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July 13, 2025

Introduction to Advanced Performance Tuning

Overview

Performance tuning is the process of optimizing data processing frameworks like Hadoop and Spark. It enhances the efficiency of big data workflows, leading to:

- Faster processing times
- Reduced resource consumption
- Improved user satisfaction

Key Concepts in Performance Tuning

1. **Understanding Data Processing Frameworks**:
   - **Hadoop**: Distributed framework using HDFS and MapReduce for efficient data processing.
   - **Spark**: In-memory engine providing APIs for high-performance data transformations.
2. **Goals of Performance Tuning**:
   - Maximize resource utilization (CPU, memory, I/O)
   - Reduce latency in data workflows
   - Enhance throughput for real-time processing

Importance of Advanced Performance Tuning

- **System Scalability**: Allows systems to scale effectively with growing data volumes.
- **Cost-Effectiveness**: Reduces operational costs by optimizing resource usage, crucial in cloud environments.
- **Improved User Experience**: Faster response times lead to seamless interactions with large datasets.

Example Techniques for Performance Optimization

1. **Data Locality**: Minimize data transfers by performing computations close to the data.
2. **Tuning Memory Management**:
   - In Spark, adjust configurations (e.g., `spark.executor.memory`) to balance resource allocation.
3. **Pipeline Optimization**:
   - In Hadoop, break jobs into smaller tasks for parallel processing and reliability.

Example Code Snippet

Spark Performance Tuning Code

```python
from pyspark.sql import SparkSession

# Initialize Spark session with optimized configurations
spark = SparkSession.builder \
    .appName("Performance Tuning Example") \
    .config("spark.executor.memory", "4g") \
    .config("spark.sql.shuffle.partitions", "200") \
    .getOrCreate()

# Perform a DataFrame operation
df = spark.read.csv("large_dataset.csv")
df = df.groupBy("category").agg({"value": "avg"})
df.show()
```

Conclusion

Summary

Advanced performance tuning is crucial for data engineers and analysts, enabling:

- Robust, scalable data workflows
- Optimal use of resources
- Timely data processing for informed decision-making

Importance of Performance Tuning - Overview

What is Performance Tuning?

Performance tuning refers to the process of optimizing a system's performance by adjusting and configuring various parameters and components within a data processing environment. In the context of big data frameworks (like Hadoop and Spark), it is crucial for ensuring efficient data management and processing.

Importance of Performance Tuning - Key Aspects

Why is Performance Tuning Important?

1. **System Efficiency**:
   - **Definition:** Measures how effectively a system uses its resources.
   - **Impact:** Reduces overhead, enhances task performance.
   - **Example:** Tuning a cluster's configuration for optimized resource allocation.
2. **Resource Utilization**:
   - **Definition:** How well computational resources are employed.
   - **Impact:** Maximizes resource usage and minimizes waste.
   - **Example:** Adjusting memory settings in Spark applications.
3. **Overall Processing Speed**:
   - **Definition:** Time taken to complete tasks.
   - **Impact:** Decreases latency and increases throughput.
   - **Example:** Optimizing join operations with broadcast joins in Spark.

Performance Tuning Strategies

Key Tuning Strategies to Consider

- **Parallel Processing:** Distribute tasks across multiple nodes.
- **Data Partitioning:** Optimize data layout to reduce movement.
- **Caching Strategies:** Utilize in-memory caching for frequently accessed data.
- **Adaptive Execution:** Dynamically adjust resource allocation based on workloads.

Conclusion and Resource Utilization Formula

Conclusion

Effective performance tuning is vital in big data environments. It enhances system efficiency and resource utilization, significantly improving the speed of processing tasks. By implementing targeted tuning strategies, organizations can achieve better performance, resulting in increased productivity and lower operational costs.

Suggested Formula for Resource Utilization

$$Resource\ Utilization\ Percentage = \left(\frac{Used\ Resources}{Total\ Available\ Resources} \right) \times 100$$

This formula helps to monitor and measure resource usage following performance tuning initiatives.

Performance Metrics - Introduction

Introduction to Performance Metrics

Performance metrics are essential for evaluating the efficiency of data processing systems. Understanding and optimizing these metrics can significantly impact the effectiveness of big data applications, systems design, and overall user satisfaction.

