Optimal Feature Selection for Decision Robustness in Bayesian Networks

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Abstract

In many applications, one can define a large set of features to support the classification task at hand. At test time, however, these become prohibitively expensive to evaluate, and only a small subset of features is used, often selected for their information-theoretic value. For threshold-based, Naive Bayes classifiers, recent work has suggested selecting features that maximize the expected robustness of the classifier, that is, the expected probability it maintains its decision after seeing more features. We propose the first algorithm to compute this expected same-decision probability for general Bayesian network classifiers, based on compiling the network into a tractable circuit representation. Moreover, we develop a search algorithm for optimal feature selection that utilizes efficient incremental circuit modifications. Experiments on Naive Bayes, as well as more general networks, show the efficacy and distinct behavior of this decision-making approach.

1 Introduction

Classification and Bayesian decision making are complicated by the fact that features – the input to our decision making process – are expensive to evaluate in many application domains. In medical diagnosis, cost prohibits the doctor from running all possible tests, necessitating selective and active sensing [Yu et al., 2009]. Similar issues arise in sensor networks [Krause and Guestrin, 2009], adaptive testing [Millán and Pérez-De-La-Cruz, 2002; Munie and Shoham, 2008], network diagnosis [Bellala et al., 2013], and seismic risk monitoring [Malings and Pozzi, 2016].

Traditionally, such problems have been tackled by selecting features that optimize the decision-theoretic value of information [Heckerman et al., 1993; Bilgic and Getoor, 2011]. These approaches seek to maximize the expected reward of observing the features. In one common instance, this means observing features that maximize the information gain, or equivalently, minimize the conditional entropy of the variable of interest (e.g., the medical diagnosis) [Zhang and Ji, 2010; Gao and Koller, 2011]. We refer to Krause and Guestrin [2009] for a more detailed discussion.

Another criterion called same-decision probability (SDP) came to the front more recently [Choi et al., 2012; Chen et al., 2014]. Given a current set of observed features, and the corresponding threshold-based decision, the SDP measures the robustness of this decision against further observations. It is the probability that our classification will be unchanged after all remaining features are revealed. SDP was successfully used to evaluate mammography-based diagnosis [Gimenez et al., 2014] and adaptive testing [Chen et al., 2015a].

Chen et al. [2015b] propose to use decision robustness for feature selection. In this context, we need to evaluate the expected robustness of a future decision based on the selected subset of features. It is compared to the hypothetical decision based on all features. The probability that these two classifiers agree is the expected SDP.

As our first contribution, we present the first algorithm for the expected SDP query on general Bayesian networks, which is PP-complete [Choi et al., 2012]. Previous expected SDP algorithms were restricted to Naive Bayes networks, where computing the SDP is (only) NP-hard [Chen et al., 2013], and is amenable to heuristic search. Our expected SDP algorithm is instead based on the knowledge compilation approach of Oztok et al. [2016] for solving PP-complete problems using sentential decision diagrams (SDDs) [Darwiche, 2011].

Our second contribution is an optimal feature selection algorithm. It searches for the subset of features that fits in our budget and is maximally robust according to expected SDP. The algorithm incrementally modifies an SDD representation of the Bayesian network during search, in order to efficiently re-evaluate the expected SDP of a large number of feature sets. It is the first optimal feature selection algorithm for general Bayesian network classifiers that optimizes robustness.

As a third contribution, we illustrate how decision robustness leads to different feature selection behavior on general Bayesian networks, compared to value of information. Moreover, the feature selection behavior depends strongly on the

1Note that NP ⊆ PP ⊆ PP ⊆ PSPACE ⊆ EXPTIME. MPE queries (NP), marginal probabilities (PP), and marginal MAP (NP) are all easier than (expected) SDP queries [Darwiche, 2009].
threshold used – a distinct property of the expected SDP criterion. We demonstrate our feature selection algorithm on both naive Bayes and general Bayesian network classifiers.

2 Same-Decision Feature Selection

We write uppercase letters for random variables and lowercase letters for their instantiation. Sets of variables are written in bold uppercase, and their joint instantiation in bold lowercase. Concatenations of sets denote their union (e.g. \( XY \)).

