

Coding club meet-up: Using ggplot2 for visualization

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Note of the day

There are several useful packages to check out:

UpSet: Visualizing Intersecting Sets (<http://caleydo.org/tools/upset/>)

Intervene: Intersection and visualization of multiple genomic region sets (<https://intervene.readthedocs.io/en/latest/index.html>)

ggplot2 extensions (<https://www.ggplot2-exts.org/ggiraph.html>)

DEGreport (<https://lpantano.github.io/DEGreport/index.html>)

The Anatomy of a plot

Load data

```
# Load packages
library(tidyverse)
library(readxl)
```

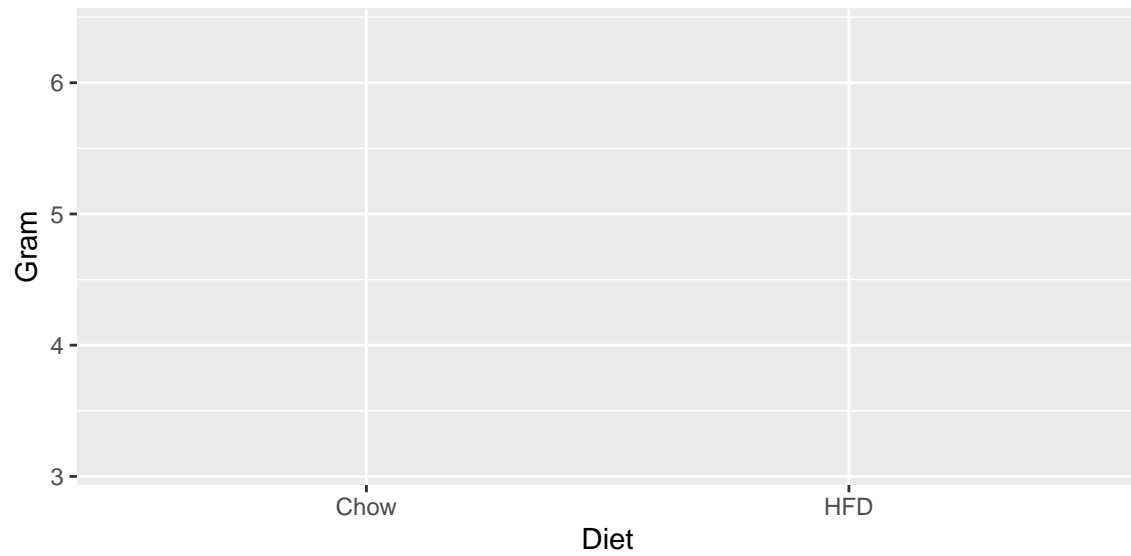
```
head(fatMass_Male)
```

```
## # A tibble: 6 x 7
##   Diet_duration Sex   Genotype      ID Diet Composition  Gram
##   <chr>         <chr> <chr>      <dbl> <fct> <chr>      <dbl>
## 1 1 week       Male GcgcreTRAP 1866 Chow Fat         3.1
## 2 1 week       Male TRAP      1867 Chow Fat         3.3
## 3 1 week       Male TRAP      1868 Chow Fat         3.1
## 4 1 week       Male GcgcreTRAP 1869 HFD Fat         3.9
## 5 1 week       Male TRAP      1872 HFD Fat         4.4
## 6 1 week       Male TRAP      1870 HFD Fat         4.3
```

1) Plot background

```
# Plot fat mass of male
p1 <- fatMass_Male %>%
  ggplot(aes(x = Diet, y = Gram, fill = Diet))

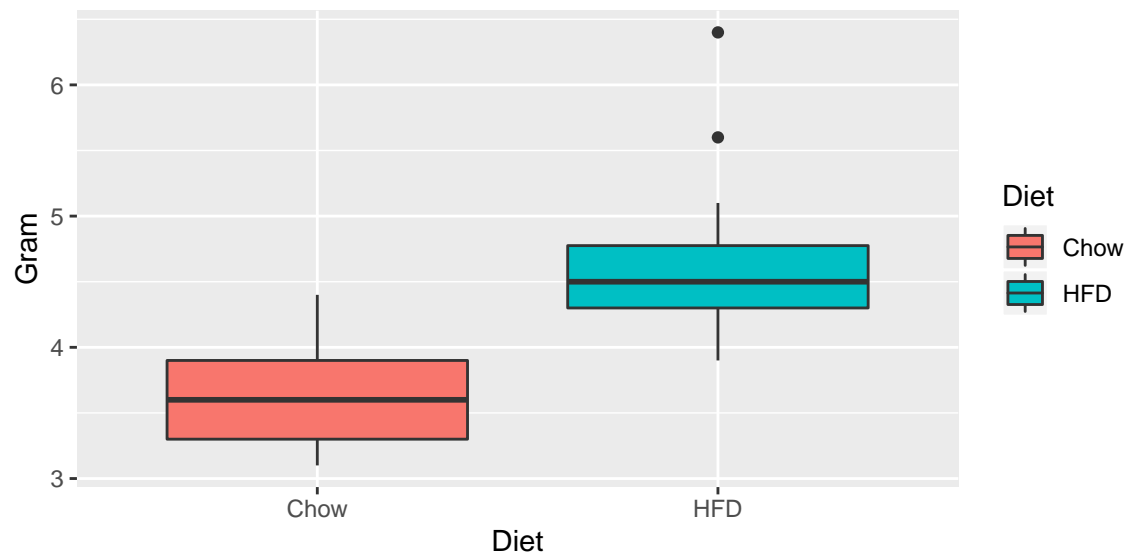
p1
```



