Multiple Objectives –
The MO in MOGA and MOGP

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General

- Notebooks
  - Don’t get behind
  - If it isn’t documented, it didn’t happen
- Labs
  - Genetic Programming - Part II Due next week?

Objectives

- After this lecture students:
  - Recognize the power of multiple objective optimization in supplying a population of solutions not just a single objectives
  - Understand how Pareto dominance can be used to affect probability of mating
  - Understand classification terms true positive, false positive, true negative, false negative, sensitivity, specificity, accuracy
  - Use Multiple Objective concepts for selection of teams for project efforts

Rate Yourself

- Email Greg.Rohling@gtri.gatech.edu
  - Write your name
  - Rate your python skills 0 to 5
    - 0 = none - I still think it is a snake
    - 2 = some experience
    - 3 = multiple years, and multiple applications
    - 5 = experienced and know pandas and scikit learn
  - Rate your machine learning skills
    - 0 = none
    - 2 = read some articles, but have never used it
    - 3 = used multiple types of machine learnings on multiple applications
    - 5 = used multiple types of machine learnings on multiple applications and understand theory
- This will serve as attendance for today, and an exercise next week

What are you looking for in a date/mate?



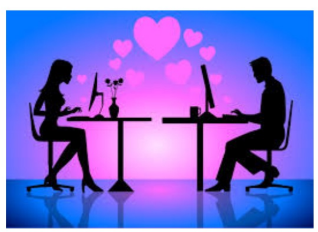
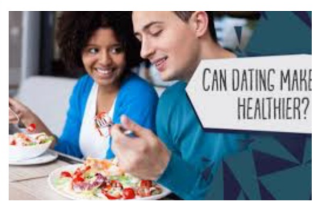


