AWS Certified ML Specialty Guide

Navigating the AWS Certified Machine Learning - Specialty exam from novice to expert

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Dedicated to

My beloved dog Lucky, whose gentle presence turned our house into a home and reminded us that love is the most powerful force of all

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Preface

The machine learning revolution is transforming industries across the globe, much like the advent of electricity once did. As organizations increasingly rely on data-driven insights and intelligent automation, the demand for skilled machine learning professionals who can harness the power of cloud computing has never been greater. Amazon Web Services has emerged as the leading platform for building, deploying, and managing machine learning solutions at scale.

This book is designed to be your comprehensive guide to mastering machine learning on AWS and successfully passing the AWS Certified Machine Learning - Specialty exam. It bridges the gap between fundamental cloud computing knowledge and advanced machine learning expertise, taking you on a journey from understanding basic concepts to building production-ready ML solutions.

Throughout this guide, you will gain hands-on experience with essential AWS services, including Amazon SageMaker, AWS Glue, Amazon Kinesis, AWS Lambda, and many others. The book is structured around the four key domains of the AWS ML Specialty certification, that is,data engineering, exploratory data analysis, modeling, and machine learning implementation and operations. Each chapter builds upon previous concepts while providing practical, real-world examples that you can apply immediately.

This book is intended for aspiring machine learning specialists, data scientists, data engineers, cloud architects, and professionals seeking to validate their expertise in AWS machine learning technologies. Whether you are beginning your machine learning journey or looking to formalize your existing knowledge, this guide will equip you with the skills and confidence needed to excel in the rapidly evolving field of cloud-based machine learning.

With this book, you will not only prepare for certification success but also develop the practical skills necessary to drive innovation and make a meaningful impact in your organization through the power of AWS machine learning.

Chapter 1: Creating Data Repositories for Machine Learning- This chapter establishes the foundation for any ML project by exploring how to identify diverse data sources and select appropriate storage solutions on AWS. The chapter covers databases, Amazon S3, Amazon EFS, and Amazon EBS, providing best practices for data repository design and integration strategies that ensure your data infrastructure can support robust machine learning workflows from simple batch processing to complex real-time analytics.

Chapter 2: Implementing Data Ingestion Solutions- This chapter discusses the critical process of moving data into your ML pipeline, covering both batch and streaming data ingestion patterns. You wi'll learn to leverage Amazon Kinesis, Amazon EMR, AWS Glue, and other AWS services to orchestrate and automate data pipelines, including scheduling and managing complex data ingestion jobs for various data types and volumes across different organizational needs.

Chapter 3: Transforming Data into Insights – This chapter focuses on converting raw data into formats suitable for machine learning analysis. The chapter explores ETL processes using AWS Glue and Amazon EMR, handling ML-specific data transformations with MapReduce, Apache Hadoop, Spark, and Hive, while providing optimization techniques to prepare data for various ML algorithms and ensuring scalable transformation workflows.

Chapter 4: Data Sanitization and Preparation- This chapter addresses the crucial task of ensuring data quality and readiness for modeling. You will learn to identify and handle missing or corrupt data, implement data cleaning and preprocessing techniques, and apply normalization and scaling methods. The chapter emphasizes data augmentation strategies and quality assessment practices essential for successful ML outcomes while maintaining data integrity throughout the preparation process.

Chapter 5: Feature Engineering- This chapter explores the art and science of extracting meaningful features from diverse data sources including text, speech, and images. The chapter covers feature identification techniques, dimensionality reduction methods, and feature transformation approaches, with practical examples demonstrating how to enhance your datasets for optimal ML model performance using AWS tools like SageMaker Feature Store and processing capabilities.

Chapter 6: Data Analysis and Visualization- This chapter teaches you to create insightful visualizations and interpret key statistics that inform ML decision-making. You will learn to generate various graph types, understand descriptive statistics, implement cluster analysis for data segmentation, and utilize AWS visualization tools including QuickSight to effectively communicate data insights to stakeholders and validate your analytical assumptions.

