optimization

July 16, 2025

1 Optimization

1.1 Imports

[344]:
```
import numpy as np
import matplotlib.pyplot as plt
from pymoo.algorithms.moo.nsga2 import NSGA2
from pymoo.algorithms.soo.nonconvex.ga import GA
from pymoo.optimize import minimize
from pymoo.core.problem import Problem
```

1.2 Define Model Curves

1.2.1 Pruning vs Accuracy

[345]:
```
def get_accuracy(p):
    #6th order polynomial coefficients
    coeffs = [85.28, -10.35, -28.44, -49.40]

    acc = sum(c * p**i for i, c in enumerate(coeffs))

    return max(acc, 0)
```

1.2.2 Pruning vs Model Size

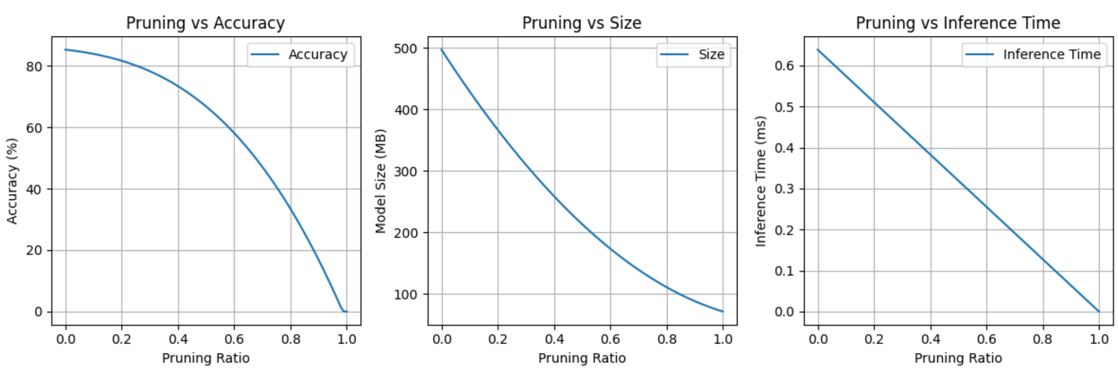
[346]:
```
def get_size(p):
    coeffs = [496.7, -706.2, 276.9, 4.020]

    return sum(c * p**i for i, c in enumerate(coeffs))
```

1.2.3 Pruning vs Inference Time

[347]:
```
def get_time(p):
    b0 = 0.06386
    b1 = -0.06386

    return (b0 + b1 * p)*10
```

1.2.4 Plot Curves

[348]:
```
p = np.linspace(0, 1, 100)
sizes = get_size(p)
accuracies = [get_accuracy(p) for p in p]
times = get_time(p)

plt.style.use('default')
plt.figure(figsize=(12, 4))

plt.subplot(1, 3, 1)
plt.plot(p, accuracies, label='Accuracy')
plt.xlabel('Pruning Ratio')
plt.ylabel('Accuracy (%)')
plt.title('Pruning vs Accuracy')
plt.grid()
plt.legend()

plt.subplot(1, 3, 2)
plt.plot(p, sizes, label='Size')
plt.xlabel('Pruning Ratio')
plt.ylabel('Model Size (MB)')
plt.title('Pruning vs Size')
plt.grid()
plt.legend()

plt.subplot(1, 3, 3)
plt.plot(p, times, label='Inference Time')
plt.xlabel('Pruning Ratio')
plt.ylabel('Inference Time (ms)')
plt.title('Pruning vs Inference Time')
plt.grid()
plt.legend()

plt.tight_layout()
plt.show()
```



1.3 Rewards

1.3.1 Accuracy Rewards

[349]:
```
def get_accuracy_reward(curr_accuracy, min_accuracy, sigma_right=4,
↪sigma_left=2):
    diff = curr_accuracy - min_accuracy
    if 0<=diff<=1e-2:
        return (np.exp(- (diff**2) / (10 * sigma_left**2)) * 100)
    else:
        return 1*(np.exp(- (abs(diff)**1.5) / (2 * sigma_right**2)) * 100)
```

1.3.2 Inference Time Reward

[350]:
```
def get_comp_time_reward(current_comp_time, sigma=0.8):
    return np.exp(- (current_comp_time**2) / (2 * sigma**2))*10
```

1.3.3 Model Size Reward

[351]:
```
def get_model_size_reward(current_model_size, max_model_size, sigma_left=2):
    diff = current_model_size - max_model_size
    if current_model_size > max_model_size:
        return np.exp(- ((diff)**2) / (10 * sigma_left**2))*99*0.5
    if current_model_size == max_model_size:
        return 99*(0.5)
    else:
        return (99+(current_model_size/max_model_size))*0.5
```

1.3.4 Better Pruning Reward

[352]:
```
def more_acc_less_size(accuracy, min_accuracy, size, max_model_size):
    if accuracy >= min_accuracy and size <= max_model_size:
        return ((accuracy-min_accuracy)*2) + (max_model_size-size)/2
    return 0
```

1.3.5 Final Reward

[353]:
```
def get_reward(p, min_accuracy=80.0, max_model_size=350.0, x=10, y=1, z=1) ->
↪float:
    accuracy = get_accuracy(p)
    time = get_time(p)
    size = get_size(p)

    acc_reward = np.array(get_accuracy_reward(accuracy, min_accuracy))
    time_reward = np.array(get_comp_time_reward(time))
```

```
    size_reward = np.array(get_model_size_reward(size, max_model_size))
    better_reward = more_acc_less_size(accuracy, min_accuracy, size,␣
 ↪max_model_size)
    global counts_of_calulating_rewards
    # counts_of_calulating_rewards += 1 # type: ignore

    x, y, z = x/(x+y+z), y/(x+y+z), z/(x+y+z)

    return (x*acc_reward + y*time_reward + z*size_reward + better_reward + p/2)
```