Performance Metrics - Key Metrics

Key Performance Metrics

1. **Latency**
2. **Throughput**
3. **Scalability**

Performance Metrics - Latency

- **Definition**: Time taken to process a single request or transaction.
- **Importance**: Low latency is crucial for real-time applications (e.g., streaming services, online transactions).
- **Example**: A request taking 200 milliseconds to return a result has a latency of 200 ms.
- **Formula**:

$$\text{Latency} = \frac{\text{Total time for processing}}{\text{Number of requests}} \tag{1}$$

Performance Metrics - Throughput

- **Definition**: Number of transactions processed in a given time period (TPS).
- **Importance**: High throughput indicates efficient handling of large volumes of requests.
- **Example**: Processing 1,000 transactions in 10 seconds results in a throughput of 100 TPS.
- **Formula**:

$$\text{Throughput} = \frac{\text{Total transactions}}{\text{Total time}} \tag{2}$$

Performance Metrics - Scalability

- **Definition**: Ability to handle increasing workloads or accommodate growth.
- **Importance**: Ensures performance consistency as data and user load increase.
- **Example**: Database doubling transaction capacity by adding more nodes demonstrates horizontal scalability.
- **Key Points to Consider**:
  - Assess scaling up (adding resources).
  - Assess scaling out (distributing loads).

Performance Metrics - Conclusion

Conclusion

Understanding and monitoring latency, throughput, and scalability are vital for enhancing data processing systems' performance. Regular attention to these metrics can improve user experiences and resource utilization.

Key Points to Remember

- Latency affects user experience; minimize it.
- Throughput reflects system capability; aim for high rates.
- Scalability ensures long-term viability in growing environments.

Profiling and Monitoring Tools - Introduction

Overview

In the realm of big data processing, particularly with frameworks like Hadoop and Spark, effectively monitoring and profiling applications is crucial for identifying performance bottlenecks. This section introduces essential tools for profiling and monitoring to help optimize performance across applications.

Profiling and Monitoring Tools - Key Concepts

- **Profiling**
  - The process of measuring space (memory) and time complexity of an application's execution.
  - Aims to identify which parts of the code consume the most resources and time.
- **Monitoring**
  - Continuous observation of application performance during operation.
  - Involves tracking metrics such as CPU usage, memory consumption, I/O operations, and network latency.

Essential Tools for Hadoop

1. **Apache Ambari**
   - *Purpose:* A web-based tool for managing Hadoop clusters.
   - *Features:* Provides metrics visualizations, alerting, and real-time monitoring of cluster components.
   - *Example:* Use Ambari to monitor the health of HDFS and track job progress in real time.
2. **Hadoop Metrics 2**
   - *Purpose:* A built-in framework for collecting metrics from Hadoop applications.
   - *Configuration:* Users can configure reporters to send metrics to various sinks, such as logging or external monitoring systems.
   - *Example:* Monitoring data blocks' health and analyzing job performance metrics directly from the Hadoop services.

Essential Tools for Spark

1. **Spark UI**
   - *Purpose:* A web UI created by Spark for applications running on a Spark cluster.
   - *Features:* Displays job details, executors, stages, and storage information.
   - *Example:* Analyze a completed job's DAG (Directed Acyclic Graph) to inspect the execution plan and performance metrics like task execution times.
2. **Spark History Server**
   - *Purpose:* Allows access to completed Spark applications' metrics.
   - *Functionality:* Provides insights into job performance and execution statistics.
   - *Example:* Review a previously run job's performance to identify stages with long execution times.

Common Monitoring Tools

- **Prometheus**
  - An open-source monitoring and alerting toolkit that can be configured to scrape metrics from Spark and Hadoop applications.
- **Grafana**
  - A visualization platform that works with Prometheus to create dashboards for visualizing metrics data.

Key Points

- **Importance of Profiling:** It allows developers to identify inefficiencies and optimize code, leading to improved application performance.
- **Real-time Monitoring:** Essential for maintaining the health of the system and ensuring optimal performance under varying workloads.
- **Integration:** Tools can often be combined (e.g., using Prometheus and Grafana together) for a more comprehensive monitoring solution.

Conclusion

This slide introduces you to the pivotal tools for profiling and monitoring your Hadoop and Spark applications. Understanding these tools will empower you to tackle performance issues proactively, ensuring efficient and effective data processing workflows.

