Abstract

Many computational problems in modern society account to probabilistic reasoning, statistics, and combinatorics. A variety of these real-world questions can be solved by representing the question in (Boolean) formulas and associating the number of models of the formula directly with the answer to the question. Since there has been an increasing interest in practical problem solving for model counting over the last years, the Model Counting (MC) Competition was conceived in fall 2019. The competition aims to foster applications, identify new challenging benchmarks, and to promote new solvers and improve established solvers for the model counting problem and versions thereof. We hope that the results can be a good indicator of the current feasibility of model counting and spark many new applications. In this paper, we report on details of the Model Counting Competition 2020, about carrying out the competition, and the results. The competition encompassed three versions of the model counting problem, which we evaluated in separate tracks. The first track featured the model counting problem (MC), which asks for the number of models of a given Boolean formula. On the second track, we challenged developers to submit programs that solve the weighted model counting problem (WMC). The last track was dedicated to projected model counting (PMC). In total, we received a surprising number of 9 solvers in 34 versions from 8 groups.

1 Introduction

Applications Many computational questions in modern society account to probabilistic reasoning, statistics, and combinatorics. Examples of such questions are autonomy for safety-critical tasks [36], identifying the reliability of energy infrastructure [23], interactions in bioinformatics [54], recognizing spam [56, 67], optimizing budgeting in viral marketing [54], learning preference distributions [13], carrying out patient case simulations [60], or predicting weather [11].

A variety of these real-world questions can be solved by representing the question in (Boolean) formulas [20, 70, 87] and associating the number of models of the formula directly with the answer to the question. Since there has been an increasing interest in practical problem solving for counting the number of models over the last years, the Model Counting (MC) Competition was conceived in October 2019 to deepen the relationship between latest theoretical and practical development on implementations for the model counting problem and their practical applications.

The competition aims at identifying new challenging benchmarks, at promoting new solvers, at improving established solvers for the model counting problem and versions thereof, and at facilitating the exchange of ideas and combining methods. While this is a “competition” and we challenge researchers and developers, there are no monetary prizes. We hope that active participation, collaboration, and long term improvements extend the feasibility of model counting in practice and spark many new applications.

We follow a direction in the community of constraint solving and mathematical problem solving, where already many competitions and challenges have been organized such as on ASP [19] (7 editions), CSP [66, 73, 79] (19 editions), SAT [43] (20 editions), SMT [41] (14 editions), MaxSAT [3] (14 editions), UAI [39] (6 editions), QBF [63] (9 editions), and various problem domains such as DIMACS (12 editions) [45] and PACE (5 editions) [25].

The submitted solvers are available at Zenodo:4292581 [29]. The benchmark instances for all tracks are available at Zenodo:3934427 [27]. The contributed and collected instances are available at Zenodo:4292168 [28].
Table 1: Overview on available model counting tools by problem domain

| Problem | Solver          | Execution | Technique | Target | Reference | Download | License |
|---------|-----------------|-----------|-----------|--------|-----------|----------|---------|
| MC      | ApproxMC        | Seq       | AC        |        | [11] Sources | MIT      |         |
|         | bdd_minisat_all | Seq       | BDD       |        | [82] Sources | MIT      |         |
|         | c2d             | Seq       | KC        | d-DNNF | [17] Binary | na       |         |
|         | Cachet          | Seq       | CC        |        | [69] Sources | zchaff   |         |
|         | d4              | Seq       | KC        | d-DNNF | [11] Binary | na       |         |
|         | DSHARP          | Seq       | KC        | d-DNNF | [58] Sources | GPL2     |         |
|         | Ganak           | Seq       | CC        |        | [72] Sources | MIT      |         |
|         | miniC2D         | Seq       | KC        | SDD    | [59] Binary | na       |         |
|         | cnf2eadt        | Seq       | KC        | EADT   | [48] Binary | na       |         |
|         | sdd             | Seq       | KC        | SDD    | [18] Binary | na       |         |
|         | sharpCDCL       | Seq       | CC        |        | na Sources | GPL2     |         |
|         | sharpSAT        | Seq       | CC        |        | [80] Sources | GPL2     |         |
|         | sts             | Seq       | AC        |        | [26] Sources | MIT      |         |
|         | countAntom      | Par       | CC        |        | [8] Sources | MIT      |         |
|         | dpdb            | Par       | DP        | PTW    | [30] Sources | GPL3     |         |
|         | gpusat          | Par       | DP        | PTW/ITW| [33] Sources | GPL3     |         |
|         | dCountAntom     | Dist      | CC        |        | [9] na         | na       |         |
|         | DMC             | Dist      | KC        | d-DNNF | [63] Binary | na       |         |
| WMC     | ADDMC           | Seq       | DP        | PTW+ADD| [21] Sources | MIT      |         |
|         | Cachet          | Seq       | CC        |        | [69] Sources | zchaff   |         |
|         | c2d             | Seq       | KC        | d-DNNF | [17] Binary | na       |         |
|         | d4              | Seq       | KC        | d-DNNF | [51] Binary | na       |         |
|         | DPMC            | Seq       | DP        | PTW+ADD+TN | [21] Sources | MIT   |         |
|         | Ganak           | Seq       | CC        |        | [72] Sources | MIT      |         |
|         | gpusat          | Par       | DP        | PTW/ITW| [32] Sources | GPL3     |         |
|         | TensorOrder     | Par       | DP        | TN     | [22] Sources | MIT      |         |
|         | miniC2D         | Seq       | KC        | SDD    | [69] Binary | na       |         |
|         | sts             | Seq       | AC        |        | [26] Sources | MIT      |         |
| PMC     | ApproxMC        | Seq       | AC        |        | [11] Sources | MIT      |         |
|         | nesthdb         | Seq       | DP        | ATW    | [42] Sources | GPL3     |         |
|         | projMC          | Seq       | KC        | d-DNNF | [32] Binary | na       |         |
|         | ganak           | Seq       | CC        |        | [72] Sources | MIT      |         |

The Problems and their complexity  Given a Boolean formula the model counting problem, MC for short\(^1\), asks to output the number of models of that formula. If in addition each literal in the formula has an associated weight and the weight of a model is the product of its weights and we are interested in the sum of weights over all models, we speak about weighted model counting, WMC for short.\(^2\) Another interesting counting problem is projected model counting, PMC for short. There, we hide some variables and we count the models after restricting them to a set \(P\) of projection variables. While the task of deciding whether a Boolean formula has a model (SAT) is already known to be \(NP\)-complete \cite{55}, its generalization to counting is believed to be even harder. Namely, MC is known to be \(#\cdot P\)-complete \cite{64} and by direct implications from a result by Toda \cite{81} any problem on the polynomial hierarchy \cite{77,78} can be solved in polynomial-time by a machine with access to an oracle that can output the model

\(^1\)The model counting problem is also known as \(#\)SAT.

