ABOUT PROBABILISTIC GRAPHICAL MODELS IN PROBABILISTIC AVALANCHE SCIENCE: THE CASE OF STOP OR GO

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ABSTRACT: In order to provide practically applicable tools for winter mountaineers to manage uncertainties and to reduce associated risks underneath an acceptable residual risk level, several risk strategies and decision frameworks have been developed. While all of these frameworks are comprehensively described in books, booklets and small paper cards, no formal representations of this expert knowledge are available for the broad public to be exploited for a) the development of novel (interactive) training material, and b) to exemplify and allow analysis of causal relationships of decision-relevant influence factors. The current avalanche science paradigm, initiated with the Reduction Method and pursued by others (e.g. Stop or Go, SnowCard), clearly propagates a probabilistic risk management approach, however, no approaches are available that try to formally capture this expert knowledge by means of – potentially promising – probabilistic graphical models. This paper introduces a formal, computer-based representation of the "Stop or Go" avalanche risk management strategy that allows for interactive experimentation to gain a deeper understanding about mutual influences of different factors in avalanche decision making. We describe the development and experiments with a Bayesian network representation of "Stop or Go". The case of "Stop or Go" represents a first step approaching a broader formalization of avalanche expert knowledge by means of probabilistic graphical models. Such formal representations facilitate the development of interactive training material – e.g., mobile decision support apps, as done in this work – for raising the level of knowledge concerning dealing with probabilities during winter mountaineering, and allow for computer-based reasoning support.

KEYWORDS: Avalanche, risk management, decision frameworks, Bayesian networks, mobile decision support app.

1. INTRODUCTION

Winter recreationists are able to access a wealth of avalanche expert knowledge that is captured in books and booklets (Munter (1997), Larcher (1999), Engler and Mersch (2001), Mair and Nairz (2010), Harvey et al. (2012), Mössmer et al. (2013), etc.). In many cases, simplified versions of this knowledge are also provided by means of small paper cards that allow for practical applicability in the outdoor terrain, e.g., Stop or Go card (cf. Fig. 1) or SnowCard (Engler and Mersch, 2001). In order to make non-experts practically familiar with state-of-the-art avalanche knowledge and decision frameworks, alpine associations and others are offering training courses on different levels of difficulty, ranging from introductory courses over a weekend towards longer-term education spanning, e.g., a whole (winter) season or more. During such courses, avalanche experts, e.g., mountain guides or avalanche experts of alpine associations, are supporting apprentices with their reasoning and decision making challenges. For novices, however, it would be useful to have such an aid or guidance (in addition to the paper cards) available also after passing an avalanche training course. This is, when they are trying to deepen their understanding through own learning sessions by experimenting with different settings of factors that are increasing or decreasing avalanche risk. Therefore, some form of formal (computer-understandable) representation of expert knowledge that facilitates the development of interactive training material would be required.

Following the classical and the analytical approaches of avalanche science, Munter (1997) initiated the current probabilistic paradigm of avalanche science with the introduction of the Reduction Method. This probabilistic paradigm propagates a risk management approach that explicitly considers the uncertainties winter mountaineers are confronted with. It also brings to the fore-

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ground that we mostly cannot answer an avalanche risk question strictly with yes or no or stop or go, but rather have to handle different levels of uncertainty captured as risk probabilities.

In addition to these uncertainties, the probabilistic avalanche paradigm addresses another major aspect winter mountaineers are confronted with – incompleteness of available information and data. In this regard, the prevailing Big Data era provides an ever increasing amount of heterogeneous information (sources) that could be exploited to extend humans' sensory abilities by integrating automatically captured information into real-time reasoning processes.

Coping with this current state and the mentioned recent developments requires a formal knowledge representation approach that is able to integrate a) existing (empirical) expert knowledge as well as b) knowledge that is extracted from data sources and data bases (historical-, statistical-, real-time data).

Addressing aforementioned issues, we suggest formally representing avalanche knowledge stemming from heterogeneous sources by means of Probabilistic Graphical Models (PGM) (Koller and Friedman, 2009). This kind of models supports modeling of uncertainties as well as different forms of knowledge, e.g., informal expert knowledge coupled with statistical data, in a single consistent model. Based on such formal representations that are allowing for computer-based reasoning, we are aiming at the development of interactive training material for raising the level of knowledge concerning dealing with probabilities during winter mountaineering.

