benchmark_analysis_concise

May 3, 2025

1 LucidBench Benchmark Analysis

This notebook provides comprehensive analysis of filesystem benchmark results across different storage devices and filesystems.

1.1 Table of Contents

1.2 1. Setup and Data Loading

[2]:
```
import os
import json
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
from scipy import stats
from pathlib import Path

# Set plot style
plt.style.use('seaborn-v0_8')
sns.set_palette('husl')
# Define consistent colors for filesystems
fs_colors = {
    'ext4': '#1f77b4',  # blue
    'ext3': '#ff7f0e',  # orange
    'ext2': '#2ca02c',  # green
    'xfs': '#d62728',   # red
```

```
    'btrfs': '#9467bd', # purple
    'ntfs': '#8c564b',  # brown
    'vfat': '#e377c2'   # pink
}

# Configure display options
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', 100)
pd.set_option('display.width', 1000)
```

[3]:
```
def load_benchmark_data(run_dir):
    """Load all benchmark and monitoring data from a run directory."""
    data = []

    for test_dir in Path(run_dir).glob('*'):
        if not test_dir.is_dir():
            continue

        # Parse test directory name
        parts = test_dir.name.split('_')
        if len(parts) < 4:
            continue

        storage_type = parts[0]
        device = parts[1]
        filesystem = parts[2]
        test_type = '_'.join(parts[3:])

        # Load test data
        test_file = test_dir / 'test.json'
        if test_file.exists():
            with open(test_file) as f:
                content = f.read()
                start_idx = content.find('{')
                if start_idx >= 0:
                    test_data = json.loads(content[start_idx:])
                else:
                    test_data = json.loads(content)

                # Load monitoring data
                monitor_file = test_dir / 'monitoring.json'
                if monitor_file.exists():
                    with open(monitor_file) as f:
                        monitor_data = json.load(f)

                        # Combine data
```

```
                        if 'test_data' in locals() and 'monitor_data' in␣
↪locals():
                            data.append({
                                'storage_type': storage_type,
                                'device': device,
                                'filesystem': filesystem,
                                'test_type': test_type,
                                'test_data': test_data,
                                'monitor_data': monitor_data
                            })

    return pd.DataFrame(data)

# Load data from the most recent run
results_dir = Path('../results')
latest_run = max(results_dir.glob('run_*'), key=os.path.getctime)
df = load_benchmark_data(latest_run)
print(f"Loaded data from {latest_run.name}")
```

```
Loaded data from run_20250427_234135
```

1.3 2. Overview and Summary Statistics

[4]:
```
def extract_performance_metrics(row):
    """Extract key performance metrics from test data."""
    test_data = row['test_data']
    job = test_data['jobs'][0]
    test_type = row['test_type']

    # Determine if this is a read or write test
    is_read_test = 'read' in test_type

    metrics = {
        'iops': job['read']['iops'] if is_read_test else job['write']['iops'],
        'bandwidth': job['read']['bw'] if is_read_test else job['write']['bw'],
        'latency': job['read']['lat_ns']['mean'] if is_read_test else␣
↪job['write']['lat_ns']['mean'],
        'runtime': job.get('runtime', None)
    }

    return pd.Series(metrics)

# Extract performance metrics
performance_df = df.apply(extract_performance_metrics, axis=1)
df = pd.concat([df, performance_df], axis=1)

# Display summary statistics
```

```python
print("\nSummary Statistics by Storage Type and Filesystem:")
summary = df.groupby(['storage_type', 'filesystem']).agg({
    'iops': ['mean', 'std', 'min', 'max'],
    'bandwidth': ['mean', 'std', 'min', 'max'],
    'latency': ['mean', 'std', 'min', 'max']
}).round(2)
display(summary)
```

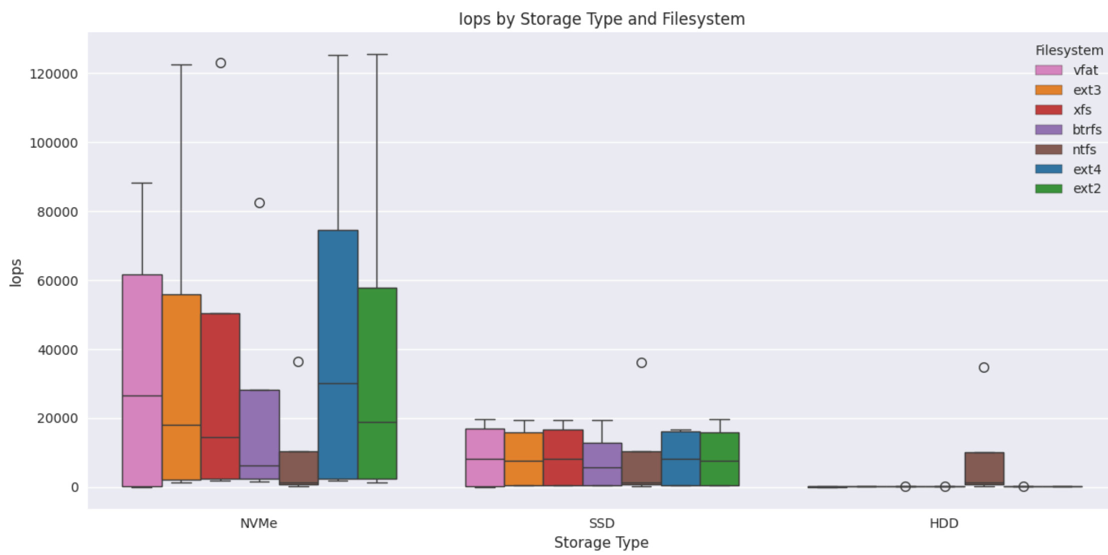
```
Summary Statistics by Storage Type and Filesystem:

                              iops                                  bandwidth   ␣
 ↪                                   latency
                              mean       std      min        max         mean   ␣
 ↪    std         min          max            mean            std           min          ␣
 ↪ max
storage_type filesystem
HDD          btrfs          243.20     31.97   224.37     291.05    117599.75  ␣
 ↪134603.50     897.0   234764.0  1.330585e+08  1.547450e+07  1.099335e+08  1.
 ↪426070e+08
             ext2           175.52     79.58   100.37     259.58     84171.50  ␣
 ↪109908.52     460.0   232410.0  2.143106e+08  9.661486e+07  1.232628e+08  3.
 ↪165003e+08
             ext3           175.02     78.72   100.09     257.37     84067.00  ␣
 ↪109836.12     463.0   232281.0  2.144025e+08  9.619820e+07  1.243215e+08  3.
 ↪171924e+08
             ext4           230.31     34.30   208.26     281.41    110971.75  ␣
 ↪127023.98     833.0   223374.0  1.409504e+08  1.838856e+07  1.137028e+08  1.
 ↪536348e+08
             ntfs          9388.24  17002.00   133.57   34873.49    686754.75  ␣
 ↪793607.88     534.0  1726761.0  7.407539e+07  1.112951e+08  9.158244e+05  2.
 ↪395449e+08
             vfat           147.35    117.02     0.00     274.80     30933.00   ␣
 ↪60613.76       0.0   121851.0  1.369791e+08  1.110981e+08  0.000000e+00  2.
 ↪678751e+08
             xfs            241.13     33.68   214.26     290.43    118222.75  ␣
 ↪135346.89     857.0   235582.0  1.344233e+08  1.687346e+07  1.101695e+08  1.
 ↪493296e+08
NVMe         btrfs        24226.72  39104.99  1633.17   82617.08   1190281.00 ␣
 ↪1242254.81   40008.0  2718278.0  8.778315e+06  8.715936e+06  3.864838e+05  1.
 ↪955125e+07
             ext2         41196.32  58379.08  1352.26  125547.89   1184340.00 ␣
 ↪1143129.40  140956.0  2709498.0  9.170515e+06  1.097653e+07  2.540123e+05  2.
 ↪350814e+07
             ext3         39995.97  57055.94  1240.08  122554.46   1103520.25 ␣
 ↪1056072.32  134917.0  2519101.0  9.943538e+06  1.197304e+07  2.602802e+05  2.
 ↪564301e+07
```

