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Towards Effective Management of Verbal Probability Expressions Using a Co-Learning Approach

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Abstract. Domain experts are one of the most important knowledge sources when building a knowledge base. However, communication about uncertain states and events is prone to misinterpretations and misunderstandings, because people prefer to convey probability estimations by verbal probability expressions (VPEs) which have a high between-subject variability. Additionally, several biases exist when expressing uncertainty verbally. Nevertheless, the application of VPEs might be necessary. Therefore, means must be identified to manage VPEs and to translate them into numeric values appropriately. In this paper, we propose a co-learning approach with example to efficiently and effectively communicate (subjective) probabilities of states and events in teams where human and AI team members are familiarized with the translation between VPEs and numeric values until both parties are capable of using solely numeric values.

Keywords. human-agent collaboration, hybrid intelligence, hybrid team, knowledge acquisition, preference paradox, subjective probability, uncertainty communication

1. Motivation

Domain experts are one of the most important knowledge sources when building a knowledge base (KB). However, knowledge acquisition remains one of the major challenges in many domains (e.g, in the field of knowledge representation and reasoning (KRR) [1]). The quality of elicited expert knowledge is heavily influenced by the means of communication. In reference to the Shannon-Weaver communication model [2], misinterpretations and misunderstandings between sender and receiver can be caused by inefficient encoding and decoding, but also by communication interferences (noise). Knowledge about uncertain states or events is especially challenging to communicate due to ambiguities, approximations that incorporate vagueness, coarseness, or simplifications, and the the fact that estimates of likelihood of states and events depend on the acquired sample and natural randomness [3, Table 1.12]. After all, an expert's shared

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opinion is nothing more than "a subjective assessment, evaluation, impression, or estimation of the quality or quantity of something of interest that seems true, valid, or probable to the expert's own mind" [3, p. 98].

Many experts prefer to use verbal probability expressions (VPEs) to convey estimations of likelihood. The application of VPEs is addressed by cross-disciplinary research in the field of psychology, cognitive science, intelligence analysis, climate analysis, but also industrial engineering. (Non-exhaustive) synonymous terms are verbal probabilities, probabilistic phrases, judgment terms, verbal uncertainty expressions and words of estimative probabilities. We adopt the term verbal probability expression which was used by Beyth-Marom [4] and adopted by Teigen [5]. In this paper, we first review the history of research on VPEs and then apply the learned insights to uncertainty communication in a human-agent team. One widely agreed on hypothesis is the so-called *preference paradox*. The *preference paradox* describes that a sender prefers to use words to communicate uncertainties while a receiver prefers to receive numeric estimations about uncertainties [6,7]. While the *preference paradox* might be cumbersome between human experts, a collaborating human-agent team could naturally react to the preferences as the software agent (or robot) "thinks" numerically and can be enhanced with natural speaking capabilities.

Additionally, the human-agent team cannot only react, but also diminish the *preference paradox* by engaging into co-learning [8,9]. In the co-learning scenario, software agents learn the set of VPEs that individual human team colleagues use and use this information to assign (objective) probability ranges to the expressions. Furthermore, software agents can regularly provide feedback to human team members to improve their understanding of their individual *verbal-to-numeric* probability mapping until all team members feel comfortable using numeric values. In this matter, we make the following three contributions:

- Summarize the main results of research done in the field of VPEs
- Provide an example to show the potential of using VPEs in human-agent teams
- Outline future research directions including two research questions

2. Literature overview

We roughly distinguish research on VPEs in two trend waves. A central element of the second wave (2013 – now) is the empirical research on numerically bounded linguistic probability (NBLP) schemes [10]. As the second wave is still ongoing, an overview of NBLP schemes is provided in this section and relevant insights of the wave are discussed in section 4.

