

Dimensionality Reduction

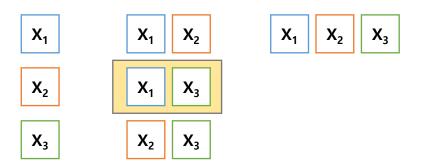
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AGENDA

01	Dimensionality Reduction
02	Variable Selection Methods
03	Shrinkage Methods
04	R Exercise

Exhaustive Search

- Exhaustive search
 - √ Search all possible combinations
 - Ex) 3 variables X₁
- X₁ X₂ X₃
 - A total of 7 possible subsets are tested



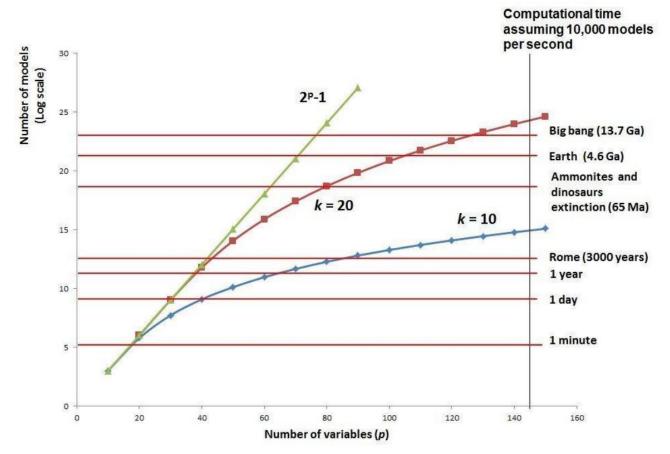
- ✓ Performance criteria for variable selection
 - Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), Adjusted R²,
 Mallow's C_p, etc.





Exhaustive Search

- Exhaustive search
 - ✓ Assume that we have a computer that can evaluate 10,000 models/second



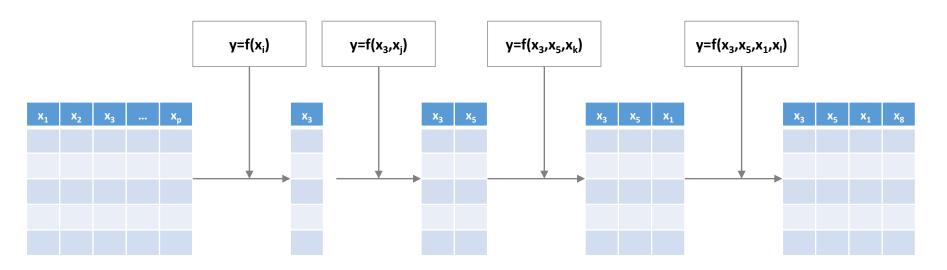




Forward Selection

Forward selection

- √ From the model with no variable, significant variables are sequentially added
- ✓ Once the variable is selected, it will never be removed (The number of variables gradually increases)



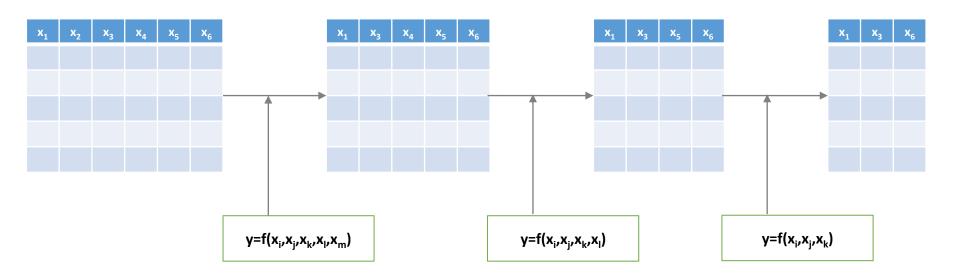




Backward Elimination

Backward Elimination

- √ From the model with all variables, irrelevant variables are sequentially removed.
- ✓ Once a variable is removed, it will never be selected (The number of variables gradually decreases)