2) First layer

```
p2 <- p1 + geom_boxplot()
```

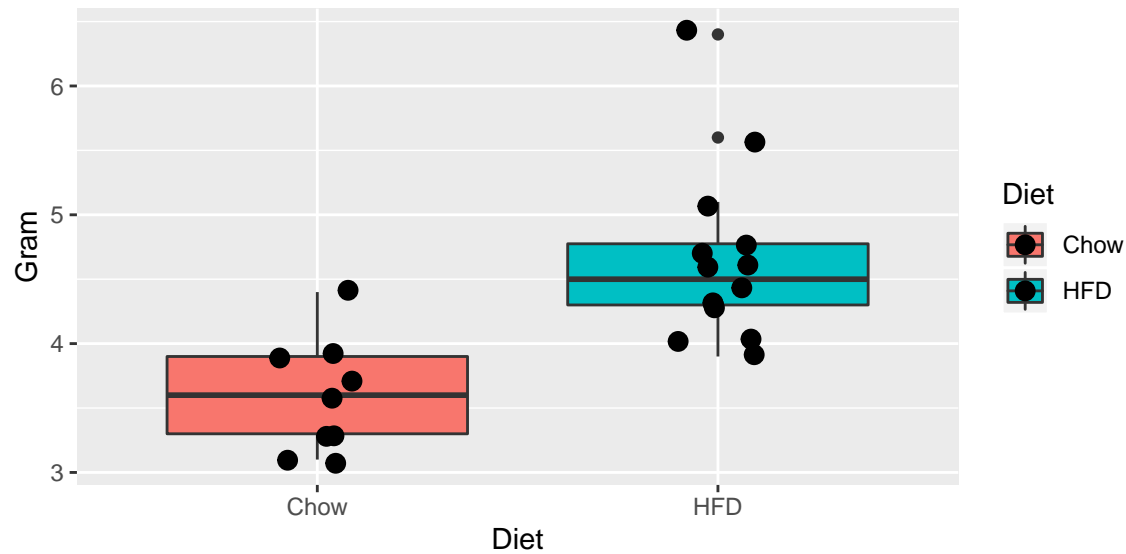
p2



3) Another layer

```
p3 <- p2 + geom_jitter(width = .1, size = 3)
```

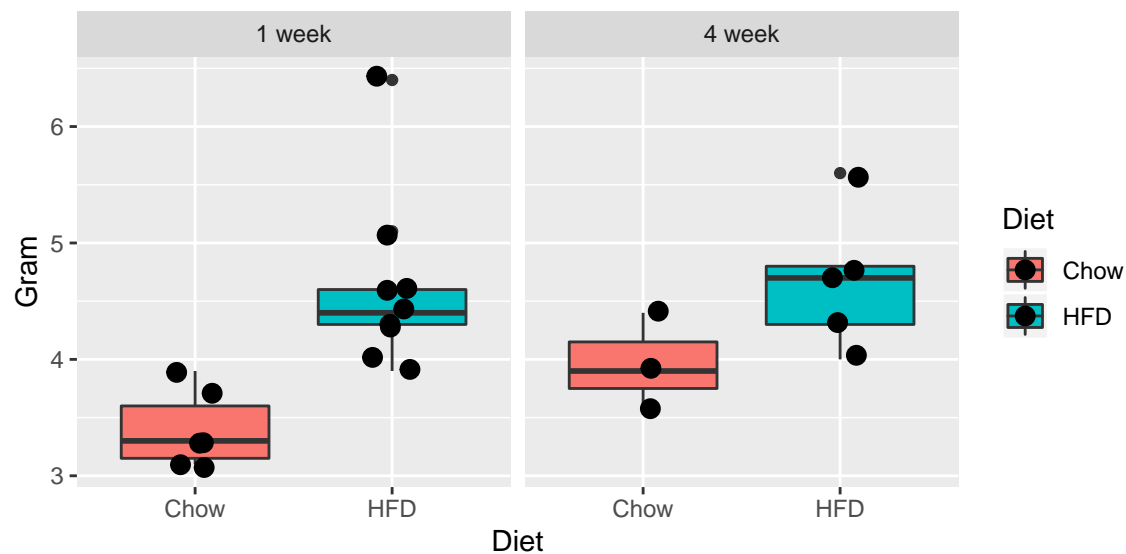
p3



4) Lay out panels in a grid

```
p4 <- p3 + facet_grid(cols = vars(Diet_duration))
```

p4



5) Complete with a customized look

```
My_theme <- theme(
  axis.line = element_line(colour = "black"),
  axis.text.x = element_text(color = "black", size = 14, face = "bold"),
  axis.text.y = element_text(color = "black", size = 14, face = "bold"),
  axis.title.x = element_text(color = "black", size = 14, face = "bold"),
  axis.title.y = element_text(color = "black", size = 14, face = "bold"),
  strip.text.x = element_text(color = "black", size = 14, face = "bold"), # Horizontal facet labels
```

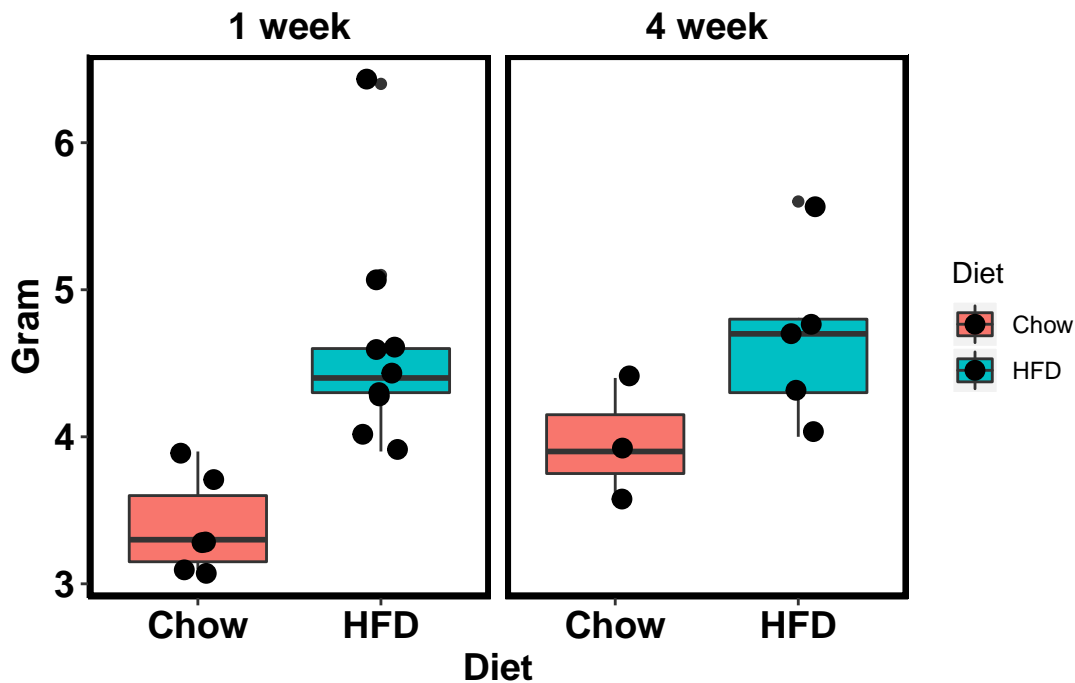
```

strip.background = element_rect(fill = "white"), # Background of facet labels
panel.grid.major = element_blank(), panel.grid.minor = element_blank(),
panel.background = element_blank(),
panel.border = element_rect(colour = "black", fill = NA, size = 2),
plot.margin = unit(c(0.5, 0.5, 0.5, 0.5), "cm"),
plot.title = element_text(color = "black", size = 16, face = "bold")
)

p5 <- p4 + My_theme

p5

```



Geometric objects (geoms)

Dot plot with fitted line

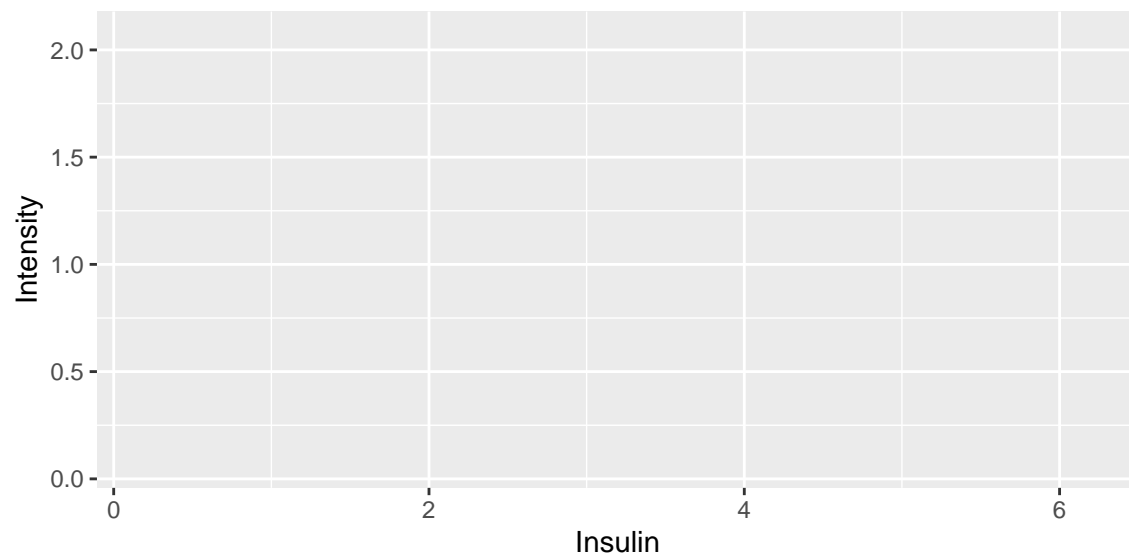
Dataset: Standard curve of insulin ELISA, performed on different dates

