Metaheuristic Optimization

5. Hill Climbing

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Outline

1. Hill Climbing
2. Problems: Local Optima

website

Metaheuristics

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- In Random Sampling, we actually don't do that, we do not *refine* solutions.
- What could be the easiest possible way to realize the metaheuristic idea?

A local search algorithm solves an optimization problem by iteratively moving from *one* candidate solution to a neighboring candidate solution until a termination criterion is met. [1–4]

"*neighboring*" here means: can be reached by applying a search operation once.

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Input: f: the objective function subject to minization
Input: [implicit] shouldTerminate: the termination criterion
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Output: p_{best}: the best individual ever discovered

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4. go back to 2, until termination criterion is met

- Let us implement and test a hill climber

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  4. Implement suitable termination criterion
  5. Implement objective functions f

Implementing HC

Listing: The Hill Climbing Algorithm

```java
public class HC<G, X> extends OptimizationAlgorithm<G, X> {
  public Individual<G, X> solve(final IObjectiveFunction<X> f) {
    Individual<G, X> pstar, pnew;

    pstar = new Individual<>();
    pnew = new Individual<>();
    pstar.g = this.nullary.create(this.random);
    pstar.x = this.gpm.gpm(pstar.g);
    pstar.v = f.compute(pstar.x);

    while (!(this.termination.shouldTerminate())) {
      pnew.g = this.unary.mutate(pstar.g, this.random);
      pnew.x = this.gpm.gpm(pnew.g);
      pnew.v = f.compute(pnew.x);

      if (pnew.v <= pstar.v) {
        pstar.assign(pnew);
      }
    }
    return pstar;
  }
}
```

Applying Hill Climbing: $\mathbb{G} = \mathbb{X} = \mathbb{R}^n$

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Listing: A definition for a Subspace of $\mathbb{R}^n$

```
public class Rn {
  /** the maximum coordinate value */
  public final double max;

  /** the minimum coordinate value */
  public final double min;

  /** the dimension */
  public final int dim;
}
```

Search Space + Operators

Listing: A nullary search operation in $\mathbb{R}^n$

```
public final class RnNullaryUniform extends Rn implements
    INullarySearchOperation<double[]> {


  @Override
  public final double[] create(final Random r) {
    final double[] g = new double[this.dim];

    for (int i = g.length; (--i) >= 0;) {
      g[i] = (this.min + (r.nextDouble() * (this.max -
          this.min)));
    }

    return g;
  }
}
```

Listing: A unary search operation in $\mathbb{R}^n$

```
public final class RnUnaryNormal extends Rn implements
    IUnarySearchOperation<double[]> {


  @Override
  public final double[] mutate(final double[] genotype, final Random r) {
    double d;

    final double[] g = genotype.clone();
    final int i = r.nextInt(g.length);

    do {
      d = (g[i] + (r.nextGaussian() * (this.max - this.min) * 0.01d));
    } while ((d < this.min) || (d > this.max));

    g[i] = d;
    return g;
  }
}
```

Listing: An alternative unary search operation in $\mathbb{R}^n$

```
public class RnUnaryNormal2 extends Rn implements IUnarySearchOperation<double[]> {

  @Override
  public double[] mutate(final double[] genotype, final Random r) {
    double d;

    final double[] g = genotype.clone();

    for (int i = g.length; (--i) >= 0;) {
      do {
        d = (g[i] + (r.nextGaussian() * (this.max - this.min) * 0.01d));
      } while ((d < this.min) || (d > this.max));
      g[i] = d;
    }

    return g;
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}
```

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1. $f(x) = \sum_{i=0}^{n-1} x_i^2$ Sphere Function [5–10]
2. $f(x) = \sum_{i=0}^{n-1} \left(\sum_{j=0}^{i} x_j \right)^2$ Schwefel's Problem 1.2 [5, 9]
3. $f(x) = \max\{|x_i| \; \forall i \in 0..(n-1)\}$ Schwefel's Problem 2.21 [5, 9]
4. $f(x) = -\sum_{i=0}^{n-1} \left(x_i \sin \sqrt{|x_i|} \right)$ Schwefel's Problem 2.26 [5, 9]

Listing: The Sphere Function $f(x) = \sum_{i=1}^{n} x_i^2$

```
/** the sphere function */
public class Sphere extends Rn implements IObjectiveFunction<double[]> {
  @Override
  public final double compute(final double[] x) {
    double s = 0d;

    for (int i = this.dim; (--i) >= 0;) {
      s += (x[i] * x[i]);
    }

    return s;
  }
}
```

Listing: Schwefel's Function 2.21 $f(x) = \max\{|x_i|\ \forall i \in 0..(n-1)\}$

```
/** Schwefel problem 2.21 */
public class Schwefel_2_21 extends Rn implements IObjectiveFunction<double[]> {
  @Override
  public final double compute(final double[] x) {
    double m = 0d;

    for (int i = this.dim; (--i) >= 0;) {
      final double d = Math.abs(x[i]);
      if (d > m) {
        m = d;
      }
    }

    return m;
  }
}
```

Applying Hill Climbing: $\mathbb{G} = \mathbb{X} = \mathbb{R}^n$

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- We have implemented some objective functions...
- Now we can test our algorithm!