\(^2\)The problem of weighted model counting is often also referred to as weighted counting, sum-of-product, partition function, or probability of evidence.
count for a given formula. While WMC is of similar complexity, PMC is even harder assuming standard complexity theoretical assumptions, more precisely, PMC is complete for the class \( \# \cdot \text{NP} \). [23]

**Existing Solvers** Many state-of-the-art solvers rely on standard techniques from SAT-based solving [40, 69, 80], knowledge compilation [51], or approximate solving [11, 12] by means of sampling using SAT solvers, and a few solvers employ dynamic programming. Table 1 provides a brief overview on recent solvers and the used techniques. We give abbreviations in a footnote below. [3] The website beyondnp.org provides a good overview. There are also preprocessors available such as B+E [49] and pmc [50]. Many solvers are highly competitive and solve various instances. However, there has still not been a competition on the topics related to model counting, which spawned our interest in organizing one.

### 2 The Problems

Before we state the considered problems, we briefly provide formal notions from propositional logic. For a comprehensive introduction and more detailed information, we refer to other sources [6, 47]. Let \( U \) be a universe of propositional variables. A literal is a variable \( x \) or its negation \( \neg x \). We call \( x \) a positive literal and \( \neg x \) a negative literal. A clause is a finite set of literals, interpreted as the disjunction of these literals. A (Boolean) formula (in conjunctive normal form) is a finite set of clauses, interpreted as the conjunction of its clauses. We let \( \text{var}(F) \) and \( \text{lits}(F) \) be the set of the variables and set of literals, respectively, that occur in \( F \). An assignment is a mapping \( \tau : X \to \{0, 1\} \) defined for a set \( X \subseteq U \) of variables. For \( x \in X \), we define \( \tau(\neg x) = 1 - \tau(x) \). By \( 2^X \) we denote the set of all assignments \( \tau : X \to \{0, 1\} \). The formula \( F \) under assignment \( \tau \) is the formula \( F_\tau \) obtained from \( F \) by (i) removing all clauses \( c \) that contain a literal set to 1 by \( \tau \) and then (ii) removing from the remaining clauses all literals set to 0 by \( \tau \). An assignment \( \tau \) satisfies a given formula \( F \) if \( F_\tau = \emptyset \). For a satisfying assignment \( \tau \), we call the set \( M \) of variables that are assigned to true by \( \tau \) as a model of \( F \), i.e., \( M = \{ x \mid x \in \tau^{-1}(1) \} \).

### 2.1 Model Counting (Track 1)

The definitions from the previous section motivate the problem of Track 1.

![Distribution over number instances and runtime intervals (track1).](image1)

![Distribution over number instances and runtime intervals (track2).](image2)

![Distribution over number instances and runtime intervals (track3).](image3)

Figure 1: Distribution over the number of selected private instances for Track 1 (MC), Track 2 (WMC), and Track 3 (PMC) grouped by the used hardness intervals. Colors indicate the “practical” hardness of the instances (easy, medium, hard, very hard).
**Problem:** MODEL COUNTING (MC)
**Input:** A Boolean formula $F$ in conjunctive normal form.
**Task:** Output the number of models of the formula $F$.

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### Data Format

The input format for providing a formula (.mcc2020.cnf) was taken from the DIMACS-format for formulas in conjunctive normal form [83]. We modified the problem description in the header to “mc” in order to indicate that we aim for the model count. More details on the format can be found in Appendix B.1.

### Instances

In order to establish a suitable set of benchmark instances from various areas, we posted an open call for benchmarks and collected benchmarks from previously known sources. Overall we received 1,220 instances from 6 groups in March 2020. Further, we took 1,619 instances from a benchmark collection initiated by Daniel Fremont [31, 37]. We did not check for duplicates. We processed all instances by using the preprocessors B+E Apr2016 [19] and pmc 1.1 [50], separately. Then, we included the unpreprocessed, the preprocessed instances (B+E), and the preprocessed instances (pmc). For pmc, we used the documented options “-vivification” “-eliminateLit” “-litImplied” “-iterate=10” “-equiv” “-orGate” “-affine”. We started B+E with the option “-limSolver=1000”. The contributors and origins of the instances are as follows:

1. 100 instances from VLSAT [https://cadp.inria.fr/resources/vlsat/], which are obtained by decomposing Petri nets into networks of automata contributed by Bouvier and Garavel [7];
2. 303 instances from 5 domains including
   (a) 29 instances from Bayes [cril.univ-artois.fr],
   (b) 32 instances from Blasted SMT [github:meelgroup/sampling-benchmarks],
   (c) 135 instances from Functional synthesis [qbflib.org],
   (d) 54 instances from Program synthesis [github:dfremont/counting-benchmarks], and
   (e) 53 instances from Quantitative information flow [github:dfremont/counting-benchmarks] contributed by Lai, Golia, and Meel [28];
3. 596 instances from Program Analysis [zenodo.4292167], which are generated by a symbolic execution bug finding tool called CAnalyze contributed by Möhle, Ge, and Biere [28];
4. 12 instances from RandomHard [zenodo.4292167], which are randomly generated benchmarks aiming for increasing difficulty with increasing its number of literals contributed by Spence [28];
5. 70 instances from ModelRB [zenodo.4292167], which are randomly generated instances that resemble many hard instances for exact phase transitions in CSP contributed by Yin, Wang, and Xu [28]; and
6. 139 instances from RandomGen [zenodo.4292167], which are randomly generated instances for testing solvers including instances on graph coloring, monotone CNFs, and 2CNFs contributed by Pehoushek [28];
7. 1,619 instances from dfremont [github:dfremont/counting-benchmarks], which is a collection of various benchmark instances originating in multiple domains retrieved from the collection by Fremont [37].

