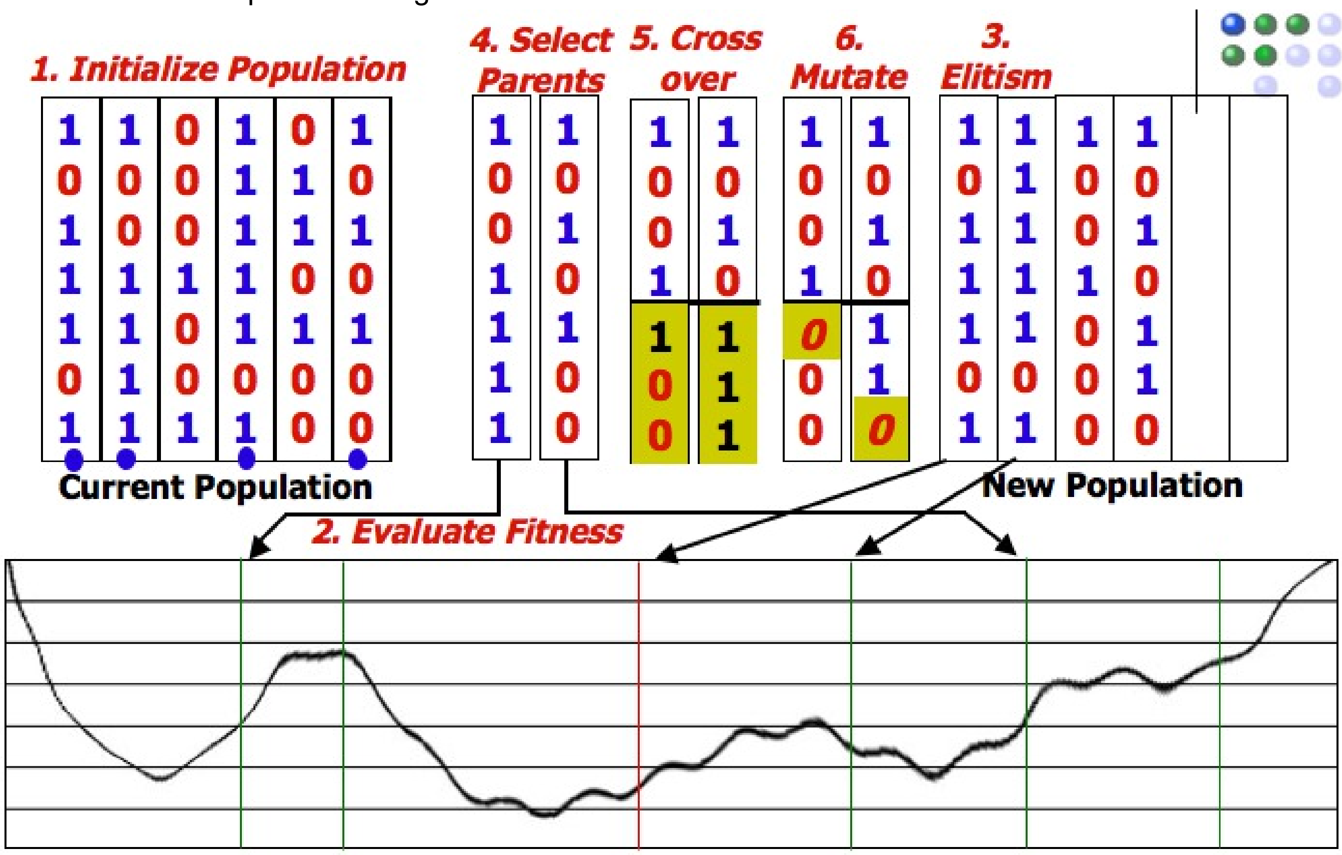
Genetic Algorithm Workshop

In this workshop we will code up a genetic algorithm for a simple mathematical optimization problem.

Genetic Algorithm is a

- Meta-heuristic
- Inspired by Natural Selection
- Traditionally works on binary data. Can be adopted for other data types as well.

