

Differential expression (F2-28, Elite and PI127826 2020 plants)

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1 Data import

1.1 Import scaled counts

```
scaled_counts <- read.delim("../Supplemental_data_RNA-seq/scaled_counts.tsv",  
                             check.names = F,  
                             stringsAsFactors = F) %>%  
mutate(gene = gsub(pattern = "mRNA:", replacement = "", x = gene)) %>%  
dplyr::select("gene", "F2-28_concat", "Elite_2020", "PI127826_2020")
```

1.2 Mapping summary

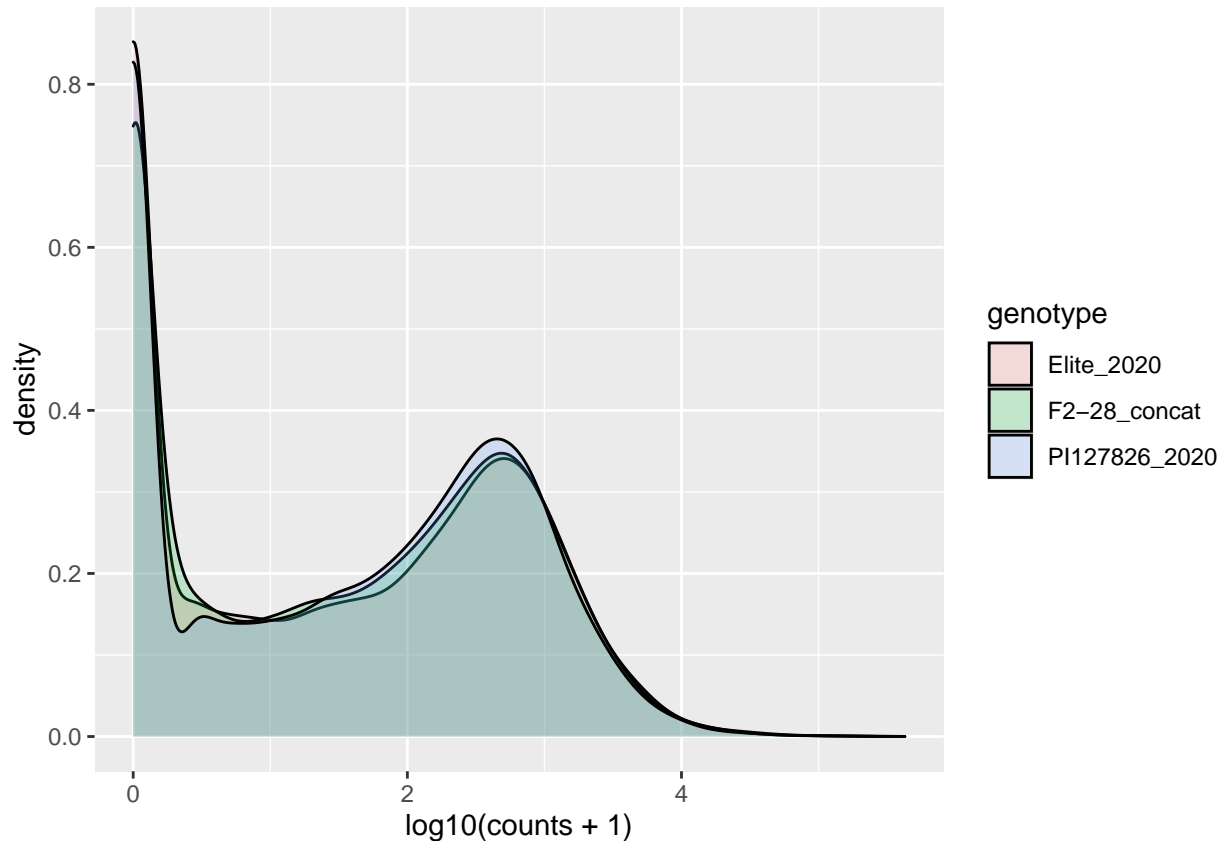
```
read.csv("../Supplemental_data_RNA-seq/mapping_summary.csv",
          col.names = c("row_id", "attribute", "Elite", "F2-28", "PI127826"),
          stringsAsFactors = F,
          check.names = F) %>%
  knitr::kable()
```

