Paper Writing Workshop

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Content

- What are you writing - Types of Paper Writing
- Purpose of Paper Writing
- Who is your audience
- Anatomy of a Research Paper
- Other Important Pieces of a Research Paper

Types of Paper Writing

- School Paper
    - Experiment Reports
- Conference/Workshop Paper
    - Surveys
    - Research Proposal
    - Research Report (Publishable Paper)

Why do we write papers?

- Reporting experiments
- Summarizing findings that contributes new knowledge to a body of knowledge
- Aggregating information about historical work done within a body of knowledge or specific subdomain

Paper Writing Tool

- Text Editor
  - MS Word
  - Latex
- Reference Tool
  - Mendeley
  - Zotero
- Spell Checker

Who is your Audience?

- People with similar background or within similar domain as the author’s
- People that can reproduce the work you’ve done give the appropriate methodology

Knowing your audience helps to know the level of details to include in your research paper.

Problem Statement Definition

- Must have element of novelty (new work)
- Must be feasible. How would the problem be solved?
- Must be ethical (approved by a designated ethics board)

Anatomy of a Technical Paper

- Abstract
- Introduction
- Related Work (Literature review)
- Methodology
  - Dataset Description
- Experiment, Results, Discussion
- Conclusion
- References

Anatomy of a Research Paper

ABSTRACT

- The shortest section of a paper about 100 - 150 words
- Executive Summary of Paper
- States the research problem/question
- Researcher’s contribution and answer to the research question
- How the answer was tested
- The impact of the research work
- Contains keywords about the research

Anatomy of a Research Paper - The Abstract

Addressing Function Approximation Error in Actor-Critic Methods

Scott Fujimoto[1] Herke van Hoof[2] David Meger[1]

arXiv:1802.09477v3 [cs.AI] 22 Oct 2018

1

2

Abstract

In value-based reinforcement learning methods such as deep Q-learning, function approximation errors are known to lead to overestimated value estimates and suboptimal policies. We show that this problem persists in an actor-critic setting and propose novel mechanisms to minimize its effects on both the actor and the critic. Our algorithm builds on Double Q-learning, by taking the minimum value between a pair of critics to limit overestimation. We draw the connection between target networks and overestimation bias, and suggest delaying policy updates to reduce per-update error and further improve performance. We evaluate our method on the suite of OpenAI gym tasks, outperforming the state of the art in every environment tested.

1. Introduction

In reinforcement learning problems with discrete action spaces, the issue of value overestimation as a result of function approximation errors is well-studied. However, similar issues with actor-critic methods in continuous control domains have been largely left untouched. In this paper, we show overestimation bias and the accumulation of error in temporal difference methods are present in an actor-critic setting. Our proposed method addresses these issues, and greatly outperforms the current state of the art.

Overestimation bias is a property of Q-learning in which the maximization of a noisy value estimate induces a consistent overestimation (Thrun & Schwartz, 1993). In a function approximation setting, this noise is unavoidable given the imprecision of the estimator. This inaccuracy is further exaggerated by the nature of temporal difference learning (Sutton, 1988), in which an estimate of the value function is updated using the estimate of a subsequent state. This means using an imprecise estimate within each update will lead to an accumulation of error. Due to overestimation bias, this accumulated error can cause arbitrarily bad states to be estimated as high value, resulting in suboptimal policy updates and divergent behavior.

This paper begins by establishing this overestimation property is also present for deterministic policy gradients (Silver et al., 2014), in the continuous control setting. Furthermore, we find the ubiquitous solution in the discrete action setting, Double DQN (Van Hasselt et al., 2016), to be ineffective in an actor-critic setting. During training, Double DQN estimates the value of the current policy with a separate target value function, allowing actions to be evaluated without maximization bias. Unfortunately, due to the slow-changing policy in an actor-critic setting, the current and target value estimates remain too similar to avoid maximization bias. This can be dealt with by adapting an older variant, Double Q-learning (Van Hasselt, 2010), to an actor-critic format by using a pair of independently trained critics. While this allows for a less biased value estimation, even an unbiased estimate with high variance can still lead to future overestimations in local regions of state space, which in turn can negatively affect the global policy. To address this concern, we propose a clipped Double Q-learning variant which leverages the notion that a value estimate suffering from overestimation bias can be used as an approximate upper-bound to the true value estimate. This favors underestimations, which do not tend to be propagated during learning, as actions with low value estimates are avoided by the policy.

