

Spring 2018 STAT115 Homework 6

Cancer Genomics, Due Sun 4/22

(your name)

2018-04-10

```
library(FirebrowseR)
library(limma)
library(survival)
# etc.
```

In this homework, we are going to explore the data analysis of TCGA.

Part I: Data from TCGA

Q1. Go to TCGA's website (<https://cancergenome.nih.gov/>) and play with its data portal. How many *Glioblastoma Multiforme* (GBM) cases in TCGA meet all of the following requirements?

1. Female;
2. Diagnosed at the age between 35 and 55;
3. Still alive.

Q2. TCGA GDC website <https://portal.gdc.cancer.gov/> provides all raw data for downloading, while the Broad Firehose provides analyses of interpreted and summarized data packaged in a form amenable to immediate algorithmic analysis. Go to the FireBrowse portal (<http://firebrowse.org/>), and download clinical data for GBM. What's the average age at diagnosis of all GBM patients?

Part II: Tumor Subtypes

You are given a number of TCGA glioblastoma (GBM) samples and 10 commercially available normal brains (it is unethical to take matched normal brain from GBM tumor patients), including their expression, DNA methylation, mutation profiles as well as patient survival. Please note that we only selected a subset of the samples to make this HW, which were simplified to give students a flavor of cancer genomics studies, so some findings from these data might not reflect the real biology of GBM.

Q3. The expression data(GBM_expr.txt) is in Affymetrix microarray format. Find the differential genes between cancer and normal. How many genes do you get?

```
gbm_expr <- read.table("data/GBM_expr.txt")
```

Q4. Find 1000 genes with the biggest variation in gene expression from all the samples (cancer and normal). What's the 1000th gene?

Q5. Do a K-means (k=3) clustering from all the expression profiles, differential genes (Q3), and more variable genes (Q4). Do cancer and normal separate in different clusters? Do the cancer samples consistently separate into 2 clusters, regardless of the genes you use?

```
set.seed(20180410)
```

Q6. How many genes are differentially expressed between the two GBM subtypes (with $FDR < 0.05$ and $\log FC > 1.5$)?

Q7. **For Graduate Students:** From the DNA methylation profiles (GBM_meth.txt), what are the genes significantly differentially methylated between the two subtypes? How many differentially expressed genes have an epigenetic (DNA methylation) cause?

```
gbm_meth <- read.table("data/GBM_meth.txt")  
# logit transformation  
gbm_meth <- as.data.frame(qlogis(as.matrix(gbm_meth)))
```

Part III: Survival analysis

Q8. With the survival data of the GBM tumors (GBM_clin.txt), make a Kaplan-Meier Curve to compare the two subtypes of GBM patients. Is there a significant difference in patient outcome between the two subtypes?

```
gbm_clin <- read.table("data/GBM_clin.txt")  
rownames(gbm_clin) <- gsub("-", ".", rownames(gbm_clin))
```

Q9. Use the differential genes between the two GBM subtypes (Q6) as a gene signature to do a Cox regression of all the samples. Try two different FDR and logFC cutoff settings (e.g. $FDR < 0.03$, $\log FC > 2$). Do these gene signatures give significant predictive power of patient outcome?

Q10. **For Graduate Students:** Many studies use gene signatures to predict prognosis of patients. Take a look at this paper: <http://journals.plos.org/ploscompbiol/article?id=10.1371/journal.pcbi.1002240>

It turns out that most published gene signatures are not significantly more associated with outcome than random predictors.

Write a script to randomly sample Y genes in this expression data as a gene signature and do Cox regression on the sampled signature to predict patient outcome. Automate the script and random sample followed by Cox regression 100 times. How does your signature in Q9 compared to random signatures in predicting outcome?

```
set.seed(20180410)
```

Part IV: Mutation analysis

Q11. The MAF files contain the mutations of each tumor compared to the normal DNA in the patient blood. Write a python program to parse out the mutations present in each tumor sample, and write out a table. Rank the mutations by how many times the specific mutation happens in the tumor samples provided, and submit the table with the top 20 mutations.

Q12. Are there any mutations that are specifically enriched in one subtype of GBM over the other?

Q13. Go to cBioPortal (<http://www.cbioportal.org>). Input each gene in Q12, and click Submit. You can see how often each gene is mutated in all TCGA cancer types. Based on this, which of the genes in Q12 is likely a cancer driver gene?

Q14. From the mutation tab on the cBioPortal result page, is this mutation a gain or loss of function mutation on the gene you identified from Q13?

Part V: Precision Medicine

A loved one was recently diagnosed with GBM, and from exome-seq of the tumor you identified the top mutation in Q12. You wonder whether there are drugs that can target this mutation to treat the cancer.

Q15. Go to <https://www.clinicaltrials.gov> to find clinical trials that target the gene in Q12. How many trials are related to glioblastoma or glioma? How many of these are actively recruiting patients which your loved one could potentially join? (Hint: search the disease name with gene name)

Part VI: CRISPR Screens

We will learn to analyze CRISPR screen data from this paper: <https://www.ncbi.nlm.nih.gov/pubmed/?term=26673326>. To identify therapeutic targets for glioblastoma (GBM), the author performed genome-wide CRISPR-Cas9 knockout (KO) screens in patient-derived GBM stem-like cell line (GSCs0131).

MAGECK tutorial:

- <https://sourceforge.net/p/mageck/wiki/Home/>
- <https://sourceforge.net/projects/mageck/>

Q16. Use MAGECK to do a basic QC of the CRISPR screen data (e.g. read mapping, ribosomal gene selection, replicate consistency, etc).

Q17. Analyze CRISPR screen data with MAGECK to identify positive and negative selection genes. How many genes are selected as positive or negative selection genes? Which pathways are enriched for positive and negative selection genes separately?

Q18. **For Graduate students:** Genes uniquely negatively selected in the GBM cell lines compared to many other cell lines could be potential drug targets for GBM. For the negatively selected genes, filter out those that are pan essential (PanEssential.txt). Take the remaining top 10 genes, and check whether those genes have drugs or are druggable from this website: <http://www.oasis-genomics.org/>. Go to Analysis → Pan Cancer Report, type the top genes and check the following table for druggability.

							SUMMARY	Adrenal	Bladder	
Gene (Click to descending sort this column)										
Gene	Dr	TS	On	Im	Se	Su				
BRAF	6		Y							
EGFR	6		Y	Y	Y	Y				
KRAS	2		Y							

Figure 1: Druggability Table for Q18.