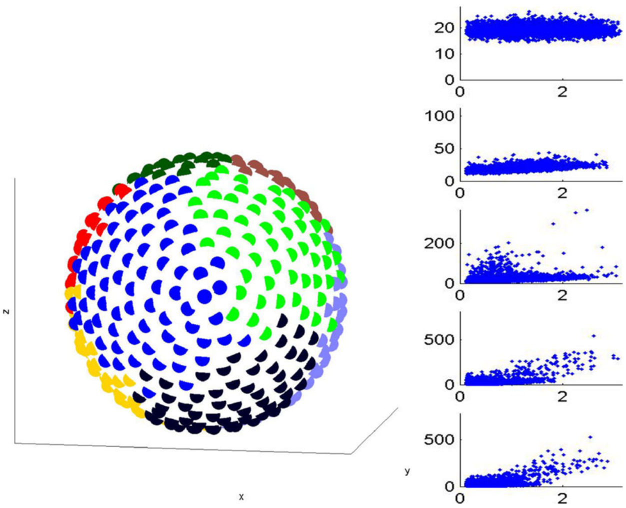

Fig. 2 From: Jarman et al. 2014. Adaptive rewiring on a sphere *left* Differently colored units reveal the community structure (modularity) resulting from adaptive rewiring with a wiring cost function. *Right* Correlation between spatial distance of connections (x-axis) and their topological "betweenness centrality" (Y-axis). From *top* to *bottom* initial state and subsequent states during the evolution of the small world network. The correlation as it emerges with the network evolutions shows that links between modules tend to be of long range

transition from immature to mature systems. Second, and only after that, should we be start preparing the system for information processing functions.

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Bayesian mental models of conditionals

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Conditionals play a crucial role in psychology of thinking, whether one is concerned with truth table tasks, the Wason selection task, or syllogistic reasoning tasks. Likewise, there has been detailed discussion on normative models of conditionals in philosophy, in logics (including non-standard logics), in epistemology as well as in philosophy of science. Here a probabilistic Bayesian account of the induction of conditionals based on categorical data is proposed that draws on different traditions and suggests a synthesis of several aspects of some earlier approaches.

Three Main Accounts of Conditionals

There is much controversy in philosophy and psychology over how indicative conditionals should be understood, and to whether this relates to the material implication, to conditional probabilities, or to some other formalization (e.g. Anderson, Belnap 1975; Ali, Chater, Oaksford 2011; Byrne, Johnson-Laird 2009; Edgington 2003; Beller 2003; Evans, Over 2004, Kern-Isberner 2001; Krynski, Tenenbaum 2007; Pfeiffer 2013; Johnson-Laird 2006; Leitgeb 2007; Oaksford, Chater 2007, cf. 2010; Oberauer 2006; Oberauer, Weidenfeld, Fischer 2007; Over, Hadjichristidis, Evans, Handley, Sloman 2007;). Three main influential approaches, on which we will build, may be distinguished:

One class of approaches is based on the material implication. A psychological variant replaces this interpretation (with a T F T T truth table by mental models akin either to complete truth tables or to only the first two cases of such a truth table (Johnson-Laird 2006; cf. Byrne, Johnson-Laird 2009). The present approach adopts the idea that a conditional 'if p then q' may be represented with reference either to a full 2 × 2 contingency table or simply with reference to the cells relating to the antecedent p (i.e., p & q, p & non-q).

Another class uses a conditional probability interpretation, thus referring only to the first two cells of a contingency table (Stalnaker 1968, cf. Eddington 2003; Evans, Over 2004; Oberauer et al. 2007; Pfeifer 2013). This is often linked to assuming the hypothetical or counterfactual occurrence of the antecedent p (cf. Ramsey test). Here we take conditional probabilities as a starting-point for a probabilistic understanding of conditionals, while adding advantages of the mental model approach. Moreover, here an extended Bayesian version of this approach is advocated, concerned not with a hypothetical frequentist (observed or imagined) relative frequency of q given p, but rather with an inference about an underlying generative probability of q given p that now depends on priors and sample size.

