Intra-relation Reconstruction from Inter-relation: miRNA to Gene Expression

Dokyoon Kim^{1,2,†}, Hyunjung Shin^{3,†,*}, Su-Yeon Lee^{1,2}, Ju Han Kim^{1,2,*}

¹Seoul National University Biomedical Informatics (SNUBI), Div. of Biomedical Informatics, Seoul National University College of Medicine, Seoul 110-799, Korea ²Systems Biomedical Informatics Research Center, Seoul National University, Seoul 110-799, Korea

³Department of Industrial & Information Systems Engineering, Ajou University, San 5, Wonchun-dong, Yeoungtong-gu, 443-749, Suwon, Korea

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Abstract

Gene expression profiling has been used to molecularly characterize various tumors and tissues. However, regulation of gene expression by microRNAs (miRNAs) has attracted much attention recently. MicroRNAs are regulators of gene expression, mainly functioning by decreasing mRNA levels of their multiple targets. Normally, intra-relations from gene expression or miRNA data can be constructed for explaining cancer phenotype. However, intra-relations are not fully elucidating complex cancer mechanism because the information that miRNAs and target genes are strongly associated with different biological processes is missing. As the recent studies for target prediction of miRNAs are getting increased, the inter-relation between miRNA and gene expression can be constructed from biological experimental data and genomic knowledge. In this study, we propose an integrated framework that combines genomic dataset from gene expression and genomic knowledge from inter-relation between miRNA and gene expression for the molecular-based classification of clinical outcomes. According to our results, accuracy of prediction model increases because of incorporation of information fused over genomic dataset (gene expression) and genomic knowledge (target relation between miRNA and gene expression). This suggests that gene expression regulation through mechanisms that involve miRNAs has valid knowledge for elucidating the cancer phenotype.

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Abstract (Summary)

Normally, intra-relations from gene expression or miRNA data can be constructed for explaining cancer phenotype

However, intra-relations are not fully elucidating complex cancer mechanism because the information that miRNAs and target genes are strongly associated with different biological processes is missing

In this study, we propose an integrated framework that combines genomic dataset from gene expression and genomic knowledge from inter-relation between miRNA and gene expression for the molecular-based classification of clinical outcomes

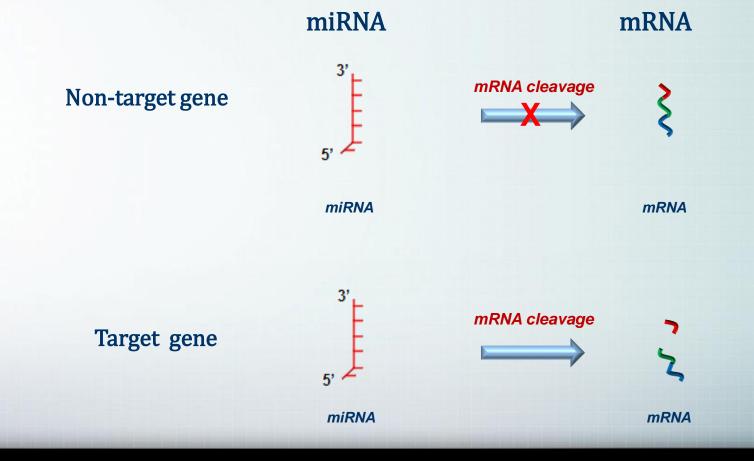
Contents



- Gene expression profiling has been used to molecularly characterize various tumors and tissues
- However, regulation of gene expression by microRNAs (miRNAs) has attracted much attention recently
- miRNAs regulate many genes associated with different biological processes such as development, stress response, apoptosis, proliferation, and tumourigenesis

Regulation mechanism of miRNA and target genes

 miRNAs are involved in the post-transcriptional regulation of genes either by mRNA cleavage and degradation or by repressing the translation of mRNA into protein



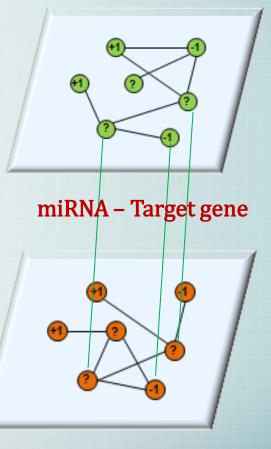
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Motivation