Chapter 7: Framing Business Problems as ML Problems- This chapter bridges the gap between business challenges and technical ML solutions. The chapter helps you assess when ML is appropriate, differentiate between supervised and unsupervised learning approaches, and select suitable models for various business scenarios through real-world case studies and best practices for problem definition, ensuring alignment between business objectives and technical implementation.

Chapter 8: Selecting Appropriate ML Models- This chapter provides comprehensive coverage of the ML model landscape, including XGBoost, logistic regression, decision trees, and neural networks such as RNNs and CNNs. You will develop intuition about model selection criteria based on data characteristics and problem types, while learning to leverage AWS tools and SageMaker's built-in algorithms for effective model implementation and comparison.

Chapter 9: Training ML Models- This chapter covers methodologies and best practices for effective model training, including data splitting strategies, optimization techniques, and compute resource selection. The chapter addresses GPU vs CPU considerations, Spark and non-Spark platforms, and provides guidance on updating and retraining strategies to maintain model relevance using SageMaker training jobs and distributed training capabilities.

Chapter 10: Hyperparameter Optimization- This chapter focuses on refining ML models for peak performance through systematic tuning approaches. You will learn regularization techniques including dropout and L1/L2 regularization, cross-validation methods, neural network architecture optimization, and tree-based model tuning. The chapter demonstrates how to leverage AWS solutions like SageMaker Automatic Model Tuning for efficient hyperparameter optimization at scale.

Chapter 11: Evaluating ML Models- This chapter centers on comprehensive model evaluation techniques to ensure optimal performance and avoid common pitfalls. The chapter covers detecting and handling bias and variance, understanding evaluation metrics such as AUC-ROC, precision, recall, and F1 score, and implementing both offline and online evaluation strategies using AWS tools for continuous model assessment and validation.

Chapter 12: Building ML Solutions for Performance and Scalability- This chapterdiscusses the creation of machine learning solutions that are high-performing, scalable, resilient, and fault-tolerant. You will explore monitoring with AWS CloudTrail and Amazon CloudWatch, deploying solutions across multiple regions and availability zones, creating and managing AMIs and Docker containers, implementing auto-scaling, and following AWS best practices for enterprise-grade ML deployments.

Chapter 13: Recommending and Implementing Appropriate ML Services- This chapter teaches you to choose and implement the most suitable AWS machine learning services for specific scenarios. The chapter covers AWS ML application services including Amazon Polly, Lex, and Transcribe, understanding service quotas, making build-versus-buy decisions with SageMaker built-in algorithms, and optimizing costs through strategic use of spot instances and AWS Batch for deep learning workloads.

Chapter 14: Applying AWS Security Practices to ML Solutions- This chapter focuses on implementing fundamental AWS security practices essential for production ML systems. You will learn about IAM roles and policies for ML workflows, S3 bucket security configurations, VPC networking for secure deployments, and encryption and anonymization techniques to protect sensitive data throughout the ML pipeline while maintaining compliance with organizational security requirements.

Chapter 15: Deploying and Operationalizing ML Solutions- This chapter covers the complete lifecycle of ML model deployment and operational management. The chapter addresses exposing and interacting with ML endpoints, implementing A/B testing strategies, establishing retraining pipelines, and debugging and troubleshooting techniques to ensure models continue performing optimally in production environments using SageMaker endpoints and monitoring capabilities.

Appendix- This chapter provides a comprehensive practice test that simulates the actual AWS Certified Machine Learning - Specialty exam experience. This chapter includes sample questions across all four domains, detailed explanations for correct and incorrect answers, and strategic guidance for exam preparation, helping you assess your readiness and identify areas requiring additional study before taking the certification exam.

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Chapter 1
Creating Data Repositories for Machine Learning

Introduction

Machine learning (**ML**) is transforming the way we interact with technology, enabling systems to learn from data and make intelligent decisions without being explicitly programmed. From personalized recommendations and fraud detection to natural language processing and predictive analytics. At the core of every successful ML project lies one indispensable element: data. This chapter zeroes in on two foundational pillars essential for creating robust data repositories: identifying the myriad sources of data and selecting the optimal storage mediums to house this data. From understanding the content and location of primary data sources, such as user-generated data, to evaluating the strengths and use cases of various AWS storage solutions like Amazon S3, Amazon **Elastic File System** (**EFS**), and Amazon **Elastic Block Store** (**EBS**), this chapter equips you with the knowledge to architect data repositories that are not only scalable and secure but also precisely tailored to the needs of your ML applications.