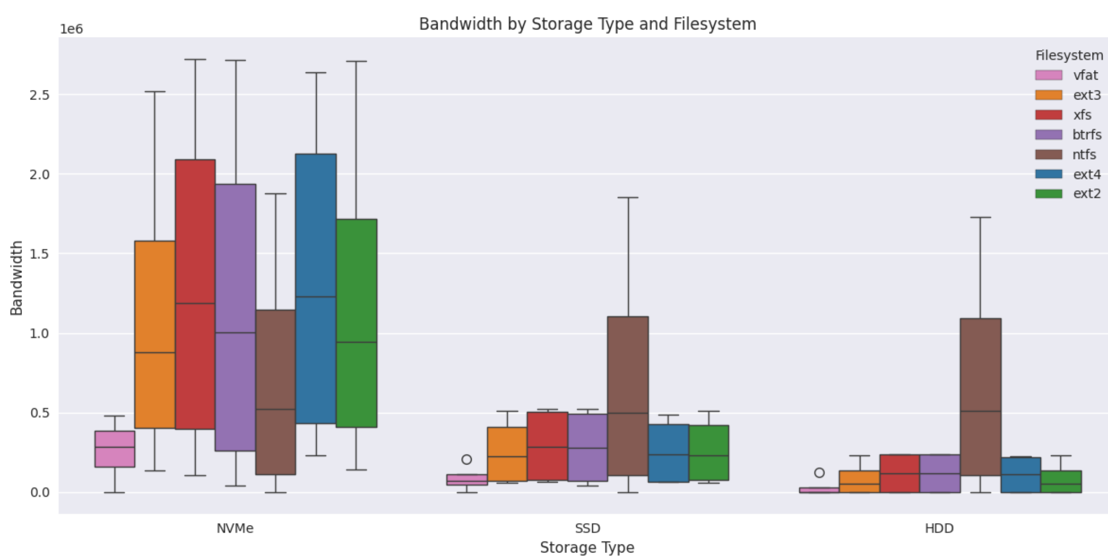
```
            ext4        46855.52  58478.42  1913.12  125367.77  1332587.50 ␣
↪1155650.63  230253.0  2639587.0  7.463895e+06  8.344051e+06  2.544177e+05  1.
↪670154e+07
            ntfs         9796.01  17711.95   127.51   36343.27   731068.50  ␣
↪860525.91     510.0  1878326.0  7.631343e+07  1.173010e+08  8.791321e+05  2.
↪509305e+08
            vfat        35424.96  43129.55     0.00   88323.45   261890.75  ␣
↪206723.22       0.0   482651.0  1.713611e+07  3.362955e+07  0.000000e+00  6.
↪757906e+07
            xfs         38455.01  57503.74  1840.07  123014.55  1300392.00 ␣
↪1216288.80  105236.0  2720041.0  7.700020e+06  8.346075e+06  2.592703e+05  1.
↪736146e+07
SSD         btrfs        7820.49   9191.93   472.71   19544.02   282023.75  ␣
↪256573.54   43018.0   522850.0  3.370955e+07  3.632652e+07  1.635174e+06  6.
↪764454e+07
            ext2         8780.89   9840.12   378.73   19586.37   259106.75  ␣
↪225977.00   58635.0   511625.0  3.798088e+07  4.246213e+07  1.631772e+06  8.
↪414086e+07
            ext3         8755.49   9816.28   368.01   19533.83   256287.25  ␣
↪224075.12   58481.0   511687.0  3.859024e+07  4.335040e+07  1.636321e+06  8.
↪658831e+07
            ext4         8391.63   9188.55   399.80   16600.85   256014.75  ␣
↪222208.72   64373.0   483883.0  3.788818e+07  4.179290e+07  1.925732e+06  7.
↪996131e+07
            ntfs         9761.84  17687.43   130.27   36272.87   713318.75  ␣
↪846692.76     521.0  1853426.0  7.554200e+07  1.144046e+08  8.806148e+05  2.
↪456175e+08
            vfat         9016.33  10386.80     0.00   19611.28    87070.00   ␣
↪85648.63      0.0   204820.0  4.076104e+07  7.912891e+07  0.000000e+00  1.
↪594474e+08
            xfs          9095.30  10038.48   483.08   19507.66   289783.25  ␣
↪253221.60   63519.0   522915.0  3.310901e+07  3.615384e+07  1.638377e+06  6.
↪620603e+07
```

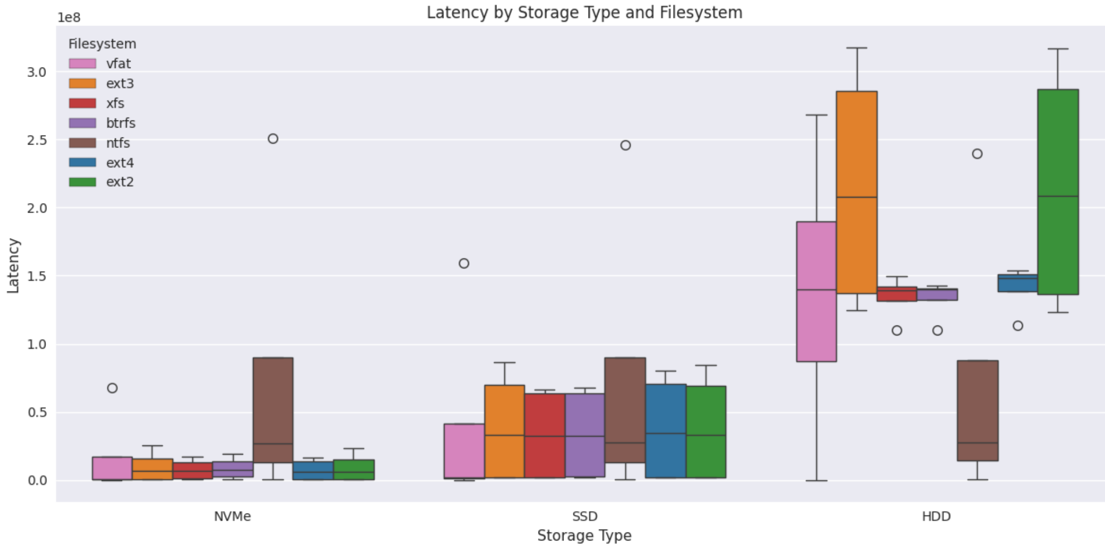
1.4 3. Performance Analysis by Storage Type

[5]:
```
def plot_storage_performance(df, metric):
    """Plot performance metrics by storage type."""
    plt.figure(figsize=(12, 6))

    # Create box plot
    sns.boxplot(data=df, x='storage_type', y=metric, hue='filesystem',␣
↪palette=fs_colors)

    plt.title(f'{metric.title()} by Storage Type and Filesystem')
    plt.xlabel('Storage Type')
    plt.ylabel(metric.title())
```

```
    plt.xticks(rotation=0)
    plt.legend(title='Filesystem')
    plt.tight_layout()
    plt.show()

# Plot performance metrics
for metric in ['iops', 'bandwidth', 'latency']:
    plot_storage_performance(df, metric)
```





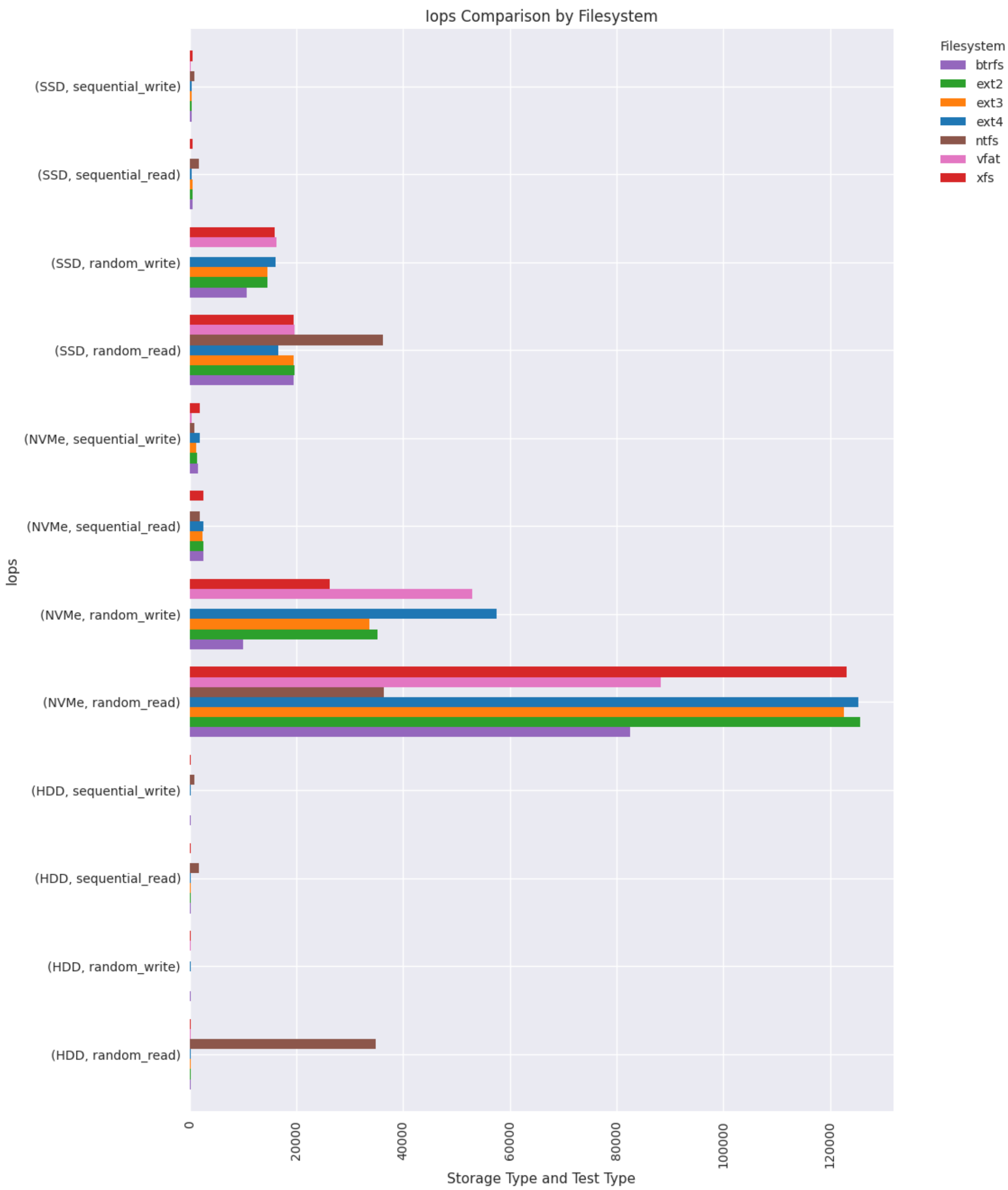


1.5 4. Filesystem Comparison

[6]:
```
def analyze_filesystem_performance(df):
    """Analyze filesystem performance across different test types."""
    # Create pivot table for each metric
    metrics = ['iops', 'bandwidth', 'latency']

    for metric in metrics:
        pivot = pd.pivot_table(
            df,
            values=metric,
            index=['storage_type', 'test_type'],
            columns='filesystem',
            aggfunc='mean'
        )

        print(f"\n{metric.upper()} Comparison:")
        display(pivot)

        # Plot comparison
        fig, ax = plt.subplots(figsize=(12, 15))
        # Use a distinct color palette with high contrast colors
        pivot.plot(kind='barh', width=0.8, ax=ax, color=fs_colors)  # Increased␣
↪bar width and custom colors
        plt.title(f'{metric.title()} Comparison by Filesystem')
        plt.xlabel('Storage Type and Test Type')
        plt.ylabel(metric.title())
        plt.xticks(rotation=90)
```