2.1. First Research Wave of VPEs (1967 – 1996)

In the beginning of research on VPEs, several studies (predominantly in the linguistic and medical field) were conducted to infer the numeric interpretation of expressions [4,11,12,13,14,15,16] (non-exhaustive). The set of expressions varies among studies containing single adjectives, adverbs or nouns (e.g., *rare*, *likely*, and *toss-up*). Additionally, word combinations with modifiers (e.g, *very likely*), hedges (e.g., *almost never*),

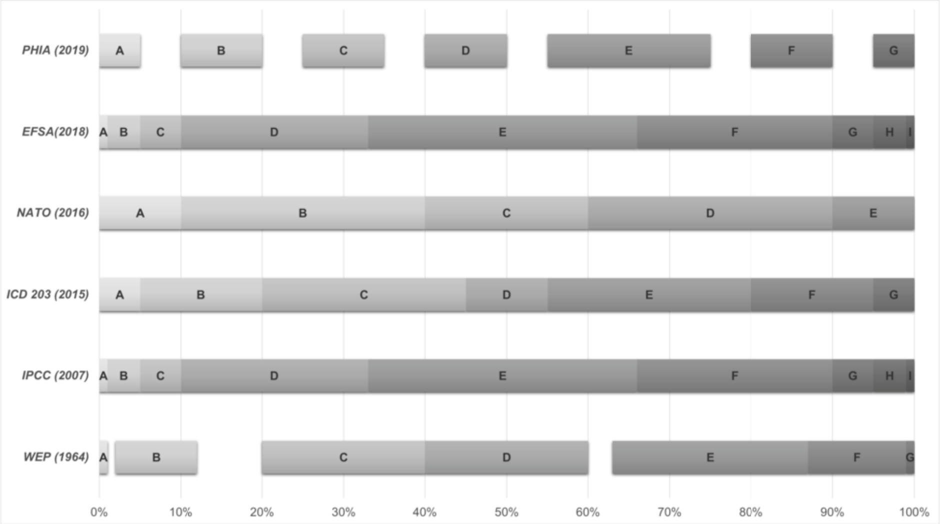


Figure 1. Illustration of the structures of established NBLP schemes. All probability ranges are mapped with their label in Table 1. The ranges were optimized for visibility and should thus not be used as direct reference. For instance, "impossible (A)" of the WEP scheme refers to 0%, but is displayed as the range between 0 – 1%. Also, overlapping ranges like IPCC's and EFSA's "more likely than not" (> 50%) are removed.

Table 1. Overview of verbal probability expressions (VPEs) used by numerically bounded linguistic probability (NBLP) schemes with reference (R) to Figure 1 indicating the probability ranges. The VPEs are ordered by ordinal rank from lowest (A) to highest (I).

R	**WEP (1964)**	**IPCC (2007)**	**ICD 203 (2015) I**	**ICD 203 (2015) II**	**NATO (2016)**	**EFSA (2018)**	**PHIA (2019)**
A	Impossible	Exception-ally unlikely	Almost no chance	Remote	Highly unlikely	Almost impossible	Remote chance
B	Almost certainly not	Extremely unlikely	Very unlikely	Highly improbable	Unlikely	Extremely unlikely	Highly unlikely
C	Probably not	Very unlikely	Unlikely	Improbable (improbably)	Even chance	Very unlikely	Unlikely
D	Chances about even	Unlikely	Roughly even chance	Roughly even odds	Likely	Unlikely	Realistic possibility
E	Probable	About as likely as not	Likely	Probable (probably)	Highly unlikely	About as likely as not	Likely (probable)
F	Almost certain	Likely	Very likely	Highly probable	-	Likely	Highly likely
G	Certain	Very likely	Almost certain(ly)	Nearly certain	-	Very likely	Almost certain
H	-	Extremely likely	-	-	-	Extremely likely	-
I	-	Virtually certain	-	-	-	Almost certain	-

negations (e.g., *not unreasonable*), and phrases (e.g., *liable to happen*) were considered. The number of VPEs varied between 12 [13] and 52 [15] expressions.

In summary, the results of the studies indicate that subjects can consistently rank VPEs on an ordinal scale. The maximal number of discriminable probability ranks appears to be seven in accordance with results from Miller [17]. The between-subject variability of probability estimations in all studies, however, was conspicuous indicating the nonexistence of an unconditioned consensus. [18]

Another research track focused on epistemic modalities. The terms *possible*, *probable* and *certain* [19] can be ranked on an ordinal scale without assigned numeric probability ranges. Also, speakers' expression of uncertainty about the truthfulness of a statement is composed of the speakers' belief that the statement is true and their confidence in their belief [20,21,22]. Therefore, in the context of the probabilistic estimation of uncertain events, we also must distinguish between the estimated probability and the speakers' confidence.

