Modernizing Systems Observability with AI and LLMs

November 2024

DATADOG

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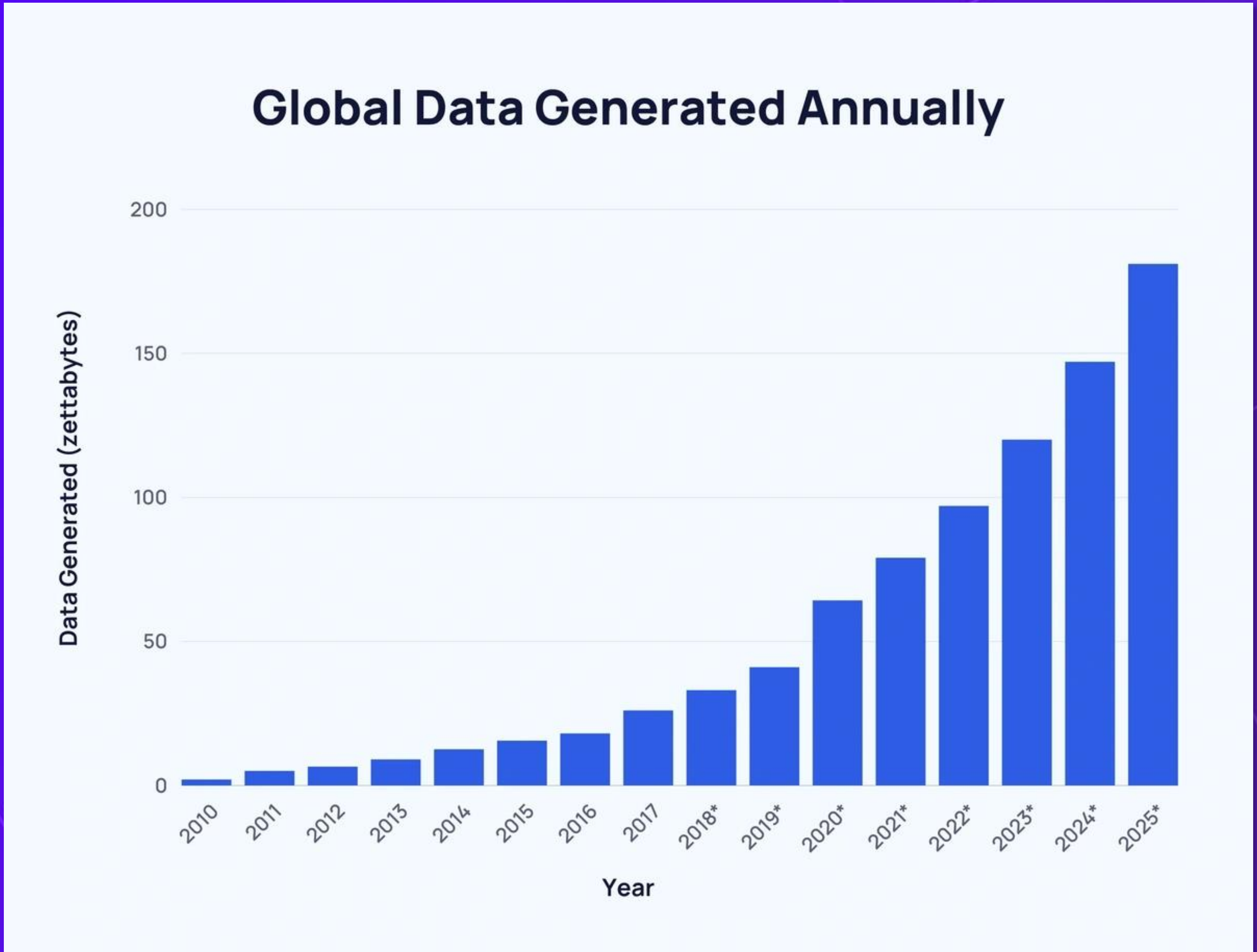
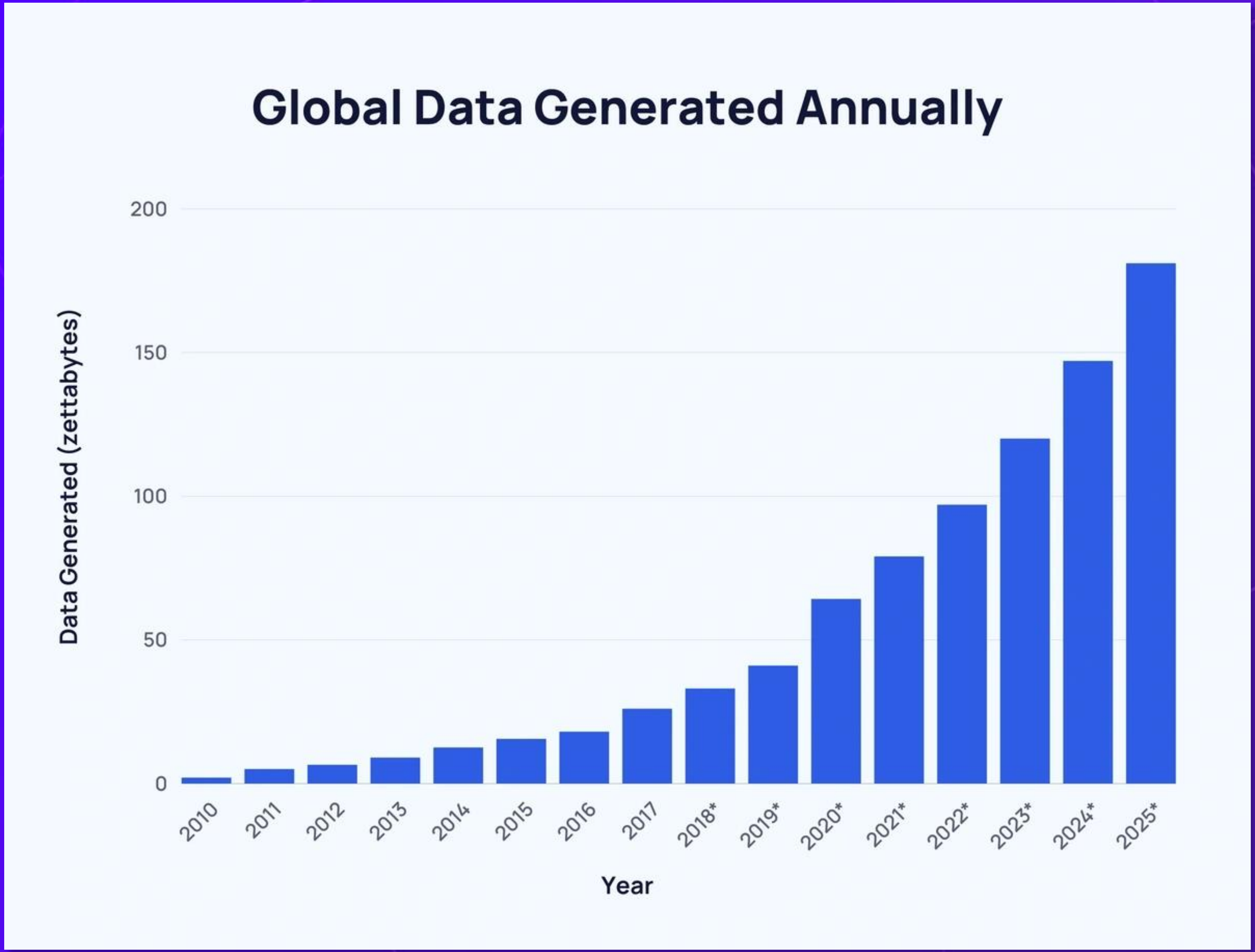
Resources