You can find an example illustrating GA below



In [1]:

```
%matplotlib inline
# All the imports
from __future__ import print_function, division
from math import *
import random
import sys
import matplotlib.pyplot as plt

# TODO 1: Enter your unity ID here
__author__ = "achaluv"

class O:
    """
    Basic Class which
        - Helps dynamic updates
        - Pretty Prints
    """
    def __init__(self, **kwargs):
        self.has().update(**kwargs)
    def has(self):
        return self.__dict__
    def update(self, **kwargs):
        self.has().update(kwargs)
        return self
    def __repr__(self):
        show = [':%s %s' % (k, self.has()[k])
                for k in sorted(self.has().keys())
                if k[0] is not "_"]
        txt = ' '.join(show)
        if len(txt) > 60:
            show = map(lambda x: '\t' + x + '\n', show)
        return '{' + ' '.join(show) + '}'

print("Unity ID: ", __author__)
```

```
Unity ID:  achaluv
```

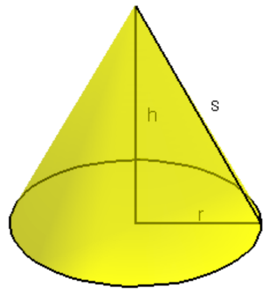
The optimization problem

The problem we are considering is a mathematical one

Right circular cone:

r = base radius
h = height
s = slant height

V = volume
B = base area
S = lateral surface area
T = total area



$$s = \sqrt{r^2 + h^2}$$

$$V = \frac{\pi}{3} r^2 h$$

$$B = \pi r^2$$
$$S = \pi r s$$
$$T = B + S = \pi r (r + s)$$

Decisions: *r* in [0, 10] cm; *h* in [0, 20] cm

Objectives: minimize *S*, *T*

Constraints: *V* > 200cm^3

In [13]:

```
# Few Utility functions
def say(*lst):
    """
    Print whithout going to new line
    """
    print(*lst, end="")
    sys.stdout.flush()

def random_value(low, high, decimals=2):
    """
    Generate a random number between low and high.
    decimals incidicate number of decimal places
    """
    return round(random.uniform(low, high),decimals)

def gt(a, b): return a > b

def lt(a, b): return a < b

def shuffle(lst):
    """
    Shuffle a list
    """
    random.shuffle(lst)
    return lst

class Decision(O):
    """
    Class indicating Decision of a problem
    """
    def __init__(self, name, low, high):
        """
        @param name: Name of the decision
        @param low: minimum value
        @param high: maximum value
        """
        O.__init__(self, name=name, low=low, high=high)

class Objective(O):
    """
    Class indicating Objective of a problem
    """
    def __init__(self, name, do_minimize=True):
        """
        @param name: Name of the objective
        @param do_minimize: Flag indicating if objective has to
be minimized or maximized
        """
        O.__init__(self, name=name, do_minimize=do_minimize)

class Point(O):
    """
    Represents a member of the population
```

```
    """
    def __init__(self, decisions):
        O.__init__(self)
        self.decisions = decisions
        self.objectives = None

    def __hash__(self):
        return hash(tuple(self.decisions))

    def __eq__(self, other):
        return self.decisions == other.decisions

    def clone(self):
        new = Point(self.decisions)
        new.objectives = self.objectives
        return new

class Problem(O):
    """
    Class representing the cone problem.
    """
    def __init__(self):
        O.__init__(self)
        # TODO 2: Code up decisions and objectives below for the
problem
        # using the auxilary classes provided above.
        self.decisions = [Decision('r',0,10), Decision('h',0,2
0)]
        self.objectives = [Objective('S'),Objective('T')]

    @staticmethod
    def evaluate(point):
        [r, h] = point.decisions
        l = sqrt(r**2 + h**2)
        S=pi*r*l
        T=pi *r*(r+l)
        point.objectives = [S,T]
        # TODO 3: Evaluate the objectives S and T for the point.
        return point.objectives

    @staticmethod
    def is_valid(point):
        [r, h] = point.decisions
        # TODO 4: Check if the point has valid decisions
        V = pi*(r**2)*h/3
        return V > 200

    def generate_one(self):
        # TODO 5: Generate a valid instance of Point.
        while True:
            point = Point([random_value(d.low,d.high) for d in s
elf.decisions])
            if Problem.is_valid(point):
```

```
                return point
cone = Problem()
point = cone.generate_one()
cone.evaluate(point)
print (point)
```

```
{       :decisions [5.79, 11.16]
        :objectives [228.6929364586194, 334.01200273682895]
}
```

Great. Now that the class and its basic methods is defined, we move on to code up the GA.