Structure

The chapter covers the following topics:

- Introduction to data in ML
- Identifying data sources

- Analyzing data characteristics
- Determining storage mediums

Objectives

By the end of this chapter, readers will be able to identify and evaluate potential data sources for ML, understanding their content, location, and relevance. We will analyze data characteristics to inform the selection of appropriate storage solutions and choose the most suitable AWS storage mediums based on the specific needs of ML projects, considering factors like data type, access patterns, and scalability requirements. We will understand how to implement best practices for secure, cost-efficient, and compliant data storage on AWS and apply this knowledge to build real-world ML projects, ensuring a solid foundation for building scalable and robust data repositories.

Introduction to data in ML

In the enthralling world of ML, data is not just king; it is the very lifeblood that powers the algorithms, breathing intelligence into models that can predict, classify, and make decisions with astonishing accuracy. Data acts as the critical ingredient in concocting models that can foresee stock market trends, personalize your streaming service recommendations, or even diagnose diseases from medical images. You are now able to use your smartphone camera and identify plants or translate text in real-time, all of which is made possible through ML models trained on vast datasets of images and languages. Such practical applications underscore the quintessence of data: without diverse, high-quality datasets, ML models would be like ships without compasses adrift in a sea of potential, but lacking the direction needed to reach ground-breaking innovations.

As we explore the digital age, the exponential growth of data in all its forms has become a defining characteristic of our time. The latest statistics paint a staggering picture. According to the *International Data Corporation (IDC)*, the global datasphere is expected to grow to 175 zettabytes by 2025, a testament to the sheer volume of information generated, captured, and stored across the globe. This monumental growth is fueled by advancements in **Internet of Things** (**IoT**) devices, social media, high-resolution video content, and the increasing digitization of industries and personal lives. Each byte of this vast ocean of data holds potential insights for ML models, making the identification and strategic storage of data more crucial than ever.

The volume of data generated by various industry verticals has seen immense growth due to advancements in digital technology, the IoT, and increased internet usage worldwide, as illustrated in the following figure:

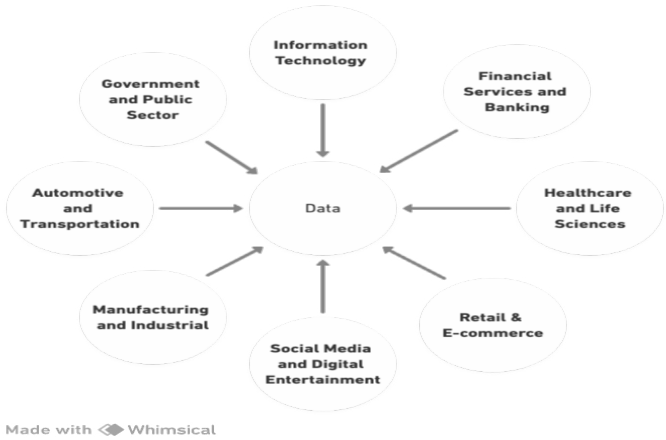

***Figure 1.1**: Top industry verticals generating huge amounts of data*

Identifying this data, sifting through structured databases, unstructured social media posts, or semi-structured IoT sensor readings is the first step in harnessing its power. The challenge lies not only in collecting this data but in effectively storing it in ways that make it accessible and usable for ML projects. For instance, health care industries are leveraging **Electronic Health Records** (**EHRs**) to train ML models that can predict patient outcomes, improve diagnoses, and personalize treatment plans. This application requires meticulously organized and securely stored data to ensure patient privacy and compliance with regulations like the **Health Insurance Portability and Accountability Act** (**HIPAA**).

