benchmark_analysis_concise

May 11, 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

[41]:
```
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)
```

[42]:
```
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)#.sort_values('filesystem')

print(f"Loaded data from {latest_run.name}")
```

```
Loaded data from run_20250427_234135
```

1.3 2. Overview and Summary Statistics

[43]:
```
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)
```

```python
# Display summary statistics
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)
```

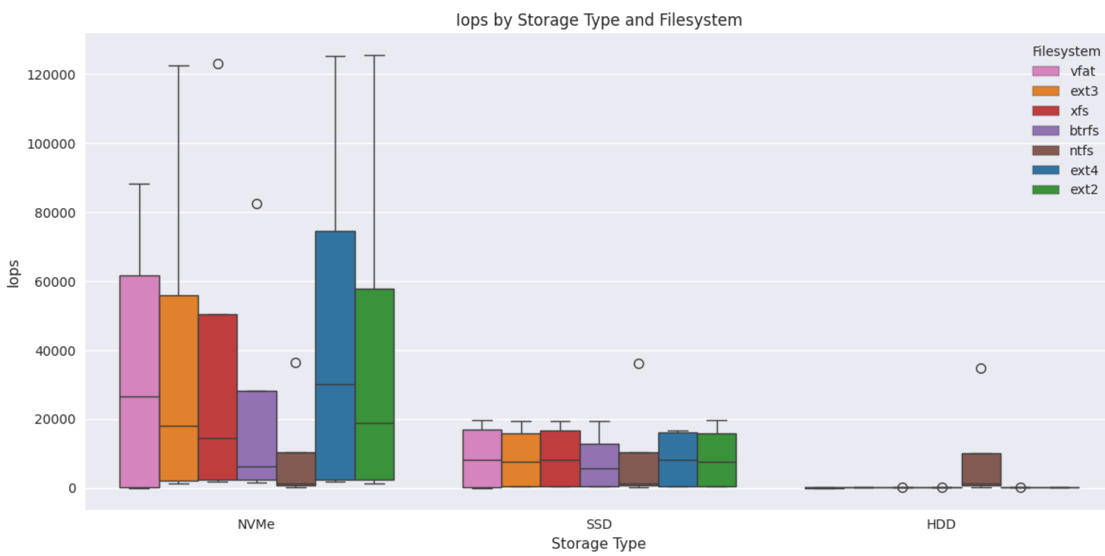
```
Summary Statistics by Storage Type and Filesystem:
                              iops                                  bandwidth    ␣
 ↪                                         latency
                              mean        std      min        max        mean    ␣
 ↪    std        min         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
```

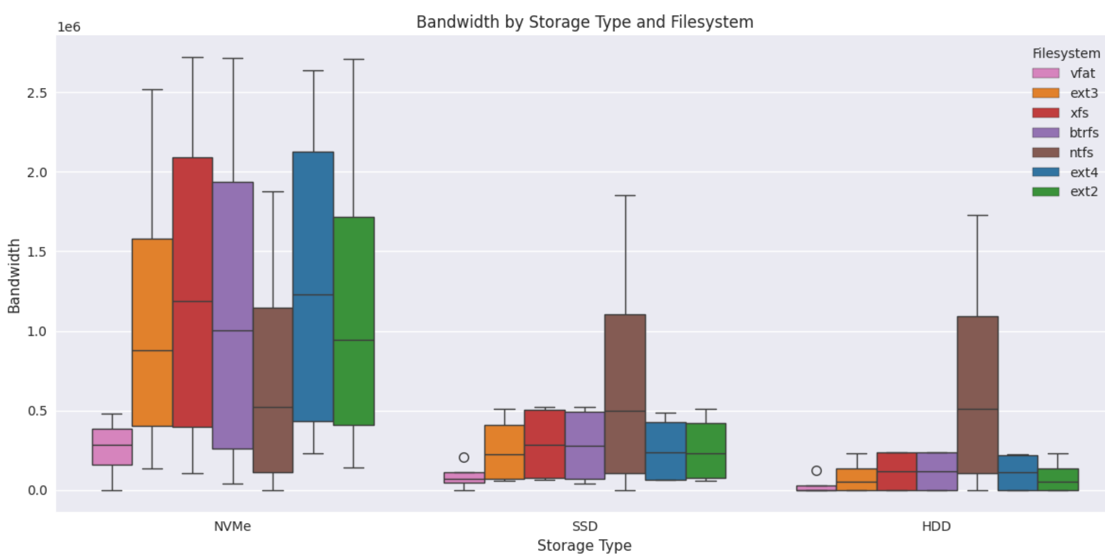
```
              ext3         39995.97  57055.94  1240.08  122554.46  1103520.25 ␣
↪1056072.32  134917.0  2519101.0  9.943538e+06  1.197304e+07  2.602802e+05  2.
↪564301e+07
              ext4         46855.52  58478.42  1913.12  125367.77  1332587.50 ␣
↪1155650.63  230253.0  2639587.0  7.463895e+06  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
```

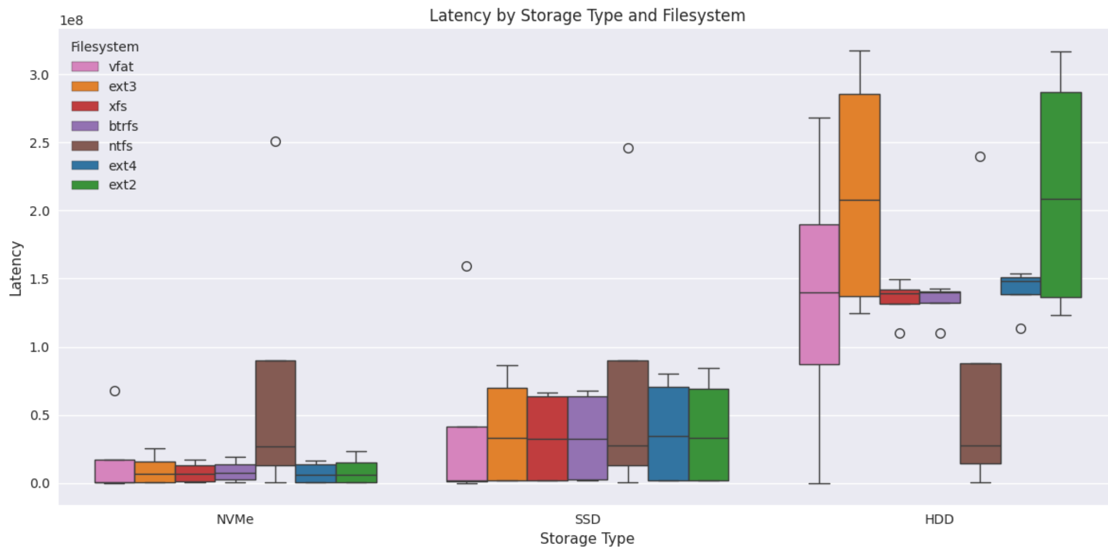
1.4 3. Performance Analysis by Storage Type