For the model counting competition, we are interested in challenging instances of varying size that are still within reach for the participants, but challenge them and require reasonable efforts to score a high rank. In order to get a
instances & $n_{\text{min}}$ & $n_{\text{max}}$ & $n_{\text{avg}}$ & $n_{\text{med}}$ & $m_{\text{min}}$ & $m_{\text{max}}$ & $m_{\text{avg}}$ & $m_{\text{med}}$ \\
public & 1.0 & 7.7M & 113k & 3.6k & 1.0 & 5.7M & 95.2k & 5.3k \\
private & 78.0 & 205.0k & 42.6k & 3.6k & 78.0 & 539k & 40.5k & 5.6k \\
all & 1.0 & 7.7M & 77.8k & 3.7k & 1.0 & 5.7M & 67.8k & 5.4k \\

(a) Overview on the number of variables and clauses for the public, private, and all instances. $n$ and $m$ represent the number of variables and clauses, respectively. max refers to the maximum; avg refers to the mean; med refers to the median.

Figure 2: Basic statistics on the selected instances for MC2020/Track1 (Model Counting).

2.2 Weighted Model Counting (Track 2)

Weighted model counting generalizes model counting as follows. Let $F$ be a formula and assume that $\text{Mod}(F)$ denotes the set of models of $F$. We let a weight function $w$ be a function that maps each literal in $F$ to a real between 0 and 1, i.e., $w : \text{lits}(F) \to [0, 1]$. While one often restricts $w(v) + w(\neg v) = 1$, we explicitly allow $0 \leq w(v) + w(\neg v) \leq 2$. Then, for an assignment $\tau$ to the variables in $F$, the weight of the assignment $\tau$ is the...


\[
\begin{array}{l|lllll}
\text{instances} & n_{\text{avg}} & n_{\text{min}} & n_{\text{max}} & m_{\text{avg}} & m_{\text{med}} \\
\hline
\text{public} & 2.03k & 181 & 5.7k & 1.26k & 432 \\
\text{private} & 1.47k & 216 & 12.8k & 1.19k & 398 \\
\text{all} & 1.75k & 181 & 12.8k & 1.22k & 418 \\
\end{array}
\]

(a) Overview on the number of variables and clauses for the public, private, and all instances. \( n \) and \( m \) represent the number of variables and clauses, respectively. max refers to the maximum; avg refers to the mean; med refers to the median.

(b) Overview on the number of variables of the private instances. The red dotted line indicates the median over number of variables and the green dashed line represents the mean over number of variables.

Figure 3: Basic statistics on the selected instances for MC2020/Track2 (Weighted Model Counting).

The weighted model count (wmc) of formula is the sum of weights over all its models, i.e.,

\[ wmc(F, w) := \sum_{M \in \text{Mod}(F)} w(M). \]

**Problem:** Weighted Model Counting (WMC)

**Input:** A Boolean formula \( F \) in conjunctive normal form and a weight function \( w \).

**Task:** Output the weighted model count \( wmc(F, w) \).

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**Data Format** The input format for providing a formula (.mcc2020.wcnf) was taken from the DIMACS-format for formulas in conjunctive normal form [83] and its modification in the solver Cachet [89]. We modified the problem description in the header to “wmc” in order to indicate that we aim for the weighted model count. In contrast to cachet, we define the weight function slightly different. Weights are given explicitly unless we assume that both the positive and negative literal have weight 1, i.e., \( w(v) = w(\neg v) = 1 \) for variable \( v \). If a weight is stated for a literal, then we assume both the weight for the positive and negative literal are given. For a literal \( \ell \), we provide weights as floating point numbers between \( 0 \leq w(\ell) \leq 1 \). More details on the format can be found in Appendix B.2.

**Instances** For this track, we took publicly available [31, 37] instances and modified some weights. Overall the set consists of 1091 instances. While one can apply the preprocessor pmc [50] also to WMC, we did not apply

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5The description for format that Cachet uses for weighted model counting is given in the file “README.txt” of the solver package, which is available online at [https://www.cs.rochester.edu/u/kautz/Cachet/cachet-wmc-1-21.zip](https://www.cs.rochester.edu/u/kautz/Cachet/cachet-wmc-1-21.zip)

6According to the documentation of pmc at [http://www.cril.univ-artois.fr/kc/pmc.html](http://www.cril.univ-artois.fr/kc/pmc.html) the options “-vivification” “-eliminateLit” “-litImplied” “-iterate=10” preserve all models.
preprocessing here. Further, we did not check for duplicates. Similar to the previous track, we first estimated the “practical hardness” of the instances. Therefore, we used the solvers Cachet \[69\], d4 \[51\], and miniC2D \[59\] on all instances with a timeout of 2 hours. From the classified instances, we chose 200 instances by sampling uniformly at random among the distribution given in Figure 1. We numbered the instances from 1 to 200 with increasing hardness, selected the odd numbered instances as private and even numbered instances as public instances. Figure 3 shows statistics on the resulting instances for Track 2. The 100 public instances were disclosed at \(mccompetition.org\) in beginning of May. Both public and private instances are available for download at Zenodo:3934427 \[27\]. The links also refer to a document that contains the mapping of the selected instances and the original instance.

### 2.3 Projected Model Counting (Track 3)

While the previous two tracks featured the model counting problem and its weighted version, we might have situations during modeling where we have to introduce auxiliary variables that are important for the satisfiability of the formula, but they increase the number of solutions and should not be counted. So multiple solutions that include auxiliary variables count as just one solution for us if we ignore the auxiliary variables. However, if we are only interested to obtain the number of solutions with respect to the variables of interest, we generalize the problem to projected model counting as follows. Therefore, let \(F\) be a Boolean formula and \(P \subseteq \text{var}(F)\) be a set of variables, called \textit{projection variables}. We define the projected model count \(\text{pmc}(F,P)\) of the formula by

\[
\text{pmc}(F,P) := |\{M \cap P \mid M \in \text{Mod}(F)\}|.
\]

This gives then raise to the following problem:

\begin{center}
\begin{tabular}{ | l | l |}
\hline
\textbf{Problem:} & PROJECTED MODEL COUNTING PROBLEM (PMC) \\
\hline
\textbf{Input:} & A Boolean formula \(F\) in conjunctive normal form and a set \(P \subseteq \text{var}(F)\) of \textit{projection variables}. \\
\hline
\textbf{Task:} & Output the projected model count \(\text{pmc}(F,P)\). \\
\hline
\end{tabular}
\end{center}

\textit{Sometimes the problem is referred to as \#∃SAT and was originally coined under the name #NSAT, for “nondeterministic SAT” by Valiant \[84\].}

#### Data Format

The input format for providing a formula (.mcc2020_pcnf) was taken from the DIMACS-format for formulas in conjunctive normal form \[83\] and its modification as used in the solver Ganak \[72\]. We modified the problem description in the header to “pmc” in order to indicate that we aim for the projected model count. Further, we indicate projection variables by a line starting with “vp” followed by the respective variables and terminated by a 0. More details on the format can be found in Appendix B.3.