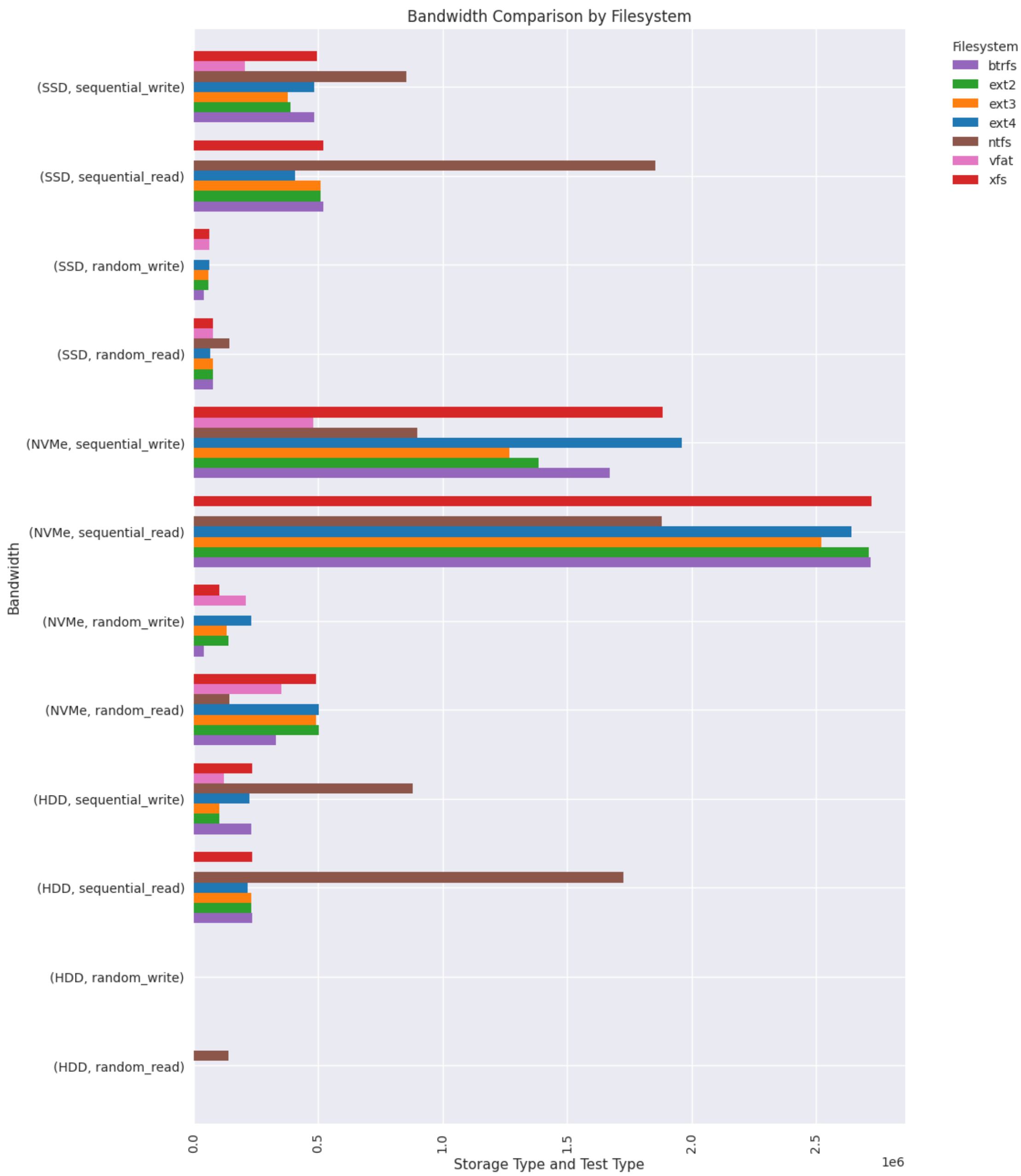
```
        plt.legend(title='Filesystem', bbox_to_anchor=(1.05, 1), loc='upper␣
↪left')
        # Ensure plot takes up full figure size while leaving room for legend
        plt.subplots_adjust(left=0.2, right=0.85, top=0.9, bottom=0.1)
        plt.show()

analyze_filesystem_performance(df)
```

```
IOPS Comparison:

filesystem                               btrfs            ext2            ext3         ␣
 ↪   ext4          ntfs           vfat            xfs
storage_type test_type
HDD          random_read          291.049988      259.577509      257.369935      ␣
 ↪281.408540  34873.486763    274.804210     290.429866
             random_write         224.369636      115.179494      115.785790      ␣
 ↪208.261990     133.572202    195.559394     214.259616
             sequential_read      229.262286      226.962930      226.837238      ␣
 ↪213.433380    1686.290655      0.000000     229.776731
             sequential_write     228.100462      100.370016      100.092860      ␣
 ↪218.139213     859.601259    119.024787     230.060661
NVMe         random_read        82617.081626   125547.892720   122554.464703 ␣
 ↪125367.766619  36343.269097  88323.450135  123014.547161
             random_write       10002.060361    35239.145046    33729.284611  ␣
 ↪57563.460694     127.512081  52904.944501   26309.112806
             sequential_read     2654.569021     2645.994832     2460.060060   ␣
 ↪2577.721838    1834.303627      0.000000    2656.290532
             sequential_write    1633.173844     1352.261472     1240.084771   ␣
 ↪1913.124708     878.969957    471.454880    1840.071878
SSD          random_read        19544.024454    19586.371787    19533.830104  ␣
 ↪16600.848585  36272.865643  19611.281514   19507.664831
             random_write       10754.625641    14658.838003    14620.412716  ␣
 ↪16093.314507     130.271774  16253.968254   15879.815847
             sequential_read      510.595861      499.634057      499.695010      ␣
 ↪399.804783    1809.986743      0.000000     510.659519
             sequential_write     472.706290      378.733241      368.014376      ␣
 ↪472.542686     834.215886    200.068383     483.075834
```



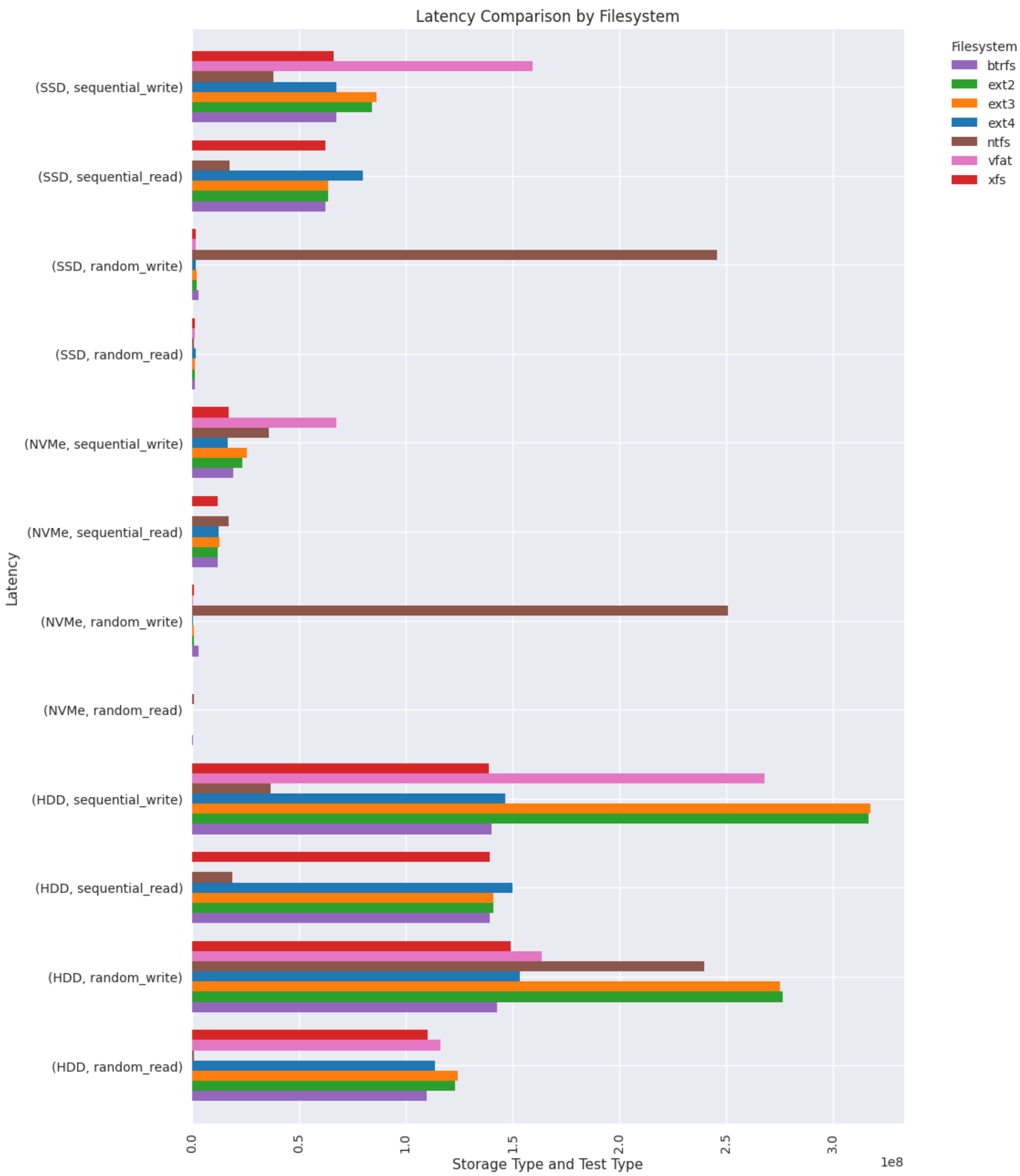

```
BANDWIDTH Comparison:

filesystem                          btrfs       ext2       ext3       ext4       ntfs      vfat       xfs
storage_type test_type
HDD          random_read           1164.0     1038.0     1029.0     1125.0   139493.0    1099.0    1161.0
```

```
               random_write         897.0      460.0      463.0      833.0     ␣
 ↪534.0     782.0      857.0
               sequential_read    234764.0   232410.0   232281.0   218555.0 ␣
 ↪1726761.0       0.0    235291.0
               sequential_write   233574.0   102778.0   102495.0   223374.0  ␣
 ↪880231.0  121851.0   235582.0
NVMe           random_read        330468.0   502191.0   490217.0   501471.0  ␣
 ↪145373.0  353293.0   492058.0
               random_write        40008.0   140956.0   134917.0   230253.0     ␣
 ↪510.0   211619.0   105236.0
               sequential_read   2718278.0  2709498.0  2519101.0  2639587.0 ␣
 ↪1878326.0       0.0  2720041.0
               sequential_write  1672370.0  1384715.0  1269846.0  1959039.0  ␣
 ↪900065.0  482651.0  1884233.0
SSD            random_read         78176.0    78345.0    78135.0    66403.0  ␣
 ↪145091.0   78445.0    78030.0
               random_write        43018.0    58635.0    58481.0    64373.0     ␣
 ↪521.0    65015.0    63519.0
               sequential_read    522850.0   511625.0   511687.0   409400.0 ␣
 ↪1853426.0       0.0    522915.0
               sequential_write   484051.0   387822.0   376846.0   483883.0  ␣
 ↪854237.0  204820.0   494669.0
```




```
LATENCY Comparison:

filesystem                             btrfs          ext2          ext3         ␣
 ↪ext4          ntfs          vfat          xfs
storage_type test_type
HDD          random_read       1.099335e+08  1.232628e+08  1.243215e+08  1.
 ↪137028e+08  9.158244e+05  1.164325e+08  1.101695e+08
```

```
              random_write      1.426070e+08  2.765953e+08  2.751344e+08  1.
 ↪536348e+08  2.395449e+08  1.636089e+08  1.493296e+08
              sequential_read   1.394754e+08  1.408839e+08  1.409617e+08  1.
 ↪498208e+08  1.878933e+07  0.000000e+00  1.391576e+08
              sequential_write  1.402183e+08  3.165003e+08  3.171924e+08  1.
 ↪466432e+08  3.705144e+07  2.678751e+08  1.390365e+08
NVMe          random_read       3.864838e+05  2.540123e+05  2.602802e+05  2.
 ↪544177e+05  8.791321e+05  3.616420e+05  2.592703e+05
              random_write      3.195223e+06  9.062730e+05  9.469127e+05  5.
 ↪548055e+05  2.509305e+08  6.037502e+05  1.213946e+06
              sequential_read   1.198030e+07  1.201364e+07  1.292395e+07  1.
 ↪234481e+07  1.727433e+07  0.000000e+00  1.196540e+07
              sequential_write  1.955125e+07  2.350814e+07  2.564301e+07  1.
 ↪670154e+07  3.616977e+07  6.757906e+07  1.736146e+07
SSD           random_read       1.635174e+06  1.631772e+06  1.636321e+06  1.
 ↪925733e+06  8.806149e+05  1.630163e+06  1.638377e+06
              random_write      2.973479e+06  2.180709e+06  2.186319e+06  1.
 ↪986038e+06  2.456175e+08  1.966600e+06  2.012452e+06
              sequential_read   6.258500e+07  6.397019e+07  6.395002e+07  7.
 ↪996131e+07  1.750670e+07  0.000000e+00  6.257917e+07
              sequential_write  6.764454e+07  8.414086e+07  8.658831e+07  6.
 ↪767964e+07  3.816323e+07  1.594474e+08  6.620603e+07
```