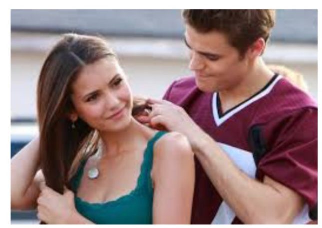



Chat Survey

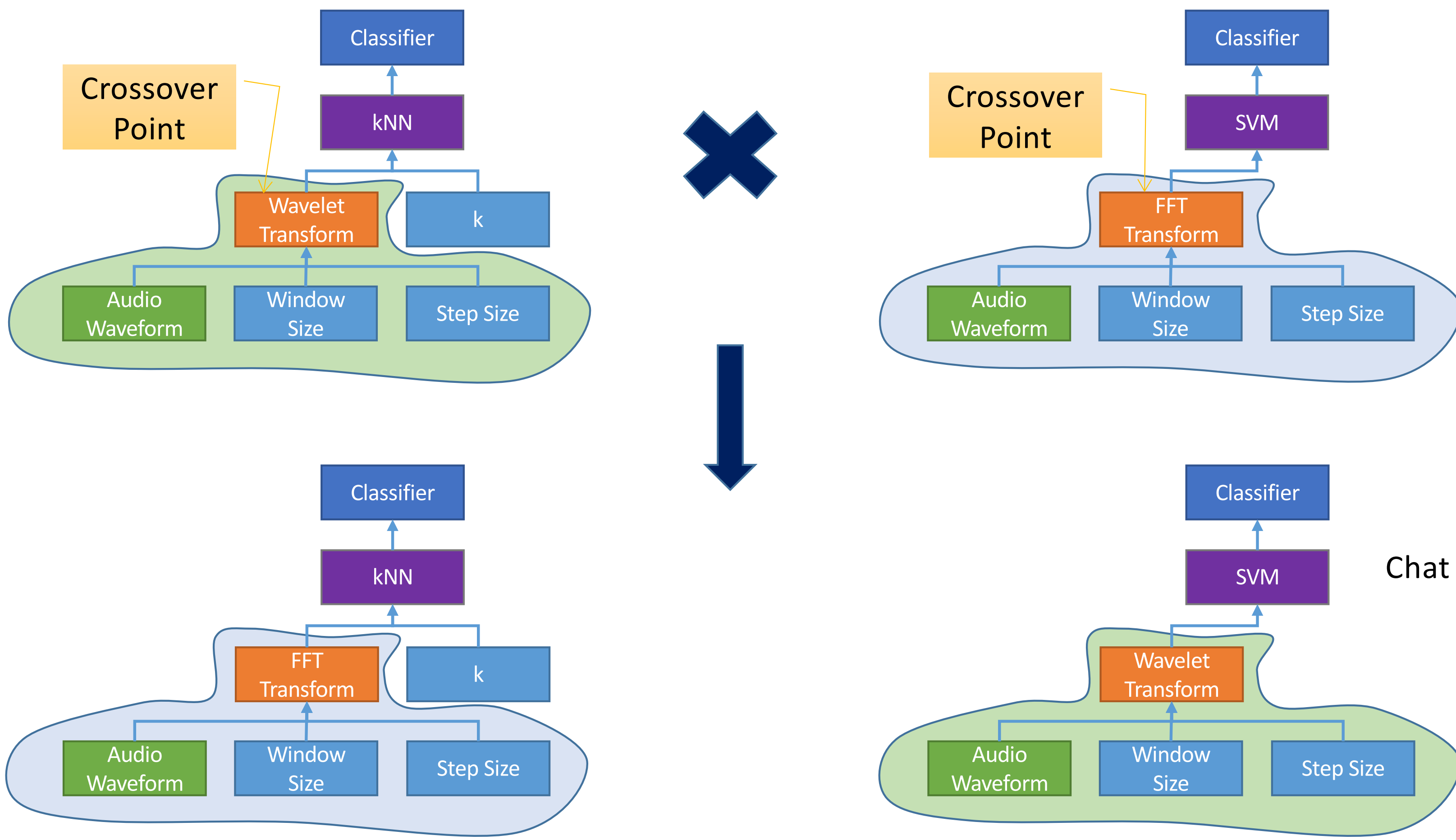




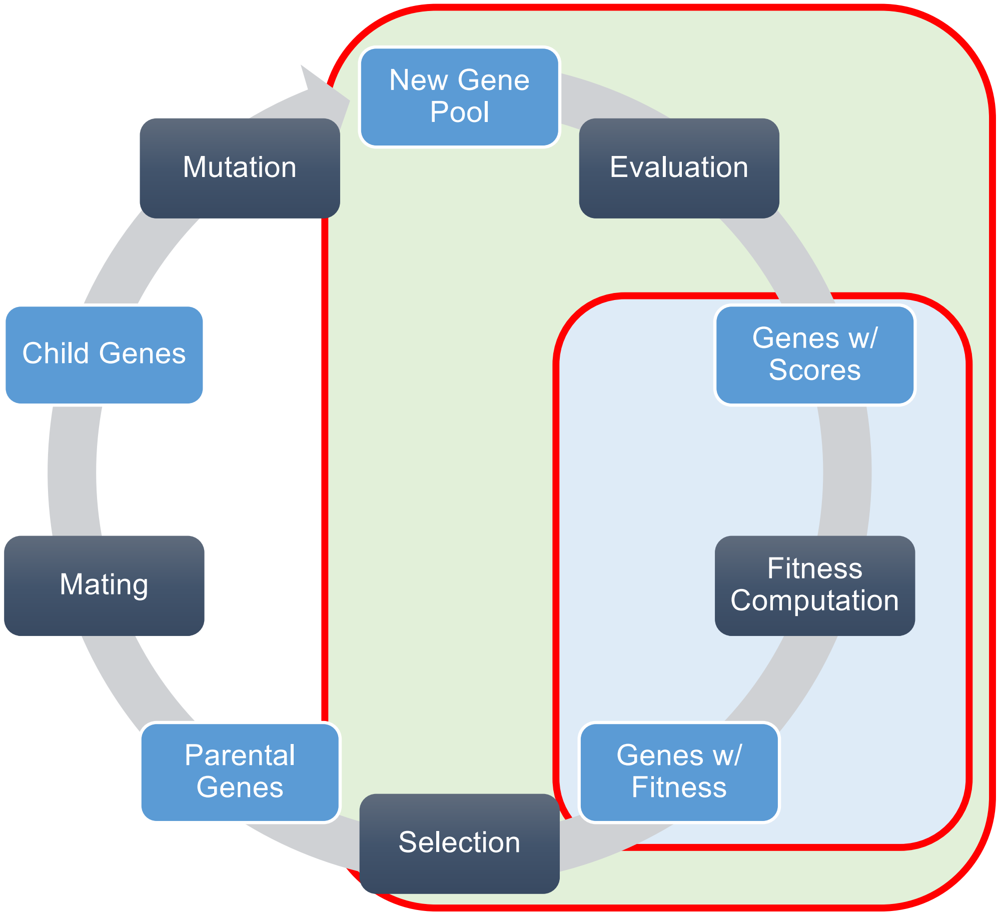


What is an algorithm looking for in a mate?



