

Modernizing Systems Observability with AI and LLMs



SCaLE 22x

March 2025



DATADOG



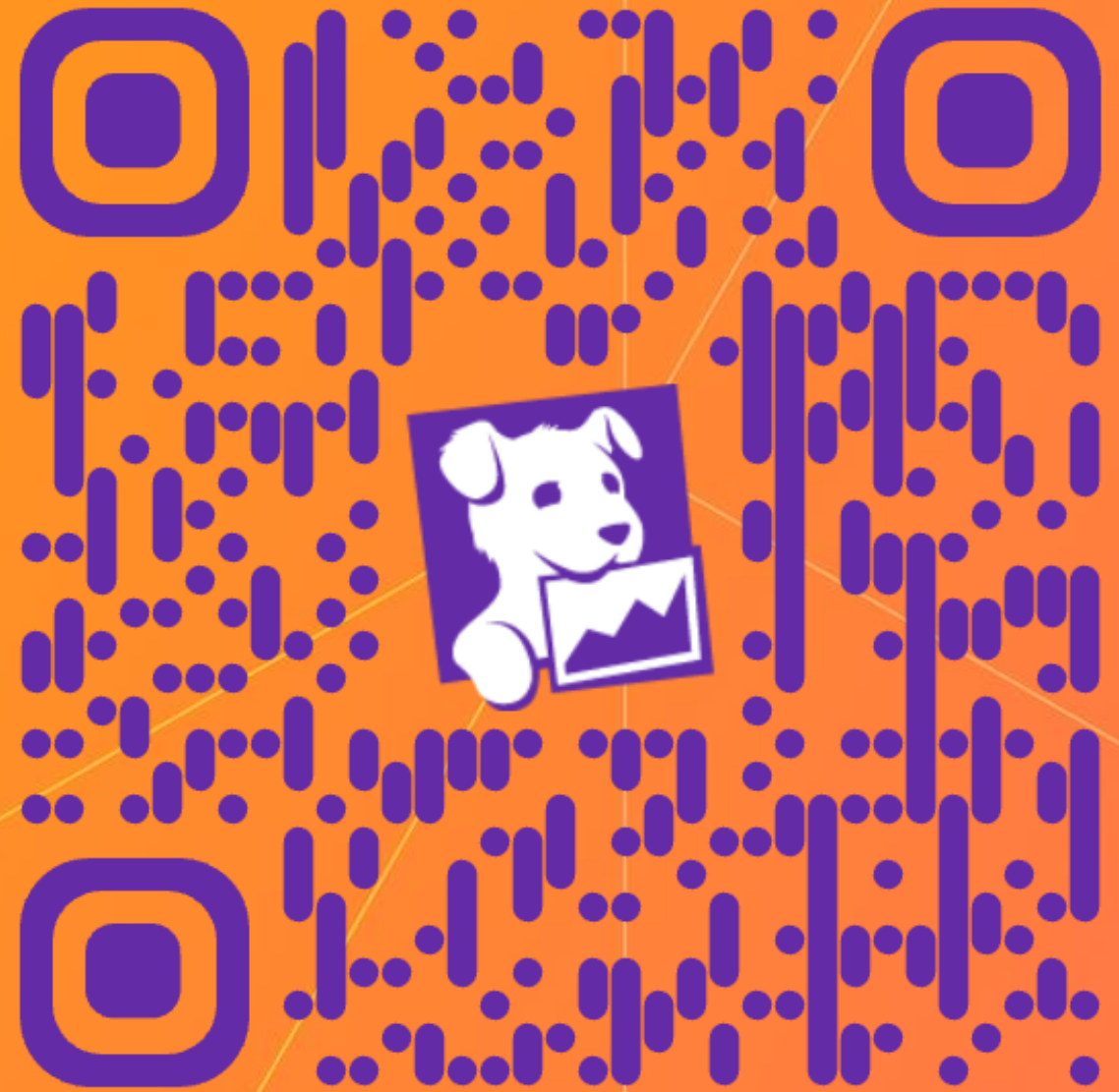
Jason Hand

Senior Developer Advocate : SRE – DevOps – AI : Datadog

Resources

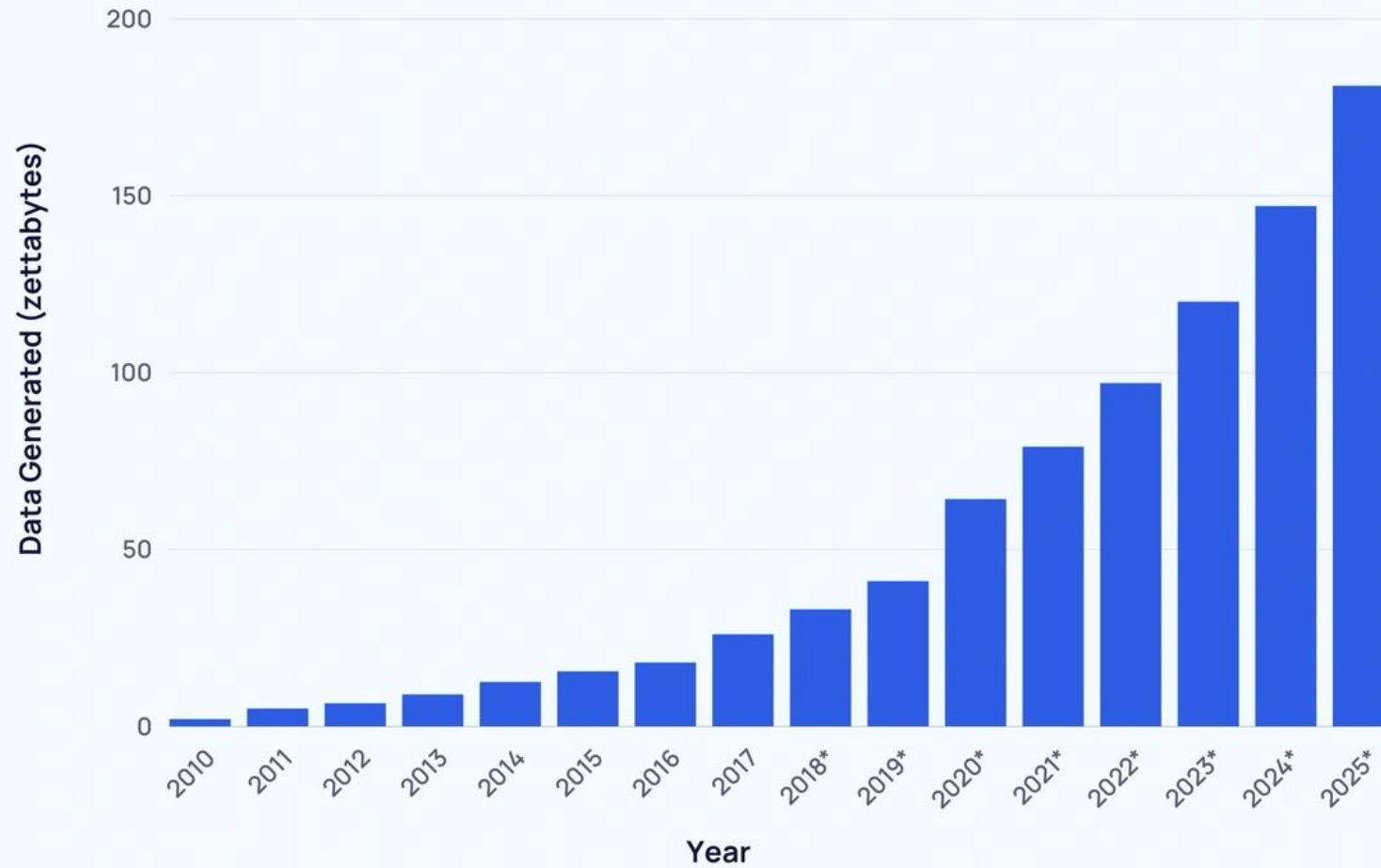
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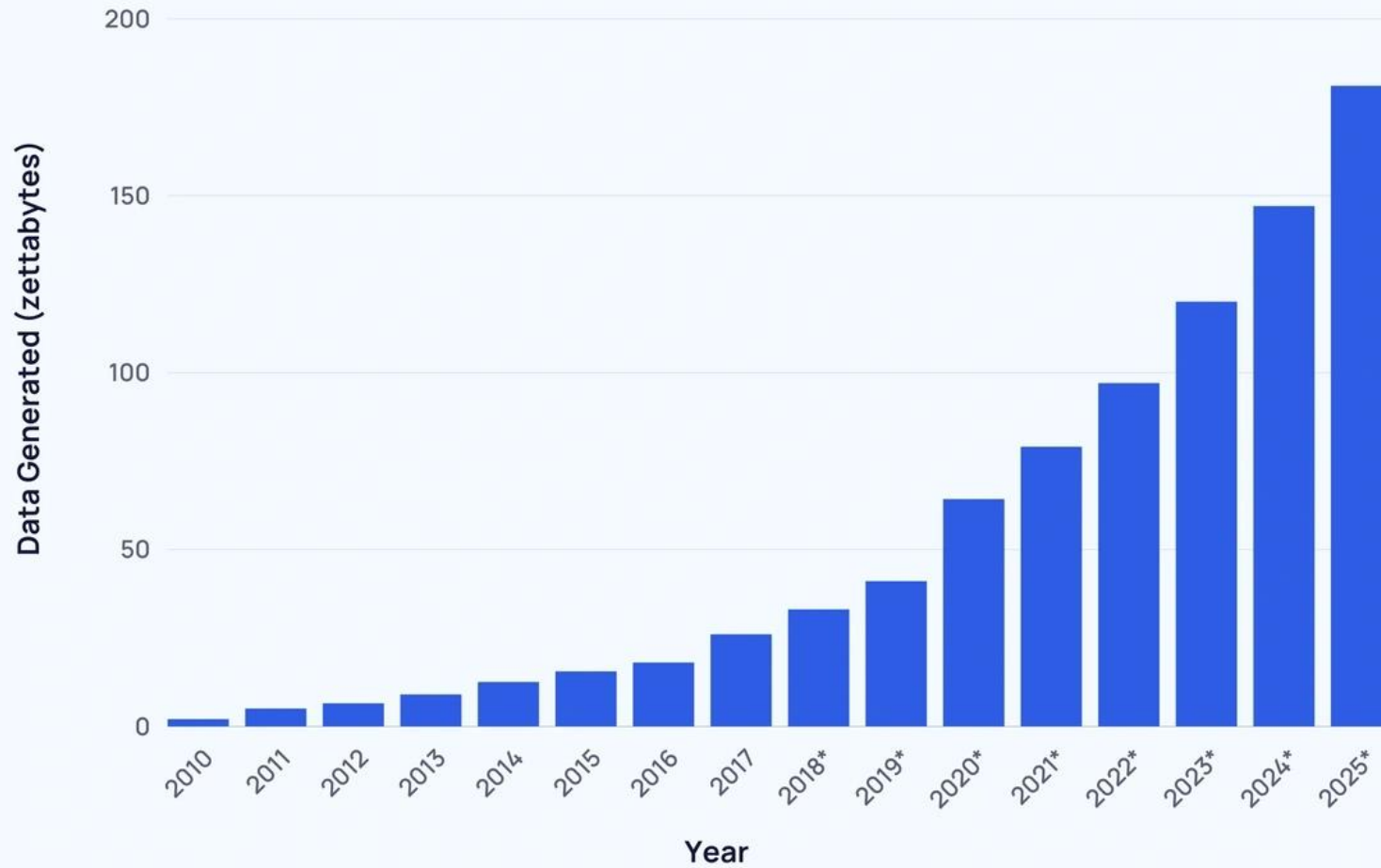