1.4 Importance Values

[378]:
```
i_org = np.array([0.03044561, 0.02201545, 0.12376647, 0.09755174, 0.04860051,
       0.00832497, 0.03501421, 0.00934147, 0.05674529, 0.15345743,
       0.237974  , 0.17676284])
i = i_org.copy()
```

1.5 Params

[379]:
```
MAX_MODEL_SIZES = [0]*12
GLOBAL_MIN_ACCURACY = 0.0
```

[380]:
```
def init():
    global MAX_MODEL_SIZES, GLOBAL_MIN_ACCURACY
    MAX_MODEL_SIZES = [100.0] * 12

    for j in range(12):
        MAX_MODEL_SIZES[j] = MAX_MODEL_SIZES[j] * np.random.uniform(1.0, 5.0)

    GLOBAL_MIN_ACCURACY = 10 * np.random.uniform(5, 8.2)

    print("\n" + "="*60)
    print(f"MAX_MODEL_SIZES: {np.round(MAX_MODEL_SIZES, 2)}")
    print(f"GLOBAL_MIN_ACCURACY: {GLOBAL_MIN_ACCURACY:.2f}%")
    print("="*60)
```

1.6 Main Optimization

1.6.1 Problem Def

[381]:
```
class MultiViewProblem(Problem):
    def __init__(self):
        super().__init__(
            n_var=12,
            n_obj=12,
            xl=np.zeros(12),
            xu=np.ones(12)
        )
```

```
    def _evaluate(self, X, out, *args, **kwargs):
        pop_size, _ = X.shape
        F = np.zeros((pop_size, 12))

        for j in range(12):
            ps = X[:, j]
            vals = np.zeros(pop_size)
            for k, p in enumerate(ps):
                # Use global min accuracy for consistency
                r = get_reward(p, GLOBAL_MIN_ACCURACY, MAX_MODEL_SIZES[j])
                weighted_r = r * i[j]
                vals[k] = -weighted_r  # minimize negative reward
            F[:, j] = vals

        out["F"] = F

class SingleObjectiveProblem(Problem):
    def __init__(self):
        super().__init__(
            n_var=12,
            n_obj=1,
            xl=np.zeros(12),
            xu=np.ones(12)
        )

    def _evaluate(self, X, out, *args, **kwargs):
        pop_size, _ = X.shape
        F = np.zeros((pop_size, 1))

        for k in range(pop_size):
            p_vec = X[k, :]
            total_reward = 0
            penalty = 0

            weighted_acc = 0
            for j, p in enumerate(p_vec):
                acc = get_accuracy(p)
                size = get_size(p)
                weighted_acc += acc * i[j]

                # Apply penalty for size violations
                if size > MAX_MODEL_SIZES[j]:
                    penalty += (size - MAX_MODEL_SIZES[j]) ** 2 * 100  # Increased penalty

                r = get_reward(p, GLOBAL_MIN_ACCURACY, MAX_MODEL_SIZES[j])
```

```
                total_reward += r * i[j]

            # Strong penalty if weighted accuracy below global min accuracy
            if weighted_acc < GLOBAL_MIN_ACCURACY:
                penalty += (GLOBAL_MIN_ACCURACY - weighted_acc) ** 2 * 10000  #␣
↪Much stronger penalty

            F[k, 0] = -(total_reward - penalty)

        out["F"] = F
```

1.6.2 Check if feasible

[382]:
```
def is_feasible_corrected(p_vec):
    accs = np.array([get_accuracy(p) for p in p_vec])
    sizes = np.array([get_size(p) for p in p_vec])
    weighted_acc = np.sum(accs * i)

    # Check global accuracy constraint
    if weighted_acc < GLOBAL_MIN_ACCURACY:
        return False, accs, sizes

    # Check size constraints
    if np.any(sizes > MAX_MODEL_SIZES):
        return False, accs, sizes

    return True, accs, sizes
```

