

Bioinformatics

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University of Vermont

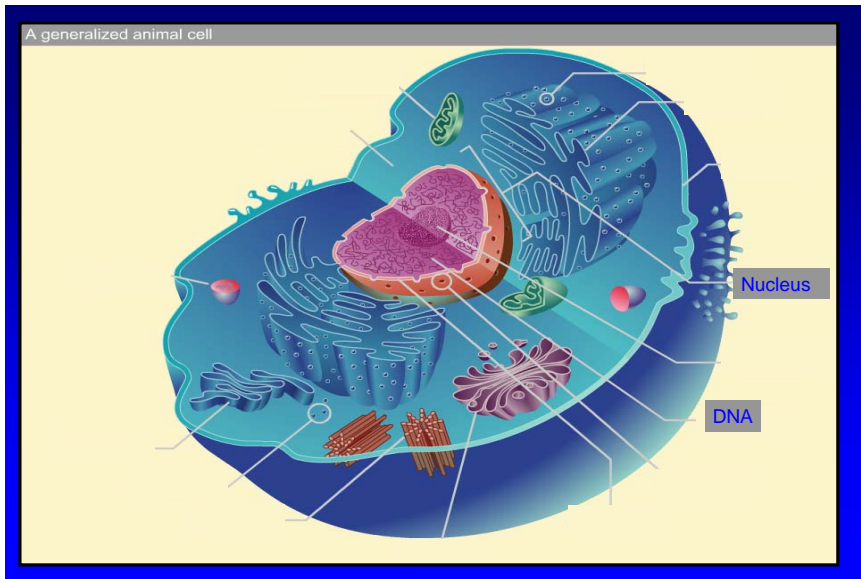
www.epistasis.org
jason.h.moore@dartmouth.edu

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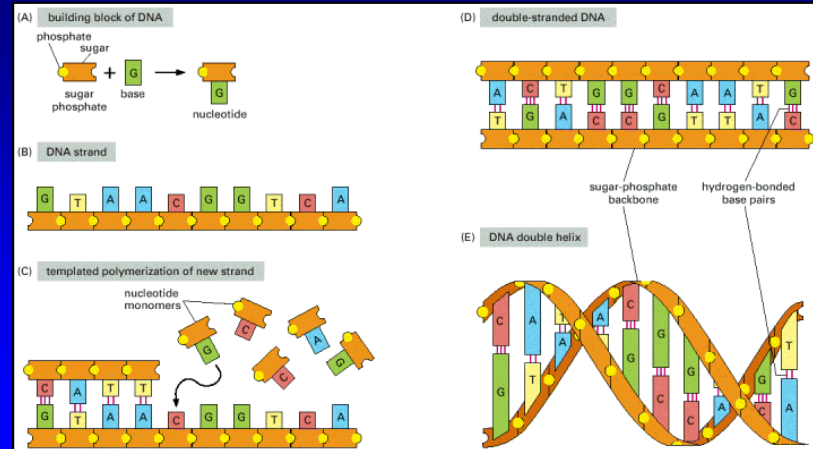
1