- Intra-relation: the relation between entities on a specific biological level
- Inter-relation: the relation between different levels
- Normally, intra-relations from gene expression or miRNA data can be constructed for explaining cancer phenotype
- However, intra-relations are not fully elucidating complex cancer mechanism because the information that miRNAs and target genes are strongly associated with different biological processes is missing

miRNA



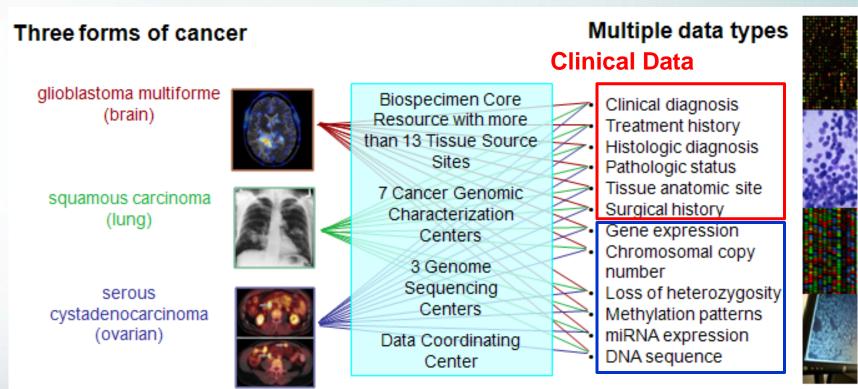
Gene expression

Purpose of the study

- How informative is inter-relationship between miRNA and gene expression for cancer clinical outcome prediction?
- Propose an integrated framework that combines genomic dataset from gene expression and genomic knowledge from inter-relation between miRNA and gene expression for the molecular-based classification of clinical outcomes



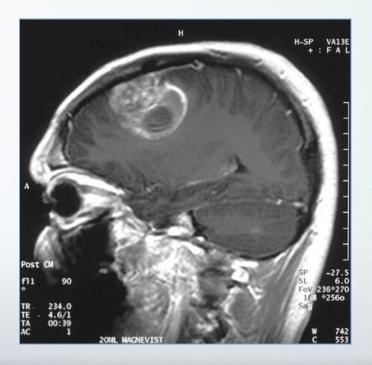
TCGA: Connecting multiple sources, experiments, and data types

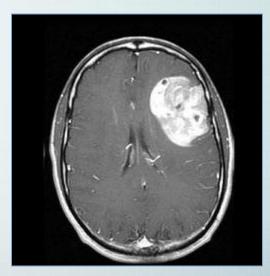


Multi-layers of genomic Data

Glioblastoma Multiforme (GBM)

- Most common and aggressive primary brain tumor in adults
 - Median survival of one year
 - One of the hallmarks of GBM is its inherent tendency to recur





Data description

Data type	Platform	Num of Features	
Gene Expression	Affymetrix HT Human Genome U133 Array Plate Set	12,043	
miRNA	Agilent Human miRNA Microarray Rel12.0	799	

Clinical outcome	Num of samples (Neg / Pos)	
Survival status (short-term vs. long-term)	82 (54 / 28)	

miRNA – target gene relation

- In order to get target information between miRNA and mRNA
 - Used miRecords which is integrated resources of miRNA that store target interactions produced by 11 established miRNA target prediction program

Xiao et al., 2009

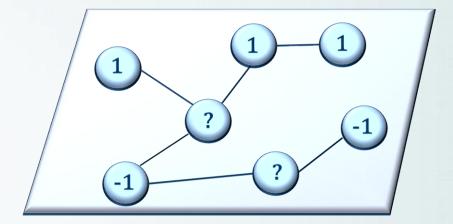
 Among 11 algorithms, a binary relation between miRNA and mRNA was set when more than 3 algorithms provide the target relation



Approaches

- G_o: Original graph from gene expression
- **G**_{D50}: Gene expression graph with 50% damages
- G_R: Reconstructed graph via inter-relationship between miRNA and gene expression
- G_A: Augmented graph by 50% damaged graph and reconstructed graph

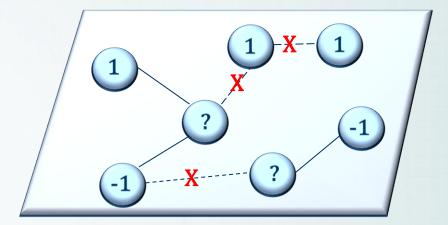
G_o: Original graph from gene expression



Gene expression (G_0)