Given the connection of noise to overestimation bias, this paper contains a number of components that address variance reduction. First, we show that target networks, a common approach in deep Q-learning methods, are critical for variance reduction by reducing the accumulation of errors. Second, to address the coupling of value and policy, we propose delaying policy updates until the value estimate has converged. Finally, we introduce a novel regularization strategy, where a SARSA-style update bootstraps similar action estimates to further reduce variance.

Our modifications are applied to the state of the art actor-critic method for continuous control, Deep Deterministic Policy Gradient algorithm (DDPG) (Lillicrap et al., 2015), to form the Twin Delayed Deep Deterministic policy gradient

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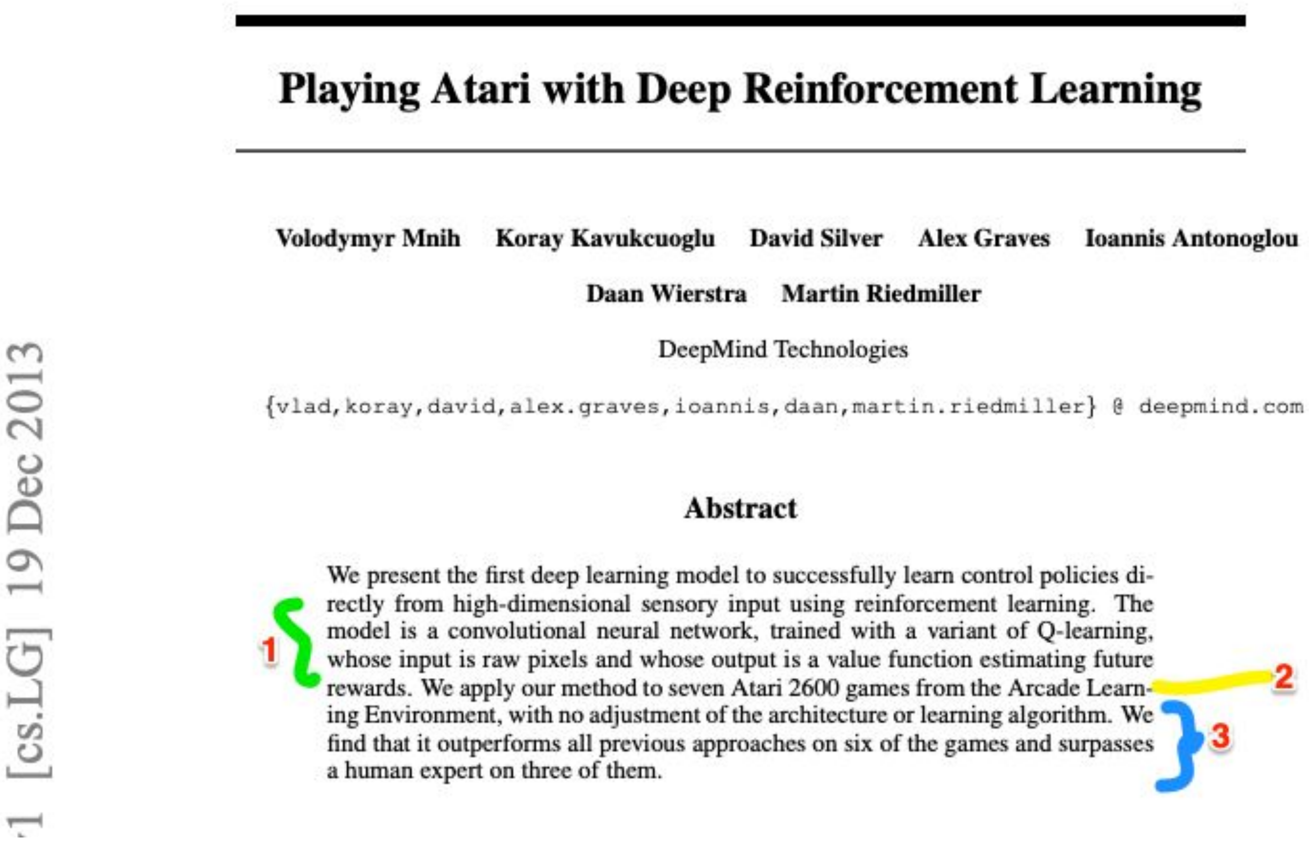
1 - Highlights the Research Problem/Question

2 - Highlights **specific contribution** towards answering research question

Source: https://arxiv.org/pdf/1802.09477.pdf

Anatomy of a Research Paper - The Abstract



Playing Atari with Deep Reinforcement Learning

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Abstract

We present the first deep learning model to successfully learn control policies directly from high-dimensional sensory input using reinforcement learning. The model is a convolutional neural network, trained with a variant of Q-learning, whose input is raw pixels and whose output is a value function estimating future rewards. We apply our method to seven Atari 2600 games from the Arcade Learning Environment, with no adjustment of the architecture or learning algorithm. We find that it outperforms all previous approaches on six of the games and surpasses a human expert on three of them.