dtdg.co/ai-native-devcon

How much data is generated annually, globally?



https://explodingtopics.com/blog/data-generated-per-day



90%

Produced in the past two years

https://explodingtopics.com/blog/data-generated-per-day

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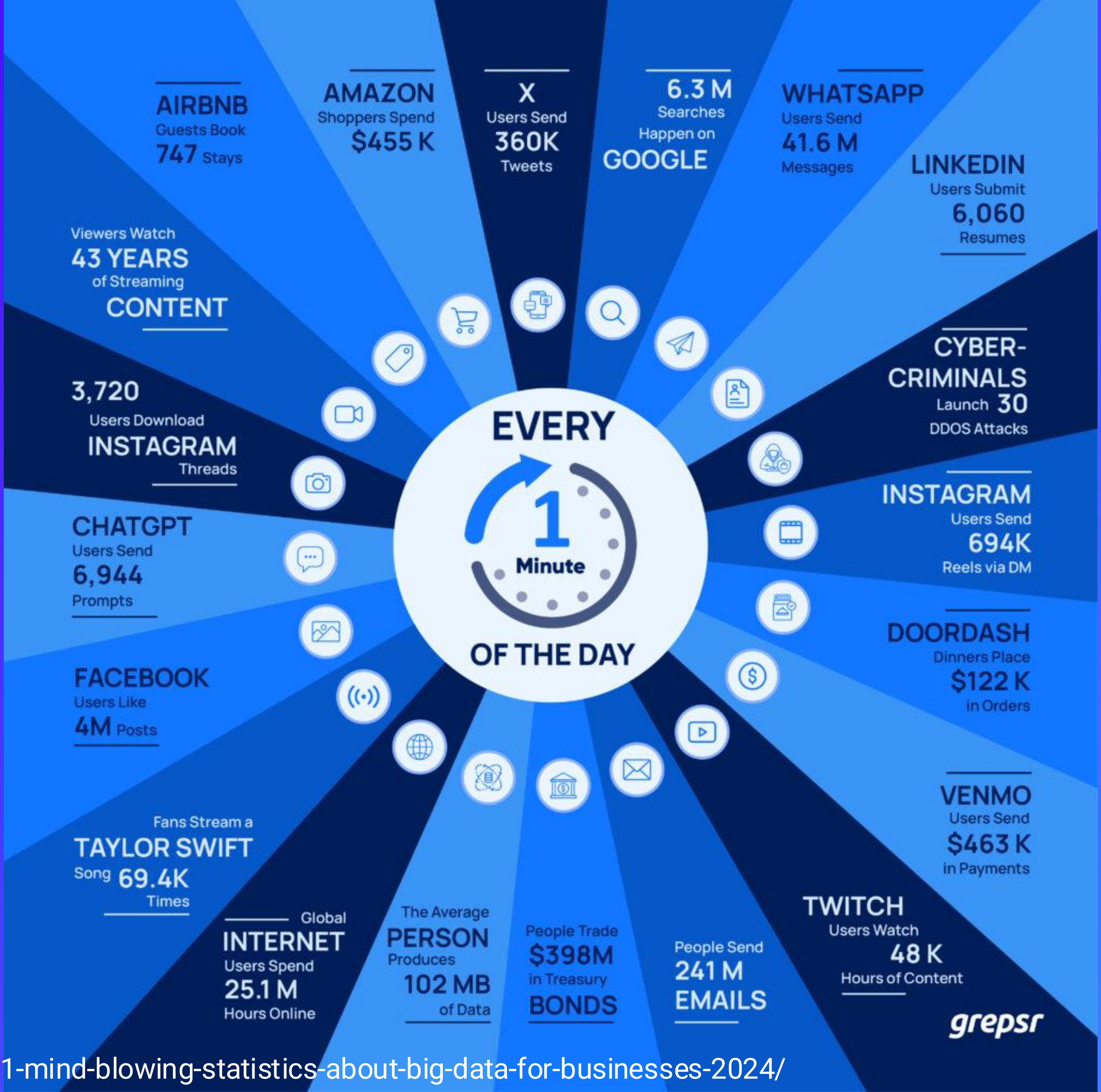
“By 2025, the world will generate an astounding 180 zettabytes of data, with approximately 30% of this being real-time data created by connected users having digital interactions every 18 seconds”

https://www.seagate.com/files/www-content/our-story/trends/files/idc-seagate-dataage-whitepaper.pdf (page 5)



https://www.grepsr.com/blog/31-mind-blowing-statistics-about-big-data-for-businesses-2024/