**How much data is
generated annually,
globally?**

Global Data Generated Annually



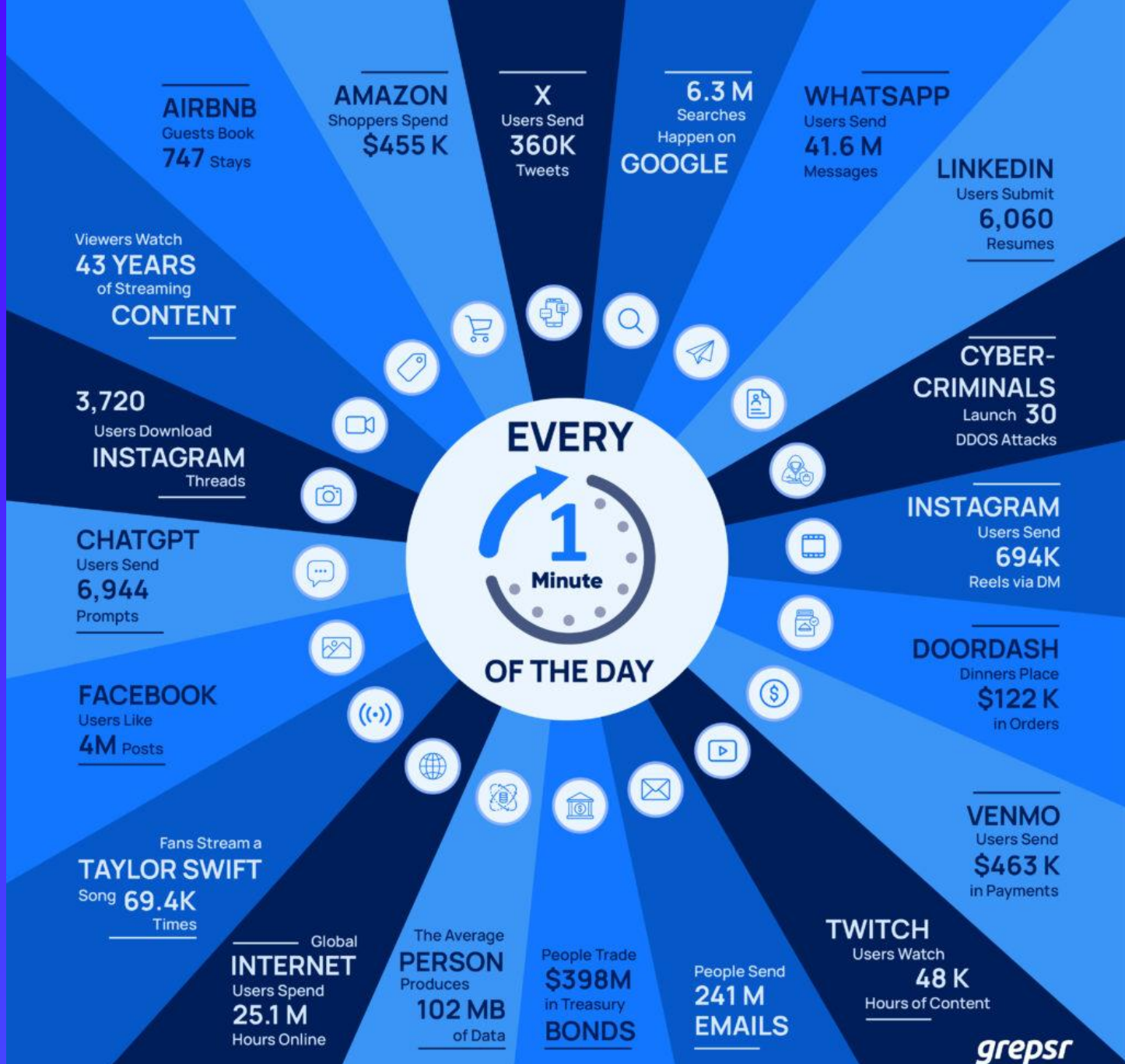
Global Data Generated Annually



90%

Produced in the past
two years

“By **2025**, the world will generate an astounding **180 zettabytes** of data, with approximately **30%** of this being **real-time data** created by connected users having digital interactions every **18 seconds**”