#### Instances

Similar to the previous tracks, we posted an open call to submit new benchmark sets. We received two submissions and included in addition the publicly available instances \[37\] instances. Overall the set consists of 985 instances. We applied the preprocessor pmc \[50\] using the options “vivification” “eliminateLit” “litImplied” “iterate=10” to the sets dfremont and 2-QBF and included the resulting instances. Due to time constraints and runtime limitations on the cluster, we were unable to apply the preprocessing to the benchmark set Neural. We did not check for duplicates. The contributors and origins of the instances are as follows:

1. 403 instances from dfremont-project (\texttt{github:dfremont/counting-benchmarks}), which is a collection of various instances originating in multiple domains \[37\] from which we took the preprocessing instances only;

2. 162 instances from 2-QBF (Zenodo:4292168), which originate in the QBF Evaluation 2017 and 2018 \[61, 62\] and have been converted to a model counting problem (\texttt{github:berkeley-abc/abc}) \[57\] contributed by Golia and Meel \[28\].

3. 420 instances from Neural (Zenodo:4292168), which are instances that originate in verifying neural networks (\texttt{github:teobaluta}) contributed by Baluta, Shen, Shinde, Meel, and Saxena \[28\].
| instances | $m_{\text{min}}$ | $m_{\text{avg}}$ | $m_{\text{med}}$ | $p_{\text{min}}$ | $p_{\text{max}}$ | $p_{\text{avg}}$ |
|-----------|----------------|----------------|----------------|----------------|----------------|----------------|
| public    | 385           | 355k           | 586k           | 28             | 726            | 138            |
| private   | 1.15k         | 325k           | 184k           | 42             | 813            | 136            |
| all       | 385           | 340k           | 557k           | 28             | 813            | 137            |

(a) Overview on the number of variables and clauses for the public, private, and all instances. $m$ and $p$ represent the number of clauses and projection variables, respectively. max refers to the maximum; avg refers to the mean; med refers to the median.

Figure 4: Basic statistics on the selected instances for MC2020/Track3 (Projected Model Counting).

(b) Overview on the number of projection variables of the private instances. The red dotted line indicates the median over number of variables and the green dashed line represents the mean over number of variables.

Again, we ran existing solvers on all instances with a timeout of 2 hours, namely, clasp [38], Ganak [72], and projMC [52]. However, we had to exclude the results from projMC, since it segfaulted notably often on our systems. From the instances, we chose 200 instances by sampling uniformly at random among the distribution given in Figure 1. Then, we followed the same approach as on the two other tracks. Both public and private instances, including a mapping to the original source, are available for download at Zenodo:3934427 [27].

3 Competition Settings

In the following, we state the submission requirements for the 1st Model Counting Competition and basic information on the system on which we ran the challenge.

Submission Requirements and Limits In order to facilitate participation of many teams, we had a very relaxed submission policy, namely the software needs to be executable on the evaluation system (Linux) and initial submissions have to be done on the cloud evaluation platform optil.io [85]. Since our evaluation resources were limited and we were interested in the solving behavior on a larger number of instances while allowing the participants to have a “training” phase on public instances, we restricted the runtime to 1,800 seconds (Track 1+2) and 3,600 seconds (Track 3) and the available main memory to 8GB per instance. Note that in general, we considered a solver to be better than another, if it solves more instances faster than the other solver.

Hardware Finally, we evaluated the solvers on a cluster running on Ubuntu 16.04.1 LTS Linux machines and a Linux kernel 4.4.0-184. The cluster comprised 9 nodes each equipped with two Intel Xeon E5-2650 CPUs consisting of 12 physical cores 256 GB RAM. We forced performance governors to 2.2 GHz clock speed [71], disabled hyper threading, and enforced the process that handles the solver invocation to run on cores 0,1,14,15 and enforced solvers to run on cores 2–6, 7–11, 14–18, and 19–23. We explicitly disabled transparent huge pages [34].
4 Participants and Results

For the model counting competition, we received submissions from 9 teams participants coming from 8 countries and four regions: France, Germany, India, Japan, Singapore, Poland, USA. 17 versions were submitted for Track 1, 11 versions for Track 2, and 6 versions for Track 3.

4.1 Track 1: Model Counting

Figure 5a illustrates runtime results for all submitted solvers as CDF plot. Table 5b gives a detailed overview on the standings and solvers. We allowed each solver 30 minutes per instance. We ranked the solvers based on the number of solved instances for which a model count was outputted and the model count was within a 10% accuracy. More precisely, we precomputed the model count $c_{\text{pre}}$ for most of the instances. For instances where we knew a model count, we marked an instance as solved accurately by a solver if the model count $c_{\text{solver}}$ outputted by the solver satisfied the following equation:

$$c_{\text{pre}} - \frac{1}{10}c_{\text{pre}} \leq c_{\text{solver}} \leq c_{\text{pre}} + \frac{1}{10}c_{\text{pre}}.$$

In order to open up the competition for solvers that allow only approximate model counting, we decided not to disqualify solvers that output solutions that are outside the accuracy interval. We counted solutions to instances for which we did not know the model count as successful, if the solver was the only solver that outputted the model count and if an exact solver also outputted a solution if the model count was within the accuracy interval. Table 5b also contains an overview on the total number of solutions each solver outputted as well as the number of solved instances within accuracy 1% (column #1) and 0% (column #0).

Winning Team  Mate Soos, Shubham Sharma, Subhajit Roy, and Kuldeep S. Meel won this year’s Track 1 with their submission nus-barganak by solving 75 private instances in overall 12.8 hours at an average of 604 seconds when considering the solved instances. According to their submission script, the authors employ a combination of tools, which one might consider already as a portfolio solver. Initially, they compute the independent support using B+E [49] and rewrite the input instance including the support variables for projection. Then, they run a competition version of Ganak (ganak_plus_panini) [72]. If Ganak fails, they run approxmc [74, 75].

Runner-up  Mate Soos, Shubham Sharma, Subhajit Roy, and Kuldeep S. Meel scored also the second rank with their submission nus-narasimha by solving 73 private instances in 6.7 hours at an average runtime of 324 seconds over the solved instances. According to their submission script and the shasums on the submitted binaries, the version almost identical to the winning submission. However, here they use fixed timeouts for Ganak [72] and run approxmc much earlier, which is clearly visible from the runtime results illustrated in Figure 5a.