The paper is structured as follows: Sec. 2 presents the work's focus. Sec. 3 reviews related work. Sec. 4 briefly introduces probabilistic graphical models, which are depicted in more detail by a Bayesian network model of the Stop or Go decision strategy in Sec. 5. Sec. 6 presents an application of this formal model: the Stop or Go Android App. Sec. 7 discusses practical aspects of formal representations of avalanche know-how and the introduced App. Sec. 8 concludes the work.

2. PROBLEM DESCRIPTION

As already mentioned in the introduction, wealth of avalanche expert knowledge is published in textual form (books, booklets, paper cards etc.). The focus of this paper is to investigate formal representations of this knowledge that explicitly fit the current probabilistic avalanche science paradigm. As specific use case, we are focusing on the development of a suitable formal representation of the Stop or Go risk management framework (Larcher, 1999; Mössmer et al., 2013). Especially, we are addressing the decision strategy part of the accompanying Stop or Go paper card (cf. Fig. 1).

Fig. 1: Part of the Stop or Go paper card (decision strategy) that is considered in this work, source: Mössmer et al. (2013), modified.

3. RELATED WORK

Very briefly, we point to related work, as to the best of our knowledge no work explicitly applying probabilistic graphical models for formalizing avalanche decision frameworks for winter mountaineers could have been identified.

On a more general scale, research has been performed on expert systems for avalanche risk assessment and forecasting. McClung (1994) exploited a probabilistic reasoning (Pearl, 1988) approach for the integration of expert knowledge. However, this non-numerical model part was explicitly separated from a numerical part that analyzed a historical database of weather, snow and avalanche occurrence information. Schweizer and Föhn (1994) reported on a system development effort aiming at modeling the decision making process of expert avalanche forecasters. While the system was not explicitly targeted towards use by recreationists, the authors emphasized the instructive nature of interactive model usage by junior forecasters.

More recently, Grêt-Regamey and Straub (2006) applied Bayesian networks, but also their work is not specifically targeted towards support for winter mountaineers. In line with the work at hand and also addressing avalanche education, DiGiacomo (2006) proposed an approach to avalanche decision-making based on Bayesian (personal avalanche danger level) belief updating upon appearance of new evidences (of influence factors).

4. PROBABILISTIC GRAPHICAL MODELS

Estimation of avalanche danger levels and impacts of factors for risk reduction are continuously accompanied by uncertainties. This is what the probabilistic avalanche science paradigm is about.

According to Koller and Friedman (2009), PGMs offer a framework to graphically represent uncertainties between multiple interrelated aspects, e.g., factors influencing avalanche danger levels. They use a graph-based representation, where nodes represent variables of a problem domain, e.g., danger level or critical new snow depth, and the edges are indicating direct probabilistic interactions between them.

There exist several representation forms of PGMs. In this paper, we are focusing on Bayesian network (BN) representations (Pearl, 1985). BNs are directed acyclic graphs (DAG) that allow for the modeling of direct dependencies, independencies as well as conditional independencies between the model nodes. In contrast to rule-based systems which are asymmetric, BNs allow for multidirectional propagation of (new) evidences and, thereby, updating a priori beliefs of a whole model (network). This is achieved by the fundamental aspect of BNs – Bayes rule, stemming from Reverend Thomas Bayes (1701/02-1761):

$$P(O \mid E=e) = \frac{P(E=e \mid O)\, P(O)}{P(E=e)},$$

where O stands for outcome and E for evidence – following the notions used by DiGiacomo (2006). P(O) is called the prior probability (belief) about O, P(O|E=e) is the posterior belief about O. P(E=e|O) is the likelihood of the evidence E=e given outcome O. Using this rule, a priori probability distributions over the states of single model nodes can be updated based on new evidences of other nodes. While, e.g., one might model a direct impact of a critical new snow depth on avalanche danger level, new evidence on the latter might be used to reason about changes to critical new snow depth.

Further books addressing risk/situation assessment and decision making with BNs have been recently published by Fenton and Neil (2012) and Kjærulff and Madsen (2013).

5. STOP OR GO BAYESIAN NETWORK MODEL

The main goal of the presented work is to develop formal (computer-processible) representations of avalanche know-how that up to now is primarily captured in informal (textual) form. Specifically, as first step, we aimed at the development of a formal representation of the Stop or Go decision strategy and risk management framework. The corresponding approach will be described in the following paragraphs.

