

Aleksander Lempinen

**MLOps approach for application specific performance
tuning for machine learning systems**

Master's Thesis in Information Technology

October 27, 2023

University of Jyväskylä

Faculty of Information Technology

Author: Aleksander Lempinen

Contact information: aleksander.lempinen@gmail.com

Supervisor: Tommi Mikkonen

Title: MLOps approach for application specific performance tuning for machine learning systems

Työn nimi: TODO samma på finska

Project: Master's Thesis

Study line: Educational Technology

Page count: 30+0

Abstract: TODO abstract

Keywords: L^AT_EX, gradu3, Master's Theses, Bachelor's Theses, user's guide

Suomenkielinen tiivistelmä: TODO tiivistelmä suomeksi

Avainsanat: MLOPS, TODO

Glossary

ML

Machine Learning

MLOps

Machine Learning Operations

TODO

TODO

List of Tables

Table 1. Summary of the datasets used.	13
Table 2. Summary of the algorithms.....	14

Contents

1	INTRODUCTION	1
2	MACHINE LEARNING OPERATIONS	3
2.1	Machine Learning	3
2.1.1	Practical machine learning	3
2.1.2	Model evaluation	4
2.2	DevOps	5
2.2.1	Benefits of DevOps	6
2.2.2	Performance evaluation.....	7
2.3	MLOps.....	8
2.3.1	Production machine learning systems	8
2.3.2	Hyperparameter optimization	9
2.3.3	Performance prediction and early stopping.....	10
3	METHODS.....	12
3.1	Research setup.....	12
3.1.1	Scope	12
3.1.2	Research Questions	12
3.1.3	Proposed method	13
3.2	Experimental setup	13
3.2.1	Methodology	13
3.2.2	Software and Hardware.....	13
3.2.3	Datasets	13
3.2.4	Metrics	14
3.2.5	Algorithms	14
3.2.6	Validation	14
3.3	Experiments	14
3.3.1	Preliminary experiments.....	14
3.3.2	System performance	14
3.3.3	Computational budget	14
4	RESULTS	15
5	DISCUSSION.....	16
5.1	Research Questions revisited	16
5.1.1	Research question RQ1.....	16
5.1.2	Research question RQ2.....	16
5.1.3	Research question RQ3.....	16
5.2	Interpretation	16
5.2.1	Implications for research	16
5.2.2	Implications for practice.....	16
5.3	Limitations.....	16
5.3.1	Datasets	16

5.3.2	Machine Learning algorithms	16
5.3.3	Metrics	16
5.3.4	Training and validation	16
5.3.5	Inference	16
5.4	Related Work	16
5.5	Future Work	17
6	CONCLUSIONS.....	18
	BIBLIOGRAPHY	19

1 Introduction

Machine learning (ML) and Artificial Intelligence (AI) have been a hot topic of discussion in the past decade. While there is a mountain of academic research on ML methods and tools, there is a lack of attention paid to practical real-world challenges encountered when developing or running ML systems. DevOps has previously addressed similar challenges in software engineering and a field of MLOps which is DevOps applied to ML has emerged. Machine learning operations (MLOps) focuses on solving challenges related to operating real world machine learning systems (Kreuzberger, Kühl, and Hirschl 2023).

Machine learning (ML) systems are widely adopted and many organizations successfully have ML models running in production. Examples of machine learning systems in different fields include recommender systems , targeted ads (Domingos October 2012), drug design (Domingos October 2012) or search engines (Domingos October 2012).

Most recent breakthroughs that have generated media attention have been in the fields of computer vision in the form of latent diffusion models (LDM) (Rombach et al. April 2022) such as Stable Diffusion (Stability AI August 2022) for generating images from prompts and natural language processing in the form of large language models (LLM) (Touvron et al. February 2023) such as ChatGPT (OpenAI November 2022). There have also been great developments in tooling for machine learning such as Tensorflow, Pytorch or scikit-learn for model development, Ray, Horovod or DeepSpeed for distributed training and MLFlow or Tensorboard for machine learning monitoring.

TODO computational budgets, cost, efficiency

Despite wide adoption and many successes, there are still challenges with machine learning systems in practice . The required amount of computation for machine learning has been on the rise. According to an OpenAI technical blog the trend is exponential and more compute leads to better performance (Amodei and Hernandez May 2018). Increased compute requirements also mean increased costs such as financial, operational or environmental. Strubell et al. (April 2020) in their extended abstract bring attention to the environmental impact of training models and in particular hyperparameter tuning, during which costs of

Find ref

Find ref

TF, Py-torch, scikit-learn refs

Ray, Horovod and DeepSpeed refs

MLFlow, Tensorboard refs

Find ref, state of MLOps?

training many relatively inexpensive models quickly adds up.