Third Place  Adnan Darwiche and Arthur Choi accomplished a safe third place with their submission c2d. The result was in fact very close to the team that obtained already the first and the second place on the private instances. If we take a look at the instances and assume very high precision, the solver c2d would rank even better. While the developers experimented with B+E [49] as preprocessor, their final submission ran only an updated version of the solver c2d with the options “-in_memory” “-count” “-dt_method 6”.

Inconsistencies in the Outputted Model Count  On the model counting track, we observed on that some exact solvers outputted a solution that slightly varied from the precomputed model count and that results were not necessarily consistent results. Namely, on the private instances we observed the following picture: The solver c2d differed on 3 instances to the solution, which we initially precomputed with one solver, and c2d gave a solution that was even outside the 10% accuracy margin on one instance for a precomputed solution. The submission MCSim, which is based on the exact solver sharpSAT, outputted one instance a model count that varied from the precomputed value. Similar, the solver d4 gave on one instance a slightly different solution.

4.2 Track 2: Weighted Model Counting

Figure 6a illustrates runtime results for all submitted solvers as CDF plot. Table 6b gives a detailed overview on the standings and solvers. We counted solutions (accuracy) and ranked the solvers as on the previous track.
(a) Runtime results illustrated as cumulated solved instances. The y-axis labels consecutive integers that identify instances. The x-axis depicts the runtime. The instances are ordered by running time, individually for each solver.

(b) Detailed standings of the submitted solvers. POS refers to the position of the solver. \( n \) indicates the number of instances on which the solver terminated successfully. \# indicates the number of instances that have been solved with a result that was within an accuracy of 10% to the precomputed model count, \#_1 within an accuracy of 1%, and \#_0 exactly as the precomputed solution. TLE refers to the number of instances were the runtime limit was exceeded. Note that if the sum over columns \( n \) and TLE is not 100, we either observed a memory overflow or the solver terminated early without outputting a solution on the remaining instances. \( t_{avg}[s] \) contains the average runtime over all solved instances in seconds, \( t_{sum}[h] \) states the cumulative runtime over all solved instances in hours.

Figure 5: Overview on the results for Track 1 (Model Counting) on the 100 private instances.

Table 6b also contains an overview on more details in terms of accuracy, we refer to a more detailed discussion below.

**Winning Teams** The winner podium on the weighted model counting track is shared by two teams whose submissions both solved 69 instances within a 10% accuracy. One team consists of Jean-Marie Lagniez and Pierre Marquis who submitted the solver \texttt{d4} \cite{d4} and the second team of Jeffrey Dudek, Vu Phan, and Moshe Vardi who submitted the solver \texttt{ADDMC} as source code under MIT license \cite{ADDMC}. While the solver \texttt{d4} solves the instances in total in 8.7 hours and on average in 437 seconds with higher accuracy, the solver \texttt{ADDMC} outputted the model counts for
(a) Runtime results illustrated as cumulated solved instances. The y-axis labels consecutive integers that identify instances. The x-axis depicts the runtime. The instances are ordered by running time, individually for each solver.

| POS | submission            | #  | #1  | #0  | n  | TLE | t_{avg}[s] | t_{sum}[h] |
|-----|-----------------------|----|-----|-----|----|-----|------------|------------|
| 1   | d4                    | 69 | 63* | 58* | 73 | 1   | 437        | 8.7        |
|     | ADDMC                 | 69 | 62* | 29* | 74 | 0   | 21         | 0.4        |
| 3   | c2d                   | 38 | 34* | 4*  | 38 | 9   | 46         | 0.5        |
| 4   | nus-smsharma1         | 27 | 27* | 22* | 44 | 36  | 156        | 1.9        |
| 5   | nus-onlyapprox        | 22 | 22* | 17* | 94 | 0   | 38         | 1.0        |

(b) Detailed standings of the submitted solvers. POS refers to the position of the solver. # indicates the number of instances on which the solver terminated successfully. #1 indicates the number of instances that have been solved with a result that was within an accuracy of 10% to the precomputed model count, #0 within an accuracy of 1%, and #0 exactly as the precomputed solution. The symbol * indicates that the result is unreliable due to imprecise pre-computations. See discussion in the section on weighted model counting. TLE refers to the number of instances were the runtime limit was exceeded. Note that if the sum over columns n and TLE is not 100, we either observed a memory overflow or the solver terminated early without outputting a solution on the remaining instances. t_{avg}[s] contains the average runtime over all solved instances in seconds, t_{sum}[h] states the cumulative runtime over all solved instances in hours.

Figure 6: Overview on the results for Track 2 (Weighted Model Counting) on the 100 private instances.

the instances in total in incredible 0.4 hours and 21 seconds on average. However, the solver trades the fast runtime with a very high memory consumption. The solver d4 runs first the preprocessor B+E [49] and subsequently a knowledge compiler that transforms the input formula into a deterministic decomposable negation normal form from which it reads the number of solution. In contrast, the solver ADDMC employs dynamic programming and use algebraic decision diagrams as data structure.

**Third Place** Adnan Darwiche and Arthur Choi accomplished a safe third place with their submission c2d [16, 17] by solving 38 instances within the expected 10% accuracy. The submission computes a deterministic decomposable negation normal form from the input instance using the solver c2d with the options “-in_memory” “-count” “-dt_method 6”. Then, to obtain high accuracy, it determines the model count independently using a small Python program. While Table 6b suggests that c2d is not an exact solver, it is in fact the most accurate solver we received.
We refer to a short discussion on accuracy below.

Accuracy  In the result tables, we illustrate for each track the accuracy with respect to the precomputed solution, i.e., the number of instances solved within accuracy of 1% and 0% of the precomputed solution. However, we precomputed the weighted model count with the solvers Cachet, d4, and miniC2D, which output the weighted model count only with a small number of decimal places. Hence, if the solution is very close to 0, one obtains a high inaccuracy to the precomputed value. In consequence, we need to be aware that the results presented in Table 6b need detailed interpretation. When looking at the number of solved instances with higher accuracy for the solver c2d is seems quite inaccurate. However, the opposite is actually the case. The approach used in c2d provides much higher precision than our precomputed result. At this point we would like to thank Arthur Choi who pointed out the following remarks: Most knowledge compilation based model counters can save their circuits to a file and the model count can then be computed independently with a short Python script. This can be used to ensure a high/infinite precision integer/float arithmetic. The solver c2d represents floating point numbers using rational numbers, which provides a high precision for weighted model counting. In the probabilistic inference competitions at UAI, solvers are required to report the log of the probability, which is the log of the weighted model count. In fact, that value is much less likely to underflow and a log-sum-exp trick is used to carry out the actual arithmetic of counting. We will likely pick up this suggestion for the next iteration.

