CICS 490E Research Summary

Evaluate effects of different kind of prior knowledge in causal structure learning from data

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Project description

Basically, we examined on how the prior knowledge affect the result of learning causal structure from a given dataset. In specific, we add incorrect edges to the blacklist and white list as prior knowledge and examine the result of the learned network from different size of generated data.

> We will perform experiments to understand the relationship between informativeness of the prior and dataset sample size. From the survey of the previous works, one consistent finding was that if prior beliefs are closer to the true model, then they improve the learning process but if priors are misleading or incorrect, they harm the learning process [1]. We want to further understand this phenomenon by doing various experiments which systematically vary dataset size and prior correctness. We will also focus on understanding the relationship between how complicated the prior is (expressiveness of prior e.g. edge orientation vs path) and learning accuracy.

> - Vary the correctness of the prior provided by the user of the algorithm and run algorithm for fixed dataset size. This can be done by providing arguments to the structure learning algorithm in the form of blacklists and whitelists. For more information, check these examples.
> - Vary the size of the dataset and keep the correctness of the prior fixed.

Hypothesis

- The quantity of correct and incorrect prior information affects the results of learned network proportionally.
- The size of data where the network was learned from doesn't affect much to the result.

Method

We use the F1 score as the scorer function to compare the learned network with ground truth. It computes how many edged are different between the 2 networks.

Process

1. We first train a networking from the alarm dataset using a hill-climbing (HC) algorithm, which is recommended by Purva saying that she has achieved best performance, as the learned network without any prior knowledge.
2. To see how incorrect prior knowledge affects the result, we firstly tried to add every ground truth edge into the blacklist and examine the result. The F1 score varies in a relatively small range, which should have something to do with the detail implementation of HC algorithm, otherwise the F1 score is expected to be similar.
3. Then we tried to choose n random incorrect edges into the blacklist, where n goes from 1 to the number of edges in the ground truth network. The result shows, almost, as the number of incorrect edges increases, the F1 score decreases.
4. To see how correct prior knowledge affects the result, we did repeat step 2 and 3 and add the edges to the white list.
5. At last, to see how the size of data affects the result, we generate new data from the original dataset and the ground truth model. And choose 20 incorrect random edges added to the blacklist.

Conclusion

- The more incorrect prior knowledge given, the worse the result is.
- The more correct prior knowledge give, the better the result is.
- The size of data where the network learned from doesn't have much to do with the result.

Codes and Results

alarm.R

aris

2021-04-30

```
# # Install packages
# install.packages(c("bnlearn", "bnviewer"))
# if (!requireNamespace("BiocManager", quietly = TRUE))
#   install.packages("BiocManager")
# BiocManager::install()
# BiocManager::install(c("graph", "Rgraphviz"))
# install.packages("ggplot2")

# Load packages
library("bnlearn")
library("bnviewer")
library("Rgraphviz")
```

```
## Loading required package: graph
```

```
## Loading required package: BiocGenerics
```

```
## Loading required package: parallel
```

```
##
## Attaching package: 'BiocGenerics'
```

```
## The following objects are masked from 'package:parallel':
##
##     clusterApply, clusterApplyLB, clusterCall, clusterEvalQ,
##     clusterExport, clusterMap, parApply, parCapply, parLapply,
##     parLapplyLB, parRapply, parSapply, parSapplyLB
```

```
## The following objects are masked from 'package:bnlearn':
##
##     path, score
```

```
## The following objects are masked from 'package:stats':
##
##     IQR, mad, sd, var, xtabs
```

```
## The following objects are masked from 'package:base':
##
##     anyDuplicated, append, as.data.frame, basename, cbind, colnames,
##     dirname, do.call, duplicated, eval, evalq, Filter, Find, get, grep,
##     grepl, intersect, is.unsorted, lapply, Map, mapply, match, mget,
##     order, paste, pmax, pmax.int, pmin, pmin.int, Position, rank,
##     rbind, Reduce, rownames, sapply, setdiff, sort, table, tapply,
##     union, unique, unsplit, which.max, which.min
```

```
##
## Attaching package: 'graph'
```