That’s not <u>**my**</u> data

Application generated data

Data

Generated from servers

Data

Generated from the cloud

Data

Generated from your users

Data

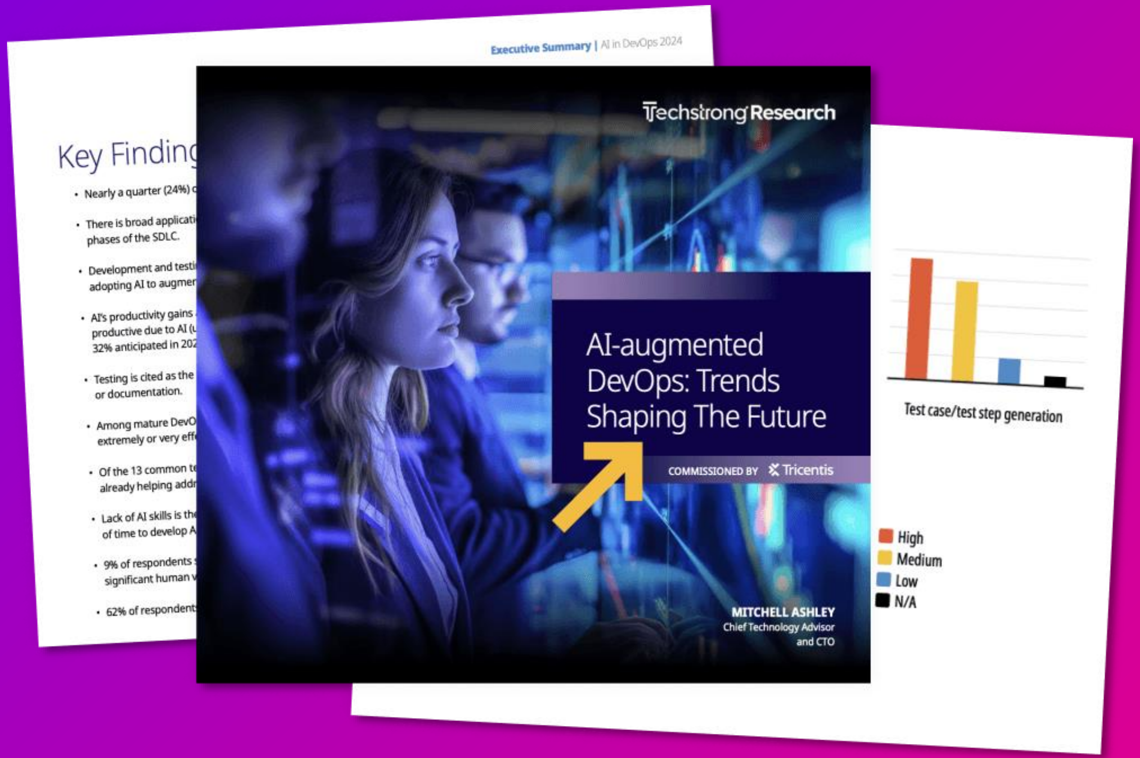
Generated from your disruptions

63%

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

https://devops.com/survey-surfaces-spike-in-observability-investments-among-devops-teams/