##	Calibrator	Insulin	Date	Intensity
## 1	Cal 1	0.194	20.02.2019	0.0690
## 2	Cal 2	0.497	20.02.2019	0.0875
## 3	Cal 3	1.470	20.02.2019	0.2495
## 4	Cal 4	2.960	20.02.2019	0.5775
## 5	Cal 5	6.200	20.02.2019	1.5090
## 6	Cal 1	0.194	26.02.2019	0.0605
## 7	Cal 2	0.497	26.02.2019	0.0915
## 8	Cal 3	1.470	26.02.2019	0.2610
## 9	Cal 4	2.960	26.02.2019	0.6490
## 10	Cal 5	6.200	26.02.2019	1.7905

1) Plot background of standard curve

```
Ins_p1 <- Ins_Cal_v2 %>%  
  ggplot(aes(x = Insulin, y = Intensity))
```

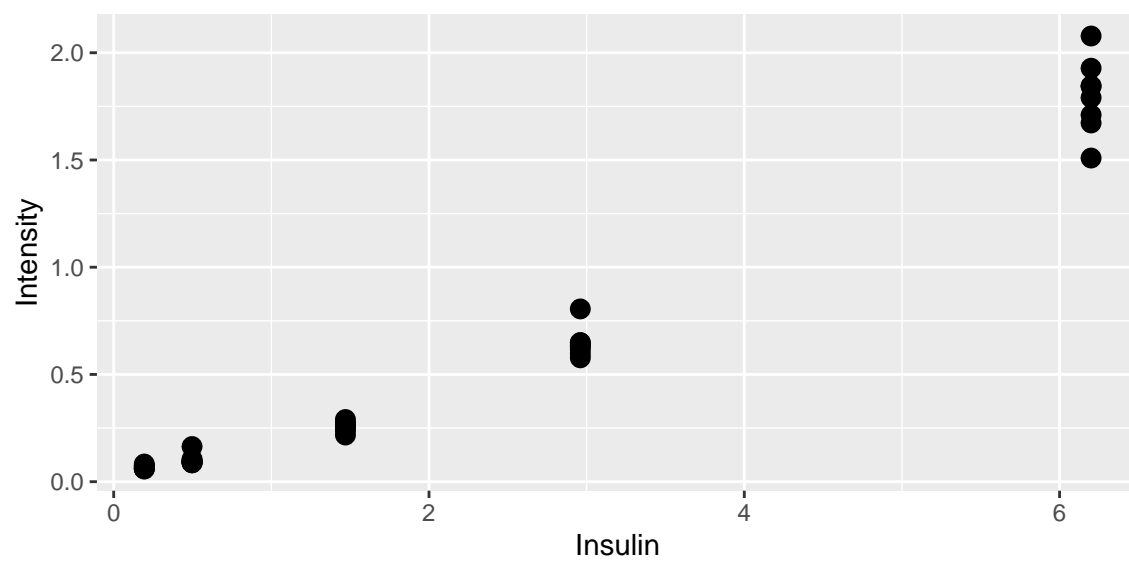
Ins_p1



2) Add individual data points

```
Ins_p2 <- Ins_p1 + geom_point(size = 3)
```

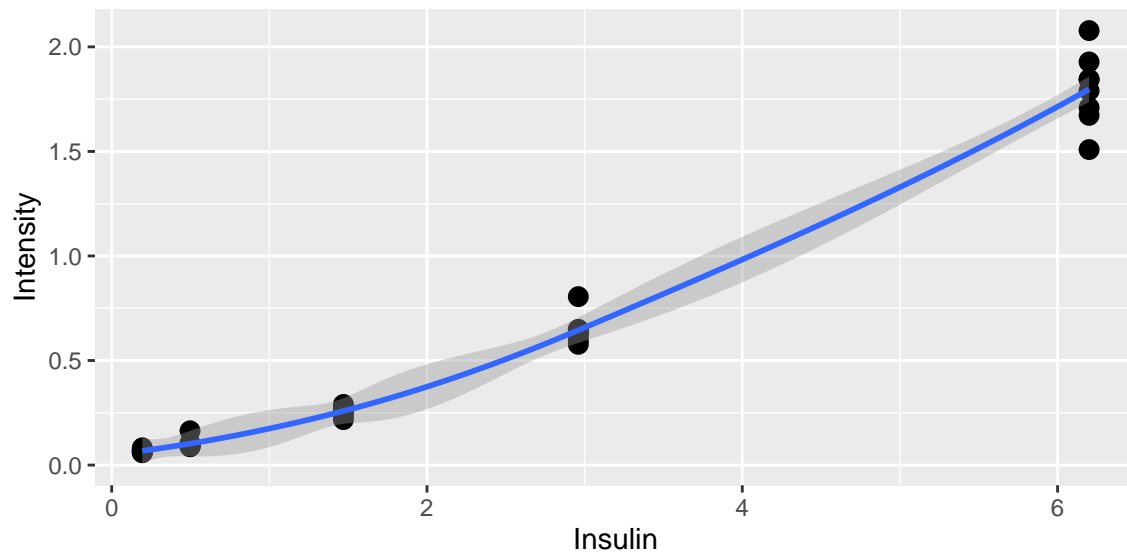
Ins_p2



3.1) Add smoothed conditional means with standard error

```
Ins_p3 <- Ins_p2 + geom_smooth(span = 0.8, method = "loess", formula = y ~ x)
```

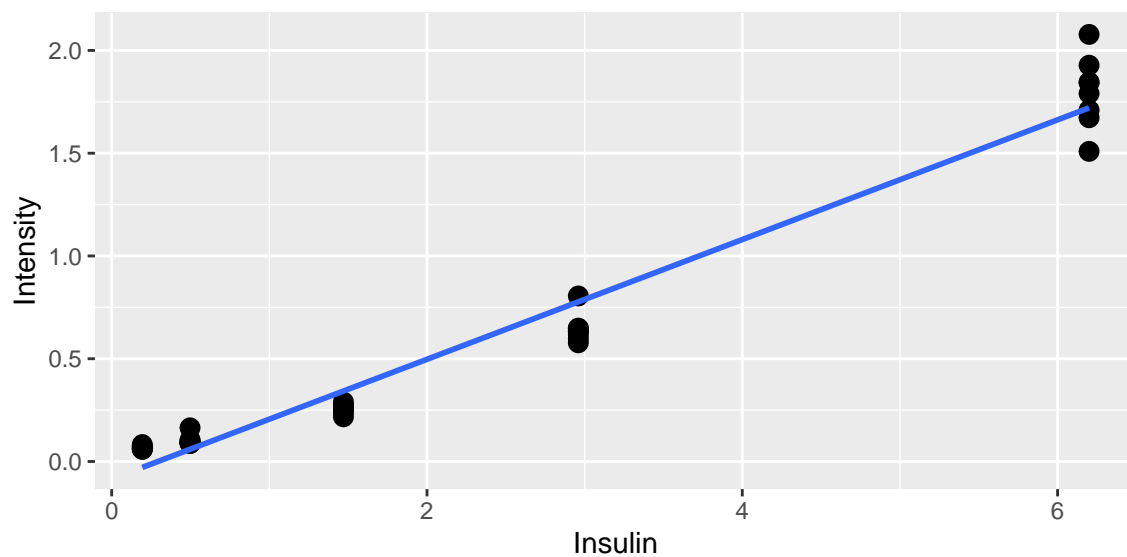
Ins_p3



3.2) Add a line of best fit

```
Ins_p4 <- Ins_p2 + geom_smooth(method = "lm", se = FALSE)
```