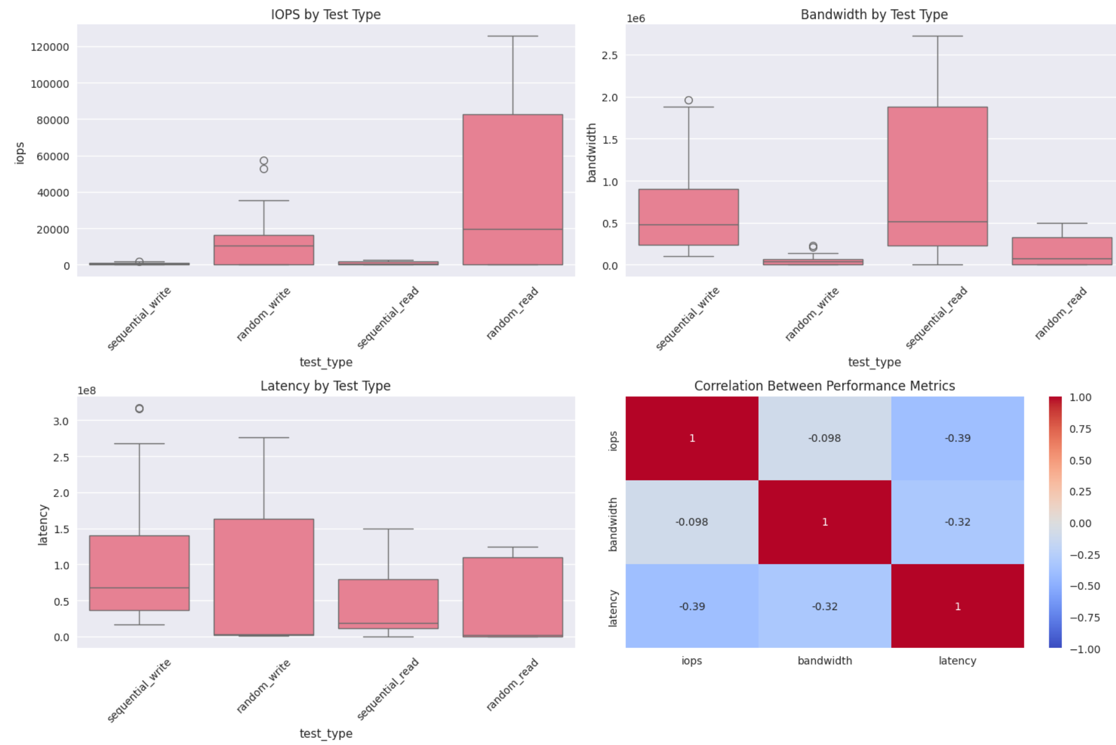
1.6 5. I/O Pattern Analysis

[7]:
```python
def analyze_io_patterns(df):
    """Analyze I/O patterns across different test types."""
    # Group by test type and calculate statistics
    io_stats = df.groupby('test_type').agg({
        'iops': ['mean', 'std', 'min', 'max'],
        'bandwidth': ['mean', 'std', 'min', 'max'],
```

```
        'latency': ['mean', 'std', 'min', 'max']
    }).round(2)

    print("\nI/O Pattern Statistics:")
    display(io_stats)

    # Plot I/O patterns
    fig, axes = plt.subplots(2, 2, figsize=(15, 10))

    # IOPS by test type
    sns.boxplot(data=df, x='test_type', y='iops', ax=axes[0,0])
    axes[0,0].set_title('IOPS by Test Type')
    axes[0,0].set_xticks(range(len(df['test_type'].unique())))
    axes[0,0].set_xticklabels(df['test_type'].unique(), rotation=45)

    # Bandwidth by test type
    sns.boxplot(data=df, x='test_type', y='bandwidth', ax=axes[0,1])
    axes[0,1].set_title('Bandwidth by Test Type')
    axes[0,1].set_xticks(range(len(df['test_type'].unique())))
    axes[0,1].set_xticklabels(df['test_type'].unique(), rotation=45)

    # Latency by test type
    sns.boxplot(data=df, x='test_type', y='latency', ax=axes[1,0])
    axes[1,0].set_title('Latency by Test Type')
    axes[1,0].set_xticks(range(len(df['test_type'].unique())))
    axes[1,0].set_xticklabels(df['test_type'].unique(), rotation=45)

    # Create a more meaningful visualization showing relationship between␣
↪metrics
    # Use a heatmap to show correlation between key performance metrics
    correlation = df[['iops', 'bandwidth', 'latency']].corr()
    sns.heatmap(correlation, annot=True, cmap='coolwarm', vmin=-1, vmax=1,␣
↪ax=axes[1,1])
    axes[1,1].set_title('Correlation Between Performance Metrics')

    plt.tight_layout()
    plt.show()

analyze_io_patterns(df)
```

```
I/O Pattern Statistics:

                     iops                                     bandwidth           ␣
↪                latency
                     mean       std     min        max         mean         std ␣
↪      min         max          mean          std          min           max
test_type
```

```
random_read        42426.36  47169.54  257.37  125547.89   169705.00   188678.13 ␣
 ↪  1029.0   502191.0  3.392246e+07  5.348442e+07    254012.28  1.243215e+08
random_write       14546.37  17550.69  115.18   57563.46    58185.10    70202.60 ␣
 ↪   460.0   230253.0  9.132045e+07  1.119830e+08    554805.46  2.765953e+08
sequential_read     1041.52   1047.36    0.00    2656.29  1066514.10  1072498.11 ␣
 ↪     0.0  2720041.0  5.514969e+07  5.533024e+07         0.00  1.498208e+08
sequential_write     685.42    584.35  100.09    1913.12   701863.43   598375.13 ␣
 ↪102495.0  1959039.0  1.019477e+08  9.465585e+07  16701543.24  3.171924e+08
```



1.7 6. Resource Utilization

1.7.1 Analytics based on the monitoring data

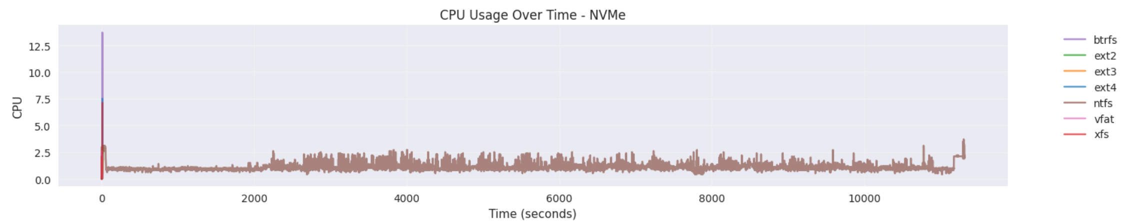
This section analyzes CPU, memory, and disk I/O utilization patterns across different storage types and filesystems. Note that the NTFS results show significantly higher resource utilization due to its much longer elapsed time (7132 seconds) compared to other filesystems (20-70 seconds), which may skew the overall resource utilization metrics.