46%



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

https://devops.com/survey-usage-of-ai-rapidly-expands-once-devops-teams-adopt/

Primary Focus Areas

- Development and Testing
- Operations and Monitoring

Expected Benefits

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

https://devops.com/survey-usage-of-ai-rapidly-expands-once-devops-teams-adopt/

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

https://devops.com/survey-usage-of-ai-rapidly-expands-once-devops-teams-adopt/

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

https://devops.com/survey-usage-of-ai-rapidly-expands-once-devops-teams-adopt/

How AI and LLMs are Redefining Observability

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Gartner's Magic Quadrant

Leaders

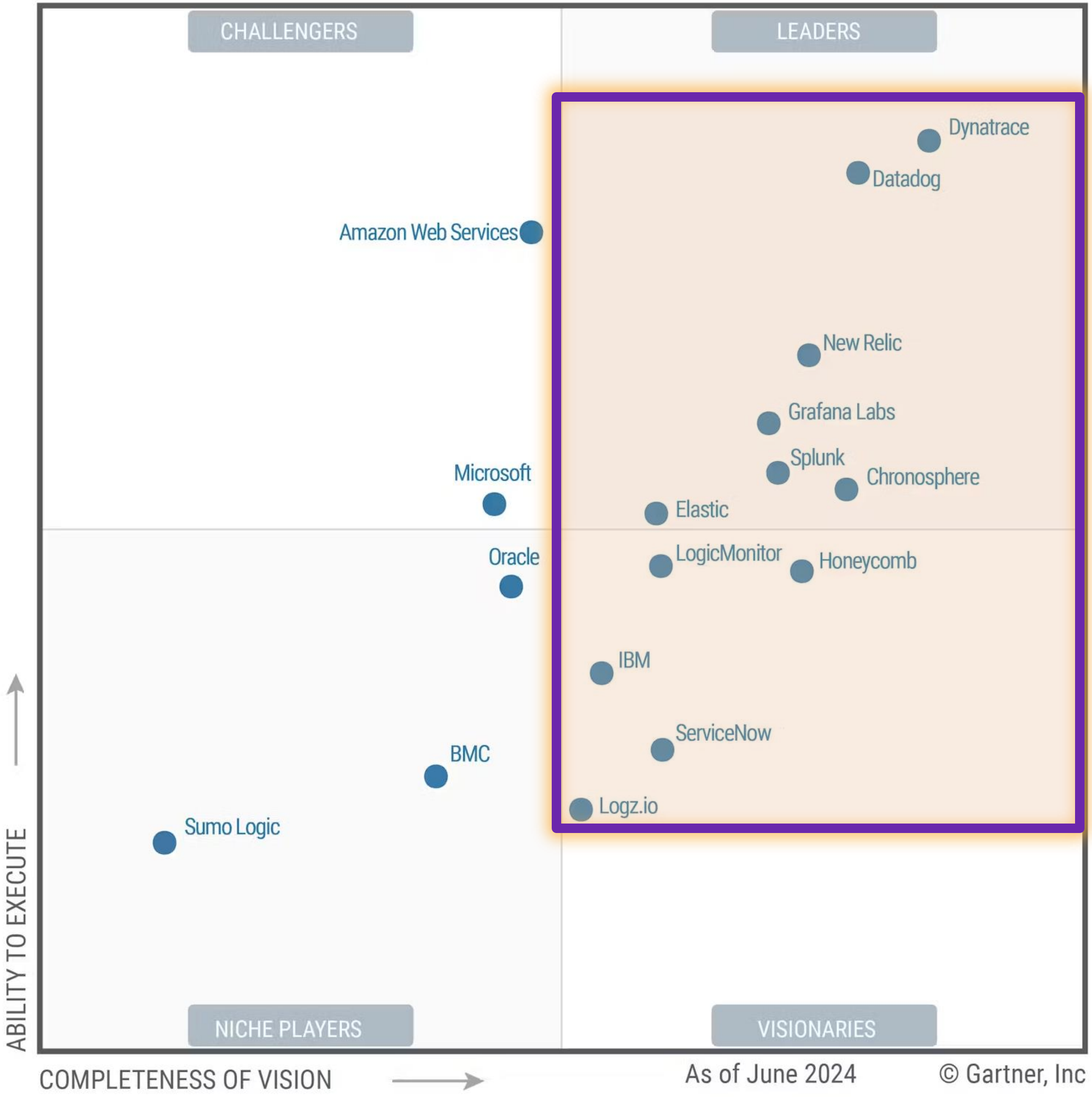
- Dynatrace
- Datadog
- New Relic
- Grafana Labs
- Splunk
- Chronoshphere
- Elastic