Chat Survey

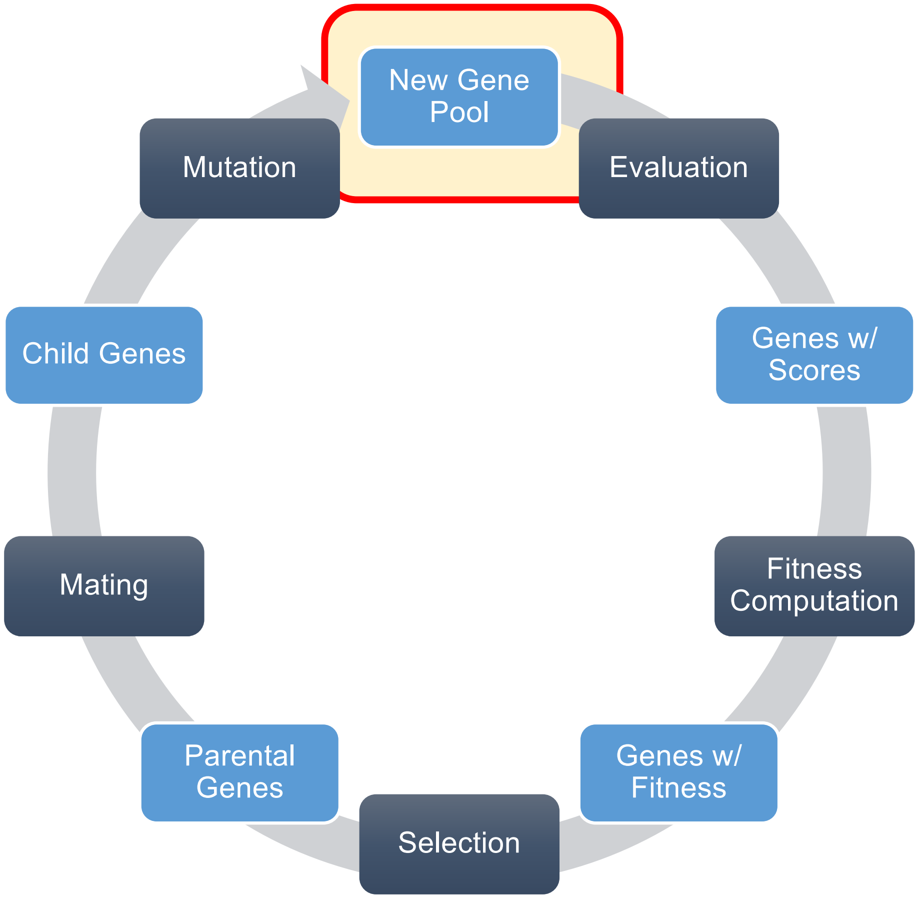
Lecture Scope



- Today's lecture focuses the translation of the vector of scores from evaluation into a fitness value

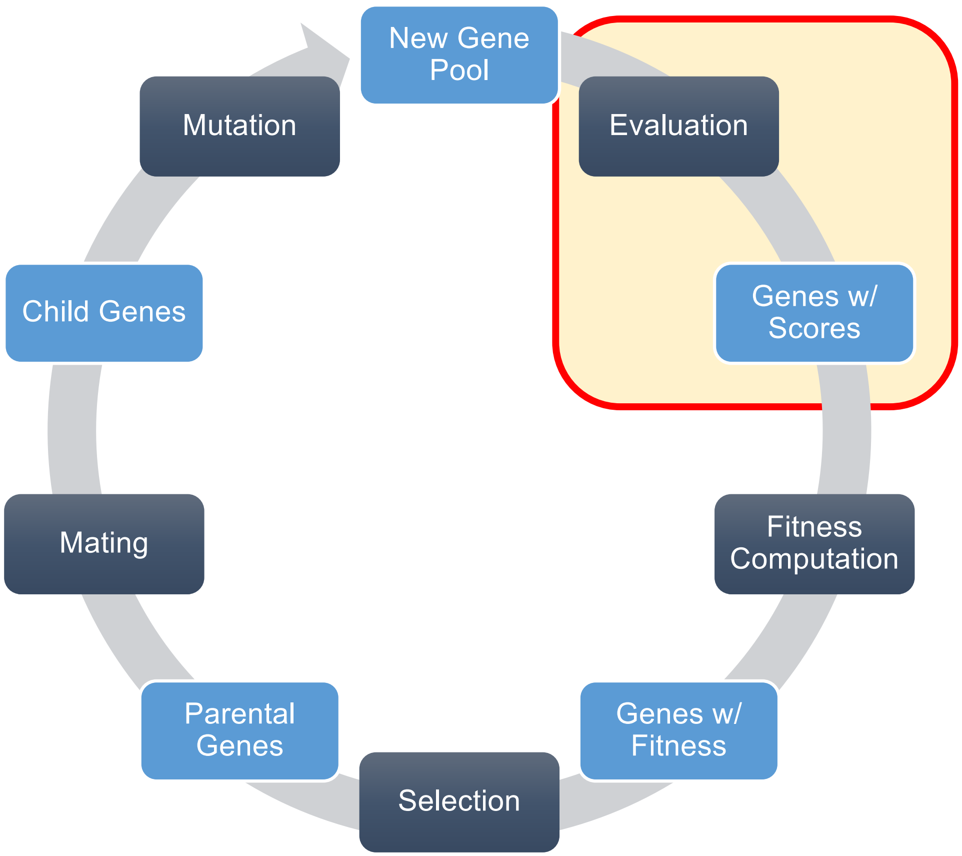
- But to understand the context we will look at the slightly larger picture

