Mining non-dominated rules with respect to support and anti-support

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Poszukiwanie reguł niezdominowanych ze względu na wsparcie i anty-wsparcie

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Plan

Introduction

- Discovering rules from data is the domain of inductive reasoning (IR)
- IR uses data about a sample of larger reality to start inference
- $S=\langle U, A\rangle$ – *data table*, where U and A are finite, non-empty sets
  U – *universe*; A – set of *attributes*
- $S=\langle U, C, D\rangle$ – *decision table*, where C – set of *condition attributes*,
  D – set of *decision attributes*, $C\cap D=\varnothing$

e.g.

Characterization of nationalities

U	Height	Hair	Eyes	Nationality	Support
1	tall	blond	blue	Swede	270
2	medium	dark	hazel	German	90
3	medium	blond	blue	Swede	90
4	tall	blond	blue	German	360
5	short	red	blue	German	45
6	medium	dark	hazel	Swede	45

C (Height, Hair, Eyes) *D* (Nationality)

Introduction

- With every subset of attributes $B\subseteq A$, one can associate a formal language of formulas L, called *decision language*
- Formulas are built from attribute-value pairs (q,v), where $q\in B$ and $v\in V_a$ (domain of a), using logical connectives $\wedge$, $\vee$, $\neg$
- All formulas in L are partitioned into *condition* and *decision formulas* (called *premise* and *conclusion*, resp.)
- *Decision rule* or *association rule* induced from S is a *consequence relation*: $\phi\rightarrow\psi$ *read as* ***if*** ϕ, ***then*** ψ
  where ϕ and ψ are condition and decision formulas expressed in L

Introduction

- The number of rules generated from massive datasets can be very large and only a few of them are likely to be useful
- In all practical applications, like medical practice, market basket, it is crucial to know how good the rules are
- To measure the relevance and utility of rules, quantitative measures called attractiveness or interestingness measures, have been proposed

  (e.g. support, confidence, lift, gain, conviction, Piatetsky-Shapiro,...)
- There is no evidence which measure(s) is (are) the best

Basic quantitative characteristics of rules

- Notation:
  - $sup(\circ)$ is the number of all objects from U, having property ° in S
    e.g. $sup(\phi)$, $sup(\psi)$
- Basic quantitative characteristics of rules
  - *Support* of decision rule $\phi\rightarrow\psi$ in S:
    $$sup(\phi\rightarrow\psi)=sup(\phi\wedge\psi)$$
  - *Confidence* (called also *certainty factor*) of decision rule $\phi\rightarrow\psi$ in S (Łukasiewicz, 1913):
    $$conf(\phi\rightarrow\psi)=\frac{sup(\phi\rightarrow\psi)}{sup(\phi)}$$

Bayesian confirmation measures

- Among widely studied interestingness measures, there is a group of ***Bayesian confirmation measures***
- Measures of confirmation quantify the strength of confirmation that premise ϕ gives to conclusion ψ
- „ψ is verified more often, when ϕ is verified, rather than when ϕ is not verified"

$$c(\phi,\psi)\begin{cases} >0 \ \ if \ \ Pr(\psi|\phi) > Pr(\psi) \\ =0 \ \ if \ \ Pr(\psi|\phi) = Pr(\psi) \\ <0 \ \ if \ \ Pr(\psi|\phi) < Pr(\psi) \end{cases}$$

- Its meaning is different from a simple statistics of co-occurrence of properties ϕ and ψ in universe *U*

Bayesian confirmation measures

- Assuming $Fr(\psi)=\frac{sup(\psi)}{\text{card(U)}}$:

$$c(\phi,\psi)\begin{cases} >0 \ \ if \ \ Pr(\psi|\phi) > Pr(\psi) \\ =0 \ \ if \ \ Pr(\psi|\phi) = Pr(\psi) \\ <0 \ \ if \ \ Pr(\psi|\phi) < Pr(\psi) \end{cases}$$

$$\Downarrow$$

$$c(\phi,\psi)\begin{cases} >0 \ \ if \ \ conf(\phi\rightarrow\psi) > Fr(\psi) \\ =0 \ \ if \ \ conf(\phi\rightarrow\psi) = Fr(\psi) \\ <0 \ \ if \ \ conf(\phi\rightarrow\psi) < Fr(\psi) \end{cases}$$

