## Benchmark of error rate inference from UMI-tagged data and PCR error model

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Load data

```
df <- data.frame()</pre>
for (q in c(20,25,30)){
for (proj in c(73, 82)) {
  for (sample in c("encyclo", "kappa-hf-taq", "phusion", "sd-hs", "snp-detect",
                    "taq-hs", "tersus", "tersus-snp-buff", "truseq", "velox")) {
    .df <- read.table(</pre>
        paste(
          paste(q, "-1", paste("polerr", proj, sep=""), sep="_"),
          paste("polerr", proj, ".", sample, ".variant.caller.txt", sep=""), sep ="/"),
                                 header=T, sep="\t", stringsAsFactors = F)
    .df$q <- q
    .df$proj <- proj
    .df$sample <- sample
    df <- rbind(df, .df)</pre>
  }
}
}
df <- subset(df, freq > 0 & freq < 0.001 &</pre>
                !grepl("D", mutation) & !grepl("I", mutation) & global.est == 0 &
                coverage > 0)
df$mut.split <- sapply(df$mutation, function(x) strsplit(as.character(x),"[S:>]"))
df$mutation.pos <- as.integer(sapply(df$mut.split, function(x) x[2]))</pre>
df$mutation.from <- sapply(df$mut.split, function(x) x[3])</pre>
df$mutation.to <- sapply(df$mut.split, function(x) x[4])</pre>
df$mut.split <- NULL</pre>
```

Model estimates for error rate:

```
library(ggplot2)

## Warning: package 'ggplot2' was built under R version 3.2.4

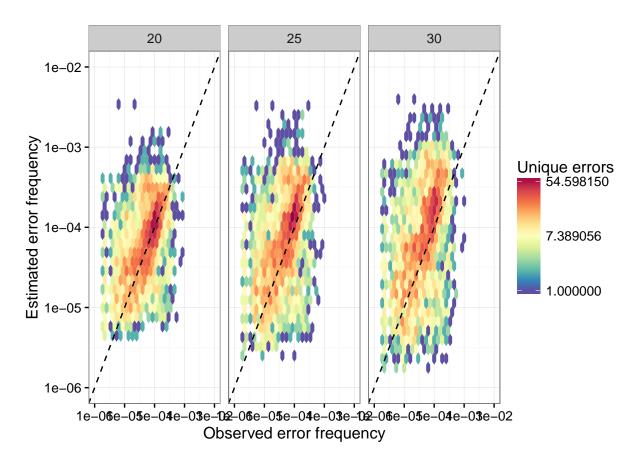
library(RColorBrewer)

rf <- colorRampPalette(rev(brewer.pal(11,'Spectral')))

r <- rf(32)

ggplot(df, aes(x=freq, y=error.rate)) +
    stat_binhex() +</pre>
```

## Warning: package 'hexbin' was built under R version 3.2.5

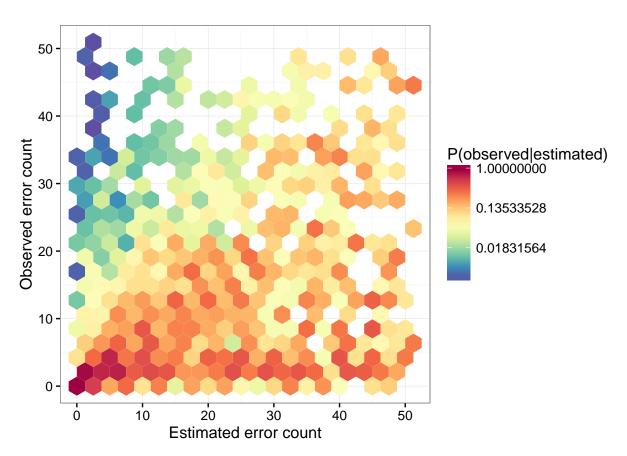


```
for (qq in c(20, 25, 30)) {
  print(with(subset(df, q == qq), cor(freq, error.rate, method = "spearman")))
}
```

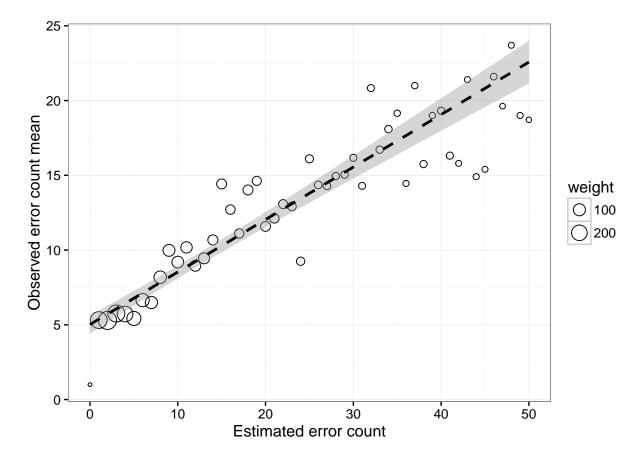
```
## [1] 0.4343872
## [1] 0.4344433
## [1] 0.4356582
```