1.6.3 Optimize with relaxed contraints

[383]:
```
def optimize_with_relaxed_constraints(min_acc, max_sizes):
    # sourcery skip: low-code-quality

    class RelaxedSingleObjectiveProblem(Problem):
        def __init__(self):
            super().__init__(
                n_var=12,
                n_obj=1,
                xl=np.zeros(12),
                xu=np.ones(12)
            )

        def _evaluate(self, X, out, *args, **kwargs):
            pop_size, _ = X.shape
            F = np.zeros((pop_size, 1))

            for k in range(pop_size):
```

```
            p_vec = X[k, :]
            total_reward = 0
            penalty = 0

            weighted_acc = 0
            for j, p in enumerate(p_vec):
                acc = get_accuracy(p)
                size = get_size(p)
                weighted_acc += acc * i[j]

                # Apply penalty for size violations
                if size > max_sizes[j]:
                    penalty += (size - max_sizes[j]) ** 2 * 100

                r = get_reward(p, min_acc, max_sizes[j])
                total_reward += r * i[j]

            # Penalty if weighted accuracy below relaxed min accuracy
            if weighted_acc < min_acc:
                penalty += (min_acc - weighted_acc) ** 2 * 5000

            F[k, 0] = -(total_reward - penalty)

        out["F"] = F

# Run optimization with relaxed constraints
problem = RelaxedSingleObjectiveProblem()
algorithm = GA(pop_size=200)

res = minimize(
    problem,
    algorithm,
    termination=('n_gen', 500),
    verbose=False
)

best_p_vec = res.X
accs = np.array([get_accuracy(p) for p in best_p_vec]) # type: ignore
sizes = np.array([get_size(p) for p in best_p_vec]) # type: ignore
weighted_acc = np.sum(accs * i)

# Check against relaxed constraints
acc_feasible = weighted_acc >= min_acc
size_feasible = np.all(sizes <= max_sizes)

print("\n RELAXED OPTIMIZATION RESULT:")
print("p values:         ", np.round(best_p_vec, 3)) # type: ignore
```

```
    print("view accuracies %:", np.round(accs, 2))
    print("weighted acc %:   ", np.round(weighted_acc, 2))
    print("model sizes:      ", np.round(sizes, 1))
    print("relaxed max sizes:", np.round(max_sizes, 1))
    print("original max sizes:", np.round(MAX_MODEL_SIZES, 1))

    if acc_feasible and size_feasible:
        print("FEASIBLE with relaxed constraints!")
        total_r = sum(get_reward(p, min_acc, max_sizes[j]) * i[j] for j, p in␣
↪enumerate(best_p_vec)) # type: ignore
        print("total reward:     ", np.round(total_r, 2))
        return best_p_vec, accs, sizes, weighted_acc, total_r
    else:
        print("Still infeasible even with relaxed constraints")

        # Show violations
        if not acc_feasible:
            print(f"Accuracy violation: {weighted_acc:.2f}% < {min_acc:.2f}%")

        if not size_feasible:
            violations = [(j, size, max_sizes[j]) for j, size in␣
↪enumerate(sizes) if size > max_sizes[j]]
            print(f"Size violations: {len(violations)}")
            for j, size, max_size in violations[:5]:  # Show first 5
                print(f"  View {j+1}: {size:.1f} > {max_size:.1f}")

        return best_p_vec, accs, sizes, weighted_acc, None
```

1.6.4 Relax Contraints

[384]:
```
def relax_constraints_progressively():
    """Progressively relax constraints to find feasible solutions"""
    print("\n" + "="*60)
    print("PROGRESSIVE CONSTRAINT RELAXATION")
    print("="*60)

    relaxation_scenarios = [
        {"acc_relax": 0, "size_relax": 1.0, "desc": "Original constraints"},
        {"acc_relax": 2, "size_relax": 1.05, "desc": "Relax accuracy by 2%,␣
↪size by 5%"},
        {"acc_relax": 5, "size_relax": 1.1, "desc": "Relax accuracy by 5%, size␣
↪by 10%"},
        {"acc_relax": 8, "size_relax": 1.15, "desc": "Relax accuracy by 8%,␣
↪size by 15%"},
        {"acc_relax": 10, "size_relax": 1.2, "desc": "Relax accuracy by 10%,␣
↪size by 20%"},
    ]
```

```
    for scenario in relaxation_scenarios:
        print(f"\n--- {scenario['desc']} ---")

        # Temporarily adjust constraints
        relaxed_min_acc = GLOBAL_MIN_ACCURACY - scenario['acc_relax']
        relaxed_max_sizes = [size * scenario['size_relax'] for size in␣
↪MAX_MODEL_SIZES]

        print(f"Target accuracy: {relaxed_min_acc:.1f}%")
        print(f"Max sizes: {np.round(relaxed_max_sizes, 1)}")

        # Test feasibility with relaxed constraints
        feasible_count = 0
        best_solution = None
        best_weighted_acc = 0

        for _ in range(500):
            p_vec = np.random.beta(2, 8, 12)
            accs = np.array([get_accuracy(p) for p in p_vec])
            sizes = np.array([get_size(p) for p in p_vec])
            weighted_acc = np.sum(accs * i)

            # Check relaxed constraints
            acc_feasible = weighted_acc >= relaxed_min_acc
            size_feasible = np.all(sizes <= relaxed_max_sizes)

            if acc_feasible and size_feasible:
                feasible_count += 1
                if weighted_acc > best_weighted_acc:
                    best_weighted_acc = weighted_acc
                    best_solution = (p_vec, accs, sizes, weighted_acc)

        print(f"Feasible solutions found: {feasible_count}/500 ({feasible_count/
↪5:.1f}%)")

        if feasible_count > 0:
            print(f"Best weighted accuracy found: {best_weighted_acc:.2f}%")

            # If we found feasible solutions, run optimization with relaxed␣
↪constraints
            if feasible_count >= 10:  # If reasonably feasible
                print("Running optimization with relaxed constraints...")
                return optimize_with_relaxed_constraints(relaxed_min_acc,␣
↪relaxed_max_sizes)
        else:
            print("No feasible solutions found with these constraints.")
```

```
    print("\nEven with maximum relaxation, no feasible solutions found.")
    print("Constraints may be fundamentally incompatible.")
    return None
```