Genotype -> Phenotype

2



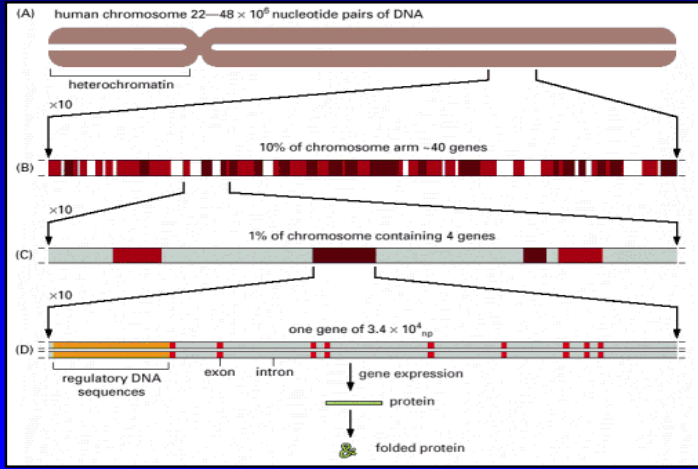
DNA



Alberts et al. 2002

4

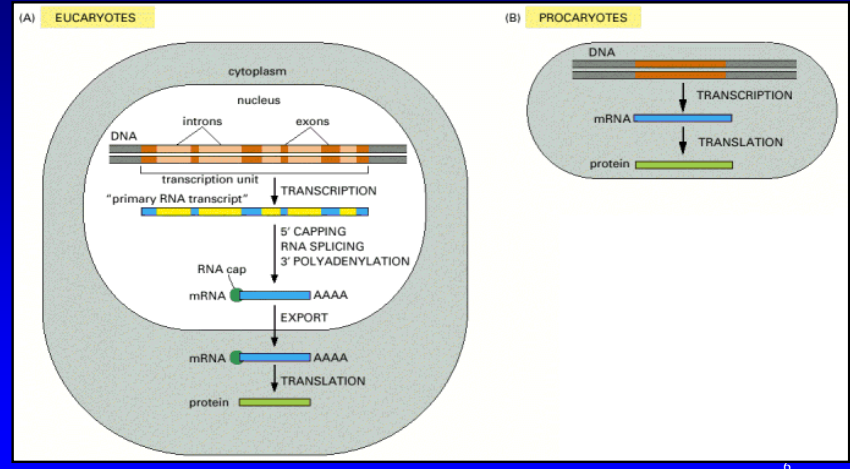
Chromosome Structure



Alberts et al. 2002

5

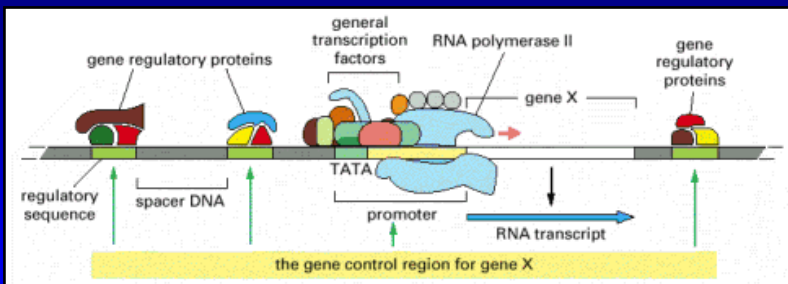
Transcription



Alberts et al. 2002

6

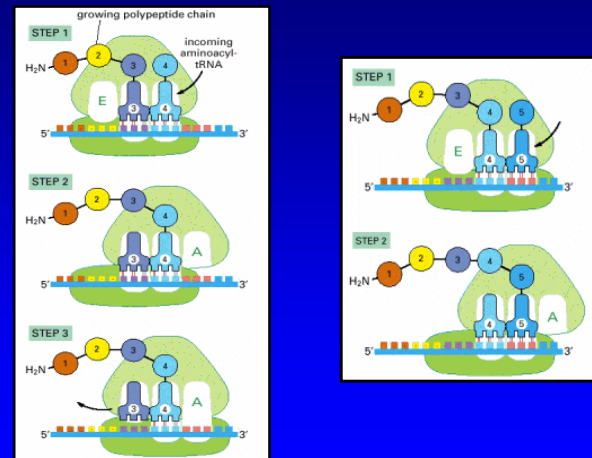
Regulation of Transcription



Alberts et al. 2002

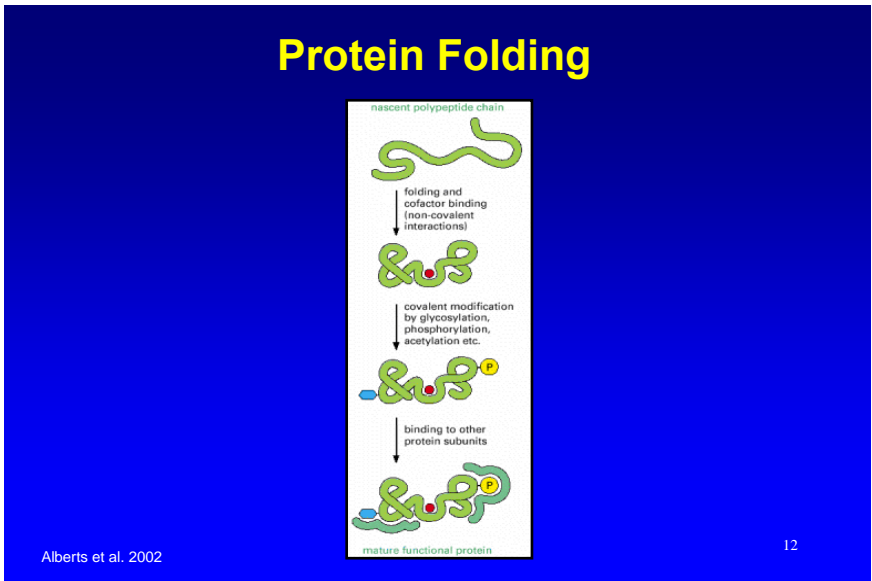
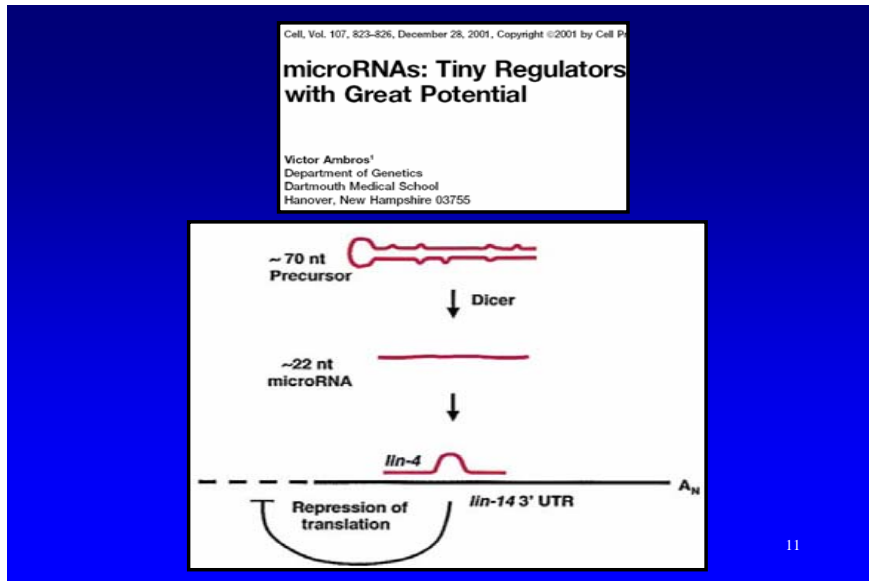
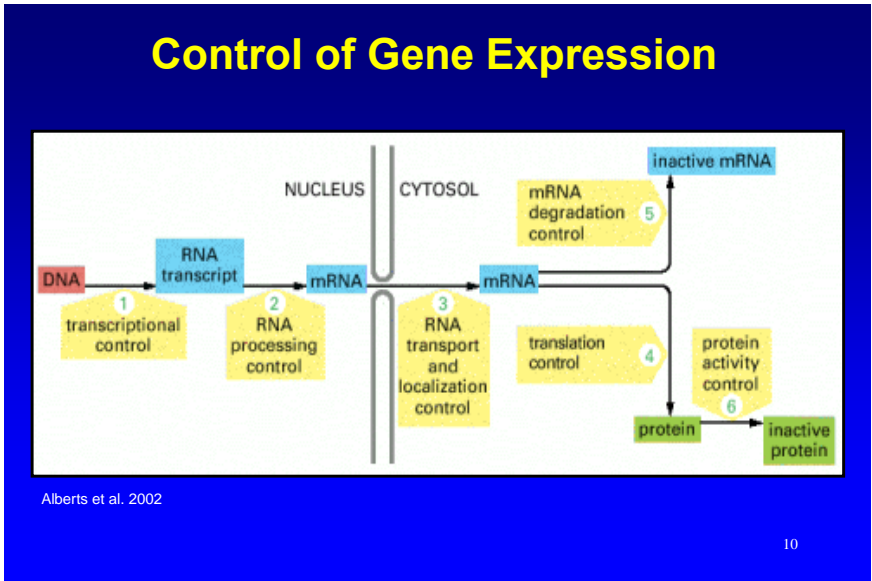
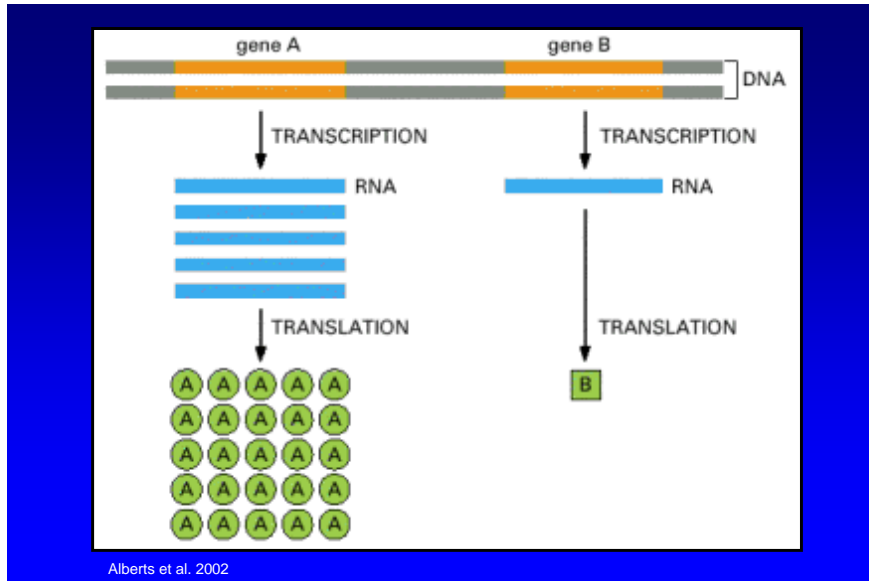
7

Translation



Alberts et al. 2002

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Amino Acids

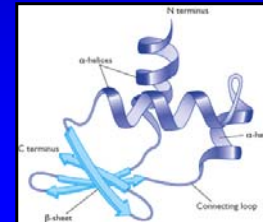
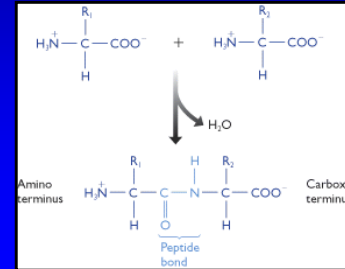
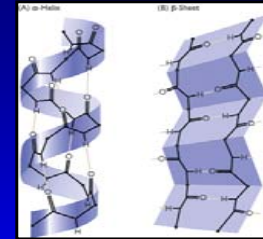
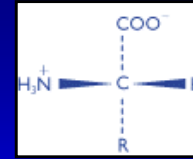
AMINO ACID			SIDE CHAIN			AMINO ACID			SIDE CHAIN		
Aspartic acid	Asp	D	negative	Alanine	Ala	A	nonpolar				
Glutamic acid	Glu	E	negative	Glycine	Gly	G	nonpolar				
Arginine	Arg	R	positive	Valine	Val	V	nonpolar				
Lysine	Lys	K	positive	Leucine	Leu	L	nonpolar				
Histidine	His	H	positive	Isoleucine	Ile	I	nonpolar				
Asparagine	Asn	N	uncharged polar	Proline	Pro	P	nonpolar				
Glutamine	Gln	Q	uncharged polar	Phenylalanine	Phe	F	nonpolar				
Serine	Ser	S	uncharged polar	Methionine	Met	M	nonpolar				
Threonine	Thr	T	uncharged polar	Tryptophan	Trp	W	nonpolar				
Tyrosine	Tyr	Y	uncharged polar	Cysteine	Cys	C	nonpolar				

POLAR AMINO ACIDS
NONPOLAR AMINO ACIDS

Alberts et al. 2002

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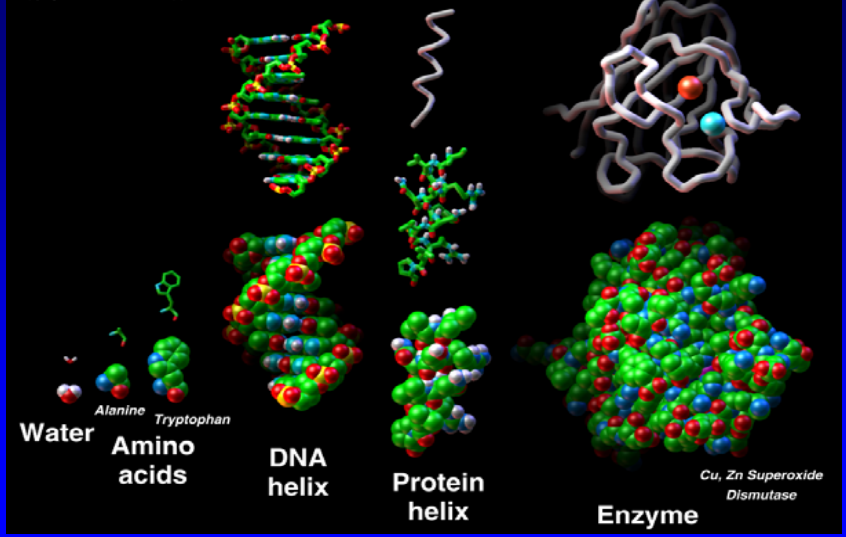
Amino Acids → Peptides → Proteins



