













 krishkatyal added author details ✓


51 contributors

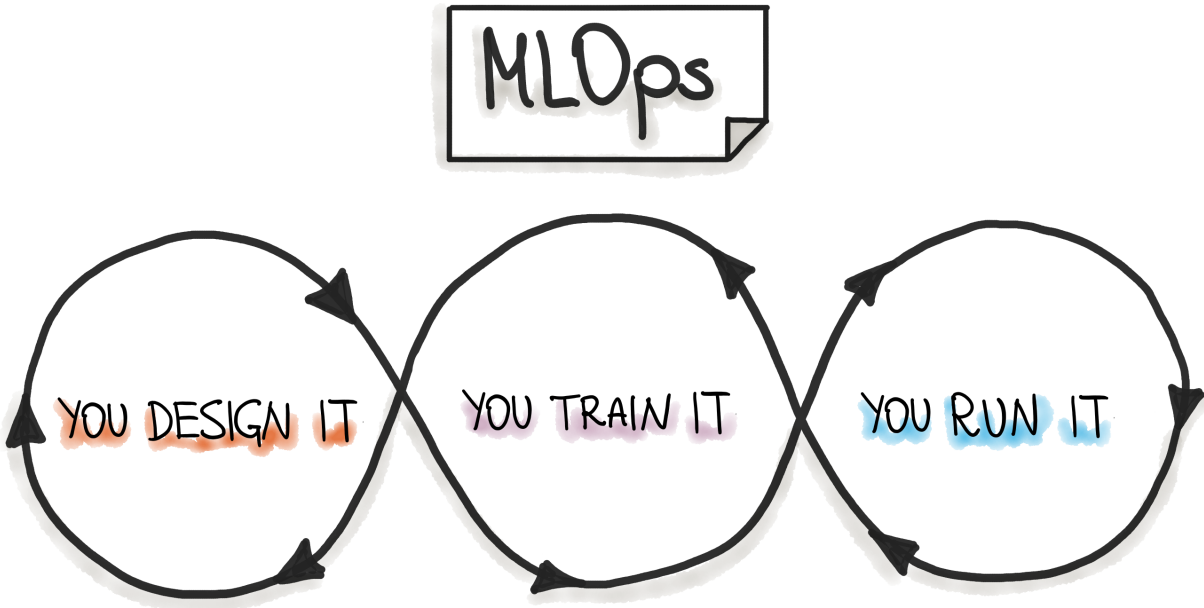
 +35

680 lines (606 sloc) | 70.9 KB


# Awesome MLOps


 awesome

Made With  Love



@visenger

An awesome list of references for MLOps - Machine Learning Operations  [ml-ops.org](https://ml-ops.org)

 1.8k

## Table of Content

MLOps Core	MLOps Communities
------------	-------------------

<a href="#">MLOps Books</a>	<a href="#">MLOps Articles</a>
<a href="#">MLOps Workflow Management</a>	<a href="#">MLOps: Feature Stores</a>
<a href="#">MLOps: Data Engineering (DataOps)</a>	<a href="#">MLOps: Model Deployment and Serving</a>
<a href="#">MLOps: Testing, Monitoring and Maintenance</a>	<a href="#">MLOps: Infrastructure</a>
<a href="#">MLOps Papers</a>	<a href="#">Talks About MLOps</a>
<a href="#">Existing ML Systems</a>	<a href="#">Machine Learning</a>
<a href="#">Software Engineering</a>	<a href="#">Product Management for ML/AI</a>
<a href="#">The Economics of ML/AI</a>	<a href="#">Model Governance, Ethics, Responsible AI</a>
<a href="#">MLOps: People &amp; Processes</a>	<a href="#">Newsletters About MLOps, Machine Learning, Data Science and Co.</a>

## MLOps Core

### ▼ Click to expand!

1. [Machine Learning Operations: You Design It, You Train It, You Run It!](#)
2. [MLOps SIG Specification](#)
3. [ML in Production](#)
4. [Awesome production machine learning: State of MLOps Tools and Frameworks](#)
5. [Udemy "Deployment of ML Models"](#)
6. [Full Stack Deep Learning](#)
7. [Engineering best practices for Machine Learning](#)
8. [🚀 Putting ML in Production](#)
9. [Stanford MLSys Seminar Series](#)
10. [IBM ML Operationalization Starter Kit](#)
11. [Productize ML. A self-study guide for Developers and Product Managers building Machine Learning products.](#)
12. [MLOps \(Machine Learning Operations\) Fundamentals on GCP](#)
13. [ML full Stack preparation](#)
14. [MLOps Guide: Theory and Implementation](#)
15. [Practitioners guide to MLOps: A framework for continuous delivery and automation of machine learning.](#)

## MLOps Communities

▼ Click to expand!

1. [MLOps.community](#)
2. [CDF Special Interest Group - MLOps](#)
3. [RsqrAI - Robust and Responsible AI](#)
4. [DataTalks.Club](#)
5. [Synthetic Data Community](#)
6. [MLOps World Community](#)

## MLOps Courses

---

1. [MLOps Zoomcamp \(free\)](#)
2. [Coursera's Machine Learning Engineering for Production \(MLOps\) Specialization](#)

## MLOps Books

---

▼ Click to expand!

