Supplementary Material for Enhancing Robotic Program Synthesis Through Environmental Context

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A Implementation Details

A.1 Hardware and Software Configurations

All experiments were conducted on Ubuntu 20.04.5 LTS (Linux version 5.15.0-46-generic) utilizing Python 3.9.0, PyTorch 1.12.1 [9], and PyTorch-Geometric 2.3.0 [5]. The hardware employed consisted of 24 Intel(R) Xeon(R) Gold 5317 CPUs @ 3.00GHz, 8 modules of 32GB memory (with a speed of 3200MT/s), and 2 NVIDIA A40 GPUs with 48GB of memory each (NVIDIA UNIX x86_64 Kernel Module 510.108.03, CUDA version 11.6, cuDNN version 8.3).

A.2 Network Architecture

For the program synthesizing stage, the structure of the I/O encoder is elaborated in Table 1, where we employ $d_{k_1} \times d_{k_2}$-s-d_o Conv to denote the 2D convolution with kernel size $d_{k_1} \times d_{k_2}$, stride s, and output channel d_o. Additionally, BN refers to batch normalization [8], and d_i-d_o Linear denotes the fully-connected layer with input feature d_i and output feature d_o. The I/O encoder utilizes residual networks [7] and takes I/O pair with size $5 \times 5 \times 3$ as inputs.

Table 1: The structure of the I/O encoder for synthesizing stage.

Layers	Output
3×3-1-32 Conv BN LeakyReLU	$5 \times 3 \times 32$
3×3-1-32 Conv BN LeakyReLU	$5 \times 3 \times 32$
3×3-1-64 Conv	$5 \times 3 \times 64$
3×3-1-64 Conv	$5 \times 3 \times 64$
3×3-1-64 Conv BN LeakyReLU	$5 \times 3 \times 64$
3×3-1-64 Conv	$5 \times 3 \times 64$
3×3-1-64 Conv	$5 \times 3 \times 64$
3×3-1-64 Conv BN LeakyReLU	$5 \times 3 \times 64$
960-512 Linear	512

To improve candidate programs through environmental contexts, the decoder's structure is elaborated in Table 2. Here, we utilize d_o-h GATv2Conv to represent the dynamic graph attention variant [1] with output channel d_o and multiple attention heads h, and d_o-n_l denotes the n_l layered bi-directional LSTM with output feature d_o. Additionally, $|\mathcal{V}|$ refers to the size of the Vizdoom DSL vocabulary and L_t denotes the length of a candidate program. The decoder receives the environmental context, which comprises a depth buffer with dimensions of $30 \times 40 \times 15$ and an RGB automap buffer

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with dimensions of $30 \times 120 \times 15$, obtained by executing program segments through the Vizdoom interpreter, along with the candidate program embedding, as inputs.

Table 2: The decoder structure aimed at enhancing program synthesis through environmental contexts.

Layers	Output
128-2 GATv2Conv LeakyReLU	$L_t \times 256$
128-2 GATv2Conv	$L_t \times 256$
3×3-1-8 Conv BN LeakyReLU	$30 \times 40 \times 8$
3×3-1-8 Conv BN LeakyReLU	$30 \times 40 \times 8$
9600-128 Linear	128
3×3-1-8 Conv BN LeakyReLU	$30 \times 120 \times 8$
3×3-1-8 Conv BN LeakyReLU	$30 \times 120 \times 8$
28800-128 Linear	128
256-2 LSTM	256
256-$\lvert\mathcal{V}\rvert$ Linear	$\lvert\mathcal{V}\rvert$

A.3 Hyper-parameters

LGRL [2]: We employ the identical architecture as the original implementation[1], which utilizes 2D convolution BN ReLU for I/O encoding. We set the kernel size to $d_{k_1} = 3$ and $d_{k_2} = 3$, convolutional stacks to $[64, 64, 64]$, fully-connected stack to 512, embedding size to 256, 2 layered LSTM hidden size to 256, and batch size to 8. The model is trained using Adam optimizer, with a learning rate of 10^{-4}, learned syntax penalty of 10^{-5}.

SED [6]: We utilize the I/O encoder architecture, as illustrated in Table 1, based on the original implementation[2]. For the synthesis model, we set the kernel size to $d_{k_1} = 3$ and $d_{k_2} = 3$, convolutional stacks to $[64, 64, 64]$, gradient clip to 5, warm-up to 40, bi-directional LSTM hidden size to 256, and batch size to 8. The model is trained using SGD optimizer, with a learning rate of 10^{-3} and decay rate of 0.5 after 100000 steps. For the debugger model, we set the mutate distribution to $[1, 2, 3]$, learning rate to 10^{-4}, and max beam to 50, while keeping other parameters the same.

Inferred Trace [10]: The architecture and parameters are similar to LGRL, with the addition of an extra 3×3-1-15 Conv BN LeakyReLU layer and a Linear layer for the encoder to infer execution traces. The decoder also includes a 3×3-1-8 Conv BN LeakyReLU layer and a Linear layer to incorporate the execution features.

Latent Execution [3]: The architecture used is identical to the original one[3]. We have set the embedding size to 1024, the hidden size of the 2 layered LSTM to 512, the hidden size of the single-layered MLP to 512, and the number of attention layers to 2. Additionally, we have set the gradient clip to 5, the batch size to 8, and enabled latent execution. The model has been trained using the SGD optimizer, with a learning rate of 10^{-4} and a decay rate of 0.9 after 6000 steps.

Transformer [12]: In order to facilitate I/O embedding learning, we have utilized the encoder structure (Table 1) on top of the Transformer. The Transformer embedding size has been set to 512, with 2 attention heads, 2 encoder layers, and 2 decoder layers. The remaining parameters are similar to LGRL.

EVAPS[4]: To enhance the quality of candidate programs by incorporating environmental contexts, we have utilized the decoder structure presented in Table 2. We have set the kernel size to $d_{k_1} = 3$ and $d_{k_2} = 3$, the convolutional stacks to $[64, 64, 64]$, the fully-connected stack to 512, the embedding size to 256, the hidden size of the 2 layered LSTM to 256, and the batch size to 4. Additionally, we have set the batch normalization momentum to 0.1 and the negative slope of the leakyReLU to 0.01.

[1] `https://github.com/bunelr/GandRL_for_NPS`

[2] `https://github.com/sunblaze-ucb/SED`

[3] `https://github.com/Jungyhuk/latent-execution`

[4] Implementation available at: `https://anonymous.4open.science/r/EVAPS-review`

The model has been trained using the Adam optimizer, with a learning rate of 10^{-4} and a learned syntax penalty of 10^{-5}.

B Additional Experimental Results

B.1 Dataset Properties

Overall Synthesis Benchmark. As delineated in Section 4.1, the dataset is engendered by adhering to the tenets of antecedent studies [2, 4, 6, 11], culminating in $100,000$ unique samples. The mean program sequence length for these instances amounts to 13.37 tokens, while the average steps necessitated for task completion is 4.59 steps. The program sequence length spans a range of 5 to 20 tokens, and the steps required vary between a minimum of 2 and a maximum of 13.

Task Complexity. The number of samples in each complexity category is visualized in Figure 1. Overall, the distribution of samples remains equitable, precluding the model from capturing invalid features and generating wrong tokens. The detailed information of each category is presented in Table 3.

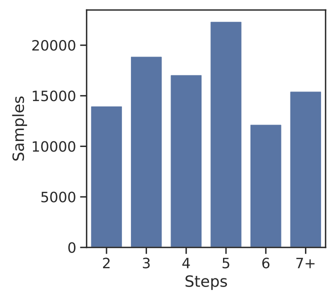

Figure 1: Distribution of the number of samples in each category.

Table 3: Detailed program information of varying levels of complexity.

Complexity	Program Length			Steps	
	Min	Max	Avg	Avg	Max
2	5	20	11.85	-	
3	6	20	14.18	-	
4	7	20	13.67	-	
5	8	20	13.52	-	
6	9	20	13.24	-	
7+	10	19	13.27	8.11	13

B.2 Additional Results

Task Complexity. Table 4 demonstrates the primary outcomes of the EVAPS model in comparison to other techniques when confronted with diverse levels of task complexity. Overall, as the task complexity escalates, EVAPS excels in decomposing tasks into more straightforward actions and exhibiting superior generalization. This underscores the efficacy of utilizing environmental contexts. Meanwhile, SED can still produce comparable outcomes by rectifying errors through execution traces.

