Human Genome Annotation

[Tutorial] Human Genome Annotation

1. Introduction

1.1. What is gene annotation?

Over the past years, we have learnt that there are a number of chromosomes and genes in our genome. Counting the number of chromosomes is fairly easy but students might find difficult to say how many genes we have in our genome. If you can get an answer for this, could you tell how many genes encode protein and how many do not?

To answer this question, we need to access the database for gene annotation. Gene annotation is the process of making nucleotide sequence meaningful - where genes are located? whether it is protein-coding or noncoding. If you would like to get an overview of gene annotation, please find this link(http://www.biolyse.ca/what-is-gene-annotation-in-bioinformatics/).

One of well-known collaborative efforts in gene annotation is the GENCODE consortium. It is a part of the Encyclopedia of DNA Elements (The ENCODE project consortium) and aims to identify all gene features in the human genome using a combination of computational analysis, manual annotation, and experimental validation (Harrow et al. 2012). You might find another database for gene annotation, like RefSeq, CCDS, and need to understand differences between them.

Figure 1. Comparison of GENCODE and RefSeq gene annotation and the impact of reference geneset on variant effect prediction (Frankish et al. 2015). A) Mean number of alternatively spliced transcripts per multi-exon protein-coding locus B) Mean number of unique CDS per multi-exon protein-coding locus C) Mean number of unique (non-redundant) exons per multi-exon protein-coding locus D) Percentage genomic coverage of unique (non-redundant) exons at multi-exon protein-coding loci.

In this tutorial, we will access to gene annotation from the GENCODE consortium and explore genes and functional elements in our genome.

1.2. Aims

What we will do with this dataset:

Be familiar with gene annotation modality. Tidy data and create a table for your analysis. Apply tidyverse functions for data munging.

Please note that there is better solution for getting gene annotation in R if you use a biomart. Our tutorial is only designed to have a practice on tidyverse exercise.

2. Explore your data

2.1. Unboxing your dataset

This tutorial will use a gene annotation file from the GENCODE. You will need to download the file from the GENCODE. If you are using terminal, please download file using wget:

```
# Run from your terminal, not R console
# wget ftp://ftp.ebi.ac.uk/pub/databases/gencode/Gencode_human/release_31/gencode.v31.basic.annotation.

# Once you downloaded the file, you won't need to download it again. So please comment out the command
```

Once you download the file, you can print out the first few lines using the following bash command (we will learn UNIX commands later):

```
# Run from your terminal, not R console
# gzcat gencode.v31.basic.annotation.gtf.gz | head -7
```

The file is the GFT file format, which you will find most commonly in gene annotation. Please read the file format thoroughly in the link above.

For the tutorial, we need to load two packages. If the package is not installed in your system, please install it.

tidyverse, a package you have learnt from the chapter 5. readr, a package provides a fast and friendly way to read. Since the file gencode.v31.basic.annotation.gtf.gz is pretty large, you will need some function to load data quickly into your workspace. readr in a part of tidyverse, so you can just load tidyverse to use readr functions.

```
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --

## v ggplot2 3.3.5     v purrr   0.3.4
## v tibble  3.1.4     v dplyr   1.0.7
## v tidyr   1.1.3     v stringr 1.4.0
## v readr   2.0.1     v forcats 0.5.1

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(readr)
```