1. ["Machine Learning Engineering" by Andriy Burkov, 2020](#)
2. ["ML Ops: Operationalizing Data Science" by David Sweenor, Steven Hillion, Dan Rope, Dev Kannabiran, Thomas Hill, Michael O'Connell](#)
3. ["Building Machine Learning Powered Applications" by Emmanuel Ameisen](#)
4. ["Building Machine Learning Pipelines" by Hannes Hapke, Catherine Nelson, 2020, O'Reilly](#)
5. ["Managing Data Science" by Kirill Dubovikov](#)
6. ["Accelerated DevOps with AI, ML & RPA: Non-Programmer's Guide to AIOps & MLOps" by Stephen Fleming](#)
7. ["Evaluating Machine Learning Models" by Alice Zheng](#)
8. [Agile AI. 2020. By Carlo Appugliese, Paco Nathan, William S. Roberts. O'Reilly Media, Inc.](#)
9. ["Machine Learning Logistics". 2017. By T. Dunning et al. O'Reilly Media Inc.](#)
10. ["Machine Learning Design Patterns" by Valliappa Lakshmanan, Sara Robinson, Michael Munn. O'Reilly 2020](#)
11. ["Serving Machine Learning Models: A Guide to Architecture, Stream Processing Engines, and Frameworks" by Boris Lublinsky, O'Reilly Media, Inc. 2017](#)
12. ["Kubeflow for Machine Learning" by Holden Karau, Trevor Grant, Ilan Filonenko, Richard Liu, Boris Lublinsky](#)
13. ["Clean Machine Learning Code" by Moussa Taifi. Leanpub. 2020](#)
14. [E-Book "Practical MLOps. How to Get Ready for Production Models"](#)
15. ["Introducing MLOps" by Mark Treveil, et al. O'Reilly Media, Inc. 2020](#)
16. ["Machine Learning for Data Streams with Practical Examples in MOA", Bifet, Albert and Gavaldà, Ricard and Holmes, Geoff and Pfahringer, Bernhard, MIT Press, 2018](#)
17. ["Machine Learning Product Manual" by Laszlo Sragner, Chris Kelly](#)

18. ["Data Science Bootstrap Notes" by Eric J. Ma](#)
19. ["Data Teams" by Jesse Anderson, 2020](#)
20. ["Data Science on AWS" by Chris Fregly, Antje Barth, 2021](#)
21. ["Engineering MLOps" by Emmanuel Raj, 2021](#)
22. [Machine Learning Engineering in Action](#)
23. [Practical MLOps](#)
24. ["Effective Data Science Infrastructure" by Ville Tuulos, 2021](#)
25. [AI and Machine Learning for On-Device Development, 2021, By Laurence Moroney. O'Reilly](#)
26. [Designing Machine Learning Systems ,2022 by Chip Huyen , O'Reilly](#)
27. [Reliable Machine Learning. 2022. By Cathy Chen, Niall Richard Murphy, Kranti Parisa, D. Sculley, Todd Underwood. O'Reilly](#)

## MLOps Articles

---

▼ Click to expand!

1. [Continuous Delivery for Machine Learning \(by Thoughtworks\)](#)
2. [What is MLOps? NVIDIA Blog](#)
3. [MLSpec: A project to standardize the intercomponent schemas for a multi-stage ML Pipeline.](#)
4. [The 2021 State of Enterprise Machine Learning | State of Enterprise ML 2020: PDF and Interactive](#)
5. [Organizing machine learning projects: project management guidelines.](#)
6. [Rules for ML Project \(Best practices\)](#)
7. [ML Pipeline Template](#)
8. [Data Science Project Structure](#)
9. [Reproducible ML](#)
10. [ML project template facilitating both research and production phases.](#)
11. [Machine learning requires a fundamentally different deployment approach. As organizations embrace machine learning, the need for new deployment tools and strategies grows.](#)
12. [Introducing Flyte: A Cloud Native Machine Learning and Data Processing Platform](#)
13. [Why is DevOps for Machine Learning so Different?](#)
14. [Lessons learned turning machine learning models into real products and services – O'Reilly](#)
15. [MLOps: Model management, deployment and monitoring with Azure Machine Learning](#)
16. [Guide to File Formats for Machine Learning: Columnar, Training, Inferencing, and the Feature Store](#)
17. [Architecting a Machine Learning Pipeline How to build scalable Machine Learning systems](#)

18. [Why Machine Learning Models Degrade In Production](#)
19. [Concept Drift and Model Decay in Machine Learning](#)
20. [Machine Learning in Production: Why You Should Care About Data and Concept Drift](#)
21. [Bringing ML to Production](#)
22. [A Tour of End-to-End Machine Learning Platforms](#)
23. [MLOps: Continuous delivery and automation pipelines in machine learning](#)
24. [AI meets operations](#)
25. [What would machine learning look like if you mixed in DevOps? Wonder no more, we lift the lid on MLOps](#)
26. [Forbes: The Emergence Of ML Ops](#)
27. [Cognilytica Report "ML Model Management and Operations 2020 \(MLOps\)"](#)
28. [Introducing Cloud AI Platform Pipelines](#)
29. [A Guide to Production Level Deep Learning](#)
30. [The 5 Components Towards Building Production-Ready Machine Learning Systems](#)
31. [Deep Learning in Production \(references about deploying deep learning-based models in production\)](#)
32. [Machine Learning Experiment Tracking](#)
33. [The Team Data Science Process \(TDSP\)](#)
34. [MLOps Solutions \(Azure based\)](#)
35. [Monitoring ML pipelines](#)
36. [Deployment & Explainability of Machine Learning COVID-19 Solutions at Scale with Seldon Core and Alibi](#)
37. [Demystifying AI Infrastructure](#)
38. [Organizing machine learning projects: project management guidelines.](#)
39. [The Checklist for Machine Learning Projects \(from Aurélien Géron, "Hands-On Machine Learning with Scikit-Learn and TensorFlow"\)](#)
40. [Data Project Checklist by Jeremy Howard](#)
41. [MLOps: not as Boring as it Sounds](#)
42. [10 Steps to Making Machine Learning Operational. Cloudera White Paper](#)
43. [MLOps is Not Enough. The Need for an End-to-End Data Science Lifecycle Process.](#)
44. [Data Science Lifecycle Repository Template](#)
45. [Template: code and pipeline definition for a machine learning project demonstrating how to automate an end to end ML/AI workflow.](#)
46. [Nitpicking Machine Learning Technical Debt](#)
47. [The Best Tools, Libraries, Frameworks and Methodologies that Machine Learning Teams Actually Use – Things We Learned from 41 ML Startups](#)
48. [Software Engineering for AI/ML - An Annotated Bibliography](#)
49. [Intelligent System. Machine Learning in Practice](#)
50. [CMU 17-445/645: Software Engineering for AI-Enabled Systems \(SE4AI\)](#)
51. [Machine Learning is Requirements Engineering](#)