2.2. *Overview of NBLP schemes*

NBLP schemes are pre-defined templates that translate a set of VPEs to numeric values. Multiple organizations have developed their own NBLP schemes (based on results of the first research wave) to make qualitative expert judgments easier to compare and reduce the potential of misinterpretation. In the following, we outline six established NBLP schemes. The structures of the NBLP schemes are illustrated in Figure 1. The expression sets of the schemes are displayed in Table 1.

- The Intergovernmental Panel on Climate Change (IPCC) introduced a first version of its *calibrated language* in 2005 [23] which was refined in 2007 [24, p. 23]. The refined version contains the expressions "extremely (un)likely". Its application was more described in detail in 2010 [25]. The expressions are referred to as *likelihood terms*. The purpose of the calibrated language is to faciliate communication among the working groups of the IPCC. Experts are encouraged to complement any likelihood assessment with an confidence level on an ordinal 5-point scale that ranges between very low confidence and very high confidence. The scheme has the option to say "more than 50%" which overlaps with other categories. The expressions are defined as thresholds and the scheme itself should not be used when listing facts [25].
- The NBLP scheme from the European Food Safety Authority (EFSA) Scientific Committee is derived from the IPCC scheme [26, p. 61]. The main difference is that the expression "more likely than not" was separated from the other expressions to prevent overlapping ranges. Also the IPCC expression "exceptionally unlikely" was renamed to "almost impossible", assumingly to avoid misinterpretations to the similar sounding expression "extremely unlikely". While the IPCC scheme interprets VPEs as thresholds, the EFSA scheme interprets them as probability ranges. Another important feature is that the EFSA scheme explicitly permits experts the option to abstain from assigning a probability due to missing information or other reasons.
- The Intelligence Community Directive (ICD) 203 [27, p. 3] introduced another NBLP scheme with the goals to enable objective judgments, mitigate bias, and provide assessments in time. The scheme offers two alternative expression sets.

One set mainly modifies the expression “likely”, the other set modifies the expression “probable”. The ICD scheme illustrates the interchangeability of the words “likelihood” and “probability”. Additionally, it addresses the issue that the effect of modifiers is yet unclear by using for one set the modifier “very” and for the other set the adverb “highly”. Items of the expression sets should also not be mixed to avoid additional confusion. The numeric range is between 0.01 and 0.99 “to reflect the uncertain nature of intelligence estimates” [28]. The probability estimation should be complemented by a confidence level, although no set of confidence expressions was mentioned in the original publication [27].
- The North Atlantic Treaty Organization (NATO) formulated a NBLP scheme in 2016 as part of the NATO Allied Joint Doctrine for Intelligence Procedures 2.1 [29]. The original publication is confidential, but the scheme is described in articles like [28]. With a set of five expressions, the NATO scheme is the smallest one that we could find.
- The Professional Head of Intelligence Assessment (PHIA) Probability Yardstick was developed in the early 2000 by the UK Defence Intelligence. The yardstick has multiple versions and we refer to the latest version that was published in a technical report in 2019 [30, p. 29]. The yardstick’s goals are to foster standardized processes that promote objective results in time. The yardstick does not cover the full probability range, but leaves 5% gaps between categories. The gaps create a distance between the categories and shall motivate experts to confidently decide on one probability range. Another feature is that probabilities can also be expressed in fractions which allows to address the lower and upper bound of categories (e.g., the fraction $\frac{1}{20}$ denotes the upper bound of “remote change” (5%)).
- The established term *words of estimative probabilities* (WEP) originates from a proposal of Sherman Kent in 1964 [31] which was, however, never adopted by the Central Intelligence Agency (CIA).The WEP scheme is considered the first of its kind. Instead of translating expressions to numeric thresholds or ranges, expressions are translated to precise numbers with tolerances (e.g. “Probable” translates to $75\% \pm 12\%$). The WEP scheme has three probability gaps.

While the use of NBLP schemes are certainly an easy and structured way to facilitate uncertainty communication, a remaining problem is that users must agree and commit to use the proposed VPEs for specific probability values. Recent research, however, indicates that “most people struggle to suppress the meanings they normally associate with such terms” [28]. The overall goal is to prepare and motivate people to express their estimations numerically. Instead of establishing a standard VPE set for all, we see the development of individual NBLP schemes as part of the solution. A human-agent team can engage in a co-learning process to develop an individual NBLP scheme where the model can be trained as secondary task and the human is familiarized with expressing uncertainty numerically over time. The concept is illustrated in the next section.