Stepwise Selection

• Stepwise Selection

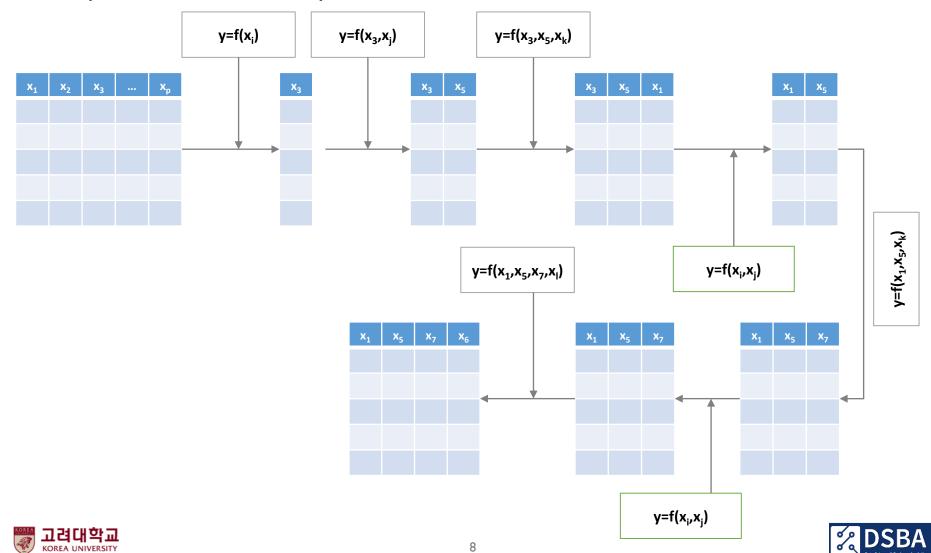
- ✓ From the model with no variable, conduct the forward selection and backward elimination alternately
- ✓ Takes longer time than forward selection/backward elimination, but has more chances
 to find the optimal set of variables
- ✓ Variables that is either selected/removed can be reconsidered for selection/removal
- ✓ The number of variables increases in the early period, but it can either increase or decrease





Stepwise Selection

Stepwise selection example



Stepwise Selection

Stepwise Selection

- √ Stepwise selection process
 - Start with model with no predictors.
 - ▶ Add variable with largest *F*-statistic (provided *P* less than some cut-off).
 - ▶ Refit with this variable added. Recompute all F statistics for adding one of the remaining variables and add variable with largest F statistic.
 - ▶ At each step after adding a variable try to eliminate any variable not significant at some level (that is, do BACKWARD elimination till that stops).
 - After doing the backwards steps take another FORWARD step.
 - Continue until every remaining variable is significant at cut-off level and every excluded variable is insignificant OR until variable to be added is same as last deleted variable.

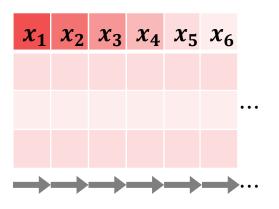




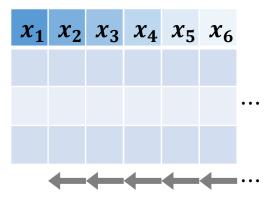
Comparison among FS/BE/SS

Illustrative Example

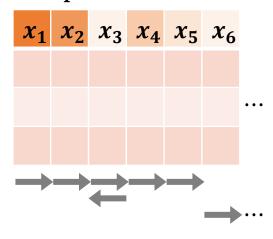
Forward Selection



Backward Elimination



Stepwise Selection







Performance Metrics

Akaike Information Criteria (AIC)

✓ Sum of squared error (SSE) with the number of variables as a penalty term

$$AIC = n \cdot ln\left(\frac{SSE}{n}\right) + 2k$$

Bayesian Information Criteria (BIC)

✓ SSE, number of variables, standard deviation obtained by the model with all variables

$$BIC = n \cdot ln\left(\frac{SSE}{n}\right) + \frac{2(k+2)n\sigma^2}{SSE} - \frac{2n^2\sigma^4}{SSE^2}$$





Performance Metrics

Adjusted R²

√ Simple R² increases when the number of variable increases

Model 1:
$$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k + \epsilon$$

Model 2: $y = \beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k + \ldots + \beta_{k+m} x_{k+m} \epsilon$ $R^2(M2) \ge R^2(M1)$

 \checkmark Use the adjusted R² that account for the number of variables (k)

Adjusted
$$R^2 = 1 - \left(\frac{n-1}{n-k-1}\right)(1-R^2) = 1 - \frac{n-1}{n-k-1}\frac{SSE}{SST}$$





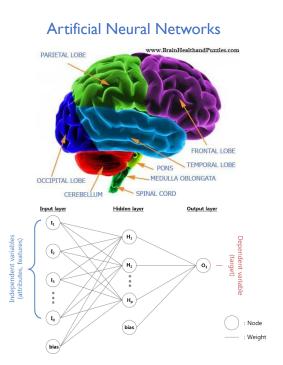
- Limitations of the previous variable selection methods
 - ✓ Exhaustive search: guarantee the optimal subset, but takes too long time (practically impossible for many tasks)
 - ✓ Local search (forward/backward/stepwise): efficient search but the search space is very limited, which leads to a low probability of finding the optimal solution

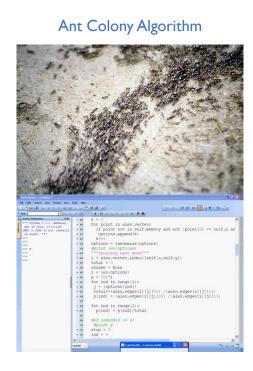
- Idea
 - ✓ Improve the performance of local searches with a little additional computational time!