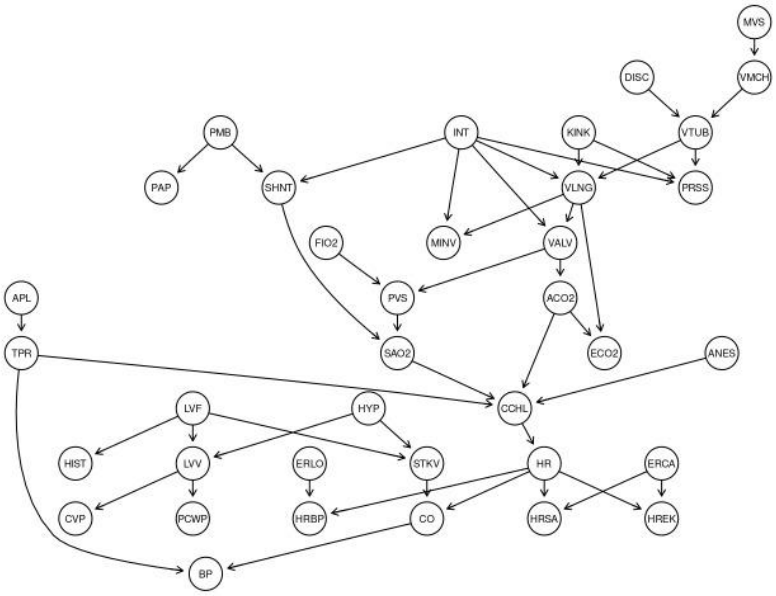
```
## The following objects are masked from 'package:bnlearn':
##
##     degree, nodes, nodes<-
```

```
## Loading required package: grid
```

```
library("ggplot2")

setwd('~/Projects/cics490e_research')
# setwd('E:/Projects/cics490e_research')

# Compute f1 score given tp, fp, fn
f1 <- function(m) {
  tp <- m$tp
  fp <- m$fp
  fn <- m$fn

  return(tp / (tp + (fp + fn) / 2))
}

# Load Dataset
data('alarm')
head(alarm)
```