Common Performance Bottlenecks - Introduction

Introduction

In data processing workflows, performance bottlenecks are areas where the system's performance is limited or constrained, causing delays and inefficiencies. Identifying and addressing these bottlenecks is crucial for optimizing application performance, especially in environments using big data frameworks like Hadoop and Spark.

Common Performance Bottlenecks - Types

1. I/O Bottlenecks
    - **Definition**: Slower I/O operations than computation rate.
    - **Implications**: Increased latency, longer job execution times.
    - **Example**: Slow disk read speeds delay Spark job processing.
2. Network Bottlenecks
    - **Definition**: Limiting factor in performance due to data transfer over the network.
    - **Implications**: High latency and reduced throughput.
    - **Example**: Large Hadoop shuffle operations flood the network.
3. CPU Bottlenecks
    - **Definition**: Full utilization of CPU processing capacity.
    - **Implications**: Resource contention and increased job completion time.
    - **Example**: Complex Spark transformations overutilize CPU.

Common Performance Bottlenecks - Continuation

4. **Memory Bottlenecks**
   - **Definition**: Lack of memory leads to spills to disk or out-of-memory errors.
   - **Implications**: Severe performance degradation.
   - **Example**: Insufficient RDDs memory in Spark causes data to spill to disk.
5. **Data Skew**
   - **Definition**: Uneven data distribution across partitions.
   - **Implications**: Increased execution time due to unequal workloads.
   - **Example**: Join operations with an unequal record count delay job completion.
6. **Resource Configuration**
   - **Definition**: Poor cluster resource configuration.
   - **Implications**: Inefficient resource utilization.
   - **Example**: Low executor memory in Spark leads to frequent garbage collection.

Key Points and Conclusion

Key Points to Emphasize

- Regular monitoring and profiling can help identify bottlenecks early.
- Use tools like Hadoop's ResourceManager UI and Spark's web UI for insights.
- Optimization strategies: data partitioning, memory allocation adjustments, network tuning.

Conclusion

Understanding and mitigating performance bottlenecks is essential in data processing workflows. Addressing these issues through strategic optimizations can lead to significant improvements in system performance and user satisfaction.

Advanced Tuning Techniques for Hadoop - Introduction

As data processing needs grow, optimizing big data frameworks like Hadoop becomes crucial for maintaining efficiency and performance. This slide focuses on advanced performance tuning techniques specific to Hadoop, emphasizing tuning MapReduce tasks and optimizing HDFS configurations.

Advanced Tuning Techniques for Hadoop - Part 1

Key Concepts

1. **MapReduce Optimization:**
    - **Combiner Function:** Optional step that reduces data shuffled across the network.
    - **Speculative Execution:** Runs duplicate instances of slow tasks to speed up job completion.
    - **Tuning Mapper and Reducer Counts:** Adjust the number of map and reduce tasks based on input and data size.
2. **HDFS Configuration Optimization:**
    - **Block Size Adjustment:** Increasing block size for large files can improve performance.
    - **Replication Factor:** Adjust based on data access frequency for better read performance.
    - **Data Locality:** Optimize task runs on nodes where data resides for better efficiency.

Advanced Tuning Techniques for Hadoop - Part 2

Java Code Optimization

- Minimize unnecessary objects, use StringBuilder for concatenation, and utilize primitive types to reduce overhead.

```java
public class WordCountMapper extends Mapper<LongWritable, Text, Text,
    IntWritable> {
    private final static IntWritable one = new IntWritable(1);
    private Text word = new Text();

    public void map(LongWritable key, Text value, Context context)
            throws IOException, InterruptedException {
        StringTokenizer itr = new StringTokenizer(value.toString());
        while (itr.hasMoreTokens()) {
            word.set(itr.nextToken());
            context.write(word, one);
        }
```

Advanced Tuning Techniques for Hadoop - Conclusion

By employing advanced tuning techniques discussed, users can enhance Hadoop performance and ensure their big data applications run smoothly and efficiently.

- Proper tuning of MapReduce and HDFS configurations is essential.
- Utilizing combiners reduces data during shuffling.
- Efficient data locality and appropriate block sizes improve processing speeds.
- Test each configuration change to analyze its impact on performance.