2.1 Motivation and Intuition

Imagine a scenario where a program chair (PC) wants to determine the true quality \( D \) of a submitted paper. Two reviewers, \( R_1 \) and \( R_2 \), independently evaluate the paper, and their assessments are summarized by area chair \( AC \). Figure 1 depicts this scenario as a Bayesian network. The PC wants to ascertain that accepted papers are high quality with at least 60% probability. This means that papers with two positive reviews get accepted regardless of the \( AC \)'s evaluation, as

\[
\Pr(D = + | R_1 = +, R_2 = +) = 0.84 \geq 0.60,
\]

and all other papers get rejected. We refer to this ideal classifier as \( C^* \). In practice, however, the PC only has time to observe a single evaluation. The question then is: which feature should the decision be based on; \( R_1, R_2, \) or \( AC \)?

This scenario gives rise to three possible classifiers, \( C_{R_1}, C_{R_2}, \) and \( C_{AC} \), depending on which feature is selected. For our threshold of 60%, these make the following decisions.

\[
\begin{align*}
C_{R_1} & = \left\{ \begin{array}{l}
\Pr(D = + | R_1 = +) = 0.47 \rightarrow \text{reject} \\
\Pr(D = + | R_1 = -) = 0.09 \rightarrow \text{reject}
\end{array} \right. \\
C_{R_2} & = \left\{ \begin{array}{l}
\Pr(D = + | R_2 = +) = 0.60 \rightarrow \text{accept} \\
\Pr(D = + | R_2 = -) = 0.10 \rightarrow \text{reject}
\end{array} \right. \\
C_{AC} & = \left\{ \begin{array}{l}
\Pr(D = + | AC = +) = 0.61 \rightarrow \text{accept} \\
\Pr(D = + | AC = -) = 0.12 \rightarrow \text{reject}
\end{array} \right.
\]

It is customary to evaluate these classifiers with information-theoretic measures, such as information gain, or equivalently, the conditional entropy \( H(D | F) \) of \( D \) given feature \( F \):

\[
\begin{align*}
H(D | R_1) & = 0.30 \cdot \text{h}(0.47) + 0.70 \cdot \text{h}(0.09) = 0.59 \text{ bits} \\
H(D | R_2) & = 0.20 \cdot \text{h}(0.60) + 0.80 \cdot \text{h}(0.10) = 0.57 \text{ bits} \\
H(D | AC) & = 0.16 \cdot \text{h}(0.61) + 0.84 \cdot \text{h}(0.12) = 0.60 \text{ bits},
\end{align*}
\]

where \( \text{h}(p) \) is the entropy of a Bernoulli with probability \( p \). This tells us that \( C_{R_1} \) is the best classifier, yielding most certainty about \( D \), and the area chair’s review \( C_{AC} \) is the worst, providing the least amount of information (i.e., high entropy).

Next, we formalize the robustness of a current decision as the ones made by the ideal classifier \( C^* \). The most informative classifier \( C_{R_2} \) agrees with the optimal classifier on 90% of the papers, in all cases except when \( R_1 = - \) and \( R_2 = + \). Classifier \( C_{R_1} \) also makes the same decision in 90% of the cases. Our least informative classifier \( C_{AC} \), however, outperforms both. When it rejects a paper because \( AC = - \), the ideal classifier \( C^* \) agrees 99% of the time, namely in those cases where the \( AC \) did not overrule the reviewers. When \( C_{AC} \) accepts a paper because \( AC = + \), the ideal classifier \( C^* \) agrees 56% of the time, in those cases where the reviewers both voted accept. These quantities are called same-decision probabilities. Overall, we expect \( C_{AC} \) to make the same decisions as \( C^* \) on 92% of the papers, which is its expected same-decision probability.

In conclusion, to optimize the decision, the PC should follow the AC evaluation, not an individual reviewer, even though their evaluations contain more information.

2.2 Problem Statement

Next, we formalize the robustness of a current decision against future observations as the same-decision probability.

