Taliban Terrorism: A Bayesian Network Analysis

Nicholas Bradley

26/06/2021

Discrete Bayesian Network Analysis of Taliban Terrorism

This project will provide two separate analyses. The first will explore a network comprising binary variables, while the second will examine the network based on categorical variables with several levels.

Libraries

```
library(easypackages) # enables the libraries function for easier library loading
suppressPackageStartupMessages(
  libraries("bnlearn", # for Bayesian Network functionality
            "dplyr",
            "data.table", # for set.names function
            "tidyverse" # for fct_lump function
  ))
```

Set Working Directory

```
setwd("C:/R Portfolio/Bayesian Network")
```

Load Raw Data Set

```
GTD <- read.csv("globalterrorismdb_0919dist.csv")
```

Data Filtering

This section removes all non terrorism incidents and terrorism incidents that have not been geographically certified. This geographic certification is important as otherwise specific attack locations aren't accurate. One final step involves selection of only data that features the Taliban

```
# Remove All Non Terrorist Incidents #

GTDDT <- GTD %>% dplyr::filter(doubtterr == 0)

# Remove all unverified geographic data

GTDDTS <- GTDDT %>% dplyr::filter(specificity == 1)

# Remove all non Taliban data

Taliban <- GTDDTS %>% dplyr::filter(gname == "Taliban")
```

Rename Columns

Here, columns are renamed, so they are tidier

```
setnames(Taliban, old = c("iyear",
                          "imonth",
                          "iday",
                          "provstate",
                          "city",
                          "multiple",
                          "success",
                          "suicide",
                          "attacktype1_txt",
                          "gname",
                          "targtype1_txt",
                          "weaptype1_txt",
                          "nkill",
                          "nwound"),
                  new = c("Year",
                          "Month",
                          "Day",
                          "Province",
                          "City",
                          "Multiple",
                          "Success",
                          "Suicide",
                          "Attack",
                          "Group",
                          "Target",
                          "Weapon",
                          "Dead",
                          "Wounded"))
```

Select Specific Columns

```
Taliban <- dplyr::select(Taliban,
                         Year,
                         Month,
                         Province,
                         City,
                         Suicide,
                         Multiple,
                         Success,
                         Attack,
                         Target,
                         Group,
                         Weapon,
                         Dead)
```

Remove NA Values

```
colSums(is.na(Taliban)) # count the NA's in each column
```

```
##      Year     Month Province     City  Suicide Multiple  Success   Attack
```

```
##        0        0        0        0        0        0        0        0
##   Target    Group   Weapon     Dead
##        0        0        0       93
```

```r
Taliban <- na.omit(Taliban) # remove NA's
colSums(is.na(Taliban)) # No NA values remain
```

```
##     Year    Month Province     City  Suicide Multiple  Success   Attack
##        0        0        0        0        0        0        0        0
##   Target    Group   Weapon     Dead
##        0        0        0        0
```

Remove NA Values

```r
colSums(is.na(Taliban)) # count the NA's in each column
```

```
##     Year    Month Province     City  Suicide Multiple  Success   Attack
##        0        0        0        0        0        0        0        0
##   Target    Group   Weapon     Dead
##        0        0        0        0
```

```r
Taliban <- na.omit(Taliban) # remove NA's
colSums(is.na(Taliban)) # No NA values remain
```

```
##     Year    Month Province     City  Suicide Multiple  Success   Attack
##        0        0        0        0        0        0        0        0
##   Target    Group   Weapon     Dead
##        0        0        0        0
```

Save and Load Cleaned Data Set

```r
setwd("C:/R Portfolio/Bayesian Network")
write.csv(Taliban, file = "Taliban.csv", row.names = F)
Taliban <- read.csv("Taliban.csv")
```

Collate together small count category levels

Target

```r
Taliban <- Taliban %>%
  mutate(Target = fct_lump(fct_infreq(Target), n = 5)) %>%
  group_by(Target)
```

Recode Variable Levels

Attack

```r
Taliban <- Taliban %>%
  mutate(Attack = recode(Attack,
                         "Bombing/Explosion" = "Bomb",
                         "Facility/Infrastructure Attack" = "Infrastructure",
```

```
                         "Hostage Taking (Kidnapping)" = "HostageKidnap",
                         "Hostage Taking (Barricade Incident)" = "HostageBarricade",
                         "Armed Assault" = "ArmedAssault",
                         "Unarmed Assault" = "UnarmedAssault",
                         "Unknown" = "UnknownAttack"))
```

Target

```
Taliban <- Taliban %>%
  mutate(Target = recode(Target,
                         "Private Citizens & Property" = "Private",
                         "Government (General)" = "GovernmentGeneral",
                         "Other" = "OtherTarget"))
```

Provincial - Attack Network

Province and City variables are correlated with each, and so are separated Attack and Weapon are correlated with each other, and so are separated The analysis only concerns provincial and attack type variables. Weapon type and city variables could feature in a future analysis.

```
Taliban <- dplyr::select(Taliban,
                         Province,
                         Suicide,
                         Multiple,
                         Success,
                         Attack,
                         Target,
                         Group,
                         Dead)
```

One Hot Encoding

All variables are converted into separate binary variables where each categorical level becomes such a binary variable. The purpose is to indicate Bayesian network association between specific variables, rather than attack and target variables which each comprise several levels.

Province

```
for(unique_value in unique(Taliban$Province)){

  Taliban[paste("Province",
              unique_value,
              sep = ".")] <- ifelse(Taliban$Province == unique_value, 1, 0)
}
```

Target

```
for(unique_value in unique(Taliban$Target)){

  Taliban[paste("Target",
              unique_value,
              sep = ".")] <- ifelse(Taliban$Target == unique_value, 1, 0)
}
```

Attack

```
for(unique_value in unique(Taliban$Attack)){

  Taliban[paste("Attack",
                unique_value,
                sep = ".")] <- ifelse(Taliban$Attack == unique_value, 1, 0)
}
```

Dead

```
for(unique_value in unique(Taliban$Dead)){

  Taliban[paste("Dead",
                unique_value,
                sep = ".")] <- ifelse(Taliban$Dead == unique_value, 1, 0)
}
```

Save Data File

```
setwd("C:/R Portfolio/Bayesian Network")
write.csv(Taliban, file = "Tbn.csv", row.names = F)
```

Load Data File

```
Tbn_Corrected <- read.csv("Tbn_Corrected.csv")
```

Selection of Variables with highest counts

To simplify the network construction, and to avoid situations where the total of pairwise counts between any two totals were less than ten, the five provinces with most attacks were selected, as was the five dead totals with the highest counts The five provinces are: Helmand, Kandahar, Kabul, Ghazni and Kunduz The five dead counts are zero, one, two, three and four The five targets with the highest attack counts are police, private, GovernmentGeneral, Military and Business The four attack types with the highest counts are Bomb, Armed Assault, Assassination and Hostage Kidnap. Unknown attack has a higher count than hostage kidnap, but it is overlooked as any attack could be an unknown attack.

```
Taliban4 <- dplyr::select(Tbn_Corrected,
                          Helmand,
                          Kandahar,
                          Kabul,
                          Ghazni,
                          Kunduz,
                          Police,
                          Private,
                          GovernmentGeneral,
                          Military,
                          Business,
                          Bomb,
                          ArmedAssault,
                          Assassination,
                          HostageKidnap,
                          ZeroDead,
```

```
                        OneDead,
                        TwoDead,
                        ThreeDead,
                        FourDead)
```

Network Creation

```
dag2 <- empty.graph(nodes = c("Helmand",
                              "Kandahar",
                              "Kabul",
                              "Ghazni",
                              "Kunduz",
                              "Police",
                              "Private",
                              "GovernmentGeneral",
                              "Military",
                              "Business",
                              "Bomb",
                              "ArmedAssault",
                              "Assassination",
                              "HostageKidnap",
                              "ZeroDead",
                              "OneDead",
                              "TwoDead",
                              "ThreeDead",
                              "FourDead"
))

arc.set = matrix(c("Bomb", "Business",
                   "Bomb", "GovernmentGeneral",
                   "Bomb", "Military",
                   "Bomb", "Police",
                   "Bomb", "Private",
                   "Bomb", "Helmand",
                   "Bomb", "Kandahar",
                   "Bomb", "Kabul",
                   "Bomb", "Ghazni",
                   "Bomb", "Kunduz",
                   "Bomb", "ZeroDead",
                   "Bomb", "OneDead",
                   "Bomb", "TwoDead",
                   "Bomb", "ThreeDead",
                   "Bomb", "FourDead",
                   "ArmedAssault", "Business",
                   "ArmedAssault", "GovernmentGeneral",
                   "ArmedAssault", "Military",
                   "ArmedAssault", "Police",
                   "ArmedAssault", "Private",
                   "ArmedAssault", "Helmand",
                   "ArmedAssault", "Kandahar",
                   "ArmedAssault", "Kabul",
                   "ArmedAssault", "Ghazni",
                   "ArmedAssault", "Kunduz",
```

```
"ArmedAssault", "ZeroDead",
"ArmedAssault", "OneDead",
"ArmedAssault", "TwoDead",
"ArmedAssault", "ThreeDead",
"ArmedAssault", "FourDead",
"Assassination", "Business",
"Assassination", "GovernmentGeneral",
"Assassination", "Military",
"Assassination", "Police",
"Assassination", "Private",
"Assassination", "Helmand",
"Assassination", "Kandahar",
"Assassination", "Kabul",
"Assassination", "Ghazni",
"Assassination", "Kunduz",
"Assassination", "ZeroDead",
"Assassination", "OneDead",
"Assassination", "TwoDead",
"Assassination", "ThreeDead",
"Assassination", "FourDead",
"HostageKidnap", "Business",
"HostageKidnap", "GovernmentGeneral",
"HostageKidnap", "Military",
"HostageKidnap", "Police",
"HostageKidnap", "Private",
"HostageKidnap", "Helmand",
"HostageKidnap", "Kandahar",
"HostageKidnap", "Kabul",
"HostageKidnap", "Ghazni",
"HostageKidnap", "Kunduz",
"HostageKidnap", "ZeroDead",
"HostageKidnap", "OneDead",
"HostageKidnap", "TwoDead",
"HostageKidnap", "ThreeDead",
"HostageKidnap", "FourDead",
"Business", "Helmand",
"Business", "Kandahar",
"Business", "Kabul",
"Business", "Ghazni",
"Business", "Kunduz",
"Business", "ZeroDead",
"Business", "OneDead",
"Business", "TwoDead",
"Business", "ThreeDead",
"Business", "FourDead",
"GovernmentGeneral", "Helmand",
"GovernmentGeneral", "Kandahar",
"GovernmentGeneral", "Kabul",
"GovernmentGeneral", "Ghazni",
"GovernmentGeneral", "Kunduz",
"GovernmentGeneral", "ZeroDead",
"GovernmentGeneral", "OneDead",
"GovernmentGeneral", "TwoDead",
```

```
"GovernmentGeneral", "ThreeDead",
"GovernmentGeneral", "FourDead",
"Military", "Helmand",
"Military", "Kandahar",
"Military", "Kabul",
"Military", "Ghazni",
"Military", "Kunduz",
"Military", "ZeroDead",
"Military", "OneDead",
"Military", "TwoDead",
"Military", "ThreeDead",
"Military", "FourDead",
"Police", "Helmand",
"Police", "Kandahar",
"Police", "Kabul",
"Police", "Ghazni",
"Police", "Kunduz",
"Police", "ZeroDead",
"Police", "OneDead",
"Police", "TwoDead",
"Police", "ThreeDead",
"Police", "FourDead",
"Private", "Helmand",
"Private", "Kandahar",
"Private", "Kabul",
"Private", "Ghazni",
"Private", "Kunduz",
"Private", "ZeroDead",
"Private", "OneDead",
"Private", "TwoDead",
"Private", "ThreeDead",
"Private", "FourDead",
"Helmand", "ZeroDead",
"Helmand", "OneDead",
"Helmand", "TwoDead",
"Helmand", "ThreeDead",
"Helmand", "FourDead",
"Kandahar", "ZeroDead",
"Kandahar", "OneDead",
"Kandahar", "TwoDead",
"Kandahar", "ThreeDead",
"Kandahar", "FourDead",
"Kabul", "ZeroDead",
"Kabul", "OneDead",
"Kabul", "TwoDead",
"Kabul", "ThreeDead",
"Kabul", "FourDead",
"Ghazni", "ZeroDead",
"Ghazni", "OneDead",
"Ghazni", "TwoDead",
"Ghazni", "ThreeDead",
"Ghazni", "FourDead",
"Kunduz", "ZeroDead",
```

```
                   "Kunduz", "OneDead",
                   "Kunduz", "TwoDead",
                   "Kunduz", "ThreeDead",
                   "Kunduz", "FourDead"
                   ),
                              ncol = 2, byrow = TRUE,
                             dimnames = list(NULL, c("from", "to")))

arcs(dag2) = arc.set
```

Convert variables into factors

```
names <- names(Taliban4)
Taliban4[names] <- lapply(Taliban4[names], factor)
```

Province Node Blacklist

This blacklist informs R to avoid creating any arcs between these arcs. For instance, there is no point creating arcs between two provincial variables or two attack type variables. The blacklist is saved in an object called BA_BL

```
BA_BL <- matrix(c(
  "Helmand", "Kandahar",
  "Kandahar", "Helmand",
  "Helmand", "Kabul",
  "Kabul", "Helmand",
  "Helmand", "Ghazni",
  "Ghazni", "Helmand",
  "Helmand", "Kunduz",
  "Kunduz", "Helmand",
  "Kandahar", "Kabul",
  "Kabul", "Kandahar",
  "Kandahar", "Ghazni",
  "Ghazni", "Kandahar",
  "Kandahar", "Kunduz",
  "Kunduz", "Kandahar",
  "Kabul", "Ghazni",
  "Ghazni", "Kabul",
  "Kabul", "Kunduz",
  "Kunduz", "Kabul",
  "Ghazni", "Kunduz",
  "Kunduz", "Ghazni",
  "Business", "GovernmentGeneral",
  "GovernmentGeneral", "Business",
  "Business", "Military",
  "Military", "Business",
  "Business", "Police",
  "Police", "Business",
  "Business", "Private",
  "Private", "Business",
  "GovernmentGeneral", "Military",
  "Military", "GovernmentGeneral",
  "GovernmentGeneral", "Police",
```

```
  "Police", "GovernmentGeneral",
  "GovernmentGeneral", "Private",
  "Private", "GovernmentGeneral",
  "Military", "Police",
  "Police", "Military",
  "Private", "Military",
  "Military", "Private",
  "Private", "Police",
  "Police", "Private",
  "Bomb", "ArmedAssault",
  "ArmedAssault", "Bomb",
  "Bomb", "Assassination",
  "Assassination", "Bomb",
  "Bomb", "HostageKidnap",
  "HostageKidnap", "Bomb",
  "ArmedAssault", "Assassination",
  "Assassination", "ArmedAssault",
  "ArmedAssault", "HostageKidnap",
  "HostageKidnap", "ArmedAssault",
  "Assassination", "HostageKidnap",
  "HostageKidnap", "Assassination",
  "ZeroDead", "OneDead",
  "OneDead", "ZeroDead",
  "ZeroDead", "TwoDead",
  "TwoDead", "ZeroDead",
  "ZeroDead", "ThreeDead",
  "ThreeDead", "ZeroDead",
  "ZeroDead", "FourDead",
  "FourDead", "ZeroDead",
  "OneDead", "TwoDead",
  "TwoDead", "OneDead",
  "OneDead", "ThreeDead",
  "ThreeDead", "OneDead",
  "OneDead", "FourDead",
  "FourDead", "OneDead",
  "TwoDead", "ThreeDead",
  "ThreeDead", "TwoDead",
  "TwoDead", "FourDead",
  "FourDead", "TwoDead",
  "ThreeDead", "FourDead",
  "FourDead", "ThreeDead"
),
ncol = 2,
byrow = TRUE,
dimnames = list(NULL, c("from", "to")))
```

Create Score Based Networks #

R features two score based networks, Tabu and Hill Climbing (HC)

Tabu

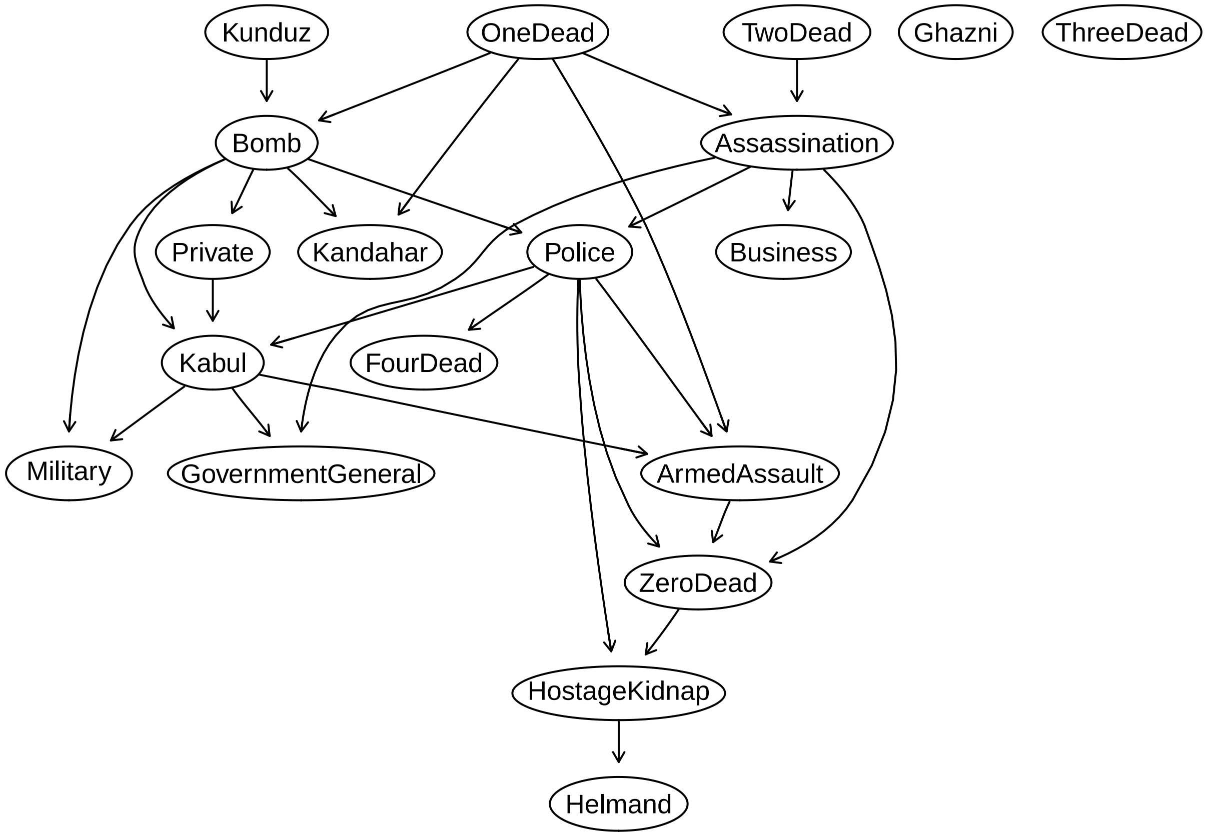
```
set.seed(226)
Tabu_BA <- tabu(Taliban4,
```

```
                blacklist = BA_BL)
Tabu_BA
```

```
##
##   Bayesian network learned via Score-based methods
##
##   model:
##    [Ghazni][Kunduz][OneDead][TwoDead][ThreeDead][Bomb|Kunduz:OneDead]
##    [Assassination|OneDead:TwoDead][Kandahar|Bomb:OneDead]
##    [Police|Bomb:Assassination][Private|Bomb][Business|Assassination]
##    [Kabul|Police:Private:Bomb][FourDead|Police]
##    [GovernmentGeneral|Kabul:Assassination][Military|Kabul:Bomb]
##    [ArmedAssault|Kabul:Police:OneDead]
##    [ZeroDead|Police:ArmedAssault:Assassination][HostageKidnap|Police:ZeroDead]
##    [Helmand|HostageKidnap]
##   nodes:                                 19
##   arcs:                                  27
##     undirected arcs:                     0
##     directed arcs:                       27
##   average markov blanket size:           3.68
##   average neighbourhood size:            2.84
##   average branching factor:              1.42
##
##   learning algorithm:                    Tabu Search
##   score:                                 BIC (disc.)
##   penalization coefficient:              4.007664
##   tests used in the learning procedure:  1084
##   optimized:                             TRUE
```

```
# Plot Tabu Network

graphviz.plot(Tabu_BA,
              layout = "dot",
              shape = "ellipse")
```

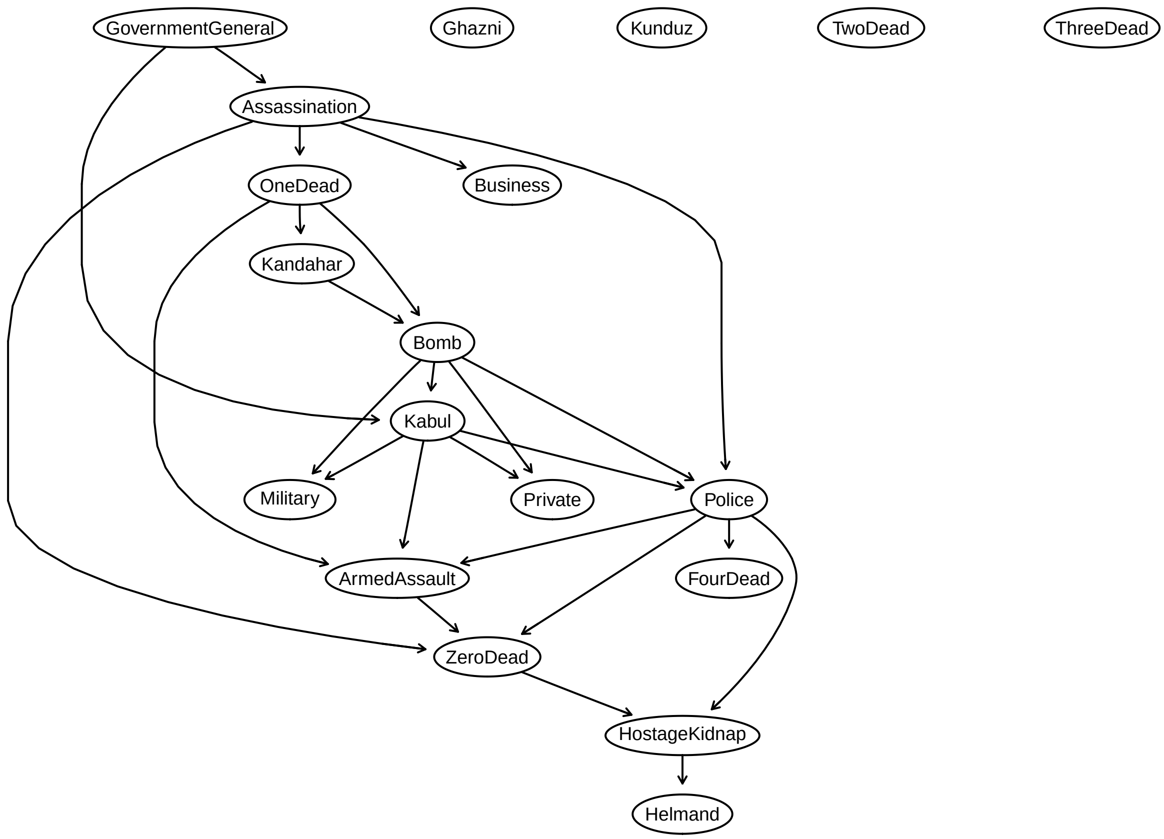


Hill Climbing

```
set.seed(227)
HC_BA <- hc(Taliban4,
            blacklist = BA_BL)

# Plot Hill Climbing Network

graphviz.plot(HC_BA,
              layout = "dot",
              shape = "ellipse")
```



Network Goodness of Fit Scores

Hill Climbing

```
score(HC_BA, Taliban4, type = "bde")
```

```
## [1] -21566.79
```

```
score(HC_BA, Taliban4, type = "aic")
```

```
## [1] -21394.66
```

```
score(HC_BA, Taliban4, type = "bic")
```

```
## [1] -21578.13
```

```
score(HC_BA, Taliban4, type = "loglik")
```

```
## [1] -21333.66
```

Tabu

```r
score(Tabu_BA, Taliban4, type = "bde")
```

```
## [1] -21537.62
```

```r
score(Tabu_BA, Taliban4, type = "aic")
```

```
## [1] -21360.17
```

```r
score(Tabu_BA, Taliban4, type = "bic")
```

```
## [1] -21555.67
```

```r
score(Tabu_BA, Taliban4, type = "loglik")
```

```
## [1] -21295.17
```

For bde, aic, bic and loglik scores, Tabu is lower (closer to zero), so it is a better model

Using the Discrete Bayesian Network

Using the Bayesian Network Structure

To determine if there is any conditional dependence, the dsep funcion ca be used. Where two variables are connected to each other through a third, then of the dsep is false, this indicates that there is conditional dependence if the path through the third variable is not blocked. The path only becomes blocked if the two variables condition on the third

```r
dsep(Tabu_BA, x = "GovernmentGeneral", y = "Business")
```

```
## [1] FALSE
```

```r
dsep(Tabu_BA, x = "GovernmentGeneral", y = "OneDead")
```

```
## [1] FALSE
```

The false output indicates the variables are not deseparated and so are conditionally dependant on each other

```r
path(Tabu_BA, from = "GovernmentGeneral", to = "Business")
```

```
## [1] FALSE
```

```r
dsep(Tabu_BA, x = "GovernmentGeneral", y = "Business", z = "Assassination")
```

```
## [1] TRUE
```

When assassination is conditioned on, the path is blocked and they become desparated.

Probabilistic Representation

Because Tabu is a better fitting model according to all scoring metrics, it will be used rather than HC to represent the probabilities

Estimating the parameters: Conditional Probability Tables

Maximum Likelihood Estimates

```
bn.mle <- bn.fit(Tabu_BA, Taliban4, method = "mle")
```

Bayesian Estimation

```
bn.bayes <- bn.fit(Tabu_BA, Taliban4, method = "bayes", iss = 10)
```

Conditional Probability Tables

Maximum Likelihood Estimates

```
bn.mle$Bomb
```

```
##
##   Parameters of node Bomb (multinomial distribution)
##
## Conditional probability table:
##
## , , OneDead = 0
##
##     Kunduz
## Bomb         0         1
##    0 0.4984575 0.6846154
##    1 0.5015425 0.3153846
##
## , , OneDead = 1
##
##     Kunduz
## Bomb         0         1
##    0 0.6744574 0.4827586
##    1 0.3255426 0.5172414
```

```
bn.mle$Target
```

```
## NULL
```

```
bn.mle$Province
```

```
## NULL
```

```
bn.mle$Dead
```

```
## NULL
```

Bayesian Setting

```r
bn.bayes$Attack
```

```
## NULL
```

```r
bn.bayes$Target
```

```
## NULL
```

```r
bn.bayes$Province
```

```
## NULL
```

```r
bn.bayes$Dead
```

```
## NULL
```

Exact Inference

To install RGBL - needed for gRain:

```r
if (!requireNamespace("BiocManager", quietly = TRUE))
  install.packages("BiocManager")

BiocManager::install("RBGL")
```

```
## Warning: package(s) not installed when version(s) same as current; use ‘force = TRUE‘ to
##   re-install: ’RBGL’
```

```r
library(gRain)
library(gRbase)

junction <- compile(as.grain(bn.bayes))

# The probability of bomb attack considering data as a whole

querygrain(junction, nodes = "Bomb")$Bomb
```

```
## Bomb
##         0         1
## 0.5406656 0.4593344
```

```r
# The probability of actual Bomb attack (indicated by 1) in Helmand

group <- setEvidence(junction, nodes = "Bomb", states = "1")
querygrain(group, nodes = "Helmand")$Helmand
```

```
## Helmand
##         0         1
## 0.8941306 0.1058694
```

```r
# The probability of actual Bomb attack (indicated by 1) against Government General Target

group <- setEvidence(junction, nodes = "Bomb", states = "1")
querygrain(group, nodes = "GovernmentGeneral")$GovernmentGeneral
```

```
## GovernmentGeneral
##         0         1
## 0.8098622 0.1901378
```

```r
# The probability of actual Bomb attack with one dead (indicated by 1) against Government General Targe
# The probability of attack against Governmental General Target per province and per attack

BT <- setEvidence(junction, nodes = "OneDead", states = "1")
GPA <- querygrain(BT, nodes = c("Bomb", "Helmand"),
                  type = "joint")

GPA
```

```
##        Bomb
## Helmand          0          1
##       0 0.59302963 0.30082127
##       1 0.07046389 0.03568521
```

```r
SxT <- cpdist(bn.bayes, nodes = c("Bomb", "Helmand"),
              evidence = (OneDead == "1"))
```

Approximate inference

Approximate probabilistic inference of attack against Police Target in Helmand Province based on maximum likelihood estimate

Conditional Independence Tests

Conditional independence tests focus on the presence of individual arcs. As each arc indicates a probabilistic dependence, conditional independence tests assess whether that probabilistic dependence is supported by the data. If the null hypothesis (of conditional independence) is rejected, the arc can be considered for inclusion in the DAG.

```r
ci.test("Kabul", "ZeroDead", c("ArmedAssault", "Police"), test = "mi", data = Taliban4)
```

```
##
##  Mutual Information (disc.)
##
## data:  Kabul ~ ZeroDead | ArmedAssault + Police
## mi = 8.1864, df = 4, p-value = 0.08498
## alternative hypothesis: true value is greater than 0
```

```r
ci.test("Kabul", "ZeroDead", c("ArmedAssault", "Police"), test = "x2", data = Taliban4)
```

```
##
##  Pearson's X^2
##
## data:  Kabul ~ ZeroDead | ArmedAssault + Police
## x2 = 8.5442, df = 4, p-value = 0.07356
## alternative hypothesis: true value is greater than 0
```

Both tests generate insignificant p-values, thus indicating that dependent relationship encoded by kabul and ZeroDead is not significant given its parents.