grepsr



That's not my data

Application generated data



Data

Generated from servers



Data

Generated from the cloud



Data

Generated from your users



Data

Generated from your disruptions

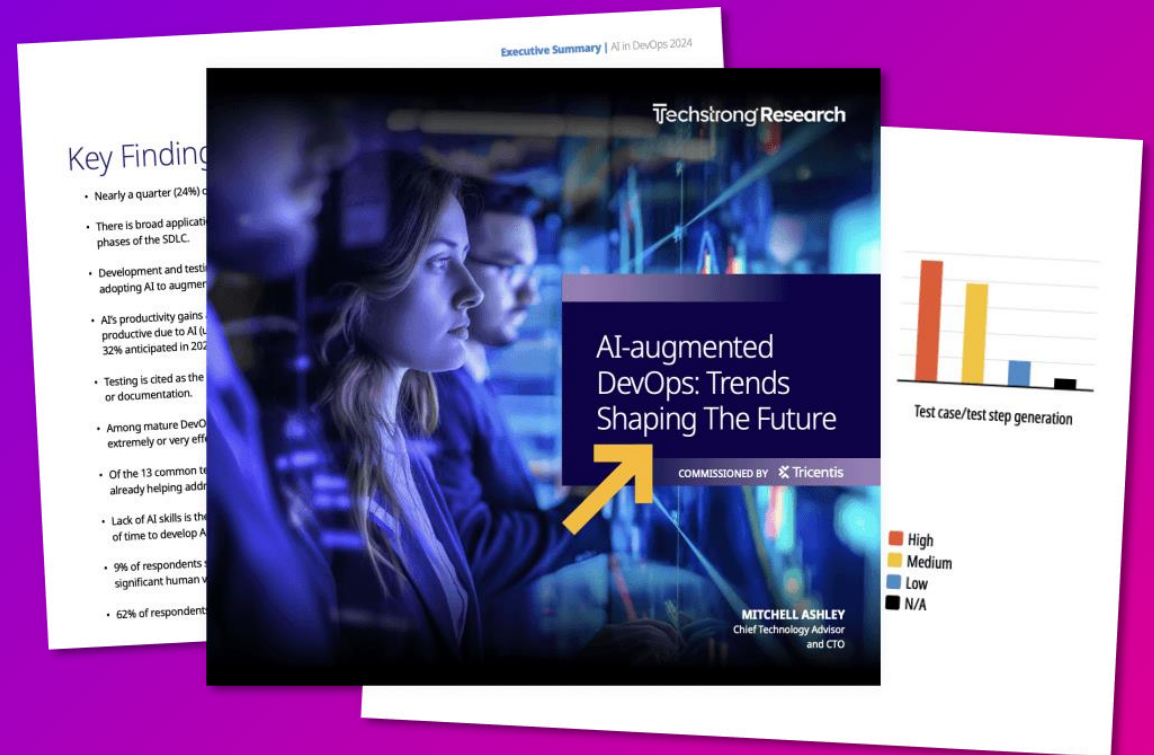
63%



will be making additional investments in observability over the next two years, with 21% describing those investments as significant..

46%

plan to adopt AI tools to augment DevOps teams in the next 12 months.



Primary Focus Areas

- **Development and Testing**
- **Operations and Monitoring**

Expected Benefits

- **Increased productivity**
- **Reduce skills gap**
- **Improve software quality**
- **Lower operational costs**

Expected Benefits

Increased productivity

Code Development

- **Improvements in writing code**
- **Gains in debugging and defect prevention**
- **Automated code reviews and optimization reduce errors**
- **AI copilots help write code faster and understand code structures**

Expected Benefits

Increased productivity

Testing and Quality

- **Enhanced testing efficiency**
- **Improvements in test script generation**
- **Automated testing and quality assurance processes**
- **AI helps detect, auto-heal, and predict defects during development**

How **AI and LLMs** are Modernizing Observability

What can be done .. **today?**



As of June 2024

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Current AI or LLM-enabled Observability Capabilities

Anomaly Detection	AI-driven RCA	Predictive Analytics
Natural Language Query Processing	Automated Incident Correlation	Business Impact Analysis
Security Threat Detection	AI-assisted Log Analysis	Incident Clustering and Intelligence
Behavioral Analysis	Virtual Agents and Predictive Tools	Proactive Alerts

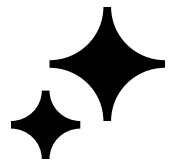
Notable Trends



Incident Management

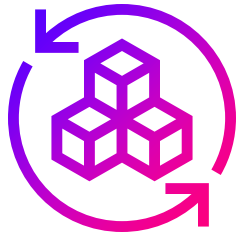


Predictive Capabilities



Query Intelligence

Incident Management



Automated RCA



**Intelligent
Classification**

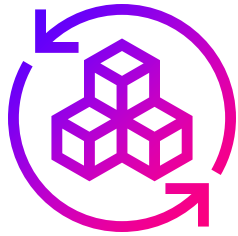


**Real-time
Response
Automation**



**Advanced Analytics
and Reporting**

Predictive Capabilities



**Early Issues
Detection and
Prevention**



**Performance
Optimization**

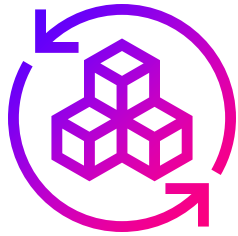


**Security and
Compliance
Enhancement**



**Cost Reduction and
Efficiency**

Natural Language Querying



**Query
Transformation**



**Personalized
Experience**



Smart Assistance



Task Simplification



Datadog Platform

Infrastructure

Infrastructure Monitoring
 Containers
 Serverless
 Network Performance Monitoring
 Network Device Monitoring
 Metrics
 Cloud Cost Management
 Cloudcraft