The Stop or Go card (cf. Fig. 1) and the accompanying booklet by Mössmer et al. (2013) have been used as guiding sources of knowledge throughout the whole modeling process.

5.1 Check 1 model part

As first step (shown in Fig. 2), the components of Check 1, i.e., avalanche danger level, slope angle, (relevant) area of analysis, and “Check 1” itself have been modeled as chance nodes, including the respective states as given on the card. The arcs between them define direct dependencies. Additionally, a node to process information concerning advantaged aspect(s) as provided by avalanche warning services (AWS) has been added. Remaining in a definitely advantaged aspect (with danger levels two or three) allows analyzing a Stop or Go decision with a danger level reduced by one (Mössmer et al., 2013). Modeling this fact needs a further node “Av. Dang. Level for Analysis”. To complete Check 1, a submodel allows analyzing the impacts of “Go Factors” in the case that Check 1 leads to a Stop decision.

We can now use this model to perform Check 1 by entering evidences on the model nodes. Evidence means that we have clear information about the states of a specific node. For instance, the AWS might define danger level 3 for the region of our trip. While we might use statistical data, e.g., danger level distribution in a specific region, for a priori definition of a node’s states, we might now select danger level 3 with 100% (hard) evidence. We use further information from the AWS to set evidence about remaining in advantaged aspects and also set the relevant slope angle (30-34°) for the current decision situation. Based on the evidences entered for the nodes “Avalanche Danger Level”, “Slope Angle” and “Advantaged Aspect”, the Bayesian inference engine calculates updates for the whole model including the dependent nodes “Av. Dang. Level for Analysis”, “Area of Analysis”, and performs Stop or Go “Check 1” in the corresponding node. These calculations are based on definitions that are done for each state of model nodes by assigning values (expert knowledge or statistical data) to each combination of parent nodes’ states. The bottom part of Fig. 2 partly shows the definitions of nodes “Check 1” and “Av. Dang. Level for Analysis”. In the former case, we see the definition for the currently calcu-