- Meta-Heuristic Approach
 - √ Solve a complex problem by doing trials and errors efficiently
 - ✓ Among the optimization algorithms, many of them mimic the way of a natural system works



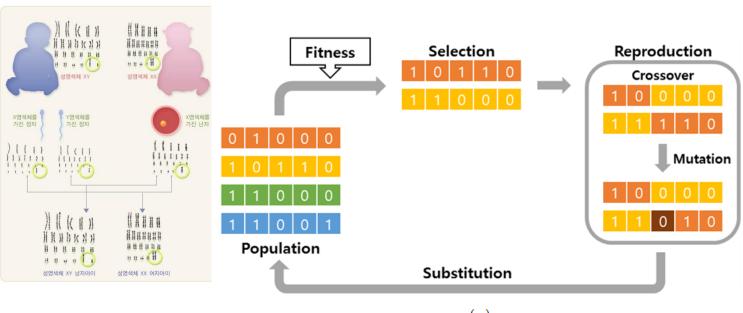


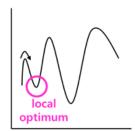
Particle Swarm Optimization

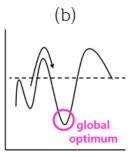




- An Evolutionary Algorithm that mimics the Reproduction of Creatures
 - \checkmark Find a superior solutions and preserve by repeating the reproduction process
 - Selection: Select a superior solution to improve the quality
 - Crossover: Search various alternatives based on the current solutions
 - Mutation: Give a chance to escape the local optima





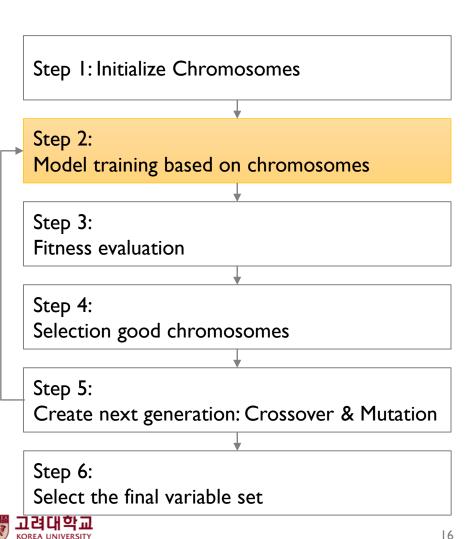


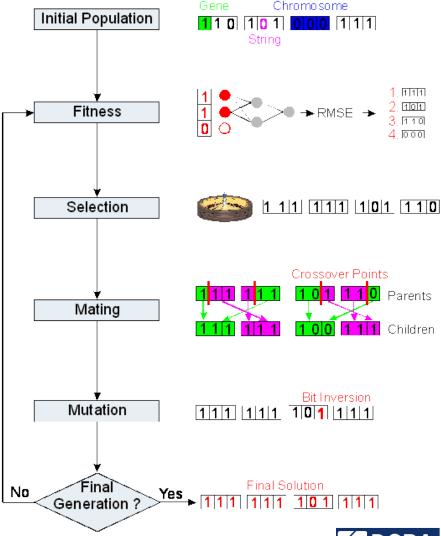




(a)

Genetic Algorithm for Feature Selection





GA Step 1: Initialization

Encoding Chromosomes

- ✓ Genetic algorithm can be used not only for variable selection, but for a wide range of optimization problems
- ✓ Encoding scheme can be different for different tasks
- ✓ Binary encoding is commonly used for variable selection

