The 5th International Verification of Neural Networks Competition (VNN-COMP 2024): Summary and Results

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Abstract

This report summarizes the 5th International Verification of Neural Networks Competition (VNN-COMP 2024), held as a part of the The 7th International Symposium on AI Verification (SAIV), that was co-llocated with the 36th International Conference on Computer-Aided Verification (CAV). VNN-COMP is held annually to facilitate the fair and objective comparison of state-of-the-art neural network verification tools, encourage the standardization of tool interfaces, and bring together the neural network verification community. To this end, standardized formats for networks (ONNX) and specification (VNN-LIB) were defined, tools were evaluated on equal-cost hardware (using an automatic evaluation pipeline based on AWS instances), and tool parameters were chosen by the participants before the final test sets were made public. In the 2024 iteration, 8 teams participated on a diverse set of 12 regular and 8 extended benchmarks. This report summarizes the rules, benchmarks, participating tools, results, and lessons learned from this iteration of this competition.

1 Introduction

Deep learning based systems are increasingly being deployed in a wide range of domains, including recommendation systems, computer vision, and autonomous driving. While the nominal performance of these methods has increased significantly over the last years, they largely lack formal guarantees on their behavior. However, in safety-critical applications, including autonomous systems, robotics, cybersecurity, and cyber-physical systems (CPS), such guarantees are essential for certification and reliability.

While the literature on the verification of traditionally designed systems is wide and successful, neural network verification remains an open problem, despite significant efforts over the last years. In 2020, the International Verification of Neural Networks Competition (VNN-COMP) was established to facilitate comparison between existing approaches, bring researchers working on this problem together, and help shape future directions of the field. VNN-COMP has been held annually since then [11, 54, 16, 15]. In 2024, the 5th iteration of the annual VNN-COMP¹ was held as a part of the 7th International Symposium on AI Verification (SAIV) that was collocated with the 36th International Conference on Computer-Aided Verification (CAV).

This 5th iteration of the VNN-COMP continues last year's trend of increasing standardization and automatization, aiming to enable a fair comparison between the participating tools

¹https://sites.google.com/view/vnn2024/home

and to simplify the evaluation of a large number of tools on a variety of (real-world) problems. As in the last iteration, VNN-COMP 2024 standardizes (1) neural network and specification formats, ONNX for neural networks and VNN-LIB [22] for specifications, (2) evaluation hardware, providing participants the choice of a range of cost-equivalent AWS instances with different trade-offs between CPU and GPU performance, and (3) evaluation pipelines, enforcing a uniform interface for the installation and evaluation of tools.

The competition was kicked off with the solicitation for participation in February 2024. Rule discussion started in April and rules are finalized in May 2024 (see an overview in Section 2). From April to June 2024, benchmarks were proposed and discussed. Meanwhile, the organizing team decided to continue using AWS as the evaluation platform and started to implement an automated submission and testing system for both benchmarks and tools. By mid-July 2024, eight teams submitted their tools and the organizers evaluated all entrants to obtain the final results, discussed in Section 5 and presented at SAIV on July 23, 2024. Discussions were structured into three issues on the official GitHub repository²: rules discussion, benchmarks discussion, and tool submission. All submitted benchmarks³ and final results⁴ were aggregated in separate GitHub repositories.

The remainder of this report is organized as follows: Section 2 discusses the competition rules, Section 3 lists all participating tools, Section 4 lists all benchmarks, Section 5 summarizes the results, and Section 6 concludes the report, discussing potential future improvements.

²https://github.com/verivital/vnncomp2024/issues/

³https://github.com/ChristopherBrix/vnncomp2024_benchmarks

⁴https://github.com/ChristopherBrix/vnncomp2024_results

2 Rules

Terminology An *instance* is defined by a property specification (pre- and post-condition), a network, and a timeout). For example, one instance might consist of an MNIST classifier with one input image, a given local robustness threshold ϵ , and a specific timeout. A *benchmark* is defined as a set of related instances. For example, one benchmark might consist of a specific MNIST classifier with 100 input images, potentially different robustness thresholds ϵ , and one timeout per input.

Run-time caps Run-times are capped on a per-instance basis, i.e., any verification instance will timeout (and be terminated) after at most X seconds, determined by the benchmark proposer. These can be different for each instance. The total per-benchmark runtime (sum of all per-instance timeouts) may not exceed 6 hours per benchmark. For example, a benchmark proposal could have six instances with a one-hour timeout, or 100 instances with a 3.6-minute timeout, each. To enable a fair comparison, we measure the startup overhead for each tool by running it on a range of tiny networks and subtract the minimal overhead from the total runtime.

Hardware To allow for comparability of results, all tools were evaluated on equal-cost hardware using Amazon Web Services (AWS). Each team could decide between a range of AWS instance types (see Table 1) providing a CPU, GPU, or mixed focus.

	vCPUs	RAM [GB]	GPU
p3.2xlarge	8	61	V100 GPU with 16 GB memory
m5.16xlarge	64	256	×
g5.8xlarge	32	128	A10G GPU with 24 GB memory $$

Table 1: Available AWS instances.

Scoring The final score is aggregate as the sum of all benchmark scores. Each benchmark score is the number of points (sum of instance scores discussed below) achieved by a given tool, normalized by the maximum number of points achieved by any tool on that benchmark. Thus, the tool with the highest sum of instance scores for a benchmark will get a benchmark score of 100, ensuring that all benchmarks are weighted equally, regardless of the number of constituting instances.

Instance score Each instance is scored is as follows:

- Correct hold (property proven): 10 points;
- Correct violated (counterexample found): 10 points;
- Incorrect result: -150 points (penalty increased compared to 2022);
- Timeout / Runtime Error / Unknown: 0 points.

However, the ground truth for any given instance is generally not known a priori. In the case of disagreement between tools, we, therefore, place the burden of proof on the tool claiming that a specification is violated, i.e. that a counterexample can be found, and deem it correct exactly if it produces a valid counterexample.

The provided counterexamples were supposed to define both the input and the resulting output of the networks. However, for some tools and instances, the output definition was

either missing or differed from the network output as computed by the onnxruntime package used to evaluate counterexamples (by performing inference given the inputs). The competition rules were ambiguous how this would be handled. We decided to discard all outputs in the counterexample files and base the evaluation solely on the given inputs and their respective outputs as computed by the onnxruntime. A ranking using the alternative evaluation, where incorrect or missing outputs result in a penalty can be found in Appendix B.

Time bonus As opposed to previous years, no time bonus was awarded. Instead, all tools that are compute the correct result within the time limit receive the same amount of points.

Overhead Correction The overhead of tools was measured, but only used to adapt the timeouts. It did not influence the scores, as no time bonus was awarded. To measure the tool-specific overhead, we created trivial network instances and included those in the measurements. We then observed the minimum verification time over all instances and considered that to be the overhead time for the tool.

Format As since 2021, we standardized neural networks to be in onnx format, specifications in vnnlib format, and counterexamples in a format similar to the vnnlib format. Further, tool authors were required to provide scripts fully automating the installation process of their tool, including the acquisition of any licenses that might be needed. Similar to the previous year, a preparation and execution script had to be provided for running their tool on a specific instance consisting of a network file, specification file, and timeout. The specifications are interpreted as definitions of counterexamples, meaning that a property is proven "correct" if the specification is shown to be unsatisfiable, conversely, the property is shown to be violated if a counterexample fulfilling the specification is found. Specifications consisted of disjunctions over conjunctions in both pre- and post-conditions, allowing a wide range of properties from adversarial robustness over multiple hyper-boxes to safety constraints to be encoded. For example, robustness with respect to inputs in a hyper-box had to be encoded as disjunctive property, where any of the other classes is predicted.

Tracks For the first time, the competition was split into two tracks, both of them scored: A "regular" track, and an "extended" track. The regular track consists of benchmarks selected by the tool participants based on a voting process, where a benchmark is included in the regular track if at least 50% of tool participants voted for it to be scored. Benchmarks with at least 1 vote and not included in the regular track were scored in the extended track. All benchmarks received at least one vote, so no benchmark was unscored.

3 Participants

We list the tools and teams that participated in the VNN-COMP 2024 in Table 2 and reproduce their own descriptions of their tools below.

Table 2: Summary of the key features of participating tools. The hardware column describes the used AWS instance with p3 and g5 making GPUs available, see Table 1 for more details. Licenses refer to the external licenses required to use the corresponding tool, not the licensing of the tool itself.

Tool	References	Organizations	Place	Hardware	Licenses
α,β -CROWN	[83, 84, 74, 86, 58]	UIUC, UCLA, Drexel, Duke, RWTH Aachen	1	g5	GUROBI
CORA	[3, 43, 47, 44]	Technical University of Munich	7	g5	MATLAB
Marabou	[38, 79]	Hebrew University of Jerusalem, Stanford University, NRI Secure	3	m5	GUROBI
NeVer2	[23, 33]	Università degli Studi di Genova, Università degli Studi di Sassari, University of Kent	6	g5	-
NeuralSAT	[26, 27]	George Mason University	8	g5	GUROBI
nnenum	[12, 10]	Stony Brook University	4	m5	-
NNV	[72, 49]	Vanderbilt University	5	m5	MATLAB
PyRAT	[48, 5]	Universite Paris-Saclay, CEA, List	2	m5	-

3.1 α,β -CROWN

Team Co-leaders: Huan Zhang (UIUC) and Zhouxing Shi (UCLA); Team members: Duo Zhou (UIUC), Jorge Chavez (UIUC), Xiangru Zhong (UIUC), Hongji Xu (Duke, working as an intern supervised by Prof. Huan Zhang at UIUC), Kaidi Xu (Drexel), Hao Chen (UIUC)

The team **acknowledges** (ordered by last names) Christopher Brix (RWTH Aachen), Sanil Chawla (UIUC), Qirui Jin (University of Michigan), Suhas Kotha (CMU), and Zhuolin Yang (UIUC) who were involved into the development of the verifier during 2023 - 2024 but did not directly work on any benchmarks of the competition.

Description α,β -CROWN (alpha-beta-CROWN) is an efficient neural network verifier based on the linear bound propagation framework and built on a series of works on bound-propagation-based neural network verifiers: CROWN [87], auto_LiRPA [83], α -CROWN [84], β -CROWN [74], GCP-CROWN [86], GenBaB [58], BICCOS [90]. The core techniques in α,β -CROWN combine the efficient and GPU-accelerated linear bound propagation method with branch-and-bound methods specialized for neural network verification.

The linear bound propagation algorithms in α,β -CROWN are based on our auto_Lirpa library [83], which supports general neural network architectures (including convolutional layers, pooling layers, residual connections, recurrent neural networks, and Transformers) and a wide range of nonlinear functions (e.g., ReLU, tanh, trigonometric functions, sigmoid, max pooling and average pooling), and is efficiently implemented on GPUs with Pytorch and CUDA. We jointly optimize intermediate layer bounds and final layer bounds using gradient ascent

(referred to as α -CROWN or optimized CROWN/LiRPA [84]). Most importantly, we use branch and bound [17] (BaB) and incorporate split constraints in BaB into the bound propagation procedure efficiently via the β -CROWN algorithm [74], use cutting-plane method in GCP-CROWN [86] and BICCOS [90] to further tighten the bound, and support general nonlinearities in the branch-and-bound by GenBaB [58]. For smaller networks, we also use a mixed integer programming (MIP) formulation [65] combined with tight intermediate layer bounds from α -CROWN (referred to as α -CROWN + MIP [86]). The combination of efficient, optimizable and GPU-accelerated bound propagation with BaB produces a powerful and scalable neural network verifier.

New in this year, we have: improved branch-and-bound for general nonlinear functions by GenBaB [58] which leverages the more flexible nature of general nonlinearities to make smarter branching decisions; improved algorithms for input-space branch-and-bound; developed new Branch-and-bound Inferred Cuts with COnstraint Strengthening (BICCOS) [90], a cutting plane (cut) approach that leverages inferred cuts from verified subproblems during branch-and-bound framework to achieve scalability for large networks without dependence on external MIP solvers; and introduced new strategies for better time and GPU utilization. Multiple papers are in progress or in submission.

Link https://github.com/Verified-Intelligence/alpha-beta-CROWN (main version)

Competition submission https://github.com/Verified-Intelligence/alpha-beta-CROWN_vnncomp2024 (only for reproducing competition results; please use the main version for other purposes)

Hardware and licenses CPU and GPU with 32-bit or 64-bit floating point; Gurobi license required for certain benchmarks.

Participated benchmarks All benchmarks.

3.2 CORA

Team Lukas Koller, Tobias Ladner, Matthias Althoff (Technical University of Munich)

Description CORA [7] enables the formal verification of neural networks, both in open-loop as well as in closed-loop scenarios. Open-loop verification refers to the task where properties of the output set of a neural network are verified, e.g. correctly classified images given noisy input, as also considered at VNN-COMP. In closed-loop scenarios, the neural network is used as a controller of a dynamic system, e.g., controlling a car while keeping a safe distance over some time horizon.

This is realized using reachability analysis, mainly using polynomial zonotopes [43, 47], allowing a non-convex enclosure of the output set of a neural network. Moreover, CORA can also train robust neural networks [44], which requires an efficient batch-wise propagation of zonotopes through a neural network on a GPU. This can also be used during verification by efficiently propagating the splitted sets batch-wise.

Link https://github.com/kollerlukas/cora-vnncomp2024

Commit 6f1923030baafadfadca3982b72fdea217a92479

Hardware and licenses GPU, MATLAB license.

Participated Benchmarks acasxu, cifar100, collins-rul-cnn, cora, dist-shift, nn4sys, safenlp, tinyimagenet, tllverifybench.

3.3 Marabou

Team Haoze Wu (Stanford University), Clark Barrett (Stanford University), Guy Katz (Hebrew University of Jerusalem)

Description Marabou [38, 79] is a user-friendly Neural Network Verification toolkit that can answer queries about a network's properties by encoding and solving these queries as constraint satisfaction problems. It has both Python/C++ APIs through which users can load neural networks and define arbitrary linear properties over the neural network. Marabou supports many different linear, piecewise-linear, and non-linear [81, 76] operations and architectures (e.g., FFNNs, CNNs, residual connections, Graph Neural Networks [78]).

Under the hood, Marabou employs a uniform solving strategy for a given verification query. In particular, Marabou performs complete analysis that employs a specialized convex optimization procedure [82] and abstract interpretation [63, 78]. It also uses the Split-and-Conquer algorithm [80] for parallelization. ⁵

Link https://github.com/NeuralNetworkVerification/Marabou

Commit 1a3ca6010b51bba792ef8ddd5e1ccf9119121bd8

Hardware and Licenses CPU, no license required. Can also be accelerated with Gurobi (which requires a license)

Participated benchmarks acasxu, cgan, collins_rul_cnn, dist_shift, linearizenn, metaroom, nn4sys, safenlp, tllverifybench, cifar100, tinyimagenet.

3.4 NeVer2

Team Setefano Demarchi, Armando Tacchella (University of Genova), Elena Botoeva (University of Kent)

Description NeVer2 [23] is an open-source, cross-platform tool aimed at designing, training, and verifying neural networks. It seamlessly integrates popular learning libraries with our verification backend, offering their functionalities also via a graphical interface.

NeVer2 relies on the pyNeVer [33] Python API, which provides the verification capability employing an abstraction-refinement algorithm, which uses symbolic bounds propagation to compute stable and unstable neurons and an iterative refinement procedure to grow a search tree for proving the safety or the unsafety of a verification query, which is expressed using star sets [70].

The algorithm propagates the abstraction provided by symbolic propagation and, if there is an intersection with the unsafe post-conditions, checks whether there is a counter-example to state the unsafety of the network, or to refine the abstraction branching on unstable ReLU neurons. The next refinement target is decided based on the presence of unstable neurons in early layers, or by the approximation area of the linear relaxation. In the form it is presented, this behaves as a complete algorithm. However, it can be easily turned into an incomplete one by incorporating some early stopping criteria, e.g., a timeout, or the maximum depth/number of refined neurons in a branch. Currently, NeVer2 supports only feed-forward architectures with ReLU layers.

 $^{^5}$ Thanks to the authors of the $\alpha-\beta$ -CROWN team, an unsoundness issue of the competition version of Marabou on the ViT benchmarks was discovered. The networks in that benchmark contain bilinear and softmax connections. For this benchmark, the competition version of Marabou first performs DeepPoly-style abstract interpretation and then encodes the verification problem in the Gurobi optimizer. It turns out that Gurobi can report "Infeasible" on benchmarks where counter-examples are expected. The Marabou team is actively looking into resolving this issue.

Link https://github.com/nevertools/pynever

Commit a7212f843a7e5137bdc54181b98b271f6b724747

Hardware and licenses CPU, no license required.

Participated benchmarks acasxu, cora, safenlp, tllverifybench.

3.5 nnenum

Team Ali Arjomandbigdeli (Student), Stanley Bak (Supervisor) (Stony Brook University)

Description The nnenum tool [10] uses multiple levels of abstraction to achieve high-performance verification of ReLU networks without sacrificing completeness [9]. The core verification method is based on reachability analysis using star sets [70], combined with the ImageStar method [67] to propagate stes through all linear layers supported by the ONNX runtime, such as convolutional layers with arbitrary parameters. The tool is written in Python 3 and uses GLPK for LP solving. New this year, we added support for single lower and single upper bounds propagation in addition to zonotopes, similar to the DeepPoly method or the CROWN approach. We also added an option to use Gurobi instead of GLPK for LP solving.

Link https://github.com/aliabigdeli/nnenum

Commit bcd65bcea050454b1a16a5fc5e8f94064af21085

Hardware and licences CPU, Gurobi license (optional)

Participated benchmarks acasxu, cgan, collins-rul-cnn, cora, linearizenn, metaroom, safeNLP, nn4sys, tllverifybench, vggnet16.

3.6 NNV

Team Diego Manzanas Lopez (Vanderbilt University), Samuel Sasaki (Vanderbilt University), Taylor T. Johnson (Vanderbilt University)

Description The Neural Network Verification (NNV) Tool [72, 49] is a formal verification software tool for deep learning models and cyber-physical systems with neural network components written in MATLAB and available at https://github.com/verivital/nnv. NNV uses a star-set state-space representation and reachability algorithm that allows for a layer-by-layer computation of exact or overapproximate reachable sets for feed-forward [70], convolutional [67], semantic segmentation (SSNN) [71], and recurrent (RNN)[69] neural networks, as well as neural network control systems (NNCS) [68, 72] and neural ordinary differential equations (Neural ODEs) [52]. The star-set based algorithm is naturally parallelizable, which allows NNV to be designed to perform efficiently on multi-core platforms. Additionally, if a particular safety property is violated, NNV can be used to construct and visualize the complete set of counterexample inputs for a neural network (exact-analysis). For this competition, updated from last year's, we tailor the solver approach depending on the benchmark at hand, although all follow a similar flow. First, we perform a simulation-guided search for counterexamples for a fixed number of samples. If no counterexamples are found (i.e., demonstrate that the property is SAT), then we utilize an iterative refinement approach using reachability analysis to verify the property (UNSAT). This consists of performing reachability analysis using a relaxapproximation method [71], if not verified, then a less conservative approximation based on zonotope pre-filtering approach [66], and finally using the exact analysis when possible [67] until the specification is verified or there is a timeout. Based on the benchmark to evaluate, the initial reachability analysis may be any of the overapproximation methods or the exact method, based on the complexity of the benchmarks (size of network, input, etc).

Link https://github.com/verivital/nnv

 ${\bf Commit}\ 50 da 012 e7 bf 390788322329591 e9 edd 3c45 b4 f0 f$

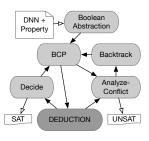
Hardware and licenses CPU, MATLAB license.

Participated Benchmarks Regular track except for LinearizeNN.

3.7 NeuralSAT

Team Hai Duong and Thanhvu Nguyen (George Mason).

Description NeuralSAT [26, 27] integrates conflict-driven clause learning (CDCL) in SAT/SMT-solving with an DNN abstraction-based theory solver for infeasibility checking. The figure on the right gives an overview of NeuralSAT, which implements the DPLL(T) framework used in modern SMT solvers such as Z3 and CVC. The design of NeuralSAT is inspired by the core algorithms used in SMT solvers such as CDCL components (light shades) and theory solving (dark shade). The tool is written in Python and uses Gurobi for LP solving. Unlike many other modern VNN verification tools, NeuralSAT does not require parameter tuning and works out of the box,



e.g., the rool runs on the wide-range of benchmarks in VNN-COMPs without any tuning.

New: In VNN-COMP'24, NeuralSAT has been improved with neuron stability, parallel beam search, and restarting strategies, which improved its performance significantly [27].

Link https://github.com/dynaroars/neuralsat

Commit 5693c3da130942283744ce56c2e74ac6c16eef94

Hardware and licences GPU, Gurobi License

Participated benchmarks acasxu, cgan, collins-rul-cnn, dist-shift, nn4sys, vggnet16, tllverifybench, trafic-signs-recognition, reach-prob-density, metaroom.

3.8 PyRAT

Team Augustin Lemesle, Julien Lehmann, Tristan Le Gall (CEA-List)

Description PyRAT (Python Reachability Assessment Tool) [48] is an abstract interpretation based tool to verify the safety and robustness of neural networks. PyRAT implements several abstract domains such as Intervals, Zonotopes, Constrained Zonotopes, or Polyhedras to efficiently compute the reachable states for different architectures of neural networks such as dense, convolutional, residual or recurrent neural networks. It supports multiple non-linear activation functions (ReLU, Sigmoid, Softmax, Floor, ...) with precise abstractions while maintaining floating-point soudness. PyRAT is correct in that the output bounds reached will always be a sound over-approximation of the results and complete for ReLU based networks in that it will always give a true or false result given enough time. Depending on the benchmark, different verification modes and domains can be selected. For smaller networks and problems, PyRAT can leverage branch and bound strategies on the inputs with heuristics like ReCIPH [28]. While on larger ReLU networks, PyRAT will use branch and bound strategies on the ReLU neurons in conjunction with fast GPU computation.

Link https://git.frama-c.com/pub/pyrat

Commit be7352ca5628669ae6a2ae5149c52a99fe86ed6a

Hardware and licenses CPU and GPU, closed source CEA licence.

Participated benchmarks All benchmarks.

4 Benchmarks

In this section, we provide an overview of all scored benchmarks, reproducing the benchmark proposers' descriptions. Artifacts for all benchmarks are available in the repository⁶.

Category	Benchmark	Application	Network Types	# Params	Effective Input Dim	Track
	cGAN	Image Generation & Image Prediction	Conv. + Vision Transformer	500k - 68M	5	regular
	NN4Sys	Dataset Indexing & Cardinality Prediction	ReLU + Sigmoid	33k - 37M	1-308	regular
	LinearizeNN	NN controller approximation	$\label{eq:FC. + Conv. + Vision Transformer + Residual + ReLU} FC. + Conv. + Vision Transformer + Residual + ReLU$	203k	4	regular
Complex	ml4acopf	Power System	Complex (ReLU + Trigonometric + Sigmoid)	4k- $680k$	22 - 402	extended
	ViT	Vision	$Conv. \ + \ Residual \ + \ Softmax \ + \ BatchNorm$	68k - 76k	3072	extended
	Collins Aerospace	-	${\rm FC+Conv.+Residual,LeakyReLU+MaxPool+Square}$	1.8M	1.2M	extended
	LSNC	Lyapunov stability of NN controllers	FC + Residual, ReLU + Sin + Cos	210, 406	8	extended
	CCTSDB	-	$\label{eq:fc} FC + Conv. + Residual, ReLU + MaxPool + Clip$	100k	2	extended
	Collins RUL CNN	Condition Based Maintenance	Conv. + ReLU, Dropout	60k - 262k	400 - 800	regular
	VGGNet16	Image Classification	Conv. + ReLU + MaxPool	138M	150k	extended
corre-	Traffic Signs Recognition	Image Classification	Conv. + Sign + MakPool + BatchNorm	905k - 1.7M	2.7k - 12k	extended
CNN & ResNet	cifar100	Image Classification	FC+Conv.+Residual,ReLU+BatchNorm	$2.5\mathrm{M}$ - $3.8\mathrm{M}$	3072	regular
	tinyimagenet	Image Classification	FC + Conv. + Residual, ReLU + BatchNorm	3.6M	9408	regular
	Metaroom	-	Conv. $+$ FC, ReLU	466k - 7.4M	5376	regular
	Yolo	-	${\rm FC+Conv.+Residual,ReLU+Sigmoid}$	$22\mathrm{k}$ - $37\mathrm{M}$	1 - 308	extended
	TLL Verify Bench	Two-Level Lattice NN	Two-Level Lattice NN $(FC. + ReLU)$	17k - 67M	2	regular
	Acas XU	Collision Detection	FC. + ReLU	13k	5	regular
FC	Dist Shift	Distribution Shift Detection	FC. + ReLU + Sigmoid	342k - 855k	792	regular
	safeNLP	Sentence classification	FC. + ReLU	4k	30	regular
	CORA	Image Classification	FC. + ReLU	575k,1.1M	784, 3072	regular

Table 3: Overview of all scored benchmarks.

4.1 cGAN

Proposed by Feiyang Cai, Ali Arjomandbigdeli, Stanley Bak (Stony Brook University)

Motivation While existing neural network verification benchmarks focus on discriminative models, the exploration of practical and widely used generative networks remains neglected in terms of robustness assessment. This benchmark introduces a set of image generation networks specifically designed for verifying the robustness of the generative networks.

Networks The generative networks are trained using conditional generative adversarial networks (cGAN), whose objective is to generate camera images that contain a vehicle obstacle located at a specific distance in front of the ego vehicle, where the distance is controlled by the input distance condition. The network to be verified is the concatenation of a generator and a discriminator. The generator takes two inputs: 1) a distance condition (1D scalar) and 2) a noise vector controlling the environment (4D vector). The output of the generator is the generated image. The discriminator takes the generated image as input and outputs two values: 1) a real/fake score (1D scalar) and 2) a predicted distance (1D scalar). Several different models with varying architectures (CNN and vision transformer) and image sizes (32x32, 64x64) are provided for different difficulty levels.

Specifications The verification task is to check whether the generated image aligns with the input distance condition, or in other words, verify whether the input distance condition matches the predicted distance of the generated image. In each specification, the inputs (condition distance and latent variables) are constrained in small ranges, and the output is the predicted distance with the same center as the condition distance but with slightly larger range.

 $^{^6 \}verb|https://github.com/ChristopherBrix/vnncomp2024_benchmarks/tree/main/benchmarks|$

 $\mathbf{Link} \text{ https://github.com/feiyang-cai/cgan_benchmark2023}$

4.2 NN4Sys

Proposed by the α,β -CROWN team with collaborations with Cheng Tan, Haoyu He and Shuyi Lin at Northeastern University.

Application The benchmark contains networks for database learned index, video streaming learned adaptive bitrate, and learned cardinality estimation which map inputs from various dimensions to 1-dimension outputs.

- Background: learned index, learned cardinality, and learned adaptive bitrate are all instances in neural networks for computer systems (NN4Sys), which are neural network based methods performing system operations. These classes of methods show great potential but have one drawback—the outputs of an NN4Sys model (a neural network) can be arbitrary, which may lead to unexpected issues in systems.
- What to verify: our benchmark provides multiple pairs of (1) trained NN4Sys model and (2) corresponding specifications. We design these pairs with different parameters such that they cover a variety of user needs and have varied difficulties for verifiers. We describe benchmark details in our NN4SysBench report: http://naizhengtan.github.io/doc/papers/nn4sys23lin.pdf.
- Translating NN4Sys applications to a VNN benchmark: the original NN4Sys applications have some sophisticated structures that are hard to verify. We tailored the neural networks and their specifications to be suitable for VNN-COMP. For example, learned index [46] contains multiple NNs in a tree structure that together serve one purpose. However, this cascading structure is inconvenient/unsupported to verify because there is a "switch" operation—choosing one NN in the second stage based on the prediction of the first stage's NN. To convert learned indexes to a standard form, we train a monolithic (larger) NN.
- A note on broader impact: using NNs for systems is a broad topic, but many existing works lack strict safety guarantees. We believe that NN Verification can help system developers gain confidence to apply NNs to critical systems. We hope our benchmark can be an early step toward this vision.

Networks This benchmark has twelve networks with different parameters: two for learned indexes, four for learned cardinality estimation and six for learned adaptive bitrate. The learned index uses fully-connected feed-forward neural networks. The other two—the learned cardinality and the learned adaptive bitrate—has a relatively sophisticated internal structure. Please see our NN4SysBench report (URL listed above) for details

Specifications For learned indexes, the specification aims to check if the prediction error is bounded. The specification is a collection of pairs of input and output intervals such that any input in the input interval should be mapped to the corresponding output interval. For learned cardinality estimation and learned adaptive bitrate, the specifications check the prediction error bounds (similar to the learned indexes) and monotonicity of the networks. By monotonicity specifications, we mean that for two inputs, the network should produce a larger output for the larger input, which is required by cardinality estimation or adaptive bitrate.

Link: https://github.com/Khoury-srg/VNNComp23_NN4Sys

4.3 LinearizeNN

Proposed by Ali Arjomandbigdeli, Stanley Bak (Stony Brook University).

Motivation Assuming having a neural network controller approximation with a piecewise linear model in the form of a set of linear models with added noise to account for local linearization error. The objective of this benchmark is to investigate the neural network output falls within the range we obtain from our linear model output plus some uncertainty.

The idea of this benchmark came from one of our recent paper [8] in which we approximated the NN controller with a piecewise linear model, and we wanted to check if the neural network output falls within the range we obtained from our linear model output plus some uncertainty.

Networks The neural network controller we used in this benchmark is an image-based controller for an Autonomous Aircraft Taxiing System whose goal is to control an aircraft's taxiing at a steady speed on a taxiway. This network was introduced in the paper "Verification of Image-based Neural Network Controllers Using Generative Models" [39]. The neural network integrates a concatenation of the cGAN (conditional GAN) and controller, resulting in a unified neural network controller with low-dimensional state inputs. In this problem, the inputs to the neural network consist of two state variables and two latent variables. The aircraft's state is determined by its crosstrack position (p) and heading angle error (θ) with respect to the taxiway center line. Two latent variables with a range of -0.8 to 0.8 are introduced to account for environmental changes.

Because in this case the output spec depends on both the input and output and considering the VNN-LIB limitation, we added a skip-connection layer to the neural network to have the input values present in the output space. We also added one linear layer after that to create a linear equation for each local model.

Specifications As mentioned earlier, the aim of this benchmark is to examine whether the neural network output stays within the range defined by the linear model's output, including a margin for uncertainty. Given input $x \in X$ and output $Y = f_{NN}(x)$, the query is of the form: $A_{mat} \times X + b + U_{lb} \leq Y \leq A_{mat} \times X + b + U_{ub}$ for each linear model in its abstraction region.

4.4 ml4acopf

Proposed by Haoruo Zhao, Michael Klamkin, Mathieu Tanneau, Wenbo Chen, and Pascal Van Hentenryck (Georgia Institute of Technology), and Hassan Hijazi, Juston Moore, and Haydn Jones (Los Alamos National Laboratory).

Motivation Machine learning models are utilized to predict solutions for an optimization model known as AC Optimal Power Flow (ACOPF) in the power system. Since the solutions are continuous, a regression model is employed. The objective is to evaluate the quality of these machine learning model predictions, specifically by determining whether they satisfy the constraints of the optimization model. Given the challenges in meeting some constraints, the goal is to verify whether the worst-case violations of these constraints are within an acceptable tolerance level.

Networks The neural network designed comprises two components. The first component predicts the solutions of the optimization model, while the second evaluates the violation of each constraint that needs checking. The first component consists solely of general matrix multiplication (GEMM) and rectified linear unit (ReLU) operators. However, the second component has a more complex structure, as it involves evaluating the violation of AC constraints using nonlinear functions, including sigmoid, quadratic, and trigonometric functions such as sine and cosine. This complex evaluation component is incorporated into the network due to a limitation of the VNNLIB format, which does not support trigonometric functions. Therefore, these constraints violation evaluation are included in the neural network.

Specifications In this benchmark, four different properties are checked, each corresponding to a type of constraint violation:

- 1. Power balance constraints: the net power at each bus node is equal to the sum of the power flows in the branches connected to that node.
- 2. Thermal limit constraints: power flow on a transmission line is within its maximum and minimum limits.
- 3. Generation bounds: a generator's active and reactive power output is within its maximum and minimum limits.
- 4. Voltage magnitude bounds: a voltage's magnitude output is within its maximum and minimum limits.

The input to the model is the active and reactive load. The chosen input point for perturbation is a load profile for which a corresponding feasible solution to the ACOPF problem is known to exist. For the feasibility check, the input load undergoes perturbation. Although this perturbation does not exactly match physical laws, the objective is to ascertain whether a machine learning-predicted solution with the perturbation can produce a solution that does not significantly violate the constraints.

The scale of the perturbation and the violation threshold are altered by testing whether an adversarial example can be easily found using projected gradient descent with the given perturbation. The benchmark, provided with a fixed random seed, is robust against the simple projected gradient descent that is implemented.

Link https://github.com/AI40PT/ml4acopf_benchmark

4.5 ViT

Proposed by the α,β -CROWN team.

Motivation Transformers [73] based on the self-attention mechanism have much more complicated architectures and contain more kinds of nonlinerities, compared to simple feedforward networks with relatively simple activation functions. It makes verifying Transformers challenging. We aim to encourage the development of verification techniques for Transformer-based models, and we also aim to benchmark neural network verifiers on relatively complicated neural network architectures and more general nonlinearities. Therefore, we propose a new benchmark with Vision Transformers (ViTs) [24]. This benchmark is developed based on our work on neural network verification for models with general nonlinearities [58].

Networks The benchmark contains two ViTs, as shown in Table 4. Considering the difficulty of verifying ViTs, we modify the ViTs and make the models relatively shallow and narrow, with significantly reduced number of layers and attention heads. Following [60], we also replace the layer normalization with batch normalization. The models are mainly trained with PGD training [50], and we also add a weighted IBP [31, 59] loss for one of the models as a regularization.

Model	PGD_2_3_16	IBP_3_3_8
Layers	2	3
Attention heads	3	3
Patch size	16	8
Weight of IBP loss	0	0.01
Training ϵ	$\frac{2}{255}$	$\frac{1}{255}$
Clean accuracy	59.78%	62.21%

Table 4: Networks in the ViT benchmark.

Specifications The specifications are generated from the robustness verification problem with ℓ_{∞} perturbation. We use the CIFAR-10 dataset with perturbation size $\epsilon = \frac{1}{255}$ at test time. We have filtered the CIFAR-10 test set to exclude instances where either adversarial examples can be found (by PGD attack [50] with 100 steps and 1000 restarts) or the vanilla CROWN-like method [87, 60] can already easily verify. We randomly keep 100 instances for each model, with a timeout threshold of 100 seconds. Note that since instances with adversarial examples have mostly been excluded during the filtering process, this version of the benchmark may not be able to reflect soundness issues in verifiers, and we refer readers to [91] for discussions on testing soundness with models including ViT.

Link https://github.com/shizhouxing/ViT_vnncomp2023

4.6 LSNC

Proposed by the α,β -CROWN team.

Motivation We develop a benchmark for the problem of verifying the Lyapunov stability of NN controllers in nonlinear dynamical systems within a region-of-intrest and a region-of-attraction. This is important for providing stability guarantees that are essential for safety-critical applications with NN controllers. It is also a useful application of neural network verification as recently demonstrated in [85, 57], and we refer readers to those works for more details on the problem.

Networks and Specifications Models are adopted from [85]. We adopt two models for the 2D quadrotor dynamical system with state feedback and output feedback, respectively. Each

model consists of a controller which is a shallow ReLU network, a Lyapunov function which is a quadratic function, and nonlinear operators modelling the dynamics of a 2D quadrotor. The model for output feedback further consists of a shallow LeakyReLU network as the observer. The verification objective of the Lyapunov stability has been encoded in the ONNX graphs and VNNLIB specifications. Specifications for the benchmark are randomly generated and consist of random sub-regions within the original region-of-interest. The size of the random sub-regions is controlled by a factor ϵ (0 < ϵ ≤ 1) which is applied to each input dimension, and it has been adjusted for a suitable difficulty given the timeout. For the state feedback model, we set $\epsilon = 0.5$ and the timeout is 100s; for the output feedback model, we set $\epsilon = 0.3$ and timeout is 200s. For each of the two models, we randomly generate 20 instances.

Link https://github.com/shizhouxing/LSNC_VNNCOMP2024

4.7 Collins-RUL-CNN

Proposed by Collins Aerospace, Applied Research & Technology (website).

Motivation Machine Learning (ML) is a disruptive technology for the aviation industry. This particularly concerns safety-critical aircraft functions, where high-assurance design and verification methods have to be used in order to obtain approval from certification authorities for the new ML-based products. Assessment of correctness and robustness of trained models, such as neural networks, is a crucial step for demonstrating the absence of unintended functionalities [29, 41]. The key motivation for providing this benchmark is to strengthen the interaction between the VNN community and the aerospace industry by providing a realistic use case for neural networks in future avionics systems [40].

Application Remaining Useful Life (RUL) is a widely used metric in Prognostics and Health Management (PHM) that manifests the remaining lifetime of a component (e.g., mechanical bearing, hydraulic pump, aircraft engine). RUL is used for Condition-Based Maintenance (CBM) to support aircraft maintenance and flight preparation. It contributes to such tasks as augmented manual inspection of components and scheduling of maintenance cycles for components, such as repair or replacement, thus moving from preventive maintenance to predictive maintenance (do maintenance only when needed, based on component's current condition and estimated future condition). This could allow to eliminate or extend service operations and inspection periods, optimize component servicing (e.g., lubricant replacement), generate inspection and maintenance schedules, and obtain significant cost savings. Finally, RUL function can also be used in airborne (in-flight) applications to dynamically inform pilots on the health state of aircraft components during flight. Multivariate time series data is often used as RUL function input, for example, measurements from a set of sensors monitoring the component state, taken at several subsequent time steps (within a time window). Additional inputs may include information about the current flight phase, mission, and environment. Such highly multi-dimensional input space motivates the use of Deep Learning (DL) solutions with their capabilities of performing automatic feature extraction from raw data.

Networks The benchmark includes 3 convolutional neural networks (CNNs) of different complexity: different numbers of filters and different sizes of the input space. All networks contain only convolutional and fully connected layers with ReLU activations. All CNNs perform the regression function. They have been trained on the same dataset (time series data for mechanical component degradation during flight).

Specifications We propose 3 properties for the NN-based RUL estimation function. First, two properties (robustness and monotonicity) are local, i.e., defined around a given point. We provide a script with an adjustable random seed that can generate these properties around input

points randomly picked from a test dataset. For robustness properties, the input perturbation (delta) is varied between 5% and 40%, while the number of perturbed inputs varies between 2 and 16. For monotonicity properties, monotonic shifts between 5% and 20% from a given point are considered. Properties of the last type ("if-then") require the output (RUL) to be in an expected value range given certain input ranges. Several if-then properties of different complexity are provided (depending on range widths).

Link https://github.com/loonwerks/vnncomp2022

Paper Available in [40] or on request.

4.8 VGGNET16

Proposed by Stanley Bak, Stony Brook University

Motivation This benchmark tries to scale up the size of networks being analyzed by using the well-studied VGGNET-16 architecture [62] that runs on ImageNet. Input-output properties are proposed on pixel-level perturbations that can lead to image misclassification.

Networks All properties are run on the same network, which includes 138 million parameters. The network features convolution layers, ReLU activation functions, as well as max pooling layers.

Specifications Properties analyzed ranged from single-pixel perturbations to perturbations on all 150528 pixles (L-infinity perturbations). A subset of the images was used to create the specifications, one from each category, which was randomly chosen to attack. Pixels to perturb were also randomly selected according to a random seed.

Link https://github.com/stanleybak/vggnet16_benchmark2022/

4.9 Traffic Signs Recognition

Proposed by Mădălina Eraşcu and Andreea Postovan (West University of Timisoara, Romania)

Motivation Traffic signs play a crucial role in ensuring road safety and managing traffic flow in both city and highway driving. The recognition of these signs, a vital component of autonomous driving vision systems, faces challenges such as susceptibility to adversarial examples [64] and occlusions [88], stemming from diverse traffic scene conditions.

Networks Binary neural networks (BNNs) show promise in computationally limited and energy-constrained environments within the realm of autonomous driving [35]. BNNs, where weights and/or activations are binarized to ± 1 , offer reduced model size and simplified convolution operations for image recognition compared to traditional neural networks (NNs).

We trained and tested various BNN architectures using the German Traffic Sign Recognition Benchmark (GTSRB) dataset [4]. This multi-class dataset, containing images of German road signs across 43 classes, poses challenges for both humans and models due to factors like perspective change, shade, color degradation, and lighting conditions. The dataset was also tested using the Belgian Traffic Signs [1] and Chinese Traffic Signs [2] datasets. The Belgium Traffic Signs dataset, with 62 classes, had 23 overlapping classes with GTSRB. The Chinese Traffic Signs dataset, with 58 classes, shared 15 classes with GTSRB. Pre-processing steps involved relabeling classes in the Belgium and Chinese datasets to match those in GTSRB and eliminating non-overlapping classes (see [55] for details).

We provide three models with the structure in Figures 1, 2, and 3. They contain QConv, Batch Normalization (BN), Max Pooling (ML), Fully Connected/Dense (D) layers. Note that

the QConv layer binarizes the corresponding convolutional layer. All models were trained for 30 epochs. The model from Figure 1 was trained with images having the dimension 64px x 64 px, the one from Figure 2 with 48px x 48 px and the one from Figure 3 with 30px x 30 px. The two models involving Batch Normalization layers introduce real valued parameters besides the binary ones, while the third one contains only binary parameters (see Table 5) for statistics.

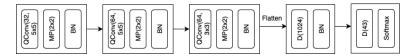


Figure 1: Accuracy Efficient Architecture for GTSRB and Belgium dataset

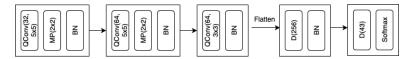


Figure 2: Accuracy Efficient Architecture for Chinese dataset

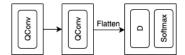


Figure 3: XNOR(QConv) architecture

Specifications To evaluate the adversarial robustness of the networks above, we assessed perturbations within the infinity norm around zero, with the radius denoted as $\epsilon = \{1, 3, 5, 10, 15\}$. This involved randomly selecting three distinct images from the GTSRB dataset's test set for each model and generating VNNLIB files for each epsilon in the set. In total, we created 45 VNNLIB files. Due to a 6-hour total timeout constraint for solving all instances, each instance had a maximum timeout of 480 seconds. To review the generated VNNLIB specification files submitted to VNNCOMP 2023, as well as to generate new ones, please refer to https://github.com/apostovan21/vnncomp2023.

Link https://github.com/apostovan21/vnncomp2023

4.10 CIFAR100

Proposed by the α,β -CROWN team.

Motivation This benchmark is reused from VNN-COMP 2022 with a reduced complexity (only two out of the four models with medium sizes are retained). See details in Section 4.5 of the report of VNN-COMP 2022 [54].

Networks We provide two ResNet models on CIFAR-100 with different model widths and depths (input dimension $32 \times 32 \times 3$, 100 classes):

- CIFAR100-ResNet-medium: 8 residual blocks, 17 convolutional layers + 2 linear layers
- CIFAR100-ResNet-large: 8 residual blocks, 19 convolutional layers + 2 linear layers (almost identical to standard ResNet-18 architecture)

Table 5: Training and Testing Statistics

Accuracy #Params

Input size Model name		Accuracy		#Params			
Input size	Wiodei name	German	China	Belgium	Binary	Real	Total
$64px \times 64px$	Figure 1	96.45	81.50	88.17	1772896	2368	1775264
$48px \times 48px$	Figure 2	95.28	83.90	87.78	904288	832	905120
$30 \mathrm{px} \times 30 \mathrm{px}$	Figure 3	81.54	N/A	N/A	1005584	0	1005584

Specifications We randomly select 100 images from the CIFAR-100 test set with a verification timeout of 100 seconds for each of the two models. We filtered out the samples which can be verified by vanilla CROWN (which is used during training) to make the benchmark more challenging. The filtering process is done offline on a machine with a GPU due to the large sizes of these models. A small proportion of instances (around 18%) with adversarial examples have been retained for potentially identifying unsound results.

Link https://github.com/huanzhang12/vnncomp2024_cifar100_benchmark

4.11 TinyImagenet

Proposed by the α,β -CROWN team.

Motivation This benchmark is reused from VNN-COMP 2022. See details in Section 4.5 of the report of VNN-COMP 2022 [54].

Networks We provide a ResNet for TinyImageNet (input dimension $64 \times 64 \times 3$, 200 classes):

• TinyImageNet-ResNet-medium: 8 residual blocks, 17 convolutional layers + 2 linear layers

Specifications We randomly select 200 images from the TinyImageNet test set with a verification timeout of 100 seconds for each of the two models. A filtering procedure has been adopted similar to the CIFAR100 benchmark.

Link https://github.com/huanzhang12/vnncomp2024_tinyimagenet_benchmark

4.12 TLL Verify Bench

Proposed by James Ferlez (University of California, Irvine)

Motivation This benchmark consists of Two-Level Lattice (TLL) NNs, which have been shown to be amenable to fast verification algorithms (e.g. [30]). Thus, this benchmark was proposed as a means of comparing TLL-specific verification algorithms with general-purpose NN verification algorithms (i.e. algorithms that can verify arbitrary deep, fully-connected ReLU NNs).

Networks The networks in this benchmark are a subset of the ones used in [30, Experiment 3]. Each of these TLL NNs has n=2 inputs and m=1 output. The architecture of a TLL NN is further specified by two parameters: N, the number of local linear functions, and M, the number of selector sets. This benchmark contains TLLs of sizes N=M=8,16,24,32,40,48,56,64, with 30 randomly generated examples of each (the generation procedure is described in [30, Section 6.1.1]). At runtime, the specified verification timeout determines how many of these networks are included in the benchmark so as to achieve an overall 6-hour run time; this selection process is deterministic. Finally, a TLL NN has a natural representation using multiple computation paths [30, Figure 1], but many tools are only compatible with fully-connected networks. Hence, the ONNX models in this benchmark implement TLL NNs by "stacking" these computation paths to make a fully connected NN (leading to sparse weight matrices: i.e. with many zero weights and biases). The TLLnet class (https://github.com/jferlez/TLLnet) contains the code necessary to generate these implementations via the exportONNX method.

Specifications All specifications have as input constraints the hypercube $[-2,2]^2$. Since all networks have only a single output, the output properties consist of a randomly generated real number and a randomly generated inequality direction. Random output samples from the network are used to roughly ensure that the real number property has an equal likelihood of being within the output range of the NN and being outside of it (either above or below all NN outputs on the input constraint set). The inequality direction is generated independently and with each direction having an equal probability. This scheme biases the benchmark towards verification problems for which counterexamples exist.

Link https://github.com/jferlez/TLLVerifyBench

Commit 199d2c26d0ec456e62906366b694a875a21ff7ef

4.13 ACAS Xu

Networks The ACASXu benchmark consists of ten properties defined over 45 neural networks used to issue turn advisories to aircraft to avoid collisions. The neural networks have 300 neurons arranged in 6 layers, with ReLU activation functions. There are five inputs corresponding to the aircraft states, and five network outputs, where the minimum output is used as the turn advisory the system ultimately produces.

Specifications We use the original 10 properties [37], where properties 1-4 are checked on all 45 networks as was done in later work by the original authors [38]. Properties 5-10 are checked on a single network. The total number of benchmarks is therefore 186. The original verification times ranged from seconds to days—including some benchmark instances that did not finish. This year we used a timeout of around two minutes (116 seconds) for each property, in order to fit within a total maximum runtime of six hours.

4.14 safeNLP

Proposed by Marco Casadio, Ekaterina Komendantskaya, Luca Arnaboldi, Tanvi Dinkar.

Motivation While considerable research has been dedicated to the verification of DNN-based systems in domains such as computer vision, there has been a notable lack of focus on the verification of natural language processing (NLP) systems. This is particularly critical given the rise of conversational agents across various domains, where inaccurate or misleading responses can cause real-world harm. For example, recent EU legislation [45] requires chatbots to disclose their non-human nature when queried, and developers of the chatbots should provide firm, and if possible, formal, guarantees that such disclosure will be given in an accurate manner. Medical assistants give another example where formal guarantees about the conversational agent responses are needed in order to safeguard against chatbots generating harmful medical advice [13]. While some initial work has been done in this area of NLP verification [36, 34, 77, 89, 75, 42, 25, 61, 14], no agreement on commonly accepted benchmarks has been reached in this domain. To address this gap, we introduce safeNLP, the first such benchmark.

