Direct Mining of Discriminative Patterns for Classifying Uncertain Data

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Classification on Certain Data

Example:

A toy example about certain categorical dataset containing 4 classes.

Evaluation	Price	Looking	Tech. Spec.	Quality
Unacceptable	+	-	/	-
Acceptable	/	-	/	/
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- Train a classifier using the feature data converted from training data.

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- Different feature types - Binary, Numeric (New, NDPMine)

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- Uncertain Rule-based Classifier - Ripper-based uRule

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A new associative classification algorithm working on uncertain data.

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- How to cover instances?

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$$E(conf_x{}^c) = \sum_{w_i \in W} conf_{x,w_i}{}^c \times P(w_i) = \sum_{w_i \in W} \frac{sup_{x,w_i}{}^c}{sup_{x,w_i}} \times P(w_i)$$

where $P(w_i)$ is the probability of world w_i. $conf_{x,w_i}{}^c$ is the respected confidence of x on class c in world w_i, while sup_{x,w_i} ($sup_{x,w_i}{}^c$) is the respected support of x (on class c) in world w_i.

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$O(\prod_{A_k \in \mathbb{A}^u} |dom_{A_k}|^{|T|})$ possible worlds.

Efficient Computation of Expected Confidence

Since $E(conf_x{}^c) = E_{|T|}(conf_x{}^c) = \sum_{i=0}^{|T|} E_{i,|T|}(conf_x{}^c)$. The computation is divided into $|T| + 1$ steps with $E_{i,|T|}(conf_x{}^c) = E_{i,|T|}(sup_x{}^c)/i$ $(0 \leq i \leq |T|)$ computed in ith step.

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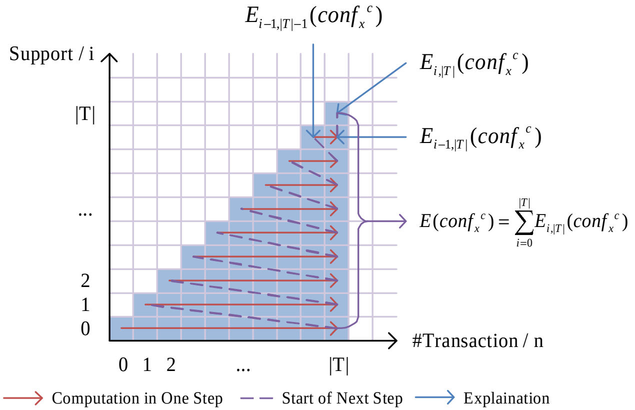

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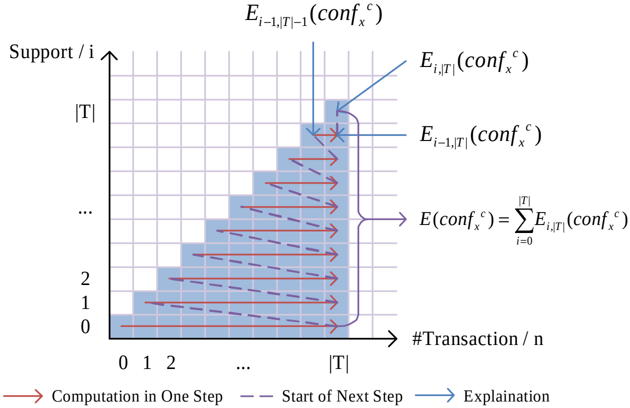

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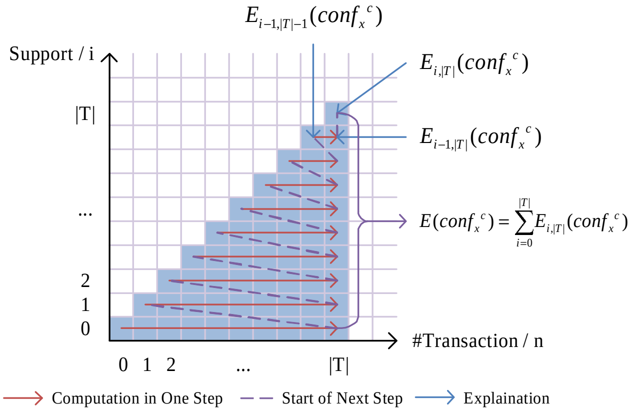