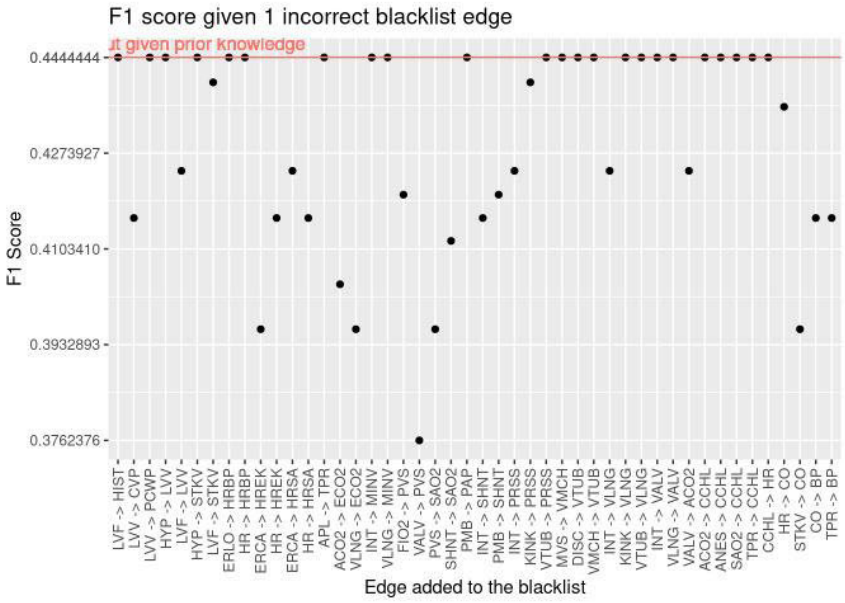
```
##     CVP   PCWP  HIST    TPR     BP     CO HRBP HREK HRSA    PAP   SAO2   FIO2
## 1 NORMAL NORMAL FALSE    LOW NORMAL   HIGH HIGH HIGH HIGH NORMAL NORMAL    LOW
## 2 NORMAL NORMAL FALSE NORMAL    LOW    LOW HIGH HIGH HIGH NORMAL    LOW NORMAL
## 3 NORMAL   HIGH FALSE NORMAL NORMAL   HIGH HIGH HIGH HIGH NORMAL    LOW NORMAL
## 4 NORMAL NORMAL FALSE    LOW    LOW   HIGH HIGH HIGH HIGH NORMAL NORMAL NORMAL
## 5 NORMAL NORMAL FALSE    LOW    LOW NORMAL HIGH HIGH HIGH NORMAL    LOW NORMAL
## 6 NORMAL NORMAL FALSE    LOW NORMAL   HIGH HIGH HIGH HIGH NORMAL    LOW NORMAL
##     PRSS ECO2 MINV    MVS   HYP   LVF   APL  ANES   PMB    INT  KINK  DISC
## 1   HIGH ZERO HIGH NORMAL FALSE FALSE FALSE FALSE FALSE NORMAL FALSE  TRUE
## 2   HIGH ZERO ZERO NORMAL FALSE FALSE FALSE FALSE FALSE NORMAL FALSE FALSE
## 3 NORMAL ZERO ZERO NORMAL FALSE FALSE FALSE FALSE FALSE NORMAL FALSE FALSE
## 4   HIGH ZERO ZERO NORMAL FALSE FALSE FALSE FALSE FALSE NORMAL FALSE FALSE
## 5    LOW ZERO ZERO NORMAL FALSE FALSE FALSE FALSE FALSE NORMAL FALSE FALSE
## 6   HIGH HIGH ZERO NORMAL FALSE FALSE FALSE  TRUE FALSE NORMAL FALSE FALSE
##      LVV   STKV CCHL  ERLO   HR  ERCA   SHNT    PVS   ACO2 VALV VLNG VTUB
## 1 NORMAL NORMAL HIGH FALSE HIGH FALSE NORMAL NORMAL NORMAL HIGH  LOW ZERO
## 2 NORMAL    LOW HIGH FALSE HIGH FALSE NORMAL    LOW    LOW ZERO ZERO  LOW
## 3 NORMAL NORMAL HIGH FALSE HIGH FALSE NORMAL    LOW    LOW ZERO ZERO  LOW
## 4 NORMAL NORMAL HIGH FALSE HIGH FALSE NORMAL NORMAL    LOW ZERO ZERO  LOW
## 5 NORMAL NORMAL HIGH FALSE HIGH FALSE NORMAL    LOW    LOW ZERO ZERO  LOW
## 6 NORMAL NORMAL HIGH FALSE HIGH FALSE NORMAL    LOW    LOW ZERO ZERO  LOW
##     VMCH
## 1 NORMAL
## 2 NORMAL
## 3 NORMAL
## 4 NORMAL
## 5 NORMAL
## 6 NORMAL
```

```
# Ground truth network
modelstring <- paste0("[HIST|LVF][CVP|LVV][PCWP|LVV][HYP][LVV|HYP:LVF][LVF]",
                      "[STKV|HYP:LVF][ERLO][HRBP|ERLO:HR][HREK|ERCA:HR][ERCA][HRSA|ERCA:HR][ANES]",
                      "[APL][TPR|APL][ECO2|ACO2:VLNG][KINK][MINV|INT:VLNG][FIO2][PVS|FIO2:VALV]",
                      "[SAO2|PVS:SHNT][PAP|PMB][PMB][SHNT|INT:PMB][INT][PRSS|INT:KINK:VTUB][DISC]",
                      "[MVS][VMCH|MVS][VTUB|DISC:VMCH][VLNG|INT:KINK:VTUB][VALV|INT:VLNG]",
                      "[ACO2|VALV][CCHL|ACO2:ANES:SAO2:TPR][HR|CCHL][CO|HR:STKV][BP|CO:TPR]")
dag_true <- model2network(modelstring)
graphviz.plot(dag_true)
```