Application In [19], we have undertaken a large-scale study of the existing literature on NLP verification, and distilled common patterns among the existing approaches. Usually, given a dataset consisting of sentences divided into classes, Large Language Models (LLMs) are used to embed these sentences into real-vector spaces, after which smaller neural networks are trained to classify the embedded vectors (relative to the originally given classes). For verification, one can generate meaning-preserving sentence perturbations, again embed them into vector spaces, and verify that subspaces that contain the (embeddings of) the perturbed sentences are classified correctly. Also, in line with classical verification pipelines [20], one can use these input subspaces

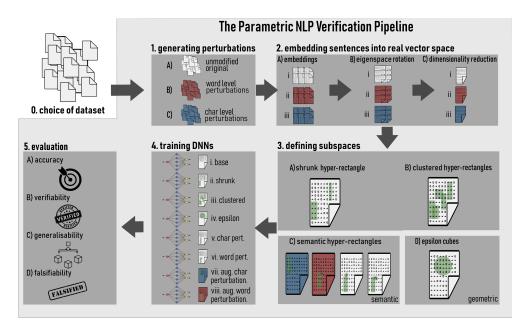


Figure 4: Generic approach to generating the NLP verification pipelines [18, 19] deployed to obtain the safeNLP benchmark.

to train the neural network to be robust on them. The problem was that each of the existing approaches [36, 34, 77, 89, 75, 42, 25, 61, 14] used parts of this pipeline in different ways, which made it difficult to compare or audit the results. In [18, 19], we made a generic implementation of this pipeline, where each of the components of the pipeline is implemented in a modular and transparent way. For example, we can choose and vary embedding functions, training modes, algorithms for sentence perturbations and algorithms for robust training, independently and modularly; as shown in Figure 4. This implementation was used to generate the presented VNNCOMP benchmark.

- Datasets: Although there was no clear consensus in [36, 34, 77, 89, 75, 42, 25, 61, 14], the most frequently used dataset in prior works was the IMDB dataset containing film reviews. Its disadvantage is unclear relation to safety critical domains that usually motivate verification efforts. On the other hand, none of the previously used datasets concerned safety-critical applications of NLP. We decided to address this problem, and therefore applied our generic NLP verification pipeline on two safety-critical datasets: R-U-A-Robot [32], which focuses on the chatbot disclosure problem, and Medical [6], which addresses the issue of harmful advice provided by medical chatbots. Both datasets are pre-processed into two classes, positive and negative, to simplify the verification task. For further details on the pre-processing steps and datasets, see [19] and the benchmark GitHub repository.
- Input Space: In both datasets, sentences are transformed into fixed-size vector representations, i.e. embeddings, which serve as the inputs to the neural networks. For this VNNCOMP benchmark, we used Sentence-BERT [56].
- What to Verify: For each dataset, we generated meaning-preseving sentence perturbations at character and word level as in Moradi et al. [53] and at sentence level with

Vicuna [21]. For each positive sentence in the dataset, the smallest hypercube containing the embeddings of all of its obtained perturbations formed one input subspace for verification. Such subspaces were obtained for all positive sentences from the given data set, and were subject to VNCCOMP verification challenge.

• A note on broader impact: Verified models can serve as filters for larger NLP systems: e.g. to screen inputs to ensure they meet safety criteria before being passed on to more complex models.

Networks The safeNLP benchmark includes two neural networks, each corresponding to a different dataset (R-U-A-Robot and Medical). Both networks share the same architecture, consisting of two fully-connected layers. The hidden layer has 128 units with a ReLU activation function, while the output layer has 2 units representing the two classification classes (positive/negative). To enhance the robustness of the networks to the specified safety requirements, they are trained using a custom PGD (Projected Gradient Descent) [51] adversarial training technique. In particular, the PGD attack explores the above-mentioned subspaces of the input space (cf. also Figure 4).

Specifications The benchmark uses hyper-rectangles in the 30-dimensional embedding space as the subspaces of choice, offering a computationally efficient way to define more precise and adaptable regions compared to the traditional ϵ -cubes. The specifications require verifying that, for a given network and hyper-rectangle, every point within the hyper-rectangle is classified as the positive class by the network. To meet time constraints, we randomly select 1,080 such specifications, each linked to one of the two networks and a corresponding hyper-rectangle, with a timeout of 20 seconds per specification.

Link https://github.com/ANTONIONLP/safeNLP

4.15 Real-world distribution shifts

Proposed by the Marabou team.

Motivation While robustness against handcrafted perturbations (e.g., norm-bounded) for perception networks are more commonly investigated, robustness against real-world distribution shifts [81] are less studied but of practical interests. This benchmark set contains queries for verifying the latter type of robustness.

Networks The network is a concatenation of a generative model and a MNIST classifier. The generative model is trained to take in an unperturbed image and an embedding of a particular type of distribution shifts in latent space, and produce a perturbed image. The distribution shift captured in this case is the "shear" perturbation.

Specifications The verification task is to certify that a classifier correctly classifies all images in a perturbation set, which is a set of images generated by the generative model given a fixed image and a ball centering the mean perturbations on this image (in the latent space). This mean perturbation is computed by a prior network.

Link https://github.com/wu-haoze/dist-shift-vnn-comp

4.16 CORA Benchmark

Proposed by the CORA team.

Motivation The verification of neural networks can be quite slow, i.e., the verification of a single instance can take multiple days – which is often hard to justify, particularly in safety-critical scenarios. To encourage the fast verification of neural networks, our benchmark focuses on the verification time by setting a small timeout and testing three different (adversarial) training techniques that aim to ease the verifiability.

Networks The benchmark consists of one ReLU-neural network architecture (7x250 + ReLU), which was trained on three datasets, (MNIST, SVHN, and CIFAR10), using three different (adversarial) training methods, i.e., standard (point), interval-bound propagation, and setbased. Both interval-bound propagation and set-based training are training methods that improve the robustness of the trained neural network and aim to ease later verification. The neural networks are taken from the first evaluation run of [44]; please refer to [44] for the training details.

Specifications All networks are trained on classification tasks. The goal is to verify that no image within a given input set is incorrectly classified.

Link https://github.com/kollerlukas/cora-vnncomp2024-benchmark

4.17 Additional Benchmarks

We have not yet obtained benchmark descriptions for the following benchmarks: Collins Aerospace, CCTSDB, Metaroom, and yolo. We will update the report when these descriptions are available. Artifacts of the benchmarks are available in the repository⁷.

⁷https://github.com/ChristopherBrix/vnncomp2024_benchmarks/tree/main/benchmarks

5 Results

Each tool was run on each of the benchmarks and produced a csv result file, that was provided as feedback to the tool authors using the online execution platform. The final csv files for each tool as well as scoring scripts are available online: https://github.com/ChristopherBrix/vnncomp2024_results. The results were automatically analyzed to compute scores and create the statistics presented in this section.

Update: Note that the two tools NeuralSAT and CORA were penalized for instances where they returned the correct result, but in a format that did not match the expected one. We report the updated results in Section B.

5.1 Regular Track

The regular track contained all the benchmarks that were voted for by at least half of all participants.

#	Tool	Score
1	α - β -CROWN	1200.0
2	PyRAT	1000.8
3	Marabou	751.0
4	nnenum	572.5
5	NNV	530.0
6	NeVer2	262.3
7	CORA	251.7
8	NeuralSAT	0

Table 6: Overall Score

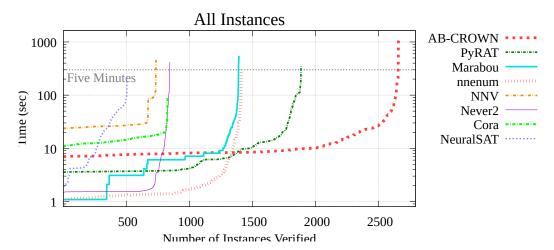


Figure 5: Cactus Plot for All Instances (Regular Track).

5.2 Extended Track

All benchmarks that were voted for by at least one team and did not make it into the regular track were part of the extended track. Every benchmark was voted for at least once, so no benchmark was unscored.

Table 7: Overall Score

#	Tool	Score
1	α - β -CROWN	900.0
2	PyRAT	398.5
3	nnenum	72.2
4	NeuralSAT	46.4

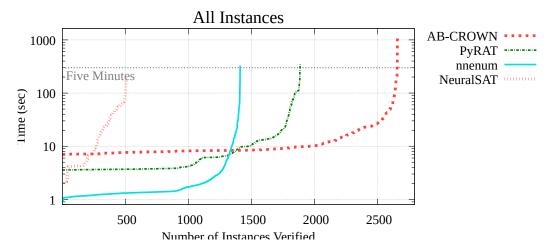


Figure 6: Cactus Plot for All Instances (Extended Track).

5.3 Other Stats

This section presents other statistics related to the measurements that are interesting but did not play a direct role in scoring this year. The results reflect the tool performance on the regular track.

Table 8: Overhead

#	Tool	Seconds
1	NeuralSAT	0.3
2	nnenum	0.9
3	Marabou	1.1
4	NeVer2	1.5
5	PyRAT	3.5
6	α - β -CROWN	7.0
7	CORA	9.9
8	NNV	23.5

Table 9: Num Benchmarks Participated

#	Tool	Count
1	PyRAT	12
2	Marabou	12
3	α - β -CROWN	12
4	nnenum	9
5	NNV	9
6	NeuralSAT	8
7	CORA	8
8	NeVer2	4

Table 10: Num Instances Verified

#	Tool	Count
1	α - β -CROWN	2285
2	PyRAT	1760
3	nnenum	1398
4	Marabou	1394
5	NeVer2	848
6	CORA	828
7	NNV	736
8	NeuralSAT	489

Table 11: Num SAT

#	Tool	Count
1	α - β -CROWN	993
2	PyRAT	890
3	nnenum	755
4	Marabou	704
5	NeVer2	526
6	CORA	327
7	NNV	308

Table 12: Num UNSAT

#	Tool	Count
1	α - β -CROWN	1292
2	PyRAT	870
3	Marabou	690
4	nnenum	643
5	CORA	501
6	NeuralSAT	489
7	NNV	428
8	NeVer2	322

6 Conclusion and Ideas for Future Competitions

This report summarizes the 5th Verification of Neural Networks Competition (VNN-COMP), held in 2024. While we observed a significant increase in the diversity, complexity, and scale of the proposed benchmarks, the best-performing tools seem to converge to GPU-enabled linear bound propagation methods using a branch-and-bound framework. In addition to the standardization of input formats (onnx and vnnlib) and evaluation hardware, introduced for VNN-COMP 2021, VNN-COMP 2024 also continued the standardized format for counter-examples and fully automated evaluation pipeline introduced in VNN-COMP 2022, requiring authors to provide complete installation scripts. We hope that this increased standardization and automatization does not only simplify the evaluation during the competition but also enables practitioners and researchers to more easily apply a range of state-of-the-art verification methods to their individual problems.

VNN-COMP 2024, successfully implemented a range of improvement opportunities identified during the previous iteration. These included requiring witnesses of found counter-examples to disambiguate tool disagreement, increasing automatization to enable a smoother final evaluation, and making a broader range of AWS instances available to allow for a better fit with tools' requirements. However, some issues were identified in the evaluation particularly with respect to clarity of some output formats and parsing for computing scores, and further improvements will be made to avoid such issues in the future. Further ideas for future competitions include the

Table 13: Incorrect Results (or Missing CE)

#	Tool	Count
1	Marabou	403
2	NeuralSAT	281
3	CORA	101
4	nnenum	2

use of scored benchmarks specifically designed for year-on-year progress tracking, the reduction of tool tuning, a batch-processing mode, and more rigorous soundness evaluation.

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Tool and benchmark authors listed in Section 3 and Section 4 participated in the preparation and review of this report.

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A Detailed Results

In this section, we provide more fine-grained results.

A.1 Regular Track

Table 14: Benchmark 2024-acasxu-2023

#	Tool	Verified	Falsified	Fastest	Penalty	Points	Score	Solved
1	α - β -CROWN	139	47	0	0	1860	100.0	100.0%
2	nnenum	139	46	0	0	1850	99.5	99.5%
3	PyRAT	137	47	0	0	1840	98.9	98.9%
4	Marabou	134	45	0	1	1640	88.2	96.2%
5	NeVer2	121	40	0	0	1610	86.6	86.6%
6	NNV	70	27	0	0	970	52.2	52.2%
7	CORA	134	7	0	36	-3990	0	75.8%
8	NeuralSAT	138	0	0	46	-5520	0	74.2%

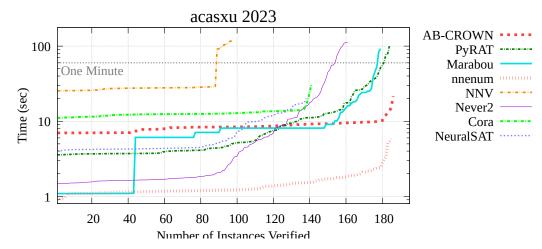


Figure 7: Cactus Plot for acasxu 2023.

Table 15: Benchmark 2024-cgan-2023

#	Tool	Verified	Falsified	Fastest	Penalty	Points	Score	Solved
1	PyRAT	8	13	0	0	210	100.0	100.0%
2	α - β -CROWN	8	13	0	0	210	100.0	100.0%
3	nnenum	6	11	0	0	170	81.0	81.0%
4	NNV	6	11	0	0	170	81.0	81.0%
5	Marabou	0	13	0	0	130	61.9	61.9%
6	NeuralSAT	8	0	0	11	-1570	0	38.1%

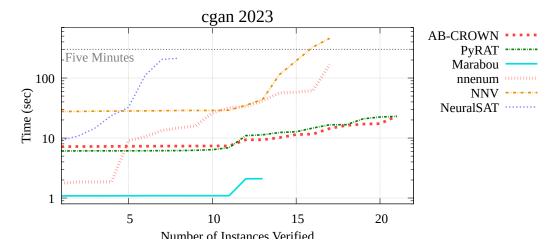


Figure 8: Cactus Plot for cgan 2023.

Table 16: Benchmark 2024-cifar100

#	Tool	Verified	Falsified	Fastest	Penalty	Points	Score	Solved
1	α - β -CROWN	117	32	0	0	1490	100.0	74.5%
2	PyRAT	67	25	0	0	920	61.7	46.0%
3	Marabou	0	30	0	0	300	20.1	15.0%
4	NeuralSAT	89	0	0	23	-2560	0	44.5%

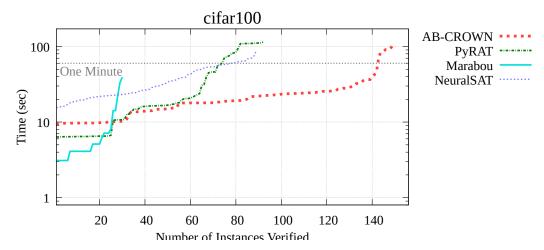


Figure 9: Cactus Plot for cifar100.

Table 17: Benchmark 2024-collins-rul-cnn-2023

#	Tool	Verified	Falsified	Fastest	Penalty	Points	Score	Solved
1	nnenum	30	32	0	0	620	100.0	100.0%
2	NNV	30	32	0	0	620	100.0	100.0%
3	Marabou	30	32	0	0	620	100.0	100.0%
4	α - β -CROWN	30	32	0	0	620	100.0	100.0%
5	PyRAT	30	28	0	0	580	93.5	93.5%
6	CORA	0	19	0	11	-1460	0	30.6%
7	NeuralSAT	30	0	0	32	-4500	0	48.4%

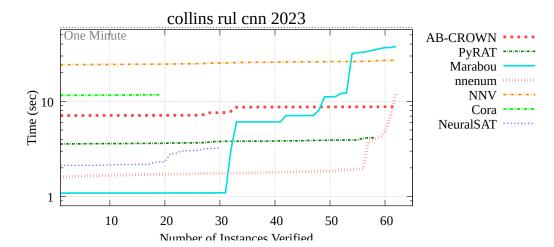


Figure 10: Cactus Plot for collins rul cnn 2023.

Table 18: Benchmark 2024-cora

#	Tool	Verified	Falsified	Fastest	Penalty	Points	Score	Solved
1	α - β -CROWN	24	134	0	0	1580	100.0	87.8%
2	Marabou	22	134	0	0	1560	98.7	86.7%
3	PyRAT	22	128	0	0	1500	94.9	83.3%
4	NNV	15	47	0	0	620	39.2	34.4%
5	NeVer2	17	11	0	0	280	17.7	15.6%
6	nnenum	20	6	0	0	260	16.5	14.4%
7	CORA	21	5	0	54	-7840	0	14.4%
8	NeuralSAT	23	0	0	134	-19870	0	12.8%

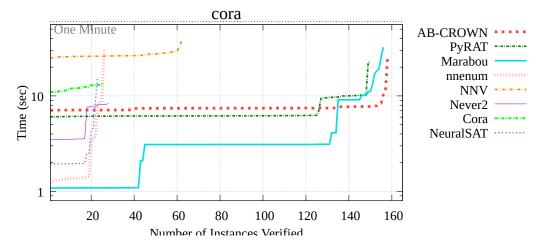


Figure 11: Cactus Plot for cora.

Table 19: Benchmark 2024-dist-shift-2023

#	Tool	Verified	Falsified	Fastest	Penalty	Points	Score	Solved
1	PyRAT	63	8	0	0	710	100.0	98.6%
2	CORA	63	8	0	0	710	100.0	98.6%
3	α - β -CROWN	63	8	0	0	710	100.0	98.6%
4	Marabou	62	7	0	0	690	97.2	95.8%
5	NNV	51	5	0	0	560	78.9	77.8%

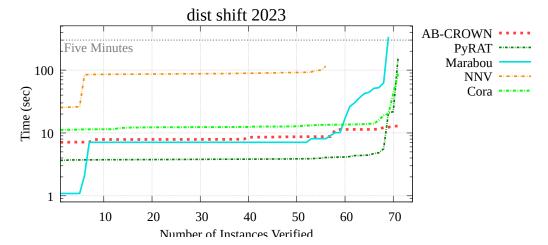


Figure 12: Cactus Plot for dist shift 2023.

Table 20: Benchmark 2024-linearizenn

#	Tool	Verified	Falsified	Fastest	Penalty	Points	Score	Solved
1	PyRAT	59	1	0	0	600	100.0	100.0%
2	Marabou	59	1	0	0	600	100.0	100.0%
3	α - β -CROWN	59	1	0	0	600	100.0	100.0%
4	nnenum	59	0	0	1	440	73.3	98.3%

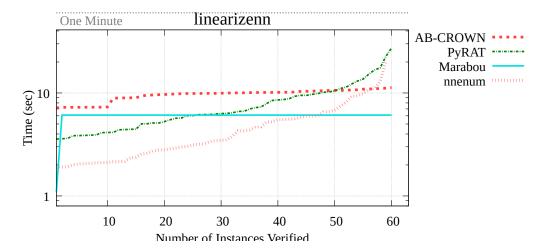


Figure 13: Cactus Plot for linearizenn.

Table 21: Benchmark 2024-metaroom-2023

#	Tool	Verified	Falsified	Fastest	Penalty	Points	Score	Solved
1	α - β -CROWN	91	7	0	0	980	100.0	98.0%
2	PyRAT	91	6	0	0	970	99.0	97.0%
3	NNV	90	2	0	0	920	93.9	92.0%
4	Marabou	46	7	0	0	530	54.1	53.0%
5	nnenum	44	2	0	0	460	46.9	46.0%
6	NeuralSAT	91	0	0	7	-140	0	91.0%

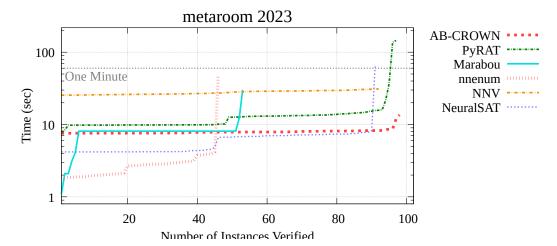


Figure 14: Cactus Plot for metaroom 2023.

Table 22: Benchmark 2024-nn4sys-2023

#	Tool	Verified	Falsified	Fastest	Penalty	Points	Score	Solved
1	α - β -CROWN	194	0	0	0	1940	100.0	100.0%
2	PyRAT	53	0	0	0	530	27.3	27.3%
3	Marabou	24	0	0	0	240	12.4	12.4%
4	nnenum	22	0	0	0	220	11.3	11.3%
5	CORA	2	0	0	0	20	1.0	1.0%

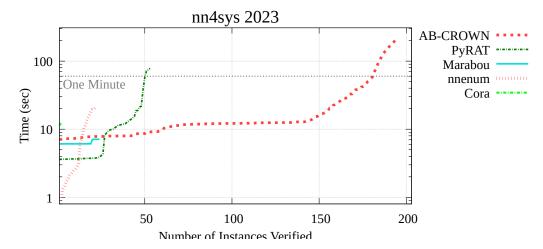


Figure 15: Cactus Plot for nn4sys 2023.

Table 23: Benchmark 2024-safenlp

#	Tool	Verified	Falsified	Fastest	Penalty	Points	Score	Solved
1	α - β -CROWN	421	659	0	0	10800	100.0	100.0%
2	nnenum	321	642	0	1	9480	87.8	89.2%
3	PyRAT	277	586	0	0	8630	79.9	79.9%
4	NeVer2	161	466	0	0	6270	58.1	58.1%
5	CORA	266	269	0	0	5350	49.5	49.5%
6	NNV	166	165	0	0	3310	30.6	30.6%
7	Marabou	300	375	0	402	-53550	0	62.5%

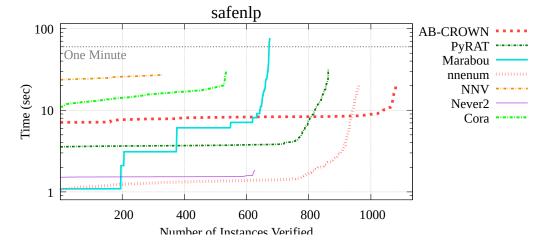


Figure 16: Cactus Plot for safenlp.

Table 24: Benchmark 2024-tinyimagenet

#	Tool	Verified	Falsified	Fastest	Penalty	Points	Score	Solved
1	α -β-CROWN	131	43	0	0	1740	100.0	87.0%
2	PyRAT	48	31	0	0	790	45.4	39.5%
3	Marabou	0	43	0	0	430	24.7	21.5%
4	NNV	0	2	0	0	20	1.1	1.0%
5	CORA	0	2	0	0	20	1.1	1.0%
6	NeuralSAT	95	0	0	11	-700	0	47.5%

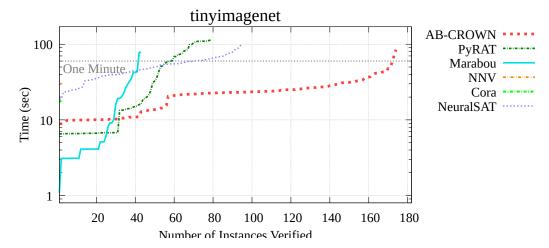


Figure 17: Cactus Plot for tinyimagenet.

Table 25: Benchmark 2024-tllverifybench-2023

#	Tool	Verified	Falsified	Fastest	Penalty	Points	Score	Solved
1	PyRAT	15	17	0	0	320	100.0	100.0%
2	NeVer2	23	9	0	0	320	100.0	100.0%
3	CORA	15	17	0	0	320	100.0	100.0%
4	α - β -CROWN	15	17	0	0	320	100.0	100.0%
5	Marabou	13	17	0	0	300	93.8	93.8%
6	nnenum	2	16	0	0	180	56.2	56.2%
7	NNV	0	17	0	0	170	53.1	53.1%
8	NeuralSAT	15	0	0	17	-2400	0	46.9%

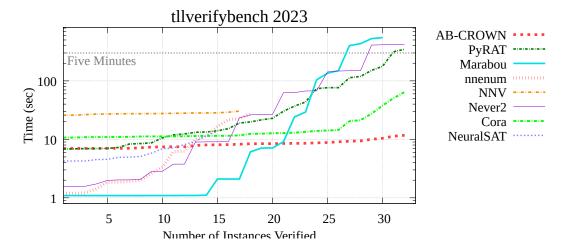


Figure 18: Cactus Plot for tllverifybench 2023.

A.2 Extended Track

Table 26: Benchmark 2024-cctsdb-yolo-2023

#	Tool	Verified	Falsified	Fastest	Penalty	Points	Score	Solved
1	α - β -CROWN	11	28	0	0	390	100.0	100.0%
2	PyRAT	0	2	0	0	20	5.1	5.1%

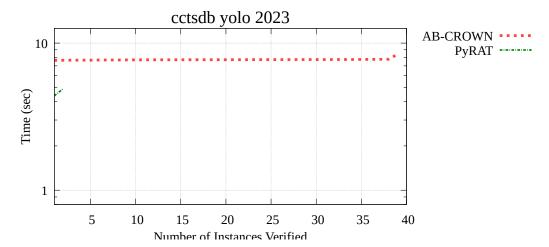


Figure 19: Cactus Plot for cctsdb yolo 2023.

Table 27: Benchmark 2024-collins-aerospace-benchmark

#	Tool	Verified	Falsified	Fastest	Penalty	Points	Score	Solved
1	PyRAT	0	6	0	0	60	100.0	100.0%
2	α - β -CROWN	0	6	0	0	60	100.0	100.0%

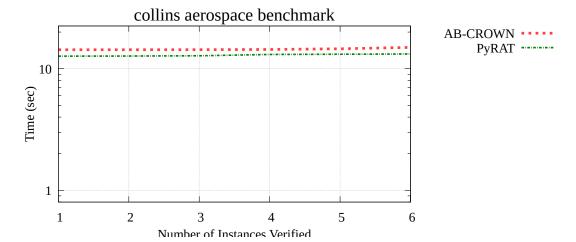


Figure 20: Cactus Plot for collins aerospace benchmark.

Table 28: Benchmark 2024-1snc

#	Tool	Verified	Falsified	Fastest	Penalty	Points	Score	Solved
1	α - β -CROWN	40	0	0	0	400	100.0	100.0%
2	PyRAT	15	0	0	0	150	37.5	37.5%

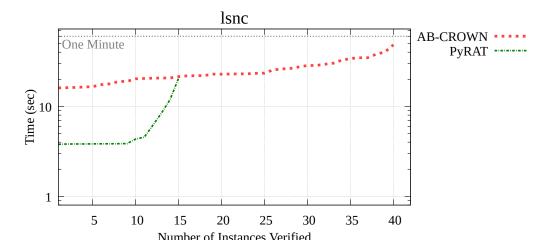


Figure 21: Cactus Plot for lsnc. $\,$

Table 29: Benchmark 2024-ml4acopf-2023

#	Tool	Verified	Falsified	Fastest	Penalty	Points	Score	Solved
1	α - β -CROWN	22	0	0	0	220	100.0	95.7%
2	PyRAT	15	0	0	0	150	68.2	65.2%

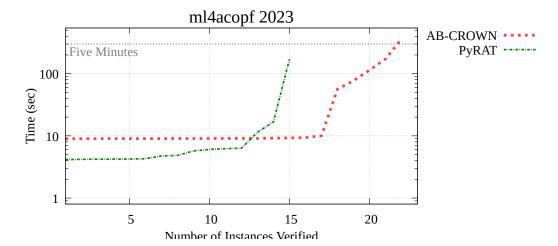


Figure 22: Cactus Plot for ml4acopf 2023.

Table 30: Benchmark 2024-ml4acopf-2024

#	Tool	Verified	Falsified	Fastest	Penalty	Points	Score	Solved
1	α - β -CROWN	59	3	0	0	620	100.0	89.9%
2	PyRAT	29	3	0	0	320	51.6	46.4%

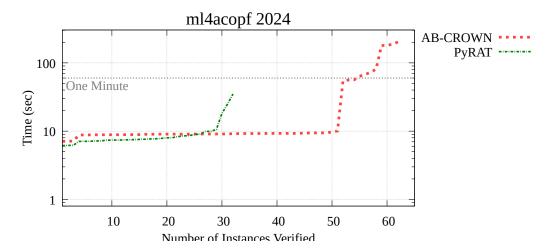


Figure 23: Cactus Plot for ml4acopf 2024.

Table 31: Benchmark 2024-traffic-signs-recognition-2023

#	Tool	Verified	Falsified	Fastest	Penalty	Points	Score	Solved
1	α - β -CROWN	0	45	0	0	450	100.0	100.0%
2	PyRAT	0	4	0	0	40	8.9	8.9%
3	NeuralSAT	0	0	0	11	-1650	0	0.0%

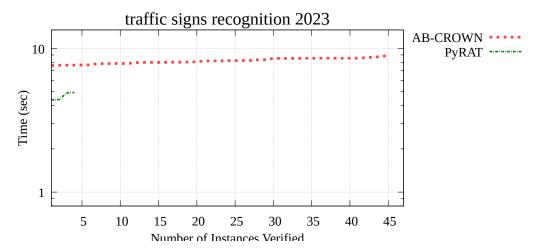


Figure 24: Cactus Plot for traffic signs recognition 2023.

Table 32: Benchmark 2024-vggnet16-2023

#	Tool	Verified	Falsified	Fastest	Penalty	Points	Score	Solved
1	α - β -CROWN	18	0	0	0	180	100.0	100.0%
2	nnenum	13	0	0	0	130	72.2	72.2%
3	PyRAT	10	0	0	0	100	55.6	55.6%
4	NeuralSAT	6	0	0	0	60	33.3	33.3%

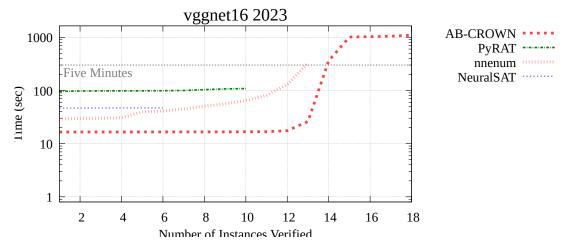


Figure 25: Cactus Plot for vggnet16 2023.

Table 33: Benchmark 2024-vit-2023

#	Tool	Verified	Falsified	Fastest	Penalty	Points	Score	Solved
1	α - β -CROWN	84	0	0	0	840	100.0	42.0%
2	NeuralSAT	11	0	0	0	110	13.1	5.5%

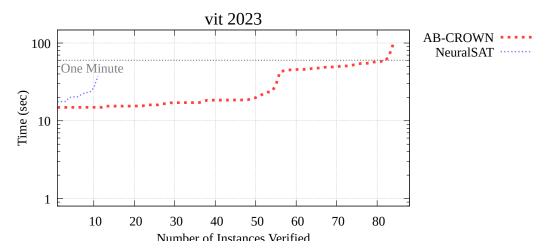


Figure 26: Cactus Plot for vit 2023.

Table 34: Benchmark 2024-yolo-2023

#	Tool	Verified	Falsified	Fastest	Penalty	Points	Score	Solved
1	α - β -CROWN	60	0	0	0	600	100.0	83.3%
2	PyRAT	43	0	0	0	430	71.7	59.7%

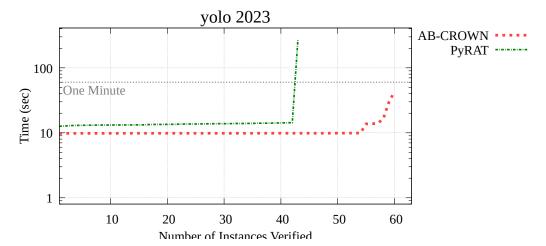


Figure 27: Cactus Plot for yolo 2023.

B Results After Tool Updates

As mentioned in Section 5, the two tools NeuralSAT and CORA provided the results in a way that differed from the expected output format. Even though this difference was minor, it caused the evaluation to penalize them, even though they were able to correctly identify both SAT and UNSAT instances.

While the expected format was described in the VNN-COMP rules, in subsequent VNN-COMP instances, we plan to address this as follows to avoid this issue. First, we plan to release more details regarding the specification of the format tools should use to report SAT instances and counterexamples. Second, we plan to execute the aggregate scoring code at submission time, instead of post hoc: tool authors did not detect that there were problems at submission time, as the returned instances as SAT or UNSAT appeared correct, but were aggregated when executing the scoring scripts later for preparation of the scores. Third, we plan to add an error handling mechanism in the scoring script, so that in the event of a format problem or parsing problem of the results files from the tools, we do not count these as unsound (i.e., wrong) results, but rather count them as an error and exclude results (so just score them as 0 instead of a negative penalty). There are some pros/cons of this with respect to scoring, so we will get participant feedback in the next iteration when discussing the scoring mechanisms.

After fixing these issues, the following results were achieved.

B.1 Regular Track

Table 35: Overall Score

#	Tool	Score
1	α-β-CROWN	1200.0
2	NeuralSAT	1113.1
3	PyRAT	1000.8
4	Marabou	751.0
5	nnenum	572.5
6	NNV	530.0
7	CORA	439.5
8	NeVer2	262.3

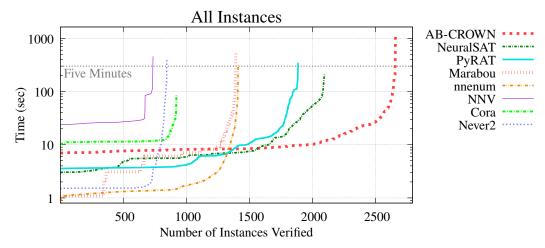


Figure 28: Cactus Plot for All Instances (Regular Track).

B.2 Extended Track

Table 36: Overall Score

#	Tool	Score
1	α - β -CROWN	900.0
2	PyRAT	398.5
3	nnenum	72.2
4	NeuralSAT	70.9

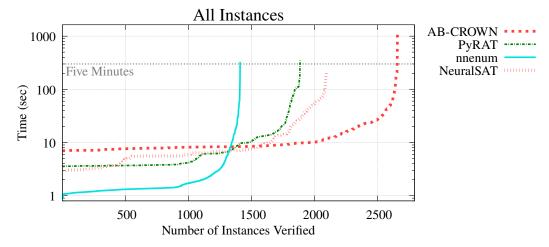


Figure 29: Cactus Plot for All Instances (Extended Track).

B.3 More Results

The full list of results for this setting can be generated using the scripts in https://github.com/ChristopherBrix/vnncomp2024_results.

B.4 Detailed Results

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (X).

Category	Id	Result	α-β- C	PyRAT	Marab	NNen	NNV	NeVer2	CORA	NSAT
Acasxu 2023	0	UNSAT	9.87	7.87	8.11	1.51	-	3.42	12.1	4.61
Acasxu 2023	1	UNSAT		9.92	8.10	1.42	-	4.00	11.1	4.46
Acasxu 2023	2	UNSAT		11.4	8.10	1.71	-	10.7	11.1	9.90
Acasxu 2023	3 4	UNSAT UNSAT		9.29	8.10	$1.71 \\ 1.42$	-	8.11	12.5	9.83
Acasxu 2023 Acasxu 2023	5	UNSAT		7.25 8.80	8.10 8.10	1.70	_	2.90 3.86	11.6 12.5	4.33 4.44
Acasxu 2023	6	UNSAT		6.90	8.10	1.37	_	2.40	11.3	4.26
Acasxu 2023	7	UNSAT		6.17	8.10	1.50	_	1.93	12.4	4.33
Acasxu 2023	8	UNSAT		5.25	8.10	1.34	-	1.92	12.5	4.25
Acasxu 2023	9	UNSAT	9.03	11.2	8.10	1.69	-	5.73	13.5	4.43
Acasxu 2023	10	UNSAT		14.2	8.11	1.89	-	16.3	11.5	9.73
Acasxu 2023	11	UNSAT		11.0	8.10	1.78	-	8.40	12.6	9.87
Acasxu 2023	12	UNSAT		9.44	8.10	1.45	-	5.28	12.5	7.47
Acasxu 2023	13	UNSAT		17.6	10.1	1.89	-	55.6	13.5	7.32
Acasxu 2023 Acasxu 2023	14 15	UNSAT UNSAT		17.2 35.5	9.11 25.2	1.82 2.21	-	37.2	12.7 11.8	10.0 11.5
Acasxu 2023 Acasxu 2023	16	UNSAT		35.0	18.1	$\frac{2.21}{2.17}$	-	-	11.8	12.9
Acasxu 2023	17	UNSAT		37.3	25.2	2.38	_	_	12.5	13.2
Acasxu 2023	18	UNSAT		12.8	8.10	1.61	_	9.15	11.6	4.48
Acasxu 2023	19	UNSAT		11.1	8.10	1.53	-	11.0	12.5	9.88
Acasxu 2023	20	UNSAT	9.25	11.4	8.10	1.53	-	6.18	12.5	4.80
Acasxu 2023	21	UNSAT	9.23	8.81	8.10	1.46	-	6.60	12.3	6.44
Acasxu 2023	22	UNSAT		14.3	8.10	1.72	-	14.4	12.5	6.01
Acasxu 2023	23	UNSAT		25.7	13.1	2.43	-	100	12.4	11.7
Acasxu 2023	24	UNSAT		29.2	19.1	2.39	-	110	12.5	11.1
Acasxu 2023 Acasxu 2023	$\frac{25}{26}$	UNSAT UNSAT		26.6 26.6	16.1 46.2	2.17 1.99	-	110	12.6 11.5	11.2 14.4
Acasxu 2023 Acasxu 2023	27	UNSAT		14.1	9.10	1.93	-	15.7	14.0	12.0
Acasxu 2023	28	UNSAT		13.0	8.10	1.79	_	5.83	12.7	4.82
Acasxu 2023	29	UNSAT		11.1	8.10	1.71	_	8.73	12.4	5.02
Acasxu 2023	30	UNSAT	9.23	9.59	8.10	1.52	-	10.8	13.7	7.38
Acasxu 2023	31	UNSAT	9.36	17.6	8.10	1.82	-	29.1	12.2	10.4
Acasxu 2023	32	UNSAT		33.3	24.2	2.80	-	-	12.4	12.7
Acasxu 2023	33	UNSAT		55.6	39.2	2.29	-	-	12.5	16.6
Acasxu 2023	34	UNSAT		25.9	24.2	2.09	-	-	12.7	13.4
Acasxu 2023	35	UNSAT		51.7	53.3	3.34	-	0 00	12.8	17.4
Acasxu 2023 Acasxu 2023	$\frac{36}{37}$	UNSAT UNSAT		11.1 10.8	8.10 8.10	$1.50 \\ 1.67$	-	8.28 6.17	13.6 12.5	5.86 5.12
Acasxu 2023	38	UNSAT		9.88	8.10	1.65	_	4.55	13.6	4.46
Acasxu 2023	39	UNSAT		8.72	8.10	1.63	_	6.60	12.8	5.48
Acasxu 2023	40	UNSAT		13.5	8.10	1.56	-	15.6	12.4	10.0
Acasxu 2023	41	UNSAT	9.50	22.9	14.1	1.94	-	48.3	14.0	16.5
Acasxu 2023	42	UNSAT	9.56	21.1	11.1	1.97	-	83.8	12.4	10.5
Acasxu 2023	43	UNSAT		39.1	23.2	2.09	-	-	12.6	12.9
Acasxu 2023	44	UNSAT		29.7	16.1	2.31	-	112	12.8	11.7
Acasxu 2023	45	UNSAT		10.7	15.1	1.49	-	59.7	14.6	4.88
Acasxu 2023	46	SAT	7.00	11.3	1.09	1.19	-	113	X	X
Acasxu 2023 Acasxu 2023	$\frac{47}{48}$	SAT SAT	$7.40 \\ 7.02$	30.8 7.52	92.4 1.09	1.73 1.20	-	20.4 8.97	X	X
Acasxu 2023	49	SAT	7.45	44.5	-	1.17	_	-	12.9	X
Acasxu 2023	50	SAT	7.36	17.6	1.09	1.78	_	_	X	X
Acasxu 2023	51	UNSAT		12.6	18.1	1.77	_	74.3	31.4	8.45
Acasxu 2023	52	UNSAT	9.59	12.9	24.2	2.09	-	-	15.9	16.8
Acasxu 2023	53	UNSAT	9.57	13.1	22.2	1.86	-	94.3	24.5	17.2
Acasxu 2023	54	SAT	7.07	4.44	1.09	1.14	-	4.96	X	X
Acasxu 2023	55	SAT	7.04	3.57	1.09	1.20	25.7	1.71	X	X
Acasxu 2023	56	SAT	7.00	3.65	1.09	1.16	25.6	1.75	X	X
Acasxu 2023	57	SAT	7.02	4.41	1.09	1.18	25.0	1.63	X	X
Acasxu 2023 Acasxu 2023	$\frac{58}{59}$	SAT	6.98 7.00	5.37 4.39	1.09	1.21	25.9	3.24 2.62	X	X
Acasxu 2023 Acasxu 2023	60	SAT SAT	7.00	4.04	1.09 1.10	1.19 1.18	25.6 25.6	4.46	×	â
Acasxu 2023	61	SAT	6.99	4.38	1.09	1.17	25.5	17.7	x	×
Acasxu 2023	62	SAT	7.02	11.7	1.09	1.28	-	5.11	X	X

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (X).

Category	Id	Result	α - β - \mathbf{C}	PyRAT	Marab	NNen	NNV	NeVer2	CORA	NSAT
Acasxu 2023	63	SAT	7.01	3.98	1.09	1.11	26.0	1.65	×	×
Acasxu 2023	64	SAT	7.37	10.4	1.09	1.18	-	13.2	X	X
Acasxu 2023	65	UNSAT	21.6	- 5.00	1 00	5.43	26.0	1 67		
Acasxu 2023 Acasxu 2023	$\frac{66}{67}$	SAT SAT	7.00 7.00	5.20 5.23	1.09 1.09	1.10 1.12	$26.0 \\ 26.6$	1.67 6.12	X	X
Acasxu 2023	68	SAT	7.00	3.65	1.09	1.12	25.5	2.71	x	x
Acasxu 2023	69	SAT	7.02	11.8	1.10	1.40	-	-	X	X
Acasxu 2023	70	SAT	7.02	3.99	1.09	1.14	-	44.9	X	X
Acasxu 2023	71	SAT	6.99	4.02	1.09	1.14	25.5	1.65	X	X
Acasxu 2023	72	SAT	7.05	3.92	1.09	1.19	-	1.64	X	X
Acasxu 2023	73	UNSAT	11.7	78.3	1 00	5.84	-	1.04	-	20.1
Acasxu 2023 Acasxu 2023	$\frac{74}{75}$	SAT	$7.00 \\ 7.04$	4.34 7.59	1.09 1.09	1.10 1.15	25.7 25.6	1.64 1.65	X	X
Acasxu 2023 Acasxu 2023	76	SAT SAT	7.04	3.92	1.09	1.13	20.0	1.66	x	â
Acasxu 2023	77	SAT	6.98	5.58	1.09	1.19	25.6	1.66	X	X
Acasxu 2023	78	SAT	6.99	4.40	1.09	1.19	26.3	4.06	X	X
Acasxu 2023	79	SAT	7.01	3.99	1.09	1.21	25.7	4.88	X	X
Acasxu 2023	80	SAT	7.01	7.35	1.09	1.18	-	-	X	X
Acasxu 2023	81	SAT	7.00	5.39	1.09	1.17	-	1.63	X	X
Acasxu 2023	82	SAT	7.01	5.33	1.09	1.20	-	1.65	X	X
Acasxu 2023 Acasxu 2023	83 84	SAT SAT	7.58 7.03	103 5.17	83.4 1.09	1.51 1.19	-	2.06	×	×
Acasxu 2023 Acasxu 2023	85	SAT	7.03	4.03	1.09	1.19	25.5	1.63	x	x
Acasxu 2023	86	SAT	7.05	11.2	1.09	1.22	26.9	7.01	X	X
Acasxu 2023	87	SAT	7.01	5.00	1.09	1.16	25.8	1.64	X	X
Acasxu 2023	88	SAT	7.02	3.57	1.09	1.14	26.2	22.2	X	X
Acasxu 2023	89	SAT	7.02	3.59	1.10	1.18	25.8	3.40	X	X
Acasxu 2023	90	UNSAT		79.7	17.4	1.53	-	-	13.0	17.0
Acasxu 2023	91	UNSAT	8.55	6.49	9.10	1.48	-	10.7	12.2	4.76
Acasxu 2023	92	UNSAT	8.83	6.74	13.2	1.37 1.21	27.0	1 60	10.5	14.3
Acasxu 2023 Acasxu 2023	93 94	UNSAT UNSAT	8.31	3.73 3.77	7.10 8.10	1.23	$27.8 \\ 27.5$	1.69 2.22	$12.5 \\ 11.2$	4.24 4.21
Acasxu 2023	95	UNSAT	7.82	3.73	6.10	1.15	27.1	1.52	12.2	4.21
Acasxu 2023	96	SAT	7.03	3.60	1.09	1.14	25.5	1.55	12.0	X
Acasxu 2023	97	SAT	6.99	3.57	1.09	1.19	25.7	1.54	11.8	X
Acasxu 2023	98	SAT	7.04	3.61	1.09	1.18	25.4	1.54	11.9	X
Acasxu 2023	99	UNSAT		4.73	8.10	1.40	-	4.52	11.2	7.93
Acasxu 2023	100	UNSAT	8.85	5.05	9.11	1.39	-	18.2	11.5	4.45
Acasxu 2023 Acasxu 2023	$\frac{101}{102}$	UNSAT UNSAT	8.84 7.83	5.24 3.74	8.10 6.09	1.37 0.96	28.4	5.57 1.50	14.3 13.5	5.12 4.27
Acasxu 2023	103	UNSAT	8.36	3.71	8.10	1.21	27.9	1.67	13.6	4.16
Acasxu 2023	104	UNSAT	7.80	3.71	6.09	1.20	27.4	1.51	13.8	4.21
Acasxu 2023	105	UNSAT	7.80	3.70	6.09	1.17	28.0	1.48	13.5	4.57
Acasxu 2023	106	UNSAT	7.82	3.64	6.09	1.17	27.6	1.51	11.1	4.22
Acasxu 2023	107		7.83	3.71	6.09	0.94	27.9	1.49	12.2	4.17
Acasxu 2023	108		8.38	4.49	8.10	1.13	28.0	1.85	12.8	5.86
Acasxu 2023	109	UNSAT	8.47	5.22	8.10	1.50 1.36	20.2	8.86	13.8 14.1	4.30
Acasxu 2023 Acasxu 2023	$\frac{110}{111}$		8.46 8.71	3.69 4.10	7.10 8.10	1.26	28.3 106	5.68 1.89	12.5	4.34 4.18
Acasxu 2023	112	UNSAT	8.23	3.68	6.09	1.14	27.2	1.63	11.4	4.24
Acasxu 2023	113	UNSAT	8.47	4.10	8.10	1.15	104	1.74	13.6	5.42
Acasxu 2023	114	UNSAT	7.77	3.70	6.09	1.10	28.0	1.49	12.5	4.08
Acasxu 2023	115	UNSAT	8.22	4.06	7.10	1.09	28.1	1.78	12.6	4.37
Acasxu 2023	116	UNSAT		3.69	6.09	1.09	28.7	1.67	12.4	4.31
Acasxu 2023	117	UNSAT		5.13	8.10	1.12	108	11.2	12.4	5.98
Acasxu 2023 Acasxu 2023	$\frac{118}{119}$	UNSAT UNSAT		5.63 5.24	10.1 8.10	1.38 1.52	-	24.4 32.2	12.8 13.0	4.84 4.51
Acasxu 2023 Acasxu 2023	120	UNSAT		3.65	6.09	1.16	28.7	1.61	12.4	4.18
Acasxu 2023 Acasxu 2023	121	UNSAT		3.72	6.09	1.25	27.8	1.51	12.4	4.18
Acasxu 2023	122	UNSAT		4.07	8.11	1.16	28.8	1.77	12.6	5.42
Acasxu 2023	123	UNSAT		3.68	6.09	1.16	27.4	1.66	12.2	4.25
Acasxu 2023	124	UNSAT	7.77	3.69	6.09	1.15	27.9	1.47	12.1	4.39
Acasxu 2023	125	UNSAT		3.71	8.10	1.14	27.4	1.68	13.1	4.36
Acasxu 2023	126	UNSAT		7.62	9.11	1.42	-	19.7	12.6	5.51
Acasxu 2023	127	UNSAT		4.03	7.10	1.17	28.2	1.86	11.4	4.27
Acasxu 2023 Acasxu 2023	$\frac{128}{129}$	UNSAT UNSAT		4.13 3.72	7.10 6.10	1.24	27.8 27.8	1.91 1.63	13.9 12.4	$4.26 \\ 4.20$
110a3AU 2020	149	UNSAL	0.01	0.12	0.10	1.09	41.0	1.00	14.4	4.20

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (X).