Applications

Application Performance Monitoring
 Distributed Tracing
 Continuous Profiler
 Database Monitoring
 Universal Service Monitoring
 Data Streams Monitoring
 Data Jobs Monitoring
 LLM Observability

Digital Experience

Synthetics
 Mobile App Testing
 Browser Real User Monitoring
 Mobile Real User Monitoring
 Session Replay

Logs

Log Management
 Observability Pipelines
 Audit Trail
 Log Forwarding
 Error Tracking
 Sensitive Data Scanner

Security

Cloud Security Management
 Application Security Management
 Software Composition Analysis
 Cloud SIEM

Software Delivery

CI Visibility
 Test Visibility
 Intelligent Test Runner
 Continuous Testing

Cloud Service Management

Incident Management
 Event Management
 Workflow Automation
 App Builder



AI

Natural Language Querying • Root Cause Analysis • Anomaly Detection • Impact Analysis • Proactive Alerts • Autonomous Investigations • Bits AI

Shared Platform Services

Dashboards • CoScreen • Teams • Agent • OpenTelemetry • Notebooks • Service Catalog • IDE Plugins • ChatOps • SLOs • Case Management



UNIFIED METRICS, LOGS, TRACES, SESSIONS

800+ INTEGRATIONS

Toto: Time Series Optimized Transformer for Observability

Technical Report

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This technical report describes the Time Series Optimized Transformer for Observability (Toto), a new state-of-the-art foundation model for time series forecasting developed by Datadog. In addition to advancing the state-of-the-art on generalized time series benchmarks in domains such as electricity and weather, this model is the first general-purpose time series forecasting foundation model to be specifically tuned for observability metrics.

Toto was trained on a dataset of one trillion time series data points – the largest among all currently published time series foundation models. Alongside publicly available time series datasets, 75% of the data used to train Toto consists of fully anonymous numerical metric data points from the Datadog platform.

In our experiments, Toto outperforms existing time series foundation models on observability data. It does this while also excelling at general-purpose forecasting tasks, achieving state-of-the-art zero-shot performance on multiple open benchmark datasets.

In this report, we detail the following key contributions:

- **Proportional factorized space-time attention:** We introduce an advanced attention mechanism that allows for efficient grouping of multivariate time series features, reducing computational overhead while maintaining high accuracy.
- **Student-T mixture model head:** This novel use of a probabilistic model that robustly generalizes Gaussian mixture models enables Toto to more accurately capture the complex dynamics of time series data and provides superior performance over traditional approaches.
- **Domain-specific training data:** In addition to general multi-domain time series data, Toto is specifically pre-trained on a large-scale dataset of Datadog observability metrics, encompassing unique characteristics not present in open-source datasets. This targeted training ensures enhanced performance in observability metric forecasting.

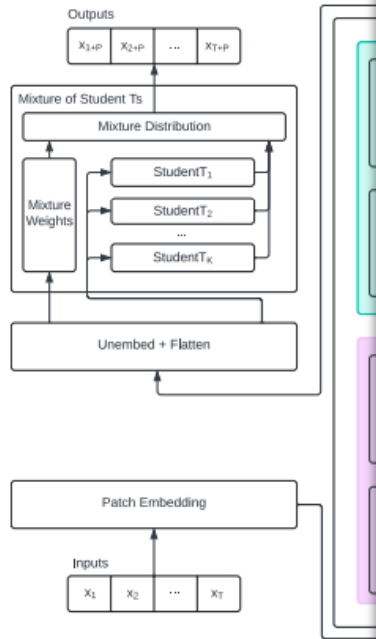


Figure 1. Toto architecture diagram. Input time series of T steps is embedded using the patch embedding layer. They then pass through each segment of the transformer. Each segment of the transformer consists of one space-wise transformer. The outputs are projected to form the parameters of the mixture model. The forecasts for the input series, shifted P steps (the patch width)

1 Background

We present Toto, a groundbreaking time series forecasting foundation model developed by Datadog. Toto is specifically designed to handle the complexities of observability data, leveraging a state-of-the-art transformer architecture to deliver unparalleled accuracy and performance. Toto is trained on a massive dataset of diverse time series data, enabling it to excel in zero-shot predictions. This model is tailored to meet the demanding requirements of real-time analysis as well as compute and memory-efficient scalability to very large data volumes, providing robust so-

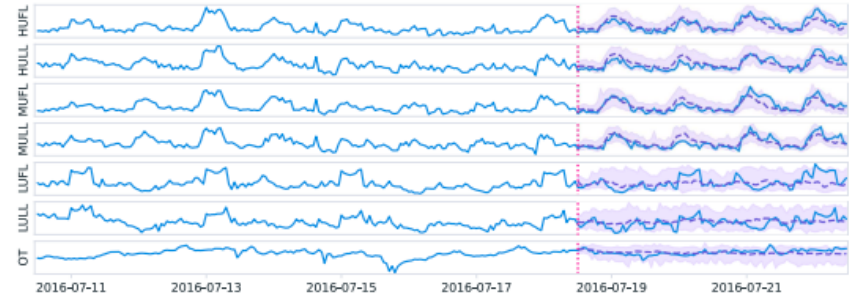


Figure 2. Example of Toto's 96-step zero-shot forecasts on the ETTh1 dataset, showing multivariate probabilistic predictions. Solid lines represent ground truth, dashed lines represent median point forecasts, and shaded regions represent 95% prediction intervals.

latency [1]. Additionally, Datadog integrates specific metrics from numerous SaaS products, cloud services, open-source frameworks, and other third-party tools. The platform allows users to apply various time series models to proactively alert on anomalous behavior, leading to a reduction in time to detection (TTD) and time to resolution (TTR) of production incidents [2].