Ins_p4



```
# Linear regression  
# Intensity = Intercept + ( $\beta$  * Insulin)  
linearMod <- lm(Intensity ~ Insulin, data = Ins_Cal_v2)  
summary(linearMod)
```

```
##
## Call:
## lm(formula = Intensity ~ Insulin, data = Ins_Cal_v2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.21166 -0.09604  0.02879  0.09088  0.35734
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.085262   0.028121  -3.032  0.00436 **
## Insulin      0.291278   0.008924  32.640 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1237 on 38 degrees of freedom
## Multiple R-squared:  0.9656, Adjusted R-squared:  0.9647
## F-statistic: 1065 on 1 and 38 DF,  p-value: < 2.2e-16
```

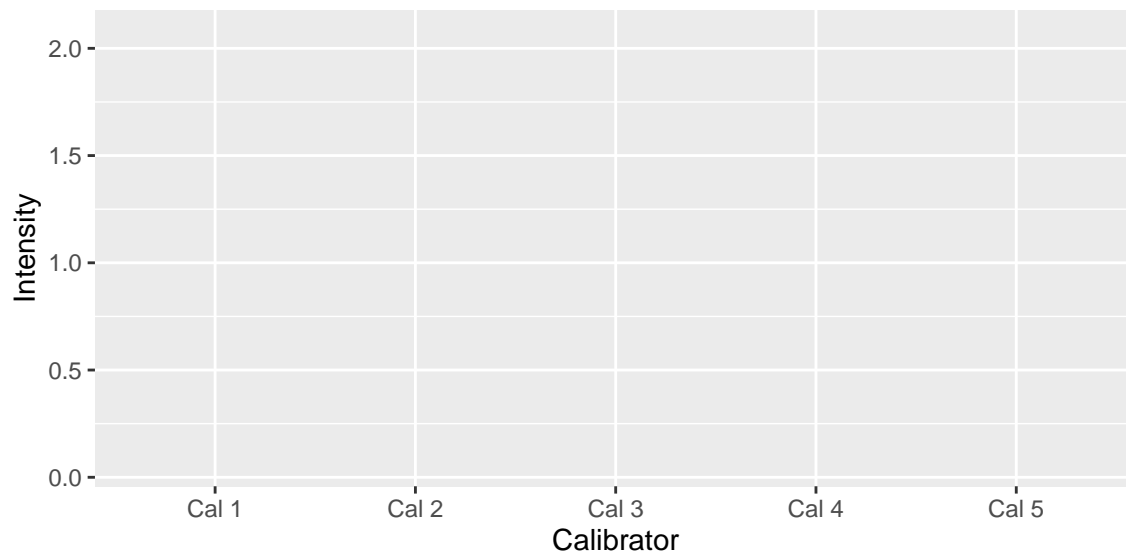
Bar chart

Dataset (same as above): Standard curve of insulin ELISA, performed on different dates

1) Plot background of bar chart

```
Ins_Bar_p1 <- Ins_Cal_v2 %>%
  ggplot(aes(x = Calibrator, y = Intensity, fill = Date))
```

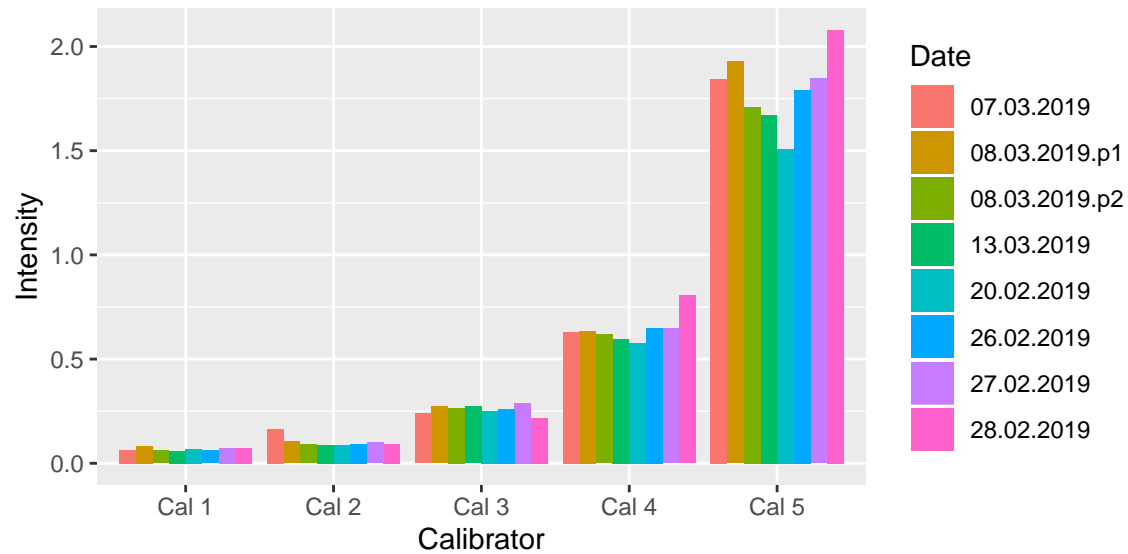
Ins_Bar_p1



2) Add bars in groups

```
Ins_Bar_p2 <- Ins_Bar_p1 + geom_bar(stat = "identity", position = position_dodge())
```

Ins_Bar_p2



3) Add bars with means with standard error

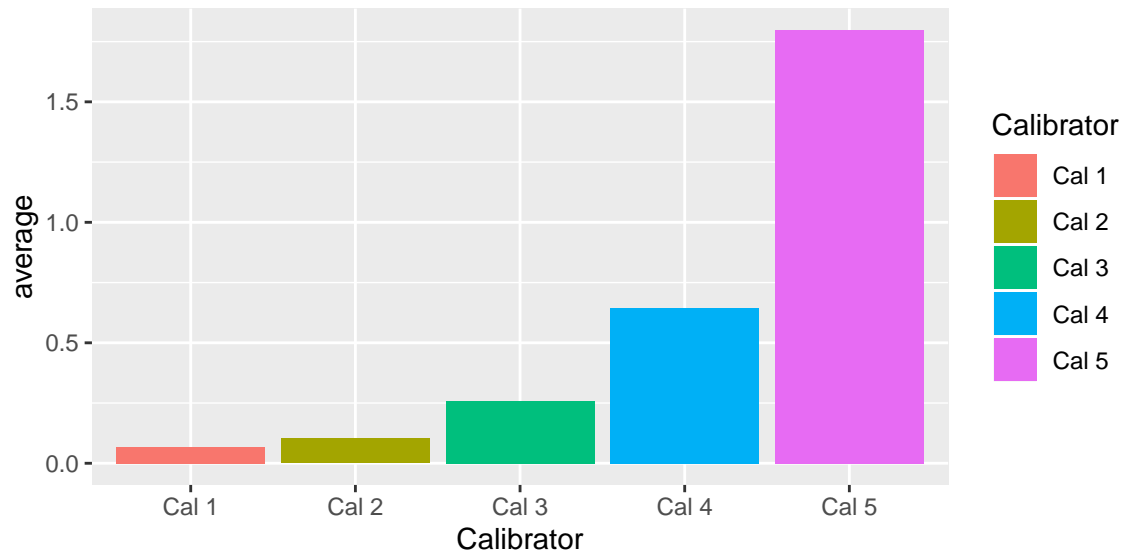
```
# Calculate mean and se
Ins_Stat <- Ins_Cal_v2 %>%
  group_by(Insulin, Calibrator) %>%
  summarise(
    average = mean(Intensity, na.rm = TRUE),
    se = sd(Intensity, na.rm = TRUE) / sqrt(length(Intensity))
  )
```

```
Ins_Stat
```

```
## # A tibble: 5 x 4
## # Groups:   Insulin [5]
##   Insulin Calibrator average      se
##   <dbl> <fct>         <dbl> <dbl>
## 1  0.194 Cal 1         0.068 0.00291
## 2  0.497 Cal 2         0.102 0.00905
## 3  1.47  Cal 3         0.258 0.00800
## 4  2.96  Cal 4         0.645 0.0245
## 5  6.2   Cal 5         1.80  0.0608
```