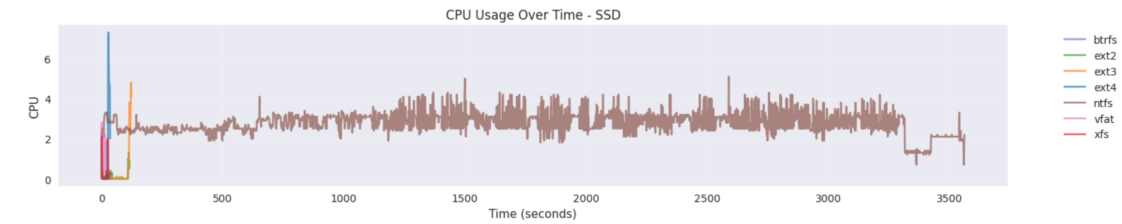
[8]:
```
def plot_resource_trends(df, metric, title):
    """
    Plot resource usage trends over time for different storage types and␣
 ↪filesystems.

    Args:
```

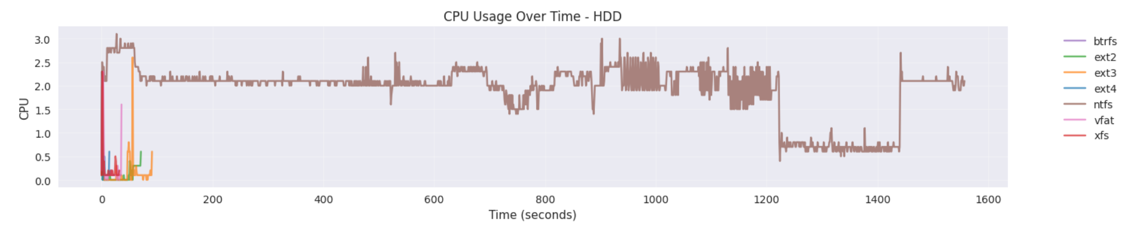
```
        df: DataFrame containing the monitoring data
        metric: Metric to plot (e.g., 'cpu_percent', 'memory_percent')
        title: Title for the plot
    """
    # Create subplots for each storage type
    storage_types = df['storage_type'].unique()
    fig, axes = plt.subplots(len(storage_types), 1, figsize=(15,␣
↪3*len(storage_types)))

    for idx, storage_type in enumerate(storage_types):
        ax = axes[idx]

        # Filter data for current storage type
        storage_df = df[df['storage_type'] == storage_type]

        for filesystem, group in storage_df.groupby('filesystem'):
            if 'monitor_data' in group.iloc[0] and 'stats' in group.
↪iloc[0]['monitor_data']:
                stats = pd.DataFrame(group.iloc[0]['monitor_data']['stats'])
                stats['timestamp'] = pd.to_datetime(stats['timestamp'])
                ax.plot(range(len(stats)), stats[metric],
                        label=filesystem,
                        color=fs_colors[filesystem],
                        alpha=0.7)

        ax.set_title(f'{title} Usage Over Time - {storage_type}')
        ax.set_xlabel('Time (seconds)')
        ax.set_ylabel(title)
        ax.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
        ax.grid(True, alpha=0.3)

    plt.tight_layout()
    plt.show()

# Plot Disk I/O Throughput
def plot_io_throughput(df):
    """
    Plot disk I/O throughput over time for different storage types and␣
↪filesystems.

    Args:
        df: DataFrame containing the monitoring data
    """
    fig, axes = plt.subplots(3, 1, figsize=(15, 9))
    storage_types = df['storage_type'].unique()

    for idx, storage_type in enumerate(storage_types):
```

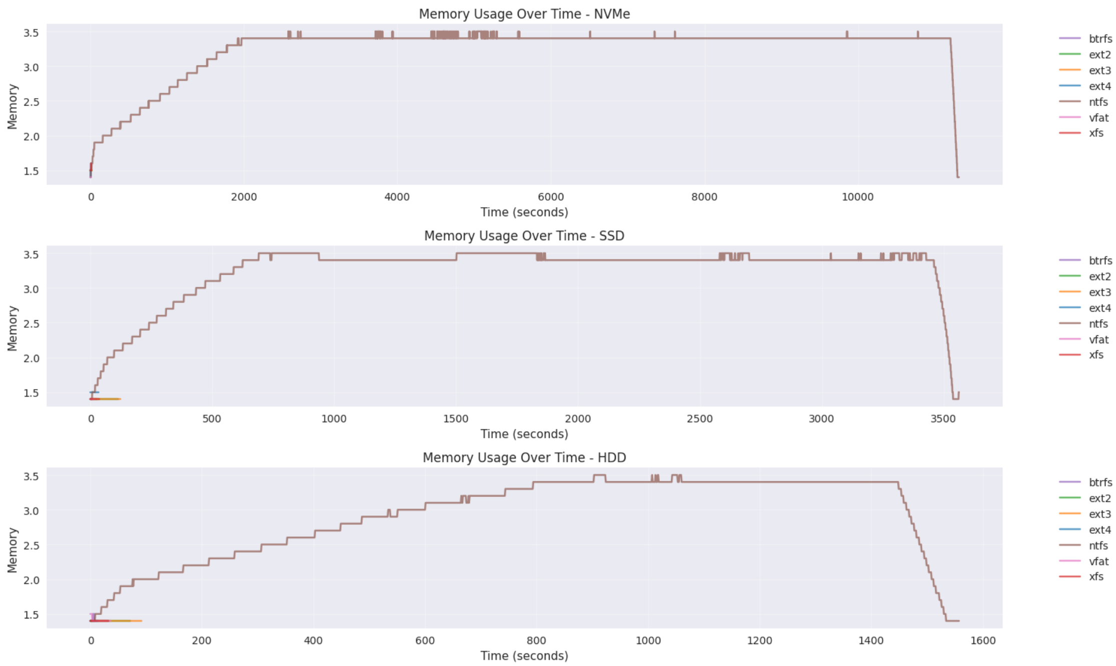
```
        ax = axes[idx]

        for filesystem, group in df[df['storage_type'] == storage_type].
↪groupby('filesystem'):
            if 'monitor_data' in group.iloc[0] and 'stats' in group.
↪iloc[0]['monitor_data']:
                stats = pd.DataFrame(group.iloc[0]['monitor_data']['stats'])
                stats['timestamp'] = pd.to_datetime(stats['timestamp'])

                # Calculate I/O throughput (MB/s)
                stats['io_throughput'] = (stats['disk_read_bytes'].diff() +
                                        stats['disk_write_bytes'].diff()) /␣
↪1024 / 1024

                ax.plot(range(len(stats)), stats['io_throughput'],
                        label=filesystem,
                        color=fs_colors[filesystem],
                        alpha=0.7)

        ax.set_title(f'Disk I/O Throughput Over Time - {storage_type}')
        ax.set_xlabel('Time (seconds)')
        ax.set_ylabel('Throughput (MB/s)')
        ax.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
        ax.grid(True, alpha=0.3)

    plt.tight_layout()
    plt.show()

# Plot CPU Usage
plot_resource_trends(df, 'cpu_percent', 'CPU')

# Plot Memory Usage
plot_resource_trends(df, 'memory_percent', 'Memory')

# Plot Disk I/O Throughput
plot_io_throughput(df)

# Resource usage summary statistics
resource_summary = pd.DataFrame()
for (storage_type, filesystem), group in df.groupby(['storage_type',␣
↪'filesystem']):
    if 'monitor_data' in group.iloc[0] and 'stats' in group.
↪iloc[0]['monitor_data']:
        stats = pd.DataFrame(group.iloc[0]['monitor_data']['stats'])
        # Convert timestamp strings to datetime objects
        stats['timestamp'] = pd.to_datetime(stats['timestamp'])
        summary = {
```

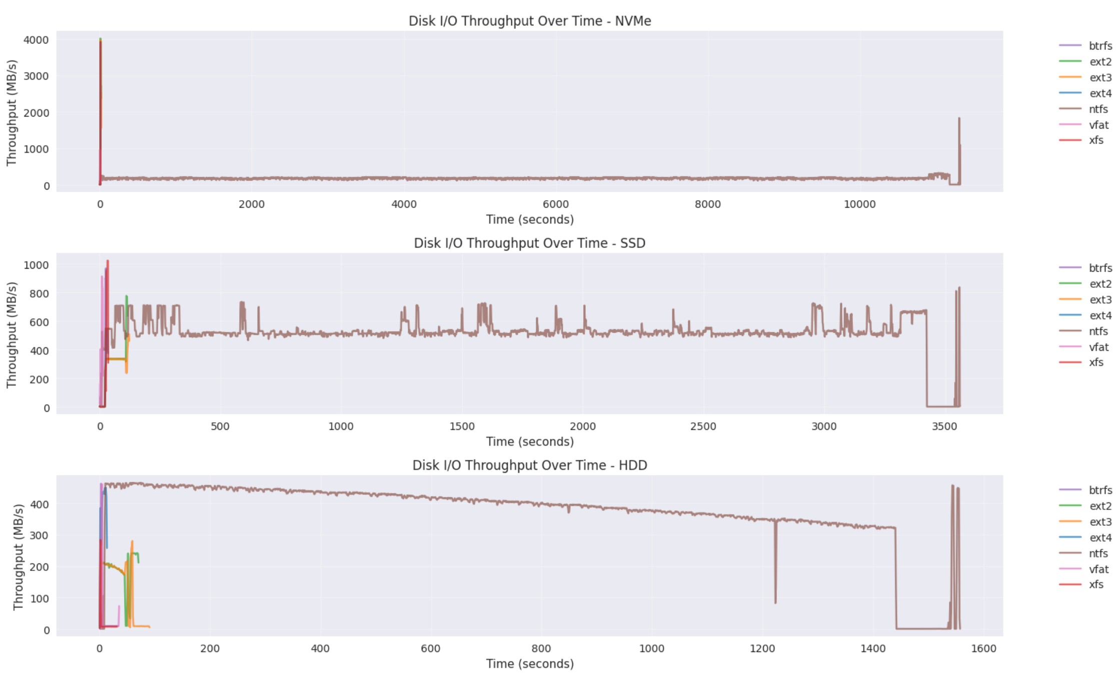
```
            'Storage Type': storage_type,
            'Filesystem': filesystem,
            'Avg CPU %': stats['cpu_percent'].mean(),
            'Max CPU %': stats['cpu_percent'].max(),
            'Avg Memory %': stats['memory_percent'].mean(),
            'Max Memory %': stats['memory_percent'].max(),
            'Total Read (GB)': stats['disk_read_bytes'].max() / 1024**3,
            'Total Write (GB)': stats['disk_write_bytes'].max() / 1024**3,
            'Elapsed Time (s)': (stats['timestamp'].max() - stats['timestamp'].
 ↪min()).total_seconds()
        }
        resource_summary = pd.concat([resource_summary, pd.
 ↪DataFrame([summary])], ignore_index=True)

display(resource_summary)
```