1.6.5 Multi Objective Pruning

[385]:
```
def optimize_pruning():  # sourcery skip: low-code-quality
    print("Running multi-objective optimization (NSGA-II)...")
    problem = MultiViewProblem()
    algorithm = NSGA2(pop_size=500)  # Increased population size

    res = minimize(
        problem,
        algorithm,
        termination=('n_gen', 1000),  # Increased generations
        verbose=False
    )

    pareto_ps = res.X

    feasible = []
    for p_vec in pareto_ps: # type: ignore
        valid, accs, sizes = is_feasible_corrected(p_vec)
        if valid:
            feasible.append((p_vec, accs, sizes))

    if feasible:
        best = None
        best_reward = -np.inf
        for p_vec, accs, sizes in feasible:
            total_r = sum(get_reward(p, GLOBAL_MIN_ACCURACY,␣
↪MAX_MODEL_SIZES[j]) * i[j]
                          for j, p in enumerate(p_vec))
            if total_r > best_reward:
                best_reward = total_r
                best = (p_vec, accs, sizes, total_r)

        p_vec, accs, sizes, total_r = best
        weighted_acc = np.sum(accs * i)

        print("\n  FEASIBLE solution found with NSGA-II:")
        print("i values:        ", np.round(i, 3))
        print("p values:         ", np.round(p_vec, 3))
        print("view accuracies %:", np.round(accs, 2))
        print("weighted acc %:   ", np.round(weighted_acc, 2))
        print("model sizes:      ", np.round(sizes, 1))
```

```
        print("max sizes:        ", np.round(MAX_MODEL_SIZES, 1))
        print("total reward:     ", np.round(total_r, 2))

        return p_vec, accs, sizes, weighted_acc, total_r

    else:
        print("\nNo feasible solution found with NSGA-II. Trying␣
↪single-objective optimization...")
        single_problem = SingleObjectiveProblem()
        single_algorithm = GA(pop_size=200)  # Increased population size

        single_res = minimize(
            single_problem,
            single_algorithm,
            termination=('n_gen', 1000),  # Increased generations
            verbose=False
        )

        best_p_vec = single_res.X
        valid, accs, sizes = is_feasible_corrected(best_p_vec)

        accs = np.array([get_accuracy(p) for p in best_p_vec])
        sizes = np.array([get_size(p) for p in best_p_vec])
        weighted_acc = np.sum(accs * i)

        if valid:
            total_r = sum(get_reward(p, GLOBAL_MIN_ACCURACY,␣
↪MAX_MODEL_SIZES[j]) * i[j]
                          for j, p in enumerate(best_p_vec))

            print("\n  FEASIBLE solution found with single-objective GA:")
            print("p values:         ", np.round(best_p_vec, 3))
            print("view accuracies %:", np.round(accs, 2))
            print("weighted acc %:   ", np.round(weighted_acc, 2))
            print("model sizes:      ", np.round(sizes, 1))
            print("max sizes:        ", np.round(MAX_MODEL_SIZES, 1))
            print("total reward:     ", np.round(total_r, 2))
            return best_p_vec, accs, sizes, weighted_acc, total_r
        else:
            print("\n  Best compromise solution (may violate some constraints):
↪")
            print("p values:         ", np.round(best_p_vec, 3))
            print("view accuracies %:", np.round(accs, 2))
            print("weighted acc %:   ", np.round(weighted_acc, 2))
            print("model sizes:      ", np.round(sizes, 1))
            print("max sizes:        ", np.round(MAX_MODEL_SIZES, 1))
```

```
            # Check constraint violations
            if weighted_acc < GLOBAL_MIN_ACCURACY:
                print(f"\nGlobal accuracy violation: {weighted_acc:.2f}% <␣
↪{GLOBAL_MIN_ACCURACY}%")

            if size_violations := [
                (j, size, MAX_MODEL_SIZES[j])
                for j, size in enumerate(sizes)
                if size > MAX_MODEL_SIZES[j]
            ]:
                print("\nSize violations:")
                for j, size, max_size in size_violations:
                    print(f"  View {j+1}: {size:.1f} > {max_size}")

            print("\n" + "="*60)
            print("STARTING PROGRESSIVE CONSTRAINT RELAXATION...")
            print("="*60)

            # Try progressive relaxation
            relaxation_result = relax_constraints_progressively()
            if relaxation_result is not None:
                return relaxation_result

            return best_p_vec, accs, sizes, weighted_acc, None
```

1.6.6 Find a Feasible Starting Point

[386]:
```
def find_feasible_starting_point():
    """Find a feasible starting point by working backwards from constraints"""
    print("Searching for feasible starting point...")

    # Start with p values that give high accuracy but might violate size␣
↪constraints
    best_p = None
    best_weighted_acc = 0

    for _ in range(1000):
        # Generate random p values, biased towards lower pruning (higher␣
↪accuracy)
        p_vec = np.random.beta(2, 8, 12)  # Biased towards lower values

        accs = np.array([get_accuracy(p) for p in p_vec])
        sizes = np.array([get_size(p) for p in p_vec])
        weighted_acc = np.sum(accs * i)

        # Check if this meets the global accuracy constraint
        if weighted_acc >= GLOBAL_MIN_ACCURACY:
```

```
            # Check size constraints
            if np.all(sizes <= MAX_MODEL_SIZES):
                print(f"Found feasible starting point! Weighted accuracy:␣
↪{weighted_acc:.2f}%")
                return p_vec, accs, sizes, weighted_acc
            else:
                # Track best accuracy even if size constraints are violated
                if weighted_acc > best_weighted_acc:
                    best_weighted_acc = weighted_acc
                    best_p = p_vec

    if best_p is not None:
        accs = np.array([get_accuracy(p) for p in best_p])
        sizes = np.array([get_size(p) for p in best_p])
        print(f"Best found: Weighted accuracy: {best_weighted_acc:.2f}% (meets␣
↪global min)")
        return best_p, accs, sizes, best_weighted_acc
    else:
        print("No feasible starting point found - constraints may be too tight")
        return None, None, None, None
```