52. [Machine Learning Reproducibility Checklist](#)
53. [Machine Learning Ops. A collection of resources on how to facilitate Machine Learning Ops with GitHub.](#)
54. [Task Cheatsheet for Almost Every Machine Learning Project](#) A checklist of tasks for building End-to-End ML projects
55. [Web services vs. streaming for real-time machine learning endpoints](#)
56. [How PyTorch Lightning became the first ML framework to run continuous integration on TPUs](#)
57. [The ultimate guide to building maintainable Machine Learning pipelines using DVC](#)
58. [Continuous Machine Learning \(CML\) is CI/CD for Machine Learning Projects \(DVC\)](#)
59. [What I learned from looking at 200 machine learning tools | Update: MLOps Tooling Landscape v2 \(+84 new tools\) - Dec '20](#)
60. [Big Data & AI Landscape](#)
61. [Deploying Machine Learning Models as Data, not Code — A better match?](#)
62. ["Thou shalt always scale" — 10 commandments of MLOps](#)
63. [Three Risks in Building Machine Learning Systems](#)
64. [Blog about ML in production \(by maiot.io\)](#)
65. [Back to the Machine Learning fundamentals: How to write code for Model deployment. Part 1, Part 2, Part 3](#)
66. [MLOps: Machine Learning as an Engineering Discipline](#)
67. [ML Engineering on Google Cloud Platform \(hands-on labs and code samples\)](#)
68. [Deep Reinforcement Learning in Production. The use of Reinforcement Learning to Personalize User Experience at Zynga](#)
69. [What is Data Observability?](#)
70. [A Practical Guide to Maintaining Machine Learning in Production](#)
71. [Continuous Machine Learning. Part 1, Part 2. Part 3 is coming soon.](#)
72. [The Agile approach in data science explained by an ML expert](#)
73. [Here is what you need to look for in a model server to build ML-powered services](#)
74. [The problem with AI developer tools for enterprises \(and what IKEA has to do with it\)](#)
75. [Streaming Machine Learning with Tiered Storage](#)
76. [Best practices for performance and cost optimization for machine learning \(Google Cloud\)](#)
77. [Lean Data and Machine Learning Operations](#)
78. [A Brief Guide to Running ML Systems in Production Best Practices for Site Reliability Engineers](#)
79. [AI engineering practices in the wild - SIG | Getting software right for a healthier digital world](#)
80. [SE-ML | The 2020 State of Engineering Practices for Machine Learning](#)
81. [Awesome Software Engineering for Machine Learning \(GitHub repository\)](#)
82. [Sampling isn't enough, profile your ML data instead](#)

83. [Reproducibility in ML: why it matters and how to achieve it](#)
84. [12 Factors of reproducible Machine Learning in production](#)
85. [MLOps: More Than Automation](#)
86. [Lean Data Science](#)
87. [Engineering Skills for Data Scientists](#)
88. [DAGsHub Blog. Read about data science and machine learning workflows, MLOps, and open source data science](#)
89. [Data Science Project Flow for Startups](#)
90. [Data Science Engineering at Shopify](#)
91. [Building state-of-the-art machine learning technology with efficient execution for the crypto economy](#)
92. [Completing the Machine Learning Loop](#)
93. [Deploying Machine Learning Models: A Checklist](#)
94. [Global MLOps and ML tools landscape \(by MLReef\)](#)
95. [Why all Data Science teams need to get serious about MLOps](#)
96. [MLOps Values \(by Bart Grasza\)](#)
97. [Machine Learning Systems Design \(by Chip Huyen\)](#)
98. [Designing an ML system \(Stanford | CS 329 | Chip Huyen\)](#)
99. [How COVID-19 Has Infected AI Models \(about the data drift or model drift concept\)](#)
100. [Microkernel Architecture for Machine Learning Library. An Example of Microkernel Architecture with Python Metaclass](#)
101. [Machine Learning in production: the Booking.com approach](#)
102. [What I Learned From Attending TWIMLcon 2021 \(by James Le\)](#)
103. [Designing ML Orchestration Systems for Startups. A case study in building a lightweight production-grade ML orchestration system](#)
104. [Towards MLOps: Technical capabilities of a Machine Learning platform | Prosus AI Tech Blog](#)
105. [Get started with MLOps A comprehensive MLOps tutorial with open source tools](#)
106. [From DevOps to MLOPS: Integrate Machine Learning Models using Jenkins and Docker](#)
107. [Example code for a basic ML Platform based on Pulumi, FastAPI, DVC, MLFlow and more](#)
108. [Software Engineering for Machine Learning: Characterizing and Detecting Mismatch in Machine-Learning Systems](#)
109. [TWIML Solutions Guide](#)
110. [How Well Do You Leverage Machine Learning at Scale? Six Questions to Ask](#)
111. [Getting started with MLOps: Selecting the right capabilities for your use case](#)
112. [The Latest Work from the SEI: Artificial Intelligence, DevSecOps, and Security Incident Response](#)
113. [MLOps: The Ultimate Guide. A handbook on MLOps and how to think about it](#)
114. [Enterprise Readiness of Cloud MLOps](#)
115. [Should I Train a Model for Each Customer or Use One Model for All of My Customers?](#)