Category	Id	Result	α - β - \mathbf{C}	PyRAT	Marab	NNen	NNV	NeVer2	CORA	NSAT
Acasxu 2023	130	UNSAT	8.43	3.73	8.10	1.20	27.6	1.72	11.2	4.33
Acasxu 2023	131	UNSAT	8.22	3.71	8.10	1.18	27.8	1.68	11.4	4.23
Acasxu 2023	132		7.92	3.69	6.10	0.88	27.1	1.48	12.5	4.06
Acasxu 2023	133	UNSAT		3.74	7.10	1.09	27.5	1.83	12.5	4.35
Acasxu 2023	134	UNSAT		3.68	6.10	0.89	27.8	1.50	13.6	4.26
Acasxu 2023	135		8.65	12.7	8.12	1.36	-	21.0	19.5	4.37
Acasxu 2023	136		8.45	6.49	8.10	1.32	-	11.2	13.1	9.63
Acasxu 2023 Acasxu 2023	137 138	UNSAT UNSAT	8.47	7.16 4.69	8.10 7.10	1.26 1.16	92.6	13.9 1.77	13.2 11.5	4.37 4.29
Acasxu 2023	139		8.31	4.10	7.10	1.23	-	2.21	12.5	4.29
Acasxu 2023	140		8.24	4.35	7.10	1.20	27.8	1.79	12.5	4.20
Acasxu 2023	141		7.05	3.59	1.09	1.09	25.5	1.55	13.1	X
Acasxu 2023	142		7.00	3.63	1.09	1.12	25.6	1.56	11.8	X
Acasxu 2023	143		7.00	3.60	1.09	1.18	25.8	1.54	13.1	X
Acasxu 2023	144		8.38	4.67	8.10	1.25	118	1.99	11.5	4.40
Acasxu 2023	145		8.37	4.59	8.10	1.24	116	2.06	11.4	4.47
Acasxu 2023	146	UNSAT	8.26	4.04	6.09	1.19	27.7	1.63	12.4	4.21
Acasxu 2023	147	UNSAT	8.39	3.71	6.09	1.19	28.0	1.62	12.4	4.17
Acasxu 2023	148	UNSAT	8.36	4.05	8.10	1.21	27.7	1.72	13.2	4.22
Acasxu 2023	149	UNSAT	8.37	3.74	8.10	1.23	27.9	1.73	12.7	4.35
Acasxu 2023	150	UNSAT	8.41	3.73	6.09	1.19	27.4	1.61	12.3	4.26
Acasxu 2023	151	UNSAT	8.80	4.14	8.10	1.21	102	1.89	12.4	4.25
Acasxu 2023	152	UNSAT	7.82	3.67	6.10	0.94	27.4	1.49	12.3	4.06
Acasxu 2023	153		8.44	4.13	8.10	1.16	27.5	2.08	13.1	4.38
Acasxu 2023	154		8.49	4.08	7.10	1.23	27.8	1.75	12.2	4.24
Acasxu 2023	155		7.99	3.67	6.09	1.08	27.5	1.61	12.4	4.23
Acasxu 2023	156		8.21	3.69	6.09	1.08	27.2	1.63	12.2	4.11
Acasxu 2023	157		8.35	4.05	8.10	1.14	28.0	1.75	13.9	4.27
Acasxu 2023	158	UNSAT		3.71	8.10	1.18	29.2	1.64	12.4	4.35
Acasxu 2023	159	UNSAT		3.67	6.09	1.12	28.4	1.61	11.2	4.24
Acasxu 2023	160		8.48	4.30	8.10	1.12	90.9	1.76	11.4	4.19
Acasxu 2023	161	UNSAT		4.06	8.10	1.21	27.4	1.70	12.3	4.26
Acasxu 2023	162		7.81	3.71	6.09	1.12	27.7	1.51	11.2	4.30
Acasxu 2023	163	UNSAT		4.10	8.10	1.10	27.9	1.76	12.4	4.38
Acasxu 2023 Acasxu 2023	164 165	UNSAT UNSAT	8.36	4.42	8.10 8.10	1.09 1.17	27.6 94.4	1.81	11.5	4.24
Acasxu 2023	166	UNSAT		4.07 3.76	7.10	1.10	27.9	1.78 1.65	11.2 12.5	4.22 4.27
Acasxu 2023	167	UNSAT		3.68	6.09	1.13	28.3	1.60	12.3	4.23
Acasxu 2023	168		8.22	3.72	6.10	1.08	28.1	1.60	13.5	4.31
Acasxu 2023	169	UNSAT		3.76	6.09	1.15	28.0	1.60	13.8	4.34
Acasxu 2023	170	UNSAT		3.71	6.09	1.20	28.0	1.58	12.7	4.23
Acasxu 2023	171		8.35	3.71	7.10	1.13	28.5	1.74	12.3	4.39
Acasxu 2023	172	UNSAT		3.69	6.10	1.08	27.9	1.64	12.2	4.27
Acasxu 2023	173	UNSAT		3.71	7.10	1.09	28.7	1.84	12.5	4.23
Acasxu 2023	174		8.22	3.73	6.10	1.11	27.7	1.59	12.4	4.19
Acasxu 2023	175	UNSAT	8.47	3.68	7.10	1.21	27.6	1.64	12.5	4.29
Acasxu 2023	176	UNSAT	7.77	3.70	6.10	1.16	28.6	1.60	13.7	4.45
Acasxu 2023	177	UNSAT	7.92	3.72	6.09	1.15	27.6	1.50	13.6	4.22
Acasxu 2023	178	UNSAT	8.40	3.72	8.10	1.14	28.0	1.69	13.8	4.40
Acasxu 2023	179	UNSAT	8.26	3.71	6.10	1.19	27.6	1.62	11.4	4.29
Acasxu 2023	180		13.7	-	-	1.88	-	-	-	17.4
Acasxu 2023	181	UNSAT	15.5	61.4	-	5.17	-	-	13.0	14.6
Acasxu 2023	182		7.40	13.7	X	-	-	-	-	X
Acasxu 2023	183		7.04	9.39	1.09	1.22	-	-	-	X
Acasxu 2023	184		13.0	25.9	-	3.15	-	-	-	12.3
Acasxu 2023	185	UNSAT	12.1	8.81	27.2	1.61	-	56.1	12.3	12.8
Cgan 2023	0		7.33	6.90	1.09	13.4	28.4	-	-	X
Cgan 2023	1		7.33	6.25	1.09	32.1	29.2	-	-	X
Cgan 2023	2		7.38	6.40	1.09	14.7	27.8	-	-	X
Cgan 2023	3		11.6	14.7	1.00	26.1	194	-	-	9.22
Cgan 2023	4		7.35	6.11	1.09	10.5	28.0	-	-	X
Cgan 2023	5 6	UNSAT		22.4	1.00	56.6	- 29 1	-	-	23.8
Cgan 2023	6		7.18	6.09	1.09	1.85	28.1	-	-	X
Cgan 2023	7		7.31	6.12	1.09	16.0	27.7	-	-	X
Cgan 2023	8		23.3	20.9	-	168	220	-	-	213
Cgan 2023	9		16.2	12.4	1.00	41.5	328	-	-	205
Cgan 2023	10	SAT	7.24	6.12	1.09	1.85	28.8	-	-	X

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

Category	Id	Result	α - β - \mathbf{C}	PyRAT	Marab	NNen	NNV	NeVer2	CORA	NSAT
Cgan 2023	11	SAT	7.21	6.17	1.09	1.86	28.8	-	-	X
Cgan 2023	12	UNSAT	17.4	12.7	-	33.5	44.2	-	-	32.5
Cgan 2023	13	UNSAT	17.1	16.6	-	58.1	460	-	-	111
Cgan 2023	14	SAT	7.27	6.16	1.09	1.76	28.2	-	-	X
Cgan 2023	15	SAT	7.38	6.13	1.09	61.7	28.6	-	-	X
Cgan 2023	16	UNSAT		11.3	1 00	- 0.02	35.1	-	-	10.8
Cgan 2023	17	SAT	7.30	6.11	1.09	9.03	28.8 114	-	-	X
Cgan 2023 Cgan 2023	18 19	UNSAT SAT	9.36	11.0 16.7	2.10	_	-	_	_	14.6
Cgan 2023	20	SAT	9.34	23.0	2.10	-	-	-	-	-
Cifar100	0	UNSAT	42.3	_	_	_	_	_	_	74.9
Cifar100	1	UNSAT	17.9	16.3	-	-	-	-	-	22.7
Cifar100	2	SAT	9.81	6.42	3.10	-	-	-	-	X
Cifar100	3	UNSAT	26.0	-	-	-	-	-	-	38.7
Cifar100	4		32.9	-	-	-	-	-	-	56.7
Cifar100	5	?	-	-	-	-	-	-	-	-
Cifar100	6	UNSAT	18.0	14.9	-	-	-	-	-	21.6
Cifar100	7	?	-	-	-	-	-	-	-	-
Cifar100	8	UNSAT		-	-	-	-	-	-	53.9
Cifar100 Cifar100	9 10	? ?	-	-	_	-	-	-	-	_
Cifar100	11	UNSAT	15.0	10.6	_	_	_	_	-	16.3
Cifar100	12	SAT	9.72	6.34	39.3	_	-	-	-	X
Cifar100 Cifar100	13	SAT	9.65	6.43	3.10	_	_	_	-	x
Cifar100	14	?	-	-	-	_	_	_	_	
Cifar100	15	SAT	9.70	6.44	5.11	_	_	_	_	X
Cifar100	16	?	-	-	-	_	_	-	-	-
Cifar100	17	UNSAT	30.0	-	-	-	-	-	-	48.8
Cifar100	18	UNSAT	18.9	-	-	-	-	-	-	26.8
Cifar100	19	UNSAT	18.0	110	-	-	-	-	-	23.9
Cifar100	20	SAT	9.82	6.36	3.10	-	-	-	-	X
Cifar100	21	SAT	9.72	6.41	4.10	-	-	-	-	X
Cifar100	22		18.0	73.0	-	-	-	-	-	24.5
Cifar100	23	UNSAT		-	-	-	-	-	-	42.7
Cifar100	24	?	0.71	- C 40	4 1 1	-	-	-	-	-
Cifar100 Cifar100	$\frac{25}{26}$	SAT UNSAT	9.71	6.48 20.2	4.11	-	-	-	-	X 23.1
Cifar100	$\frac{20}{27}$	UNSAT		20.2	_	_	_	_	_	23.1
Cifar100 Cifar100	28	SAT	9.82	6.44	14.2	_	_	_	-	X
Cifar100	29	UNSAT		19.5	-	_	_	_	_	22.1
Cifar100	30	?	-	-	_	_	_	_	_	-
Cifar100	31	SAT	9.66	6.44	4.10	-	-	-	-	X
Cifar100	32	UNSAT	35.7	-	-	-	-	-	-	53.4
Cifar100	33	UNSAT	19.0	109	-	-	-	-	-	28.5
Cifar100	34	UNSAT		12.7	-	-	-	-	-	21.6
Cifar100	35	UNSAT		-	-	-	-	-	-	26.3
Cifar100	36	UNSAT		109	-	-	-	-	-	30.1
Cifar100	37	?	-	-	-	-	-	-	-	-
Cifar100 Cifar100	38	?	17.0	19.7	_	_	-	-	-	21.9
Cifar100 Cifar100	39 40	UNSAT		12.7		-		-		21.8 23.5
Cifar100	41	UNSAT SAT	18.0 9.69	23.8 6.40	6.12	_	-	-	-	∠3.3 X
Cifar100	42		18.0	16.5	-	_	_	_	_	23.1
Cifar100	43	?	-	-	_	_	_	_	_	-
Cifar100	44	?	_	_	_	_	_	_	_	_
Cifar100	45	UNSAT	29.0	-	-	-	_	_	-	44.5
Cifar100	46	UNSAT		10.7	-	-	_	_	-	15.6
Cifar100	47	SAT	9.67	6.45	8.13	-	-	-	-	X
Cifar100	48	?	-	-	-	-	-	-	-	-
Cifar100	49	UNSAT		-	-	-	-	-	-	-
Cifar100	50	SAT	9.70	-	7.12	-	-	-	-	20.9
Cifar100	51	SAT	9.69	6.42	7.12	-	-	-	-	X
Cifar100	52	SAT	9.72	-	33.3	-	-	-	-	X
Cifar100	53	UNSAT		71.4	-	-	-	-	-	25.3
Cifar100	54	SAT	9.71	6.40	3.10	-	-	-	-	X
Cifar100	55 56	SAT	9.71	6.48	4.11	-	-	-	-	X
Cifar100	56	UNSAT	41.4	109	-	-	-	-	-	35.0

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (X).

Category	Id	Result	α - β - \mathbf{C}	PyRAT	Marab	NNen	NNV	NeVer2	CORA	NSAT
Cifar100	57		14.8	10.8	-	-	-	-	-	15.9
Cifar100	58	?	-	-	-	-	-	-	-	-
Cifar100	59	UNSAT	14.9	10.7	-	-	-	-	-	16.1
Cifar100	60	SAT	9.69	6.44 75.1	5.11	-	-	-	-	X 29.7
Cifar100 Cifar100	$\frac{61}{62}$	UNSAT UNSAT	$19.2 \\ 36.4$	73.1 -	_	_	_	_	_	56.9
Cifar100	63		84.6	_		-	_	_	_	-
Cifar100	64	UNSAT	17.9	39.6	_	_	_	_	_	24.4
Cifar100	65	UNSAT		-	-	-	-	-	-	54.2
Cifar100	66	UNSAT	21.7	110	-	-	-	-	-	38.7
Cifar100	67	UNSAT	18.4	82.1	-	-	-	-	-	26.6
Cifar100	68	UNSAT		20.4	-	-	-	-	-	22.0
Cifar100	69	UNSAT	18.3	23.0	-	-	-	-	-	22.6
Cifar100	70	? ?	_	-	-	-	-	-	-	-
Cifar100 Cifar100	$\frac{71}{72}$	UNSAT	14.1	10.9	_	-	-	-	-	17.2
Cifar100	73		19.2	10.9	-	_	_	-	_	35.1
Cifar100	74	UNSAT		20.5	_	_	_	_	_	22.5
Cifar100	75	?	-	-	_	_	_	_	-	-
Cifar100	76	?	-	-	-	-	-	-	-	-
Cifar100	77	UNSAT		111	-	-	-	-	-	29.5
Cifar100	78	UNSAT	19.0	-	-	-	-	-	-	27.2
Cifar100	79	?	-	-	-	-	-	-	-	-
Cifar100	80	SAT	9.71	6.38	4.10	-	-	-	-	X
Cifar100 Cifar100	81 82	?	- 17.9	16.4	-	-	-	_	-	22.1
Cifar100	83	UNSAT UNSAT	17.9	16.4	-	-	_	_	_	22.1
Cifar100	84	UNSAT	19.7	-		_	_	_	_	33.8
Cifar100	85	SAT	9.21	_	5.11	_	_	_	_	X
Cifar100	86	UNSAT	25.6	-	-	-	-	-	-	37.9
Cifar100	87	?	-	-	-	-	-	-	-	-
Cifar100	88	UNSAT	20.2	-	-	-	-	-	-	31.7
Cifar100	89	UNSAT		-	-	-	-	-	-	35.5
Cifar100	90		19.7	-	-	-	-	-	-	32.4
Cifar100 Cifar100	$\frac{91}{92}$	UNSAT	19.1	-	-	-	-	-	-	30.9
Cifar100	93	?	_	_	_	_	_	-	_	-
Cifar100	94	UNSAT	26.2	_	_	_	_	_	_	39.4
Cifar100	95	UNSAT		_	_	_	_	_	_	49.2
Cifar100	96	?	-	-	-	-	-	-	-	-
Cifar100	97	UNSAT	17.8	18.0	-	-	-	-	-	22.5
Cifar100	98	UNSAT		10.6	-	-	-	-	-	15.6
Cifar100	99	SAT	9.73	6.40	3.10	-	-	-	-	X
Cifar100	100	UNSAT	25.6	15 0	-	-	-	-	-	10.5
Cifar100 Cifar100	$\frac{101}{102}$	UNSAT UNSAT	13.9	15.8	-	-	-	-	-	19.5 61.5
Cifar100	102	UNSAT	23.4 23.7	20.8	_	_	_	_	_	48.1
Cifar100	104	SAT	10.1	-	_	_	_	-	-	-
Cifar100	105	UNSAT		16.8	-	-	-	-	-	17.9
Cifar100	106	?	-	-	-	-	-	-	-	-
Cifar100	107	UNSAT	22.0	80.4	-	-	-	-	-	-
Cifar100	108	?	-	-	-	-	-	-	-	-
Cifar100	109	UNSAT		30.5	4.10	-	-	-	-	-
Cifar100	110	SAT	10.1	-	4.10	-	-	-	-	X
Cifar100 Cifar100	$\frac{111}{112}$? ?	_	_	_	_	_	-	_	_
Cifar100	113	UNSAT	14.9	14.7	_	_	_	-	_	19.0
Cifar100	114	?	-		_	_	_	_	_	-
Cifar100	115	UNSAT	91.6	110	-	-	-	-	-	-
Cifar100	116	?	-	-	-	-	-	-	-	-
Cifar100	117	UNSAT	13.6	16.4	-	-	-	-	-	-
Cifar100	118	UNSAT		-	-	-	-	-	-	-
Cifar100	119	UNSAT		-	-	-	-	-	-	-
Cifar100	120	UNSAT		94.5	-	-	-	-	-	50.1
Cifar100	121	? UNSAT	- 27.6	_	-	-	-	-	-	-
Cifar100 Cifar100	$\frac{122}{123}$?	27.0	_	_	_	-	-	_	-
C1141 100	120		-							

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (X).

Category	Id	Result	<i>α</i> -β-C	PyRAT	'Marab	NNen	NNV	NeVer2	CORA	NSAT
Cifar100	124	UNSAT	40.3	-	-	-	-	-	-	88.2
Cifar100	125	UNSAT	22.5	-	-	-	-	-	-	43.1
Cifar100	126	UNSAT		-	-	-	-	-	-	64.5
Cifar100 Cifar100	$\frac{127}{128}$?	-	- 112	-	-	-	-	_	-
Cifar100	129	UNSAT SAT	10.2	6.53	4.10	_	_	_	_	_
Cifar100	130	?	-	-	-	-	_	_	_	_
Cifar100	131	UNSAT	25.6	_	_	_	_	_	_	_
Cifar100	132	UNSAT		22.3	-	-	-	-	-	-
Cifar100	133	UNSAT	32.6	-	-	-	-	-	-	64.3
Cifar100	134	UNSAT	23.7	110	-	-	-	-	-	-
Cifar100	135		13.7	13.6	-	-	-	-	-	18.5
Cifar100	136	UNSAT	15.4	17.4	-	-	-	-	-	25.5
Cifar100	137		24.9	-	-	-	-	-	-	58.1
Cifar100 Cifar100	$\frac{138}{139}$? ?	-	-	-	_	-	_	-	-
Cifar100	140		23.9	44.9	_	_	_	_	-	36.6
Cifar100	141	UNSAT		-	_	_	_	_	_	-
Cifar100	142	UNSAT		16.1	_	_	_	_	_	21.1
Cifar100	143	?	-	-	-	-	-	-	-	-
Cifar100	144	UNSAT	91.4	-	-	-	-	-	-	-
Cifar100	145	UNSAT	48.9	-	-	-	-	-	-	-
Cifar100	146	UNSAT	14.8	16.4	-	-	-	-	-	19.6
Cifar100	147	?	-	-	-	-	-	-	-	-
Cifar100	148	SAT	10.3	-	7.12	-	-	-	-	-
Cifar100	149	SAT	11.0	6.68	14.2	-	-	-	-	-
Cifar100	150	UNSAT	14.1	16.1	-	_	-	-	-	20.8
Cifar100 Cifar100	$\frac{151}{152}$		27.3	-	-	-	-	-	_	_
Cifar100	153	UNSAT	15.5	17.2	-	_	_	_	_	_
Cifar100	154	UNSAT		45.9	_	_	_	_	_	56.1
Cifar100	155		15.3	16.3	-	-	_	_	-	23.3
Cifar100	156	?	-	-	-	-	-	-	-	-
Cifar100	157	?	-	-	-	-	-	-	-	-
Cifar100	158	?	-	-	-	-	-	-	-	-
Cifar100	159	UNSAT		-	-	-	-	-	-	-
Cifar100	160	?	-	- 01 4	-	-	-	-	-	-
Cifar100	161	UNSAT	22.2	21.4	-	-	-	-	-	52.0
Cifar100 Cifar100	$\frac{162}{163}$	UNSAT UNSAT		56.7 -	-	-	-	_	-	59.0 -
Cifar100 Cifar100	164	?	24.1	-			_	-	_	_
Cifar100	165	UNSAT	14.4	16.5	_	_	_	_	_	24.5
Cifar100	166	UNSAT		46.0	-	-	_	_	-	57.9
Cifar100	167	?	-	-	-	-	-	-	-	-
Cifar100	168	UNSAT	13.6	14.8	-	-	-	-	-	18.6
Cifar100	169	SAT	10.2	6.53	22.2	-	-	-	-	-
Cifar100	170	UNSAT	13.9	16.5	-	-	-	-	-	19.9
Cifar100	171	UNSAT		46.2	-	-	-	-	-	53.5
Cifar100 Cifar100	$\frac{172}{173}$	SAT SAT	9.90 10.1	6.50	4.11	-	-	_	_	53.0 ×
Cifar100	173	UNSAT		111	4.11	-	_	_	_	_^
Cifar100 Cifar100	175	UNSAT		16.9	_	_	_	_	_	19.6
Cifar100	176	?	-	-	-	-	_	-	-	-
Cifar100	177	UNSAT	35.3	114	-	-	-	-	-	-
Cifar100	178	?	-	-	-	-	-	-	-	-
Cifar100	179	?	-	-	-	-	-	-	-	-
Cifar100	180	UNSAT		31.5	-	-	-	-	-	-
Cifar100	181	?	-	-	-	-	-	-	-	-
Cifar100	182	UNSAT		-	-	-	-	-	-	62.6
Cifar100	183	UNSAT		6 56	- 5 11	_	-	-	-	69.1
Cifar100 Cifar100	184	SAT UNSAT	$9.52 \\ 22.5$	6.56 83.9	5.11	-	-	-	-	60.2
Cifar100	$\frac{185}{186}$	UNSAT		-	_	_	_	_	-	70.4
Cifar100	187	UNSAT		-	_	_	_	_	_	60.0
Cifar100	188	SAT	10.3	6.51	3.10	-	_	-	-	-
Cifar100	189	SAT	10.1	6.52	4.11	-	-	-	-	X
Cifar100	190	UNSAT		17.9	-	-	-	-	-	-

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

Category	Id	Result	α-β-С	PyRAT	Marab	NNen	NNV	NeVer2	CORA	NSAT
Cifar100	191	UNSAT	21.8	61.3	-	-	-	-	-	-
Cifar100	192	UNSAT		-	-	-	-	-	-	-
Cifar100	193	SAT	9.63	6.49	4.11	-	-	-	-	X
Cifar100	194	?	-	-	-	-	-	-	-	-
Cifar100	195	UNSAT		55.6	-	-	-	-	-	68.6
Cifar100	196	UNSAT		-	-	-	-	-	-	-
Cifar100 Cifar100	197 198	UNSAT UNSAT		-	_	_	_	_	-	-
Cifar100	199	UNSAT		-	-	-	-	-	-	63.7
Collins Rul Cnn 2023	. 0	UNSAT		3.85	6.09	1.71	25.8	_	_	2.13
Collins Rul Cnn 2023		SAT	7.14	3.62	1.09	1.81	24.6	-	11.6	Z.13 X
Collins Rul Cnn 2023		UNSAT		3.82	6.09	1.86	25.3	-	-	2.12
Collins Rul Cnn 2023		UNSAT		3.81	6.09	1.92	25.8	-	-	2.13
Collins Rul Cnn 2023		UNSAT		3.81	6.09	1.83	26.3	-	-	2.13
Collins Rul Cnn 2023	5	SAT	7.12	3.62	1.09	1.63	25.3	-	11.6	X
Collins Rul Cnn 2023	6	SAT	7.15	3.59	1.09	1.72	25.0	-	11.6	X
Collins Rul Cnn 2023	7	UNSAT	8.72	3.83	6.09	1.83	25.7	-	-	2.15
Collins Rul Cnn 2023		UNSAT		3.78	6.09	1.97	26.0	-	-	2.12
Collins Rul Cnn 2023		SAT	7.11	3.60	1.09	1.73	24.5	-	11.7	X
Collins Rul Cnn 2023		SAT	7.10	3.59	1.09	1.68	24.4	-	11.6	X
Collins Rul Cnn 2023		SAT	7.13	3.59	1.09	1.71	24.5	-	11.6	X 0.10
Collins Rul Cnn 2023		UNSAT		3.82	6.09	1.72	26.2	-	-	2.13
Collins Rul Cnn 2023		UNSAT		3.81	6.09	1.65	25.6	-	-	2.13
Collins Rul Cnn 2023 Collins Rul Cnn 2023		UNSAT SAT	7.12	3.78 3.58	6.09 1.09	1.62 1.72	$26.0 \\ 24.4$	-	11.7	2.14 X
Collins Rul Cnn 2023		SAT	7.12	3.56	1.09	1.60	25.0	-	-	x
Collins Rul Cnn 2023		UNSAT		3.89	7.10	1.79	25.7	_	_	2.28
Collins Rul Cnn 2023		UNSAT		3.83	8.13	1.72	26.0	_	_	2.12
Collins Rul Cnn 2023		SAT	7.15	3.61	1.09	1.75	24.6	_	X	X
Collins Rul Cnn 2023		SAT	7.57	-	1.09	7.21	24.1	_	11.7	X
Collins Rul Cnn 2023		SAT	7.15	3.66	1.09	1.84	24.4	-	11.6	X
Collins Rul Cnn 2023	22	SAT	7.11	3.61	1.09	1.67	25.7	-	11.6	X
Collins Rul Cnn 2023	23	SAT	7.12	3.60	1.10	1.75	24.6	-	X	X
Collins Rul Cnn 2023	24	UNSAT	8.71	3.81	7.09	1.71	26.9	-	-	2.31
Collins Rul Cnn 2023		UNSAT		3.85	7.10	1.61	26.9	-	-	2.17
Collins Rul Cnn 2023		SAT	7.11	3.63	1.09	1.75	24.6	-	11.6	X
Collins Rul Cnn 2023		SAT	7.11	3.62	1.09	1.90	24.7	-	11.7	X
Collins Rul Cnn 2023		SAT	7.13	3.60	1.09	1.77	24.4	-	11.6	X 0.17
Collins Rul Cnn 2023		UNSAT		3.82	7.09	1.75	26.2	-	-	2.17
Collins Rul Cnn 2023		UNSAT	7.11	3.92	7.10	1.65	26.4 24.3		11.7	2.16
Collins Rul Cnn 2023 Collins Rul Cnn 2023		SAT SAT	7.11	3.67 3.58	1.09 1.09	1.75 1.79	24.3	-	11.7 ×	X
Collins Rul Cnn 2023		SAT	7.15	3.58	1.09	1.74	24.6	_	11.6	x
Collins Rul Cnn 2023		UNSAT		3.90	12.2	1.83	26.1	_	-	2.17
Collins Rul Cnn 2023		UNSAT		3.81	11.2	1.67	26.2	-	-	2.17
Collins Rul Cnn 2023		UNSAT		3.89	11.2	1.77	26.3	-	-	2.18
Collins Rul Cnn 2023	37	SAT	7.13	3.57	1.09	1.66	24.4	-	11.7	X
Collins Rul Cnn 2023	38	SAT	7.14	3.60	1.09	1.85	25.3	-	11.6	X
Collins Rul Cnn 2023		UNSAT		3.85	7.10	1.75	26.0	-	-	2.17
Collins Rul Cnn 2023		UNSAT		3.89	11.2	1.90	25.9	-	-	2.32
Collins Rul Cnn 2023		SAT	7.87	-	1.09	12.4	24.4	-	11.6	X
Collins Rul Cnn 2023		SAT	7.12	3.62	1.09	1.78	24.4	-	11.7	X
Collins Rul Cnn 2023		UNSAT		3.91	12.1	1.71	26.1	-	-	3.04
Collins Rul Cnn 2023		SAT	7.12	3.66	1.09	1.76	24.9	-	X	X
Collins Rul Cnn 2023		SAT	7.12	3.62	1.09	1.75	24.7	-	X	X
Collins Rul Cnn 2023 Collins Rul Cnn 2023		SAT SAT	7.12 7.12	3.66 3.66	1.09	1.82 1.69	$25.2 \\ 24.7$	_	X X	X
Collins Rul Cnn 2023		UNSAT		3.85	34.7	1.09	25.7	_	_ ^	3.05
Collins Rul Cnn 2023		SAT	7.64	3.73	1.09	3.83	24.8	-	×	X
Collins Rul Cnn 2023		SAT	7.62	-	1.09	4.18	24.7	-	x	x
Collins Rul Cnn 2023		UNSAT		3.86	32.6	1.72	25.9	-	-	3.18
Collins Rul Cnn 2023		UNSAT		3.92	31.6	1.82	26.3	-	-	3.23
Collins Rul Cnn 2023		SAT	7.12	3.69	1.09	1.84	25.4	-	X	X
Collins Rul Cnn 2023	54	UNSAT		4.15	36.8	1.68	27.0	-	-	2.83
Collins Rul Cnn 2023		UNSAT		3.92	35.8	1.68	26.0	-	-	3.21
Collins Rul Cnn 2023		SAT	7.26	3.67	1.09	3.99	24.4	-	-	X
Collins Rul Cnn 2023	57	UNSAT	8.76	4.10	33.8	1.63	26.2	-	-	2.84

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (X).

Colline Rul Cun 2023 58	Category	Id	Result	t α-β-C	PyRAT	' Marab	NNen	NNV	NeVer2	CORA	NSAT
Collins Rul Cnn 2023 60 UNSAT 8.52 4.14 32.8 ISI 27.0 - 3.19 Collins Rul Cnn 2023 61 UNSAT 8.76 3.93 36.8 I.71 26.1 - 3.03 3.03 Cora 0 SAT 7.44 7.01 3.10	Collins Rul Cnn	2023 58	SAT	7.60	-	3.10	4.83	24.5	-	Х	Х
Collins Rul Cnn 2023 61			UNSAT						-	-	
Cora											
Cora	Collins Rul Cnn	2023 61	UNSAT	8.76	3.93	36.8	1.71	26.1	-	-	3.03
Cora	Cora	0	SAT	7.44	7.01	3.10	-	-	-	-	X
Cora 3 SAT 7.44 6.06 3.10 - - 3.52 - X Cora 4 7 -				-	-	-	-	-			
Cora 4 ? -											
Cora 5 UNNAT 7.76 10.0 10.1 1.43 29.2 3.50 12.1 1.95 Cora 6 SAT 7.42 6.12 3.10 - 3.55 - X Cora 7 ? - - - - - - X Cora 9 SAT 7.42 6.19 3.10 - - - - - - X Cora 10 ? - <											
Cora 6 SAT 7.42 6.12 3.10 -											
Cora 7 ? -											
Cora 9 SAT 7.42 6.19 3.10 -	Cora		?	-	-		-	-	-	-	
Cora 10 ? - X Cora 12 SAT 7.41 - 3.12 - - - - X Cora 14 UNSAT 7.70 9.67 9.13 1.38 27.6 7.66 11.8 1.96 Cora 15 SAT 7.42 6.14 3.12 - </td <td></td> <td></td> <td>UNSAT</td> <td></td> <td>9.74</td> <td></td> <td>1.34</td> <td>28.0</td> <td>3.47</td> <td>13.0</td> <td>1.95</td>			UNSAT		9.74		1.34	28.0	3.47	13.0	1.95
Cora 11 UNSAT 7.73 9.99 9.11 1.32 2.87 8.10 1.21 1.95 Cora 13 ? - - - - - X Cora 14 UNSAT 7.70 9.67 9.13 1.38 2.76 7.66 11.8 1.96 Cora 16 7 - - - - - - - - X Cora 16 ? -				7.42	6.19						
Cora 12 SAT 7.41 - 3.12 - <				7 72	- 0.00						
Cora 13 ? - <td></td>											
Cora 14 UNSAT 7.70 9.67 9.13 1.38 27.6 7.66 11.8 1.96 Cora 16 ? .					_						
Cora 15 SAT 7.42 6.14 3.12 -					9.67		1.38				
Cora 17 UNSAT 7.74 9.76 9.10 1.24 28.0 8.39 11.0 1.95 Cora 18 8 AT 7.44 6.14 3.11 - <td< td=""><td></td><td></td><td>SAT</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></td<>			SAT								
Cora 18 SAT 7.44 6.14 3.11 -											
Cora 19 ? - <td></td>											
Cora 20 UNSAT 7.73 9.65 10.1 1.37 27.3 8.12 11.0 1.96 Cora 21 SAT 7.41 6.11 3.10 - - 3.52 - X Cora 22 ? -											
Cora 21 SAT 7.41 6.11 3.10 - - 3.52 - X Cora 22 ? -											
Cora 22 ? - <td></td>											
Cora 24 SAT 7.43 6.08 3.10 - 25.1 3.52 12.2 X Cora 25 ? - X Cora 28 SAT 7.46 6.10 3.10 - - - - X Cora 28 SAT 7.45 10.2 3.10 - - - X Cora 30 SAT 7.07 6.10 1.09 1.37 25.0 - 12.1 X Cora 30 SAT 7.07 6.10 1.09 1.37 25.0 - 12.1 X Cora 30 SAT 7.42 - 4.11 - - - - X Cora 33 SAT 7.42 2.9 3.12 - - -											
Cora 25 ? - <td>Cora</td> <td>23</td> <td>UNSAT</td> <td>7.75</td> <td>9.99</td> <td>10.1</td> <td>1.32</td> <td>32.5</td> <td>3.48</td> <td>11.4</td> <td>1.95</td>	Cora	23	UNSAT	7.75	9.99	10.1	1.32	32.5	3.48	11.4	1.95
Cora 26 UNSAT 7.72 9.51 9.11 1.39 28.7 7.85 10.9 1.95 Cora 27 SAT 7.40 6.10 3.10 - - 3.66 - X Cora 29 SAT 7.45 10.2 3.10 8.55 - 3.51 - X Cora 30 SAT 7.07 6.10 1.09 1.37 25.0 - 12.1 X Cora 31 SAT 7.42 2 4.11 - - - - - X Cora 32 UNSAT 7.72 10.0 11.1 1.28 - 3.47 11.0 1.95 Cora 33 SAT 7.42 22.9 3.12 -							-				
Cora 27 SAT 7.40 6.10 3.10 - - 3.56 - X Cora 28 SAT 7.46 - 3.10 - - - X Cora 29 SAT 7.45 10.2 3.10 8.55 - 3.51 - X Cora 31 SAT 7.42 - 4.11 - - - X Cora 32 UNSAT 7.72 10.0 11.1 1.28 - - - X Cora 34 ? - - - - - - X Cora 34 ? - - - - - - - - X Cora 36 SAT 7.45 - 3.10 - - - - - - - - - - - - - -											
Cora 28 SAT 7.46 - 3.10 - - - X Cora 29 SAT 7.45 10.2 3.10 8.55 - 3.51 - X Cora 30 SAT 7.07 6.10 1.09 1.37 25.0 - 12.1 X Cora 31 SAT 7.42 2 4.11 - - - - X Cora 32 UNSAT 7.72 10.0 11.1 1.28 - 3.47 11.0 1.95 Cora 34 ? -<											
Cora 29 SAT 7.45 10.2 3.10 8.55 - 3.51 - X Cora 30 SAT 7.07 6.10 1.09 1.37 25.0 - 12.1 X Cora 31 SAT 7.42 - 4.11 - - - X Cora 32 UNSAT 7.72 10.0 11.1 1.28 - 3.47 11.0 1.95 Cora 33 SAT 7.42 22.9 3.12 - </td <td></td>											
Cora 30 SAT 7.07 6.10 1.09 1.37 25.0 - 12.1 X Cora 31 SAT 7.42 - 4.11 - - - X Cora 32 UNSAT 7.72 10.0 11.1 1.28 - - - X Cora 34 ? - - - - - - X Cora 35 UNSAT 7.70 9.67 9.11 1.37 27.7 7.81 11.2 1.95 Cora 36 SAT 7.45 - </td <td></td>											
Cora 32 UNSAT 7.72 10.0 11.1 1.28 - 3.47 11.0 1.95 Cora 33 SAT 7.42 22.9 3.12 - - - - X Cora 34 ? - <td< td=""><td>Cora</td><td></td><td></td><td>7.07</td><td></td><td></td><td></td><td>25.0</td><td></td><td>12.1</td><td></td></td<>	Cora			7.07				25.0		12.1	
Cora 33 SAT 7.42 22.9 3.12 -			SAT					-			
Cora 34 ? - <td></td>											
Cora 35 UNSAT 7.70 9.67 9.11 1.37 27.7 7.81 11.2 1.95 Cora 36 SAT 7.45 - 3.10 - - - - X Cora 37 ? - - - - - - X Cora 38 UNSAT 8.28 10.1 17.2 8.43 - - - 4.20 Cora 39 SAT 7.39 6.08 4.11 - - - - - X Cora 40 ? -											
Cora 36 SAT 7.45 - 3.10 - <											
Cora 37 ? - <td></td>											
Cora 39 SAT 7.39 6.08 4.11 - - - - X Cora 40 ? -									-		
Cora 40 ? - <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td>-</td> <td>-</td> <td></td> <td></td>								-	-		
Cora 41 UNSAT 7.73 9.41 9.11 1.38 26.7 7.53 12.0 1.98 Cora 42 SAT 7.43 6.06 3.10 - - - - - X Cora 43 SAT 7.44 - 3.10 - - - - X Cora 44 UNSAT 7.71 10.0 13.1 1.35 - 3.48 11.2 1.95 Cora 45 SAT 7.04 6.10 1.09 1.34 25.7 3.51 13.4 X Cora 46 ? - <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td>-</td> <td></td> <td></td>									-		
Cora 42 SAT 7.43 6.06 3.10 - - - - - X Cora 43 SAT 7.44 - 3.10 - - - - X Cora 44 UNSAT 7.71 10.0 13.1 1.35 - 3.48 11.2 1.95 Cora 45 SAT 7.04 6.10 1.09 1.34 25.7 3.51 13.4 X Cora 46 ? - <t< td=""><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>7 59</td><td></td><td></td></t<>									7 59		
Cora 43 SAT 7.44 - 3.10 - - - - X Cora 44 UNSAT 7.71 10.0 13.1 1.35 - 3.48 11.2 1.95 Cora 45 SAT 7.04 6.10 1.09 1.34 25.7 3.51 13.4 X Cora 46 ? -											
Cora 44 UNSAT 7.71 10.0 13.1 1.35 - 3.48 11.2 1.95 Cora 45 SAT 7.04 6.10 1.09 1.34 25.7 3.51 13.4 X Cora 46 ? -											
Cora 46 ? - <td></td> <td></td> <td></td> <td></td> <td>10.0</td> <td></td> <td>1.35</td> <td>-</td> <td>3.48</td> <td>11.2</td> <td></td>					10.0		1.35	-	3.48	11.2	
Cora 47 SAT 7.41 6.07 1.09 8.28 25.3 3.53 11.2 X Cora 48 SAT 7.41 6.06 3.10 - 25.1 3.55 12.4 X Cora 49 ? - X -							1.34	25.7			X
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Cora 60 SAT 7.11 6.17 1.09 - 25.9 \times Cora 61 SAT 7.16 6.20 1.09 - 26.3 \times											
				7.11	6.17	1.09	-	25.9	-	-	X
Cora 62 SAT 7.45 6.23 1.09 X											
	Cora	62	SAT	7.45	6.23	1.09	-	-	-	-	Х

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

Cora Cora Cora Cora Cora Cora Cora Cora	63 64 65 66 67 68 69 70 71 72 73 74 75 76 77	SAT	7.09 7.43 7.46 7.10 7.44 7.10 7.12 7.46 7.12 7.13 7.11 7.43	6.17 6.16 6.16 6.21 6.17 6.24 6.21 6.25 6.20 6.21 6.20	1.09 3.10 3.10 1.09 1.09 1.09 2.09 1.09	3.58 - - - - 3.45 -	25.9 - 26.1 26.3 27.3 26.0	- - - -	X	X X X X
Cora Cora Cora Cora Cora Cora Cora Cora	65 66 67 68 69 70 71 72 73 74 75 76	SAT SAT SAT SAT SAT SAT SAT SAT SAT SAT	7.46 7.10 7.44 7.10 7.12 7.46 7.12 7.13 7.11 7.43	6.16 6.21 6.17 6.24 6.21 6.25 6.20 6.21	3.10 1.09 1.09 1.09 1.09 2.09 1.09	- - - 3.45	26.1 26.3 27.3	- - -	-	X X X
Cora Cora Cora Cora Cora Cora Cora Cora	66 67 68 69 70 71 72 73 74 75 76	SAT SAT SAT SAT SAT SAT SAT SAT SAT	7.10 7.44 7.10 7.12 7.46 7.12 7.13 7.11 7.43	6.21 6.17 6.24 6.21 6.25 6.20 6.21	1.09 1.09 1.09 1.09 2.09 1.09	- 3.45 -	26.1 26.3 27.3	- - -		X X
Cora Cora Cora Cora Cora Cora Cora Cora	67 68 69 70 71 72 73 74 75 76	SAT SAT SAT SAT SAT SAT SAT SAT	7.44 7.10 7.12 7.46 7.12 7.13 7.11 7.43	6.17 6.24 6.21 6.25 6.20 6.21	1.09 1.09 1.09 2.09 1.09	3.45	$26.3 \\ 27.3$	-	-	X
Cora Cora Cora Cora Cora Cora Cora Cora	68 69 70 71 72 73 74 75 76 77	SAT SAT SAT SAT SAT SAT SAT SAT	7.10 7.12 7.46 7.12 7.13 7.11 7.43	6.24 6.21 6.25 6.20 6.21	1.09 1.09 2.09 1.09	3.45	27.3	-	-	
Cora Cora Cora Cora Cora Cora Cora Cora	69 70 71 72 73 74 75 76 77	SAT SAT SAT SAT SAT SAT SAT	7.12 7.46 7.12 7.13 7.11 7.43	6.21 6.25 6.20 6.21	1.09 2.09 1.09	-			-	
Cora Cora Cora Cora Cora Cora Cora Cora	70 71 72 73 74 75 76 77	SAT SAT SAT SAT SAT SAT	7.46 7.12 7.13 7.11 7.43	6.25 6.20 6.21	2.09 1.09		20.0		~	x
Cora Cora Cora Cora Cora Cora Cora Cora	71 72 73 74 75 76 77	SAT SAT SAT SAT SAT	7.12 7.13 7.11 7.43	$6.20 \\ 6.21$	1.09	-	25.7	-	X	â
Cora Cora Cora Cora Cora Cora Cora Cora	72 73 74 75 76 77	SAT SAT SAT SAT	7.13 7.11 7.43	6.21		_	25.7 25.7	_	x	â
Cora Cora Cora Cora Cora Cora Cora Cora	73 74 75 76 77	SAT SAT SAT	$7.11 \\ 7.43$		1.09	_	25.9	_		X
Cora Cora Cora Cora Cora Cora Cora	74 75 76 77	SAT SAT	7.43		1.09	_	26.2	_	_	X
Cora Cora Cora Cora Cora Cora	75 76 77	SAT		6.20	3.10	_	-	_	_	×
Cora Cora Cora Cora Cora	76 77		7.44	6.19	3.10	_	_	_	_	X
Cora Cora Cora Cora	77		7.11	6.19	1.09	_	_	_	X	X
Cora Cora Cora		SAT	7.46	6.20	3.10	_	_	_	X	X
Cora		SAT	7.11	6.22	1.09	-	26.1	-	X	X
	79	SAT	7.44	6.17	3.10	-	-	-	X	X
Cora	80	SAT	7.48	6.17	3.10	-	-	-	X	X
	81	SAT	7.13	6.25	1.09	-	26.2	-	X	X
Cora	82	SAT	7.10	6.12	1.09	-	26.0	-	X	X
Cora	83	SAT	7.41	6.18	3.10	-	-	-	-	X
Cora	84	SAT	7.12	6.25	1.09	-	26.5	-	-	X
Cora	85	SAT	7.13	6.15	1.09	-	26.4	-	-	X
Cora	86	SAT	7.45	6.19	3.10	-	-	-	-	X
Cora	87	SAT	7.10	6.16	1.09	-	25.9	-	X	X
Cora	88	SAT	7.11	6.22	1.09	-	25.9	-	-	X
Cora	89	SAT	7.43	6.23	2.09	-	26.2	-	-	X
Cora	90	SAT	7.12	6.17	1.09	-	26.0	-	-	X
Cora	91	SAT	7.10	6.14	1.09	-	26.0	-	-	X
Cora	92	SAT	7.12	6.17	1.09	-	25.6	-	-	X
Cora	93	SAT	7.14	6.16	1.09	-	26.3	-	-	X
Cora	94	SAT	7.10	6.18	1.09	-	26.3	-	_	X
Cora Cora	95 96	SAT SAT	$7.45 \\ 7.08$	6.22 6.20	3.10	-	26.4	_		x
Cora	90 97	SAT	7.43	6.25	$\frac{1.09}{3.10}$	-	20.4	-	X	x
Cora	98	SAT	7.43	6.15	1.09	_	25.8	_	^	x
Cora	99	SAT	7.11	6.18	1.09	_	26.1	-	×	â
Cora	100	SAT	7.44	6.16	3.10	_	26.3	_	x	×
Cora	101	SAT	7.44	6.13	3.10	_	26.1	_	X	X
Cora	102	SAT	7.12	6.18	1.09	_	25.6	_	X	X
Cora	103	SAT	7.11	6.22	1.09	_	25.9	_		X
Cora	104	SAT	7.44	6.14	3.10	_	-	_	-	X
Cora	105	SAT	7.13	6.18	1.09	_	25.7	_	X	X
Cora	106	SAT	7.10	6.20	1.09	-	25.9	-	-	X
Cora	107	SAT	7.44	6.18	3.10	-	-	-	-	X
Cora	108	SAT	7.10	6.22	1.09	-	27.6	-	-	X
Cora	109	SAT	7.43	6.18	3.10	-	-	-	-	X
Cora	110	SAT	7.42	6.18	3.10	-	-	-	-	X
Cora	111	SAT	7.11	6.22	1.09	-	26.9	-	X	X
Cora	112	SAT	7.11	6.18	1.09	-	26.3	-	-	X
Cora	113	SAT	7.44	6.18	3.10	-	-	-	-	X
Cora	114	SAT	7.12	6.16	1.10	-	26.4	-	X	X
Cora	115	SAT	7.11	6.19	1.09	-	26.5	-	-	X
Cora	116	SAT	7.43	6.16	3.10	-	-	-	-	X
Cora	117	SAT	7.11	6.16	1.09	-	26.0	-	-	X
Cora	118	SAT	7.12	6.23	1.09	-	27.0	-	X	X
Cora	119	SAT	7.45	6.20	3.10	-	-	-	X	X
Cora	120	SAT	7.46	6.12	3.10	-	-	-	X	X
Cora	121	SAT	7.45	6.22	3.10	-	-	-	X	X
Cora	122	SAT	7.46	6.20	3.10	-	-	-	X	X
Cora	123	SAT	7.43	6.20	3.10	-	-	-		X
Cora	124	SAT	7.42	6.16	3.10	-	-	-	X 12.2	X
Cora Cora	$\frac{125}{126}$	SAT SAT	$7.44 \\ 7.46$	6.19 6.20	3.10 3.10	_	_	_	13.3 X	X
Cora	$\frac{120}{127}$	SAT	7.46	6.19	3.10	-	-	_	â	x
Cora	128	SAT	7.45	6.16	3.10	_	_	_		x
Cora	129	SAT	7.45	6.21	3.10	_	_	_	×	x

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (X).

