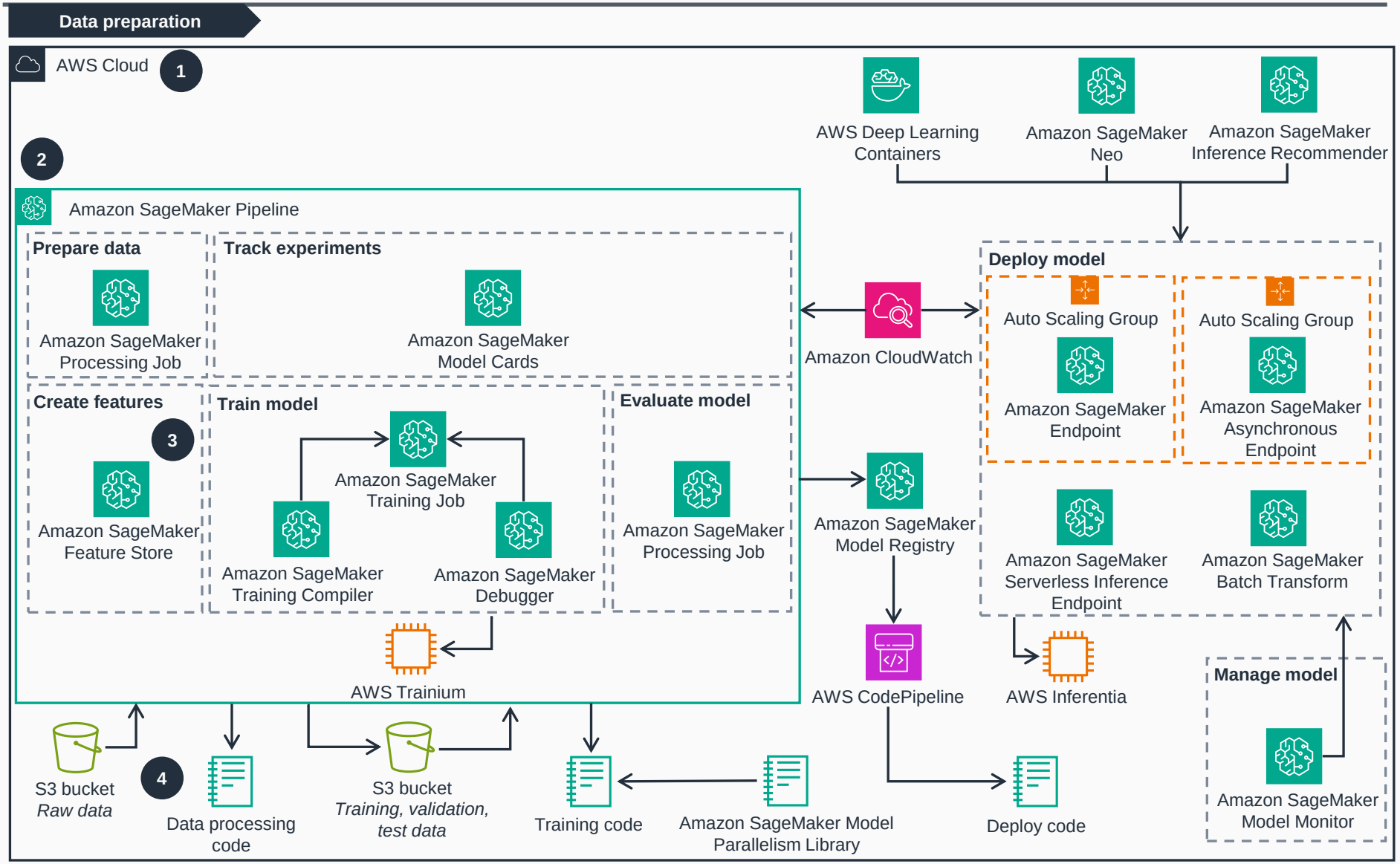
Guidance for Optimizing MLOps for Sustainability on AWS

Data preparation

This architecture diagram helps you align to MLOps sustainability goals. This slide focuses on data preparation.