116. [MLOps-Basics \(GitHub repo\)](#) by raviraja
117. [Another tool won't fix your MLOps problems](#)
118. [Best MLOps Tools: What to Look for and How to Evaluate Them](#) (by NimbleBox.ai)
119. [MLOps vs. DevOps: A Detailed Comparison](#) (by NimbleBox.ai)
120. [A Guide To Setting Up Your MLOps Team](#) (by NimbleBox.ai)

## MLOps: Workflow Management

---

1. [Open-source Workflow Management Tools: A Survey](#) by Ploomber
2. [How to Compare ML Experiment Tracking Tools to Fit Your Data Science Workflow](#) (by dagshub)
3. [15 Best Tools for Tracking Machine Learning Experiments](#)

## MLOps: Feature Stores

---

▼ Click to expand!

1. [Feature Stores for Machine Learning](#) Medium Blog
2. [MLOps with a Feature Store](#)
3. [Feature Stores for ML](#)
4. [Hopsworx: Data-Intensive AI with a Feature Store](#)
5. [Feast: An open-source Feature Store for Machine Learning](#)
6. [What is a Feature Store?](#)
7. [ML Feature Stores: A Casual Tour](#)
8. [Comprehensive List of Feature Store Architectures for Data Scientists and Big Data Professionals](#)
9. [ML Engineer Guide: Feature Store vs Data Warehouse](#) (vendor blog)
10. [Building a Gigascale ML Feature Store with Redis, Binary Serialization, String Hashing, and Compression](#) (DoorDash blog)
11. [Feature Stores: Variety of benefits for Enterprise AI.](#)
12. [Feature Store as a Foundation for Machine Learning](#)
13. [ML Feature Serving Infrastructure at Lyft](#)
14. [Feature Stores for Self-Service Machine Learning](#)
15. [The Architecture Used at LinkedIn to Improve Feature Management in Machine Learning Models.](#)
16. [Is There a Feature Store Over the Rainbow? How to select the right feature store for your use case](#)

## MLOps: Data Engineering (DataOps)

---



## ▼ Click to expand!

1. [The state of data quality in 2020 – O'Reilly](#)
2. [Why We Need DevOps for ML Data](#)
3. [Data Preparation for Machine Learning \(7-Day Mini-Course\)](#)
4. [Best practices in data cleaning: A Complete Guide to Everything You Need to Do Before and After Collecting Your Data.](#)
5. [17 Strategies for Dealing with Data, Big Data, and Even Bigger Data](#)
6. [DataOps Data Architecture](#)
7. [Data Orchestration — A Primer](#)
8. [4 Data Trends to Watch in 2020](#)
9. [CSE 291D / 234: Data Systems for Machine Learning](#)
10. [A complete picture of the modern data engineering landscape](#)
11. [Continuous Integration for your data with GitHub Actions and Great Expectations. One step closer to CI/CD for your data pipelines](#)
12. [Emerging Architectures for Modern Data Infrastructure](#)
13. [Awesome Data Engineering. Learning path and resources to become a data engineer](#)
14. [Data Quality at Airbnb Part 1 | Part 2](#)
15. [DataHub: Popular metadata architectures explained](#)
16. [Financial Times Data Platform: From zero to hero. An in-depth walkthrough of the evolution of our Data Platform](#)
17. [Alki, or how we learned to stop worrying and love cold metadata \(Dropbox\)](#)
18. [A Beginner's Guide to Clean Data. Practical advice to spot and avoid data quality problems \(by Benjamin Greve\)](#)
19. [ML Lake: Building Salesforce's Data Platform for Machine Learning](#)
20. [Data Catalog 3.0: Modern Metadata for the Modern Data Stack](#)
21. [Metadata Management Systems](#)
22. [Essential resources for data engineers \(a curated recommended read and watch list for scalable data processing\)](#)
23. [Comprehensive and Comprehensible Data Catalogs: The What, Who, Where, When, Why, and How of Metadata Management \(Paper\)](#)
24. [What I Learned From Attending DataOps Unleashed 2021 \(by James Le\)](#)
25. [Uber's Journey Toward Better Data Culture From First Principles](#)
26. [Cerberus - lightweight and extensible data validation library for Python](#)
27. [Design a data mesh architecture using AWS Lake Formation and AWS Glue. AWS Big Data Blog](#)
28. [Data Management Challenges in Production Machine Learning \(slides\)](#)
29. [The Missing Piece of Data Discovery and Observability Platforms: Open Standard for Metadata](#)
30. [Automating Data Protection at Scale](#)
31. [A curated list of awesome pipeline toolkits](#)

32. [Data Mesh Architecture](#)
33. [The Essential Guide to Data Exploration in Machine Learning \(by NimbleBox.ai\)](#)

## MLOps: Model Deployment and Serving

---

▼ Click to expand!