Category	Id	Result	α - β - \mathbf{C}	PyRAT	Marab	NNen	NNV	NeVer2	CORA	NSAT
Cora	130	SAT	7.44	6.20	3.10	-	-	-	×	X
Cora	131	SAT	7.44	6.20	3.10	-	-	-	-	X
Cora	132	SAT	7.43	6.17	3.10	-	-	-	-	X
Cora Cora	133	SAT	7.42	6.22	3.10	-	-	-	-	X
Cora	$\frac{134}{135}$	UNSAT SAT	7.44	6.17	3.10	-	_	_	X	×
Cora	136	SAT	7.44	6.17	3.10	_	-	-	X	x
Cora	137	UNSAT		22.3	32.3	_	_	_	_ ′′	9.01
Cora	138	SAT	7.47	6.20	3.10	-	-	-	-	X
Cora	139	SAT	7.44	6.20	3.10	-	-	-	-	X
Cora	140	SAT	7.46	6.16	3.12	-	-	-	12.4	X
Cora	141	SAT	7.11	6.18	1.09	-	26.5	-	X	X
Cora	142	UNSAT	-	- 0.10	- 0.10	-	-	-	X	-
Cora	143	SAT	7.47	6.18	3.10	-	-	-	X	X
Cora Cora	$\frac{144}{145}$	SAT ?	7.45	6.13	3.10	-	-	-	-	X
Cora	146	SAT	7.45	6.11	3.10	_	-	-	×	×
Cora	147	SAT	7.43	6.15	3.10	_	_	_		x
Cora	148	SAT	7.44	6.15	3.10	_	_	_	_	X
Cora	149	SAT	7.43	6.15	3.10	-	-	-	X	X
Cora	150	SAT	7.44	-	3.10	-	-	-	-	X
Cora	151	SAT	7.44	6.19	3.10	-	-	-	X	X
Cora	152	UNSAT		10.2	19.2	29.8	-	-	X	4.69
Cora	153	SAT	7.42	6.14	3.10	-	-	-	-	X
Cora	154	SAT	7.44	6.14	3.10	-	-	-	-	X
Cora	155	SAT	7.42	6.11	3.10	-	-	-	,	X
Cora	156	SAT	7.45	6.17	3.10	-	-	-	X	X
Cora Cora	$\frac{157}{158}$	SAT SAT	7.43 7.50	6.16 6.17	3.10	_	-	-	X	X
Cora	159	SAT	7.43	6.19	3.10	_	-	-	-	x
Cora	160	SAT	7.43	6.22	3.10	_	_	_	_	x
Cora	161	UNSAT	11.0	-	-	_	_	_	13.0	15.8
Cora	162	SAT	7.46	6.15	3.10	-	-	-	X	X
Cora	163	SAT	7.44	6.17	3.10	-	-	-	X	X
Cora	164	UNSAT	24.8	-	-	-	-	-	-	-
Cora	165	SAT	7.46	6.17	3.10	-	-	-	X	X
Cora	166	SAT	7.44	6.17	3.10	-	-	-	X	X
Cora	167	SAT	7.44	6.16	3.10	-	-	-	X	Х
Cora	168	SAT	7.44	6.18	3.10	-	-	-	X	X
Cora Cora	$\frac{169}{170}$	SAT SAT	$7.46 \\ 7.44$	6.13 6.27	3.13	_	26.3	-	X	X
Cora	171	UNSAT	-	0.27	J.11	_	20.3	-	×	_^
Cora	172	UNSAT	_	_	_	_	_	_	X	_
Cora	173	UNSAT		10.3	25.2	_	_	_	X	2.51
Cora	174	SAT	7.43	6.19	4.11	-	-	-	-	X
Cora	175	SAT	7.43	6.14	3.10	-	-	-	-	X
Cora	176	UNSAT	7.89	10.2	18.2	3.74	-	-	12.4	2.52
Cora	177	SAT	7.43	6.18	3.10	-	-	-	-	X
Cora	178	SAT	7.41	6.19	3.10	-	-	-	-	X
Cora	179	SAT	7.44	6.12	3.10	-	-	-	X	X
Dist Shift 2023	0	UNSAT	8.63	3.87	30.2	-	88.9	-	12.7	
Dist Shift 2023	1	UNSAT	7.87	3.86	7.10	-	91.7	-	12.3	-
Dist Shift 2023	2	UNSAT		4.38	7.10	-	-	-	11.5	-
Dist Shift 2023	3	UNSAT		3.73	7.10	-	85.3	-	12.4	-
Dist Shift 2023	4	UNSAT		3.76	7.10	-	85.9	-	12.3	-
Dist Shift 2023	5	UNSAT		3.82	7.10	-	89.3	-	12.3	-
Dist Shift 2023	6	UNSAT		3.74	7.10	-	- or c	-	11.2	-
Dist Shift 2023 Dist Shift 2023	7 8	UNSAT		3.82	8.10	-	85.6	-	12.6 13.4	-
Dist Shift 2023 Dist Shift 2023	9	UNSAT UNSAT		3.72 5.60	7.10 7.10	-	85.3	-	42.6	-
Dist Shift 2023 Dist Shift 2023	10	UNSAT		3.79	26.2	_	90.3	-	12.2	_
Dist Shift 2023	11	UNSAT		3.72	7.10	-	93.3	-	11.4	-
Dist Shift 2023	12	UNSAT		3.77	36.3	-	86.3	-	14.0	-
Dist Shift 2023	13	UNSAT		3.81	7.10	-	89.0	-	11.5	-
Dist Shift 2023	14	UNSAT		3.83	7.10	-	86.6	-	13.8	-
Dist Shift 2023	15	UNSAT	8.70	3.76	7.10	-	90.3	-	13.1	-
Dist Shift 2023	16	SAT	7.14	3.85	1.09	-	25.4	-	12.7	-

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (X).

Catagony	Id	Rogult	0-8 C	D _v D AT	Manak	NNo-	NINIX	NeVer2	COP 4	NSAT
Category Dist Shift 2023	17			3.84	7.10				12.2	NSAI
Dist Shift 2023 Dist Shift 2023	18	UNSAT SAT	7.15	3.67	1.09	-	$86.5 \\ 25.8$	-	13.6	_
Dist Shift 2023	19	UNSAT		4.44	62.5	-	89.0	-	11.9	_
Dist Shift 2023	20	UNSAT		4.14	338	_	91.6	_	13.0	_
Dist Shift 2023	21	UNSAT		3.89	10.1	_	86.4	_	12.4	_
Dist Shift 2023	22	SAT	7.11	3.67	1.09	_	25.7	_	12.4	_
Dist Shift 2023	23	UNSAT	7.93	3.80	8.10	_	115	_	12.4	_
Dist Shift 2023	24	UNSAT		3.74	7.10	-	86.8	-	12.4	-
Dist Shift 2023	25	UNSAT	11.4	3.78	7.10	-	-	-	12.4	-
Dist Shift 2023	26	UNSAT	11.4	4.14	51.4	-	-	-	13.6	-
Dist Shift 2023	27	UNSAT	8.73	3.77	7.10	-	87.8	-	12.7	-
Dist Shift 2023	28	UNSAT		3.75	7.10	-	99.6	-	13.2	-
Dist Shift 2023	29	UNSAT		3.78	7.10	-	87.4	-	12.3	-
Dist Shift 2023	30	UNSAT		3.82	7.10	-	85.0	-	12.2	-
Dist Shift 2023	31	UNSAT		3.84	7.10	-	85.8	-	13.5	-
Dist Shift 2023	32	SAT	11.1	155	7.10	-	-	-	16.0	-
Dist Shift 2023	33	UNSAT		4.22	-	-	98.5	-	12.6	-
Dist Shift 2023	34	UNSAT		3.75	7.09	-	89.9	-	12.4	-
Dist Shift 2023	35	UNSAT		3.80	7.10	-	87.4	-	12.7	-
Dist Shift 2023 Dist Shift 2023	$\frac{36}{37}$	UNSAT		3.81	17.2 7.09	-	87.8 -	-	12.4 20.2	_
Dist Shift 2023	38	SAT UNSAT	7.10 7.91	21.8 3.84	7.09	_	87.7	_	11.4	_
Dist Shift 2023 Dist Shift 2023	39	UNSAT		3.82	7.10	_	86.7	-	12.6	-
Dist Shift 2023 Dist Shift 2023	40	UNSAT		3.84	7.10	_	87.7	-	11.5	_
Dist Shift 2023	41	UNSAT		3.73	7.10	_	85.7	_	11.1	_
Dist Shift 2023	42	UNSAT		3.77	7.10	_	91.3	_	13.3	_
Dist Shift 2023	43	UNSAT		3.76	7.10	_	89.9	_	12.1	_
Dist Shift 2023	44	UNSAT		3.80	42.4	_	86.1	-	12.4	_
Dist Shift 2023	45	UNSAT	7.91	3.81	7.10	-	88.1	-	12.3	-
Dist Shift 2023	46	UNSAT	8.76	4.07	7.10	-	-	-	11.5	-
Dist Shift 2023	47	UNSAT	7.87	3.78	7.10	-	84.2	-	12.2	-
Dist Shift 2023	48	SAT	7.14	3.97	1.09	-	26.4	-	12.8	-
Dist Shift 2023	49	UNSAT	7.90	3.89	9.11	-	85.9	-	12.3	-
Dist Shift 2023	50	UNSAT	7.93	3.79	7.10	-	86.6	-	12.3	-
Dist Shift 2023	51	UNSAT		3.75	7.10	-	92.2	-	14.0	-
Dist Shift 2023	52	UNSAT		3.77	8.10	-	87.5	-	11.4	-
Dist Shift 2023	53	UNSAT		3.75	8.10	-	87.5	-	12.7	-
Dist Shift 2023	54	UNSAT		3.72	52.5	-	88.7	-	11.3	-
Dist Shift 2023	55 56	UNSAT		4.37	7.10	_	071	-	13.7	_
Dist Shift 2023 Dist Shift 2023	56	UNSAT		3.85	10.1	_	87.1	-	11.4	_
Dist Shift 2023	57 58	UNSAT UNSAT		3.82 3.79	7.10 7.10	-	91.4 86.4	-	12.6 13.7	-
Dist Shift 2023 Dist Shift 2023	59	UNSAT		4.42	-	_	-	_	12.4	_
Dist Shift 2023	60	UNSAT		3.85	7.10	_	85.9	_	12.5	_
Dist Shift 2023	61	UNSAT		3.78	7.10	_	87.9	_	13.4	_
Dist Shift 2023	62	SAT	7.12	3.94	1.09	_	25.6	_	12.5	_
Dist Shift 2023	63	UNSAT		3.88	7.10	_	85.6	_	12.3	_
Dist Shift 2023	64	UNSAT		3.88	7.10	-	91.2	-	11.3	-
Dist Shift 2023	65	UNSAT		4.83	44.4	-	-	-	87.7	-
Dist Shift 2023	66	UNSAT	11.4	4.11	7.10	-	-	-	13.5	-
Dist Shift 2023	67	UNSAT	8.69	4.08	7.10	-	-	-	13.5	-
Dist Shift 2023	68	UNSAT		3.82	7.10	-	88.6	-	12.3	-
Dist Shift 2023	69	UNSAT	12.2	4.71	7.10	-	-	-	12.4	-
Dist Shift 2023	70	?	-	-	-	-	-	-	-	-
Dist Shift 2023	71	SAT	7.16	20.7	2.09	-	-	-	19.0	
Linearizenn	0	SAT	7.15	9.30	1.09	X	-	-	-	-
Linearizenn	1	UNSAT		3.91	6.10	1.91	-	-	-	-
Linearizenn	2	UNSAT		4.14	6.09	1.90	-	-	-	-
Linearizenn	3	UNSAT		3.59	6.09	2.10	-	-	-	-
Linearizenn	4	UNSAT		3.87	6.09	2.11	-	-	-	-
Linearizenn	5	UNSAT		3.85	6.10	2.04	-	-	-	-
Linearizenn	6	UNSAT		6.02	6.10	2.86	-	-	-	-
Linearizenn	7	UNSAT		4.41	6.10	2.39	-	-	-	-
Linearizenn	8	UNSAT		3.57	6.10	2.15	-	-	-	-
Linearizenn	9	UNSAT UNSAT		4.39	6.10	2.55 2.34	-	-	-	-
Linearizenn Linearizenn	10 11	UNSAT		4.44 3.86	6.10	2.34	-	-	-	_
rinear (zeilli	TI	UNSAT	1.41	9.00	0.00	4.11	-	-	-	-

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

Category	Id	Result α - β -C	C PyRAT	Marab	NNer	NNV	NeVer2	CORA	NSAT
Linearizenn	12	UNSAT 10.7	9.48	6.10	9.85	-	-	-	-
Linearizenn	13	UNSAT 10.1	6.24	6.10	5.22	-	-	-	-
Linearizenn Linearizenn	14	UNSAT 10.2	6.42	6.10	5.50	-	-	-	-
Linearizenn Linearizenn	$\frac{15}{16}$	UNSAT 10.1 UNSAT 9.73	6.63 5.68	6.09 6.10	5.63 4.29	-	-	-	_
Linearizenn	17	UNSAT 10.1	6.18	6.10	5.24	_	-	_	_
Linearizenn	18	UNSAT 11.0	11.4	6.10	4.70	_	_	_	_
Linearizenn	19	UNSAT 9.88	6.62	6.09	3.18	-	-	-	-
Linearizenn	20	unsat 9.84	7.29	6.10	3.20	-	-	-	-
Linearizenn	21	unsat 10.1	6.98	6.10	3.51	-	-	-	-
Linearizenn	22	UNSAT 9.56	6.03	6.09	3.12	-	-	-	-
Linearizenn	23	UNSAT 9.90	7.21	6.10	3.44	-	-	-	-
Linearizenn Linearizenn	$\frac{24}{25}$	UNSAT 11.1 UNSAT 10.9	22.6 13.6	6.10 6.10	9.31 5.99	-	-	-	-
Linearizenn	26	UNSAT 10.5	12.2	6.10	6.02	_	-	_	_
Linearizenn	27	UNSAT 10.0	7.89	6.10	3.47	_	_	_	_
Linearizenn	28	UNSAT 10.2	9.88	6.10	4.37	_	_	_	_
Linearizenn	29	UNSAT 10.5	8.45	6.09	4.29	-	-	-	-
Linearizenn	30	unsat 11.3	27.3	6.10	20.4	-	-	-	-
Linearizenn	31	unsat 10.7	17.6	6.09	10.8	-	-	-	-
Linearizenn	32	Unsat 10.4	13.0	6.10	8.12	-	-	-	-
Linearizenn	33	UNSAT 10.1	11.0	6.10	7.41	-	-	-	-
Linearizenn	34	UNSAT 10.2	9.68	6.10	5.56	-	-	-	-
Linearizenn	35	UNSAT 10.6	16.7	6.09	12.9	-	-	-	-
Linearizenn Linearizenn	$\frac{36}{37}$	UNSAT 10.9	10.5 6.18	6.09 6.10	$11.0 \\ 4.63$	-	-	-	-
Linearizenn	38	UNSAT 9.78 UNSAT 9.90	6.16	6.10	3.80	_	-	_	_
Linearizenn	39	UNSAT 9.90	6.33	6.09	3.37	_	_	_	_
Linearizenn	40	UNSAT 9.53	5.02	6.10	2.81	_	_	_	_
Linearizenn	41	UNSAT 9.65	5.02	6.10	2.74	-	-	-	-
Linearizenn	42	UNSAT 11.1	15.2	6.09	9.39	-	-	-	-
Linearizenn	43	unsat 10.4	9.48	6.10	5.79	-	-	-	-
Linearizenn	44	unsat 10.0	8.63	6.09	5.52	-	-	-	-
Linearizenn	45	UNSAT 10.6	10.1	6.10	6.57	-	-	-	-
Linearizenn	46	UNSAT 10.4	8.80	6.09	5.97	-	-	-	-
Linearizenn Linearizenn	$\frac{47}{48}$	UNSAT 10.6 UNSAT 10.6	10.3 8.56	6.10 6.10	$6.53 \\ 6.79$	-	-	-	_
Linearizenn	49	UNSAT 10.0 UNSAT 10.1	6.31	6.09	3.03	-	-	_	_
Linearizenn	50	UNSAT 9.88	5.71	6.09	2.99	_	-	_	_
Linearizenn	51	UNSAT 9.63	5.11	6.10	2.59	_	_	_	_
Linearizenn	52	unsat 9.99	5.48	6.09	2.80	-	-	-	-
Linearizenn	53	unsat 9.91	5.27	6.10	2.93	-	-	-	-
Linearizenn	54	unsat 9.95	5.11	6.10	2.16	-	-	-	-
Linearizenn	55	unsat 7.25	3.63	6.10	1.92	-	-	-	-
Linearizenn	56	UNSAT 8.94	4.14	6.09	2.02	-	-	-	-
Linearizenn	57	UNSAT 8.99	4.12	6.10	2.06	-	-	-	-
Linearizenn Linearizenn	58 59	UNSAT 8.95	3.90 4.44	6.10 6.10	2.08 2.15	-	-	-	-
Linearizeiiii	99	UNSAT 8.97	4.44	0.10	2.10				
Metaroom 2023	0	unsat 8.03	15.1	-	2.71	29.1	-	-	7.22
Metaroom 2023	1	UNSAT 7.86	13.2	-	-	27.2	-	-	7.15
Metaroom 2023	2	UNSAT 7.60	9.86	8.10	- 07	25.6	-	-	4.19
Metaroom 2023	3	UNSAT 8.17	14.3	0.10	3.07	30.6	-	-	7.86
Metaroom 2023 Metaroom 2023	$\frac{4}{5}$	UNSAT 7.63	9.89 13.0	8.10	-	$26.0 \\ 25.9$	-	-	4.18 7.33
Metaroom 2023 Metaroom 2023	о 6	UNSAT 7.89 UNSAT 7.79	9.93	8.10	2.15	29.0	-	-	4.36
Metaroom 2023	7	UNSAT 8.11	16.0	-	3.83	29.5	-	_	7.03
Metaroom 2023	8	UNSAT 7.57	9.78	8.10	-	25.4	_	_	4.18
Metaroom 2023	9	UNSAT 7.61	9.81	8.10	-	25.6	-	-	4.18
Metaroom 2023	10	UNSAT 7.60	9.85	8.10	-	25.5	-	-	4.18
Metaroom 2023	11	unsat 7.88	12.8	-	-	26.3	-	-	7.19
Metaroom 2023	12	unsat 7.81	13.2	-	-	26.8	-	-	7.50
Metaroom 2023	13	UNSAT 7.87	13.1	-	-	27.2	-	-	6.81
Metaroom 2023	14	UNSAT 7.60	9.94	8.10	1.89	28.6	-	-	4.21
Metaroom 2023	15	UNSAT 7.87	12.9	- 0.10	1 05	26.5	-	-	6.83
Metaroom 2023	16	UNSAT 7.60	9.90	8.10	1.85	28.2	-	-	4.19
Metaroom 2023 Metaroom 2023	17 18	UNSAT 7.58 UNSAT 7.61	9.88 9.80	8.10 8.10	-	$26.5 \\ 26.6$	-	-	$4.22 \\ 4.23$
111000100111 2020	10	UNDAL 1.UI	0.00	0.10	-	20.0			1.20

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

Category	Id	Result	α - β - \mathbf{C}	PyRAT	Marab	NNen	NNV	NeVer2	CORA	NSAT
Metaroom 2023	19	UNSAT	8.25	13.6	-	2.68	30.2	-	-	7.82
Metaroom 2023	20		7.85	9.96	8.10	1.99	28.3	-	-	4.53
Metaroom 2023	21		8.03	13.5	-	2.79	28.9	-	-	7.48
Metaroom 2023	22		7.60	9.85	8.10	1.80	28.2	-	-	4.18
Metaroom 2023 Metaroom 2023	$\frac{23}{24}$	UNSAT UNSAT	7.89	12.6 9.77	8.10	-	$26.4 \\ 25.5$	-	-	7.25 4.18
Metaroom 2023	25	UNSAT		13.3	-	2.83	29.5	-	_	7.19
Metaroom 2023	26		7.94	13.3	_	3.04	29.2	_	_	7.18
Metaroom 2023	27	UNSAT		13.8	-	2.75	30.2	-	-	7.16
Metaroom 2023	28	UNSAT	12.0	10.2	8.10	3.91	29.1	-	-	4.84
Metaroom 2023	29	SAT	8.64	145	30.2	-	-	-	-	X
Metaroom 2023	30	UNSAT		14.1	-	2.96	31.0	-	-	7.12
Metaroom 2023	31	UNSAT		9.84	8.10	1.86	28.6	-	-	4.39
Metaroom 2023 Metaroom 2023	$\frac{32}{33}$	UNSAT UNSAT		9.81 9.82	8.10 8.10	-	26.1 25.9	-	-	4.19 4.21
Metaroom 2023	34	UNSAT		9.88	8.10	1.94	28.8	_	-	4.18
Metaroom 2023	35		7.58	9.86	8.10	-	25.9	_	-	4.19
Metaroom 2023	36	SAT	8.56	-	12.1	-	-	-	-	X
Metaroom 2023	37	UNSAT	7.77	12.7	-	-	26.4	-	-	7.58
Metaroom 2023	38	UNSAT		9.95	8.10	1.91	29.7	-	-	4.52
Metaroom 2023	39	UNSAT		15.7	-	3.78	31.1	-	-	7.05
Metaroom 2023	40	UNSAT		13.3	-	2.82	29.1	-	-	7.35
Metaroom 2023 Metaroom 2023	$\frac{41}{42}$	UNSAT UNSAT	7.65	13.1 9.88	8.10	-	26.2 25.7	-	_	6.95 4.20
Metaroom 2023	43	UNSAT		9.88	8.10	1.83	28.9	-	-	4.19
Metaroom 2023	44	UNSAT		13.1	-	-	26.1	_	-	6.69
Metaroom 2023	45	SAT	8.23	7.81	1.09	-	26.3	-	-	X
Metaroom 2023	46	UNSAT	7.88	12.6	-	-	26.9	-	-	8.20
Metaroom 2023	47	SAT	8.24	8.46	2.09	-	26.4	-	-	X
Metaroom 2023	48		7.88	13.0	-	-	27.3	-	-	6.83
Metaroom 2023	49	UNSAT		13.5	-	2.86	29.1	-	-	7.28
Metaroom 2023 Metaroom 2023	$\frac{50}{51}$	UNSAT UNSAT	7.65	15.6 9.90	8.10	3.91	$30.8 \\ 25.9$	-	_	7.02 4.20
Metaroom 2023	52	UNSAT		9.80	8.10	_	26.2	_	_	4.18
Metaroom 2023	53	UNSAT		9.87	8.10	2.03	29.5	_	-	4.37
Metaroom 2023	54	UNSAT		13.8	-	2.71	29.7	-	-	7.02
Metaroom 2023	55	UNSAT	7.86	13.1	-	-	26.7	-	-	7.23
Metaroom 2023	56	UNSAT		14.0	-	2.82	29.6	-	-	6.85
Metaroom 2023	57		7.60	9.91	8.10	1 07	25.8	-	-	4.19
Metaroom 2023 Metaroom 2023	58 59	UNSAT UNSAT		9.86 14.1	8.10	1.97 2.95	28.7 29.6	-	-	4.19 7.03
Metaroom 2023	60		7.89	13.0	_	-	27.5	-	-	6.85
Metaroom 2023	61	UNSAT		9.86	8.10	_	25.7	_	_	4.18
Metaroom 2023	62		7.99	13.1	-	2.68	29.3	-	-	6.81
Metaroom 2023	63	?	-	-	-	-	-	-	-	-
Metaroom 2023	64	?	-	-	-	-	-	-	-	-
Metaroom 2023	65	UNSAT		12.9	- 0.10	-	26.2	-	-	7.33
Metaroom 2023	$\frac{66}{67}$	UNSAT UNSAT	7.61	9.91	8.10	2.07	26.9	-	_	4.19
Metaroom 2023 Metaroom 2023	68	UNSAT		9.81 9.85	8.10 8.10	2.07 1.98	29.5 28.8	-	_	4.19 4.18
Metaroom 2023	69	UNSAT		12.7	-	-	26.3	_	_	7.25
Metaroom 2023	70		13.6	21.6	8.10	48.6	-	-	-	66.9
Metaroom 2023	71	UNSAT	7.60	9.80	8.10	2.05	28.1	-	-	4.18
Metaroom 2023	72	UNSAT		9.81	8.10	-	25.6	-	-	4.21
Metaroom 2023	73	SAT	8.27	137	3.10	3.74	-	-	-	X
Metaroom 2023	74	UNSAT		9.83	8.10	1 00	26.9	-	-	4.20
Metaroom 2023 Metaroom 2023	75 76	UNSAT		9.89	8.10	2.00	29.0	-	-	4.18 7.02
Metaroom 2023 Metaroom 2023	$\frac{76}{77}$	UNSAT UNSAT		14.6 9.89	8.10	2.99 2.01	28.8 29.0	-	_	4.38
Metaroom 2023	78	SAT	7.95	10.2	2.10	4.18	-	_	_	X
Metaroom 2023	79	UNSAT		13.3	-	-	26.4	-	-	6.68
Metaroom 2023	80	UNSAT		9.84	8.10	-	25.8	-	-	4.21
Metaroom 2023	81	UNSAT	7.88	13.4	-	-	26.5	-	-	6.63
Metaroom 2023	82	UNSAT		10.1	8.10	2.11	29.3	-	-	4.26
Metaroom 2023	83	UNSAT		14.5	-	2.82	29.8	-	-	7.36
Metaroom 2023 Metaroom 2023	84 85	UNSAT		14.7	-	2.88 2.80	30.0	-	-	7.36 7.74
wictaroull 2020	00	UNSAT	5.00	13.5	-	2.00	30.5	-	-	1.14

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

Category	Id	Result	α - β - \mathbf{C}	PyRAT	Marab	NNen	NNV	NeVer2	CORA	NSAT
Metaroom 2023	86	UNSAT	7.87	13.3	-	-	26.1	-	-	6.66
Metaroom 2023	87	UNSAT	8.14	14.4	-	3.08	29.2	-	-	6.99
Metaroom 2023	88	UNSAT		9.85	8.10	-	25.8	-	-	4.22
Metaroom 2023	89	UNSAT		13.4	-	-	27.7	-	-	6.85
Metaroom 2023	90	UNSAT		9.77	8.10	1 00	25.5	-	-	4.23
Metaroom 2023 Metaroom 2023	91 92	UNSAT	8.56	9.81 36.9	8.11 4.11	1.88	29.0	-	-	4.22
Metaroom 2023	93	SAT UNSAT		13.0	4.11	-	27.2	_	_	X 6.79
Metaroom 2023	94	UNSAT		13.5	_	_	26.8	_	_	6.68
Metaroom 2023	95	UNSAT		9.86	8.10	_	25.5	_	-	4.20
Metaroom 2023	96	UNSAT		9.92	8.10	2.07	29.3	-	-	4.35
Metaroom 2023	97	UNSAT	7.60	9.90	8.10	-	26.0	-	-	4.20
Metaroom 2023	98	UNSAT	8.13	15.3	-	3.18	30.6	-	-	7.37
Metaroom 2023	99	UNSAT	7.61	9.79	8.10	-	26.1	-	-	4.22
Nn4sys 2023 Nn4sys 2023	0 1	UNSAT UNSAT		3.66	6.09	-	-	-	-	-
Nn4sys 2023 Nn4sys 2023	2	UNSAT		3.62	6.09	_	_	_	_	_
Nn4sys 2023	3	UNSAT		3.77	7.12	_	_	_	_	_
Nn4sys 2023	4	UNSAT		-	-	_	_	_	_	_
Nn4sys 2023	5	UNSAT		3.65	6.09	-	-	-	-	-
Nn4sys 2023	6	UNSAT	7.84	3.66	6.09	-	-	-	-	-
Nn4sys 2023	7	UNSAT	9.14	-	-	-	-	-	-	-
Nn4sys 2023	8	UNSAT		-	-	-	-	-	-	-
Nn4sys 2023	9	UNSAT		-	-	-	-	-	-	-
Nn4sys 2023	10	UNSAT		3.63	6.10	-	-	-	-	-
Nn4sys 2023	$\frac{11}{12}$	UNSAT UNSAT		3.66 3.62	6.10	-	-	-	-	_
Nn4sys 2023 Nn4sys 2023	13	UNSAT		3.60	6.10	_	_	-	_	_
Nn4sys 2023	14	UNSAT		3.71	7.10	_	_	_	-	_
Nn4sys 2023	15	UNSAT		-	-	-	-	-	-	-
Nn4sys 2023	16	UNSAT	9.14	-	-	-	-	-	-	-
Nn4sys 2023	17	UNSAT	9.16	-	-	-	-	-	-	-
Nn4sys 2023	18	UNSAT		3.66	6.09	-	-	-	-	-
Nn4sys 2023	19	UNSAT		3.70	6.09	-	-	-	-	-
Nn4sys 2023 Nn4sys 2023	$\frac{20}{21}$	UNSAT UNSAT		3.76	7.10	-	-	-	-	-
Nn4sys 2023 Nn4sys 2023	22	UNSAT		3.73	6.09	_	_	-	_	_
Nn4sys 2023	23	UNSAT		3.77	7.10	_	_	_	-	-
Nn4sys 2023	$^{-3}$	UNSAT		3.63	6.10	-	-	-	-	-
Nn4sys 2023	25	UNSAT		-	-	-	-	-	-	-
Nn4sys 2023	26	UNSAT	8.64	-	-	-	-	-	-	-
Nn4sys 2023	27	UNSAT		3.66	6.09	-	-	-	-	-
Nn4sys 2023	28	UNSAT		3.66	6.09	-	-	-	-	-
Nn4sys 2023	29	UNSAT		3.63	6.09	-	-	-	-	-
Nn4sys 2023 Nn4sys 2023	30	UNSAT UNSAT		3.73	6.09	-	-	-	-	-
Nn4sys 2023 Nn4sys 2023	$\frac{31}{32}$	UNSAT		3.71	7.10	_	-	_	-	-
Nn4sys 2023	33	UNSAT		3.74	6.09	_	_	-	-	-
Nn4sys 2023	34	UNSAT		-	-	-	-	-	-	-
Nn4sys 2023	35	UNSAT		-	-	-	-	-	-	-
Nn4sys 2023	36	UNSAT		-	-	-	-	-	-	-
Nn4sys 2023	37	UNSAT		-	-	-	-	-	-	-
Nn4sys 2023	38	UNSAT		-	-	-	-	-	-	-
Nn4sys 2023 Nn4sys 2022	39	UNSAT		-	-	-	-	-	-	-
Nn4sys 2023 Nn4sys 2023	$\frac{40}{41}$	UNSAT UNSAT		-	-	-	-	-	-	-
Nn4sys 2023 Nn4sys 2023	42	UNSAT		-	_	_	-	_	-	-
Nn4sys 2023 Nn4sys 2023	43	UNSAT		-	_	_	_	-	-	-
Nn4sys 2023	44	UNSAT		-	-	-	-	-	-	-
Nn4sys 2023	45	UNSAT		-	-	-	-	-	-	-
Nn4sys 2023	46	UNSAT		-	-	-	-	-	-	-
Nn4sys 2023	47	UNSAT		-	-	-	-	-	-	-
Nn4sys 2023	48	UNSAT		-	-	-	-	-	-	-
Nn4sys 2023	49	UNSAT		-	-	-	-	-	-	-
Nn4sys 2023 Nn4sys 2023	50 51	UNSAT UNSAT		-	-	-	-	-	-	-
Nn4sys 2023 Nn4sys 2023	52	UNSAT		_	_	_	-	_	-	_
1.111030 2020	52	UNDAI	14.1							

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

Category	Id	Result α - β -	·C PyRA	Γ Mara	b NNe	n NNV	NeVer2	CORA	NSAT
Nn4sys 2023	53	UNSAT 12.5	-	-	-	-	-	-	-
Nn4sys 2023	54	UNSAT 11.7	-	-	-	-	-	-	-
Nn4sys 2023	55 56	UNSAT 12.2	-	-	-	-	-	-	-
Nn4sys 2023 Nn4sys 2023	56 57	UNSAT 12.0 UNSAT 11.9	-	_	-	-	_	_	-
Nn4sys 2023	58	UNSAT 11.8	_	_	_	_	_	_	_
Nn4sys 2023	59	UNSAT 12.4	-	-	-	-	-	-	-
Nn4sys 2023	60	unsat 11.7	-	-	-	-	-	-	-
Nn4sys 2023	61	UNSAT 12.2	-	-	-	-	-	-	-
Nn4sys 2023	62	UNSAT 12.1	-	-	-	-	-	-	-
Nn4sys 2023	63	UNSAT 11.9	-	-	-	-	_	-	-
Nn4sys 2023 Nn4sys 2023	$\frac{64}{65}$	UNSAT 11.9 UNSAT 12.2	-	_	-	_	-	-	_
Nn4sys 2023	66	UNSAT 11.9	_	_	_	_	_	_	_
Nn4sys 2023	67	Unsat 12.0	-	-	-	-	-	-	-
Nn4sys 2023	68	unsat 11.9	-	-	-	-	-	-	-
Nn4sys 2023	69	Unsat 12.5	-	-	-	-	-	-	-
Nn4sys 2023	70	UNSAT 12.4	-	-	-	-	-	-	-
Nn4sys 2023	71	UNSAT 12.4	-	-	-	-	-	-	-
Nn4sys 2023 Nn4sys 2023	72 73	UNSAT 12.8 UNSAT 12.5	-	-	-	-	_	-	-
Nn4sys 2023 Nn4sys 2023	74	UNSAT 13.2	-	-	_	_	_	-	_
Nn4sys 2023	75	UNSAT 12.9	_	_	_	_	_	_	_
Nn4sys 2023	76	Unsat 12.6	-	-	-	-	-	-	-
Nn4sys 2023	77	unsat 12.5	-	-	-	-	-	-	-
Nn4sys 2023	78	unsat 12.4	-	-	-	-	-	-	-
Nn4sys 2023	79	UNSAT 12.4	-	-	-	-	-	-	-
Nn4sys 2023	80	UNSAT 12.4	-	-	_	-	-	-	-
Nn4sys 2023 Nn4sys 2023	81 82	UNSAT 12.5 UNSAT 12.7	-	_	-	_	-	-	-
Nn4sys 2023	83	UNSAT 12.4	_	_	_	_	_	_	_
Nn4sys 2023	84	UNSAT 12.2	-	-	-	-	-	-	-
Nn4sys 2023	85	unsat 12.2	-	-	-	-	-	-	-
Nn4sys 2023	86	Unsat 12.5	-	-	-	-	-	-	-
Nn4sys 2023	87	UNSAT 12.8	-	-	-	-	-	-	-
Nn4sys 2023 Nn4sys 2023	88 89	UNSAT 12.3 UNSAT 12.2	-	-	-	-	_	-	_
Nn4sys 2023 Nn4sys 2023	90	UNSAT 12.2 UNSAT 12.2	-	-	-	-	_	-	_
Nn4sys 2023	91	UNSAT 12.2	_	_	_	_	_	_	_
Nn4sys 2023	92	Unsat 12.5	-	-	-	-	-	-	-
Nn4sys 2023	93	unsat 12.2	-	-	-	-	-	-	-
Nn4sys 2023	94	UNSAT 12.5	-	-	-	-	-	-	-
Nn4sys 2023	95	UNSAT 12.4	-	-	-	-	_	-	-
Nn4sys 2023 Nn4sys 2023	96 97	UNSAT 12.3 UNSAT 12.5	-	-	-	-	-	-	_
Nn4sys 2023	98	UNSAT 13.3	_	_	_	_	_	_	_
Nn4sys 2023	99	UNSAT 12.5	-	-	-	-	-	-	-
Nn4sys 2023	100	unsat 12.3	-	-	-	-	-	-	-
Nn4sys 2023	101	UNSAT 12.4	-	-	-	-	-	-	-
Nn4sys 2023	102	UNSAT 12.8	-	-	-	-	-	-	-
Nn4sys 2023	103	UNSAT 12.8 UNSAT 12.8	-	-	-	-	-	-	-
Nn4sys 2023 Nn4sys 2023	104 105	UNSAT 7.08	3.82	6.09	0.95	-	_	12.4	_
Nn4sys 2023	106	UNSAT 7.10		6.10	0.94	_	_	11.2	_
Nn4sys 2023	107	UNSAT 7.30		-	1.33	-	-	-	-
Nn4sys 2023	108	unsat 7.27	8.79	-	1.46	-	-	-	-
Nn4sys 2023	109	UNSAT 7.29	9.48	-	1.72	-	-	-	-
Nn4sys 2023	110	UNSAT 7.33	9.93	-	1.85	-	-	-	-
Nn4sys 2023	111	UNSAT 7.26		-	2.11	-	-	-	-
Nn4sys 2023 Nn4sys 2023	112 113	UNSAT 7.26 UNSAT 7.30		-	$\frac{2.23}{2.43}$	-	-	-	-
Nn4sys 2023 Nn4sys 2023	113	UNSAT 7.30 UNSAT 7.28		_	2.43	_	_	-	-
Nn4sys 2023	115	UNSAT 7.41		-	2.77	-	-	-	-
Nn4sys 2023	116	UNSAT 7.41	11.8	-	3.02	-	-	-	-
Nn4sys 2023	117	Unsat 7.50		-	6.55	-	-	-	-
Nn4sys 2023	118	UNSAT 7.55	13.4	-	7.20	-	-	-	-
Nn4sys 2023	119	UNSAT 7.65	14.7	-	10.4	-	-	-	-

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (X).

Category	Id	Result	α-β-C	PvRAT	Marah	NNen	NNV	NeVer2	CORA	NSAT
Nn4sys 2023	120		7.67	11.9	-	11.4		-	-	-
Nn4sys 2023	121	UNSAT		11.6	_	14.4	_	_	_	_
Nn4sys 2023	122	UNSAT		18.8	_	15.7	_	_	_	_
Nn4sys 2023	123	UNSAT		18.7	_	17.7	_	_	_	_
Nn4sys 2023	124	UNSAT		21.7	_	19.7	_	_	_	_
Nn4sys 2023	125	UNSAT		12.2	-	19.5	-	-	-	_
Nn4sys 2023	126	UNSAT		21.1	_	21.7	_	_	_	_
Nn4sys 2023	127	UNSAT		71.8	-	-	-	-	-	-
Nn4sys 2023	128	UNSAT		78.3	-	-	-	-	_	-
Nn4sys 2023	129	UNSAT	9.34	4.09	-	-	-	-	-	-
Nn4sys 2023	130	UNSAT	9.63	38.0	-	-	-	-	-	-
Nn4sys 2023	131	UNSAT	10.3	57.6	-	-	-	-	-	-
Nn4sys 2023	132	UNSAT	10.5	74.5	-	-	-	-	-	-
Nn4sys 2023	133	UNSAT	12.8	-	-	-	-	-	-	-
Nn4sys 2023	134	UNSAT	13.6	-	-	-	-	-	-	-
Nn4sys 2023	135	UNSAT	14.6	-	-	-	-	-	-	-
Nn4sys 2023	136	UNSAT	15.4	-	-	-	-	-	-	-
Nn4sys 2023	137	UNSAT	9.46	4.37	-	-	-	-	-	-
Nn4sys 2023	138	UNSAT	10.5	-	-	-	-	-	_	-
Nn4sys 2023	139	UNSAT		-	-	-	-	-	_	-
Nn4sys 2023	140	UNSAT		-	_	-	-	-	_	_
Nn4sys 2023	141	UNSAT		-	_	-	-	-	_	_
Nn4sys 2023	142	UNSAT	11.4	-	_	-	-	_	_	_
Nn4sys 2023	143	UNSAT		-	_	-	-	_	_	_
Nn4sys 2023	144	UNSAT		-	_	-	-	_	_	_
Nn4sys 2023	145	UNSAT		-	_	-	-	-	_	-
Nn4sys 2023	146	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	147		20.3	_	_	_	_	_	_	_
Nn4sys 2023	148	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	149	UNSAT		-	_	-	-	_	_	_
Nn4sys 2023	150		26.0	_	_	_	_	_	_	_
Nn4sys 2023	151	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	152	UNSAT		-	_	-	-	_	_	_
Nn4sys 2023	153	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	154	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	155	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	156	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	157	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	158	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	159	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	160	UNSAT		15.3	_	_	_	_	_	_
Nn4sys 2023	161	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	162	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	163	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	164	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	165	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	166	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	167	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	168	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	169	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	170	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	171	UNSAT		13.9	_	_	_	_	_	_
Nn4sys 2023	172	UNSAT		-	_	_	_	_	_	_
Nn4sys 2023	173	UNSAT		-	_	-	-	-	-	-
Nn4sys 2023	174	UNSAT		-	_	_	_	_	_	-
Nn4sys 2023	175	UNSAT		-	_	_	_	_	_	_
Nn4sys 2023	176	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	177	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	178	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	179	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	180	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	181	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023 Nn4sys 2023	182	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023 Nn4sys 2023	183	UNSAT		-	_	_	_	_	_	_
Nn4sys 2023	184	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023	185	UNSAT		_	_	_	_	_	_	_
Nn4sys 2023 Nn4sys 2023	186	UNSAT		-	_	_	_	-	_	_
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Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

Category	Id	Result	α - β - \mathbf{C}	PyRAT	Marab	NNen	NNV	NeVer2	CORA	NSAT
Nn4sys 2023	187	UNSAT	140	-	-	-	-	-	-	-
Nn4sys 2023	188	UNSAT	149	-	-	-	-	-	-	-
Nn4sys 2023	189	UNSAT	161	-	-	-	-	-	-	-
Nn4sys 2023 Nn4sys 2023	$\frac{190}{191}$	UNSAT UNSAT	173 182	-	-	-	-	-	-	-
Nn4sys 2023 Nn4sys 2023	191	UNSAT	193	_	-	_	_	-	-	_
Nn4sys 2023	193	UNSAT	206	-	-	-	-	-	-	-
Safenlp	0	UNSAT	7.41	4.06	6.09	1.16	25.9	-	12.1	-
Safenlp	1	SAT	7.81	3.70	3.10	1.34	-	1.53	-	-
Safenlp	2	SAT	8.23	4.11	X	1.36	-	-	-	-
Safenlp	3	SAT	8.33	3.98	X	1.28	-	1.53	-	-
Safenlp	4	UNSAT	8.31	2 69	X	3.06	- 22.7	1 50	11.5	-
Safenlp Safenlp	5 6	SAT UNSAT	7.65 8.44	3.62 4.07	1.09 6.09	1.39 1.53	23.7	1.52	12.6 12.5	-
Safenlp	7	SAT	8.24	3.61	X	1.36	_	1.53	12.0	_
Safenlp	8	SAT	8.12	3.71	x	1.37	_	1.53	_	-
Safenlp	9	SAT	8.29	3.71	3.10	1.40	-	1.52	-	-
Safenlp	10	SAT	8.32	3.67	6.09	1.36	-	1.53	11.3	-
Safenlp	11	SAT	8.33	3.70	X	1.33	-	-	-	-
Safenlp	12	UNSAT	8.77	-	X	-	-	-	-	-
Safenlp	13	UNSAT	8.47	5.20	6.09	1.97	-	1 50	12.0	-
Safenlp	14	SAT	7.85	3.65	1.09	1.35	24.7	1.52	12.7	_
Safenlp Safenlp	$\frac{15}{16}$	SAT SAT	8.23 8.14	3.72	3.10	2.16 1.31	_	1.53	-	_
Safenlp	17	SAT	7.59	3.60	1.09	1.33	24.5	-	12.0	_
Safenlp	18	SAT	7.78	3.67	1.09	1.35	23.8	1.53	12.3	_
Safenlp	19	UNSAT	7.13	3.73	6.09	1.13	25.9	1.55	13.2	-
Safenlp	20	SAT	7.77	3.69	1.09	1.30	24.3	1.53	13.8	-
Safenlp	21	UNSAT	8.59	6.35	6.09	2.35	-	-	-	-
Safenlp	22	SAT	7.77	3.59	1.09	1.25	24.3	-	12.4	-
Safenlp	23	SAT	7.83	3.71	1.09	1.38	23.8	-	12.4	-
Safenlp Safenlp	$\frac{24}{25}$	UNSAT SAT	8.38 8.34	23.4 3.72	6.09	3.57 1.34	-	1.53	_	-
Safenlp	26 26	UNSAT		17.8	X 7.10	3.76	-	1.33	_	_
Safenlp	27	SAT	8.18	3.71	X	1.36	_	1.53	_	_
Safenlp	28	UNSAT		6.59	7.10	2.66	-	-	23.7	-
Safenlp	29	SAT	7.91	3.64	1.09	1.42	-	1.52	12.4	-
Safenlp	30	SAT	7.71	3.66	1.09	1.30	-	1.53	12.6	-
Safenlp	31	SAT	8.13	-	X	-	-		-	-
Safenlp	32	UNSAT	7.14	3.76	6.09	1.15	26.1	1.52	12.0	-
Safenlp Safenlp	$\frac{33}{34}$	UNSAT SAT	8.52 7.83	3.70	7.10 1.09	5.10 1.38	23.9	1.53	13.1	-
Safenlp	35	SAT	8.32	4.02	X	2.02	-	-	-	_
Safenlp	36	UNSAT	8.57	17.8	X	2.59	_	_	12.9	_
Safenlp	37	SAT	8.34	3.71	X	1.34	-	-	-	-
Safenlp	38	SAT	8.35	3.62	X	1.35	23.8	1.52	13.8	-
Safenlp	39	SAT	8.32	3.69	X	1.36	-	1.53	-	-
Safenlp	40	SAT	8.11	3.63	Х	1.36	-	1.53	10.1	-
Safenlp	$\frac{41}{42}$	UNSAT	7.11	3.75	X	1.19	26.5	1.52	12.1 12.4	-
Safenlp Safenlp	43	SAT SAT	7.87 7.79	3.72 3.61	1.09	1.41 1.18	23.9 24.0	1.53	12.4	-
Safenlp	44	SAT	8.11	3.67	X	1.37	-	1.53	-	_
Safenlp	45	SAT	8.32	3.69	X	1.40	_	1.53	_	_
Safenlp	46	UNSAT		-	8.11	18.7	-	-	-	-
Safenlp	47	UNSAT		3.79	6.09	1.21	26.1	1.52	12.7	-
Safenlp	48	UNSAT		-	7.10	-	-	-	-	-
Safenlp	49	UNSAT		11.4	6.09	2.29	-	-	11.6	-
Safenlp	50	SAT	8.34	3.72	3.10	1.36	23.6	1.53	12.9	-
Safenlp Safenlp	51 52	SAT UNSAT	7.89	3.65	1.09	1.46	24.1	1.52	12.9	-
Safenip Safenip	$\frac{52}{53}$	SAT	7.13 8.32	3.77 3.70	6.09 X	1.21 1.40	25.2 23.8	1.52 1.53	13.3 13.0	-
Safenlp	54	SAT	8.32	3.68	â	1.35	∠3.6 -	1.52	-	_
~~····	55	SAT	8.33	3.68	x	1.41	_	-	-	-
Safenlp				3.60	1.09	1.38	_	1.52	13.3	_
Safenlp Safenlp	56	SAT	7.83	3.00	1.00			1.02	10.0	
	$\frac{56}{57}$	SAT	8.32	3.69	3.10	1.41	-	1.53	14.0	-
Safenlp			8.32 8.31							

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (X).