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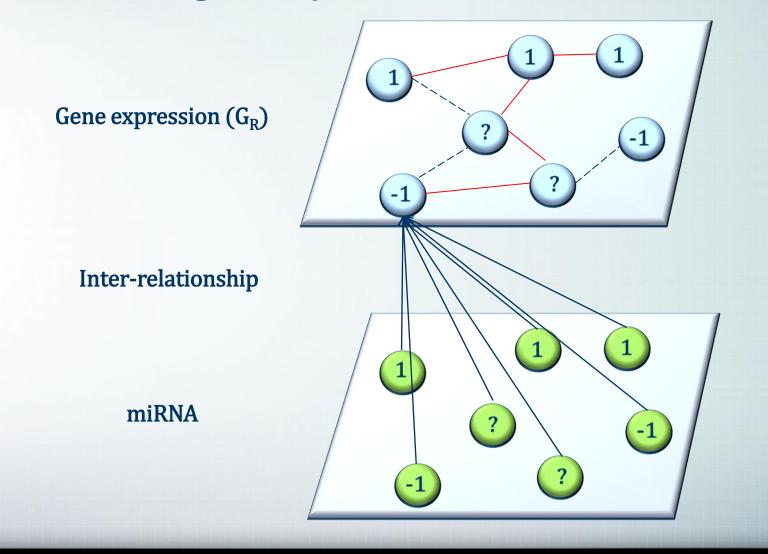
G_{D50}: Gene expression graph with 50% damages



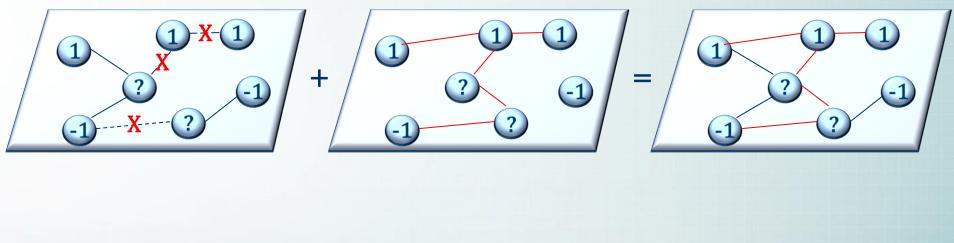
Gene expression (G_{D50})

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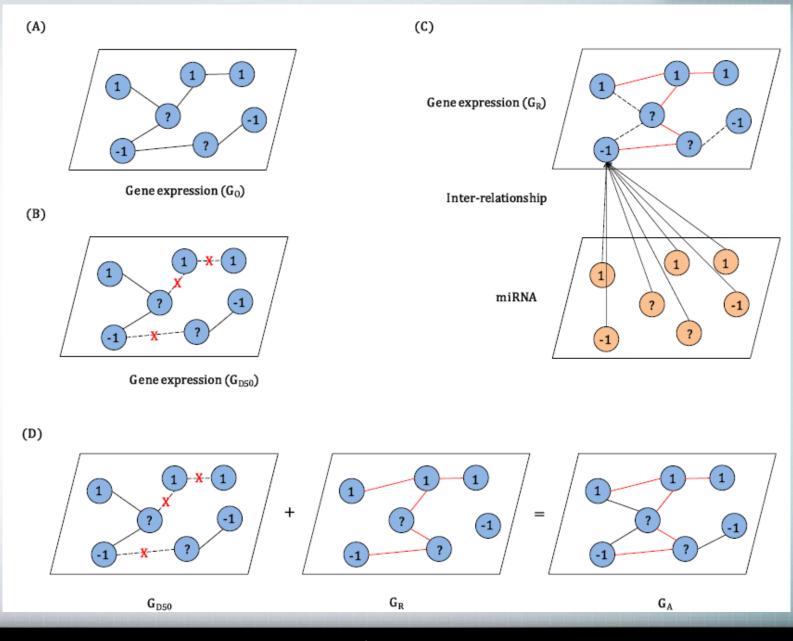
G_R: Reconstructed graph via inter-relationship between miRNA and gene expression



