

LPAD-based fall risk assessment

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Abstract. About 30% of persons over 65 are subject to at least one fall during a year. A number of published studies identify statistical relations between risk factors and the probability of fall in terms of *odds ratios*. In this paper we present a tool based on the representation of risk factors as odds ratios. Such representation is exploited to automatically build a computational logic probabilistic program, that in turn computes the fall risk of the subject given the presence/absence of risk factors in his/her status.

Keywords: Odds Ratio, Logic Programming with Annotated Disjunctions (LPAD), Fall Risk Factor, Risk Assessment

1 Introduction

Epidemiological studies have shown in the past that almost 30% of people aged 65 or more are subject to an unintentional fall each year [12]. Falls consequences range from health- and psychological-related aspects (such as hip fracture and loss of self-confidence or personal autonomy), to financial burdens supported by the relatives as well as by the social health and welfare systems. A number of publicly- and privately-financed initiatives and projects are dealing with the many aspects related to the falls, such as fall risk assessment, fall risk prevention, falls detection, fall treatment etc. In particular, fall risk assessment/evaluation consists in determining the probability of a subject to experience a fall within a certain time window. Several risk assessment tools exist (e.g., see [9,7,8,5], or the review in [4]), each tool based on a different approach and/or different assumptions. However, as discussed in [11], only few tools have been tested and applied in different settings (e.g., community, home-support, acute-care settings), while the majority of them has been “tuned” for specific settings or for specific population sub-groups.

Usually, fall risk assessment tools focus on the presence or absence of *fall risk factors* in the subject under evaluation. A huge literature is available on risk factors, defined as “aspects of personal behaviour or lifestyle, environmental exposure, or inborn or inherited characteristic, which, on the basis of epidemiological evidence, are known to be associated with falls”. For an example of a

systematic review, see [6]. The majority of these contributions follow a classic epidemiological approach, and compute as results the odds ratio, w.r.t. the fall event, of the two cohorts experiencing (and not, respectively) the risk factor. The odds ratio is a measure of effect size, describing the strength of association between two values. It can be defined in terms of group-wise odds: the odds ratio is the ratio of the odds of an event occurring in one group to the odds of it occurring in another group.

Within the European project Farseeing³ we are investigating new models for assessing the fall risk of a subject. The approach we introduce in this work aims to exploit the existing literature, and in particular the statistical results, to directly compute the probability of a fall within a year as a consequence of a patient exhibiting one or more risk factors. To this end, we introduced a light classification of risk factors (a minimal ontology), and for each factor we take into consideration the Odds Ratios (OR) published in the literature. Starting from the ORs, we generate a Logic Program with Annotated Disjunction (LPAD, [13]). The program receives as input the characteristics of a subject, in terms of the list of known risk factors affecting her/him, and computes the overall fall probability by combining each contribution following the *Distribution Semantics* [10].

2 Architecture

The overall architecture of our tool is shown in Figure 1. The information about the risk factors is stored as an ontology expressed in the OWL language: from such knowledge base, a first component computes probabilities (from odds ratios) and generates three LPAD rule sets containing higher and lower bounds (from the confidence intervals) and average odds ratios. Then, these LPADs and a subject profile are fed to a Prolog engine extended to support also LPAD clauses: the subject profile specifies which are the risk factors the subject is exposed to. The Prolog engine computes the higher, lower and average estimates of risk probability, that are returned to the user.

The Ontology. Risk factors are represented through a simple ontology, containing a list of all relevant risk factors and an odds ratio for each of them. The majority of risk factors cited in the scientific literature can be classified into three different *types*, depending on how they contribute to the fall risk:

- a *Dichotomic risk factors* are the most common: either the risk factor is present or not; its contribution to the fall risk is fixed, and depends only on the presence/absence of the risk factor. Typical examples of dichotomic risk factors are Parkinson or diabetes.
- b *Scalar risk factors* too are either present or not in the subject's profile. However, these risk factors are observed with a certain degree: usually with more than two possible "levels", starting from zero (absence of the factor) to

³ <http://farseeingresearch.eu/>

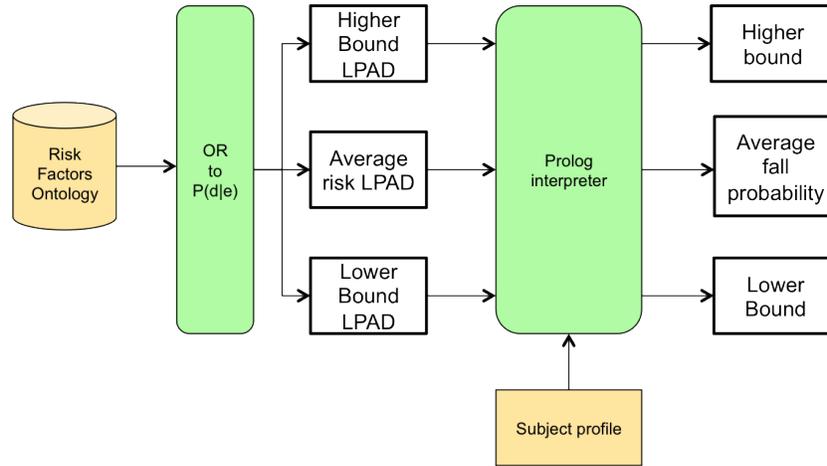


Fig. 1. Architectural overview

n (maximum magnitude of the risk factor). These risk factors contribute to the fall risk depending on their “level”: a typical case is a linear contribution based on such level. Examples of this kind of factor are the age of the subject or the number of medications.

