

Epistemic Network Analysis and Ordered Network Analysis in Learning Analytics

1. Introduction

This chapter provides a tutorial on conducting *epistemic network analysis* (ENA) and *ordered network analysis* (ONA) using R. We introduce these two techniques together because they share similar theoretical foundations, but each addresses a different challenge for analyzing large-scale qualitative data on learning processes.

ENA and ONA are methods for quantifying, visualizing, and interpreting network data. Taking coded data as input, ENA and ONA represent associations between codes in undirected or directed weighted network models, respectively. Both techniques measure the strength of association among codes and illustrate the structure of connections in network graphs, and they quantify changes in the composition and strength of those connections over time. Importantly, ENA and ONA enable comparison of networks both visually and via summary statistics, so they can be used to explore a wide range of research questions in contexts where patterns of association in coded data are hypothesized to be meaningful and where comparing those patterns across individuals or groups is important.

In the following sections, we will (1) briefly review literature relevant to the application of ENA and ONA, (2) provide a step-by-step guide to implementing ENA and ONA in R, and (3) suggest additional resources and examples for further exploration. By the end of this chapter, readers will be able to apply these techniques in their own research.

2. Literature review

2.1 Epistemic network analysis (ENA)

ENA is a method for identifying and quantifying connections in coded data and representing them in undirected weighted network models (Shaffer et al., 2016). There are two key features that differentiate ENA from other networks analysis tools or multivariate analyses: (1) ENA produces summary statistics that can be used to compare the differences in the content of networks rather than just their structure; and (2) ENA network visualizations provide information that is mathematically consistent with those summary statistics, which facilitates meaningful interpretation of statistical differences (Bowman et al., 2021). These features enable researchers to analyze a wide range of phenomena in learning analytics, including complex thinking and knowledge construction (Csanadi et al., 2018; Oshima et al., 2018), collaborative problem solving (Bressler et al., 2019; Swiecki et al., 2020;), socio-emotional aspects of learning (Prieto et al., 2021), mentoring (Zhang et al., 2022), and teacher professional development (Bauer et al., 2019; Fernandez-Nieto et al., 2021; Phillips et al., 2023)

One key feature that makes ENA an effective method in modeling collaborative interaction is that ENA can model individuals' unique contributions to collaborative discourse *while accounting for* group context, and thus both individuals *and* groups can be analyzed in the same model. This feature is particularly valuable in collaborative learning environments, where the interactions and contributions of each individual are related and should not be treated as a series of isolated events. For example, Swiecki et al., (2020) analyzed the communications of air defense warfare teams in training exercises and found that ENA was not only able to reveal differences in individual performance identified in a qualitative analysis of the collaborative discourse, but also to test those differences statistically.

2.2 Ordered network analysis (ONA)

Ordered Network Analysis (ONA) extends the theoretical and analytical advantages of ENA to account for the order of events by producing *directed* weighted networks rather than undirected models (Tan et al., 2022). Like ENA, ONA takes coded data as input, identifies and measures connections among coded items, and visualizes the structure of connections in a metric space that enables both statistical and visual comparison of networks. However, ONA models the order in which codes appear in the data, enabling analysis of phenomena in which the order of events is hypothesized to be important.

For example, Tan et al. (2022) used ONA to model the performance of military teams learning to identify, assess, and respond to potential threats detected by radar. The findings demonstrate that ONA could detect qualitative differences between teams in different training conditions that were not detected with unordered models and show that they are statistically significant. In their work, Tan et al. (2022) argued that ONA possesses an advantage over methods such as Sequential Pattern Mining (SPM), which is widely used to identify frequent sequential patterns. In contrast to SPM, which prioritizes the specific micro-sequential order of events, ONA models processes by accounting for the co-temporal order of interactions between the units of analysis in response and what they are responding to. Consequently, ONA is a more appropriate methodological choice when modeling processes in ill-formed problem-solving scenarios, where collaborative interactions do not follow a prescribed sequence of steps but where the order of activities is still important.

ONA has also been used to analyze log data from online courses. For example, Fan et al. (2021) analyzed self-regulated learning tactics employed by learners in Massive Open Online Courses (MOOC) using ONA and process mining. The authors found that ONA provided more nuanced interpretations of learning tactics compared to process mining because ONA models learning tactics across four dimensions: frequency, continuity, order, and the role of specific learning actions within broader tactics.

Like ENA, ONA produces summary statistics for network comparison and mathematically consistent network visualizations that enable interpretation of statistical measures. Unlike ENA, ONA models the order in which codes appear in data, enabling researchers to investigate whether and to what extent the order of events is meaningful in a given context.

In the following sections, we provide a step-by-step guide to conducting ENA and ONA analyses in R.

3. Epistemic network analysis in R

In this section, we demonstrate how to conduct an ENA analysis using the `rENA` package. If you are not familiar with ENA as an analytic technique, we recommend that you first read Shaffer (2017), Shaffer & Ruis (2017), and Bowman et al. (2022) to familiarize yourself with the theoretical and methodological foundations of ENA.

3.1 Install the `rENA` package and load the library

Before installing the `rENA` package, be sure that you are using R version 4.1 or newer. To check your R version, type `R.version` in your console. To update your R version (if needed), download and install R from the official R website: <https://cran.r-project.org/>

First, install the `rENA` package and then load the `rENA` library after installation is complete.

```
install.packages("rENA")
```

```
library(rENA)
```

We also install the other package that is required for accessing the `view()` function section 3.7.3 in `rENA`.

```
install.packages("tma")
```

```
library(tma )
```

3.2 Dataset

The dataset we will use as an example, `RS.data`, is included in the `rENA` package. Note that the `RS.data` file in the package is only a subset of the full dataset, and is thus intended for demonstration purposes only.

To start, pass `RS.data` from the `rENA` package to a data frame named **data**.

```
data = rENA::RS.data
```

Use the `head()` function in R to subset and preview the first three rows present in the input data frame to familiarize yourself with the data structure.

```
head(data,3)
```

```
##      UserName Condition CONFIDENCE.Pre CONFIDENCE.Post CONFIDENCE.Change
## 1    steven z FirstGame              7              8              1
## 2    akash v FirstGame              6              8              2
## 3 alexander b FirstGame              5              7              1
## C.Level.Pre NewC.Change  C.Change      Timestamp ActivityNumber GroupNa
me
```

```

## 1    High.Pre  Pos.Change Pos.Change 9/17/2013 9:43      1 Electr
ic
## 2    High.Pre  Pos.Change Pos.Change 9/17/2013 9:44      1 Electr
ic
## 3      Low.Pre  Pos.Change Pos.Change 9/17/2013 9:46      1 Electr
ic
##  GameHalf GameDay      text Data Technical.Constraints
## 1    First      1      Steven    0          0
## 2    First      1 Hey, I am Akash    0          0
## 3    First      1      I'm Alex    0          0
##  Performance.Parameters Client.and.Consultant.Requests Design.Reasoning
## 1              0              0          0
## 2              0              0          0
## 3              0              0          0
##  Collaboration
## 1              0
## 2              0
## 3              0

```

RS.data consists of discourse from *RescuShell*, an online learning simulation where students work as interns at a fictitious company to solve a realistic engineering design problem in a simulated work environment. Throughout the internship, students communicate with their project teams and mentors via online chat, and these chats are recorded in the “text” column. A set of qualitative codes were applied to the data in the “text” column, where a value of 0 indicates the absence of the code and a value of 1 indicates the presence of the code in a given line.

Further details about the RS.data dataset can be found in Shaffer & Arastoopour (2014). Analyses of data from *RescuShell* and other engineering virtual internships can be found in Arastoopour et al. (2016) and Chesler et al. (2015).

3.3 Construct an ENA model

To construct an ENA model, there is a function called `ena` which enables researchers to set the parameters for their model. This function wraps two other functions—`ena.accumulate.data` and `ena.make.set`—which can be used together to achieve the same result.

In the following sections, we will demonstrate how to set each parameter and explain how different choices affect the resulting ENA model.

3.3.1 Specify units

In ENA, *units* can be individuals, ideas, organizations, or any other entity whose structure of connections you want to model. To set the units parameter, specify which column(s) in the data contain the variables that identify unique units.

For this example, choose the “Condition” column and the “UserName” column to define the units. The “Condition” column has two unique values: FirstGame, and SecondGame,

representing novice users and relative expert users, respectively, as some students participated in *RescuShell* after having already completed a different engineering virtual internship. The “UserName” column includes unique user names for all students ($n=48$). This way of defining the units means that ENA will construct a network for each student in each condition.

```
unitCols = c("Condition", "UserName")
```

To verify that the units are correctly specified, subset and preview the unique values in the units columns. There are 48 units from two conditions, which means that the ENA model will produce 48 individual-level networks for each of the units, and each unit is uniquely associated with either the novice group (FirstGame) or the relative expert group (SecondGame).

```
head(unique(data[, unitCols]),3)
```

```
##      Condition      UserName
## 1 FirstGame      steven z
## 2 FirstGame      akash v
## 3 FirstGame alexander b
```

3.3.2 Specify codes

Next, specify the columns that contain the *codes*. Codes are concepts whose pattern of association you want to model for each unit. ENA represent codes as nodes in the networks and co-occurrences of codes as edges. Most researchers use binary coding in ENA analyses, where the values in the code columns are either 0 (indicating that the code is not present in that line) or 1 (indicating that the code is present in that line). *RS.data* contains six code columns, all of which will be used here.

To specify the code columns, enter the code column names in a vector.

```
codeCols = c('Data', 'Technical.Constraints', 'Performance.Parameters', 'Client.and.Consultant.Requests', 'Design.Reasoning', 'Collaboration')
```

To verify that the codes are correctly specified, preview the code columns selected.

```
head(data[,codeCols],3)
```

##	Data	Technical.Constraints	Performance.Parameters
## 1	0	0	0
## 2	0	0	0
## 3	0	0	0
##	Client.and.Consultant.Requests	Design.Reasoning	Collaboration
## 1	0	0	0
## 2	0	0	0
## 3	0	0	0

3.3.3 Specify conversations

The conversation parameter determines which lines in the data *can* be connected. Codes in lines that are not in the same conversation cannot be connected. For example, you may want to model connections within different time segments, such as days, or different steps in a process, such as activities.

In our example, choose the “Condition”, “GroupName”, and “ActivityNumber” columns to define the conversations. These choices indicate that connections can only happen between students who were in the same condition (FirstGame or SecondGame) and on the same project team (group), and within the same activity. This definition of conversation reflects what actually happened in the simulation: in a given condition, students only interacted with those who were in the same group, and each activity occurred on a different day.

To specify the conversation parameter, enter the column names in a vector.

```
conversationCols = c("Condition", "GroupName", "ActivityNumber")
```

To verify that the conversations are correctly specified, subset and preview the unique values in the conversation columns.

```
head(unique(data[, conversationCols]),3)

##   Condition GroupName ActivityNumber
## 1 FirstGame   Electric             1
## 12 FirstGame   Electric             3
## 15 FirstGame   Electric             4
```

3.3.4 Specify the window

Once the conversation parameter is specified, a window method needs to be specified. Whereas the conversation parameter specifies which lines *can be* related, the window parameter determines which lines within the same conversation *are* related. The most common window method used in ENA is called a moving stanza window, which is what will be used here.

Briefly, a moving stanza window is a sliding window of fixed length that moves through a conversation to detect and accumulate code co-occurrences in recent temporal context. The lines within a designated stanza window are considered related to each other. For instance, if the moving stanza window is 7, then each line in the conversation is linked to the six preceding lines. See Siebert-Evenstone et al. (2017) and Ruis et al. (2019) for more detailed explanations of windows in ENA models.

Here, set the window.size.back ¹parameter equal to 7.