[44]:
```python
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)
```

```python
    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)
```





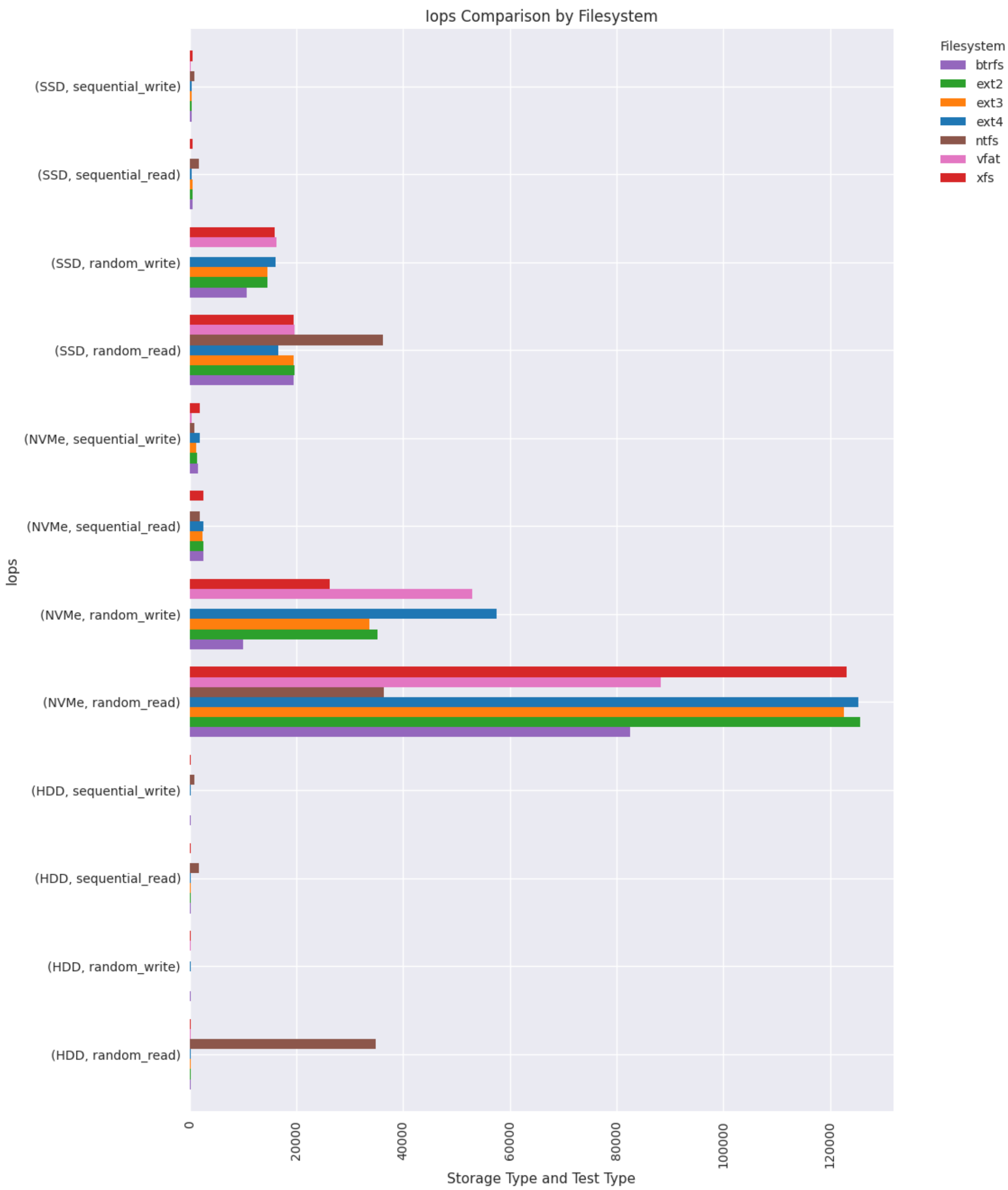


1.5 4. Filesystem Comparison

[45]:
```
df=df.sort_values('filesystem')

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
```