Desirable properties of confirmation measures

- Desirable properties of *c*(ϕ,ψ):
  - ***monotonicity* (M)** (Greco, Pawlak, Słowiński 2004):

    a=$sup(\phi\rightarrow\psi)$, ***b***=$sup(\neg\phi\rightarrow\psi)$, ***c***=$sup(\phi\rightarrow\neg\psi)$, ***d***=$sup(\neg\phi\rightarrow\neg\psi)$

    c(ϕ,ψ) = ***F***(***a***, ***b***, ***c***, ***d***), where ***F*** is a function non-decreasing with respect to ***a*** and ***d*** and non-increasing with respect to ***b*** and ***c***

  - ***hypothesis symmetry*** (Eells, Fitelson 2002): ***c***(ϕ,ψ)= - ***c***(ϕ, $\neg\psi$)

Properties of monotonicity (M)

- The property of monotonicity (M) takes into account four evidences in assessment of the impact of property ϕ on $\phi\rightarrow\psi$
- E.g. (Hempel) consider rule $\phi\rightarrow\psi$: ***if x is a raven, then x is black***
- ϕ is the property ***to be a raven*** and ψ is the property ***to be black***
  - ***a*** – the number of objects in ***S*** which are black ravens
  - ***b*** – the number of objects in ***S*** which are black non-ravens
  - ***c*** – the number of objects in ***S*** which are non-black ravens
  - ***d*** – the number of objects in ***S*** which are non-black non-ravens

Confirmation measure *f* and *s*

- As shown by (Greco, Pawlak, Słowiński 2004), confirmation measure *f* (Good 1984, Heckerman 1988, Pearl 1988, Fitelson 2001)

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

and confirmation measure *s* (Christensen 1999)

$$s(\phi\rightarrow\psi)=conf(\phi\rightarrow\psi)-conf(\neg\phi\rightarrow\psi)$$

are the only ones that enjoy both property of monotonicity (M) and hypothesis symmetry (HS), among the most well known confirmation measures

Utility of confidence vs. utility of confirmation *measures* (1)

- Utility of scales:
  - $conf(\phi\rightarrow\psi)$ is the truth value of the knowledge pattern ***„if*** ϕ, ***then*** ψ",
  - $f(\phi\rightarrow\psi)$, $s(\phi\rightarrow\psi)$ say to what extend ψ is satisfied more frequently when ϕ is satisfied rather than when ϕ is not satisfied

Utility of confidence vs. utility of confirmation measures e.g. 1

- Consider the possible result of rolling a die: 1,2,3,4,5,6, and let the conclusion be ψ=„the result is 6"
  - ϕ_1 ="the result is divisible by 3" $conf(\phi_1\rightarrow\psi)$=1/2, $f(\phi_1\rightarrow\psi)$=2/3
  - ϕ_2 ="the result is divisible by 2" $conf(\phi_2\rightarrow\psi)$=1/3, $f(\phi_2\rightarrow\psi)$=3/7
  - ϕ_3 ="the result is divisible by 1" $conf(\phi_3\rightarrow\psi)$=1/6, $f(\phi_3\rightarrow\psi)$=0
- In particular, rule $\phi_3\rightarrow\psi$, can 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 $f(\phi_3\rightarrow\psi)=0$
- This example clearly shows that the value of f has a more useful interpretation than *conf*

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Utility of confidence vs. utility of confirmation measures e.g. 2

- Consider the possible result of rolling a die: 1,2,3,4,5,6, and let the premise be ϕ=„the result is divisible by 2"
  - ψ_1="the result is 6" $conf(\phi\rightarrow\psi_1)$=1/3, $f(\phi\rightarrow\psi_1)$=3/7
  - ψ_2="the result is ***not*** 6" $conf(\phi\rightarrow\psi_2)$=2/3, $f(\phi\rightarrow\psi_2)$=–3/7
- In this example, rule $\phi\rightarrow\psi_2$ has greater confidence than rule $\phi\rightarrow\psi_1$
- However, rule $\phi\rightarrow\psi_2$ is less interesting than rule $\phi\rightarrow\psi_1$ because premise ϕ reduces the probability of conclusion ψ_2 from 5/6=$sup(\psi_2)$ to 2/3= $conf(\phi\rightarrow\psi_2)$, while it augments the probability of conclusion ψ_1 from 1/6=$sup(\psi_1)$ to 1/3= $conf(\phi\rightarrow\psi_1)$
- In consequence, premise ϕ disconfirms conclusion ψ_2, which is expressed by a negative value of $f(\phi\rightarrow\psi_2)=-3/7$, and it confirms conclusion ψ_1, which is expressed by a positive value of $f(\phi\rightarrow\psi_1)$=3/7