In e-commerce, companies analyze customer behavior, preferences, and feedback from various sources to tailor recommendations, optimize supply chains, and enhance customer service. Here, the diversity of data, from transaction logs to customer service interactions, demands versatile storage solutions like *Amazon S3* for unstructured data or *Amazon RDS* for transactional data, ensuring scalability and high availability.

Furthermore, the advent of smart cities and autonomous vehicles underscores the importance of real-time data processing and storage. Traffic patterns, sensor data from vehicles, and environmental information must be stored in a manner that supports rapid access and analysis, often employing edge computing solutions alongside cloud storage to minimize latency.

The importance of identifying and categorically storing this data cannot be overstated. It enables organizations to not only make informed decisions and innovate but also to ensure ethical considerations are met in handling personal and sensitive information. As we continue to generate data at an unprecedented rate, the strategies we adopt for its identification, storage, and usage will dictate the trajectory of advancements in **machine learning** (**ML**) and **artificial intelligence** (**AI**), shaping the future of technology and its impact on society.

Identifying data sources

The objective of identifying the location of data and understanding how it can be collected is crucial for building effective ML models. This process involves a nuanced understanding of various data types, such as user data, transactional data, and sensor data, and the methodologies employed to collect these data efficiently and ethically. Let us explore these components in detail.

Identifying location of data

The location of data will depend on the category of data, and the following are the important categories to be aware of:

- **User data**: Typically found in web applications, social media platforms, customer feedback forms, and online purchase histories.
- **Transactional data**: Located in e-commerce platforms, banking systems, and any digital platform where transactions occur. This data is usually stored in transactional databases or ledgers and can be accessed through database queries or transaction logs.
- **Sensor data**: Generated by IoT devices, smartphones, industrial equipment, and environmental sensors. A practical example includes smart home devices that continuously send data about temperature, humidity, or energy usage to a centralized server for analysis and optimization.

Collecting data

The following are the most common ways of collecting data:

- **Web scraping**: Employing bots or crawlers to collect data from websites. This is particularly useful for gathering user opinions, reviews, and product information from various online sources. *Amazon Kendra Web Crawler* is a very good example.
- **Application programming interfaces (APIs)**: Leveraging APIs provided by platforms (like *Twitter*, *Facebook*, or *Google Maps*) to systematically collect data that includes the extraction of user posts, comments, and likes to analyze trends and sentiments. This method ensures structured data collection and is governed by the platform's data usage policies, ensuring ethical data usage.
- **Database queries**: Running **Structured Query Language** (**SQL**) queries on databases to extract transactional or operational data, which can then be used for trend analysis, financial forecasting, or customer behavior modeling. For example, an e-commerce platform might store transactional data in a **relational database management system** (**RDBMS**), where each transaction record details purchases, returns, and payment methods.

- **Direct collection from IoT devices**: This data is often streamed in real-time and requires technologies capable of handling big data streams, such as *Apache Kafka* or *Amazon Kinesis*. Utilizing **Message Queuing Telemetry Transport** (**MQTT**) or similar protocols to collect data directly from sensors or IoT devices in real-time, providing a continuous stream of data for analysis.

File formats for ML

Selecting the appropriate file format for storing and processing data is a critical step in preparing for ML workflows. The choice of format affects everything from data ingestion speed and storage efficiency to compatibility with ML tools and libraries. AWS services offer flexibility in handling a wide range of data formats, each suited for different types of tasks and stages in the ML lifecycle.

The following is an overview of commonly used file formats and their relevance in ML workflows:

- **Comma-separated values** (**CSV**) is a popular choice for structured, tabular data such as training datasets and feature sets. It is human-readable, easy to generate and parse, and widely supported by ML libraries like pandas and scikit-learn. However, it lacks support for hierarchical data and becomes inefficient when handling large or complex datasets due to its lack of compression and indexing capabilities.
- **JavaScript Object Notation** (**JSON**) is commonly used for semi-structured data from APIs or logs, especially when dealing with nested elements like metadata or sensor readings. It supports hierarchical structures and is widely compatible across programming languages, making it a flexible choice for many ML workflows. However, JSON can be verbose, and parsing large files may be slow without optimized tools or libraries.
- **Parquet** is a columnar storage format ideal for big data applications and large-scale model training, especially when using services like *Amazon Athena* or *AWS Glue*. It offers efficient compression and fast query performance, making it well-suited for analytics workloads. However, Parquet is less human-readable and usually requires a processing engine like *Apache Spark* for effective use.
- **Optimized row columnar** (**ORC**) is designed for high-performance data processing, particularly in *Amazon EMR* or *Hive-based workflows*. It provides high compression and faster read performance for large-scale datasets.
- **Avro** is well-suited for data serialization and streaming pipelines, particularly with tools like Kafka or AWS Kinesis. It uses a compact binary format and supports schema-based, row-oriented storage, making it efficient for message passing and data exchange. However, Avro is not human-readable and requires careful schema management to ensure compatibility across systems.