1. [AI Infrastructure for Everyone: DeterminedAI](#)
2. [Deploying R Models with MLflow and Docker](#)
3. [What Does it Mean to Deploy a Machine Learning Model?](#)
4. [Software Interfaces for Machine Learning Deployment](#)
5. [Batch Inference for Machine Learning Deployment](#)
6. [AWS Cost Optimization for ML Infrastructure - EC2 spend](#)
7. [CI/CD for Machine Learning & AI](#)
8. [Itaú Unibanco: How we built a CI/CD Pipeline for machine learning with \*online training\* in Kubeflow](#)
9. [101 For Serving ML Models](#)
10. [Deploying Machine Learning models to production — Inference service architecture patterns](#)
11. [Serverless ML: Deploying Lightweight Models at Scale](#)
12. [ML Model Rollout To Production. Part 1 | Part 2](#)
13. [Deploying Python ML Models with Flask, Docker and Kubernetes](#)
14. [Deploying Python ML Models with Bodywork](#)
15. [Framework for a successful Continuous Training Strategy. When should the model be retrained? What data should be used? What should be retrained? A data-driven approach](#)
16. [Efficient Machine Learning Inference. The benefits of multi-model serving where latency matters](#)

## MLOps: Testing, Monitoring and Maintenance

---

▼ Click to expand!

1. [Building dashboards for operational visibility \(AWS\)](#)
2. [Monitoring Machine Learning Models in Production](#)
3. [Effective testing for machine learning systems](#)
4. [Unit Testing Data: What is it and how do you do it?](#)
5. [How to Test Machine Learning Code and Systems \(Accompanying code\)](#)
6. [Wu, T., Dong, Y., Dong, Z., Singa, A., Chen, X. and Zhang, Y., 2020. Testing Artificial Intelligence System Towards Safety and Robustness: State of the Art. IAENG](#)

- [International Journal of Computer Science, 47\(3\).](#)
7. [Multi-Armed Bandits and the Stitch Fix Experimentation Platform](#)
8. [A/B Testing Machine Learning Models](#)
9. [Data validation for machine learning. Polyzotis, N., Zinkevich, M., Roy, S., Breck, E. and Whang, S., 2019. Proceedings of Machine Learning and Systems](#)
10. [Testing machine learning based systems: a systematic mapping](#)
11. [Explainable Monitoring: Stop flying blind and monitor your AI](#)
12. [WhyLogs: Embrace Data Logging Across Your ML Systems](#)
13. [Evidently AI. Insights on doing machine learning in production. \(Vendor blog.\)](#)
14. [The definitive guide to comprehensively monitoring your AI](#)
15. [Introduction to Unit Testing for Machine Learning](#)
16. [Production Machine Learning Monitoring: Outliers, Drift, Explainers & Statistical Performance](#)
17. [Test-Driven Development in MLOps Part 1](#)
18. [Domain-Specific Machine Learning Monitoring](#)
19. [Introducing ML Model Performance Management \(Blog by fiddler\)](#)
20. [What is ML Observability? \(Arize AI\)](#)
21. [Beyond Monitoring: The Rise of Observability \(Arize AI & Monte Carlo Data\)](#)
22. [Model Failure Modes \(Arize AI\)](#)
23. [Quick Start to Data Quality Monitoring for ML \(Arize AI\)](#)
24. [Playbook to Monitoring Model Performance in Production \(Arize AI\)](#)
25. [Robust ML by Property Based Domain Coverage Testing \(Blog by Efemara\)](#)
26. [Monitoring and explainability of models in production](#)
27. [Beyond Monitoring: The Rise of Observability](#)
28. [ML Model Monitoring – 9 Tips From the Trenches. \(by NU bank\)](#)
29. [Model health assurance at LinkedIn. By LinkedIn Engineering](#)
30. [How to Trust Your Deep Learning Code \(Accompanying code\)](#)
31. [Estimating Performance of Regression Models Without Ground-Truth \(Using NannyML\)](#)
32. [How Hyperparameter Tuning in Machine Learning Works \(by NimbleBox.ai\)](#)

## MLOps: Infrastructure & Tooling

---

▼ Click to expand!

1. [MLOps Infrastructure Stack Canvas](#)
2. [Rise of the Canonical Stack in Machine Learning. How a Dominant New Software Stack Will Unlock the Next Generation of Cutting Edge AI Apps](#)
3. [AI Infrastructure Alliance. Building the canonical stack for AI/ML](#)
4. [Linux Foundation AI Foundation](#)

5. [ML Infrastructure Tools for Production | Part 1 — Production ML — The Final Stage of the Model Workflow | Part 2 — Model Deployment and Serving](#)
6. [The MLOps Stack Template \(by valohai\)](#)
7. [Navigating the MLOps tooling landscape](#)
8. [MLOps.toys curated list of MLOps projects \(by Aporia\)](#)
9. [Comparing Cloud MLOps platforms, From a former AWS SageMaker PM](#)
10. [Machine Learning Ecosystem 101 \(whitepaper by Arize AI\)](#)
11. [Selecting your optimal MLOps stack: advantages and challenges. By Intellerts](#)
12. [Infrastructure Design for Real-time Machine Learning Inference. The Databricks Blog](#)
13. [The 2021 State of AI Infrastructure Survey](#)
14. [AI infrastructure Maturity matrix](#)
15. [A Curated Collection of the Best Open-source MLOps Tools. By Censius](#)
16. [Best MLOps Tools to Manage the ML Lifecycle \(by NimbleBox.ai\)](#)

## MLOps Papers

---

A list of scientific and industrial papers and resources about Machine Learning operationalization since 2015. [See more.](#)

## Talks About MLOps

---

▼ Click to expand!