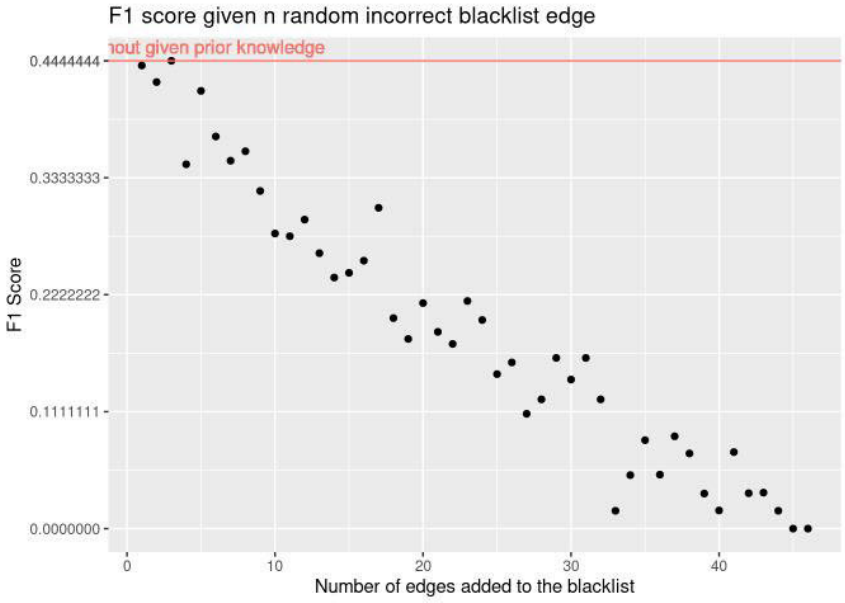



```
# Given 1 incorrect edge to blacklist
n <- dim(dag_true$arcs)[1]
arcs <- dag_true$arcs
df_b1 <- data.frame(edge=character(), f1=numeric())

for (i in 1:n) {
  e <- arcs[i,]
  net <- hc(alarm, blacklist = e)

  df_b1[i,] <- c(paste(e, collapse = ' -> '), f1(compare(dag_true, net)))
}
df_b1$f1 = as.numeric(df_b1$f1)

gt_f1 = f1(compare(dag_true, hc(alarm)))

ggplot(df_b1, aes(x=edge, y=f1, group=1)) +
  scale_x_discrete(limits=df_b1$edge) +
  scale_y_continuous(breaks = sort(c(seq(min(df_b1$f1), max(df_b1$f1), length.out=5), gt_f1))) +
  geom_point() +
  geom_hline(aes(yintercept=gt_f1, color='red')) +
  geom_text(aes(5,gt_f1,label = 'Without given prior knowledge', vjust = -0.5, color='red')) +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1)) +
  labs(title = "F1 score given 1 incorrect blacklist edge",
       x='Edge added to the blacklist', y='F1 Score') +
```

```
  theme(legend.position = "none")
```

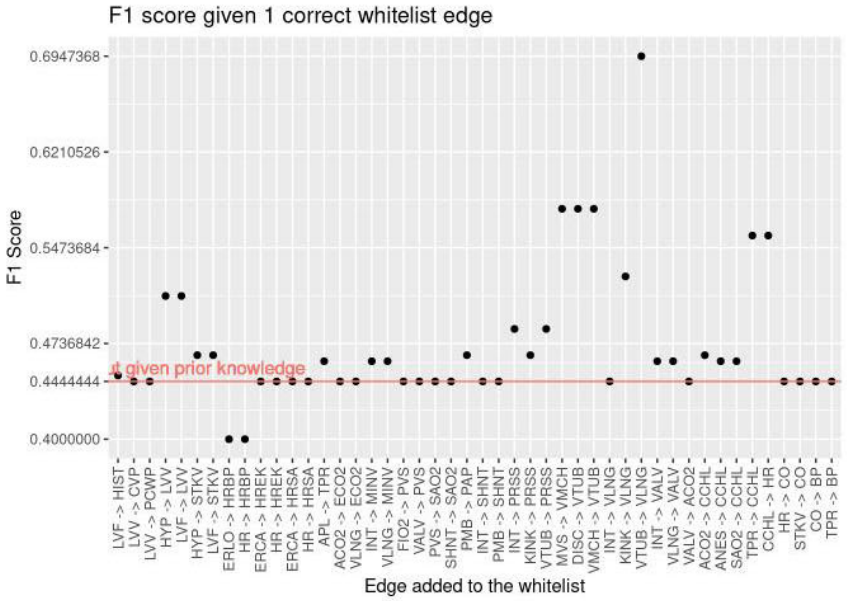



```
ggsave(
  'blacklist_1_f1.png',
  device = 'png',
  path = 'figures',
  width = 32,
  height = 18,
  units = 'cm'
)

# Given n random incorrect edge to blacklist
df_bn <- data.frame(f1=numeric())

for (i in 1:n) {
  e <- arcs[sample(1:n, i),]
  net <- hc(alarm, blacklist = e)

  df_bn[i,] <- f1(compare(dag_true, net))
}

ggplot(df_bn, aes(x=(1:n), y=f1)) +
  scale_y_continuous(breaks = sort(c(seq(min(df_bn$f1), max(df_bn$f1), length.out=5), gt_f1))) +
  geom_point() +
  geom_hline(aes(yintercept=gt_f1, color='red')) +
  geom_text(aes(5,gt_f1,label = 'Without given prior knowledge', vjust = -0.5, color='red')) +
  labs(title = "F1 score given n random incorrect blacklist edge",
       x='Number of edges added to the blacklist', y='F1 Score') +
  theme(legend.position = "none")
```