Arc Strengths

```
arc.strength(Tabu_BA, Taliban4, criterion = "x2")
```

```
##              from                to     strength
## 1   ArmedAssault          ZeroDead 3.923041e-23
## 2         Police      ArmedAssault 1.215932e-34
## 3           Bomb            Police 2.218513e-24
## 4         Police          ZeroDead 3.776835e-15
## 5        OneDead      ArmedAssault 8.521654e-13
## 6           Bomb          Military 9.039176e-09
## 7        OneDead              Bomb 1.847538e-14
## 8           Bomb             Kabul 4.758968e-27
## 9           Bomb           Private 9.770827e-05
## 10      ZeroDead     HostageKidnap 4.991236e-07
## 11 Assassination          ZeroDead 1.521059e-07
## 12        Police          FourDead 5.647585e-05
## 13         Kabul          Military 4.406766e-06
## 14 HostageKidnap           Helmand 1.061238e-03
## 15         Kabul      ArmedAssault 5.033607e-06
## 16 Assassination            Police 6.594900e-08
## 17        Police     HostageKidnap 5.979880e-04
## 18       OneDead          Kandahar 2.447607e-06
## 19          Bomb          Kandahar 4.365210e-06
## 20        Kunduz              Bomb 2.023788e-05
## 21 Assassination GovernmentGeneral 7.280116e-58
## 22         Kabul GovernmentGeneral 1.717077e-08
## 23        Police             Kabul 8.151419e-13
## 24       Private             Kabul 1.448677e-13
## 25 Assassination          Business 4.558389e-04
## 26       OneDead     Assassination 4.620351e-30
## 27       TwoDead     Assassination 4.847019e-06
```

All arcs have very significant p-values, which means they are well supported by the data

```
dag4 <- set.arc(dag2, from = "ZeroDead", to = "Kabul")
nparams(dag4, Taliban4)
```

```
## [1] 76884
```

```
score(dag4, data = Taliban4, type = "bic")
```

```
## [1] -328850.5
```

```
score(dag2, data = Taliban4, type = "bic")
```

```
## [1] -359629.4
```

The bic score for the Bayesian Network that features the new arc, has a lower score than the network without it, which suggests adding this arc is actually beneficial to the network

```
score(Tabu_BA, data = Taliban4, type = "bic")
```

```
## [1] -21555.67
```

The bic score for the learned network via Tabu algorithm, has a much lower score.

```
arc.strength(Tabu_BA, Taliban4, criterion = "bic")
```

```
##              from               to   strength
## 1    ArmedAssault         ZeroDead -47.050470
## 2          Police     ArmedAssault -64.551324
## 3            Bomb           Police -46.871487
## 4          Police         ZeroDead -22.637740
## 5         OneDead     ArmedAssault -12.254906
## 6            Bomb         Military -14.237108
## 7         OneDead             Bomb -24.156475
## 8            Bomb            Kabul -50.655514
## 9            Bomb          Private  -3.559579
## 10       ZeroDead    HostageKidnap  -6.047642
## 11  Assassination         ZeroDead  -4.605559
## 12         Police         FourDead  -3.798552
## 13          Kabul         Military  -3.467926
## 14  HostageKidnap          Helmand  -2.574372
## 15          Kabul     ArmedAssault  -2.044631
## 16  Assassination           Police  -9.154775
## 17         Police    HostageKidnap  -1.496101
## 18        OneDead         Kandahar  -3.614687
## 19           Bomb         Kandahar  -4.494981
## 20         Kunduz             Bomb  -2.872054
## 21  Assassination GovernmentGeneral -93.882662
## 22          Kabul GovernmentGeneral  -7.786207
## 23         Police            Kabul -17.802465
## 24        Private            Kabul -23.574014
## 25  Assassination         Business  -5.821328
## 26        OneDead    Assassination -49.659518
## 27        TwoDead    Assassination  -2.389990
```