4.3 Track 3: Projected Model Counting

Figure 7a provides overview on runtime results for all submitted solvers as CDF plot. Table 6a lists the of participating solvers, including average runtime and total runtime of the solvers. Similar to the previous setting we check for 10% range within our precomputed value, but we allowed each solver 60 minutes per instance.

Winning Teams  Mate Soos, Shubham Sharma, Subhajit Roy, and Kuldeep S. Meel from the National University of Singapore (NUS) obtained the first place by solving 100 instances with their two submission nus-bareganak and nus-narasimha, which are contrary to their names portfolio solvers. The submission nus-bareganak used the solver ganak running for 500s and if ganak did not finish in time approxmc for the remaining time with parameter $\epsilon = 0.3$ and $\delta = 0.15$. The submission nus-narasimha runs a preprocessing step, then ganak, but prefers approxmc in the overall runtime. While the submission nus-bareganak solves the instances in total in 21.1 hours and on average in 759 seconds, the submission nus-narasimha outputted the projected model counts for the instances in total in 25.6 hours and 923 seconds on average.

Runner-up  The submission nus-onlyapprox by Mate Soos, Shubham Sharma, Subhajit Roy, and Kuldeep S. Meel ranks second. It obtained the projected model count to only one instance less that the other two portfolio submissions by using only approxmc instead of a portfolio. To our surprise, its total runtime was only 9.5 hours and 344 seconds on average.

Third Place  The third place goes to Kenji Hashimoto from the Nagoya University missing the first two ranks just by very few solved instances. Kenji’s solver GPMC is a component caching-based solver that was implemented on top of sharpSAT and glucose. It solved overall 93 in 11.7 hours at an average runtime of 454 seconds.

Fourth Place  Since the NUS group submitted two portfolio solvers in variations, we would like to point out a notable result by Jean-Marie Lagniez and Pierre Marquis who submitted the solver d4, which solved 37 instances at a total runtime of 21.0 hours with an average runtime of 2047 seconds. The submission runs first a preprocessor (vivification, literal elimination, implied literal identification) followed by the knowledge compiler d4 in projected counting mode.

7For (weighted) model counting with an arbitrarily high precision, one might require to use an additional library such as mpmath or gmp.
Figure 7: Overview on the results for Track 3 (Projected Model Counting) on the 100 private instances.

4.4 General Remarks

Overall, we were happy that many solvers performed quite well on the challenging benchmarks. For the projected counting benchmarks, we noticed that they might have been too easy. In the light of knowledge compilers, it is surprising that on our benchmark sets on Track 1 and Track 2 the results of the KC-based solvers c2d and d4 are flipped while using similar approaches in principle. This suggests that they implement different strategies, simplifications, or might even have differences in the actual compilation approach. We think it can be interesting to peruse why it is actually the case. When taking a look on the rising techniques of approximate solvers, we received interesting, fast, and quite accurate submissions, however, it is worth pointing out that the submissions seem to
profit a lot from a solving portfolio that also includes exact solving techniques. A great-performing newcomer in projected model counting was the solver GPMC, which is based on component-caching techniques. During the competition we ran into a few organizational and technical issues, which we quickly want to discuss below.

**Accuracy, Correctness, Stability, and Verification of Results** In contrast to what we heard from early SAT competitions, we noticed that most of the submitted solvers are very stable and produced no segfaults or entirely unreliable results. Still, accuracy and correctness of the various solvers might be improved. Above we mentioned that judging on the accuracy and correctness of the different solvers should be improved for the next iteration. So far, we precomputed a model count, but stored the result with lower precision for the weighted model counting instances. In consequence, an exact solver with much higher precision shows on quite a number of instances lower accuracy with respect to our naïve metric whereas it is actually much more precise. This problem might even result in instances shown as inaccurately solved when the numbers get closer to 0. Hence, we suggest for a next iteration to use as output the log of the weighted model count. Further, we observed cases where two solvers outputted different results, a situation that we also saw with exact solvers. Hence, we are facing elaborate questions that might originating in (i) bad accuracy, more specifically, (ia) having a method that is not exact (which is a conceptual topic of approximation); (ib) having inappropriate arithmetic precision such as fixed-point numbers with exact methods (which might happen in component-caching based solvers or DP-based solvers); (ic) having an output at low precision while the result was computed correctly (which might easily happen with knowledge compilers); or (ii) bugs in a supposedly exact solver. From our perspective, this clearly suggests new developments and further research. For Issue (ia) one could only allow for exact techniques or explicitly mark imprecise techniques. For Issues (ib) and (ic), a different way of outputting the information or novel output format might help. For addressing the correctness as stated in Issue (ii), we believe that it will be useful to design techniques to prove the exact model count for model counting in order to validate the actual model count. Since various model counters are based on CDCL-solving, extending techniques similar to propositional satisfiability and ideas in knowledge compilation or probabilistic inference might a direction to pursue.

**Execution** In the beginning, we used the platform Optil.io, which provided us with a uniform interface when handling submissions where we could on top see a leader board during an active competition phase. The idea with the leader board did not pan out as we could open the submissions not much in advance and then some groups submitted at the very last moment. On top, some contestants were mostly used to the StarExec system, required to submit dynamically linked binaries, and needed to generate temporary output. Since the submission system was not primarily designed for this use, debugging of the submissions was seen in some cases as quite cumbersome. To provide a uniform and reproducible evaluation platform, we decided to run the experiments on the Taurus Cluster, which we could unfortunately not complete due to a major security incident on European high performance research clusters. Luckily, Stefan Woltran and Toni Pisjak helped out on very short notice by providing resources on a cluster at TU Wien. Still, we went far beyond our initially intended schedule and finished some results only a day prior to the presentation at the SAT conference. In the competition, we used the tool runsolver to control the execution. It is known that this tool suffers from the sampling based issues, namely measuring resources results in immediately expired information and enforcing limits might not do anything if the used RSS (resident set size) exceeds the indented maximum limit only in sudden resource spikes. We did not observe immediate indicators that would prevent using runsolver in our setting. Still, we suggest to use a cgroups based system in the future, while knowing that the system does not work out of the box and installing this system requires root privileges. For the next iteration, we suggest to try StarExec and Mate Soos offered support in configuring the system.