1. Choose a Region based on both business requirements and sustainability goals. When regulations and legal aspects allow, use one of the **AWS Regions where the electricity consumed is attributable to 100% renewable energy** or Regions where the grid has a published carbon intensity that is lower than other locations (or Regions). When selecting a Region, aim to minimize data movement across networks—store your data close to your producers and train your models close to your data.

2. Adopt a serverless architecture for your pipeline so it only provisions resources when work needs to be done. Use **Amazon SageMaker Pipeline** to avoid maintaining compute infrastructure at all times. You can extend a template provided by **Amazon SageMaker Projects**, such as **MLOps template for model building, training, deployment, and Amazon SageMaker Model Monitor**.

3. Reduce duplication and re-run of feature engineering code across teams and projects by using **Amazon SageMaker Feature Store**.

4. Reduce the volume of data to be stored and adopt sustainable storage options to limit the carbon impact of your workload. Use energy-efficient, archival-class storage for infrequently accessed data, such as your raw data. If you can easily re-create an infrequently accessed dataset, like training, validation and test data, use the **Amazon Simple Storage Service (Amazon S3) One Zone-Infrequent Access** class to minimize the total data stored. Manage the lifecycle of all your data and automatically enforce deletion timelines to minimize the total storage requirements of your workload using **Amazon S3 Lifecycle policies**. **Amazon S3 Intelligent-Tiering** will automatically move your data to the most energy-efficient access tier when access patterns change. Define data retention periods that support your sustainability goals while meeting your business requirements, not exceeding them.

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AWS Reference Architecture

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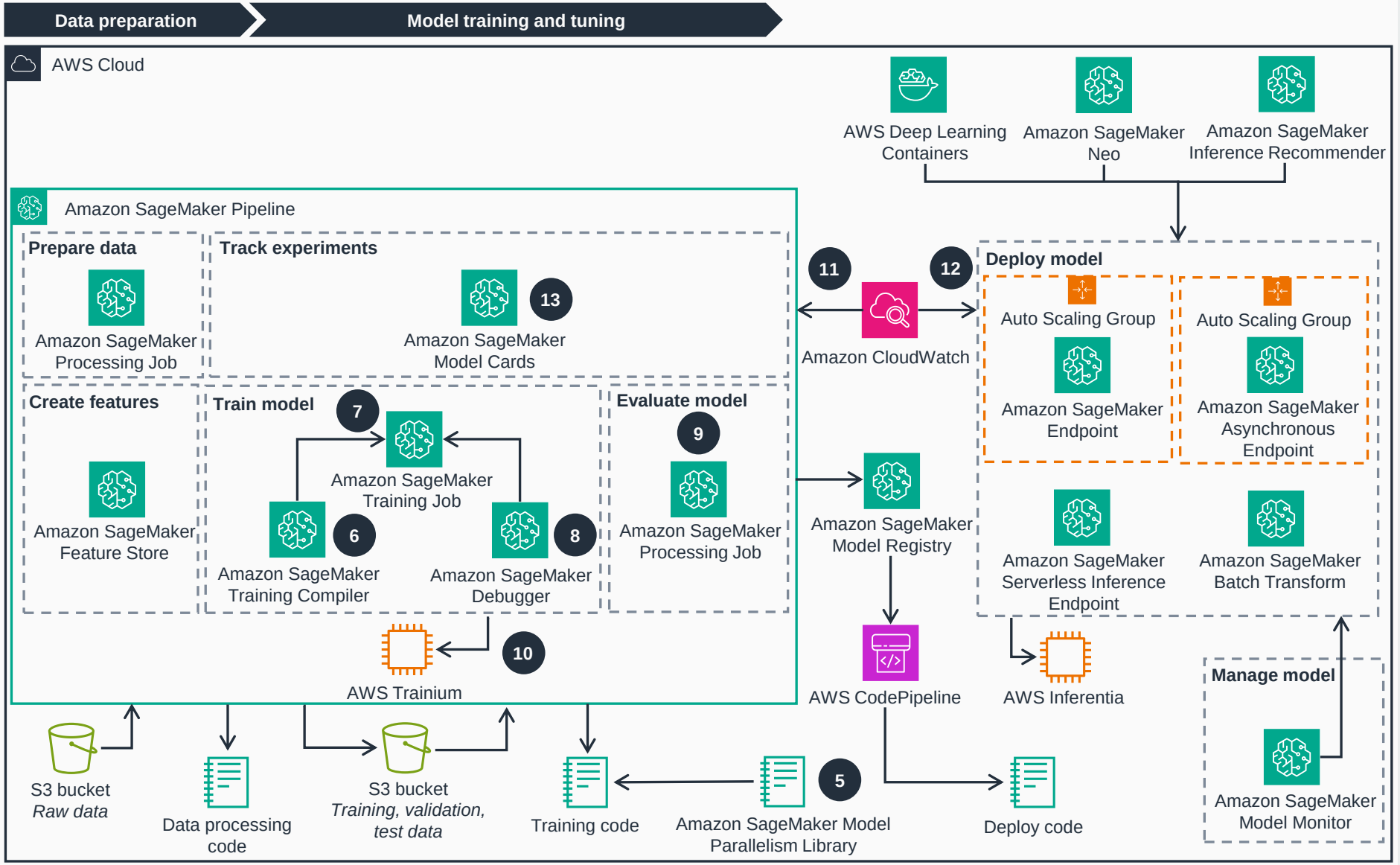
Model training and tuning