Category	Id	Result	α-β- C	PyRAT	' Marab	NNen	NNV	NeVer2	CORA	NSAT
Safenlp	60	SAT	8.31	3.70	3.10	1.37	-	-	-	-
Safenlp	61	UNSAT	8.36	4.53	6.09	1.38	-	-	12.2	-
Safenlp	62	SAT	7.70	3.58	1.09	1.34	24.1	1.52	12.6	-
Safenlp Safenlp	$\frac{63}{64}$	SAT SAT	$7.82 \\ 8.25$	3.58 3.71	1.09 X	1.39 1.38	23.9	1.54	12.8	-
Safenlp	65	SAT	8.36	3.70	1.09	1.39	_	1.53	_	_
Safenlp	66	SAT	8.36	3.64	3.10	1.40	_	1.52	13.2	_
Safenlp	67	SAT	7.84	3.63	1.09	1.44	24.0	1.53	12.7	-
Safenlp	68	SAT	8.14	4.13	X	1.33	-	1.53	-	-
Safenlp	69	SAT	7.53	3.63	X	1.16	23.9	1.73	12.0	-
Safenlp	70	UNSAT	8.53	10.4	6.09	3.12	-	-	-	-
Safenlp	$\frac{71}{72}$	SAT	8.32	-	X	1.89	-	-	-	_
Safenlp Safenlp	73	UNSAT SAT	8.42 8.09	4.13	6.09 X	7.14 1.72	-	1.52	_	_
Safenlp	74	SAT	8.38	-	3.10	1.96	_	-	_	_
Safenlp	75	SAT	8.24	_	3.10	-	_	_	-	-
Safenlp	76	SAT	7.94	3.68	X	1.32	-	-	-	-
Safenlp	77	SAT	7.60	3.66	1.09	1.13	24.4	1.78	11.9	-
Safenlp	78	UNSAT	8.97	-	X	-	-	-	-	-
Safenlp	79	UNSAT	7.11	3.85	6.09	1.19	26.0	1.52	11.6	-
Safenlp	80	UNSAT	7.38	3.87	6.09	1.23	26.4	1.52	12.9	-
Safenlp Safenlp	81 82	SAT SAT	8.29 7.83	3.67 3.65	3.10 1.09	1.39 1.35	- 24.9	1.53 1.53	13.0	-
Safenlp	83	SAT	8.21	3.59	X	1.37	24.5	1.52	13.7	_
Safenlp	84	SAT	8.20	3.70	X	1.35	-	1.53	-	_
Safenlp	85	SAT	7.77	3.69	1.09	1.42	24.4	1.53	11.4	-
Safenlp	86	UNSAT	8.90	-	7.10	-	-	-	-	-
Safenlp	87	SAT	8.25	3.69	X	1.52	-	1.53	-	-
Safenlp	88	SAT	8.30	-	3.10	1.63	-	-	-	-
Safenlp	89	SAT	8.09	3.66	χ,	1.41	- 05 C	1.53	11.0	-
Safenlp Safenlp	90 91	UNSAT UNSAT	7.11 8.50	3.74 10.8	6.09 6.09	1.17 4.13	25.6	1.52	11.0	-
Safenlp	92	SAT	8.37	-	X	1.37	_	_	-	_
Safenlp	93	SAT	8.31	3.68	X	1.39	_	1.53	_	-
Safenlp	94	SAT	7.81	3.68	1.09	1.37	-	1.52	12.3	-
Safenlp	95	SAT	8.24	3.69	3.10	1.26	-	1.53	13.4	-
Safenlp	96	SAT	7.64	3.61	1.09	1.29	24.2	1.52	13.3	-
Safenlp	97	UNSAT	8.93	-	8.10	- 0.01	-	-	-	-
Safenlp Safenlp	98 99	UNSAT SAT	8.50 8.20	3.61	X	3.31 1.33	24.0	1.53	15.6 12.9	-
Safenlp	100	SAT	7.64	3.59	x	1.19	25.0	1.77	13.2	_
Safenlp	101	SAT	8.09	3.66	X	1.36	-	1.52	-	-
Safenlp	102	SAT	8.27	3.67	X	1.30	-	1.52	-	-
Safenlp	103	UNSAT	8.38	9.00	6.09	2.62	-	-	29.7	-
Safenlp	104	SAT	7.83	3.62	1.09	1.25	23.9	1.53	12.2	-
Safenlp	105	UNSAT	8.40	7.98	6.09	2.27	- 04.1	1.50	11.8	-
Safenlp Safenlp	$\frac{106}{107}$	SAT	7.65 7.11	3.63 3.80	1.09 X	1.24 1.10	$24.1 \\ 26.1$	1.53 1.52	13.3 13.1	_
Safenlp	107	UNSAT UNSAT	8.38	12.1	6.09	2.91	20.1 -	1.02	12.4	_
Safenlp	109	UNSAT	7.12	3.79	X	1.15	26.5	1.52	13.5	_
Safenlp	110	UNSAT	10.8	-	30.3	-	-	-	-	-
Safenlp	111	SAT	7.86	3.67	1.09	1.42	-	1.52	12.3	-
Safenlp	112	UNSAT	7.14	3.78	6.09	1.18	26.1	1.56	11.8	-
Safenlp	113	SAT	8.31	110	3.10	-	-	-	-	-
Safenlp	114	UNSAT		14.9	7.10	2.39	24.2	1 59	13.2	-
Safenlp Safenlp	$\frac{115}{116}$	SAT SAT	7.83 8.20	3.66 3.70	1.09 X	1.41 1.25	24.2	1.53 1.52	13.1	-
Safenlp	117	SAT	8.27	3.64	â	1.30	-	-	13.6	-
Safenlp	118	UNSAT	8.35	4.04	7.10	1.34	_	-	13.6	_
Safenlp	119	UNSAT		14.1	7.10	4.53	-	-	-	-
Safenlp	120	UNSAT	11.2	-	12.1	-	-	-	-	-
Safenlp	121	SAT	7.75	3.66	1.09	1.38	-	1.53	13.4	-
Safenlp	122	UNSAT		14.3	6.09	2.75	-	-	-	-
Safenlp	123	SAT	7.83	3.62	1.09	1.38	-	-	11.1	-
Safenlp Safenlp	124	SAT	8.33	4.06	3.10	1.41	-	-	-	-
Safenip	$\frac{125}{126}$	UNSAT SAT	$10.6 \\ 8.34$	-	8.11 3.10	1.67	_	_	-	-
Satemp	120	OAI	0.04	-	0.10	1.01	-			•

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

Category	Id	Result	α - β - \mathbf{C}	PyRAT	' Marab	NNen	NNV	NeVer2	CORA	NSAT
Safenlp	127	SAT	8.15	3.66	3.10	1.40	-	1.53	-	-
Safenlp	128	SAT	7.82	3.57	1.09	1.23	24.1	-	12.3	-
Safenlp	129	SAT	8.28	3.61	3.10	1.40	-	1.53	-	-
Safenlp	130	SAT	7.68	3.62	1.09	1.35	23.9	1.50	12.8	-
Safenlp	131	SAT	7.71	3.61	X	1.40	24.4	1.52	13.1	-
Safenlp	132	UNSAT	12.3	-	27.3	1 10	-	1 50	10.0	-
Safenlp	133	UNSAT	7.11	3.83	6.09	1.12	25.7	1.58	12.8	-
Safenlp	134	SAT	8.35	3.68	3.10	1.30	-	1.53	-	_
Safenlp Safenlp	135 136	UNSAT SAT	8.96 8.31	_	7.10 X	18.8 1.70	_	-	_	_
Safenlp	137	SAT	8.37	3.67	3.10	1.41	-	1.53	_	_
Safenlp	138	SAT	7.84	3.65	1.09	1.39	23.6	-	11.3	_
Safenlp	139	SAT	8.32	3.66	X	1.33	-	1.53	-	_
Safenlp	140	SAT	7.74	3.67	1.09	1.36	24.1	-	13.1	_
Safenlp	141	SAT	8.19	3.72	X	1.43	-	1.53	_	_
Safenlp	142	UNSAT	7.12	3.78	X	1.21	26.4	1.52	10.8	_
Safenlp	143	UNSAT	8.47	-	6.09	11.9	-	-	-	_
Safenlp	144	SAT	8.25	-	3.10	_	-	_	-	_
Safenlp	145	UNSAT	7.13	3.80	7.10	1.14	25.9	1.52	11.1	_
Safenlp	146	UNSAT	10.3	-	9.11	-	-	-	-	-
Safenlp	147	UNSAT	13.5	-	-	-	-	-	-	-
Safenlp	148	UNSAT	7.13	3.84	X	1.15	25.8	1.52	11.0	-
Safenlp	149	SAT	7.90	3.75	1.09	1.32	23.8	1.53	13.3	-
Safenlp	150	UNSAT	7.18	3.80	6.09	1.08	26.9	1.52	13.8	-
Safenlp	151	SAT	8.34	3.71	X	1.24	-	1.52	-	-
Safenlp	152	UNSAT	8.59	-	X	-	-	-	-	-
Safenlp	153	UNSAT	8.60	13.3	6.09	2.83	-	-	13.1	-
Safenlp	154	UNSAT	7.15	3.79	X	1.19	25.6	1.52	13.9	-
Safenlp	155	SAT	8.32	3.72	3.10	1.36	-	1.52	-	-
Safenlp	156	SAT	7.83	3.58	1.09	1.41	24.2	1.53	12.3	-
Safenlp	157	SAT	8.34	3.71	X	1.30	-	1.53	-	-
Safenlp	158	UNSAT		-	6.09	5.67	-	-	14.2	-
Safenlp	159	SAT	8.17	- 0.01	3.10	1.25	-	1.53	10.0	-
Safenlp	160	SAT	7.84	3.61	1.09	1.25	24.4	1.53	12.2	-
Safenlp	161	SAT	8.25	9.74	X	1.30	- 25 6	1 52	11 1	-
Safenlp	162 163	UNSAT	7.13	3.74	X 3.10	1.14 1.36	25.6	1.53	11.1	_
Safenlp	164	SAT	8.30 8.35	3.70 3.71	3.10	1.37	-	1.53 1.52	-	_
Safenlp Safenlp	165	SAT SAT	7.88	3.68	1.09	1.33	23.6	1.54	13.0	-
Safenlp	166	SAT	7.84	3.63	1.09	1.33	24.0	-	13.6	_
Safenlp	167	SAT	8.35	-	X	-	-	_	-	_
Safenlp	168	SAT	8.38	_	3.10	_	_	_	_	_
Safenlp	169	SAT	7.83	3.63	1.09	X	_	1.53	12.2	_
Safenlp	170	UNSAT	10.2	-	9.11		_	-	-	_
Safenlp	171	SAT	8.19	3.75	3.10	1.41	_	_	_	_
Safenlp	172	UNSAT	8.29	5.72	X	1.65	-	_	12.2	_
Safenlp	173	UNSAT	9.03	-	7.10	-	-	-	-	-
Safenlp	174	SAT	7.84	3.71	X	1.28	-	1.53	12.2	-
Safenlp	175	SAT	8.19	3.63	3.10	1.32	-	1.53	-	-
Safenlp	176	SAT	7.85	3.67	1.09	1.28	24.7	1.53	12.0	-
Safenlp	177	SAT	8.42	-	X	1.84	-	-	-	-
Safenlp	178	SAT	8.10	3.69	X	1.33	-	1.53	12.0	-
Safenlp	179	UNSAT	8.54	8.23	X	2.03	-	-	13.3	-
Safenlp	180	UNSAT	7.18	3.82	X	1.15	25.6	1.52	13.6	-
Safenlp	181	UNSAT		-	X	-	-	-	-	-
Safenlp	182	SAT	8.36	-	X	2.01	-	-	-	-
Safenlp	183	SAT	8.32	3.68	X	1.43	-	1.53	-	-
Safenlp	184	SAT	7.59	3.66	6.09	1.31	24.3	1.53	12.2	-
Safenlp	185	UNSAT		21.2	7.10	3.36	-	1 50	-	-
Safenlp	186	SAT	8.21	3.65	3.10	1.37	-	1.53	10.5	-
Safenlp	187	SAT	7.66	3.66	3.10	1.34	-	1.53	12.5	-
Safenlp	188	SAT	8.19	3.71	X	1.28	-	1.52	-	-
Safenlp	189	SAT	8.35	3.68	X	1.32	-	1.53	11.0	-
Safenlp	190	SAT	7.84	3.67	1.09	1.35	23.9	-	13.7	-
Safenlp	191	SAT	7.57	3.63	1.09	1.23	23.9	-	13.8	-
Safenlp	192	UNSAT		5.47	7.10	1.33	-	1 54	14.0	-
Safenlp	193	UNSAT	7.16	3.75	6.09	1.11	26.3	1.54	14.1	-

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

Safenlp 194 SAT 8.31 3.70 X 1.25 - - Safenlp 195 UNSAT 1.16 3.70 X 1.09 26.5 1.56 11.0 Safenlp 196 UNSAT 8.32 - 7.10 18.0 - - 1.11 Safenlp 198 WAT 7.88 3.63 1.09 1.25 2.45 1.53 1.21 Safenlp 200 SAT 8.36 3.74 X 1.25 1.53 1.25 Safenlp 201 UNSAT 7.15 3.81 6.09 1.08 2.55 1.57 11.9 Safenlp 201 WART 8.39 3.67 3.10 1.32 1.53 1.25 1.53 - Safenlp 203 SAT 8.21 3.71 3.10 1.24 1.53 1.25 2.5 Safenlp 205 SAT 8.39 3.66 1.09 1.26	NSAT	CORA	NeVer2	NNV	NNen	T Marab	PyRA	<i>α</i> - <i>β</i> - C	Result	Id	Category
Safenip	-										*
Safenip 197 SAT 7.69 3.67 X 1.36 2.28 1.53 12.1 Safenip 199 SAT 7.88 3.63 1.09 1.25 24.5 1.53 14.2 Safenip 200 SAT 8.36 3.74 X 1.25 2.45 1.53 - Safenip 201 UNSAT 7.13 3.81 6.09 1.08 26.1 1.52 1.53 - Safenip 203 SAT 8.09 3.67 3.10 1.32 - 1.53 1.25 Safenip 204 SAT 8.35 3.69 X 1.25 - 1.53 - Safenip 206 SAT 8.30 3.73 X 1.45 - - 1.53 1.25 Safenip 207 SAT 8.39 3.66 1.09 1.26 - 1.53 1.37 Safenip 211 SAT 8.36 3.05	-		1.56								
Safenip 198 USNAT 8.32 - 6.09 2.29 - - 14.1 Safenip 199 SAT 7.88 3.63 1.09 1.25 24.5 1.53 1.4.2 Safenip 200 SAT 8.36 3.74 X 1.25 - 1.53 - 1.9 Safenip 201 UNSAT 7.13 3.72 6.09 1.08 26.1 1.53 - 1.53 - Safenip 204 SAT 8.35 3.69 3.67 3.10 1.22 - 1.53 - Safenip 206 SAT 8.31 3.71 3.10 1.24 - 1.53 1.25 Safenip 207 SAT 8.14 3.71 X 1.34 - 1.53 1.25 Safenip 210 UNSAT 7.18 3.80 6.09 1.05 25.3 1.51 1.41 Safenip 211 SA	-										
Safenip 199 SAT 7.88 3.63 1.09 1.25 2.45 1.53 1.42 Safenip 201 UNSAT 7.15 3.81 6.09 1.08 25.5 1.57 11.9 Safenip 202 UNSAT 7.13 3.72 6.09 1.08 26.1 1.52 1.33 1.8 Safenip 203 SAT 8.09 3.67 3.10 1.32 - 1.53 1.25 Safenip 205 SAT 8.35 3.69 X 1.24 - 1.53 1.25 Safenip 206 SAT 8.30 3.73 X 1.45 - 1.53 12.5 Safenip 208 SAT 8.39 3.66 1.09 1.26 - 1.53 1.37 Safenip 210 UNSAT 7.18 3.80 6.09 1.05 25.3 1.51 1.41 Safenip 211 SAT 8.36 3.65<	-										
Safenip 200 SAT 8.36 3.74 X 1.25 - 1.57 11.9 Safenip 201 UNSAT 7.15 3.81 6.09 1.08 25.5 1.57 11.9 Safenip 202 UNSAT 7.13 3.72 6.09 1.08 26.1 1.52 1.38 Safenip 204 SAT 8.09 3.67 3.10 1.22 - 1.53 - Safenip 206 SAT 8.21 3.71 3.10 1.24 - 1.53 - Safenip 206 SAT 8.30 3.66 1.09 1.26 - 1.53 1.37 Safenip 209 UNSAT 7.18 3.80 6.09 1.05 25.3 1.51 14.1 Safenip 210 UNSAT 7.15 3.79 6.09 1.18 26.3 1.52 - Safenip 212 UNSAT 7.15 3.79 6.09 </td <td>-</td> <td></td>	-										
Safenlip 201 UNSAT 7.15 3.81 6.09 1.08 25.5 1.57 11.9 Safenlip 202 UNSAT 7.13 3.72 6.09 1.08 26.1 1.52 1.38 Safenlip 204 SAT 8.35 3.69 X 1.25 - 1.53 - Safenlip 206 SAT 8.30 3.71 3.10 1.24 - 1.53 - Safenlip 206 SAT 8.30 3.73 X 1.45 - - - Safenlip 209 UNSAT 7.18 3.80 6.09 1.05 2.53 1.51 14.1 Safenlip 210 UNSAT 7.18 3.86 1.09 1.26 - 1.53 1.37 Safenlip 211 SAT 7.18 3.79 6.09 1.16 2.6 1.53 13.7 Safenlip 211 UNSAT 7.14 3.74 4.0<	-										
Safenlp 202 unsart 7.13 3.72 6.09 1.08 26.1 1.52 1.88 Safenlp 204 sat 8.09 3.67 3.10 1.32 - 1.53 - Safenlp 205 sat 8.21 3.71 3.10 1.24 - 1.53 1.5 Safenlp 206 sat 8.30 3.73 X 1.45 - - Safenlp 207 sat 8.14 3.71 X 1.34 - 1.53 1.37 Safenlp 209 unsat 7.18 3.80 6.09 1.05 25.3 1.51 1.41 Safenlp 211 sat 8.36 3.65 3.10 1.37 - 1.52 - - - - - - - - - - 1.32 1.31 2.25 3.13.1 1.32 2.3 1.51 1.41 1.52 1.53 13.7	-										
Safenlp 203 sat manner 8.09 3.67 3.10 1.32 - 1.53 - Safenlp 205 sat 8.35 3.69 X 1.25 - 1.53 - Safenlp 206 sat 8.20 3.71 X 1.45 - - Safenlp 206 sat 8.30 3.73 X 1.45 - - Safenlp 208 sat 8.39 3.66 1.09 1.26 - 1.53 1.31 Safenlp 210 UNSAT 7.18 3.80 6.09 1.05 2.53 1.51 14.1 Safenlp 211 sat 8.36 3.65 3.10 1.37 - 1.52 - Safenlp 211 sat 7.14 3.72 3.10 1.29 24.0 1.53 13.7 Safenlp 215 UNSAT 7.14 3.74 6.09 1.16 25.6 1	_										
SafenIp 204 sat 8.35 3.69 X 1.25 - 1.53 - SafenIp 205 sat 8.21 3.71 3.10 1.24 - 1.53 1.25 SafenIp 206 sat 8.30 3.73 X 1.34 - - SafenIp 207 sat 8.14 3.71 X 1.34 - 1.53 - SafenIp 209 unsat 7.18 3.80 6.09 1.05 25.3 1.51 14.1 SafenIp 211 sat 8.36 3.65 3.10 1.37 - - - - - SafenIp 211 sat 8.36 3.65 3.10 1.37 - 1.52 2.2 SafenIp 211 sat 7.91 3.72 3.10 1.29 24 1.53 1.37 SafenIp 215 sat 7.14 3.74 6.09 <	-										*
Safenilp 205 SAT 8.21 3.71 3.10 1.24 - 1.53 12.5 Safenilp 206 SAT 8.30 3.73 X 1.45 - 1.53 - Safenilp 208 SAT 8.39 3.66 1.09 1.26 - 1.53 13.7 Safenilp 210 UNSAT 7.18 3.80 6.09 1.05 2.3 15.1 14.1 Safenilp 211 SAT 8.36 3.65 3.10 1.29 24.0 15.3 13.7 Safenilp 213 SAT 7.15 3.79 M 1.13 26.9 1.53 13.7 Safenilp 215 UNSAT 7.14 3.74 6.09 1.16 25.9 1.53 13.7 Safenilp 215 UNSAT 7.14 3.74 8.0 9.1 1.6 25.9 1.53 13.7 Safenilp 215 SAT 7.83 <th< td=""><td>_</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></th<>	_										
Safenlip 206 SAT 8.14 3.73 X 1.45 - - - Safenlip 208 SAT 8.14 3.71 X 1.34 - 1.53 - Safenlip 209 UNSAT 7.18 3.80 6.09 1.05 25.3 1.51 14.1 Safenlip 211 SAT 8.36 3.65 3.10 1.25 25.3 1.52 - Safenlip 211 SAT 7.15 3.79 6.09 1.18 26.3 1.52 1.23 Safenlip 214 UNSAT 7.15 3.79 X 1.13 25.9 1.53 13.7 Safenlip 214 UNSAT 7.15 3.79 X 1.13 25.9 1.53 13.9 Safenlip 216 UNSAT 7.15 3.61 1.09 1.16 24.2 1.53 13.7 Safenlip 216 UNSAT 7.75 3.61 1.0	_										
Safenlp 207 SAT 8.14 3.71 X 1.34 - 1.53 - Safenlp 208 SAT 8.39 3.66 1.09 1.26 - 1.53 13.7 Safenlp 210 UNSAT 7.18 3.80 6.09 1.05 25.3 1.51 14.1 Safenlp 211 SAT 8.36 3.65 3.10 1.37 - 1.52 - Safenlp 212 UNSAT 7.15 3.79 8.09 1.18 26.3 1.52 1.23 Safenlp 213 SAT 7.15 3.79 X 1.13 25.9 1.53 13.7 Safenlp 215 UNSAT 8.44 13.72 3.10 1.29 24.0 1.53 13.7 Safenlp 215 UNSAT 7.14 3.74 1.60 9 1.16 25.9 1.53 13.7 Safenlp 216 UNSAT 7.15 3.61<	_										*
SafenIp 208 SAT 8.39 3.66 1.09 1.26 - 1.53 13.1 SafenIp 209 UNSAT 7.18 3.80 6.09 1.05 25.3 1.51 14.1 SafenIp 210 UNSAT 10.2 - 9.11 - - - SafenIp 211 SAT 8.36 3.65 3.10 1.29 24.0 1.53 12.3 SafenIp 214 UNSAT 7.15 3.79 K 1.13 25.9 1.53 13.7 SafenIp 214 UNSAT 7.14 3.74 6.09 1.16 25.6 1.53 13.7 SafenIp 216 UNSAT 7.14 3.74 6.09 1.16 24.2 1.52 14.1 SafenIp 216 UNSAT 7.75 3.61 1.09 1.28 2.4 1.53 1.41 SafenIp 219 SAT 7.87 3.61 1.09 <td< td=""><td>-</td><td></td><td></td><td>-</td><td></td><td></td><td></td><td></td><td></td><td></td><td>*</td></td<>	-			-							*
Safenlp 209 UNSAT 7.1.8 3.80 6.09 1.05 25.3 1.51 14.1 Safenlp 211 SAT 8.36 3.65 3.10 1.37 - 1.52 - Safenlp 212 UNSAT 7.15 3.79 6.09 1.18 26.3 1.52 1.23 Safenlp 213 SAT 7.91 3.79 X 1.13 25.9 1.53 13.7 Safenlp 215 UNSAT 7.14 3.74 6.09 1.16 25.6 1.53 13.7 Safenlp 215 UNSAT 7.44 3.74 6.09 1.16 25.6 1.53 13.7 Safenlp 215 UNSAT 7.83 3.62 1.09 1.26 24.2 1.52 1.53 13.7 Safenlp 217 SAT 8.32 3.61 1.09 1.26 24.2 1.52 14.2 Safenlp 220 SAT 7.87	-	13.7		-							
Safenlp 211 SAT 8.36 3.65 3.10 1.37 - 1.52 - Safenlp 212 unsar 7.15 3.79 6.09 1.18 26.3 1.52 12.3 Safenlp 214 unsar 7.15 3.79 X 1.13 25.9 1.53 13.7 Safenlp 215 unsar 7.44 3.74 6.09 1.16 25.6 1.58 13.7 Safenlp 216 unsar 8.44 13.2 X 2.56 - - 13.7 Safenlp 217 sar 7.83 3.62 1.09 1.26 24.2 1.52 14.2 Safenlp 218 sar 7.75 3.61 1.09 1.28 - 1.53 13.1 Safenlp 220 sar 8.32 3.64 3.10 1.42 - - - Safenlp 220 sar 8.42 3.70 X	-			25.3							*
Safenlp 212 UNSAT 7.15 3.79 6.09 1.18 26.3 1.52 12.3 Safenlp 214 UNSAT 7.15 3.79 X 1.13 25.9 1.53 13.7 Safenlp 215 UNSAT 7.14 3.74 6.09 1.16 25.6 1.58 13.7 Safenlp 216 UNSAT 7.44 3.74 6.09 1.16 25.6 1.53 13.7 Safenlp 216 UNSAT 7.83 3.62 1.09 1.26 24.2 1.53 14.1 Safenlp 218 SAT 7.75 3.61 1.09 1.26 24.2 1.53 14.1 Safenlp 218 SAT 7.78 3.61 1.09 1.28 - 1.53 14.1 Safenlp 220 SAT 8.34 3.68 X 1.36 - 1.53 1 Safenlp 221 SAT 8.24 3.71 <	-	-		-	-		-	10.2	UNSAT		*
SafenIp 213 SAT 7.91 3.72 3.10 1.29 24.0 1.53 13.9 SafenIp 214 UNSAT 7.14 3.74 6.09 1.16 25.6 1.58 13.7 SafenIp 216 UNSAT 8.44 13.2 X 2.56 - - 13.7 SafenIp 217 SAT 7.73 3.62 1.09 1.26 24.2 1.52 14.2 SafenIp 218 SAT 7.75 3.61 1.09 1.28 - 1.53 14.1 SafenIp 219 SAT 8.32 3.61 1.09 1.39 - 1.53 14.1 SafenIp 221 SAT 8.32 3.61 1.09 1.32 - 1.53 1.51 SafenIp 221 SAT 8.32 3.66 0.9 1.32 2.5 1.51 1.1 SafenIp 222 SAT 8.42 3.71 X	-	-	1.52	-	1.37	3.10	3.65	8.36	SAT	211	Safenlp
Safenlp 214 UNSAT 7.15 3.79 X 1.13 25.9 1.53 13.7 Safenlp 216 UNSAT 7.14 3.74 6.09 1.16 25.6 1.58 13.7 Safenlp 216 UNSAT 8.44 13.2 X 2.56 - - 13.7 Safenlp 218 SAT 7.75 3.61 1.09 1.26 24.2 1.52 14.2 Safenlp 218 SAT 7.75 3.61 1.09 1.28 - 1.53 14.1 Safenlp 220 SAT 7.87 3.61 1.09 1.39 - 1.53 14.1 Safenlp 220 SAT 7.78 3.61 1.09 1.39 - 1.53 14.1 Safenlp 220 SAT 7.78 3.61 1.09 1.33 - 1.53 12.1 Safenlp 223 UNSAT 7.13 3.76 1.09 <td>-</td> <td>12.3</td> <td>1.52</td> <td>26.3</td> <td>1.18</td> <td>6.09</td> <td>3.79</td> <td>7.15</td> <td>UNSAT</td> <td>212</td> <td>Safenlp</td>	-	12.3	1.52	26.3	1.18	6.09	3.79	7.15	UNSAT	212	Safenlp
SafenIp 215 UNSAT 7.14 3.74 6.09 1.16 25.6 1.58 13.7 SafenIp 216 UNSAT 7.83 3.62 1.09 1.26 24.2 1.52 14.2 SafenIp 218 SAT 7.75 3.61 1.09 1.28 - 1.53 14.1 SafenIp 219 SAT 8.32 3.64 3.10 1.42 - - - SafenIp 220 SAT 7.87 3.61 1.09 1.32 - 1.53 14.1 SafenIp 221 SAT 8.34 3.68 X 1.36 - 1.53 1.5 SafenIp 222 SAT 8.42 3.70 X 1.46 - - - - SafenIp 222 SAT 8.24 3.71 X 1.40 - - - - SafenIp 225 SAT 7.74 3.65	-	13.9	1.53	24.0	1.29	3.10	3.72	7.91		213	Safenlp
Safenlp 216 UNSAT 8.44 13.2 X 2.56 - - 137 Safenlp 217 SAT 7.83 3.62 1.09 1.26 24.2 1.52 14.2 Safenlp 219 SAT 8.32 3.64 3.10 1.42 - - - Safenlp 220 SAT 7.87 3.61 1.09 1.39 - 1.53 13.1 Safenlp 221 SAT 8.34 3.68 X 1.36 - - - - Safenlp 222 SAT 8.42 3.70 X 1.46 - - - Safenlp 223 UNSAT 7.15 3.76 6.09 1.21 26.66 1.52 11.1 Safenlp 224 SAT 7.74 3.65 1.09 1.32 23.5 1.53 12.2 Safenlp 226 UNSAT 7.13 3.79 6.09	-						3.79		UNSAT		Safenlp
Safenlp 217 SAT 7.83 3.62 1.09 1.26 24.2 1.52 14.1 Safenlp 218 SAT 7.75 3.61 1.09 1.28 - 1.53 14.1 Safenlp 220 SAT 7.87 3.61 1.09 1.39 - 1.53 13.1 Safenlp 221 SAT 8.34 3.68 X 1.36 - 1.53 - Safenlp 222 SAT 8.42 3.70 X 1.46 - - - Safenlp 223 UNSAT 7.15 3.76 6.09 1.21 26.6 1.52 11.1 Safenlp 224 SAT 8.24 3.71 X 1.40 -	-		1.58	25.6							
Safenlp 218 SAT 7.75 3.61 1.09 1.28 - 1.53 14.1 Safenlp 219 SAT 8.32 3.64 3.10 1.42 - - - - - - - - 1.53 13.1 Safenlp 221 SAT 8.34 3.68 X 1.36 - 1.53 - - - - Safenlp 222 SAT 8.42 3.70 X 1.46 -	-										*
Safenip 219 SAT 8.32 3.64 3.10 1.42 - - - Safenip 220 SAT 7.87 3.61 1.09 1.39 - 1.53 13.1 Safenip 221 SAT 8.34 3.68 X 1.36 - - Safenip 222 SAT 8.42 3.70 X 1.46 - - Safenip 223 UNSAT 7.15 3.76 6.09 1.21 26.6 1.52 11.1 Safenip 224 SAT 8.24 3.71 X 1.40 - - - Safenip 226 UNSAT 7.13 3.79 6.09 1.16 26.1 1.55 14.4 Safenip 228 UNSAT 7.14 3.79 6.09 1.14 - 1.53 - Safenip 230 UNSAT 7.11 3.79 6.09 1.24 26.5 1.51	-										*
SafenIp 220 SAT 7.87 3.61 1.09 1.39 - 1.53 13.1 SafenIp 221 SAT 8.34 3.68 X 1.36 - 1.53 - SafenIp 222 SAT 8.42 3.70 X 1.46 - - SafenIp 223 UNSAT 7.15 3.76 6.09 1.21 26.6 1.52 11.1 SafenIp 224 SAT 7.74 3.65 1.09 1.32 23.5 1.53 12.2 SafenIp 226 UNSAT 7.14 3.65 1.09 1.32 23.5 1.53 12.2 SafenIp 226 UNSAT 7.11 3.60 1.09 1.42 2.6 1.53 - SafenIp 223 UNSAT 7.11 3.79 6.09 1.24 26.5 1.51 11.9 SafenIp 231 SAT 7.13 3.60 1.09 1.35	-										*
SafenIp 221 SAT 8.34 3.68 X 1.36 - 1.53 - SafenIp 222 SAT 8.42 3.70 X 1.46 - - - SafenIp 223 UNSAT 7.15 3.76 6.09 1.21 26.6 1.52 11.1 SafenIp 224 SAT 8.24 3.71 X 1.40 - - - SafenIp 225 SAT 7.74 3.65 1.09 1.32 23.5 1.53 12.2 SafenIp 226 UNSAT 7.13 3.79 6.09 1.16 26.1 1.55 14.4 SafenIp 228 UNSAT 7.14 3.79 6.09 1.14 2.6.5 1.51 11.9 SafenIp 230 UNSAT 7.11 3.79 6.09 1.14 25.6 1.56 14.0 SafenIp 231 SAT 7.80 3.65 1.09	-										
SafenIp 222 SAT 8.42 3.70 X 1.46 - - - SafenIp 223 UNSAT 7.15 3.76 6.09 1.21 26.6 1.52 11.1 SafenIp 224 SAT 8.24 3.71 X 1.40 - - SafenIp 225 SAT 7.74 3.65 1.09 1.32 23.5 1.53 12.2 SafenIp 226 UNSAT 7.13 3.79 6.09 1.16 26.1 1.55 14.4 SafenIp 228 UNSAT 7.13 3.79 6.09 1.14 - 1.53 - SafenIp 228 UNSAT 7.11 3.79 6.09 1.24 26.5 1.51 11.9 SafenIp 230 UNSAT 7.11 3.79 6.09 1.24 25.6 1.56 14.0 SafenIp 231 SAT 7.13 3.60 3.10 1.28	-										*
SafenIp 223 UNSAT 7.15 3.76 6.09 1.21 26.6 1.52 11.1 SafenIp 224 SAT 8.24 3.71 X 1.40 - - SafenIp 225 SAT 7.74 3.65 1.09 1.32 23.5 1.53 12.2 SafenIp 226 UNSAT 7.13 3.79 6.09 1.16 26.1 1.55 14.4 SafenIp 228 UNSAT 10.1 - 7.10 - - - - SafenIp 229 UNSAT 7.14 3.79 6.09 1.14 - 1.53 - SafenIp 230 UNSAT 7.11 3.79 6.09 1.14 25.6 1.56 14.0 SafenIp 231 SAT 7.73 3.60 1.09 1.35 24.7 - 12.5 SafenIp 233 SAT 7.80 3.65 1.09 1.45	-										*
Safenlp 224 SAT 8.24 3.71 X 1.40 - - - Safenlp 225 SAT 7.74 3.65 1.09 1.32 23.5 1.53 12.2 Safenlp 226 UNSAT 7.13 3.79 6.09 1.16 26.1 1.55 14.4 Safenlp 228 UNSAT 10.1 - 7.10 - - - - Safenlp 229 UNSAT 7.14 3.79 6.09 1.24 26.5 1.51 11.9 Safenlp 230 UNSAT 7.11 3.79 6.09 1.24 26.5 1.56 14.0 Safenlp 231 SAT 7.13 3.60 3.01 1.28 - 1.53 - Safenlp 233 SAT 7.80 3.65 1.09 1.45 24.3 1.53 13.0 Safenlp 233 UNSAT 8.69 15.8 6.09	-										*
Safenlp 225 SAT 7.74 3.65 1.09 1.32 23.5 1.53 12.2 Safenlp 226 unsat 7.13 3.79 6.09 1.16 26.1 1.55 14.4 Safenlp 228 unsat 10.1 - 7.10 - - - Safenlp 229 unsat 7.14 3.79 6.09 1.24 26.5 1.51 11.9 Safenlp 230 unsat 7.11 3.79 6.09 1.24 26.5 1.51 11.9 Safenlp 230 unsat 7.11 3.79 6.09 1.14 25.6 1.56 14.0 Safenlp 231 sat 8.16 3.60 3.10 1.28 - 1.53 - 1.53 - Safenlp 231 sat 7.80 3.65 1.09 1.35 24.7 - 1.25 Safenlp 234 unsat 8.69 15.8	-										*
Safenlp 226 UNSAT 7.13 3.79 6.09 1.16 26.1 1.55 14.4 Safenlp 227 SAT 8.30 3.75 3.10 1.41 - 1.53 - Safenlp 228 UNSAT 7.14 3.79 6.09 1.24 26.5 1.51 11.9 Safenlp 230 UNSAT 7.11 3.79 6.09 1.14 25.6 1.56 14.0 Safenlp 231 SAT 7.13 3.60 1.09 1.35 24.7 - 1.25 Safenlp 233 SAT 7.80 3.65 1.09 1.45 24.3 1.53 13.0 Safenlp 233 SAT 7.80 3.65 1.09 1.45 24.3 1.53 12.5 Safenlp 233 SAT 8.69 15.8 6.09 4.23 - - - Safenlp 236 SAT 8.17 - X	-										
Safenlp 227 SAT 8.30 3.75 3.10 1.41 - 1.53 - Safenlp 228 UNSAT 10.1 - 7.10 - <td>_</td> <td></td>	_										
Safenlp 228 UNSAT 10.1 - 7.10 - - - - Safenlp 229 UNSAT 7.14 3.79 6.09 1.24 26.5 1.51 11.9 Safenlp 230 UNSAT 7.11 3.79 6.09 1.14 25.6 1.56 14.0 Safenlp 231 SAT 8.16 3.60 3.01 1.28 - 1.53 - Safenlp 232 SAT 7.73 3.60 1.09 1.35 24.7 - 12.5 Safenlp 233 SAT 7.80 3.65 1.09 1.45 24.3 1.53 13.0 Safenlp 234 UNSAT 8.69 15.8 6.09 4.23 - - - 12.9 Safenlp 235 UNSAT 8.33 4.29 X 1.41 - - - - 12.9 Safenlp 236 SAT 8.17 - <td>-</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td>*</td>	-										*
Safenlp 229 UNSAT 7.14 3.79 6.09 1.24 26.5 1.51 11.9 Safenlp 230 UNSAT 7.11 3.79 6.09 1.14 25.6 1.56 14.0 Safenlp 231 SAT 8.16 3.60 3.10 1.28 - 1.53 - Safenlp 232 SAT 7.73 3.60 1.09 1.35 24.7 - 12.5 Safenlp 234 UNSAT 8.69 15.8 6.09 4.23 - - - Safenlp 235 UNSAT 8.33 4.29 X 1.41 - - 12.9 Safenlp 236 SAT 8.17 - X 1.51 - - 12.9 Safenlp 237 SAT 7.80 3.61 1.09 1.35 - 1.53 - Safenlp 238 SAT 8.09 3.61 1.09 1.35 <td></td>											
Safenlp 230 UNSAT 7.11 3.79 6.09 1.14 25.6 1.56 14.0 Safenlp 231 SAT 8.16 3.60 3.10 1.28 - 1.53 - Safenlp 232 SAT 7.73 3.60 1.09 1.35 24.7 - 12.5 Safenlp 233 SAT 7.80 3.65 1.09 1.45 24.3 1.53 13.0 Safenlp 234 UNSAT 8.69 15.8 6.09 4.23 - - - - Safenlp 236 SAT 8.17 - X 1.51 - - - 12.9 Safenlp 236 SAT 8.17 - X 1.51 - - - 12.9 Safenlp 237 SAT 7.80 3.61 1.09 1.35 - 1.53 - Safenlp 238 SAT 8.09 3	_	11.9		26.5							
Safenlp 231 SAT 8.16 3.60 3.10 1.28 - 1.53 - Safenlp 232 SAT 7.73 3.60 1.09 1.35 24.7 - 12.5 Safenlp 233 SAT 7.80 3.65 1.09 1.45 24.3 1.53 13.0 Safenlp 234 UNSAT 8.69 15.8 6.09 4.23 1.53 1.29 Safenlp 235 UNSAT 8.33 4.29 X 1.41 - - 12.9 Safenlp 236 SAT 8.17 - X 1.51 - - 12.9 Safenlp 237 SAT 7.80 3.61 1.09 1.35 - 1.53 - Safenlp 238 SAT 8.09 3.61 1.09 1.35 - 1.53 - Safenlp 239 UNSAT 8.45 21.5 7.10 6.32 -	_										*
Safenlp 232 SAT 7.73 3.60 1.09 1.35 24.7 - 12.5 Safenlp 233 SAT 7.80 3.65 1.09 1.45 24.3 1.53 13.0 Safenlp 234 UNSAT 8.69 15.8 6.09 4.23 -<	-										*
Safenlp 233 SAT 7.80 3.65 1.09 1.45 24.3 1.53 13.0 Safenlp 234 UNSAT 8.69 15.8 6.09 4.23 - - - Safenlp 235 UNSAT 8.33 4.29 X 1.41 - - 12.9 Safenlp 236 SAT 8.17 - X 1.51 - - - Safenlp 237 SAT 7.80 3.61 1.09 1.35 - 1.53 - Safenlp 238 SAT 8.09 3.69 3.10 1.37 - 1.53 - Safenlp 239 UNSAT 8.45 21.5 7.10 6.32 -	-	12.5		24.7					SAT		
Safenlp 235 UNSAT 8.33 4.29 X 1.41 - - 12.9 Safenlp 236 sAT 8.17 - X 1.51 - - - Safenlp 237 sAT 7.80 3.61 1.09 1.35 - 1.53 - Safenlp 238 sAT 8.09 3.69 3.10 1.37 - 1.53 - Safenlp 239 UNSAT 8.45 21.5 7.10 6.32 - - - - Safenlp 240 UNSAT 8.59 - X - - - - - Safenlp 241 UNSAT 7.11 3.77 X 1.08 26.6 1.53 11.1 Safenlp 242 sAT 8.18 4.20 X 1.39 - 1.52 - Safenlp 244 UNSAT 8.53 5.71 6.09 <	-		1.53	24.3				7.80	SAT		*
Safenlp 236 SAT 8.17 - X 1.51 - - - Safenlp 237 SAT 7.80 3.61 1.09 1.35 - 1.53 - Safenlp 238 SAT 8.09 3.69 3.10 1.37 - 1.53 - Safenlp 239 UNSAT 8.45 21.5 7.10 6.32 - - - - Safenlp 240 UNSAT 8.59 - X - <td< td=""><td>-</td><td>-</td><td>-</td><td>-</td><td>4.23</td><td>6.09</td><td>15.8</td><td>8.69</td><td>UNSAT</td><td>234</td><td>Safenlp</td></td<>	-	-	-	-	4.23	6.09	15.8	8.69	UNSAT	234	Safenlp
Safenlp 237 SAT 7.80 3.61 1.09 1.35 - 1.53 - Safenlp 238 SAT 8.09 3.69 3.10 1.37 - 1.53 - Safenlp 239 UNSAT 8.45 21.5 7.10 6.32 - - - Safenlp 240 UNSAT 8.59 - X - - - - Safenlp 241 UNSAT 7.11 3.77 X 1.08 26.6 1.53 11.1 Safenlp 242 SAT 8.15 3.68 6.09 1.24 - 1.53 14.4 Safenlp 243 SAT 8.18 4.20 X 1.39 - 1.52 - Safenlp 244 UNSAT 8.53 5.71 6.09 1.81 - - 11.1 Safenlp 245 UNSAT 8.53 5.71 6.09 1.17 <t< td=""><td>-</td><td>12.9</td><td>-</td><td>-</td><td>1.41</td><td>×</td><td>4.29</td><td>8.33</td><td>UNSAT</td><td>235</td><td>Safenlp</td></t<>	-	12.9	-	-	1.41	×	4.29	8.33	UNSAT	235	Safenlp
Safenlp 238 SAT 8.09 3.69 3.10 1.37 - 1.53 - Safenlp 239 UNSAT 8.45 21.5 7.10 6.32 - - - Safenlp 240 UNSAT 8.59 - X - - - - Safenlp 241 UNSAT 7.11 3.77 X 1.08 26.6 1.53 11.1 Safenlp 242 SAT 8.15 3.68 6.09 1.24 - 1.53 14.4 Safenlp 243 SAT 8.18 4.20 X 1.39 - 1.52 - Safenlp 244 UNSAT 8.94 - 7.10 - <td< td=""><td>-</td><td>-</td><td>-</td><td>-</td><td>1.51</td><td>×</td><td>-</td><td>8.17</td><td>SAT</td><td>236</td><td>Safenlp</td></td<>	-	-	-	-	1.51	×	-	8.17	SAT	236	Safenlp
Safenlp 239 UNSAT 8.45 21.5 7.10 6.32 - - - Safenlp 240 UNSAT 8.59 - X - - - - Safenlp 241 UNSAT 7.11 3.77 X 1.08 26.6 1.53 11.1 Safenlp 242 SAT 8.15 3.68 6.09 1.24 - 1.53 14.4 Safenlp 243 SAT 8.18 4.20 X 1.39 - 1.52 - Safenlp 244 UNSAT 8.94 - 7.10 - - - - - - 1.52 - 1.11 <td< td=""><td>-</td><td>-</td><td></td><td>-</td><td></td><td></td><td></td><td></td><td>SAT</td><td></td><td></td></td<>	-	-		-					SAT		
Safenlp 240 UNSAT 8.59 - X -	-										*
Safenlp 241 UNSAT 7.11 3.77 X 1.08 26.6 1.53 11.1 Safenlp 242 SAT 8.15 3.68 6.09 1.24 - 1.53 14.4 Safenlp 243 SAT 8.18 4.20 X 1.39 - 1.52 - Safenlp 244 UNSAT 8.94 - 7.10 - - - - - Safenlp 245 UNSAT 8.53 5.71 6.09 1.17 26.7 1.58 14.0 Safenlp 246 UNSAT 7.13 3.80 6.09 1.17 26.7 1.58 14.0 Safenlp 247 UNSAT 8.25 7.54 6.09 2.01 - - 14.3 Safenlp 248 SAT 8.26 3.69 X 1.33 - - - Safenlp 249 SAT 8.26 3.69 X	-										
Safenlp 242 SAT 8.15 3.68 6.09 1.24 - 1.53 14.4 Safenlp 243 SAT 8.18 4.20 X 1.39 - 1.52 - Safenlp 244 UNSAT 8.94 - 7.10 - - - - 1.11 Safenlp 245 UNSAT 7.13 3.80 6.09 1.17 26.7 1.58 14.0 Safenlp 247 UNSAT 8.25 7.54 6.09 2.01 - - 14.3 Safenlp 248 SAT 8.23 3.65 X 1.33 - - - 14.3 Safenlp 249 SAT 8.26 3.69 X 1.39 - 1.53 12.6 Safenlp 250 UNSAT 8.48 5.08 6.09 1.41 - - 14.5 Safenlp 251 SAT 7.83 3.64 <	-										
Safenlp 243 SAT 8.18 4.20 X 1.39 - 1.52 - Safenlp 244 UNSAT 8.94 - 7.10 - - - - 1.11 Safenlp 245 UNSAT 8.53 5.71 6.09 1.81 - - 11.1 Safenlp 246 UNSAT 7.13 3.80 6.09 1.17 26.7 1.58 14.0 Safenlp 247 UNSAT 8.25 7.54 6.09 2.01 - - 14.3 Safenlp 248 SAT 8.23 3.65 X 1.33 - - - Safenlp 249 SAT 8.26 3.69 X 1.39 - 1.53 12.6 Safenlp 250 UNSAT 8.48 5.08 6.09 1.41 - - 14.5 Safenlp 251 SAT 7.83 3.64 X 1	-										*
Safenlp 244 UNSAT 8.94 - 7.10 - - - - - Safenlp 245 UNSAT 8.53 5.71 6.09 1.81 - - 11.1 Safenlp 246 UNSAT 7.13 3.80 6.09 1.17 26.7 1.58 14.0 Safenlp 247 UNSAT 8.25 7.54 6.09 2.01 - - 14.3 Safenlp 248 SAT 8.23 3.65 X 1.33 - - - Safenlp 249 SAT 8.26 3.69 X 1.39 - 1.53 12.6 Safenlp 250 UNSAT 8.48 5.08 6.09 1.41 - - 14.5 Safenlp 251 SAT 7.83 3.64 X 1.34 24.2 1.53 14.7 Safenlp 252 UNSAT 9.88 - 18.2 -	-										
Safenlp 245 UNSAT 8.53 5.71 6.09 1.81 - - 11.1 Safenlp 246 UNSAT 7.13 3.80 6.09 1.17 26.7 1.58 14.0 Safenlp 247 UNSAT 8.25 7.54 6.09 2.01 - - 14.3 Safenlp 248 SAT 8.23 3.65 X 1.33 - - - Safenlp 249 SAT 8.26 3.69 X 1.39 - 1.53 12.6 Safenlp 250 UNSAT 8.48 5.08 6.09 1.41 - - 14.5 Safenlp 251 SAT 7.83 3.64 X 1.34 24.2 1.53 14.7 Safenlp 252 UNSAT 9.88 - 18.2 - - - - Safenlp 253 SAT 7.83 3.62 1.09 1.36	-										*
Safenlp 246 UNSAT 7.13 3.80 6.09 1.17 26.7 1.58 14.0 Safenlp 247 UNSAT 8.25 7.54 6.09 2.01 - - 14.3 Safenlp 248 SAT 8.23 3.65 X 1.33 - - - Safenlp 249 SAT 8.26 3.69 X 1.39 - 1.53 12.6 Safenlp 250 UNSAT 8.48 5.08 6.09 1.41 - - 14.5 Safenlp 251 SAT 7.83 3.64 X 1.34 24.2 1.53 14.7 Safenlp 252 UNSAT 9.88 - 18.2 - - - - Safenlp 253 SAT 7.83 3.62 1.09 1.36 - - 12.4	-										*
Safenlp 247 UNSAT 8.25 7.54 6.09 2.01 - - 14.3 Safenlp 248 SAT 8.23 3.65 X 1.33 - - - Safenlp 249 SAT 8.26 3.69 X 1.39 - 1.53 12.6 Safenlp 250 UNSAT 8.48 5.08 6.09 1.41 - - 14.5 Safenlp 251 SAT 7.83 3.64 X 1.34 24.2 1.53 14.7 Safenlp 252 UNSAT 9.88 - 18.2 - - - - - Safenlp 253 SAT 7.83 3.62 1.09 1.36 - - 12.4	_										
Safenlp 248 SAT 8.23 3.65 X 1.33 - - - Safenlp 249 SAT 8.26 3.69 X 1.39 - 1.53 12.6 Safenlp 250 UNSAT 8.48 5.08 6.09 1.41 - - 14.5 Safenlp 251 SAT 7.83 3.64 X 1.34 24.2 1.53 14.7 Safenlp 252 UNSAT 9.88 - 18.2 - - - - - Safenlp 253 SAT 7.83 3.62 1.09 1.36 - - 12.4	-									0.45	G C 1
Safenlp 249 SAT 8.26 3.69 X 1.39 - 1.53 12.6 Safenlp 250 UNSAT 8.48 5.08 6.09 1.41 - - 14.5 Safenlp 251 SAT 7.83 3.64 X 1.34 24.2 1.53 14.7 Safenlp 252 UNSAT 9.88 - 18.2 - - - - Safenlp 253 SAT 7.83 3.62 1.09 1.36 - - 12.4	-										
Safenip 250 UNSAT 8.48 5.08 6.09 1.41 - - 14.5 Safenip 251 SAT 7.83 3.64 X 1.34 24.2 1.53 14.7 Safenip 252 UNSAT 9.88 - 18.2 - - - - Safenip 253 SAT 7.83 3.62 1.09 1.36 - - 12.4	_										
Safenlp 251 SAT 7.83 3.64 X 1.34 24.2 1.53 14.7 Safenlp 252 UNSAT 9.88 - 18.2 - - - - Safenlp 253 SAT 7.83 3.62 1.09 1.36 - - 12.4	_										
Safenip 252 UNSAT 9.88 - 18.2 - - - - Safenip 253 SAT 7.83 3.62 1.09 1.36 - - 12.4	-										
Safenlp 253 sat 7.83 3.62 1.09 1.36 12.4	-										
	-	12.4		-	1.36		3.62				
	-	-	1.53	-	1.43	3.10	3.63	8.22	SAT	254	Safenlp
Safenlp 255 SAT 8.18 3.72 X 1.61	-	-	-	-	1.61				SAT		
Safenlp 256 UNSAT 7.12 3.72 X 1.15 26.2 1.52 12.0	-	12.0	1.52	26.2							
Safenlp 257 UNSAT 8.39 4.04 6.09 1.70 14.0	-	14.0		-	1.70			8.39	UNSAT		Safenlp
Safenlp 258 SAT 7.74 3.58 1.09 1.33 24.4 - 14.4	-	14.4			1.33	1.09		7.74	SAT	258	
Safenlp 259 SAT 8.26 3.67 X 1.33	-										
Safenlp 260 UNSAT 8.42 4.77 6.09 2.15 12.3	-	12.3	-	-	2.15	6.09	4.77	8.42	UNSAT	260	Safenlp