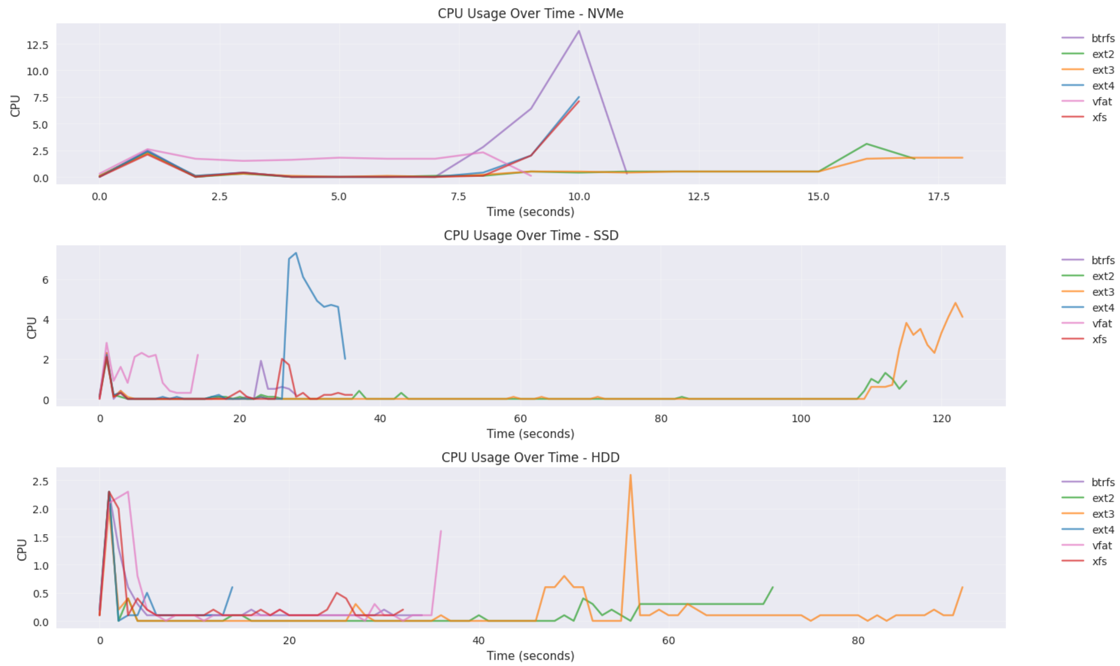

```
  Storage Type Filesystem  Avg CPU %  Max CPU %  Avg Memory %  Max Memory % ␣
↪Total Read (GB)  Total Write (GB)  Elapsed Time (s)
0          HDD      btrfs   0.222857        2.3      1.408571           1.5    ␣
↪  304.714440       3234.096130         68.070094
```

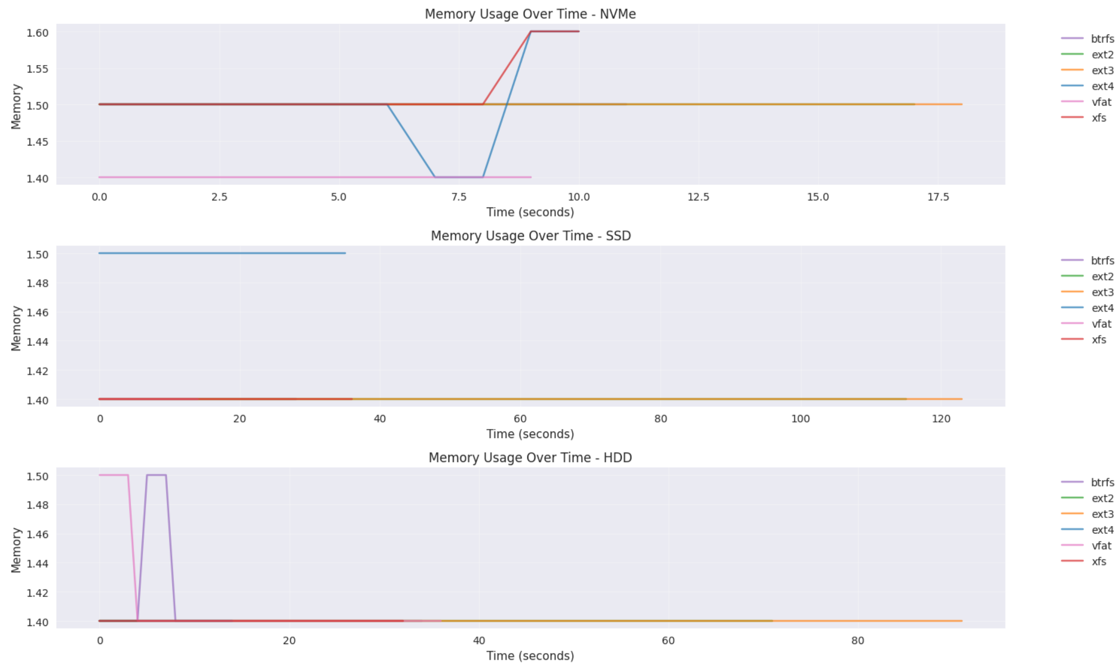
1	HDD	ext2	0.127778	2.3	1.400000	1.4	291.600677	3161.113423	142.137219
2	HDD	ext3	0.143478	2.6	1.400000	1.4	291.850449	3171.901868	182.176519
3	HDD	ext4	0.306667	2.3	1.400000	1.4	300.175681	3222.764630	28.030823
4	HDD	ntfs	1.918164	3.1	2.910205	3.5	287.261601	2553.800095	3117.673241
5	HDD	vfat	0.332432	2.3	1.410811	1.5	285.962682	861.352174	72.074149
6	HDD	xfs	0.272727	2.3	1.400000	1.4	300.442266	3224.521772	64.065516
7	NVMe	btrfs	2.175000	13.7	1.500000	1.5	403.187676	18510.434410	22.021028
8	NVMe	ext2	0.616667	3.1	1.500000	1.5	374.987468	18340.320305	34.032300
9	NVMe	ext3	0.621053	2.2	1.500000	1.5	383.167312	18474.386311	36.033045
10	NVMe	ext4	1.163636	7.5	1.500000	1.6	387.047649	18476.867687	20.020993
11	NVMe	ntfs	1.032052	3.7	3.253597	3.5	366.742051	16343.229915	22656.318134
12	NVMe	vfat	1.530000	2.6	1.400000	1.4	364.681422	10745.573076	18.020437
13	NVMe	xfs	1.063636	7.1	1.518182	1.6	395.067607	18494.670954	20.019552
14	SSD	btrfs	0.251724	2.3	1.400000	1.4	357.946311	10729.734252	56.053894
15	SSD	ext2	0.085345	2.0	1.400000	1.4	325.684270	10549.563048	230.214684
16	SSD	ext3	0.324194	4.8	1.400000	1.4	329.797954	10612.727878	246.229640
17	SSD	ext4	1.391667	7.3	1.500000	1.5	337.921325	10687.398364	70.066876
18	SSD	ntfs	2.742155	5.1	3.247685	3.5	317.388026	8631.487349	7132.278231
19	SSD	vfat	1.273333	2.8	1.400000	1.4	314.693250	3253.701227	28.031059
20	SSD	xfs	0.227027	2.1	1.400000	1.4	349.935400	10711.527850	72.070390

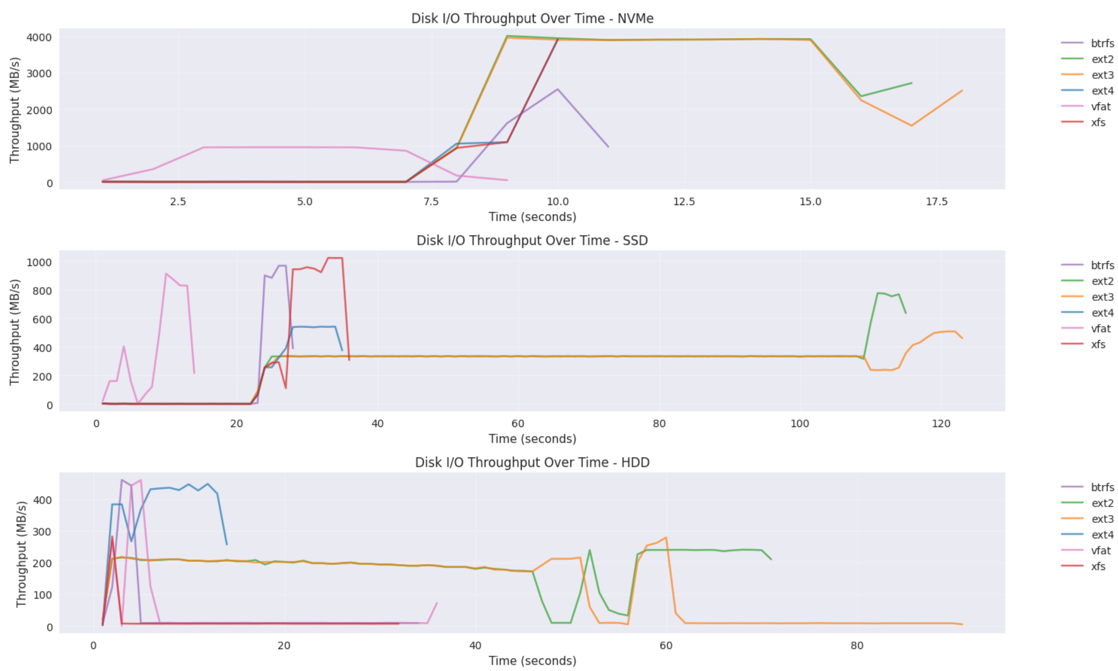
1.7.2 Resource Usage Analysis (excluding NTFS)

The following analysis excludes NTFS filesystem results due to caching effects that significantly distort the measurements. The significantly longer elapsed time for NTFS tests suggests substantial overhead from formatting and mounting operations before the actual benchmark begins.