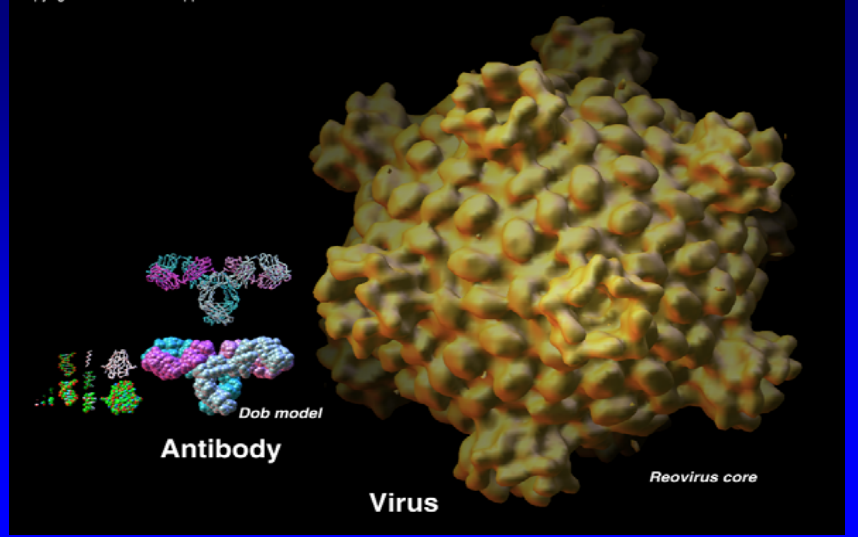
Brown 2002

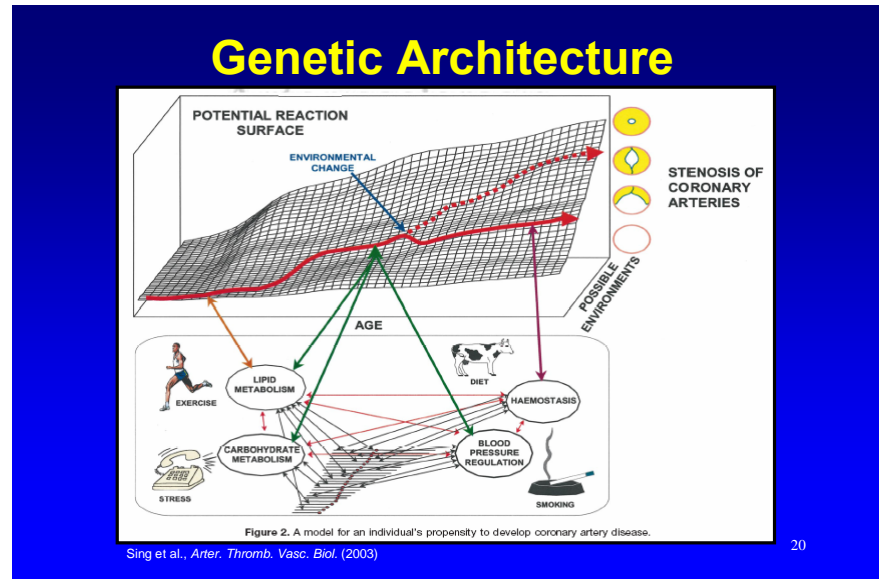
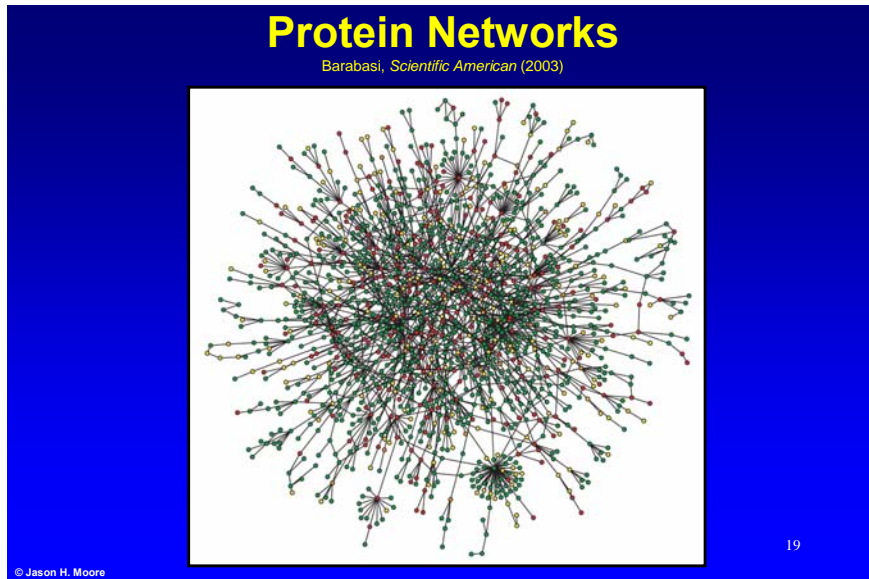
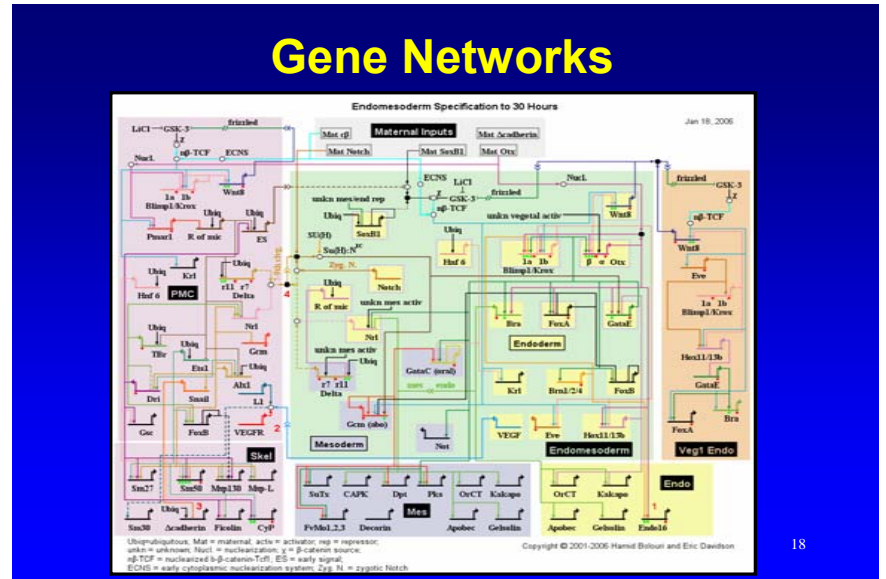
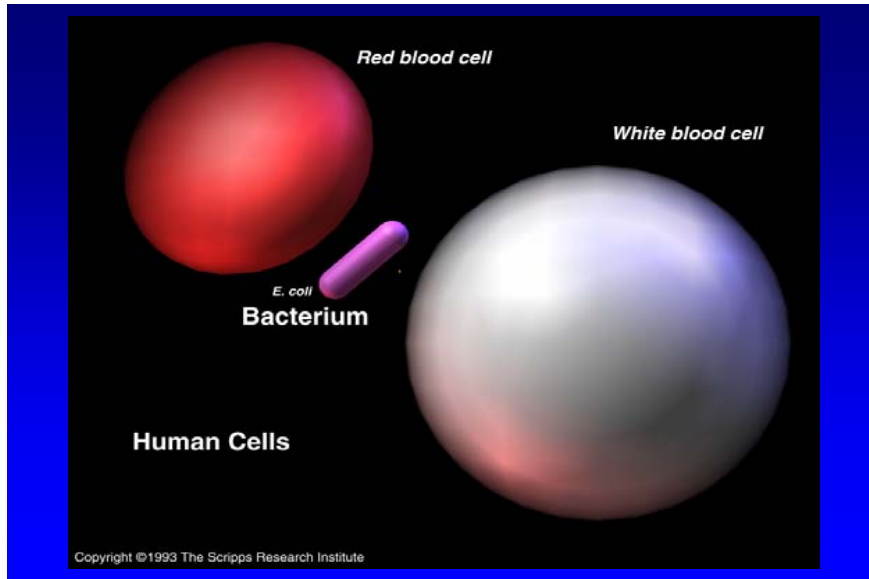
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The Tree of Life



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Molecular Phylogenetics

Multiple alignment

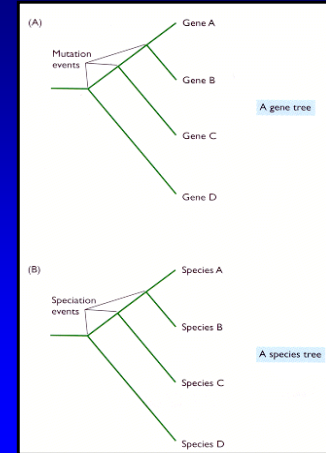
```

1 AGGCCAAGCCATAGCTGTCC
2 AGGCAAAGACATACCTGACC
3 AGGCCAAGACATAGCTGTCC
4 AGGCAAAGACATACCTGTCC
    
```

Distance matrix

	1	2	3	4
1	-	0.20	0.05	0.15
2		-	0.15	0.05
3			-	0.10
4				-

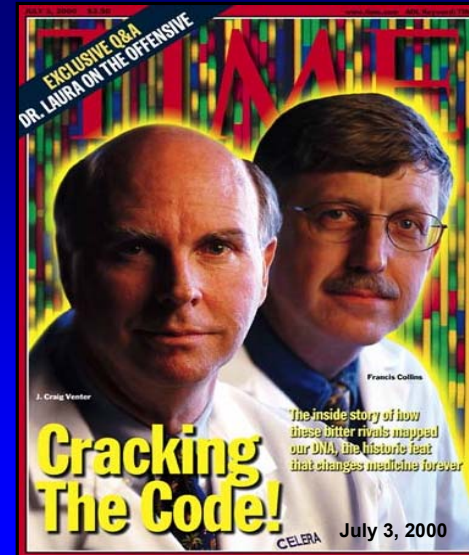
Brown 2002



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Measuring DNA

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OPINION NATURE REVIEWS | GENETICS
VOLUME 6 | APRIL 2005 | 333

The Human Genome Diversity Project: past, present and future

L. Luca Cavalli-Sforza

Africans	Europeans	Western Asians	Eastern Asians	Oceania
1) Bantu	8) Occitan	16) Baluch	28) Han (S. China)	46) Malesian
2) Mandinka	9) Adygei	17) Druze	29) Han (N. China)	47) Papuan
3) Yoruba	10) Russian	18) Palestinian	30) Dai	
4) San	11) Basque	31) Daur	31) Daur	
5) Mbuti pygmy	12) French	32) Hazlan	32) Hazlan	
6) Siaka	13) North Italian	33) Lahu	33) Lahu	
7) Mozabite	14) Sardinian	34) Miao	34) Miao	
	15) Tuscan	35) Orong	35) Orong	
		36) She	36) She	
		37) Tuja	37) Tuja	
		38) Tu	38) Tu	
		39) Xibo	39) Xibo	
		40) Yi	40) Yi	
		41) Mongola	41) Mongola	
		42) Miao	42) Miao	
		43) Cambodian	43) Cambodian	
		44) Japanese	44) Japanese	
		45) Yabut	45) Yabut	
				48) Karitiana
				49) Surui
				50) Colombian
				51) Maya
				52) Pima

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Transposon Repeat Polymorphism

Sequence variation in the human angiotensin converting enzyme

nature genetics • volume 22 • may 1999

Mark J. Rieder¹, Scott L. Taylor¹, Andrew G. Clark² & Deborah A. Nickerson¹

```

1 ggctggcgt ggtggctcaa gctgtaate ccagcactt ggagagctga ggtgggcga
61 tcgcttgagc ccaggagttc aagcaccgac tggcaaacat ggcacaaact cgtctctaca
121 aaaaaaaaa agctggctt ggtggctgct gcaactacag tccagctac tcttgaact
181 ggggggagag gaccacctga gccagagag tcaagctac agtgagctgt gactgcacta
241 ctcccccaca gctgcttga cagagtgaga cttccccca aaaaaaag agagagaaa
    
```

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SNPs

Single Nucleotide Polymorphisms

Subject #1	Subject #2	Subject #3
-- AG G TCA --	-- AG G TCA --	-- AG C TCA --
-- AG G TCA --	-- AG G TCA --	-- AG C TCA --

Two *alleles* (G and C)

Three *genotypes* (GG, GC, CC)

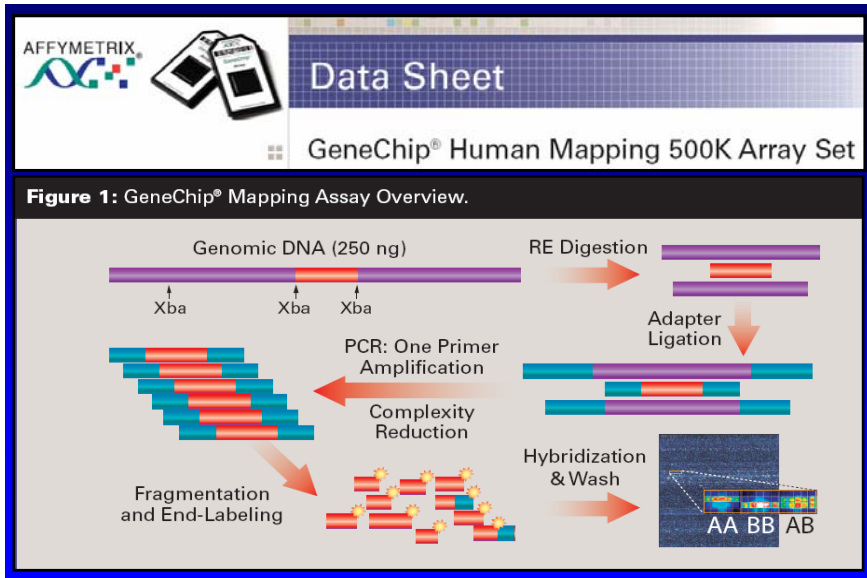
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SNPs

Single Nucleotide Polymorphisms

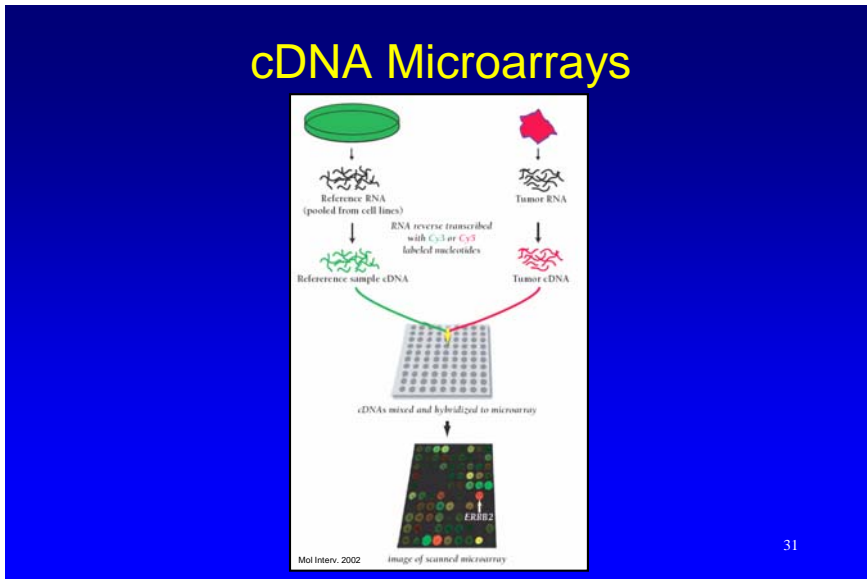
- ~ 1 SNP every 100 bp
- ~ 30 million SNPs
- ~500,000 SNPs in coding DNA
 - Synonymous (silent)
 - Nonsynonymous
 - Deleterious effect
 - Beneficial effect
 - No effect

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Measuring RNA

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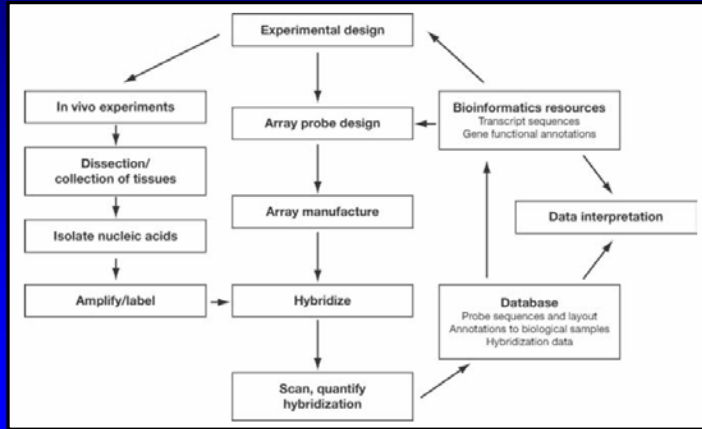
Ann. Rev. Biochem. 2005, 74:53-82
 doi: 10.1146/annurev-biochem.74.082803.133212
 Copyright © 2005 by Annual Reviews. All rights reserved
 First published online as a Review in Advance on January 13, 2005

APPLICATIONS OF DNA MICROARRAYS IN BIOLOGY

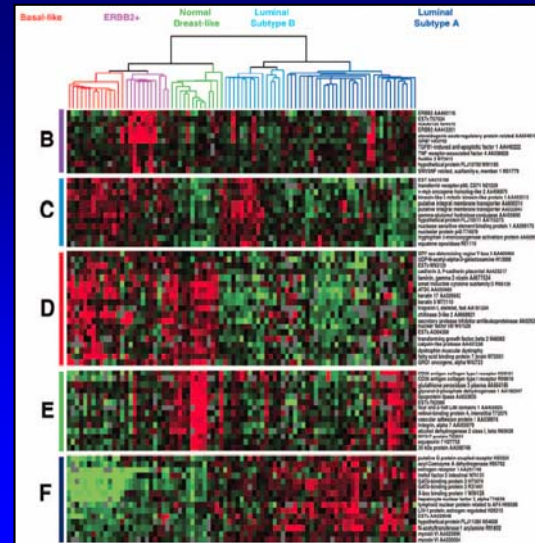
Roland B. Stoughton
 GHC Technologies, Incorporated, La Jolla, California 92037;
 email: roland_stoughton@ghctechnologies.com

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Process Flow for Microarrays



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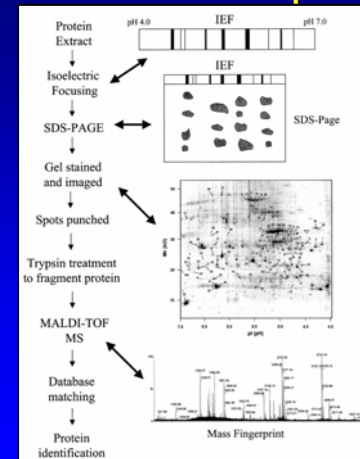


Mol Interv. 3002

Measuring Proteins

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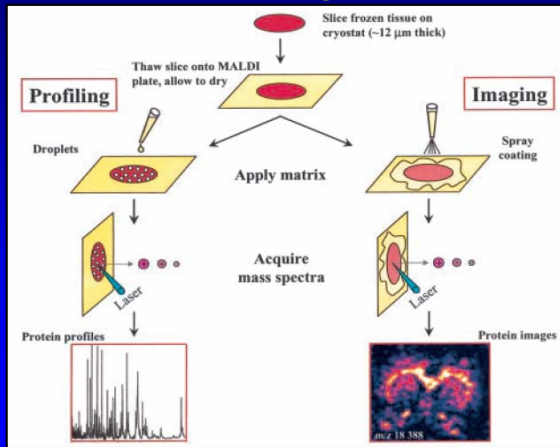
2D Gels and Mass Spectrometry



Metabolic Engineering 4, 98-106 (2002)

36

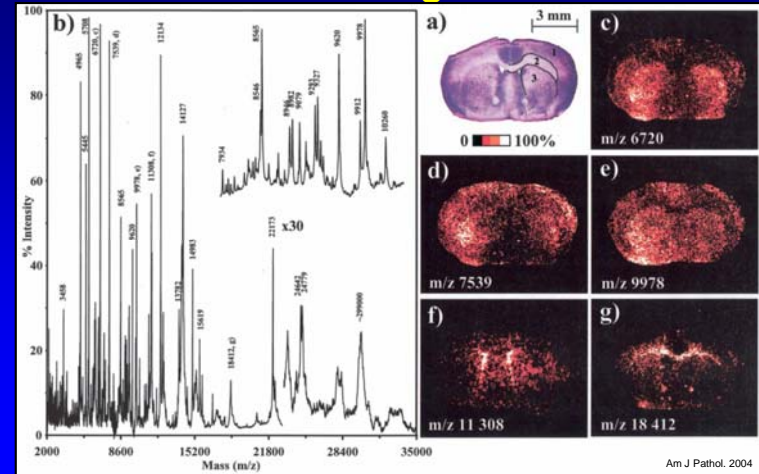
Protein Profiling in Tissues



Am J Pathol. 2004

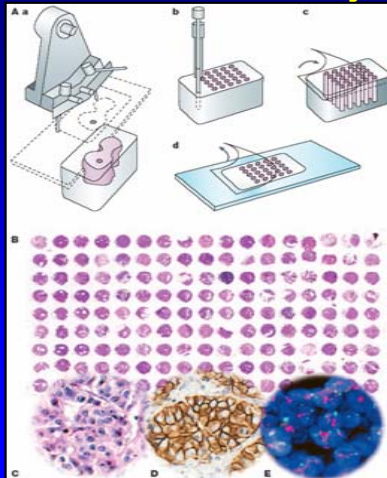
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Protein Profiling in Tissues



Am J Pathol. 2004

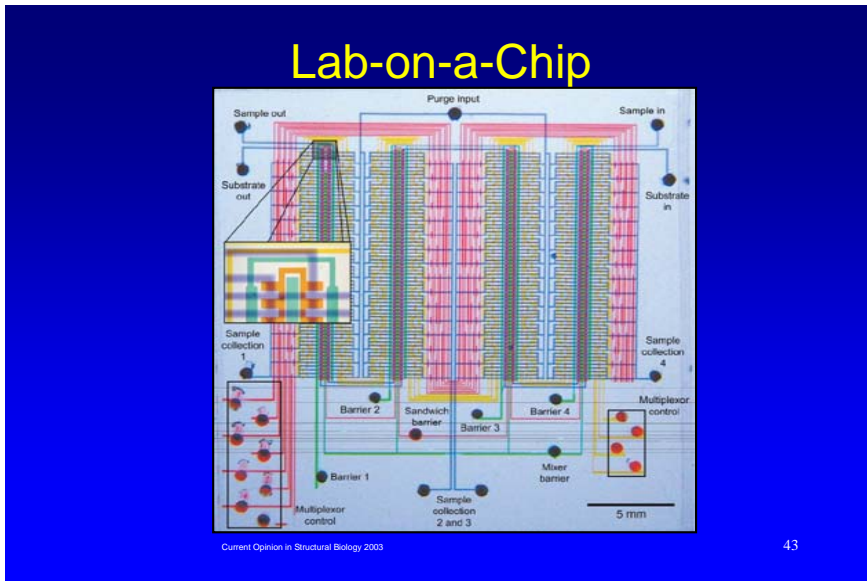
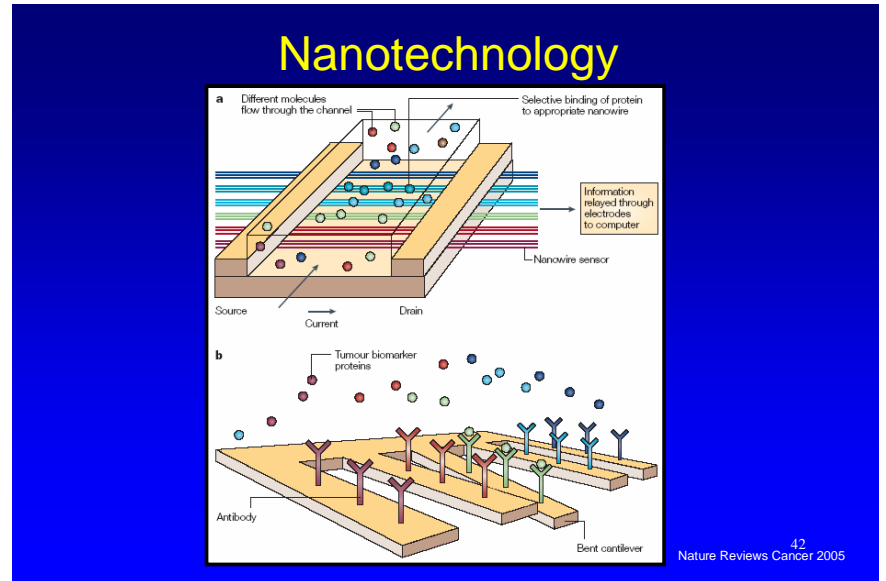
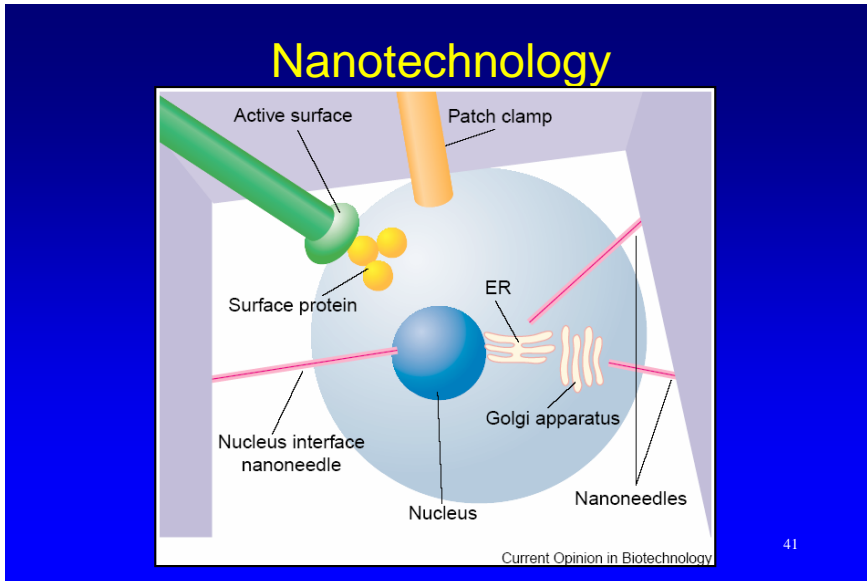
Tissue Microarrays



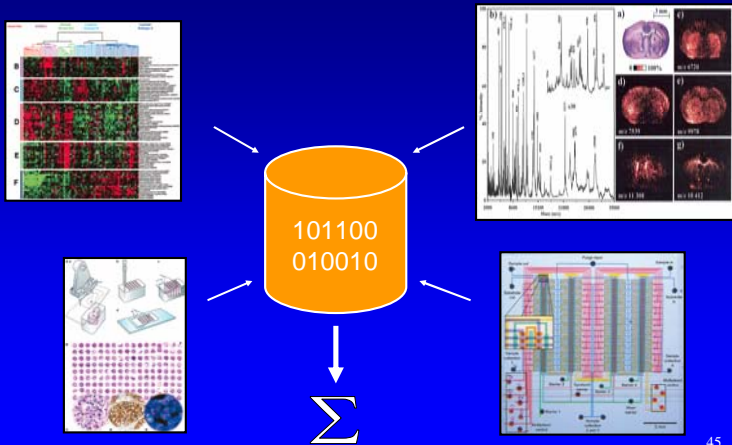
Nat Rev Drug Discov. 2003 39

Emerging Technologies

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Bioinformatics: Databases



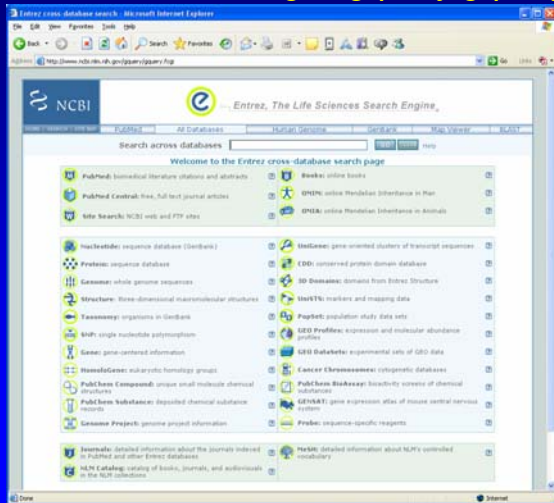
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<http://www.ncbi.nlm.nih.gov>



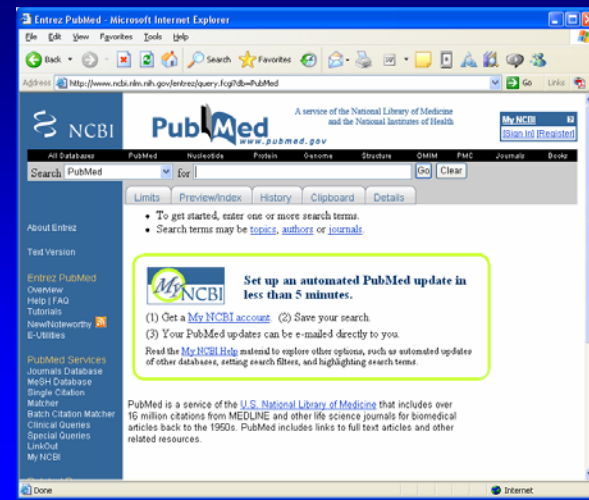
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<http://www.ncbi.nlm.nih.gov/gquery/gquery.fcgi>



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<http://www.ncbi.nlm.nih.gov/entrez/query.fcgi?db=PubMed>



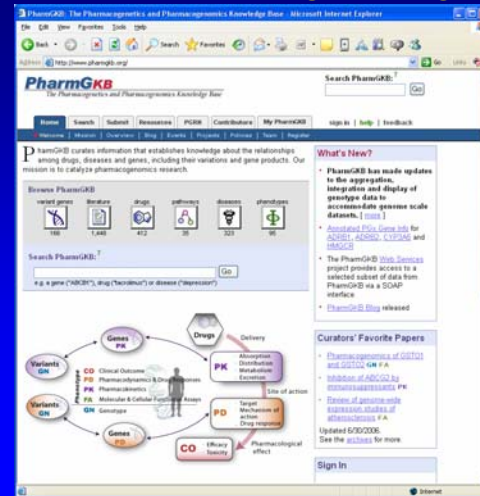
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<http://www.ncbi.nlm.nih.gov/geo/>



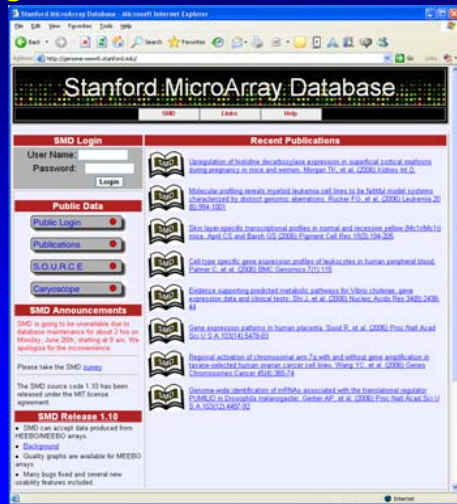
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www.pharmgkb.org



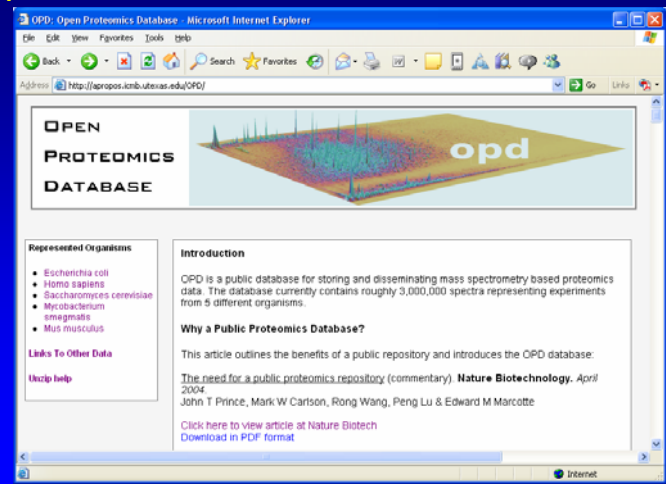
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<http://genome-www5.stanford.edu/>



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<http://bioinformatics.icmb.utexas.edu/OPD/>



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Analysis

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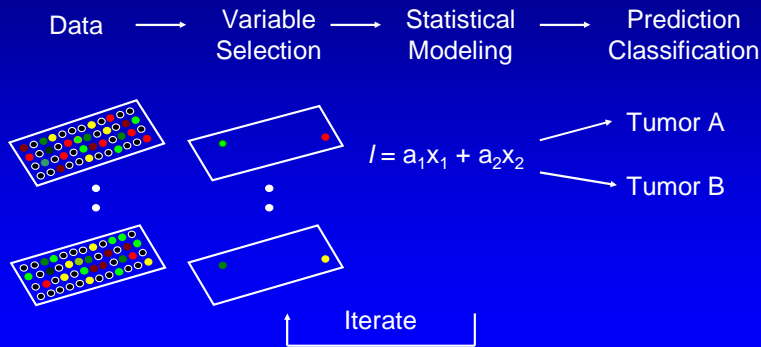
Mining Biomolecular Patterns

- Can we classify and/or predict biological and clinical endpoints using genetic, genomic, and/or proteomic data?
- Which biomolecules are important?
- What is their pattern or statistical relationship?

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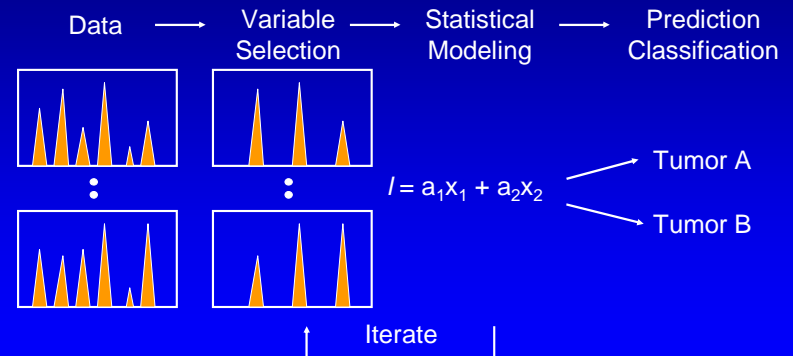
Objectives



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Objectives



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Hypothesis Testing

"The truth is out there"

		Truth	
		H_0 False	H_0 True
Decision	Reject H_0	Yes! Type I Error	Type I Error
	Accept H_0	Type II Error	Yes! Type II Error

Type I error
Type II error
Type III error

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Cross-Validation (CV)

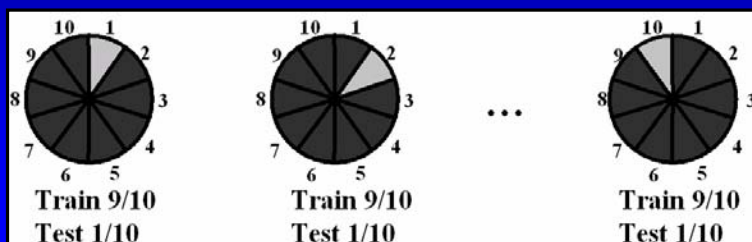
- Data-driven methods susceptible to overfitting
- Biological datasets often have more variables than observations (i.e. wide data)
- The value of any statistical model is its ability to make predictions in new data
- Cross-validation (CV) allows generalizability to be estimated in a single dataset

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Cross-Validation (CV)

- CV uses independent portions of the data to estimate the testing accuracy



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Cross-Validation (CV)

Hastie et al. *The Elements of Statistical Learning* (2001)
Ripley BD. *Pattern Recognition and Neural Networks* (1996)

- Leave One Out Cross Validation (LOOCV)
 - Better for small datasets
 - Unbiased estimate of prediction error
 - High variance due to similarity of training sets
- n -fold CV (e.g. 5-fold or 10-fold CV)
 - Better for larger datasets
 - Estimate of prediction error may be biased
 - Lower variance
 - May need to repeat several times and average results

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Cross-Validation Consistency (CVC)

Ritchie et al., *American Journal of Human Genetics* 69:138-147 (2001)

Moore et al., *Genetic Epidemiology* 23:57-69 (2002)

Moore, *Lecture Notes in Computer Science* 2611, Springer-Verlag, Berlin (2003).

- CV can be difficult with data-driven methods
- Can find different models with each CV dataset
- CVC is a measure of how consistently particular variables or combination of variables are identified in each CV interval.
- CVC can be used as a measure of association
- Once important variables are found, a model can be fit to the entire dataset using just those variables.

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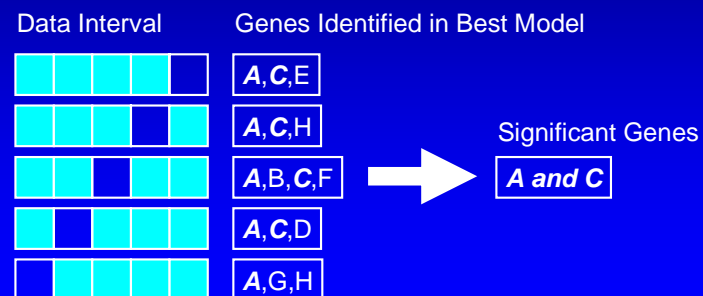
Cross-Validation Consistency (CVC)

Ritchie et al., *American Journal of Human Genetics* 69:138-147 (2001)

Moore et al., *Genetic Epidemiology* 23:57-69 (2002)

Moore, *Lecture Notes in Computer Science* 2611, Springer-Verlag, Berlin (2003).

CVC Example with 5-fold CV

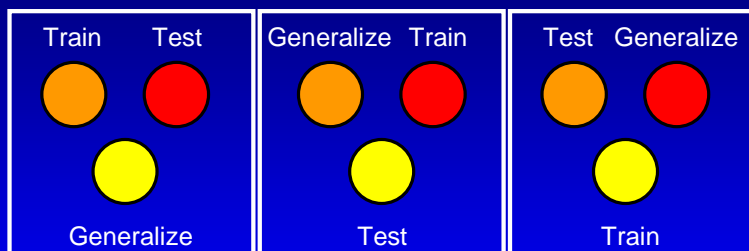


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Generalizability: The Three-Way Data Split

Rowland, *Lecture Notes in Computer Science* 2611, Springer-Verlag, Berlin (2003).



1. Choose model that $\min[\text{abs}(E_{\text{train}} - E_{\text{test}})]$
2. Evaluate generalizability of the final model
3. The model with the best prediction error may not generalize the best.

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Permutation Testing

P. Good, *Permutation Tests: A Practical Guide to Resampling Methods for Testing Hypotheses* (2000)

- Many data-driven methods are nonparametric and model-free.
- Permutation testing can be used to assess statistical significance to allow formal hypothesis testing.
- Basic Idea: Randomize data so it is consistent with null hypothesis.

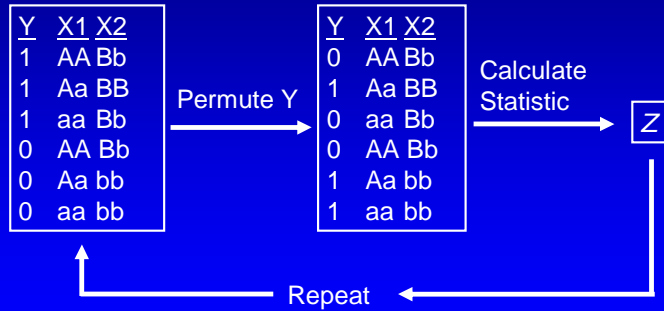
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Permutation Testing

P. Good, *Permutation Tests: A Practical Guide to Resampling Methods for Testing Hypotheses* (2000)

Example



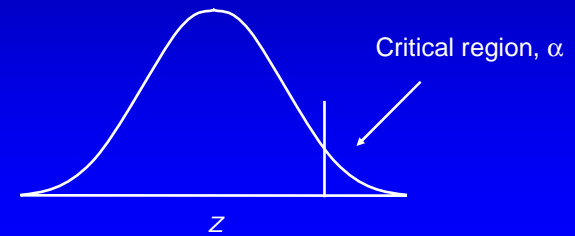
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Permutation Testing

P. Good, *Permutation Tests: A Practical Guide to Resampling Methods for Testing Hypotheses* (2000)

Distribution of Statistic under the Null Hypothesis from Many Permutations



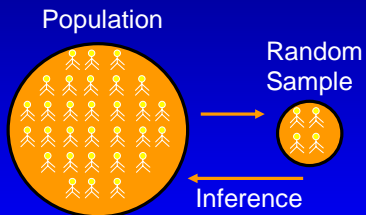
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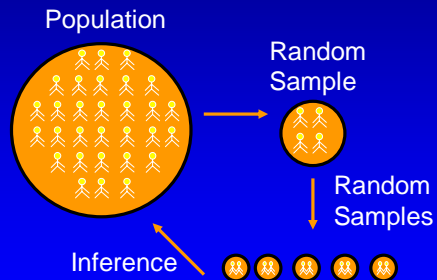
Bootstrapping

B. Efron, *Annals of Statistics* 7:1-26 (1979)
 AC Davidson and DV Hinkley, *Bootstrap Methods and their Application* (1997)
 CE Lunneborg, *Data Analysis by Resampling: Concepts and Applications* (2000)

Distribution Known



Distribution Unknown



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Genetic Programming

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Is GP an appropriate
computational tool for solving
complex biological problems??

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Vanilla GP - NO!



70

Modern GP - YES!



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Case Study:
Symbolic Modeling

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Genetic Architecture

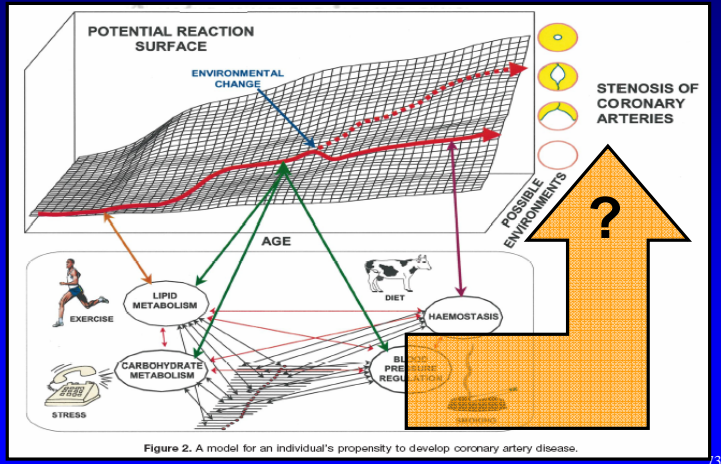


Figure 2. A model for an individual's propensity to develop coronary artery disease.

Sing et al., *Arter. Thromb. Vasc. Biol.* (2003)

Genetic Analysis of Atrial Fibrillation

Tsai et al., *Circulation* (2004)
Moore et al., *Journal of Theoretical Biology* (2006)

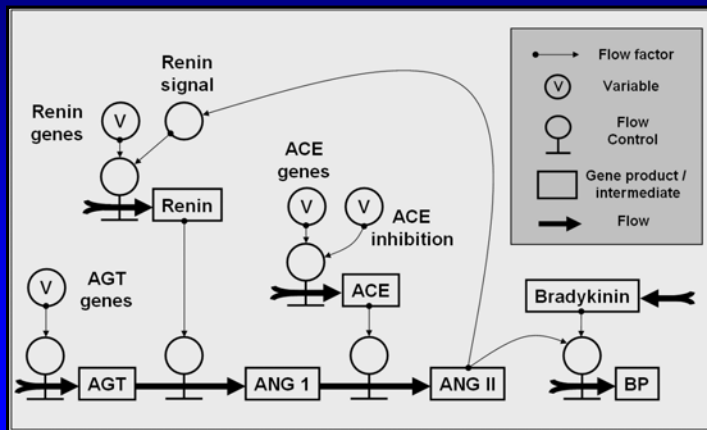
- 250 consecutive patients admitted with AF from Taipei, Taiwan
- 250 age and gender matched controls
- 3 candidate genes
 - *Angiotensin converting enzyme (ACE)* gene
 - I/D polymorphism
 - *Angiotensinogen (AGT)*
 - T174M, M235T, G-6A, A-20C, G-152A, and G-217A polymorphisms
 - *Angiotensin II type I receptor (AT-1)*
 - A1166C polymorphism

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Renin-Angiotensin System

Tsai et al., *Circulation* (2004)
Moore et al., *Journal of Theoretical Biology* (2006)

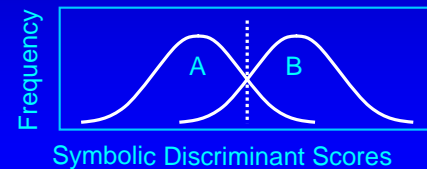
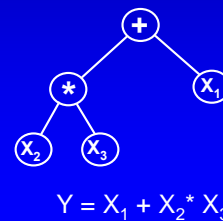


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Symbolic Discriminant Analysis

Moore et al., In: De Raedt, L., Flach, P. (eds) *Lecture Notes in Artificial Intelligence* 2167 (2001)
Moore et al., *Genetic Epidemiology* 23, 57-69 (2002)
Moore, *Lecture Notes in Computer Science* 2611, Springer-Verlag, Berlin (2003)

- Supervised classification approach
- Can use GP to build discriminant functions
- Accuracy is fitness function



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SDA Modeling using Modern GP

Moore et al., *Human Heredity* (2007)

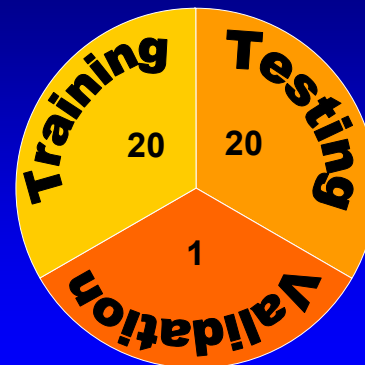
- Parameter Sweeps
 - STEP 1: Full factorial experimental design
 - STEP 2: ANOVA
- Coarse-Grained Search
 - STEP 3: 10^5 SDA runs
- Expert Knowledge
 - STEP 4: Statistical model of 100 best trees
- Fine-Grained Knowledge-Based Search
 - STEP 5: 10^9 SDA runs using EDA
- Model Interpretation
 - STEP 6: Function mapping
 - STEP 7: Interaction dendrogram

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Cross-Validation Strategy

Moore et al., *Human Heredity*, (2007)



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Parameter Sweep

Moore et al., *Human Heredity*, (2007)

- STEP 1: Full factorial experimental design
 - Population Size (P): {100, 500, 1000}
 - Generations (G): {100, 500, 1000}
 - Tree Depth (T): {1, 2, 3}
 - Function Set (F):
 - 1: {+, -, *, /}
 - 2: {<, >, <=, >=, =, !=, max, min}
 - 3: 12
 - 4: {AND, OR, NOT, NOR, XOR}
 - 5: 14
 - 6: 24
 - 7: 124
 - $3 \times 3 \times 3 \times 7 = 189$ level combinations
 - 189 levels * 10 random seeds = 1890 SDA runs

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Parameter Sweep

Moore et al., *Human Heredity*, (2007)

- STEP 2: 4-Way Analysis of Variance (ANOVA)

Treatment	DF	F	P-Value
Depth	2	715.6	<0.001
Function	6	1028.2	<0.001
Generations	2	1.8	0.161
Population	2	10.7	<0.001
D*F*P	24	2.4	0.001

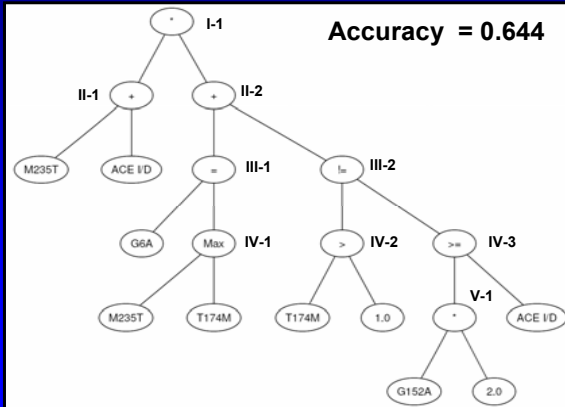
80

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Fine-Grained Search

Moore et al., *Human Heredity*, (2007)

- STEP 5: 10^9 SDA runs using an EDA



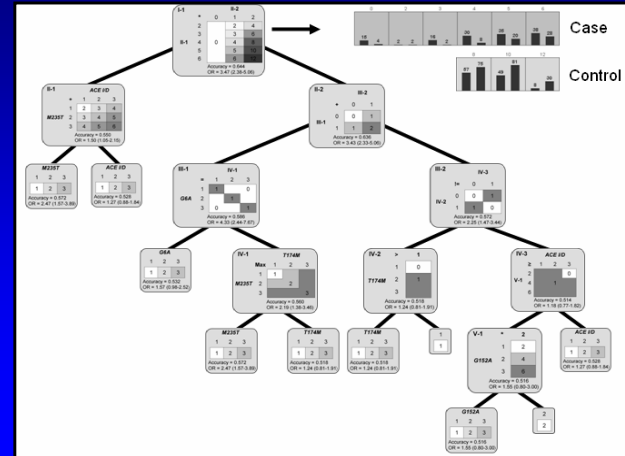
85

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Interpretation

Moore et al., *Human Heredity*, (2007)

- STEP 6: Function Mapping



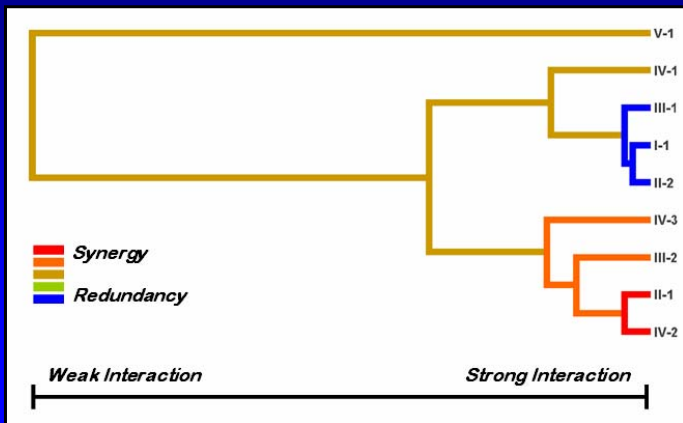
86

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Interpretation

Moore et al., *Human Heredity*, (2007)
Moore et al., *Journal of Theoretical Biology* (2006)

- STEP 6: Interaction Dendrogram

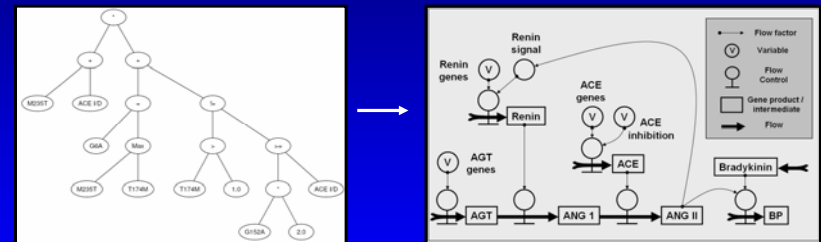


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Interpretation

Moore et al., *Human Heredity*, (2007)



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Interpretation

Moore, *Nature Genetics* (2005)
Moore and Williams, *BioEssays* (2005)

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Modern GP - YES!

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Additional Examples

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- Moore, J.H. Genome-wide analysis of epistasis using multifactor dimensionality reduction: feature selection and construction in the domain of human genetics. In: Knowledge Discovery and Data Mining: Challenges and Realities with Real World Data, IGI, in press (2006).

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