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

Category	Id	Result	α-β- C	PyRAT	`Marab	NNen	NNV	NeVer2	CORA	NSAT
Safenlp	261	UNSAT	7.14	3.79	X	1.21	25.6	1.54	14.0	-
Safenlp	262	SAT	7.89	3.59	1.09	1.35	24.1	1.53	14.2	-
Safenlp	263	UNSAT	10.8	-	53.5	1.07	-	1 50	- 10.1	-
Safenlp	264	SAT	7.74	3.63	X	1.37	24.7	1.52	12.1	-
Safenlp Safenlp	$\frac{265}{266}$	UNSAT UNSAT	7.15 9.28	3.75 -	X 7.10	1.11	26.4	1.59	12.9	_
Safenlp	267	SAT	8.08	3.64	3.10	1.32	-	1.53	-	_
Safenlp	268	SAT	8.35	3.64	3.10	1.38	_	1.52	_	_
Safenlp	269	SAT	7.83	3.60	1.09	1.27	_	1.53	12.0	-
Safenlp	270	SAT	8.29	3.67	3.10	1.39	-	1.53	-	-
Safenlp	271	UNSAT	10.3	-	10.1	-	-	-	-	-
Safenlp	272	SAT	7.81	3.61	1.09	1.40	24.0	1.53	12.0	-
Safenlp	273	UNSAT	7.14	3.77	X	1.13	25.6	1.52	14.2	-
Safenlp	274	SAT	8.23	-	3.10	1.33	-	1.52	-	-
Safenlp	275	SAT	8.20	3.61	1.09	1.43	23.9	1.53	12.3	-
Safenlp	276	SAT	7.58	3.68	1.09	1.35	24.6	1.53	14.5	-
Safenlp	277	UNSAT	9.08	2 62	X 1.09	1.38	-	1 59	-	_
Safenlp Safenlp	$\frac{278}{279}$	SAT SAT	7.83 8.24	3.62 3.71	X	1.28	-	1.53 1.52	_	_
Safenlp	280	SAT	8.20	3.72	3.10	1.32	_	1.02	_	_
Safenlp	281	UNSAT	10.1	-	13.1	-	_	-	_	_
Safenlp	282	SAT	8.34	4.06	3.10	1.32	-	-	-	-
Safenlp	283	SAT	8.12	3.67	X	1.27	-	1.53	_	-
Safenlp	284	SAT	7.83	3.58	1.09	1.35	-	1.53	13.3	-
Safenlp	285	SAT	7.81	3.66	1.09	1.32	24.6	1.53	14.9	-
Safenlp	286	UNSAT	7.13	3.74	6.09	1.11	25.8	1.52	14.0	-
Safenlp	287	SAT	8.33	3.67	X	1.38	-	1.53	-	-
Safenlp	288	SAT	7.80	3.68	1.09	1.39	23.9	1.52	12.1	-
Safenlp	289	UNSAT	7.12	3.84	X	1.15	25.9	1.52	15.2	-
Safenlp	290	SAT	8.15	3.74	X	1.30	-	1.53	-	-
Safenlp Safenlp	$\frac{291}{292}$	SAT UNSAT	$8.35 \\ 16.7$	3.69	3.10 22.2	1.32	-	-	-	_
Safenlp	293	SAT	8.32	3.67	X X	1.38	_	_	12.7	_
Safenlp	$\frac{293}{294}$	UNSAT	8.32	6.57	6.09	1.89	_	_	14.4	_
Safenlp	295	SAT	7.70	3.58	3.10	1.45	_	1.53	14.9	_
Safenlp	296	SAT	8.34	4.35	X	1.36	-	-	-	-
Safenlp	297	UNSAT	8.32	4.74	X	1.62	-	-	13.1	-
Safenlp	298	SAT	8.29	3.63	X	1.31	-	1.52	-	-
Safenlp	299	SAT	7.83	3.64	1.09	1.37	-	-	12.6	-
Safenlp	300	SAT	7.80	3.64	1.09	1.40	-	1.52	14.9	-
Safenlp	301	SAT	7.78	3.59	1.09	1.36	-	1.53	14.9	-
Safenlp	302	SAT	7.85	3.63	1.09	1.32	- 04.4	1.53	14.0	-
Safenlp	$\frac{303}{304}$	SAT	7.63	3.66 3.68	X	1.40 1.38	24.4	1.53	14.1 14.7	_
Safenlp Safenlp	$304 \\ 305$	SAT UNSAT	8.16 9.01	J.00	7.10	-	_	1.53	-	_
Safenlp	306	UNSAT	7.12	3.79	6.09	1.07	25.9	1.53	12.7	_
Safenlp	307	SAT	8.15	-	3.10	1.80	-	-	-	_
Safenlp	308	SAT	8.33	3.70	1.09	1.31	-	-	12.6	-
Safenlp	309	SAT	7.71	3.65	1.09	1.37	23.6	-	14.7	-
Safenlp	310	UNSAT	7.16	3.80	6.09	1.16	26.2	1.57	15.2	-
Safenlp	311	SAT	8.30	-	X	1.62	-	-	-	-
Safenlp	312	UNSAT	8.42	8.61	X	2.01	-	-	11.6	-
Safenlp	313	SAT	7.86	3.63	1.09	1.29	24.5	1.53	15.1	-
Safenlp	314	SAT	7.56	3.68	1.09	1.28	24.7	1.53	14.6	-
Safenlp Safenlp	315	SAT	8.32	3.71	X 1.09	1.39	-	1.53	12.3	_
Safenip	$\frac{316}{317}$	SAT SAT	$8.01 \\ 7.59$	3.63 3.70	7.09 X	1.35 1.36	-	1.53 1.52	14.9	_
Safenlp	318	SAT	8.23	3.70	â	1.39	-	1.53	-	-
Safenlp	319	UNSAT	8.62	-	x	10.4	_	-	16.7	_
Safenlp	320	SAT	8.34	6.35	X	1.41	-	-	-	-
Safenlp	321	SAT	8.16	-	X	1.39	-	-	-	-
Safenlp	322	SAT	8.08	3.70	3.10	1.34	_	1.52	-	-
Safenlp	323	SAT	8.30	3.68	3.10	1.33	-	1.53	-	-
Safenlp	324	SAT	8.37	3.69	X	1.28	-	-	-	-
Safenlp	325	UNSAT	7.14	3.79	6.09	1.08	25.2	1.59	12.7	-
Safenlp	326	UNSAT	7.14	3.76	6.10	1.08	25.6	1.51	15.0	-
Safenlp	327	SAT	8.13	3.72	3.10	1.26	-	1.52	-	-

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

Category	Id	Result	α-β-С	PyRAT	' Marab	NNen	NNV	NeVer2	CORA	NSAT
Safenlp	328	SAT	8.41	3.70	×	1.40	-	-	-	-
Safenlp	329	SAT	8.39	-	3.10	2.01	-	-	-	-
Safenlp	330	UNSAT	8.34	11.9	X	2.39	-	-	12.8	-
Safenlp	331	UNSAT	8.47	2 65	X 3.10	4.44	-	1 52	15.5	_
Safenlp Safenlp	$\frac{332}{333}$	SAT SAT	8.24 8.10	3.65 3.71	3.10	1.35 1.61	-	1.53	-	_
Safenlp	334	SAT	8.32	3.69	3.10	1.39	_	1.52	14.4	_
Safenlp	335	UNSAT	7.14	3.80	6.09	1.16	25.9	1.52	15.1	_
Safenlp	336	UNSAT	12.0	-	76.6	-	-	-	-	-
Safenlp	337	UNSAT	10.2	-	8.11	-	-	-	-	-
Safenlp	338	UNSAT	8.56	-	7.10	10.7	-	-	-	-
Safenlp	339	UNSAT	7.14	3.79	6.09	1.16	26.2	1.52	12.1	-
Safenlp	340	SAT	8.33	3.63	Х	1.38	-	1.53	-	-
Safenlp	341	SAT	8.25	3.68	X	1.40	-	1.53	10.4	-
Safenlp	$\frac{342}{343}$	SAT	7.65	3.64	1.09 1.09	1.35 1.31	-	1.52	12.4 14.9	-
Safenlp Safenlp	$\frac{343}{344}$	SAT SAT	7.86 8.00	3.60 3.71	7.09 X	1.39	-	1.52 1.53	14.9	_
Safenlp	345	SAT	8.30	3.66	3.10	1.38	_	-	_	_
Safenlp	346	SAT	8.30	-	X	1.46	_	1.53	_	_
Safenlp	347	SAT	8.26	-	X	1.34	-	-	-	-
Safenlp	348	SAT	7.81	3.68	1.09	1.19	23.9	-	12.5	-
Safenlp	349	SAT	8.17	3.69	3.10	1.37	-	1.53	-	-
Safenlp	350	SAT	7.84	3.65	1.09	1.30	24.6	1.53	12.6	-
Safenlp	351	SAT	8.07	3.63	2.10	1.32	-	-	-	-
Safenlp	352	SAT	8.32	3.75	3.10	1.35	-	1.53	10.0	-
Safenlp	353	SAT	7.70	3.65	1.09	1.25	-	1.52	12.9	-
Safenlp Safenlp	$\frac{354}{355}$	SAT SAT	8.31 8.40	3.67	X	1.41	-	1.53	_	_
Safenlp	356	SAT	8.21	3.65	x	1.36	_	-	_	
Safenlp	357	UNSAT	8.34	15.7	X	2.45	_	_	12.7	_
Safenlp	358	SAT	8.30	3.68	3.10	1.35	_	1.52	-	_
Safenlp	359	SAT	7.81	3.64	1.09	1.34	-	1.53	11.5	-
Safenlp	360	UNSAT	8.42	10.00	6.09	2.68	-	-	-	-
Safenlp	361	SAT	8.19	3.69	1.09	1.34	24.4	1.53	12.6	-
Safenlp	362	SAT	8.09	-	3.10	-	-	-	-	-
Safenlp	363	UNSAT	8.44	4.00	χ,	1 00	-	-	10.7	-
Safenlp	364	UNSAT UNSAT	8.31 8.26	4.90 22.2	6.09 X	1.80 2.86	-	-	$12.7 \\ 14.7$	_
Safenlp Safenlp	$\frac{365}{366}$	SAT	7.85	3.68	1.09	1.40	24.1	1.53	15.7	_
Safenlp	367	SAT	7.82	3.57	1.09	1.35	24.3	-	15.0	_
Safenlp	368	UNSAT	8.65	-	X	-	-	_	-	_
Safenlp	369	SAT	8.29	4.03	X	1.36	-	1.54	-	-
Safenlp	370	UNSAT	8.44	-	17.2	-	-	-	-	-
Safenlp	371	SAT	7.84	3.70	2.10	1.29	-	1.53	12.9	-
Safenlp	372	SAT	8.14	3.66	X	1.36	-	1.53	-	-
Safenlp	373	UNSAT	8.26	6.58	6.09	2.07	-	-	12.9	-
Safenlp	374	UNSAT	$8.52 \\ 8.35$	3 60	7.10	3.33	-	_	21.9	_
Safenlp Safenlp	$\frac{375}{376}$	SAT UNSAT	8.35 7.14	3.69 3.77	X 9.12	1.36 1.19	26.8	1.53	12.8	_
Safenlp	377	SAT	8.22	3.63	2.10	1.39	20.6	-	12.0	_
Safenlp	378	UNSAT	7.16	3.85	X	1.16	26.3	1.52	13.2	_
Safenlp	379	UNSAT	7.14	3.80	X	1.15	25.8	1.53	15.5	-
Safenlp	380		17.2	-	24.2	-	-	-	-	-
Safenlp	381	SAT	7.87	3.71	X	1.46	-	1.52	-	-
Safenlp	382	SAT	8.26	-	X	2.34	-	-	-	-
Safenlp	383	UNSAT	8.29	-	X	9.69	-	-	16.8	-
Safenlp	384	SAT	7.57	3.61	1.09	1.23	23.8	-	14.7	-
Safenlp	385	SAT	8.18	3.61	X	1.25	- 25.4	1.50	19.7	-
Safenlp Safenlp	$\frac{386}{387}$	UNSAT SAT	$7.12 \\ 8.32$	$3.82 \\ 3.71$	X X	1.08 1.36	$25.4 \\ 24.0$	1.59 1.54	$12.7 \\ 15.4$	-
Safenlp	388	UNSAT		18.0	â	2.96	24.U -	-	15.4	_
Safenlp	389	SAT	8.32	-	x	2.19	-	_	-	_
Safenlp	390	UNSAT	7.12	3.83	6.09	1.15	26.6	1.52	13.3	_
Safenlp	391	SAT	8.19	3.69	X	1.36	-	1.53	-	-
Safenlp	392	SAT	7.85	3.68	1.09	1.42	-	1.53	12.9	-
Safenlp	393	SAT	8.39	3.72	3.10	1.40	-	1.53	15.6	-
Safenlp	394	SAT	8.27	3.73	Х	1.33	-	1.53	-	-

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

Category	Id	Result	α - β - \mathbf{C}	PyRAT	Marab	NNen	NNV	NeVer2	CORA	NSAT
Safenlp	395	UNSAT	7.12	3.77	6.09	1.16	26.6	1.52	12.4	-
Safenlp	396	SAT	7.82	3.66	2.09	1.41	25.6	1.53	14.6	-
Safenlp	397	UNSAT	7.12	3.82	6.09	1.20	26.1	1.52	14.2	-
Safenlp	398	SAT	8.31 7.98	2 67	3.10	1.63 1.44	-	1 52	-	_
Safenlp Safenlp	$\frac{399}{400}$	SAT UNSAT	7.14	3.67 3.80	3.10 X	1.16	26.8	1.53 1.52	13.1	_
Safenlp	401	UNSAT	8.85	-	7.10	8.03	-	-	-	_
Safenlp	402	UNSAT	7.14	3.78	6.09	1.21	26.2	1.52	13.3	_
Safenlp	403	UNSAT	7.42	3.80	8.11	1.22	26.6	-	15.8	-
Safenlp	404	SAT	8.24	3.66	X	1.36	-	1.53	-	-
Safenlp	405	SAT	7.74	3.58	1.09	1.39	24.7	1.53	13.4	-
Safenlp	406	SAT	8.19	3.56	X	1.48	-	1.53	-	-
Safenlp	407	UNSAT	8.86	-	8.11	-	-	-	-	-
Safenlp	408	SAT	8.32	- 0.00	X	1.93	-	1.50	10.0	-
Safenlp	409	SAT	7.62	3.62	1.09	1.36	24.0	1.52	13.2 16.2	_
Safenlp Safenlp	$410 \\ 411$	SAT SAT	$7.59 \\ 8.24$	3.59 3.63	1.09 3.10	1.32 1.32	24.U -	1.53 1.54	10.2	-
Safenlp	412	UNSAT	8.26	4.02	6.09	1.39	_	-	13.2	_
Safenlp	413	UNSAT	11.2	-	71.6	-	_	_	-	_
Safenlp	414	SAT	7.84	3.61	1.09	1.33	24.3	1.52	12.8	-
Safenlp	415	UNSAT	7.13	3.76	6.09	1.15	26.8	1.53	15.7	-
Safenlp	416	UNSAT	8.37	12.5	6.09	2.81	-	-	-	-
Safenlp	417	SAT	8.33	3.69	3.10	1.31	-	1.53	-	-
Safenlp	418	SAT	7.69	3.65	1.09	1.24	24.7	-	12.8	-
Safenlp	419	UNSAT	8.55	-	X	2.62	-	-	16.0	-
Safenlp	420	UNSAT	10.2	-	10.1	-	-	-	-	-
Safenlp	421	SAT	8.32	2.00	X	1 40	-	1 50	-	-
Safenlp Safenlp	$\frac{422}{423}$	SAT SAT	8.33 8.32	3.60 3.70	X 8.11	1.40 1.37	-	1.53 1.53	-	-
Safenlp	424	SAT	8.34	3.70	X	1.25	_	1.53	_	-
Safenlp	425	SAT	8.31	4.18	X	1.37	_	-	_	_
Safenlp	426	UNSAT	9.77	-	8.11	-	_	_	-	_
Safenlp	427	SAT	7.76	3.65	1.09	1.26	24.7	-	13.4	-
Safenlp	428	SAT	8.34	-	3.10	1.50	-	-	-	-
Safenlp	429	UNSAT	8.80	-	7.10	16.9	-	-	-	-
Safenlp	430	SAT	7.74	3.59	2.10	1.24	-	1.53	13.3	-
Safenlp	431	SAT	8.25	3.69	X	1.26	-	1 50	10.0	-
Safenlp	432	UNSAT	7.13	3.77	X	1.09	25.8	1.59	13.6	-
Safenlp Safenlp	$\frac{433}{434}$	SAT SAT	8.12 8.02	3.63	3.10	1.93 1.32	-	1.53	-	_
Safenlp	435	SAT	8.22	3.65	X	1.29	_	1.53	-	_
Safenlp	436	SAT	7.55	3.60	8.11	1.15	23.9	-	13.6	_
Safenlp	437	UNSAT	8.87	-	X	_	-	_	_	-
Safenlp	438	SAT	7.96	3.64	3.10	1.28	-	1.52	-	-
Safenlp	439	SAT	8.23	3.60	X	1.33	-	1.53	-	-
Safenlp	440	SAT	8.19	3.64	X	1.27	-	1.53	13.6	-
Safenlp	441	SAT	7.80	3.65	1.09	1.27	24.6	1.53	15.7	-
Safenlp	442	UNSAT	7.12	3.83	X	1.11	26.0	1.57	15.4	-
Safenlp Safenlp	$\frac{443}{444}$	SAT SAT	8.33 8.32	3.65 3.74	X	1.26 1.39	-	1.52 1.53	-	_
Safenlp Safenlp	444	UNSAT	10.8	5.74	x	1.39	_	1.00	_	_
Safenlp	446	UNSAT	7.13	3.80	6.09	1.18	25.6	1.52	13.0	_
Safenlp	447	UNSAT		11.5	6.09	2.34	-	-	22.3	-
Safenlp	448	SAT	8.06	3.60	1.09	1.30	24.8	1.53	14.2	-
Safenlp	449	SAT	7.83	3.63	1.09	1.40	23.9	1.53	16.3	-
Safenlp	450	UNSAT	11.1	-	14.2	-	-	-	-	-
Safenlp	451	SAT	8.33	3.71	X	1.39	-	1.53	-	-
Safenlp	452	UNSAT		3.75	6.09	1.16	26.0	1.52	13.7	-
Safenlp	453	SAT	8.35	3.68	X	1.37	24.2	-	18.6	-
Safenlp Safenlp	$\frac{454}{455}$	SAT UNSAT	8.25 7.13	3.64 3.77	1.09 6.09	1.35 1.15	24.3 27.1	-	14.7 15.5	-
Safenlp	456	UNSAT		3.76	7.10	1.13	25.9	1.52	15.6	_
Safenlp	$450 \\ 457$	SAT	8.34	5.70 -	γ.10 χ	-	20.9 -	-	-	_
Safenlp	458	SAT	7.83	3.68	1.09	1.41	24.5	-	13.9	_
Safenlp	459	UNSAT	8.92	-	7.10	14.4	-	-	-	-
Safenlp	460	SAT	8.34	3.73	X	1.45	-	1.53	12.6	-
Safenlp	461	SAT	8.33	3.69	3.10	1.39	-	1.53	16.3	-

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

Category	Id	Result	α-β-C	PyRAT	' Marab	NNen	NNV	NeVer2	CORA	NSAT
Safenlp	462	UNSAT	7.13	3.78	X	1.16	26.0	1.53	15.8	-
Safenlp	463	SAT	7.69	3.57	1.09	1.32	-	1.53	15.9	-
Safenlp	464	SAT	7.87	3.71	1.09	1.42	24.3	1 50	16.2	-
Safenlp Safenlp	$\frac{465}{466}$	SAT SAT	8.31 8.32	3.68 3.66	2.10 3.10	1.36 1.26	-	1.53 1.53	-	_
Safenlp	467	UNSAT	8.23	4.25	6.09	1.40	_	-	12.7	_
Safenlp	468	UNSAT	8.66	13.1	7.10	3.12	_	_	15.9	_
Safenlp	469	UNSAT	8.50	-	7.10	20.9	-	-	-	-
Safenlp	470	SAT	7.72	3.62	X	1.42	24.1	1.53	13.3	-
Safenlp	471	UNSAT	8.37	6.91	6.09	2.12	-	-	15.7	-
Safenlp	472	SAT	8.33	3.65	Х	1.38	23.9	1.53	16.4	-
Safenlp	473	SAT UNSAT	7.57 7.09	3.65	X	1.24	23.9 26.2	1.68	15.4	-
Safenlp Safenlp	$\frac{474}{475}$	SAT	8.09	3.82 3.60	X 3.10	1.17 1.39	20.2	1.53	16.0 14.9	_
Safenlp	476	SAT	8.30	3.64	X	1.38	_	1.53	-	_
Safenlp	477	SAT	7.75	3.58	1.09	1.36	_	1.53	14.3	_
Safenlp	478	UNSAT	9.57	-	18.2	-	-	-	-	-
Safenlp	479	SAT	8.36	3.70	3.10	1.31	-	1.53	-	-
Safenlp	480	SAT	8.22	3.72	1.09	1.28	24.4	1.53	13.7	-
Safenlp	481	SAT	7.78	3.60	1.09	1.31	-	1.53	12.0	-
Safenlp	482	SAT	8.16	3.65	3.10	1.24	-	1.52	13.9	-
Safenlp Safenlp	$\frac{483}{484}$	SAT SAT	8.34 8.33	3.69 3.73	X X	1.25 1.26	-	1.53 1.53	-	_
Safenlp	485	SAT	7.70	3.57	1.09	1.45	24.4	-	12.7	_
Safenlp	486	UNSAT	8.66	-	X	-	_	_	-	_
Safenlp	487	SAT	8.34	3.73	X	1.28	-	1.53	-	-
Safenlp	488	SAT	8.23	3.62	X	1.37	-	1.53	-	-
Safenlp	489	UNSAT	7.12	3.84	6.09	1.16	25.8	1.52	13.4	-
Safenlp	490	SAT	7.84	3.61	1.09	1.37	24.0	1.53	16.3	-
Safenlp	491	SAT	8.21	3.68	X	1.40	-	1.53	-	-
Safenlp Safenlp	$\frac{492}{493}$	SAT UNSAT	$8.16 \\ 7.14$	3.63 3.79	3.10 X	1.26 1.18	26.6	1.52 1.52	12.8	-
Safenlp	494	SAT	8.32	-	3.10	1.99	-	-	-	_
Safenlp	495	SAT	8.10	3.72	3.10	1.35	_	1.52	-	_
Safenlp	496	SAT	7.76	3.59	1.09	1.45	25.0	-	14.3	-
Safenlp	497	UNSAT	7.14	3.83	6.09	1.18	25.8	1.52	16.9	-
Safenlp	498	SAT	8.09	3.70	3.10	1.38	-	1.53	-	-
Safenlp	499	UNSAT	7.14	3.78	6.09	1.16	25.9	1.59	13.6	-
Safenlp Safenlp	$500 \\ 501$	SAT SAT	8.21 8.16	3.66 4.12	X 3.10	1.42 1.41	-	1.53	-	_
Safenlp	502	UNSAT	8.52	11.8	7.10	3.17	_	_	_	_
Safenlp	503	SAT	8.34	3.65	X	1.35	_	1.53	_	_
Safenlp	504	SAT	7.65	3.62	1.09	1.31	24.8	-	13.4	-
Safenlp	505	SAT	8.27	-	X	1.39	-	-	-	-
Safenlp	506	UNSAT	8.31	11.2	7.10	3.00	-	-	-	-
Safenlp	507	UNSAT	10.7	2.70	15.2	1 40	-	1 50	10.5	-
Safenlp Safenlp	$\frac{508}{509}$	SAT	7.73 7.15	3.72 3.81	1.09 6.09	1.42 1.16	23.9 25.6	1.53 1.52	12.5 16.1	-
Safenip	510	UNSAT UNSAT	8.46	4.75	6.09	1.51	∠3.0 -	1.32	15.8	_
Safenlp	511	UNSAT	7.13	3.80	7.10	1.13	26.6	1.52	16.2	_
Safenlp	512	UNSAT	7.10	3.81	6.09	1.09	25.9	1.53	16.1	-
Safenlp	513	SAT	7.79	3.66	1.09	1.09	24.7	-	16.2	-
Safenlp	514	SAT	8.18	3.67	3.10	1.39	-	1.52	15.7	-
Safenlp	515	SAT	7.65	3.58	1.09	1.31	-	1.52	16.6	-
Safenlp	516	UNSAT		-	7.10	5.26	-	-	-	-
Safenlp Safenlp	$517 \\ 518$	UNSAT SAT	$8.90 \\ 7.92$	3.68	7.10 X	1.28	-	1.53	-	-
Safenlp	519	SAT	8.31	-	x	1.28	-	-	-	_
Safenlp	520	SAT	8.36	-	x	1.81	_	-	_	_
Safenlp	521	UNSAT		11.1	6.09	2.85	_	-	17.9	-
Safenlp	522	SAT	8.32	3.75	X	1.36	-	-	-	-
Safenlp	523	UNSAT	8.72	-	7.10	-	-	-	-	-
Safenlp	524	UNSAT		-	X	5.68	-	-	14.0	-
Safenlp	525	SAT	8.34	3.64	X	1.29	24.1	1.53	16.9	-
Safenlp	526	SAT	8.34	3.70	3.10	1.28	26.1	1.53	12.0	-
Safenlp Safenlp	$\frac{527}{528}$	UNSAT SAT	7.11 7.84	3.77 3.69	6.09 1.09	1.11 1.38	26.1	1.52 1.53	13.9 15.9	-
Seremb	040	SAI	1.04	5.03	1.09	1.50	-	1.00	10.0	-

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

<u> </u>		D		D D 1=	34 :	DID!	*****	NT N7 -	GOD:	NICAT
Category	Id	Result		PyRAT			NNV	NeVer2	CORA	NSAT
Safenlp	529	SAT	8.33	3.67	X	1.35	-	1.53	-	-
Safenlp	530	UNSAT	10.3	-	23.2	-	-	-	-	-
Safenlp	531	SAT	8.33	4.05	X	1.41	-	1.53	17.9	-
Safenlp	532	SAT	7.60	3.63	1.09	1.40	23.9	1.53	16.2	-
Safenlp	533	UNSAT	8.87	4 22	X	1.54	_	-	14.6	_
Safenlp	$534 \\ 535$	UNSAT	8.45	4.33	X 7.10	1.04	-	-		-
Safenlp Safenlp	536	UNSAT SAT	9.03 7.71	3.60	1.09	1.26	24.2	_	14.1	_
Safenlp	537	SAT	8.27	3.70	X	1.26	-	_	-	_
Safenlp	538	UNSAT	13.9	-	17.2	-	_	_	_	_
Safenlp	539	UNSAT		_	7.10	_	_	_	_	_
Safenlp	540	SAT	7.78	3.72	X	1.32	24.3	1.52	14.0	_
Safenlp	541	SAT	7.68	3.54	1.09	1.34	24.5	1.52	16.6	_
Safenlp	542	SAT	8.08	3.68	X	1.29	_	1.52	_	_
Safenlp	543	SAT	8.09	3.60	3.10	1.38	-	-	_	_
Safenlp	544	SAT	8.03	4.38	X	1.60	-	1.54	-	-
Safenlp	545	SAT	8.18	3.69	7.10	1.29	-	1.53	-	-
Safenlp	546	UNSAT	8.56	-	X	-	-	-	-	-
Safenlp	547	SAT	8.22	3.72	X	1.27	24.3	1.53	14.7	-
Safenlp	548	SAT	8.10	3.65	X	1.27	-	-	-	-
Safenlp	549	SAT	7.68	3.59	1.09	1.24	24.8	1.53	13.9	-
Safenlp	550	UNSAT	8.30	7.36	6.09	2.29	-	-	16.9	-
Safenlp	551	SAT	8.31	3.68	X	1.25	-	1.53	16.0	-
Safenlp	552	SAT	8.29	3.69	3.10	1.27	-	1.53	-	-
Safenlp	553	UNSAT	8.52	19.9	X	2.46	-	-	14.4	-
Safenlp	554	SAT	7.76	3.69	1.09	1.25	-	1.53	-	-
Safenlp	555	UNSAT		-	7.10	-	-	-	-	-
Safenlp	556	SAT	7.64	3.62	1.09	1.26	-	1.53	-	-
Safenlp	557	SAT	8.16	4.10	4.11	1 49	-	1 50	-	-
Safenlp	558	SAT	8.18	4.18	X	1.43	26.2	1.52	- 14.5	-
Safenlp Safenlp	559	UNSAT	7.12	3.83	6.09	1.14		1.53		_
Safenip	$\frac{560}{561}$	SAT SAT	8.07 8.25	3.65 3.68	X	1.32 1.40	-	1.53 1.53	-	_
Safenip	562	SAT	8.13	3.69	3.10	1.35	_	1.53	_	_
Safenlp	563	SAT	7.80	3.74	1.09	1.27	_	1.53	14.3	_
Safenlp	564	SAT	8.16	3.69	3.10	1.24	_	1.55	-	_
Safenlp	565	SAT	8.07	3.66	3.10	1.24	_	1.53	14.0	_
Safenlp	566	UNSAT	10.4	-	11.1	-	_	-	-	_
Safenlp	567	UNSAT	8.26	5.76	6.09	2.08	_	_	14.7	_
Safenlp	568	SAT	7.84	3.59	1.09	1.31	-	1.53	17.3	_
Safenlp	569	UNSAT	7.13	3.76	6.09	1.22	26.3	1.52	16.8	-
Safenlp	570	UNSAT	8.46	-	7.10	20.2	-	-	-	-
Safenlp	571	SAT	8.09	3.61	3.10	1.30	-	1.79	-	-
Safenlp	572	UNSAT	8.52	7.82	6.09	2.25	-	-	16.7	-
Safenlp	573	UNSAT	7.13	3.74	6.09	1.16	25.4	1.52	16.6	-
Safenlp	574	SAT	7.82	3.60	1.09	1.34	24.7	-	16.5	-
Safenlp	575	UNSAT	7.11	3.78	X	1.17	25.8	1.58	15.9	-
Safenlp	576	UNSAT	7.13	3.79	6.09	1.22	26.0	1.57	16.4	-
Safenlp	577	SAT	8.37	3.65	3.10	1.49	-	1.52	-	-
Safenlp	578	SAT	7.88	3.64	1.09	1.40	24.8	1.53	14.4	-
Safenlp	579	UNSAT	10.2	-	9.12	-	-	-	-	-
Safenlp	580	UNSAT	8.92	-	7.10	-	-		-	-
Safenlp	581	SAT	8.23	3.64	X	1.33	-	1.53	-	-
Safenlp	582	UNSAT	10.8	-	30.3	1 01	-	-	145	-
Safenlp	583	UNSAT	8.44	7.41	7.10	1.81	-	-	14.5	-
Safenlp	584	SAT	7.83	3.59	1.09	1.35	24.2	1 50	17.5	-
Safenlp	585	SAT	7.73	3.64	1.09	1.40	-	1.53	16.5	-
Safenlp Safenlp	586 587	SAT	8.16	3.73	3.10	1.29	-	1.52	-	-
Safenlp Safenlp	587	SAT	8.37		1.09		-	1.52	-	_
Safenip Safenip	$\frac{588}{589}$	SAT SAT	8.28 8.20	3.70	3.10 X	1.39 1.89	-	1.53	-	_
Safenip	590	SAT	8.32	3.72	3.10	1.37	_	1.52	_	_
Safenip	591	UNSAT		21.3	3.10 X	3.23	-	1.02	14.3	_
Safenlp	592	UNSAT	7.42	3.85	6.09	1.19	26.2	-	17.3	-
Safenlp	593	SAT	8.28	3.65	1.09	1.34	-	1.53	-	-
Safenlp	594	SAT	8.33	3.66	X	1.33	_	1.52	-	_
Safenlp	595	SAT	8.32	4.07	3.10	1.40	_	1.52	-	_
*										

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

Cataman	т.,	D - ''		DD 4.77	N/- '	NINT	NINTS?	NI-37 0	COP 1	NIC AC
Category	Id	Result		PyRAT			NNV	NeVer2	CORA	NSAT
Safenlp	596	SAT	8.34	3.76	X	1.47	-		-	-
Safenlp	597	SAT	8.35	3.71	X	1.39	-	1.53	141	-
Safenlp	598	UNSAT	7.11	3.78	6.09	1.22	25.5	1.58	14.1	-
Safenlp Safenlp	599 600	SAT SAT	8.29 8.20	3.65 3.72	X 3.10	1.36 1.34	-	1.52 1.53	-	_
Safenip	601	SAT	8.32	-	3.10	1.49	_	-	_	_
Safenlp	602	SAT	7.56	3.64	1.09	1.28	24.2	1.53	14.6	
Safenlp	603	SAT	8.20	3.63	X	1.30	-	1.52	-	_
Safenlp	604	UNSAT	7.13	3.75	X	1.20	26.2	1.52	14.9	_
Safenlp	605	UNSAT	7.14	3.76	X	1.17	25.7	1.52	16.6	_
Safenlp	606	UNSAT	7.14	3.77	7.10	1.22	25.5	1.52	16.3	-
Safenlp	607	SAT	8.14	3.71	3.10	1.36	-	1.53	15.9	-
Safenlp	608	SAT	8.15	3.67	X	1.41	-	1.53	-	-
Safenlp	609	SAT	8.20	-	3.10	1.59	-	-	-	-
Safenlp	610	UNSAT	7.14	3.80	X	1.17	26.8	1.59	14.4	-
Safenlp	611	SAT	8.34	3.64	X	1.35	-	1.53	-	-
Safenlp	612	UNSAT	10.5	-	9.11	-	-	-	-	-
Safenlp	613	UNSAT	14.1	-	24.2	-	-	-	-	-
Safenlp	614	UNSAT	8.36	23.3	6.09	4.52	-	-	-	-
Safenlp	615	UNSAT	9.02	19.4	7.10	3.58	- 07.1	1.50	14.9	-
Safenlp	616	UNSAT	7.12	3.75	X	1.23	27.1	1.52	14.3	_
Safenlp Safenlp	$617 \\ 618$	UNSAT		-	X	1.67	_	-	_	-
Safenip	619	SAT SAT	8.39 8.38	3.72	3.10	1.24	_	1.53	_	_
Safenlp	620	UNSAT	8.31	-	6.10	7.46	_	-	_	_
Safenlp	621	SAT	8.29	_	3.10	1.91	_	_	_	_
Safenlp	622		7.17	3.78	X	1.19	26.7	1.52	14.3	_
Safenlp	623	UNSAT	7.15	3.74	6.09	1.13	26.1	1.53	16.7	_
Safenlp	624	UNSAT	9.00	-	X	-	-	-	-	-
Safenlp	625	SAT	7.59	3.69	1.09	1.33	24.0	-	14.8	-
Safenlp	626	SAT	8.35	-	X	1.38	-	-	-	-
Safenlp	627	UNSAT	8.74	-	7.10	20.1	-	-	-	-
Safenlp	628	SAT	8.29	3.68	X	1.44	-	1.52	-	-
Safenlp	629	SAT	8.30	3.74	3.10	1.40	-	1.52	13.9	-
Safenlp	630	SAT	7.91	3.72	3.10	1.30	-	1.53	-	-
Safenlp	631	SAT	8.18	3.57	3.10	1.32	-	-	140	-
Safenlp	632	UNSAT	8.46	4.30	X	1.73	-	-	14.3	-
Safenlp	633 634	UNSAT	8.37 7.83	2 50	X	4.80 1.27	24.4	1 59	16.7 16.7	-
Safenlp Safenlp	635	SAT UNSAT	7.13	3.59 3.81	â	1.07	26.7	1.53 1.52	17.1	_
Safenlp	636	SAT	7.63	3.70	1.09	1.24	23.7	1.55	17.1	_
Safenlp	637	SAT	8.12	3.66	X	1.27	-	1.53	16.6	_
Safenlp	638	SAT	7.75	3.62	1.09	1.24	_	-	17.2	_
Safenlp	639	SAT	8.38	3.72	X	1.25	-	1.52	-	_
Safenlp	640	SAT	8.14	3.69	3.10	1.26	-	1.53	_	_
Safenlp	641	UNSAT	8.83	-	7.10	-	-	-	-	-
Safenlp	642	UNSAT	8.26	5.46	X	1.81	-	-	14.9	-
Safenlp	643	UNSAT	8.95	-	8.11	17.7	-	-	-	-
Safenlp	644	SAT	7.83	3.60	1.09	1.08	24.0	1.53	14.4	-
Safenlp	645	SAT	8.18	3.65	X	1.37	-	1.52	-	-
Safenlp	646	SAT	8.32	4.14	X	1.32	-	-	-	-
Safenlp	647	UNSAT	8.35	10.8	6.09	2.31	-	-	145	-
Safenlp	648	UNSAT		4.10	6.09	1.67	-	1 50	14.5	-
Safenlp Safenlp	649	UNSAT	7.11 8.34	3.77	7.10	1.12 1.33	25.5	1.53	17.5	-
Safenip	$650 \\ 651$	SAT UNSAT	7.17	3.63 3.81	1.09 6.09	1.09	26.0	1.53 1.52	17.0 16.5	-
Safenlp	652	UNSAT	7.12	3.75	6.09	1.07	26.5	1.52	17.2	_
Safenlp	653	SAT	8.25	-	3.10	1.25	-	-	-	_
Safenlp	654	SAT	7.63	3.64	1.09	1.22	24.7	1.53	14.6	_
Safenlp	655	SAT	8.16	3.66	3.10	1.25	-	1.52	-	_
Safenlp	656	UNSAT		17.9	6.09	2.27	_	-	15.0	-
Safenlp	657	UNSAT	7.15	3.74	X	1.17	26.3	1.52	17.6	-
Safenlp	658	UNSAT		3.84	6.09	1.20	26.4	1.52	16.6	-
Safenlp	659	UNSAT	7.46	4.06	X	1.22	26.4	-	16.9	-
Safenlp	660	UNSAT		12.3	6.09	3.09	-	-	-	-
Safenlp	661	SAT	8.33	3.73	3.10	1.37	-	1.53	-	-
Safenlp	662	SAT	8.15	3.65	X	1.33	-	1.53	-	-

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

<u> </u>		.	0.5	D. F. :=		****			goz :	NIG : -
Category	Id	Result	α - β - \mathbf{C}	PyRAT	Marab	NNen	NNV	NeVer2	CORA	NSAT
Safenlp	663	SAT	8.34	4.03	3.10	1.44	-	1.53	-	-
Safenlp	664	UNSAT	7.12	3.73	6.09	1.17	25.5	1.52	14.4	-
Safenlp	665	SAT	7.83	3.58	1.09	1.42	24.8	1.53	17.4	-
Safenlp	666	SAT	8.12	3.68	X	1.38	-	1.53	16.4	-
Safenlp	667	SAT	7.85	3.59	1.09	1.42 1.14	26.1	1.53	16.1	-
Safenlp	668 669	UNSAT	7.13	3.75	6.09 3.10	1.14	26.1	1.52 1.52	17.1	-
Safenlp Safenlp	670	SAT SAT	8.31 7.86	3.63 3.67	3.10 X	1.35	-	1.52	17.0 16.9	_
Safenlp	671	SAT	7.87	3.58	1.09	1.40	23.9	-	17.9	_
Safenlp	672	UNSAT	8.30	13.3	X	2.56	-	_	16.2	_
Safenlp	673	SAT	7.69	3.63	1.09	1.39	24.0	_	16.7	_
Safenlp	674	SAT	8.13	3.68	3.10	1.38	-	1.53	-	_
Safenlp	675	SAT	8.08	3.71	X	1.39	_	1.53	_	_
Safenlp	676	SAT	7.84	3.63	1.09	1.39	_	-	15.4	_
Safenlp	677	UNSAT	8.44	17.2	X	2.56	-	-	17.9	-
Safenlp	678	SAT	7.82	3.66	1.09	1.41	23.6	1.53	16.8	-
Safenlp	679	UNSAT	8.43	8.01	6.09	2.25	-	-	27.8	-
Safenlp	680	UNSAT	8.94	-	8.11	14.1	-	-	-	-
Safenlp	681	UNSAT	7.13	3.81	6.09	1.09	26.7	1.53	15.3	-
Safenlp	682	UNSAT	7.13	3.79	X	1.18	25.4	1.59	17.8	-
Safenlp	683	SAT	7.83	3.69	1.09	1.29	24.3	-	17.3	-
Safenlp	684	SAT	8.20	-	X	1.27	-	1.52	-	-
Safenlp	685	UNSAT	8.28	4.13	X	1.29	-	-	15.0	-
Safenlp	686	SAT	7.79	3.67	1.09	1.32	24.1	-	17.9	-
Safenlp	687	SAT	8.34	3.68	X	1.30	-	1.53	16.8	-
Safenlp	688	SAT	8.18	-	X	1.35	-	1.53	-	-
Safenlp	689	SAT	8.06	3.63	X	1.39	-	1.53	-	-
Safenlp	690	SAT	8.26	-	X	1.33	-		-	-
Safenlp	691	SAT	8.09	3.62	X	1.38	-	1.53	-	-
Safenlp	692	UNSAT	10.0	2.70	X	1 49	04.1	1 50	144	-
Safenlp	693 694	SAT	7.89	3.70	1.09	1.43	24.1	1.53	14.4 19.0	_
Safenlp Safenlp	695	UNSAT SAT	8.34 8.26	7.99 3.75	6.09 X	2.06 1.36	-	1.53	-	_
Safenlp	696	SAT	8.32	3.69	3.10	1.36	_	1.52	_	_
Safenlp	697	UNSAT	9.46	-	15.2	-	_	-	_	_
Safenlp	698	SAT	8.38	3.69	3.10	1.23	_	1.52	_	_
Safenlp	699	SAT	7.76	3.64	1.09	1.10	25.0	1.83	15.7	_
Safenlp	700	SAT	7.78	3.64	X	1.33	24.8	1.53	16.9	_
Safenlp	701	SAT	7.82	3.60	1.09	1.30	-	1.53	17.3	-
Safenlp	702	UNSAT	7.17	3.79	6.09	1.11	26.4	1.52	16.9	_
Safenlp	703	SAT	8.23	3.72	3.10	1.31	-	1.53	_	-
Safenlp	704	SAT	8.30	3.74	3.10	1.34	-	1.52	-	-
Safenlp	705	UNSAT	8.40	14.9	X	2.29	-	-	15.1	-
Safenlp	706	UNSAT	8.52	6.23	6.09	2.04	-	-	17.9	-
Safenlp	707	SAT	8.33	3.72	3.10	1.26	-	1.54	-	-
Safenlp	708	UNSAT	10.8	-	24.2	-	-	-	-	-
Safenlp	709	UNSAT	7.12	3.76	X	1.19	26.1	1.52	15.1	-
Safenlp	710	SAT	7.64	3.57	2.10	1.38	-	1.53	-	-
Safenlp	711	UNSAT	8.91	-	7.10	12.2	-	-	-	-
Safenlp	712	SAT	8.35	3.63	3.10	1.36	-	1.53	-	-
Safenlp	713	SAT	8.32	3.57	2.10	1.30	-	-	15.0	-
Safenlp	714	SAT	8.32	3.65	X	1.24	-	_	-	-
Safenlp	715	UNSAT		2.74	7.10	1 00	-		14.0	-
Safenlp Safenlp	716	UNSAT	7.13	3.74	6.09	1.22 1.28	25.7	1.58	14.6	-
Safenlp	717 718	SAT SAT	8.09 8.21	3.62 3.64	X	1.27	-	1.52 1.52	16.2	_
Safenlp	719	SAT	8.24	3.65	x	1.28	_	1.53	-	_
Safenlp	720	SAT	8.38	3.72	â	1.28	-	1.53	-	-
Safenlp	721	SAT	8.13	3.71	x	1.24	_	1.53	_	_
Safenlp	722	UNSAT		3.70	6.09	1.09	25.7	1.57	14.9	_
Safenlp	723	UNSAT		3.81	6.09	1.10	26.7	1.55	19.0	-
Safenlp	724	UNSAT		8.94	6.09	2.54	-	-	17.3	_
Safenlp	725	SAT	7.83	3.57	X	1.35	24.6	1.53	17.3	_
Safenlp	726	UNSAT		8.93	6.09	2.58	-	-	17.9	-
Safenlp	727	SAT	7.84	3.66	1.09	1.35	24.7	1.53	17.4	-
Safenlp	728	SAT	8.18	3.62	1.09	1.33	-	1.53	-	-
Safenlp	729	SAT	8.17	3.69	3.10	1.37	-	1.53	16.1	-

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (X).