Let's load the GTF file into your workspace. We will use read_delim function from the readr package. This is much faster loading than read.delim or read.csv from R base. However, please keep in mind that some parameters and output class for read_delim are slightly different from them.

```
library(tidyverse)
d = read_delim('gencode.v31.basic.annotation.gtf.gz', delim = '\t', skip = 5, progres = F, col_names =
```

```
## Rows: 1756502 Columns: 9

## -- Column specification --------------------------------------------------------
## Delimiter: "\t"
## chr (7): X1, X2, X3, X6, X7, X8, X9
## dbl (2): X4, X5
```

```
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
d
```

```
## # A tibble: 1,756,502 x 9
##    X1    X2     X3            X4    X5 X6    X7    X8    X9
##    <chr> <chr>  <chr>      <dbl> <dbl> <chr> <chr> <chr> <chr>
##  1 chr1  HAVANA gene       11869 14409 .     +     .     "gene_id \"ENSG0000022~
##  2 chr1  HAVANA transcript 11869 14409 .     +     .     "gene_id \"ENSG0000022~
##  3 chr1  HAVANA exon       11869 12227 .     +     .     "gene_id \"ENSG0000022~
##  4 chr1  HAVANA exon       12613 12721 .     +     .     "gene_id \"ENSG0000022~
##  5 chr1  HAVANA exon       13221 14409 .     +     .     "gene_id \"ENSG0000022~
##  6 chr1  HAVANA transcript 12010 13670 .     +     .     "gene_id \"ENSG0000022~
##  7 chr1  HAVANA exon       12010 12057 .     +     .     "gene_id \"ENSG0000022~
##  8 chr1  HAVANA exon       12179 12227 .     +     .     "gene_id \"ENSG0000022~
##  9 chr1  HAVANA exon       12613 12697 .     +     .     "gene_id \"ENSG0000022~
## 10 chr1  HAVANA exon       12975 13052 .     +     .     "gene_id \"ENSG0000022~
## # ... with 1,756,492 more rows
```

Can you find out what the parameters mean? Few things to note are:

The GTF file contains the first few lines for comments (#). In general, the file contains description, provider, date, format. The GTF file does not have column names so you will need to assign 'FALSE for col_names.

This is sort of canonical way to load your dataset into R. However, we are using a GTF format, which is specific to gene annotation so we can use a package to specifically handle a GTF file.

Here I introduce the package rtracklayer. Let's install the package first.

```
if(!requireNamespace("BiocManager", quietly = TRUE))
  install.packages("BiocManager")

BiocManager::install("rtracklayer")
```

```
## Bioconductor version 3.13 (BiocManager 1.30.16), R 4.1.1 (2021-08-10)
```

```
## Warning: package(s) not installed when version(s) same as current; use `force = TRUE` to
##   re-install: 'rtracklayer'
```

```
## Installation paths not writeable, unable to update packages
##   path: C:/Program Files/R/R-4.1.1/library
##   packages:
##     lattice, mgcv, nlme, survival
```

```
## Old packages: 'digest', 'lubridate', 'readr', 'stringi', 'tibble', 'tidyr',
##   'xfun'
```

Then, now you can read the GTF file using this package. Then, you can check the class of the object d.

```
d = rtracklayer::import('gencode.v31.basic.annotation.gtf.gz')
class(d)
```

```
## [1] "GRanges"
## attr(,"package")
## [1] "GenomicRanges"
```

You will find out that this is GRanges class. This is from the package Genomic Range, specifically dealing with genomic datasets but we are not heading into this in this tutorial. So please find this information if you are serious on this.

We are converting d into a data frame as following:

```
d = d %>% as.data.frame()
```