3. Applying co-learning to manage uncertain communication

3.1. Use case: smartphone repair

To illustrate the co-learning process, we adopt the fictional use case from Van Zoelen et al. [32] in which a service technician collaborates with an AI agent to analyze a broken smartphone and to perform the necessary steps to repair the smartphone. In the collaboration scenario, the AI agent supports the service technician with relevant information that it (pro-actively or re-actively) retrieves from the company's knowledge base. On the other hand, the service technician provides feedback on the results to the AI agent. The collaboration model of the service technician and the AI agent qualifies as hybrid team which "consists of agents. An agent is an entity that is autonomous, intentional, social, reactive, and proactive [33]. So a human is an agent. A machine can also be an agent, but only if it meets the criteria above" [8]. Additionally, the scenario addresses the challenges of developing a taxonomy model and of providing an appropriate communication model which were identified by Van den Bosch et al. [8].

If we consider a specific scenario where a damaged smartphone irregularly shuts down, the service technician might make several observations of the behavior of the smartphone during the analysis that must be communicated to the AI agent with a level of uncertainty due to the inconsistent behavior of the smartphone. As the service technician practices a think-aloud approach while performing the analysis as his primary task, the formulation of probability estimations is secondary. In that case, we argue that it is more beneficial to permit the service technician to begin by annotating his assumptions and observations with VPEs, until reasoning on the knowledge base can provide precise numeric probability estimates. To achieve a mutual understanding of uttered VPEs, the hybrid team must engage in a co-learning process.

3.2. Phases of the co-learning process

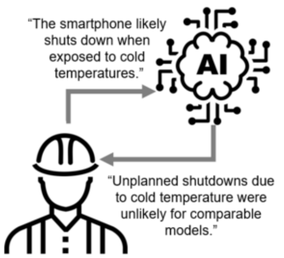
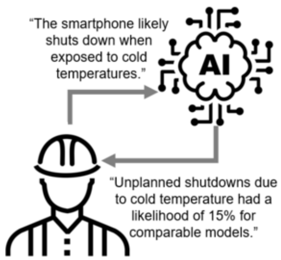
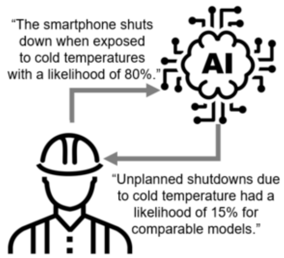
To prepare the service technician for expressing uncertainty in numeric values only, we consider three phases of communication in the hybrid team. In the first phase, the service technician uses only VPEs to convey probabilistic observations to the AI agent. In this scenario, the service technician is introduced to the NATO scheme for familiarizing himself with the thoughtful application of VPEs. After the service technician is familiarized, the service technician can add his own expressions. After each expressed observation or belief of the service technician is recorded, the AI agent confirms each utterance by repeating it.

In the second phase, the service technician continues to use VPEs. After a statement is recorded, the AI agent replaces the VPE by the calculated numeric estimate when repeating the statement. In case the service technician is not satisfied with the suggested probability, the service technician can correct the suggested probability by proposing a numeric value which the AI agents records for future processing.

In the third phase, the service technician only uses numeric values to define the probabilistic character of an event. As soon as the service technician feels comfortable using only numeric values, the service technician's beliefs are less prone to be misunderstood by (human) colleagues and shared beliefs can be easier processed. The three phases are summarized in Table 2.

In all phases, whenever the agent is asked by the service technician to query the knowledge base, the agent tries to mitigate subjective bias by presenting recorded knowledge about probabilistic events. If there are shared beliefs, the annotated probability will always be based on numeric aggregation. However, based on the service technician's preferences, the numeric range or value can still be translated to a VPE, following the service technician's individual and subjective interpretation.

Table 2. Outline of the three phases of the co-learning process in the context of the use case.