Category	Id	Result	α-β-(C PyRAT	' Marab	NNen	NNV	NeVer2	CORA	NSAT
Safenlp	730	SAT	8.13	3.66	X	1.41	-	1.53	-	-
Safenlp	731	UNSAT	8.60	-	X	-	-	-	-	-
Safenlp	732	UNSAT	8.83	2 0 4	7.10 6.09	14.6	26.5	1 56	15 7	-
Safenlp Safenlp	$733 \\ 734$	UNSAT UNSAT	7.12 7.11	3.84 3.87	6.09 X	1.16 1.20	$26.5 \\ 27.1$	1.56 1.52	15.7 17.4	_
Safenlp	735	UNSAT	7.11	3.83	â	1.13	26.7	1.58	16.8	_
Safenlp	736	SAT	8.32	3.62	3.10	1.27	-	1.53	-	_
Safenlp	737	UNSAT	8.50	-	X	-	_	-	_	-
Safenlp	738	SAT	8.24	3.64	X	1.34	24.4	-	15.3	-
Safenlp	739	SAT	8.17	3.64	3.10	1.39	-	1.53	18.1	-
Safenlp	740	SAT	8.33	3.97	X	1.80	-	-	-	-
Safenlp	741	UNSAT	7.11	3.78	6.09	1.08	26.8	1.54	15.6	-
Safenlp	742	UNSAT	9.50	-	7.10	1.00	-	-	-	-
Safenlp	743	SAT	8.31	3.68	X	1.26	-	-	-	-
Safenlp Safenlp	$744 \\ 745$	SAT SAT	8.31 8.32	3.68	3.10 X	1.27 2.35	-	_	_	_
Safenlp	746	SAT	8.10	4.03	â	1.38	_	1.53	_	
Safenlp	747	SAT	8.34	3.60	X	1.27	_	1.52	_	_
Safenlp	748	SAT	8.16	3.67	X	1.47	_	-	_	_
Safenlp	749	SAT	7.87	3.56	1.09	1.23	24.2	1.53	15.5	-
Safenlp	750	SAT	7.83	3.60	1.09	1.26	-	-	18.3	-
Safenlp	751	UNSAT	9.62	-	16.2	-	-	-	-	-
Safenlp	752	UNSAT	8.77	-	7.10	-	-	-	-	-
Safenlp	753	SAT	8.23	3.71	X	1.37	-	1.53	-	-
Safenlp	754	SAT	8.28	3.65	X	1.35	-	1.53	10.0	-
Safenlp	755	UNSAT	7.14	3.80	6.09	1.10	27.2	1.52	16.2	-
Safenlp	756	SAT	7.73 8.33	3.61 8.21	1.09	1.24 2.34	24.9	1.53	18.7	_
Safenlp Safenlp	757 758	UNSAT UNSAT	8.55	-	6.09 7.10	9.97	_	_	17.0	_
Safenlp	759	SAT	8.23	3.62	3.10	1.36	24.5	1.53	14.2	_
Safenlp	760	SAT	8.35	-	3.10	1.53	-	-	-	_
Safenlp	761	SAT	8.11	3.61	X	1.31	_	-	-	-
Safenlp	762	UNSAT	16.8	-	39.4	-	-	-	-	-
Safenlp	763	UNSAT	7.14	3.78	X	1.12	27.0	1.52	15.5	-
Safenlp	764	SAT	8.19	3.66	X	1.24	-	1.53	-	-
Safenlp	765	SAT	7.82	3.61	1.09	1.25	-	1.53	15.7	-
Safenlp	766	UNSAT	7.13	3.78	6.09	1.07	27.3	1.52	16.7	-
Safenlp Safenlp	767 768	UNSAT	7.14 8.11	3.76	6.19 X	1.07	25.5 -	1.56	15.9	-
Safenlp	769	SAT UNSAT	8.99	-	7.10	_	_	_	-	_
Safenlp	770	UNSAT	7.40	3.78	6.09	1.15	27.1	1.52	15.1	_
Safenlp	771	UNSAT	7.14	3.83	6.09	1.12	27.3	1.52	18.2	-
Safenlp	772	SAT	8.33	3.66	X	1.31	-	1.53	-	-
Safenlp	773	UNSAT	7.11	3.76	7.10	1.12	-	1.53	16.2	-
Safenlp	774	SAT	8.32	-	3.10	1.29	-	1.53	-	-
Safenlp	775	SAT	7.88	3.66	1.09	1.27	-	1.55	15.1	-
Safenlp	776	UNSAT	8.78	2 60	7.10	14.9	-	1 50	-	-
Safenlp	777	SAT	8.04	3.62 6.50	X 6.09	1.36	-	1.52	16.0	-
Safenlp Safenlp	778 779	UNSAT SAT	$8.36 \\ 8.32$	$6.59 \\ 3.70$	X	1.96 1.33	-	1.53	-	_
Safenlp	780	SAT	8.25	4.10	x	1.33	_	-	_	_
Safenlp	781	UNSAT	7.11	3.76	6.09	1.16	25.7	1.52	15.6	-
Safenlp	782	SAT	8.12	3.69	3.10	1.29	-	1.52	-	-
Safenlp	783	SAT	7.97	3.57	X	1.33	-	1.52	17.6	-
Safenlp	784	SAT	8.24	4.06	3.10	1.74	-	-	-	-
Safenlp	785	SAT	8.12	3.66	X	1.38	-	1.53		-
Safenlp	786	SAT	8.29	3.66	3.10	1.33	-	1.53	14.6	-
Safenlp	787	UNSAT		3.79	7.10	1.16	25.4	1.51	17.5	-
Safenlp Safenlp	788 780	SAT UNSAT	8.34	3.69	3.10	1.27	- 27.2	1.53 1.52	- 15.7	-
Safenlp	789 790	UNSAT		3.88 7.34	X 6.09	1.08 2.35	-	1.52	15.7 26.1	-
Safenip	791	SAT	8.30	3.66	× ×	1.33	-	1.53	-	_
Safenlp	792	UNSAT		8.43	6.09	2.49	_	-	_	_
Safenlp	793	SAT	7.68	3.60	X	1.17	24.7	1.53	15.6	-
Safenlp	794	SAT	7.83	3.63	1.09	1.45	24.8	1.52	19.1	-
Safenlp	795	SAT	7.84	3.69	1.09	1.34	24.8	1.53	17.6	-
Safenlp	796	SAT	8.23	3.65	X	1.32	-	1.52	-	-

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

Category	Id	Result	α-β- C	PyRAT	' Marab	NNen	NNV	NeVer2	CORA	NSAT
Safenlp	797	SAT	8.32	3.69	X	1.42	-	1.53	-	-
Safenlp	798	UNSAT	7.13	3.78	6.09	1.25	26.9	1.52	16.0	-
Safenlp	799	SAT	8.11	3.68	X	1.36	-	1.53	-	-
Safenlp	800	SAT	8.36 7.11	3.78	3.10	1.88 1.15	- 26.7	1.52	- 15.9	_
Safenlp Safenlp	801 802	UNSAT UNSAT	8.38	3.10 -	X 6.09	6.99	20.7	1.02	15.9	_
Safenlp	803	UNSAT	7.12	3.79	6.09	1.16	26.1	1.53	15.7	_
Safenlp	804	UNSAT	8.54	-	7.10	14.5	-	-	-	_
Safenlp	805	SAT	8.25	3.72	X	1.30	-	1.53	-	-
Safenlp	806	SAT	7.84	3.72	1.09	1.32	-	1.53	16.1	-
Safenlp	807	UNSAT	9.49	-	11.1	-	-	-	-	-
Safenlp	808	UNSAT	7.12	3.80	6.09	1.17	26.9	1.52	16.0	-
Safenlp	809	SAT UNSAT	8.15	3.69 3.76	3.10	1.36 1.20	- 25.7	1.53	- 15.9	-
Safenlp Safenlp	810 811	UNSAT	7.14 9.60	5.70 -	X 8.11	1.20	20.7	1.00	15.9	_
Safenlp	812	UNSAT	12.1	-	67.6	_	_	_	_	_
Safenlp	813	SAT	8.28	_	X	1.74	_	_	_	_
Safenlp	814	UNSAT		-	7.10	-	-	-	-	-
Safenlp	815	SAT	8.18	3.67	X	1.29	-	1.53	-	-
Safenlp	816	SAT	7.64	3.64	1.09	1.15	24.4	1.84	15.9	-
Safenlp	817	UNSAT	7.12	3.83	X	1.15	27.0	1.52	19.8	-
Safenlp	818	UNSAT	8.91	2.70	7.10	1 15	-	1.50	15 4	-
Safenlp Safenlp	819	UNSAT	7.11	3.78	6.09	1.15	$26.2 \\ 24.3$	1.59	15.4	_
Safenlp Safenlp	820 821	SAT UNSAT	8.31 8.47	3.62 9.71	1.09 6.09	1.44 2.50	24.3 -	1.52	18.8	_
Safenlp	822	SAT	8.35	-	×	1.35	_	_	_	_
Safenlp	823	SAT	8.08	3.63	X	1.36	_	1.53	_	_
Safenlp	824	SAT	8.23	4.04	X	1.48	-	-	-	-
Safenlp	825	SAT	8.29	3.72	1.09	1.27	24.7	1.53	15.8	-
Safenlp	826	UNSAT	8.54	-	X	-	-	-	-	-
Safenlp	827	SAT	8.31	3.73	X	1.54	-	1.53	-	-
Safenlp	828	UNSAT	7.13	3.76	X 1.09	1.19	27.0	1.52	15.8	-
Safenlp Safenlp	829 830	SAT SAT	8.26 8.15	3.69 3.68	7.09 X	1.32 1.39	-	1.52 1.53	-	_
Safenlp	831	UNSAT	9.74	-	11.1	-	_	-	_	
Safenlp	832	UNSAT	8.51	4.69	6.09	1.74	_	_	15.5	_
Safenlp	833	SAT	7.58	3.61	X	1.22	-	1.53	18.4	-
Safenlp	834	SAT	8.18	3.63	X	1.26	-	1.53	-	-
Safenlp	835	SAT	8.40	3.67	X	1.29	-	1.52	-	-
Safenlp	836	SAT	8.10	3.58	3.10	1.47	-	1.53	-	-
Safenlp	837	SAT	8.15	3.65	X	1.34	24.0	1.53	16.0	-
Safenlp Safenlp	838 839	SAT SAT	7.87 7.88	3.72 3.65	1.09 1.09	1.39 1.37	24.0 23.8	1.53 1.53	16.2 18.8	-
Safenlp	840	SAT	7.77	3.67	X	1.33	20.0	1.52	16.9	_
Safenlp	841	SAT	8.22	-	3.10	1.79	_	-	-	-
Safenlp	842	UNSAT	8.48	4.68	6.09	1.49	-	-	16.1	-
Safenlp	843	UNSAT	8.41	8.83	6.09	8.00	-	-	19.2	-
Safenlp	844	UNSAT	8.55	9.47	6.09	2.20	-	-	16.9	-
Safenlp	845	UNSAT	7.13	3.75	X	1.14	26.3	1.57	17.5	-
Safenlp	846	SAT	7.88	3.64	1.09	1.38	25.9	1.53	16.2	-
Safenlp Safenlp	847 848	UNSAT SAT	7.14 8.16	3.78 3.63	X	1.08 1.41	25.8	1.52	16.2	_
Safenip	849	SAT	8.14	3.03 4.08	3.10	1.26	_	1.53	_	_
Safenlp	850	SAT	8.21	3.72	X	1.36	-	1.53	_	_
Safenlp	851	UNSAT		4.16	6.09	1.41	-	-	16.4	-
Safenlp	852	UNSAT	7.17	3.78	6.09	1.20	26.2	1.52	18.7	-
Safenlp	853	UNSAT		-	25.2	-	-	-	-	-
Safenlp	854	SAT	8.35	3.65	3.10	1.31	-	1.52	-	-
Safenlp	855	SAT	8.19	3.68	χ,	1.32	-	1.52	107	-
Safenlp Safenlp	856 857	UNSAT		8.79	6.09	2.49	-	1 59	16.7	-
Safenlp Safenlp	$857 \\ 858$	SAT SAT	8.01 8.33	4.07 3.67	3.10 X	1.39 1.37	-	1.52 1.53	-	-
Safenip	859	SAT	8.35	5.07 -	3.10	1.57	_	1.00	_	_
Safenlp	860	UNSAT		-	7.10	-	_	-	-	_
Safenlp	861	UNSAT	10.7	-	9.11	-	-	-	-	-
Safenlp	862	SAT	7.75	3.68	1.09	1.33	25.4	1.52	16.4	-
Safenlp	863	UNSAT	7.12	3.79	X	1.16	26.3	1.52	19.4	-

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

Safenlp Safenlp	864									NSAT
Safenlp			10.4	32.3	9.11		-	-	-	-
	865	SAT	8.17	3.62	X	1.41	-	1.53	-	-
	866	UNSAT	9.51	17.1	9.11	- 2 75	-	-	-	-
Safenlp Safenlp	867 868	UNSAT SAT	8.29 7.66	17.1 3.65	6.09 1.09	3.75 1.43	24.9	-	16.0	_
Safenip	869	UNSAT	8.93	-	7.10	-	24.9	_	-	_
Safenlp	870	SAT	7.68	3.56	1.09	1.31	25.1	1.54	16.6	_
Safenlp	871	UNSAT	21.3	-	-	-	-	-	-	-
Safenlp	872	SAT	8.09	-	6.09	1.28	-	1.53	-	-
Safenlp	873	SAT	8.32	-	X	1.39	-	-	-	-
Safenlp	874	UNSAT	8.26	8.51	6.09	2.59	-	-	16.4	-
Safenlp	875	UNSAT	7.12	3.86	6.09	1.16	26.6	1.52	18.7	_
Safenlp Safenlp	876 877	SAT SAT	8.32 7.68	3.67 3.59	2.10 1.09	1.45 1.26	25.0	1.53	18.4 17.9	_
Safenlp	878	UNSAT	7.10	3.77	6.09	1.07	25.8	1.53	18.0	_
Safenlp	879	UNSAT	7.11	3.75	6.09	1.12	26.6	1.52	16.1	_
Safenlp	880	SAT	8.17	3.65	X	1.39	-	-	-	-
Safenlp	881	SAT	8.34	3.68	X	1.36	-	1.52	-	-
Safenlp	882	UNSAT	8.39	6.32	6.09	1.94	-	-	17.1	-
Safenlp	883	UNSAT	7.15	3.83	X	1.18	25.7	1.52	19.5	-
Safenlp	884	SAT	8.26	4.09	3.10	1.31	-	1.53	15.0	-
Safenlp	885	SAT	7.82	3.68	1.09	1.26	-	1.53	15.6	-
Safenlp Safenlp	886 887	UNSAT SAT	10.2 8.35	4.05	11.1 3.10	1.84	-	-	-	-
Safenlp	888	UNSAT	7.10	3.83	X	1.19	26.0	1.52	16.3	_
Safenlp	889		9.37	-	7.10	-	-	-	-	_
Safenlp	890	SAT	8.08	-	3.10	1.96	-	-	-	-
Safenlp	891	UNSAT	7.17	3.82	X	1.15	25.9	1.52	16.5	-
Safenlp	892	UNSAT	7.11	3.78	6.09	1.17	26.1	1.52	19.4	-
Safenlp	893	SAT	7.66	3.64	1.09	1.38	24.7	1.53	16.7	-
Safenlp	894	UNSAT	10.1		8.11	- 45	-	-	10.5	-
Safenlp Safenlp	895	UNSAT	8.37	9.72	6.09	2.45	24.7	1 59	16.5 19.1	-
Safenlp	896 897	SAT SAT	7.73 8.17	3.69 3.70	X	1.29	24.1 -	1.53 1.52	-	_
Safenlp	898	SAT	8.37	3.58	3.10	1.28	_	1.53	_	_
Safenlp	899	UNSAT	8.26	10.3	6.09	2.50	-	-	27.5	-
Safenlp	900	UNSAT	7.14	3.70	X	1.09	27.1	1.52	16.8	-
Safenlp	901	SAT	8.33	3.68	X	1.25	24.0	1.53	18.8	-
Safenlp	902	SAT	8.35	3.71	3.10	1.30	-	1.53	-	-
Safenlp	903	SAT	8.25	3.56	X	1.31	-	1.53	-	-
Safenlp Safenlp	$904 \\ 905$	UNSAT SAT	8.85 8.36	3.63	7.10 X	8.55 1.34	-	1.53	-	_
Safenlp	906	UNSAT	7.11	3.76	6.09	1.20	25.8	1.59	16.3	_
Safenlp	907	SAT	7.80	3.67	X	1.42	-	1.53	19.8	_
Safenlp	908	SAT	8.22	3.68	X	1.37	-	1.53	-	-
Safenlp	909	UNSAT	8.55	4.61	6.09	1.67	-	-	16.6	-
Safenlp	910	UNSAT	8.47	-	X	4.70	-	-	19.6	-
Safenlp	911	SAT	8.32	3.65	X	1.34	-	-	-	-
Safenlp	912	SAT	8.35	3.65	3.10	1.37	-	1.53	16.4	-
Safenlp	913	SAT	8.28	3.64	X	1.44	-	1.53	-	-
Safenlp Safenlp	$914 \\ 915$	SAT SAT	8.03 8.25	3.66 3.69	3.10 X	1.36 1.33	_	_	-	_
Safenip	916	SAT	8.24	3.69	x	1.34	24.7	1.54	16.8	_
Safenlp	917		8.97	-	7.10	-	-	-	-	_
Safenlp	918	UNSAT	7.11	3.78	X	1.18	26.7	1.59	15.7	-
Safenlp	919	SAT	8.14	-	3.10	2.53	-	-	-	-
Safenlp	920	SAT	8.22	3.69	1.09	1.24	24.0	1.53	17.1	-
Safenlp	921	SAT	7.68	3.65	1.09	1.26	24.4	1.53	18.9	-
Safenlp	922	UNSAT		5.04	6.09	1.68	-	1.50	18.2	-
Safenlp	923	SAT	8.19	3.71	X	1.34	-	1.52	19.6	-
Safenlp Safenlp	$924 \\ 925$	UNSAT SAT	8.37 7.81	3.69	X 1.09	14.3 1.27	-	1.53	19.6	-
Safenlp	926	UNSAT	8.68	5.09 -	X	-	_	1.00	-	_
Safenlp	927	SAT	7.87	3.68	X	1.29	_	1.52	_	_
Safenlp	928	SAT	7.58	3.59	1.09	1.29	23.9	-	16.8	-
	929	SAT	8.11	-	X	2.22	-	-	-	-
Safenlp			8.33	3.70	3.10	1.28	-	1.53	16.9	-

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

Category	Id	Result	α - β - \mathbf{C}	PyRAT	Marab	NNen	NNV	NeVer2	CORA	NSAT
Safenlp	931	SAT	8.24	3.66	3.10	1.28	-	1.53	-	-
Safenlp	932	SAT	8.17	3.58	1.09	1.39	-	1.53	-	-
Safenlp	933	UNSAT	7.10	3.79	X	1.15	26.3	1.52	17.1	-
Safenlp	934	SAT	8.22	3.63	X	1.25	23.9 26.2	1.53	19.6	_
Safenlp Safenlp	935 936	UNSAT SAT	7.11 7.66	3.81 3.60	6.09 1.09	1.10 1.39	24.1	1.52	17.9 17.3	_
Safenlp	937	UNSAT	8.38	3.00	X	8.33	-	-	30.6	-
Safenlp	938	SAT	8.31	3.70	x	1.34	_	1.53	-	_
Safenlp	939	UNSAT		3.72	X	1.18	26.5	1.52	16.0	_
Safenlp	940	SAT	8.31	3.67	X	1.33	-	-	-	_
Safenlp	941	UNSAT		4.72	X	1.67	_	_	16.6	_
Safenlp	942	SAT	8.28	3.73	X	1.38	_	1.52	18.7	_
Safenlp	943	UNSAT	8.55	-	X	-	-	-	_	-
Safenlp	944	UNSAT	9.08	-	7.10	-	-	-	-	-
Safenlp	945	SAT	7.73	3.72	1.09	1.33	24.8	1.52	16.3	-
Safenlp	946	UNSAT	17.5	-	-	-	-	-	-	-
Safenlp	947	SAT	7.85	3.68	3.10	1.40	-	1.53	-	-
Safenlp	948	SAT	8.40	3.60	1.09	1.43	-	1.53	17.4	-
Safenlp	949	UNSAT	9.08	-	X	-	-	-	-	-
Safenlp	950	UNSAT	7.14	3.80	7.10	1.19	26.5	1.52	16.7	-
Safenlp	951	SAT	8.34	-	X	1.60	-	-	-	-
Safenlp	952	SAT	7.97	3.65	3.10	1.32	-	1.53	-	-
Safenlp	953	SAT	8.24	-	3.10	-	-	-	-	-
Safenlp	954	SAT	8.19	3.71	3.10	1.40	-	-	-	-
Safenlp	955	SAT	8.24	3.66	3.10	1.33	-	1.53	-	-
Safenlp	956	SAT	7.85	3.60	1.09	1.32	24.7	1.53	17.2	-
Safenlp	957	UNSAT	8.50	- 0.04	X	1 40	- 0.4.0	1 50	1 7 4	-
Safenlp	958	SAT	7.83	3.64	1.09	1.42	24.3	1.53	17.4	-
Safenlp Safenlp	959	UNSAT	7.15	3.81	X	1.14	$26.0 \\ 24.9$	1.52 1.53	20.0 17.5	-
	960	SAT	7.81	3.67	1.09	1.36	24.9	1.33	- 17.3	_
Safenlp Safenlp	$961 \\ 962$	UNSAT SAT	$8.45 \\ 7.85$	12.9 3.64	7.10 1.09	3.50 1.40	24.7	_	15.7	_
Safenlp	963	SAT	7.79	3.66	1.09	1.38	24.5	1.53	18.9	_
Safenlp	964	SAT	8.03	3.59	X	1.38	-	1.52	-	_
Safenlp	965	SAT	8.20	3.66	3.10	1.34	_	-	_	_
Safenlp	966	UNSAT	8.32	-	X	8.89	_	_	16.7	_
Safenlp	967	SAT	7.84	3.64	1.09	1.38	_	1.53	19.0	_
Safenlp	968	UNSAT	8.38	-	X	5.77	-	-	-	_
Safenlp	969	UNSAT	7.13	3.77	6.09	1.21	26.9	1.52	16.9	_
Safenlp	970	SAT	7.68	3.67	1.09	1.34	25.6	-	19.6	-
Safenlp	971	UNSAT	7.11	3.78	6.09	1.16	26.1	1.57	17.4	-
Safenlp	972	UNSAT	8.73	-	7.10	7.09	-	-	-	-
Safenlp	973	UNSAT	7.14	3.87	6.09	1.07	26.7	1.52	17.2	-
Safenlp	974	SAT	8.20	-	3.10	2.03	-	-	-	-
Safenlp	975	UNSAT	7.13	3.82	X	1.08	26.8	1.52	16.4	-
Safenlp	976	SAT	8.19	3.69	X	1.25	-	-	-	-
Safenlp	977	SAT	7.69	3.63	1.09	1.32	24.8	1.53	17.0	-
Safenlp	978	UNSAT	7.12	3.81	6.09	1.13	26.5	1.51	19.9	-
Safenlp	979	SAT	8.16	- 0.00	X	1.27	-	1.52	-	-
Safenlp	980	SAT	7.70	3.62	X	1.36	- 07.1	1.53	17.2	-
Safenlp	981	UNSAT	7.11	3.80	6.09	1.18	27.1	1.53	19.8	-
Safenlp Safenlp	982	UNSAT	7.15	3.80	7.10	1.19	26.2	1.53	18.9	_
*	983	SAT	7.83	3.72	1.09	1.35	25.0	-	18.5	
Safenlp Safenlp	$984 \\ 985$	UNSAT	8.33	5.76	6.09	2.19	-	-	17.8	-
Safenlp	986	UNSAT UNSAT		3.81	9.11 X	1.10	27.2	1.52	17.1	_
Safenlp	987	SAT	7.13	3.62	1.09	1.24	24.7	1.53	20.2	_
Safenlp	988	UNSAT		3.82	19.2	1.08	27.2	1.52	18.1	_
Safenlp	989	SAT	8.36	3.68	X	1.30	-	1.53	-	_
Safenlp	990	SAT	7.69	3.63	1.09	1.41	25.2	1.53	17.0	_
Safenlp	991	SAT	8.33	-	X	1.34	-	-	-	-
Safenlp	992	UNSAT		-	X	-	_	_	_	_
Safenlp	993	SAT	8.35	3.65	3.10	1.32	_	1.53	-	-
Safenlp	994	UNSAT		15.9	6.09	3.39	-	-	_	-
Safenlp	995	UNSAT	7.11	3.81	X	1.13	26.1	1.52	17.4	-
Safenlp	996	UNSAT		3.79	6.09	1.11	26.3	1.51	18.2	-
Safenlp	997	SAT	8.11	3.73	3.10	1.25	-	1.53	-	-

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (X).

Category	Id	Result	α - β - \mathbf{C}	PyRAT	' Marab	NNen	NNV	NeVer2	CORA	NSAT
Safenlp	998	SAT	8.20	3.70	3.10	1.25	-	1.52	-	-
Safenlp	999	SAT	8.30	3.66	X	1.72	-	1.53	-	-
Safenlp	1000		8.34	3.72	Х	1.38	-	1.52	-	-
Safenlp	1001		8.14	3.63	Х	1.32	-	1.53	-	-
Safenlp	1002	UNSAT	8.48 8.15	3.62	X	10.7 1.34	-	1.53	-	_
Safenlp Safenlp		UNSAT	8.29	6.48	x	2.00	-	-	17.4	-
Safenlp		UNSAT	8.30	16.3	X	2.33	_	_	19.0	_
Safenlp	1006		7.70	3.56	1.09	1.34	24.2	1.53	18.1	_
Safenlp		UNSAT	8.53	7.65	6.09	2.03	-	-	18.7	-
Safenlp	1008	SAT	8.33	3.67	3.10	1.33	-	1.53	-	-
Safenlp	1009	SAT	8.19	3.65	1.09	1.42	-	-	17.5	-
Safenlp	1010		7.75	3.60	1.09	1.36	24.4	1.53	19.9	-
Safenlp	1011		8.37	3.58	2.10	1.35	-	1.53	-	-
Safenlp	1012		8.15	3.70	3.10	1.38	-	1.53	16.9	-
Safenlp	1013		8.26	3.64	X	1.47	24.7	1.53	20.5	-
Safenlp	1014		8.21	3.66 4.61	3.10	1.56 1.51	-	-	16.8	_
Safenlp Safenlp		UNSAT	8.41 8.31	4.01 -	X 3.10	-	_	-	-	_
Safenip	$1016 \\ 1017$		8.36	3.71	3.10	1.31	_	1.53	_	_
Safenlp	1017		8.34	3.65	3.10	1.41	_	1.52	_	_
Safenlp	1019		8.31	3.66	X	1.35	_	1.52	-	-
Safenlp		UNSAT	17.4	-	17.2	-	-	_	-	-
Safenlp	1021	SAT	7.70	3.65	1.09	1.36	24.6	-	16.7	-
Safenlp	1022	UNSAT	7.13	3.80	6.09	1.15	26.8	1.52	20.0	-
Safenlp	1023	UNSAT	7.13	3.74	6.09	1.16	26.0	1.52	19.3	-
Safenlp	1024	SAT	8.34	3.69	3.10	1.32	-	1.53	-	-
Safenlp	1025		8.25	4.47	X	1.58	-	-	-	-
Safenlp		UNSAT	8.31	5.65	6.09	1.87	-	-	16.7	-
Safenlp	1027	UNSAT	16.2		35.3	1 07	-	-	-	-
Safenlp Safenlp	1028	SAT	8.08	3.72	X	1.37	24.9	-	17.7	_
Safenip	1029 1030	SAT SAT	7.59 7.61	3.62 3.60	1.09 1.09	1.29 1.32	24.9 24.4	_	19.2	_
Safenlp	1031		7.84	3.59	1.09	1.36	_	_	18.5	_
Safenlp		UNSAT	7.11	3.82	6.09	1.18	26.6	1.52	16.5	_
Safenlp		UNSAT	8.42	12.6	6.10	2.93	-	-	-	-
Safenlp	1034	SAT	7.83	3.59	1.09	1.39	24.1	1.53	17.3	-
Safenlp	1035	UNSAT	8.72	-	7.10	4.09	-	-	-	-
Safenlp	1036	SAT	8.03	3.65	3.10	1.41	-	1.52	-	-
Safenlp	1037		7.83	3.62	1.09	1.32	24.4	1.52	17.2	-
Safenlp	1038	SAT	8.23	-	X	1.80	-	-	-	-
Safenlp	1039	UNSAT	8.90	2.50	7.10	17.7	-	1 50	10.1	-
Safenlp	1040		7.83	3.58	1.09	1.38	-	1.53	16.1	_
Safenlp Safenlp	$1041 \\ 1042$		7.71 8.33	3.72 3.66	1.09 3.10	1.34 1.32	_	1.53 1.53	_	_
Safenlp	1043		8.31	3.64	X	1.32	_	1.53	-	_
Safenlp		UNSAT	7.14	3.80	6.09	1.15	26.5	1.55	16.2	_
Safenlp	1045	SAT	7.85	3.61	1.09	1.28	-	1.53	20.1	-
Safenlp	1046		8.25	3.64	X	1.43	-	-	-	-
Safenlp		UNSAT	8.36	4.34	X	1.59	-	-	17.4	-
Safenlp	1048	SAT	8.36	3.64	3.10	1.31	-	-	-	-
Safenlp		$_{\rm UNSAT}$	8.43	4.29	6.09	1.29	-	-	17.6	-
Safenlp	1050		8.23	3.66	X	1.24	-	1.53	-	-
Safenlp	1051		7.76	3.64	6.09	1.23	24.5	1.53	16.8	-
Safenlp	1052		8.29	3.62	X	1.29	-	1.52	-	-
Safenlp Safenlp	1053 1054	UNSAT		11.9	6.09	2.19 1.32	-	1.53	-	-
Safenlp Safenlp	1054 1055		8.36 8.34	3.69 3.64	3.10 1.09	1.32	-	1.53	17.4	
Safenip	1056		8.33	5.04	3.10	1.84	_	1.02	-	-
Safenlp		UNSAT		3.77	X	1.13	26.1	1.52	17.7	-
Safenlp	1058		8.32	3.71	3.10	1.31	-	1.53	-	_
Safenlp	1059		7.86	3.59	1.09	1.24	24.2	1.52	17.3	_
Safenlp		UNSAT		4.20	6.09	1.28	-	-	19.6	-
Safenlp		UNSAT		3.84	6.09	1.11	26.5	1.57	19.5	-
Safenlp	1062	SAT	8.34	3.67	X	1.31	-	-	-	-
Safenlp	1063		8.26	3.59	3.10	1.26	-	1.53	-	-
Safenlp	1064	UNSAT	7.17	3.81	6.09	1.22	27.6	1.51	16.9	-

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

Safenlp 1066 SAT 8.17 3.66 X 1.44 - 1.53 - Safenlp 1067 UNSAT 7.12 3.82 X 1.17 26.4 1.52 1' Safenlp 1068 UNSAT 8.43 - 7.10 14.9 - - - - Safenlp 1069 SAT 8.33 3.74 3.10 1.35 - 1.53 1' Safenlp 1071 UNSAT 7.10 3.75 X 1.22 26.7 1.52 1' Safenlp 1072 SAT 7.87 3.62 1.09 1.42 - 1.53 1' Safenlp 1073 SAT 8.32 3.70 3.10 1.35 - 1.53 - Safenlp 1074 SAT 8.13 3.70 X 1.33 - 1.52 - Safenlp 1075 SAT 8.23 3.63 X	0.1
Safenlp 1067 UNSAT 7.12 3.82 X 1.17 26.4 1.52 1' Safenlp 1068 UNSAT 8.43 - 7.10 14.9 - - - - Safenlp 1069 sAT 8.37 4.10 X 1.40 - 1.52 - Safenlp 1070 sAT 8.33 3.74 3.10 1.55 - 1.53 1' Safenlp 1071 UNSAT 7.10 3.75 X 1.22 26.7 1.52 - Safenlp 1072 sAT 7.87 3.62 1.09 1.42 - 1.53 1! Safenlp 1073 sAT 8.32 3.70 3.10 1.35 - 1.53 - Safenlp 1074 sAT 8.13 3.70 X 1.33 - 1.52 - Safenlp 1075 sAT 8.23 3.63 X	7.3 7.1 - 9.9 - 9.1 7.7 -
SafenIp 1068 UNSAT 8.43 - 7.10 14.9 - - - - SafenIp 1069 sat 8.37 4.10 X 1.40 - 1.52 - SafenIp - 1.53 - 1.53 - 1.53 1' SafenIp 1071 UNSAT 7.10 3.75 X 1.22 26.7 1.52 1' SafenIp 1072 SAT 7.87 3.62 1.09 1.42 - 1.53 1' SafenIp 1073 SAT 8.32 3.70 3.10 1.35 - 1.53 - 1.53 - SafenIp 1074 SAT 8.13 3.70 X 1.33 - 1.52 - SafenIp 1075 SAT 8.23 3.63 X 1.32 - 1.53 - SafenIp 1076 SAT 8.25 4.05 X 1.30 - -	7.1 - 9.9 - 9.1 - - - - 7.7 -
Safenlp 1069 SAT 8.37 4.10 X 1.40 - 1.52 - Safenlp 1070 SAT 8.33 3.74 3.10 1.35 - 1.53 1' Safenlp 1071 UNSAT 7.10 3.75 X 1.22 26.7 1.52 1' Safenlp 1072 SAT 7.87 3.62 1.09 1.42 - 1.53 1' Safenlp 1073 SAT 8.13 3.70 X 1.35 - 1.53 - Safenlp 1074 SAT 8.23 3.63 X 1.32 - 1.53 - Safenlp 1076 SAT 8.25 4.05 X 1.30 - - - -	7.1 - 9.9 - 9.1 - - - - - 7.7 -
Safenlp 1070 SAT 8.33 3.74 3.10 1.35 - 1.53 1' Safenlp 1071 UNSAT 7.10 3.75 X 1.22 26.7 1.52 15 Safenlp 1072 SAT 7.87 3.62 1.09 1.42 - 1.53 1' Safenlp 1073 SAT 8.32 3.70 3.10 1.35 - 1.53 - Safenlp 1074 SAT 8.13 3.70 X 1.33 - 1.52 - Safenlp 1075 SAT 8.23 3.63 X 1.32 - 1.53 - Safenlp 1076 SAT 8.25 4.05 X 1.30 - - -	7.1 - 9.9 - 9.1 - - - - - 7.7 -
Safenip 1071 UNSAT 7.10 3.75 X 1.22 26.7 1.52 19 Safenip 1072 SAT 7.87 3.62 1.09 1.42 - 1.53 19 Safenip 1073 SAT 8.32 3.70 3.10 1.35 - 1.53 - Safenip 1074 SAT 8.13 3.70 X 1.33 - 1.52 - Safenip 1075 SAT 8.23 3.63 X 1.32 - 1.53 - Safenip 1076 SAT 8.25 4.05 X 1.30 - - - -	9.9 - 9.1 - - - - - - 7.7 -
Safenlp 1072 SAT 7.87 3.62 1.09 1.42 - 1.53 15 Safenlp 1073 SAT 8.32 3.70 3.10 1.35 - 1.53 - Safenlp 1074 SAT 8.13 3.70 X 1.33 - 1.52 - Safenlp 1075 SAT 8.23 3.63 X 1.32 - 1.53 - Safenlp 1076 SAT 8.25 4.05 X 1.30 - - -	9.1 - - - - - - 7.7 -
Safenip 1073 SAT 8.32 3.70 3.10 1.35 - 1.53 - Safenip 1074 SAT 8.13 3.70 X 1.33 - 1.52 - Safenip 1075 SAT 8.23 3.63 X 1.32 - 1.53 - Safenip 1076 SAT 8.25 4.05 X 1.30 - - -	- - - - - 7.7 -
Safenlp 1075 sat 8.23 3.63	- - - 7.7 -
Safenlp 1076 sat 8.25 4.05 × 1.30	- - 7.7 -
	7.7 -
	7.7 -
Tinyimagenet 0 UNSAT 22.6 98.5	60.3
Tinyimagenet 1 UNSAT 22.6	54.0
Tinyimagenet 2 sat $10.5 \ 6.62 \ 4.10$	-
Tinyimagenet 3 SAT 9.95 6.59 3.10	X
Tinyimagenet 4 UNSAT 22.9 109	40.1
Tinyimagenet 5 SAT 10.7 6.72 8.13 Tinyimagenet 6 SAT 10.1 6.64 3.10	-
Tinyimagenet 6 SAT 10.1 6.64 3.10 Tinyimagenet 7 UNSAT 33.4	78.2
Tinyimagenet 8 ?	-
Tinyimagenet 9 UNSAT 23.5	39.6
Tinyimagenet 10 UNSAT 22.4	37.9
Tinyimagenet 11 SAT 9.91 - 20.2	60.9
Tinyimagenet 12 UNSAT 25.1	44.3
Tinyimagenet 13 UNSAT 22.5 104	39.6
Tinyimagenet 14 UNSAT 24.2 Tinyimagenet 15 SAT 10.1 - 42.3	44.5
Tinyimagenet 15 SAT 10.1 - 42.3 Tinyimagenet 16 SAT 9.90 6.76 4.11	- X
Tinyimagenet 17 UNSAT 23.2 110	
Tinyimagenet 18 UNSAT 23.0	55.1
Tinyimagenet 19 SAT 10.3 - 26.2	-
Tinyimagenet 20 UNSAT 42.9	87.6
Tinyimagenet 21 UNSAT 20.8 68.8	48.5
Tinyimagenet 22 UNSAT 48.8	89.1
Tinyimagenet 23 ?	39.8
Tinyimagenet 25 SAT 10.1 - 35.3	-
Tinyimagenet 26 UNSAT 22.3 99.2	56.3
Tinyimagenet 27 SAT 9.98 6.63 9.13	X
Tinyimagenet 28 UNSAT 20.6 32.7	45.3
Tinyimagenet 29 sat 9.46 6.58 4.11	X
Tinyimagenet 30 SAT 10.2 6.76 4.11	-
Tinyimagenet 31 UNSAT 26.8	-
Tinyimagenet 32 ?	-
Tinyimagenet 33 SAT 10.1 6.56 3.10 Tinyimagenet 34 UNSAT 23.3	54.2
Tinyimagenet 35 sat 10.9 6.56 3.10	-
Tinyimagenet 36 SAT 10.7 6.59 3.10	-
Tinyimagenet 37 sat 9.87 - 22.2	X
Tinyimagenet 38 unsat 23.1 55.3	39.1
Tinyimagenet 39 UNSAT 31.9	71.5
Tinyimagenet 40 UNSAT 36.8	-
Tinyimagenet 41 UNSAT 31.2	54.2
Tinyimagenet 42 UNSAT 12.9 15.9 Tinyimagenet 43 UNSAT 26.4	25.5 59.4
Tinyimagenet 44 UNSAT 26.2	-
Tinyimagenet 45 UNSAT 32.1	_
Tinyimagenet 46 UNSAT 57.4	-
Tinyimagenet 47 SAT 9.93 6.59 29.3	×
Tinyimagenet 48 sat 9.88 - 19.2	X
Tinyimagenet 49 UNSAT 27.7	-
Tinyimagenet 50 UNSAT 41.9	95.8
Tinyimagenet 51 SAT 10.9 6.77 9.14	-

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

Category	Id	Result	α - β - \mathbf{C}	PyRAT	' Marab	NNen	NNV	NeVer2	CORA	NSAT
Tinyimagenet	52	?	-	-	-	-	-	-	-	-
Tinyimagenet	53	UNSAT	33.2	-	-	-	-	-	-	57.2
Tinyimagenet	54	UNSAT		- 0.05	-	-	-	-	-	41.1
Tinyimagenet	55 56	SAT	9.86	6.65	5.11	-	-	-	-	X
Tinyimagenet Tinyimagenet	56 57	UNSAT UNSAT		111	_	_	_	_	_	41.6
Tinyimagenet	58	UNSAT		85.6	_	_	_	_	_	-
Tinyimagenet	59	UNSAT		-	_	_	_	_	_	42.9
Tinyimagenet	60	UNSAT		81.0	-	-	-	-	-	34.1
Tinyimagenet	61	?	-	-	-	-	-	-	-	-
Tinyimagenet	62	UNSAT	21.2	60.6	-	-	-	-	-	-
Tinyimagenet	63	?	-	-	-	-	-	-	-	-
Tinyimagenet	64	UNSAT	26.3	-	-	-	-	-	-	47.2
Tinyimagenet	65	?	- 01.0	-	-	-	-	-	-	-
Tinyimagenet Tinyimagenet	66 67	UNSAT UNSAT		-	-	_	-	_	-	38.5
Tinyimagenet	68	UNSAT		114	_	_	_	_	_	57.9 73.9
Tinyimagenet	69	UNSAT		50.4	_	_	_	_	_	36.9
Tinyimagenet	70	SAT	10.9	-	4.11	_	_	_	-	-
Tinyimagenet	71	SAT	10.6	6.61	4.11	-	-	-	-	-
Tinyimagenet	72	SAT	9.96	-	32.3	-	-	-	-	-
Tinyimagenet	73	UNSAT		-	-	-	-	-	-	-
Tinyimagenet	74	UNSAT		13.3	-	-	-	-	-	18.8
Tinyimagenet	75	SAT	11.0	6.79	5.12	-	-	-	-	- 01.0
Tinyimagenet	76 77	UNSAT		-	-	-	-	_	-	61.0
Tinyimagenet Tinyimagenet	78	UNSAT UNSAT		_	_	_	_	_	_	63.5
Tinyimagenet	79	UNSAT		24.3	_	_	_	_	_	32.5
Tinyimagenet	80	UNSAT		-	_	_	_	_	_	49.4
Tinyimagenet	81	SAT	12.8	6.58	3.10	-	-	-	-	-
Tinyimagenet	82	?	-	-	-	-	-	-	-	-
Tinyimagenet	83	UNSAT	27.3	-	-	-	-	-	-	-
Tinyimagenet	84	UNSAT		108	-	-	-	-	-	42.7
Tinyimagenet	85	?	-	-	-	-	-	-	-	-
Tinyimagenet	86	UNSAT	22.9	57.8	-	-	-	-	-	-
Tinyimagenet Tinyimagenet	87 88	? UNSAT	8 00	14.3	_	-	-	_	-	18.8
Tinyimagenet	89	UNSAT		-	_	_	_	_	_	-
Tinyimagenet	90	UNSAT		_	_	_	_	_	_	59.2
Tinyimagenet	91	UNSAT		-	-	_	-	-	-	62.3
Tinyimagenet	92	UNSAT	40.9	-	-	-	-	-	-	65.4
Tinyimagenet	93	UNSAT	14.3	13.8	-	-	-	-	-	25.1
Tinyimagenet	94	UNSAT		68.8	-	-	-	-	-	50.1
Tinyimagenet	95	UNSAT		-	-	-	-	-	-	54.9
Tinyimagenet	96	SAT	10.3	6.78	78.5	-	-	-	-	-
Tinyimagenet Tinyimagenet	97 98	SAT	10.0	6.79	43.3	-	-	-	-	_
Tinyimagenet	99	! UNSAT		_	_	_	_	_	_	59.1
Tinyimagenet	100	UNSAT		_	_	_	_	_	_	40.8
Tinyimagenet	101	?	-	_	_	_	_	_	_	-
Tinyimagenet	102	UNSAT	25.1	-	-	-	-	-	-	-
Tinyimagenet	103	?	-	-	-	-	-	-	-	-
Tinyimagenet	104	UNSAT	27.2	-	-	-	-	-	-	54.5
Tinyimagenet	105	UNSAT	39.4	-	-	-	-	-	-	83.7
Tinyimagenet	106	UNSAT		-	-	-	-	-	-	44.4
Tinyimagenet	107	UNSAT		-	-	-	-	-	-	67.0
Tinyimagenet Tinyimagenet	108 109	UNSAT SAT	25.6 10.1	6.76	16.2	-	-	-	-	-
Tinyimagenet	110	?	10.1	-	10.2	_	_	-	_	_
Tinyimagenet	111	UNSAT		_	_	_	_	-	_	-
Tinyimagenet	112	SAT	10.1	6.67	3.10	-	29.2	-	17.0	_
Tinyimagenet	113	UNSAT	21.0	51.7	-	-	-	-	-	34.9
Tinyimagenet	114	UNSAT		-	-	-	-	-	-	44.4
Tinyimagenet	115	UNSAT		-	-	-	-	-	-	-
Tinyimagenet	116	UNSAT	21.9	73.4	-	-	-	-	-	38.0
Tinyimagenet	117	?	-	- 01 1	-	-	-	-	-	-
Tinyimagenet	118	UNSAT	<i>2</i> 4.0	31.1	-	-	-	-	-	65.3

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

-										
Category	\mathbf{Id}	Result	α - β - \mathbf{C}	PyRAT	Marab	NNen	NNV	NeVer2	CORA	NSAT
Tinyimagenet	119	SAT	9.02	6.50	1.09	-	30.3	-	18.0	Х
Tinyimagenet	120	UNSAT	29.3	-	-	-	-	-	-	55.0
Tinyimagenet	121	UNSAT	25.1	-	-	-	-	-	-	-
Tinyimagenet	122	UNSAT	21.6	42.9	-	-	-	-	-	48.4
Tinyimagenet	123	UNSAT	21.4	110	-	-	-	-	-	50.6
Tinyimagenet	124	SAT	10.9	6.59	4.11	-	-	-	-	-
Tinyimagenet	125	UNSAT	13.2	13.4	-	-	-	-	-	26.7
Tinyimagenet	126	?	-	-	-	-	-	-	-	-
Tinyimagenet	127	?	-	-	-	-	-	-	-	-
Tinyimagenet	128	UNSAT		-	-	-	-	-	-	-
Tinyimagenet	129	SAT	10.9	6.57	4.11	-	-	-	-	-
Tinyimagenet	130	UNSAT		18.8	-	-	-	-	-	35.1
Tinyimagenet	131	UNSAT		13.5	-	-	-	-	-	23.2
Tinyimagenet	132	UNSAT			- F 11	-	-	-	-	-
Tinyimagenet	133	SAT	13.6	6.75	5.11	-	-	-	-	-
Tinyimagenet	134	SAT	10.2	6.65	3.10	-	-	-	-	-
Tinyimagenet	135	SAT	10.0	-	42.3	-	-	-	-	- 75 C
Tinyimagenet	136	UNSAT		-	-	-	-	-	-	75.6
Tinyimagenet	137	UNSAT		10.2	-	-	-	-	-	- 22.7
Tinyimagenet	138	UNSAT		19.3	-	-	-	-	-	33.7
Tinyimagenet	139	UNSAT		109	-	-	-	-	-	51.3
Tinyimagenet	140	UNSAT		-	-	-	-	-	-	46.6
Tinyimagenet	141	UNSAT		75.1	-	-	-	-	-	56.3
Tinyimagenet	142	UNSAT		-	-	-	-	-	-	47.2
Tinyimagenet	143	UNSAT		-	-	-	-	-	-	-
Tinyimagenet	144	?	-	-	-	-	-	-	-	-
Tinyimagenet	145	UNSAT		-	-	-	-	-	-	-
Tinyimagenet	146	UNSAT		21.6	-	-	-	-	-	27.3
Tinyimagenet	147	UNSAT		-	-	-	-	-	-	39.5
Tinyimagenet	148	UNSAT		- 20.1	-	-	-	-	-	98.9
Tinyimagenet	149	UNSAT		20.1	-	-	-	-	-	26.1
Tinyimagenet	150	UNSAT		15.0	-	-	-	-	-	69.5
Tinyimagenet	151	UNSAT		15.2	_	-	-	-	-	25.1
Tinyimagenet	152	UNSAT								68.5
Tinyimagenet Tinyimagenet	153	UNSAT UNSAT		-	_	-	-	-	-	-
	154	?	43.2	-	_	-	_	-	-	-
Tinyimagenet	$\frac{155}{156}$	UNSAT		109	_	-	_	_	-	39.6
Tinyimagenet Tinyimagenet	150 157	?	-	109	_	-	_	_	-	-
	158	SAT	10.2	6.58	3.10	-	_	_	-	_
Tinyimagenet Tinyimagenet	159	SAT	9.95	6.76	4.11	-	_	_	-	-
Tinyimagenet	160	UNSAT		-	4.11	-	_	-	-	55.4
Tinyimagenet	161	UNSAT		-	_	-	_	_	_	61.6
Tinyimagenet	162	?	-	_	_	_	_		_	-
Tinyimagenet	163	UNSAT		-	-	_	_		_	59.3
Tinyimagenet	164	UNSAT		_	_	_	_	_	_	53.2
Tinyimagenet	165	UNSAT		_	_	_	_	_	_	-
Tinyimagenet	166	SAT	13.1	6.63	3.10	_	_	_	_	_
Tinyimagenet	167	?	-	-	-	_	_	_	_	_
Tinyimagenet	168	UNSAT		35.7	_	_	_	_	_	64.1
Tinyimagenet	169	UNSAT		-	_	_	_	_	_	46.3
Tinyimagenet	170	UNSAT		15.1	_	_	_	_	_	36.0
Tinyimagenet	171	UNSAT		-	_	_	_	_	_	78.7
Tinyimagenet	172	UNSAT		_	-	-	_	-	-	60.7
Tinyimagenet	173	UNSAT		59.7	_	_	_	_	_	33.3
Tinyimagenet	174	UNSAT		-	_	_	_	_	_	-
Tinyimagenet	175	UNSAT		16.2	_	_	_	_	_	24.5
Tinyimagenet	176	UNSAT		14.1	_	_	_	_	_	23.5
Tinyimagenet	177	UNSAT		-	_	_	_	_	_	-
Tinyimagenet	178	UNSAT		73.6	_	_	_	_	_	_
Tinyimagenet	179	UNSAT		14.0	_	_	_	_	_	24.0
Tinyimagenet	180	UNSAT		112	_	_	_	_	_	33.2
Tinyimagenet	181	UNSAT		-	_	_	_	_	_	-
Tinyimagenet	182	UNSAT		82.6	_	_	_	_	_	68.6
Tinyimagenet	183	SAT	10.0	-	6.12	_	_	_	_	X
Tinyimagenet	184	UNSAT		59.2	-	_	_	_	_	54.8
Tinyimagenet	185	UNSAT		14.8	-	_	_	_	-	23.5
v 5										

Table 37: Regular Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (X).