1 - Researcher’s contribution to answering research question

2 - How the research was tested

3 - Impact of the research work

Source: https://arxiv.org/pdf/1312.5602.pdf

Anatomy of a Research Paper

INTRODUCTION

- Extended form of the abstract.
- Gives background and sets tone for the research work
- Starts from broad issues to very specific area of research
- **Goal: Provides context to research question**

Writing a Great Introduction

- Summarize current understanding of research about the subject topic till date
- State the purpose of your research problem
- Highlight set of questions that would be answered by your research
- Briefly explain the methodology & what the study might reveal
- Summarize the structure of the remainder of the paper

Anatomy of a Research Paper

RELATED WORK

- This covers historical work done on the related research problems and/or related techniques.
- Categorize previous works into themes
- Summarize themes in a coherent format

Components of Literature Review

- Overview of the subject matter under consideration
- Categorize sources (related works) into different themes.
- Discuss the distinctiveness of each source and its similarities with other sources.

Anatomy of a Research Paper

METHODOLOGY

- Highly technical and contains technical jargon about the subject matter
- Covers overview of experiments to be done to answer the research question
- Reproducible to get documented results.
- Does not have to be named Methodology - dive straight to its components

Components of Methodology - Model Description

- Model Description
    - Describe clearly the model architecture
    - Cover the key areas about objective of the modelling approach
        - Minimizing a Loss function
        - Maximizing a Reward Function
    - Use mathematical expressions to describe the model as needed

Components of Methodology - Dataset Description

- What dataset would be used
  - Type: Speech, Image, Video, 3D point clouds, and so on
  - Data Mode: Single Mode, Multimodal
- How was the dataset was collected?
- Are there preprocessing done - either by you or from the data source
- How do you intend to use the data
- State overall statistics of the dataset e.g. length of dataset, training to validation proportion, etc

Components of Methodology - Baseline & Evaluation Metrics

- What baseline are you selecting?
  - Is this a state-of-the-art, competitive existing baseline
  - Are you implementing a baseline from scratch? Why?
- What evaluation metrics would you be using?
  - clearly define the metrics to be used
  - demonstrate understanding of how the metrics work
    - Give mathematical formulae if applicable

Anatomy of a Research Paper

EXPERIMENTS, RESULTS & DISCUSSION

(a) Regular ImageNet-1K trained models

method	image size	#param.	FLOPs	throughput (image / s)	ImageNet top-1 acc.
RegNetY-4G [48]	224^2	21M	4.0G	1156.7	80.0
RegNetY-8G [48]	224^2	39M	8.0G	591.6	81.7
RegNetY-16G [48]	224^2	84M	16.0G	334.7	82.9
EffNet-B3 [58]	300^2	12M	1.8G	732.1	81.6
EffNet-B4 [58]	380^2	19M	4.2G	349.4	82.9
EffNet-B5 [58]	456^2	30M	9.9G	169.1	83.6
EffNet-B6 [58]	528^2	43M	19.0G	96.9	84.0
EffNet-B7 [58]	600^2	66M	37.0G	55.1	84.3
ViT-B/16 [20]	384^2	86M	55.4G	85.9	77.9
ViT-L/16 [20]	384^2	307M	190.7G	27.3	76.5
DeiT-S [63]	224^2	22M	4.6G	940.4	79.8
DeiT-B [63]	224^2	86M	17.5G	292.3	81.8
DeiT-B [63]	384^2	86M	55.4G	85.9	83.1
Swin-T	224^2	29M	4.5G	755.2	81.3
Swin-S	224^2	50M	8.7G	436.9	83.0
Swin-B	224^2	88M	15.4G	278.1	83.5
Swin-B	384^2	88M	47.0G	84.7	84.5

Source: https://arxiv.org/pdf/2103.14030v2.pdf

- Experiments section should contain details about hyperparameters, how the dataset was used and how evaluation was performed.
- Standard to report metrics in comparison with other work
  - Make sure to report under similar settings. If necessary/possible, run multiple times and report standard deviations.