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Support-confidence Pareto border

Support-confidence Pareto border

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

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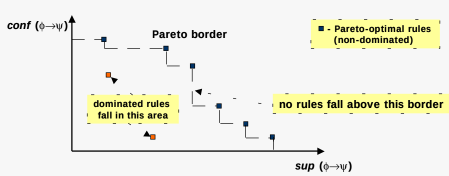
Support-confidence Pareto border

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



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

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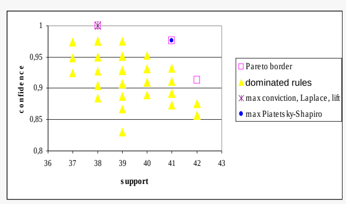
Support-confidence Pareto border

E.g. „Buses" data set, class of „good state"



- Decision rules were generated from lower approximations of preference-ordered decision classes defined according to Variable-consistency Dominance-based Rough Set Approach (VC-DRSA) (Greco, Matarazzo, Słowiński, Stefanowski 2001)

Rule induction algorithm: all rules algorithm (DOMAPRIORI)

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Support-confidence Pareto border

- The following conditions are sufficient for verifying whether rules optimal according to a measure $g(x)$ are included on the support-confidence Pareto border:

  1. $g(x)$ is monotone in support over rules with the same confidence

  and

  2. $g(x)$ is monotone in confidence over rules with the same support

- A function $g(x)$ is understood to be *monotone* in x, if x_1 p x_2 implies that $g(x_1) \leq g(x_2)$

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Support-f Pareto border

Monotonicty of *f* in support and confidence

- Is confirmation measure f included in the support-confidence Pareto border?
- Theorem 1:
  Confirmation measure f is independent of support, and, therefore, monotone in support, when the value of confidence is held fixed
- Theorem 2:
  Confirmation measure f is increasing, and, therefore, monotone in confidence
- Conclusion:

  Rules maximizing f lie on the support-confidence Pareto border
  (rules with fixed conclusion)

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Monotonicty of confidence in support and *f*

- The utility of confirmation measure f outranks utility of confidence
- Claim 1: Substitute the $conf(\phi\rightarrow\psi)$ dimension for $f(\phi\rightarrow\psi)$ in the support-confidence Pareto border
- Corollary 1:
  Confidence is independent of support, and, therefore, monotone in support, when the value of $f(\phi\rightarrow\psi)$ is held fixed
- Corollary 2:
  Confidence is increasing, and, therefore, monotone in $f(\phi\rightarrow\psi)$
- Conclusion:

  The set of rules located on the support-confidence Pareto border is exactly the same as on the support-f Pareto border

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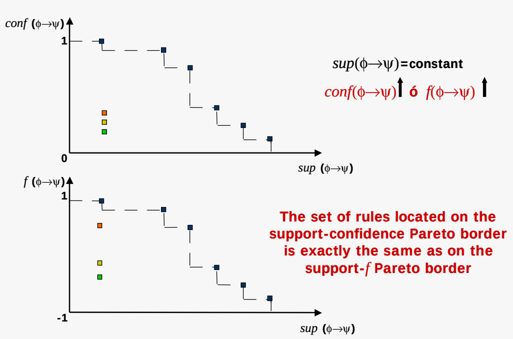
Support-confidence vs. support-*f* Pareto border



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Support-confidence vs. support-*f* Pareto border

- All the other interestingness measures that were represented on the support-confidence Pareto border also reside on support-f Pareto border
- Any non-dominated rule with a negative value of $f(\phi\rightarrow\psi)$ must be discarded from further analysis as its premise only disconfirms the conclusion – such situation cannot be expressed by the scale of confidence
- Conclusion:

  The support-f Pareto border is more meaningful than the support-confidence Pareto border

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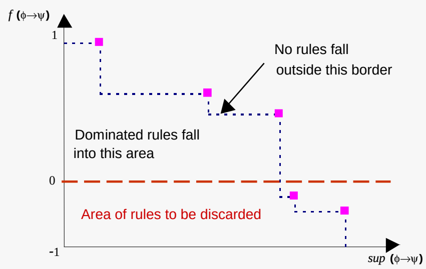
Support-*f* Pareto border is more meaningful



