

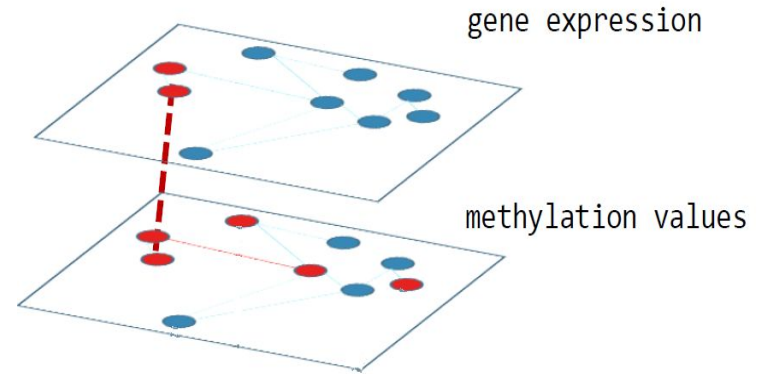
# MULTI-GNN FOR LUNG CANCER BIOMARKERS

Michael Bianco, Alessandro Artoni



# Introduction

The aim of the project is to identify biomarkers of lung cancer analyzing gene expression and methylation data.



# Data download and preprocessing

## GENE EXPRESSION



60000 GENES x 1712 SAMPLES



20000 GENES x 1712 SAMPLES



5000 GENES x 1712 SAMPLES

## METHYLATION DATA

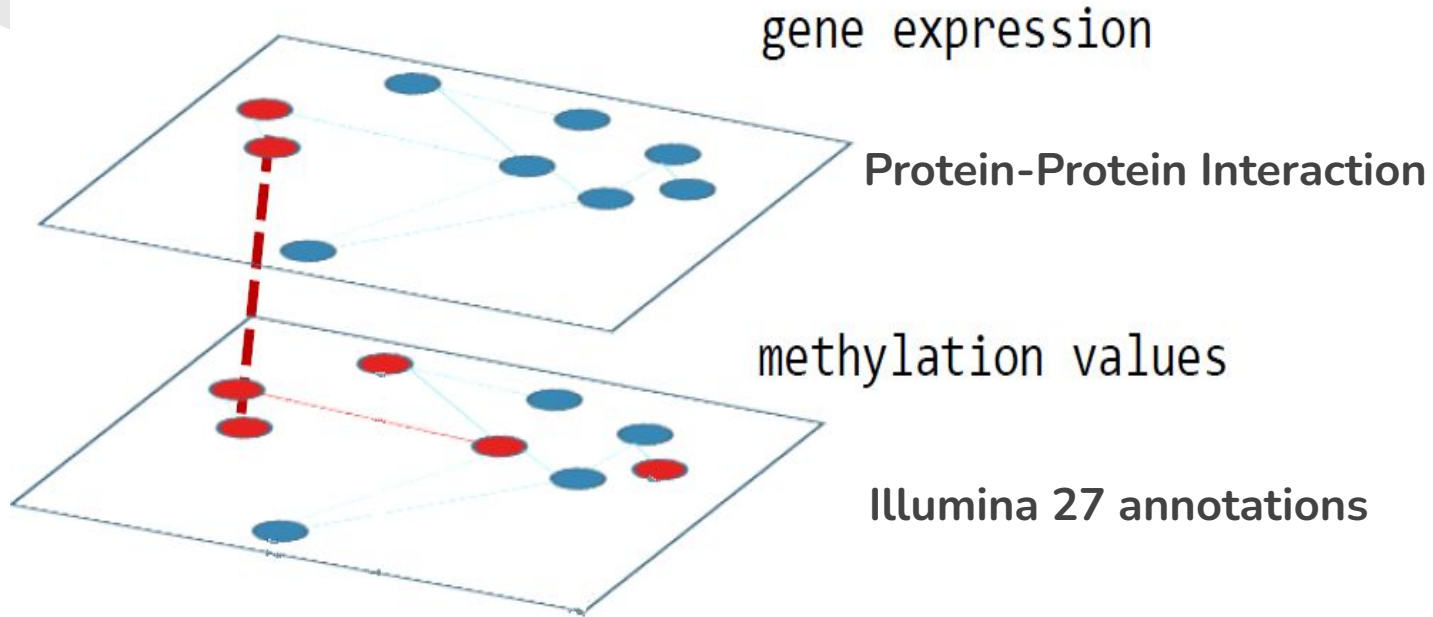


480000 SITES x 1712 SAMPLES



4235 SITES x 1712 SAMPLES

# Graph structure



# Evaluation Techniques

**Louvain:** greedy algorithm that maximizes modularity of the graph

**Lasso:** minimizes the difference between the predicted values and the actual ones

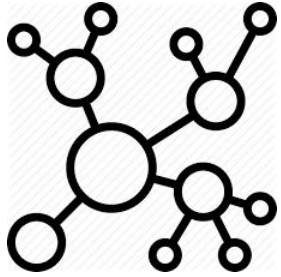
**SVM RFE:** feature selection technique used to identify the most important features for a predictive model