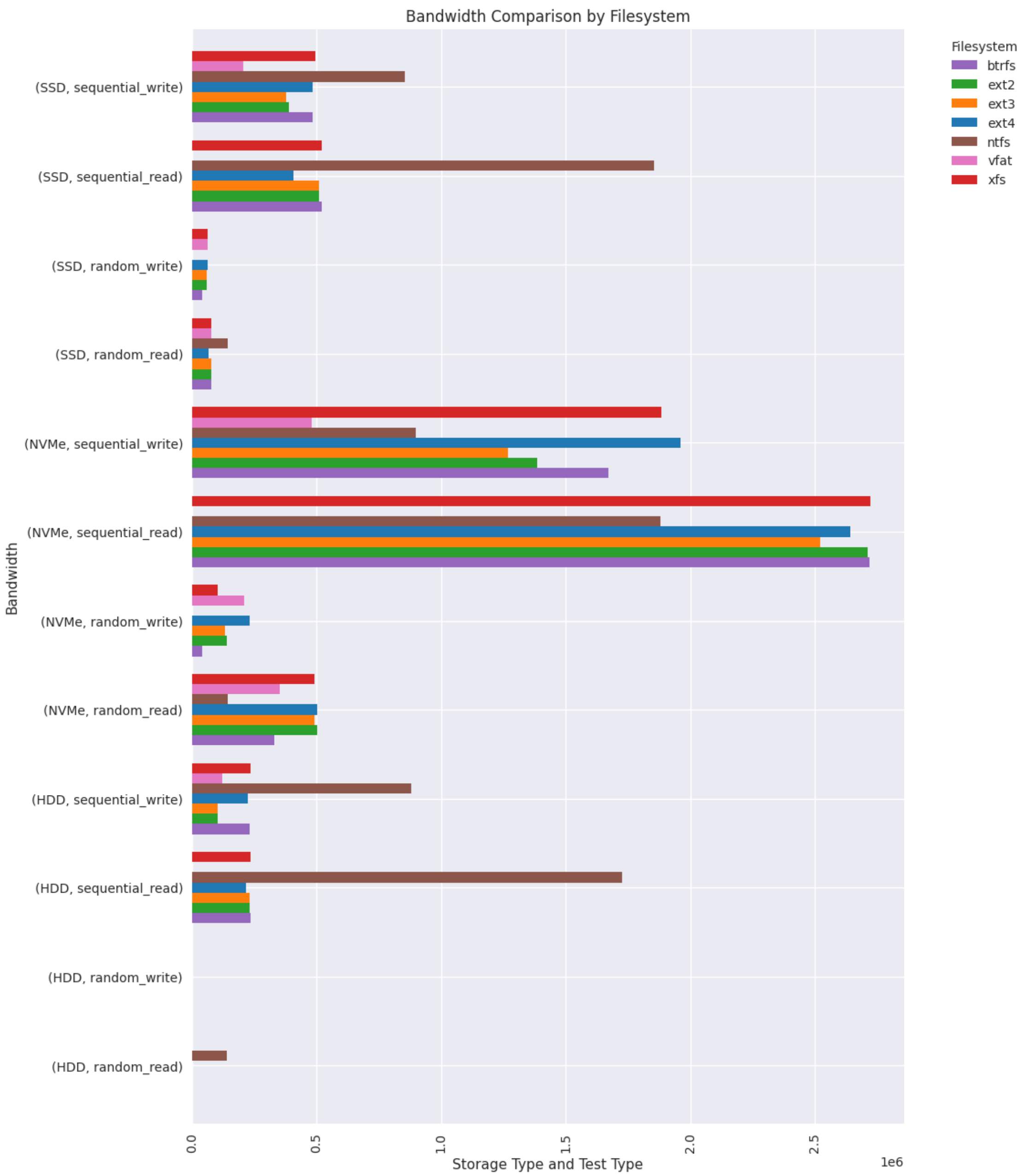
```
        plt.title(f'{metric.title()} Comparison by Filesystem')
        plt.xlabel('Storage Type and Test Type')
        plt.ylabel(metric.title())
        plt.xticks(rotation=90)
        plt.legend(title='Filesystem', bbox_to_anchor=(1.05, 1), loc='upper␣
↪left')
        # Ensure plot takes up full 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
```



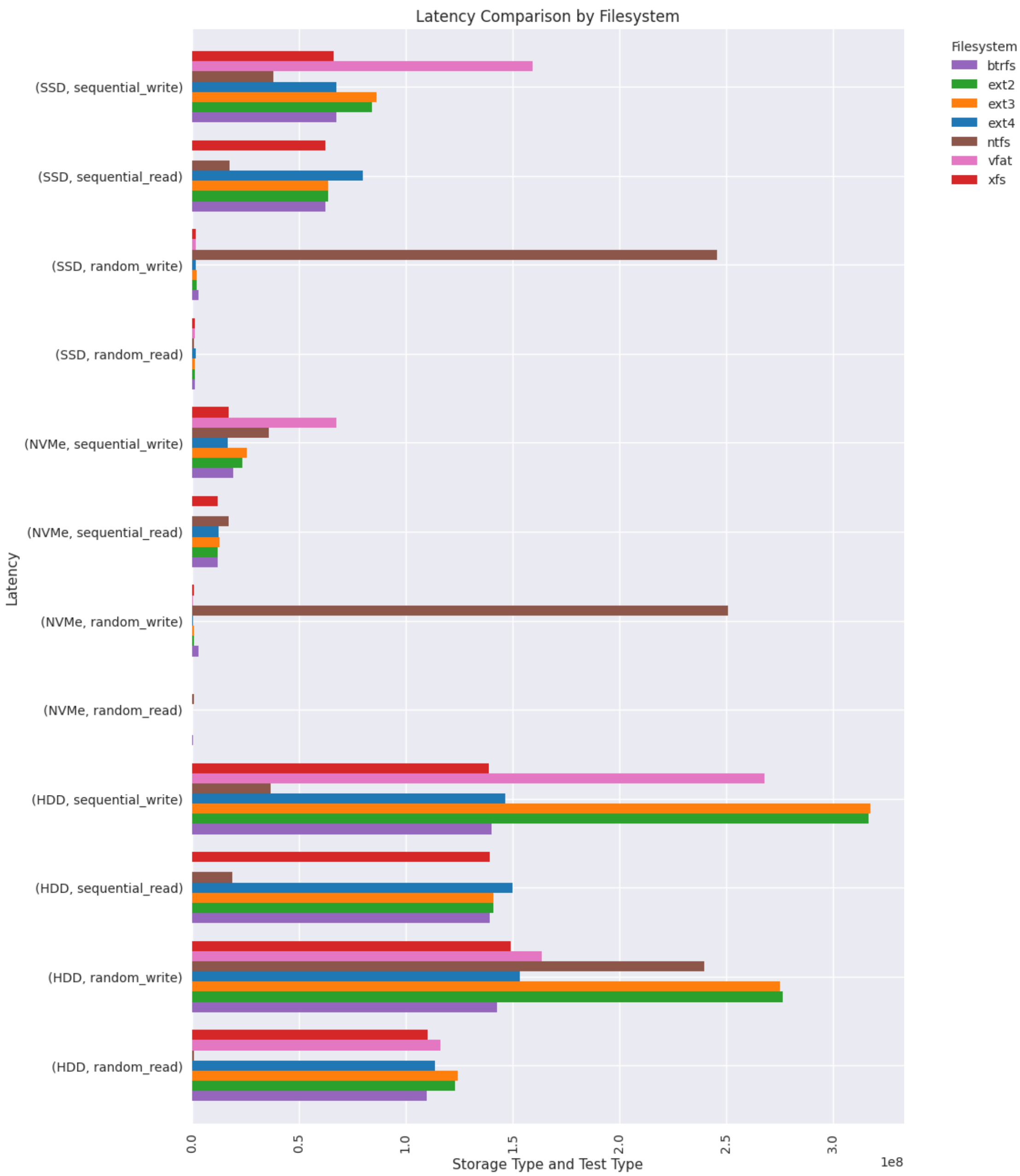

```
BANDWIDTH Comparison:

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

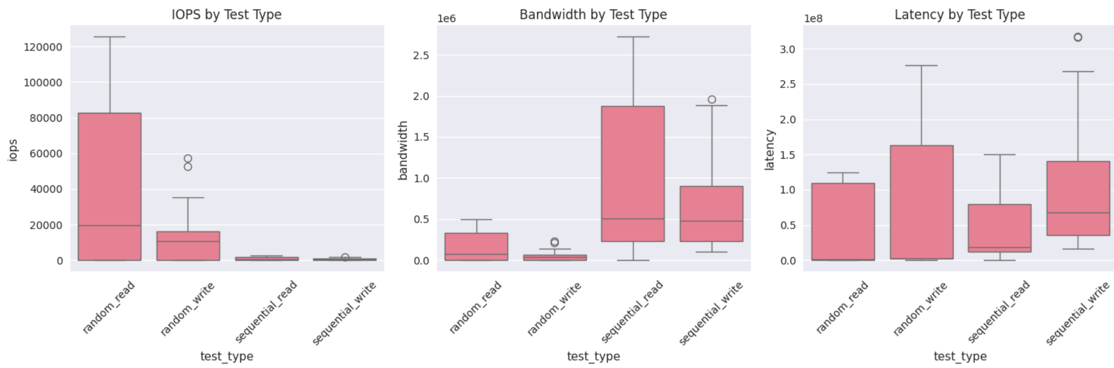
[63]:
```
def analyze_io_patterns(df):
    """Analyze I/O patterns across different test types."""
    # Group by test type and calculate statistics
    io_stats = df.groupby('test_type').agg({
        'iops': ['mean', 'std', 'min', 'max'],
        'bandwidth': ['mean', 'std', 'min', 'max'],
```

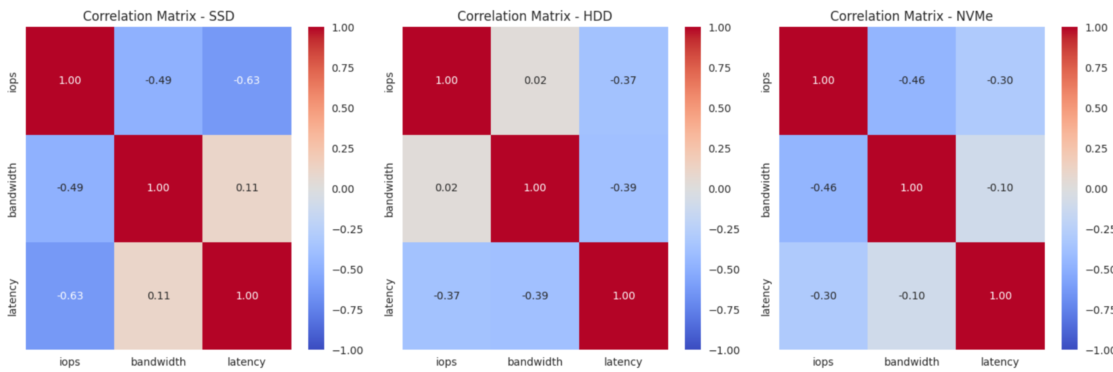
```
        'latency': ['mean', 'std', 'min', 'max']
    }).round(2)