Time Complexity:
$O(|T|^2)$

Space Complexity:
$O(|T|)$

Upper Bounds of Expected Confidence

For $\forall i (1 \le i \le |T|)$, we have

$$
\begin{aligned}
& E(conf_x{}^c) = E_{|T|}(conf_x{}^c) \\
= & \sum_{k=0}^{i-1} \frac{E_{k,|T|}(sup_x{}^c)}{k} + \sum_{k=i}^{|T|} \frac{E_{k,|T|}(sup_x{}^c)}{k} \\
\le & \sum_{k=0}^{i-1} \frac{E_{k,|T|}(sup_x{}^c)}{k} + \sum_{k=i}^{|T|} \frac{E_{k,|T|}(sup_x{}^c)}{i} \\
= & \sum_{k=0}^{i-1} \frac{E_{k,|T|}(sup_x{}^c)}{k} + \sum_{k=0}^{|T|} \frac{E_{k,|T|}(sup_x{}^c)}{i} - \sum_{k=0}^{i-1} \frac{E_{k,|T|}(sup_x{}^c)}{i} \\
= & \sum_{k=0}^{i-1} E_{k,|T|}(sup_x{}^c) \times (\frac{1}{k} - \frac{1}{i}) + \frac{E(sup_x{}^c)}{i} \\
= & bound_i(conf_x{}^c)
\end{aligned}
$$

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\begin{aligned}
E({sup_x}^c) &= bound_1({conf_x}^c) \\
&\geq \cdots \geq bound_i({conf_x}^c) \geq \cdots \\
&\geq bound_{|T|}({conf_x}^c) = E({conf_x}^c)
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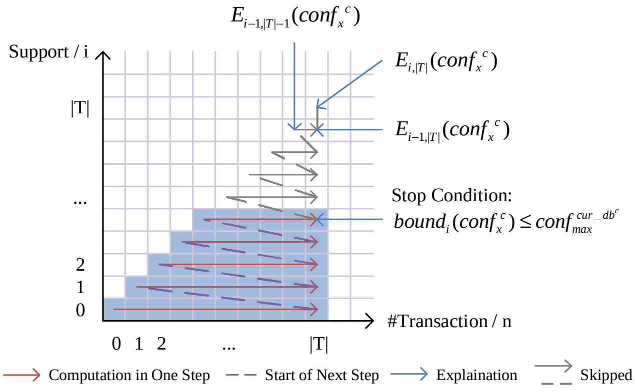
Since

$$\begin{aligned} bound_i(conf_x{}^c) &= bound_{i-1}(conf_x{}^c) \\ &\quad - \left(\frac{1}{i-1} - \frac{1}{i}\right) \times \left(E(sup_x{}^c) - \sum_{k=0}^{i-1} E_{k,|T|}(sup_x{}^c)\right) \end{aligned}$$

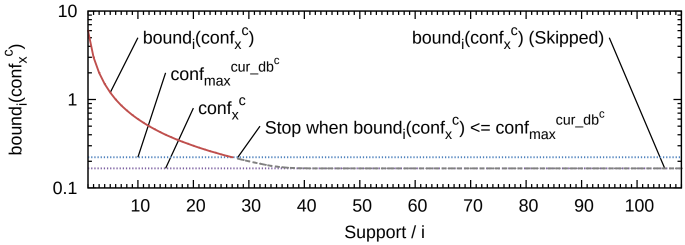
, can compute $bound_i(conf_x{}^c)$ with $bound_{i-1}(conf_x{}^c)$.

Upper Bounds of Expected Confidence



Upper Bounds of Expected Confidence

Running Example:



Algorithm Framework

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Need to sort all the uncertain attributes after certain attributes, to help shrink current projected database.

Instance Covering Strategy

Previous Strategy in HARMONY:

Just find one most discriminative covering pattern with the highest confidence for each instance. On uncertain data, the probability of the instance being covered could be very low.

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Our method:

Apply a threshold of minimum cover probability $coverProb_{min}$. Assure that the probability of each instance not covered by any pattern is less than $1 - coverProb_{min}$, by maintaining a list storing confidence values of covering patterns on class c in descending order.

Used Classifiers

SVM Classifier

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Rule-based Classifier (From HARMONY)

For each test instance we just sum up the product of the confidence of each pattern on each class and the probability of the instance containing the pattern. The class with the largest value is the predicted class of the instance.

Used Datasets

Dataset	#Instance	#Attribute	#Class	Area
australian	690	14	2	Financial
balance	635	4	3	Social
bands	539	38	2	Physical
breast	699	9	2	Life
bridges-v1	106	11	6	N/A
bridges-v2	106	10	6	N/A
car	1728	6	4	N/A
contraceptive	1473	9	3	Life
credit	690	15	2	Financial
echocardiogram	131	12	2	Life
flag	194	28	8	N/A
german	1000	19	2	Financial
heart	920	13	5	Life
hepatitis	155	19	2	Life
horse	368	27	2	Life
monks-1	556	6	2	N/A
monks-2	601	6	2	N/A
monks-3	554	6	2	N/A
mushroom	8124	22	2	Life
pima	768	8	2	Life
postoperative	90	8	3	Life
promoters	106	57	2	Life
spect	267	22	2	Life
survival	306	3	2	Life
ta_eval	151	5	3	N/A
tic-tac-toe	958	9	2	Game
vehicle	846	18	4	N/A
voting	435	16	2	Social
wine	178	13	3	Physical
zoo	101	16	7	Life

30 Public UCI Certain Datasets

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Real values have been discretizated.