1. ["MLOps: Automated Machine Learning" by Emmanuel Raj](#)
2. [DeliveryConf 2020. "Continuous Delivery For Machine Learning: Patterns And Pains" by Emily Gorcenski](#)
3. [MLOps Conference: Talks from 2019](#)
4. [Kubecon 2019: Flyte: Cloud Native Machine Learning and Data Processing Platform](#)
5. [Kubecon 2019: Running LargeScale Stateful workloads on Kubernetes at Lyft](#)
6. [A CI/CD Framework for Production Machine Learning at Massive Scale \(using Jenkins X and Seldon Core\)](#)
7. [MLOps Virtual Event \(Databricks\)](#)
8. [MLOps NY conference 2019](#)
9. [MLOps.community YouTube Channel](#)
10. [MLinProduction YouTube Channel](#)
11. [Introducing MLflow for End-to-End Machine Learning on Databricks. Spark+AI Summit 2020. Sean Owen](#)
12. [MLOps Tutorial #1: Intro to Continuous Integration for ML](#)
13. [Machine Learning At Speed: Operationalizing ML For Real-Time Data Streams \(2019\)](#)
14. [Damian Brady - The emerging field of MLOps](#)

15. [MLOps - Entwurf, Entwicklung, Betrieb \(INNOQ Podcast in German\)](#)
16. [Instrumentation, Observability & Monitoring of Machine Learning Models](#)
17. [Efficient ML engineering: Tools and best practices](#)
18. [Beyond the jupyter notebook: how to build data science products](#)
19. [An introduction to MLOps on Google Cloud](#) (First 19 min are vendor-, language-, and framework-agnostic. @visenger)
20. [How ML Breaks: A Decade of Outages for One Large ML Pipeline](#)
21. [Clean Machine Learning Code: Practical Software Engineering](#)
22. [Machine Learning Engineering: 10 Fundamentale Praktiken](#)
23. [Architecture of machine learning systems \(3-part series\)](#)
24. [Machine Learning Design Patterns](#)
25. [The laylist that covers techniques and approaches for model deployment on to production](#)
26. [ML Observability: A Critical Piece in Ensuring Responsible AI \(Arize AI at Re-Work\)](#)
27. [ML Engineering vs. Data Science \(Arize AI Un/Summit\)](#)
28. [SRE for ML: The First 10 Years and the Next 10](#)
29. [Demystifying Machine Learning in Production: Reasoning about a Large-Scale ML Platform](#)
30. [Apply Conf 2022](#)
31. [Databricks' Data + AI Summit 2022](#)
32. [RE•WORK MLOps Summit 2022](#)
33. [Annual MLOps World Conference](#)

## Existing ML Systems

---

▼ Click to expand!

1. [Introducing FBLeaer Flow: Facebook's AI backbone](#)
2. [TFX: A TensorFlow-Based Production-Scale Machine Learning Platform](#)
3. [Accelerate your ML and Data workflows to production: Flyte](#)
4. [Getting started with Kubeflow Pipelines](#)
5. [Meet Michelangelo: Uber's Machine Learning Platform](#)
6. [Meson: Workflow Orchestration for Netflix Recommendations](#)
7. [What are Azure Machine Learning pipelines?](#)
8. [Uber ATG's Machine Learning Infrastructure for Self-Driving Vehicles](#)
9. [An overview of ML development platforms](#)
10. [Snorkel AI: Putting Data First in ML Development](#)
11. [A Tour of End-to-End Machine Learning Platforms](#)
12. [Introducing WhyLabs, a Leap Forward in AI Reliability](#)
13. [Project: Ease.ml \(ETH Zürich\)](#)

14. [Bodywork: model-training and deployment automation](#)
15. [Lessons on ML Platforms — from Netflix, DoorDash, Spotify, and more](#)
16. [Papers & tech blogs by companies sharing their work on data science & machine learning in production. By Eugen Yan](#)
17. [How do different tech companies approach building internal ML platforms? \(tweet\)](#)
18. [Declarative Machine Learning Systems](#)
19. [StreamING Machine Learning Models: How ING Adds Fraud Detection Models at Runtime with Apache Flink](#)

## Machine Learning

---

▼ Click to expand!

1. Book, Aurélien Géron, "Hands-On Machine Learning with Scikit-Learn and TensorFlow"
2. [Foundations of Machine Learning](#)
3. [Best Resources to Learn Machine Learning](#)
4. [Awesome TensorFlow](#)
5. ["Papers with Code" - Browse the State-of-the-Art in Machine Learning](#)
6. [Zhi-Hua Zhou. 2012. Ensemble Methods: Foundations and Algorithms. Chapman & Hall/CRC.](#)
7. [Feature Engineering for Machine Learning. Principles and Techniques for Data Scientists. By Alice Zheng, Amanda Casari](#)
8. [Google Research: Looking Back at 2019, and Forward to 2020 and Beyond](#)
9. [O'Reilly: The road to Software 2.0](#)
10. [Machine Learning and Data Science Applications in Industry](#)
11. [Deep Learning for Anomaly Detection](#)
12. [Federated Learning for Mobile Keyboard Prediction](#)
13. [Federated Learning. Building better products with on-device data and privacy on default](#)
14. [Federated Learning: Collaborative Machine Learning without Centralized Training Data](#)
15. [Yang, Q., Liu, Y., Cheng, Y., Kang, Y., Chen, T. and Yu, H., 2019. Federated learning. Synthesis Lectures on Artificial Intelligence and Machine Learning, 13\(3\). Chapters 1 and 2.](#)
16. [Federated Learning by FastForward](#)
17. [THE FEDERATED & DISTRIBUTED MACHINE LEARNING CONFERENCE](#)
18. [Federated Learning: Challenges, Methods, and Future Directions](#)
19. [Book: Molnar, Christoph. "Interpretable machine learning. A Guide for Making Black Box Models Explainable", 2019](#)
20. [Book: Hutter, Frank, Lars Kotthoff, and Joaquin Vanschoren. "Automated Machine Learning". Springer, 2019.](#)
21. [ML resources by topic, curated by the community.](#)