row_id	attribute	Elite	F2-28	PI127826
0	Started job on	Oct 18 10:33:50	Oct 18 10:33:50	Oct 18 10:33:50
1	Started mapping on	Oct 18 10:33:51	Oct 18 10:33:51	Oct 18 10:33:51
2	Finished on	Oct 18 10:35:12	Oct 18 10:39:59	Oct 18 10:35:41
3	Mapping speed, Million of reads per hour	881.26	813.11	613.73
4	Number of input reads	19828365	83118240	18752904
5	Average input read length	75	75	75
6	UNIQUE READS:			
7	Uniquely mapped reads number	18055736	61661853	14198867
8	Uniquely mapped reads %	91.06%	74.19%	75.72%
9	Average mapped length	75.93	75.97	75.94
10	Number of splices: Total	2884753	9859004	2184309
11	Number of splices: Annotated (sjdb)	2657391	9134650	2021184
12	Number of splices: GT/AG	2848414	9700348	2143184
13	Number of splices: GC/AG	27981	92798	22373
14	Number of splices: AT/AC	876	2987	710
15	Number of splices: Non-canonical	7482	62871	18042
16	Mismatch rate per base, %	0.48%	1.15%	1.55%
17	Deletion rate per base	0.01%	0.07%	0.09%
18	Deletion average length	1.68	2.03	2.14
19	Insertion rate per base	0.01%	0.03%	0.04%
20	Insertion average length	1.49	1.72	1.75
21	MULTI-MAPPING READS:			
22	Number of reads mapped to multiple loci	768089	3757232	1700643
23	% of reads mapped to multiple loci	3.87%	4.52%	9.07%
24	Number of reads mapped to too many loci	4801	10938	2723
25	% of reads mapped to too many loci	0.02%	0.01%	0.01%
26	UNMAPPED READS:			
27	Number of reads unmapped: too many mismatches	445826	5091357	1666717
28	% of reads unmapped: too many mismatches	2.25%	6.13%	8.89%
29	Number of reads unmapped: too short	276153	4291129	928705
30	% of reads unmapped: too short	1.39%	5.16%	4.95%
31	Number of reads unmapped: other	277760	8305731	255249
32	% of reads unmapped: other	1.40%	9.99%	1.36%
33	CHIMERIC READS:			
34	Number of chimeric reads	0	0	0
35	% of chimeric reads	0.00%	0.00%	0.00%

2 QC plots

2.1 Plot density counts

```
scaled_counts %>%  
  pivot_longer(~ gene, names_to = "genotype", values_to = "counts") %>%  
  ggplot(aes(x = log10(counts + 1), fill = genotype)) +  
  geom_density(alpha = 0.2)
```



The density of genes with low count values ($\log_{10} = 0.3$) is lower for F2-28 but seems to be comparable for other genes.

