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Search for the Higgs boson at LHC by using Genetic Algorithms

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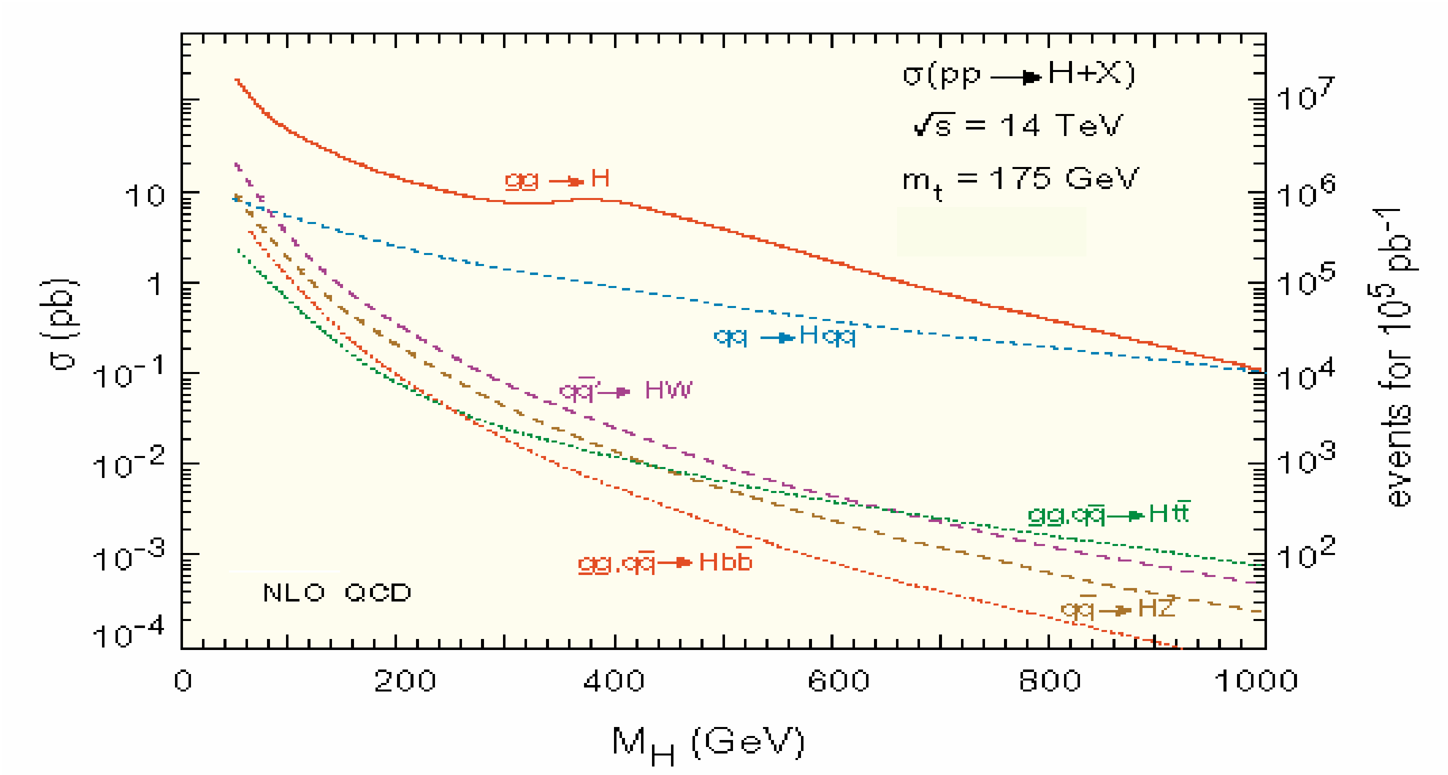
Search for the Higgs boson at LHC by using Genetic Algorithms

- Introduction
- Genetic Algorithms
- Search for the Higgs boson at LHC by using Genetic Algorithms
  - Optimization of discriminant functions
  - Optimization of Neural weights
  - Hyperplans search
  - Hypersurfaces search
- Conclusion

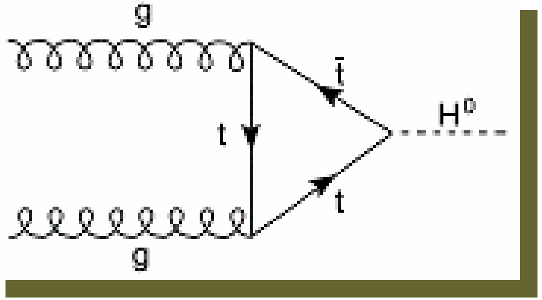
Introduction

Introduction
Higgs production at LHC

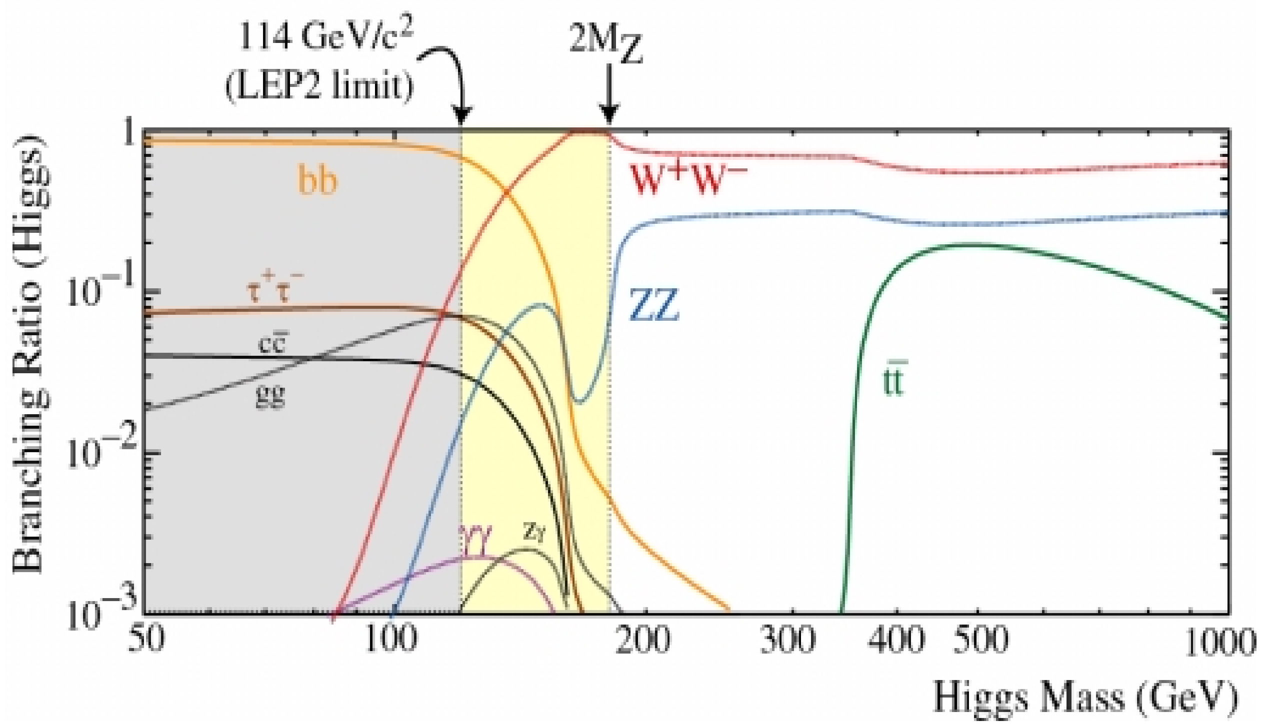


- *Several mechanisms contribute to the production of SM Higgs boson in proton collisions*

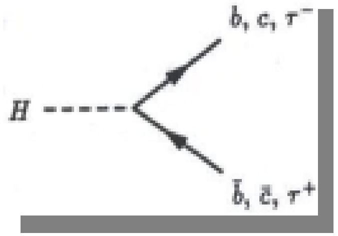
- *The dominant mechanism is the gluon fusion process,* $gg \rightarrow H$

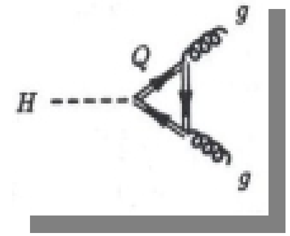


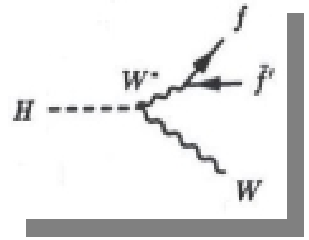
Introduction
Decay Modes



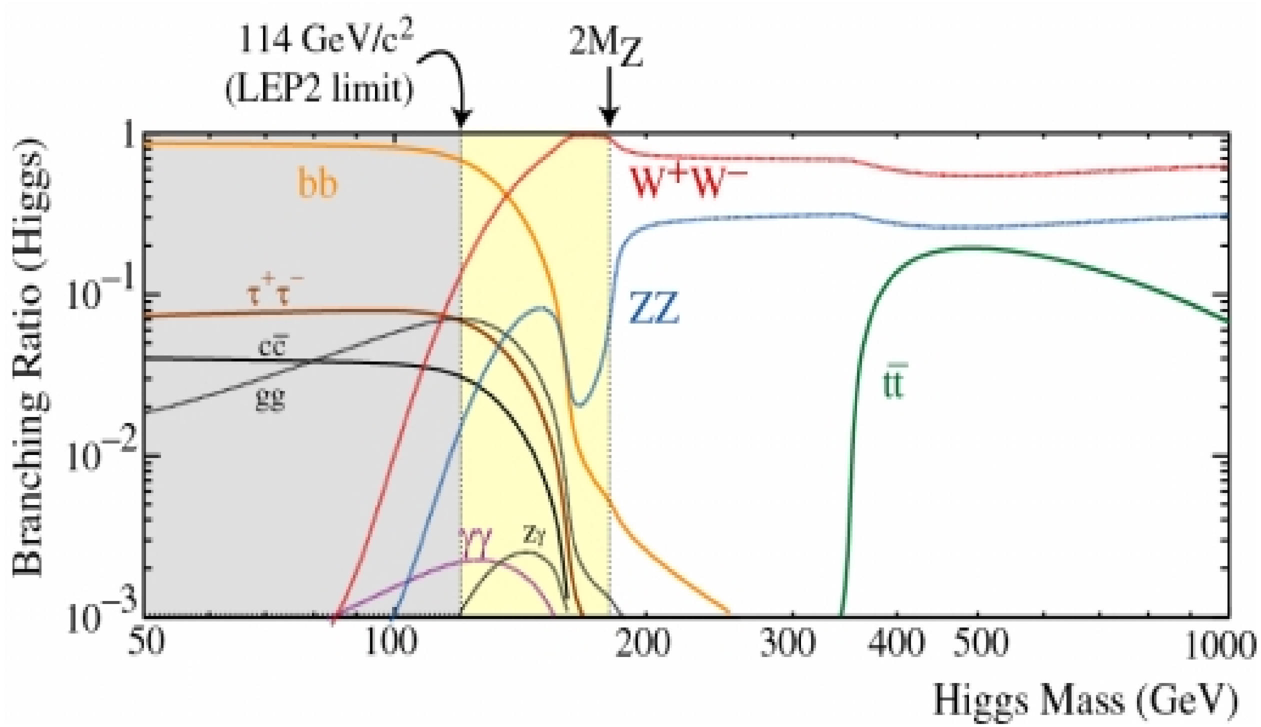
- *decay into quarks:* $H \rightarrow bb$ *and* $H \rightarrow cc$
- *leptonic decay* $H \rightarrow \tau^{+} \tau^{-}$
- *gluonic decay* $H \rightarrow g\, g$
- *decay into virtual W boson pair:* $H \rightarrow W^{+}W^{-}$







Introduction
Main discovery modes



$M_H < 2M_Z$:

- $H \to bb+X$
- $H \to W^+W^- \to l\nu l\nu$
- $H \to ZZ \to 4l$
- $H \to \gamma\gamma$

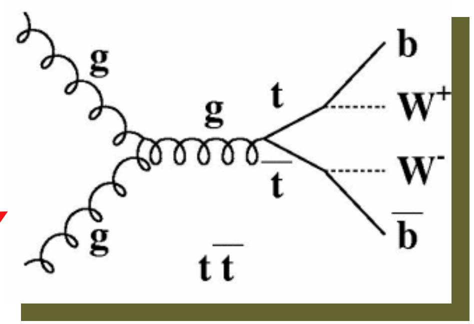
$H \rightarrow W^+W^- \rightarrow ll\nu\nu$

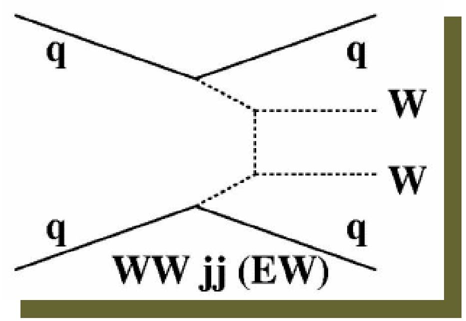
- **The decay channel chosen:**

  $H \rightarrow W^+W^- \rightarrow e^+\mu^-\nu\nu,\ \mu^+e^-\nu\nu,\ e^+e^-\nu\nu,\ \mu^+\mu^-\nu\nu.$

- **Signature:**
  - *Two charged oppositely leptons with large transverse momentum P_T.*
  - *Two energetic jets in the forward detectors.*
  - *Large missing transverse momentum P'_T*

- **Main background:**
  - *tt production: with $tt \rightarrow WbWb \rightarrow l\nu j\, l\nu j$*
  - *QCD W^+W^- +jets production*
  - *Electroweak WWjj*





$H \to W^+W^- \to ll\nu\nu$

Main Variables

- $\Delta\eta_{ll}$, $\Delta\phi_{ll}$: *the pseudo-rapidity and the azimuthal angle differences between the two leptons*

- $\Delta\eta_{jj}$, $\Delta\phi_{jj}$: *the pseudo-rapidity and the azimuthal angle differences between the two jets*

- M_{ll}, M_{jj}: *the invariant mass of the two leptons and jets,*

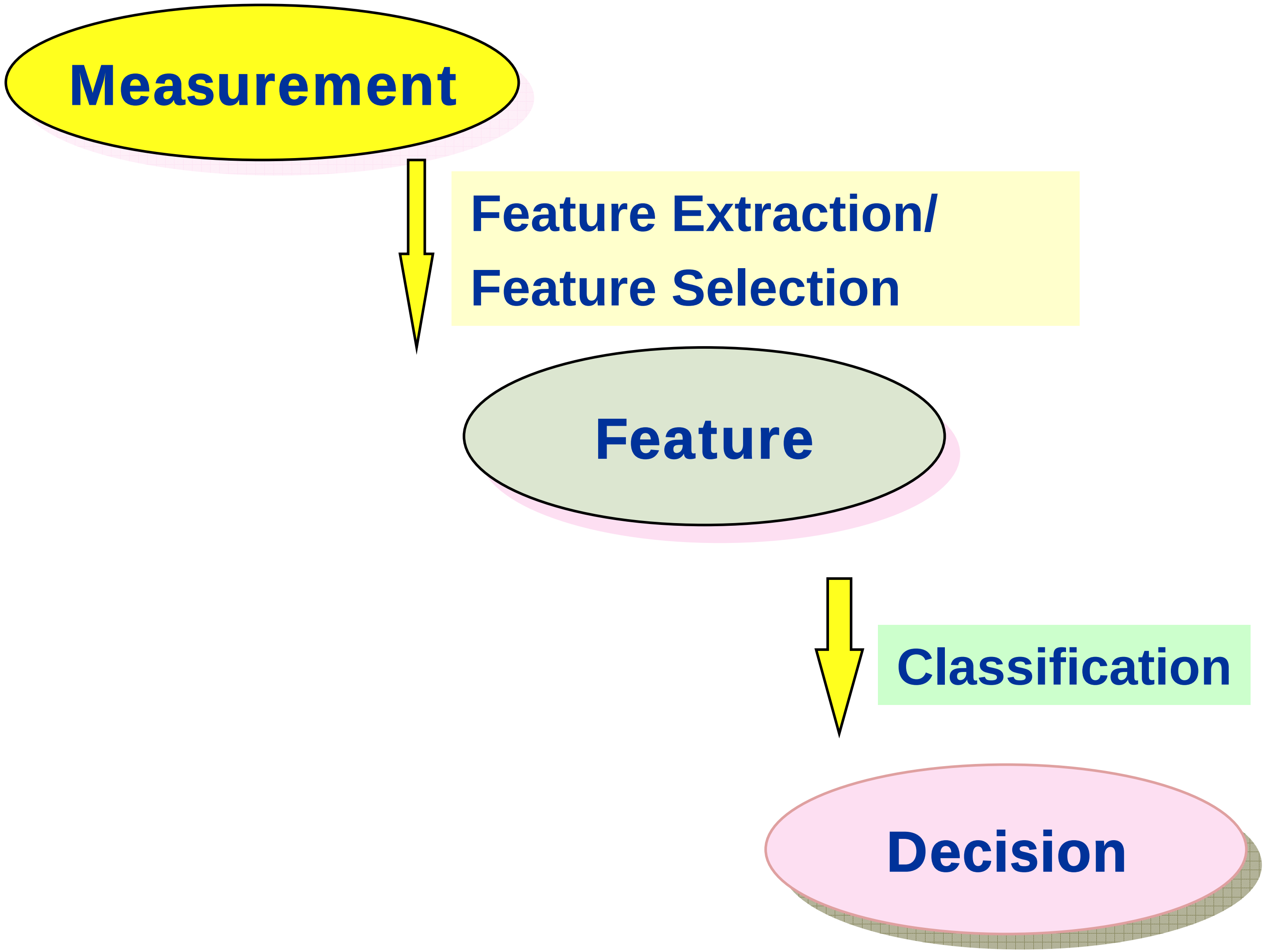
- M_{nm} *(n,m = 1,2,3) some rapidity weighted transverse momentum*

$$M_{nm} = \sum_{i \in event} \eta_i^{\,n} \cdot p_{iT}^{\,m} \qquad n, m = 1, 2,3, \ldots$$

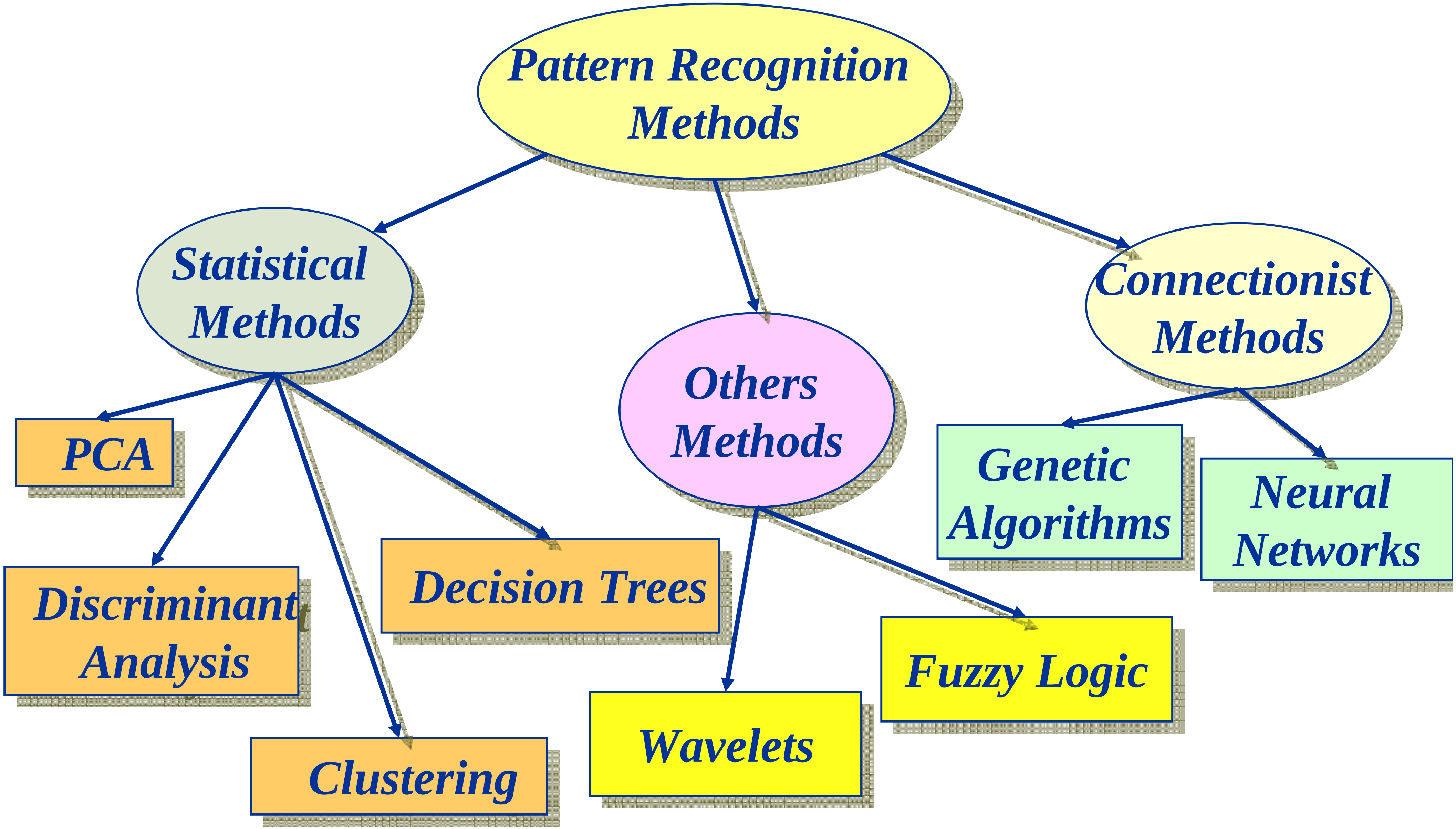
η_i *rapidity of the leptons or jets,* p_{iT} *their transverse momentums.*

Genetic Algorithms

Pattern Recognition



Pattern Recognition Methods



Genetic Algorithms

- Based on Darwin's theory of "survival of the fittest"
  Living organisms reproduce, individuals evolve / mutate, individuals survive or die based on fitness

- The output of a genetic algorithm is the set of "fittest solutions" that will survive in a particular environment

- The input is an initial set of possible solutions

- The process
  - Produce the next generation (by a cross-over function)
  - Evolve solutions (by a mutation function)
  - Discard weak solutions (based on a fitness function)

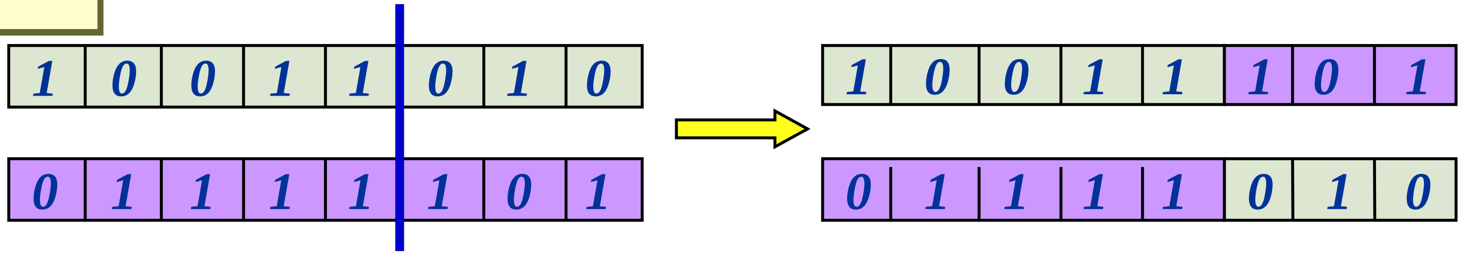
Genetic Algorithms

- **Preparation:**
  - Define an encoding to represent solutions (i. e., use a character sequence to represent a class)
  - Create possible initial solutions (and encode them as strings)
  - Perform the 3 genetic functions to operate on a cluster encoding: Crossover, Mutate, Fitness Test

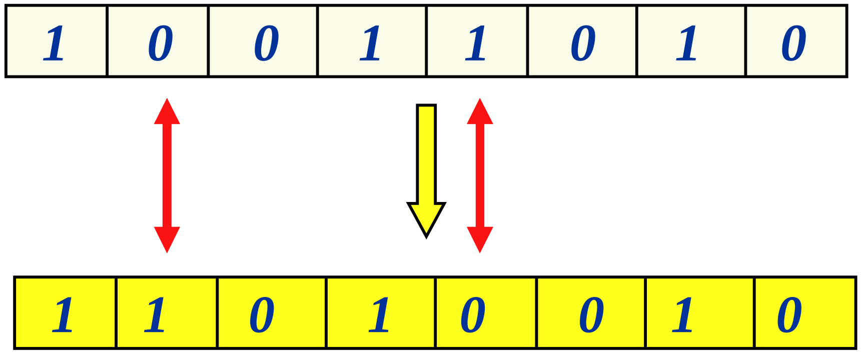
- **Why Genetic Algorithms (GAs) ?**
  - Many real life problems cannot be solved in polynomial amount of time using deterministic algorithm
  - Sometimes near optimal solutions that can be generated quickly are more desirable than optimal solutions which require huge amount of time
  - Problems can be modeled as an optimization one.

Genetic Functions

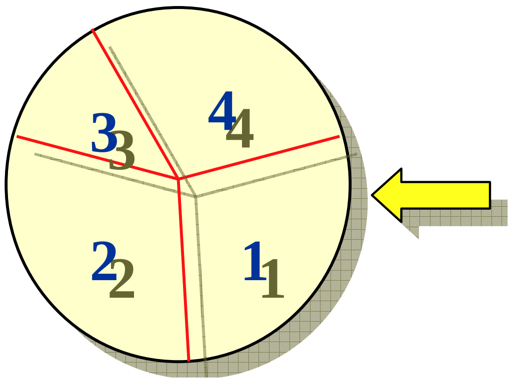
Crossover

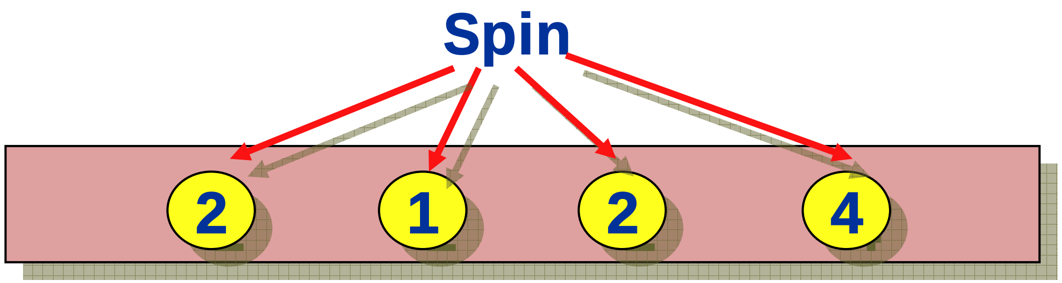


Mutation

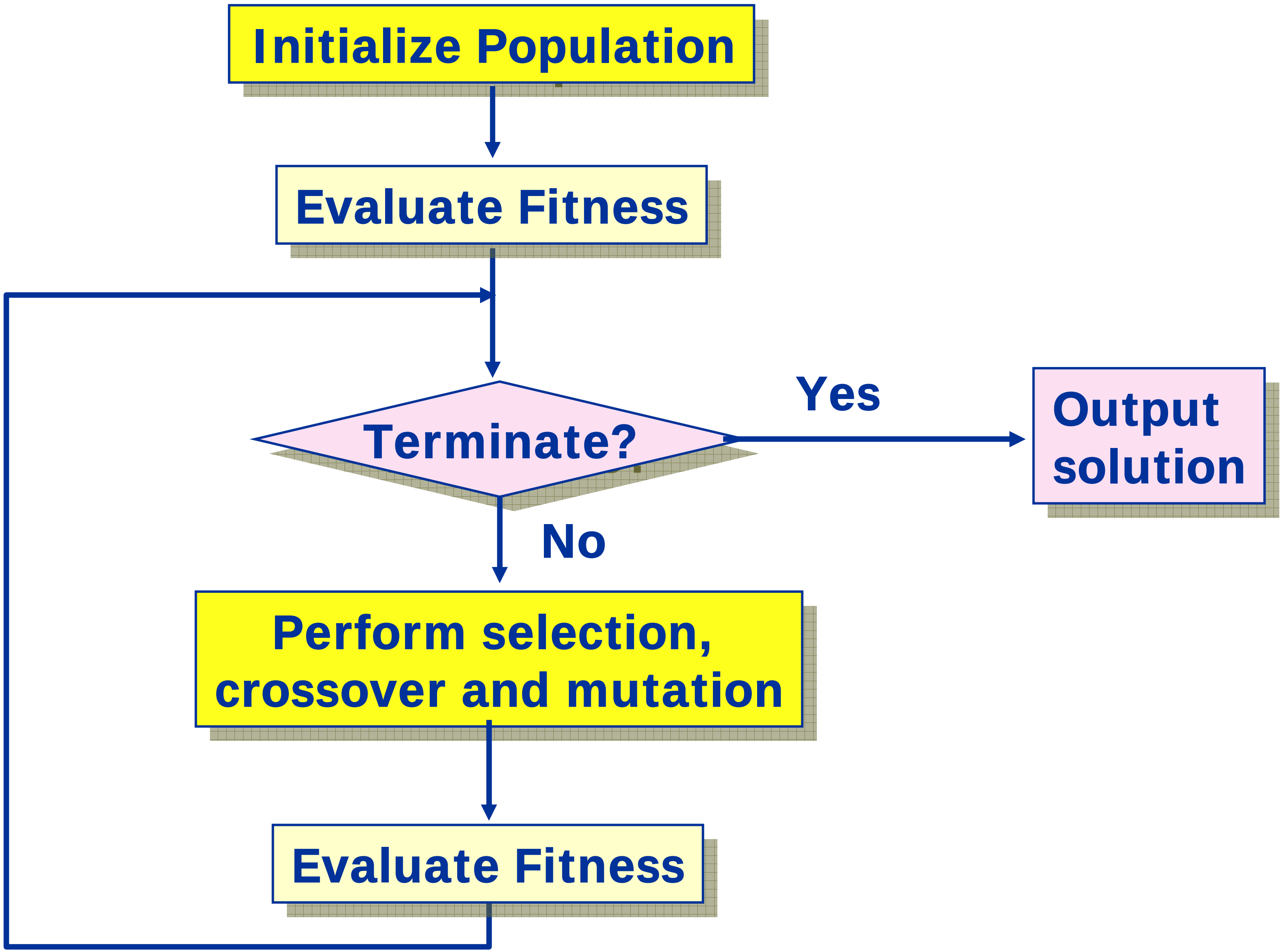


Roulette Wheel Selection





GA Flowchart



GAs for Pattern Classification

- Optimization of discriminant functions
- Optimization of Neural weights
- Hyperplans search
- Hypersurfaces search

Efficiency and Purity of Classification

- **Validation**

Test Events	Classification	
	C_1	C_2
C_1: N_1	N_{11}	N_{12}
C_2: N_2	N_{21}	N_{22}
Total	M_1	M_2

- *Efficiency for C_i classification*

$$E_i = \frac{N_{ii}}{N_i}$$

- *Purity for C_i events*

$$P_i = \frac{N_{ii}}{M_i}$$

- *Misclassification rate for C_i or Error*

$$\varepsilon_i = \frac{N_{ij}}{N_i}$$

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Search for the Higgs boson at LHC by using Genetic Algorithms

Signal

$pp \to HX \to W^+W^-X \to l^+\nu l^-\nu X$

Background

- $pp \to ttX \to WbWbX \to l\nu j\, l\nu jX$
- $pp \to qqX \to W^+W^-\, X$

- *Events generated by the LUND MC PYTHIA 6.1 at $\sqrt{s}$ = 14 TeV*
- $M_H = 115 - 150$ *GeV/c²*
- *10000 Higgs events and 10000 Background events are used*

- *Research of discriminating variables*

Variables

- $\Delta\eta_{ll}$, $\Delta\phi_{ll}$: *the pseudo-rapidity and the azimuthal angle differences between the two leptons*

- $\Delta\eta_{jj}$, $\Delta\phi_{jj}$: *the pseudo-rapidity and the azimuthal angle differences between the two jets*

- M_{ll} : *the invariant mass of the two leptons*

- M_{jj} : *the invariant mass of the two jets*

- *Rapidity-impulsion weighted Moments* M_{nm} : $(n=1, \ldots, 6)$

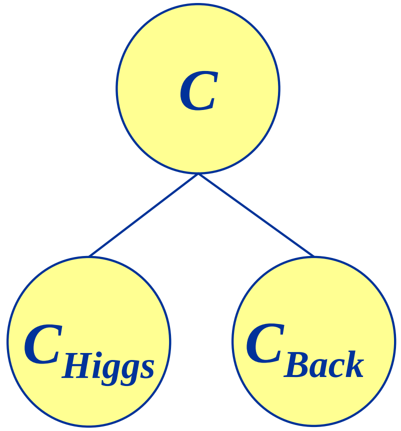
η_i *rapidity:*

$$M_{nm} = \sum_{i \in Jet} \eta_i^{\,n} \cdot p_{iT}^{\ \,m}$$

$$\eta_i = \frac{1}{2}.Log\left(\frac{E_i + p_{i//}}{E_i - p_{i//}}\right)$$

$\Delta\eta_{ll}$, $\Delta\phi_{ll}$, $\Delta\eta_{jj}$, $\Delta\phi_{jj}$, M_{ll} , M_{jj}, M_{11}, M_{21}, M_{31}, M_{41}

Optimization of Discriminant Functions (1)



- **Discriminant Analysis**

- $F(x) = (g_{signal} - g_{back})^T V^{-1} x = \Sigma \alpha_i x_i$

- ***The most separating discriminant Function $F_{Higgs/Back}$ between the classes C_{Higgs} and C_{Back} is :***

$$F_{Higgs/Back} = -0.02 + 0.12\Delta\eta_{ll} + 0.4\Delta\eta_{jj} + 0.35\,M_{ll} + 0.61\,M_{jj} + 0.74M_{11} + 1.04M_{21}$$

- ***The classification of a test event x_0 is then obtained according to the condition:***

$$\text{if } F_{Higgs/Back}(x_o) \geq 0 \text{ then } x_o \in C_{Higgs} \text{ else } x_o \in C_{Back}$$

- **Classification of test events**

Test events	Classification	
	Efficiency	Purity
C_{Higgs}	0.601	0.606
C_{Back}	0.610	0.604

Optimization of Discriminant Functions (2)

- **GA Parameters**
  - Discriminant Function
  - Fitness
  - Number of generations
  - Selection, Crossover, Mutation

-0.02	0.12	0.4	0.35	0.61	0.74	1.01	0.395
α_0^i	α_1^i	α_2^i	α_3^i	α_4^i	α_5^i	α_6^i	ε^I

Fitness Fn: ε
Misclassification rate

Test Events	Classification			
	Eff.	Purity	Eff	ε
C_{Higgs}	0.601	0.606	0.6055	0.3945
C_{Back}	0.610	0.604		

- **GA Code**
  Matlab GA Toolbox

Optimization of Discriminant Functions (3)

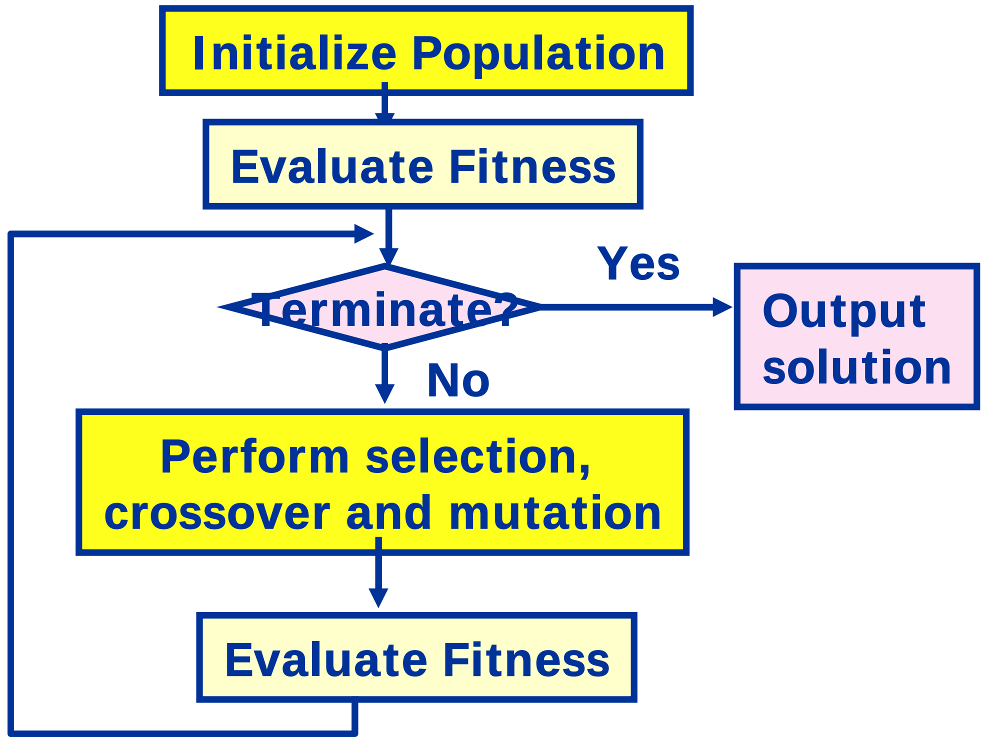
Chromosome 1	α_0^{1}	α_1^{1}	α_2^{1}	α_3^{1}	α_4^{1}	α_5^{1}	α_6^{1}	ε^{1}
....								
Chromosome N	α_0^{N}	α_1^{N}	α_2^{N}	α_3^{N}	α_4^{N}	α_5^{N}	α_6^{N}	ε^{N}

Generation of N solutions

Coefficients of F

Fitness Fn: ε

- Genetic Process



Optimization of Discriminant Functions (4)

• Optimization Results

Number of generations =10000

CPU Time: 120 s

- Optimal Disc. Fn

-0.02	0.12	0.4	0.35	0.61	0.74	1.01		0.35

Test Events	Classification			
	Eff.	Purity	Eff	ε
C_{Higgs}	0.652	0.649	0.65	0.35
C_{Back}	0.648	0.650		

Optimization of Neural Weights (1)

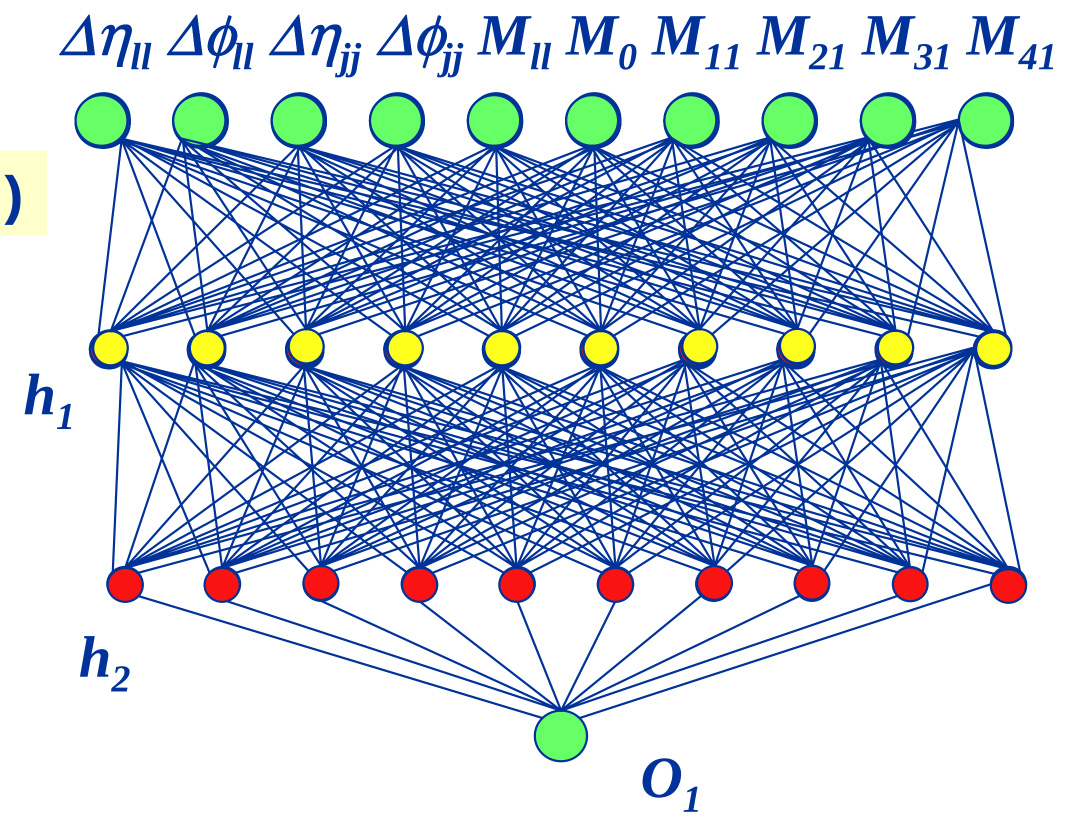
Neural Analysis

NN Architecture: (10, 10, 10, 1)

$$o_1 = \sum_i w_{i1}^{h2o} h_{2i}$$

$$h_{2i} = f\left(\sum_j w_{ji}^{h1h2} h_{1j} - \theta_i\right)$$

$$h_{1i} = f\left(\sum_j w_{ji}^{xh1} x_j - \theta_i\right)$$



Classification of test events

if $O_1(x) \geq 0.5$ then $x \in C_{Higgs}$ else $x \in C_{Back}$

Test Evts	Classification			
	Eff.	Pur.	Eff	ε
C_{Higgs}	0.654	0.663	0.661	0.338
C_{Back}	0.669	0.659		

Optimization of Neural Weights (2)

GA Parameters

- Connection Weights + thresholds

$W_{ij}^{xh1},\ \theta_i^{h1}$	$W_{ij}^{h1h2},\ \theta_i^{h2}$	W_{ij}^{h2o}	ε^I
100 +10	100 + 10	10	ε^I

- Total number of parameters to be optimized : 230
- Fitness: Misclassification rate, ε

Optimization Results

Number of generations =1000

CPU Time: 6 mn

Test Evts	Classification			
	Eff.	Pur.	Eff	ε
C_{Higgs}	0.691	0.696	0.695	0.305
C_{Back}	0.699	0.693		

Hyperplan search (1)

- $H(x) = \alpha_0 + \Sigma\, \alpha_i\, x_i = 0\,, \qquad i=1,\,10$

Hyperplan j

α_0^j	α_1^j	α_2^j	α_3^j	α_4^j	α_5^j	α_6^j	α_7^j	α_8^j	α_9^j	α_{10}^j	ε

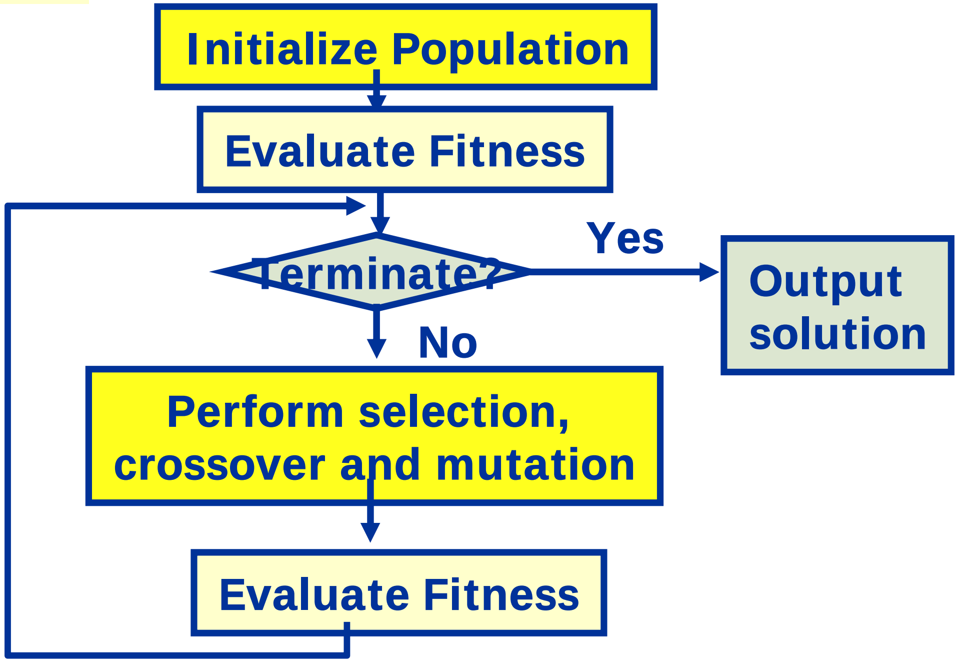
- **11 parameters to optimize**

Classification rule

$if\ H(x) \geq 0 \quad then\ \ x \in C_{Higgs} \quad else\ \ x \in C_{Back}$

Genetic Process

- Generation of N hyperplans H^j, j=1: N=20
- Number of generations =10000
- CPU Time: 4 mn



Hyperplan search (2)

- **Hyperplan search Results**

  - **Classification of test events**

Test Evts	Classification			
	Eff.	*Pur.*	*Eff*	ε
C_{Higgs}	0.661	0.655	0.656	0.344
C_{Back}	0.651	0.657		

  - **Same results than Discriminant functions optimization**

Test Events	Classification			
	Eff.	*Pur.*	*Eff*	ε
C_{Higgs}	0.652	0.649	0.65	0.35
C_{Back}	0.648	0.650		

Hypersurface search (1)

- $$S(x) = \alpha_0 + \sum_{i=1}^{10} \alpha_i\, x_i + \sum_{i=1}^{10} \beta_i\, x_i^{\,2} + \sum_{i=1}^{10} \gamma_i\, x_i^{\,3}$$

Hypersurface j

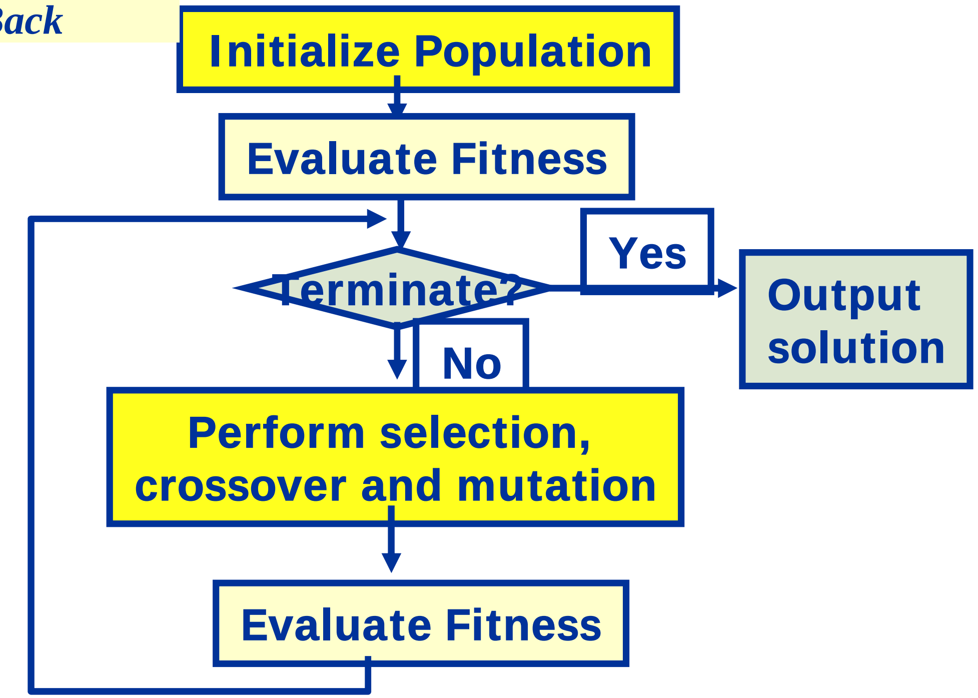
$\alpha_I^{\,j}$ $i=0{:}10$	$\beta_i^{\,j}$ $i=1{:}10$	$\gamma_i^{\,j}$ $i=1{:}10$	ε^j

- **31 parameters to optimize**

- **Classification rule**

$$if\ S(x) \geq 0\ \ then\ \ x \in C_{Higgs}\ \ else\ \ x \in C_{Back}$$

- **Genetic Process**
  - Generation of N hyperplans S^j, $j=1{:}\ N=20$
  - Number of generations =10000
  - CPU Time: 6 mn



Hypersurface search (2)

- **Hypersurface search Results**

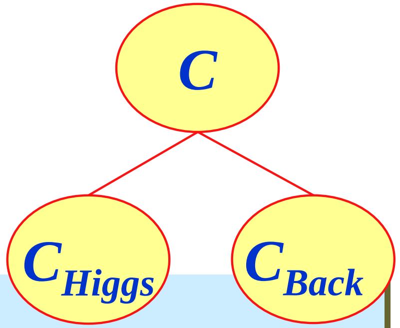
  - **Classification of test events**

Test Evts	Classification			
	Eff.	*Pur.*	*Eff*	*ε*
C_{Higgs}	0.689	0.696	0.691	0.309
C_{Back}	0.693	0.693		

  - **Same results as NN weights optimization**

Test Evts	Classification			
	Eff.	*Pur.*	*Eff*	*ε*
C_{Higgs}	0.691	0.696	0.695	0.305
C_{Back}	0.699	0.693		

Conclusion



Methods

- *Importance of Pattern Recognition Methods*
- *The improvement of an any identification is subjected to the multiplication of multidimensional effect offered by PR methods and the discriminating power of the proposed variables.*

- *Genetic Algorithms Method allows to minimize the classification error and to improve efficiencies and purities of classifications.*
- *The performances are in average 3 to 5 % higher than those obtained with other methods.*

- *Discriminant Functions Optimization : comparative to hyperplan search approach*
- *Neural Weights Optimization : comparative to hypersurface search approach*

Conclusion (continued)

- ***Variables***

Characterisation of Higgs Boson events: Other variables should be examined

- ***Physics Processes***

Other processes should be considered

Detector effects should be added to the simulated events