Table 4: The average accuracy (with standard deviation) of all methods evaluated on three metrics in six complexity categories, assessed over 5 random seeds. The **best results** are highlighted in bold.

Complexity	Top-K	Methods	Exact Match	Semantic Match	Generalization
2	Top-1	LGRL	10.39% (0.92%)	67.53% (2.75%)	66.23% (1.84%)
		SED	52.72% (1.59%)	59.22% (1.91%)	58.83% (1.51%)
		Inferred Trace	25.97% (0.92%)	58.44% (1.84%)	57.14% (2.75%)
		Latent Execution	9.94% (2.75%)	68.83% (0.92%)	68.83% (0.91%)
		Transformer	35.06% (1.84%)	44.16% (2.75%)	42.86% (1.83%)
		EVAPS	**68.83%** (7.35%)	**74.03%** (1.32%)	**74.03%** (0.91%)
	Top-5	LGRL	12.99% (4.59%)	81.82% (0.92%)	80.52% (0.92%)
		SED	66.49% (4.93%)	73.25% (3.57%)	72.93% (5.38%)
		Inferred Trace	33.77% (1.83%)	72.73% (2.75%)	70.13% (0.92%)

Table 4 continued from previous page

		Latent Execution	15.94% (3.67%)	72.73% (2.75%)	71.42% (2.54%)
		Transformer	58.44% (2.75%)	70.13% (0.92%)	67.53% (1.03%)
		EVAPS	**83.12%** (6.43%)	**85.71%** (1.84%)	**83.12%** (0.92%)
	Top-20	LGRL	23.38% (1.83%)	85.71% (0.92%)	84.42% (0.92%)
		SED	69.61% (2.53%)	81.09% (1.81%)	81.06% (2.96%)
		Inferred Trace	44.16% (3.67%)	81.82% (3.28%)	79.22% (1.84%)
		Latent Execution	26.18% (2.75%)	79.22% (0.92%)	77.92% (1.08%)
		Transformer	75.32% (0.91%)	77.92% (6.43%)	75.32% (6.42%)
		EVAPS	**87.01%** (4.59%)	**88.31%** (1.86%)	**87.01%** (2.75%)
3	Top-1	LGRL	1.92% (1.36%)	44.23% (6.12%)	39.42% (5.43%)
		SED	43.84% (0.75%)	43.86% (3.01%)	43.84% (3.96%)
		Inferred Trace	22.12% (1.36%)	49.04% (1.39%)	46.15% (0.68%)
		Latent Execution	5.91% (1.06%)	**56.73%** (3.40%)	53.84% (3.39%)
		Transformer	15.38% (4.76%)	31.73% (2.04%)	31.73% (1.36%)
		EVAPS	**54.80%** (3.40%)	**56.73%** (6.12%)	**54.80%** (5.44%)
	Top-5	LGRL	2.88% (2.04%)	67.31% (1.36%)	63.46% (0.68%)
		SED	60.00% (0.75%)	65.76% (0.94%)	63.15% (0.79%)
		Inferred Trace	30.77% (3.40%)	60.58% (0.68%)	56.73% (2.72%)
		Latent Execution	11.01% (0.68%)	62.50% (5.19%)	60.58% (5.88%)
		Transformer	34.62% (3.40%)	59.62% (5.44%)	59.62% (4.76%)
		EVAPS	**71.15%** (1.36%)	**76.92%** (0.68%)	**75.00%** (0.79%)
	Top-20	LGRL	7.69% (3.40%)	76.92% (1.35%)	74.03% (0.68%)
		SED	65.38% (0.72%)	76.92% (3.39%)	76.73% (4.28%)
		Inferred Trace	46.15% (0.69%)	74.04% (0.67%)	71.15% (1.04%)
		Latent Execution	24.55% (1.36%)	73.08% (3.39%)	71.15% (4.76%)
		Transformer	59.61% (1.36%)	81.73% (1.35%)	80.76% (2.07%)
		EVAPS	**80.77%** (2.72%)	**83.65%** (0.68%)	**81.73%** (0.91%)
4	Top-1	LGRL	4.25% (0.75%)	39.36% (1.50%)	36.17% (1.50%)
		SED	34.89% (0.98%)	34.89% (0.13%)	34.89% (0.45%)
		Inferred Trace	19.14% (2.26%)	39.36% (1.50%)	36.17% (2.25%)
		Latent Execution	5.43% (0.75%)	36.17% (2.26%)	34.04% (3.01%)
		Transformer	10.64% (0.75%)	24.47% (4.51%)	22.34% (3.44%)
		EVAPS	**43.62%** (3.76%)	**46.81%** (2.25%)	**43.62%** (2.56%)
	Top-5	LGRL	10.64% (3.01%)	57.45% (0.75%)	53.19% (0.75%)
		SED	50.21% (3.85%)	56.98% (0.57%)	56.70% (2.07%)
		Inferred Trace	29.78% (3.01%)	51.06% (3.08%)	46.81% (4.51%)
		Latent Execution	14.05% (0.75%)	38.30% (1.50%)	36.17% (2.26%)
		Transformer	35.11% (5.26%)	47.87% (4.31%)	46.81% (5.27%)
		EVAPS	**56.38%** (1.50%)	**65.96%** (3.01%)	**62.77%** (2.26%)
	Top-20	LGRL	15.96% (2.26%)	67.02% (3.76%)	64.89% (0.75%)
		SED	57.87% (3.15%)	69.16% (3.25%)	69.00% (4.94%)
		Inferred Trace	37.23% (3.15%)	59.57% (1.50%)	56.38% (2.26%)
		Latent Execution	21.88% (1.54%)	54.26% (2.25%)	52.13% (2.26%)
		Transformer	43.62% (1.50%)	62.77% (0.75%)	60.64% (0.75%)
		EVAPS	**68.08%** (0.75%)	**74.47%** (2.25%)	**72.34%** (2.26%)
5	Top-1	LGRL	13.82% (0.57%)	30.89% (4.02%)	30.08% (3.45%)
		SED	40.98% (0.67%)	40.98% (0.29%)	40.98% (0.76%)
		Inferred Trace	23.58% (0.57%)	34.96% (0.74%)	34.96% (0.48%)
		Latent Execution	4.51% (1.72%)	42.28% (1.15%)	38.21% (2.30%)
		Transformer	20.33% (1.15%)	27.64% (2.30%)	24.64% (2.29%)