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

    # Create a single row of 3 plots
    fig, axes = plt.subplots(1, 3, figsize=(15, 5))

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

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

    # Latency by test type
    sns.boxplot(data=df, x='test_type', y='latency', ax=axes[2])
    axes[2].set_title('Latency by Test Type')
    axes[2].set_xticks(range(len(df['test_type'].unique())))
    axes[2].set_xticklabels(df['test_type'].unique(), rotation=45)

    plt.tight_layout()
    plt.show()

analyze_io_patterns(df)

def plot_correlation_trellis(df, group_by='storage_type', figsize=(15, 5),␣
 ↪n_cols=4, n_rows=3):
    """
    Create a trellis plot showing correlation matrices grouped by either␣
 ↪storage type or filesystem.

    Args:
        df: DataFrame containing the data
        group_by: Column to group by ('storage_type' or 'filesystem')
        figsize: Tuple of (width, height) for the figure
        n_cols: Number of columns for filesystem plot (only used when␣
 ↪group_by='filesystem')
        n_rows: Number of rows for filesystem plot (only used when␣
 ↪group_by='filesystem')
    """
```

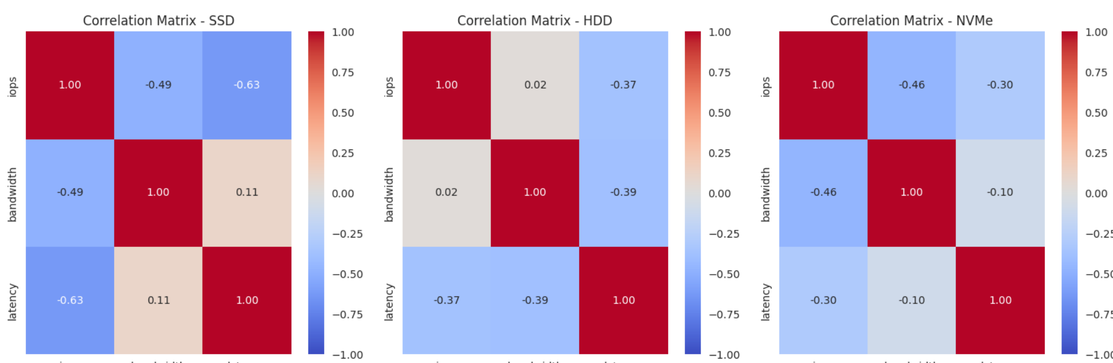
```
    groups = df[group_by].unique()

    if group_by == 'storage_type':
        fig, axes = plt.subplots(1, len(groups), figsize=figsize)
    else:  # filesystem
        fig, axes = plt.subplots(n_rows, n_cols, figsize=figsize)
        axes = axes.flatten()

    for idx, group in enumerate(groups):
        # Filter data for current group
        group_df = df[df[group_by] == group]

        # Calculate correlation matrix
        correlation = group_df[['iops', 'bandwidth', 'latency']].corr()

        # Create heatmap
        sns.heatmap(correlation,
                    annot=True,
                    cmap='coolwarm',
                    vmin=-1,
                    vmax=1,
                    ax=axes[idx],
                    fmt='.2f')
        axes[idx].set_title(f'Correlation Matrix - {group}')

    # Hide unused subplots for filesystem plot
    if group_by == 'filesystem':
        for idx in range(len(groups), len(axes)):
            axes[idx].set_visible(False)

    plt.tight_layout()
    plt.show()

# Plot all correlation matrices
plot_correlation_trellis(df)  # Overall
plot_correlation_trellis(df, group_by='storage_type')  # By storage type
plot_correlation_trellis(df, group_by='filesystem', figsize=(20, 12))  # By␣
↪filesystem
```

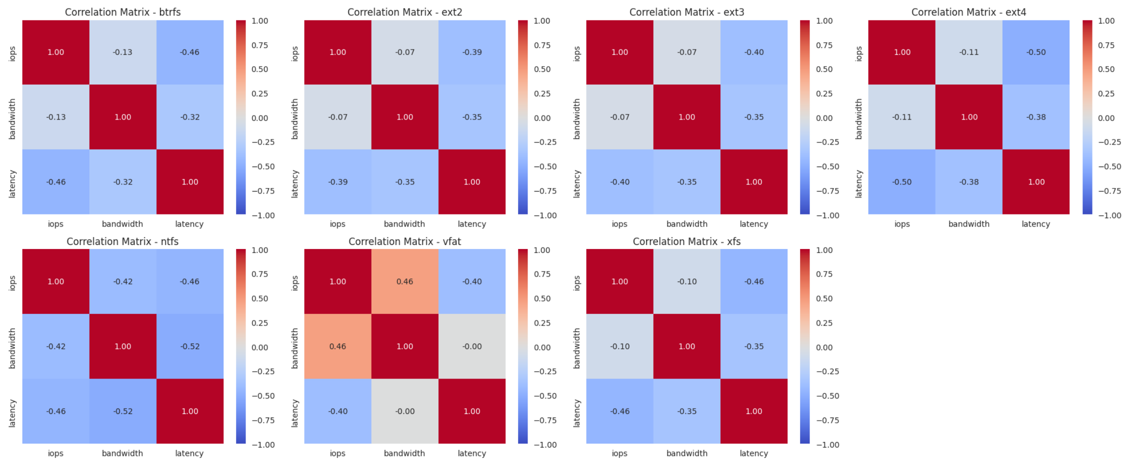
```
I/O Pattern Statistics:
                      iops                               bandwidth             ␣
↪                             latency
                      mean         std      min         max         mean            std ␣
↪      min          max            mean             std           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

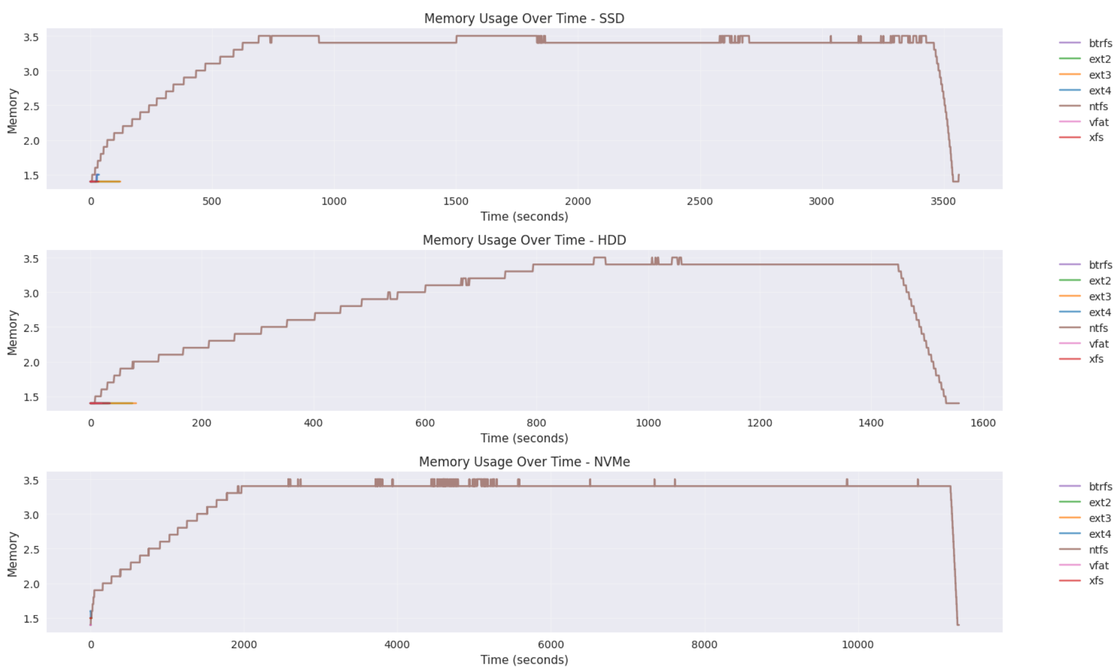
This section analyzes CPU, memory, and disk I/O utilization patterns across different storage types and filesystems. Note that the NTFS results show significantly higher resource utilization due to its much longer elapsed time (7132 seconds) compared to other filesystems (20-70 seconds), which may skew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

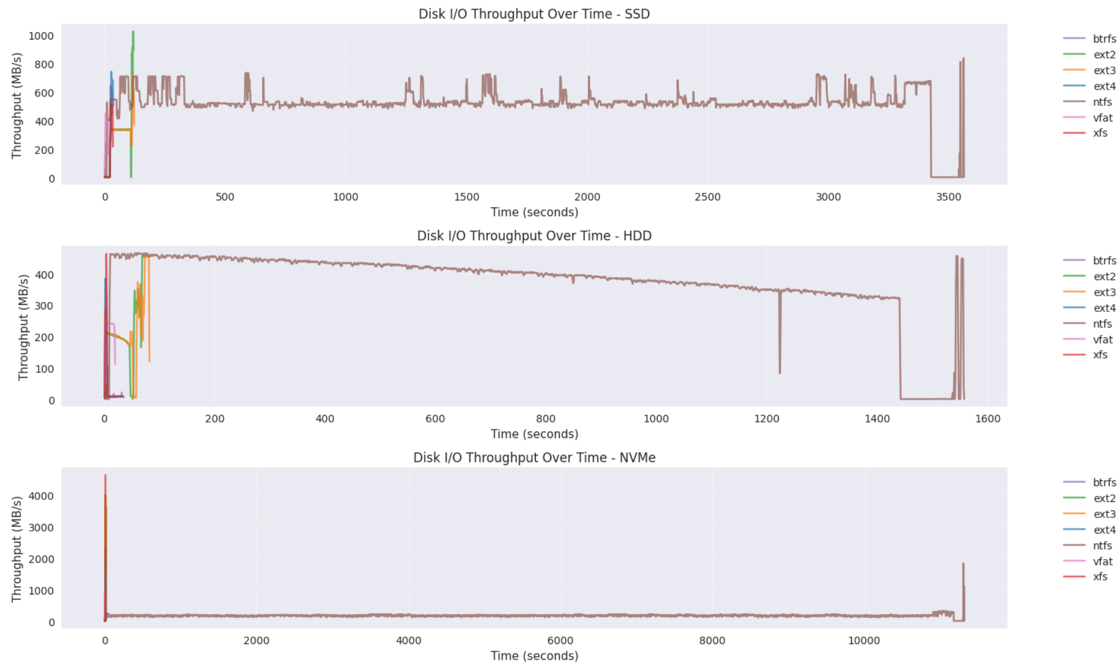
[47]:
```python
def plot_resource_trends(df, metric, title):
    """
    Plot resource usage trends over time for different storage types and filesystems.

    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)
```


CPU Usage Over Time - SSD
CPU
Time (seconds)
CPU Usage Over Time - HDD
CPU
Time (seconds)
CPU Usage Over Time - NVMe
CPU
Time (seconds)
btrfs
ext2
ext3
ext4
ntfs
vfat
xfs


Memory Usage Over Time - SSD
Memory
Time (seconds)
Memory Usage Over Time - HDD
Memory
Time (seconds)
Memory Usage Over Time - NVMe
Memory
Time (seconds)
btrfs
ext2
ext3
ext4
ntfs
vfat
xfs



	Storage Type	Filesystem	Avg CPU %	Max CPU %	Avg Memory %	Max Memory %	Total Read (GB)	Total Write (GB)	Elapsed Time (s)
0	HDD	btrfs	0.360606	2.8	1.400000	1.4	304.718675	3234.341423	64.066545
1	HDD	ext2	0.161039	2.3	1.400000	1.4	291.476358	3148.328481	152.140577
2	HDD	ext3	0.212048	2.5	1.400000	1.4	295.889257	3195.600324	164.157487
3	HDD	ext4	0.177778	2.3	1.400000	1.4	296.171502	3212.674050	70.071099
4	HDD	ntfs	1.918164	3.1	2.910205	3.5	287.261601	2553.800095	3117.673241
5	HDD	vfat	1.038095	2.3	1.400000	1.4	286.583983	870.959365	40.044080
6	HDD	xfs	0.236111	2.1	1.400000	1.4	300.441088	3224.044443	70.073526
7	NVMe	btrfs	0.961538	2.7	1.400000	1.4	407.192430	18518.884068	24.021451
8	NVMe	ext2	0.745455	3.6	1.500000	1.5	374.985746	18307.585892	42.041438
9	NVMe	ext3	0.621053	2.2	1.500000	1.5	383.167312	18474.386311	36.033045
10	NVMe	ext4	2.725000	14.0	1.558333	1.6	387.173947	18482.390499	22.018397

```
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   0.533333        2.3      1.500000            1.5     ␣
↪ 398.907250       18504.504576         22.022957
14           SSD     btrfs   1.560606        7.0      1.424242            1.5     ␣
↪ 353.939219       10717.421374         64.065586
15           SSD      ext2   0.111475        2.3      1.400000            1.4     ␣
↪ 325.628357       10517.483451        242.224811
16           SSD      ext3   0.317742        4.6      1.400000            1.4     ␣
↪ 329.741037       10579.645446        246.226569
17           SSD      ext4   0.948649        4.9      1.424324            1.5     ␣
↪ 337.916407       10682.088702         72.069450
18           SSD      ntfs   2.742155        5.1      3.247685            3.5     ␣
↪ 317.388026        8631.487349       7132.278231
19           SSD      vfat   1.264706        2.4      1.400000            1.4     ␣
↪ 315.349740        3258.143296         32.035088
20           SSD       xfs   1.361111        6.7      1.400000            1.4     ␣
↪ 345.934004       10706.646747         70.068817
```

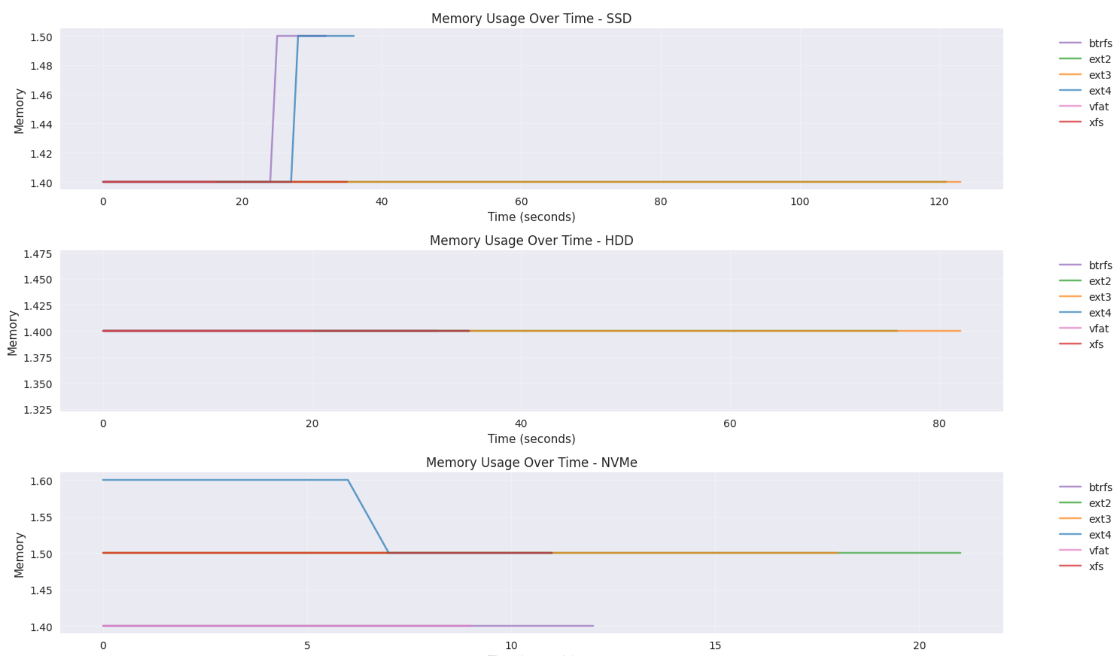
1.7.2 Resource Usage Analysis (excluding NTFS)