Lecture Scope



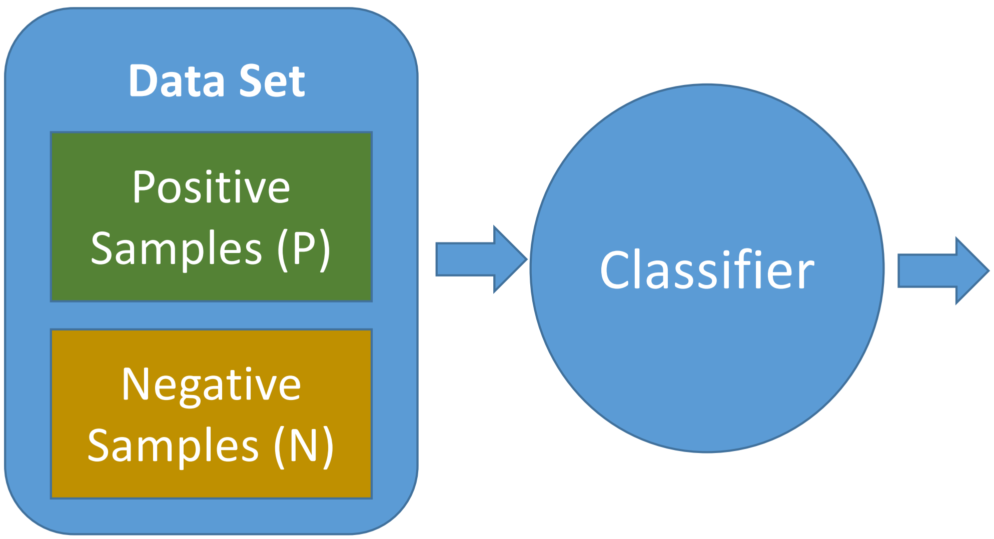
- Gene pool is the set of genome to be evaluated during the current generation
  - Genome
    - Genotypic description of an individuals
    - DNA
    - GA = set of values
    - GP = tree structure, string
  - Search Space
    - Set of all possible genome
    - For Automated Algorithm Design
      - Set of all possible algorithms
    - How big is the search space?
    - Why is this important for algorithm design?

Objective Space



- The Evaluation of a Genome associates a genome/individual (set of parameters for GA or string for GP) with a set of scores
- What are these scores
  - True Positive – TP
    - How often are we identifying the desired object
  - False Positive – FP
    - How often are we identifying something else as the desired object
  - More? – On board, next page
- Objectives
  - Set of measurements each genome (or individual) is scored against
  - Phenotype
- Objective Space – Set of objectives
- Evaluation – Maps an genome/individual
  - From a location in search space
    - Genotypic description
  - To a location in objective space
    - Phenotype description

Classification Measures



Confusion Matrix

	Predicted: Positive	**Predicted: Negative**
Actual Positive (P)	True Positive (TP)	False Negative (FN) Type II Error
Actual Negative (N)	False Positive (FP) Type I Error	True Negative (TN)

Board Example

	Predicted: Positive	**Predicted: Negative**
Actual Positive (P=11)	True Positive (TP=8)	False Negative (FN=3)
Actual Negative (N=12)	False Positive (FP=5)	True Negative (TN=7)

Algorithm = Red Objects

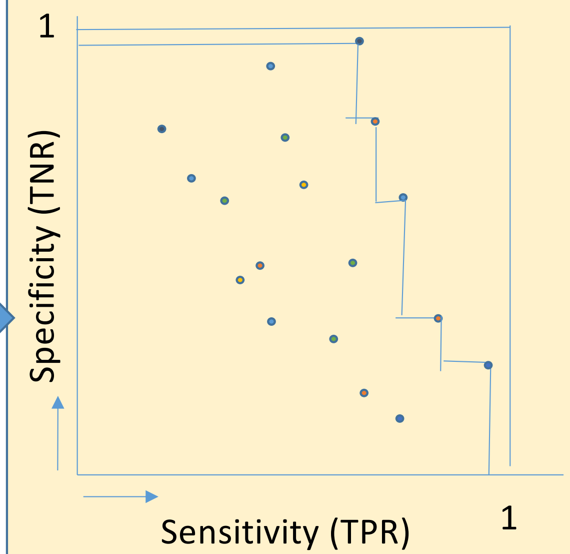
Maximization Measures

	Predicted: Positive	Predicted: Negative
Actual Positive (P)	True Positive (TP)	False Negative (FN)
Actual Negative (N)	False Positive (FP)	True Negative (TN)

- Sensitivity or True Positive Rate (TPR)
  - AKA hit rate or recall
  - TPR = TP/P = TP/(TP+FN)

- Specificity (SPC) or True Negative Rate (TNR)
  - TNR = TN/N = TN/(TN+FP)

Bigger is Better



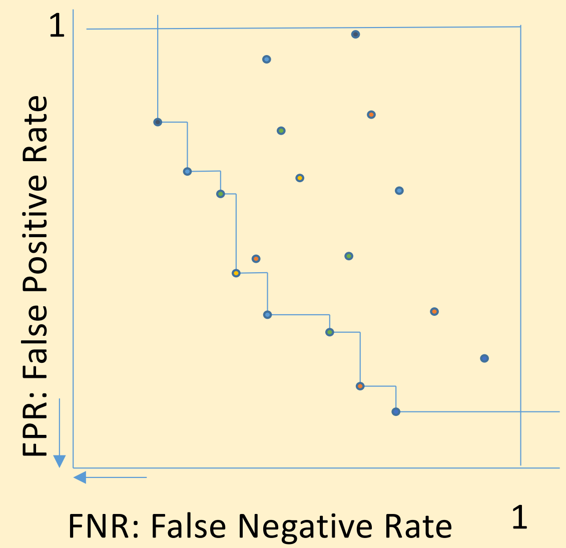
Minimization Measures

	Predicted: Positive	Predicted: Negative
Actual Positive (P)	True Positive (TP)	False Negative (FN)
Actual Negative (N)	False Positive (FP)	True Negative (TN)