Support-s Pareto border

Monotonicty of *s* in support and confidence

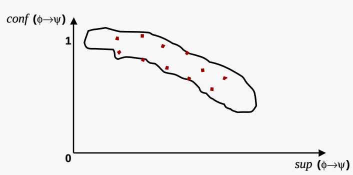
- Is confirmation measure s on rule support-confidence Pareto border?
- **Theorem 3:**
  Confirmation measure s is increasing, and, therefore, monotone in confidence when the value of support is held fixed
- **Theorem 4:**
  For a fixed value of confidence, confirmation measure s is:
  - increasing in $sup(\phi\rightarrow\psi) \Leftrightarrow s(\phi\rightarrow\psi)>0$
  - constant in $sup(\phi\rightarrow\psi) \Leftrightarrow s(\phi\rightarrow\psi)=0$
  - decreasing in $sup(\phi\rightarrow\psi) \Leftrightarrow s(\phi\rightarrow\psi)<0$
- Theorem 4 states the monotone relationship just in the non-negative range of the value of *s* (i.e. the only interesting)

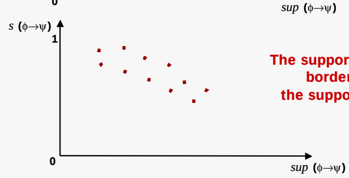
Support-confidence vs. support-*s* Pareto border

- **Theorem 5:**
  If a rule resides on the support-s Pareto border
  (in case of positive value of s),
  then it also resides on the support-confidence Pareto border,

  while one can have rules being on the support-confidence Pareto border which are not on the support-s Pareto border.
- **Conclusion:**
  The support-confidence Pareto border is, in general, larger than the support-s Pareto border

Support-confidence vs. support-*s* Pareto border





The support-confidence Pareto border is larger than the support-s Pareto border

Confirmation measures with the property of monotonicity (M)

- What are the necessary and sufficient conditions for rules maximizing a confirmation measure $c(\phi,\psi)$ with the property of monotonicity (M) to be included in the rule support-confidence Pareto border?
- Reminder of the property of monotonicity (M):
  $a=sup(\phi\rightarrow\psi)$, $b=sup(\neg\phi\rightarrow\psi)$, $c=sup(\phi\rightarrow\neg\psi)$, $d=sup(\neg\phi\rightarrow\neg\psi)$
  $c(\phi,\psi)=F(a,b,c,d)$, where F is a function non-decreasing with respect to a and d, and non-increasing with respect to b and c

Confirmation measures with the property of monotonicity (M)

- Let $F(a, b, c, d)$ be a confirmation measure with the property (M)
- Theorem 6:
  When the value of support is held fixed, then $F(a, b, c, d)$ is monotone in confidence.
- Theorem 7:
  When the value of confidence is held fixed, then $F(a, b, c, d)$ admitting derivative with respect to all its variables a, b, c and d, is monotone in support if:

$$\frac{\partial F}{\partial c}=\frac{\partial F}{\partial d}=0 \quad or \quad \frac{\frac{\partial F}{\partial a}-\frac{\partial F}{\partial b}}{\frac{\partial F}{\partial d}-\frac{\partial F}{\partial c}} \geq \frac{1}{conf(\phi \rightarrow \psi)}-1$$

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Confirmation measures with the property of monotonicity (M)

- Conclusions:
  - *Theorem 6* states that for a set of rules with the same conclusion, any Bayesian confirmation measure satisfying the property of monotonicity (M) is always non-decreasing with respect to confidence when the value of support is kept fixed
  - Due to *Theorem 7*, all those confirmation measures that are independent of $c=sup(\phi \rightarrow \neg\psi)$ and $d=sup(\neg\phi \rightarrow \neg\psi)$ are always monotone in support when the value of confidence remains unchanged

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Support-confidence vs. support-*i* Pareto border

- Theorem 8:
  Given an interestingness measure *i*, which is monotone with respect to support and confidence, if a rule resides on the support-*i* Pareto-optimal border, then it also resides on the support-confidence Pareto-optimal border

  while the opposite assertion is not necessarily true.

- Conclusion:

  The support-confidence Pareto border is, in general, larger than the support-*i* Pareto border

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Pareto borders - summary

- Inclusion of Pareto-optimal borders:
  - Support-confidence = support-*f*
  - Support-confidence Ê support-*s*
  - Support-confidence Ê support-*i*
    - *i* is any interestingness measure monotone with respect to support and confidence

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Area of interesting rules with respect to support and confidence

Which dominated rules (supp-conf) are definitely NOT interesting?

- Let us suppose that *F* is a confirmation measure with the property of monotonicity (M).
- We know that when $sup(\phi \rightarrow \psi)$=constant:
  - confidence is *monotone* (non-decreasing) w.r.t. *F*.
- Claim 2: Due to monotonicity of confidence in *F*, rules lying below the curve for which *F*=0 must be discarded.
  For those rules, the premise only disconfirms the conclusion!