Category	Id	Result	α-β-C	PyRAT	Marab	NNen	NNV	NeVer2	CORA	NSAT
Tinyimagenet	186	SAT	10.0	-	77.5	-	-	_	-	-
Tinyimagenet	187	?	-	-	-	-	-	-	-	-
Tinyimagenet	188	SAT	9.96	6.67	4.11	-	-	-	-	-
Tinyimagenet	189	?	-	-	-	-	-	-	-	-
Tinyimagenet	190	?	_	_	_	-	_	_	_	_
Tinyimagenet	191	UNSAT	31.9	-	-	-	_	_	-	_
Tinvimagenet	192	?	_	_	_	_	_	_	_	_
Tinvimagenet	193	SAT	9.96	_	19.2	_	_	_	_	Х
Tinvimagenet	194	SAT	10.3	6.71	10.1	_	_	_	_	
Tinvimagenet	195	UNSAT	35.9	_	_	_	_	_	_	_
Tinvimagenet	196	UNSAT	24.7	_	_	_	_	_	_	_
Tinyimagenet	197	UNSAT	23.8	_	_	_	_	_	_	_
Tinyimagenet	198	UNSAT	30.9	_	_	_	_	_	_	_
Tinyimagenet	199	UNSAT	32.8	_	_	_	_	_	_	67.7
Tllverifybench 2023	0	SAT	6.99	8.70	1.09	1.20	25.8	2.06	11.0	X
Tllverifybench 2023	1	UNSAT	8.71	12.4	7.10	-	-	1.58	11.7	4.27
Tllverifybench 2023	2	UNSAT	8.06	8.47	6.10	1.85	-	1.57	11.2	4.25
Tllverifybench 2023	3	UNSAT	8.03	19.0	7.10	2.63	-	1.57	11.2	4.26
Tllverifybench 2023	4	UNSAT	8.23	43.5	29.2	-	-	2.02	11.4	4.55
Tllverifybench 2023	5	SAT	6.98	6.88	1.09	1.20	27.0	1.99	10.7	X
Tllverifybench 2023	6	UNSAT	8.13	11.9	9.11	-	-	2.03	11.3	4.49
Tllverifybench 2023	7	SAT	6.98	6.80	1.11	1.22	25.9	1.72	10.7	X
Tllverifybench 2023	8	SAT	7.01	6.95	1.09	2.00	26.4	2.85	10.9	X
Tllverifybench 2023	9	SAT	7.02	6.93	1.09	1.90	28.0	3.76	10.9	X
Tllverifybench 2023	10	SAT	6.99	6.99	1.10	1.43	27.2	2.82	10.9	X
Tllverifybench 2023	11	UNSAT	8.50	30.3	24.2	_	-	3.77	11.5	4.91
Tllverifybench 2023	12	SAT	7.37	15.2	1.10	_	27.1	9.04	11.0	X
Tllverifybench 2023	13	SAT	7.03	7.26	1.09	1.84	27.9	8.98	11.2	X
Tllverifybench 2023	14	UNSAT	8.52	73.6	135	_	_	9.13	12.5	4.97
Tllverifybench 2023	15	UNSAT	8.57	76.4	150	_	_	9.07	12.8	5.09
Tllverifybench 2023	16	UNSAT	8.82	36.9	104	_	_	26.2	14.2	5.80
Tllverifybench 2023	17	UNSAT	9.28	151	432	_	_	26.7	21.3	7.14
Tllverifybench 2023	18	UNSAT	9.39	113	402	_	_	26.6	20.4	6.91
Tllverifybench 2023	19	SAT	7.17	8.31	1.09	3.36	27.5	23.3	11.2	X
Tllverifybench 2023	20	SAT	7.46	10.6	1.09	6.16	27.4	63.0	11.5	X
Tllverifybench 2023	21	SAT	7.44	13.4	1.09	6.23	27.6	67.5	12.7	X
Tllverifybench 2023	22	UNSAT		119	548	-	-	67.1	27.5	8.14
Tllverifybench 2023	23	SAT	7.47	13.2	1.09	9.85	27.6	62.8	11.4	X
Tllverifybench 2023	24	SAT	9.07	178	1.09	16.7	28.3	147	14.5	X
Tllverifybench 2023	25	UNSAT		76.5	528	-	-	149	37.7	9.20
Tllverifybench 2023	26	UNSAT		314	-	-	_	149	50.6	11.6
Tllverifybench 2023	27	SAT	7.84	14.0	1.09	11.5	29.0	149	12.4	X X
Tilverifybench 2023	28	SAT	8.40	19.8	2.10	22.4	28.2	415	13.4	x
Tilverifybench 2023	29	UNSAT		348	2.10 -	-	20.2	415	64.4	13.6
Tllverifybench 2023	30	SAT	8.43	22.9	2.10	21.7	30.3	416	13.9	X
Tllverifybench 2023	31	SAT	8.44	21.6	2.10	27.2	28.4	409	13.0	X

Table 38: Extended Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (x).

Category	Id	Result	α-β-(C PyR.	AT NN	en NSAT
Cctsdb Yolo 2023	0	UNSAT	8.39	-	-	-
Cctsdb Yolo 2023	1	SAT	7.70	-	-	-
Cctsdb Yolo 2023	2	SAT	7.76	-	-	-
Cctsdb Yolo 2023	3	SAT	7.75	-	-	-
Cctsdb Yolo 2023	4	SAT	7.70	-	-	-
Cctsdb Yolo 2023	5	UNSAT	7.65	-	-	-
Cctsdb Yolo 2023	6	SAT	7.72	-	-	-
Cctsdb Yolo 2023	7	UNSAT	7.64	-	-	-
Cctsdb Yolo 2023	8	UNSAT	7.69	-	_	-

Table 38: Extended Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (X).

Category	Id	Result	α - β - \mathbf{C}	PyRAT	NNen	NSAT
Cctsdb Yolo 2023	9	SAT	7.72	_	_	_
Cctsdb Yolo 2023	10	SAT	7.71	-	-	-
Cctsdb Yolo 2023	11	SAT	7.72	4.91	-	-
Cctsdb Yolo 2023	12	SAT	7.70	-	-	-
Cctsdb Yolo 2023 Cctsdb Yolo 2023	13	SAT	7.73	_	-	_
Cctsdb Yolo 2023	$\frac{14}{15}$	UNSAT SAT	7.65 7.73	-	-	-
Cctsdb Yolo 2023	16	SAT	7.75	_	_	_
Cctsdb Yolo 2023	17	SAT	7.71	_	_	_
Cctsdb Yolo 2023	18	SAT	7.70	-	-	-
Cctsdb Yolo 2023	19	SAT	7.72	-	-	-
Cctsdb Yolo 2023	20	SAT	7.71	4.38	-	-
Cctsdb Yolo 2023	21	SAT	7.72	-	-	-
Cctsdb Yolo 2023	22	SAT	7.76	-	-	-
Cctsdb Yolo 2023 Cctsdb Yolo 2023	$\frac{23}{24}$	UNSAT SAT	7.69 7.70	-	_	_
Cctsdb Yolo 2023	25	SAT	7.70	_	_	_
Cctsdb Yolo 2023	26	SAT	7.72	_	_	_
Cctsdb Yolo 2023	27	UNSAT	7.67	-	-	-
Cctsdb Yolo 2023	28	UNSAT	7.65	-	-	-
Cctsdb Yolo 2023	29	UNSAT	7.67	-	-	-
Cctsdb Yolo 2023	30	SAT	7.73	-	-	-
Cctsdb Yolo 2023	31	SAT	7.70	-	-	-
Cctsdb Yolo 2023	32	UNSAT	7.64	-	-	-
Cctsdb Yolo 2023 Cctsdb Yolo 2023	33 34	SAT SAT	$7.71 \\ 7.72$	_	_	_
Cctsdb Yolo 2023	35	UNSAT	7.67	_	_	_
Cctsdb Yolo 2023	36	SAT	7.72	_	_	_
Cctsdb Yolo 2023	37	SAT	7.73	-	-	-
Cctsdb Yolo 2023	38	SAT	7.71	-	-	-
Collins Aerospace Benchmark	0	SAT	15.0	12.7	-	-
Collins Aerospace Benchmark	1	SAT	14.6	12.7	-	-
Collins Aerospace Benchmark	2	SAT	14.3	13.2	-	-
Collins Aerospace Benchmark		SAT	14.3	12.8	-	-
Collins Aerospace Benchmark	4 5	SAT SAT	$14.3 \\ 14.4$	13.1 13.2	-	_
Collins Aerospace Benchmark				13.2		
Lsnc Lsnc	0 1	UNSAT UNSAT	34.0 20.6	-	-	_
Lsnc	2	UNSAT	16.4	_	-	_
Lsnc	3	UNSAT	21.9	_	_	_
Lsnc	4	UNSAT	17.8	_	-	-
Lsnc	5	UNSAT	16.2	-	-	-
Lsnc	6	UNSAT	20.6	-	-	-
Lsnc	7	UNSAT	21.4	-	-	-
Lsnc	8	UNSAT	18.9	-	-	-
Lsnc	9	UNSAT	16.1	-	-	-
Lsnc	10	UNSAT	26.0	-	-	-
Lsnc Lsnc	$\frac{11}{12}$	UNSAT UNSAT	20.2 16.6	_	_	_
Lsnc	13	UNSAT	17.4	_	_	_
Lsnc	14	UNSAT	20.7	_	_	_
Lsnc	15	UNSAT	19.0	-	-	-
Lsnc	16	UNSAT	16.0	-	-	-
Lsnc	17	UNSAT		-	-	-
Lsnc	18	UNSAT		-	-	-
Lsnc	19	UNSAT		-	-	-
Lsnc	20	UNSAT		20.6	-	-
Lenc	$\frac{21}{22}$	UNSAT		3.85 4.55	_	_
Lsnc Lsnc	23	UNSAT UNSAT		3.83	_	-
Lsnc	$\frac{23}{24}$	UNSAT		3.82	_	-
Lsnc	25	UNSAT		6.16	_	-
Lsnc	26	UNSAT		-	-	-
Lsnc	27	UNSAT		3.82	-	-
Lsnc	28	UNSAT		-	-	-
Lsnc	29	UNSAT	40.1	-	-	-

Table 38: Extended Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (X).

Category	Id	Result	α-β-	C PyRA	T NNen	NSAT
Lsnc	30	UNSAT	21.8	3.84	-	-
Lsnc	31	UNSAT		-	-	-
Lsnc	32	UNSAT		3.84	-	-
Lsnc	33	UNSAT		3.79	-	-
Lsnc Lsnc	34 35	UNSAT UNSAT		11.9 3.86	-	_
Lsnc	36	UNSAT		3.82	_	_
Lsnc	37	UNSAT		8.41	-	_
Lsnc	38	UNSAT		4.33	-	-
Lsnc	39	UNSAT	34.7	-	-	-
Ml4acopf 2023	0	UNSAT	77.2	-	-	-
Ml4acopf 2023	1	UNSAT		6.23	-	-
Ml4acopf 2023	2	UNSAT		6.06	-	-
Ml4acopf 2023	$\frac{3}{4}$	UNSAT		- 4 76	-	-
Ml4acopf 2023 Ml4acopf 2023	5	UNSAT UNSAT		4.76 -	-	_
Ml4acopf 2023	6	UNSAT		_	_	_
Ml4acopf 2023	7	UNSAT		4.15	-	-
Ml4acopf 2023	8	UNSAT	9.03	171	-	-
Ml4acopf 2023	9	UNSAT	8.98	4.28	-	-
Ml4acopf 2023	10	UNSAT		5.72	-	-
Ml4acopf 2023	11	UNSAT		4.20	-	-
Ml4acopf 2023	12	UNSAT		4.85	-	-
Ml4acopf 2023 Ml4acopf 2023	13 14	UNSAT UNSAT		4.22	-	_
Ml4acopf 2023	15	UNSAT		4.24	-	_
Ml4acopf 2023	16	UNSAT		-	_	_
Ml4acopf 2023	17	UNSAT		4.22	-	-
Ml4acopf 2023	18	UNSAT		-	-	-
Ml4acopf 2023	19	UNSAT	362	11.4	-	-
Ml4acopf 2023	20	UNSAT		6.34	-	-
Ml4acopf 2023	21	?	179	10.0	-	-
Ml4acopf 2023	22	UNSAT		16.8	-	-
Ml4acopf 2024	0	UNSAT		-	-	-
Ml4acopf 2024 Ml4acopf 2024	$\frac{1}{2}$	UNSAT UNSAT		9.91	_	_
Ml4acopf 2024 Ml4acopf 2024	3	UNSAT		9.91	-	-
Ml4acopf 2024	4	UNSAT		9.94	-	_
Ml4acopf 2024	5	UNSAT		18.2	-	-
Ml4acopf 2024	6	UNSAT	9.25	7.48	-	-
Ml4acopf 2024	7	UNSAT		8.90	-	-
Ml4acopf 2024	8	UNSAT		7.41	-	-
Ml4acopf 2024	9	SAT	7.13	6.18	-	-
Ml4acopf 2024 Ml4acopf 2024	10 11	UNSAT UNSAT		-	-	_
Ml4acopf 2024 Ml4acopf 2024	12	UNSAT		7.43	_	_
Ml4acopf 2024	13	UNSAT		-	-	_
Ml4acopf 2024	14	UNSAT		-	-	-
Ml4acopf 2024	15	UNSAT	56.1	8.31	-	-
Ml4acopf 2024	16	?	-	-	-	-
Ml4acopf 2024	17	UNSAT		-	-	-
Ml4acopf 2024	18	UNSAT		7.36	-	-
Ml4acopf 2024	19	UNSAT	180	7 0 1	-	-
Ml4acopf 2024 Ml4acopf 2024	20 21	UNSAT	9.21	7.84	-	-
Ml4acopf 2024 Ml4acopf 2024	22	UNSAT		-	-	_
Ml4acopf 2024 Ml4acopf 2024	23	UNSAT		-	-	_
Ml4acopf 2024	24	UNSAT		-	-	-
Ml4acopf 2024	25	UNSAT		8.51	-	-
Ml4acopf 2024	26	UNSAT		-	-	-
Ml4acopf 2024	27	UNSAT		8.60	-	-
Ml4acopf 2024	28	UNSAT		35.0	-	-
Ml4acopf 2024	29	UNSAT		7.17	-	-
Ml4acopf 2024 Ml4acopf 2024	30 31	UNSAT	8.86 8.87	24.9 10.6	-	-
Ml4acopf 2024 Ml4acopf 2024	32	UNSAT SAT	7.09	6.14	_	_
III IGCOPI ZUZT	52	0711	1.00	0.17		

Table 38: Extended Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (X).

Category	Id	Result	α - β - \mathbf{C}	PyRAT	NNen	NSAT
Ml4acopf 2024	33	UNSAT	9.04	-	-	-
Ml4acopf 2024	34	UNSAT	8.86	-	-	-
Ml4acopf 2024	35	UNSAT		7.21	-	-
Ml4acopf 2024	36	UNSAT		-	-	-
Ml4acopf 2024 Ml4acopf 2024	37 38	UNSAT UNSAT		-	_	-
Ml4acopf 2024	39	UNSAT		_	_	_
Ml4acopf 2024	40	SAT	7.15	6.20	_	_
Ml4acopf 2024	41	UNSAT		7.40	-	-
Ml4acopf 2024	42	UNSAT	9.03	-	-	-
Ml4acopf 2024	43	UNSAT		-	-	-
Ml4acopf 2024	44	UNSAT		7.62	-	-
Ml4acopf 2024	45	UNSAT		7.60	-	-
Ml4acopf 2024 Ml4acopf 2024	$\frac{46}{47}$	UNSAT UNSAT		7.69 8.03	_	-
Ml4acopf 2024 Ml4acopf 2024	48	UNSAT		7.10	-	-
Ml4acopf 2024	49	UNSAT		8.00	_	_
Ml4acopf 2024	50	UNSAT		7.09	-	-
Ml4acopf 2024	51	UNSAT	9.05	-	-	-
Ml4acopf 2024	52	UNSAT	10.1	7.74	-	-
Ml4acopf 2024	53	UNSAT	9.08	-	-	-
Ml4acopf 2024	54	UNSAT		7.09	-	-
Ml4acopf 2024	55	UNSAT		-	-	-
Ml4acopf 2024	56	UNSAT		- 7.58	-	-
Ml4acopf 2024 Ml4acopf 2024	57 58	UNSAT	9.73	- 1.36	_	_
Ml4acopf 2024 Ml4acopf 2024	59	UNSAT	188	-	_	_
Ml4acopf 2024	60	?	-	_	_	_
Ml4acopf 2024	61	UNSAT	56.2	-	-	-
Ml4acopf 2024	62	UNSAT	72.7	-	-	-
Ml4acopf 2024	63	UNSAT	9.44	-	-	-
Ml4acopf 2024	64	UNSAT	9.43	9.06	-	-
Ml4acopf 2024	65	?	-	-	-	-
Ml4acopf 2024	66	UNSAT		7.51	-	-
Ml4acopf 2024 Ml4acopf 2024	67 68	?	-	-	-	-
Traffic Signs Recognition 2023	0	SAT	8.02	_	_	_
Traffic Signs Recognition 2023		SAT	8.06	_	_	_
Traffic Signs Recognition 2023		SAT	7.96	-	-	-
Traffic Signs Recognition 2023	3	SAT	7.98	-	-	-
Traffic Signs Recognition 2023		SAT	7.66	4.39	-	X
Traffic Signs Recognition 2023		SAT	7.99	-	-	X
Traffic Signs Recognition 2023		SAT	7.64	-	-	-
Traffic Signs Recognition 2023 Traffic Signs Recognition 2023		SAT SAT	7.62 7.60	-	_	X X
Traffic Signs Recognition 2023		SAT	7.64	4.40	-	x
Traffic Signs Recognition 2023		SAT	8.02	-	_	
Traffic Signs Recognition 2023		SAT	8.00	-	-	-
Traffic Signs Recognition 2023	12	SAT	7.99	-	-	-
Traffic Signs Recognition 2023	13	SAT	8.04	-	-	-
Traffic Signs Recognition 2023		SAT	7.66	-	-	X
Traffic Signs Recognition 2023		SAT	8.75	-	-	-
Traffic Signs Recognition 2023		SAT	8.35	-	-	-
Traffic Signs Recognition 2023		SAT	8.24	-	-	-
Traffic Signs Recognition 2023 Traffic Signs Recognition 2023		SAT SAT	8.19 8.18	-	-	_
Traffic Signs Recognition 2023		SAT	8.33	-	_	_
Traffic Signs Recognition 2023		SAT	8.21	-	-	-
Traffic Signs Recognition 2023		SAT	8.21	-	-	-
Traffic Signs Recognition 2023		SAT	8.22	-	-	-
Traffic Signs Recognition 2023		SAT	7.83	-	-	X
Traffic Signs Recognition 2023		SAT	8.19	-	-	-
Traffic Signs Recognition 2023		SAT	7.85	4.93	-	X
Traffic Signs Recognition 2023		SAT	7.85	-	-	X X
Traffic Signs Recognition 2023 Traffic Signs Recognition 2023		SAT SAT	7.85 7.84	4.90	_	×
Traffic Signs Recognition 2023		SAT	8.96	4.90 -	_	- "

Table 38: Extended Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (X).

Category	Id	Result	α-β-C	PyRAT	NNen	NSAT
Traffic Signs Recognition	2023 31	SAT	8.61	-	-	-
Traffic Signs Recognition		SAT	8.53	-	-	-
Traffic Signs Recognition	$2023\ 33$	SAT	8.52	-	-	-
Traffic Signs Recognition		SAT	8.54	-	-	-
Traffic Signs Recognition		SAT	8.68	-	-	-
Traffic Signs Recognition		SAT	8.53	-	-	-
Traffic Signs Recognition		SAT	8.54	-	-	-
Traffic Signs Recognition		SAT	8.52	-	-	-
Traffic Signs Recognition		SAT	8.52	-	-	_
Traffic Signs Recognition Traffic Signs Recognition		SAT SAT	8.51 8.55	-	-	-
Traffic Signs Recognition		SAT	8.54		_	_
Traffic Signs Recognition		SAT	8.54	_	_	_
Traffic Signs Recognition		SAT	8.54	-	-	-
V	0	TINGAM	16 5	00.1	20.0	47.0
Vggnet16 2023	$0 \\ 1$	UNSAT	$16.5 \\ 16.5$	99.1 96.2	29.0 29.8	47.0 46.5
Vggnet16 2023 Vggnet16 2023	2	UNSAT UNSAT	16.6	98.4	30.8	-
Vggnet16 2023	3	UNSAT	16.6	97.4	29.9	47.0
Vggnet16 2023	4	UNSAT	16.6	99.8	45.0	46.5
Vggnet16 2023	5	UNSAT	16.6	107	55.9	-
Vggnet16 2023	6	UNSAT	16.6	98.4	39.6	47.1
Vggnet16 2023	7	UNSAT	16.7	104	50.5	-
Vggnet16 2023	8	UNSAT	16.7	_	81.1	-
Vggnet16 2023	9	UNSAT	16.6	98.2	41.1	46.8
Vggnet16 2023	10	UNSAT	16.6	109	64.5	-
Vggnet16 2023	11	UNSAT	17.5	-	129	-
Vggnet16 2023	12	UNSAT	361	-	-	-
Vggnet16 2023	13	UNSAT	26.1	-	328	-
Vggnet16 2023	14	UNSAT	1024	-	-	-
Vggnet16 2023	15	UNSAT	1009	-	-	-
Vggnet16 2023	16	UNSAT	1046	-	-	-
Vggnet16 2023	17	UNSAT	1092	-	-	
Vit 2023	0	UNSAT	16.0	-	-	-
Vit 2023	1	UNSAT	17.1	-	-	-
Vit 2023	2	UNSAT	16.0	-	-	-
Vit 2023	3	?	-	-	-	-
Vit 2023 Vit 2023	4 5	? ?	_	_	_	_
Vit 2023 Vit 2023	6	UNSAT	15.5	-	_	23.1
Vit 2023	7	?	-	_	_	
Vit 2023	8	?	_	_	_	_
Vit 2023	9	?	-	_	-	_
Vit 2023	10	?	-	_	-	-
Vit 2023	11	UNSAT	14.9	_	-	17.7
Vit 2023	12	UNSAT	16.6	-	-	-
Vit 2023	13	UNSAT	14.9	-	-	17.7
Vit 2023	14	?	-	-	-	-
Vit 2023	15	?	-	-	-	-
Vit 2023	16	?	-	-	-	-
Vit 2023	17	UNSAT	29.1	-	-	-
Vit 2023	18	?	140	-	-	-
Vit 2023	19	UNSAT	14.9	-	-	-
Vit 2023 Vit 2023	20			-	-	26.6
Vit 2023 Vit 2023	21 22	UNSAT	54.0 -	-	_	26.6
Vit 2023 Vit 2023	23	?	-	-	_	_
Vit 2023 Vit 2023	24	UNSAT		-	_	17.6
Vit 2023 Vit 2023	25	?	-	_	_	-
Vit 2023	26	?	_	_	_	-
Vit 2023	27	?	_	_	_	_
Vit 2023	28	?	-	-	-	-
Vit 2023	29	?	_	-	-	-
Vit 2023	30	UNSAT	44.0	-	-	-
Vit 2023	31	UNSAT		-	-	-
Vit 2023	32	UNSAT		-	-	-
Vit 2023	33	UNSAT	15.5	-	-	21.8

Table 38: Extended Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (X).

Category	Id	Result	α-β- C	PyRAT	NNen	NSAT
Vit 2023	34	UNSAT	57.0	-		
Vit 2023 Vit 2023	35	?	-	-	_	_
Vit 2023	36	?	_	_	_	_
Vit 2023	37	?	_	_	_	_
Vit 2023	38	UNSAT	47.1	-	-	-
Vit 2023	39	?	-	-	-	-
Vit 2023	40	UNSAT	15.5	-	-	-
Vit 2023	41	UNSAT	21.0	-	-	-
Vit 2023	42	?	-	-	-	-
Vit 2023	43	?	-	-	-	-
Vit 2023	44	?	-	-	-	-
Vit 2023	45	?	-	-	-	-
Vit 2023	46	UNSAT		-	-	-
Vit 2023	47	?	-	-	-	-
Vit 2023	48	?	-	-	-	-
Vit 2023	49	?	140	-	-	-
Vit 2023 Vit 2023	50 51	UNSAT	14.9	_	-	_
Vit 2023 Vit 2023	52				_	-
Vit 2023 Vit 2023	53	UNSAT	-	-	_	_
Vit 2023 Vit 2023	54	UNSAT		_	_	_
Vit 2023 Vit 2023	55	?	-	_	_	_
Vit 2023 Vit 2023	56	UNSAT	14.9	_	_	_
Vit 2023 Vit 2023	57	?	-	_	_	_
Vit 2023	58	UNSAT		_	_	20.3
Vit 2023	59	?	-	_	_	-
Vit 2023	60	?	_	_	_	_
Vit 2023	61	?	-	_	-	-
Vit 2023	62	?	-	-	-	-
Vit 2023	63	UNSAT	15.4	-	-	-
Vit 2023	64	UNSAT	16.0	-	-	20.0
Vit 2023	65	UNSAT	15.4	-	-	-
Vit 2023	66	?	-	-	-	-
Vit 2023	67	?	-	-	-	-
Vit 2023	68	?	-	-	-	-
Vit 2023	69	?	-	-	-	-
Vit 2023	70	?	-	-	-	-
Vit 2023	71	UNSAT	15.5	-	-	-
Vit 2023	72	?	100	-	-	-
Vit 2023	73	UNSAT	16.6	-	-	27.4
Vit 2023	74 75	UNSAT		-	_	37.4
Vit 2023 Vit 2023	75 76	UNSAT	15.5 -	-	_	_
Vit 2023 Vit 2023	77	UNSAT		-	_	23.3
Vit 2023 Vit 2023	78	UNSAT	14.9	-	_	-
Vit 2023	79	?	-	_	_	_
Vit 2023	80	UNSAT	17.7	_	_	_
Vit 2023	81	UNSAT	14.9	_	_	20.4
Vit 2023	82	?	_	_	-	_
Vit 2023	83	?	-	-	-	-
Vit 2023	84	?	-	-	-	-
Vit 2023	85	UNSAT	19.3	-	-	-
Vit 2023	86	?	-	-	-	-
Vit 2023	87	UNSAT	23.4	-	-	-
Vit 2023	88	?	-	-	-	-
Vit 2023	89	UNSAT	14.9	-	-	-
Vit 2023	90	?	-	-	-	-
Vit 2023	91	UNSAT	14.9	-	-	-
Vit 2023	92	?	-	-	-	-
Vit 2023	93	UNSAT	44.7	-	-	-
Vit 2023	94	?	-	-	-	-
Vit 2023	95	?	-	-	-	-
Vit 2023	96	?	-	-	-	-
Vit 2023	97	?	-	-	-	-
Vit 2023	98	?	-	-	-	-
Vit 2023	99	?	-	-	-	-
Vit 2023	100		-	-	-	-

Table 38: Extended Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (X).

Category	Id	Result	α - β - \mathbf{C}	PyRAT	NNen	NSAT
Vit 2023	101	?	-	-	-	_
Vit 2023	102		-	-	-	-
Vit 2023	103	UNSAT	50.5	-	-	-
Vit 2023	104	?	-	-	-	-
Vit 2023	105		-	-	-	-
Vit 2023		UNSAT	17.1	-	-	-
Vit 2023	107		-	-	-	-
Vit 2023	108		-	-	-	-
Vit 2023	109		-	-	-	-
Vit 2023	110	_	-	-	-	-
Vit 2023 Vit 2023	111 112		-	-	-	_
Vit 2023 Vit 2023		UNSAT		-	_	_
Vit 2023 Vit 2023	114	_	-	_	_	_
Vit 2023	115		_	_	_	_
Vit 2023				_	_	_
Vit 2023		UNSAT		_	_	_
Vit 2023	118	?	-	-	-	-
Vit 2023	119	?	-	-	-	-
Vit 2023	120	UNSAT	18.5	-	-	-
Vit 2023	121	UNSAT	45.8	-	-	-
Vit 2023	122	UNSAT	50.9	-	-	-
Vit 2023	123	?	-	-	-	-
Vit 2023		UNSAT	18.6	-	-	-
Vit 2023	125		-	-	-	-
Vit 2023	126		-	-	-	-
Vit 2023	127		-	-	-	-
Vit 2023	128		-	-	-	-
Vit 2023	129		-	-	-	-
Vit 2023	130		-	-	-	-
Vit 2023 Vit 2023	131	UNSAT	- 50.7	-	-	_
Vit 2023 Vit 2023		UNSAT		-	_	_
Vit 2023		UNSAT		_	_	_
Vit 2023	135			_	_	_
Vit 2023	136		-	_	_	_
Vit 2023	137		-	-	-	-
Vit 2023	138	UNSAT	47.3	-	-	-
Vit 2023	139	?	-	-	-	-
Vit 2023	140	?	-	-	-	-
Vit 2023	141		17.1	-	-	-
Vit 2023	142		-	-	-	-
Vit 2023	143		-	-	-	-
Vit 2023	144		-	-	-	-
Vit 2023	145		40.0	-	-	-
Vit 2023		UNSAT		-	-	-
Vit 2023		UNSAT		-	-	-
Vit 2023 Vit 2023	148 149		17.1 53.6	-	-	-
Vit 2023 Vit 2023	150			_	_	_
Vit 2023 Vit 2023	151			-	_	_
Vit 2023 Vit 2023	152		-	_	_	-
Vit 2023	153		_	_	_	_
Vit 2023		UNSAT		_	_	_
Vit 2023	155		-	_	_	_
Vit 2023	156		_	_	_	_
Vit 2023		UNSAT		-	-	-
Vit 2023	158		-	-	-	-
Vit 2023	159		-	-	-	-
Vit 2023	160		-	-	-	-
Vit 2023	161	?	-	-	-	-
Vit 2023	162	?	-	-	-	-
Vit 2023		UNSAT		-	-	-
Vit 2023		UNSAT	17.1	-	-	-
Vit 2023	165		-	-	-	-
Vit 2023		UNSAT	17.1	-	-	-
Vit 2023	167	?	-	-	-	-

Table 38: Extended Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (X).

Vit 2023	Category	Id	Result	α - β - \mathbf{C}	PyRAT	NNen	NSAT
Vit 2023 169 ? - <t< td=""><td>Vit 2023</td><td>168</td><td>?</td><td>-</td><td>-</td><td>-</td><td>-</td></t<>	Vit 2023	168	?	-	-	-	-
Vit 2023	Vit 2023	169	?	-	-	-	-
Vit 2023 172 -	Vit 2023	170		-	-	-	-
Vit 2023 173 UNSAT 2.4 - - - Vit 2023 175 UNSAT 18.5 - - - Vit 2023 176 UNSAT 18.5 - - - Vit 2023 177 ? -				-	-	-	-
Vit 2023 174 ? - <t< td=""><td></td><td></td><td></td><td>-</td><td></td><td>-</td><td>-</td></t<>				-		-	-
Vit 2023 175 UNSAT 18.4 - - - Vit 2023 176 UNSAT 18.5 - - - Vit 2023 178 UNSAT 18.5 - - - Vit 2023 179 ? - - - - Vit 2023 180 UNSAT 48.4 - - - - Vit 2023 182 UNSAT 45.6 -					-	-	-
Vit 2023 176 UNSAT 18.5 - - - Vit 2023 178 UNSAT 18.5 - - - Vit 2023 179 - - - - - Vit 2023 180 UNSAT 18.4 - - - Vit 2023 181 ? - - - - Vit 2023 183 UNSAT 18.4 - </td <td></td> <td></td> <td></td> <td></td> <td>-</td> <td>-</td> <td>-</td>					-	-	-
Vit 2023 177 -							
Vit 2023 178 UNSAT 18.5 -							
Vit 2023 179 ? - <t< td=""><td></td><td></td><td></td><td></td><td></td><td>_</td><td></td></t<>						_	
Vit 2023 180 UNSAT 18.4 - - - Vit 2023 182 UNSAT 45.6 - - - Vit 2023 183 UNSAT 18.4 - - - Vit 2023 184 UNSAT 18.7 - - - Vit 2023 186 ? - - - - - Vit 2023 188 ? - </td <td></td> <td></td> <td></td> <td>-</td> <td>_</td> <td>_</td> <td></td>				-	_	_	
Vit 2023 181 ? - - - Vit 2023 182 UNSAT 18.4 - - - Vit 2023 183 UNSAT 18.4 - - - Vit 2023 185 UNSAT 17.1 - - - Vit 2023 186 ? - - - Vit 2023 188 ? - - - Vit 2023 188 ? - - - Vit 2023 188 ? - - - Vit 2023 190 UNSAT 55.0 - - - Vit 2023 191 UNSAT 52.2 - - - Vit 2023 192 UNSAT 18.4 - - - Vit 2023 193 ? - - - Vit 2023 194 UNSAT 55.3 - - - Vit 2023 195 ? - - - Vit 2023 197 UNSAT 17.1 - - - Vit 2023 198 ? - -				18.4	_	_	-
Vit 2023 183 UNSAT 56.8 - - Vit 2023 184 UNSAT 56.8 - - Vit 2023 186 UNSAT 17.1 - - Vit 2023 186 ? - - - Vit 2023 188 ? - - - Vit 2023 188 ! - - - Vit 2023 190 UNSAT 58.0 - - - Vit 2023 191 UNSAT 58.0 - - - Vit 2023 192 UNSAT 18.4 - - - Vit 2023 192 UNSAT 55.3 - - - Vit 2023 193 ? - - - - Vit 2023 195 ? - <td></td> <td>181</td> <td>?</td> <td>-</td> <td>-</td> <td>-</td> <td>-</td>		181	?	-	-	-	-
Vit 2023 184 UNSAT 17.1 -	Vit 2023	182	UNSAT	45.6	-	-	-
Vit 2023	Vit 2023	183	UNSAT	18.4	-	-	-
Vit 2023 186 ? - <t< td=""><td>Vit 2023</td><td>184</td><td>UNSAT</td><td>56.8</td><td>-</td><td>-</td><td>-</td></t<>	Vit 2023	184	UNSAT	56.8	-	-	-
Vit 2023 187 ? - <t< td=""><td></td><td></td><td></td><td>17.1</td><td>-</td><td>-</td><td>-</td></t<>				17.1	-	-	-
Vit 2023 188 ? -				-	-	-	-
Vit 2023 189 UNSAT 23.7 -					-	-	-
Vit 2023 190 UNSAT 58.0						-	
Vit 2023 191 UNSAT 52.2 - - - Vit 2023 192 UNSAT 18.4 - - - Vit 2023 193 ? - - - - Vit 2023 194 UNSAT 55.3 - - - Vit 2023 196 ? - - - - Vit 2023 197 UNSAT 17.1 - - - Vit 2023 198 ? - - - - Vit 2023 199 UNSAT 45.9 - - - Vit 2023 199 UNSAT 9.81 14.3 - - Vit 2023 1 UNSAT 9.81 14.3 - - - Yolo 2023 1 UNSAT 9.81 13.3 - <					-	-	-
Vit 2023 192 UNSAT 18.4 -					-	-	-
Vit 2023 193 ? -						-	
Vit 2023 194 UNSAT 55.3 -				10.4	_	_	_
Vit 2023 195 ? - - - Vit 2023 197 UNSAT 17.1 - - Vit 2023 198 ? - - - Vit 2023 199 UNSAT 45.9 - - - Vit 2023 199 UNSAT 45.9 - - - Yolo 2023 1 UNSAT 9.83 14.3 - - Yolo 2023 1 UNSAT 9.81 13.3 - - Yolo 2023 2 ? - - - Yolo 2023 3 UNSAT 9.82 13.8 - - Yolo 2023 4 UNSAT 9.81 13.8 - - Yolo 2023 5 UNSAT 9.81 13.8 - - Yolo 2023 6 UNSAT 9.81 13.8 - - Yolo 2023 7 UNSAT 9.81 13.8 - - Yolo 2023 7 UNSAT 9.84 13.9 - - Yolo 2023 10 UNSAT 9.84 13.9 - - Yolo 2023 11 UNSAT 9.86<				55.3	_	_	_
Vit 2023 196 ? - <t< td=""><td></td><td></td><td></td><td></td><td></td><td>_</td><td></td></t<>						_	
Vit 2023 197 UNSAT 17.1 -				_	_	_	_
Vit 2023 199 UNSAT 45.9 - - - Yolo 2023 1 UNSAT 9.81 13.3 - - Yolo 2023 2 ? - - - - Yolo 2023 3 UNSAT 9.82 13.8 - - Yolo 2023 4 UNSAT 9.81 13.8 - - Yolo 2023 5 UNSAT 13.7 - - - Yolo 2023 6 UNSAT 9.83 14.0 -				17.1	-	-	-
Yolo 2023 0 UNSAT 9.83 14.3 - - Yolo 2023 1 UNSAT 9.81 13.3 - - Yolo 2023 2 ? - - - Yolo 2023 3 UNSAT 9.82 13.8 - - Yolo 2023 4 UNSAT 9.81 13.8 - - Yolo 2023 5 UNSAT 9.81 13.8 - - Yolo 2023 6 UNSAT 9.83 14.0 - - - Yolo 2023 7 UNSAT 9.84 - <	Vit 2023	198	?	-	-	-	-
Yolo 2023 1 UNSAT 9.81 13.3 - - Yolo 2023 2 ? - - - Yolo 2023 3 UNSAT 9.82 13.8 - - Yolo 2023 4 UNSAT 9.81 13.8 - - Yolo 2023 5 UNSAT 9.81 13.8 - - Yolo 2023 6 UNSAT 9.83 14.0 - - Yolo 2023 7 UNSAT 9.84 - - - Yolo 2023 8 UNSAT 9.84 13.9 - - Yolo 2023 9 UNSAT 9.82 - - - Yolo 2023 10 UNSAT 9.86 - - - Yolo 2023 11 UNSAT 9.84 274 - - Yolo 2023 12 UNSAT 9.83 13.2 - - Yolo 2023 14 UNSAT 9.83 13.2 - - Yolo 2023 16 UNSAT 14.0 - - - Yolo 2023 18 ? -	Vit 2023	199	UNSAT	45.9	-	-	-
Yolo 2023 1 UNSAT 9.81 13.3 - - Yolo 2023 2 ? - - - Yolo 2023 3 UNSAT 9.82 13.8 - - Yolo 2023 4 UNSAT 9.81 13.8 - - Yolo 2023 5 UNSAT 9.81 13.8 - - Yolo 2023 6 UNSAT 9.83 14.0 - - - Yolo 2023 8 UNSAT 9.84 - <t< td=""><td>Volo 2023</td><td>0</td><td>IINGAT</td><td>0.83</td><td>1/1/3</td><td>_</td><td></td></t<>	Volo 2023	0	IINGAT	0.83	1/1/3	_	
Yolo 2023 2 ? - - - Yolo 2023 3 UNSAT 9.82 13.8 - - Yolo 2023 4 UNSAT 9.81 13.8 - - Yolo 2023 5 UNSAT 9.81 13.8 - - Yolo 2023 6 UNSAT 9.83 14.0 - - Yolo 2023 8 UNSAT 9.84 - - - Yolo 2023 9 UNSAT 9.84 13.9 - - Yolo 2023 10 UNSAT 9.86 - - - Yolo 2023 11 UNSAT 9.86 - - - Yolo 2023 12 UNSAT 9.83 13.2 - - Yolo 2023 13 UNSAT 9.83 13.2 - - Yolo 2023 14 UNSAT 9.83 - - - Yolo 2023 15 UNSAT 9.83 - - - Yolo 2023 16 UNSAT 9.84 13.6 - - Yolo 2023 18 ? -							
Yolo 2023 3 UNSAT 9.81 13.8 - - Yolo 2023 5 UNSAT 13.7 - - - Yolo 2023 6 UNSAT 9.83 14.0 - - - Yolo 2023 7 UNSAT 9.84 -						_	_
Yolo 2023 5 UNSAT 13.7 -			UNSAT	9.82	13.8	-	-
Yolo 2023 6 UNSAT 9.83 14.0 - - Yolo 2023 7 UNSAT 9.84 - - - Yolo 2023 8 UNSAT 9.84 13.9 - - Yolo 2023 9 UNSAT 9.86 - - - Yolo 2023 10 UNSAT 9.86 - - - Yolo 2023 12 UNSAT 9.86 - - - Yolo 2023 13 UNSAT 9.83 13.2 - - Yolo 2023 14 UNSAT 16.2 - - - Yolo 2023 15 UNSAT 9.83 - - - Yolo 2023 16 UNSAT 14.0 - - - Yolo 2023 17 ? - - - Yolo 2023 18 ? - - - Yolo 2023 18 ? - - - Yolo 2023 20 UNSAT 9.84 13.6 <td>Yolo 2023</td> <td>4</td> <td>UNSAT</td> <td>9.81</td> <td>13.8</td> <td>-</td> <td>-</td>	Yolo 2023	4	UNSAT	9.81	13.8	-	-
Yolo 2023 7 UNSAT 9.84 - - - Yolo 2023 8 UNSAT 9.84 13.9 - - Yolo 2023 9 UNSAT 9.82 - - - Yolo 2023 10 UNSAT 9.86 - - - Yolo 2023 11 UNSAT 9.84 274 - - Yolo 2023 12 UNSAT 9.83 13.2 - - Yolo 2023 14 UNSAT 9.83 13.2 - - Yolo 2023 15 UNSAT 9.83 - - - Yolo 2023 16 UNSAT 9.83 - - - Yolo 2023 17 - - - - Yolo 2023 18 ? - - - Yolo 2023 18 ? - - - Yolo 2023 29 UNSAT 9.84 13.6 - - Yolo 2023 21 ? -	Yolo 2023	5	UNSAT	13.7	-	-	-
Yolo 2023 8 UNSAT 9.84 13.9 - - Yolo 2023 9 UNSAT 9.82 - - - Yolo 2023 10 UNSAT 9.86 - - - Yolo 2023 11 UNSAT 9.84 274 - - Yolo 2023 12 UNSAT 9.83 13.2 - - Yolo 2023 14 UNSAT 9.83 13.2 - - Yolo 2023 15 UNSAT 9.83 - - - Yolo 2023 16 UNSAT 14.0 - - - - Yolo 2023 17 ? - <td< td=""><td>Yolo 2023</td><td>6</td><td>UNSAT</td><td>9.83</td><td>14.0</td><td>-</td><td>-</td></td<>	Yolo 2023	6	UNSAT	9.83	14.0	-	-
Yolo 2023 9 UNSAT 9.82 - - - Yolo 2023 10 UNSAT 9.86 - - - Yolo 2023 11 UNSAT 9.84 274 - - Yolo 2023 12 UNSAT 9.83 13.2 - - Yolo 2023 14 UNSAT 9.83 13.2 - - Yolo 2023 15 UNSAT 9.83 - - - Yolo 2023 16 UNSAT 9.83 - - - - Yolo 2023 17 ? -			UNSAT	9.84	-	-	-
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Yolo 2023 26 ? - - - - Yolo 2023 27 ? - - - - Yolo 2023 28 UNSAT 9.82 14.1 - - Yolo 2023 29 UNSAT 9.89 13.6 - - Yolo 2023 31 UNSAT 9.85 13.2 - - Yolo 2023 32 UNSAT 13.8 - - - Yolo 2023 32 UNSAT 13.8 - - - Yolo 2023 33 ? - - - -				9.80	14.3	-	-
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Table 38: Extended Track Instance Runtimes. Fastest times are blue. Second fastest are green. Penalties are red crosses (X).

Category	Id	Result	α - β - \mathbf{C}	PyRAT	NNen	NSAT
Yolo 2023	35	UNSAT	9.82	13.0	-	-
Yolo 2023	36	UNSAT	9.86	14.1	-	-
Yolo 2023	37	UNSAT	9.85	13.2	-	-
Yolo 2023	38	UNSAT	9.84	13.4	-	-
Yolo 2023	39	UNSAT	9.84	-	-	-
Yolo 2023	40	UNSAT	9.83	13.2	-	-
Yolo 2023	41	UNSAT	43.5	-	-	-
Yolo 2023	42	UNSAT	9.83	13.9	-	-
Yolo 2023	43	UNSAT	9.80	13.2	-	-
Yolo 2023	44	UNSAT	9.88	12.7	-	-
Yolo 2023	45	UNSAT	9.84	12.6	-	-
Yolo 2023	46	UNSAT	9.82	13.2	-	-
Yolo 2023	47	UNSAT	9.82	13.0	-	-
Yolo 2023	48	UNSAT	9.85	13.2	-	-
Yolo 2023	49	UNSAT	9.82	13.5	-	-
Yolo 2023	50	UNSAT	9.83	14.0	-	-
Yolo 2023	51	?	-	-	-	-
Yolo 2023	52	UNSAT	9.81	14.1	-	-
Yolo 2023	53	UNSAT	9.88	13.7	-	-
Yolo 2023	54	UNSAT	9.85	13.2	-	-
Yolo 2023	55	UNSAT	9.85	13.7	-	-
Yolo 2023	56	UNSAT	9.82	13.5	-	-
Yolo 2023	57	UNSAT	9.82	13.8	-	-
Yolo 2023	58	UNSAT	9.84	13.1	-	-
Yolo 2023	59	UNSAT	9.90	13.1	-	-
Yolo 2023	60	UNSAT	9.86	14.2	-	-
Yolo 2023	61	UNSAT	9.82	-	-	-
Yolo 2023	62	UNSAT	9.87	-	-	-
Yolo 2023	63	UNSAT	9.82	-	-	-
Yolo 2023	64	?	-	-	-	-
Yolo 2023	65	UNSAT	9.83	13.9	-	-
Yolo 2023	66	UNSAT	9.82	13.9	-	-
Yolo 2023	67	?	-	-	-	-
Yolo 2023	68	UNSAT	9.83	13.8	-	-
Yolo 2023	69	?	-	-	-	-
Yolo 2023	70	UNSAT	9.85	12.9	-	-
Yolo 2023	71	UNSAT	9.83	13.5	-	-