The complexity and diversity of these metrics present significant challenges for time series forecasting. Observability data often requires high time resolution, down to seconds or minutes, and is typically sparse with many zero-inflated metrics. Moreover, these metrics can display extreme dynamic ranges and right-skewed distributions. The dynamic and non-stationary nature of the systems being monitored further complicates the forecasting task, necessitating advanced models that can adapt and perform under these conditions.

1.2 Traditional models

Historically, time series forecasting has relied on classical models such as ARIMA, exponential smoothing, and basic machine learning techniques [3]. While foundational, these models necessitate individual training for each metric, presenting several limitations [4]. The need to develop and maintain separate models for each metric impedes scalability, especially given the extensive range of metrics in observability

data. Moreover, these models often fail to generalize across different types of metrics, leading to suboptimal performance on diverse datasets [5, 6]. Continuous retraining and tuning to adapt to evolving data patterns further increase the operational burden. This scaling limitation has hindered the adoption of deep learning-based methods for time series analysis, even as they show promise in terms of accuracy [7].

1.3 Foundation models

Large neural network-based generative models, often referred to as "foundation models," have revolutionized time series forecasting by enabling accurate predictions on new data not seen during training, known as zero-shot prediction [8]. This capability significantly reduces the need for constant retraining on each specific metric, thus saving considerable time and computational resources. Their architecture supports the parallel processing of vast data volumes, facilitating timely insights essential for maintaining system performance and reliability [9, 10].

Through pretraining on diverse datasets, generative models exhibit strong generalization across various types of time series data. This enhances their robustness and versatility, making them suitable for a wide range of applications. Zero-shot predictions are particularly attractive in the observability domain, where the limitations of traditional methods are felt very acutely. The most common use cases for time series

Current AI or LLM-enabled Observability Capabilities

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DORA

2024

**Accelerate
State of DevOps**

Google Cloud

2024



The era of AI

- Most developers use AI for core work, boosting productivity.
- AI adoption is linked to improved team and organizational performance.
- Be relentlessly user-centric.