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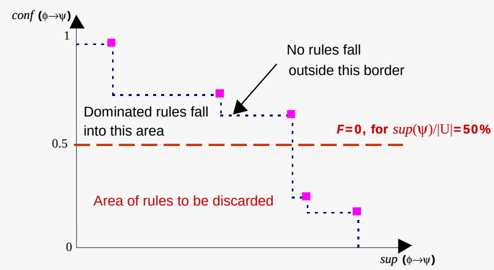
Which dominated rules (supp-conf) are definitely NOT interesting?

- Let us recall the definition of *F*:

$$c(\phi,\psi)\begin{cases} >0 & if\ \ conf(\phi\rightarrow\psi) > Fr(\psi) \\ =0 & if\ \ conf(\phi\rightarrow\psi) = Fr(\psi) \\ <0 & if\ \ conf(\phi\rightarrow\psi) < Fr(\psi) \end{cases}$$

- Let us assume that: $Fr(\psi)=\frac{sup(\psi)}{\mathrm{card}(U)}$
- Claim 3: *F*=0 ó $\boxed{conf(\phi\rightarrow\psi)=\frac{sup(\psi)}{\mathrm{card}(U)}}$
- $\frac{sup(\psi)}{\mathrm{card}(U)}$ is a constant expressing what percentage of the whole data set is taken by considered class ψ

Which dominated rules (supp-conf) are definitely NOT interesting?



For rules lying below the curve for which *F*=0 the premise only disconfirms the conclusion

Support-anti-support Pareto border

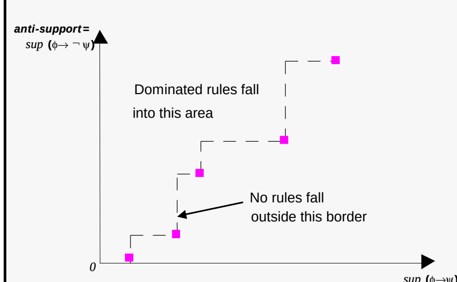
Support-anti-support Pareto border

- How to find rules optimal according to any confirmation measure with the property (M)?
- Anti-support is the number of examples which satisfy the premise of the rule but not its conclusion: $sup(\phi\rightarrow\neg\psi)$
- Theorem 9:
  When the value of support is held fixed, then *F*(*a*, *b*, *c*, *d*) is anti-monotone (non-increasing) in anti-support
- Theorem 10:
  When the value of anti-support is held fixed, then *F*(*a*, *b*, *c*, *d*) is monotone (non-decreasing) in support

Support-anti-support Pareto border

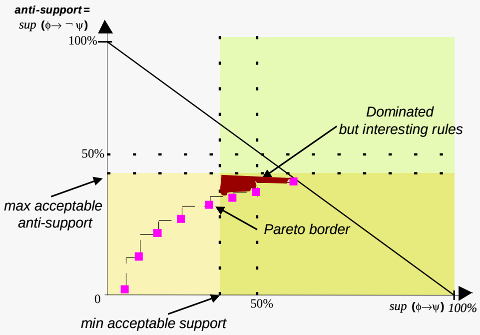
- Claim 4:
  - The best rules according to any of the confirmation measures with the property of monotonicity (M) must reside on the support-anti-support Pareto border
- The support-anti-support Pareto border is the set of rules such that there is no other rule having greater support and smaller anti-support

Support-anti-support Pareto border



The best rules according to any of the confirmation measures with the property of monotonicity (M) must reside on the support-anti-support Pareto border

Dominated rules can also be interesting



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Area of interesting rules
with respect to support and anti-support

Which dominated rules are definitely NOT interesting?

- **Let us suppose that *F* is a confirmation measure with the property of monotonicity (M).**
- **We know that when $sup(\phi\rightarrow\psi)$=constant:**
  - **anti-support is *anti-monotone* (non-increasing) w.r.t. confindence,**
  - **anti-support is *anti-monotone* (non-increasing) w.r.t. *F*.**
- **Claim 5: Due to anti-monotonicity of anti-support in *F*, rules lying above the curve for which *F*=0 must be discarded.**
  For those rules, the premise only disconfirms the conclusion

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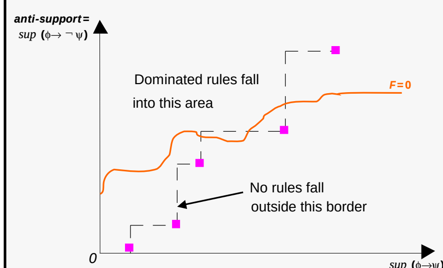
Which dominated rules are definitely NOT interesting?