Anatomy of a Research Paper

EXPERIMENTS, RESULTS & DISCUSSION

(Ablations)

Sub-Pillar	PE	Tiny-Pillar	DF	SA	Veh.	Ped.	Cyc.	Mean
					60.32	49.22	51.58	53.71
✓					60.13	52.32	54.91	55.79
✓	✓				61.35	53.50	56.58	57.14
		✓			63.11	56.89	61.74	60.58
		✓	✓		67.33	59.24	65.06	63.88
		✓	✓	✓	67.22	59.34	65.82	64.12
✓	✓	✓	✓	✓	67.32	60.49	66.04	64.62

Source: https://arxiv.org/pdf/2110.06049v1.pdf

- Ablations are *extremely* important.
- How much did **each proposed component** contribute to the final performance?

Anatomy of a Research Paper

EXPERIMENTS, RESULTS & DISCUSSION

(Ablations)

Improvements	Top-1	Δ
ResNet-200	79.0	—
+ Cosine LR Decay	79.3	**+0.3**
+ Increase training epochs	78.8 †	-0.5
+ EMA of weights	79.1	**+0.3**
+ Label Smoothing	80.4	**+1.3**
+ Stochastic Depth	80.6	**+0.2**
+ RandAugment	81.0	**+0.4**
+ Dropout on FC	80.7 ‡	-0.3
+ Decrease weight decay	82.2	**+1.5**
+ Squeeze-and-Excitation	82.9	**+0.7**
+ ResNet-D	83.4	**+0.5**

Model	Regularization	Weight Decay 1e-4	Weight Decay 4e-5	Δ
ResNet-50	None	79.7	78.7	-1.0
ResNet-50	RA-LS	82.4	82.3	-0.1
ResNet-50	RA-LS-DO	82.2	82.7	+0.5
ResNet-200	None	82.5	81.7	-0.8
ResNet-200	RA-LS	85.2	84.9	-0.3
ResNet-200	RA-LS-SD-DO	85.3	85.5	+0.2

Source: https://arxiv.org/pdf/2103.07579v1.pdf

- Ablations are *extremely* important.
- How much did **each proposed component** contribute to the final performance?
- Be careful! Consider relationships *between* components as well. Sometimes each one can lower performance but together boost performance.

Anatomy of a Research Paper

EXPERIMENTS, RESULTS & DISCUSSION

(Discussion)

- Discussion does not need to be its own section. However, it should outline the overall takeaways from your work.
- Often, these takeaways are fused in with the results & ablations.

Anatomy of a Research Paper

CONCLUSION

- Summary of work done.
- Reiterates the research question and findings from the research work that answers the research question
- Highlights what possible shortcomings of current work if any, areas for improvement, next steps/future work, possible extensions.

Anatomy of a Research Paper

REFERENCES

"In reference works, as in sin, omission is as bad as willful behaviour"

- Elizabeth McCracken

Referencing Styles

Different Referencing styles depending on the type of paper you are writing and the conference/workshop.

- IEEE Reference style - Most common for engineering papers
  - Conference Paper, Books, Journals are referenced slightly differently
  - Comprehensive guide - https://owl.purdue.edu/owl/research_and_citation/ieee_style/reference_list.html
- APA - common for social sciences and Humanities disciplines
- MLA - common for English & Media Studies paper
- MHRA
- Harvard