In addition to cost there may be other requirements for machine learning systems. For example machine learning systems on the edge might encounter system requirements such as latency and energy use or have limited resources such as memory or compute (Chen and Ran August 2019). Ways of meeting these requirements include hyperparameter tuning, reducing the amount of parameters in the model or model compression such as knowledge distillation (Chen and Ran August 2019).

Early stopping has been used as a cost optimization technique to reduce training time by stopping training when performance of the model stops improving on the validation set (Prechelt June 1998). More recent work on larger models shows that models might still improve later if training continues for a longer time (Hoffer, Hubara, and Soudry January 2018). Using early stopping with other performance metrics such as system metrics has not been as thoroughly studied.

The aim of this thesis is to investigate whether using early stopping with system metrics leads to more efficient hyperparameter tuning when there are resource constraints. Investigation is limited to a small set of widely available machine learning algorithms and datasets that do not require a lot of computation. While more complex and effective hyperparameter optimization methods exist only the simplest are used to simplify the experiments for clarity. The theoretical significance of the thesis is to show that traditional hyperparameter optimization techniques can not only be used on machine learning performance metrics but also alternative metrics such as system metrics. The practical outcomes are reducing costs and allowing for quickly and efficiently tailoring models to fit specific system metric constraints.

This thesis is structured in the following manner: Chapter 1 provides an introduction and context for the thesis. Chapter 2 contains background information about machine learning, DevOps and MLOps and how they relate to each other. Chapter 3 describes the performed experiments and their methods and design including research questions, datasets and algorithms used. Chapter 4 presents the results of the experiments. Chapter 5 revisits the research questions and discusses the interpretation of the results, limitations, related work and future work. Chapter 6 concludes the thesis by summarizing key findings.

2 Machine Learning Operations

Software involving machine learning adds additional complexity to the overall system. Developing, deploying and monitoring machine learning systems involves both traditional software system concepts and some new machine learning specific concepts. Section 2.1 introduces machine learning and evaluating model performance from a practical perspective. Section 2.2 introduces DevOps and performance evaluation. Section 2.3 combines machine learning and DevOps for production machine learning systems and introduces hyperparameter optimization and performance prediction.

2.1 Machine Learning

Real world applications of machine learning are often messy with a large number of decisions for the developer that can result in different behavior of the machine learning model. This section introduces machine learning from a practical standpoint including necessary performance metrics for model training and empirical performance evaluation.

2.1.1 Practical machine learning

Writing programs and developing algorithms to complete specific tasks is a labor intensive task requiring professional programming expertise. A different approach is to develop generic algorithms that can change behavior by learning. The field studying these types of algorithms is called machine learning. Machine learning algorithms learn by applying an optimization algorithm to adjust set of parameters called a model and this process is called training the model (LeCun, Bengio, and Hinton May 2015). A simplified machine learning workflow consists of splitting the data into training and test datasets, performing preprocessing separately for each dataset, training the model on the training dataset and finally evaluating the trained model on the test dataset.

ref

Machine learning is widely used in applications like search, drug design or ad placement and can be also known as data mining or predictive analytics (Domingos October 2012). Developing machine learning systems, which are systems that are based on machine learning,

can be a difficult task. Unlike traditional software development, experiments with both code and data as inputs are central to machine learning development (Zaharia et al. 2018) and reproducibility of the experiments is often problematic. While plenty of research focuses on machine learning methods or even datasets and data quality, the biggest bottleneck is human cycles (Domingos October 2012). Faster iterations improve the machine learning developer or researcher experience. An important metric to pay attention to and optimize is the mean iteration cycle for machine learning developers.

Machine learning can be practiced with two different goals in mind. First is explanatory modeling with the purpose of scientific theory building and testing and the second is predictive modeling mostly used outside of scientific research (Shmueli August 2010). One practical difference is that unlike predictive modeling, explanatory modeling rarely uses holdout test sets or cross validation for evaluation (Shmueli August 2010). Lack or presence of evaluation on a test set can be used as a heuristic to quickly determine whether a machine learning project is explanatory or predictive in nature. However, even explanatory modeling benefits from evaluating the predictive power (Shmueli August 2010). Domingos (October 2012) in their paper assume all machine learning is predictive in nature and state that machine learning should generalize beyond the training set. It is important to keep in mind the end goals of a machine learning project, because common practices in a research setting might not be applicable when creating machine learning systems.

Machine learning algorithms can be categorized as supervised learning, unsupervised learning or reinforcement learning. The main differences are related to whether the model learns by using "right answers" provided by labeled data in supervised learning, by finding structure in the dataset in unsupervised learning or by interacting with the world in reinforcement learning. Unsupervised learning has the advantage of not requiring labeled data which is an advantage for problems where labels are uncommon (Le et al. July 2012).