- False Negative Rate (FNR)
  - FNR = FN/P = FN/(TP+FN)
  - FNR = 1 - TPR

- Fallout or False Positive Rate (FPR)
  - FPR = FP/N = TN/(FP+TN)
  - FPR = 1 – TNR = 1 - SPC

Smaller is Better



	Predicted: Positive	Predicted: Negative
Actual Positive (P=11)	True Positive (TP=8)	False Negative (FN=3)
Actual Negative (N=12)	False Positive (FP=5)	True Negative (TN=7)

FNR = ?

FPR = ?

	Predicted: Positive	Predicted: Negative
Actual Positive (P=11)	True Positive (TP=8)	False Negative (FN=3)
Actual Negative (N=12)	False Positive (FP=5)	True Negative (TN=7)

FNR = 3/11 = 27.27%

FPR = 5/12 = 41.66%

New Algorithm = All Apples are NOT Orange

	Predicted: Positive	**Predicted: Negative**
Actual Positive (P=11)	True Positive (TP=?)	False Negative (FN=?)
Actual Negative (N=12)	False Positive (FP=?)	True Negative (TN=?)

FNR = ?

FPR = ?

New Algorithm = All Apples are NOT Orange

	Predicted: Positive	Predicted: Negative
Actual Positive (P=11)	True Positive (TP=11)	False Negative (FN=0)
Actual Negative (N=12)	False Positive (FP=8)	True Negative (TN=4)

FNR = 0

FPR = 8/12 = 0.75

Other Measures

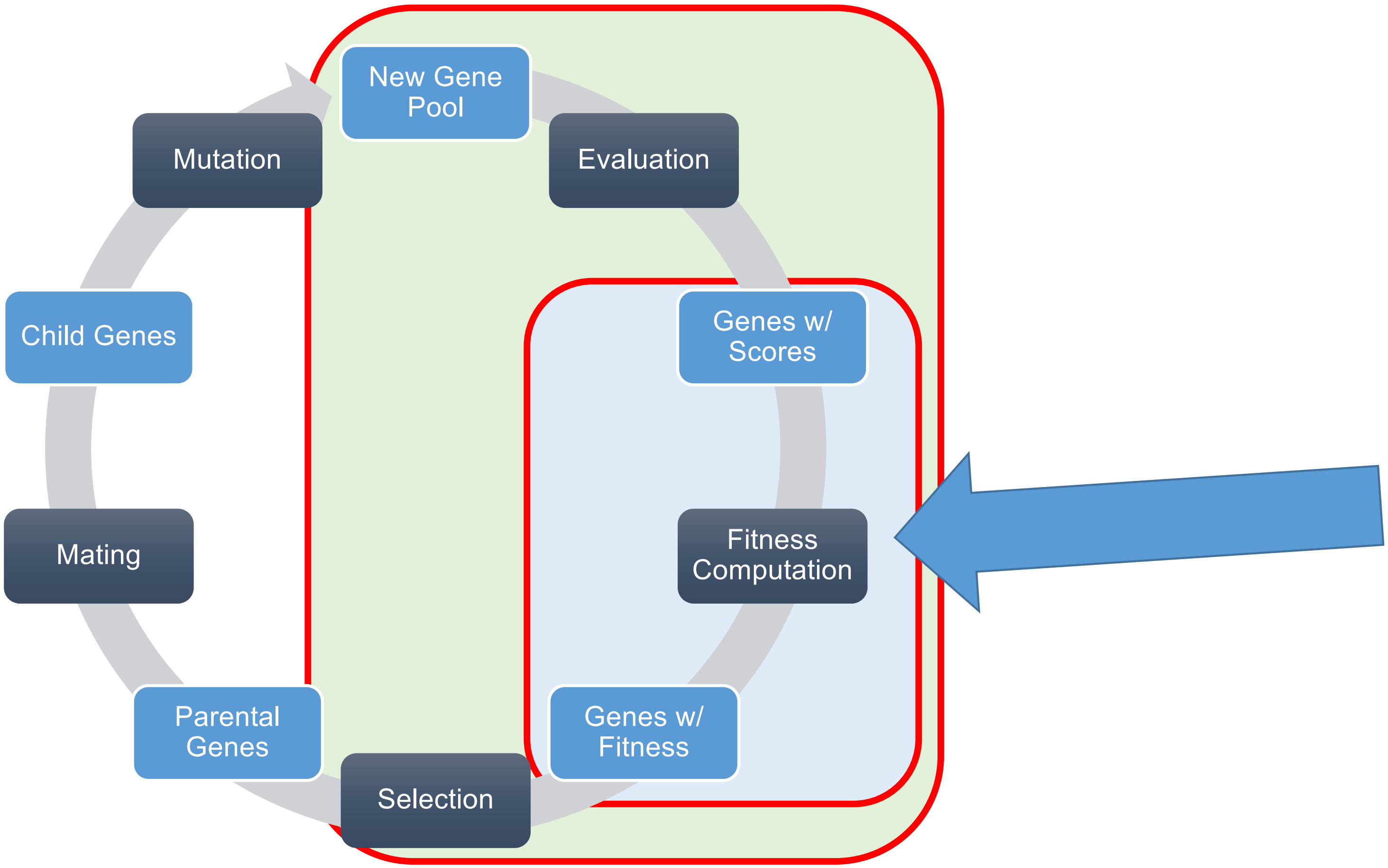
	Predicted: Positive	Predicted: Negative
Actual Positive (P)	True Positive (TP)	False Negative (FN)
Actual Negative (N)	False Positive (FP)	True Negative (TN)