Let's overview few lines from the data frame, and explore what you get in this object.

```
head(d)
```

```
##   seqnames start   end width strand source       type score phase
## 1     chr1 11869 14409  2541      + HAVANA       gene    NA    NA
## 2     chr1 11869 14409  2541      + HAVANA transcript    NA    NA
## 3     chr1 11869 12227   359      + HAVANA       exon    NA    NA
## 4     chr1 12613 12721   109      + HAVANA       exon    NA    NA
## 5     chr1 13221 14409  1189      + HAVANA       exon    NA    NA
## 6     chr1 12010 13670  1661      + HAVANA transcript    NA    NA
##              gene_id                         gene_type gene_name level
## 1 ENSG00000223972.5 transcribed_unprocessed_pseudogene   DDX11L1     2
## 2 ENSG00000223972.5 transcribed_unprocessed_pseudogene   DDX11L1     2
## 3 ENSG00000223972.5 transcribed_unprocessed_pseudogene   DDX11L1     2
## 4 ENSG00000223972.5 transcribed_unprocessed_pseudogene   DDX11L1     2
## 5 ENSG00000223972.5 transcribed_unprocessed_pseudogene   DDX11L1     2
## 6 ENSG00000223972.5 transcribed_unprocessed_pseudogene   DDX11L1     2
##      hgnc_id          havana_gene     transcript_id
## 1 HGNC:37102 OTTHUMG00000000961.2             <NA>
## 2 HGNC:37102 OTTHUMG00000000961.2 ENST00000456328.2
## 3 HGNC:37102 OTTHUMG00000000961.2 ENST00000456328.2
## 4 HGNC:37102 OTTHUMG00000000961.2 ENST00000456328.2
## 5 HGNC:37102 OTTHUMG00000000961.2 ENST00000456328.2
## 6 HGNC:37102 OTTHUMG00000000961.2 ENST00000450305.2
##                     transcript_type transcript_name transcript_support_level
## 1                              <NA>            <NA>                      <NA>
## 2                            lncRNA     DDX11L1-202                         1
## 3                            lncRNA     DDX11L1-202                         1
## 4                            lncRNA     DDX11L1-202                         1
## 5                            lncRNA     DDX11L1-202                         1
## 6 transcribed_unprocessed_pseudogene     DDX11L1-201                        NA
##     tag    havana_transcript exon_number           exon_id         ont
## 1  <NA>                 <NA>        <NA>              <NA>        <NA>
## 2 basic OTTHUMT00000362751.1        <NA>              <NA>        <NA>
## 3 basic OTTHUMT00000362751.1           1 ENSE00002234944.1        <NA>
## 4 basic OTTHUMT00000362751.1           2 ENSE00003582793.1        <NA>
## 5 basic OTTHUMT00000362751.1           3 ENSE00002312635.1        <NA>
```

```
## 6 basic OTTHUMT00000002844.2        <NA>              <NA> PGO:0000019
##   protein_id ccdsid
## 1       <NA>   <NA>
## 2       <NA>   <NA>
## 3       <NA>   <NA>
## 4       <NA>   <NA>
## 5       <NA>   <NA>
## 6       <NA>   <NA>
```

One thing you can find is that there is no columns in the data frame. Let's match which information is provided in columns. You can find the instruction page in the website (https://www.gencodegenes.org/pages/data_format.html).

Based on this, you can assign a name for 9 columns. One thing to remember is you should not use space for the column name. Spacing in the column name is actually working but not a good habit for your code. So please replace a space with underscore in the column name.

```
# Assign column names according to the GENCODE instruction.
cols = c('chrom', 'source', 'feature_type', 'start', 'end', 'score', 'strand', 'phase', 'info')
```

Now you can set up the column names into the col_names parameter, and load the file into a data frame.

```
d = read_delim('gencode.v31.basic.annotation.gtf.gz',
               delim = '\t', skip = 5,
               progress = F,
               col_names = cols)
```

```
## Rows: 1756502 Columns: 9

## -- Column specification --------------------------------------------------------
## Delimiter: "\t"
## chr (7): chrom, source, feature_type, score, strand, phase, info
## dbl (2): start, end

##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

You can find the column names are now all set.

```
head(d)
```

```
## # A tibble: 6 x 9
##   chrom source feature_type start   end score strand phase info
##   <chr> <chr>  <chr>        <dbl> <dbl> <chr> <chr>  <chr> <chr>
## 1 chr1  HAVANA gene         11869 14409 .     +      .     "gene_id \"ENSG00000~
## 2 chr1  HAVANA transcript   11869 14409 .     +      .     "gene_id \"ENSG00000~
## 3 chr1  HAVANA exon         11869 12227 .     +      .     "gene_id \"ENSG00000~
## 4 chr1  HAVANA exon         12613 12721 .     +      .     "gene_id \"ENSG00000~
## 5 chr1  HAVANA exon         13221 14409 .     +      .     "gene_id \"ENSG00000~
## 6 chr1  HAVANA transcript   12010 13670 .     +      .     "gene_id \"ENSG00000~
```

When you loaded the file, you see the message about the data class. You might want to overview this data.