2.1.2 Model evaluation

Performance evaluation of machine learning models is usually done empirically using cross-validation (Forman and Scholz, no date; Sokolova and Lapalme July 2009). Cross-validation

involves splitting the data into k -folds and using all but one of the folds for training and the last one for validating the performance of the model after which the procedure is repeated k times with each fold being used for validation (Cawley and Talbot, no date). For example 3-fold validation would use a third of the data for validation and two thirds for training repeated three times. The performance metrics collected during the computationally expensive cross validation are typically averaged (Cawley and Talbot, no date). These types of global averages might not be desirable and instead of random folds the data can be sliced according to some criterion such as by country and allow detecting performance differences between slices (Breck et al. 2017).

Machine learning training involves minimizing an optimization criterion such as log loss, squared hinge loss or Cauchy-Schwarz Divergence (Janocha and Czarnecki February 2017). Different loss metrics are chosen depending on the application such as resistance to noisy data or labels (Janocha and Czarnecki February 2017). The loss metric is sometimes not informative of model performance such as in classification tasks. In these cases performance metrics such as accuracy, precision, recall, specificity, error-rate , AUC and F-score are used (Sokolova and Lapalme July 2009; Forman and Scholz, no date). Metrics such as accuracy are well defined, but the final F-score from cross-validation may be computed in several ways resulting in different results (Forman and Scholz, no date).

Even more informative metrics can be created for specific applications. For example Torrabla and Efros (June 2011) developed performance metrics to compare different datasets and determine a "market value" for the data by using the generalization performance of machine learning models on the datasets. Defining correctness of the prediction is an important part when defining performance metrics (Lin et al. 2014)

TODO: Define batch, training step, epoch TODO: Loss math formulas TODO: Algorithm example of a training loop

2.2 DevOps

DevOps is a well known topic in the field of software engineering that brings together development and operations. This section briefly introduces DevOps and provides an overview

to the main benefits related to continuous integration, continuous deployment and continuous performance evaluation. Later it describes the importance of performance metrics with examples and wraps up the section by introducing performance prediction.

2.2.1 Benefits of DevOps

A common interpretation of DevOps is a focus on software quality, collaboration between development and operations, process speed and rapid feedback (Mishra and Otaiwi November 2020; Waller, Ehmke, and Hasselbring April 2015; Perera, Silva, and Perera September 2017). Defining DevOps is difficult as there is no consensus on the exact definition (Smeds, Nybom, and Porres 2015; Mishra and Otaiwi November 2020). DevOps can be viewed from different points of view such as culture, collaboration, automation, measurements and monitoring (Mishra and Otaiwi November 2020; Waller, Ehmke, and Hasselbring April 2015). In DevOps there is a focus on speed and quality with incremental changes that are recurrent and continuous (Mishra and Otaiwi November 2020). The goal is to bridge the gap between development and operations (Smeds, Nybom, and Porres 2015). This is done through sharing tasks and responsibilities from development to deployment and support (Mishra and Otaiwi November 2020).

Add definition

Continuous integration, continuous deployment and continuous monitoring are well known practices in DevOps (Waller, Ehmke, and Hasselbring April 2015) describing the automatic nature of integrating, deploying and monitoring code changes. Feedback includes performance metrics data which is then fed as an input during planning and development (Smeds, Nybom, and Porres 2015). Performance profiling and monitoring are similar activities and the main difference is whether it's done during the development process or during operations respectively (Waller, Ehmke, and Hasselbring April 2015) with DevOps bridging the gap between them (Brunnert et al. August 2015). Continuous benchmarking allows for detecting performance regressions during continuous integration (Waller, Ehmke, and Hasselbring April 2015) and infrastructure monitoring with a feedback loop allows for performance optimization in production (Smeds, Nybom, and Porres 2015).

Performance evaluation is a useful tool for optimizing the overall system design and tailor-

ing for a specific production environment in addition to correctly sizing resources (Brunnert et al. August 2015; Waller, Ehmke, and Hasselbring April 2015). Resource demands might change depending on the inputs (Brunnert et al. August 2015) making it important to systematically measure performance not only based on code changes but also on configuration changes or even data changes. Performance evaluation is directly tied to defining and collecting performance metrics and monitoring.

2.2.2 Performance evaluation

Performance metrics are fundamental to all activities involving performance evaluation such as profiling or monitoring (Brunnert et al. August 2015). Common metrics involve measuring the CPU, but other metrics such as memory usage, network traffic or I/O usage do not have clear definitions (Brunnert et al. August 2015). Collecting metrics happens through hardware based monitors or software monitors instrumented into software through code modification or indirectly for example through middleware interception (Brunnert et al. August 2015). Metrics can be event driven in which a monitor is triggered with every occurrence or based on sampling at fixed time intervals (Brunnert et al. August 2015). The types of metrics collected and what information is expected depends on the performance goals and the life cycle of the software (Brunnert et al. August 2015).