<table>
<tr><th>Phase I</th><th>Phase II</th><th>Phase III</th></tr>
<tr><td>Service technician uses solely VPEs. AI agent uses only VPEs if requested by service technician or probability cannot be determined from collected data.</td><td>Service technician uses VPEs and optionally numeric values. AI agent uses exclusively numeric probabilities.</td><td>Service technician and AI agent use only numeric values to communicate probabilities.</td></tr>
<tr><td>
</td><td>
</td><td>
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4. Discussion

4.1. Application of VPEs

In general, researchers argue to use numeric values to express probabilities, because numeric values are more precise and unambiguous [5,28,34]. However, practitioners may still prefer to communicate estimations using VPEs (e.g., in intelligence analysis [28]), which makes it inevitable for researchers in the domain of applied science to find means to work with VPEs. NBLP schemes seem to be an easy way to achieve that. Main criticisms of established NBLP schemes are that they are based on the opinions of a small group, were not developed with evidence-based methods [10,35], and lack empirical validation [5]. Evidence-based NBLP schemes were presented by Ho et al. [35] and Wintle et al. [36]. Also, the use of VPEs might be insufficiently expressive in scenarios where a high granularity of probability values is required.

Apart from the expression of pure probabilities, some biases must be managed when creating estimations via VPEs. Friedman and Zeckhauser [37] argue that experts should express their level of confidence together with their probabilistic assessment. Confidence addresses the robustness of the probabilistic assessment information that may be acquired in the future. The confidence level should not be confused with confidence of statistical analysis [25]. Several NBLP schemes like the IPCC scheme are used in combination with a confidence scale. Recent findings, however, indicate that experts and non-experts conflate their estimated probability with their confidence level [38]. Moreover, native and non-native speakers seem to have different numeric interpretations [39,40]. Another important aspect is the aggregation of multiple probability estimations. Participants aggregate VPEs by guesswork instead of mental computation [41] which can lead to incorrect conclusions. For instance, "when the advisors both say an event is 'likely', participants will say that it is 'very likely'" [42] instead of increasing their confidence that occurrence of the event is in fact just "likely".

Nonetheless, there is an ease of use by applying VPEs, and "in most everyday situations, verbal probabilities may not only suffice, but may also be ideal, given that they afford free-flowing communication." [34, p. 11]. It is important to keep in mind that there will always be biases when people communicate uncertainty. On the one hand, VPEs are used to "save face", to maintain credibility as an expert, to avoid being blamed, and just to be polite in some cases [5,34]. On the other hand, the application of numeric probability expressions can also be biased [43,44].

We argue that a co-learning process within hybrid teams can significantly contribute to reduce aforementioned biases.

4.2. Modelling and processing VPEs

An established view is that numeric translations of VPEs are not crisp boundaries, but can be modeled by using fuzzy sets [3,45,46,47]. While the application of fuzzy sets is agreed on, both triangular and trapezoidal fuzzy set membership functions are used in practice [18]. Several authors [46,48,49] proposed probabilistic pragmatics models that are based on the Rational Speech Act model [50,51] to formalize communication with VPEs and therefore validate and optimize the choice of VPEs used between speaker and listener. While this approach seems promising, it must be stressed that rational acts depend on the current information state and can turn out sub-optimal in hindsight after new information was acquired. Therefore, it is imperative to apply (1) appropriate methods to establish co-learning processes for estimating uncertainty and (2) to identify and capture the relevant context when realizing a co-learning process due to the highly context-dependent nature of VPEs. The lottery of guessing the next ball in a urn (used by Herbstritt and Franke [48]) might be too simple to represent complex scenarios. Also, lotteries are criticized to be too time-intensive [52]. While our described use case illustrates a potential realization of the co-learning process to process VPEs, empirical research is needed to validate these claims. Hence, we formulate the following two research questions to be addressed in future research:

RQ1 Which algorithms, mechanisms, and methods are most appropriate to establish co-learning processes for estimating uncertainty in the context of collaborative tasks in human-agent teams?

RQ2 How to appropriately identify and capture the task context to respond to the highly context-dependent nature of verbal probability expressions?

5. Conclusion

If possible, probabilities of uncertain states or events should always be conveyed using numeric means. In consideration of the *preference paradox* and depending on the context, the use of verbal probability expressions (VPEs) might be (temporarily) more beneficial or even inevitable. We propose a co-learning process within hybrid teams to diminish the *preference paradox* and other biases. In this process, human and AI team members are familiarized with the numeric translation of VPEs until numeric probability values can be efficiently communicated by both parties. Future work will address the research questions which were mentioned in section 4.

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