

## Lab Exercise 9

1)

A)

Download all **GRCh38** gene annotations from **GENCODE** (you already worked with this dataset in [Homework Exercise 3](#)).

Use Pandas to parse it into a DataFrame. Filter only the records of type **transcript**. Extract the Ensembl gene ID of each record, and keep only the gene ID, chromosome and strand fields. Use Pandas's *drop\_duplicates* function to keep only one record for each (*gene\_id*, *chr*, *strand*) combination.

You are supposed to get a DataFrame that looks like:

|    | index | gene_id         | chr  | strand |
|----|-------|-----------------|------|--------|
| 0  | 1     | ENSG00000223972 | chr1 | +      |
| 1  | 13    | ENSG00000227232 | chr1 | -      |
| 2  | 26    | ENSG00000278267 | chr1 | -      |
| 3  | 29    | ENSG00000243485 | chr1 | +      |
| 4  | 37    | ENSG00000284332 | chr1 | +      |
| 5  | 40    | ENSG00000237613 | chr1 | -      |
| 6  | 48    | ENSG00000268020 | chr1 | +      |
| 7  | 51    | ENSG00000240361 | chr1 | +      |
| 8  | 58    | ENSG00000186092 | chr1 | +      |
| 9  | 77    | ENSG00000238009 | chr1 | -      |
| 10 | 100   | ENSG00000239945 | chr1 | -      |

B)

Use Pandas grouping to count the number of transcripts in each <chromosome, strand> pair. Sort the chromosome by their relative discrepancy between the two strands (i.e. sort them by  $\frac{|N_+ - N_-|}{N_+ + N_-}$  where  $N_+$  and  $N_-$  are the number of genes on the positive and negative strands of the chromosome, respectively). Use Pandas to do all the required operations (avoid using Python native data structures).

2)

A)

Download again the **TIGER** database for tissue-specific expression of genes (you worked with it on the last Homework Exercise). Parse the downloaded file into a DataFrame of two columns, **refseq** and **tissue**, where each record is a mapping between one RefSeq ID and one tissue name. If a row in the original file contains multiple tissues, break it down to multiple rows in your DataFrame.




You are supposed to get a DataFrame that looks like:

|   | refseq    | tissue          |
|---|-----------|-----------------|
| 0 | NM_033169 | bladder         |
| 1 | NM_000253 | liver           |
| 2 | NM_000253 | small_intestine |
| 3 | NM_033168 | bladder         |
| 4 | NM_000252 | liver           |

B)

Go to the **HGNC** database of human gene names: <https://www.genenames.org/download/statistics-and-files/>.

Download their dataset of all human gene names in JSON format:

|                        |                        |       |                                                                                                                                                                                                                                                                   |
|------------------------|------------------------|-------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
|                        | fragile site           | 117   |          |
|                        | immunoglobulin gene    | 228   |          |
|                        | protocadherin          | 39    |          |
|                        | readthrough            | 131   |          |
|                        | region                 | 38    |    |
|                        | unknown                | 193   |    |
|                        | virus integration site | 8     |    |
| Total Approved Symbols |                        | 41686 |    |

This file contains a mapping between various IDs, names and symbols of human genes. In particular it has Ensembl and RefSeq IDs (thus it can be used to map between the two datasets you obtained earlier). It also has UniProt IDs, gene symbols and names, and gene groups.

Parse it into a DataFrame with the following columns:

- symbol
- name
- ensembl\_id
- refseq
- uniprot\_ids
- gene\_groups

If a record in the original file contains multiple RefSeq IDs, break it to multiple rows in your DataFrame. Note that each record can also contain multiple UniProt IDs and groups, so these two columns need to store lists of values.

By the end of the parsing, you are supposed to get a DataFrame that looks like:

|   | symbol   | name                           | ensembl_id      | refseq    | uniprot_ids | gene_groups                                        |
|---|----------|--------------------------------|-----------------|-----------|-------------|----------------------------------------------------|
| 0 | A1BG     | alpha-1-B glycoprotein         | ENSG00000121410 | NM_130786 | [P04217]    | [Immunoglobulin like domain containing]            |
| 1 | A1BG-AS1 | A1BG antisense RNA 1           | ENSG00000268895 | NR_015380 | []          | [Antisense RNAs]                                   |
| 2 | A1CF     | APOBEC1 complementation factor | ENSG00000148584 | NM_014576 | [Q9NQ94]    | [RNA binding motif containing]                     |
| 3 | A2M      | alpha-2-macroglobulin          | ENSG00000175899 | NM_000014 | [P01023]    | [C3 and PZP like, alpha-2-macroglobulin domain...] |
| 4 | A2M-AS1  | A2M antisense RNA 1            | ENSG00000245105 | NR_026971 | []          | [Antisense RNAs]                                   |

C)

Merge the three datasets you parsed into a single DataFrame. This DataFrame should map between tissues and chromosomes associated with genes.

It should look like:

|   | symbol | name                           | ensembl_id      | refseq    | uniprot_ids | gene_groups                                        | tissue  | index   | chr   | strand |
|---|--------|--------------------------------|-----------------|-----------|-------------|----------------------------------------------------|---------|---------|-------|--------|
| 0 | A1BG   | alpha-1-B glycoprotein         | ENSG00000121410 | NM_130786 | [P04217]    | [Immunoglobulin like domain containing]            | liver   | 2491117 | chr19 | -      |
| 1 | A1CF   | APOBEC1 complementation factor | ENSG00000148584 | NM_014576 | [Q9NQ94]    | [RNA binding motif containing]                     | liver   | 1339593 | chr10 | -      |
| 2 | A1CF   | APOBEC1 complementation factor | ENSG00000148584 | NM_014576 | [Q9NQ94]    | [RNA binding motif containing]                     | stomach | 1339593 | chr10 | -      |
| 3 | A2M    | alpha-2-macroglobulin          | ENSG00000175899 | NM_000014 | [P01023]    | [C3 and PZP like, alpha-2-macroglobulin domain...] | liver   | 1596480 | chr12 | -      |
| 4 | A2ML1  | alpha-2-macroglobulin like 1   | ENSG00000166535 | NM_144670 | [A8K2U0]    | [C3 and PZP like, alpha-2-macroglobulin domain...] | colon   | 1595751 | chr12 | +      |
| 5 | A2ML1  | alpha-2-macroglobulin like 1   | ENSG00000166535 | NM_144670 | [A8K2U0]    | [C3 and PZP like, alpha-2-macroglobulin domain...] | tongue  | 1595751 | chr12 | +      |

D)

Calculate the enrichments for the associations between each chromosome and each tissue, using the formula:

$$\text{enrichment factor} = \frac{\text{number of observations}}{\text{number of expected observations}}$$

In our case, the number of observations is the number of genes shared by the tissue and chromosome. The number of expected observations is the number we would expect to observe if the two were independent (think how to calculate this number). An enrichment factor of 1 indicates no enrichment, an enrichment factor greater than 1 indicates positive enrichment (i.e. more shared genes than expected at random), and an enrichment factor smaller than 1 indicates negative enrichment (i.e. less shared genes than expected at random).

Draw a heatmap showing the associations between all tissues and chromosomes. For the sake of visibility, it is recommended to use a log scale (this means that the threshold between positive and negative enrichments would be 0 instead of 1).

Looking at the resulted figure, which tissues appear enriched in expressing genes on chromosome X?