Visionaries

- LogicMonitor
- Honeycomb
- IBM
- ServiceNow
- Logz.io

Figure 1: Magic Quadrant for Observability Platforms

Gartner


CHALLENGERS
LEADERS
Dynatrace
Datadog
Amazon Web Services
New Relic
Grafana Labs
Splunk
Chronosphere
Microsoft
Elastic
Oracle
LogicMonitor
Honeycomb
IBM
ServiceNow
BMC
Logz.io
Sumo Logic
ABILITY TO EXECUTE
NICHE PLAYERS
VISIONARIES
COMPLETENESS OF VISION
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

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Toto: Time Series Optimized Transformer for Observability

Technical Report

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arXiv:2407.07874v2 [cs.LG] 11 Jul 2024

This technical report describes the Time Series Optimized Transformer for Observability (Toto), a new state-o
the-art foundation model for time series forecasting developed by Datadog. In addition to advancing the state
the art on generalized time series benchmarks in domains such as electricity and weather, this model is the fi
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 publishe
time series foundation models. Alongside publicly available time series datasets, 75% of the data used to tra
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 th
while also excelling at general-purpose forecasting tasks, achieving state-of-the-art zero-shot performance o
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 allow for efficient grouping of multivariate time series features, reducing computational overhead while mai taining high accuracy.
- **Student-T mixture model head:** This novel use of a probabilistic model that robustly generalizes Gaussia mixture models enables Toto to more accurately capture the complex dynamics of time series data an provides superior performance over traditional approaches.
- **Domain-specific training data:** In addition to general multi-domain time series data, Toto is specifical pre-trained on a large-scale dataset of Datadog observability metrics, encompassing unique characteristi not present in open-source datasets. This targeted training ensures enhanced performance in observabili metric forecasting.

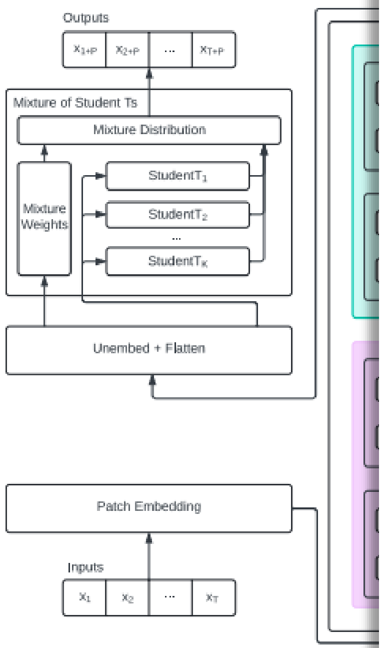

Figure 1. Toto architecture diagram. Input time series of T steps
bedded using the patch embedding layer. They then pass through
Each segment of the transformer consists of one space-wise trans
transformer outputs are projected to form the parameters of the S
the forecasts for the input series, shifted 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-

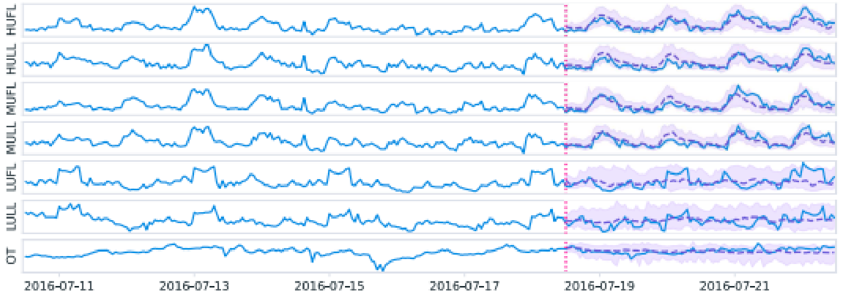

Figure 2. Example of Toto's 96-step zero-shot forecasts on the ETTh1 dataset, showing multivariate probabilistic predictions. Solid lines represent ground truth, dashed lines represent median point forecasts, and shaded regions represent 95% prediction intervals.

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 nonstationary 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

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Data

Key Takeaways

Generative AI and LLMs …

Advanced Automated Data analysis

Identify hidden patterns in complex data

Reduce manual troubleshooting

Resources

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Thank you

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