22. [An Introduction to Machine Learning Interpretability](#), by Patrick Hall, Navdeep Gill, 2nd Edition. O'Reilly 2019
23. [Examples of techniques for training interpretable machine learning \(ML\) models, explaining ML models, and debugging ML models for accuracy, discrimination, and security.](#)
24. [Paper: "Machine Learning in Python: Main developments and technology trends in data science, machine learning, and artificial intelligence"](#), by Sebastian Raschka, Joshua Patterson, and Corey Nolet. 2020
25. [Distill: Machine Learning Research](#)
26. [AtHomeWithAI: Curated Resource List by DeepMind](#)
27. [Awesome Data Science](#)
28. [Intro to probabilistic programming. A use case using Tensorflow-Probability \(TFP\)](#)
29. [Dive into Snorkel: Weak-Supervision on German Texts.](#) inovex Blog
30. [Dive into Deep Learning.](#) An interactive deep learning book with code, math, and discussions. Provides NumPy/MXNet, PyTorch, and TensorFlow implementations
31. [Data Science Collected Resources \(GitHub repository\)](#)
32. [Set of illustrated Machine Learning cheatsheets](#)
33. ["Machine Learning Bookcamp"](#) by Alexey Grigorev
34. [130 Machine Learning Projects Solved and Explained](#)
35. [Machine learning cheat sheet](#)
36. [Stateoftheart AI.](#) An open-data and free platform built by the research community to facilitate the collaborative development of AI
37. [Online Machine Learning Courses: 2020 Edition](#)
38. [End-to-End Machine Learning Library](#)
39. [Machine Learning Toolbox \(by Amit Chaudhary\)](#)
40. [Causality for Machine Learning](#)
41. [Causal Inference for the Brave and True](#)
42. [Causal Inference](#)
43. [A resource list for causality in statistics, data science and physics](#)
44. [Learning from data.](#) Caltech
45. [Machine Learning Glossary](#)
46. [Book: "Distributed Machine Learning Patterns". 2022. By Yuan Tang. Manning](#)
47. [Machine Learning for Beginners - A Curriculum](#)
48. [Making Friends with Machine Learning.](#) By Cassie Kozyrkov
49. [Machine Learning Workflow - A Complete Guide \(by NimbleBox.ai\)](#)
50. [Performance Metrics to Monitor in Machine Learning Projects \(by NimbleBox.ai\)](#)

## Software Engineering

---

▼ Click to expand!

1. [The Twelve Factors](#)
2. [Book "Accelerate: The Science of Lean Software and DevOps: Building and Scaling High Performing Technology Organizations", 2018 by Nicole Forsgren et.al](#)
3. [Book "The DevOps Handbook" by Gene Kim, et al. 2016](#)
4. [State of DevOps 2019](#)
5. [Clean Code concepts adapted for machine learning and data science.](#)
6. [School of SRE](#)
7. [10 Laws of Software Engineering That People Ignore](#)
8. [The Patterns of Scalable, Reliable, and Performant Large-Scale Systems](#)
9. [The Book of Secret Knowledge](#)
10. [SHADES OF CONWAY'S LAW](#)
11. [Engineering Practices for Data Scientists](#)

## Product Management for ML/AI

---

▼ Click to expand!

1. [What you need to know about product management for AI. A product manager for AI does everything a traditional PM does, and much more.](#)
2. [Bringing an AI Product to Market. Previous articles have gone through the basics of AI product management. Here we get to the meat: how do you bring a product to market?](#)
3. [The People + AI Guidebook](#)
4. [User Needs + Defining Success](#)
5. [Building machine learning products: a problem well-defined is a problem half-solved.](#)
6. [Talk: Designing Great ML Experiences \(Apple\)](#)
7. [Machine Learning for Product Managers](#)
8. [Understanding the Data Landscape and Strategic Play Through Wardley Mapping](#)
9. [Techniques for prototyping machine learning systems across products and features](#)
10. [Machine Learning and User Experience: A Few Resources](#)
11. [AI ideation canvas](#)
12. [Ideation in AI](#)
13. [5 Steps for Building Machine Learning Models for Business. By shopify engineering](#)
14. [Metric Design for Data Scientists and Business Leaders](#)

## The Economics of ML/AI

---

▼ Click to expand!