- Precision or Positive Predictive Value (PPV)
  - PPV = TP / (TP + FP)
  - Bigger is better
- False Discovery Rate
  - FDR = FP/(TP + FP)
  - FDR = 1 - PPV
  - Smaller is better

- Negative Predictive Value (NPV)
  - NPV = TN / (TN + FN)
  - Bigger is better

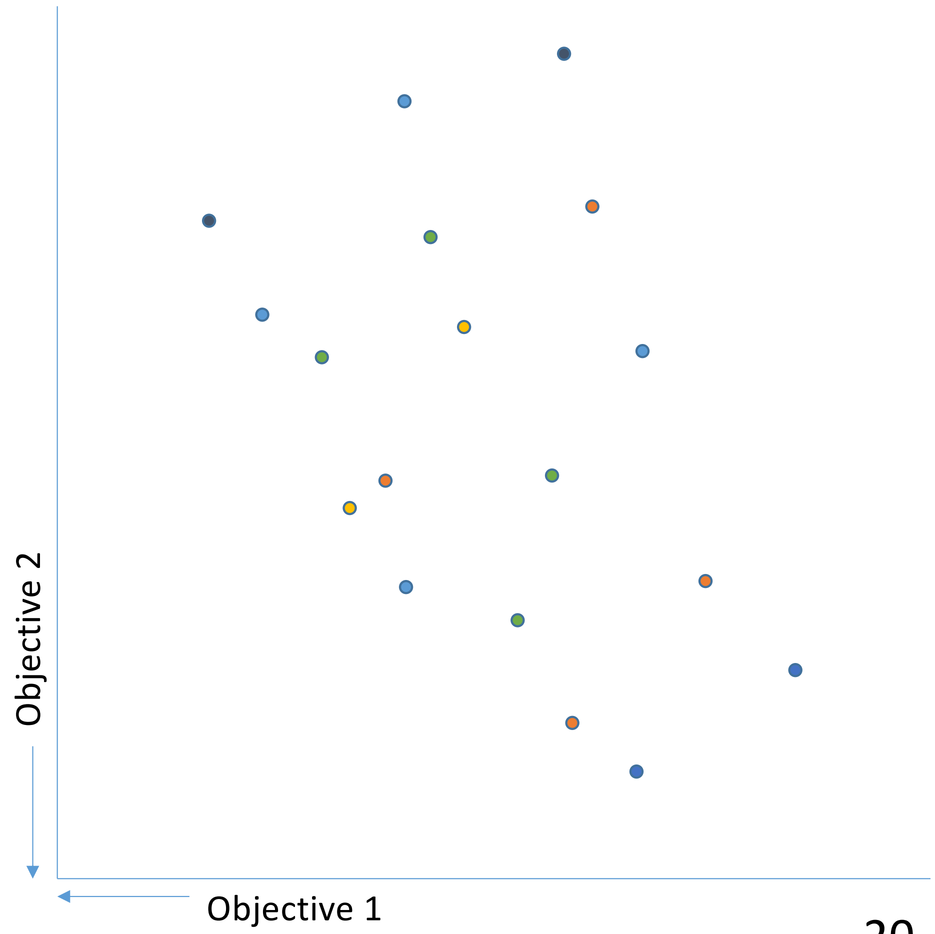
- Accuracy (ACC)
  - ACC = (TP+TN) / (P+N)
  - ACC = (TP+TN) / (TP + FP + FN + TN)
  - Bigger is better