**Downstream
impacts of AI**

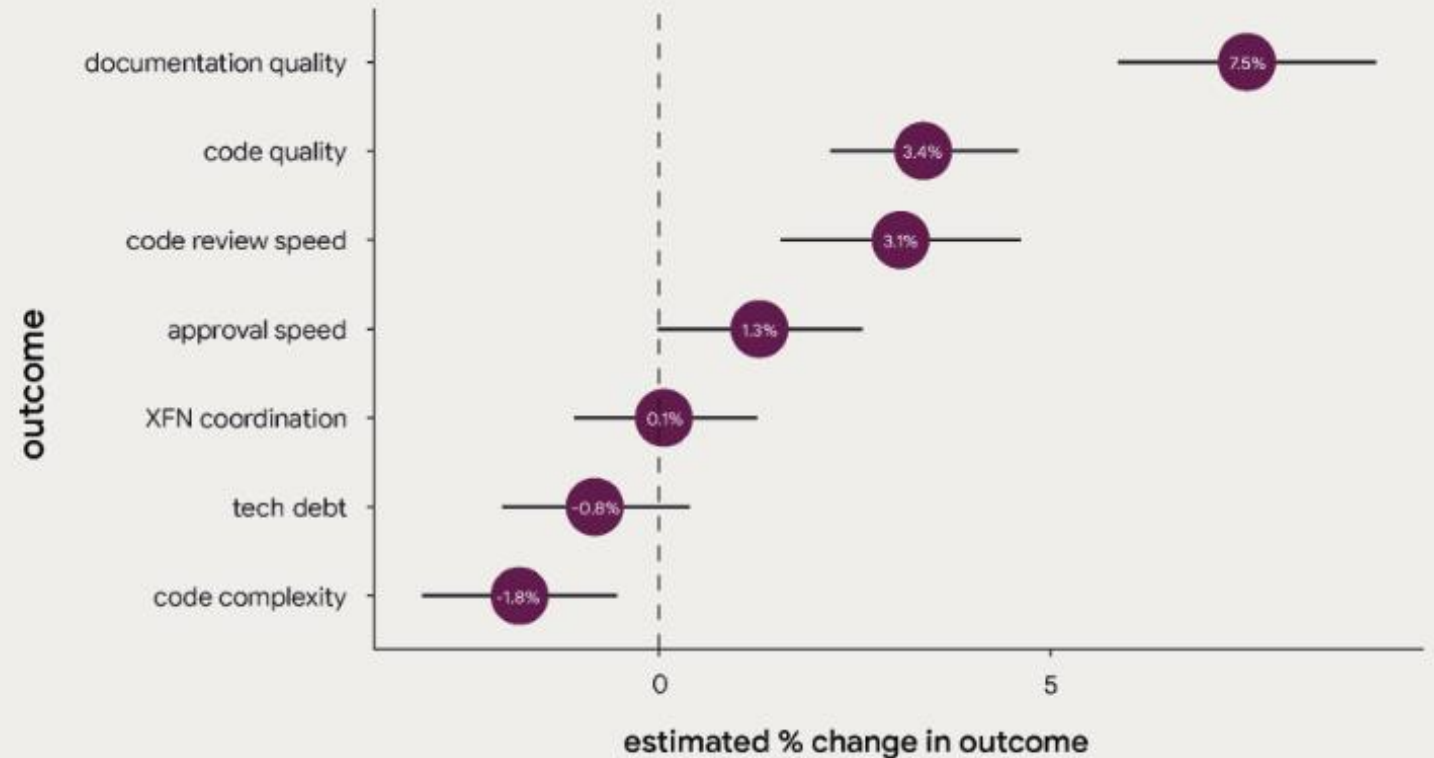
DRRA

AI is removing obstacles in the developer workflow

A 25% increase in AI adoption is associated with a...

- 7.5% increase in documentation quality
- 3.4% increase in code quality
- 3.1% increase in code review speed
- 1.3% increase in approval speed
- 0.1% increase in XFN coordination
- -0.8% decrease in tech debt
- -1.8% decrease in code complexity

If AI adoption increases by 25%..



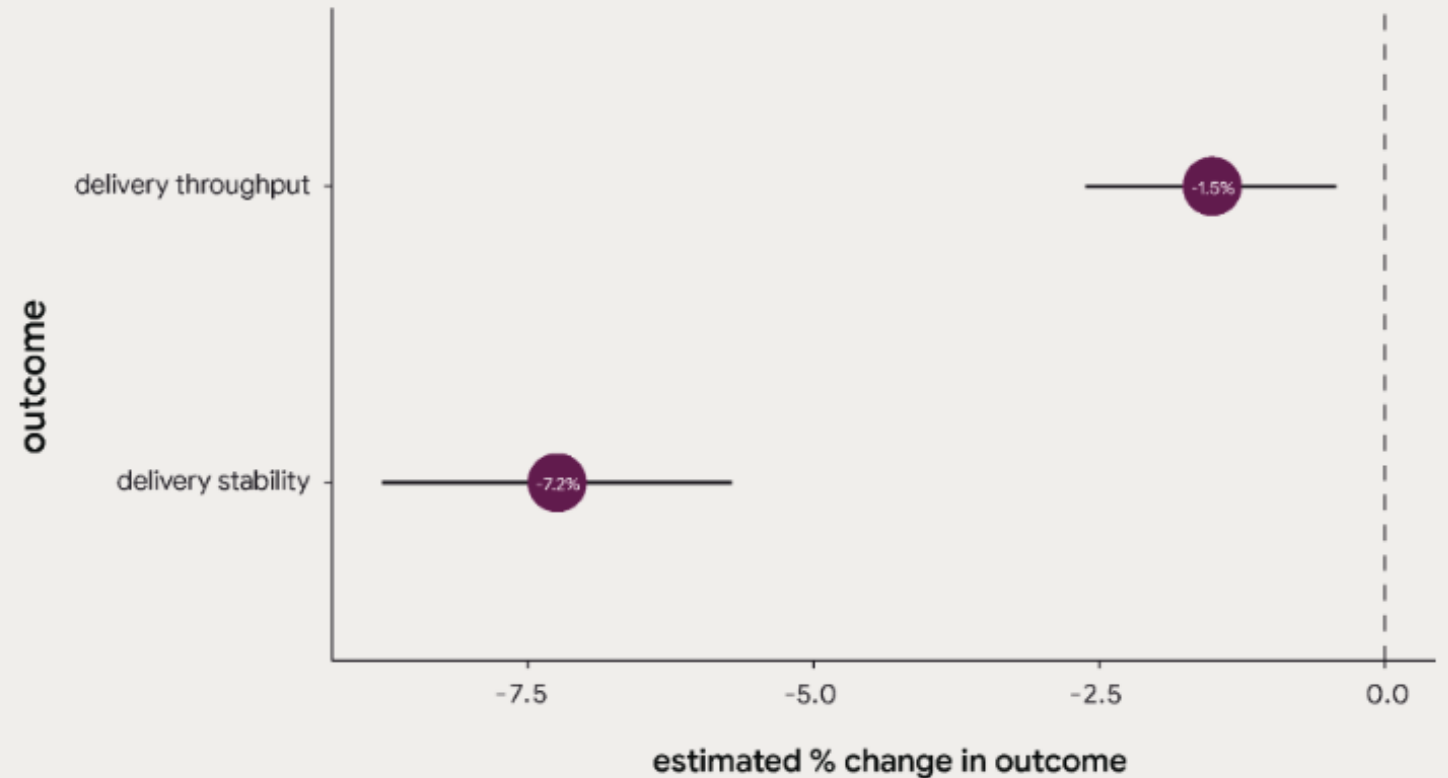
Point = estimated value
Error bar = 89% uncertainty interval

AI is hurting delivery performance

Contrary to our expectations, our findings indicate that AI adoption is negatively impacting software delivery performance.

These findings suggest gaining trust, perceived quality, and speed in one area of the development process can slow and destabilize later stages of software delivery.

If AI adoption increases by 25%..