- **Image, audio, and video formats** like *JPEG*, *PNG*, *WAV*, and *MP4* are commonly used in deep learning models such as CNNs and RNNs. These formats are natively supported by frameworks like TensorFlow and PyTorch, enabling direct integration into ML pipelines. However, they typically require extensive pre-processing and transformation before being used for training or inference.
- **TFRecord** is a binary file format developed for TensorFlow, optimized for training large-scale deep learning models. It offers efficient storage and performance within TensorFlow pipelines, especially when working with large datasets. However, its use is limited outside the TensorFlow ecosystem due to a lack of broader compatibility.

Understanding when and how to use each of these file formats is essential for building efficient and scalable ML solutions on AWS. Whether you are streaming real-time data from IoT devices, querying historical data in S3, or feeding labeled images into a training pipeline, choosing the right format will help ensure performance, compatibility, and cost-efficiency throughout the ML workflow.

Types of data involved

The following are the types of data involved:

- **Structured data**: Highly organized and easily searchable, often stored in relational databases. Examples include customer information in a **customer relationship management** (**CRM**) system or transaction details in an e-commerce database.
- **Unstructured data**: Not organized in a pre-defined manner, making it harder to collect and interpret. Examples include text data from social media posts, images, and videos from user uploads.
- **Semi-structured data**: A mix between structured and unstructured data, such as JSON or **Extensible Markup Language** (**XML**) files from web APIs. For instance, sensor data might be transmitted in JSON format, containing both structured elements (like timestamps and device IDs) and unstructured elements (like complex sensor readings).

Analyzing data characteristics

In the dynamic and ever-evolving domain of big data, the comprehension and management of vast datasets necessitate a strategic framework, encapsulated by the seminal **7 Vs** of data. These critical dimensions are as follows:

- Volume
- Velocity
- Variety
- Veracity

- Value
- Variability
- Visualization and accessibility

The above core principles are used by data professionals to decipher the complexity of data. As navigators in the intricate world of information, data scientists and technology experts leverage these pillars to convert the extensive arrays of raw data into meaningful, actionable insights. Addressing the challenges presented by the immense volume of data generated continuously, the swift pace at which it flows, the diverse forms it assumes, and the imperative for accuracy and utility, the 7 Vs provide a structured approach to data analysis. This framework not only facilitates the efficient extraction of pertinent information but also ensures that data-driven decisions are both insightful and impactful. By adhering to these principles, organizations can adeptly maneuver through the intricacies of big data, unlocking its vast potential to drive innovation and inform strategic decisions. As we engage with the multifaceted aspects of big data, the 7 Vs serve as a guiding framework, steering efforts towards the realization of data's full potential in shaping future advancements.

Refer to the following table:

Type of V	Definition and impact	Handling strategies	Use cases
Volume	The sheer size of data collected can be massive and impact storage, processing, and analysis capabilities.	Use data compression, distributed storage systems, and scalable cloud solutions.	Analyzing social media posts for trends requires managing and processing large datasets.
Velocity	The speed at which data is generated and processed is crucial for real-time data applications.	Implement real-time processing frameworks (Apache Kafka, Spark Streaming); ensure rapid data storage performance.	Real-time monitoring of stock transactions for algorithmic trading.
Variety	The range of data types and sources includes structured, unstructured, and semi-structured data.	Utilize a mix of databases (NoSQL, RDBMS) and data integration tools for various data formats.	Integrating customer data from different sources for comprehensive analytics.
Veracity	The quality and accuracy of data affect the reliability of analyses and ML model predictions.	Data validation, cleansing, and enrichment processes to improve data quality.	Ensuring accurate patient data in healthcare applications for reliable diagnoses.