Lecture Scope



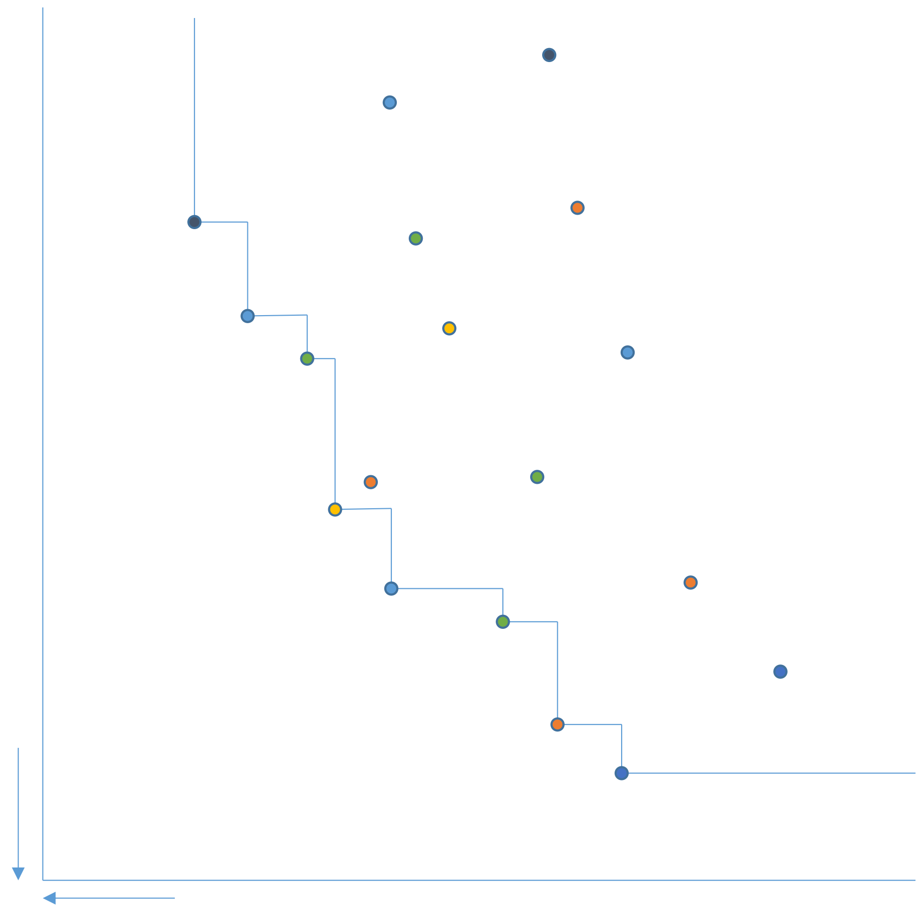
Objective Space

- Each individual is evaluated using objective functions
    - Mean squared error
    - Cost
    - Complexity
    - True positive rate
    - False positive rate
    - Etc…
- Objective scores give each individual a point in objective space
- This may be referred to as the phenotype of the individual
- Examples are shown with two objectives, but all techniques we will discuss are extensible to N objectives



