



# Monotonicity of a Bayesian confirmation measure in rule support and confidence

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## Introduction

- n Discovering rules from data is the domain of *inductive reasoning* (IR)
- n IR uses data about a *sample* of larger reality to start inference
- n  $S = \langle U, A \rangle$  – *data table*, where  $U$  and  $A$  are finite, non-empty sets  
 $U$  – *universe*;  $A$  – set of *attributes*
- n *Decision rule* or *association rule* induced from  $S$   
is a *consequence relation*:  $\phi \rightarrow \psi$  read as *if  $\phi$ , then  $\psi$*   
where  $\phi$  and  $\psi$  are condition and decision formulas  
(called **premise** and **conclusion**, resp.)

## Introduction

- n The number of rules generated from massive datasets can be very large
- n Only a few of them are likely to be *useful*
- n To measure the relevance and utility of selected rules, quantitative measures, also known as *attractiveness* or *interestingness measures* (metrics), have been proposed (e.g. support, confidence, lift, gain, *conviction*)
- n Aim: find *the most interesting rules* with respect to some attractiveness measures

## Introduction

- n  $\|\phi\|$  is the set of all objects from  $U$ , having property  $\phi$  in  $S$
- n  $\|\psi\|$  is the set of all objects from  $U$ , having property  $\psi$  in  $S$
- n Basic quantitative characteristics of rules
  - n *Support* of decision rule  $\phi \rightarrow \psi$  in  $S$ :

$$\mathit{sup}(\phi \rightarrow \psi) = \mathit{card}(\|\phi \wedge \psi\|)$$

- n *Confidence* (called also *certainty factor*) of decision rule  $\phi \rightarrow \psi$  in  $S$  (Łukasiewicz, 1913):

$$\mathit{conf}(\phi \rightarrow \psi) = \frac{\mathit{sup}(\phi \rightarrow \psi)}{\mathit{sup}(\phi)}$$

## Introduction

- n Among widely studied interestingness measures, there is a group of *Bayesian confirmation measures*
- n Measures of confirmation *quantify the strength of confirmation* that premise  $\phi$  gives to conclusion  $\psi$
- n „  $\psi$  is verified more often, when  $\phi$  is verified, rather than when  $\phi$  is not verified”
- n An important role in literature is played by a confirmation measure denoted by  $f$

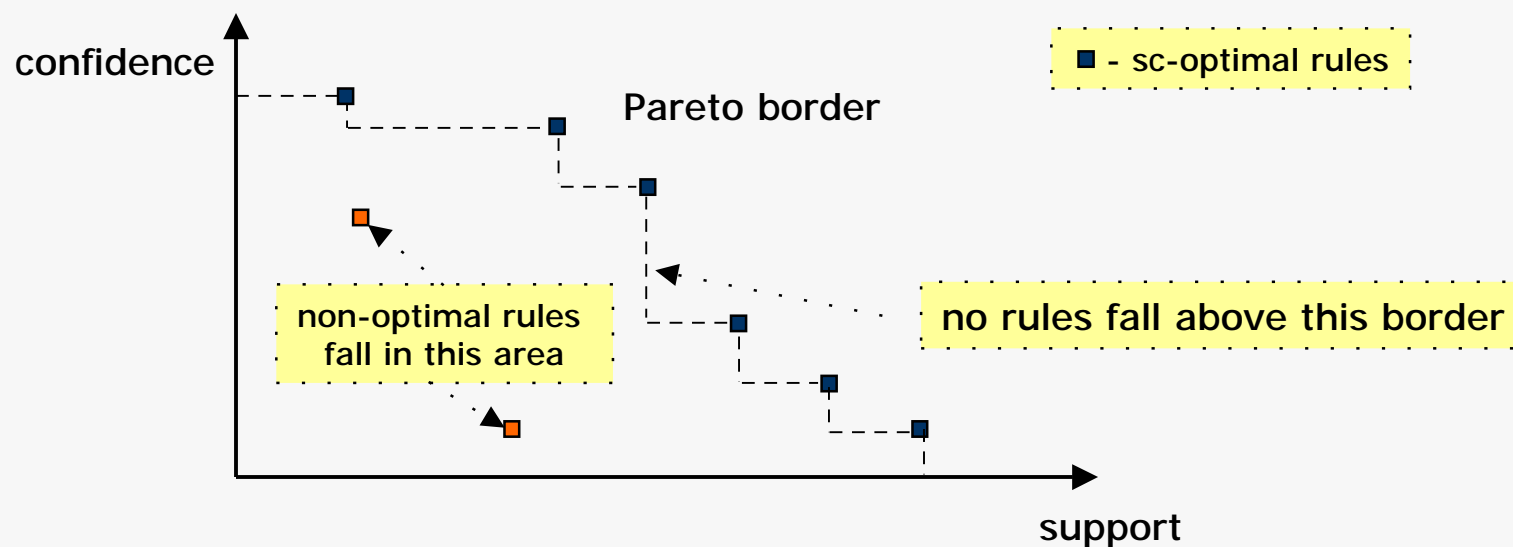
$$f(\phi \rightarrow \psi) = \frac{\mathit{conf}(\psi \rightarrow \phi) - \mathit{conf}(\neg\psi \rightarrow \phi)}{\mathit{conf}(\psi \rightarrow \phi) + \mathit{conf}(\neg\psi \rightarrow \phi)}$$

