Abstract

Recently, natural policy gradient algorithms gained widespread recognition due to their strong performance in reinforcement learning tasks [12, 13]. However, their major drawback is the need to secure the policy being in a ‘trust region’ and meanwhile allowing for sufficient exploration. The main objective of this study was to present an approach which models dynamical isometry of agents policies by estimating conditioning of its Jacobian at individual points in the environment space. We present a Jacobian Policy Optimization algorithm for policy optimization, which dynamically adapts the trust interval with respect to policy conditioning. The suggested approach was tested across a range of Atari environments. This paper offers some important insights into an improvement of policy optimization in reinforcement learning tasks.

1 Introduction

In recent years, the best results in the field of reinforcement learning (RL) were achieved by natural policy gradient methods such as Trust Region Policy Optimization (TRPO) [12], Proximal Policy Optimization (PPO) [13] and Kronecker-Factored Approximated Curvature (K-FAC) [16]. These methods are relatively complicated but outperform approaches such as deep Q-learning [8] or policy gradient methods [6] on Atari games, Mujoco, Roboschool and in other RL environments.

In RL, the distribution over inputs is changing over time and it is difficult to choose the step size that will secure an appropriate input distribution over the course of the optimization process. This problem is also relevant for PPO. It is difficult to choose a suitable clipping value that will work over the course of training. This difficulty is caused by various factors such as sparsity of rewards or highly noisy gradients [5]. A common method for handling these problems is the application of auxiliary modules. If an agent gets trapped in extreme environment states, a model can start visiting ineligible parts of the state space.

As a result, the agent has a productive strategy only in a small area of the environment, which lead to the unpredictable outputs of the policy network for unseen states. This behavior seems similar to the pathology existing in the Generative Adversarial Networks (GANs) [1] called “mode collapse” [14], the collapse lies in the fact that GANs characterize only a few modes of the true distribution.

The link between GANs and RL has been described before. Pfau et. al. [11] draws parallels between Actor-Critic (ACs) approach [17] and generative models. In this paper, the authors review GANs as ACs methods in the environment where the actor cannot effect the reward. In both GANs and ACs, the information flow is a simple feed forward pass from one model, which either generates a sample
or takes an action, to a second model, which evaluates the first model output. Both of these models suffer from several stability issues. Therefore the authors reviewed the strategies for stabilizing training for each class of models.

This paper attempts to clarify the connection between policy optimization and generator regularization through studying distribution of Jacobian singular values.

This paper also intends to determine the extent to which degree policy should be trusted in general. At certain points in the optimization process, it might be worth changing the policy. PPO algorithms try to solve this problem by computing an update at each step that minimizes the cost function, while ensuring a relatively small deviation from the previous policy. Contrary to that, we propose a method, which allows for more deviation from the old policy, when the evaluation of the old policy showed a poor result.

This paper seeks to improve the current state PPO by introducing a Jacobian policy optimization algorithm. The essential idea of this algorithm is the option for a decrease of the clip when there is a need for more trust of the old policy. Vice versa, it is possible to increase the clip when there is a need for bigger changes in the policy. To achieve this, we use method of sampling additional states and apply Jacobian clamping [9] for further regularization. It is propose to determine the clip value of the algorithm internally by using the Jacobian norm which depends on policy changes on slightly different states. To evaluate the amount of change to the clip value, the condition number of the old policy derived through sampling additional states was used.

We propose and test a policy optimization algorithm with the described regularization technique, which we call Jacobian Policy Optimization. Jacobian Policy Optimization directly estimates the condition number of an agent and, based on this, changes the policy trend. At individual points in the environment space, we study the squared singular values of the agent’s Jacobian and find correspondence between the conditioning of the Jacobian and the ratio of achieved rewards. Our aim here is not to claim state-of-the-art scores, but to provide evidence of a causal relationship between Jacobian values and the performance of a policy. We train a PPO model with squared singular value and demonstrate on Atari environments that an inclusion of squared singular Jacobian values in the model improves the scores of the agent in many cases.