For rules lying above the curve for which *F*=0
the premise only disconfirms the conclusion

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Which dominated rules are definitely NOT interesting?

- **Let us recall the definition of *F*:**

$$c(\phi,\psi)\begin{cases} >0 & if\ \ conf\,(\phi\rightarrow\psi) > Fr\,(\psi)\\ =0 & if\ \ conf\,(\phi\rightarrow\psi) = Fr\,(\psi)\\ <0 & if\ \ conf\,(\phi\rightarrow\psi) < Fr\,(\psi)\end{cases}$$

- **Claim 6: *F*=0 ó** $\boxed{anti\text{-}sup(\phi\rightarrow\psi)=sup(\phi\rightarrow\psi)\left[\frac{\mathrm{card}(U)}{sup(\psi)}-1\right]}$

- $anti\text{-}sup(\phi\rightarrow\psi)=sup(\phi\rightarrow\psi)\left[\frac{\mathrm{card}(U)}{sup(\psi)}-1\right]$ **is a linear function**

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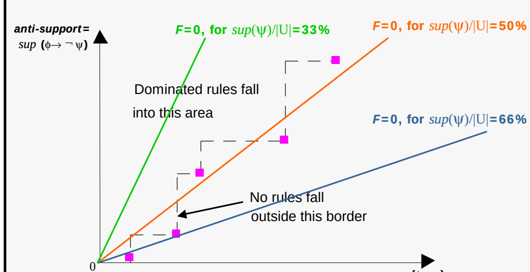
Which dominated rules are definitely NOT interesting?



For rules lying above the curve for which *F*=0
the premise only disconfirms the conclusion

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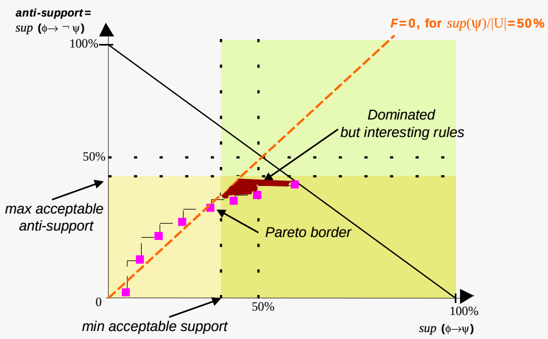
Dominated rules can also be interesting



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Summary

Summary

- Many attractiveness measures can be identified by mining the support-confidence Pareto border – very practical result
- The utility of confirmation measures outranks the utility of confidence
- Suggested new Pareto borders:
  - support-*f* Pareto border
  - support-*s* Pareto border
- Pareto border w.r.t. support and anti-support includes rules maximizing all confirmation measures with the property (M)

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Summary

- Dominated rules can also be interesting
- We have shown that for
  - support-confidence Pareto border
  - support-anti-support Pareto border

  simple linear functions narrow the area of dominated rules only to rules for which the premise confirms the conclusion

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Experimental results

Thanks to Mirek Urbanowicz

General info about the dataset

- Dataset *adult*, created in ’96 by B. Becker/R. Kohavi from census database
- 32 561 instances
- 9 nominal attributes
  - workclass: Private, Local-gov, etc.;
  - education: Bachelors, Some-college, etc.;
  - marital-status: Married, Divorced, Never-married, et.;
  - occupation: Tech-support, Craft-repair, etc.;
  - relationship: Wife, Own-child, Husband, etc.;
  - race: White, Asian-Pac-Islander, etc.;
  - sex: Female, Male;
  - native-country: United-States, Cambodia, England, etc.;
  - salary: >50K, <=50K
- throughout the experiment, *sup*(f ® y) is denoted as „support” and expressed as a relative rule support [0-1]

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The gist of the algorithm for support-anti-support rules

- **Traditional Apriori approach to generation of association rules (Agrawal et al) proceeds in a two step framework:**
  - **find frequent itemsets (i.e. sets of items which occur more frequently than the minimum support threshold),**
  - **generate rules from frequent itemsets and filter out those that do not exceed the minimum confidence threshold**
- **Generation of association rules regarding support and anti-support, in general, requires only the substitution of the parameter calculated in step 2. Confidence -> anti-support**

