>
<td>Nitrates</td>
<td>0.0306</td>
</tr>
<tr>
<td>Creatinine (mg/dL)</td>
<td>0.1570</td>
<td>Sex</td>
<td>0.0301</td>
</tr>
<tr>
<td>Left ventricular ejection fraction (%)</td>
<td>0.1453</td>
<td>NYHA class IV</td>
<td>0.0216</td>
</tr>
<tr>
<td>SF-12 physical component score</td>
<td>0.1379</td>
<td>Dihydropyridin</td>
<td>0.0200</td>
</tr>
<tr>
<td>Diastolic blood pressure (mmHg)</td>
<td>0.1244</td>
<td>Verapamil</td>
<td>0.0137</td>
</tr>
<tr>
<td>Oral anticoagulants</td>
<td>0.0882</td>
<td>Diltiazem</td>
<td>0.0079</td>
</tr>
<tr>
<td>Hypertension</td>
<td>0.0596</td>
<td>Tri-tetracyclic antidepressant</td>
<td>0.0079</td>
</tr>
<tr>
<td>Statin</td>
<td>0.0564</td>
<td>Glomerular filtration rate</td>
<td>0.0066</td>
</tr>
</tbody>
</table>

Results

The results of the application of the RIMARC algorithm on the ANTIPAF-AFNET 2 trial dataset are presented in Table 2, which tabulates the clinical parameters with their respective predictive weights. To assess the significance of the RIMARC’s model, a 10-fold cross-validation is performed. For each patient instance in the dataset, the predictive probabilities regarding the class parameter AF burden is calculated. To measure the accuracy characterized by the sensitivity and specificity for this predictive model, an ROC curve is generated with the respective c-statistics as the AUC value (Figure 1). The AUC of the ROC curve with the value of 0.815 (standard deviation = 0.046, 95% CI, P = 0.001) can be interpreted as a decent result. This can be attributed to the robustness of the RIMARC algorithm towards the missing values in the datasets.

According to the CHAID decision tree classifier, the root parameter, which is the most discriminative among the other parameters, is found to be the SF-12 mental component score of the patients ($P_w = 0.3597$) (Figure 2). With this CHAID tree classifier built, a 10 fold cross-validation is performed and the prediction accuracy of the model is assessed by the AUC value of ROC curve generated. The AUC value is found as 0.614 (standard deviation = 0.060, 95% CI, P = 0.001).

Baseline SF-12 mental component score, age, BUN, systolic blood pressure, and creatinine level of the patients were found to be predictive of AF burden by the RIMARC algorithm. The CHAID decision tree technique also confirms the effect of baseline SF-12 mental component score on indicating AF burden as a single predictive parameter among all others.

As BUN ($P_w = 0.2719$), systolic blood pressure ($P_w = 0.2240$), and creatinine ($P_w = 0.1570$) levels of the patient increases, the AF burden also increases (Figure 3). Furthermore, the risk of AF burden increases as the patient gets older ($P_w = 0.2865$). The risk increases significantly at a higher rate after age of 76.

Discussion

Using a combination of explorative data-mining analyses, we identified that SF-12 mental component score, age, BUN, systolic blood
pressure, and creatinine level of the patients are predictive of AF burden. On the basis of these findings, some additional insight into the AF burden and AF treatment is obtained.

Major finding of this analysis is the predictive power of baseline SF-12 mental component score on AF burden. The Short-Form 12 Health Survey is a generic health-related quality-of-life (QOL)
The items of the SF-12 assess physical component and mental component. Patients with AF have significantly poorer QOL compared with healthy controls, the general population, and other patients with coronary heart disease. Studies examining rate or rhythm-control strategies alone demonstrate improved QOL after intervention. The cornerstone of treatment in patients with AF is to reduce symptoms and improve the QOL. Three of the four large randomized control trials (STAF, PIAF, RACE) comparing rate vs. rhythm control demonstrated a greater improvement in QOL in patients receiving rate control. However, the AF-FIRM trial revealed a similar improvement in QOL for both rate and rhythm-control groups. In recent analysis of two large clinical trials, reported by von Eisenhart Rothe et al., AF patients prone to experiencing depressed mood, particularly in persistent ones. In accordance with our data-mining analysis, von Eisenhart Rothe et al. reported association of depressed mood with AF symptom burden over 6 months after adjustment for perceived frequency and duration of AF episodes, pulmonary diseases, and gender. In current analysis, we obtained SF-12 mental component score as a predictor of AF burden by the RIMARC algorithm. Furthermore, baseline SF-12 mental component score was the only single predictor of AF burden among all others by CHAID decision tree technique. This finding denotes that a lower QOL at baseline is the predictor of high AF burden.

The second important finding of this analysis is related to the intersection of renal function and AF burden. By means of explorative analyses, BUN and serum creatinine level of the patients were found to be predictors of AF burden. Several possible mechanisms may explain the high rate of identified AF in patients with chronic kidney disease (CKD), including older age and a high burden of risk factors such as hypertension and cardiovascular disease, excessive inflammation which has been linked to both CKD and AF, larger left atrial and left ventricular sizes among CKD patients and activation of the renin–angiotensin–aldosterone system. Other plausible pathways linking kidney disease and AF include abnormalities in mineral metabolism. It is possible that alterations in these pathways may also contribute to the risk of AF in patients with renal dysfunction through effects on cardiac structure, endothelial function, and vascular calcification. The burden of AF is even greater in patients with concomitant kidney disease. Recently published studies have highlighted the often under recognized, yet highly prevalent relation between kidney disease and AF. Furthermore, evidence has suggested that the burden of AF will likely rise in this high-risk population, making the intersection of kidney disease and AF a highly relevant clinical problem. Further investigations are needed to explore unique kidney-specific biological pathways linking AF and kidney disease, given the disproportionately high burden of disease in this population.

The prevalence of AF is related to age. The prevalence of AF is 2.5% in people older than 40 years and 6% in those older than 65 years. Approximately 70% of individuals with AF are between 65 and 85 years of age. The relationship between AF burden and age was remarkable in our analysis. The risk of AF burden increases as patient gets older, and AF burden risk increases significantly at a higher rate after the age of 76.

Atrial fibrillation and hypertension are two prevalent, and often coexistent, conditions in the general population. Both these conditions frequently coexist and their prevalence increases rapidly.
with ageing. Hypertension is still the main risk factor for the development of AF. Hypertension is associated with left ventricular hypertrophy, impaired ventricular filling, left atrial enlargement, and slowing of atrial conduction velocity. In our analysis, we observed that systolic blood pressure levels of patients predict AF burden.

Conclusions

In conclusion, on the ANTIPAF-AFNET 2 dataset, the RIMARC algorithm helped reveal the predictive power of various parameters on AF, along with the risk scores of categorical values and risk ranges for numerical parameters. Based on the highest weighted parameters found by RIMARC, some additional insight into the AF burden and AF treatment is obtained. QOL is of central importance in AF as both a treatment goal and an endpoint in the evaluation of therapies. A number of interventions for AF have been shown to improve QOL, including pharmacological and non-pharmacological rate control, antiarrhythmic drugs, and non-pharmacological rhythm control strategies. Collection of further data is needed to establish the role of QOL on the course of AF. Additional studies are necessary to understand the distinct kidney-specific pathophysiological pathways that contribute to the development of AF as well as the unique considerations in preventing and treating AF specific to patients with a broad range of renal dysfunction.

Funding

Angiotensin II-Antagonist in Paroxysmal Atrial Fibrillation (ANTIPAF-AFNET 2) trial was supported by German Ministry of Research and Education (BMBF) through the German Network of Competence in Atrial Fibrillation (AFNET; grant 01GI0204; NCT00098137).

Conflict of interest: none declared.

References