```
summary(d)
```

```
##     chrom              source          feature_type          start
##  Length:1756502     Length:1756502     Length:1756502     Min.   :      577
##  Class :character   Class :character   Class :character   1st Qu.: 32101517
##  Mode  :character   Mode  :character   Mode  :character   Median : 61732754
##                                                           Mean   : 75288563
##                                                           3rd Qu.:111760181
##                                                           Max.   :248936581
##       end               score              strand             phase
##  Min.   :      647   Length:1756502     Length:1756502     Length:1756502
##  1st Qu.: 32107331   Class :character   Class :character   Class :character
##  Median : 61738373   Mode  :character   Mode  :character   Mode  :character
##  Mean   : 75292632
##  3rd Qu.:111763007
##  Max.   :248937043
##      info
##  Length:1756502
##  Class :character
##  Mode  :character
##
##
##
```

2.2. How many feature types in the GENCODE dataset?

As instructed in the GENCODE website, the GENCODE dataset provides a range of annotations for the feature type. You can check feature types using _____ function.

```
d %>% group_by(feature_type) %>% count(feature_type)
```

```
## # A tibble: 8 x 2
## # Groups:   feature_type [8]
##   feature_type        n
##   <chr>           <int>
## 1 CDS            567862
## 2 exon           744835
## 3 gene            60603
## 4 Selenocysteine     96
## 5 start_codon     57886
## 6 stop_codon      57775
## 7 transcript     108243
## 8 UTR            159202
```

```
# table(d$feature_type)
```

How many feature types provided in the GENCODE? And how many items stored for each feature type? Please write down the number of feature types from the dataset. Also, if you are not familiar with these types, it would be good to put one or two sentences that can describe each type.

```
# There are 8 feature types in the GENCODE.
# CDS 567862 / exon 744835 / gene 60603 / Selenocysteine 96 / start_codon 57886 / stop_codon 57775 / tr
```

2.3. How many genes we have?

Let's count the number of genes in our genome. Since we know that the column feature_type contains rows with gene, which contains obviously annotations for genes. We might want to subset those rows from the data frame.

```
d1 = filter(d, feature_type == 'gene')
# d1 = d[d$feature_type == 'gene', ]
d1
```

```
## # A tibble: 60,603 x 9
##    chrom source  feature_type start    end score strand phase info
##    <chr> <chr>   <chr>        <dbl>  <dbl> <chr> <chr>  <chr> <chr>
##  1 chr1  HAVANA  gene         11869  14409 .     +      .     "gene_id \"ENSG00~
##  2 chr1  HAVANA  gene         14404  29570 .     -      .     "gene_id \"ENSG00~
##  3 chr1  ENSEMBL gene         17369  17436 .     -      .     "gene_id \"ENSG00~
##  4 chr1  HAVANA  gene         29554  31109 .     +      .     "gene_id \"ENSG00~
##  5 chr1  ENSEMBL gene         30366  30503 .     +      .     "gene_id \"ENSG00~
##  6 chr1  HAVANA  gene         34554  36081 .     -      .     "gene_id \"ENSG00~
##  7 chr1  HAVANA  gene         52473  53312 .     +      .     "gene_id \"ENSG00~
##  8 chr1  HAVANA  gene         57598  64116 .     +      .     "gene_id \"ENSG00~
##  9 chr1  HAVANA  gene         65419  71585 .     +      .     "gene_id \"ENSG00~
## 10 chr1  HAVANA  gene         89295 133723 .     -      .     "gene_id \"ENSG00~
## # ... with 60,593 more rows
```

2.4. Ensembl, Havana and CCDS.

Gene annotation for the human genome is provided by multiple organizations with different gene annotation methods and strategy. This means that information can be varying by resources, and users need to understand heterogeniety inherent in annotation databases.

The GENCODE project utlizes two sources of gene annotation.

1. Havana: Manual gene annotation (https://asia.ensembl.org/info/genome/genebuild/manual_havana.html)
2. Ensembl: Automatic gene annotation (https://asia.ensembl.org/info/genome/genebuild/automatic_coding.html)

It provides the combination of Ensembl/HAVANA gene set as the default gene annotation for the human genome. In addition, they also guarantee that all transcripts from the Consensus Coding Sequence (CCDS) set are present in the GENCODE gene set. The CCDS project is a collaborative effort to identify a core set of protein coding regions that are consistently annotated and of high quality. Initial results from the Consensus CDS (CCDS) project are now available through the appropriate Ensembl gene pages and from the CCDS project page at NCBI. The CCDS set is built by consensus among Ensembl, the National Center for Biotechnology Information (NCBI), and the HUGO Gene Nomenclature Committee (HGNC) for human (https://asia.ensembl.org/info/genome/genebuild/ccds.html).

Figure 2. Comparison of CCDS and Gencode (https://twitter.com/ensembl/status/441959722376499200).

Right. Then now we count how many genes annotated with HAVANA and ENSEMBL.