## Rule support-confidence Pareto optimal border

- n In the set of rules induced from data sets, we look for rules that are *optimal* according to a chosen *attractiveness measure*
- n This problem was addressed with respect to such measures as *lift, gain, conviction, Piatetsky-Shapiro* etc.
- n Bayardo and Agrawal (1999) proved, however, that, given a *fixed conclusion  $\psi$* , the *rule support-confidence Pareto border* includes optimal rules according to any of those attractiveness measures

## Rule support-confidence Pareto optimal border

- n Rule support-confidence Pareto border is the set of *non-dominated*, Pareto optimal rules with respect to *both rule support and confidence*



- n Mining *the border* identifies rules optimal with respect to measures such as: *lift, gain, conviction, Piatetsky-Shapiro* etc.

## Rule support-confidence Pareto optimal border

- n The following conditions are **sufficient** for verifying whether rules optimal according to a measure  $g(x)$  are included on the support-confidence Pareto optimal border:
  1.  $g(x)$  is **monotone in rule support** over rules with the same confidence, and
  2.  $g(x)$  is **monotone in confidence** over rules with the same rule support
  
- n A function  $g(x)$  is understood to be **monotone** in  $x$ , if  $x_1 < x_2$  implies that  $g(x_1) \leq g(x_2)$



## Objective of work

- n For a class of rules with fixed conclusion  $\psi$ , verify whether rules that are best according to the confirmation measure  $f$  are included in the rule support-confidence Pareto optimal border
  
- n To fulfill this objective it must be checked whether confirmation measure  $f$  is :
  1. monotone in rule support over rules with the same confidence, and
  2. monotone in confidence over rules with the same rule support

## Monotonicity of $f$ in rule support and confidence

- n Let us consider a *Bayesian confirmation measure*  $f$  defined as follows:

$$f(\phi \rightarrow \psi) = \frac{\mathit{conf}(\psi \rightarrow \phi) - \mathit{conf}(\neg\psi \rightarrow \phi)}{\mathit{conf}(\psi \rightarrow \phi) + \mathit{conf}(\neg\psi \rightarrow \phi)}$$

- n The measure  $f$  can be transformed into such a form:

$$f(\phi \rightarrow \psi) = \frac{|U|\mathit{conf}(\phi \rightarrow \psi) - \mathit{sup}(\psi)}{(|U| - 2\mathit{sup}(\psi))\mathit{conf}(\phi \rightarrow \psi) + \mathit{sup}(\psi)}$$

- n It is assumed that  $|U|$  and  $\mathit{sup}(\psi)$  are *constants* as we consider only rules with a *fixed conclusion* (i.e. from one decision class)

## Monotonicity of $f$ in rule support for fixed confidence value

$$f(\phi \rightarrow \psi) = \frac{|U|conf(\phi \rightarrow \psi) - sup(\psi)}{(|U| - 2sup(\psi))conf(\phi \rightarrow \psi) + sup(\psi)}$$

n Hypothesis:

*$f$  is monotone in rule support for fixed confidence*

n Verification:

$f$  is **independent of rule support**  $sup(\phi \rightarrow \psi)$ , so for  $conf(\phi \rightarrow \psi) = \text{const}$ ,

$f$  is constant and thus monotone in rule support

n Conclusion:

$f$  is **monotone in rule support**

## Monotonicity of $f$ in confidence for fixed rule support

$$f(\phi \rightarrow \psi) = \frac{|U|conf(\phi \rightarrow \psi) - sup(\psi)}{(|U| - 2sup(\psi))conf(\phi \rightarrow \psi) + sup(\psi)}$$

### n Hypothesis:

$f$  is monotone in confidence for fixed rule support

### n Verification schema:

n express  $f$  as a function of  $conf(\phi \rightarrow \psi)$ ,

n calculate the derivative  $f'$  of  $f$  with respect to  $conf(\phi \rightarrow \psi)$  and verify its sign