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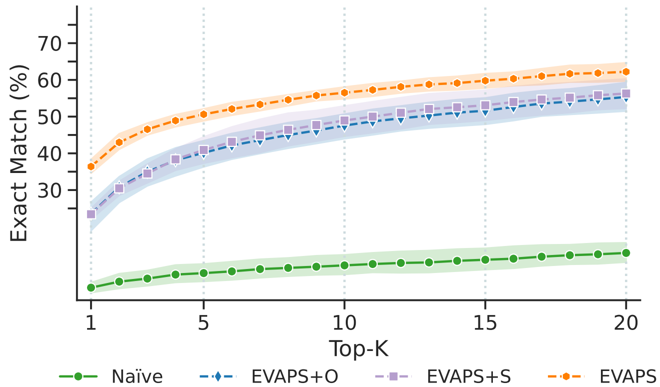
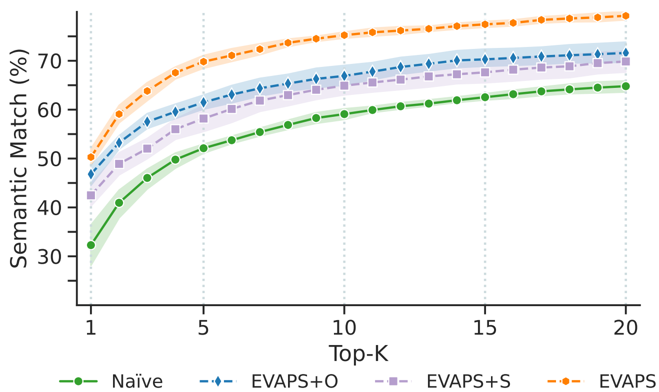
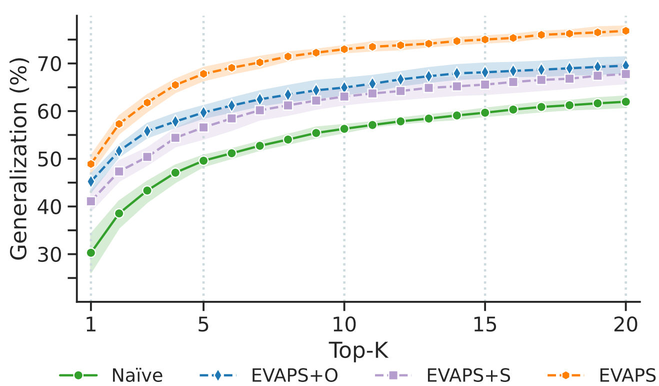
		EVAPS	**47.97%** (1.15%)	**52.03%** (1.14%)	**51.22%** (1.23%)
	Top-5	LGRL	21.14% (3.45%)	47.97% (2.87%)	47.15% (2.30%)
		SED	57.84% (3.54%)	58.54% (2.02%)	58.01% (3.07%)
		Inferred Trace	31.70% (4.02%)	50.41% (0.57%)	49.59% (1.58%)
		Latent Execution	7.07% (2.87%)	44.72% (0.57%)	43.09% (1.72%)
		Transformer	36.59% (2.53%)	43.08% (1.72%)	42.27% (1.76%)
		EVAPS	**59.35%** (0.57%)	**66.67%** (1.72%)	**65.85%** (1.65%)
	Top-20	LGRL	26.83% (2.29%)	58.54% (5.75%)	56.91% (5.17%)
		SED	65.84% (2.84%)	66.80% (1.94%)	66.78% (2.53%)
		Inferred Trace	46.34% (0.75%)	61.79% (1.15%)	60.98% (1.14%)
		Latent Execution	17.82% (3.89%)	52.85% (2.29%)	52.03% (2.53%)
		Transformer	49.59% (1.14%)	59.35% (1.15%)	58.54% (1.97%)
		EVAPS	**65.85%** (2.87%)	**71.54%** (1.74%)	**69.11%** (1.72%)
6	Top-1	LGRL	11.94% (3.17%)	29.85% (2.11%)	25.37% (1.05%)
		SED	40.60% (0.22%)	40.60% (1.83%)	40.60% (2.88%)
		Inferred Trace	20.90% (1.06%)	40.30% (2.11%)	38.81% (3.17%)
		Latent Execution	3.81% (1.06%)	32.84% (3.17%)	31.34% (4.22%)
		Transformer	8.96% (1.05%)	22.39% (2.31%)	19.40% (1.06%)
		EVAPS	**49.25%** (2.11%)	**53.73%** (3.16%)	**50.75%** (1.06%)
	Top-5	LGRL	19.40% (2.11%)	52.24% (2.11%)	46.27% (1.07%)
		SED	57.31% (0.34%)	62.71% (1.15%)	61.46% (2.21%)
		Inferred Trace	38.80% (1.06%)	64.18% (1.05%)	59.70% (1.53%)
		Latent Execution	6.94% (1.05%)	38.81% (1.06%)	32.84% (2.11%)