Advanced Tuning Techniques for Spark

- Explore Spark-specific tuning strategies.
- Focus on memory configurations, shuffle operations, and data caching.

Introduction

Apache Spark is a powerful distributed computing framework that allows for the processing of large datasets efficiently. Fine-tuning Spark applications can significantly enhance performance and resource utilization.

Key Areas of Focus

- Memory configurations
- Shuffle operations
- Data caching strategies

1. Adjusting Memory Configurations

Memory management is crucial in Spark due to its in-memory processing capabilities. Properly tuning memory settings can prevent issues such as out-of-memory errors and improve overall performance.

- `spark.executor.memory`: Total memory available for each executor.
- `spark.driver.memory`: Memory needed for the driver process.
- `spark.memory.fraction`: Fraction of heap space for execution and storage (default is 0.6).

Example

```
// Configuring executor and driver memory
val conf = new SparkConf()
  .setAppName("MyApp")
  .set("spark.executor.memory", "4g")
  .set("spark.driver.memory", "2g")
```

2. Optimizing Shuffle Operations

Shuffle operations are often the most resource-intensive part of Spark jobs. Tuning shuffle can reduce execution time and resource consumption.

- Increase the number of partitions: More partitions can balance the workload across executors.
- `spark.sql.shuffle.partitions`: Number of partitions for shuffling data (default is 200).
- Enable Tungsten and Whole-Stage Code Generation: Boost performance by optimizing the execution plan.

Shuffle Operations Example

Example

```
// Set shuffle partitions
spark.conf.set("spark.sql.shuffle.partitions", "100")
```

3. Using Efficient Data Caching

Caching data in Spark can dramatically speed up applications by reducing the need to read data repeatedly from slower sources.

- `MEMORY_ONLY`: Stores RDDs as deserialized Java objects in the JVM.
- `MEMORY_AND_DISK`: Keeps RDDs in memory but spills to disk if memory is insufficient.

Data Caching Example

Example

```
// Caching a DataFrame
val df = spark.read.parquet("hdfs://path/to/file")
df.cache() // This will cache the DataFrame in memory
```

Conclusion

Optimizing Spark performance requires attention to several critical areas:

- Memory management
- Shuffle operations
- Data caching

By applying these advanced tuning techniques, data engineers can enhance the performance of their Spark applications, ensuring efficient processing of large datasets.

Key Points

- Memory settings are foundational for execution efficiency.
- Optimize shuffle operations to mitigate expensive data movement costs.
- Use caching wisely to avoid redundant data access.

References

- Spark Documentation: `https://spark.apache.org/docs/latest/tuning.html`
- Data Engineering Best Practices.

Best Practices for Optimization

Overview

Optimizing performance in Hadoop and Spark environments is critical for ensuring efficient data processing and minimizing resource usage. This slide outlines best practices focusing on both code-level optimizations and architectural improvements.

Best Practices - Code Optimization

1. **Minimize Data Shuffling**
   - Use partitioning to reduce shuffle operations.
   - *Example:* Implement `repartition` or `coalesce` intelligently to adjust data partitions before join operations.
   - **Key Point:** Keep data co-located where possible to enhance performance.
2. **Leverage Data Caching**
   - Utilize in-memory caching when reusing datasets across different computations.
   - *Example:* In Spark, employ `df.cache()` to keep frequently accessed data frames in memory.
   - **Key Point:** Balance memory usage and caching to avoid out-of-memory errors.
3. **Optimize Serialization**
   - Choose efficient formats for data serialization, such as Avro or Parquet.
   - **Key Point:** Use Spark's built-in binary formats for faster processing.

Best Practices - Code Optimization (cont.)

4. **Use Built-in Functions**
   - Take advantage of high-level API operations optimized for performance.
   - *Example:* Instead of using `map` for filtering data, use `filter` directly.

Best Practices - Architectural Optimization

1. **Cluster Configuration**
    - Configure cluster resources effectively based on workloads.
    - *Example:* Scale your Spark executors based on job needs.
2. **Data Locality**
    - Ensure tasks run close to where the data resides (data locality).
    - **Key Point:** Use HDFS features, like rack awareness, for task placement optimization.
3. **Leverage Parallelism**
    - Use parallel processing by appropriately partitioning datasets.
    - *Example:* Set an optimal number of partitions based on cluster size.

Best Practices - Architectural Optimization (cont.)