To sum up, the contribution of this paper consists of:

- Presenting an approach, which models dynamical isometry of agent’s policies by estimating conditioning of its Jacobian at individual points in the environment space.
- Presenting a Jacobian Policy Optimization algorithm for policy optimization, which dynamically adapts trust intervals with respect to policy conditioning.
- Analyzing the behavior of Jacobian Policy Optimization in Atari environments with a focus on the relation between scores and condition number.

2 Background

2.1 Vanilla policy gradient

Williams et. al. [15] proposed the commonly used method for policy gradient estimation:

\[ \hat{g} = \mathbb{E}_t [\nabla \theta \log \pi_\theta (a_t | s_t) r_t] \]  

Where \( \pi_\theta \) is a parameterized stochastic policy. Alongside with the corresponding framework for minimizing the following surrogate objective based on a method closely related to stochastic gradient descent:

\[ L_{PG}(\theta) = \mathbb{E}_t [\log \pi_\theta (a_t | s_t) r_t] \]  

The expectation \( \mathbb{E}_t \) is taken across several timesteps up to a finite horizon with reward \( r_t \). Implementations that use automatic differentiation software work by constructing an objective function whose gradient is the policy gradient estimator.

There are many methods for estimating a policy. For example, AC methods use value function approximation to get a lower variance advantage estimate [17]. One of the main disadvantages of the vanilla policy gradient method is that the variance of vanilla policy gradient is large, and large policy updates can cause policy performance degradation.
2.2 Trust Region Policy Optimization

In TRPO, a surrogate objective for local approximation of the expected return of the policy was introduced:

\[
L_{\text{IS}}(\theta) = \hat{E}_t \left[ \frac{\pi_\theta(a_t \mid s_t)}{\pi_{\text{old}}(a_t \mid s_t)} \hat{A}_t \right]
\]

where IS stands for “importance sampling”. With recurrent policy, this gradient method requires to be run for \( T \) timesteps and then compute the advantage estimation \( \hat{A}_t \) with this trajectory:

\[
\hat{A}_t = -V(s_t) + r_t + \gamma r_{t+1} + \cdots + \gamma^{T-t+1} r_{T-1} + \gamma^T V(s_T).
\]

A truncated version of generalized advantage estimation (Eq. 5) when \( \lambda = 1 \) looks like:

\[
\hat{A}_t = \delta_t + (\gamma \lambda) \delta_{t+1} + \cdots + (\gamma \lambda)^{T-t+1} \delta_{T-1}
\]

where \( \delta_t = r_t + \gamma V(s_{t+1}) - V(s_t) \). This variant is differentiable in the same way as the vanilla policy gradient following the chain rule when \( \theta = \theta_{\text{old}} \):

\[
\nabla_\theta \log f(\theta)|_{\theta_{\text{old}}} = \nabla_\theta \left( \frac{f(\theta) \mid \theta_{\text{old}}}{f(\theta) \mid \theta_{\text{old}}} \right) \bigg|_{\theta_{\text{old}}}
\]

Due to locality of the approximation in TRPO [12] forced the policy to stay in a “trust region” and provided theoretical justification, which led to a guarantee of a strict increase in policy performance. Such a restriction is achieved by calculating each policy step based on the solution of the constrained optimization problem:

maximize \( \hat{E}_t \left[ \frac{\pi_\theta(a_t \mid s_t)}{\pi_{\text{old}}(a_t \mid s_t)} \hat{A}_t \right] \)

subject to \( \hat{E}_t [\text{KL} [\pi_{\text{old}}(\cdot \mid s_t), \pi_\theta(\cdot \mid s_t)]] \leq \delta \).