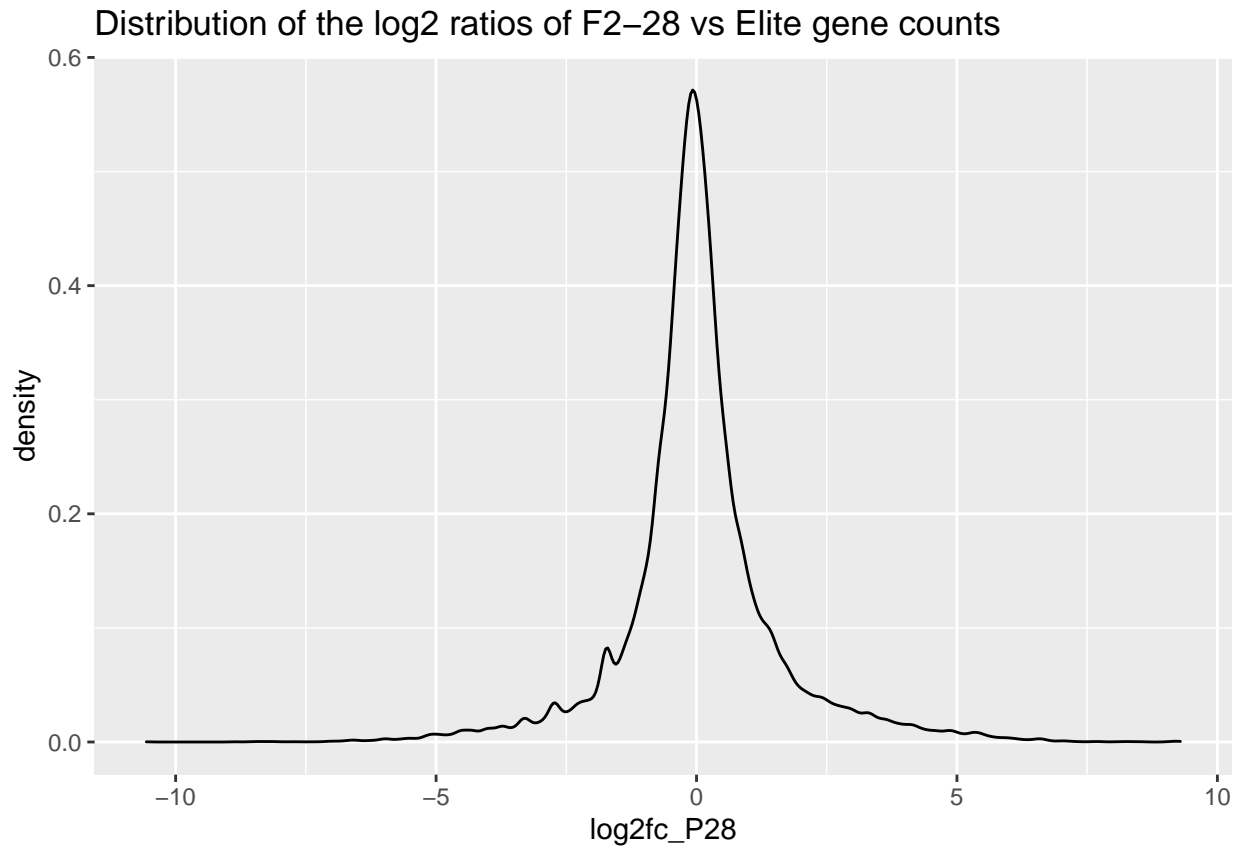
2.2 Plot log2ratio F2-28 vs Elite

First, let's extract genes with counts > 0

```
genes_sums <- scaled_counts %>% column_to_rownames("gene") %>% rowSums()  
genes_non_null <- genes_sums[genes_sums > 0]  
genes_non_null <- names(genes_non_null)
```

```
scaled_counts %>%  
  filter(gene %in% genes_non_null) %>%  
  mutate(log2fc_P28 = log2(`F2-28_concat`/Elite_2020)) %>%  
  ggplot(aes(x = log2fc_P28)) +  
  geom_density() +  
  ggtitle("Distribution of the log2 ratios of F2-28 vs Elite gene counts")
```

```
## Warning: Removed 3847 rows containing non-finite values (stat_density).
```