**Definition 1.** Let \( d \) and \( e \) be instantiations of the decision variable \( D \) and evidence variables \( E \). Let \( T \) be a threshold. Let \( X \) be a set of variables distinct from \( D \) and \( E \). The same-decision probability (SDP) in distribution \( \Pr \) is

\[
\text{SDP}_{d,T}(X | e) = \sum_x [\Pr(d | xe) =_T \Pr(d | e)] \cdot \Pr(x | e).
\]

Here, the equality \( =_T \) holds if both sides evaluate to a probability on the same side of threshold \( T \), and \( [\alpha] \) is 1 when \( \alpha \) is true and 0 otherwise.

Expected SDP measures the redundancy of a feature set \( X \) if we were to first observe another feature set \( Y \).

**Definition 2.** Let \( d \) and \( e \) be instantiations of the decision variable \( D \) and evidence variables \( E \). Let \( T \) be a threshold. Let \( X \) and \( Y \) be disjoint sets of variables. The expected same-decision probability (E-SDP) in distribution \( \Pr \) is

\[
\text{SDP}_{d,T}(X | Y, e) = \sum_y \text{SDP}_{d,T}(X | ye) \cdot \Pr(y | e)
\]

\[
= \sum_{xy} [\Pr(d | xye) =_T \Pr(d | ye)] \cdot \Pr(xy | e).
\]

We will drop subscripts \( d \) and \( T \) when clear from context.

In same-decision feature selection, we are given a set of candidate features \( F \), a positive cost function \( c(.) \), and budget \( B \). The goal is to find features \( Y \subseteq F \) maximizing \( \text{SDP}_{d,T}((F \setminus Y) | Y, e) \), subject to a cost constraint \( \sum_{Y \subseteq X} c(Y) \leq B \). That is, we select those features that fit in budget and maximize the decision robustness, measured by E-SDP against the remaining features that were not selected.
3 A Tractable Circuit Representation

This section describes the logical foundation of our algorithms. Modern approaches to discrete probabilistic inference often reduce the problem to a logical one, encoding the distribution in weighted propositional logic [Chavira and Darwiche, 2005; 2008; Sang et al., 2005; Dechter and Matescu, 2007; Fierens et al., 2015]. This technique naturally exploits structure in the distribution such as determinism and context-specific independence, and attains state-of-the-art performance [Darwiche et al., 2008; Choi et al., 2013]. In particular, we follow the knowledge compilation approach, where one compiles the logical description of the inference problem into a tractable (circuit) representation [Selman and Kautz, 1996; Darwiche and Marquis, 2002]. Knowledge compilation is particularly useful some of the harder reasoning problems in AI, referred to as problems “beyond NP”.

These include problems that are PP-hard, NP<sup>PP</sup>-hard, or even PP<sup>PP</sup>-hard, while still being of significant practical interest [Huang et al., 2006; Oztok et al., 2016]. SDP and E-SDP queries belong to this family.

We employ the same notation for propositional logic variables and random variables, as well as for their instantiations. A literal is a variable or its negation. Abusing notation, an encoding often reduce the problem to a logical one, encoding algorithms. Modern approaches to discrete probabilistic inference problems in AI, referred to as problems “beyond NP”. Indeed, Pr(x|e) = φ<sub>e</sub>(x|e), where x and e are variable instantiations, encoded using indicators from I.

3.2 Sentential Decision Diagrams

Sentential decision diagrams (SDDs) [Darwiche, 2011] are a knowledge compilation target language that allows for efficient WMC inference and incremental modifications (conjunction, disjunction, and conditioning of circuits) [Van den Broeck and Darwiche, 2015], which our algorithms will make use of. SDDs are also the most compact representation known to have these properties, exponentially smaller than ordered binary decision diagrams (OBDDs) [Bova, 2016].

Partitions SDDs are based on a new type of decomposition, called (X, Y)-partitions. Consider a sentence α and suppose that we split its variables into two disjoint sets, X and Y. It is always possible to decompose the sentence α as

\[ \alpha = (p_1(X) \land s_1(Y)) \lor \cdots \lor (p_n(X) \land s_n(Y)) \].

Sentences p<sub>i</sub> are called primes, and are mutually exclusive, exhaustive, and consistent. Sentences s<sub>i</sub> are called subs.