Since this is a demanding problem to solve itself, they used linear approximation for the objective and quadratic approximation for the constraint. Furthermore, the problem can be reformulated by replacing the constraint with a penalty:

\[
\hat{E}_t \left[ \frac{\pi_\theta(a_t \mid s_t)}{\pi_{\text{old}}(a_t \mid s_t)} \hat{A}_t \right] - \beta \hat{E}_t [\text{KL} [\pi_{\text{old}}(\cdot \mid s_t), \pi_\theta(\cdot \mid s_t)]]
\]

Nonetheless, TRPO methods typically use a constraint rather than a penalty. Due to the fact that a suitable choice of \( \beta \) is hard to achieve across dissimilar tasks. In addition to that, it is unsafe to rely on \( \beta \) in problems where environmental characteristics change during the learning process.

2.3 Proximal Policy Optimization

Unlike TRPO, PPO is a method which strikes a balance between an ease of implementation, a sample complexity, and an ease of tuning. In the PPO version featuring KL penalty, the penalty coefficient \( \beta \) dynamically scales to force a change of the trust region.

The PPO method represents an alternative approach to the natural gradient. While TRPO forces locality assumptions by using constraints, PPO clips probability ratio between the two following consecutive policies:

\[
r_t(\theta) = \frac{\pi_\theta(a_t \mid s_t)}{\pi_{\text{old}}(a_t \mid s_t)}
\]

\[
L^{\text{CLIP}}(\theta) = \hat{E}_t \left[ \min \left( r_t(\theta) \hat{A}_t, \text{clip} (r_t(\theta), 1 - \eta, 1 + \eta) \hat{A}_t \right) \right].
\]
2.4 Dynamic Isometry and Jacobian Clamping

Dynamic Isometry is a property of neural networks, which states that the distance between the inputs of a network should be the same as the distance between outputs. Recently, [10], has shown that this property can be achieved by having a mean squared singular value of a networks input-output Jacobian equal to $O(1)$. Free probability theory was applied to analytically estimate the entire distribution of Jacobian singular values as a function of non-linearity, depth, and initial distribution.

It was shown that well conditioned neural networks, e.g., with orthogonal weight initialization, can dramatically speedup training, especially for very deep networks with dozens of layers without BatchNorm [3] and residual connections [2].

Using results of Dynamic Isometry techniques, [9] have studied the dynamics of singular values of generator’s Jacobian in GANs, and the authors have noted a robust coherence between the conditioning of the Jacobian and two determinable metrics for evaluating GANs: the Inception Score and the Frechet Inception Distance (FID).

Also a Jacobian Clamping (JC) regularization technique was proposed [9]. It penalizes the condition number of the generator’s Jacobian to bring it inside the interval where the isometry property would be achieved. The authors also proposed a simple and efficient approach to estimate singular values of the Jacobian of a deep neural network:

$$J = \frac{\|G(z) - G(z + \epsilon)\|}{\|\epsilon\|},$$

where $G$ is generator, $z \sim p(z)$, $\epsilon \sim \mathcal{U}_s(0, 1)$ and $\mathcal{U}_s$ is uniformly distributed from a unit sphere.

Experiments have shown that JC can stabilize generator behaviour and help it to avoid mode collapse, which means that in general it can help networks to preserve wide coverage of a desired distribution.

3 Conditioning in RL Agents

Another experiment on PPOs verified [13] that PPOs with clipped probability ratio perform the best. However, the authors reported that it was difficult to choose the right clipping interval width.

How to form a constraint value to get the best policy? It is natural to interpret this as a value which determines how much we trust the old established policy. The idea proposed in this paper is that, given some certain trust region that is locally approximated, we want to check in some way how much the region can be trusted and accordingly update our policy with respect to this knowledge.

If we have evaluative functions that can correctly assess the correctness of a strategy, then we can change the direction of a strategy development. Turning to the methods of estimating Dynamic Isometry in deep non-linear networks and in generative opposing models, we assume that the policy assessment on the property of Dynamic Isometry will allow us, approximately, to determine how well the policy is formed.