Chromosome				Gene				
X ₁	x ₂	X ₃	X ₄	X ₅	x ₆	x ₇	x ₈	 x _d
1	0	0	1	0	1	1	0	 1

I: Use the corresponding variable in the modeling

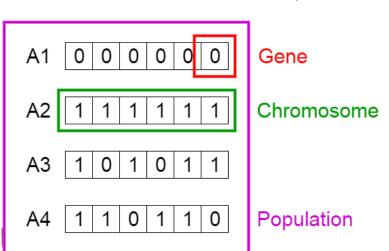
0: Do not use the variable

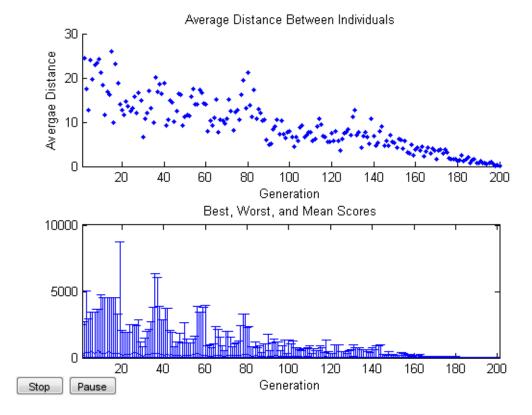




GA Step 1: Initialization

- Parameter Initialization
 - √ The number of chromosome (population)
 - √ Fitness function
 - √ Crossover mechanism
 - ✓ The rate of mutation
 - ✓ Stopping criteria
 - minimum fitness improvement
 - maximum iterations, etc.



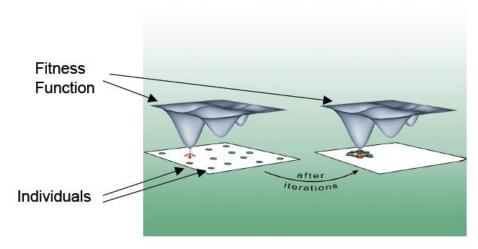




GA Step 3: Fitness Evaluation

Fitness Function

- ✓ A criterion that determines which chromosomes are better than others
- ✓ In general, the higher the fitness value, the better the chromosomes
- ✓ Common criteria that are embedded in the fitness function
 - If two chromosomes have the same fitness value, the one with fewer variables is preferred
 - If two chromosomes use the same number of variables, the one with higher predictive performance is preferred
- √ In case of multiple linear regression
 - Adjusted R2
 - Akaike information criterion (AIC)
 - Bayesian information criterion (BIC)







GA Step 4: Selection

Selection

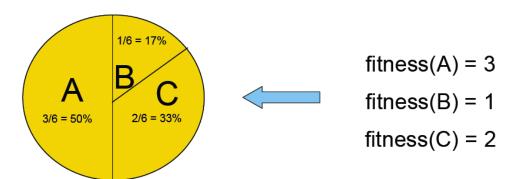
✓ Select superior chromosomes in the current population to reproduce the population
of the next generation

✓ Deterministic selection

- Select only top N% of chromosomes
- Bottom (100-N)% chromosomes are never selected

✓ Probabilistic selection

- Use the fitness value of each chromosome as the selection weight
- All chromosomes can be selected with different probabilities

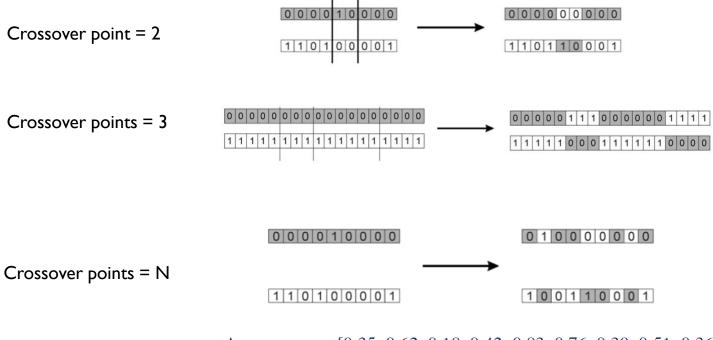






GA Step 5: Crossover & Mutation

- Crossover (Reproduction)
 - √ Two child chromosomes are produced from two parent chromosomes
 - ✓ The number of crossover points can vary from I to n (total number of genes)



Assume array: [0.35, 0.62, 0.18, 0.42, 0.83, 0.76, 0.39, 0.51, 0.36]





GA Step 5: Crossover & Mutation

Mutation

- ✓ Genetic operator used to maintain diversity from one generation of a population of chromosomes to the next
- ✓ Alters one or more gene values in a chromosome from its initial state, which result in
 entirely new gene values being added to the gene pool
- ✓ By mutation, the current solution can have a chance to escape from the local optima
- \checkmark A too mutation rate can increase the time to converge (0.01 can be a good choice)

Consider the two original off-springs selected for mutation.

Invert the value of the chosen gene as 0 to 1 and 1 to 0

The Mutated Off-spring produced are:





GA Step 5: Find the Best Solution

- Find the best variable subset
 - ✓ Select the chromosome with the highest fitness value after the stopping criteria are satisfied.
 - ✓ Generally, significant fitness improvement occurs in the early stages, which becomes marginal after some generations