1.6.7 Redistribute Accuracy Loss Between Views

[387]:
```
def redistribute_accuracy_loss(p_vec, violating_views, target_sizes, i,␣
↪GLOBAL_MIN_ACCURACY):
    # sourcery skip: low-code-quality
    new_p_vec = p_vec.copy()

    # Calculate current weighted accuracy
    current_accs = np.array([get_accuracy(p) for p in p_vec])
    _ = np.sum(current_accs * i)

    # Calculate required pruning for violating views to meet size constraints
    total_accuracy_loss = 0

    for view_idx in violating_views:
        target_size = target_sizes[view_idx]

        # Find pruning amount that gives the target size
        # Use binary search to find p that gives size <= target_size
        p_low, p_high = 0.0, 1.0
        best_p = p_vec[view_idx]

        for _ in range(50):  # Binary search iterations
            p_mid = (p_low + p_high) / 2
            size_mid = get_size(p_mid)
```

```
            if size_mid <= target_size:
                best_p = p_mid
                p_high = p_mid
            else:
                p_low = p_mid

            if abs(p_high - p_low) < 1e-6:
                break

        # Calculate accuracy loss for this view
        old_acc = get_accuracy(p_vec[view_idx])
        new_acc = get_accuracy(best_p)
        acc_loss = old_acc - new_acc

        # Weight the accuracy loss by importance
        weighted_acc_loss = acc_loss * i[view_idx]
        total_accuracy_loss += weighted_acc_loss

        # Update pruning for this view
        new_p_vec[view_idx] = best_p

        print(f"View {view_idx+1}: Adjusted pruning from {p_vec[view_idx]:.4f} to {best_p:.4f}")
        print(f"  Size: {get_size(p_vec[view_idx]):.1f} → {get_size(best_p):.1f} (max: {target_size:.1f})")
        print(f"  Accuracy: {old_acc:.2f}% → {new_acc:.2f}% (loss: {acc_loss:.2f}%)")
        print(f"  Weighted loss: {weighted_acc_loss:.2f}%")

    print(f"\nTotal weighted accuracy loss: {total_accuracy_loss:.2f}%")

    # Redistribute the accuracy loss among non-violating views
    non_violating_views = [i for i in range(12) if i not in violating_views]

    if not non_violating_views:
        print("All views violate size constraints - cannot redistribute")
        return new_p_vec, False

    # Calculate how much we need to recover in weighted accuracy
    new_weighted_acc = np.sum([get_accuracy(new_p_vec[j]) * i[j] for j in range(12)])
    accuracy_deficit = GLOBAL_MIN_ACCURACY - new_weighted_acc

    print(f"New weighted accuracy after size adjustments: {new_weighted_acc:.2f}%")
    print(f"Required global minimum: {GLOBAL_MIN_ACCURACY:.2f}%")
    print(f"Accuracy deficit to recover: {accuracy_deficit:.2f}%")
```

```
    if accuracy_deficit <= 0:
        print("No redistribution needed - global constraint already satisfied")
        return new_p_vec, True

    # Try to recover the deficit by reducing pruning in non-violating views
    print(f"\nRedistributing {accuracy_deficit:.2f}% accuracy deficit among {len(non_violating_views)} views...")

    # Sort non-violating views by their ability to improve (lower current pruning = more room to improve)
    view_flexibility = [(j, new_p_vec[j]) for j in non_violating_views]
    view_flexibility.sort(key=lambda x: x[1])  # Sort by current pruning (ascending)

    remaining_deficit = accuracy_deficit

    for view_idx, current_p in view_flexibility:
        if remaining_deficit <= 0:
            break

        # Calculate how much this view can contribute
        # Try reducing pruning to improve accuracy
        min_p = 0.0
        max_improvement_p = current_p

        if max_improvement_p >= min_p:
            # Calculate potential accuracy improvement
            current_acc = get_accuracy(current_p)
            improved_acc = get_accuracy(max_improvement_p)
            potential_improvement = (improved_acc - current_acc) * i[view_idx]

            # Take what we need or what's available, whichever is smaller
            if potential_improvement > 0:
                # Calculate exact pruning needed for this view's contribution
                needed_acc_improvement = min(remaining_deficit / i[view_idx], improved_acc - current_acc)

                # Find pruning that gives this accuracy improvement
                target_acc = current_acc + needed_acc_improvement

                # Binary search for pruning that gives target accuracy
                p_low, p_high = 0, current_p
                best_p = current_p

                for _ in range(50):
                    p_mid = (p_low + p_high) / 2
```

```
                    acc_mid = get_accuracy(p_mid)

                    if acc_mid >= target_acc:
                        best_p = p_mid
                        p_high = p_mid
                    else:
                        p_low = p_mid

                    if abs(p_high - p_low) < 1e-6:
                        break

                # Check if this adjustment violates size constraint
                new_size = get_size(best_p)
                if new_size <= MAX_MODEL_SIZES[view_idx]:
                    actual_improvement = (get_accuracy(best_p) - current_acc) * i[view_idx]
                    new_p_vec[view_idx] = best_p
                    remaining_deficit -= actual_improvement

                    print(f"View {view_idx+1}: Reduced pruning from {current_p:.4f} to {best_p:.4f}")
                    print(f"  Accuracy: {current_acc:.2f}% → {get_accuracy(best_p):.2f}%")
                    print(f"  Weighted contribution: {actual_improvement:.2f}%")
                    print(f"  Size: {get_size(current_p):.1f} → {new_size:.1f} (max: {MAX_MODEL_SIZES[view_idx]:.1f})")
                else:
                    print(f"View {view_idx+1}: Cannot reduce pruning further without violating size constraint")

    # Check final result
    final_weighted_acc = np.sum([get_accuracy(new_p_vec[j]) * i[j] for j in range(12)])
    final_success = final_weighted_acc >= GLOBAL_MIN_ACCURACY

    print(f"\n{'='*50}")
    print("REDISTRIBUTION RESULT:")
    print(f"Final weighted accuracy: {final_weighted_acc:.2f}%")
    print(f"Global minimum required: {GLOBAL_MIN_ACCURACY:.2f}%")
    print(f"Success: {"Y" if final_success else 'N'}")

    if not final_success:
        print(f"Remaining deficit: {GLOBAL_MIN_ACCURACY - final_weighted_acc:.2f}%")

    return new_p_vec, final_success
```