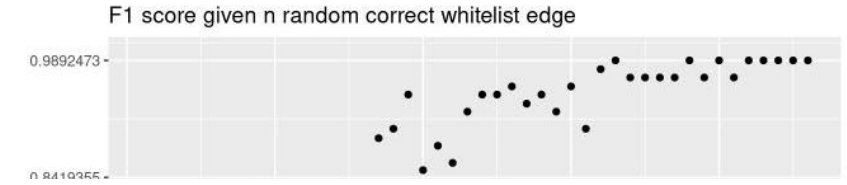


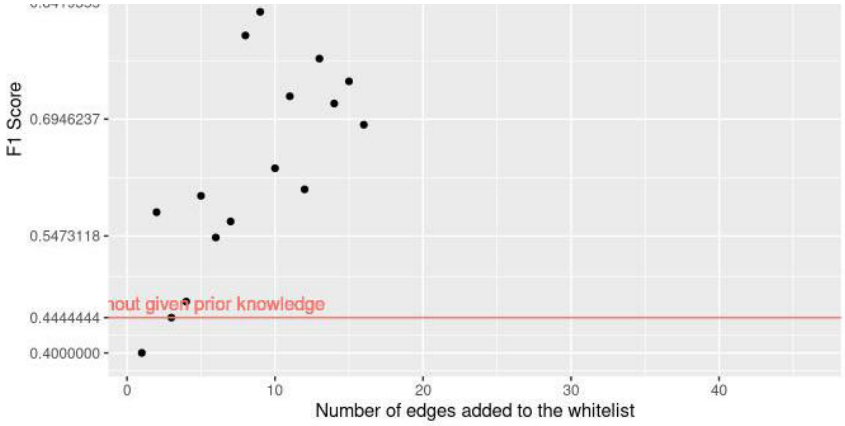

```
ggsave(
  'blacklist_n_f1.png',
  device = 'png',
  path = 'figures',
  width = 32,
  height = 18
```

```
  units = 'cm'
)


# Given 1 correct edge to the white list
df_cw1 <- data.frame(edge=character(), f1=numeric())

for (i in 1:n) {
  e <- arcs[i,]
  net <- hc(alarm, whitelist = e)

  df_cw1[i,] <- c(paste(e, collapse = ' -> '), f1(compare(dag_true, net)))
}
df_cw1$f1 = as.numeric(df_cw1$f1)

ggplot(df_cw1, aes(x=edge, y=f1, group=1)) +
  scale_x_discrete(limits=df_cw1$edge) +
  scale_y_continuous(breaks = sort(c(seq(min(df_cw1$f1), max(df_cw1$f1), length.out=5), gt_f1))) +
  geom_point() +
  geom_hline(aes(yintercept=gt_f1, color='red')) +
  geom_text(aes(5,gt_f1,label = 'Without given prior knowledge', vjust = -0.5, color='red')) +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1)) +
  labs(title = "F1 score given 1 correct whitelist edge",
       x='Edge added to the whitelist', y='F1 Score') +
  theme(legend.position = "none")
```




```
ggsave(
  'whitelist_c1_f1.png',
  device = 'png',
  path = 'figures',
  width = 32,
  height = 18,
  units = 'cm'
)


# Given n random correct edge to the white list
df_cwn <- data.frame(f1=numeric())

for (i in 1:n) {
  e <- arcs[sample(1:n, i),]
  net <- hc(alarm, whitelist = e)

  df_cwn[i,] <- f1(compare(dag_true, net))
}

ggplot(df_cwn, aes(x=(1:n), y=f1)) +
  scale_y_continuous(breaks = sort(c(seq(min(df_cwn$f1), max(df_cwn$f1), length.out=5), gt_f1))) +
  geom_point() +
  geom_hline(aes(yintercept=gt_f1, color='red')) +
  geom_text(aes(5,gt_f1,label = 'Without given prior knowledge', vjust = -0.5, color='red')) +
  labs(title = "F1 score given n random correct whitelist edge",
       x='Number of edges added to the whitelist', y='F1 Score') +
  theme(legend.position = "none")
```






```
ggsave(
  'whitelist_cn_f1.png',
  device = 'png',
  path = 'figures',
  width = 32,
  height = 18,
  units = 'cm'
)


# Given 20 random incorrect edge to the blacklist and learn the network from different size of data
df_size_b20 <- data.frame(size=numeric(), f1=numeric())

e <- arcs[sample(1:n, 20),]
for (i in c(100, 200, 500, 1000, 2000, 5000, 10000, 20000, 50000, 100000)) {
  sim <- rbn(dag_true, i, alarm, replace.unidentifiable = TRUE)

  net <- hc(sim, blacklist = e)

  df_size_b20[dim(df_size_b20)[1]+1,] <- c(i, f1(compare(dag_true, net)))
}
```

```
## Warning in check.data(x): variable PMB has levels that are not observed in the
## data.
```