When using conditioning as a policy assessment, we assume that the learning algorithm should look like this: As in Jacobian Clamping paper for GANs [10], we feed to the agent 2 mini-batches at a time, among which one batch is the current state of environment, the other is also the current state but with some added disturbance. The norm $\epsilon$ defines the size of the disturbance. We use Jacobian estimation on the old policy to see how much it changes depends on small changes of input.

4 Analysis of Conditioning and Policy Performance

We use conditioning in RL agents, to indirectly answer the questions: How stable is the formed policy? How much does it depend on small changes of the state region? Is it possible to derive some characteristic on how much we need to change the policy at each time step? And based on that, make a guess on how big the trust in the old policy should be.

To test the relationship between condition and policy performance, we conducted several experiments in two environment with different rewards dynamics. For each environment we create a set of agents with different hyperparameters (for more details see Experiments chapter). We noticed a relationship between policy indicators and reward curves, results presented in Figures 1, 2.
Figures 1 and 2 illustrate the conditional number and reward curves for games during training. Each curve is produced by models with different hyperparameters.

Exploring the PPO reward and condition curves, we assumed that the agent’s assessment of the dynamic isometric property would allow us to update the policy in more correct ranges, by evaluating the condition number of the old policy.

4.1 Jacobian Policy Optimizations

Contrasting to the standard PPO implementation, the interval in which the probability is clipped may increase and decrease during the process of agent’s training. First, we consider the condition number metric $C$, and then use this value to calculate the clip parameter in the surrogate objective. The resulting clip parameters which equal to condition number $C$ controls the minimum value to
Algorithm 1 Clipping Jacobian Policy Optimization.

**Input:** norm \( \varepsilon \), target quotients \( \lambda_{\text{max}}, \lambda_{\text{min}} \), minibatch size \( M \), number of epochs \( K \)

for iteration 1,2,..., do
  for actor 1,2,...,N do
    \( z \in R^{B \times n_z} \sim p_z \)
    \( \delta \in R^{B \times n_z} \sim U_b(0,1) \)
    \( \delta := (\delta / ||\delta||) \varepsilon \)
    for Timesteps \( t, \ldots, T \) do
      Make action with policy \( \pi_{\theta_{\text{old}}} \) at state \( S_t \)
      Compute \( J_t = \frac{||\pi_{\theta_{\text{old}}}(S_t) - \pi_{\theta_{\text{old}}}(S_t + \delta)||}{||\delta||} \)
      \( C_{t_{\text{max}}} = (\max (J_t, \lambda_{\text{max}}) - \lambda_{\text{max}})^2 \)
      \( C_{t_{\text{min}}} = (\min (J_t, \lambda_{\text{min}}) - \lambda_{\text{min}})^2 \)
      \( C_t = C_{t_{\text{min}}} + C_{t_{\text{max}}} \)
      Compute advantage estimation \( \hat{A}_t \)
    end for
  Compute mean \( C \)
  Optimize clipped surrogate \( L_{\text{CCLIP}} \) wrt \( \theta \), with \( K \) epochs and minibatch size \( M \) using \( C \) as clip parameter.
  \( \theta_{\text{old}} \leftarrow \theta \)
end for

which the clip parameter can drop.

\[
L_{\text{CCLIP}}(\theta) = \mathbb{E}_t \left[ \min \left( r_t(\theta) \hat{A}_t, \text{clip} \left( r_t(\theta), 1 - C, 1 + C \right) \hat{A}_t \right) \right] \tag{11}
\]

Using Jacobian clipping techniques, the total loss is then formed taking into account the squared-error loss \( L_t^{VF}(V_\theta(s_t) - V_t^{\text{targ}})^2 \) of the value function \( V_\theta \), with value loss coefficient \( c_1 \) and entropy \( S[\pi_\theta](s_t) \) for state \( s_t \) entropy coefficient \( c_2 \) and \( L_{\text{CCLIP}} \) is a Condition clip PPO.

\[
L_{t_{\text{CCLIP}}+VF+S}(\theta) = \mathbb{E}_t \left[ L_{t_{\text{CCLIP}}}(\theta) - c_1 L_t^{VF}(\theta) + c_2 S[\pi_\theta](s_t) \right]. \tag{12}
\]

As for the PPO algorithm, our method utilized fixed-length trajectory segments too. The learning procedure is presented in Algorithm 1.