A subclass of the conditional probability approach additionally assumes a *high* probability criterion for the predication of logical propositions (cf. Foley 2009). This is essential to important classes of non-monotonic logic (e.g., System P) demanding a high probability threshold (a ratio of exceptions ε) for the predication of a 'normic' conditional (Adams 1986; Schurz 2001, cf. 2005): $P(q|p) > 1 - \varepsilon$. We here reformulate a high probability criterion in a Bayesian way using second-order probability distributions (cf. von Sydow 2014).

Third, conditionals sometimes involve causal readings (cf. Hagmayer, Waldmann 2006; Oberauer et al. 2007) and methods of causal induction (Delta P, Power, and Causal Support; Cheng 1997; Griffiths, Tenenbaum 2005; cf. Ali et al. 2011) that make use of all four cells of a contingency table. Although conditionals have to be distinguished from causality ("if effect then cause"; "if effect E1 then effect E2"; "if cause C1 then cause C2"), conditional probabilities may not only form the basis for causality, but conditionals may be estimated based on causality. Moreover, determining the probability of conditionals may sometimes involve calculations similar to causal judgments. In any case, approaches linking conditionals and causality have not been fully developed for non-causal conditionals in situations without causal model information.

Bayesian Mental Model Approach of Conditionals (BMMC)

The Bayesian Mental Model Approach of Conditionals allows for complete and incomplete models of conditionals (here symbolized as $p \approx> q$ vs. $p \sim> q$). It nonetheless models conditionals in a probabilistic way. It is claimed that the probability of fully represented conditionals ($P(p \approx> q)$) needs not to be equated with a single conditional probability ($P(q|p)$). In contrast, the probability of conditionals concerned with the antecedent p only, $P(p \sim> q)$, is taken to be closely related to the relative frequency of the consequent given the antecedent (its extension). However, the model does not merely refer to the extensional probability $P_e(q|p)$, but is concerned with subjective generative probabilities affected by priors and sample size.

The postulates of the approach and the modelling steps will be sketched here (cf. von Sydow 2014, for a related model):

(1) Although BMMC relates to the truth values of conditionals and biconditionals, etc. (Step 6), it assigns *probabilities* to these propositions as a whole (cf. Foley 2009, von Sydow 2011).

(2) BMMC distinguishes complete vs. incomplete conditionals. This idea is adopted from mental model theory (Johnson-Laird, Byrne 1991; cf. Byrne, Johnson-Laird 2002). It is likewise assumed that standard conditionals are incomplete. However, whereas mental model theory has focused on cognitive elaboration as the cause for fleshing out incomplete conditionals, the use of complete vs. incomplete conditionals is primarily linked here to the homogeneity or inhomogeneity of the occurrence of q in the negated subclasses of the antecedent p (i.e. non-p) (cf. Beller's 2003, closed-world principle). Imagine homogeneity of non-p with $P(q|p) = P(q|\text{non-}p) = .82$ (e.g., "if one does p then one gets chocolate q" but for non-p cases one gets chocolate with the same probability as well.) Here it seems *in*appropriate to assign the high probability of $P(q|p)$ to $P(p \approx> q)$ as well, since the antecedent does not make a difference. However, consider a similar case were non-p is heterogeneous. Take nine subclasses in which $P(q|\text{non-}p) = .9$ and one in which $P(q|\text{non-}p) = .1$ (this yields the same average of $P(q|\text{non-}p) = .82$). For such a heterogeneous contrast class, the conditional is indeed taken to singles out only the specific subclass p (similar to the conditional probability approach), since there is at least one potential contrast in one subclass of non-p For the homogeneous case, however, the probability of the conditional is claimed to reflect the overall situation, and a high probability here would involve a difference between $P(q|\text{non-}p)$ and $P(q|\,p)$.

(3) BMMC represents the simpler, antecedent-only models of conditionals, not as extensional probabilities, or relative frequencies of (observed or imagined) conditionals, but as subjective estimates of generative probabilities that have produced them. Although similar to a conditional probability approach, i.e. $P_E(q|p)$, this measure depends on priors and sample size. For flat priors observing a [4; 1] input ($f(p\&q)$, $f(p\&\text{non-}q)$) yields a lower $P(p \sim> q)$ than for a larger sample size, e.g. [40; 10]. Particularly for low sample sizes, priors may overrule likelihoods, reversing high and low conditional probability judgments.