		Transformer	31.34% (1.06%)	55.22% (5.28%)	50.75% (5.26%)
		EVAPS	**64.18%** (4.22%)	**76.12%** (2.11%)	**71.64%** (1.05%)
	Top-20	LGRL	31.34% (3.17%)	65.67% (1.06%)	61.19% (1.05%)
		SED	63.28% (1.44%)	74.35% (1.70%)	74.08% (4.86%)
		Inferred Trace	47.76% (3.17%)	68.66% (2.11%)	64.18% (2.17%)
		Latent Execution	18.16% (1.38%)	47.76% (2.17%)	43.28% (2.06%)
		Transformer	55.22% (1.58%)	67.16% (3.17%)	62.69% (3.16%)
		EVAPS	**68.66%** (2.07%)	**83.58%** (2.65%)	**79.10%** (1.06%)
7+	Top-1	LGRL	9.41% (0.83%)	22.35% (0.66%)	21.18% (0.82%)
		SED	39.53% (0.83%)	39.53% (1.91%)	39.53% (2.34%)
		Inferred Trace	21.18% (3.32%)	36.47% (2.49%)	35.29% (3.27%)
		Latent Execution	3.18% (0.83%)	27.06% (2.49%)	27.06% (2.56%)
		Transformer	14.12% (3.32%)	18.82% (0.83%)	18.82% (0.89%)
		EVAPS	**52.94%** (4.99%)	**52.94%** (4.34%)	**49.41%** (3.32%)
	Top-5	LGRL	21.17% (0.83%)	54.12% (0.83%)	51.76% (0.32%)
		SED	55.53% (0.89%)	58.85% (1.35%)	58.85% (1.07%)
		Inferred Trace	42.35% (2.49%)	58.82% (1.66%)	56.47% (0.83%)
		Latent Execution	7.76% (2.70%)	31.76% (2.50%)	31.76% (1.66%)
		Transformer	32.94% (7.48%)	42.35% (8.32%)	42.35% (8.31%)
		EVAPS	**65.89%** (0.83%)	**71.76%** (2.50%)	**69.41%** (1.66%)
	Top-20	LGRL	27.06% (2.49%)	67.06% (1.56%)	63.52% (5.82%)
		SED	68.66% (2.49%)	71.29% (2.36%)	71.29% (3.01%)
		Inferred Trace	56.47% (0.83%)	70.59% (1.66%)	67.06% (1.37%)
		Latent Execution	17.64% (3.32%)	50.59% (2.31%)	49.41% (2.46%)
		Transformer	49.41% (3.25%)	63.53% (4.99%)	61.18% (4.16%)
		EVAPS	**74.12%** (0.83%)	**77.65%** (1.89%)	**75.29%** (0.81%)