```
d %>% group_by(source) %>% count(source)
```

```
## # A tibble: 2 x 2
## # Groups:   source [2]
##   source        n
##   <chr>     <int>
## 1 ENSEMBL  245185
## 2 HAVANA  1511317
```

2.5. do.call

Since the last column info contains a long string for multiple annotations, we will need to split it to extract each annotation. For example, the first line for transcript annotation looks like this:

```
# chr1    HAVANA    transcript    11869    14409    .    +    .    gene_id "ENSG00000223972.5"; transcr
```

If you would like to split transcript_support_level and create a new column, you can use strsplit function.

```
a = 'chr1    HAVANA    transcript    11869    14409    .    +    .    gene_id "ENSG00000223972.5"; trans

strsplit(a, 'transcript_support_level\\s+"')
```

```
## [[1]]
## [1] "chr1    HAVANA    transcript    11869    14409    .    +    .    gene_id \"ENSG00000223972.5\";
## [2] "1\"; hgnc_id \"HGNC:37102\"; tag \"basic\"; havana_gene \"OTTHUMG00000000961.2\"; havana_transc
```

After split the string, you can select the second item in the list ([[1]][2]).

```
strsplit(a, 'transcript_support_level\\s+"')[[1]][2]
```

```
## [1] "1\"; hgnc_id \"HGNC:37102\"; tag \"basic\"; havana_gene \"OTTHUMG00000000961.2\"; havana_transc
```

You can find the 1 in the first position, which you will need to split again.

```
b = strsplit(a, 'transcript_support_level\\s+"')[[1]][2]
strsplit(b, '\\"')
```

```
## [[1]]
##  [1] "1"                   "; hgnc_id "          "HGNC:37102"
##  [4] "; tag "              "basic"               "; havana_gene "
##  [7] "OTTHUMG00000000961.2" "; havana_transcript " "OTTHUMT00000362751.1"
## [10] ";"
```

From this, you will get the first item in the list ([[1]][1]).

Now you would like to apply strsplit function across vectors. For this, do.call function can be easily implemented to strsplit over the vectors from one column. Let's try this.

```
head(do.call(rbind.data.frame, strsplit(a, 'transcript_support_level\\s+"'))[[2]])
```

```
## [1] "1\"; hgnc_id \"HGNC:37102\"; tag \"basic\"; havana_gene \"OTTHUMG00000000961.2\"; havana_transc
```

Now you can write two lines of codes to process two steps we discussed above.

```
# First filter transcripts and create a data frame.
d2 <- d %>% filter(feature_type == 'transcript')

# Now apply the functions.
d2$transcript_support_level <- as.character(do.call(rbind.data.frame, strsplit(d2$info, 'transcript_sup

d2$transcript_support_level <- as.character(do.call(rbind.data.frame, strsplit(d2$transcript_support_le
```

Now you can check the strsplit works.

```
head(d2$transcript_support_level)
```

```
## [1] "1"  "NA" "NA" "NA" "5"  "5"
```

You can use the same method to extract other annotations, like gene_id, gene_name etc.

3. Exercises

Here I list the questions for group activity. Please note that it is an exercise for tidyverse functions, which you will need to use in your code. In addition, you will need to write an one-line code for each question using pipe %>%.

For questions, you should read some information thoroughly, including:

Gene biotype. 0 or 1 based annotation in GTF, BED format Why some features have 1 bp length? What is the meaning of zero-length exons in GENCODE? Also fun to have a review for microexons Transcript support level (TSL)

```
library(tidyverse)
library(readr)

d2 = rtracklayer::import('gencode.v31.basic.annotation.gtf.gz') %>% as.data.frame()
```

3.1. Annotation of transcripts in our genome

1. Computes the number of transcripts per gene. What is the mean number of transcripts per gene? What is the quantile (25%, 50%, 75%) for these numbers? Which gene has the greatest number of transcript?