**Data Format** We suggested a data format intending to have a distinguishable format for the tracks while keeping the format very close to the original DIMACS format and removing certain ambiguities. Since a group complained as it required reencoding the headers and breaking downwards compatibility, which might confuse users of the solvers. We will likely suggest an update to the headers and weights on WMC for the next iteration.

**Housekeeping** While the solvers performed very well and appeared quite stable in terms of the produced results, some groups followed a laissez-faire approach when constructing their submission scripts. Some solvers did not clean
up after solving leaving gigabytes of temporary data on the disk assuming that temporary directories are handled by the user or would just remove everything starting with a certain pattern in a directory when starting the script. Others, did not implement proper signal handling or included a fixed timeout. While this is clearly reasonable in a competition setting, we do not see that it fosters practical applicability of the submissions. Therefore, we suggest the definition of uniform exit codes/return values for the next iteration to avoid full log file parsing when evaluating the results and allow for simplifying the evaluation scripts. Further, we suggest not to announce a hard timeout, but instead to use a vague cutoff interval. This enforces to implement clean handling of unix system signals and not to optimize and hardcode fixed timeouts.

**Judge**  During the competition, we ran into a situation where we were imprecise with the initial competition specifications, made mistakes during the execution, or evaluation. So far, we were hopefully able to sort out all issues and complaints. However, for the next iteration, we suggest to setup one or two persons who serve as judge(s). The idea is that a judge makes final decisions if the organizers and a submitter disagree on a rule or one has to add amendments to a rule if an unforeseen situation occurs.

5 Organization

The composition of the program committee during MC 2020 was as follows:

| Program Committee | Johannes Fichte | TU Dresden |
|--------------------|-----------------|------------|
|                    | Markus Hecher   | TU Vienna & University of Potsdam |
| Student Assistant  | Florin Hamiti   | TU Dresden |

6 Conclusion and Future

We thank all the participants for their enthusiasm and strong and interesting contributions. Special thanks go to the participants who also presented work at the Model Counting Workshop at the SAT 2020 conference. We are very happy that this edition attracted many groups. While we initially ran into a few hiccups during the submission and execution phase, we were happy about strong contributions and hope that the initial execution will lead to more future editions spawning new application directions of model counting.

For the competition, we did not enforce strong requirements for submissions by allowing any kind of external libraries, binaries and by not asking for open source or public repositories of the submissions. After the competition, we released the benchmark instances and we included na"ive statistics about the instances in our report. In future, it might be interesting to investigate whether techniques for analyzing instances such as community structures in SAT solving are also interesting in the context of model counting [2]. We do not believe that the selected competition instances necessarily provide a good picture for future solvers. The competition is really just a snapshot on the current state. There might be solvers that perform well on a specific set of instances or application, then showing still practical while performing bad on this years selection. Therefore, we also released the full set of instances, which we collected or received. While this years instance selection process was fairly ad-hoc, a more sophisticated approach might prove helpful [44]. For future editions, we think that detailed solver descriptions could be interesting.

We welcome anyone who is interested in the competition to send us an email for receiving updates and joining the discussion on Slack. We look forward to the next edition. Detailed information will be posted on the website at modelcounting.org.

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A Short Solver Descriptions

ADDMC is a solver that computes the exact literal-weighted model counts of CNF formulas. The algorithm employs dynamic programming and uses Algebraic Decision Diagrams as the main data structure [21].

c2d is a compiler that converts CNF into d-DNNF circuits, on which model counting and weighted model counting can be performed in time linear in the circuit size (hence, c2d is an exact MC/WMC solver) [16, 17].

d4 d4 is a compiler associating with an input CNF formula an equivalent representation from the language Decision-DNNF. Decision-DNNF is the language consisting of the Boolean circuits with a single output (its root), where each input is a literal or a Boolean constant, and each internal gate is either a decomposable ∧ gate of the form $N = \land (N_1, \ldots, N_k)$ ("decomposable" means here that for each $i, j \in \{1, \ldots, k\}$ with $i \neq j$ the subcircuits of $N$ rooted at $N_i$ and $N_j$ do not share any common variable) or decision gates of the form $N = \text{ite}(x, N_1, N_2)$. $x$ is the decision variable at gate $N$, it does not occur in the subcircuits $N_1, N_2$, and ite is a ternary connective whose semantics is given by $\text{ite}(X, Y, Z) = (\neg X \land Y) \lor (X \land Z)$ ("ite" means "if ... then ... else ...: if $X$ then $Z$ else $Y$") [51].

GPMC is an exact projected model counter, which computes the number of models of a given formula that are different when models are restricted to the projected variables. It is a model counter combined clause learning with component decomposition and component caching. The underlying idea to deal with the projected model counting is the same as DPLL-based model counters that restrict search to projection variables and use a SAT solver for components with no unassigned projection variables, i.e., (a) GPMC selects a branch decision variable from unassigned projection variables first. (b) When there is no unassigned projection variables in a component, GPMC starts solving the satisfiability of the component. If the result is SAT, the number of models of the component is 1; otherwise 0.

mcTw implements in the core an algorithm that is based on dynamic programming on treewidth decompositions of a primal graph constructed for a given CNF formula [68].

nus-barganak/nus-narasimha are submissions that feature portfolio solvers, consisting of B+E [49], Ganak [72], and approxmc [74, 75]. The exact configuration depends on the track. We refer to details on the medalists of each track.

MCSim is a component caching based solver implemented on top of sharpSAT [80].

SUMC1 counts how many models are eliminated by each clause because they fail to satisfy it. Then, by computing the cardinality of a union of sets to determine how many models are eliminated overall it obtains the overall model count without explicitly identifying the models. The source code is available at github:ivor-spence/sumc [76].

B Data Formats

B.1 Track 1: Model Counting

The input format for providing a formula (.mcc2020.cnf) was taken from the DIMACS-format for formulas in conjunctive normal form [83]. The DIMACS-input format is used in SAT competitions. For more details, we refer to an online resource at http://www.satcompetition.org/2009/format-benchmarks2009.html We use the following version where we print symbols in typewriter font, e.g., $\text{n}$

- Line separator is the symbol $\text{n}$.
- Lines starting with character $c$ are interpreted as comments.
- Variables are consecutively numbered from 1 to $n$. 