Additionally, we also use the conditioning parameter \( C \) as a penalty in total loss. When we used this technique, we did not use the condition number in the clip parameter. Condition penalty can be applied to other natural policy optimization algorithms too.

\[
L_{t_{\text{CCLIP}}+VF+S+C}(\theta) = \mathbb{E}_t \left[ L_{t_{\text{CCLIP}}}(\theta) - c_1 L_t^{VF}(\theta) + c_2 S[\pi_\theta](s_t) \right] + C. \tag{13}
\]

Where \( L_{\text{CCLIP}} \) is a standard PPO clip method, based on hyperparameter clip value.

5 Experiments

To analyze the behaviour of our method, we tested it on 49 Atari games. We have retained hyperparameters similarly to PPO for our models. The reason for that was to allow for an estimation on how much the regularization of the clip parameter depends on the condition number can affect the quality of learning.

Our experiments are conducted on a machine with 4 separate NVIDIA GeForce GTX 1080 Ti, 16 core Intel i5-6600K processor and 128 GB RAM memory. We use PyTorch 1.0 with CUDA 9 support for implementation of all models presented in the study.

5.1 Atari Domain

Clipping Jacobian Policy Optimization For comparison with PPO in the Atari domain, we used several models. We noticed a high dependence between the \( \varepsilon \) parameter in the condition number
Figure 3: Curve of rewards received by several models on Atari problems that were trained for 10 million timesteps. The figure demonstrates results on 8 tasks where the JPO method achieved the best results. The settings in the methods correspond to Table 1.

Table 1: Comparison of JPO and PPO mean final scores on last 100 episodes \[13\] after training for 10 million timesteps. Bold values are higher than PPO.

| Game            | PPO    | JPO clip | JPO clip1 | JPO reg |
|-----------------|--------|----------|-----------|---------|
| BeamRider       | 1590.0 | 1846.0   | 427.2     | 716.5   |
| ChopperCommand  | 3516.3 | 7367.6   | 928.9     | 3943.5  |
| Gopher          | 2932.9 | 3837.4   | 858.1     | 922.1   |
| Pitfall         | -32.9  | -3.8     | -26.9     | -98.5   |
| KungFuMaster    | 23310.3| 32009.3  | 15827.9   | 46843.9 |
| PrivateEye      | 69.5   | 100.0    | 25.2      | 95.5    |
| FishingDerby    | 17.8   | 29.8     | -83.6     | -53.4   |
| Seaquest        | 1204.5 | 1816.3   | 1608.7    | 926.8   |
| Frostbite       | 314.2  | 285.8    | 276.5     | 634.5   |
| RoadRunner      | 25076.0| 8290.9   | 19820.8   | 38906.9 |
| DoubleDunk      | -14.9  | -15.4    | -16.8     | -12.7   |
| Breakout        | 274.8  | 328.7    | 121.7     | 151.7   |
| Krull           | 7942.3 | 8716.8   | 7594.9    | 6540.2  |

estimation algorithm and the speed at which value of $C$ approached the desired $\lambda$ range. In view of this, we tested several identical algorithms with their only difference being a variation in the value of $\varepsilon$. We used the condition number on the line as the clip parameter at $\varepsilon$ equal to 1 (JPO CLIP 1), and multiplying $C$ by the coefficient 0.1, when $\varepsilon$ was equal to 10 (JPO CLIP 1), see Table 1 and Figure 3.
We used a Multilayer Perceptron with two hidden layers of 64 units, and \texttt{tanh} nonlinearities based on the implementation of \cite{1}. The GAE learning rate was set to \(2.5\times10^{-4}\), the coefficient for value loss to 0.5 and the entropy coefficient to 0.01. The number of processes was 4 with number of steps set to 128. 4 PPO epochs without using linear clip decay were executed. The size of mini-batches was 4 for Pong, and 32 for other tasks.