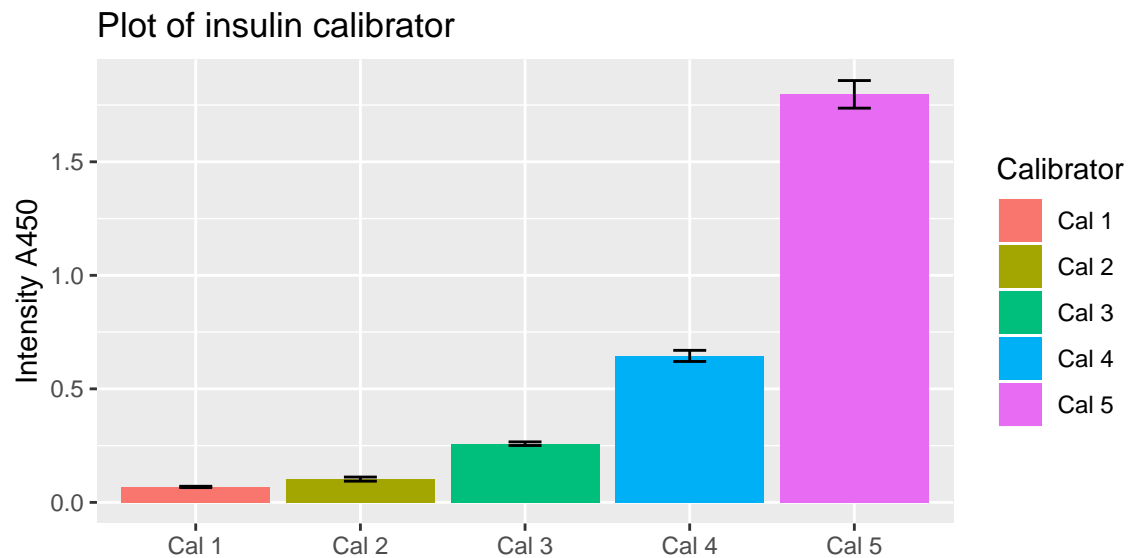
```
# First plot the mean
Ins_Bar_p3 <- Ins_Stat %>%
  ggplot(aes(x = Calibrator, y = average, fill = Calibrator)) +
  geom_bar(stat = "identity")
```

```
Ins_Bar_p3
```

```
# Then add error bars
Ins_Bar_p4 <- Ins_Bar_p3 +
  geom_errorbar(aes(ymin = average - se, ymax = average + se), width = .2) +
  labs(title = "Plot of insulin calibrator", x = NULL, y = "Intensity A450")

Ins_Bar_p4
```



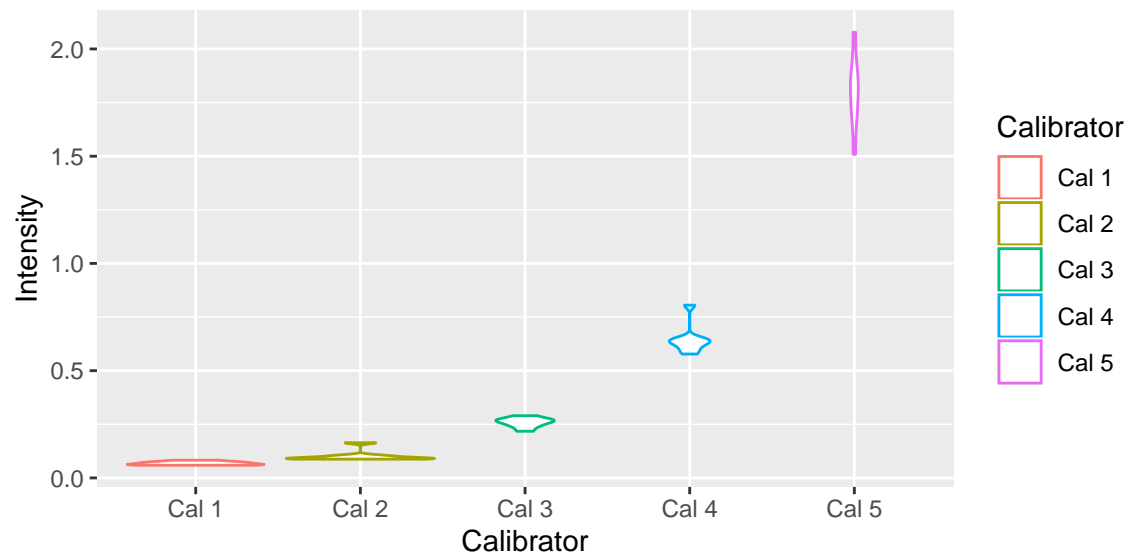
Violin plot

Dataset (same as above): Standard curve of insulin ELISA, performed on different dates

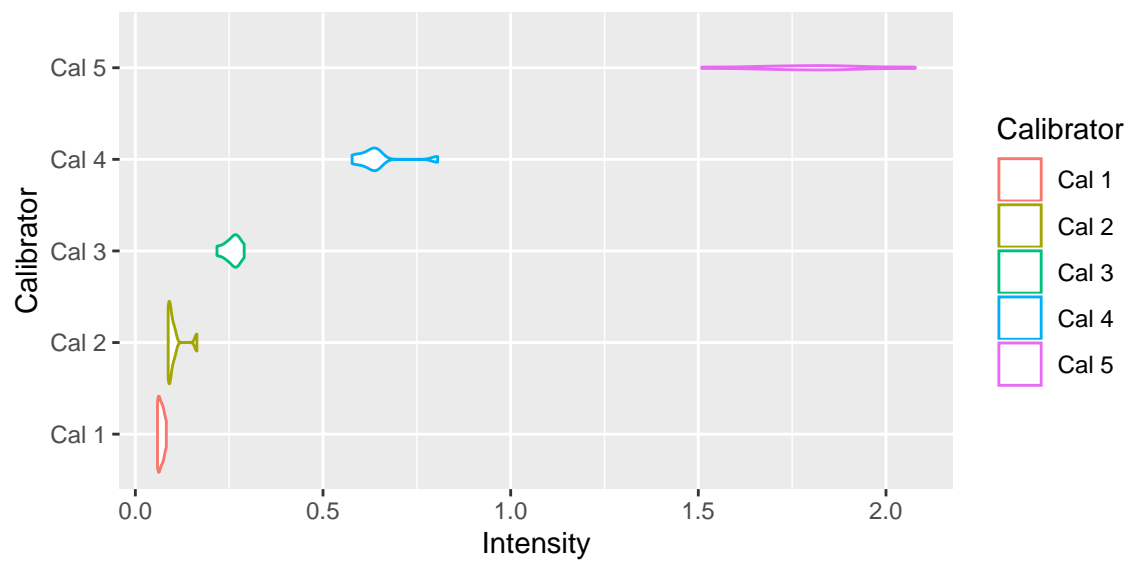
1) Basic violin plot

```
Ins_Violin_p1 <- Ins_Cal_v2 %>%
  ggplot(aes(x = Calibrator, y = Intensity, color = Calibrator)) +
  geom_violin()
```

```
Ins_Violin_p1
```