For example, consider Sentence 1 in our encoding of Pr(R<sub>1</sub>|D). By splitting the variables into X = {D, R<sub>1</sub>} and Y = {P<sub>4</sub>}, we obtain the (X, Y)-partition

\[ ((\neg D \land \neg R_1) \land P_4) \lor ((D \lor R_1) \land \neg P_4). \]

The primes are indeed mutually exclusive, exhaustive and non-false. This partition is represented in terms of logical gates by the top two layers of the SDD circuit in Figure 2a. In the graphical depiction of SDDs, primes and subs are either a constant, a literal or an input wire from another gate.

Vtrees SDDs represent a sequence of recursive (X, Y)-partitions. Determining which X and Y to use in every partition in the SDD is governed by a variable tree (vtree): a full, binary tree, whose leaves are labeled with variables; see Figure 2b. The root v of the vtree partitions variables into those appearing in the left subtree (X) and those in the right subtree (Y). This implies an (X, Y)-partition of sentence α, leading to the top two layers in Figure 2a. We say that the SDD’s root node is normalized for vtree node v. The primes and subs of

\[ \phi^w_\alpha(x) = \sum_{x \models \alpha} \prod_{\ell \in \Phi} w(\ell), \text{ and} \]

\[ \phi^w_\alpha(x|e) = \phi^w_\alpha(x \land e)/\phi^w_\alpha(e). \]

We omit w when clear from context and write φ<sub>α</sub> for φ<sub>α</sub>(⊤).

Given a weighted propositional logic encoding (α, w) of Pr,

\[ \text{Figure 2: Tractable SDD circuit representation for Sentence 1} \]

\[ \text{\[\text{a) Sentential decision diagram (SDD)} \text{ b) Variable tree (vtree)\] \}

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\[ \text{\[\text{a) Sentential decision diagram (SDD) } \text{ b) Variable tree (vtree)\] \} \]
Figure 3: Constrained vtree where $X = \{R_2, AC\}$, $Y = \{R_1\}$, $Y$-constr. node is 2 and $XY$-constr. node is 4.

Algorithm 1 SDP$_{d,T}(X \mid Y, e)$

**Input:** $d$: hypothesis; $T$: threshold $X,Y$: disjoint sets of features; $e$: evidence $S$: $Y$-constrained and $XY$-constrained SDD

**Output:** computes SDP$_{d,T}(X \mid Y, e)$

1. for each SDD node $\alpha$ in $S$ (children before parents) do
   2. if $\alpha$ is a terminal then
      3. $vr_1(\alpha) \leftarrow \phi_{\alpha}$ if $\alpha \sim e$; else 0
      4. $vr_2(\alpha) \leftarrow \phi_{\alpha}$ if $\alpha \sim de$; else 0
   5. else
      6. $vr_1(\alpha) \leftarrow \sum_{(p_i,s_i) \in \alpha} vr_1(p_i) \times vr_1(s_i)$
      7. $vr_2(\alpha) \leftarrow \sum_{(p_i,s_i) \in \alpha} vr_2(p_i) \times vr_2(s_i)$
   8. for each SDD node $\alpha$ in $S$ (children before parents) do
      9. if $\alpha$ is a terminal then
         10. $vr_3(\alpha) \leftarrow \phi_{\alpha}$
      11. else if $\alpha$ is $XY$-constrained then
         12. $\beta \leftarrow Y$-constrained ancestor of $\alpha$
         13. $vr_3(\alpha) \leftarrow vr_1(\alpha)$ if $vr_2(\beta) =_T vr_2(\beta)$; else 0
      14. else
         15. $vr_3(\alpha) \leftarrow vr_1(\alpha)$
      16. $\phi(e) \leftarrow vr_1(S)$; $Q \leftarrow vr_3(S)$
   17. return $Q/\phi(e)$

4. Computing the Expected SDP with SDDs

We now introduce our approach to compute E-SDP by compilation into SDDs. As described in Section 3, we can encode a Bayesian network into weighted propositional logic $(\alpha, w)$ and further compile it into an SDD. Then, computing the E-SDP over a set of features translates to computing the E-SDP over a set of variables of its circuit encoding.