Experiments show that the PPO algorithm is very sensitive to the value of the clip parameter. The selection of the clip parameter is very important, condition number allow to determine this value more accurately, on some tasks JPO outperforms PPO dramatically.

**Regularization Jacobian Policy Optimization** Separately, we used the value of \(C\) in the most explicit form, just as it was used in the GANs settings. We used the PPO algorithm and added value of \(C\) to the total loss, produced with \(\varepsilon\) equal to 1. Model settings were equal to the settings used in Clipping Jacobian Policy Optimization. See JPO REG in table 1 and Figure 3.

6 Discussion

The results demonstrated in this paper still do not fully describe the relationship between condition numbers and agent policy. As it was shown in some experiments in Atari environments. In fairly complex environments, the condition number almost immediately falls into the specified range. Our assumption is that it is necessary to more carefully adjust the upper limit \(\lambda_{\text{max}}\). In our experiments, the condition number is very often in the range, since \(\lambda_{\text{max}}\) was set equal to 20. Perhaps by setting a lower upper bound, it is possible to get a more accurate clip parameter of the agent.

Another method of regulating the value of Jacobians in such problems is a more careful selection of the parameter \(\varepsilon\). We noticed that JPO is very sensitive to \(\varepsilon\). Different games have a different environment dynamics, and small noise added to the states can be ignored by a policy. In an best scenario it is necessary to select \(\varepsilon\) individual for each of the environment. Demonstrate that we run a several JPO algorithms with different \(\varepsilon\), Figure 4.

![Figure 4: Reward curves for different \(\varepsilon\).](image)

We tested values from 1 to 10, since they immediately showed expressive results on the tasks of Atari. Perhaps, more correct values lie inside or outside these boundaries.

7 Conclusions and Future work

In this work we proposed a sample-efficient and computationally inexpensive optimization method for deep reinforcement learning. We used a newly proposed technique called Jacobian Policy Optimization to approximate the natural gradient update for an agent. We tested our method on the Atari domain and a in sample efficiency on average compared with PPO was observed.

For the future, an interesting field of research might be the development of techniques that control condition number in an explicit form, for example use condition number as clip parameter, and penalty in total loss at the same time. To avoid complete dependence on the value of norm \(\varepsilon\), we plan to calculate the square of the singular value through Singular Value Decomposition (SVD). Another future field of study is the application of this technique to more complex environments and tasks.
Finally, an important direction is the use of this technique in State-Of-The-Art methods which are based on PPO. We and more research on this topic needs to be undertaken that extending natural policy gradients methods with conditioning is a promising research direction.

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Figure 5: Curve of rewards received by several models on ATARI problems that were trained for 10 million timesteps. The results may not correlate a bit with the Table 2, since there we were compared with the values of the PPO specified in the PPO literature.
Table 2: Mean scores on last 100 episodes on ATARI after 10 million timesteps.