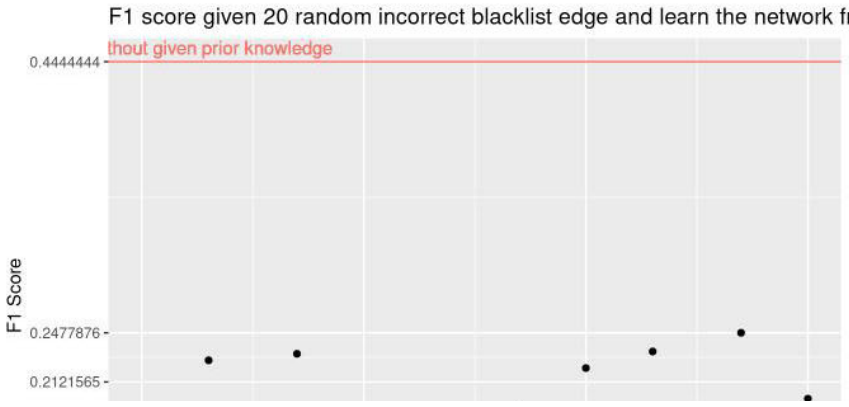
```
## Warning in check.data(x): variable PVS has levels that are not observed in the
## data.
```

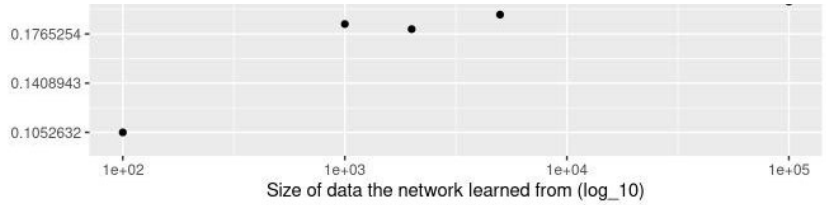
```
## Warning in check.data(x): variable SAO2 has levels that are not observed in the
## data.
```

```
## Warning in check.data(x): variable VLNG has levels that are not observed in the
## data.
```

```
## Warning in check.data(x): variable VTUB has levels that are not observed in the
## data.
```

```
df_size_b20$size = as.numeric(df_size_b20$size)
df_size_b20$f1 = as.numeric(df_size_b20$f1)

ggplot(df_size_b20, aes(x=size, y=f1)) +
  scale_x_continuous(trans='log10') +
  scale_y_continuous(breaks = sort(c(seq(min(df_size_b20$f1), max(df_size_b20$f1), length.out=5), gt_f1))) +
  geom_point() +
  geom_hline(aes(yintercept=gt_f1, color='red')) +
  geom_text(aes(200,gt_f1,label = 'Without given prior knowledge', vjust = -0.5, color='red')) +
  labs(title = "F1 score given 20 random incorrect blacklist edge and learn the network from different size of data",
       x='Size of data the network learned from (log_10)', y='F1 Score') +
  theme(legend.position = "none")
```






```
ggsave(
  'blacklist_size_20_f1.png',
  device = 'png',
  path = 'figures',
  width = 32,
  height = 18,
  units = 'cm'
)



save.image('data.RData')
```