Population

First up is to create an initial population.

In [14]:
```
def populate(problem, size):
    population = []
    # TODO 6: Create a list of points of length 'size'
    #for _ in xrange(size):
    #    population.append(problem.generate_one())
    #return population

    return [problem.generate_one() for _ in xrange(size)]

#print(populate(cone,5))
```

Crossover

We perform a single point crossover between two points

In [22]:
```
def crossover(mom, dad):
    # TODO 7: Create a new point which contains decisions from
    # the first half of mom and second half of dad
    n=len(mom.decisions)
    return Point(mom.decisions[:n//2] + dad.decisions[n//2:])

#pop = populate(cone,5)
#crossover(pop[0],pop[1])
```

Mutation

Randomly change a decision such that

In [23]:
```
def mutate(problem, point, mutation_rate=0.01):
    # TODO 8: Iterate through all the decisions in the problem
    # and if the probability is less than mutation rate
    # change the decision(randomly set it between its max and mi
n).
    dec_r = problem.decisions[0]
    dec_h = problem.decisions[1]
    for decision in problem.decisions:
        if random.random() < mutation_rate:
            point.decisions =[random_value(dec_r.low,dec_r.hig
h),random_value(dec_h.low,dec_h.high)]
    return point
```

Fitness Evaluation

To evaluate fitness between points we use binary domination. Binary Domination is defined as follows:

- Consider two points one and two.
- For every decision **o** and **t** in **one** and **two**, **o** <= **t**
- Atleast one decision **o** and **t** in **one** and **two**, **o** == **t**

Note: Binary Domination is not the best method to evaluate fitness but due to its simplicity we choose to use it for this workshop.

In [24]:
```
def bdom(problem, one, two):
    """
    Return if one dominates two
    """
    objs_one = problem.evaluate(one)
    objs_two = problem.evaluate(two)
    dominates = False
    # TODO 9: Return True/False based on the definition
    # of bdom above.
    if objs_one[0] <= objs_two[0] and objs_one[1] <= objs_two
[1]:
        if objs_one[0] < objs_two[0] or objs_one[1] < objs_two
[1]:
            return True
    return False
```

Fitness and Elitism

In this workshop we will count the number of points of the population P dominated by a point A as the fitness of point A. This is a very naive measure of fitness since we are using binary domination.

Few prominent alternate methods are

1. Continuous Domination (http://www.tik.ee.ethz.ch/sop/publicationListFiles/zk2004a.pdf) - Section 3.1
2. Non-dominated Sort (http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=996017)
3. Non-dominated Sort + Niching (http://www.egr.msu.edu/~kdeb/papers/k2012009.pdf)

Elitism: Sort points with respect to the fitness and select the top points.

In [42]:
```
def fitness(problem, population, point):
    dominates = 0
    # TODO 10: Evaluate fitness of a point.
    # For this workshop define fitness of a point
    # as the number of points dominated by it.
    # For example point dominates 5 members of population,
    # then fitness of point is 5.
    return sum([bdom(problem, point, chromosome) for chromosome
in population])

def elitism(problem, population, retain_size):
    # TODO 11: Sort the population with respect to the fitness
    # of the points and return the top 'retain_size' points of t
he population
    # of the points and return the top 'retain_size' points of t
he population
    population = sorted(population, key= lambda x: fitness(probl
em, population, x), reverse = True)
    return population[:retain_size]
```

Putting it all together and making the GA

In [43]:
```
def ga(pop_size = 100, gens = 250):
    problem = Problem()
    population = populate(problem, pop_size)
    [problem.evaluate(point) for point in population]
    initial_population = [point.clone() for point in population]
    gen = 0
    while gen < gens:
        say(".")
        children = []
        for _ in range(pop_size):
            mom = random.choice(population)
            dad = random.choice(population)
            while (mom == dad):
                dad = random.choice(population)
            child = mutate(problem, crossover(mom, dad))
            if problem.is_valid(child) and child not in populati
on+children:
                children.append(child)
        population += children
        population = elitism(problem, population, pop_size)
        gen += 1
    print("")
    return initial_population, population
```

Visualize

Lets plot the initial population with respect to the final frontier.