¹ The ENA package also enables use of an infinite stanza window. The infinite stanza window works the same way as a moving stanza window, but there is no limit on the number of previous lines that are included in the window besides the

```
window.size.back = 7
```

3.3.5 Specify groups and rotation method

When specifying the units, we chose a column that indicates two conditions: FirstGame (novice group) and SecondGame (relative expert group). To enable comparison of students in these two conditions, three additional parameters need to be specified: groupVar, groups, and mean.

```
groupVar = "Condition" # "Condition" is the column used as our grouping variable
groups = c("FirstGame", "SecondGame") # "FirstGame" and "SecondGame" are the two unique values of the "Condition" column
mean = TRUE
```

These three parameters indicate that when building the ENA model, the first dimension will maximize the difference between the two conditions: FirstGame and SecondGame. This difference maximization is achieved through `mean = TRUE`, which specifies that a *means rotation* will be performed at the dimensional reduction stage. If the means rotation is set to `FALSE` or there aren't two distinct groups in your data and you still set `mean` as `TRUE`, ENA will by default use singular value decomposition (SVD) to perform the dimensional reduction. Bowman et al. (2022) provide a mathematical explanation of the methods used in ENA to perform dimensional reductions.

3.3.6 Specify metadata

The last parameter to be specified is metadata. Metadata columns are not required to construct an ENA model, but they provide information that can be used to subset units in the resulting model.

Specify the metadata columns shown below to include data on student outcomes related to reported self-confidence before and after participating in engineering virtual internships. We will use this data to demonstrate a simple linear regression analysis that can be done using ENA outputs as predictors.

```
metaCols = c("CONFIDENCE.Change", "CONFIDENCE.Pre", "CONFIDENCE.Post", "C.Change") # optional
```

3.3.7 Construct an model

Now that all the essential parameters have been specified, the ENA model can be constructed.

The `ena` function constructs the ENA model, and we recommend that you store the output in an object (in this case, **set.ena**).

conversation itself. The infinite stanza window is less commonly used in ENA, but is specified as follows:
`window.size.back = "INF"`

```

set.ena =
  ena(
    data = data,
    units = unitCols,
    codes = codeCols,
    conversation = conversationCols,
    window.size.back = 7,
    metadata = metaCols, # optional
    groupVar = groupVar,
    groups = groups,
    mean = TRUE
  )

```

As noted above, the `ena` helper function combines the functions `ena.accumulate.data` and `ena.make.set`. The following code will construct the same ENA model specified above using these two functions.

```

accum.ena =
  ena.accumulate.data(
    text_data = RS.data[, 'text'],
    units = data[,unitCols],
    conversation = data[,conversationCols],
    metadata = data[,metaCols], # optional
    codes = data[,codeCols],
    window.size.back = 7
  )

set.ena =
  ena.make.set(
    enadata = accum.ena, # the accumulation ran above
    rotation.by = ena.rotate.by.mean, # equivalent of mean=TRUE in the ena function
    rotation.params = list(
      accum.ena$meta.data$Condition=="FirstGame", # equivalent of groups in the ena function
      accum.ena$meta.data$Condition=="SecondGame" # equivalent of groups in the ena function
    )
  )

```

3.4 Summary of key model outputs

Users can explore what is stored in the object **set** by typing `set$` and select items from the drop down list. Here, we briefly describe the top-level items in `set` that are often of interest.

3.4.1 Connection counts

Connection counts are the frequencies of unique connections a unit made. For each unit, ENA creates a cumulative adjacency vector that contains the sums of all unique code co-

occurrences for that unit across all stanza windows. Here, there are 48 units in the ENA model, so there are 48 adjacency vectors. Each term in an ENA adjacency vector represents a unique co-occurrence of codes. Thus with six codes, each vector has 15 terms (n choose two). This is because ENA models are undirected and do not model co-occurrences of the same code.

To access ENA adjacency vectors, use `set.ena$connection.counts`.

```
head(set.ena$connection.counts,3)
```

```
##          ENA_UNIT Condition      UserName CONFIDENCE.Change CONFIDENC
E.Pre
## 1:    FirstGame.steven z FirstGame    steven z              1
7
## 2:    FirstGame.akash v FirstGame    akash v              2
6
## 3: FirstGame.alexander b FirstGame alexander b              1
5
##    CONFIDENCE.Post    C.Change Data & Technical.Constraints
## 1:              8 Pos.Change              22
## 2:              8 Pos.Change              47
## 3:              7 Pos.Change              9
##    Data & Performance.Parameters Technical.Constraints & Performance.Param
eters
## 1:              18
20
## 2:              34
42
## 3:              5
8
##    Data & Client.and.Consultant.Requests
## 1:              5
## 2:             10
## 3:              5
##    Technical.Constraints & Client.and.Consultant.Requests
## 1:              6
## 2:             14
## 3:              3
##    Performance.Parameters & Client.and.Consultant.Requests
## 1:              5
## 2:             13
## 3:              3
##    Data & Design.Reasoning Technical.Constraints & Design.Reasoning
## 1:             21              26
## 2:             45              59
## 3:              5              8
##    Performance.Parameters & Design.Reasoning
## 1:             19
## 2:             38
## 3:              5
```

```
## Client.and.Consultant.Requests & Design.Reasoning Data & Collaboration
## 1: 6 7
## 2: 9 12
## 3: 2 4
## Technical.Constraints & Collaboration Performance.Parameters & Collabor
ation
## 1: 9
7
## 2: 21
11
## 3: 6
4
## Client.and.Consultant.Requests & Collaboration
## 1: 1
## 2: 2
## 3: 0
## Design.Reasoning & Collaboration
## 1: 6
## 2: 19
## 3: 5
```

3.4.2 Line weights

To compare networks in terms of their *relative* patterns of association, researchers can spherically normalize the cumulative adjacency vectors by dividing each one by its length. The resulting normalized vectors represent each unit's relative frequencies of code co-occurrence. In other words, the sphere normalization controls for the fact that different units might have different amounts of interaction or different numbers of activities than others.

Notice that in `set.ena$connection.counts`, the value for each unique code co-occurrence is an integer equal or greater than 0, because they represent the raw connection counts between each unique pair of codes. In `set.``ena``$line.weights`, those raw counts are normalized, and therefore the values are rational numbers between 0 and 1.

To access the normalized adjacency vectors, use `set.ena$line.weights`.

```
head(set.ena$line.weights,3)

##          ENA_UNIT Condition      UserName CONFIDENCE.Change CONFIDENC
E.Pre
## 1: FirstGame.steven z FirstGame      steven z              1
7
## 2: FirstGame.akash v FirstGame      akash v              2
6
## 3: FirstGame.alexander b FirstGame alexander b              1
5
## CONFIDENCE.Post C.Change Data & Technical.Constraints
## 1: 8 Pos.Change 0.4000661
## 2: 8 Pos.Change 0.4016067
```

## 3:	7 Pos.Change	0.4370786	
##	Data & Performance.Parameters Technical.Constraints & Performance.Param		
eters			
## 1:	0.3273268		0.36
36965			
## 2:	0.2905240		0.35
88826			
## 3:	0.2428215		0.38
85143			
##	Data & Client.and.Consultant.Requests		
## 1:	0.09092412		
## 2:	0.08544824		
## 3:	0.24282147		
##	Technical.Constraints & Client.and.Consultant.Requests		
## 1:	0.1091089		
## 2:	0.1196275		
## 3:	0.1456929		
##	Performance.Parameters & Client.and.Consultant.Requests		
## 1:	0.09092412		
## 2:	0.11108271		
## 3:	0.14569288		
##	Data & Design.Reasoning Technical.Constraints & Design.Reasoning		
## 1:	0.3818813	0.4728054	
## 2:	0.3845171	0.5041446	
## 3:	0.2428215	0.3885143	
##	Performance.Parameters & Design.Reasoning		
## 1:	0.3455117		
## 2:	0.3247033		
## 3:	0.2428215		
##	Client.and.Consultant.Requests & Design.Reasoning Data & Collaboration		
## 1:	0.10910895	0.1272938	
## 2:	0.07690342	0.1025379	
## 3:	0.09712859	0.1942572	
##	Technical.Constraints & Collaboration Performance.Parameters & Collabor		
ation			
## 1:	0.1636634		0.127
29377			
## 2:	0.1794413		0.093
99306			
## 3:	0.2913858		0.194
25717			
##	Client.and.Consultant.Requests & Collaboration		
## 1:	0.01818482		
## 2:	0.01708965		
## 3:	0.00000000		
##	Design.Reasoning & Collaboration		
## 1:	0.1091089		
## 2:	0.1623517		
## 3:	0.2428215		

3.4.3 ENA points

As the product of a dimensional reduction, for each unit, ENA produces an ENA point in a two-dimensional space. Since there are 48 units, ENA produces 48 ENA points.

By default, rENA visualizes ENA points on an x-y coordinate plane defined by the first two dimensions of the dimensional reduction: for a means rotation, MR1 and SVD2, and for an SVD, SVD1 and SVD2.

To access these points, use `set.ena$points`.

```
head(set.ena$points,3)
```

##	ENA_UNIT	Condition	UserName	CONFIDENCE.Change	CONFIDENC
E.Pre					
## 1:	FirstGame.steven	z FirstGame	steven z		1
7					
## 2:	FirstGame.akash	v FirstGame	akash v		2
6					
## 3:	FirstGame.alexander	b FirstGame	alexander b		1
5					
##	CONFIDENCE.Post	C.Change	MR1	SVD2	SVD3
## 1:	8 Pos.Change	-0.05423338	-0.008491458	0.06551249	
## 2:	8 Pos.Change	-0.07742095	0.031134440	0.03362490	
## 3:	7 Pos.Change	-0.30594927	-0.098348499	-0.01105519	
##	SVD4	SVD5	SVD6	SVD7	SVD8
SVD9					
## 1:	2.034477e-02	0.011885463	-0.02427483	-0.023161244	-0.01643227
85771					
## 2:	-2.531589e-05	0.006465571	0.01336324	0.001215593	-0.01390223
71313					
## 3:	9.816549e-02	-0.003662261	0.07609149	0.077059745	-0.09198643
49678					
##	SVD10	SVD11	SVD12	SVD13	SVD14
SV					
D15					
## 1:	-0.01169155	0.005448827	-0.027880312	-0.006140204	0.01230336
532					
## 2:	-0.04017379	0.035710843	-0.011559722	0.002192745	0.02967617
021					
## 3:	-0.01146149	-0.031675014	0.003382794	0.026665665	-0.01779259
445					

ENA points are thus summary statistics that researchers can use to conduct statistical tests, and they can also be used in subsequent analyses. For example, statistical differences between groups in the data can be tested using ENA dimension scores, and those scores can also be used in regression analyses to predict outcome variables, which we will demonstrate later.