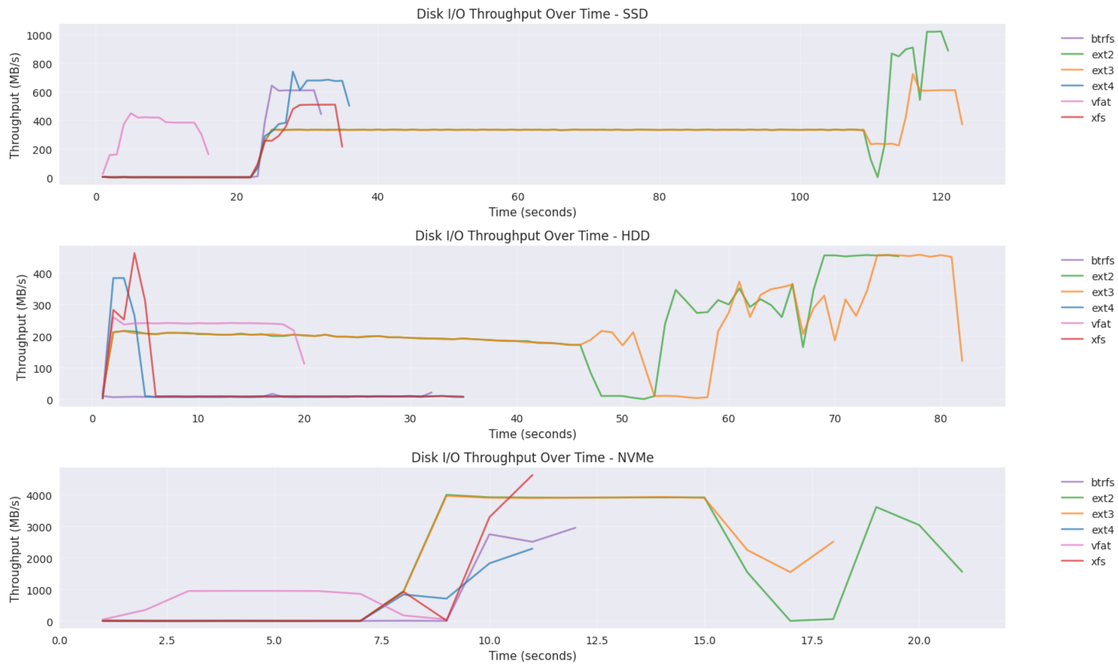
The following analysis excludes NTFS filesystem results due to caching effects that significantly distort the measurements. The significantly longer elapsed time for NTFS tests suggests substantial overhead from formatting and mounting operations before the actual benchmark begins.

[48]:

```python
# 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'])
```


CPU Usage Over Time - SSD
CPU
Time (seconds)
btrfs
ext2
ext3
ext4
vfat
xfs
CPU Usage Over Time - HDD
CPU
Time (seconds)
btrfs
ext2
ext3
ext4
vfat
xfs
CPU Usage Over Time - NVMe
CPU
Time (seconds)
btrfs
ext2
ext3
ext4
vfat
xfs


Memory Usage Over Time - SSD
Memory
Time (seconds)
btrfs
ext2
ext3
ext4
vfat
xfs
Memory Usage Over Time - HDD
Memory
Time (seconds)
btrfs
ext2
ext3
ext4
vfat
xfs
Memory Usage Over Time - NVMe
Memory
Time (seconds)
btrfs
ext2
ext3
ext4
vfat
xfs



1.7.3 Resource Usage Matrix Analysis

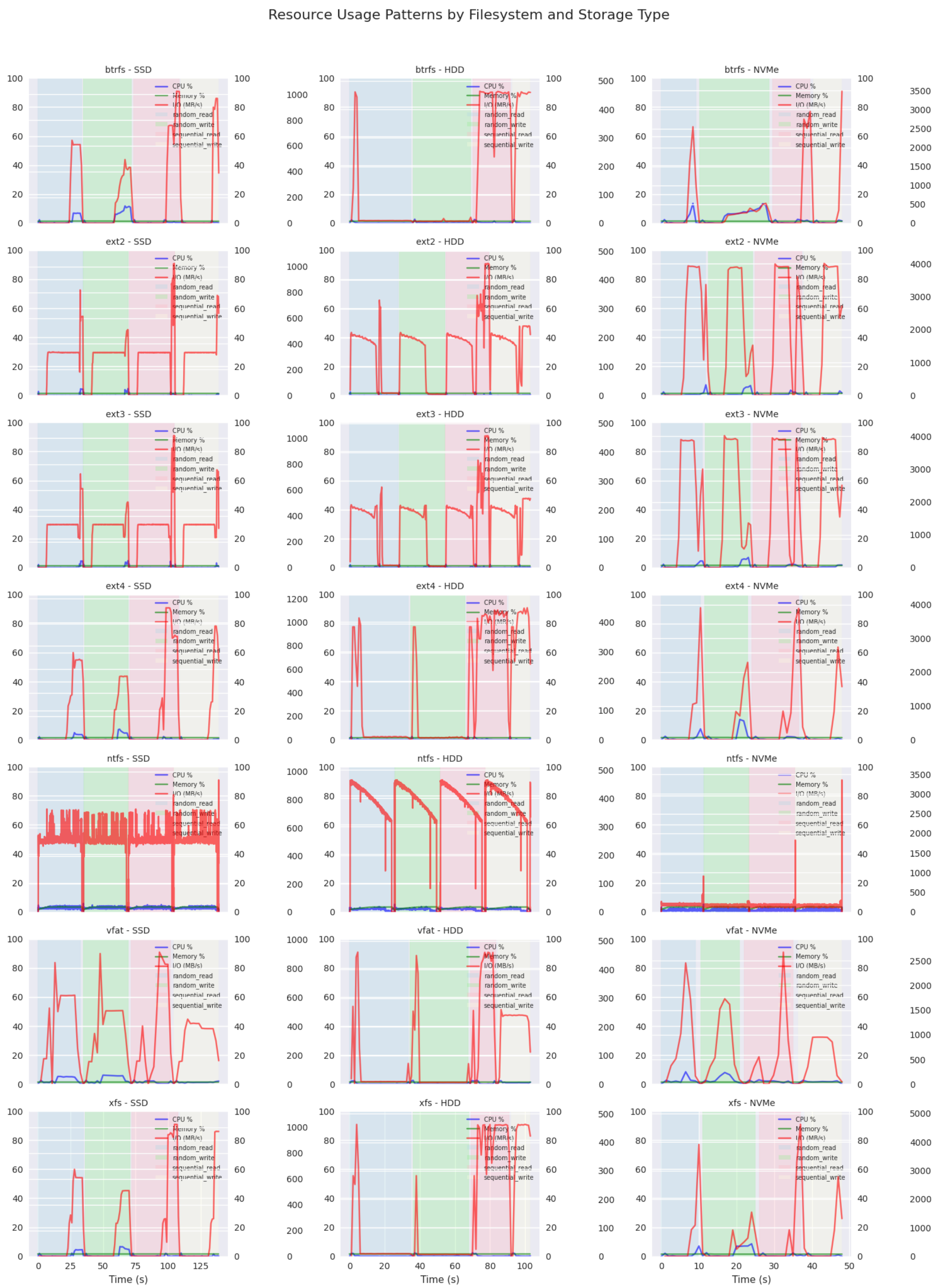
The resource usage matrix provides a comprehensive visualization of how different filesystems perform across various storage types, showing the temporal patterns of resource utilization during different test phases.