**Definition 3.** Let $d$ and $e$ be instantiations of the decision variable $D$ and evidence variables $E$. Let $T$ be a threshold. Let $X$ and $Y$ be disjoint sets of variables. The expected same-decision probability on a WMC encoding $(\alpha, w)$ of $Pr$ is

$$\text{SDP}_{d,T}(X \mid Y, e) = \sum_{x,y} [\phi^w_\alpha(d \mid xye) =_T \phi^w_\alpha(d \mid ye)] \cdot \phi_\alpha(xy \mid e).$$

Our approach to compute the E-SDP using SDDs is shown in Algorithm 1. It requires a special type of SDDs that are normalized for constrained vtrees [Oztok et al., 2016].

**Definition 4.** A vtree node $v$ is $X$-constrained, denoted $v_X$, iff it appears on the right-most path of the vtree and $X$ is exactly the set of variables outside $v$. A vtree is $X$-constrained iff it has an $X$-constrained node. An SDD is $X$-constrained iff it is normalized for an $X$-constrained vtree. An SDD node is $X$-constrained iff it is normalized for $v_X$.

In order to compute SDP$_{d,T}(X \mid Y, e)$, we require an SDD that is normalized for a vtree with a $Y$-constrained node and an $XY$-constrained node. Figure 3 depicts an example of such a vtree, which would allow us to compute SDP$(R_2, AC \mid R_1)$. Note that the $Y$-constrained node $\forall_Y$ is always an ancestor of the $XY$-constrained node $\forall_{XY}$.

The algorithm performs two bottom-up passes over the SDD and keeps three value registers per node. In the first pass (Lines 1–7), it computes the WMC of each SDD node with respect to instantiations $e$ and $de$, similar to the SDD algorithm of Oztok et al. [2016]. Intuitively, each SDD node normalized for $\forall_{XY}$ or its ancestor represents some instantiation of variables outside that vtree node (which must be variables in $XY$). For such node, $vr_1$, or $vr_2$, stores the probability of $e$, or $de$, joint with the instantiation represented by that node.

**Lemma 1.** Let $\alpha$ be an SDD node normalized for vtree $v$. Then, $vr_1(\alpha) = \phi_{\alpha}(e_v)$ and $vr_2(\alpha) = \phi_{\alpha}(d_v,e_v)$, where $e_v$ and $d_v$ denote the subset of instantiation $e$ and $d$, respectively, that pertains to the variables of vtree $v$.

During the second bottom-up pass (Lines 8–15), the algorithm simply computes the WMC for an SDD node $\alpha$ that is neither an $XY$-constrained node nor its ancestor. Next, if $\alpha$ is $XY$-constrained and represents some instantiation $xy$, then its $Y$-constrained ancestor $\beta$ must represent $y$. The if-condition of Line 13 is then analogous to the indicator function in Definition 2. More precisely, Line 13 computes $[\phi_\alpha(d \mid e) =_T \phi_\beta(d \mid e)] \phi_\alpha(e)$. We can use induction on the distance of $v$ to $\forall_{XY}$ to show that the following holds.

**Lemma 2.** Let $\alpha$ be an SDD node normalized for vtree $v$, where $v$ is $\forall_{XY}$ or one of its ancestors, but $v$ is not an ancestor of $\forall_v$. Let $\beta$ be the $Y$-constrained ancestor of $\alpha$ (that is, $\beta$ is normalized for $\forall_y$). Let $W = \text{vars}(v) \cap X$. Then,

$$vr_3(\alpha) = \sum_w [\phi_\alpha(d \mid we) =_T \phi_\beta(d \mid e)] \phi_\alpha(we).$$

It follows from above lemma that at the $Y$-constrained SDD node $\alpha$, our algorithm computes the following quantity:

$$vr_3(\alpha) = \sum_x [\phi_\alpha(d \mid xe) =_T \phi_\alpha(d \mid e)] \phi_\alpha(xe).$$

We can again use induction on the distance of $v$ to $\forall_{XY}$ to show the following.