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Represented by Ux@y, where x is uncertain degree and y is uncertain attribute number.

Accuracy Evaluation

Average accuracies on 30 datasets. For accuracy on each dataset, refer to our paper.

Using SVM Classifier:

Dataset	uHARMONY	DTU	uRule
U10@1	**79.0138**	74.8738	75.2111
U10@2	**78.6970**	73.1629	73.4107
U10@4	**77.9657**	72.2670	69.4649
U20@1	**78.9537**	74.6577	74.6287
U20@2	**78.6073**	72.5642	72.5460
U20@4	**77.8352**	69.9157	68.2066

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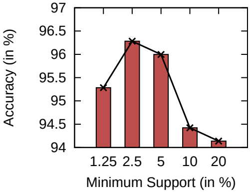
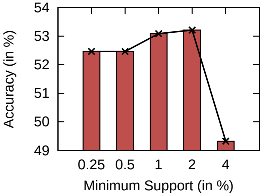
Using Rule-based Classifier:

Dataset	uHARMONY^{rule}	DTU	uRule
U10@4	**73.2517**	72.2670	69.4649

Sensitivity Test



(a) breast



(b) wine

Figure: Accuracy Evaluation of U10@1 w.r.t. Minimum Support

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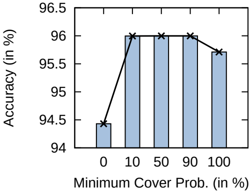

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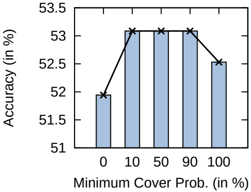

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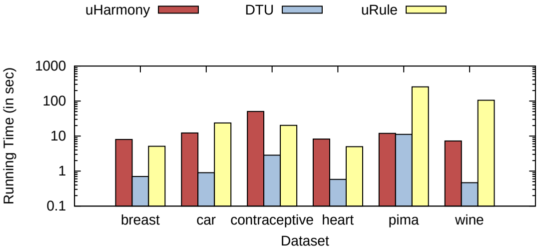
Figure: Accuracy Evaluation of U10@1 w.r.t. Minimum Cover Prob.

Runtime Efficiency



(a) Running Time (in sec)

Figure: Classification Efficiency Evaluation of U10@1

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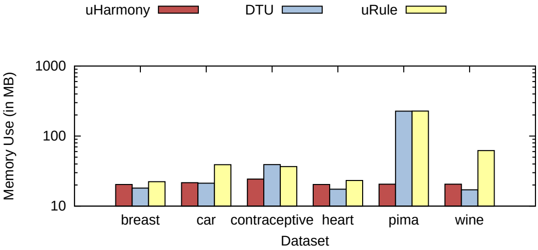
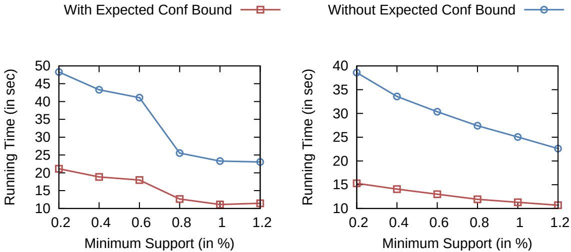


(b) Memory Use (in MB)

Figure: Classification Efficiency Evaluation of U10@1

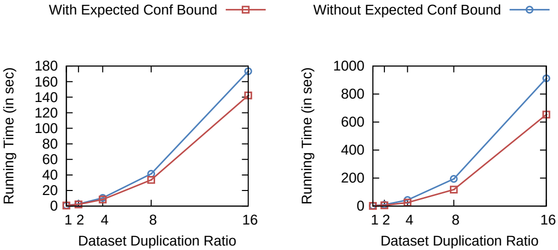
Effectiveness of the Expected Confidence Upper Bound



(a) car (b) heart

Figure: Running Time Evaluation of U10@4

Scalability Test



(a) car ($sup_{min} = 0.01$) (b) heart ($sup_{min} = 0.01$)

Figure: Scalability Evaluation (U10@1, Running Time)

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- Proposed an efficient computation of expected confidence value, together with the computation of upper bounds.
- New instance covering strategy has been proposed and tested to be effective.
- Conducted an extensive evaluation on 30 public real data, under varying uncertain parameters. With significant improvements on accuracy, comparing with two other state-of-the-art alrotihms.

Conclusions

- Proposed the first associative classification algorithm on uncertain data.
- Proposed an efficient computation of expected confidence value, together with the computation of upper bounds.
- New instance covering strategy has been proposed and tested to be effective.
- Conducted an extensive evaluation on 30 public real data, under varying uncertain parameters. With significant improvements on accuracy, comparing with two other state-of-the-art alrotihms.
- Evaluated the runtime efficiency, proved the effectiveness of using upper bounds.

The End

Thank you for Listening!

Questions or Comments?