Metrics can be divided into application metrics such as response time or throughput and resource utilization metrics such as CPU utilization or available memory (Brunnert et al. August 2015). There is little peer reviewed research available with specifics on which metrics are to be collected or how they are defined. Kounev et al. (2020) in their textbook on systems benchmarking bring up the following quality attributes for benchmark metrics: easy to measure, repeatable, reliable, linear, consistent and independent. Most metrics will not satisfy all of the above quality attributes and aggregated higher level composite metrics are required (Kounev, Lange, and Von Kistowski 2020).

Measurement based performance evaluation requires a system to test while model based performance evaluation allows to predict the performance of the future system (Brunnert et al. August 2015). This type of performance prediction allows for better planning and

comparing use cases especially when an existing legacy system exists with measured performance metrics (Brunnert et al. August 2015).

TODO: measuring CPU, memory, times (real, wall etc.)

2.3 MLOps

Machine learning operations or MLOps is a fairly new concept related to building and running real-world machine learning systems. This section introduces the concept of MLOps and provides context for the types of problems it aims to solve. Later in the section the concepts of hyperparameter optimization, performance prediction and early stopping are introduced. The section finishes with performance metrics related to machine learning systems and their business objectives and the performance of the overall system.

2.3.1 Production machine learning systems

While the focus of machine learning research has been on improving models, it is essential for the industry to be able to design production-ready machine learning pipelines (Posoldova November 2020). The data often used for research is of higher quality than real-world data that is often messy, unstructured and unlabeled (Posoldova November 2020). Continuous integration, continuous deployment and automated testing are also relevant to machine learning systems (Posoldova November 2020) which are familiar concepts from DevOps. A new concept of MLOps addresses this issue of designing and maintaining machine learning systems just like DevOps addressed it for traditional software (Kreuzberger, Kühl, and Hirschl 2023).

Bring
DevOps
to MLOps

Managing technical debt is even more important in machine learning systems, because of machine learning specific issues that cannot be solved with traditional methods (Sculley et al. 2015). Main culprit for the challenges with machine learning systems is that data changes the behavior of the system and cannot be expressed with code alone (Sculley et al. 2015). Challenges like entanglement, correction cascades or feedback loops are common with machine learning systems and are difficult to diagnose with common tools (Sculley et al. 2015).

Requirements for a machine learning system are different depending on the task. For example speech and object recognition might have no particular performance requirements during training but has strict latency and computational resource restrictions when deployed to serve large amounts users (Hinton, Vinyals, and Dean March 2015). MLOps has to take into account both machine learning performance metrics familiar from machine learning and software performance metrics familiar from DevOps and software engineering. Feedback from metrics collected during development and from monitoring of production systems are core MLOps principles (Kreuzberger, Kühl, and Hirschl 2023). For example possible meta-level requirements include users requesting data deletion, prohibitions on specific features like age or deprecated sources (Breck et al. 2017).

Performance measuring software is not new, but ML brings additional challenges in the form of models and data which requires a modified approach (Breck et al. 2017). It is also important to note, that not every data scientist or machine learning engineer working on machine learning systems has a software engineering background (Finzer 2013) and might lack the necessary knowledge to apply software engineering best practices to machine learning systems. Monitoring for machine learning systems has to be carefully designed (Sculley et al. 2015). Hyperparameter optimization is a kind of performance optimization, where the goal is to improve machine learning metrics. It is not always necessary to train the model to completion to verify that training code is correct and training loss is decreasing (Breck et al. 2017).

2.3.2 Hyperparameter optimization

Parameters given as part of a configuration to the machine learning model are called hyperparameters (Yang and Shami November 2020). Examples of hyperparameters include learning rate, number of layers in a neural network, regularization coefficients, batch size, step size or initialization conditions (Maclaurin, Duvenaud, and Adams April 2015; Baker et al. November 2017; Breck et al. 2017). Hyperparameter tuning or hyperparameter optimization can be defined as finding the optimal hyperparameter values by searching through possible hyperparameter values (Baker et al. November 2017). This hyperparameter search can also demonstrate whether the training is stable and reliable (Breck et al. 2017).

The main goal of hyperparameter optimization is to reduce the amount of expert labor required for creating high-performance machine learning models (Baker et al. November 2017). Another benefit of finding optimal hyperparameters is that it can help achieve state-of-the-art performance in machine learning systems (Maclaurin, Duvenaud, and Adams April 2015). Hyperparameter optimization techniques include grid search, random search, gradient based optimization and Bayesian optimization and they have different benefits and limitations (Yang and Shami November 2020).

Similar concepts to hyperparameter optimization are neural architecture optimization and meta modeling where model structure or modeling algorithm is treated as a tunable parameter (Baker et al. November 2017). This allows for automating the creation of neural networks from scratch (Baker et al. November 2017). The amount of potential neural network architecture configurations is large and checking them is computationally expensive (Baker et al. November 2017).