3.4.4 Rotation matrix

The rotation matrix used during the dimensional reduction can be accessed through `set.ena$rotation`. This is mostly useful when you want to construct an ENA metric space using one dataset and then project ENA points from different data into that space, as in section 5.1.

```
head(set.ena$rotation.matrix,3)

##                                codes                MR1                SVD
2
## 1:                Data & Technical.Constraints -0.297140113  0.25542803
7
## 2:                Data & Performance.Parameters  0.146745148 -0.40786334
0
## 3: Technical.Constraints & Performance.Parameters  0.006251295 -0.00672433
8
##          SVD3          SVD4          SVD5          SVD6          SVD7          SVD8
## 1:  0.4027380  0.1829314 -0.18841712 -0.22238612  0.3539426 -0.04618008
## 2:  0.4998255  0.1655853 -0.01271575  0.02831357 -0.5461929 -0.19336181
## 3: -0.0357799  0.4901334  0.29999562  0.27301947  0.1197999  0.45958816
##          SVD9          SVD10          SVD11          SVD12          SVD13          SVD14
## 1:  0.39593034  0.3556577 -0.03738872 -0.0005144122  0.30025177  0.24188117
## 2:  0.27237864 -0.1917366  0.18450254 -0.1247520324  0.17795795  0.06161493
## 3:  0.01614337 -0.2375881 -0.25630008 -0.3668342035  0.05404011  0.25435787
##          SVD15
## 1:  0.07161604
## 2:  0.04655934
## 3:  0.20907031
```

3.4.5 Metadata

`set$meta.data` returns a data frame that includes all the columns of the ENA set except for the columns representing code co-occurrences.

```
head(set.ena$meta.data,3)

##          ENA_UNIT Condition  UserName CONFIDENCE.Change CONFIDENC
E.Pre
## 1:  FirstGame.steven z FirstGame  steven z              1
7
## 2:  FirstGame.akash v FirstGame   akash v              2
6
## 3: FirstGame.alexander b FirstGame alexander b          1
5
##  CONFIDENCE.Post  C.Change
## 1:              8 Pos.Change
## 2:              8 Pos.Change
## 3:              7 Pos.Change
```

3.5 ENA visualization

Once an ENA set is constructed, it can be visualized, which facilitates interpretation of the model. Here, we will look at the two conditions, “FirstGame” (novices) and “SecondGame” (relative experts), by plotting their mean networks.

3.5.1 Plot a mean network

To plot a network, use the `ena.plot.network` function. This function requires the `network` parameter (a character vector of line weights), and the line weights come from `set$line.weights`.

First, subset line weights for each of the two groups.

```
# Subset Lineweights for FirstGame
first.game.lineweights = as.matrix(set.ena$line.weights$Condition$FirstGame)

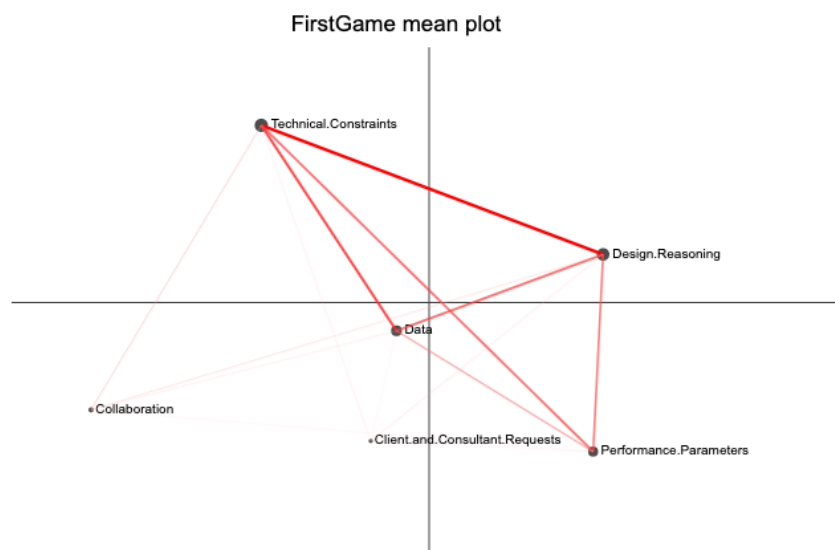
# Subset Lineweights for SecondGame
second.game.lineweights = as.matrix(set.ena$line.weights$Condition$SecondGame
)
```

Next, calculate the mean networks for the two groups, and store the line weights as vectors.

```
first.game.mean = as.vector(colMeans(first.game.lineweights))
second.game.mean = as.vector(colMeans(second.game.lineweights))
```

During plotting, use a pipe `|>` to send the output of one function into the first parameter of the subsequent function. To distinguish the two mean networks, set the color of the FirstGame mean network to red.

```
ena.plot(set.ena, title = "FirstGame mean plot") |>
  ena.plot.network(network = first.game.mean, colors = c("red"))
```



and the color of the SecondGame mean network to blue.

```
ena.plot(set.ena, title = "SecondGame mean plot") |>  
  ena.plot.network(network = second.game.mean, colors = c("blue"))
```



As you can see from the two network visualizations above, their node positions are exactly same. All ENA networks from the same model have the same node positions, which are determined by an optimization routine that attempts to place the nodes such that the centroid of each unit's network and the location of the ENA point in the reduced space are co-located.

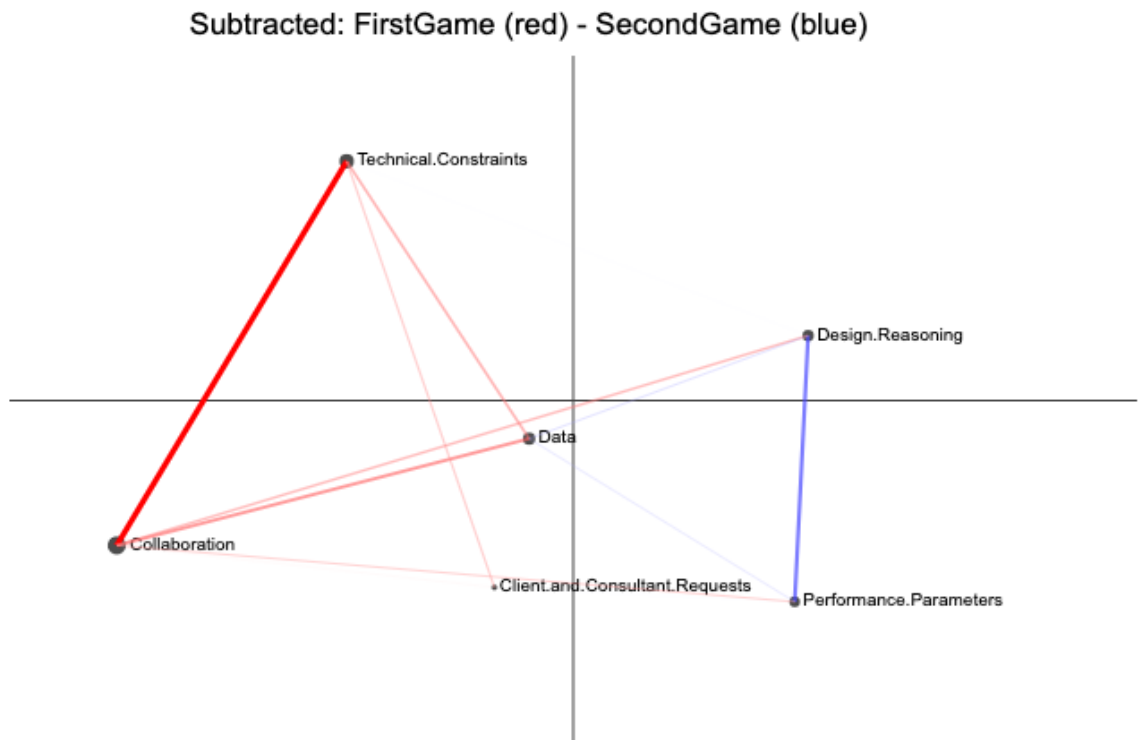
Because of the fixed node positions, ENA can construct a subtracted network, which enables the identification of the most salient differences between two networks. To do this, ENA subtracts the weight of each connection in one network from the corresponding weighted connection in another network, then visualizes the differences in connection strengths. Each edge is color-coded to indicate which of the two networks contains the stronger connection, and the thickness and saturation of the edges corresponds to the magnitude of the difference.

To plot a subtracted network, first calculate the subtracted network line weights by subtracting one group's line weights from the other. (Because ENA computes the absolute values of the differences in edge weights, the order of the two networks in the subtraction doesn't matter.)

```
subtracted.mean = first.game.mean - second.game.mean
```

Then, use the `ena.plot` function to plot the subtracted network. If the differences are relatively small, a multiplier can be applied to rescale the line weights, improving legibility.

```
ena.plot(set.ena, title = "Subtracted: FirstGame (red) - SecondGame (blue)")
|>
  ena.plot.network(network = subtracted.mean * 5, # Optional rescaling of the
    line weights
    colors = c("red", "blue"))
```



Here, the subtracted network shows that on average, students in the FirstGame condition (red) made more connections with Technical.Constraints and Collaboration than students in the SecondGame condition (blue), while students in the SecondGame condition made more connections with Design.Reasoning and Performance.Parameters than students in the FirstGame condition. This is because students with more experience of engineering design practices did not need to spend as much time and effort managing the collaborative process and learning about the basic technical elements of the problem space, and instead spent relatively more time focusing on more complex analysis and design reasoning tasks.

Note that this subtracted network shows no connection between Technical.Constraints and Design.Reasoning, simply because the strength of this connection was similar in both conditions. Thus, subtraction networks should always be visualized along with the two networks being subtracted.

3.5.2 Plot a mean network and its points

The ENA point or points associated with a network or mean network can also be visualized.

To visualize the points associated with each of the mean networks plotted above, use `set$points` to subset the rows that are in each condition and plot each condition as a different color.

```
# Subset rotated points for the first condition
first.game.points = as.matrix(set.ena$points$Condition$FirstGame)

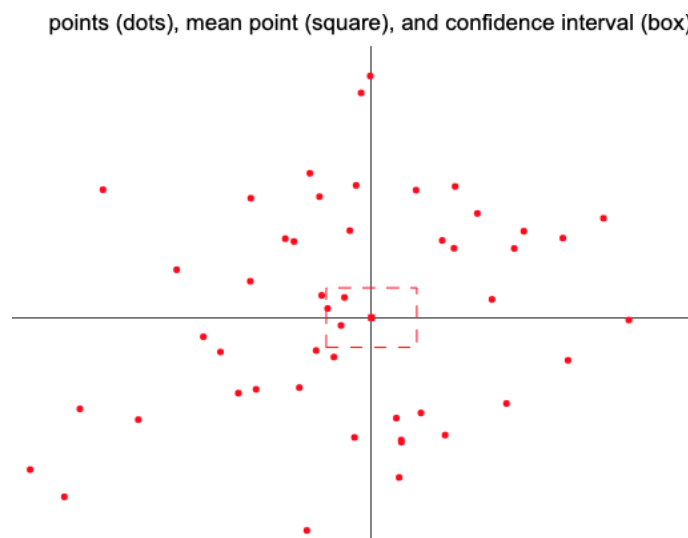
# Subset rotated points for the second condition
second.game.points = as.matrix(set.ena$points$Condition$SecondGame)
```

Then, plot the FirstGame mean network the same as above using `ena.plot.network`, use `|>` to pipe in the FirstGame points that we want to include, and plot them using `ena.plot.points`.

Each point in the space is the ENA point for a given unit. The red and blue squares on the x-axis are the means of the ENA points for each condition, along with the 95% confidence interval on each dimension.

Since we used a means rotation to construct the ENA model, the resulting space highlights the differences between FirstGame and SecondGame by constructing a rotation that places the means of each condition as close as possible to the x-axis of the space and maximizes the distance between them.

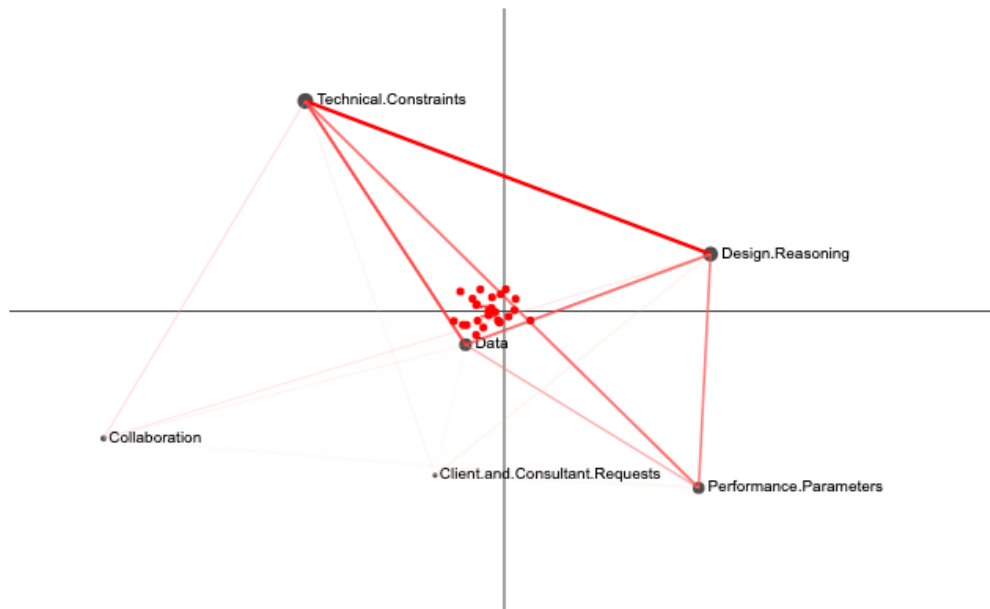
```
ena.plot(set.ena, title = "points (dots), mean point (square), and confidence interval (box)") |>
  ena.plot.points(points = first.game.points, colors = c("red")) |>
  ena.plot.group(point = first.game.points, colors = c("red"),
                 confidence.interval = "box")
```



```
ena.plot(set.ena, title = "FirstGame mean network and its points") |>
  ena.plot.network(network = first.game.mean, colors = c("red")) |>
  ena.plot.points(points = first.game.points, colors = c("red")) |>
```

```
ena.plot.group(point = first.game.points, colors =c("red"),
               confidence.interval = "box")
```

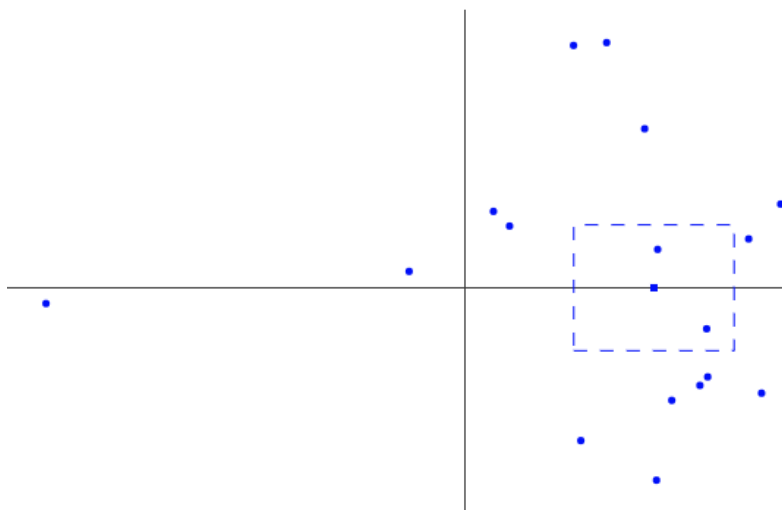
FirstGame mean network and its points



Then, do the same for the SecondGame condition.

```
ena.plot(set.ena, title = "points (dots), mean point (square), and confidence interval (box)" |>
  ena.plot.points(points = second.game.points, colors = c("blue")) |>
  ena.plot.group(point = second.game.points, colors =c("blue"),
                 confidence.interval = "box")
```

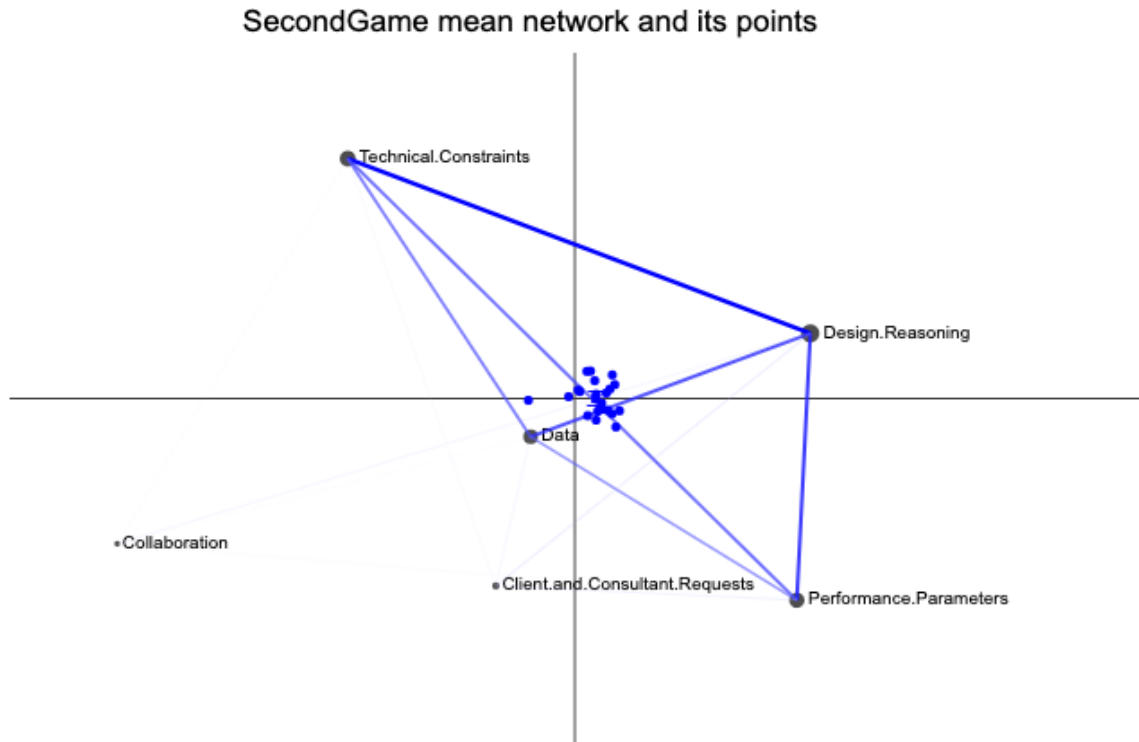
points (dots), mean point (square), and confidence interval (box)



```

ena.plot(set.ena, title = "SecondGame mean network and its points") |>
  ena.plot.network(network = second.game.mean, colors = c("blue")) |>
  ena.plot.points(points = second.game.points, colors = c("blue")) |>
  ena.plot.group(point = second.game.points, colors = c("blue"),
    confidence.interval = "box")

```

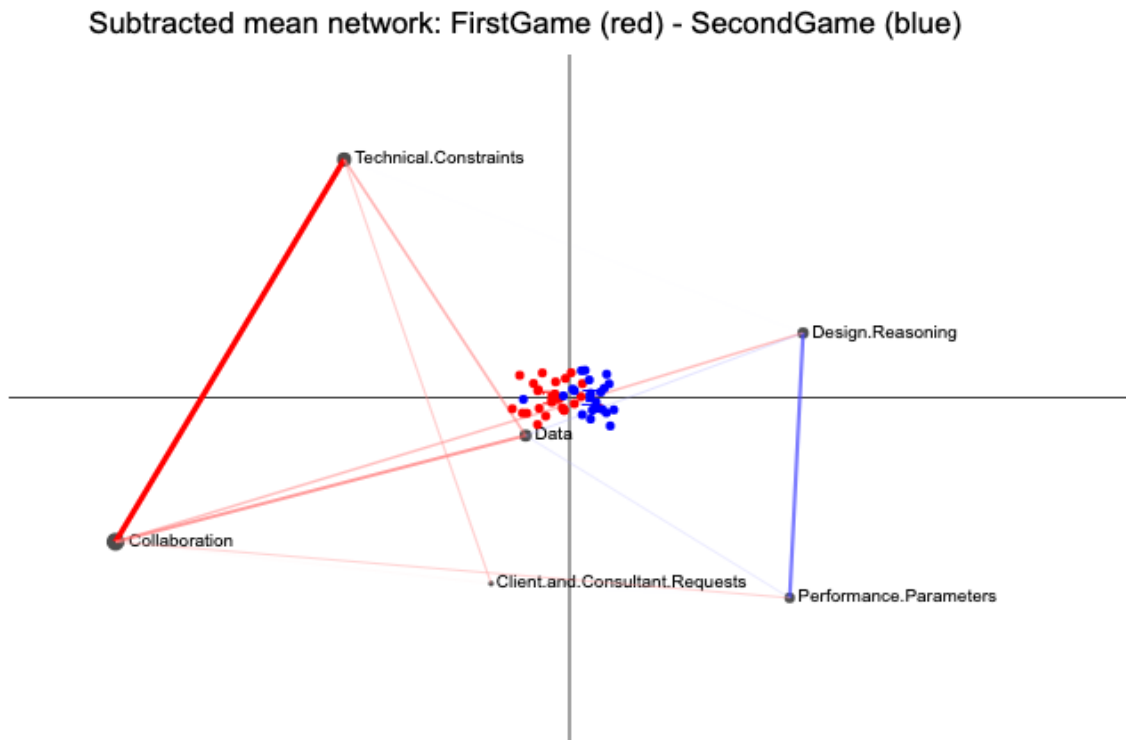


Lastly, do the same for subtraction as well.

```

ena.plot(set.ena, title = "Subtracted mean network: FirstGame (red) - SecondGame (blue)") |>
  ena.plot.network(network = subtracted.mean * 5,
    colors = c("red", "blue")) |>
  ena.plot.points(points = first.game.points, colors = c("red")) |>
  ena.plot.group(point = first.game.points, colors = c("red"),
    confidence.interval = "box") |>
  ena.plot.points(points = second.game.points, colors = c("blue")) |>
  ena.plot.group(point = second.game.points, colors = c("blue"),
    confidence.interval = "box")

```



Note that the majority of the red points (FirstGame) are located on the left side of the space, and the blue points (SecondGame) are mostly located on the right side of the space. This is consistent with the line weights distribution in the mean network: the FirstGame units make relatively more connections with nodes on the left side of the space, while the SecondGame units make relatively more connections with nodes on the right side of the space. The positions of the nodes enable interpretation of the dimensions, and thus interpretation of the locations of the ENA points.

3.5.3 Plot an individual unit network and its point

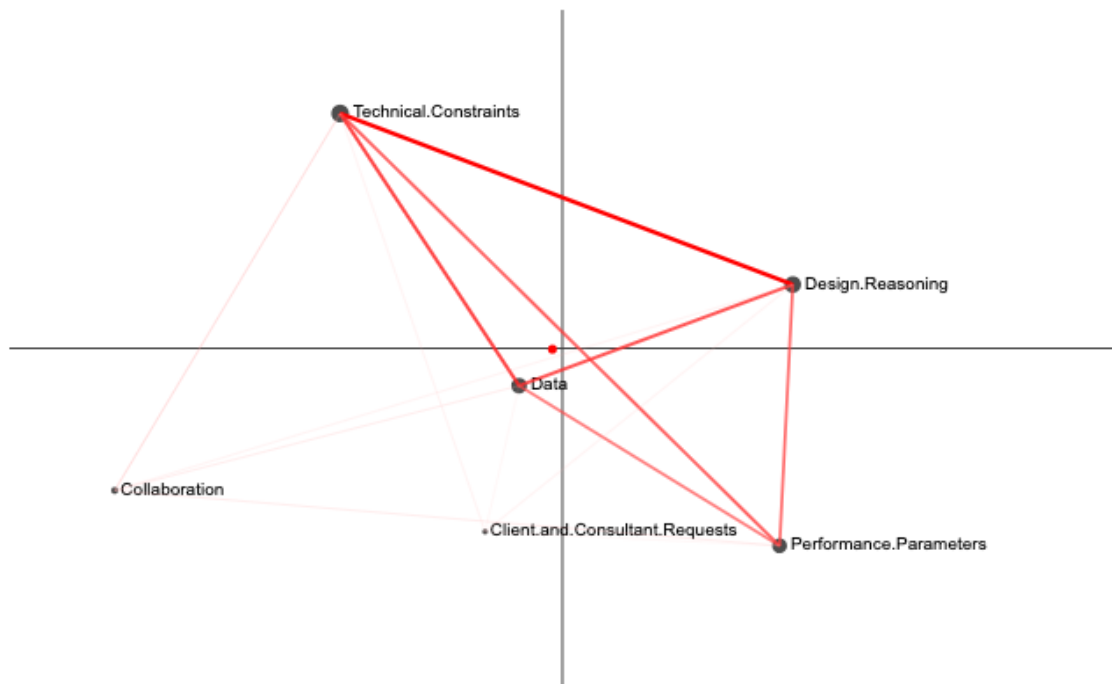
Plotting the network and ENA point for a single unit uses the same approach. First, subset the line weights and point for a given unit.

```
unit.A.line.weights = as.matrix(set.ena$line.weights$ENA_UNIT$`FirstGame.steven z`) # subset line weights
unit.A.point = as.matrix(set.ena$points$ENA_UNIT$`FirstGame.steven z`) # subset ENA point
```

Then, plot the network and point for that unit.

```
ena.plot(set.ena, title = "Individual network: FirstGame.steven z") |>
  ena.plot.network(network = unit.A.line.weights, colors = c("red"))
|>
  ena.plot.points(points = unit.A.point, colors = c("red"))
```

Individual network: FirstGame.steven z

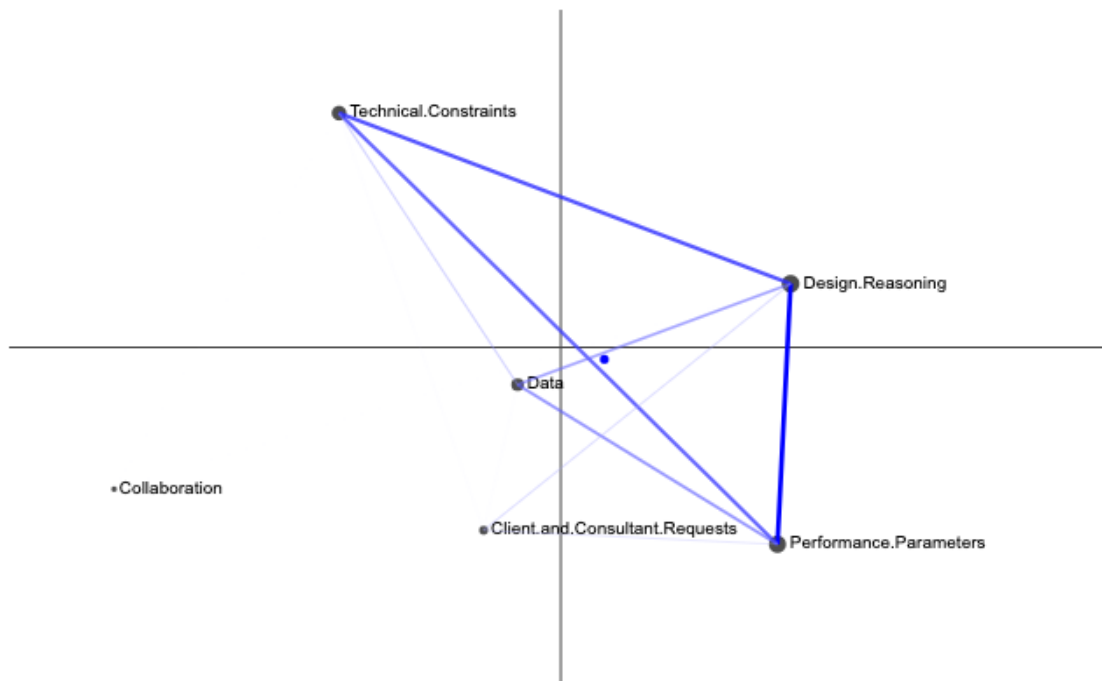


Following the exact same procedure, we can, for example, choose a unit from the other condition to plot and also construct a subtracted plot for those two units.

```
unit.B.line.weights = as.matrix(set.ena$line.weights$ENA_UNIT$`SecondGame.samuel o`) # subset line weights
unit.B.point = as.matrix(set.ena$points$ENA_UNIT$`SecondGame.samuel o`) # subset ENA point

ena.plot(set.ena, title = "Individual network: SecondGame.samuel o") |>
  ena.plot.network(network = unit.B.line.weights, colors = c("blue"))
|>
  ena.plot.points(points = unit.B.point, colors = c("blue"))
```

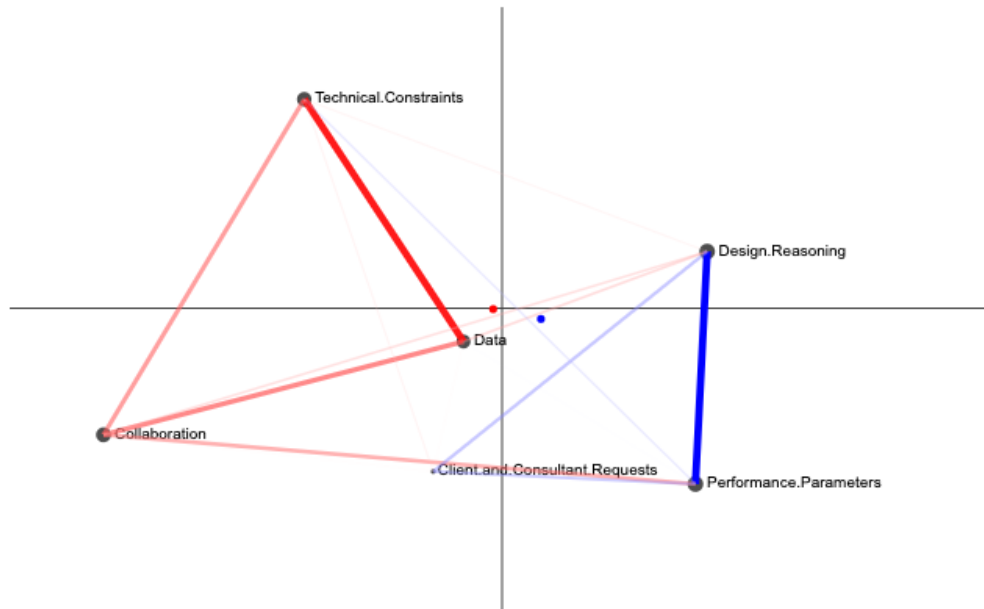
Individual network: SecondGame.samuel o



To visually analyze the differences between the two individual networks, plot their subtracted network.

```
ena.plot(set.ena, title = "Subtracted network: FirstGame.steven z (red) - SecondGame.samuel o (blue)") |>
  ena.plot.network(network = (unit.A.line.weights - unit.B.line.weights) * 5,
    colors = c("red", "blue")) |>
  ena.plot.points(points = unit.A.point, colors = c("red")) |>
  ena.plot.points(points = unit.B.point, colors = c("blue"))
```

Subtracted network: FirstGame.steven z (red) - SecondGame.samuel o (blue)



In this unit-level subtracted network, Unit A (red) made relatively more connections with codes such as Technical.Constraints, Data, and Collaboration, while Unit B (blue) made relatively more connections with Design.Reasoning and Performance.Parameters.

3.5.4 Plot everything, everywhere, all at once

The helper function `ena.plotter` enables users to plot points, means, and networks for each condition at the same time. This gives the same results as above more parsimoniously. However, this approach does not enable customization of edge and point colors.

#with helper function

```
plot = ena.plotter(set.ena,
  points = T,
  mean = T,
  network = T,
  print.plots = T,
  groupVar = "Condition",
  groups = c("SecondGame", "FirstGame"),
  subtractionMultiplier = 5)
```

3.6 Compare groups statistically

In addition to visual comparison of networks, ENA points can be analyzed statistically. For example, here we might test whether the patterns of association in one condition are significantly different from those in the other condition.

To demonstrate both parametric and non-parametric approaches to this question, the examples below use a Student's *t* test and a Mann-Whitney *U* test to test for differences between the FirstGame and SecondGame condition.

First, install the `lsr` package to enable calculation of effect size (Cohen's d) for the t test.

```
install.packages('lsr')
library(lsr)
```

Then, subset the points to test for differences between the points of the two conditions.

```
ena_first_points_d1 = as.matrix(set.ena$points$Condition$FirstGame)[,1]
ena_second_points_d1 = as.matrix(set.ena$points$Condition$SecondGame)[,1]

ena_first_points_d2 = as.matrix(set.ena$points$Condition$FirstGame)[,2]
ena_second_points_d2 = as.matrix(set.ena$points$Condition$SecondGame)[,2]
```

Conduct the t test on the first and second dimensions.

```
# parametric tests
t_test_d1 = t.test(ena_first_points_d1, ena_second_points_d1)
t_test_d1

##
## Welch Two Sample t-test
##
## data: ena_first_points_d1 and ena_second_points_d1
## t = -6.5183, df = 45.309, p-value = 5.144e-08
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -0.2687818 -0.1419056
## sample estimates:
## mean of x mean of y
## -0.09411588 0.11122786

t_test_d2 = t.test(ena_first_points_d2, ena_second_points_d2)
t_test_d2

##
## Welch Two Sample t-test
##
## data: ena_first_points_d2 and ena_second_points_d2
## t = 1.9334e-16, df = 43.175, p-value = 1
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -0.07768526 0.07768526
## sample estimates:
## mean of x mean of y
## 1.935145e-19 -7.254914e-18
```

Compute any other statistics that may be of interest. A few examples are given below.

```
mean(ena_first_points_d1)

## [1] -0.09411588
```



```

mean(ena_second_points_d1)
## [1] 0.1112279
mean(ena_first_points_d2)
## [1] 1.935145e-19
mean(ena_second_points_d2)
## [1] -7.254914e-18
sd(ena_first_points_d1)
## [1] 0.1115173
sd(ena_second_points_d1)
## [1] 0.1063515
sd(ena_first_points_d2)
## [1] 0.1267104
sd(ena_second_points_d2)
## [1] 0.1380851
length(ena_first_points_d1)
## [1] 26
length(ena_second_points_d1)
## [1] 22
length(ena_first_points_d2)
## [1] 26
length(ena_second_points_d2)
## [1] 22
cohensD(ena_first_points_d1, ena_second_points_d1)
## [1] 1.880622
cohensD(ena_first_points_d2, ena_second_points_d2)
## [1] 5.641688e-17

```

Here, along the x axis (MR1), a two-sample t test assuming unequal variance shows that the FirstGame (mean=-0.09, SD=0.11, N=26) condition is statistically significantly different for $\alpha=0.05$ from the SecondGame condition (mean=0.11, SD=0.10, N=22; $t(45.31)=-6.52$,

$p=0.00$, Cohen's $d=1.88$). Along the y axis (SVD2), a two-sample t test assuming unequal variance shows that the FirstGame condition (mean=0.11, SD=0.13, N=26) is not statistically significantly different for $\alpha=0.05$ from the SecondGame condition (mean=0.00, SD=1.3, N=22; $t(43.17)=0$, $p=1.00$).

The Mann-Whitney U test is a non-parametric alternative to the independent two-sample t test.