**Lemma 3.** Let $\alpha$ be an SDD node normalized for vtree $v$ that is $\forall_{Y}$ or one of its ancestors. Let $Z = \text{vars}(v) \cap Y$. Then,

$$vr_3(\alpha) = \sum_{x,z} [\phi_\alpha(d \mid xze) =_T \phi_\alpha(d \mid ze)] \phi_\alpha(xze).$$

The complete proofs of above lemmas are found in the appendix. Line 16 now computes the quantity

$$Q = \sum_{x,y} [\phi_S(d \mid xye) =_T \phi_S(d \mid ye)] \cdot \phi_S(xye).$$
Algorithm 2 FS-SDD($Q, d, b$)

**Input:**
- $d$: hypothesis;  
- $T$: threshold;  
- $e$: evidence;  
- $B$: budget;  
- $F$: \{ $F_1, \ldots, F_k$\}, set of features  
- $c$: cost function;  
- $S$: F-constrained SDD

**Data:**
- $Q \leftarrow \{\}$: features selected;  
- $b \leftarrow B$: budget left  
- $k \leftarrow 0$: depth;  
- $Y$: best subset;  
- $p \leftarrow$ best E-SDP

**Output:** Subset $Y \subseteq F$ with best E-SDP within budget $B$

1. if $b < 0$ or $k > n$ then return
2. else if $c(F_k) \leq b$ then
3. \hspace{1em} $Z \leftarrow Q \cup \{F_k\}$
4. \hspace{1em} move variable in $S$ to make it $Z$-constrained
5. \hspace{1em} if $SDP((F \setminus Z) | Z, e) > p$ then
6. \hspace{2em} $Y \leftarrow Z$
7. \hspace{2em} $p \leftarrow SDP((F \setminus Z) | Z, e)$
8. \hspace{1em} FS-SDD($Z, k + 1, b - c(F_k)$)
9. FS-SDD($Q, k + 1, b$)

Dividing $Q$ by $\forall r_1(S) = \phi_S(e)$ yields the expected SDP.

**Proposition 1.** Alg. 1 computes $SDP_{d,T}(X | Y, e)$.

Note that the algorithm performs a constant amount of work at each SDD node. Thus, we have the following.

**Proposition 2.** Alg. 1 runs in time linear in the size of SDD $S$.

5 Feature Selection using SDDs

A naive approach to feature selection computes E-SDP for each possible subset of features that respects the budget and chooses the best one. However, this requires exponentially many compilations of SDDs since our E-SDP algorithm expects a different $Y$-constrained SDD for each subset $Y$.

We can improve upon this approach by introducing an operation to move a variable within a vtree and adjusting the SDD accordingly. Suppose we want to move a variable $X$ of an SDD $\alpha$, normalized for vtree $v$. If we condition $\alpha$ on $X$ being true, the resulting SDD $\beta = \alpha | X$ no longer contains the variable $X$. Similarly, we can obtain an SDD for $\gamma = \alpha | \neg X$. Since $X$ is not used for $\beta$ and $\gamma$, we can move it to a new location to obtain a new vtree $v'$, and $\beta$ and $\gamma$ will still be normalized for vtree $v'$. Finally, we join them to get a new SDD $\alpha' = (X \land \beta) \lor (\neg X \land \gamma)$, using an efficient APPLY function [Darwiche, 2011; Van den Broeck and Darwiche, 2015], which is normalized for vtree $v'$ and still represents the same Boolean formula as $\alpha$. Thus, once we compile an SDD, we can move variables around to make a $Y$-constrained node for each subset $Y$, instead of recomputing the SDD.

Our proposed algorithm FS-SDD, shown in Algorithm 2, generates candidate subsets by depth-first searching an inclusion-exclusion tree, as described in Korf [2009] and Chen et al. [2015b]. At each depth of the tree, we either include or exclude the variable pertaining to that depth in the subset. We backtrack if the cost so far exceeds the budget. Each time we include a variable in the subset, the expected SDP over that subset is computed using Algorithm 1, updating the optimal subset and its E-SDP as necessary.