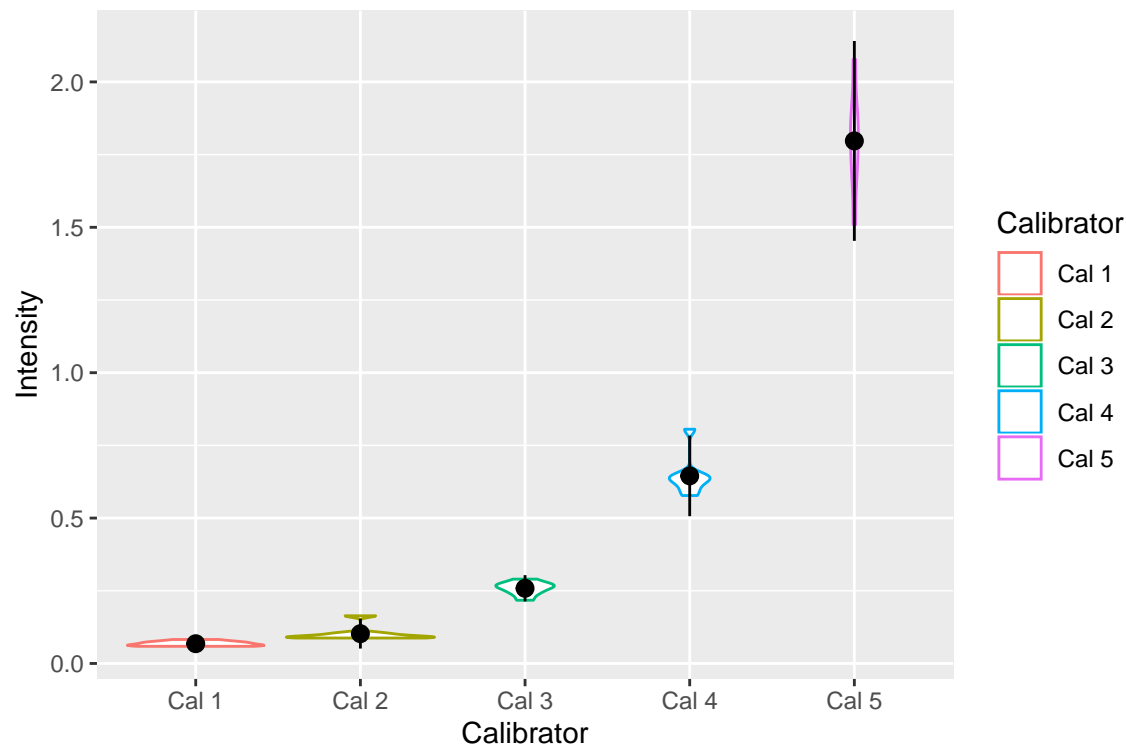


```
# Rotate the violin plot
Ins_Violin_p1 + coord_flip()
```



2) Add mean with standard deviation

```
Ins_Violin_p1 + stat_summary(fun.data = mean_sdl, geom = "pointrange", color = "black")
```



Venn diagram

Dataset for venn diagram

```
##           A    B    C
## Gene_1 TRUE TRUE TRUE
## Gene_2 TRUE TRUE FALSE
## Gene_3 TRUE TRUE FALSE
## Gene_4 TRUE TRUE FALSE
## Gene_5 TRUE TRUE TRUE
## Gene_6 TRUE TRUE FALSE
```

1) Use vennCounts from the package limma to compute classification counts

```
# Load packages
library(ggforce)
library(limma)

# Compute classification counts
counts_venn <- vennCounts(df_venn)
class(counts_venn) <- "matrix"

# Add x and y coordinates for the count annotations
counts_venn <- as.data.frame(counts_venn)[-1, ] %>%
  mutate(
    x = c(0, 1.2, 0.8, -1.2, -0.8, 0, 0),
    y = c(1.2, -0.6, 0.5, -0.6, 0.5, -1, 0)
  )
```

```
counts_venn
```

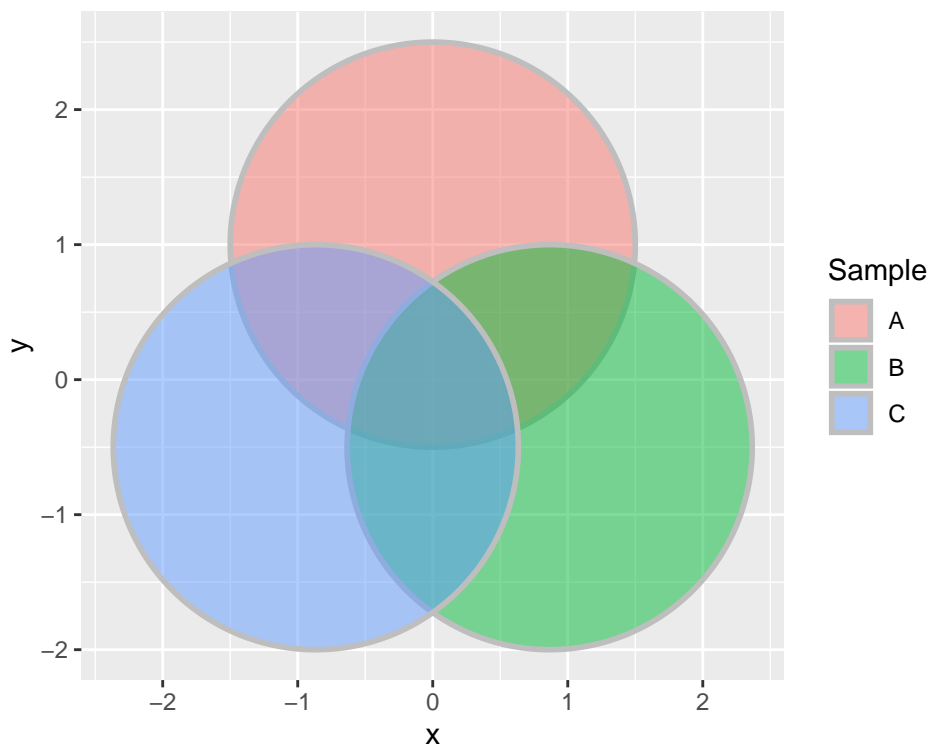
```
##   A B C Counts    x    y
## 1 0 0 1      6 0.0  1.2
## 2 0 1 0      4 1.2 -0.6
## 3 0 1 1      5 0.8  0.5
## 4 1 0 0     12 -1.2 -0.6
## 5 1 0 1     11 -0.8  0.5
## 6 1 1 0     27  0.0 -1.0
## 7 1 1 1     32  0.0  0.0
```

2) Define basic structure for the circles

```
# Define x and y coordinates for the circles
venn_structure <- data.frame(
  x = c(0, 0.866, -0.866),
  y = c(1, -0.5, -0.5),
  Sample = c("A", "B", "C")
)

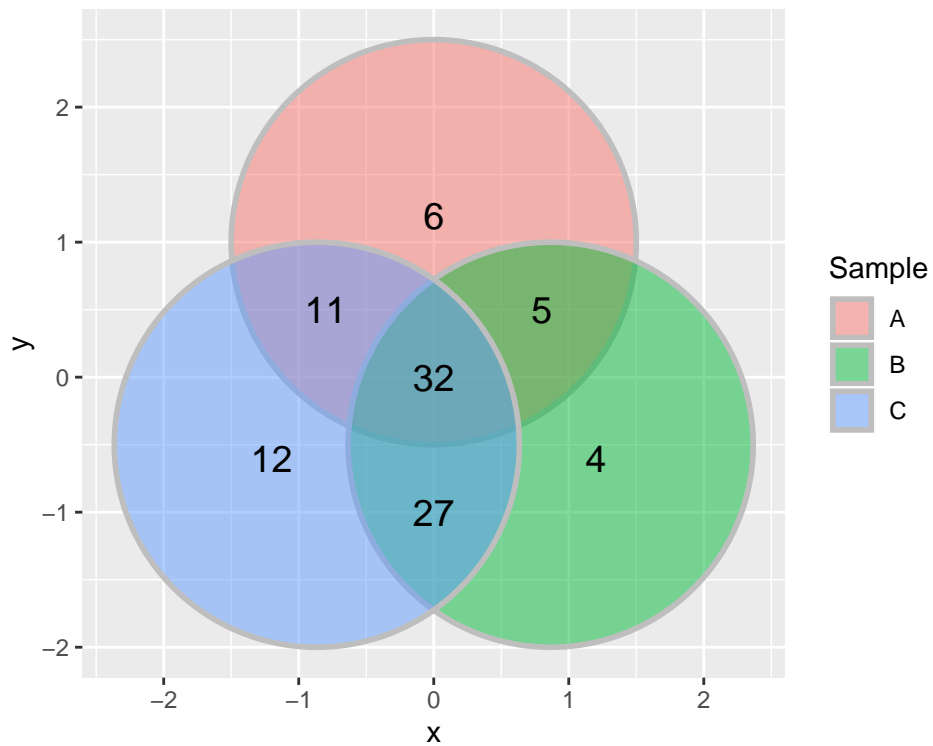
venn_p1 <- venn_structure %>% ggplot(aes(x0 = x, y0 = y, r = 1.5, fill = Sample)) +
  geom_circle(alpha = .5, size = 1, colour = "grey") +
  coord_fixed()

venn_p1
```