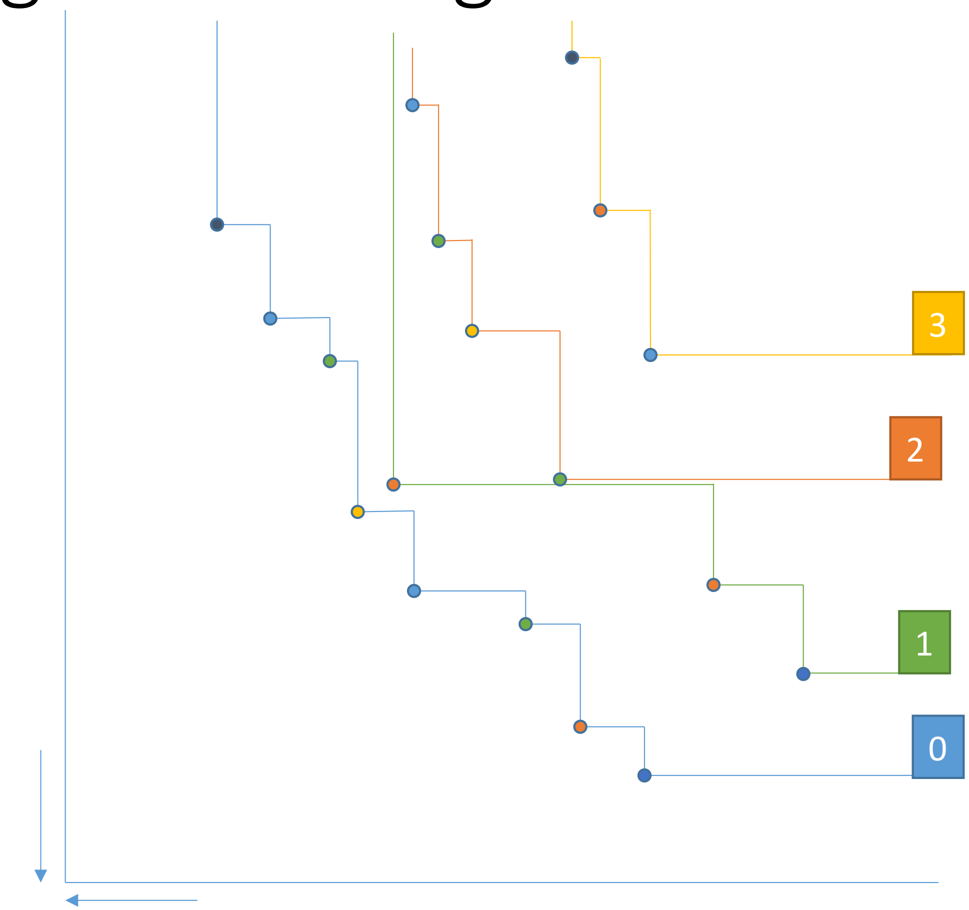
Pareto Optimality

- An individual is Pareto optimal if there is no other individual in the population that outperforms the individual on all objectives
- The set of all Pareto individuals is known as the Pareto frontier
- These individuals represent unique contributions
- We want to drive selection by favoring Pareto individuals
  - But maintain diversity by giving all individuals some probability of mating



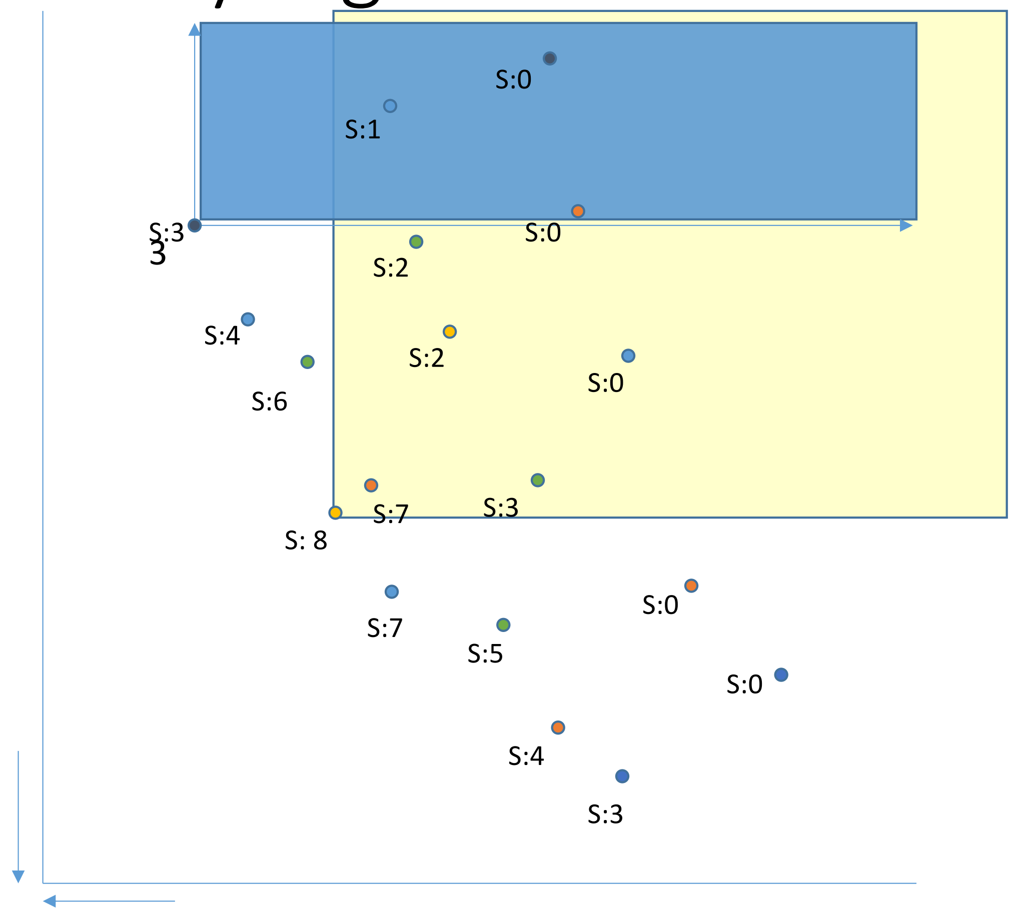
Nondominated Sorting Genetic Algorithm II (NSGA II)

- Population is separated into nondomination ranks
- Individuals are selected using a binary tournament
- Lower Pareto ranks beat higher Pareto ranks
  - For example, an individual on the blue front will beat out an individual on the green front
- Ties on the same front are broken by crowding distance
  - Summation of normalized Euclidian distances to all points within the front
  - Higher crowding distance wins



Strength Pareto Evolutionary Algorithm 2 (SPEA2)

- Each individual is given a strength *S*
  - *S* is how many others in the population it dominates



Strength Pareto Evolutionary Algorithm 2 (SPEA2)

- Each individual is given a strength *S*
  - *S* is how many others in the population it dominates
- Each individual receives a rank *R*
  - *R* is the sum of *S's* of the individuals that dominate it
  - Pareto individuals are nondominated and receive an R of 0
- A distance to the kth nearest neighbor ($\boldsymbol{\sigma}^k$) is calculated and a fitness of $R + 1/(\boldsymbol{\sigma}^k + 2)$ is obtained