Analysis We illustrate that moving a variable each search iteration of FS-SDD is efficient, if the input SDD $S$ is normalized for a vtree that is right-linear outside of its F-constrained node.\(^3\) For example, for $F = \{R_1, R_2, AC\}$, Figure 4a satisfies this requirement, but Figure 3 does not. Each time we compute E-SDP over $Z = Q \cup \{F_k\}$, we already have a Q-constrained node from the last recursive step, and variable $F_k$ should appear inside the Q-constrained vtree but outside the F-constrained vtree. We can simply move $F_k$, using the operation defined previously, right after the nth variable in the vtree where $n$ is the size of $Q$. Figure 4 gives an example of such operation where $Q = \{R_1\}$ and $F_k = AC$. In other words, the $F$ variables appear in the same order in the vtree as in the path to the current search point in the inclusion-exclusion tree. This also maintains the right-linear structure outside the F-constrained node, so we only need to move one variable in each search step.

6 Experimental Evaluation

We now empirically evaluate our SDD-based approach for decision-robust feature selection.

Naïve Bayes We evaluated our system on Naïve Bayes network learned from datasets provided by the UCI repository [Bache and Lichman, 2013], BFC (http://www.berkeleymedclinic.org/), and CRESST (http://www.cse.ucla.edu/). We performed experiments using three variations of our SDD-based algorithm. We compare to MAXDR which, to our knowledge, is the only exact algorithm for feature selection based on E-SDP [Chen et al., 2015b]. Since both algorithms find exact solutions, we compare their running times.

For each network, we find the optimal subset for E-SDP with the budget set to 1/3 the number of features. In all experi-

\(^3\)A vtree is right-linear if each left child is a leaf.
Table 6: Running time (s) on general Bayesian networks.

<table>
<thead>
<tr>
<th>Network</th>
<th>source</th>
<th># nodes</th>
<th>naive</th>
<th>FS-SDD</th>
</tr>
</thead>
<tbody>
<tr>
<td>alarm</td>
<td>UAI</td>
<td>76</td>
<td>23.581</td>
<td>14.732</td>
</tr>
<tr>
<td>win95pts</td>
<td>UAI</td>
<td>37</td>
<td>143.920</td>
<td>19.061</td>
</tr>
<tr>
<td>tcc4e</td>
<td>HRL</td>
<td>168</td>
<td>28.072</td>
<td>6.667</td>
</tr>
<tr>
<td>emdec6g</td>
<td>UAI</td>
<td>203</td>
<td>105.660</td>
<td>6.667</td>
</tr>
<tr>
<td>diagnose</td>
<td>UAI</td>
<td>145</td>
<td>97.969</td>
<td>6.667</td>
</tr>
</tbody>
</table>

Figure 7: Expected SDP by threshold. Large markers indicate a change in the optimal selected subset.

high-treewidth networks. [Choi et al., 2013] We also want to stress that the running time includes initial SDD compilation time, which in practice would be performed in an offline phase. Once we compile a constrained SDD, we can make observations and find the next optimal subset in an online fashion, thereby making decisions in a sequential manner.

Threshold-Based Decisions Lastly, we demonstrate that decision robustness is not only a function of the probability distribution and features but also of the threshold, unlike other measures of value of information. For networks alarm and win95pts, we used FS-SDD to select features from F, which the set of all leaf nodes in each network. No evidence was asserted, the decision variable was chosen randomly from root nodes, and the budget was set to 1/3 the size of F. Using the same decision variable, we repeatedly evaluated our algorithm with decision thresholds in \{0.1, 0.2, \ldots, 0.9\}. Figure 7 shows different E-SDP for different thresholds. In fact, FS-SDD selects different features as the threshold changes. For example, three leaf nodes are chosen as an optimal subset for alarm for \(T \in [0.1, 0.6]\), whereas one leaf node can achieve expected SDP of 1.0 for \(T \in [0.7, 1.0]\). Intuitively, the E-SDP measures redundancy of remaining features given a selected set of features, taking into account the decision procedure defined by the threshold. On the other hand, other measures such as information gain are unaware of the decision procedure and choose the same features regardless of changes in threshold.

7 Conclusion We presented the first algorithm to compute the expected same-decision probability on general Bayesian network, as well as the first algorithm to use this measure of decision robustness for feature selection on general networks. This approach yields distinct results from other selection criteria. Our algorithms exploit the properties of sentential decision diagrams to evaluate and search feature sets efficiently.

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