- c *Synergy risk factors* exist when more than one of risk factor of other type are present contemporaneously. Synergy risk factors capture the well known nature of sets of risk factors to be synergistic and produce an increment to the risk that is bigger than the one produced by the factors when considered independently.

The ontology stores also data about the confidence intervals of the odds ratio (typically at 95%). Having confidence intervals data permits to run three risk assessing algorithms: one using the lower extremes, one using the upper extremes and another with the average values; this may give the user a feeling of the uncertainty in quantitative knowledge about risk factors.

Moreover, the ontology contains also the *estimators*, i.e. the concepts that provide indication of a subject being exposed to a risk factor. Indeed, certain risk factors can be directly characterised: e.g., either a subject suffers the Parkinson disease or not, depending on a medical diagnosis. However, there is a number of risk factors that are determined on the basis of many different assessments and criteria: e.g. , the visual impairment is a known risk factor, whose presence in a subject is determined on different medical exams (often alternative exams), such as the visual acuity on a three meter distance, the visual stereognosis, or the contrast sensitivity of the subject.

Generated LPAD The generated LPADs are sets of rules that, depending on the risk factor type, are differently defined. Given the list of estimators L for a specific subject, the rules are Prolog clauses of the form:

```
fall(L) : Pi :- member(Ri, L).
```

where P_i is the probability associated to risk factor R_i . Estimators can be easily taken into account by introducing further conditions in the bodies of the rules. For example, in the case of the visual impairment, we model the different estimators with the following rule:

```
fall(L) : 0.06 :- visionImpairment(L).
visionImpairment(L) :- member(visualAcuity3M(X),L), X =< 5.
visionImpairment(L) :- member(visualStereognosis(X),L), X =< 3.
visionImpairment(L) :- member(contrastSensitivity(X),L), X =< 16.
```

Subject profile The subject profile is a simple Prolog list of the estimators that characterise the subject. It has the form: [age(71), 'Parkinson', 'diabetes'], indicating that for example the subject has an age of 71, and she/he suffers diabetes and Parkinson diseases.

Moreover, the current version of our tool supports three different alternatives:

- if the subject suffers a risk factor, such risk factor is listed in the profile and it is labelled with a term `true`, and the risk probability associated to the factor directly contributes to the overall fall risk;
- if the subject does not suffer the risk factor, then the factor is not present in the list
- if the subject is unsure about suffering a risk factor, then the factor is present in the list with a label “unknown”: in that case specific LPAD rules are used, and the distribution probability of the specific risk factor over the population is used to compute the overall fall risk.

3 Conclusions

In this paper we have introduced a tool for assessing the fall risk depending on a specific subject profile. Our architecture is still in a prototypical stage, and many aspects still need to be researched and developed. At the moment of writing, we are evaluating the quality of our tool by using a prototype based on the statistical findings in [6], and the InChianti data set available within the Farseeing Project. Although first results show that our approach performs similarly to other existing approaches, the validation is far to be completed, and definitely more investigation is required.

The current implementation is based on the findings in the scientific literature. We plan as future work to apply learning algorithms, like Expectation-Maximization, for parameters and structures of LPADs [3,2,1], in particular on the datasets available within the Farseeing Project: for example, the possibility of using the same LPAD structure but with parameters learned on specific situations is a promising way to customize the tool and gain better results for specific cases.

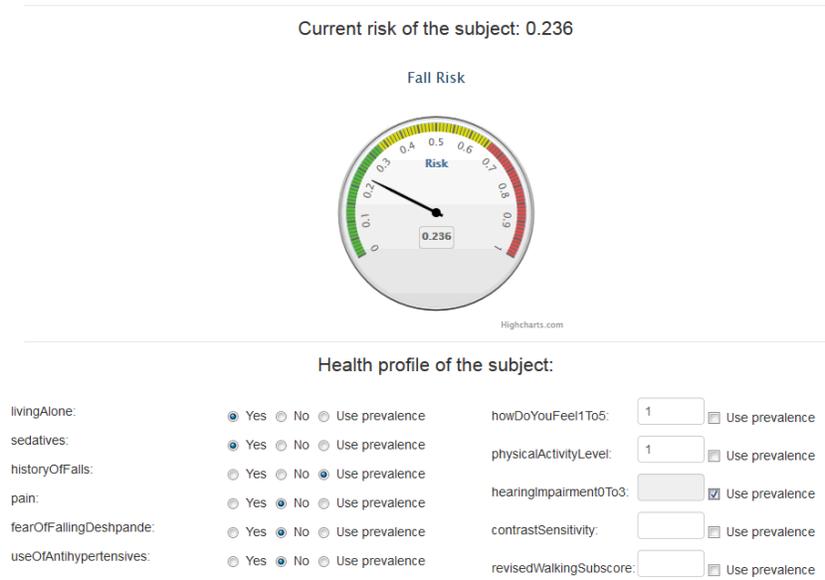


Fig. 2. Web-based interface to the Fall Risk Assessment Tool - FRAT

Finally, we are implementing a web-based application (see Figure 2), that allows the users to define the subject profile by means of a sort of questionnaire, and directly computes the fall risk.

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