

# EE 542: Internet and Cloud Computing - Project Proposal

<b>Project Proposal</b>		Date: 10/25/18 Academic/Industry Mentor Name: Young Cho E-mail: youngcho@isi.edu	Evaluation criteria: 1. Innovation (15) 2. Final Design Report (25) 3. Completeness(10) 4. Practicality(25) 5. Complexity(10) 6. Design working in H/W(10) 7. All-undergrad team(5)
Team Name/mission statement  Trojans / Fight On			
Team Member	e-mail	Role/Responsibility	
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<p><b>Problem statement: What problem it solves? Or, what feature does it improve?</b>          Identify top contributing and/or interacting factors for Breast Cancer (for various subtypes), discover genomic and metabolic pathways of breast tumor growth and metastasis, and develop equivalent but simple classification model leading to better understanding of domain knowledge.</p> <p><b>Measure of success: How will you know you have achieved your goal?</b>          Ability to use a small subset of the original features and an interpretable model to classify normal and cancerous tissue subtypes.</p> <p><b>Proposal (100-200 words): How will your solution solve the problem described, or improve the feature selected?</b>          Cancer is studied at many levels -- in fact many studies focus on analysis of either upstream DNA genetic variations (i.e. SNP, copy number), or downstream proteomic microRNA gene expression levels. However, it is believed that cancer is caused by a combination of genetic predisposition and epigenetic (gene-environment) factors. For example, although genes are hereditary, DNA methylation can cause genes that were dormant before to be expressed. Silencing of tumor suppressor genes by DNA methylation is a probable mechanism that triggers cancer tumor proliferation.</p> <p>Based on the knowledge that cancer can be caused by a combination of factors in multiple levels of the genomic pathway, we will use an integrated approach - examining genome-wide data (including DNA copy number variation, microRNA, DNA methylation) to build a model that captures the interaction of the data.</p> <p>Dataset: GDC database (miRNA gene expression, RNA gene expression, DNA methylation)</p> <p>Our project can be organized into five phases:</p> <p>Phase 1: Build big data pipeline on AWS EMR</p> <ul style="list-style-type: none"> <li>- To enable fast processing, we will be using Apache Spark map-reduce on the AWS EMR platform, managed by Hadoop YARN.</li> </ul> <p>Phase 2: Understand the data via K-means clustering</p> <ul style="list-style-type: none"> <li>- Hierarchical clustering (i.e. divisive, agglomerative)</li> <li>- Distance measure: pearson correlation, normalized mutual information score</li> </ul> <p>Phase 3: Feature selection</p> <ul style="list-style-type: none"> <li>- Use non-linear feature selection algorithms (i.e. XGBoost + recursive feature elimination, kernelized Lasso feature selection etc.) to zero-in on important features.</li> </ul> <p>Phase 4: Build new features, or find optimal way to combine features</p> <ul style="list-style-type: none"> <li>- Pairwise pearson correlation coefficients between features from Phase 3</li> </ul>			

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- Topological overlap matrix transformation -- measures node connectivity

## Phase 5: Build model

- We aim to use interpretable models (such as Logistic Regression, SVM, Random Forest) to model non-linear dependencies of biomarkers and genes .
- Convolutional Neural Network will most likely give the highest accuracy, but does not provide much insight on the domain knowledge.

## Phase 6: Validation

- To overcome sub-optimal amount of data, we do multiple iterations of K-fold cross-validation to ensure that the model isn't overfitted to the training data.
- If time permits, we can utilize the same preprocessing, feature selection and classifier on data of same cancer type from a different database to validate our findings.

## Phase 8: Build correlation network

- Present results showing the inferred correlation network of important features

## Comparison with Published Results:

Reference	Data	Algorithm	Results
[3]	TCGA DNA methylation profiles for all cancer types	Random Forest, SVM	97%
[2]	Wisconsin Breast Cancer dataset	SVM and RVM hybrid model	96.41%
[4]	TCGA DNA methylation profiles for all cancer types	Convolutional Neural Network	92%

## References:

- [1] R. Radha, "Using K-Means Clustering Technique To Study Of Breast Cancer," pp. 211–214, 2014.
- [2] S. Kumari, "BREAST CANCER CLASSIFICATION USING BIG DATA APPROACH," PARIPEX - INDIAN J. Res., no. January, 2018.
- [3] F. Celli, F. Cumbo, and E. Weitschek, "Classification of large DNA methylation datasets for identifying cancer drivers." 2018.
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- [5] H. Behravan, J. M. Harti, M. Teng, and P. Katri, "Machine learning identifies interacting genetic variants contributing to breast cancer risk : A case study in Finnish cases and controls," no. February, pp. 1–13, 2018.
- [6] G. V Glinsky, T. Higashiyama, and A. B. Glinskii, "Classification of Human Breast Cancer Using Gene Expression Profiling as a Component of the Survival Predictor Algorithm," vol. 10, no. 858, pp. 2272–2283, 2004.

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