Formally, the model uses cases of q or non-q, conditional on p, as input (taken as Bernoulli trials with an unchanging generative probability θ). Given a value of θ the Binomial distribution provides us with the likelihood of the data, $P(D|\,\theta)$, with input $k = f(q|p)$ in $n = f(q|p) + f(q|p)$ trials:

$$B(k|\theta, n) = \binom{n}{k} \theta^k (1-\theta)^{n-k}$$

We obtain a likelihood density function for all θ (cf. middle Fig. 1), resulting in a Beta distribution, now with the generative probability θ as an unknown parameter (with $\alpha - 1 = f(x = q|p)$ and $\beta - 1 = f(x = \neg q|p)$:

$$Beta(\alpha, \beta) = P(\theta|\alpha, \beta) = const. \cdot \theta^{\alpha-1}(1-\theta)^{\beta-1}$$

As prior for θ we take the conjugate Beta distribution (e.g., Beta(1,1) as flat prior) to calculate easily a Beta posterior probability

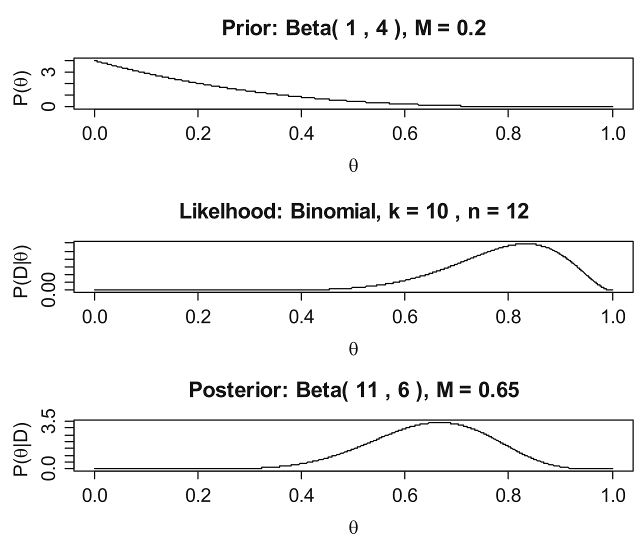

Fig. 1 Example for the prior for θ, the Binomial likelihood and the Beta posterior distribution over θ

distribution for θ (Fig. 1) that depends on sample size and priors. Its mean is a rational point estimate for the subjective probability of q given p.

(4) In contrast, given fully represented conditionals (no heterogeneous contrast class), the probability of a conditional even more clearly differs from (extensional) conditional probabilities (cf. Leitgeb 2007). One option would be to apply a general probabilistic pattern logic (von Sydow 2011) to conditionals. In this case, conditionals, however, would yield the same results as inclusive disjunctions $P(p \approx > q) = P(\neg p \vee q)$. Albeit here concerned with all four cells of a logical truth table, another option is that conditionals have a direction even in non-causal settings. This assumption will be pursued here. A *hypothetical causal-sampling assumption* that asserts hypothetical antecedent-sampling for conditionals (Fiedler 2000), as if assuming that the antecedent would have caused the data (cf. Stalnaker 1968; Evans, Over 2004). (In the presence of additional causal knowledge, one may correct for this, but this is not modelled here.) Based on the generative models of conditional probabilities (Step 3), here generative versions of delta P (Allan, Jenkins 1980) or causal power (Cheng 1997) are suggested as another possible formalization of a full conditional.

Formally, the two conditional probability distributions (for $q|p$ and $q|$non-p) are determined based Step 3. To proceed from the two beta posterior distributions on the interval [0, 1], to a distribution for Delta P, relating to $P(q|p)$-$P(q|$non-$p)$ in the interval $[-1, 1]$, one can use standard sampling techniques (e.g. inversion or rejection method, Lynch 2007). For the sequential learning measure for causal power one proceeds analogously. The means of the resulting probability distributions may be taken as point estimates. However, these Delta P and causal power may not be flexible enough (see Step 6).