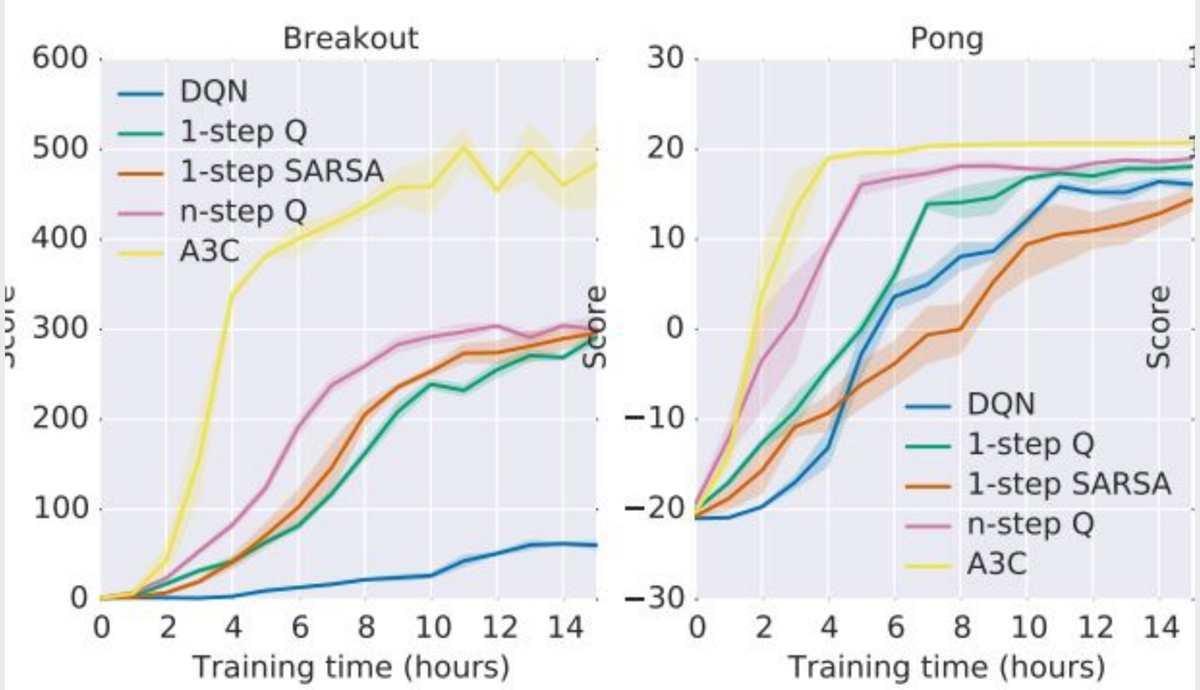
What other things are important?

- Reproducibility
- A good story/narrative
- General points
- “Troubling Trends in Machine Learning Scholarship”

Reproducibility

- When writing your paper, ask yourself: “can someone reproduce my results from reading this paper?”
- If the answer is no, you *need* to release code or add extra details in the paper or the supplementary.
- If your paper isn’t reproducible, 1) you’ll get emails, 2) the paper won’t be cited, 3) or the next paper will cite and say “we could not reproduce the results of this paper”

Reproducibility



- Whenever possible, include error bars/standard deviations.
- Extremely important in RL, where performance is usually unstable, but even on classification/object detection/language modeling/etc, if there is instability, should report average of multiple runs.

A good story/narrative

- Is there a point existing works have overlooked that you consider?
- Does previous work fail in certain cases (low-resource, certain classes) that your method is better suited for?
- Can you relate your work to some core intuitive notion that will give readers an “aha!” moment?

General points

- A research paper is an *argument* in support of your work, not just a list of observations.
- The reader should be **convinced** that your method is better than existing work.

General points

- Try not to make up your own technical terms or make things seem unnecessarily complicated.
- Although it might seem cool, it can confuse readers or annoy ones who are not awed.
- Bad example: “We extract complementary semantics via feature entanglement over space and time.”
- Better example: “Given RGB video, we run a first CNN over the temporal dimension, run a second CNN over the spatial dimensions, and then combine their results.”

“Troubling Trends in Machine Learning Scholarship”

Source: https://arxiv.org/pdf/1807.03341v2.pdf

- This is a paper from 2018 that has been trending recently.
- It details some common (bad) trends in ML papers that impede understanding/add noise to research.

“Troubling Trends in Machine Learning Scholarship”

“Explanation vs Speculation”

Source: https://arxiv.org/pdf/1807.03341v2.pdf

- Papers should explicitly make clear what is formal reasoning and informal speculation.
- For instance, internal-covariate shift is not clearly stated and has been repeated as fact when it could be false.
- Other papers, as positive examples, have quarantined a "motivation" section for informal intuitions.

“Troubling Trends in Machine Learning Scholarship”

“Failure to Identify the Sources of Empirical Gains”

Source: https://arxiv.org/pdf/1807.03341v2.pdf

- Ablations are very important.
- Some papers do not clarify the sources of gains in performance, and other papers have found that actually, hyper-parameter tuning was a more important factor.

“Troubling Trends in Machine Learning Scholarship”

Misuse of Language: Suggestive Definitions

Source: https://arxiv.org/pdf/1807.03341v2.pdf

- Some works define equations in a manner that imbues them with human-level priors such as "curiosity" or "fear." Others overstate/incorrectly claim "human-level" performance.
- This is confusing and dangerous for the field.
- What the agent learns is not necessarily the human notion of curiosity - using anthropogenic terms gives laymen unrealistic expectations about AI.

References

- https://library.concordia.ca/help/writing/literature-review.php?guid=components