Tuning hyperparameters is generally a difficult task (Maclaurin, Duvenaud, and Adams April 2015). Traditional hyperparameter tuning methods such as Bayesian optimization are unfeasible for more than 10-20 hyperparameters (Maclaurin, Duvenaud, and Adams April 2015). More advanced techniques are required if a larger amount of tunable hyperparameters is desired. Performance prediction is an important step to reduce the amount of computation required for neural architecture search and hyperparameter optimization (Baker et al. November 2017).

TODO: add things from (Shallue et al. 2019) TODO: Computational budget, steps,

2.3.3 Performance prediction and early stopping

Data gathered at the beginning of model training can be used to predict performance of the trained model given the chosen hyperparameters (Baker et al. November 2017). A small sample of hyperparameter configurations can be used for training a performance prediction model which then can be used to predict the performance for the rest of hyperparameter configurations with only a small amount of training (Baker et al. November 2017).

Early stopping is a technique in which model training is halted before completion to avoid

wasting computational resources (Prechelt June 1998). Early stopping can be based on a threshold value decided upon ahead of time or based on a performance prediction model (Baker et al. November 2017). Low thresholds for rejection of suboptimal solutions will radically reduce the amount of computation required, but run the risk of rejecting an optimal solution as well (Baker et al. November 2017).

Machine learning systems in addition to machine learning performance metrics and system performance metrics will have their performance metrics tied to product or organization metrics such as user churn rate or click-through rate (Shankar et al. September 2022). Important metrics from a machine learning system performance perspective include CPU usage, GPU usage, task completion time, inference time and latency (Cardoso Silva et al. December 2020). Choosing the right metrics to evaluate a machine learning system is important and the metrics will be different for different machine learning systems (Shankar et al. September 2022).

3 Methods

3.1 Research setup

3.1.1 Scope

In this thesis the choice of machine learning algorithms is limited to implementations with iterative training and a possibility for metric collection between training steps.

The scope of the study is limited to 5 performance metrics of 3 different ML models trained and tested on 3 different datasets using a distributed computing framework Ray Tune (Liaw et al. July 2018).

TODO different models, different datasets

TODO Vertailukriteeristö: tapana ohjelmistopuolella + tapana koneoppimispuolella

TODO different resources (memory, time, accuracy)

3.1.2 Research Questions

This master's thesis asks the following research questions:

- *RQ1*: How do changes in hyperparameters affect system performance during model training?
- *RQ2*: How does early stopping on system performance criteria affect computational budgets during model training?

3.1.3 Proposed method

3.2 Experimental setup

3.2.1 Methodology

TODO Methodology used is expanded from an existing methodology for machine learning experiment design (Fernandez-Lozano et al. December 2016) to include AutoML and

3.2.2 Software and Hardware

Experiments were performed using Ray Tune (2.7.1) (Liaw et al. July 2018). MLFlow (2.7.1) (Chen et al. June 2020) was used for collecting metrics and tracking experiments. Scikit-learn (1.3.2) (Pedregosa et al. November 2011) for training and evaluating machine learning models. Hardware consisted of TODO processor and Nvidia 3060 GPU.

3.2.3 Datasets

Datasets used are chosen from Penn Machine Learning Benchmarks (Olson et al. December 2017). Mnist dataset was chosen because of popularity and familiarity in the machine learning community. The rest of the datasets were chosen by hand instead of randomly sampled to represent small and large datasets in both classification and regression tasks, because the dataset repository is unbalanced. Table 1 summarizes the machine learning task and dimensionality of the datasets.

Dataset	Type	Task	Examples	Features
mnist	image	classification	70000	784
kddcup	tabular	classification	494020	41
diabetes	tabular	classification	768	8
1191_BNG_pbc	tabular	regression	1000000	19
529_pollen	tabular	regression	3848	5

Table 1. Summary of the datasets used.

3.2.4 Metrics

3.2.5 Algorithms

Algorithms used require support of training in batches and are summarized in Table 2. Algorithms linear regression, logistic regression and support vector machine (SVM) are based on stochastic gradient descent (SGD) implementation found in Scikit-learn (Pedregosa et al. November 2011).

Algorithm	Task	Loss	Datasets
Linear regression	regression	squared_loss	1191_BNG_pbc, 529_pollen
Logistic regression	classification	log	mnist, kddcup, diabetes
Support Vector Machine (SVM)	classification	hinge	mnist, kddcup, diabetes

Table 2. Summary of the algorithms

3.2.6 Validation

3.3 Experiments

3.3.1 Preliminary experiments

3.3.2 System performance

3.3.3 Computational budget

4 Results

TODO This is a results chapter

5 Discussion

5.1 Research Questions revisited

5.1.1 Research question RQ1

5.1.2 Research question RQ2

5.1.3 Research question RQ3

5.2 Interpretation

5.2.1 Implications for research

5.2.2 Implications for practice

5.3 Limitations

5.3.1 Datasets

5.3.2 Machine Learning algorithms

5.3.3 Metrics

5.3.4 Training and validation

5.3.5 Inference

5.4 Related Work

To find relevant related work both reverse snowballing and forward snowballing is used on a set of MLOps papers previously known to the author.