1.6.8 Handle Size Violations

[388]:
```
def handle_size_violations(p_vec, i, global_min_accuracy, MAX_MODEL_SIZES):
    print("\n" + "="*60)
    print("HANDLING SIZE CONSTRAINT VIOLATIONS")
    print("="*60)

    # Identify violating views
    current_sizes = np.array([get_size(p) for p in p_vec])
    violating_views = [i for i, size in enumerate(current_sizes) if size >␣
↪MAX_MODEL_SIZES[i]]

    if not violating_views:
        print("No size violations detected.")
        accs = np.array([get_accuracy(p) for p in p_vec])
        weighted_acc = np.sum(accs * i)
        return p_vec, True, {
            'weighted_accuracy': weighted_acc,
            'view_accuracies': accs,
            'view_sizes': current_sizes,
            'violations': []
        }

    print(f"Found {len(violating_views)} views violating size constraints:")
    for view_idx in violating_views:
        print(f"  View {view_idx+1}: {current_sizes[view_idx]:.1f} >␣
↪{MAX_MODEL_SIZES[view_idx]:.1f}")

    # Redistribute accuracy loss
    adjusted_p_vec, success = redistribute_accuracy_loss(
        p_vec, violating_views, MAX_MODEL_SIZES, i, global_min_accuracy
    )

    # Calculate final metrics
    final_accs = np.array([get_accuracy(p) for p in adjusted_p_vec])
    final_sizes = np.array([get_size(p) for p in adjusted_p_vec])
    final_weighted_acc = np.sum(final_accs * i)

    remaining_violations = [
        {
            'view': j + 1,
            'size': final_sizes[j],
            'max_size': MAX_MODEL_SIZES[j],
            'violation': final_sizes[j] - MAX_MODEL_SIZES[j],
        }
        for j in range(12)
        if final_sizes[j] > MAX_MODEL_SIZES[j]
```

```
    ]
    final_metrics = {
        'weighted_accuracy': final_weighted_acc,
        'view_accuracies': final_accs,
        'view_sizes': final_sizes,
        'violations': remaining_violations,
        'global_constraint_met': final_weighted_acc >= global_min_accuracy
    }

    return adjusted_p_vec, success and not remaining_violations, final_metrics
```

1.6.9 Check if redistribution was successful

[389]:
```
def successful_redist(adjusted_p_vec, i, metrics, total_r):
    # Calculate new total reward
    new_total_r = sum(get_reward(p, GLOBAL_MIN_ACCURACY, MAX_MODEL_SIZES[j]) *␣
 ↪i[j]
                    for j, p in enumerate(adjusted_p_vec))

    print("\nSUCCESSFUL REDISTRIBUTION:")
    print("Adjusted p values:    ", np.round(adjusted_p_vec, 3))
    print("View accuracies %:    ", np.round(metrics['view_accuracies'], 4))
    print("Weighted accuracy %:  ", np.round(metrics['weighted_accuracy'], 4))
    print("Model sizes:          ", np.round(metrics['view_sizes'], 2))
    print("Max sizes:            ", np.round(MAX_MODEL_SIZES, 2))
    print("New total reward:     ", np.round(new_total_r, 2))
    print("Original total reward:", np.round(total_r, 2))

    return adjusted_p_vec, metrics['view_accuracies'], metrics['view_sizes'],␣
 ↪metrics['weighted_accuracy'], new_total_r
```

1.6.10 Optimize with Redist

[390]:
```
def optimize_pruning_with_redistribution():
    print("Running enhanced optimization with redistribution...")

    # First try standard optimization
    result = optimize_pruning()

    if result is None:
        print("Standard optimization failed. Trying redistribution approach...")
        return None

    p_vec, accs, sizes, weighted_acc, total_r = result

    # Fix: Use proper variable names to avoid conflicts
```

```
    size_violations = [view_idx for view_idx, size in enumerate(sizes) if size␣
↪> MAX_MODEL_SIZES[view_idx]] # type: ignore

    if not size_violations:
        print("No size violations - solution is already feasible!")
        return result

    print(f"\nDetected {len(size_violations)} size violations. Applying␣
↪redistribution...")

    # Debug: Print the actual violations
    print("Size violations detected:")
    for view_idx in size_violations:
        print(f"  View {view_idx+1}: {sizes[view_idx]:.1f} >␣
↪{MAX_MODEL_SIZES[view_idx]:.1f}") # type: ignore

    # Apply redistribution
    adjusted_p_vec, success, metrics = handle_size_violations(
        p_vec, i, GLOBAL_MIN_ACCURACY, MAX_MODEL_SIZES # type: ignore
    )

    if success:
        return successful_redist(adjusted_p_vec, i, metrics, total_r)

    print("Redistribution failed - returning original solution with violations")
    return result
```