The gist of the algorithm for support-anti-support rules

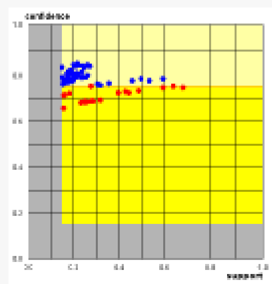
- **Since** $conf(\phi\rightarrow\psi)=sup(\phi\rightarrow\psi)/sup(\phi)$ **all the data needed to calculate it are already gathered in step 1 of Apriori**
- **Claim 7: calculation of anti-support (instead of confidence) does not introduce any more computational overhead to the algorithm**
- **Let us observe that:** $anti\text{-}sup(\phi\rightarrow\psi) = sup(\phi\rightarrow\neg\psi) = sup(\phi)\text{-}sup(\phi\rightarrow\psi)$.
- **All the data required to calculate anti-support are also gathered in step 1 of Apriori**
- **The data needed to calculate anti-support is the same as to calculate confidence, and moreover subtraction is easier than division**

The gist of the algorithm for support-anti-support rules

- **Claim 8: When generating association rules from a frequent set it is advisable to first generate rules with few conclusion elements (for optimisation reasons)**
- **Let us observe three different rules constructed from the same frequent itemset** $\{a, b, c, d\}$**:**
  - r_1: $a\text{->}bcd$ $\quad anti\text{-}sup(r_1) = sup(a)\text{-}sup(abcd)$
  - r_2: $ab\text{->}cd$ $\quad anti\text{-}sup(r_2) = sup(ab)\text{-}sup(abcd)$
  - r_3: $abc\text{->}d$ $\quad anti\text{-}sup(r_3) = sup(abc)\text{-}sup(abcd)$
- $anti\text{-}sup(r_1) \geq anti\text{-}sup(r_2) \geq anti\text{-}sup(r_3)$
- **Conclusion:** $anti\text{-}sup(r_3)$ **> max_acceptable anti-support =>** $anti\text{-}sup(r_2)$ **> max_acceptable anti-support**

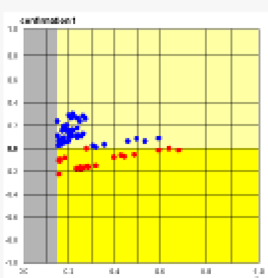
Generate and verify r_3 first!

Support-confidence (workclass=Private)



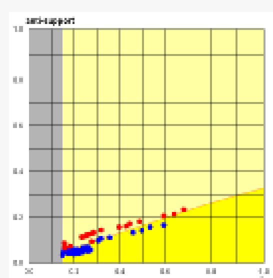
- ● indicates rules with negative confirmation
- the class constitutes over 70% of the whole dataset
- rules with high confidence can be disconfirming
- even some rules from the Pareto border need to be discarded

Support-f (workclass=Private)



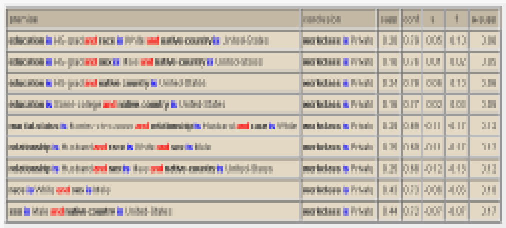
- ● indicates rules with negative confirmation
- this diagram does not (explicitly) show the ratio of the class cardinality to the whole dataset
- even some rules from the Pareto border need to be discarded

Support-anti-support (workclass=Private)



- ● indicates rules with negative confirmation
- the class constitutes over 70% of the whole dataset
- even some rules from the Pareto border need to be discarded

Few rules describing class: workclass=Private



- the table contains few examples of rules with the conclusion workclass=Private

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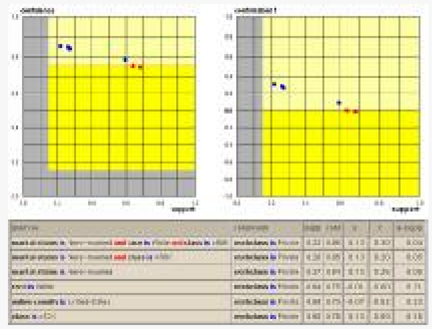
Support-confidence Pareto border vs. support-f



- both Pareto borders contain the same rules

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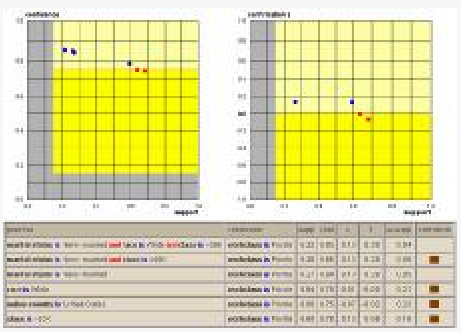
Support-confidence Pareto border vs. support-s