[9]:
```
# Plot CPU Usage
plot_resource_trends(df[df['filesystem'] != 'ntfs'], 'cpu_percent', 'CPU')

# Plot Memory Usage
plot_resource_trends(df[df['filesystem'] != 'ntfs'], 'memory_percent', 'Memory')

# Plot Disk I/O Throughput
plot_io_throughput(df[df['filesystem'] != 'ntfs'])
```







1.7.3 Resource Usage Matrix Analysis

The resource usage matrix provides a comprehensive visualization of how different filesystems perform across various storage types, showing the temporal patterns of resource utilization during different test phases.

[10]:
```
def plot_resource_matrix(df):
    # Get unique storage types and filesystems
    storage_types = df['storage_type'].unique()
    filesystems = df['filesystem'].unique()

    # Create a figure with subplots matrix
    fig, axes = plt.subplots(len(filesystems), len(storage_types),
                            figsize=(15, 20),
                            squeeze=False)

    # Set title for the entire figure
    fig.suptitle('Resource Usage Patterns by Filesystem and Storage Type',
                fontsize=16, y=1.02)

    # Test phases in order
    test_phases = ['random_read', 'random_write', 'sequential_read',␣
↪'sequential_write']
    phase_colors = ['lightblue', 'lightgreen', 'lightpink', 'lightyellow']

    # Create plots for each combination
    for i, filesystem in enumerate(sorted(filesystems)):
        for j, storage_type in enumerate(storage_types):
            ax = axes[i, j]

            # Get all data for this combination
            mask = (df['storage_type'] == storage_type) & (df['filesystem'] ==␣
↪filesystem)
            subset = df[mask]

            if len(subset) > 0:
                # Combine monitoring data from all test phases
                all_stats = []
                cumulative_time = 0

                for test_type in test_phases:
                    test_data = subset[subset['test_type'] == test_type]
                    if len(test_data) > 0 and 'monitor_data' in test_data.
↪iloc[0] and 'stats' in test_data.iloc[0]['monitor_data']:
                        stats = pd.DataFrame(test_data.
↪iloc[0]['monitor_data']['stats'])
                        stats['timestamp'] = pd.to_datetime(stats['timestamp'])
                        stats['relative_time'] = range(len(stats))
                        stats['absolute_time'] = stats['relative_time'] +␣
↪cumulative_time
                        stats['test_phase'] = test_type
```

```
                    all_stats.append(stats)
                    cumulative_time += len(stats)

            if all_stats:
                combined_stats = pd.concat(all_stats)

                # Calculate I/O throughput
                combined_stats['io_throughput'] =␣
↪(combined_stats['disk_read_bytes'].diff() +
                                                                   ␣
↪combined_stats['disk_write_bytes'].diff()) / 1024 / 1024

                # Plot three metrics on the same subplot
                ax2 = ax.twinx()
                ax3 = ax.twinx()
                ax3.spines['right'].set_position(('outward', 60))

                # Plot phase backgrounds
                for phase_idx, phase in enumerate(test_phases):
                    phase_data =␣
↪combined_stats[combined_stats['test_phase'] == phase]
                    if not phase_data.empty:
                        start_time = phase_data['absolute_time'].min()
                        end_time = phase_data['absolute_time'].max()
                        ax.axvspan(start_time, end_time,
                                 color=phase_colors[phase_idx],
                                 alpha=0.3,
                                 label=phase)

                # Plot metrics
                line1 = ax.plot(combined_stats['absolute_time'],
                              combined_stats['cpu_percent'],
                              color='blue', label='CPU %', alpha=0.6)
                line2 = ax2.plot(combined_stats['absolute_time'],
                               combined_stats['memory_percent'],
                               color='green', label='Memory %', alpha=0.6)
                line3 = ax3.plot(combined_stats['absolute_time'],
                               combined_stats['io_throughput'],
                               color='red', label='I/O (MB/s)', alpha=0.6)

                # Set labels and limits
                ax.set_ylim(0, 100)
                ax2.set_ylim(0, 100)
                ax3.set_ylim(0, combined_stats['io_throughput'].max() * 1.1)

                # Add legend
                lines = line1 + line2 + line3
```

```
                    labels = [l.get_label() for l in lines]
                    ax.legend(lines + [plt.Rectangle((0,0),1,1, fc=c, alpha=0.
↪3) for c in phase_colors],
                             labels + test_phases,
                             loc='upper right',
                             fontsize='x-small')

            # Set title for each subplot
            ax.set_title(f'{filesystem} - {storage_type}', fontsize=10)

            # Only show x-axis labels for bottom row
            if i == len(filesystems) - 1:
                ax.set_xlabel('Time (s)')

            # Clean up unnecessary ticks
            if i != len(filesystems) - 1:
                ax.set_xticks([])

    # Adjust layout
    plt.tight_layout()
    plt.show()

# Create the matrix plot
plot_resource_matrix(df)
```


Resource Usage Patterns by Filesystem and Storage Type
btrfs - NVMe
btrfs - SSD
btrfs - HDD
ext2 - NVMe
ext2 - SSD
ext2 - HDD
ext3 - NVMe
ext3 - SSD
ext3 - HDD
ext4 - NVMe
ext4 - SSD
ext4 - HDD
ntfs - NVMe
ntfs - SSD
ntfs - HDD
vfat - NVMe
vfat - SSD
vfat - HDD
xfs - NVMe
xfs - SSD
xfs - HDD
CPU %
Memory %
I/O (MB/s)
random_read
random_write
sequential_read
sequential_write
Time (s)

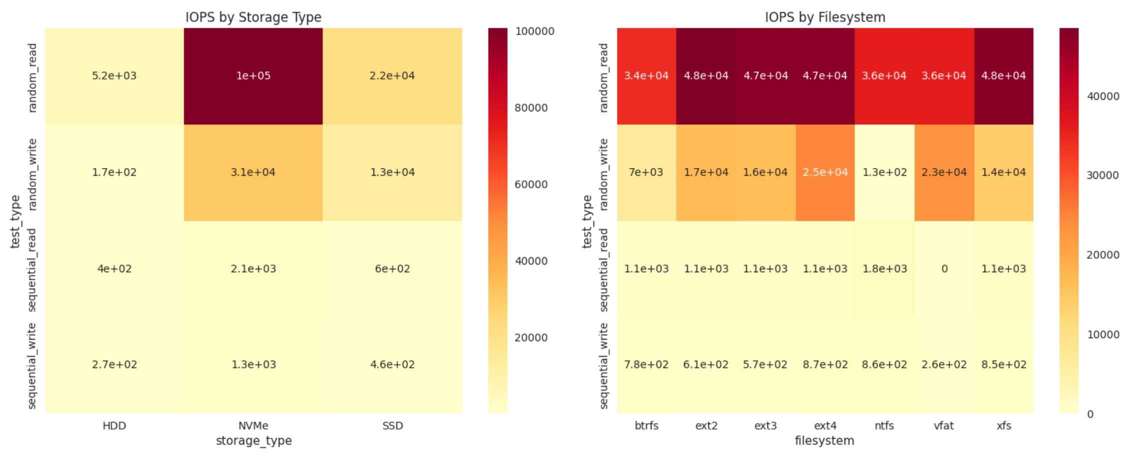
1.8 7. Comparative Analysis

This section presents a comparative analysis of storage performance metrics across different configurations. It examines three key performance indicators (IOPS, bandwidth, and latency) by comparing both storage types (HDD, SSD, NVMe) and filesystems (ext4, xfs, btrfs, etc.). The analysis includes both tabular data and visual heatmaps to facilitate easy comparison of performance characteristics.

[11]:
```python
def perform_comparative_analysis(df):
    """Perform comparative analysis between different configurations."""
    # Create comparison matrix
    metrics = ['iops', 'bandwidth', 'latency']

    for metric in metrics:
        # Compare storage types
        storage_comparison = pd.pivot_table(
            df,
            values=metric,
            index='test_type',
            columns='storage_type',
            aggfunc='mean'
        )

        print(f"\n{metric.upper()} Comparison by Storage Type:")
        display(storage_comparison)

        # Compare filesystems
        fs_comparison = pd.pivot_table(
            df,
            values=metric,
            index='test_type',
            columns='filesystem',
            aggfunc='mean'
        )

        print(f"\n{metric.upper()} Comparison by Filesystem:")
        display(fs_comparison)

        # Plot comparison heatmaps
        fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 6))

        sns.heatmap(storage_comparison, annot=True, cmap='YlOrRd', ax=ax1)
        ax1.set_title(f'{metric.upper()} by Storage Type')

        sns.heatmap(fs_comparison, annot=True, cmap='YlOrRd', ax=ax2)
        ax2.set_title(f'{metric.upper()} by Filesystem')

        plt.tight_layout()
```

```
        plt.show()

perform_comparative_analysis(df)
```

```
IOPS Comparison by Storage Type:

storage_type              HDD           NVMe           SSD
test_type
random_read       5218.303830  100538.353152  21522.412417
random_write       172.426875   30839.360014  12627.320963
sequential_read    401.794746    2118.419987    604.339425
sequential_write   265.055608    1332.734501    458.479528


IOPS Comparison by Filesystem:

filesystem              btrfs          ext2          ext3          ext4
 ↪ ntfs          vfat           xfs
test_type
random_read       34150.718689  48464.614005  47448.554914  47416.674581  35829.
 ↪873834  36069.845286  47604.213953
random_write       6993.685213  16671.054181  16155.161039  24621.679064    130.
 ↪452019  23118.157383  14134.396090
sequential_read    1131.475723   1124.197273   1062.197436   1063.653334   1776.
 ↪860342      0.000000   1132.242261
sequential_write    777.993532    610.454910    569.397336    867.935536    857.
 ↪595701    263.516017    851.069458
```