Running

Listing: A simple test program for HC on a 5d Sphere function

```
/** a simple test class applying the hill climber to a function */
public class HCOnSphere {
  public static void main(final String[] args) {
    final HC<double[], double[]> algorithm;
    final Rn searchSpace;
    Individual<double[], double[]> result;

    algorithm = new HC<>();
    searchSpace = new Rn(-10, 10, 5);

    algorithm.nullary = new RnNullaryUniform(searchSpace);
    algorithm.unary = new RnUnaryNormal(searchSpace);

    for (int i = 1; i < 100; i++) {
      algorithm.termination = new MaxSteps(1000000);
      result = algorithm.solve(new Sphere(searchSpace));

      System.out.println("run␣" + i + "␣has␣result␣quality␣" + result.v);
    }
  }
}
```

image source: [11]

Robocode [11]

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- Programming game in Java

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- Program the "AI" driving a small battle robot

Applying Hill Climbing: Robocode!

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- Goal: Our robot should survive

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Robocode [11]:

- Programming game in Java
- Program the "AI" driving a small battle robot
- Goal: Our robot should survive...and kill many others!
- Let us take a look at that game...

Applying ill Climbing: Robocode!

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- Let us look at the code of an example robot: `sample.Tracker`

Applying ill Climbing: Robocode!

Tracker.java 10.10.2012

```
  /**
   * run:  Tracker's main run function
   */
  public void run() {
    // Set colors
    setBodyColor(new Color(128, 128, 50));
    setGunColor(new Color(50, 50, 20));
    setRadarColor(new Color(200, 200, 70));
    setScanColor(Color.white);
    setBulletColor(Color.blue);

    // Prepare gun
    trackName = null; // Initialize to not tracking anyone
    setAdjustGunForRobotTurn(true); // Keep the gun still when we turn
    gunTurnAmt = 10; // Initialize gunTurn to 10

    // Loop forever
    while (true) {
      // turn the Gun (looks for enemy)
      turnGunRight(gunTurnAmt);
      // Keep track of how long we've been looking
      count++;
      // If we've haven't seen our target for 2 turns, look left
      if (count > 2) {
        gunTurnAmt = -10;
      }
      // If we still haven't seen our target for 5 turns, look right
      if (count > 5) {
        gunTurnAmt = 10;
      }
      // If we *still* haven't seen our target after 10 turns, find another
      target
      if (count > 11) {
        trackName = null;
      }
```

Applying ill Climbing: Robocode!

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- It has lots of numerical constants in it...

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Example Robot: Tracker.java

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- Idea: Turn them into parameters that the hill climber can configure

Applying ill Climbing: Robocode!

OptiBot.java 11.10.2012

```
    while (true) {
      if (this.m_trackName != null) {
        if (this.m_rand.nextDouble() < BEHAVIOR[RANDOM_FIRE]) {
          this.setFire(map(BEHAVIOR[RANDOM_FIRE_POWER], 3d));
        }
      }

      // turn the Gun (looks for enemy)
      this.setTurnGunRight(this.m_gunTurnAmt);
      // Keep track of how long we've been looking
      this.m_count += map(BEHAVIOR[COUNT_ADDER], 1d);
      // If we've haven't seen our target for 2 turns, look left
      if (this.m_count > map(BEHAVIOR[COUNT_LIMIT], 2d)) {
        this.m_gunTurnAmt = (map(BEHAVIOR[GUN_TURN_AMOUNT_OVER_LIMIT],
        -10d));
      }
      // If we still haven't seen our target for 5 turns, look right
      if (this.m_count > (map(BEHAVIOR[COUNT_LIMIT_2], 5d))) {
        this.m_gunTurnAmt = map(BEHAVIOR[INIT_GUN_TURN_AMOUNT], 10d);
      }
      // If we *still* haven't seen our target after 10 turns, find another
      // target
      if (this.m_count > map(BEHAVIOR[COUNT_LIMIT_RESET_TRACK], 10d)) {
        this.m_trackName = null;
      }

      if (BEHAVIOR[RANDOM_01] > this.m_rand.nextDouble()) {
        if (this.getOthers() > 1) {
          this.m_trackName = null;
        }
      }

      this.execute();
    }
```

- Goal: Create a powerful robot via optimization!
- Let us look at the code of an example robot: `sample.Tracker`
- It has lots of numerical constants in it...
- ...who knows whether these values are good?
- Idea: Turn them into parameters that the hill climber can configure...and maybe add one or two actions
- Find the best values for the parameters of that new AI `optibot.OptiBot`!

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Applying ill Climbing: Robocode!

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- But how to pass the parameter values to our `OptiBot`?
- Let `OptiBot` load a configuration file when it starts!
- Candidate solutions $x =$ string with text representation of the `double` values of the parameters

Running

Listing: A Genotype-Phenotype Mapping translating double[] to String

```java
public class RobocodeGPM implements IGPM<double[], String> {
  /** the internal string builder */
  private final StringBuilder m_sb;

  /** the robocode gpm */
  public RobocodeGPM() {
    super();
    this.m_sb = new StringBuilder();
  }


  public String gpm(final double[] genotype) {
    boolean notfirst = false;
    this.m_sb.setLength(0);
    for (final double d : genotype) {
      if (notfirst) {
        this.m_sb.append('␣');
      } else {
        notfirst = true;
      }
      this.m_sb.append(d);
    }
    return this.m_sb.toString();
  }
}
```

Applying Hill Climbing: Robocode!