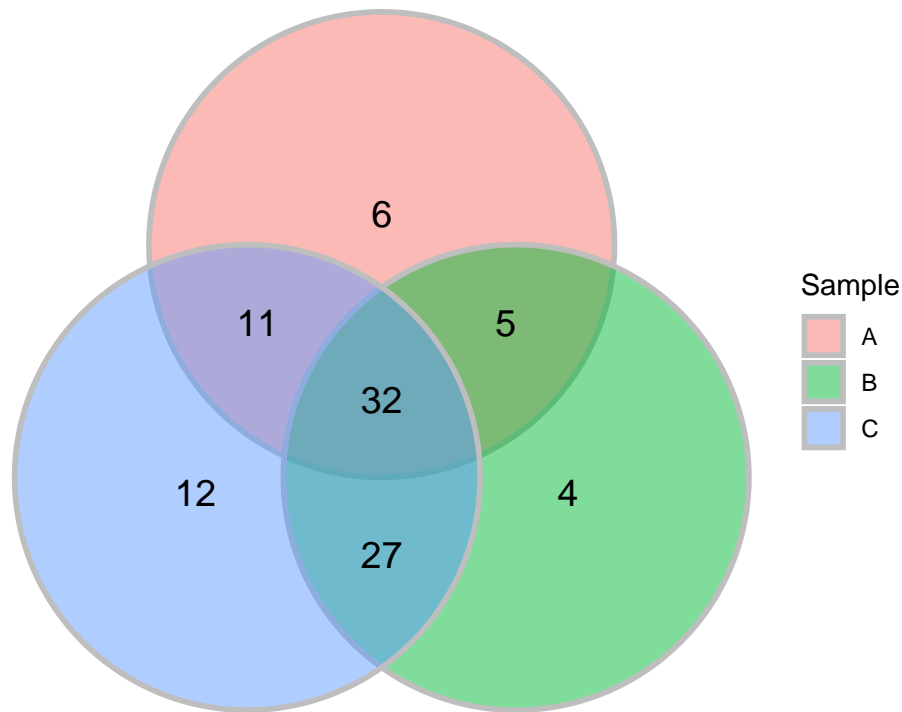
3) Venn diagram with annotation of the counts

```
venn_p2 <- venn_p1 +  
  annotate("text", x = counts_venn$x, y = counts_venn$y, label = counts_venn$Counts, size = 5)  
venn_p2
```



4) Finally to remove the grey background

```
venn_p2 + theme_void()
```



PCA plot

Dataset from RNA-seq tpm counts

```
# Load kallisto counts
kallisto_count <- read.csv("~/mRNA_IP/count/kallisto_count_19112019.csv")

kallisto_df <- kallisto_count[c(1, 5, 6, 7)] %>%
  spread(target_id, tpm, fill = NA, convert = FALSE, drop = TRUE, sep = NULL)

kallisto_df[1:9, 1:6]
```

```
##           sample    condition ENSMUST00000000001.4
## 1  InsicreTRAP input 1      Input          2.827743
## 2  InsicreTRAP input 2      Input          3.489938
## 3    InsicreTRAP IP 1        IP          13.005613
## 4    InsicreTRAP IP 2        IP          7.870618
## 5 InsicreTRAP supernatant 1 Supernatant          3.790337
## 6 InsicreTRAP supernatant 2 Supernatant          2.254487
## 7          TRAP input      Input          2.103856
## 8          TRAP IP        IP          8.197811
## 9    TRAP supernatant Supernatant          1.719226
## ENSMUST00000000003.13 ENSMUST00000000010.8 ENSMUST00000000028.13
## 1           0           0          0.00000000
## 2           0           0          0.00000000
## 3           0           0          1.14064983
## 4           0           0          0.00000000
## 5           0           0          0.00000000
## 6           0           0          0.00000000
```

```
## 7          0          0          0.07130594
## 8          0          0          0.00000000
## 9          0          0          0.00000000
```

```
# Calculate principal component analysis based on tpm
```

```
pca <- prcomp(kallisto_df[, -c(1, 2)])
```

```
summary(pca)[6]
```

```
## $importance
```

```
##          PC1          PC2          PC3          PC4
## Standard deviation 49291.05206 32069.63898 15287.04431 10993.04070
## Proportion of Variance 0.62116 0.26294 0.05975 0.03090
## Cumulative Proportion 0.62116 0.88410 0.94384 0.97474
##          PC5          PC6          PC7          PC8
## Standard deviation 6782.76140 5623.08604 4228.81560 1814.02052
## Proportion of Variance 0.01176 0.00808 0.00457 0.00084
## Cumulative Proportion 0.98650 0.99459 0.99916 1.00000
##          PC9
## Standard deviation 1.77849e-10
## Proportion of Variance 0.00000e+00
## Cumulative Proportion 1.00000e+00
```

PCA plot

Option 1: By using ggplot2

```
# Create data frame for PC
```

```
df_pca <- as.data.frame(pca$x)
```

```
df_pca$condition <- kallisto_df$condition
```

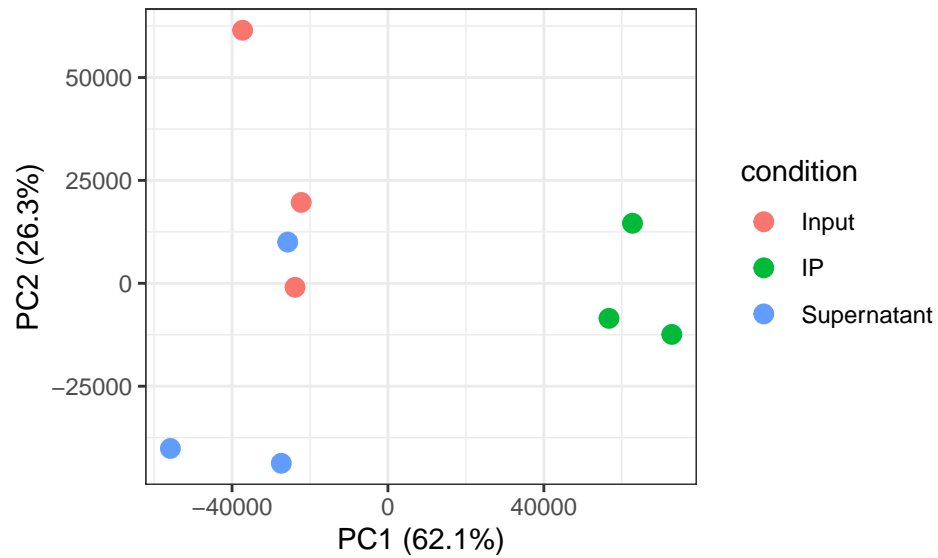
```
head(df_pca)
```

```
##          PC1          PC2          PC3          PC4          PC5          PC6
## 1 -37293.90 61478.383 1827.194 2199.2406 7091.6674 -676.2481
## 2 -22245.09 19649.611 12676.412 -513.6848 -13776.1041 -1781.4077
## 3 62742.51 14587.313 -21694.384 -15161.7450 -4035.3473 5238.8259
## 4 56707.74 -8511.307 11915.603 20109.9504 -965.5041 6760.0376
## 5 -25722.87 10023.528 -22962.362 11406.5635 2351.6401 -2047.2995
## 6 -55818.90 -40126.540 -8128.496 1312.4749 -5314.0585 -3507.3695
##          PC7          PC8          PC9          condition
## 1 3775.757 -1725.25237 -1.988686e-10 Input
## 2 -4706.968 -1114.96439 3.476534e-10 Input
## 3 1603.261 -82.63524 6.650248e-11 IP
## 4 2216.807 273.58882 5.147383e-10 IP
## 5 -5165.664 2339.50146 -1.255307e-10 Supernatant
## 6 7266.615 185.97976 -1.526460e-10 Supernatant
```

```
# Plot PCA with ggplot2
```