**PCA:** dimensionality reduction technique used to identify the principal components that captures the majority of the information

**Select KBest:** selects the K most important features from a given dataset

# Methylation Data Integration

## Learnable Layer Integration

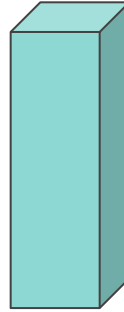


GENE  
EXPRESSION

(1712, 5000, 2)

METHYLATION  
DATA

CONV. LAYER



(1712, 5000, 1)

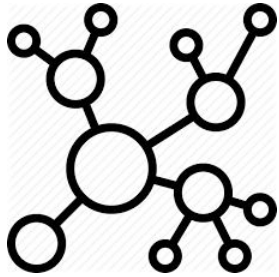


FC LAYER

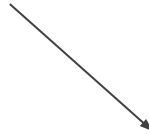
TUMOR  
/  
NON TUMOR

# Methylation Data Integration

## A-Priori Deterministic Design Integration



GENE  
EXPRESSION



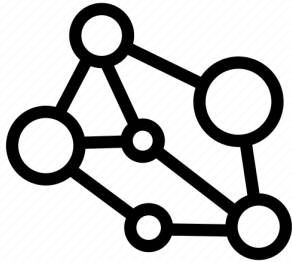
$$gene\_expression\_value * (1 + (1 - mean\_meth\_values))$$



WGCNA

$$10^{0.5 + 0.5 * corr(i,j)}$$

METHYLATION  
DATA



# Overall Results

With our analysis we have found the following known biomarkers for lung cancer

- Gene + Meth learnable layer integration: CPXCR1 (tumor suppr.), TRIM55, TMEM171 (colon cancer), GABRG1, ZBBX (nasoph. cancer), ACP7 (brain tumor)
- Gene + Meth a-priori integration: DEFA3, SPP1, CXCL13, AKR1B10, LIM2, IGSF9, ADCY8, PLAC1, CHRNA4, FAM83A, KRT16, LEP.
- Gene expression: PITX2, BARX1 (over expr.), CST1, PRAME (over expr.).



# Biomarkers Found

	<b>Biomarkers for LC</b>	<b>Tumor Suppressor</b>	<b>Biomarkers for other tumors</b>
<b>Learnable layer method</b>	TRIM55, GABRG1	CPXCR1	TMEM171, ZBBX, ACP7
<b>A-priori integration</b>	DEFA3, SPP1, CXCL13, AKR1B10, LIM2, IGSF9, ADCY8, PLAC1, CHRNA4, FAM83A, KRT16, LEP	X	X
<b>Gene expression</b>	PITX2, CST1, BARX1, PRAME	X	X

## Methylation Data Integration Learnable Layer Integration

- ✓ Self-learned representation of the overall data (gene + meth)
- ✓ One weight for each gene
- ✓ Weights are updated taking into account the whole dataset every epoch
- ✗ Finds more tumor suppressor genes with respect to known biomarkers

## Methylation Data Integration A-Priori Deterministic Design Integration

- ✓ Finds more known biomarkers for lung cancer
- ✓ Based on a formula following knowledge about biological transcriptome process
- ✗ Increments every gene expression value, using a fixed deterministic function

# Gene Expression Classification


## Network

```
GCN(  
  (conv1): GCNConv(5000, 128)  
  (conv2): GCNConv(128, 64)  
  (conv3): GCNConv(64, 2)  
  (classifier): Linear(in_features=2, out_features=2, bias=True)  
)
```

## Results

SVM	RF	DTC	KN	GCN
99.2%	98.7%	97.2%	98%	98.2%

# Graph Convolutional Network


$$\mathbf{h}_v^{(l)} = \sigma \left( \sum_{u \in N(v)} \mathbf{w}^{(l)} \frac{\mathbf{h}_u^{(l-1)}}{|N(v)|} \right)$$

GCN layer performs 2 phases

- Message passing: multiply node features with weight matrix  $W$  and normalize by node degree.
- Message aggregation: sum over messages from neighbors, then apply sigmoid activation function.

# Methylation Data Classification

## Network

```
GCN(  
  (conv1): GCNConv(4235, 128)  
  (conv2): GCNConv(128, 64)  
  (conv3): GCNConv(64, 2)  
  (classifier): Linear(in_features=2, out_features=2, bias=True)  
)
```

## Results

SVM	RF	DTC	KN	GCN
99.1%	98.2%	96.7%	96.2%	99.1%



# Conclusion

Thanks to our methods we found that a multi modal approach is better than working on a single modality, because the intersection between our five methods in the multi omics approach found one gene, meanwhile the single omics found zero genes. In addition, the multi omics approach found much more biomarkers than the single omics one. Further analysis can be performed to validate or check our results from a biological point of view, maybe adding some a-priori knowledge on gene expression transcription and methylation.

# THANKS FOR THE ATTENTION

Michael Bianco, Alessandro Artoni