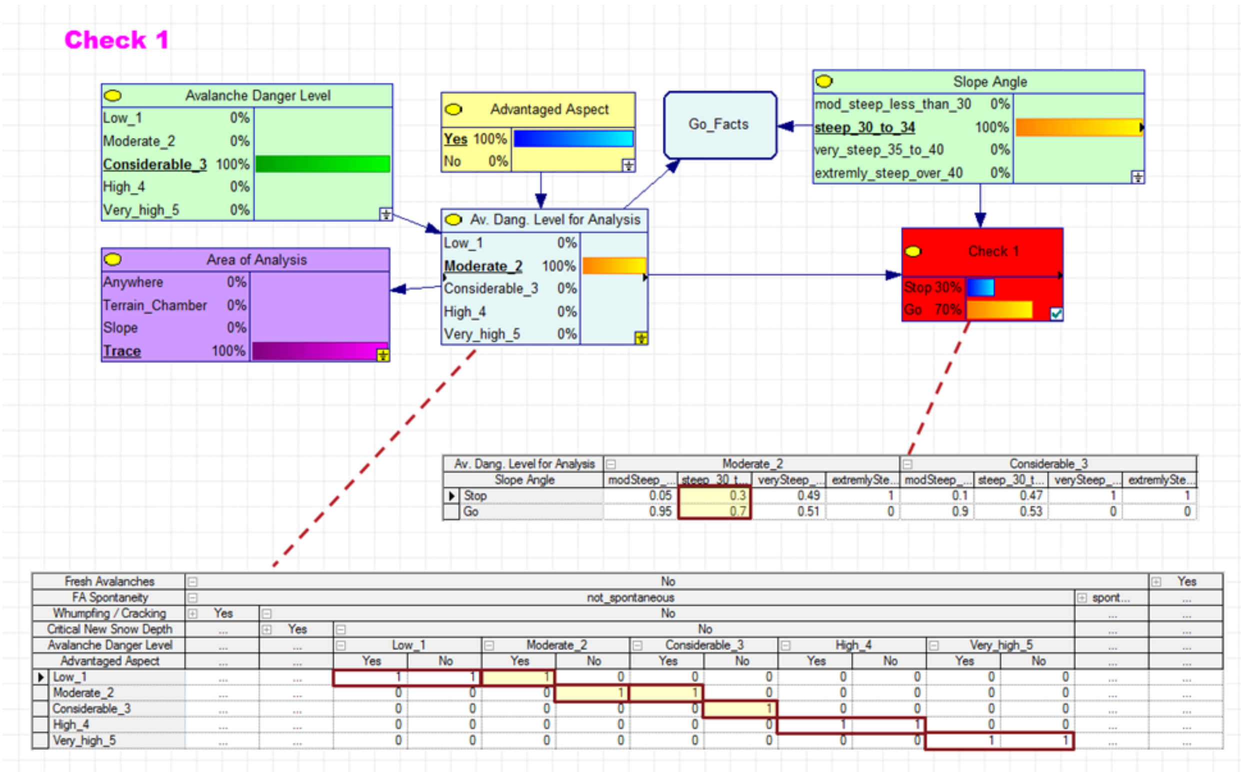

Fig. 2: “Check 1” part of the Stop or Go Bayesian network model including excerpts of the definitions of nodes “Check 1” and “Av. Dang. Level for Analysis”.

lated Check 1 result depending on a moderate danger level (2) and steep terrain (30-34°) – according to our definition it leads to a 70% Go decision. The latter node definition also includes influence factors that are defined in another model part. However, the given excerpt shows the impact of the node “Advantaged Aspect”, as explained above, on the danger level that is used for subsequent analyses (node “Av. Dang. Level for Analysis”). According to the Stop or Go card, a moderate avalanche danger level (2) requires us to keep track on the area around the trace (20m radius), as shown in node “Area of Analysis”.

5.2 Go Factors check and Check 2 model parts

In the same way as explained above, also the influences of Go Factors and Check 2 are modeled. The resulting formal knowledge model of Stop or Go is shown in Fig. 3.

If Check 1 results in a Stop decision, the availability of one or more Go Factors can turn the Check 1 result into a Go decision. As depicted on the card, three Go Factors are considered in the model: skiing frequency, wood, and melt freeze crust or ice. Our model foresees different weights of Go Factors depending on the effective avalanche danger level. Wood represents the most prominent Go Factor and it is valid at any danger level. Its availability results in a strong increase of a Check 1 Go value. Melt freeze crust or ice is very unlikely at danger levels 3 to 5 and, therefore, is weighted higher at danger levels 1 and 2. A high skiing frequency is very unlikely at danger levels 4 and 5. Following, this Go Factor is weighted higher at danger levels 1 to 3. Additionally, Go Factor “frequently skied slopes” is modeled to be valid only in the absence of moist snow conditions, according to the descriptions in the used booklet. This knowledge concerning “Go Factors” is modeled in the definition of the node with the same name.

Check 2 consists of the five danger signs: new snow, fresh snow drift, whumpfing and cracking, fresh avalanches, and moist snow. In our model, the danger sign new snow has been renamed as “Critical New Snow Depth” and extended by its defining factors according to Mössmer et al. (2013) and Munter (1997). Also the most important danger sign of Check 2 – fresh snow drift – has been modeled in detail according to the definition of Mössmer et al. (2013). Criticality of a new snow situation is determined by the new snow depth and the conditions (situation) during the snow fall period and hereafter. The influence factors for “Fresh