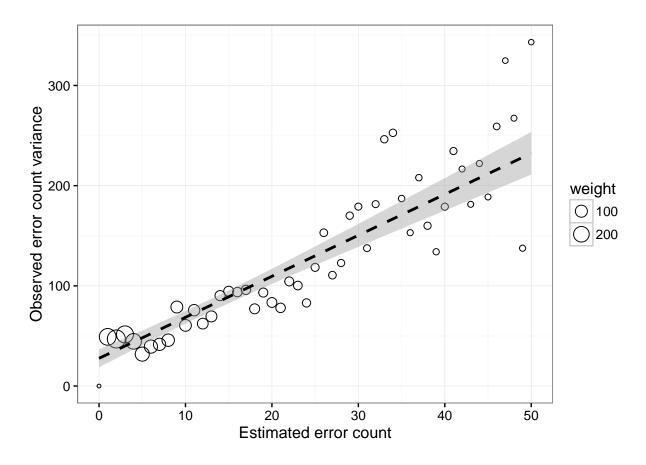
We'll use Bayesian model when computing P-values (and Q-scores) of erroneous variants based on estimated error rate and their count, accounting for a high degree of uncertainty in error rate estimates. Thus, we'll compute P-values based on Negative Binomial distribution instead of Poisson model. To estimate its parameters, lets fit Gamma distribution (conjugate prior of Poisson distribution) to P(lambda|error rate estimate \* coverage). First lets plot the conditional probability:

```
library(plyr)
df.1 \leftarrow subset(df, q == 20)
df.1$count.est <- round(df.1$coverage * df.1$error.rate)</pre>
df.1$count.obs <- round(df.1$coverage * df.1$freq)</pre>
df.1 <- subset(df.1, count.est <= 50 & count.obs <= 50)</pre>
# Compute mean and variance for lambda, we'll need it later
df.1 <- ddply(df.1, .(count.est), transform, f.mean = mean(freq * coverage))</pre>
df.1 <- ddply(df.1, .(count.est), transform, f.var = var(freq * coverage))</pre>
df.1.s <- ddply(df.1, .(count.est, count.obs),</pre>
                 summarize,
                 weight = length(count.est), f.mean = f.mean[1], f.var = f.var[1])
df.1.m <- ddply(df.1.s, .(count.est), transform, weight.norm = weight / sum(weight))</pre>
# requires install.packages("hexbin")
ggplot(df.1.m, aes(x=count.est, y=count.obs, weight=weight.norm)) +
  geom_hex(bins = 20) +
  xlab("Estimated error count") +
  ylab("Observed error count") +
  scale_fill_gradientn("P(observed|estimated)", colors=r, trans="log") +
  theme bw()
```



Gamma distribution parameters alpha and beta can be estimated through mean and variance of observed count of erroneous variants (lambda). We'll first fit estimated error count to these parameters:





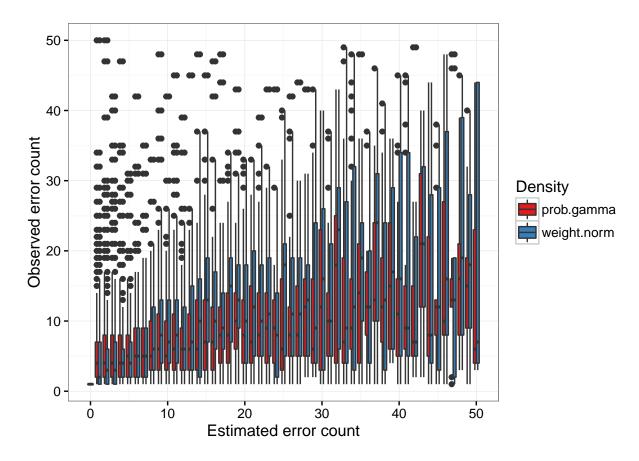
Compute probabilities based on Gamma distribution, compare fitted and observed P(lambda|error rate estimate \* coverage):

```
ggplot(df.1.m.1, aes(x=count.est, group = interaction(variable,count.est), fill=variable)) +
    geom_boxplot(aes(y=count.obs, weight=value)) +
    xlab("Estimated error count") +
    ylab("Observed error count") +
    scale_fill_brewer(palette = "Set1", "Density") +
    theme_bw()

## Warning in rq.fit.br(wx, wy, tau = tau, ...): Solution may be nonunique
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```

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```



Lets now compute P-values for errors using fitted Negative Binomial model and compare them to real P-values of error counts:

```
ggplot(df.1.m, aes(x=-10*log10(pval), y=-10*log10(pval.true))) +
   stat_density2d(aes(fill=..level.., weight=weight), geom="polygon") +
   geom_abline(intercept = 0, slope = 1, color = "black", linetype="dashed") +
   scale_x_continuous("Computed Q score", limits=c(0,20)) +
   scale_y_continuous("True Q score", limits=c(0,20)) +
   scale_fill_gradientn(colors=r) +
   theme_bw()
```