■ indicates rules that appeared on both Pareto borders

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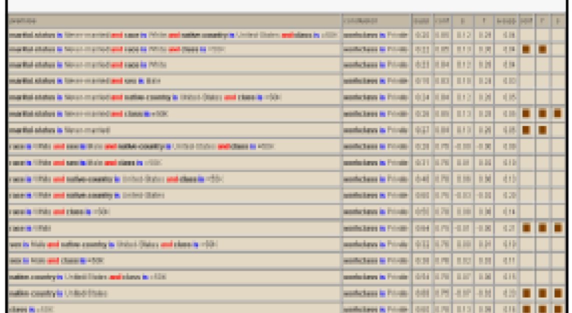
Comparison of all Pareto borders



■ indicates rules that appeared on a particular Pareto border

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Final remarks

- The experiment is an illustration of all the studied and proved features of different Pareto-borders on a real dataset
- Further research will include
  - conducting of such an experiment for decision rules, at-least/at-most rules
  - searching for optimisation tricks (mostly structural) to improve the efficiency of the algorithm for rule generation

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Thank you!

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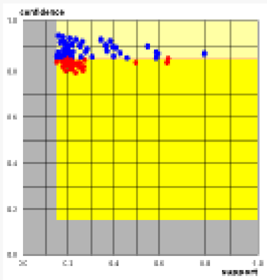
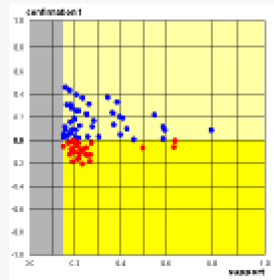
Support-confidence (race=White)



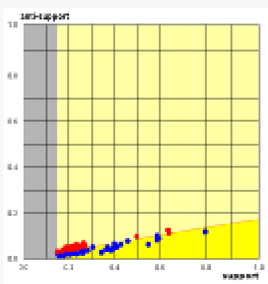
indicates rules with negative confirmation

Support-f (race=White)



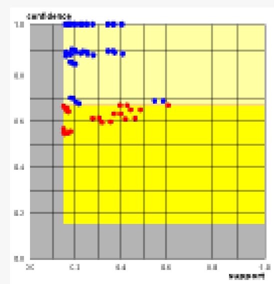
indicates rules with negative confirmation

Support-anti-support (race=White)



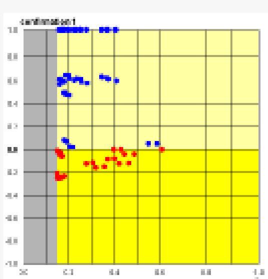
- indicates rules with negative confirmation

Support-confidence (sex=Male)



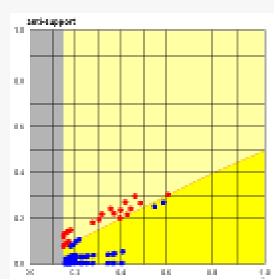
indicates rules with negative confirmation

Support-f (sex=Male)



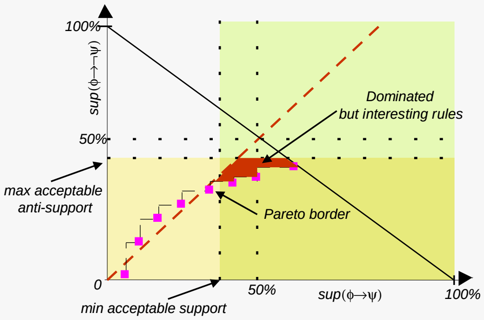
indicates rules with negative confirmation

Support-anti-support (sex=Male)



- indicates rules with negative confirmation
- the (sex=Male) class is smaller than workclass=Private

Support-anti-support Pareto border



More detailed info about the dataset

- **the dataset was downloaded from the repository of Univ. of California, Irvine**
- **32 561 instances**
- **9 nominal attributes**
  - **workclass:** Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked;
  - **education:** Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool;
  - **marital-status:** Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse;
  - **occupation:** Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces;
  - **relationship:** Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried;
  - **race:** White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.sex: Female, Male;
  - **sex :** Male, Female;
  - **native-country:** United-States, Cambodia, England, etc.;
  - **salary:** >50K, <=50K