Benchmarking ML systems (Cardoso Silva et al. December 2020)

5.5 Future Work

TODO This is a discussion chapter

6 Conclusions

Summary

TODO This is a conclusions chapter

Bibliography

Amodei, Dario, and Danny Hernandez. May 2018. *AI and Compute*. <https://openai.com/research/ai-and-compute>. Visited on July 29, 2023.

Baker, Bowen, Otkrist Gupta, Ramesh Raskar, and Nikhil Naik. November 2017. *Accelerating Neural Architecture Search Using Performance Prediction*, arXiv:1705.10823. Visited on January 25, 2023. <https://doi.org/10.48550/arXiv.1705.10823>. arXiv: 1705.10823 [cs].

Breck, Eric, Shanqing Cai, Eric Nielsen, Michael Salib, and D. Sculley. 2017. “The ML Test Score: A Rubric for ML Production Readiness and Technical Debt Reduction”. In *Proceedings of IEEE Big Data*.

Brunnert, Andreas, Andre van Hoorn, Felix Willnecker, Alexandru Danciu, Wilhelm Hasselbring, Christoph Heger, Nikolas Herbst, et al. August 2015. *Performance-Oriented DevOps: A Research Agenda*, arXiv:1508.04752. Visited on January 17, 2023. <https://doi.org/10.48550/arXiv.1508.04752>. arXiv: 1508.04752 [cs].

Cardoso Silva, Lucas, Fernando Rezende Zagatti, Bruno Silva Sette, Lucas Nildaimon dos Santos Silva, Daniel Lucrédio, Diego Furtado Silva, and Helena de Medeiros Caseli. December 2020. “Benchmarking Machine Learning Solutions in Production”. In *2020 19th IEEE International Conference on Machine Learning and Applications (ICMLA)*, 626–633. <https://doi.org/10.1109/ICMLA51294.2020.00104>.

Cawley, Gavin C, and Nicola L C Talbot. No date. “On Over-fittingg inModel Selectionn andSubsequent Selection Biass inPerformance Evaluation”.

Chen, Andrew, Andy Chow, Aaron Davidson, Arjun DCunha, Ali Ghodsi, Sue Ann Hong, Andy Konwinski, et al. June 2020. “Developments in MLflow: A System to Accelerate the Machine Learning Lifecycle”. In *Proceedings of the Fourth International Workshop on Data Management for End-to-End Machine Learning*, 1–4. DEEM’20. New York, NY, USA: Association for Computing Machinery. ISBN: 978-1-4503-8023-2, visited on October 25, 2023. <https://doi.org/10.1145/3399579.3399867>.

Chen, Jiasi, and Xukan Ran. August 2019. “Deep Learning With Edge Computing: A Review”. *Proceedings of the IEEE* 107, number 8 (): 1655–1674. ISSN: 0018-9219, 1558-2256, visited on July 29, 2023. <https://doi.org/10.1109/JPROC.2019.2921977>.

Domingos, Pedro. October 2012. “A Few Useful Things to Know about Machine Learning”. *Communications of the ACM* 55, number 10 (): 78–87. ISSN: 0001-0782, visited on March 14, 2023. <https://doi.org/10.1145/2347736.2347755>.

Fernandez-Lozano, Carlos, Marcos Gestal, Cristian R. Munteanu, Julian Dorado, and Alejandro Pazos. December 2016. “A Methodology for the Design of Experiments in Computational Intelligence with Multiple Regression Models”. *PeerJ* 4 (): e2721. ISSN: 2167-8359, visited on February 15, 2023. <https://doi.org/10.7717/peerj.2721>.

Finzer, William. 2013. “The Data Science Education Dilemma”. *Technology Innovations in Statistics Education* 7 (2). Visited on January 17, 2023. <https://doi.org/10.5070/T572013891>.

Forman, George, and Martin Scholz. No date. “Apples-to-Apples in Cross-Validation Studies: Pitfalls in Classifier Performance Measurement”.

Hinton, Geoffrey, Oriol Vinyals, and Jeff Dean. March 2015. *Distilling the Knowledge in a Neural Network*, arXiv:1503.02531. Visited on February 3, 2023. <https://doi.org/10.48550/arXiv.1503.02531>. arXiv: 1503.02531 [cs, stat].