Point = estimated value
Error bar = 89% uncertainty interval

AI Adoption



The report finds that AI adoption is rapidly increasing, with **76%** of respondents relying on AI for tasks like code writing, summarizing information, and code explanation. AI adoption is positively correlated with increased flow, productivity, job satisfaction, code quality, and internal documentation quality. However, it is associated with a decrease in delivery stability, suggesting a potential need for adapting change management practices in the age of AI-powered development.

Key metrics

81% of respondents say their company has shifted resources into developing AI.

67% of respondents report that AI is helping them improve their code.

39% of respondents reported having little or no trust in AI.

A **25%** increase in AI adoption is associated with a...

7.5% increase in documentation quality.

3.4% increase in code quality.

3.1% increase in code review speed.

1.3% increase in approval speed.

1.8% decrease in code complexity (this is a good thing!).

Change Management Techniques & Practices

- Establish a sense of urgency
- Create a vision for the future
- Communicate effectively

DORA Metrics

- **Deployment frequency**
- **Lead time for changes**
- **Change failure rate**
- **Time to restore service**

Data



Key Takeaways



Advanced Automated
Data analysis



Identify hidden
patterns in complex
data



Reduce manual
troubleshooting

Trends

Generative AI and LLMs ... in Observability Platforms



Agentic AI:
Autonomous
Workflows



Unified AI/ML:
Monitoring End-to-end
visibility from app &
infra to model

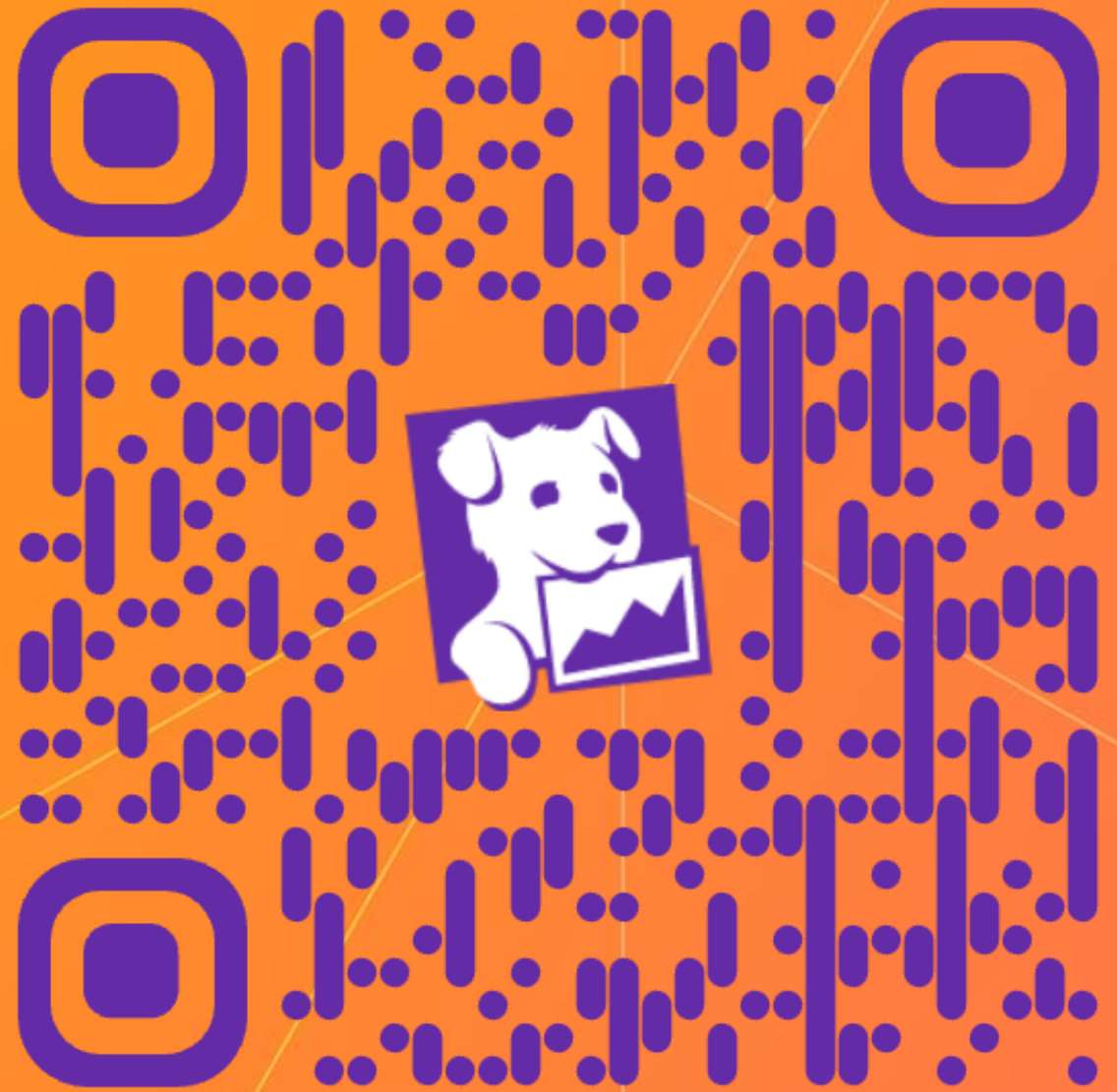


Cost Optimization:
Forecasting LLM token
usage

Resources

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NOTE: Authenticate first



Thank you



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DATADOG