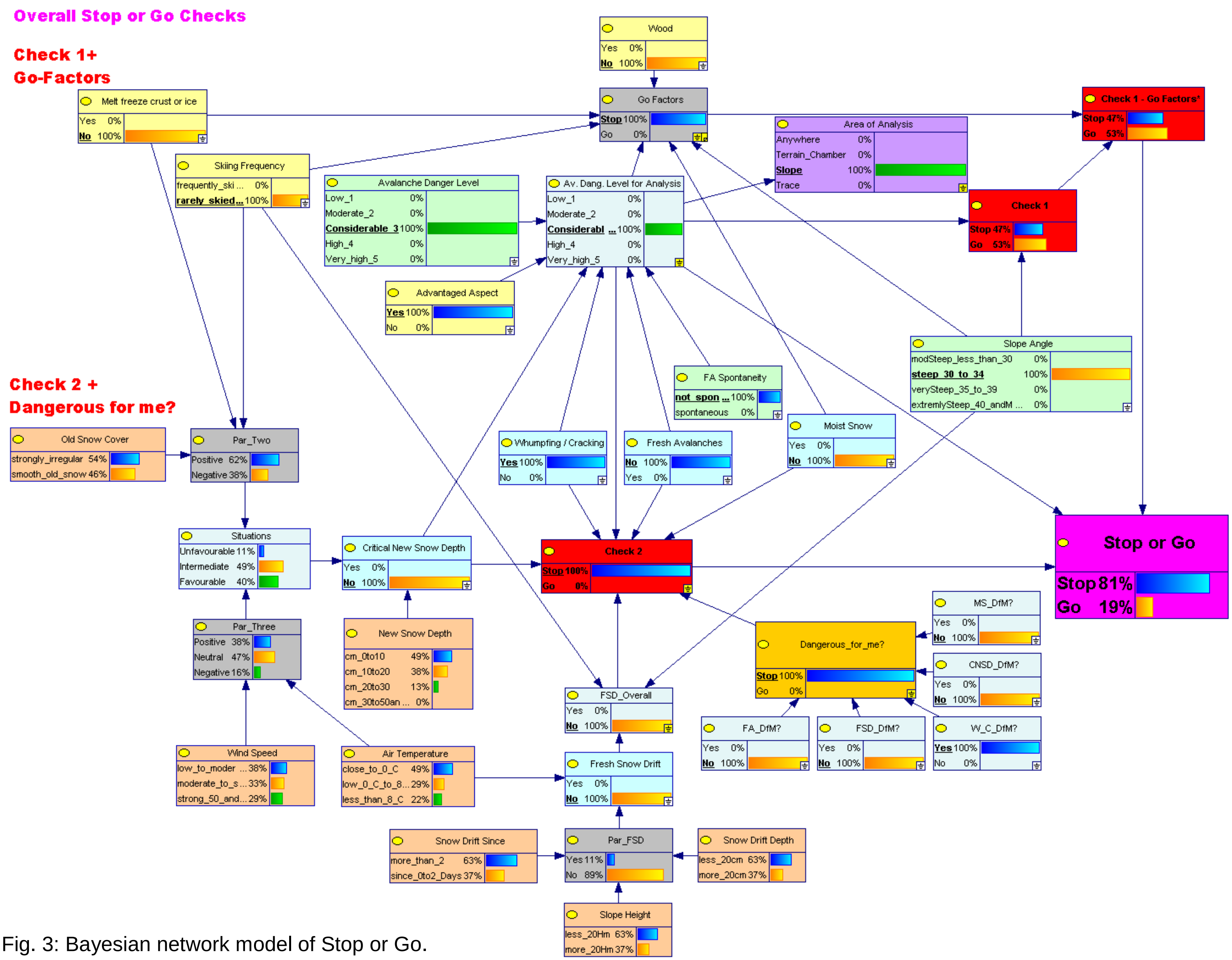

Fig. 3: Bayesian network model of Stop or Go.

Snow Drift" situations may be set on the associated child nodes. Each of the five danger signs is accompanied by a node explicitly asking the question if it is "Dangerous for me?" This modeling decision allows a two-step process: 1) reducing the Go value of Check 1 if one or more of these signs are given, and 2) leading to a definite overall Stop decision if at least one of the "Dangerous for me?" questions will be answered with yes.

5.3 *Cross-links between the different checks*

The original Stop or Go decision strategy foresees a sequential ordering of performing Check 1, potentially followed by a Go Factors check, and then Check 2 to verify a Check 1 Go decision by investigating potential danger signs.

Our knowledge model allows reusing observations (entered evidences) of one check in other checks as well. Evidences of the Go Factors check concerning the availability of "Melt freeze crust or ice" and about the "Skiing Frequency" are handed forward to Check 2 danger sign verification of "Critical New Snow Depth". Information about the skiing frequency is also relevant for rating the danger level of "Fresh Snow Drift". The other way around, the model also allows re-evaluating Check 1 based on evidences entered through Check 2. Besides the slope angle, the avalanche danger level is the major determining factor of Check 1. The model allows using information entered at Check 2 to update the belief about the danger level for the given decision situation. This makes sense as the official danger level information is valid for a huge geographical region while the observations that we enter through Check 2 are related to the local situation. Therefore, the model reuses evidences about "Critical New Snow Depth", "Whumpfing / Cracking", "Fresh Avalanches" and the spontaneity of fresh avalanches (node "FA Spontaneity") for updating the danger level relevant for our local situation. Additionally – as already mentioned – information about Check 2 danger sign "Moist Snow" is also used for evaluating the Go Factor "Skiing Frequency".