(5) Let us first return to incomplete conditionals (Step 3). Even here the probability of a conditional $P(p \sim > q)$ may have to be distinguished from the conditional probability, even if modelled as a generative conditional probability (Step 3). To me there are to other plausible options: One option would be to model probabilities of conditionals along similar lines as other connectives have been modelled in von Sydow (2011). Here I propose another option, closely related to another proposal von Sydow (2014). This builds on the general idea of high probability accounts (Adams 1986; Schurz 2001, cf. 2005; Foley 2009), here specifying acceptance intervals over θ. This seems particularly suitable if concerned with the alternative testing of the hypotheses $p \sim > q$, $p \sim >$ non-q, and, $p \sim > q \vee$non-q (e.g., "if one does p then one either gets chocolate q or does not"). This links to the debate concerning conjunction fallacies and other inclusion fallacies (given p, '$q\vee$non-q' refers to the tautology and includes the affirmation q; cf. von Sydow 2011, 2014).

Formally, we start with ideal generative probabilities on the θ scale ($\theta_q = 1$; $\theta_{non\text{-}q} = 0$; p and $\theta_{q \vee non\text{-}q} = .5$) (cf. von Sydow 2011). We then vary for each of the three hypotheses H, the acceptance threshold ε (over all, or all plausible, values). For $\varepsilon = .2$, the closed acceptance inter-val for the consequent q would be [.8, 1]; for non-q, [0, .2]; and for '$q\vee$non-q', [.4, .6]. Based on Step 3 we calculate for all tested hypotheses the integral over θ in the specified interval of the posterior probability distribution:

$$\int_{\theta_1}^{\theta_2} \text{Posterior distribution}(\theta, H)$$

This specifies the subjective probability that for given observed data the posterior probability of H is within the acceptance interval (cf. von Sydow 2011). The probability of each hypothesis is determined by adding up the outcomes for H over different levels of ε and normalizing the results over the alternative hypothesis (e.g., alternative conditionals). This provides us with a kind of pattern probability P_p of the hypotheses, predicting systematic (conditional) inclusion fallacies (e.g., allowing for $P_p(q \vee non\text{-}q|p) < P_p(q|p)$). (Additionally, such intervals over θ may help to model quantifiers: "If x are p then most x are q", cf. Bocklisch 2011).

(6) In continuation of Step 4, and analogous to Step 5, we detail the alternative testing of $p \approx > q$, $p \approx >$non-q, and $p \approx > (q \vee$ non-$q)$ for *complete* conditionals. Since this includes representation of non-p as well, we can also model the converse conditionals ($< \approx$, probabilistic necessary conditions) and biconditionals ($< \approx >$, probabilistic necessary and sufficient conditions) as alternatives to conditionals ($\approx >$, probabilistic sufficient conditions). First, to determine homogeneity of non-p subclasses (cf. Step 2), Step 5 is to be applied repeatedly, revealing whether each subclass is rather q, non-q, or $q\vee$ non-q. If the dominant results for all subclasses do not differ, we can determine the probability of a fully represented conditional. We make use of the results for the incomplete conditionals (for p or non-p; cf. Step 5). Related to conditionals, converse conditionals or biconditionals (or their full mental models), we interpret ideal conditionals $p \approx > q$, at least in the presence of alternative biconditionals, as the combination of $p \sim > q$ and non-$p \sim > (q\vee$non-$q)$; ideal biconditionals $p < \approx > q$ as combinations of $p \sim > q$ and non-$p \sim >$ non-q; and ideal converse conditionals $p < \approx q$ as the combination of $p \sim > (q \vee$ non-$q)$ and *non-p* $\sim > q$. Sometimes a connective may refer to more than one truth table: In the absence of biconditionals, $P(p \approx > q)$ is taken to be the mixture of a conditional and a biconditional. Likewise the approach allows to model, for instance, "if p then q or non-q" ($p \approx > (q\vee$non-$q)$) as average of two truth table instantiations (with non-p either being q or, in another model, non-q).