Value	The usefulness of data in deriving insights and making informed decisions highlights the need to focus on relevant data.	Use analytics and business intelligence tools to extract actionable insights; discard irrelevant data.	Using customer purchase history and preferences for personalized marketing campaigns.
Variability	Inconsistencies in data over time can complicate processing and analysis.	Develop adaptive models and data pipelines to accommodate data pattern changes.	Seasonal analysis of sales data to predict inventory needs.
Visualization and accessibility	How easily data can be accessed and visualized for analysis is crucial for data exploration and decision-making.	Leverage visualization tools (e.g., Amazon QuickSight, Tableau, Power BI) and ensure data is stored in accessible, secure formats.	Creating dashboards for business KPIs that pull data from multiple sources for real-time monitoring.

***Table 1.1**: The 7 Vs of data*

Table 1.1 encapsulates the essence of understanding and managing data characteristics effectively for ML and data analytics projects. Each **V** represents a critical dimension of data that professionals must navigate to unlock the full potential of their data-driven initiatives.

Determining storage mediums

In the realm of ML and AI, the selection of appropriate storage mediums is a critical decision that profoundly influences the efficiency, scalability, and overall success of ML projects. As we embark on the journey of **determining storage mediums** for ML applications, particularly within the ecosystem of **Amazon Web Services** (**AWS**), it is essential to approach this task with a blend of technical acumen and strategic foresight. This topic delves into the intricate process of selecting and optimizing storage solutions that not only accommodate the vast and varied nature of ML datasets but also align with the computational demands and data access patterns inherent to ML workflows.

The evolution of cloud computing and storage technologies has presented ML practitioners with a plethora of storage options, each with its unique characteristics, cost profiles, and performance metrics. From the highly scalable and durable **Amazon Simple Storage Service** (**Amazon S3**), designed for data lake architectures, to the high-performance file systems offered by *Amazon FSx for Lustre*, and *Amazon EFS for smaller datasets*. Additionally, the advent of AWS Lake Formation further simplifies the setup and management of secure data lakes, enabling seamless access to clean and cataloged data for ML model training and inference.

As we navigate the complexities of determining storage mediums, it is imperative to consider factors such as data volume, velocity, and variety, alongside the requirements for data security, compliance, and cost-efficiency. Moreover, the integration of these storage solutions with Amazon SageMaker, AWS's fully managed service for building, training, and deploying ML models, highlights the importance of seamless data flow and accessibility in accelerating the ML model development lifecycle.

This exploration will not only highlight the technical specifications and ideal use cases for each AWS storage option but will also offer insights into best practices for lifecycle management, data storage optimization, and the strategic deployment of storage resources in support of ML objectives. Whether dealing with the ingestion and storage of real-time sensor data, managing large-scale datasets in a data lake, or ensuring low-latency access to training data, the careful determination of storage mediums stands as a cornerstone of effective ML architecture on AWS.

Determining storage mediums is a topic that demands a thoughtful and informed approach, marrying the technical capabilities of AWS storage services with the nuanced requirements of ML applications. Through this lens, we endeavour to equip ML practitioners with the knowledge and tools necessary to make informed storage decisions, paving the way for innovative, scalable, and cost-effective ML solutions.