### n Conclusions:

since  $f'$  is always  $\geq 0$  then  $f$  is monotone in confidence

## Support-confidence monotonicity of $f$ - conclusions

- n The Bayesian confirmation measure  $f$  is:
  1. independent of rule support and therefore monotone in rule support
  2. and monotone in confidence
  
- n Rules optimal with respect to  
 *$f$  lie on the rule support-confidence Pareto border*  
(sic: we consider rules with fixed conclusion)

## Utility of confidence vs. utility of confirmation $f$ (1)

n What's the use of looking for rules with optimal  $f$  since they lie on the Pareto border?

n The result *does not deny the interest of  $f$*  in expressing the attractiveness of rules; it just states the monotonicity of  $f$  in confidence of rules for a fixed conclusion

n *Utility of scales:*

while  $conf(\phi \rightarrow \psi)$  is the truth value of the knowledge pattern "if  $\phi$ , then  $\psi$ ",

the  $f(\phi \rightarrow \psi)$  says to what extent  $\psi$  is satisfied more frequently when  $\phi$  is satisfied rather than when  $\phi$  is not satisfied

## Utility of confidence vs. utility of confirmation $f$ (2)

- n Consider the possible result of rolling a die: 1,2,3,4,5,6, and let the conclusion  $\psi = \text{"the result is 6"}$ 
  - n  $\phi_1 = \text{"the result is divisible by 3"}$        $conf(\phi_1 \rightarrow \psi) = 1/2, f(\phi_1 \rightarrow \psi) = 2/3$
  - n  $\phi_2 = \text{"the result is divisible by 2"}$        $conf(\phi_2 \rightarrow \psi) = 1/3, f(\phi_2 \rightarrow \psi) = 3/7$
  - n  $\phi_3 = \text{"the result is divisible by 1"}$        $conf(\phi_3 \rightarrow \psi) = 1/6, f(\phi_3 \rightarrow \psi) = 0$
- n This example acknowledges the monotonicity of confirmation in confidence, it also clearly shows that **the value of  $f$  has a more useful interpretation than  $conf$**
- n In particular, in case of rule  $\phi_3 \rightarrow \psi$ , which can also be read as "in any case, the result is 6"; indeed, the "any case" does not add any information which could confirm that the result is 6, and this fact is expressed by  $f(\phi_3 \rightarrow \psi) = 0$

## Utility of confidence vs. utility of confirmation $f$ (3)

- n Consider the possible result of rolling a die: 1,2,3,4,5,6, and let the premise be kept fixed at  $\phi = \text{"the result is divisible by 2"}$ 
  - n  $\psi_1 = \text{"the result is 6"}$        $conf(\phi \rightarrow \psi_1) = 1/3, f(\phi \rightarrow \psi_1) = 3/7$
  - n  $\psi_2 = \text{"the result is not 6"}$        $conf(\phi \rightarrow \psi_2) = 2/3, f(\phi \rightarrow \psi_2) = -3/7$
- n In this example, rule  $\phi \rightarrow \psi_2$  has greater confidence than rule  $\phi \rightarrow \psi_1$
- n However, rule  $\phi \rightarrow \psi_2$  is less interesting than rule  $\phi \rightarrow \psi_1$  because *premise  $\phi$  reduces the probability of conclusion  $\psi_2$*  from  $5/6 = sup(\psi_2)$  to  $2/3 = conf(\phi \rightarrow \psi_2)$ , while it augments the probability of conclusion  $\psi_1$  from  $1/6 = sup(\psi_1)$  to  $1/3 = conf(\phi \rightarrow \psi_1)$
- n In consequence, *premise  $\phi$  disconfirms conclusion  $\psi_2$* , which is expressed by a negative value of  $f(\phi \rightarrow \psi_2) = -3/7$ , and it confirms conclusion  $\psi_1$ , which is expressed by a positive value of  $f(\phi \rightarrow \psi_1) = 3/7$



## Conclusions

- n Confirmation measure *f is monotone* in rule support and confidence
- n For a particular class of rules with a fixed conclusion  $\psi$ , rules *optimal with respect to f* are included on the rule support-confidence *Pareto optimal border*
- n As semantics of  $f(\phi \rightarrow \psi)$  is more useful than that of  $conf(\phi \rightarrow \psi)$ , and as both these measures are monotonically linked while being independent of the support,  
  
it would be reasonable to search for the most interesting rules taking into account *just confirmation  $f(\phi \rightarrow \psi)$  and support  $sup(\phi \rightarrow \psi)$*

**Thank you!**