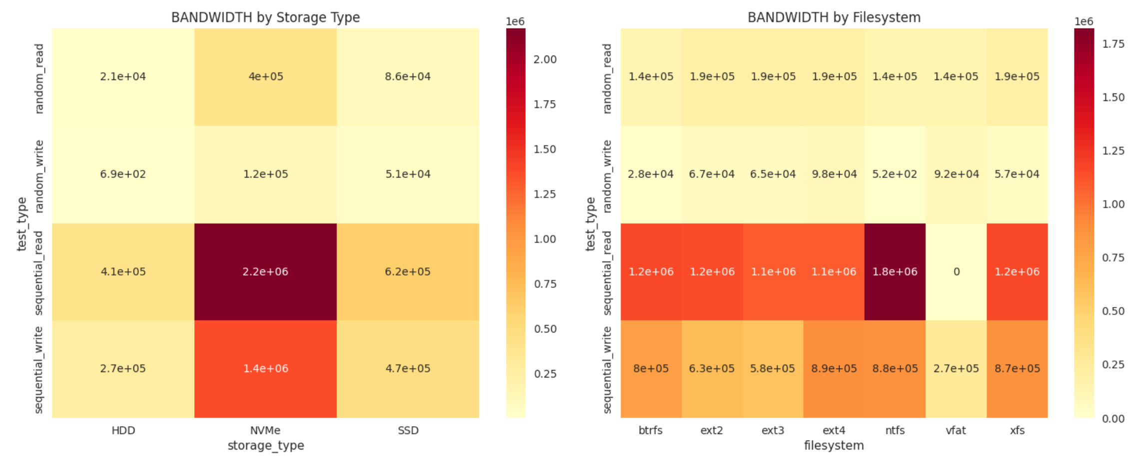



```
BANDWIDTH Comparison by Storage Type:

storage_type              HDD           NVMe           SSD
test_type
```

```
random_read        20872.714286  4.021530e+05   86089.285714
random_write         689.428571  1.233570e+05   50508.857143
sequential_read   411437.428571  2.169262e+06  618843.285714
sequential_write  271412.142857  1.364703e+06  469475.428571
```

```
BANDWIDTH Comparison by Filesystem:
```

```
filesystem               btrfs          ext2          ext3          ext4      ␣
 ↪ ntfs      vfat          xfs
test_type
random_read       1.366027e+05  1.938580e+05  1.897937e+05  1.896663e+05  1.
 ↪433190e+05  144279.0  1.904163e+05
random_write      2.797433e+04  6.668367e+04  6.462033e+04  9.848633e+04  5.
 ↪216667e+02   92472.0  5.653733e+04
sequential_read   1.158631e+06  1.151178e+06  1.087690e+06  1.089181e+06  1.
 ↪819504e+06       0.0  1.159416e+06
sequential_write  7.966650e+05  6.251050e+05  5.830623e+05  8.887653e+05  8.
 ↪781777e+05  269774.0  8.714947e+05
```

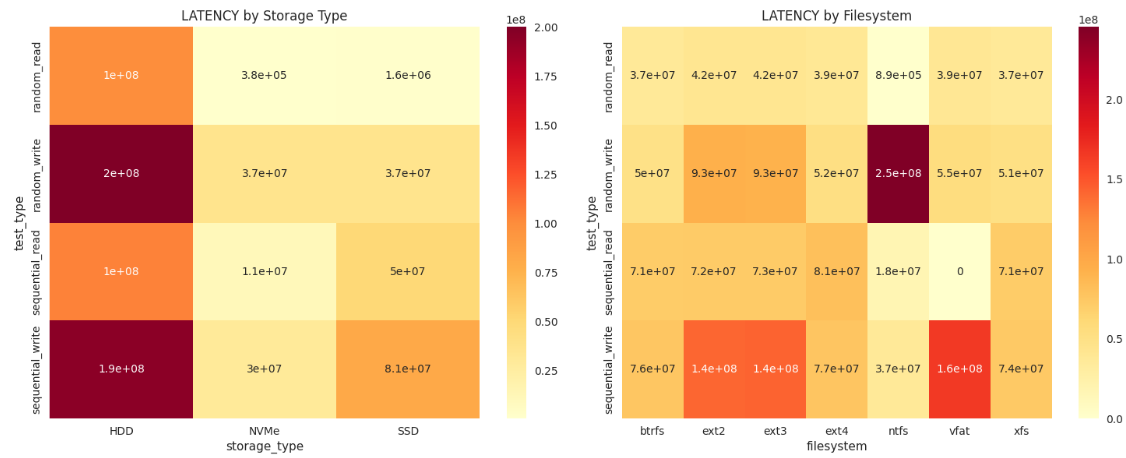



```
LATENCY Comparison by Storage Type:
```

```
storage_type               HDD          NVMe           SSD
test_type
random_read       9.981976e+07  3.793198e+05  1.568308e+06
random_write      2.000650e+08  3.690734e+07  3.698901e+07
sequential_read   1.041555e+08  1.121463e+07  5.007891e+07
sequential_write  1.949310e+08  2.950203e+07  8.141000e+07
```

```
LATENCY Comparison by Filesystem:
```

```
filesystem                  btrfs         ext2          ext3          ext4          ␣
↪ ntfs          vfat          xfs
test_type
random_read       3.731838e+07  4.171621e+07  4.207270e+07  3.862764e+07  8.
↪918571e+05  3.947476e+07  3.735570e+07
random_write      4.959191e+07  9.322743e+07  9.275589e+07  5.205853e+07  2.
↪453643e+08  5.539308e+07  5.085198e+07
sequential_read   7.134690e+07  7.228924e+07  7.261188e+07  8.070896e+07  1.
↪785679e+07  0.000000e+00  7.123406e+07
sequential_write  7.580469e+07  1.413831e+08  1.431413e+08  7.700812e+07  3.
↪712815e+07  1.649672e+08  7.420135e+07
```



1.9 8. Recommendations and Conclusions

This section presents the final analysis and recommendations based on the benchmark results. The analysis uses a geometric mean approach to calculate overall performance scores, taking into account IOPS, bandwidth, and latency metrics. The recommendations are derived from academic literature on storage benchmarking and statistical analysis of results.

[12]:
```
def generate_recommendations(df):
    """Generate recommendations based on benchmark results."""
    # Calculate performance scores using geometric mean of normalized metrics
    # Useful insights from publications:
    # M. Seltzer and K. A. Smith, "Workload-specific file system benchmarks,"␣
↪2001. Accessed: May 03, 2025. [Online]. Available: https://www.
↪semanticscholar.org/paper/
↪Workload-specific-file-system-benchmarks-Seltzer-Smith/
↪686de8280485ad66f0b8037ff61e61b494ce3bc0
```

```python
    # P. M. Chen and D. A. Patterson, "A new approach to I/O performance evaluation: self-scaling I/O benchmarks, predicted I/O performance," SIGMETRICS Perform. Eval. Rev., vol. 21, no. 1, pp. 1-12, Jun. 1993, doi: 10.1145/166962.166966.
    # P. J. Fleming and J. J. Wallace, "How not to lie with statistics: the correct way to summarize benchmark results," Commun. ACM, vol. 29, no. 3, pp. 218-221, Mar. 1986, doi: 10.1145/5666.5673.


    # Normalize each metric relative to its mean
    normalized_iops = df['iops'] / df['iops'].mean()
    normalized_bandwidth = df['bandwidth'] / df['bandwidth'].mean()
    normalized_latency = df['latency'].mean() / df['latency']  # Invert latency since lower is better

    # Calculate geometric mean as recommended by Fleming & Wallace
    # Geometric mean preserves ratios and prevents domination by any single metric
    df['performance_score'] = (normalized_iops * normalized_bandwidth * normalized_latency) ** (1/3)

    # Group by storage type and filesystem
    recommendations = df.groupby(['storage_type', 'filesystem']).agg({
        'performance_score': 'mean',
        'iops': 'mean',
        'bandwidth': 'mean',
        'latency': 'mean'
    }).round(2)

    print("\nPerformance Scores and Recommendations:")
    display(recommendations)

    # Plot performance scores
    plt.figure(figsize=(10, 6))



    sns.barplot(data=df, x='storage_type', y='performance_score', hue='filesystem',
                palette=fs_colors)
    plt.title('Overall Performance Score by Storage Type and Filesystem')
    plt.xlabel('Storage Type')
    plt.ylabel('Performance Score')
    plt.legend(title='Filesystem')
    plt.tight_layout()
    plt.show()
```

```
generate_recommendations(df)
```

```
Performance Scores and Recommendations:
                          performance_score      iops   bandwidth       latency
storage_type filesystem
HDD          btrfs                     0.09    243.20   117599.75  1.330585e+08
             ext2                      0.07    175.52    84171.50  2.143106e+08
             ext3                      0.07    175.02    84067.00  2.144025e+08
             ext4                      0.09    230.31   110971.75  1.409504e+08
             ntfs                      1.36   9388.24   686754.75  7.407539e+07
             vfat                      0.04    147.35    30933.00  1.369791e+08
             xfs                       0.09    241.13   118222.75  1.344233e+08
NVMe         btrfs                     3.19  24226.72  1190281.00  8.778315e+06
             ext2                      4.96  41196.32  1184340.00  9.170515e+06
             ext3                      4.79  39995.97  1103520.25  9.943538e+06
             ext4                      5.63  46855.52  1332587.50  7.463895e+06
             ntfs                      1.43   9796.01   731068.50  7.631343e+07
             vfat                      5.12  35424.96   261890.75  1.713611e+07
             xfs                       4.74  38455.01  1300392.00  7.700020e+06
SSD          btrfs                     0.97   7820.49   282023.75  3.370955e+07
             ext2                      1.06   8780.89   259106.75  3.798088e+07
             ext3                      1.06   8755.49   256287.25  3.859024e+07
             ext4                      1.02   8391.63   256014.75  3.788818e+07
             ntfs                      1.42   9761.84   713318.75  7.554200e+07
             vfat                      1.32   9016.33    87070.00  4.076104e+07
             xfs                       1.11   9095.30   289783.25  3.310901e+07
```