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• The problem description is given by a unique line of the form `p cnf NumVariables NumClauses` that we expect to be the first line (except comments). More precisely, the line starts with character p (no other line may start with p), followed by the problem descriptor cnf, followed by number n of variables followed by number m of clauses each symbol is separated by space each time.

• The remaining lines indicate clauses consisting of decimal integers separated by space. Lines are terminated by character 0. The line `2 -1 3 0\n` indicates the clause “2 or not 1 or 3”.

• Empty lines or lines consisting of spaces may occur and only will be ignored.

**Example 1.** The following text describes the CNF formula (set of clauses)

\[
\{\neg x_1, \neg x_2\}, \{x_2, x_3, \neg x_4\}, \{x_4, x_5\}, \{x_4, x_6\}\]

including a problem description line and two comments.

```
c This file describes a DIMACS CNF in MC 2020 format
c with 6 variables and 4 clauses
p cnf 6 4
-1 -2 0
2 3 -4 0
c this is a comment and will be ignored
4 5 0
4 6 0
```

The solution is given in the following format:

```
c This file describes that the model count is 22
s mc 22
```

**B.2 Track 2: Weighted Model Counting**

The input format for providing a formula (.mcc2020_wcnf) was taken from the DIMACS-format for formulas in conjunctive normal form [83]. The DIMACS-input format is used in SAT competitions. For more details, we refer to an online resource at [http://www.satcompetition.org/2009/format-benchmarks2009.html](http://www.satcompetition.org/2009/format-benchmarks2009.html). Cachet used a similar format, however, the current avoids implicit assumptions about weights. We use the following version where we print symbols in typewriter font, e.g., `\n`

- Line separator is the symbol `\n`.
- Lines starting with character `c` are interpreted as comments.
- Variables are consecutively numbered from 1 to n.
- The problem description is given by a unique line of the form `p wcnf NumVariables NumClauses` that we expect to be the first line (except comments). More precisely, the line starts with character p (no other line may start with p), followed by the problem descriptor wcnf, followed by number n of variables followed by number m of clauses each symbol is separated by space each time.
- The weight function is given by lines of the form `w Literal Weight 0` defining the floating point Weight for Literal, where 0 ≤ Weight ≤ 1. We assume that no more than 9 significant digits are given after the decimal point. If the weight for a literal is not defined, it is considered to be of weight 1.

---

8See: file README.txt in [https://www.cs.rochester.edu/u/kautz/Cachet/cachet-wmc-1-21.zip](https://www.cs.rochester.edu/u/kautz/Cachet/cachet-wmc-1-21.zip)
The remaining lines indicate clauses consisting of decimal integers separated by space. Lines are terminated by character 0. The Line \(-1\ 3\ 0\n\) indicates the clause “2 or not 1 or 3”.

Empty lines or lines consisting of spaces may occur and only will be ignored.

Example 2. The following text describes the CNF formula (set of clauses)

\[
\{\neg x_1, \neg x_2\}, \{x_2, x_3, \neg x_4\}, \{x_4, x_5\}, \{x_4, x_6\}\]

with weight function \(\{x_1 \mapsto 0.4, \neg x_1 \mapsto 0.6, x_2 \mapsto 1, \neg x_2 \mapsto 1, x_3 \mapsto 1, \neg x_3 \mapsto 1, x_4 \mapsto 0.5, \neg x_4 \mapsto 0.5, x_5 \mapsto 1, \neg x_5 \mapsto 1\}\) including a problem description line and two comments.

c This file describes a weighted CNF in MC 2020 format with 6 variables and 4 clauses
p wcnf 6 4
w 1 0.4 0
w -1 0.6 0
w 4 0.5 0
w -4 0.5 0
w 5 1.0 0
w -5 1.0 0
-1 -2 0
2 3 -4 0
c this is a comment and will be ignored
4 5 0
4 6 0

The solution should be given in the following format:

c This file describes that the weighted model count is 6.0
s wmc 6.0

B.3 Track 3: Projected Model Counting

The input format for providing a formula (.mcc2020.pcnf) was taken from the DIMACS-format for formulas in conjunctive normal form [33]. The DIMACS-input format is used in SAT competitions. For more details, we refer to an online resource at [http://www.satcompetition.org/2009/format-benchmarks2009.html](http://www.satcompetition.org/2009/format-benchmarks2009.html) Ganak used a similar format stating the projection variables as comment. We use the following version where we print symbols in typewriter font, e.g., \(\|n\)

- Line separator is the symbol \(\n\).
- Lines starting with character c are interpreted as comments.
- Variables are consecutively numbered from 1 to n.
- The problem description is given by a unique line of the form p pcnf NumVariables NumClauses that we expect to be the first line (except comments). More precisely, the line starts with character p (no other line may start with p), followed by the problem descriptor wcnf, followed by number n of variables followed by number m of clauses each symbol is separated by space each time.

\(9\)See [https://github.com/meelgroup/ganak]
• Projection variables, i.e., variables that are important and which are the ones that will be considered for the count, are given by a line of the form \texttt{vp VARID1 VARID2 VARID3 0}. The line is expected to be unique meaning that no other line may start with \texttt{vp}. The line may occur at any time after the \texttt{p} line, especially for encoding the line may also occur as last line in the file. VARIDX represents decimal integers which such that \(1 \leq \text{VARIDX} \leq n\) and where \(n\) refers to the number of variables. The integers are separated by space and the line is terminated by character 0. For example, line \texttt{vp 1 2 0} indicates the set \{1, 2\}.

• The remaining lines indicate clauses consisting of decimal integers separated by space. Lines are terminated by character 0. The Line \texttt{2 -1 3 0} indicates the clause “2 or not 1 or 3”.

• Empty lines or lines consisting of spaces may occur and only will be ignored.

\textbf{Example 3.} The following text describes the CNF formula (set of clauses)

\[
\{ \neg x_1, \neg x_2 \}, \{ x_2, x_3, \neg x_4 \}, \{ x_4, x_5 \}, \{ x_4, x_6 \} 
\]

with projection set \{x_1, x_2\} including a problem description line and two comments.

c This file describes a projected CNF in MC 2020 format
c with 6 variables and 4 clauses and 2 projected variables
\texttt{p pcnf 6 4 2}
\texttt{vp 1 2 0}
\texttt{-1 -2 0}
\texttt{2 3 -2 0}
c this is a comment and will be ignored
\texttt{4 5 0}
\texttt{4 6 0}

The solution should be given in the following format:

c This file describes that the projected model count is 3
\texttt{s pmc 3}
c