Because of these cross-links, the model allows to evaluate the outcomes of different Stop or Go checks in parallel rather than in a predefined sequence. The latter, however, is also possible – for adhering to the Stop or Go decision strategy.

The Bayesian network model of Stop or Go has been developed using the GeNIe 2.0 (Graphical Network Interface) software package[1].

6. THE STOP OR GO APP

The objectives and advantages of formal representations of avalanche expert knowledge are manifold. The Stop or Go model, as described in the previous section, can be used for interactive desktop experimentation with mutual influences of the modeled Stop or Go components.

As smartphones are gaining in importance as part of mountaineers' safety equipment, we have been developing an Android Stop or Go App. A motivation for building such an App is to provide a 'virtual instructor' that can be used by novices – but also by more experienced winter mountaineers – to get expert feedback in Stop or Go decision situations. This kind of feedback extends the possibilities of the Stop or Go paper card and, therefore, is anticipated to represent a beneficial training aid.

To support recognition, the design of the App follows the style of the paper card. Other than the Bayesian network model which does not force an ordering of the different Stop or Go checks, the App principally follows the paper card. Fig. 4 (a) presents the Stop or Go Check start screen awaiting the user to enter the danger level by touching the corresponding bar. The Go and Stop bars at the top show the corresponding overall Stop or Go scores based on the information given. In this initial state, values as predefined in the knowledge model are shown. Fig. 4 (b) depicts the state of Check 1 after entering the danger level (3), the slope angle (30-34°) and evidence about remaining in advantaged aspect. This results in a reduced danger level (2), which is shown in bold letters together with the resulting area of analysis. Having no Go Factor available and entering the observations "Whumpfing / Cracking" along with a "Yes" on the question "Dangerous for me?" on Check 2 results in Fig. 4 (c). The overall Stop or Go value at the top indicates a strong Stop decision. The observation of "Whumpfing / Cracking" is an indicator for a considerable danger level (3), which leads to an updated result of Check 1 (incl. Go Factor check) which is shown at the bottom (53% Go value vs. 70% assuming a moderate (2) danger level). Fig. 4 (d) summarizes the entered information and the results of the particular checks leading to the overall Stop or Go result at the top – Stop decision with 81% significance.

[1] https://dslpitt.org/genie/

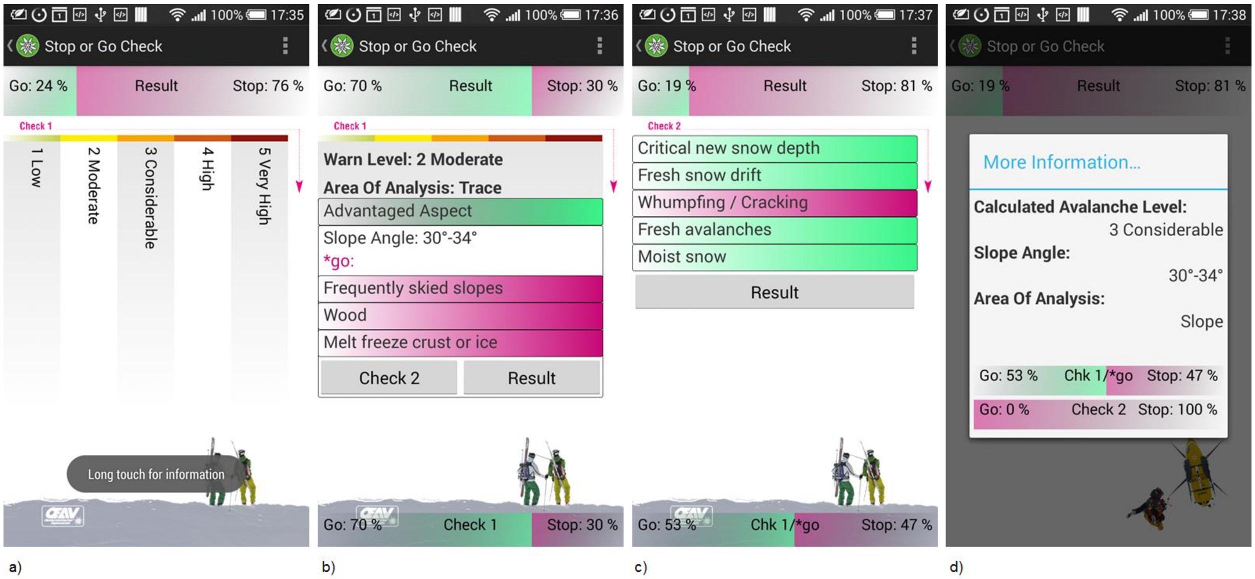

Fig. 4: Screenshots of the Stop or Go App, a) Check 1 initial screen, b) Check 1 awaiting input on Go Factors, c) Check 2 with entered danger sign “Whumpfing / Cracking”, d) results summary.