This architecture diagram helps you align to MLOps sustainability goals. This slide focuses on model training and tuning.



5 For distributed training of large deep learning models, use **Amazon SageMaker Model Parallelism Library** in your training code to maximize usage of graphics processing units (GPUs).

6 Use **Amazon SageMaker Training Compiler** to compile your deep learning models from their high-level language representation to hardware-optimized instructions to reduce training time. This can speed up deep learning model training by up to 50%.

7 Use **Bayesian optimization search** rather than random or grid search. Bayesian search typically requires 10 times fewer jobs than random search to find the best hyperparameters.

8 Use **Amazon SageMaker Debugger** to detect **under-utilization of system resources** and identify training problems. **SageMaker Debugger built-in rules** can monitor your training jobs and automatically stop them upon bug detection.

9 Define acceptable performance criteria: evaluate the accuracy of your models using **Amazon SageMaker Processing Jobs** and make trade-offs between your model's accuracy and its carbon footprint. Establish performance criteria that support your sustainability goals while meeting your business requirements, not exceeding them.

10 Use **AWS Trainium** to train deep learning models at up to 52% less energy than comparable **Amazon Elastic Compute Cloud (Amazon EC2)** instances. Consider **Managed Spot Training**, which takes advantage of unused **Amazon EC2** capacity, to improve your overall resource efficiency and reduce idle capacity of cloud resources.

11 Right-size your training jobs with **Amazon CloudWatch** metrics.

12 Reduce the volume of **CloudWatch** logs you keep. By **setting limited retention time** for your notebooks and training logs, you'll avoid unnecessary log storage.