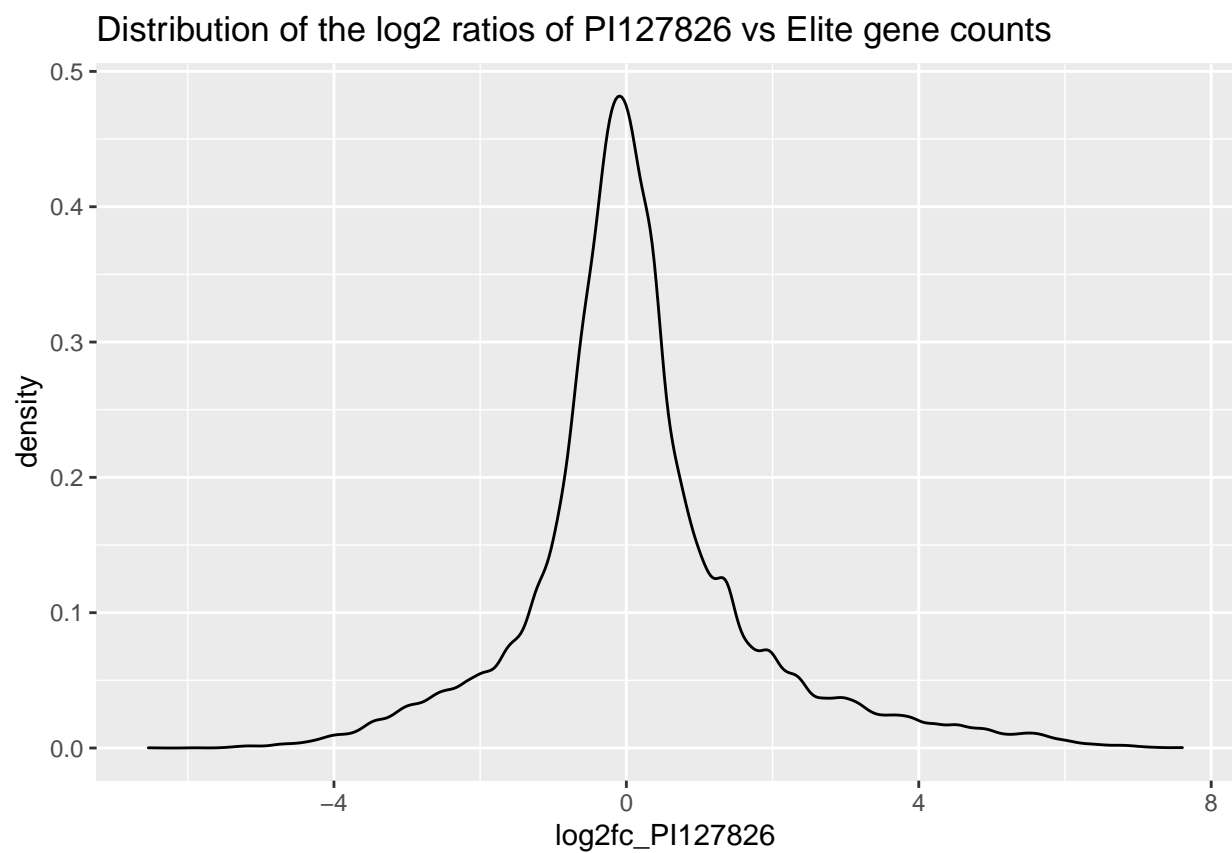


The log2ratio distribution looks OK.

2.3 Plot log2ratio PI127826 vs Elite

```
scaled_counts %>%  
  filter(gene %in% genes_non_null) %>%  
  mutate(log2fc_PI127826 = log2(PI127826_2020/Elite_2020)) %>%  
  ggplot(aes(x = log2fc_PI127826)) +  
  geom_density() +  
  ggtitle("Distribution of the log2 ratios of PI127826 vs Elite gene counts")
```

```
## Warning: Removed 4589 rows containing non-finite values (stat_density).
```



3 Compute DE genes based on log2ratio Z-score

3.1 Calculate log2ratios

A positive log2ratio for F2-28 and PI127826 means that the gene is more expressed in F2-28 and PI127826 (relative to the Elite line).

Let's calculate the log2ratio and remove the "Infinite" values.

```
log2ratio <-
  scaled_counts %>%
  filter(gene %in% genes_non_null) %>%
  mutate(log2ratio_P28 = log2(`F2-28_concat`/Elite_2020)) %>%
  mutate(log2ratio_PI127826 = log2(PI127826_2020/Elite_2020)) %>%
  select(gene, log2ratio_P28, log2ratio_PI127826) %>%
  filter(!grepl(pattern = "Inf", x = log2ratio_P28)) %>%
  filter(!grepl(pattern = "Inf", x = log2ratio_PI127826))
```

```
head(log2ratio)
```

```
##           gene log2ratio_P28 log2ratio_PI127826
## 1 Solyc00g005040.2.1   -0.9349052      -1.8336997
## 2 Solyc00g005050.2.1    0.1267105       0.4482855
## 3 Solyc00g005080.1.1    0.5886568       0.3679341
## 4 Solyc00g005150.1.1    1.8213175       2.4553970
## 5 Solyc00g005840.2.1    1.1218088       0.7093396
## 6 Solyc00g005860.1.1   -1.2478445      -2.9539940
```

A total of **22793** have a finite log2ratio in both F2-28 vs Elite and PI127826 vs Elite.