Hoffer, Elad, Itay Hubara, and Daniel Soudry. January 2018. *Train Longer, Generalize Better: Closing the Generalization Gap in Large Batch Training of Neural Networks*, arXiv:1705.08741. Visited on August 2, 2023. <https://doi.org/10.48550/arXiv.1705.08741>. arXiv: 1705.08741 [cs, stat].

Janocha, Katarzyna, and Wojciech Marian Czarnecki. February 2017. *On Loss Functions for Deep Neural Networks in Classification*, arXiv:1702.05659. Visited on August 27, 2023. <https://doi.org/10.48550/arXiv.1702.05659>. arXiv: 1702.05659 [cs].

Kounev, Samuel, Klaus-Dieter Lange, and Jóakim Von Kistowski. 2020. *Systems Benchmarking: For Scientists and Engineers*. Cham: Springer International Publishing. ISBN: 978-3-030-41704-8 978-3-030-41705-5, visited on August 23, 2023. <https://doi.org/10.1007/978-3-030-41705-5>.

- Kreuzberger, Dominik, Niklas Kühl, and Sebastian Hirschl. 2023. “Machine Learning Operations (MLOps): Overview, Definition, and Architecture”. *IEEE Access* 11:31866–31879. ISSN: 2169-3536. <https://doi.org/10.1109/ACCESS.2023.3262138>.
- Le, Quoc V., Marc’Aurelio Ranzato, Rajat Monga, Matthieu Devin, Kai Chen, Greg S. Corrado, Jeff Dean, and Andrew Y. Ng. July 2012. *Building High-Level Features Using Large Scale Unsupervised Learning*, arXiv:1112.6209. Visited on February 3, 2023. <https://doi.org/10.48550/arXiv.1112.6209>. arXiv: 1112.6209 [cs].
- LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. May 2015. “Deep Learning”. *Nature* 521, number 7553 (): 436–444. ISSN: 1476-4687, visited on June 15, 2023. <https://doi.org/10.1038/nature14539>.
- Liaw, Richard, Eric Liang, Robert Nishihara, Philipp Moritz, Joseph E. Gonzalez, and Ion Stoica. July 2018. *Tune: A Research Platform for Distributed Model Selection and Training*, arXiv:1807.05118. Visited on February 22, 2023. <https://doi.org/10.48550/arXiv.1807.05118>. arXiv: 1807.05118 [cs, stat].
- Lin, Tsung-Yi, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C. Lawrence Zitnick. 2014. “Microsoft COCO: Common Objects in Context”. In *Computer Vision – ECCV 2014*, edited by David Fleet, Tomas Pajdla, Bernt Schiele, and Tinne Tuytelaars, 740–755. Lecture Notes in Computer Science. Cham: Springer International Publishing. ISBN: 978-3-319-10602-1. https://doi.org/10.1007/978-3-319-10602-1_48.
- Maclaurin, Dougal, David Duvenaud, and Ryan P. Adams. April 2015. *Gradient-Based Hyperparameter Optimization through Reversible Learning*, arXiv:1502.03492. Visited on February 3, 2023. <https://doi.org/10.48550/arXiv.1502.03492>. arXiv: 1502.03492 [cs, stat].
- Mishra, Alok, and Ziadoon Otaiwi. November 2020. “DevOps and Software Quality: A Systematic Mapping”. *Computer Science Review* 38 (): 100308. ISSN: 1574-0137, visited on January 17, 2023. <https://doi.org/10.1016/j.cosrev.2020.100308>.

Olson, Randal S., William La Cava, Patryk Orzechowski, Ryan J. Urbanowicz, and Jason H. Moore. December 2017. “PMLB: A Large Benchmark Suite for Machine Learning Evaluation and Comparison”. *BioData Mining* 10, number 1 (): 36. ISSN: 1756-0381, visited on February 22, 2023. <https://doi.org/10.1186/s13040-017-0154-4>.

OpenAI. November 2022. *Introducing ChatGPT*. <https://openai.com/blog/chatgpt>. Visited on July 24, 2023.

Pedregosa, Fabian, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, et al. November 2011. “Scikit-Learn: Machine Learning in Python”. *The Journal of Machine Learning Research* 12, number null (): 2825–2830. ISSN: 1532-4435.

Perera, Pulasthi, Roshali Silva, and Indika Perera. September 2017. “Improve Software Quality through Practicing DevOps”. In *2017 Seventeenth International Conference on Advances in ICT for Emerging Regions (ICTer)*, 1–6. <https://doi.org/10.1109/ICTER.2017.8257807>.

Posoldova, Alexandra. November 2020. “Machine Learning Pipelines: From Research to Production”. *IEEE Potentials* 39, number 6 (): 38–42. ISSN: 1558-1772. <https://doi.org/10.1109/MPOT.2020.3016280>.