- What is the objective function $f : \mathbb{X} \mapsto \mathbb{R}$?

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- The battle score!...but how to compute it?

2. Take candidate solution (parameter string) and store it in configuration file
3. Run Robocode

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- Plug this into our existing hill climbing implementation!

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Listing: A simple test program for HC on the Robocode problem.

```
public class HCOnRobocode {
  public static void main(final String[] args) {
    final HC<double[], String> hc = new HC<>();
    final Rn rn = new Rn(-1.5d, 1.5d, 20);

    hc.gpm = new RobocodeGPM();
    hc.nullary = new RnNullaryUniform(rn);
    hc.unary = new RnUnaryNormal2(rn);
    hc.termination = new MaxSteps(5000);

    System.out.println(hc.solve(new RobocodeObjective()));
  }
}
```

Applying Hill Climbing: Robocode!

Applying Hill Climbing: Combinatorial Problems?

- How about hill climbers for combinatorial problems?
- Let us try, say, to solve a bin packing problem [12]

Listing: A nullary search operation Creating Permutations.

```
public class PermutationNullaryUniform implements INullarySearchOperation<int[]> {
  /** the length of the permutations */
  public final int n;
  @Override
  public int[] create(final Random r) {
    int i, j, t;

    final int[] g = new int[this.n];

    for (i = this.n; (--i) >= 0;) {
      g[i] = i;
    }

    for (i = this.n; (--i) >= 0;) {
      j = r.nextInt(this.n); // see[13–15]
      t = g[j];
      g[j] = g[i];
      g[i] = t;
    }
    return g;
  }
}
```

Listing: Modify a Permutation by Swapping Elements.

```java
public class PermutationUnarySwap implements IUnarySearchOperation<int[]> {
  @Override
  public int[] mutate(final int[] p, final Random r) {
    int i, j, t;

    final int[] g = p.clone();
    do {
      i = r.nextInt(g.length);
      do {
        j = r.nextInt(g.length);
      } while (j == i);
      t = g[i];
      g[i] = g[j];
      g[j] = t;
    } while (r.nextBoolean());

    return g; // return new permutation
  }
}
```

Objective Function

Listing: A simple objective function for the Bin Packing problem.

```
public class BinPackingObjective implements IObjectiveFunction<int[]> {

  /** the size of the bins */
  public final int binSize;

  /** the sizes of the objects */
  public final int[] objects;
  @Override
  public double compute(final int[] x) {
    int bins, remainingSize, curSize;

    bins = 0; // assume zero bins
    remainingSize = 0; // then there also is no space left in them

    for (final int i : x) { // iterate over all elements in the permutation
      curSize = this.objects[i]; // get size of current element
      if (curSize > remainingSize) { // if element does not fit in current bin
          anymore
        bins++; // open a new bin
        remainingSize = this.binSize; // remaining space = bin size
      }
      remainingSize -= curSize; // put object in bin: remaining size reduced
    }
    return bins; // return total number of bins required
  }
}
```

Running

Listing: A simple test program for HC on the Bin Packing problem.

```java
public class HCOnBinPacking {
  public static void main(final String[] args) {
    final HC<int[], int[]> hc = new HC<>();
    final BinPackingObjective f = BinPackingObjective.EXAMPLE_PROBLEM;

    hc.nullary = new PermutationNullaryUniform(f.objects.length);
    hc.unary = new PermutationUnarySwap();

    System.out.println("Hill␣Climbing");
    for (int i = 1; i < 100; i++) {
      hc.termination = new MaxSteps(100000);
      final Individual<int[], int[]> res = hc.solve(f);
      System.out.println(res.v);
    }
  }
}
```

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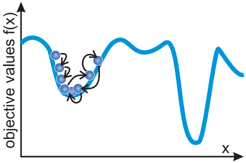

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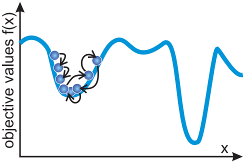

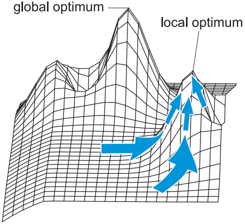

Hill Climbing: Problems

- Hill climbers will “move” through the search space towards better candidate solutions
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Definition (Premature Convergence)

An optimization process has *prematurely converged* to a local optimum if it is no longer able to explore other parts of the search space than the area currently being examined *and* there exists another region that contains a superior solution [16, 17].

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- Is it good?
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- Comparison with algorithms that do not use this information!

谢谢

Thank you

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Caspar David Friedrich, “Der Wanderer über dem Nebelmeer”, 1818
http://en.wikipedia.org/wiki/Wanderer_above_the_Sea_of_Fog

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