one-worded-vs-multi-worded

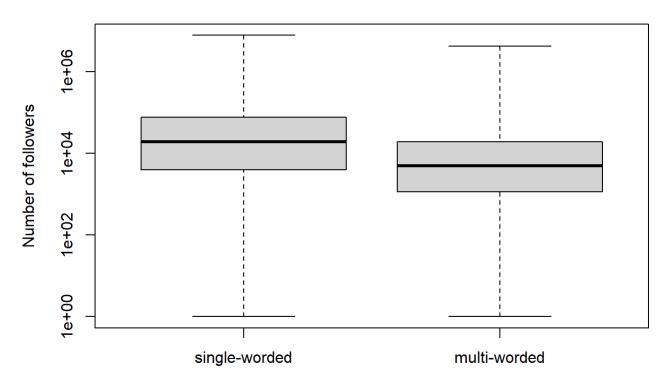
Here I looked at how company's name effects its popularity on LinkedIn. I found that companies with a single word in their name have about 4 times more followers on average. Therefore, I suggest that companies with names like e.g. "Liberty Tax Service" use abbreviation: "LTS"; Companies with names like "Ashland Inc" should simply use Ashland. #

```
linkedin<-read.csv("C:\\Users\\irakl\\Desktop\\temp_datalab_records_linkedin_company\\linkedin.c</pre>
sv", header = TRUE)
# work with most recent data
library(dplyr)
##
## Attaching package: 'dplyr'
## The following objects are masked from 'package:stats':
##
       filter, lag
##
## The following objects are masked from 'package:base':
##
       intersect, setdiff, setequal, union
##
linkedin recent <-
  linkedin %>%
  group by(company name) %>%
  filter(as_of_date == max(as_of_date))
# produce a column that indicates whether company name is one-worded or multi-worded.
linkedin recent %>%
  select(company name,followers count,industry) %>%
    multi_worded_name = sapply(strsplit(company_name, " "), length) != 1 # e.g. Hewlett-Packard
 is considered one-worded with this code
  ) ->
  name role
```

Following analysis shows that companies with single-worded name tend to attract few hundred percent more followers.

```
name_role_plus <- name_role
name_role_plus$followers_count <- name_role_plus$followers_count + 1 # added 1 follower to every
one to plot on log scale
boxplot(followers_count ~ multi_worded_name, data = name_role_plus, log = "y", range = 0, names=
c("single-worded","multi-worded"), xlab = "Type of company's name",
    ylab = "Number of followers", main = "Dependence of company popularity on its name")</pre>
```

Dependence of company popularity on its name



Type of company's name

```
t.test(followers_count~multi_worded_name,data = name_role_plus)
```

```
##
## Welch Two Sample t-test
##
## data: followers_count by multi_worded_name
## t = 7.4801, df = 1259.9, p-value = 1.387e-13
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## 79354.43 135778.24
## sample estimates:
## mean in group FALSE mean in group TRUE
## 143259.80 35693.47
```

```
# produce follower's vector for companies with multi-worded names
name_role %>%
    filter(multi_worded_name == TRUE) %>%
    ungroup() %>%
    select(followers_count) ->
    multi_worded
colnames(multi_worded) <- NULL

# produce follower's vector for companies with single-worded names
name_role %>%
    filter(multi_worded_name == FALSE) %>%
    ungroup() %>%
    select(followers_count) ->
    single_worded
colnames(single_worded) <- NULL</pre>
```

```
ratio <- sapply(single_worded, mean, na.rm = TRUE)/sapply(multi_worded, mean, na.rm = TRUE)
rt = toString(round(ratio))
paste("Companies with names consisting of a single word have about",rt," times more followers")</pre>
```

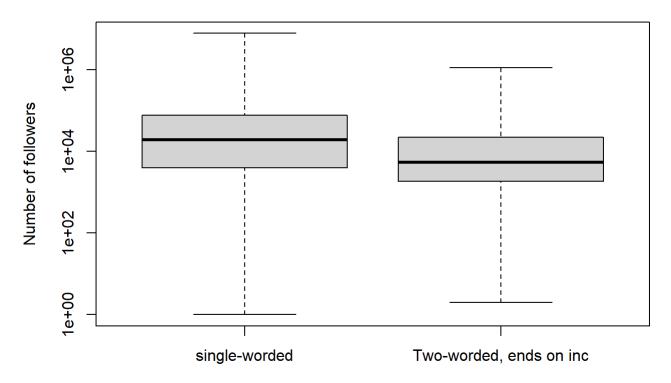
```
## [1] "Companies with names consisting of a single word have about 4 times more followers"
```

```
View(inc_role)
```

Following analysis clearly demonstrates the importance of one simple change companies can make to increase their number of followers on LinkedIn: removing Inc at the end of their name. For example, GGP Inc. would become GGP.

```
inc_role_plus <- inc_role
inc_role_plus$followers_count <- inc_role_plus$followers_count + 1 # added 1 follower to everyon
e to plot on log scale
boxplot(followers_count ~ ends_with_inc, data = inc_role_plus, log = "y", range = 0, names=c("si
ngle-worded", "Two-worded, ends on inc"), xlab = "Type of company's name",
    ylab = "Number of followers", main = "Dependence of company popularity on its name")</pre>
```

Dependence of company popularity on its name



Type of company's name

```
t.test(followers_count~ends_with_inc,data = inc_role_plus)
```

```
##
## Welch Two Sample t-test
##
## data: followers_count by ends_with_inc
## t = 6.5527, df = 1310, p-value = 8.102e-11
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## 74222.42 137655.38
## sample estimates:
## mean in group FALSE mean in group TRUE
## 143259.8 37320.9
```