1. [Book: "Prediction Machines: The Simple Economics of Artificial Intelligence"](#)
2. [Book: "The AI Organization" by David Carmona](#)
3. [Book: "Succeeding with AI". 2020. By Veljko Kronic. Manning Publications](#)



4. [A list of articles about AI and the economy](#)
5. [Gartner AI Trends 2019](#)
6. [Global AI Survey: AI proves its worth, but few scale impact](#)
7. [Getting started with AI? Start here! Everything you need to know to dive into your project](#)
8. [11 questions to ask before starting a successful Machine Learning project](#)
9. [What AI still can't do](#)
10. [Demystifying AI Part 4: What is an AI Canvas and how do you use it?](#)
11. [A Data Science Workflow Canvas to Kickstart Your Projects](#)
12. [Is your AI project a nonstarter? Here's a reality check\(list\) to help you avoid the pain of learning the hard way](#)
13. [What is THE main reason most ML projects fail?](#)
14. [Designing great data products. The Drivetrain Approach: A four-step process for building data products.](#)
15. [The New Business of AI \(and How It's Different From Traditional Software\)](#)
16. [The idea maze for AI startups](#)
17. [The Enterprise AI Challenge: Common Misconceptions](#)
18. [Misconception 1 \(of 5\): Enterprise AI Is Primarily About The Technology](#)
19. [Misconception 2 \(of 5\): Automated Machine Learning Will Unlock Enterprise AI](#)
20. [Three Principles for Designing ML-Powered Products](#)
21. [A Step-by-Step Guide to Machine Learning Problem Framing](#)
22. [AI adoption in the enterprise 2020](#)
23. [How Adopting MLOps can Help Companies With ML Culture?](#)
24. [Weaving AI into Your Organization](#)
25. [What to Do When AI Fails](#)
26. [Introduction to Machine Learning Problem Framing](#)
27. [Structured Approach for Identifying AI Use Cases](#)
28. [Book: "Machine Learning for Business" by Doug Hudgeon, Richard Nichol, O'reilly](#)
29. [Why Commercial Artificial Intelligence Products Do Not Scale \(FemTech\)](#)
30. [Google Cloud's AI Adoption Framework \(White Paper\)](#)
31. [Data Science Project Management](#)
32. [Book: "Competing in the Age of AI" by Marco Iansiti, Karim R. Lakhani. Harvard Business Review Press. 2020](#)
33. [The Three Questions about AI that Startups Need to Ask. The first is: Are you sure you need AI?](#)
34. [Taming the Tail: Adventures in Improving AI Economics](#)
35. [Managing the Risks of Adopting AI Engineering](#)
36. [Get rid of AI Saviorism](#)
37. [Collection of articles listing reasons why data science projects fail](#)

38. [How to Choose Your First AI Project by Andrew Ng](#)
39. [How to Set AI Goals](#)
40. [Expanding AI's Impact With Organizational Learning](#)
41. [Potemkin Data Science](#)
42. [When Should You Not Invest in AI?](#)
43. [Why 90% of machine learning models never hit the market. Most companies lack leadership support, effective communication between teams, and accessible data](#)

## Model Governance, Ethics, Responsible AI

---

This topic is extracted into our new [Awesome ML Model Governace repository](#)

## MLOps: People & Processes

---

▼ Click to expand!

1. [Scaling An ML Team \(0–10 People\)](#)
2. [The Knowledge Repo project is focused on facilitating the sharing of knowledge between data scientists and other technical roles.](#)
3. [Scaling Knowledge at Airbnb](#)
4. [Models for integrating data science teams within companies A comparative analysis](#)
5. [How to Write Better with The Why, What, How Framework. How to write design documents for data science/machine learning projects? \(by Eugene Yan\)](#)
6. [Technical Writing Courses](#)
7. [Building a data team at a mid-stage startup: a short story. By Erik Bernhardsson](#)
8. [The Cultural Benefits of Artificial Intelligence in the Enterprise. by Sam Ransbotham, François Cadelon, David Kiron, Burt LaFountain, and Shervin Khodabandeh](#)

## Newsletters About MLOps, Machine Learning, Data Science and Co.

---

▼ Click to expand!

1. [ML in Production newsletter](#)
2. [MLOps.community](#)
3. [Andriy Burkov newsletter](#)
4. [Decision Intelligence by Cassie Kozyrkov](#)
5. [Laszlo's Newsletter about Data Science](#)
6. [Data Elixir newsletter for a weekly dose of the top data science picks from around the web. Covering machine learning, data visualization, analytics, and strategy.](#)
7. [The Data Science Roundup by Tristan Handy](#)

8. [Vicki Boykis Newsletter about Data Science](#)
9. [KDnuggets News](#)
10. [Analytics Vidhya](#), Any questions on business analytics, data science, big data, data visualizations tools and techniques
11. [Data Science Weekly Newsletter](#): A free weekly newsletter featuring curated news, articles and jobs related to Data Science
12. [The Machine Learning Engineer Newsletter](#)
13. [Gradient Flow](#) helps you stay ahead of the latest technology trends and tools with in-depth coverage, analysis and insights. See the latest on data, technology and business, with a focus on machine learning and AI
14. [Your guide to AI by Nathan Benaich](#). Monthly analysis of AI technology, geopolitics, research, and startups.
15. [O'Reilly Data & AI Newsletter](#)
16. [deeplearning.ai's newsletter by Andrew Ng](#)
17. [Deep Learning Weekly](#)
18. [Import AI](#) is a weekly newsletter about artificial intelligence, read by more than ten thousand experts. By Jack Clark.
19. [AI Ethics Weekly](#)
20. [Announcing Projects To Know](#), a weekly machine intelligence and data science newsletter
21. [TWIML: This Week in Machine Learning and AI newsletter](#)
22. [featurestore.org: Monthly Newsletter on Feature Stores for ML](#)
23. [DataTalks.Club Community: Slack, Newsletter, Podcast, Weeekly Events](#)
24. [Machine Learning Ops Roundup](#)
25. [Data Science Programming Newsletter by Eric Ma](#)
26. [Marginally Interesting by Mikio L. Braun](#)
27. [Synced](#)
28. [The Ground Truth: Newsletter for Computer Vision Practitioners](#)
29. [SwirlAI: Data Engineering, MLOps and overall Data focused Newsletter by Aurimas Griciūnas](#)