G_A: Augmented graph by 50% damaged graph and reconstructed graph



 $\mathbf{G}_{\mathbf{R}}$

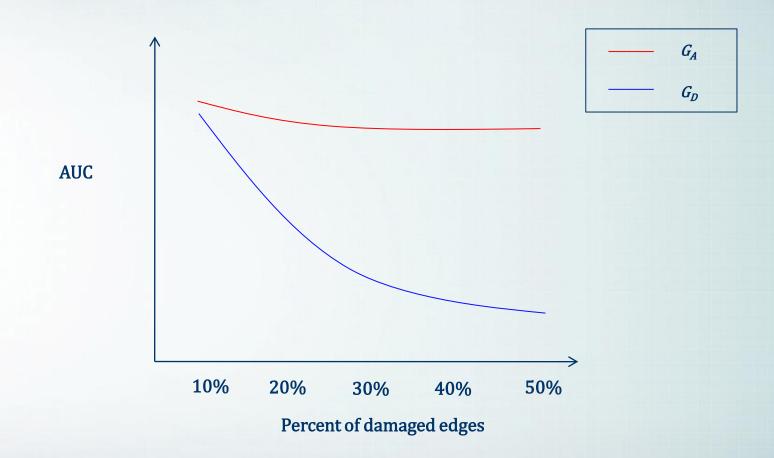


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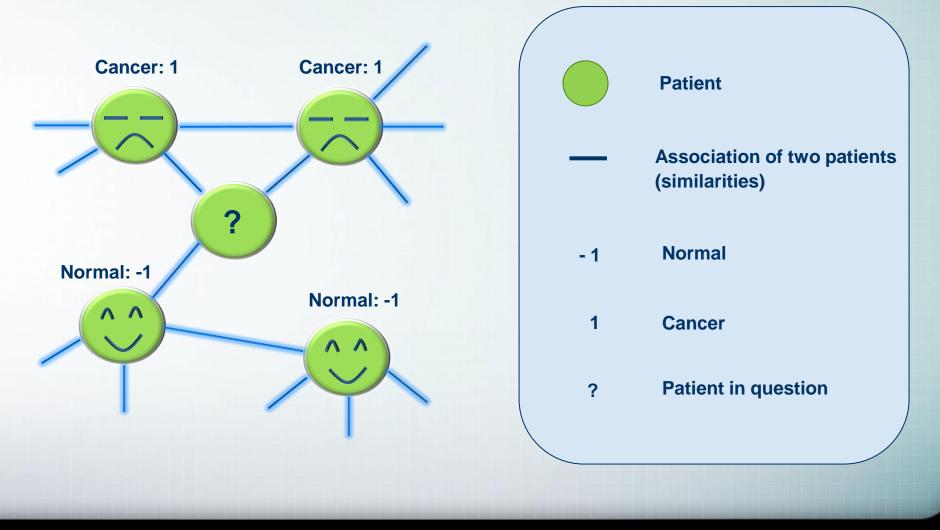
Expected Results



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Prediction based on intra-relation from mRNAs

Graph-based semi-supervised learning (SSL)



Graph-based Semi-Supervised Learning (SSL)

Objective function

$$\min_{f} = (f - y)^{T} (f - y) + \mu f^{T} L f$$

Loss Smoothness

- Loss condition: In labeled nodes, final output should be closed to the given label
- Smoothness condition: final output should not be too different from the adjacent node's output
- L is called the graph Laplacian matrix where

$$L = D - W$$
, $D = diag(d_i)$, $d_i = \sum_j w_{ij}$

Solution

$$f = (I + \mu L)^{-1} y$$

Shin et al., 2007

Tsuda *et al.*, 2005

Input for SSL: Weight Matrix (W)