(a) Exact Match



(b) Semantic Match



(c) Generalization

Figure 2: The visualized ablation results, depicting a range from Top-1 to Top-20, and are accompanied by a 95% confidence interval band.

Ablation Study. Figure 2 illustrates the comprehensive ablation results evaluated on three metrics. It can be inferred that the generalization ability is enhanced by leveraging partial observations or aligning code symbols, and this improvement is particularly noticeable in predicting exact matched sequences. Furthermore, the interval band for EVAPS is smaller than that of EVAPS+O and EVAPS+S, indicating that the model's stability and robustness are enhanced by incorporating both modules.

C Broader Impact

The fundamental concept of utilizing environmental observations and aligning them with code symbols to enhance program synthesis generalization capability can be implemented in actual robotic devices. Although the idea holds promise for real-world scenarios, the current focus is on program generation. We anticipate that the proposed method will not generate any biased or offensive content. However, when gathering observation data from the surroundings, it is imperative to avoid infringing on privacy. Robots are bound to interact with the environment, and to enable the proposed model, environmental data collection is necessary. Typically, the data comprises RGB images that may contain facial data or result in other forms of privacy infringement. Therefore, it is crucial to ensure that the collected environmental data is desensitized before further analysis. We recommend utilizing the proposed algorithm solely for research purposes.

References

[1] Shaked Brody, Uri Alon, and Eran Yahav. How attentive are graph attention networks? In *ICLR*, 2022.

[2] Rudy Bunel, Matthew Hausknecht, Jacob Devlin, Rishabh Singh, and Pushmeet Kohli. Leveraging grammar and reinforcement learning for neural program synthesis. In *ICLR*, 2018.

[3] Xinyun Chen, Dawn Song, and Yuandong Tian. Latent execution for neural program synthesis beyond domain-specific languages. In *NeurIPS*, 2021.

[4] Xuguang Duan, Qi Wu, Chuang Gan, Yiwei Zhang, Wenbing Huang, Anton Van Den Hengel, and Wenwu Zhu. Watch, reason and code: Learning to represent videos using program. In *ACM MM*, 2019.

[5] Matthias Fey and Jan Eric Lenssen. Fast graph representation learning with pytorch geometric. In *ICLR (RLGM Workshop)*, 2019.

[6] Kavi Gupta, Peter Ebert Christensen, Xinyun Chen, and Dawn Song. Synthesize, execute and debug: Learning to repair for neural program synthesis. In *NeurIPS*, 2020.

[7] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *CVPR*, 2016.

[8] Sergey Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In *ICML*, 2015.

[9] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. Pytorch: An imperative style, high-performance deep learning library. In *NeurIPS*, 2019.

[10] Eui Chul Shin, Illia Polosukhin, and Dawn Song. Improving neural program synthesis with inferred execution traces. In *NeurIPS*, 2018.

[11] Shao-Hua Sun, Hyeonwoo Noh, Sriram Somasundaram, and Joseph Lim. Neural program synthesis from diverse demonstration videos. In *ICML*, 2018.

[12] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *NeurIPS*, 2017.