First, install the rcompanion package to calculate the effect size (r) for a Mann-Whitney U test.

```
install.packages('rcompanion')
library(rcompanion)
```

```
## Warning: package 'rcompanion' was built under R version 4.1.2
```

Then, conduct a Mann-Whitney U test on the first and second dimensions.

```
# non parametric tests
w_test_d1 = wilcox.test(ena_first_points_d1, ena_second_points_d1)
w_test_d2 = wilcox.test(ena_first_points_d2, ena_second_points_d2)

w_test_d1

##
## Wilcoxon rank sum exact test
##
## data: ena_first_points_d1 and ena_second_points_d1
## W = 50, p-value = 8.788e-08
## alternative hypothesis: true location shift is not equal to 0

w_test_d2

##
## Wilcoxon rank sum exact test
##
## data: ena_first_points_d2 and ena_second_points_d2
## W = 287, p-value = 0.9918
## alternative hypothesis: true location shift is not equal to 0
```

Compute any other statistics that may be of interest. A few examples are given below.

```
median(ena_first_points_d1)

## [1] -0.08464154

median(ena_second_points_d1)

## [1] 0.1300029

median(ena_first_points_d2)

## [1] -0.007252397
```

```

median(ena_second_points_d2)
## [1] 0.0003031848
length(ena_first_points_d1)
## [1] 26
length(ena_second_points_d1)
## [1] 22
length(ena_first_points_d2)
## [1] 26
length(ena_second_points_d2)
## [1] 22
abs(wilcoxonR(ena_first_points_d1, ena_second_points_d1))
##      r
## 0.863
abs(wilcoxonR(ena_first_points_d2, ena_second_points_d2))
##      r
## 0.863

```

Here, along the x axis (MR1), a Mann-Whitney U test shows that the FirstGame condition (Mdn=-0.08, N=26) was statistically significantly different for $\alpha=0.05$ from the SecondGame condition (Mdn=-0.007, N=22; $U=50$, $p=0.00$, $r=0.86$). Along the y axis (SVD2), a Mann-Whitney U test shows that the FirstGame condition (Mdn=0.13, N=26) is not statistically significantly different for $\alpha=0.05$ from the SecondGame condition (Mdn=0.00, N=22; $U=287$, $p=0.99$). The absolute value of r value in Mann-Whitney U test varies from 0 to close to 1. The interpretation values for r commonly in published literature is: $0.10 - < 0.3$ (small effect), $0.30 - < 0.5$ (moderate effect) and ≥ 0.5 (large effect).

3.7 Model evaluation

In this section, we introduce three ways users can evaluate the quality of their ENA models.

3.7.1 Variance explained

Briefly, variance explained (also called explained variation) refers to the proportion of the total variance in a dataset that is accounted for by a statistical model or set of predictors.

In ENA, to represent high-dimensional vectors in a two-dimensional space, ENA uses either singular value decomposition or means rotation combined with SVD. For each of the reduced dimensions, the variance in patterns of association among units explained by that dimension can be computed.

```
head(set.ena$model$variance,2)
```

```
##          MR1          SVD2  
## 0.3204602 0.2445006
```

Here, the first dimension is MR1 and the second dimension is SVD2. The MR1 dimension has the highest variance explained at 32%.

As with any statistical model, greater explained variance does not necessarily indicate a better model, as it may be due to overfitting, but it provides one indicator of model quality.

3.7.2 Goodness of fit

Briefly, a model's goodness of fit refers to how well a model fits or represents the data. A model with a high goodness of fit indicates that it accurately represents the data and can make reliable predictions.

In ENA, a good fit means that the positions of the nodes in the space—and thus the network visualizations—are consistent with the mathematical properties of the model. In other words, we can confidently rely on the network visualizations to interpret the ENA model. The process that ENA uses to achieve high goodness of fit is called co-registration. The mathematical details of co-registration are beyond the scope of this chapter and can be found in Bowman et al., (2022).

To test a model's goodness of fit, use `ena.correlations`. The closer the value is to 1, the higher the model's goodness of fit is. Most ENA models have a goodness of fit that is well above 0.90.

```
ena.correlations(set.ena)
```

```
##      pearson  spearman  
## 1  0.993766  0.994119  
## 2  0.9850392 0.9850519
```

3.7.3 Close the interpretative loop

Another approach to evaluate an ENA model is to confirm the alignment between quantitative model (in our case, our ENA model) and the original qualitative data. In other words, we can return to the original data to confirm that quantitative findings give a fair representation of the data. This approach is an example of what's called as closing the interpretative loop in Quantitative Ethnography field (Shaffer, 2017).

For example, based on our visual analysis of the network of "SecondGame.samuel o" in previous section, we are interested in what the lines are in the original data that contributed to the connection between Design.Reasoning and Performance.Parameters.

Let's first review what "SecondGame.samuel o" ENA network looks like.

```
ena.plot(set.ena, title = "Individual network: SecondGame.samuel o") |>  
  ena.plot.network(network = as.matrix(set.ena$line.weights$ENA_UNIT$  
`SecondGame.samuel o`), colors = c("blue")) |>
```

```
ena.plot.points(points = as.matrix(set.ena$points$ENA_UNIT$`SecondGame.samuel o`), colors = c("blue"))
```

To do so, we use `view()` function and specify required parameters as below.

This is going to activate a window shows up in your Viewer panel. If it is too small to read, you can click on the “Show in new window” button to view it in your browser for better readability.

In the Viewer panel, hover over your cursor on any of the lines that are in bold, a size of 7 lines rectangle shows up, representing that in a moving stanza window of size 7, the referent line (the line in bold) and its preceding 6 lines. The 1 and 0 in Technical.Constraints column and Design.Reasoning column shows where the connections happened.

QEID	Condition	UserName	GroupName	ActivityNumber	text	Performance.Parameters	Design.Reasoning
2464	SecondGame	jackson p	Hydraulic	5	I would look at the numbers and saw how good each power source or control sensor was at each	1	1
2465	SecondGame	samuel o	Hydraulic	5	I had to weigh the pros and cons of each power source and sensor	0	0
2466	SecondGame	shane t	Hydraulic	5	So what did you guys choose as the best battery and sensor?	0	1
2467	SecondGame	brandon f	Hydraulic	5	The area covered by the NiCd graph really stood out to me as the clear front runner	0	0
2468	SecondGame	brandon f	Hydraulic	5	The area covered by the NiCd graph really stood out to me as the clear front runner	0	0
2469	SecondGame	jackson p	Hydraulic	5	The graphs gave us an approximation by showing the area that each individual battery type took	0	0
2470	SecondGame	samuel o	Hydraulic	5	The helped illustrate which devices were good and had with different attributes	1	1
2471	SecondGame	shane t	Hydraulic	5	They gave us a visual of the data, made it easier to compare them and see the best choice	0	1
2472	SecondGame	casey f	Hydraulic	5	@Brandon: I agree. It covers the most area on the graph.	0	0
2473	SecondGame	jackson p	Hydraulic	5	I agree with NiCd too	0	0
2474	SecondGame	samuel o	Hydraulic	5	@Brandon: I agree. I like the NiCd also	0	0
2475	SecondGame	jackson p	Hydraulic	5	when it came to the different attributes, i think that all were important in their own way but i think	1	0
2476	SecondGame	casey f	Hydraulic	5	Well not one source/sensor can be the best in every area so we had to sacrifice certain attributes.	1	1
2477	SecondGame	samuel o	Hydraulic	5	No, I just was mindful of the how one device scores relative to other ones	0	1
2478	SecondGame	shane t	Hydraulic	5	I also chose the NiCd battery	0	1
2479	SecondGame	brandon f	Hydraulic	5	to agree on which power source and control sensor we should use	0	0
2480	SecondGame	brandon f	Hydraulic	5	to agree on which power source and control sensor we should use	0	0
2481	SecondGame	jackson p	Hydraulic	5	Test the battery out with an actual prototype	0	1
2482	SecondGame	casey f	Hydraulic	5	@Shane: I agree	0	0
2483	SecondGame	jackson p	Hydraulic	5	do more research on the nickel cadmium battery and see how we can optimize it	0	1
2484	SecondGame	samuel o	Hydraulic	5	design prototype	0	1

For example, line 2477 Samuel shared his [Design.Reasoning] about “mindful of (the) how one device scores relative to other ones”, to reference back to what Casey said in line 2476 about [Performance.Parameters] “not one source/censor can be the best in every area so we had to sacrifice certain attributes”, as well as what Jackson said in line 2475 about safety as one of the [Performance.Parameters] “when it came to the different attributes, i think that all were important in their own way but i think safety is one of the most important”.

This is a qualitative example of a connection made between Performance.Parameters and Design.Reasoning.

3.8 Using ENA model outputs in other analyses

It is often useful to use the outputs of ENA models in subsequent analyses. The most commonly used outputs are the ENA points, i.e., `set$points`. For example, we can use a linear regression analysis to test whether ENA points on the first two dimensions are predictive of an outcome variable, in this case, change in confidence in engineering skills.

```
regression_data = set.ena$points
regression_data$CONFIDENCE.Change = as.numeric(regression_data$CONFIDENCE.Change)
```

```
## Warning: NAs introduced by coercion
```

```

condition_regression = lm(CONFIDENCE.Change ~ MR1 + SVD2 + Condition,
                          data = regression_data,
                          na.action = na.omit)
summary(condition_regression)

##
## Call:
## lm(formula = CONFIDENCE.Change ~ MR1 + SVD2 + Condition, data = regression_data,
##     na.action = na.omit)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.18092 -0.24324 -0.08171  0.30716  1.88404
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)      1.1111     0.1490   7.457 2.82e-09 ***
## MR1             -0.4540     0.8616  -0.527   0.601
## SVD2              0.3268     0.7154   0.457   0.650
## ConditionSecondGame -0.3484     0.2566  -1.358   0.182
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.6374 on 43 degrees of freedom
## (1 observation deleted due to missingness)
## Multiple R-squared:  0.1228, Adjusted R-squared:  0.0616
## F-statistic: 2.007 on 3 and 43 DF, p-value: 0.1273

```

The results of this regression analysis show that ENA points are not a significant predictor of the students' pre-post change in confidence (MR1: $t=-0.53$, $p=0.60$; SVD2: $t=0.46$, $p=0.65$; Condition: $t=-1.36$, $p=0.18$). The overall model was also not significant ($F(3, 43)=2.01$, $p=0.13$) with an adjusted r-squared value of 0.06.

Recall that the dataset we are using is a small subset of the full `RS.data`, and thus results that are significant for the whole dataset may not be for this sample.

4. Ordered Network Analysis with R

This section demonstrates how to conduct an ONA analysis using the `ona` R package. If you are new to ONA as an analytic technique, Tan et al. (2022) provides a more detailed explication of its theoretical and methodological foundations.

Because ONA shares some conceptual and procedural similarities with ENA, you may also want to read the recommended papers from the ENA section (Shaffer et al., 2016; Shaffer & Ruis, 2017; Bowman et al., 2022).

4.1 Install the ONA package and load the library

Install the ona package and load the ona library after installing.

```
install.packages("ona")  
library(ona)
```

Then, install the other package that is required for ONA analysis.

```
install.packages("tma")  
library(tma )
```

4.2 Dataset

(Refer to section 3.2 for a detailed description of the dataset used here.)

Load the RS.data dataset.

```
data = ona::RS.data
```

4.3 Construct an ONA model

To construct an ONA model, identify which columns in the data to use for the parameters required by the ONA modeling function. The parameters are defined identically in both ENA and ONA; see Section 3.3 for detailed explanations.

4.3.1 Specify units

Select the *units* as in Section 3.3.1.

```
my_units <- c("Condition", "UserName")
```

4.3.2 Specify codes

Select the *codes* as in Section 3.3.2.

```
my_codes = c(  
  'Data',  
  'Technical.Constraints',  
  'Performance.Parameters',  
  'Client.and.Consultant.Requests',  
  'Design.Reasoning',  
  'Collaboration')
```

4.3.3 Specify conversations

The parameter to specify *conversations* in rENA is called “conversation”; in ONA, the equivalent is called “my_hoo_rules”, where “hoo” is an abbreviation of “horizon of observation.”