1.6.11 Params

[409]:
```
init()
```

```
============================================================
MAX_MODEL_SIZES: [396.94 446.72 236.25 183.97 483.84 398.09 100.33 137.14 318.26
460.51
 468.65 294.01]
GLOBAL_MIN_ACCURACY: 64.59%
============================================================
```

1.6.12 Main Loop

[410]:
```
print("Testing redistribution approach...")
print("="*70)
print("Global minimum accuracy:", GLOBAL_MIN_ACCURACY)
print("Max model sizes:", np.round(MAX_MODEL_SIZES, 2))
print("="*70)
```

```python
test_result = find_feasible_starting_point()
if test_result[0] is not None:
    print("Running optimization with redistribution...")
    final_result = optimize_pruning_with_redistribution()

    if final_result is not None:
        print("\nFINAL OPTIMIZED SOLUTION WITH REDISTRIBUTION COMPLETE")
        print("Adjusted p values:        ", np.round(final_result[0], 3))
        print("View accuracies %:        ", np.round(final_result[1], 2))
        print("Weighted accuracy %:      ", np.round(final_result[3], 2))
        print("Required global accuracy: ", GLOBAL_MIN_ACCURACY)
        print("Model sizes:              ", np.round(final_result[2], 1))
        print("Max sizes:                ", np.round(MAX_MODEL_SIZES, 1))
        print("Total reward:             ", np.round(final_result[4], 2)) if␣
↪final_result[4] is not None else print("No total reward calculated.")

        print(f"{'View':<6} {'Size':<10} {'Max Size':<12} {'Accuracy (%)':<15}␣
↪{'Importance':<10}, {'Prune':<10}")
        print("-" * 70)

        views_violated = []

        for view in range(12):
            size = final_result[2][view]
            max_size = MAX_MODEL_SIZES[view]
            acc = final_result[1][view]
            importance = i[view]
            prune = final_result[0][view]
            if np.round(size, 1) > np.round(max_size, 1):
                views_violated.append(view + 1)
            print(f"{view+1:<6}, {size:<10.1f}, {max_size:<12.1f}, {acc:<15.
↪2f}, {importance*100:<12.2f}, {prune:<10.3f}")
        print("\n" + "="*70)
        print("Final Weighted Accuracy: ", np.round(final_result[3], 1),␣
↪"Required:", np.round(GLOBAL_MIN_ACCURACY, 1))
        print("Views violating size constraints:", views_violated if␣
↪views_violated else "None")
        if np.round(final_result[3], 1) >= np.round(GLOBAL_MIN_ACCURACY, 1):
            print("Solution meets global accuracy requirement!")
        else:
            print("Solution does NOT meet global accuracy requirement.")

else:
    print("Constraints appear too tight even for redistribution approach.")
```

```
Testing redistribution approach…
======================================================================
```

```
Global minimum accuracy: 64.58665441584051
Max model sizes: [396.94 446.72 236.25 183.97 483.84 398.09 100.33 137.14 318.26
460.51
 468.65 294.01]
======================================================================
Searching for feasible starting point…
Best found: Weighted accuracy: 84.30% (meets global min)
Running optimization with redistribution…
Running enhanced optimization with redistribution…
Running multi-objective optimization (NSGA-II)…

No feasible solution found with NSGA-II. Trying single-objective optimization…

 Best compromise solution (may violate some constraints):
p values:          [0.494 0.501 0.503 0.572 0.507 0.502 0.844 0.707 0.492 0.5
0.502 0.499]
view accuracies %: [67.28 66.75 66.61 60.78 66.25 66.66 26.58 46.25 67.4  66.8
66.64 66.89]
weighted acc %:    64.59
model sizes:       [216.  212.9 212.2 184.  210.2 212.5 100.3 137.1 216.6 213.2
212.3 213.7]
max sizes:         [396.9 446.7 236.2 184.  483.8 398.1 100.3 137.1 318.3 460.5
468.7 294. ]

Global accuracy violation: 64.59% < 64.58665441584051%

============================================================
STARTING PROGRESSIVE CONSTRAINT RELAXATION…
============================================================

============================================================
PROGRESSIVE CONSTRAINT RELAXATION
============================================================

--- Original constraints ---
Target accuracy: 64.6%
Max sizes: [396.9 446.7 236.2 184.  483.8 398.1 100.3 137.1 318.3 460.5 468.7
294. ]
Feasible solutions found: 0/500 (0.0%)
No feasible solutions found with these constraints.

--- Relax accuracy by 2%, size by 5% ---
Target accuracy: 62.6%
Max sizes: [416.8 469.1 248.1 193.2 508.  418.  105.3 144.  334.2 483.5 492.1
308.7]
Feasible solutions found: 0/500 (0.0%)
No feasible solutions found with these constraints.
```