```
d2 %>% filter(type == 'transcript') %>% count(gene_id) %>% summarise(num = n) %>% pull(num) %>% mean()
```

```
## [1] 1.7861
```

```
d2 %>% filter(type == 'transcript') %>% count(gene_id) %>% summarise(num = n) %>% pull(num) %>% quantil
```

```
## 25% 50% 75%
##   1   1   2
```

```
d2 %>% filter(type == 'transcript') %>% group_by(gene_id) %>% count() %>% ungroup() %>% top_n(1, n)
```

```
## # A tibble: 1 x 2
##   gene_id                n
##   <chr>              <int>
## 1 ENSG00000109339.22    87
```

2. Compute the number of transcripts per gene among gene biotypes. For example, compare the number of transcript per gene between protein-coding genes, long noncoding genes, pseudogenes.

```
d2 %>% filter(type == 'transcript') %>% count(gene_type) %>% summarise(num = n) %>% pull(num) %>% mean(
```

```
## [1] 2706.075
```

```
d2 %>% filter(type == 'transcript') %>% count(gene_type) %>% summarise(num = n) %>% pull(num) %>% quanti
```

```
##    25%    50%    75%
##   5.75  50.50 891.00
```

```
d2 %>% filter(type == 'transcript') %>% group_by(gene_type) %>% count() %>% ungroup() %>% top_n(1, n)
```

```
## # A tibble: 1 x 2
##   gene_type          n
##   <chr>          <int>
## 1 protein_coding 57846
```

3. Final task is to compute the number of transcripts per gene per chromosome.

```
d2 %>% filter(type == 'transcript') %>% count(seqnames) %>% summarise(num = n) %>% pull(num) %>% mean()
```

```
## [1] 4329.72
```

```
d2 %>% filter(type == 'transcript') %>% count(seqnames) %>% summarise(num = n) %>% pull(num) %>% quantil
```

```
##  25%  50%  75%
## 2618 4350 5612
```

```
d2 %>% filter(type == 'transcript') %>% group_by(seqnames) %>% count() %>% ungroup() %>% top_n(1, n)
```

```
## # A tibble: 1 x 2
##   seqnames     n
##   <fct>    <int>
## 1 chr1      9827
```

3.2. Gene length in the GENCODE

1. What is the average length of human genes?

```
d2 %>% filter(type == 'gene') %>% summarise(mean(width))
```

```
##   mean(width)
## 1    32629.02
```

2. Is the distribution of gene length differed by autosomal and sex chromosomes? Please calculate the quantiles (0%, 25%, 50%, 75%, 100%) of the gene length for each group.

```
d2 %>% mutate(chrom = ifelse(seqnames %in% c('chrX', 'chrY'), 'sex chromosome', ifelse(seqnames == 'chrl
```

```
## `summarise()` has grouped output by 'chrom'. You can override using the `.groups` argument.
```

```
## # A tibble: 10 x 2
## # Groups:   chrom [2]
##    chrom              qnt
##    <chr>            <dbl>
##  1 autosome             8
##  2 autosome           565
##  3 autosome          3779
##  4 autosome         25813
##  5 autosome       2473537
##  6 sex chromosome      48
##  7 sex chromosome     473
##  8 sex chromosome    1912
##  9 sex chromosome   13502
## 10 sex chromosome 2241765
```

3. Is the distribution of gene length differed by gene biotype? Please calculate the quantiles (0%, 25%, 50%, 75%, 100%) of the gene length for each group.

```
d2 %>% group_by(gene_type) %>% summarise(qnt = quantile(width, ))
```

```
## `summarise()` has grouped output by 'gene_type'. You can override using the `.groups` argument.
```

```
## # A tibble: 200 x 2
## # Groups:   gene_type [40]
##    gene_type         qnt
##    <chr>           <dbl>
##  1 IG_C_gene           3
##  2 IG_C_gene          92
##  3 IG_C_gene        312.
##  4 IG_C_gene         336
##  5 IG_C_gene        8914
##  6 IG_C_pseudogene    34
##  7 IG_C_pseudogene   293
##  8 IG_C_pseudogene   316
##  9 IG_C_pseudogene   424
## 10 IG_C_pseudogene  5211
## # ... with 190 more rows
```

3.3. Transcript support levels (TSL)

The GENCODE TSL provides a consistent method of evaluating the level of support that a GENCODE transcript annotation is actually expressed in humans.

1. With transcript, how many transcripts are categorized for each TSL?