Prechelt, Lutz. June 1998. “Automatic Early Stopping Using Cross Validation: Quantifying the Criteria”. *Neural Networks* 11, number 4 (): 761–767. ISSN: 0893-6080, visited on August 2, 2023. [https://doi.org/10.1016/S0893-6080\(98\)00010-0](https://doi.org/10.1016/S0893-6080(98)00010-0).

Rombach, Robin, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. April 2022. *High-Resolution Image Synthesis with Latent Diffusion Models*, arXiv:2112.10752. Visited on July 22, 2023. <https://doi.org/10.48550/arXiv.2112.10752>. arXiv: 2112.10752 [cs].

Sculley, D., Gary Holt, Daniel Golovin, Eugene Davydov, Todd Phillips, Dietmar Ebner, Vinay Chaudhary, Michael Young, Jean-François Crespo, and Dan Dennison. 2015. “Hidden Technical Debt in Machine Learning Systems”. In *Advances in Neural Information Processing Systems*, volume 28. Curran Associates, Inc. Visited on August 13, 2023.

Shallue, Christopher J., Jaehoon Lee, Joseph Antognini, Jascha Sohl-Dickstein, Roy Frostig, and George E. Dahl. 2019. “Measuring the Effects of Data Parallelism on Neural Network Training”. *Journal of Machine Learning Research* 20 (112): 1–49. ISSN: 1533-7928, visited on September 28, 2023.

Shankar, Shreya, Rolando Garcia, Joseph M. Hellerstein, and Aditya G. Parameswaran. September 2022. *Operationalizing Machine Learning: An Interview Study*, arXiv:2209.09125. Visited on December 7, 2022. <https://doi.org/10.48550/arXiv.2209.09125>. arXiv: 2209.09125 [cs].

Shmueli, Galit. August 2010. “To Explain or to Predict?” *Statistical Science* 25, number 3 (). ISSN: 0883-4237, visited on March 14, 2023. <https://doi.org/10.1214/10-STS330>. arXiv: 1101.0891 [stat].

Smeds, Jens, Kristian Nybom, and Ivan Porres. 2015. “DevOps: A Definition and Perceived Adoption Impediments”. In *Agile Processes in Software Engineering and Extreme Programming*, edited by Casper Lassenius, Torgeir Dingsøy, and Maria Paasivaara, 166–177. Lecture Notes in Business Information Processing. Cham: Springer International Publishing. ISBN: 978-3-319-18612-2. https://doi.org/10.1007/978-3-319-18612-2_14.

Sokolova, Marina, and Guy Lapalme. July 2009. “A Systematic Analysis of Performance Measures for Classification Tasks”. *Information Processing & Management* 45, number 4 (): 427–437. ISSN: 0306-4573, visited on August 27, 2023. <https://doi.org/10.1016/j.ipm.2009.03.002>.

Stability AI. August 2022. *Stable Diffusion Public Release*. <https://stability.ai/blog/stable-diffusion-public-release>. Visited on July 24, 2023.

Strubell, Emma, Ananya Ganesh, and Andrew McCallum. April 2020. “Energy and Policy Considerations for Modern Deep Learning Research”. *Proceedings of the AAAI Conference on Artificial Intelligence* 34, number 09 (): 13693–13696. ISSN: 2374-3468, visited on July 29, 2023. <https://doi.org/10.1609/aaai.v34i09.7123>.

Torrallba, Antonio, and Alexei A. Efros. June 2011. “Unbiased Look at Dataset Bias”. In *CVPR 2011*, 1521–1528. Colorado Springs, CO, USA: IEEE. ISBN: 978-1-4577-0394-2, visited on August 27, 2023. <https://doi.org/10.1109/CVPR.2011.5995347>.

Touvron, Hugo, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, et al. February 2023. *LLaMA: Open and Efficient Foundation Language Models*, arXiv:2302.13971. Visited on July 24, 2023. <https://doi.org/10.48550/arXiv.2302.13971>. arXiv: 2302.13971 [cs].

Waller, Jan, Nils C. Ehmke, and Wilhelm Hasselbring. April 2015. “Including Performance Benchmarks into Continuous Integration to Enable DevOps”. *ACM SIGSOFT Software Engineering Notes* 40, number 2 (): 1–4. ISSN: 0163-5948, visited on January 17, 2023. <https://doi.org/10.1145/2735399.2735416>.

Yang, Li, and Abdallah Shami. November 2020. “On Hyperparameter Optimization of Machine Learning Algorithms: Theory and Practice”. *Neurocomputing* 415 (): 295–316. ISSN: 09252312, visited on January 25, 2023. <https://doi.org/10.1016/j.neucom.2020.07.061>. arXiv: 2007.15745 [cs, stat].

Zaharia, M., A. Chen, A. Davidson, A. Ghodsi, S. Hong, A. Konwinski, Siddharth Murching, et al. 2018. “Accelerating the Machine Learning Lifecycle with MLflow”. *IEEE Data Eng. Bull.*, visited on March 14, 2023.