Technically it is suggested that one can obtain the pattern probabilities of the combination of the incomplete models by assuming their independence and by multiplying their outcome; e.g.: $P_p(p \approx > q) = P_p(p \sim > q)$ * $P_p($non-$p \sim > q\vee$non-$q)$. If the hypothesis-space is incomplete or if other logical hypotheses are added (von Sydow 2011; 2014), the results need to be normalized to obtain probabilities for alternative logical hypotheses.

Conclusion

Overall the sketched model is suggested to provide an improved rational model for assessing generative probabilities for conditionals, biconditionals, etc. The model predicts differences for complete and incomplete mental models of conditionals, influences of priors, influences of sample size, probabilistic interpretations of converse conditionals and biconditionals, hypothesis-space dependence, and conditional inclusion fallacies. Although all these phenomena seem plausible in some situations, none of the previous models, each with their specific advantages, seems to cover all predictions. Throughout its steps the present computational model may contribute to predicting a class of conditional probability judgments (perhaps complementing extensional conditionals) by potentially integrating some divergent findings and intuitions from other accounts into a Bayesian framework of generative probabilities of conditionals.

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Visualizer verbalizer questionnaire: evaluation and revision of the German translation

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Abstract
Many everyday abilities depend on various cognitive styles. With the *Visualizer-Verbalizer Questionnaire* (VVQ) we here translated a well-established inventory to distinguish between verbalizers and visualizers into German language and evaluated it. In our experiment 476 participants answered the VVQ in an online study. Results of this experiment suggest that indeed only eight items measure, what they are supposed to. To find out, whether these eight items are usable as a future screening tool, we currently run further studies. The VVQ translation will be discussed with respect to the original VVQ.

Keywords
Cognitive styles, Evaluation, Translation, Visualizer, Verbalizer, VVQ

Introduction

"When I learn or think about things, I imagine them very pictorially." People often describe their ability of learning or thinking in one of two possible directions. Either they state that they are the "vivid type", whose thoughts are full of colors and images or they describe themselves as the "word-based"-person, which seems often a bit cold and more rational.

In the nineteen-seventies Baddeley and Hitch (1974) demonstrated how important the working memory is for everyday life. It seems as if the way of how we learn and describe things is more or less unconscious, but this fundamental ability is determined by individual preferences. Individual preferences and individual abilities are very important for various human skills, e.g. wayfinding, decision making. Therefore, they have to be taken into account throughout the whole domain of spatial cognition (e.g., Pazzaglia, Moè 2013).

One way of dealing with the necessary interindividual differentiation in wayfinding performance is to distinguish between people's cognitive style (Klein 1951) or—more precisely—the preferred components of their working memory. In their model Baddeley and Hitch (1974) assumed that the central executive is a kind of attentive coordinator of verbal and visuo-spatial information in certain ways. Riding (2001) stated that one of the main dimensions of cognitive styles is the visualizer-verbalizer-dimension. Therefore it is common in cognitive research to differentiate between preferring visual (*visualizer*) and/or verbal (*verbalizer*) information (e.g. Richardson 1977; Pazzaglia, Moè 2013). Considering this classification it can be assumed that visualizers seem to be people with high-imagery preferences and verbalizers tend to have low-imagery preferences. These two styles are generally accounted for with self-report-instruments.

As Jonasson and Grabowski (1993) concluded, the primarily used tool to distinguish between visualizer and verbalizer is the *Visualizer-Verbalizer Questionnaire* (VVQ; Richardson 1977). The VVQ contains 15 items. Participants have to answer each of the given items by judging in how they apply to their style of thinking (dichotomy; yes/no). Still there is an unsolved problem concerning the VVQ. The verbal subscale indeed surveys verbal abilities (e.g., Kirby et al. 1988), whereas the items of the visual subscale are only partly connected to visuo-spatial abilities (e.g., Edwards, Wilkins 1981; Kirby et al. 1988). Another problem concerning the VVQ is that it is rather hard to find people that can clearly be assigned to one of the "extremes" of the visualizer-verbalizer-dimension, since most participants are located somewhere in between and may not be assigned