```
d2 %>% filter(type == 'transcript') %>% count(transcript_support_level)
```

```
##   transcript_support_level     n
## 1                        1 31801
## 2                        2 13372
## 3                        3  7228
## 4                        4  2245
## 5                        5 13674
## 6                       NA 27843
## 7                     <NA> 12080
```

2. From the first question, please count the number of transcript for each TSL by gene biotype.

```
d2 %>% filter(type == 'transcript') %>% group_by(gene_type, transcript_support_level) %>% count(transcri
```

```
## # A tibble: 91 x 3
## # Groups:   gene_type, transcript_support_level [91]
##    gene_type       transcript_support_level     n
##    <chr>           <chr>                    <int>
##  1 IG_C_gene       1                            1
##  2 IG_C_gene       5                            1
##  3 IG_C_gene       NA                           7
##  4 IG_C_gene       <NA>                         5
##  5 IG_C_pseudogene NA                           9
##  6 IG_D_gene       NA                          37
##  7 IG_J_gene       NA                          18
##  8 IG_J_pseudogene NA                           3
##  9 IG_pseudogene   NA                           1
## 10 IG_V_gene       5                            3
## # ... with 81 more rows
```

3. From the first question, please count the number of transcript for each TSL by source.

```
d2 %>% filter(type == 'transcript') %>% group_by(source, transcript_support_level) %>% count(transcript_
```

```
## # A tibble: 14 x 3
## # Groups:   source, transcript_support_level [14]
##    source  transcript_support_level     n
##    <fct>   <chr>                    <int>
##  1 HAVANA  1                        29434
##  2 HAVANA  2                        12052
##  3 HAVANA  3                         6964
##  4 HAVANA  4                         2116
##  5 HAVANA  5                        10157
```

```
##  6 HAVANA  NA                      19962
##  7 HAVANA  <NA>                    11901
##  8 ENSEMBL 1                        2367
##  9 ENSEMBL 2                        1320
## 10 ENSEMBL 3                         264
## 11 ENSEMBL 4                         129
## 12 ENSEMBL 5                        3517
## 13 ENSEMBL NA                       7881
## 14 ENSEMBL <NA>                      179
```

3.4. CCDS in the GENCODE

1. With gene, please create a data frame with the columns - gene_id, gene_name, hgnc_id, gene_type, chromosome, start, end, and strand. Then, please create new columns for presence of hgnc and ccds. For example, you can put 1 in the column isHgnc, if hgnc annotation is avaiable, or 0 if not. Then, you can put 1 in the column isCCDS, if ccds annotation is avaiable, or 0 if not.

```
df <- d2 %>% filter(type == 'gene') %>% summarise(gene_id = gene_id, gene_name = gene_name, hgnc_id = hg
```

2. Please count the number of hgnc by gene biotypes.

```
df %>% group_by(gene_type) %>% filter(isHgnc == 1) %>% count()
```

```
## # A tibble: 36 x 2
## # Groups:   gene_type [36]
##    gene_type           n
##    <chr>           <int>
##  1 IG_C_gene          14
##  2 IG_C_pseudogene     9
##  3 IG_D_gene          37
##  4 IG_J_gene          18
##  5 IG_J_pseudogene     3
##  6 IG_V_gene         142
##  7 IG_V_pseudogene   185
##  8 lncRNA           3970
##  9 miRNA            1856
## 10 misc_RNA         1033
## # ... with 26 more rows
```

3. Please count the number of hgnc by level. Please note that level in this question is not TSL. Please find information in this link: 1 (verified loci), 2 (manually annotated loci), 3 (automatically annotated loci).