13 Document your model's environmental impact using **Amazon SageMaker Model Cards**.

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AWS Reference Architecture

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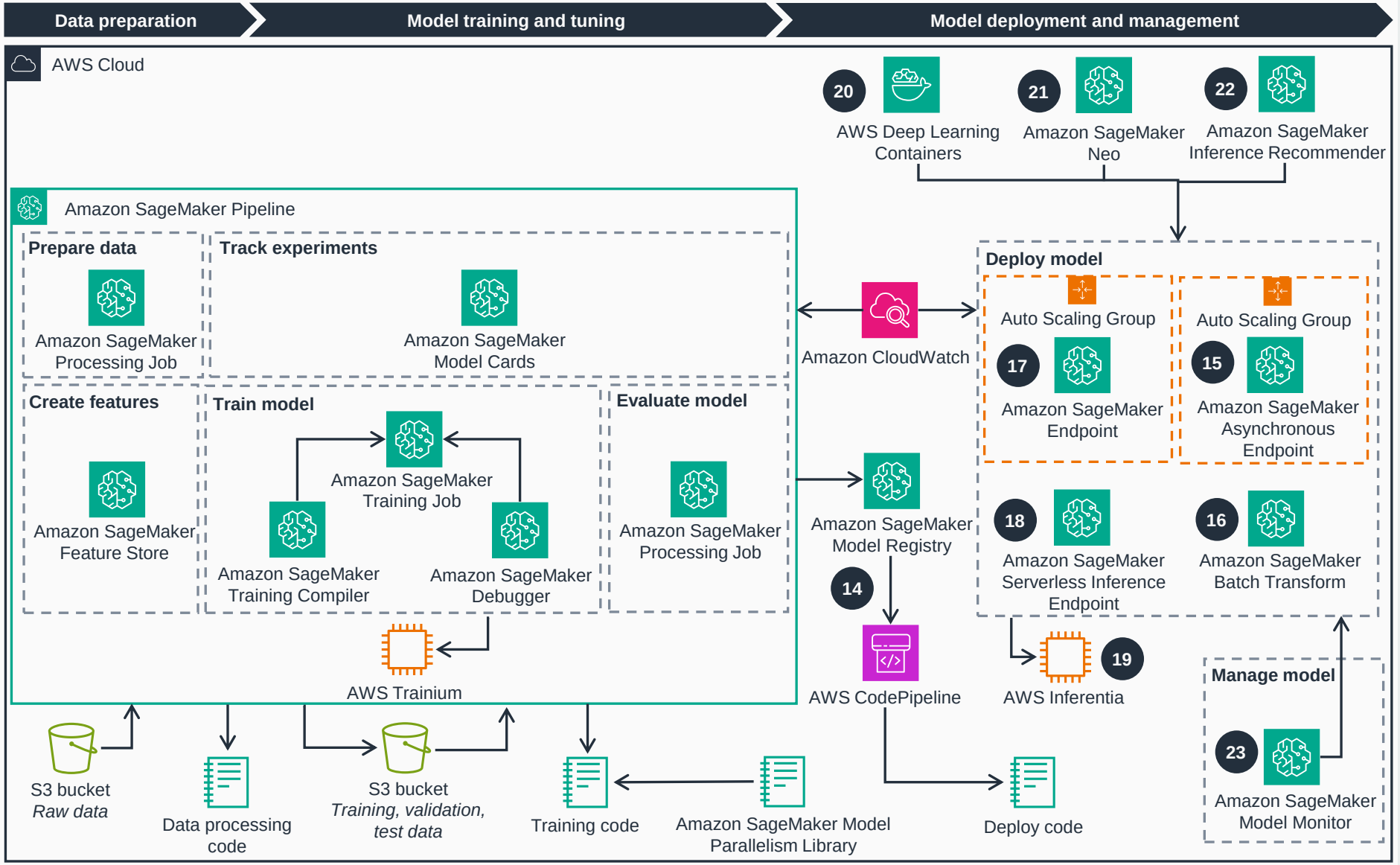
Model deployment and management

This architecture diagram helps you align to MLOps sustainability goals. This slide focuses on model deployment and management.



14 Automate the deployment of your models. Use **Amazon SageMaker Model Registry** and **AWS CodePipeline** to run your deployment code.

15 If your users can tolerate latency, deploy your model on **Amazon SageMaker Asynchronous Endpoints** with auto scaling groups to reduce idle resources between tasks and minimize the impact of load spikes.

16 When you don't need real-time inference, use **Amazon SageMaker Batch Transform**. Unlike persistent endpoints, clusters are decommissioned when batch transform jobs finish.

17 Deploy **multiple models behind a single Amazon SageMaker endpoint** with **auto scaling inference endpoints**, which is more sustainable than deploying a single model behind one endpoint.

18 If your workload has intermittent or unpredictable traffic, use **Amazon SageMaker Serverless Inference Endpoints**, which automatically launch compute resources and scale depending on traffic.

19 Use **AWS Inferentia** to deploy your deep learning models, which provides up to 50% better performance per watt over comparable **EC2** instances.

20 For Large Model Inference (LMI), use tensor parallelization available in the **Deep learning containers for LMI** to reduce latency.

21 Improve efficiency of your models by compiling them into optimized forms with **Amazon SageMaker Neo**.

22 Right-size your endpoints by using metrics from **CloudWatch** or **Amazon SageMaker Inference Recommender**, which recommends the proper instance type to host your model.

23 Monitor your ML model in production using **SageMaker Model Monitor**, automate model drift detection, and only retrain when predictive performance has fallen below defined key performance indicators (KPIs).

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