3.2 Calculate Z-scores and associated p-values

Let's calculate the Z-score of the log2ratio + its associated p-value

```
log2ratio_zscores_pvals <-
  log2ratio %>%
  mutate(zscore_P28 = scale(log2ratio_P28, center = T, scale = T)) %>%
  mutate(zscore_PI127826 = scale(log2ratio_PI127826, center = T, scale = T)) %>%
  mutate(pval_P28 = pnorm(q = abs(zscore_P28), mean = 0, sd=1, log.p = FALSE, lower.tail=FALSE)) %>%
  mutate(pval_PI127826 = pnorm(q = abs(zscore_PI127826), mean = 0, sd=1, log.p = FALSE, lower.tail=FALSE)) %>%
  arrange(desc(log2ratio_P28)) %>%
  as_tibble()
```

```
head(log2ratio_zscores_pvals)
```

```
## # A tibble: 6 x 7
##   gene log2ratio_P28 log2ratio_PI127~ zscore_P28[,1] zscore_PI127826~
##   <chr>      <dbl>      <dbl>      <dbl>      <dbl>
## 1 Soly~      9.29      6.73      6.18      4.23
## 2 Soly~      9.22      6.02      6.13      3.77
## 3 Soly~      9.21      6.86      6.12      4.31
## 4 Soly~      9.18      3.37      6.10      2.06
## 5 Soly~      9.05      5.21      6.02      3.25
## 6 Soly~      8.56      3.88      5.69      2.39
## # ... with 2 more variables: pval_P28[,1] <dbl>, pval_PI127826[,1] <dbl>
```

3.3 Add original counts and annotations

Add back the scaled counts.

```
log2ratio_zscores_pvals_with_counts <- inner_join(scaled_counts, log2ratio_zscores_pvals, by = "gene")
```

Add descriptions

```
annots <- read.csv("info/ITAG2.4_loci_gene_descriptions.csv", stringsAsFactors = F)
```

```
final <-  
  log2ratio_zscores_pvals_with_counts %>%  
  mutate(locus = substr(gene, start = 1, stop = 14)) %>%  
  inner_join(x = ., y = annots, by = "locus") %>%  
  as_tibble()
```

```
dim(final)
```

```
## [1] 22793    12
```

3.4 Write to CSV file

```
write.csv(final,  
  file = "tables/diff_res_F2-28orPI127826_vs_Elite.csv",  
  row.names = F,  
  quote = F)
```


4 MEP and MVA pathway gene analysis

4.1 Import MEP and MVA gene identifiers

```
mep_mva_gene_ids <- read.csv("info/mep_mva_terpene_gene_ids.csv",  
                             stringsAsFactors = F)
```

4.2 Filter for significant DE genes

Should be significant ($p < 0.05$) in **either** PI127826 vs Elite *AND* F2-28 vs Elite.

```
signif_genes <- filter(final, pval_P28 < 0.05 | pval_PI127826 < 0.05) %>% pull(gene)
```

4.3 Keep only MEP and MVA genes significant

```
mep_mva_genes <- inner_join(final, mep_mva_gene_ids)
```

```
## Joining, by = "locus"
```

```
mep_mva_gene_signif <-  
  mep_mva_genes %>%  
  filter(gene %in% signif_genes)
```

```
# show table
```

```
mep_mva_gene_signif %>%  
  select(name, gene, pathway, pval_P28, pval_PI127826) %>%  
  knitr::kable()
```

name	gene	pathway	pval_P28	pval_PI127826
HMGR	Solyc02g038740.2.1	MVA	0.08318780	0.01081294
HMGR	Solyc03g032010.2.1	MVA	0.13853560	0.03476849
pMVK	Solyc06g066310.2.1	MVA	0.01070946	0.01499932

```
write.csv(mep_mva_gene_signif,  
          file = "tables/mep_mva_gene_signif.csv",  
          row.names = F,  
          quote = F)
```

4.4 Plot all MEP and MVA genes

```
for (i in seq_along(mep_mva_genes$gene)){
  tmp_df <- mep_mva_genes[i,]
  tmp_df$title4plot <- paste(tmp_df$name, tmp_df$gene, sep = "_")

  p <-
    tmp_df %>%
    # mutate(plot_title = paste(name, gene, sep = "_")) %>%
    select(title4plot, `F2-28_concat`, Elite_2020, PI127826_2020) %>%
    pivot_longer(- title4plot, names_to = "genotype", values_to = "counts") %>%
    ggplot(. , aes(x = genotype, y = counts, fill = genotype)) +
    geom_bar(stat = "identity") +
    ggtitle(tmp_df$title4plot)

  print(p)
}
```