Here is an in-depth look at the specified areas:

- **Amazon S3 as storage for a data lake**:
    - **Options and lifecycle configuration**: Amazon S3, serving as a centralized storage repository for data lakes, is critical for ML workflows in SageMaker. It provides a durable, scalable platform for storing training data, model artifacts, and output results.
    - **SageMaker integration benefits**: The direct integration between S3 and SageMaker facilitates easy access to datasets for training and inference, supporting various data formats essential for ML models. Amazon S3 data storage options offer a tailored, flexible solution for managing datasets within Amazon SageMaker workflows, catering to a wide range of ML project requirements from active model training to long-term dataset archiving. With services like S3 Standard for readily accessible data, essential for iterative model training and real-time analytics, to S3 Intelligent-Tiering, which automatically optimizes costs for datasets with unpredictable access patterns, SageMaker users can efficiently manage their ML data lifecycle. For datasets accessed less frequently but requiring quick retrieval when needed, S3 Standard-IA and S3 One Zone-IA provide cost-effective alternatives. Moreover, for the long-term storage of historical data, which might be used for trend analysis or compliance purposes within SageMaker projects, S3 Glacier and S3 Glacier Deep Archive offer secure, extremely low-cost storage solutions with flexible retrieval times. These diverse

S3 storage classes enable SageMaker users to streamline their ML workflows, ensuring data is stored in the most appropriate, cost-effective manner without compromising the performance and scalability of their ML models.

Table 1.2 is a summary of Amazon S3 data storage options, detailing their description, cost implications, latency characteristics, and practical use cases to provide a comprehensive overview tailored for quick reference:

S3 storage option	Description	Cost	Latency	Practical use case
S3 Standard	General-purpose storage for frequently accessed data.	Moderate, with higher costs for frequent access.	Low	Ideal for active content distribution and big data analytics.
S3 Intelligent-Tiering	Automatically moves data between two access tiers based on changing access patterns without performance impact.	Lower than Standard for infrequently accessed data, with a monitoring and automation fee.	Low to moderate	Suitable for data with unknown or changing access patterns.
S3 Standard-IA	Infrequently accessed data requires rapid access when needed.	Lower storage cost than Standard, but with retrieval fees.	Low	Perfect for long-term storage of data that is accessed less frequently.
S3 One Zone-IA	Similar to Standard-IA but stored in a single availability zone for cost savings.	Lower than Standard-IA, with a risk of data loss if the AZ is compromised.	Low	Ideal for secondary backup copies or storing data that can be recreated.
S3 Glacier	Low-cost storage option for archiving data that is rarely accessed and can tolerate retrieval times of several hours.	Very low storage cost, with additional retrieval fees based on speed.	High (minutes to hours)	Suitable for archiving compliance records and digital media archives.

S3 Glacier Deep Archive	The lowest-cost storage option for long-term archiving, where data retrieval times of 12 hours are acceptable.	Lowest storage cost, with retrieval fees.	Very high (12 hours)	Ideal for archiving data that may only need to be accessed once or twice a year

***Table 1.2**: AWS storage options*

Table 1.2 offers a snapshot of the diverse range of Amazon S3 data storage options, helping users navigate the trade-offs between cost, latency, and access needs to select the most appropriate solution for their specific use cases, from active data analytics and content distribution to long-term data archiving.

- **Amazon FSx for Lustre**:
    - **High-performance file system for ML**: Amazon FSx for Lustre provides a high-performance file system optimized for workloads requiring fast processing of large datasets, such as complex simulations, genome sequencing, and ML/DL tasks.
    - **SageMaker integration benefits**: Amazon FSx for Lustre improves data transfer speed for Amazon SageMaker ML by eliminating the initial Amazon S3 download step. When FSx for Lustre is used as an input data source for SageMaker, ML training jobs are accelerated, leading to faster startup and training times. This integration also reduces the total cost of ownership by avoiding repetitive downloads of common objects for iterative jobs on the same dataset, thus saving on S3 request costs123.

      The high-performance file system provided by FSx for Lustre offers shared storage with sub-millisecond latencies, up to hundreds of GBs/s of throughput, and millions of IOPS, which significantly enhances the speed of data transfer and processing for SageMaker ML workloads.
- **Amazon EFS**:
    - **EFS for ML model training**: Amazon EFS offers a simple, scalable, elastic file system for Linux-based workloads. For ML tasks in SageMaker that require a shared file system, EFS is ideal for smaller datasets and scenarios where low latency is crucial.
    - **SageMaker integration benefits**: The integration of Amazon EFS with SageMaker allows for the direct interaction between SageMaker and Amazon EFS, reducing the start-up time by eliminating the data download step when using the file input mode.