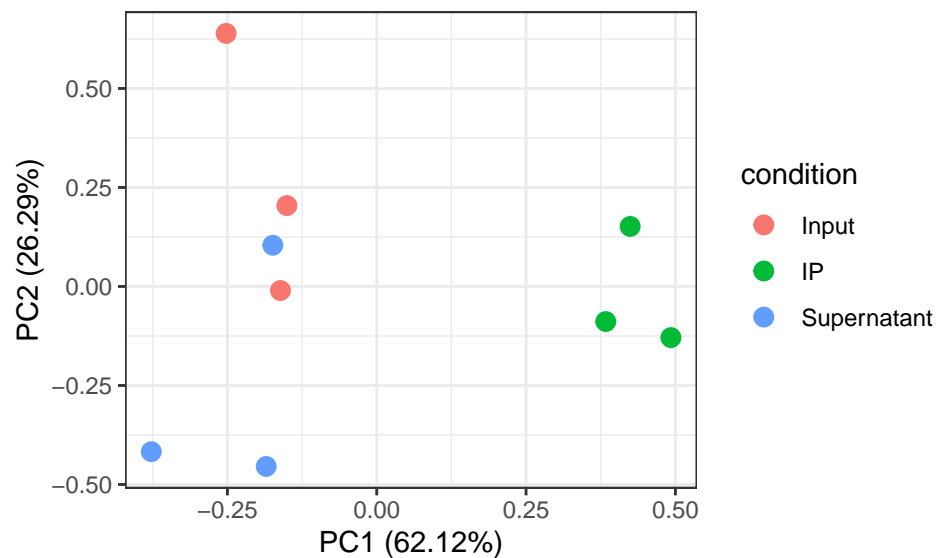
```
pca_p1 <- ggplot(df_pca, aes(x = PC1, y = PC2, color = condition))
```

```
pca_p1 + geom_point(size = 3) + theme_bw() + labs(x = "PC1 (62.1%)", y = "PC2 (26.3%)")
```



Option 2: By using package ggfortify

```
library(ggfortify)
pca_v2_p1 <- autoplot(pca, data = kallisto_df, colour = "condition", size = 3) +
  theme_bw()
pca_v2_p1
```



Heatmap

Dataset from RNA-seq tpm counts

```
df_tpm <- kallisto_count %>%
  filter(tpm > 0) %>%
  select(c(1, 5, 6))
head(df_tpm)
```



```
##           target_id      tpm                sample
## 1 ENSMUST00000000001.4  2.827743      Ins1creTRAP input 1
## 2 ENSMUST00000000001.4  3.489938      Ins1creTRAP input 2
## 3 ENSMUST00000000001.4 13.005613      Ins1creTRAP IP 1
## 4 ENSMUST00000000001.4  7.870618      Ins1creTRAP IP 2
## 5 ENSMUST00000000001.4  3.790337 Ins1creTRAP supernatant 1
## 6 ENSMUST00000000001.4  2.254487 Ins1creTRAP supernatant 2
```

Subset a list of interested genes

```
# Ins1: ENSMUST00000039652.5
# Mafa: ENSMUST00000062002.5
# Pdx1: ENSMUST00000085591.6
# Gcg: ENSMUST00000102733.9
# Sst: ENSMUST00000004480.4
# Amy1: ENSMUST00000106540.7
# Pnlip: ENSMUST00000057270.8

geneList <- c("ENSMUST00000039652.5", "ENSMUST00000062002.5", "ENSMUST00000085591.6", "ENSMUST00000102733.9", "ENSMUST00000106540.7", "ENSMUST00000057270.8")

# Subset interested genes
df_subset <- subset(df_tpm, df_tpm$target_id %in% geneList)

# Calculate z scores
df_subset$z <- runif(df_subset$tpm, min = -10, max = 10)

head(df_subset)

##           target_id      tpm                sample      z
## 3791 ENSMUST00000004480.4 17.137394      Ins1creTRAP input 1  6.9918464
## 3792 ENSMUST00000004480.4 17.707016      Ins1creTRAP input 2  3.0645192
## 3793 ENSMUST00000004480.4 20.647121      Ins1creTRAP IP 1    9.0177151
## 3794 ENSMUST00000004480.4 17.401344      Ins1creTRAP IP 2    2.3444610
## 3795 ENSMUST00000004480.4  9.881168 Ins1creTRAP supernatant 1 -0.1431873
## 3796 ENSMUST00000004480.4  7.103728 Ins1creTRAP supernatant 2  9.5201313

# Set the theme for heatmap
theme_heatmap <- theme(
  axis.line = element_line(colour = "black"),
  axis.text.x = element_text(color = "black", size = 12, face = "bold", angle = 45, hjust = 1),
  axis.text.y = element_text(color = "black", size = 16, face = "bold"),
  axis.title.x = element_blank(),
  axis.title.y = element_blank(),
  legend.title = element_blank(),
  legend.text = element_text(color = "black", size = 16, face = "bold"),
  legend.key = element_rect(fill = "white"), # Remove grey background of the legend
  panel.grid.major = element_blank(), panel.grid.minor = element_blank(),
  panel.background = element_blank(),
  panel.border = element_rect(colour = "black", fill = NA, size = 2),
  plot.margin = unit(c(0.5, 0.5, 0.5, 0.5), "cm")
)

# heatmap by geom_tile
df_subset %>% ggplot(aes(x = sample, y = target_id)) +
  geom_tile(aes(fill = z)) +
```

Heatmap showing the expression of insulin-related genes (Amy1, Gcg, Pdx1, Mafa, Pnlip, Ins1, Sst) across various samples. The color scale ranges from -5 (white) to 5 (red).

Gene	Ins1creTRAP input 1	Ins1creTRAP input 2	Ins1creTRAP IP 1	Ins1creTRAP IP 2	Ins1creTRAP supernatant 1	Ins1creTRAP supernatant 2	TRAP input	TRAP IP	TRAP supernatant
Amy1	1	0	4	1	5	-5	1	1	2
Gcg	0	2	4	2	3	-5	0	2	0
Pdx1	2	0	3	2	3	1	2	0	2
Mafa	2	2	4	0	0	1	2	0	2
Pnlip	2	3	0	2	2	4	0	4	3
Ins1	4	0	3	2	2	0	2	2	3
Sst	3	2	4	2	2	4	0	2	2