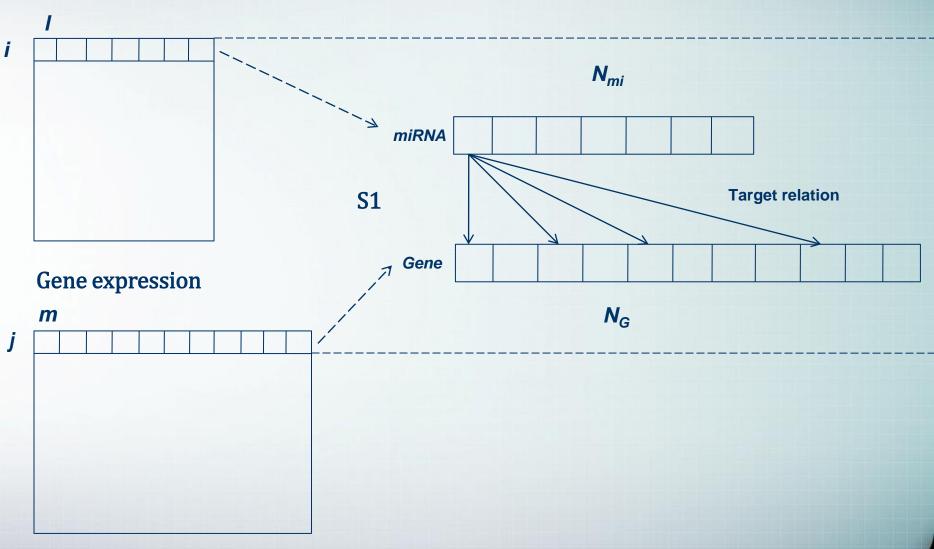
Exp-weighted K-NN graphs

$$W_{ij} = \exp(-\frac{d(i,j)^2}{\alpha^2})$$

- Nodes *i*, *j* are connected by an edge if *i* is in *j*'s *K*-nearest-neighborhood or vice versa
- d: Euclidean distance
- Hyperparameter α controls the decay rate

Data Description

miRNA



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Prediction based on inter-relation from miRNA to mRNA

S1 S2 SN S1 Wij S2 miRNA SN

Gene expression

Inter-relationship weight matrix

$$f_{ij} = \sum_{l=1}^{N_{mi}} \sum_{m=1}^{N_G} miRNA(i,l) \bullet gene(j,m)$$

where miRNA and gene are target relation

$$Z_{ij} = \frac{f_{ij} - \overline{f}}{std(f)}$$

$$w_{ij} = \frac{1}{1 + e^{-Z_{ij}}}$$

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Integration of multiple networks

Two graphs can be integrated from finding optimum combination coefficients

$$\min_{\alpha} y^T (I + \sum_{k=1}^K \alpha_k L_k)^{-1} y$$

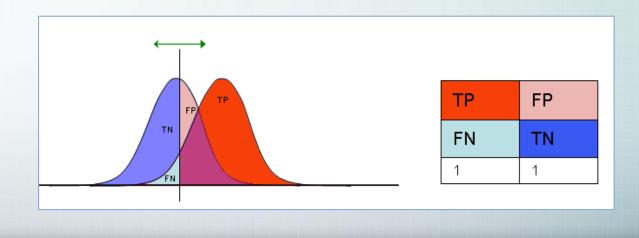
$$\sum_{k} \alpha_{k} \leq \mu$$

$$f = (I + \sum_{k=1}^{K} \alpha_k L_k)^{-1} y$$

Tsuda et al., 2005 Shin et al., 2007

Experiment setting

- G_o: Original graph from gene expression
- G_D: Gene expression graph with damages (10% ~ 90%)
- G_R: Reconstructed graph via inter-relationship between miRNA and gene expression
- **G**_A: Augmented graph by damaged graph and reconstructed graph
- Performance measure: AUC (Area under the ROC curve)



Experiment Setting

Model Parameter Selection

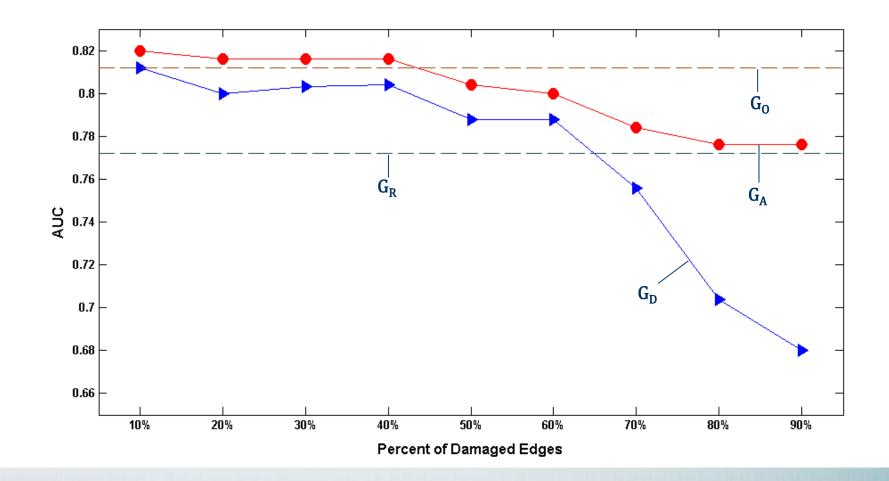
Parameters should be selected by user when learning with SSL