Choose the combination of “Condition” column, “GroupName” column, and “ActivityNumber” column to define the conversation parameter.

The syntax to specify conversations using `my_hoo_rules` in ONA is slightly different from the syntax to specify conversation in ENA, but the conceptual definition is the same.

```
my_hoo_rules <- conversation_rules(  
  (Condition %in% UNIT$Condition &  
    GroupName %in% UNIT$GroupName &  
    ActivityNumber %in% UNIT$ActivityNumber))
```

4.3.4 Specify the window

Specify a moving stanza window size by passing a numerical value to the `window_size` parameter.

```
window_size = 7
```

To specify an infinite stanza window in ONA, set the size of the moving window equal to or larger than the number of lines in the longest conversation. For example, set `window_size = 4000`, which is greater than the total number of rows in our dataset (`nrows=3,824`).

4.3.5 Specify metadata

As in ENA, metadata columns can be included if desired. Metadata columns are not required to construct an ONA model, but they provide information that can be used to subset units in the resulting model.

```
metaCols = c("CONFIDENCE.Change", "CONFIDENCE.Pre", "CONFIDENCE.Post", "C.Change")
```

4.3.6 Accumulate connections

Now that all the parameters are specified, connections can be accumulated. For each unit, the ONA algorithm uses a moving stanza window to identify connections formed from a current line of data (e.g., a turn of talk), or *response*, to the preceding lines within the window (the *ground*).

Unlike in ENA, where connections among codes are recorded in a symmetric adjacency matrix, ONA accounts for the order in which the connections occur by constructing an *asymmetric adjacency matrix* for each unit; that is, the number of connections from code A to code B may be different than the number of connections from B to A.

To accumulate connections, pass the parameters specified to the `contexts` and `accumulate_contexts` functions, and store the output in an object (in this case, **accum.ona**).

```
accum.ona <-  
  contexts(data,  
    units_by = my_units,  
    hoo_rules = my_hoo_rules) |>
```



```
accumulate_contexts(codes = my_codes,
                    decay.function = decay(simple_window, window_size = 7),
                    meta.data = metaCols,
                    return.ena.set = FALSE) # keep this as FALSE to get an
ONa model, otherwise it will return an undirected model)
```

4.3.7 Construct an ONa model

After accumulation, call the model function to construct an ONa model. ONa currently implements *singular value decomposition* (SVD) and *means rotation* (MR) to perform dimensional reduction.

To create an ONa model using SVD, pass the `accum.ona` object to the model function.

```
set.ona <-
  model(accum.ona)
```

When there are two discrete groups to compare, a means rotation can be used, as described in Section 3.3.5.

A means rotation is specified using `rotate.using = "mean"` in the model function. Additionally, the model function expects `rotation.params` to be a list with two named elements, each containing a logical vector representing the rows of units to be included in each group.

Here, construct the ONa model as shown below.

```
set.ona <-
  model(accum.ona,                                # the previously run accumulatio
ion above
        rotate.using = "mean",                    # means rotation method
        rotation.params =                          # two groups for means rotatio
n in a list
        list(FirstGame=accum.ona$meta.data$Condition=="FirstGame",
              SecondGame=accum.ona$meta.data$Condition=="SecondGame")
        )
```

4.4 Summary of key model outputs

Information about an ONa model is now stored in the R object `set.ona`.

As in `rENA`, users can explore the data stored in the object by typing `set.ona$` and select items from the drop down list. Here, we briefly explain the top-level items in `set.ona$`.

4.4.1 Connection counts

Because ONa accounts for the order in which the connections occur by constructing an *asymmetric adjacency matrix* for each unit, connection counts *from* code A *to* code B and *from* B *to* A, as well as self-connections for each code (from A to A) are recorded. Thus, because six codes were included in the model, the cumulative adjacency vector for each unit contains 36 terms (n^2).

```
head(set.ona$connection.counts,3)
```

```
##      Condition      UserName      ENA_UNIT Data to Data
## 1: FirstGame      steven z      FirstGame::steven z      26
## 2: FirstGame      akash v      FirstGame::akash v      72
## 3: FirstGame      alexander b      FirstGame::alexander b      11
##      Technical.Constraints to Data Performance.Parameters to Data
## 1:      44.0      32
## 2:      102.5      66
## 3:      21.5      15
##      Client.and.Consultant.Requests to Data Design.Reasoning to Data
## 1:      12      52
## 2:      10      88
## 3:      4      14
##      Collaboration to Data Data to Technical.Constraints
## 1:      8      27.0
## 2:      12      106.5
## 3:      1      11.5
##      Technical.Constraints to Technical.Constraints
## 1:      63
## 2:      193
## 3:      40
##      Performance.Parameters to Technical.Constraints
## 1:      29.5
## 2:      90.5
## 3:      15.5
##      Client.and.Consultant.Requests to Technical.Constraints
## 1:      8.5
## 2:      23.5
## 3:      1.0
##      Design.Reasoning to Technical.Constraints
## 1:      62.0
## 2:      160.5
## 3:      23.0
##      Collaboration to Technical.Constraints Data to Performance.Parameters
## 1:      11.0      24
## 2:      29.0      77
## 3:      15.5      10
##      Technical.Constraints to Performance.Parameters
## 1:      35.5
## 2:      91.5
## 3:      17.5
##      Performance.Parameters to Performance.Parameters
## 1:      34
## 2:      72
## 3:      10
##      Client.and.Consultant.Requests to Performance.Parameters
## 1:      5.5
## 2:      20.5
## 3:      3.0
```

```

## Design.Reasoning to Performance.Parameters
## 1: 42
## 2: 77
## 3: 14
## Collaboration to Performance.Parameters Data to Client.and.Consultant.R
requests
## 1: 7.5
6
## 2: 14.5
18
## 3: 1.0
5
## Technical.Constraints to Client.and.Consultant.Requests
## 1: 7.5
## 2: 19.5
## 3: 7.0
## Performance.Parameters to Client.and.Consultant.Requests
## 1: 11.5
## 2: 18.5
## 3: 3.0
## Client.and.Consultant.Requests to Client.and.Consultant.Requests
## 1: 5
## 2: 12
## 3: 1
## Design.Reasoning to Client.and.Consultant.Requests
## 1: 15.5
## 2: 9.0
## 3: 3.0
## Collaboration to Client.and.Consultant.Requests Data to Design.Reasonin
g
## 1: 2 19
## 2: 3 86
## 3: 0 10
## Technical.Constraints to Design.Reasoning
## 1: 50.0
## 2: 152.5
## 3: 17.0
## Performance.Parameters to Design.Reasoning
## 1: 20
## 2: 69
## 3: 9
## Client.and.Consultant.Requests to Design.Reasoning
## 1: 5.5
## 2: 16.0
## 3: 2.0
## Design.Reasoning to Design.Reasoning Collaboration to Design.Reasoning
## 1: 59 6.0
## 2: 136 33.5
## 3: 19 4.0
## Data to Collaboration Technical.Constraints to Collaboration

```

```
## 1:          0          7.0
## 2:         15         27.0
## 3:          6         18.5
##   Performance.Parameters to Collaboration
## 1:          0.5
## 2:          8.5
## 3:          6.0
##   Client.and.Consultant.Requests to Collaboration
## 1:          0
## 2:          2
## 3:          0
##   Design.Reasoning to Collaboration Collaboration to Collaboration
## 1:          5.0          0
## 2:         42.5         14
## 3:          7.0          9
```

4.4.2 Line weights

To compare networks in terms of their *relative* patterns of association, researchers can spherically normalize the cumulative adjacency vectors by dividing each one by its length. The resulting normalized vectors represent each unit's relative frequencies of code co-occurrence. In other words, the sphere normalization controls for the fact that different units might have different amounts of interaction or different numbers of activities than others.

In `set.ona$connection.counts`, the value for each unique co-occurrence of codes is an integer equal or greater than 0, because they represent the directional connection counts between each pair of codes. In `set.ona$line.weights`, the connection counts are sphere normalized, and so the values are between 0 and 1.

```
head(set.ona$line.weights,3)

##   Condition      UserName      ENA_UNIT ENA_DIRECTION Data to Data
## 1: FirstGame    steven z    FirstGame::steven z    response  0.1543564
## 2: FirstGame    akash v    FirstGame::akash v    response  0.1619657
## 3: FirstGame alexander b FirstGame::alexander b    response  0.1424314
##   Technical.Constraints to Data Performance.Parameters to Data
## 1:          0.2612185          0.1899771
## 2:          0.2305762          0.1484686
## 3:          0.2783886          0.1942246
##   Client.and.Consultant.Requests to Data Design.Reasoning to Data
## 1:          0.07124140          0.3087127
## 2:          0.02249524          0.1979581
## 3:          0.05179323          0.1812763
##   Collaboration to Data Data to Technical.Constraints
## 1:          0.04749427          0.1602931
## 2:          0.02699429          0.2395743
## 3:          0.01294831          0.1489055
##   Technical.Constraints to Technical.Constraints
## 1:          0.3740173
```

```

## 2: 0.4341581
## 3: 0.5179323
## Performance.Parameters to Technical.Constraints
## 1: 0.1751351
## 2: 0.2035819
## 3: 0.2006988
## Client.and.Consultant.Requests to Technical.Constraints
## 1: 0.05046266
## 2: 0.05286381
## 3: 0.01294831
## Design.Reasoning to Technical.Constraints
## 1: 0.3680806
## 2: 0.3610486
## 3: 0.2978111
## Collaboration to Technical.Constraints Data to Performance.Parameters
## 1: 0.06530462 0.1424828
## 2: 0.06523619 0.1732133
## 3: 0.20069875 0.1294831
## Technical.Constraints to Performance.Parameters
## 1: 0.2107558
## 2: 0.2058314
## 3: 0.2265954
## Performance.Parameters to Performance.Parameters
## 1: 0.2018506
## 2: 0.1619657
## 3: 0.1294831
## Client.and.Consultant.Requests to Performance.Parameters
## 1: 0.03265231
## 2: 0.04611524
## 3: 0.03884492
## Design.Reasoning to Performance.Parameters
## 1: 0.2493449
## 2: 0.1732133
## 3: 0.1812763
## Collaboration to Performance.Parameters Data to Client.and.Consultant.R
equests
## 1: 0.04452587 0.035
62070
## 2: 0.03261810 0.040
49143
## 3: 0.01294831 0.064
74153
## Technical.Constraints to Client.and.Consultant.Requests
## 1: 0.04452587
## 2: 0.04386571
## 3: 0.09063815
## Performance.Parameters to Client.and.Consultant.Requests
## 1: 0.06827301
## 2: 0.04161619
## 3: 0.03884492

```

```

## Client.and.Consultant.Requests to Client.and.Consultant.Requests
## 1: 0.02968392
## 2: 0.02699429
## 3: 0.01294831
## Design.Reasoning to Client.and.Consultant.Requests
## 1: 0.09202014
## 2: 0.02024571
## 3: 0.03884492
## Collaboration to Client.and.Consultant.Requests Data to Design.Reasoning
## 1: 0.011873567 0.1127989
## 2: 0.006748571 0.1934590
## 3: 0.000000000 0.1294831
## Technical.Constraints to Design.Reasoning
## 1: 0.2968392
## 2: 0.3430524
## 3: 0.2201212
## Performance.Parameters to Design.Reasoning
## 1: 0.1187357
## 2: 0.1552171
## 3: 0.1165348
## Client.and.Consultant.Requests to Design.Reasoning
## 1: 0.03265231
## 2: 0.03599238
## 3: 0.02589661
## Design.Reasoning to Design.Reasoning Collaboration to Design.Reasoning
## 1: 0.3502702 0.03562070
## 2: 0.3059352 0.07535905
## 3: 0.2460178 0.05179323
## Data to Collaboration Technical.Constraints to Collaboration
## 1: 0.000000000 0.04155748
## 2: 0.03374286 0.06073714
## 3: 0.07768984 0.23954367
## Performance.Parameters to Collaboration
## 1: 0.002968392
## 2: 0.019120952
## 3: 0.077689840
## Client.and.Consultant.Requests to Collaboration
## 1: 0.000000000
## 2: 0.004499048
## 3: 0.000000000
## Design.Reasoning to Collaboration Collaboration to Collaboration
## 1: 0.02968392 0.000000000
## 2: 0.09560476 0.03149333
## 3: 0.09063815 0.11653476

```

4.4.3 ONA points

For each unit, ONA produces an ONA point in a two-dimensional space formed by the first two dimensions of the dimensional reduction.