In [46]:
```
def plot_pareto(initial, final):
    initial_objs = [point.objectives for point in initial]
    final_objs = [point.objectives for point in final]
    initial_x = [i[0] for i in initial_objs]
    initial_y = [i[1] for i in initial_objs]
    final_x = [i[0] for i in final_objs]
    final_y = [i[1] for i in final_objs]
    plt.scatter(initial_x, initial_y, color='b', marker='+', lab
el='initial')
    plt.scatter(final_x, final_y, color='r', marker='o', label
='final')
    plt.title("Scatter Plot between initial and final population
of GA")
    plt.ylabel("Total Surface Area(T)")
    plt.xlabel("Curved Surface Area(S)")
    plt.legend(loc=9, bbox_to_anchor=(0.5, -0.175), ncol=2)
    plt.show()
```

In [47]:
```
initial, final = ga()
plot_pareto(initial, final)
```

```
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```
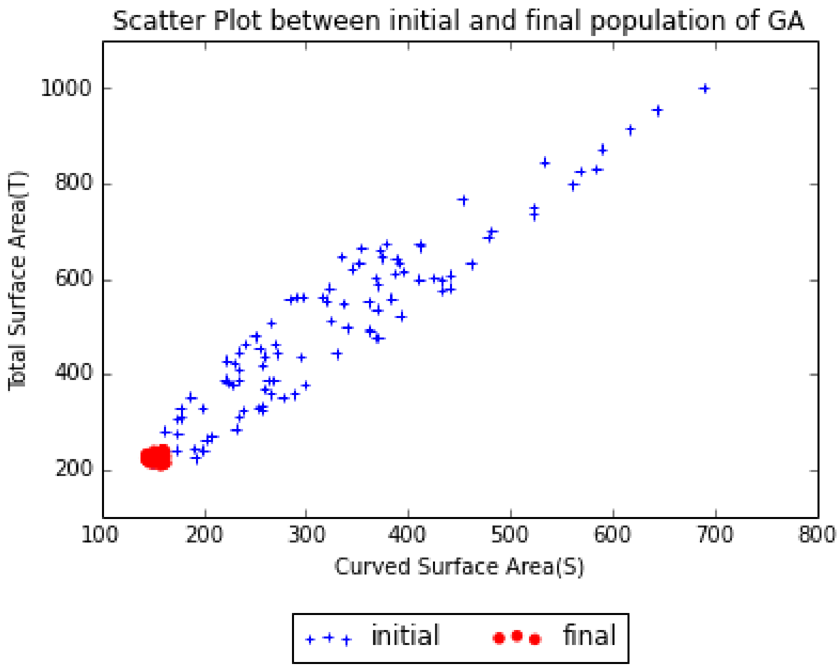
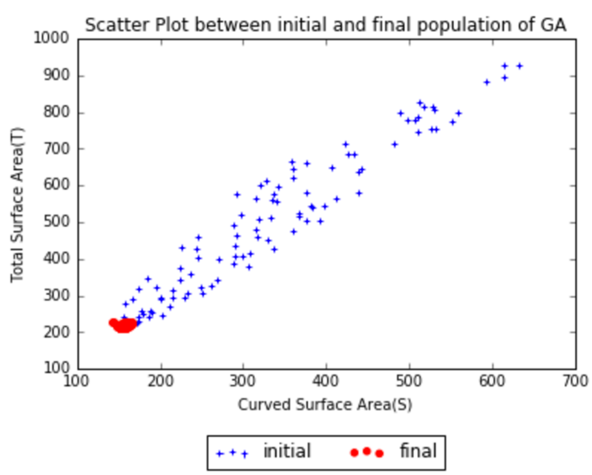



Here is a sample output



In [ ]: