

In Vitro Molecular Evolution

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Natural Computation

- Neural Computation
 - ◆ A network of neurons
- Evolutionary Computation
 - ◆ A population of chromosomes
- Molecular Computation
 - ◆ A test tube of molecules
- Molecular Evolutionary Computation ← This tutorial
 - ◆ A test tube of “evolving” molecules
 - ◆ “In vitro molecular evolution”

Scope of This Tutorial

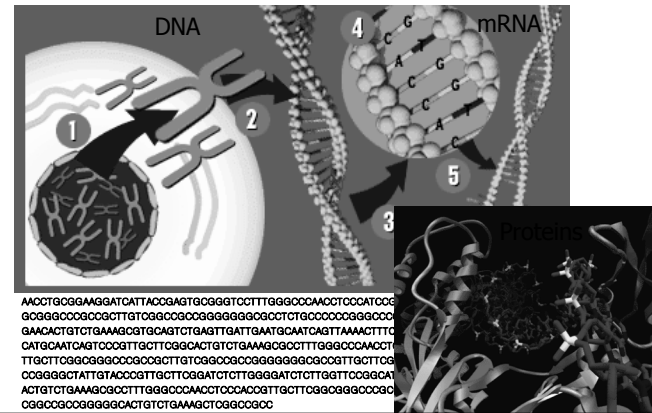
- What is “in vitro evolution”?
- How do we exploit this as EC technology, i.e. for molecular evolutionary computation (MEC)?
- What new opportunities this offers to EC researchers?
 - ◆ In theory and in applications
 - ◆ In science and in technology
- What challenges the new applications face?
- Where can I find more materials?

Overview

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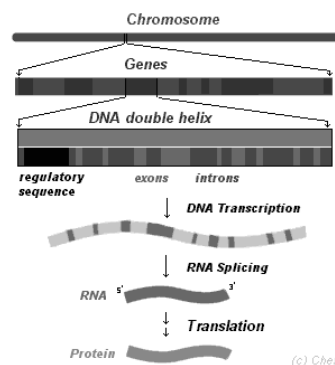
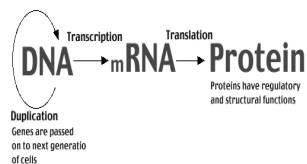
Molecular Computation (without Evolution)

Biomolecular Information Processing

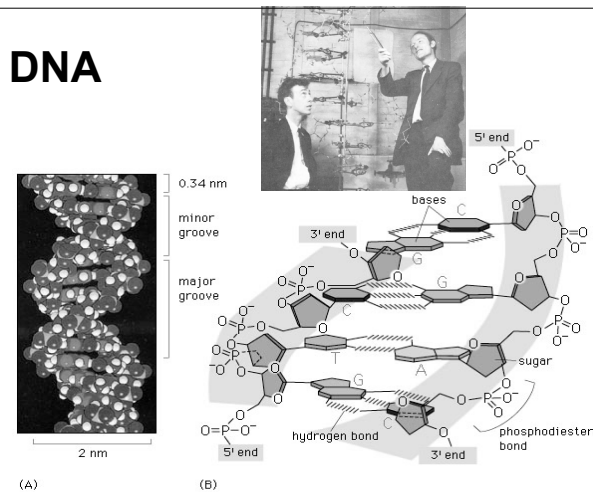


Chromosomes, Genes, DNA, RNA, Pr oteins, and the Central Dogma

Central Dogma



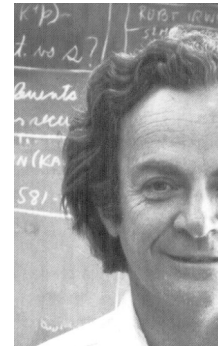
DNA



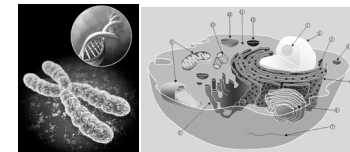
Molecular Computing: A Brief History

- Feynman (1959)
 - ♦ Potential of molecules
- Benett (1982)
 - ♦ DNA and thermodynamic computation
- Seeman (1991)
 - ♦ Self-assembly of a DNA cube
- Conrad (1992)
 - ♦ Lock-and-key paradigm for molecular computing
- Adleman (1994)
 - ♦ Experimental demonstration of DNA computing

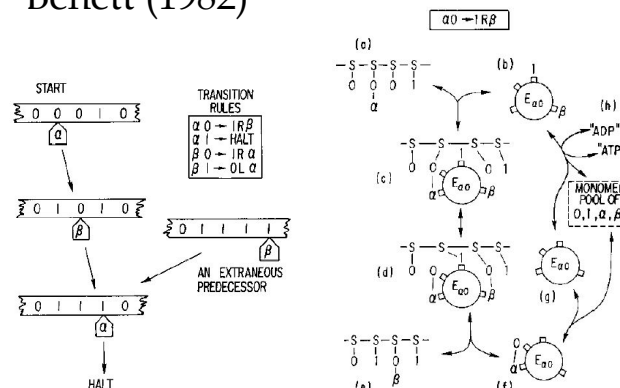
Feynman (1959)



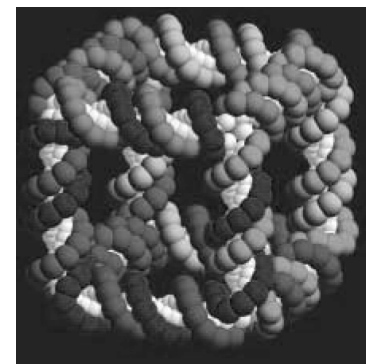
- “There’s Plenty of Room at the Bottom”
 - Biological molecules can carry enormous amounts of information in an exceedingly small space.
- Inborn computing power!

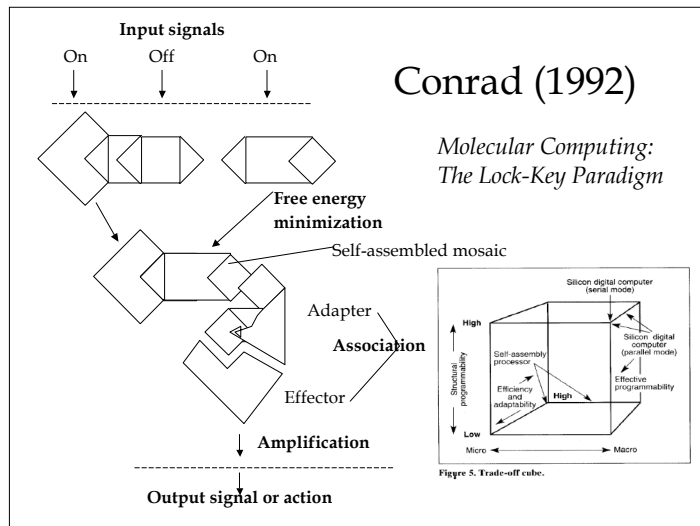


Benett (1982)



Seeman (1991)





Adleman (1994)

FOR HIS DNA COMPUTATION, ADLEMAN CHOSE THIS SIMPLE ARRANGEMENT OF 7 CITIES AND 13 STREETS.

Discover magazine published an article in comic strip format about Leonard Adleman's discovery of DNA computation. Not only entertaining, but also the most understandable explanation of molecular computation I have ever seen.

An Example Problem Illustrated

Hamiltonian Path Problem

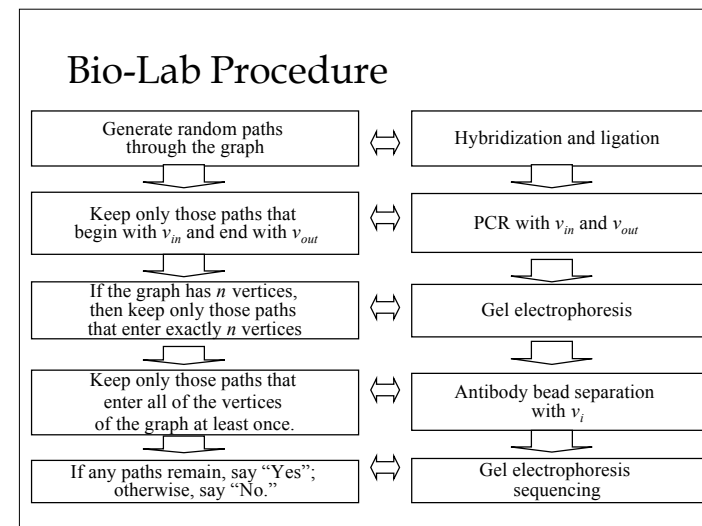
Consider a map of cities connected by certain nonstop flights (top right). For instance, in the example shown here, it is possible to travel directly from Boston to Detroit but not vice versa. The goal is to determine whether a path exists that will commence at the start city (Atlanta), finish at the end city (Detroit) and pass through each of the remaining cities exactly once. In DNA computation, each city is assigned a DNA sequence (ACTTGCAG for Atlanta) that can be thought of as a first name (ACTT) followed by a last name (GCAG). DNA flight numbers can then be defined by concatenating the last name of the city of origin with the first name of the city of destination (bottom right).

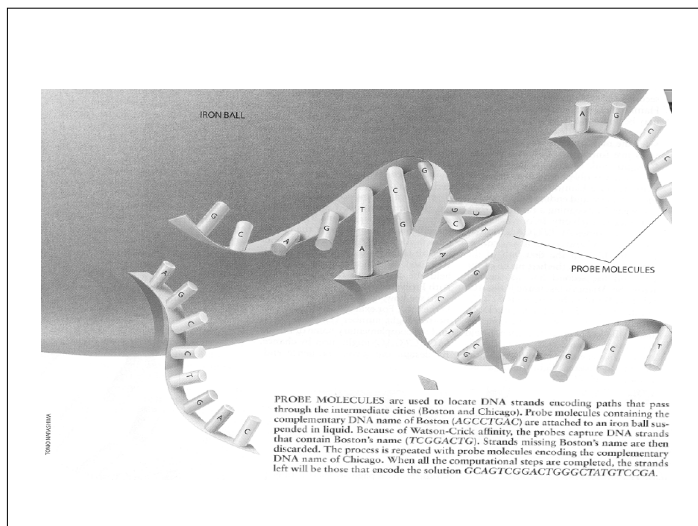
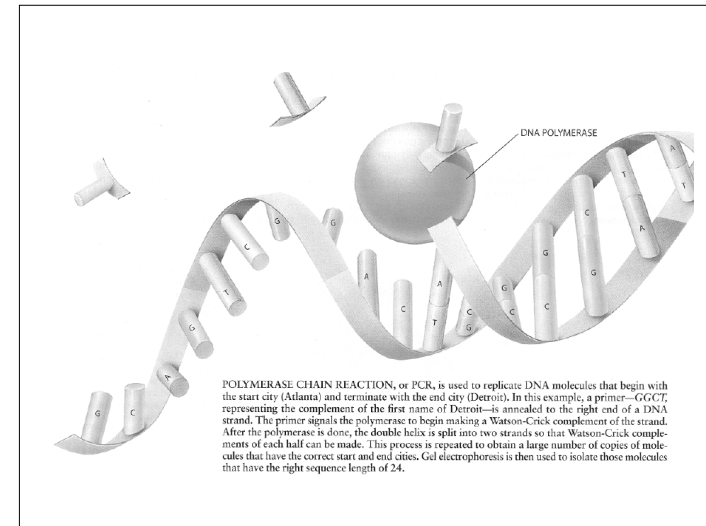
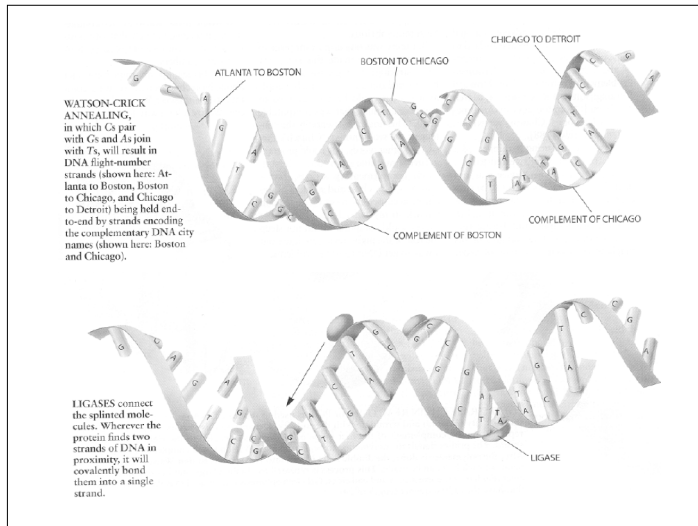
The complementary DNA city names are the Watson-Crick complements of the DNA city names in which every C is replaced by a G, every G by a C, every A by a T, and every T by an A. (To simplify the discussion here, details of the 3' versus 5' ends of the DNA molecules have been omitted.) For this particular problem, only one Hamiltonian path exists, and it passes through Atlanta, Boston, Chicago and Detroit in that order. In the computation, this path is represented by GCAGTCGGACTTGGCTATGTCGGA, a DNA sequence of length 24. Shown at the left is the map with seven cities and 14 nonstop flights used in the actual experiment. —L.A.A.

CITY	DNA NAME	COMPLEMENT
ATLANTA	ACTTGCAG	TGAACGTC
BOSTON	TCGGACTG	AGCCTGAC
CHICAGO	CGCTATGT	CCGATACA
DETROIT	CCGAGCAA	GGCTCGTT

FLIGHT	DNA FLIGHT NUMBER
ATLANTA - BOSTON	GCAGTCGG
ATLANTA - DETROIT	GCAGCCGA
BOSTON - CHICAGO	ACTGGGCT
BOSTON - DETROIT	ACTGCCGA
BOSTON - ATLANTA	ACTGACTT
CHICAGO - DETROIT	ATGTCGCA

[Adleman, *Scientific American* 1998]





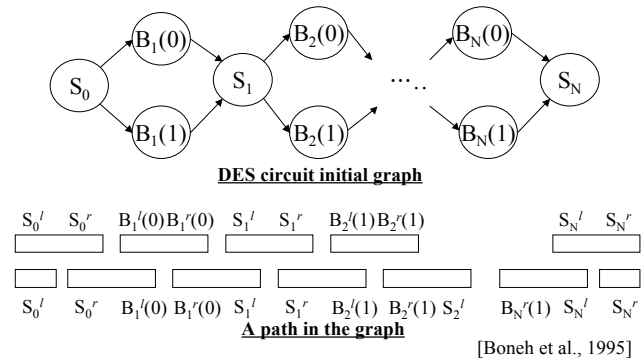
Basic Ideas in DNA Computing

- Exhaustive search
- Parallelism
- Density
- Miniaturization
- Energy efficiency

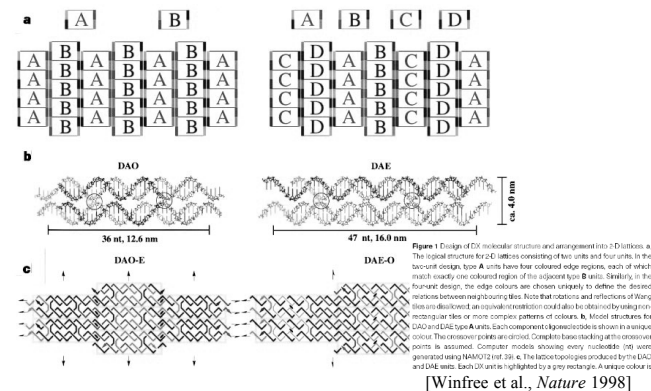
Recent Applications

- Computational
 - ◆ Cryptography (Boneh et al., 1995)
 - ◆ Chess (Landweber et al., *PNAS* 2000)
 - ◆ 20-var 3-SAT (Adleman, *Science* 2002)
 - ◆ Tic-Tac-Toe (Stojanovic, *Nature Biotech* 2004)
- Biology and Medicine
 - ◆ Genetic switch (Weiss et al., *PNAS* 2002)
 - ◆ Gene control (Benenson et al., *Nature* 2004)
- Nanotechnology
 - ◆ DNA crystals (Winfree & Seeman et al., *Nature* 1998)
 - ◆ Molecular tweezer (Yurke & Turberfield et al., *Nature* 2000)
 - ◆ TX complexes (Reif & Seeman et al, *Nature* 2000)
 - ◆ Tiles (LaBean & Reif, 2003)

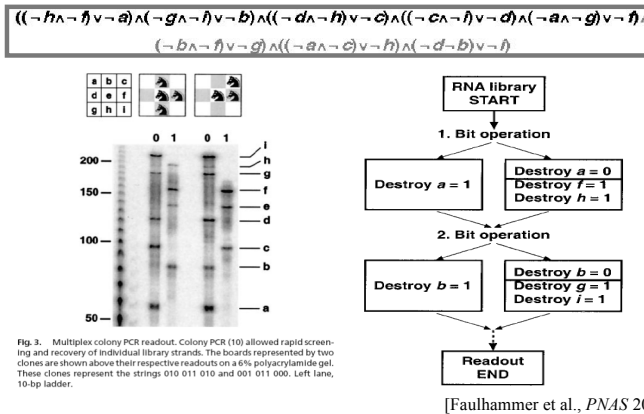
Breaking DES



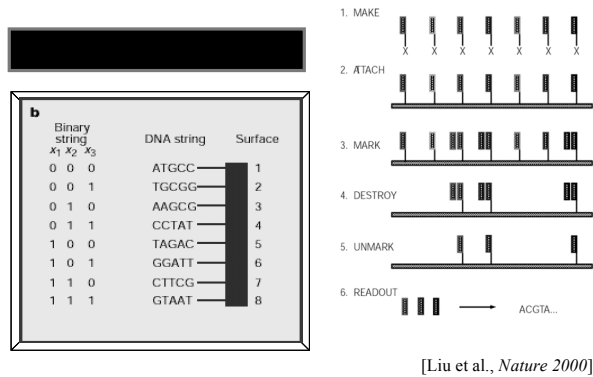
Self-Assembly of DNA Crystals



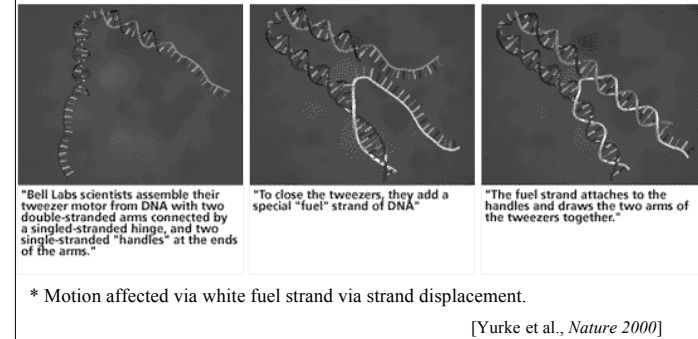
RNA Solution to a Chess Problem



Solving a 3-SAT Problem on Chip



Making a Molecular Tweezer



Solving a 20-var 3-CNF Problem

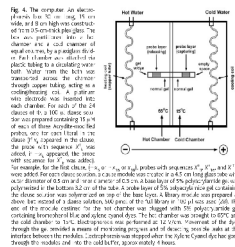
A

$\Phi = (\neg x_5 \text{ or } \neg x_{16} \text{ or } x_{18}) \text{ and } (x_5 \text{ or } x_{12} \text{ or } \neg x_6) \text{ and } (\neg x_{13} \text{ or } \neg x_2 \text{ or } x_{20}) \text{ and } (x_{12} \text{ or } \neg x_9 \text{ or } \neg x_6) \text{ and } (x_{10} \text{ or } \neg x_4 \text{ or } x_6) \text{ and } (x_9 \text{ or } x_{12} \text{ or } \neg x_5) \text{ and } (\neg x_1 \text{ or } x_4 \text{ or } \neg x_{11}) \text{ and } (x_{13} \text{ or } \neg x_2 \text{ or } \neg x_{19}) \text{ and } (x_9 \text{ or } x_{17} \text{ or } x_6) \text{ and } (x_{15} \text{ or } x_9 \text{ or } \neg x_{17}) \text{ and } (\neg x_5 \text{ or } \neg x_9 \text{ or } \neg x_{12}) \text{ and } (x_6 \text{ or } x_{11} \text{ or } x_4) \text{ and } (\neg x_{16} \text{ or } \neg x_{17} \text{ or } x_2) \text{ and } (\neg x_6 \text{ or } x_{19} \text{ or } x_{13}) \text{ and } (\neg x_{12} \text{ or } \neg x_9 \text{ or } x_6) \text{ and } (x_{12} \text{ or } x_1 \text{ or } x_{14}) \text{ and } (x_{20} \text{ or } x_3 \text{ or } x_2) \text{ and } (x_{10} \text{ or } \neg x_7 \text{ or } \neg x_6) \text{ and } (\neg x_5 \text{ or } x_9 \text{ or } \neg x_{12}) \text{ and } (x_{18} \text{ or } \neg x_{20} \text{ or } x_3) \text{ and } (\neg x_{10} \text{ or } \neg x_{18} \text{ or } \neg x_{16}) \text{ and } (x_1 \text{ or } \neg x_{15} \text{ or } \neg x_{14}) \text{ and } (x_9 \text{ or } \neg x_7 \text{ or } \neg x_{15}) \text{ and } (\neg x_6 \text{ or } x_{16} \text{ or } \neg x_{10})$

B

$x_1=F, x_2=T, x_3=F, x_4=F, x_5=F, x_6=F, x_7=T, x_8=T, x_9=F, x_{10}=T, x_{11}=T, x_{12}=T, x_{13}=F, x_{14}=F, x_{15}=T, x_{16}=T, x_{17}=T, x_{18}=F, x_{19}=F, x_{20}=F$

Fig. 1. The computational problem. (A) 20-variable 3-CNF Boolean formula Φ . The symbol " \neg " indicates "not." (B) The unique truth assignment satisfying Φ .



[Braich et al., *Science* 2002]

Directed Evolution of a Genetic Circuit

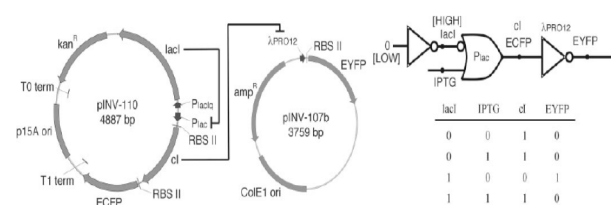


Fig. 1. The plasmid diagram shows the implementation of the present circuit. Plasmid pINV-110 constitutively expresses the LacI repressor, which inhibits transcription from the P_{lacI} promoter in the absence of IPTG. The expression of the Cl repressor and EYFP fluorescent marker is controlled by P_{lacI}, which is inducible by externally added IPTG. Repressor Cl acts on pINV-107b to repress the transcription of the EYFP gene, the output fluorescence indicator. The two plasmids contain different origins of replication as well as different antibiotic resistance genes, which allow them to be maintained stably within a single cell. The logic diagram (Upper Right) represents the logical representation of the same biochemical circuit. The P_{lacI} promoter comprises an IMPLIES logic gate with respect to the two inputs LacI and IPTG and the output Cl, whose truth table is shown below the diagram. The output of the IMPLIES gate, Cl, is the input to the inverter based on the λPRO12 promoter, ultimately controlling expression of the fluorescent output, EYFP. Note that the levels of EYFP output are the inverse of the input Cl in the truth table. In this study, we targeted mutations to the Cl protein.

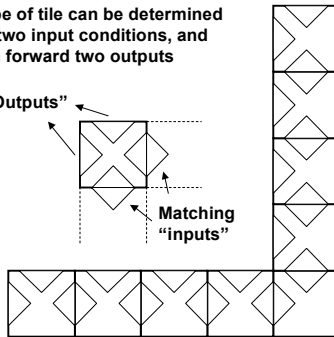
[Weiss et al., *PNAS* 2002]

Binary Counter

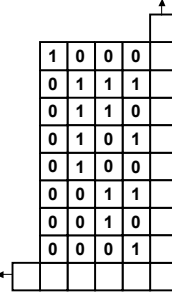
Type of tile can be determined by two input conditions, and can forward two outputs

“Outputs”

Matching “inputs”

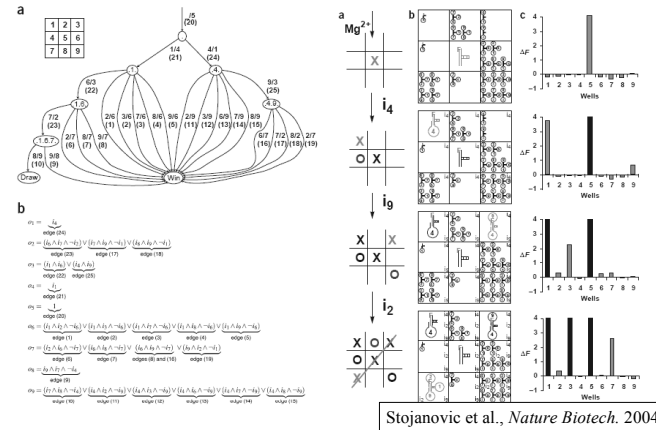


Assembly grows in this direction

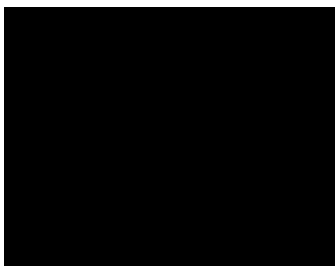


[Winfree et al., *DNAC* 2003]

Playing a Tic-Tac-Toe Game

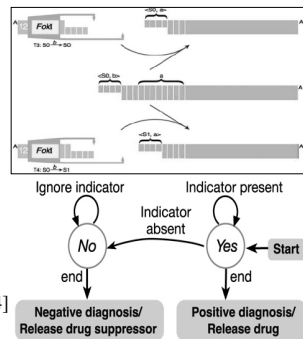


DNA as Smart Drugs



[Benenson et al., *Nature* 2001 & *Nature*, 2004]

PPAP2B↓ & GSTP1↓ & PIM1↑ & HEPSIN↑ → Administer GTTGGTATTGCACAT



Difficulties in Current Molecular Computing Paradigms

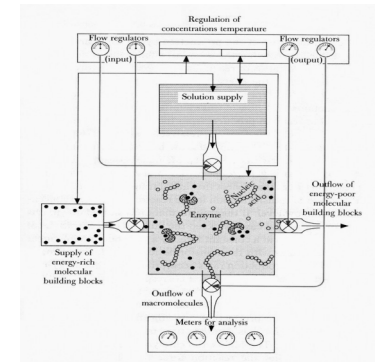
- Scalability
 - ◆ For big problems, exhaustive search is not effective.
- Reliability
 - ◆ DNA reaction is error-prone.
- Fault tolerance
 - ◆ What if a single molecule malfunctions?
- Design
 - ◆ How to design the decision (or diagnosis) rules?

In Vitro Evolution (without Computation)

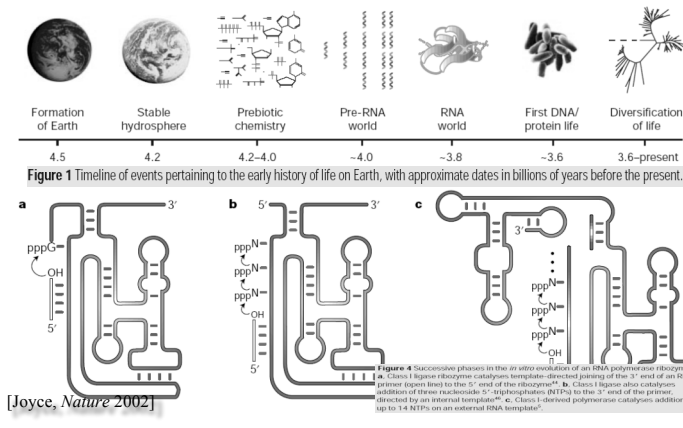
Eigen's Theory of Molecular Evolution (1979)



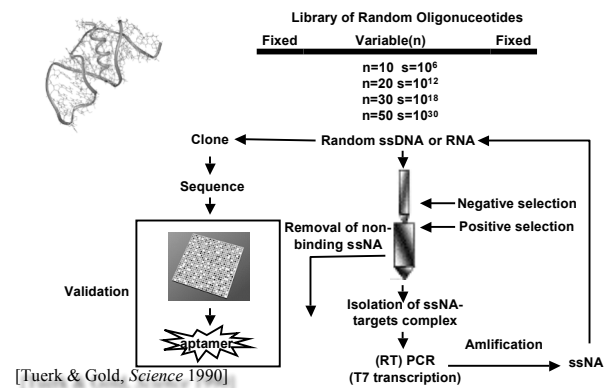
Manfred Eigen
(1927 -)

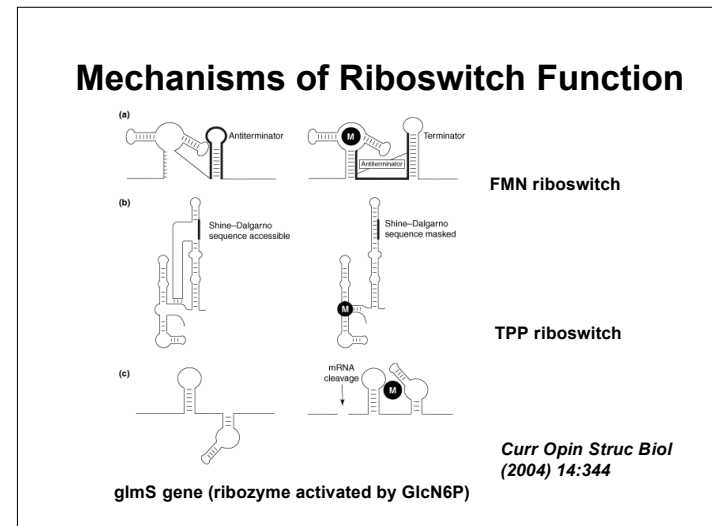
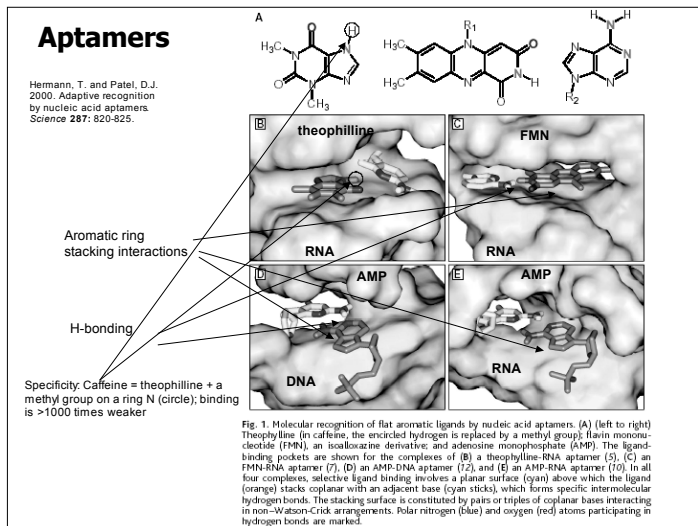


In Vitro Evolution Experiments



SELEX (Systematic Evolution of Ligands by EXponential Enrichment)





Applications for SELEX

Insights into the prebiotic earth

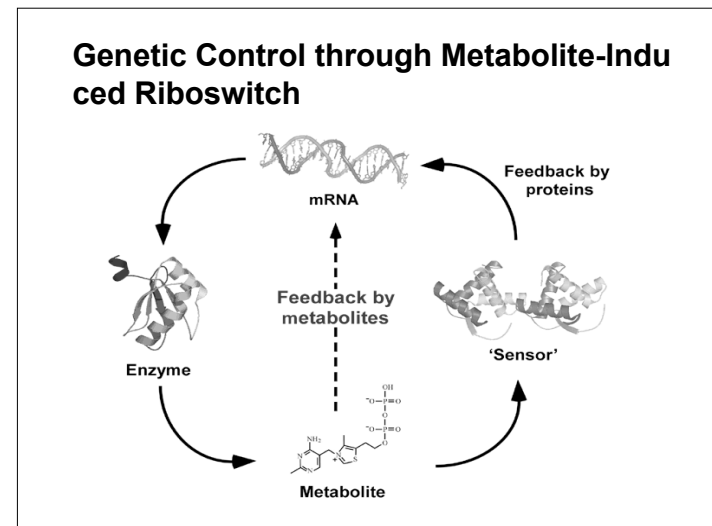
- Identification of the catalytic potential of RNA and DNA; Selection for enzymatic functions (ligase, polymerase, RNase, peptide bond formation, Diels-Alder reaction)

Applied (Medical) research

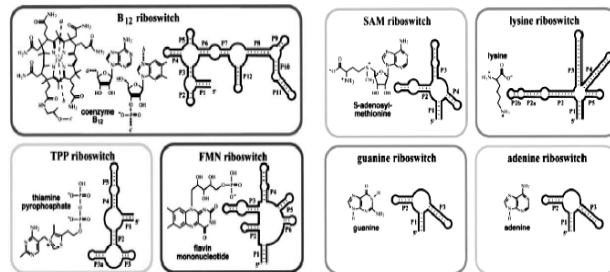
- diagnostic (ELISA, FACS) and therapeutic use of aptamers as replacement and or extension to antibodies (K_d 's in the pM to nM range)

Genomic SELEX and regulatory loops

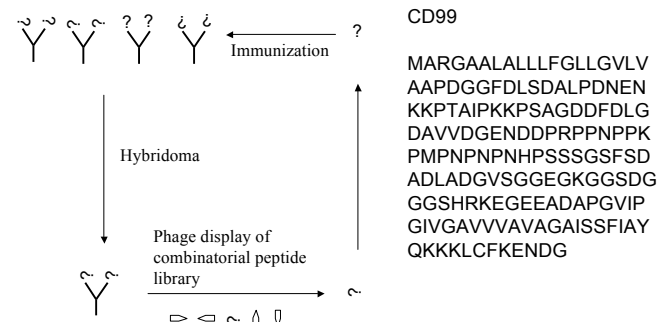
- random integration of genomic sequences into SELEX oligonucleotides; selection for unidentified binding sites to regulatory proteins (MetJ; MS2 coat protein, U1A protein)



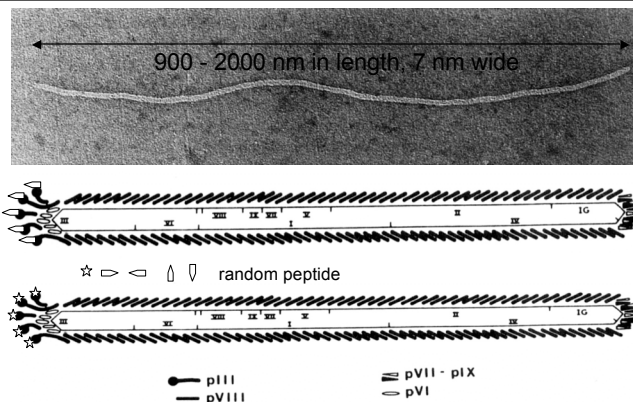
Metabolite-Induced Riboswitch



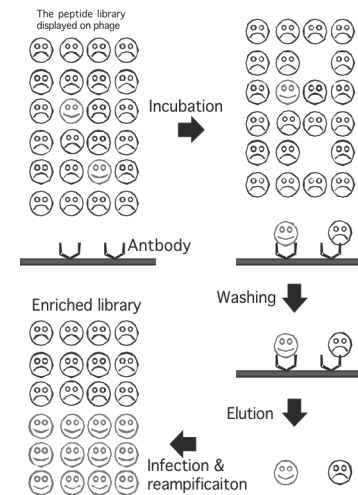
Peptide Library

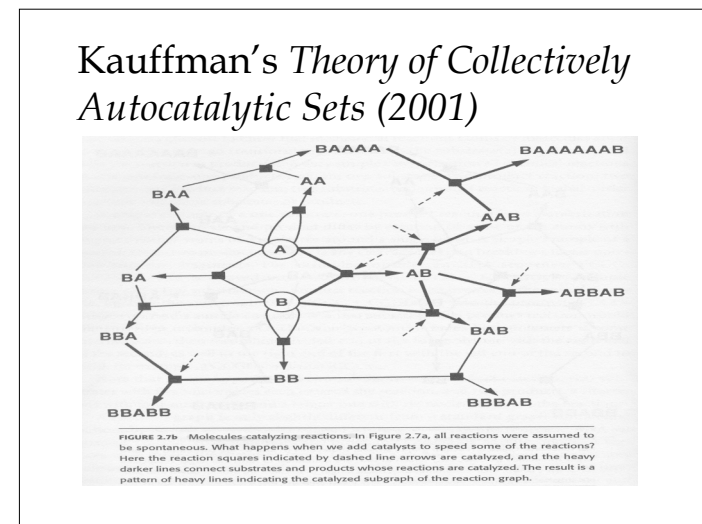
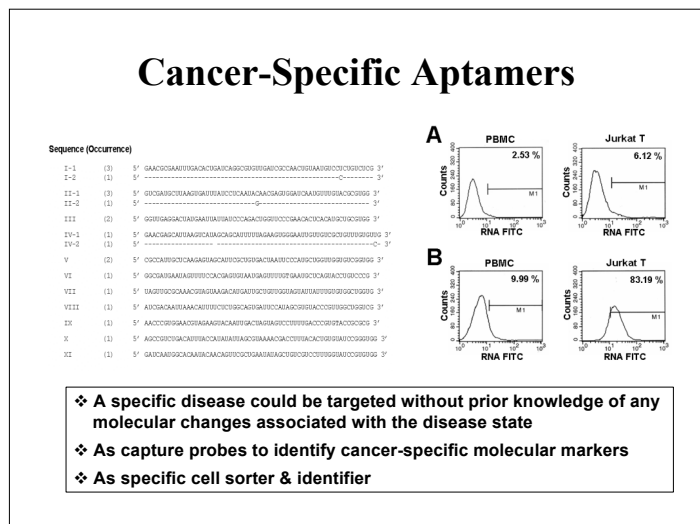
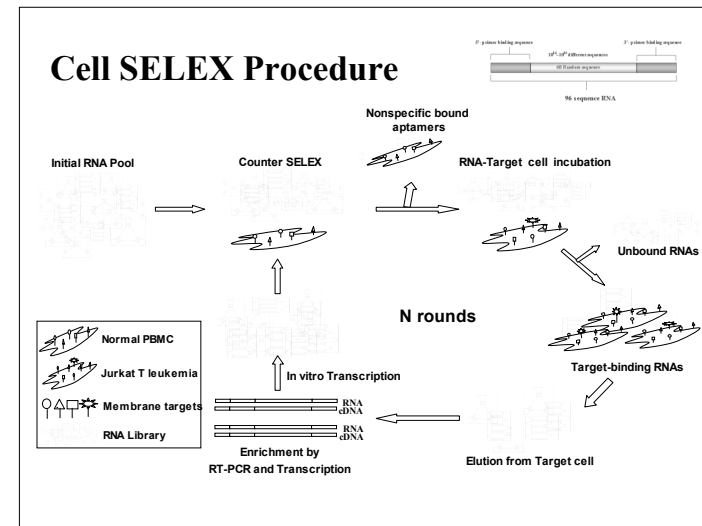
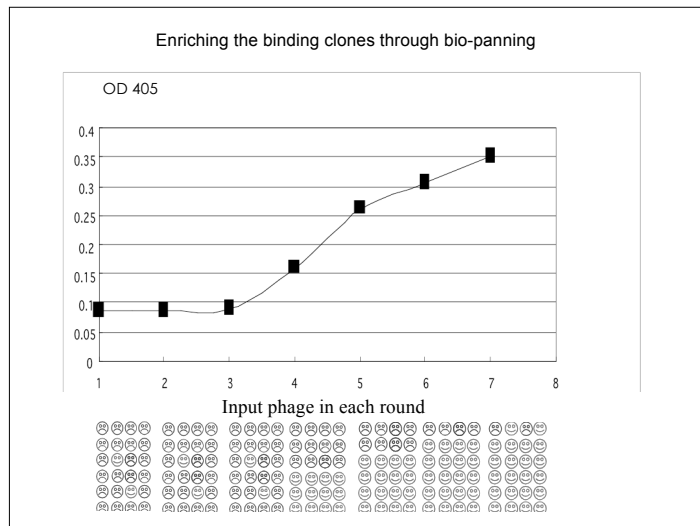


Phage Display of Peptide Library



Bio-Panning





In Vitro (Molecular) Evolution: Synonyms

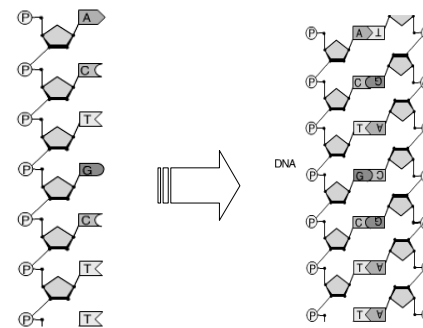
- In vitro selection
- Directed evolution
- In vitro evolution
- Molecular evolution
- SELEX
- Bio-panning
- “In vitro molecular evolution”

Molecular Evolutionary Computation (MEC) in Vitro: Theory

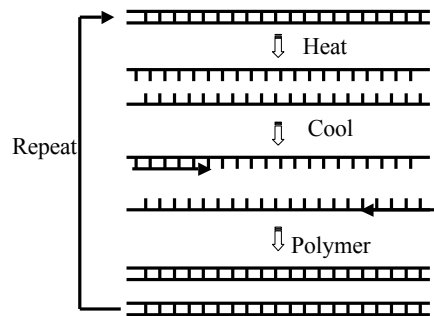
Motivation: In Vitro Evolution as EC Technology

- Each DNA molecule represents an individual at nanoscale
- A huge population of up to Avogadro number (6×10^{23}) molecules
- Molecular recognition by chemistry
- Exponential self-replication by PCR
- Massively parallel variation-selection operators
- Ultra-low energy consumption
- Evolvable “wet” “molecular” hardware

Molecular Recognition



Self-Replication



In Vitro Evolutionary Computation

- Problems in Existing DNA Computing Paradigms: Revisited
 - ◆ Scalability
 - For big problems, exhaustive search does not work.
 - ◆ Reliability
 - DNA reaction is error-prone.
 - ◆ Fault tolerance
 - What if a single molecule malfunctions?
 - ◆ Design
 - How to design the decision (or diagnosis) rules?
- In Vitro Evolution + Molecular Computation
 - = Molecular Evolutionary Computation (MEC)
 - = Bayesian Evolution + Probabilistic Library Model

Why Try Molecular EC?

- 6.022×10^{23} molecules / mole
- Massively Parallel Search
 - ◆ Desktop: 10^9 operations / sec
 - ◆ Supercomputer: 10^{12} operations / sec
 - ◆ 1 μ mol of DNA: 10^{26} reactions
- Favorable Energetics: Gibbs Free Energy
 - ◆ 1 J for 2×10^{19} operations
- Storage Capacity: 1 bit per cubic nanometer
- The fastest supercomputer vs. DNA computer
 - ◆ 10^6 op/sec vs. 10^{14} op/sec
 - ◆ 10^9 op/J vs. 10^{19} op/J (in ligation step)
 - ◆ 1bit per 10^{12} nm³ vs. 1 bit per 1 nm³
(video tape vs. molecules)

The Theory of Bayesian Evolution

- Evolution as a Bayesian inference process
- Evolutionary computation (EC) is viewed as an iterative process of *generating the individuals of ever higher posterior probabilities* from the priors and the observed data.

Bayesian Formulation of EC

- Bayes' rule for combining priors and likelihoods:

$$P(A|D) = \frac{P(D|A)P(A)}{P(D)} = \frac{P(D|A)P(A)}{\int_A P(D|A)P(A)}$$

- Evolutionary computation (EC) can estimate the posterior probability of model A_i using the population $A(g)$:

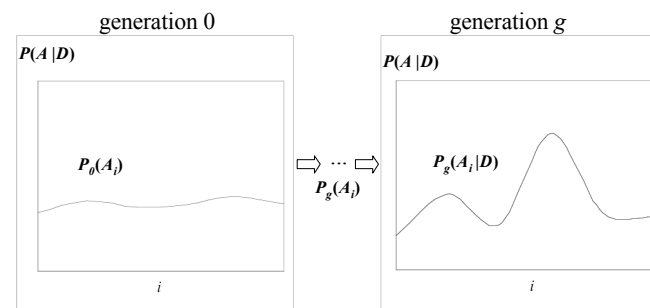
$$P_g(A_i|D) = \frac{P(D|A_i)P_{g-1}(A_i)}{\sum_{A_j \in A(g)} P(D|A_j)P_{g-1}(A_j)}$$

- The fittest model for the Bayesian EC to find is:

$$A_{MAP}^g = \min_{g \leq g_{\max}} \arg \max_{A_i \in A(g)} \{P_g(A_i|D)\}$$

[Zhang, CEC-99]

Bayesian Evolutionary Computation



Bayesian Evolutionary Algorithm (BEA)

- Sample M individuals A_i ($i=1, \dots, M$) from $P_0(A)$. Set $g=1$.
- Compute the posterior fitness $P_i(g) = P_g(A_i|D)$ for $i=1, \dots, M$:

$$P_g(A_i|D) = \frac{P(D|A_i)P_{g-1}(A_i)}{\sum_{A_j \in A(g)} P(D|A_j)P_{g-1}(A_j)}$$

- Generate offspring A'_i by sampling from the posterior distribution using variation operators, such as mutation and recombination:

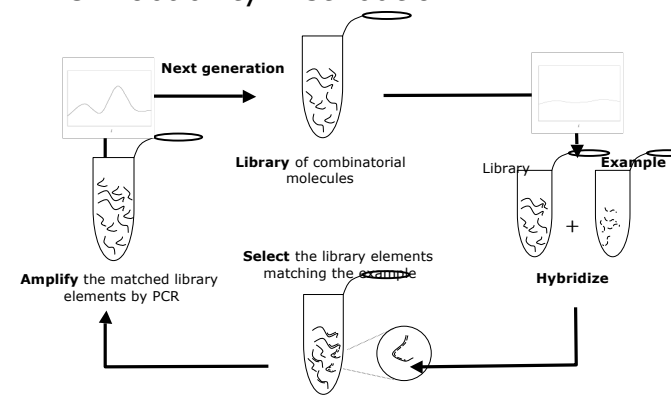
$$P'_{g+1}(A'_i|D) = \sum_{A_j \in A(g)} P_g(A_j|D)P(A'_i|A_j)$$

- Select the individuals into the next generation with acceptance probability

$$\alpha_g(A'_i|A_i) = \min \left\{ 1, \frac{P_g(A'_i|D)}{P_g(A_i|D)} \right\}$$

- Revise the priors $P_g(A) = h(P_{g-1}(A), P_g(A|D))$. Set $g=g+1$ and go to step 2.

PLM: Using Molecules to Represent the Probability Distribution



The Probabilistic Library Model (PLM)

- A library of DNA molecules represents the empirical distribution of data variables.
- Each library element consists of n variables, X_1, \dots, X_n .
- A big number of molecules are maintained in the library.
 - ♦ $L = \{x_i \mid i = 1, \dots, N\}$
 - ♦ N : typically 10^{15} with 10 nM
- Duplications of elements are allowed. And the number of duplications is proportional to the strength of the element.
- The library is so maintained that it represents the joint probability distribution of the data variables.
 - ♦ $P(X) = P(X_1, \dots, X_n)$ [Zhang, DNAC-2004]

The PLM (cont'd)

- The probability of variable X_k having value x_k is computed chemically by putting in the library the complementary sequence $-x_k$ of the query sequence x_k and extracting the hybridized sequences followed by normalization.
 - ♦ $P(X_k=x_k) \sim c(x_k)/|L|$
- Conditional probabilities are computed by the relative frequencies of the molecules.
 - ♦ $P(X_i|X_k) = P(X_i, X_k) / P(X_k)$
 - ♦ Here $P(X_i=x_i, X_k=x_k) \sim c(x_i, x_k)/|L|$ and $P(X_k=x_k) \sim c(x_k)/|L|$
- The library as an ensemble
- Probabilistic computation
- Massively parallel computation of probabilities

The PLM as a Pattern Classifier

- Assume L contains sequence patterns x_i with known labels y_i (training set)
 - ♦ $L = \{(x_i, y_i) \mid i = 1, \dots, N\}$
 - ♦ $x_i = \{A, T, G, C\}^n$: observable input, e.g. DNA sequence
 - ♦ $y_i = \{0, 1\}$, observable output, e.g. cancer or normal
- Given a query sequence x_q
 - ♦ Put $-x_q$ into the test tube $-x$: complementary to x
- Find the correct class y_q for x_q (classification)
 - ♦ $y_q = 1$: cancer
 - ♦ $y_q = 0$: normal

Classification Decision: Probabilistic Formulation

- $P(X)$: Probability of observing protein sequence X
- $P(X, Y)$: Probability of sequence X being in class Y
- $P(X, Y, Z)$: Probability of sequence X being in class Y with some parameter Z
- $P(Y|X)$: Conditional probability of class Y given X

Classification Learning: In Vitro Evolution

1. Start with library L of random samples (molecules)
2. Given a training sample $s = (x, y)$
3. Classify s using L
 - ◆ Extract $x \rightarrow N(x) := P(x)$
 - ◆ Extract $Y \rightarrow N(x, Y) := P(x, Y)$
 - ◆ $y^* = \operatorname{argmax}_Y N(x, Y)$
4. Update L
 - ◆ If $y^* = y$, $P(y^*|x) \leftarrow d N(y^*|x)$ with $d > 1$
 - ◆ Otherwise, $P(y^*|x) \leftarrow d N(y^*|x)$ with $d < 1$



The Learning Rule Leads to Bayesian Update



Update of $N(y^*|x)$ leads to update of the posterior probability distribution $P(z|y, x)$, resulting in a Bayesian learning rule for classification learning with DNA computing

[Zhang, DNA10]

PLM vs. Probabilistic Model-Building GAs (or EDAs)

- Some recent genetic and evolutionary algorithms build explicit probabilistic models for the population.
- These distribution-estimation algorithms (EDAs) generate offspring by sampling from the probabilistic model rather than using crossover and mutation.
- Like EDAs, the probabilistic library model (PLM) generates the offspring by sampling from a probability distribution.
- Unlike in EDAs, in PLM no extra probabilistic model is built. The PLM itself represents a probability distribution.
- The use of a huge number of molecules (10^{15} or more) enables the test tube to represent the empirical probability distribution.

Molecular Programming (MP): In Vitro Evolution of Genetic Programs

Molecular Programming (MP): Evolving Genetic Programs in a Test Tube

- Theory
 - ◆ Bayesian evolution [Zhang, CEC-99; Zhang, Handbook-2003]
- Model
 - ◆ Probabilistic library model [Zhang, DNA10 & DNA11]
- Algorithm
 - ◆ Molecular algorithms [Zhang, GP-98]
- Representation
 - ◆ Decision lists [Zhang, GECCO-2005]
- Operators
 - ◆ Molecular operators for variation and selection [Zhang, GECCO-2005]

Molecular Programming of the PLM

1. Let the library L represent the current distribution $P(X, Y)$.
2. Get a training example (\mathbf{x}, y) .
3. Classify \mathbf{x} using L as follows
 - 3.1 Extract all molecules matching \mathbf{x} into M .
 - 3.2 From M separate the molecules into classes:
Extract the molecules with label $Y=0$ into M^0
Extract the molecules with label $Y=1$ into M^1
 - 3.3 Compute $y^* = \arg\max_{y \in \{0,1\}} |M^y|/|M|$
4. Update L
 - If $y^* = y$, then $L_n \leftarrow L_{n-1} + \{\Delta c(\mathbf{u}, \mathbf{v})\}$ for $\mathbf{u} = \mathbf{x}$ and $\mathbf{v} = y$ for $(\mathbf{u}, \mathbf{v}) \in L_{n-1}$,
 - If $y^* \neq y$, then $L_n \leftarrow L_{n-1} - \{\Delta c(\mathbf{u}, \mathbf{v})\}$ for $\mathbf{u} = \mathbf{x}$ and $\mathbf{v} \neq y$ for $(\mathbf{u}, \mathbf{v}) \in L_{n-1}$
5. Goto step 2 if not terminated. [Zhang, GECCO-2005]

Step 1: Probability Distribution in the Library

$$D = \{(\mathbf{x}_i, y_i)\}_{i=1}^K \mid \mathbf{x}_i = (x_{i_1}, x_{i_2}, \dots, x_{i_n}) \in \{0,1\}^n, y_i \in \{0,1\}$$

$$P(X, Y) \approx \frac{1}{|L|} \sum_{i=1}^{|L|} f_i^{(n)}(X_1, X_2, \dots, X_n, Y)$$

Step 2: Presentation of an Example (or Query)

$$P(\mathbf{x}_i, y_i \mid \mathbf{x}_q, y_q) = \frac{\exp(-\Delta G(\mathbf{x}_i, y_i \mid \mathbf{x}_q, y_q))}{\sum_j \exp(-\Delta G(\mathbf{x}_j, y_j \mid \mathbf{x}_q, y_q))}$$

Step 3: Classify the Example (Decision Making)

$$\begin{aligned} y^* &= \arg \max_{y \in \{0,1\}} P(Y \mid \mathbf{x}) \\ &= \arg \max_{y \in \{0,1\}} \frac{P(Y, \mathbf{x})}{P(\mathbf{x})} \quad c(\mathbf{x})/|L| = |M|/|L| \approx P(\mathbf{x}) \end{aligned}$$

$$\begin{aligned} y^* &= \arg \max_{y \in \{0,1\}} c(Y \mid \mathbf{x}) / |M| \\ &= \arg \max_{y \in \{0,1\}} c(Y \mid \mathbf{x}) \quad c(Y \mid \mathbf{x})/|M| = |M^y|/|M| \approx P(Y \mid \mathbf{x}) \\ &\approx \arg \max_{y \in \{0,1\}} P(Y \mid \mathbf{x}) \end{aligned}$$

Step 4: Update the Library (Learning)

$$L \leftarrow L + \{(\mathbf{u}, v)\} \quad L \leftarrow L - \{(\mathbf{u}, v)\}$$

$$P_n(X, Y | \mathbf{x}, y) = (1 + \delta) P_{n-1}(X, Y | \mathbf{x}, y)$$

$$\delta = \frac{P(\mathbf{x}, y | X, Y) - P(\mathbf{x}, y)}{P(\mathbf{x}, y)}$$

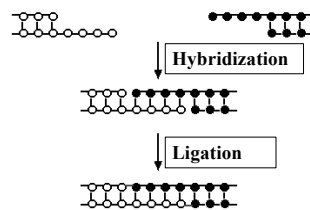
$$\delta = \frac{\Delta c(\mathbf{x}, y)}{c_{n-1}(\mathbf{x}, y)}$$

Molecular Operators

- Variation
 - ♦ Ligation
 - ♦ Restriction
 - ♦ Mutation (PCR)
- Selection
 - ♦ Gel electrophoresis
 - ♦ Affinity separation (beads)
 - ♦ Capillary electrophoresis
- Amplification
 - ♦ Polymerase chain reaction (PCR)
 - ♦ Rolling circle amplification (RCA)

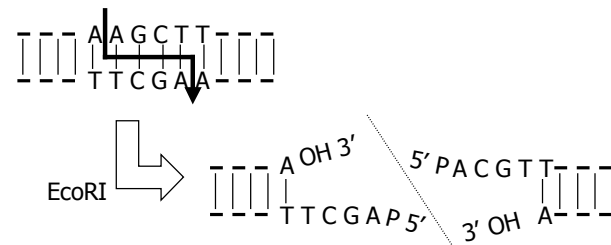
Variation: Hybridization & Ligation

- Hybridization
 - ♦ base-pairing between two complementary single-strand molecules to form a double stranded DNA molecule
- Ligation
 - ♦ Joining DNA molecules together
- Usually used for candidate solution generation.



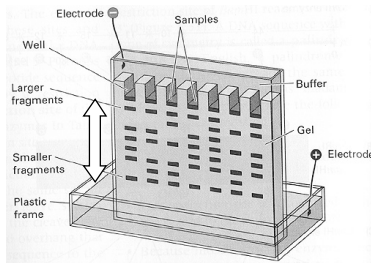
Variation: Restriction

- Cut the specific DNA site.
- Solution detection or filtering step

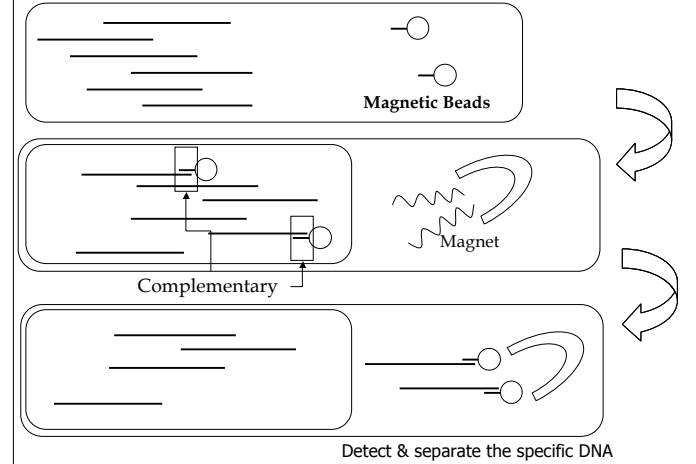


Selection: Gel Electrophoresis

- Detection desired solutions.
- Separate solution molecules by length

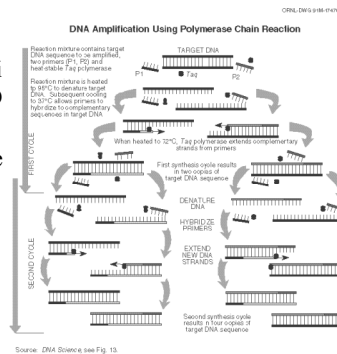


Selection: Bead Separation

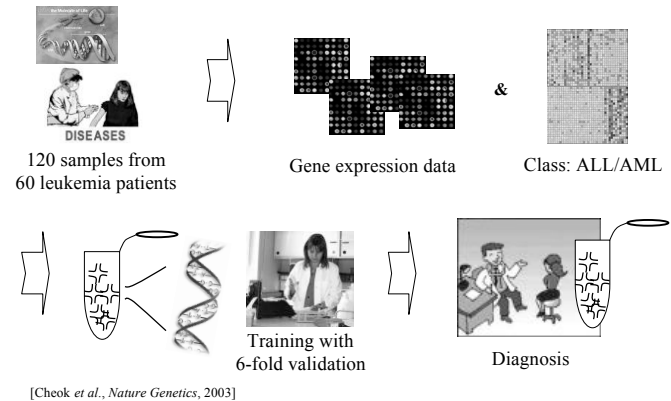


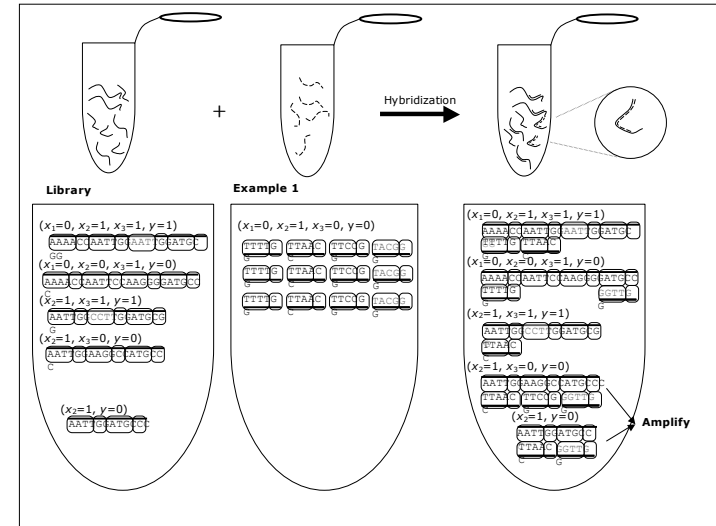
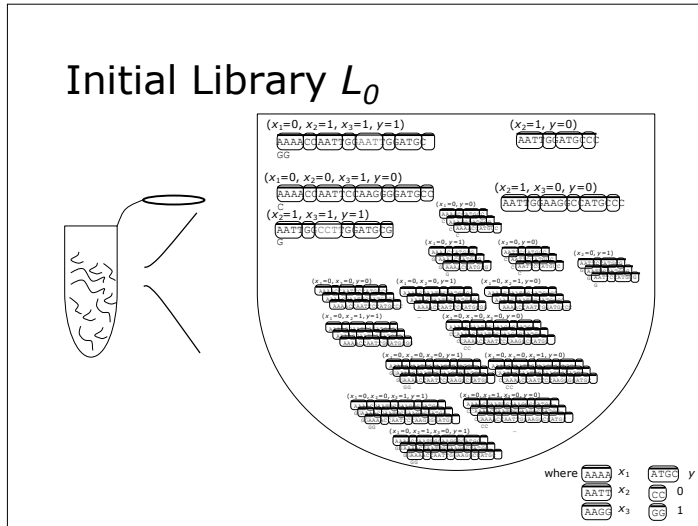
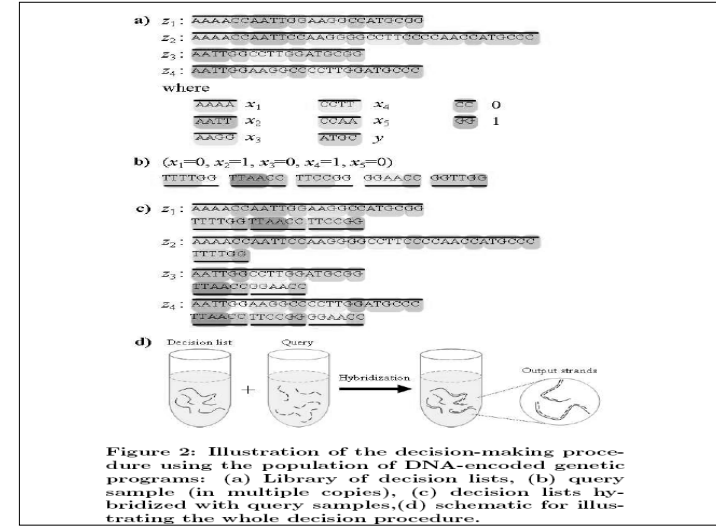
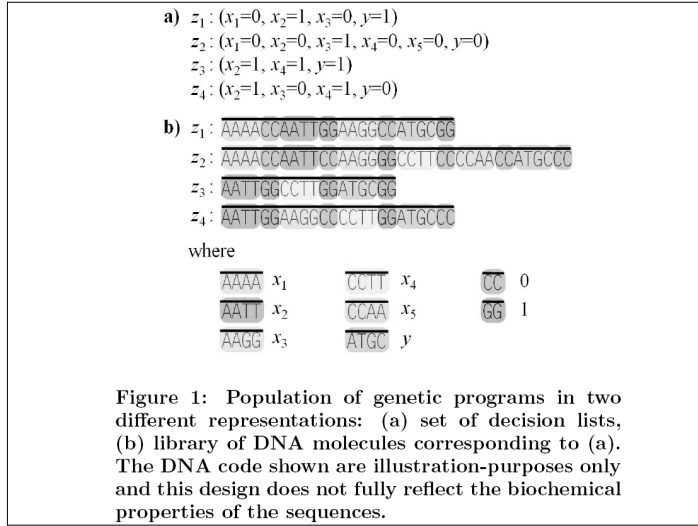
Amplification: PCR

- Polymerase chain reaction
- Amplifies (produces identical copies of) selected dsDNA molecules.
- Make 2^n copies (n : number of iteration)
- Used to filter solutions or detection.

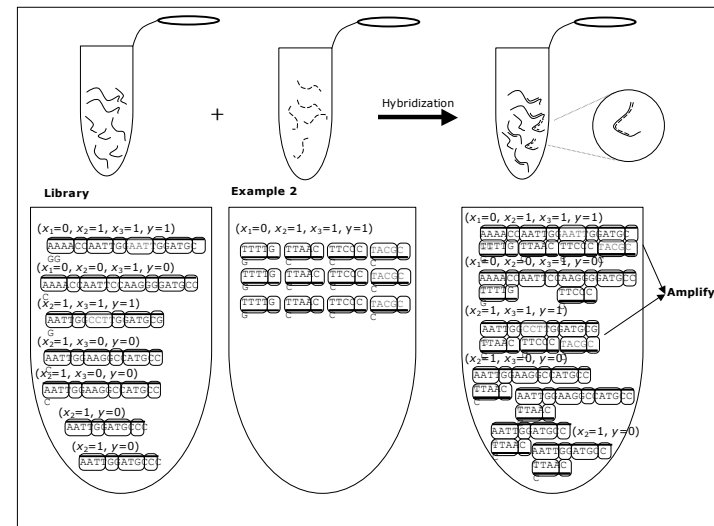
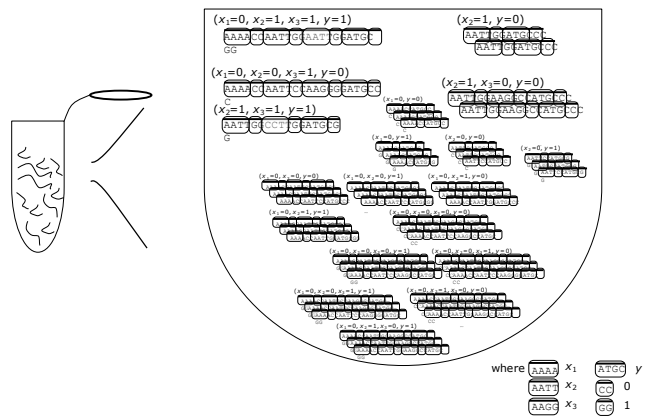


Application to Leukemia Diagnosis

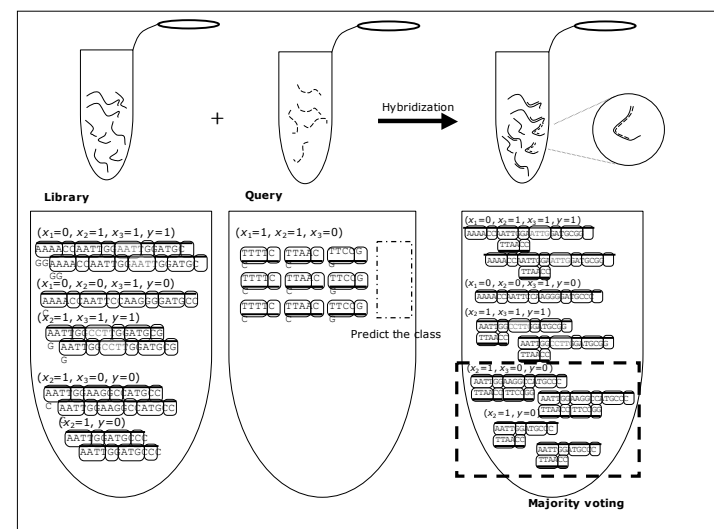
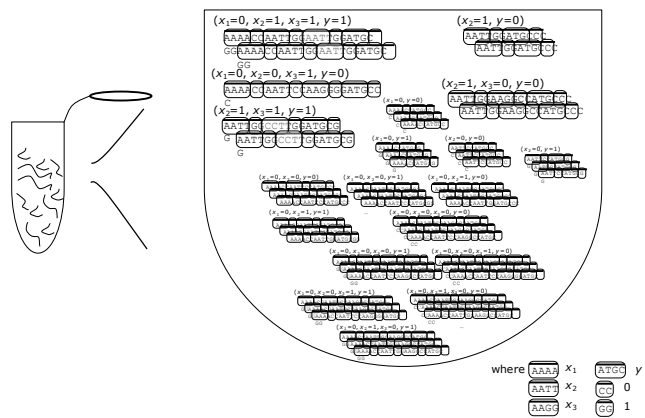




Updated Library L_1



Updated Library L_2



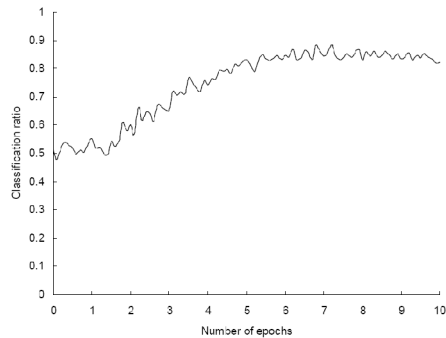


Figure 5: Fitness evolution of the population of molecular genetic programs. Though there are fluctuations the fitness values tend to converge 90 % accuracy. The reproduction rate was 0.01.

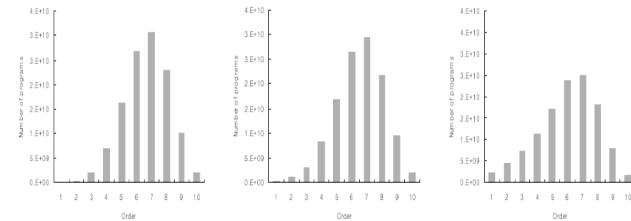


Figure 6: Distribution of the size of genetic programs. Shown are the number of programs of each size in the final population in a run. It shows the tendency that, as generation goes on, smaller programs are used more frequently than larger ones. The reproduction rate was 0.01.

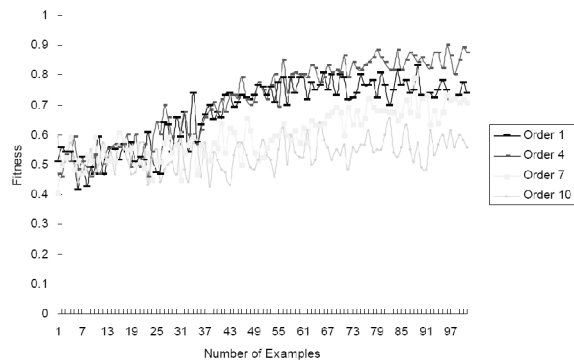


Figure 7: Fitness curve for runs with fixed-size programs. Shown are average fitness values for runs with programs of fixed-order 1, 4, 7, and 10.

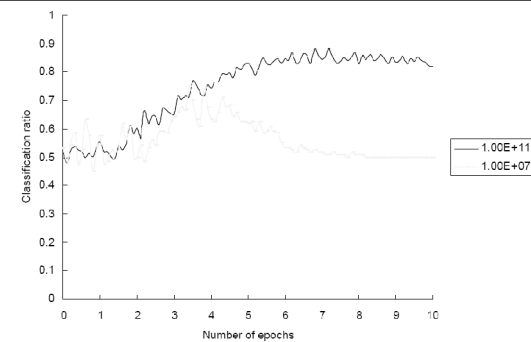
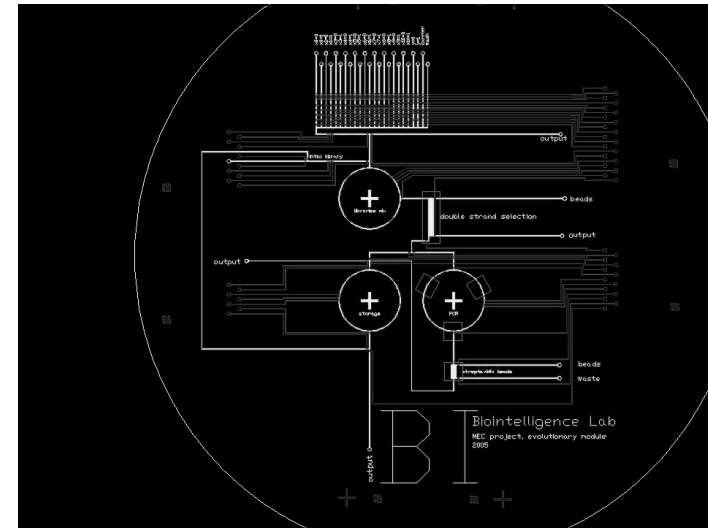


Figure 8: Effect of population size on ensemble performance. Shown are the best-fitness curves for population sizes of 10^{11} (in our experiments) 10^7 and (subsampling case for testing). The results show that too much subsampling degrades the performance.

MP vs. GP

	Genetic Programming (GP)	Molecular Programming (MP)
Representation	Variable-size trees	Variable-length lists
Variation	Random crossover, mutation	Combinatorial sampling
Selection	Proportional selection	Amplification (PCR)
Population size	$\sim O(10^4)$	$\sim O(10^{15})$
Parallelism	Can be parallelized	Inherently parallel
Solution	Single individual	Ensemble of individuals
Interaction	2D matrix	3D collision
Material	Silicon (dry, hard)	Carbon (wet, soft)



Molecular Programming (MP) as a New Paradigm for Molecular Computing

- Scalability
 - ♦ *Problem:* For big problems, exhaustive search does not work.
 - ♦ *Solution:* Evolutionary search
- Reliability
 - ♦ *Problem:* DNA reaction is error-prone.
 - ♦ *Solution:* Probabilistic formulation
- Fault tolerance
 - ♦ *Problem:* What if a single molecule malfunctions?
 - ♦ *Solution:* Ensemble machine approach
- Design
 - ♦ *Problem:* How to design the decision (or diagnosis) rules?
 - ♦ *Solution:* Evolutionary learning from examples

New Issues for the EC Researchers

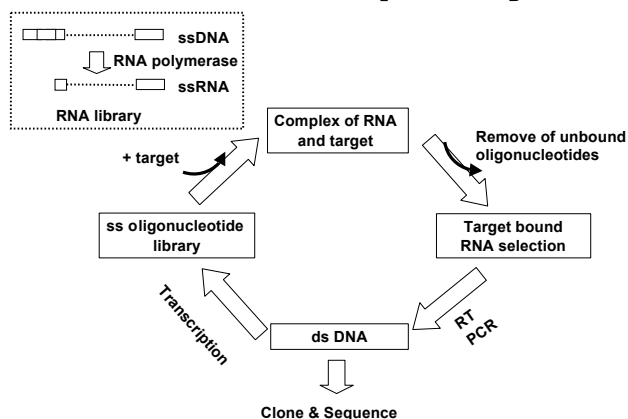
In Vitro Evolution vs. In Silico Evolution

	In Vitro Evolution	In Silico Evolution
Processing	Ballistic	Hardwired
Medium	Liquid (wet)	Solid (dry)
Communication	3D collision	2D switching
Configuration	Amorphous (asynchronous)	Fixed (synchronous)
Parallelism	Massively parallel	Sequential
Speed	Fast (millisec)	Ultra-fast (nanosec)
Reliability	Low	High
Density	Ultrahigh	Very high
Reproducibility	Probabilistic	Deterministic

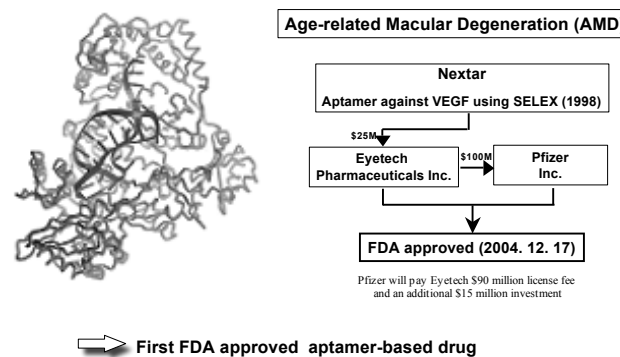
New Research Issues

- Representation
 - ◆ New representation schemes under molecular constraints
 - ◆ 2D and 3D structures for molecular genetic programs
 - ◆ Parsimony/bloat issues
- Operators
 - ◆ New molecular operators under thermodynamic constraints
 - ◆ Biochemical wet operators
 - ◆ Physical implementation of operators (e.g. physical simulated annealing)
- Theory
 - ◆ The role of a huge population size
 - ◆ Theory for guiding experimental procedures (e.g., SELEX)
 - ◆ EC theories of the origins of life
- Applications
 - ◆ Physical evolution
 - ◆ Bio, pharma, medicine
 - ◆ Nanotechnology
 - ◆ Molecular electronics
 - ◆ Molecular robotics

In Vitro Selection of RNA Aptamers by SELEX



Anti-VEGF Aptamer (Macugen)



RNA Aptamers into Therapeutics

- Easily screened
- High affinity and specificity
- Reduced in size and chemically synthesized
- Easily modified for bioavailability or delivery
- Reversible antagonist; regulatable
- Highly expressed
- May not induce immune response



-
- 1) As drug leads – lessen form VEGF₁₆₅
 - 2) As gene therapy

RNA Aptamers into Diagnostics

- Molecular ligand to variable molecules including carbohydrates and lipids
- High affinity and specificity
- Spot onto solid surface with high density
- Mass production with low cost, rapidly and high purity
- Reversible denaturation: stable and long storage
- Fixed with variable reporter



Rivalry to Antibody
Nanochip/biosensor

Applications for SELEX

Insights into the prebiotic earth

- Identification of the catalytic potential of RNA and DNA; Selection for enzymatic functions (ligase, polymerase, RNase, peptide bond formation, Diels-Alder reaction)

Applied (Medical) research

- diagnostic (ELISA, FACS) and therapeutic use of aptamers as replacement and or extension to antibodies (K_d 's in the pM to nM range)

Genomic SELEX and regulatory loops

- random integration of genomic sequences into SELEX oligonucleotides; selection for unidentified binding sites to regulatory proteins (MetJ; MS2 coat protein, U1A protein)

Programmable Patterning of DNA Lattices

(John Reif, Duke)

A New, Powerful Technology

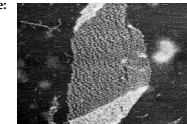
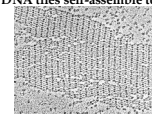
- for the construction of molecular scale structures
- for Rendering Patterns at the Molecular Level.



A 2D DNA lattice is constructed by a self-assembly process:

- Begins with the assembly of DNA tile nanostructures:
 - DNA tiles of size 14 x 7 nanometers
 - Composed of short DNA strands with Holliday junctions

- These DNA tiles self-assemble to form a 2D lattice:

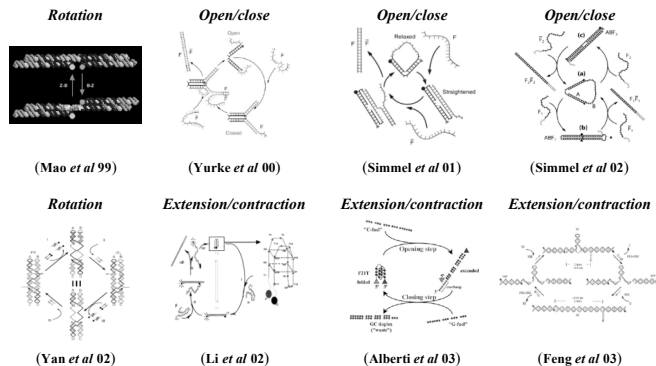


-The Assembly is Programmable:

- Tiles have sticky ends that provide programming for the patterns to be formed.
- Alternatively, tiles self-assemble around segments of a DNA strand encoding a 2D pattern.
- Patterning: Each of these tiles has a surface perturbation depending on the pixel intensity.
 - pixel distances 7 to 14 nanometers
 - not diffraction limited

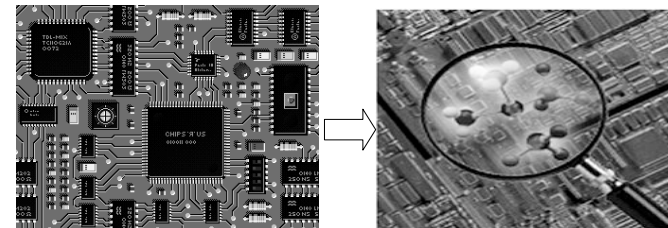
Key Applications: Assembly of molecular electronic components & circuits, molecular robotic components, image rendering, cryptography, mutation detection.

DNA-Based Nanorobotics Devices



Evolvable Biomolecular Hardware

- Sequence programmable and evolvable molecular systems can be constructed as cell-free chemical systems using biomolecules such as DNA and proteins.



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More Information at

- <http://bi.snu.ac.kr/MEC/>
- <http://cbit.snu.ac.kr/>

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- Duke Univ. <http://www.cs.duke.edu/~reif/> (John Reif)
- Harvard Univ. <http://genetics.mgh.harvard.edu/szostakweb/> (Jack Szostak)
- New York Univ. <http://seemanlab4.chem.nyu.edu/> (Ned Seeman)
- Scripps Res. Inst. <http://exobio.ucsd.edu/joyce.htm/> (Gerald Joyce)
- Seoul National Univ. <http://bi.snu.ac.kr/> (Tak Zhang)
- Univ. of Bonn <http://famulok.chemie.uni-bonn.de/> (Michael Famulok)
- Univ. of Tokyo <http://nicosia.is.s.u-tokyo.ac.jp/> (Masami Hagiya)
- Univ. of Southern California <http://www.usc.edu/dept/molecular-science/> (Leon Adleman)
- Univ. of Vienna <http://www.tbi.univie.ac.at/> (Peter Schuster)
- Weizmann Inst. of Tech. <http://www.weizmann.ac.il/mathusers/lbn/> (Ehud Shapiro)