[65]:
```
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()
```

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



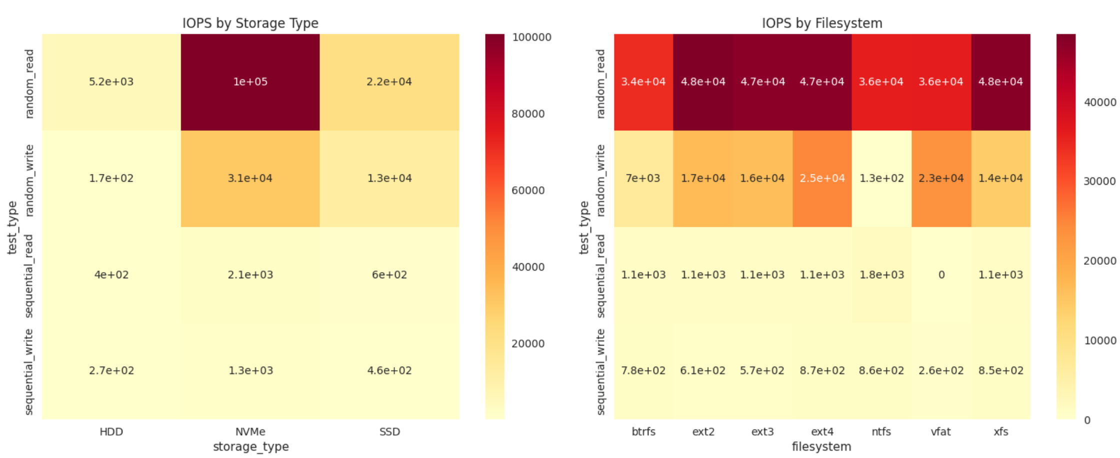
1.8 7. Comparative Analysis

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.

[50]:
```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)
```

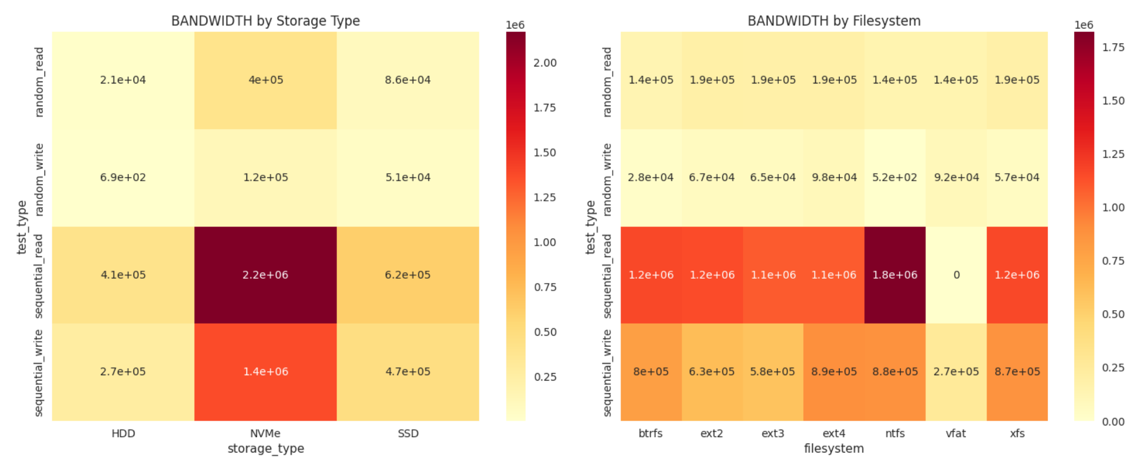
```python
        ax2.set_title(f'{metric.upper()} by Filesystem')

        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
```



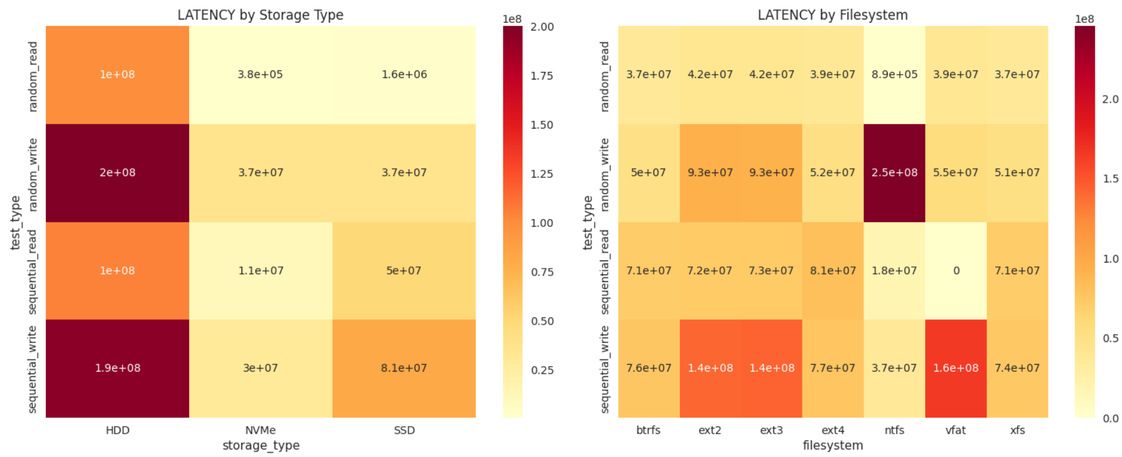
```
BANDWIDTH Comparison by Storage Type:

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.

[51]:
```python
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
```