| GAME         | PPO  | JPO CLIP | JPO CLIP1 | JPO REG |
|--------------|------|----------|-----------|---------|
| ALIEN        | 1850.3 | 1823.0  | 1277.9 | 2066.9 |
| AMidar       | 674.6  | 627.1 | 273.2  | 704.6  |
| ASSault      | **4971.9** | 3798.6 | 2079.4 | 2187.0 |
| ASTerix      | **4532.5** | 3318.0 | 2077.3 | 3541.4 |
| ASTEROIDS    | **2097.5** | 1935.2 | 1052.3 | 1456.3 |
| ATLANTIS     | **2311815.0** | 571144.8 | 365956.8 | 753534.1 |
| BANKHEIST    | 1280.6 | 1159.6 | 938.9 | 797.6  |
| BATTLEZONE   | **17366.7** | 15640.3 | 3572.2 | 4483.2 |
| BEAMRIDER    | 1590.0 | **1846.0** | 472.2 | 716.5  |
| BOWLING      | 40.1  | 30.0 | 30.2  | 0.0    |
| BOXING       | 94.6  | 92.6 | 5.5  | 90.7   |
| BREAKOUT     | 274.8 | **328.7** | 121.7 | 151.7  |
| CENTIPEDE    | **4386.4** | 3582.6 | 2370.3 | 2064.3 |
| CHOPPERCOMMAND | 3516.3 | 1846.0 | 472.2 | 716.5  |
| CRAZYCLIMBER | 110202.0 | 114412.5 | 57160.0 | 114271.5 |
| DEMONATTACK  | **11378.4** | 9271.8 | 1588.6 | 5505.9 |
| DOUBLEDUNK   | -14.9 | -15.4 | -16.8 | -12.7 |
| ENDuro       | 758.3  | 703.0 | 67.4  | 709.5  |
| FISHINGDERBY | 17.8  | **29.8** | -83.0 | -53.4 |
| FREeway      | 32.5  | 32.6 | 25.8  | 32.4   |
| FROSTbite    | 314.2 | 285.8 | 276.6 | 634.5  |
| GOPHER       | 2932.9 | **3837.4** | 858.3 | 922.1  |
| GRAVITAR     | 737.2  | **776.4** | 529.6 | 49.9   |
| ICEHockey    | -4.2  | -5.0 | -8.901 | -1.9  |
| JAMESBOND    | 560.7  | **586.6** | 369.9 | 748.3  |
| KANGaroo     | **9928.7** | 4405.7 | 1770.6 | 599.6  |
| KRULL        | 7942.3 | **8716.8** | 7594.9 | 6540.2 |
| KUNGFuMaster | 23310.3 | 32099.3 | 15827.9 | **46843.9** |
| MONTEZUMARevenge | 42.0 | 0.1 | 0.0 | 0.0    |
| MsPacman     | 2096  | 1958.7 | 2012.8 | **2673.2** |
| NAMEThisGame | **6254.9** | 5954.3 | 3359.1 | 5389.5 |
| PItfall      | -32.9 | -3.8 | -26.9 | -98.4  |
| Pong         | 20.7  | 20.0 | 18.4 | 15.1   |
| PrivateEye   | 69.5  | **100.0** | 25.2 | 95.5   |
| Qbert        | 14293.3 | 13942.3 | 11847.7 | **14651.1** |
| RIVERraID    | **8393.6** | 8025.4 | 4682.2 | 8052.4 |
| ROADRunner   | 25076.0 | 8290.9 | 19820.8 | **38906.8** |
| ROBOTANK     | 5.5   | 3.2 | **6.0** | 2.1    |
| SEAquest     | 1204.5 | **1816.3** | 1608.7 | 926.7  |
| SPACEInvANDers | 942.5 | **1049.3** | 332.3 | 470.6  |
| STARgunner   | 32689.0 | **32716.3** | 3922.0 | 16209.4 |
| TenNIS       | -14.8 | -21.9 | -20.8 | -7.4   |
| TIMEpiLOT    | 4342.0 | 4203.0 | 3196.1 | **4676.6** |
| TUTANKHAM    | **254.4** | 157.2 | 132.5 | 101.2  |
| UPnDown      | 95445.0 | 23416.9 | 11122.4 | **108405.6** |
| VENTURE      | 0.0   | **2.0** | 1.8 | 0.0    |
| VIDEOPinBALL | **37389.0** | 36468.1 | 14634.4 | 24388.0 |
| WIZARDofWor | 4185.3 | **4584.9** | 673.1 | 2473.3 |
| ZAXXON       | **5008.7** | 2293.1 | 19.4 | 3654.3 |