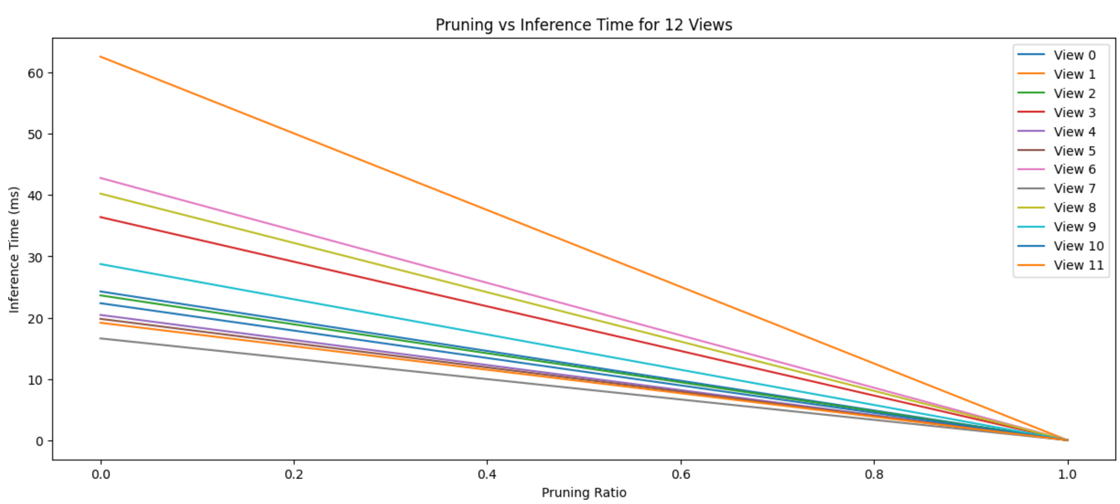
```
--- Relax accuracy by 5%, size by 10% ---
Target accuracy: 59.6%
Max sizes: [436.6 491.4 259.9 202.4 532.2 437.9 110.4 150.9 350.1 506.6 515.5
323.4]
Feasible solutions found: 0/500 (0.0%)
No feasible solutions found with these constraints.

--- Relax accuracy by 8%, size by 15% ---
Target accuracy: 56.6%
Max sizes: [456.5 513.7 271.7 211.6 556.4 457.8 115.4 157.7 366.  529.6 538.9
338.1]
Feasible solutions found: 0/500 (0.0%)
No feasible solutions found with these constraints.

--- Relax accuracy by 10%, size by 20% ---
Target accuracy: 54.6%
Max sizes: [476.3 536.1 283.5 220.8 580.6 477.7 120.4 164.6 381.9 552.6 562.4
352.8]
Feasible solutions found: 0/500 (0.0%)
No feasible solutions found with these constraints.

Even with maximum relaxation, no feasible solutions found.
Constraints may be fundamentally incompatible.
No size violations - solution is already feasible!

FINAL OPTIMIZED SOLUTION WITH REDISTRIBUTION COMPLETE
Adjusted p values:          [0.494 0.501 0.503 0.572 0.507 0.502 0.844 0.707
0.492 0.5   0.502 0.499]
View accuracies %:          [67.28 66.75 66.61 60.78 66.25 66.66 26.58 46.25 67.4
66.8  66.64 66.89]
Weighted accuracy %:        64.59
Required global accuracy:  64.58665441584051
Model sizes:                [216.  212.9 212.2 184.  210.2 212.5 100.3 137.1
216.6 213.2 212.3 213.7]
Max sizes:                  [396.9 446.7 236.2 184.  483.8 398.1 100.3 137.1
318.3 460.5 468.7 294. ]
No total reward calculated.
View   Size       Max Size     Accuracy (%)    Importance, Prune
----------------------------------------------------------------------
1     , 216.0     , 396.9       , 67.28          , 3.04         , 0.494
2     , 212.9     , 446.7       , 66.75          , 2.20         , 0.501
3     , 212.2     , 236.2       , 66.61          , 12.38        , 0.503
4     , 184.0     , 184.0       , 60.78          , 9.76         , 0.572
5     , 210.2     , 483.8       , 66.25          , 4.86         , 0.507
6     , 212.5     , 398.1       , 66.66          , 0.83         , 0.502
7     , 100.3     , 100.3       , 26.58          , 3.50         , 0.844
8     , 137.1     , 137.1       , 46.25          , 0.93         , 0.707
9     , 216.6     , 318.3       , 67.40          , 5.67         , 0.492
```

```
10     , 213.2     , 460.5      , 66.80        , 15.35       , 0.500
11     , 212.3     , 468.7      , 66.64        , 23.80       , 0.502
12     , 213.7     , 294.0      , 66.89        , 17.68       , 0.499

======================================================================
Final Weighted Accuracy:  64.6 Required: 64.6
Views violating size constraints: None
Solution meets global accuracy requirement!
```

1.7 Optimizing Computation Time

[368]:
```python
times = {}

plt.figure(figsize=(15, 6))
for v in range(12):
    k = np.random.randint(10, 100)
    t = [(get_time(p)*k) for p in np.linspace(0, 1, 100)]
    plt.plot(np.linspace(0, 1, 100), t, label=f'View {v}')
    times[v] = np.array(t)
    # print(f"View {v+1} inference time: {t[-50]:.2f} ms at p=0.5")

plt.xlabel('Pruning Ratio')
plt.ylabel('Inference Time (ms)')
plt.title('Pruning vs Inference Time for 12 Views')
plt.legend()
```

[368]: <matplotlib.legend.Legend at 0x169da9f90>



[369]:
```python
f_p = np.array([
    0.1, 0.5, 0.3, 0.4, 0.6, 0.2, 0.8, 0.9, 0.1, 0.7, 0.15, 0.32
```

```
])

bottleneck = 0.0
view_bottleneck = 0

for v in range(12):
    t = times[v]
    p = f_p[v]
    new_b = t[int(p*100)]

    if new_b > bottleneck:
        bottleneck = new_b
        view_bottleneck = v

bottleneck, view_bottleneck
```

[369]: (np.float64(36.167981818181815), 8)

[370]:
```
times_at_p = np.array([
    times[v][int(f_p[v]*100)] for v in range(12)
]
)
```

[412]:
```
times_at_p.sort()
times_at_p.mean()
```

[412]: np.float64(16.753036700336704)

[ ]:
```
!jupyter nbconvert --to pdf optimization.ipynb
```