4. **Monitor and Adjust**
   - Utilize tools like Apache Ambari or Spark UI for monitoring performance metrics.
   - **Key Point:** Continuous monitoring helps identify bottlenecks and inform adjustments.
5. **Conclusion**
   - Integrating these best practices leads to significant performance improvements in Hadoop and Spark.

Code Snippet Example

```python
# Example of caching and using built-in functions in Spark
from pyspark.sql import SparkSession

spark = SparkSession.builder.appName("OptimizationExample").getOrCreate()

# Load data and cache it
dataframe = spark.read.parquet("data/sample_data.parquet")
dataframe.cache()

# Use built-in functions for filtering
filtered_data = dataframe.filter(dataframe['value'] > 100)
filtered_data.show()
```

Case Studies and Real-World Examples - Introduction

Performance tuning and optimization are critical in big data systems to ensure efficiency and responsiveness. This slide highlights real-world case studies demonstrating successful implementations of performance tuning strategies in industry contexts.

Case Study 1 - eCommerce Retailer

Background: A large eCommerce platform noticed that their page load times were negatively impacting user experience and conversion rates.

Tuning Strategies Implemented:

- **Caching Mechanisms:** Implemented distributed caching (using Memcached) to store frequently accessed data.
- **Database Optimization:** Analyzed queries using execution plans; employed indexing and partitioning to speed up data retrieval.

Results:

- Page load times improved by over 50%.
- Conversion rates increased by 20%, boosting revenue significantly.

Key Takeaway: Caching and optimizing database queries can yield substantial performance improvements that directly impact business outcomes.

Case Study 2 - Financial Services

Background: A financial services firm needed to process data in real-time to keep up with market demands and regulatory requirements.

Tuning Strategies Implemented:

- **Stream Processing Frameworks:** Migrated from batch processing to a stream processing architecture using Apache Spark Streaming.
- **Resource Allocation:** Configured dynamic resource allocation in Spark to optimize hardware usage and ensure minimal downtime during processing spikes.

Results:

- Achieved sub-second latency in data processing.
- Enabled real-time fraud detection, significantly reducing the risk of financial loss.

Key Takeaway: Transitioning from batch to streaming data processing can enhance responsiveness, allowing organizations to adapt quickly to changing conditions.

Case Study 3 - Social Media Analytics

Background: A social media platform faced challenges when scaling their analytics for real-time user engagement tracking.

Tuning Strategies Implemented:

- **Data Partitioning:** Utilized data partitioning to ensure even distribution and quicker access times.
- **Distributed Systems:** Leveraged Apache Hadoop's HDFS (Hadoop Distributed File System) to store large data sets across multiple nodes.

Results:

- Improved data processing speed by handling larger data volumes without degrading performance.
- Enabled the platform to support an increased user base without additional infrastructure costs.

Key Takeaway: Effective data partitioning and leveraging distributed systems are crucial for managing scalability in growing environments.

Conclusion and Key Points

These case studies illustrate how targeted performance tuning strategies can lead to significant improvements in efficiency and responsiveness in data processing frameworks like Hadoop and Spark.

Key Points to Remember:

- Optimize caching and database queries for improved performance.
- Transition to real-time streaming for enhanced responsiveness.
- Employ data partitioning and distributed systems to scale efficiently.

This content not only showcases effective strategies through practical examples but also encourages students to think critically about the implementation of performance tuning in their own projects.

Hands-On Lab: Implementing Tuning Strategies

Overview

This lab session focuses on applying advanced performance tuning techniques within Hadoop and Spark. Participants will engage in real-world scenarios that challenge their understanding of optimization strategies and their impact on big data processing.

Learning Objectives

- **Identify Performance Bottlenecks:** Learn to pinpoint inefficiencies in data processing tasks.
- **Apply Tuning Techniques:** Gain hands-on experience with memory and resource management, optimizing job configurations, and improving query performance.
- **Utilize Tools and Metrics:** Explore built-in monitoring tools in Hadoop and Spark for performance evaluation.