```
d2 %>% mutate(isHgnc = ifelse(is.na(hgnc_id) == T, 0, 1)) %>% filter(isHgnc == 1) %>% group_by(level) %
```

```
## # A tibble: 3 x 2
## # Groups:   level [3]
##   level       n
##   <chr>   <int>
## 1 1      107054
## 2 2     1279964
## 3 3      237265
```

3.5. Transcripts in the GENCODE

1. Which gene has the largest number of transcripts?

```
d2 %>% filter(type == 'transcript') %>% group_by(gene_id) %>% count() %>% ungroup() %>% top_n(1, n)
```

```
## # A tibble: 1 x 2
##   gene_id                n
##   <chr>              <int>
## 1 ENSG00000109339.22    87
```

2. Please calculate the quantiles (0%, 25%, 50%, 75%, 100%) of the gene length for protein coding genes and long noncoding genes.

```
d2 %>% filter(type == 'gene', gene_type %in% c('lncRNA', 'protein_coding')) %>% group_by(gene_type) %>%
```

```
## `summarise()` has grouped output by 'gene_type'. You can override using the `.groups` argument.
```

```
## # A tibble: 10 x 2
## # Groups:   gene_type [2]
##    gene_type           qnt
##    <chr>             <dbl>
##  1 lncRNA              68
##  2 lncRNA            1874.
##  3 lncRNA            6272.
##  4 lncRNA           24774.
##  5 lncRNA         1375317
##  6 protein_coding     117
##  7 protein_coding    9632.
##  8 protein_coding   27212
##  9 protein_coding   70809
## 10 protein_coding 2473537
```

3. Please count the number of transcripts by chromosomes.

```
d2 %>% filter(type == 'transcript') %>% group_by(seqnames) %>% count()
```

```
## # A tibble: 25 x 2
## # Groups:   seqnames [25]
##    seqnames     n
##    <fct>    <int>
##  1 chr1      9827
##  2 chr2      7432
##  3 chr3      6157
##  4 chr4      4662
##  5 chr5      5203
##  6 chr6      5455
##  7 chr7      5292
##  8 chr8      4350
##  9 chr9      3949
## 10 chr10     4157
## # ... with 15 more rows
```

3.6. Autosomal vs. Sex chromosomes.

1. Please calculate the number of genes per chromosome.

```
d2 %>% filter(type == 'gene') %>% group_by(seqnames) %>% count()
```

```
## # A tibble: 25 x 2
## # Groups:   seqnames [25]
##    seqnames     n
##    <fct>    <int>
##  1 chr1      5471
##  2 chr2      4196
##  3 chr3      3185
##  4 chr4      2651
##  5 chr5      2983
##  6 chr6      3059
##  7 chr7      3014
##  8 chr8      2482
##  9 chr9      2327
## 10 chr10     2332
## # ... with 15 more rows
```

2. Please compare the number of genes between autosomal and sex chromosome (Mean, Median).

```
d2 %>% mutate(chrom = ifelse(seqnames %in% c('chrX', 'chrY'), 'sex chromosome', ifelse(seqnames == 'chrl
```

```
## `summarise()` has grouped output by 'chrom'. You can override using the `.groups` argument.
```

```
## # A tibble: 2 x 3
##   chrom           mean median
##   <chr>          <dbl>  <dbl>
## 1 autosome       2617.  2604.
## 2 sex chromosome 1494.  1494.
```

3. Please divide the genes into groups 'protein coding' and 'long noncoding', and then compare the number of genes in each chromosomes within groups.

```
d2 %>% filter(type == 'gene', gene_type %in% c('lncRNA', 'protein_coding')) %>% group_by(seqnames, gene_
```

```
## # A tibble: 49 x 3
## # Groups:   seqnames, gene_type [49]
##    seqnames gene_type          n
##    <fct>    <chr>          <int>
##  1 chr1     lncRNA          1416
##  2 chr1     protein_coding  2048
##  3 chr2     lncRNA          1241
##  4 chr2     protein_coding  1247
##  5 chr3     lncRNA           861
##  6 chr3     protein_coding  1075
##  7 chr4     lncRNA           790
##  8 chr4     protein_coding   751
##  9 chr5     lncRNA           950
## 10 chr5     protein_coding   886
## # ... with 39 more rows
```