- *K* : *K*NN
- *μ* : SSL
- Combination of parameters
 - $K = \{3, 4, 5, 6, 7, 8, 9, 10, 20, 30\}$
 - μ = {0.001, 0.01, 0.05, 0.1, 0.2, 0.5, 0.7, 1.0, 10.0, 100.0, 1000.0}

Results

Results

Result comparison

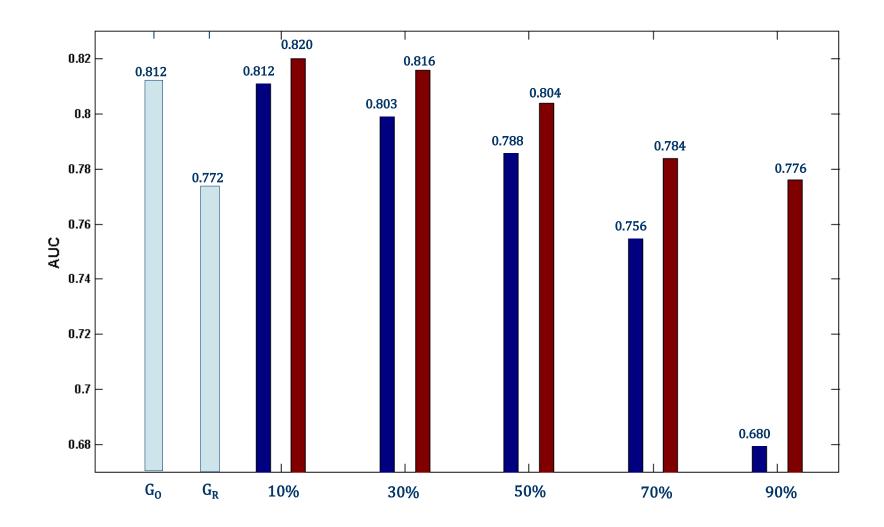


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Significance test of the performance differences

Percent of damaged edges	AUC of G _D	AUD of G _A	P-value
10%	0.812	0.820	1.87e-02
30%	0.803	0.816	2.09e-03
50%	0.788	0.804	3.43e-05
70%	0.756	0.784	9.59e-08
90%	0.680	0.776	1.24e-13

Improving performance from augmented knowledge based on inter-relation between miRNA and miRNA



Results

Conclusion

Discussion & Conclusion

- Proposed an integrated framework that combines genomic dataset and genomic knowledge
 - In order to provide a preliminary insight on the question that is how informative is inter-relationship between and gene expression
- Inter-relation from miRNA and target gene could help constructing intrarelation from gene expression for better cancer clinical outcome prediction
- Our results suggests that genomic knowledge is complementary to the prediction power of explaining cancer phenotype
 - Even though genomic data such as gene expression has incomplete information

Future work

- Gene expression regulation through mechanisms that involve miRNAs is valid knowledge for elucidating the cancer phenotype
 - Because miRNAs regulate many genes associated with different biological processes
- Reconstructing intra-relation from miRNA
- Combining gene expression, miRNA, and inter-relation

The Second phase of TCGA Project

Featured Article



October 6, 2009 • Volume 6 / Number 19

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IN DEPTH

Experts Tackle the Challenge of

The Cancer Genome Atlas Project to Map 20 Tumor Types

During a visit to the NIH campus last week, President Barack Obama announced that NIH will spend \$275 million over the next 2 years to catalogue the genetic changes driving more than 20 types of cancer.

The grant, which includes \$175 million in Recovery Act funds, will support the second phase of The Cancer Genome Atlas (TCGA) project. This collaborative effort led by NCI and the National Human Genome Research Institute (NHGRI) aims to discover the molecular alterations that occur in major types and subtypes of cancer.

Leaders of the project said that the TCGA pilot study, launched in 2006, has demonstrated the feasibility of using integrated genomic strategies to characterize the molecular alterations in cancer. The first three cancers profiled were brain, lung, and ovarian.



During a visit to NIH on Wednesday, September 30, President Barack Obama toured a laboratory with (from left to right) Secretary of Health and Human Services Kathleen Sebelius, National Institute of Allergy and Infectious Diseases Director Dr. Anthony Fauci, and NIH Director Dr. Francis Collins.

Thank You I

Any Question?

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