The Stop or Go App has been developed using the Eclipse Android Developer Tools (Eclipse ADT, 32-bit version)[2] for Windows 7 Professional. Automated reasoning on the developed GeNIe 2.0 Bayesian network model was performed using the jSMILE for Android library of Java classes[3].

7. DISCUSSION: PRACTICAL ISSUES

Two principles guided the main objective of developing a formal representation of existing avalanche know-how with Stop or Go as first case. We were aiming at investigating modeling approaches that are 1) easy to understand and usable by experts of different disciplines, and 2) that are seamlessly supported by computer-based reasoning techniques.

7.1 Advantages of Bayesian network modeling

Bayesian networks turn out to fulfill these requirements. They support an intuitively understandable formal representation of expert knowledge. The graphical nature allows depicting complex interrelationships between factors influencing avalanche danger levels and the components of the Stop or Go decision strategy within a single model. In textbooks, this knowledge is usually spread over a multitude of pages, sometimes making it hard to establish a coherent picture.

The probabilistic approach allows quantifying different levels of (un-)certainty – a fact that is inherent in avalanche decision making. A further advantage of the probabilistic graphical model representation of Stop or Go is that influences of some factors might be weighted differently depending on their combination with other factors. E.g., Go Factors might have different impacts depending on the effective danger level.

In the current first versions, the formal model and the App are seen as research tools allowing us to interactively experiment with and illustrate the possibilities of formal, computer-based avalanche knowledge representations. While the model provides a broad graphical overview of the modeled Stop or Go factors and their relationships, the App narrows the focus of attention towards a particular factor at one point in time. Both, the formal model and the App, can be applied for interactive learning about mutual influences of different factors in avalanche decision making. Additionally, the Stop or Go App can potentially be applied as a ‘virtual instructor’ that provides feedback in decision situations during winter mountaineering – an added value that the paper card cannot deliver.

7.2 Lessons learned

The discussion process for finding adequate formal representations of the Stop or Go descriptions (card, booklet) stimulated intense (re-)considerations of the decision strategy. In this sense, the process of formal modeling can be recognized as

[2] http://developer.android.com/sdk/index.html
[3] https://dslpitt.org/genie/index.php/downloads

a quality assurance technique. It enables formal verifications of existing avalanche expert knowledge, potentially leading to the identification of contradictions or missing links etc.

An interesting, but also demanding aspect was the question about introducing new viewpoints. During model development, we were continuously confronted with the problem of strictly adhering to the given Stop or Go descriptions versus making adaptations that the application of Bayesian networks offered. In some cases – where it obviously added benefit –, we decided to allow slight deviations, e.g., when applying different weights of Go Factors depending on the effective avalanche danger level. Additionally, the BN approach allows us to model feedback paths from Check 2 to Check 1 nodes, e.g., for adapting the avalanche danger level based on local observations.

The model can be modified based upon new or updated avalanche know-how. One could for instance integrate additional signs indicating new snow drift.

8. CONCLUSION & OUTLOOK

Höller (2010) questions the provision of new results in snow and avalanche science brought by the introduction of the strategic decision methods in the 1990s and states further, that the last two decades have brought relatively moderate improvements in snow research in general.

With the introduced approach of formalizing snow and avalanche expert knowledge, we are aiming at further improvements. The case of "Stop or Go" represents a first step approaching a broader formalization of avalanche expert knowledge by means of probabilistic graphical models. Such formal representations facilitate the development of interactive training material for raising the level of knowledge concerning dealing with probabilities during winter mountaineering, and allow for computer-based reasoning support.

Besides the introduced App and its potential use cases, further potential application domains of formalized avalanche expert knowledge allowing for computer-based reasoning support may be envisaged. Especially, the increasing amount of real-time data in the ongoing Big Data era, potentially provided through mobile devices of winter mountaineers, might enable completely new ways of avalanche danger situation assessment and risk management.

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