Hands-On Activities

1. **Setup Environment**
   - Launch a distributed Hadoop and Spark cluster (can be cloud-based).
   - Ensure access to sample datasets for testing.
2. **Application of Tuning Techniques**
   - **Memory Configuration in Spark:**

```python
from pyspark.sql import SparkSession

spark = SparkSession.builder \
    .appName("ExampleApp") \
    .config("spark.executor.memory", "4g") \
    .config("spark.driver.memory", "2g") \
    .getOrCreate()
```

   - **MapReduce Job Tuning in Hadoop:**

```xml
<property>
    <name>mapreduce.map.memory.mb</name>
```

Performance Metrics Evaluation

- Use **Spark UI** and **Hadoop Job Tracker** to analyze performance post-optimization.
- Check execution plans and resource usage to identify improvement areas.

Key Points to Emphasize

- **Importance of Resource Allocation:** Efficient allocation significantly enhances performance; consider resources based on job complexity.
- **Iterative Testing:** Performance tuning is an iterative process. Test configurations systematically and track metrics to ensure improvements.

Conclusion and Assessment

Conclusion

By the end of the lab, participants will have practical experience in implementing tuning strategies for Hadoop and Spark, enhancing their capabilities in managing big data workflows effectively.

Assessment

- Group discussion on findings.
- Each participant will present one tuning strategy they implemented and its impact on performance.

Conclusion and Future Directions - Key Points Recap

- **Performance Tuning Importance**: Effective performance tuning is critical for big data applications to ensure speed, efficiency, and resource optimization.
- **Tuning Techniques**:
  - **Resource Management**: Effective use of CPU, memory, and I/O resources (e.g., adjusting executor memory in Spark).
  - **Data Storage Optimization**: Choosing the right format (e.g., Parquet or ORC) for data storage to minimize read times and improve compression.
  - **Query Optimization**: Techniques like indexing and partitioning are essential for enhancing query performance in databases like Hive.

Conclusion and Future Directions - Emerging Trends

- **Auto Tuning and Machine Learning**: Leveraging algorithms to automatically adjust parameters based on workload characteristics, adapting configurations dynamically based on historical performance.
- **Serverless Architectures**: Evolving cloud services where scaling and optimization become inherent, allowing developers to focus on code rather than infrastructure management.
- **Real-time Data Processing**: Growth in tools such as Apache Kafka and Flink highlights the need for tuning strategies that support continuous data streams over static batch processing.

Conclusion and Future Directions - Future Directions

- **Containerization**: Using Docker and Kubernetes for microservices allows for better resource allocation and scaling.
    - *Example*: Running Spark jobs in Kubernetes can optimize resource usage dynamically.
- **Enhanced Data Lakes**: Transitioning from traditional data warehouses to data lakes with optimized storage layers facilitates advanced analytics.
- **AI-Powered Anomaly Detection**: Utilizing AI to identify and automatically rectify performance bottlenecks is rapidly growing.

Conclusion and Future Directions - Final Thoughts

- Continuous learning and adaptation are imperative in performance tuning. Keep up with new tools and techniques in the big data ecosystem.
- Experimenting with tuning strategies in labs can help understand practical implications and benefits.
- **Key Takeaway**: Performance tuning is a blend of art and science, requiring both best practices and innovative solutions. Embrace new technologies as the big data landscape evolves.

Questions and Discussion - Overview

- Create a conducive environment for discussion on performance tuning and optimization strategies.
- Clarify concepts and share experiences.
- Address specific questions to solidify understanding and application.

Learning Objectives

1. Foster a collaborative learning atmosphere.
2. Encourage participant inquiries on performance tuning.
3. Share practical insights and strategies from real-world experiences.

Key Concepts to Encourage Discussion

Performance Tuning Basics

Define performance tuning as optimizing systems for maximum efficiency. Discuss the importance of identifying bottlenecks (e.g., CPU, memory, I/O constraints).

Common Strategies

- **Profiling**: Measuring performance; Example: JProfiler for Java applications.
- **Caching**: Storing frequently accessed data; Example: Redis or Memcached in web applications.
- **Parallel Processing**: Distributing tasks; Example: Apache Spark's parallel task execution.

Discussion Facilitation and Encouragement

Questions to Facilitate Discussion

- What strategies have you found most effective?
- Any specific tools for measuring performance?
- Share scenarios where optimization didn't meet expectations.
- Which performance tuning areas do you find challenging?

Encouragement for Participants

- Share experiences or challenges.
- No question is too basic.
- Collaborate and learn from each other's successes and mistakes.