The results indicate that removal of any arc learned by Tabu would worsen the bic score, thus reducing the goodness of fit to the data. Therefore, the network learned by the Tabu algorithm is a good fit to the data

```
arc.strength(dag2, data = Taliban4, criterion = "bic")
```

```
##                  from                to    strength
## 1                Bomb          Business    32.05995
## 2                Bomb GovernmentGeneral    26.49841
## 3                Bomb          Military    26.53013
## 4                Bomb            Police    13.74986
## 5                Bomb           Private    24.78964
## 6                Bomb           Helmand  1019.01046
```

```
## 7              Bomb          Kandahar  1010.48561
## 8              Bomb             Kabul   995.63039
## 9              Bomb            Ghazni  1015.31358
## 10             Bomb            Kunduz  1021.73188
## 11             Bomb          ZeroDead 32792.91007
## 12             Bomb           OneDead 32814.45966
## 13             Bomb           TwoDead 32815.28642
## 14             Bomb         ThreeDead 32818.32068
## 15             Bomb          FourDead 32810.52647
## 16      ArmedAssault          Business    30.95659
## 17      ArmedAssault GovernmentGeneral    31.15268
## 18      ArmedAssault          Military    32.06008
## 19      ArmedAssault            Police    25.18557
## 20      ArmedAssault           Private    31.60627
## 21      ArmedAssault           Helmand  1022.44148
## 22      ArmedAssault          Kandahar  1015.66449
## 23      ArmedAssault             Kabul  1022.43003
## 24      ArmedAssault            Ghazni  1019.62402
## 25      ArmedAssault            Kunduz  1021.57290
## 26      ArmedAssault          ZeroDead 32766.31760
## 27      ArmedAssault           OneDead 32785.92072
## 28      ArmedAssault           TwoDead 32820.91767
## 29      ArmedAssault         ThreeDead 32821.74856
## 30      ArmedAssault          FourDead 32811.87531
## 31     Assassination          Business    24.16347
## 32     Assassination GovernmentGeneral   -42.73564
## 33     Assassination          Military    25.69020
## 34     Assassination            Police    23.39538
## 35     Assassination           Private    31.65343
## 36     Assassination           Helmand  1019.86813
## 37     Assassination          Kandahar  1010.77916
## 38     Assassination             Kabul  1020.27527
## 39     Assassination            Ghazni  1022.37008
## 40     Assassination            Kunduz  1024.02447
## 41     Assassination          ZeroDead 32795.61969
## 42     Assassination           OneDead 32777.55125
## 43     Assassination           TwoDead 32817.48012
## 44     Assassination         ThreeDead 32825.51259
## 45     Assassination          FourDead 32821.86089
## 46     HostageKidnap          Business    31.38130
## 47     HostageKidnap GovernmentGeneral    30.67425
## 48     HostageKidnap          Military    29.34590
## 49     HostageKidnap            Police    23.78692
## 50     HostageKidnap           Private    21.04730
## 51     HostageKidnap           Helmand  1020.03687
## 52     HostageKidnap          Kandahar  1022.88045
## 53     HostageKidnap             Kabul  1023.78287
## 54     HostageKidnap            Ghazni  1020.13153
## 55     HostageKidnap            Kunduz  1024.27194
## 56     HostageKidnap          ZeroDead 32809.58890
## 57     HostageKidnap           OneDead 32817.31822
## 58     HostageKidnap           TwoDead 32822.57258
## 59     HostageKidnap         ThreeDead 32822.76753
## 60     HostageKidnap          FourDead 32821.82598
```

```
## 61           Business           Helmand  1021.09975
## 62           Business          Kandahar  1025.22163
## 63           Business             Kabul  1022.93014
## 64           Business            Ghazni  1021.53745
## 65           Business            Kunduz  1024.38781
## 66           Business          ZeroDead 32806.75796
## 67           Business           OneDead 32819.45454
## 68           Business           TwoDead 32818.54247
## 69           Business         ThreeDead 32820.86361
## 70           Business          FourDead 32822.33742
## 71  GovernmentGeneral           Helmand  1018.65401
## 72  GovernmentGeneral          Kandahar  1022.40451
## 73  GovernmentGeneral             Kabul  1016.56135
## 74  GovernmentGeneral            Ghazni  1025.29880
## 75  GovernmentGeneral            Kunduz  1023.10859
## 76  GovernmentGeneral          ZeroDead 32791.43225
## 77  GovernmentGeneral           OneDead 32818.44003
## 78  GovernmentGeneral           TwoDead 32818.33376
## 79  GovernmentGeneral         ThreeDead 32822.78089
## 80  GovernmentGeneral          FourDead 32815.25959
## 81           Military           Helmand  1023.42430
## 82           Military          Kandahar  1021.47046
## 83           Military             Kabul  1017.42133
## 84           Military            Ghazni  1023.21352
## 85           Military            Kunduz  1022.40070
## 86           Military          ZeroDead 32796.19985
## 87           Military           OneDead 32814.36686
## 88           Military           TwoDead 32817.81122
## 89           Military         ThreeDead 32825.05768
## 90           Military          FourDead 32819.47093
## 91             Police           Helmand  1021.58293
## 92             Police          Kandahar  1023.80069
## 93             Police             Kabul  1000.88140
## 94             Police            Ghazni  1020.06989
## 95             Police            Kunduz  1024.47580
## 96             Police          ZeroDead 32714.89198
## 97             Police           OneDead 32794.30306
## 98             Police           TwoDead 32815.79228
## 99             Police         ThreeDead 32817.19186
## 100            Police          FourDead 32816.79226
## 101           Private           Helmand  1022.62017
## 102           Private          Kandahar  1020.62496
## 103           Private             Kabul  1004.02195
## 104           Private            Ghazni  1024.54107
## 105           Private            Kunduz  1024.12834
## 106           Private          ZeroDead 32780.67328
## 107           Private           OneDead 32805.02419
## 108           Private           TwoDead 32814.44742
## 109           Private         ThreeDead 32822.40373
## 110           Private          FourDead 32826.13858
## 111           Helmand          ZeroDead 32806.53954
## 112           Helmand           OneDead 32810.27757
## 113           Helmand           TwoDead 32814.17095
## 114           Helmand         ThreeDead 32816.09495
```

```
## 115          Helmand          FourDead 32821.54070
## 116         Kandahar          ZeroDead 32815.34936
## 117         Kandahar           OneDead 32807.86462
## 118         Kandahar           TwoDead 32818.66447
## 119         Kandahar         ThreeDead 32818.10422
## 120         Kandahar          FourDead 32821.29514
## 121            Kabul          ZeroDead 32818.31607
## 122            Kabul           OneDead 32817.36817
## 123            Kabul           TwoDead 32821.15930
## 124            Kabul         ThreeDead 32822.06037
## 125            Kabul          FourDead 32820.11516
## 126           Ghazni          ZeroDead 32818.93771
## 127           Ghazni           OneDead 32809.55852
## 128           Ghazni           TwoDead 32819.98844
## 129           Ghazni         ThreeDead 32821.10594
## 130           Ghazni          FourDead 32825.67299
## 131           Kunduz          ZeroDead 32809.25576
## 132           Kunduz           OneDead 32814.12474
## 133           Kunduz           TwoDead 32817.12298
## 134           Kunduz         ThreeDead 32821.84093
## 135           Kunduz          FourDead 32823.48895
```

All the arcs apart from Assassination GovernmentGeneral would worsen the bic score, thus indicating it is not a good fit to the data.