Here, the MR1 column represents the x-axis coordinate for each unit, and the SVD2 column represents the y-axis coordinate for each unit.

```
head(set.ona$points,3)
```

```
##      Condition      UserName      ENA_UNIT ENA_DIRECTION      MR1
## 1: FirstGame      steven z      FirstGame::steven z      response 0.00753635
## 2: FirstGame      akash v      FirstGame::akash v      response -0.07719283
## 3: FirstGame alexander b FirstGame::alexander b      response -0.20600855
##      SVD2      SVD3      SVD4      SVD5      SVD6      SVD
7
## 1: -0.05350532 0.02308722 0.03365899 0.18576251 -0.064647347 -0.01638733
9
## 2: 0.01840812 -0.01485049 -0.03634380 0.02065882 -0.003406081 -0.00802670
5
## 3: -0.05806135 -0.08409658 0.13340227 0.03017168 -0.046102014 -0.09567464
9
##      SVD8      SVD9      SVD10      SVD11      SVD12      SVD
13
## 1: 0.02504138 -0.04662639 0.01654204 -0.0050339193 0.001089911 0.020150
19
## 2: -0.01584017 -0.01879391 0.03338419 -0.0082095228 -0.004596587 0.050346
82
## 3: -0.10337234 0.14247946 0.01749875 0.0005982879 -0.073284812 -0.019597
35
##      SVD14      SVD15      SVD16      SVD17      SVD18      S
VD19
## 1: -0.03170014 0.014028551 -0.03292583 -0.01286482 0.0002353795 -0.01426
1325
## 2: -0.02280942 0.042727200 0.02373320 -0.02829064 -0.0208970211 0.01012
0401
## 3: -0.01633710 -0.002697103 -0.03717024 0.02019079 -0.0119060565 -0.00651
8936
##      SVD20      SVD21      SVD22      SVD23      SVD24
## 1: 0.01159296 0.0009366777 -0.033851942 -0.003230414 -0.016553686
## 2: -0.01752303 0.0045814224 -0.006533689 -0.007668149 0.017903544
## 3: -0.03746771 0.0075254949 0.038768078 0.008012232 0.009589488
##      SVD25      SVD26      SVD27      SVD28      SVD29
## 1: 2.124235e-03 0.008351416 0.024600338 -0.0003563738 0.006848068
## 2: -4.643724e-05 -0.013146155 -0.003761067 -0.0172067645 -0.009072690
## 3: 1.347210e-03 0.014229380 0.006423058 0.0020076670 0.003970270
##      SVD30      SVD31      SVD32      SVD33      SVD34
SVD35
## 1: 0.009214306 0.000689622 0.001926662 -0.0001196152 0.0057286766 0.0031
16433
## 2: -0.006574454 0.001518995 0.006561024 0.0037200464 0.0019185441 0.0064
47044
## 3: -0.003266165 0.004738366 0.003057179 0.0018318401 0.0008428842 -0.0048
84616
##      SVD36
```

```
## 1: 0.003361801
## 2: -0.001230173
## 3: 0.001080194
```

4.4.4 Rotation matrix

The rotation matrix used during the dimensional reduction can be accessed through `set.ona$rotation`. This is mostly useful when you want to construct an ONA metric space using one dataset and then project ONA points from different data into that space, as in section 5.2.

```
head(set.ona$rotation.matrix,3)
```

```
##              codes      MR1      SVD2      SVD3
## 1:              Data to Data -0.06930733 -0.4261566 0.041261221
## 2: Technical.Constraints to Data -0.18483941 -0.3305414 -0.001705309
## 3: Performance.Parameters to Data 0.16511484 -0.4098705 -0.057056137
##              SVD4      SVD5      SVD6      SVD7      SVD8      SVD9
## 1: -0.24813254 -0.12386178 -0.1212851 -0.1813800 -0.02634818 0.02463562
## 2: -0.09652822 0.29776415 -0.2487902 0.4530700 -0.08131861 0.19027807
## 3: -0.06943836 0.02894105 -0.1666548 -0.1512543 0.26221091 0.15918103
##              SVD10     SVD11     SVD12     SVD13     SVD14     SVD15
## 1: -0.1685089 0.02779782 0.1634913 0.03515259 -0.1307011 0.11108864
## 2: -0.2985731 0.03356852 -0.1788196 0.24614774 -0.1162268 -0.06526278
## 3: 0.2634069 0.30265567 0.0364710 -0.16880948 0.2246206 0.04608908
##              SVD16     SVD17     SVD18     SVD19     SVD20     SVD21
## 1: 0.1678676 -0.21955326 0.4390146 0.263975884 -0.03791243 -0.26637411
## 2: 0.2427948 0.31464439 -0.1658976 -0.023955700 -0.04756904 0.05450570
## 3: -0.1521164 -0.06523085 -0.3436932 0.005934216 -0.21114098 0.07531336
##              SVD22     SVD23     SVD24     SVD25     SVD26     SVD27
## 1: -0.16378180 -0.04863544 -0.03046897 0.01129295 0.07990007 -0.10906748
## 2: 0.09542229 0.04913771 0.09391774 -0.07213795 -0.01391693 -0.03060512
## 3: 0.18550364 -0.20153993 0.11835360 -0.08759355 -0.06613629 0.01739627
##              SVD28     SVD29     SVD30     SVD31     SVD32     SVD3
3
## 1: 0.1218933 0.05135484 -0.08227500 0.09675121 -0.205485302 -0.15944684
3
## 2: -0.0431860 -0.04667436 -0.03855961 -0.06592640 -0.006227139 -0.00619161
0
## 3: 0.1294605 0.01342884 -0.17369350 0.07209455 -0.153340746 -0.00982495
5
##              SVD34     SVD35     SVD36
## 1: -0.12907089 0.14685408 0.01703190
## 2: 0.02971639 0.11327562 0.07985307
## 3: 0.17078477 -0.02710075 0.06842069
```

4.4.5 Metadata

`set.ona$meta.data` gives a data frame that includes all the columns except for the code connection columns.


```
head(set.ona$meta.data,3)

##      Condition      UserName      ENA_UNIT
## 1: FirstGame    steven z    FirstGame::steven z
## 2: FirstGame    akash v      FirstGame::akash v
## 3: FirstGame alexander b    FirstGame::alexander b
```

4.5 ONA visualization

Once an ONA model is constructed, ONA networks can be visualized. The plotting function in ONA is called `plot`, and it works similarly to the same function in ENA.

Before plotting, you can set up several global parameters to ensure consistency across plots. These parameters will be clearer in subsequent sections.

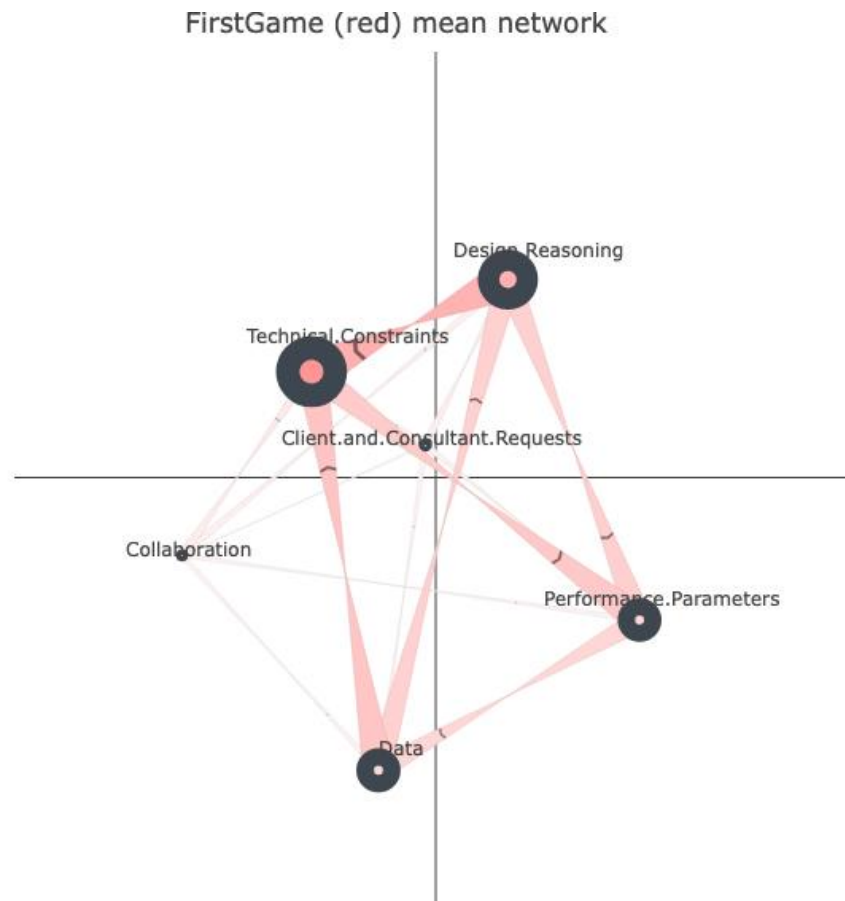
```
node_size_multiplier = 0.4 # scale up or down node sizes
node_position_multiplier = 1 # zoom in or out node positions
point_position_multiplier = 1.5 # zoom in or out the point positions
edge_arrow_saturation_multiplier = 1.5 # adjust the chevron color lighter or darker
edge_size_multiplier = 1 # scale up or down edge sizes
```

4.5.1 Plot a mean network

Mean ONA networks can be plotted for each of the conditions along with their subtracted network.

First, plot the mean network for the FirstGame condition. Use a pipe `|>` to connect the `edges` function and the `nodes` function. Users are only required to specify the `weights` parameter, as the remaining parameters have default values unless specified otherwise.

```
plot(set.ona, title = "FirstGame (red) mean network") |>
  edges(
    weights = set.ona$line.weights$Condition$FirstGame,
    edge_size_multiplier = edge_size_multiplier,
    edge_arrow_saturation_multiplier = edge_arrow_saturation_multiplier,
    node_position_multiplier = node_position_multiplier,
    edge_color = c("red")) |>
  nodes(
    node_size_multiplier = node_size_multiplier,
    node_position_multiplier = node_position_multiplier,
    self_connection_color = c("red"))
```



Since this is the first ONA network visualization in this chapter, we briefly explain how to read an ONA network.

Node size: In ONA, the node size is proportional to the number of occurrences of that code as a *response* to other codes in the data, with larger nodes indicating more responses. For example, in this plot, students in the FirstGame condition responded most frequently with discourse about Technical.Constraints.

Self-connections: The color and saturation of the circle within each node is proportional to the number of *self-connections* for that code: that is, when a code is both what students *responded to* and what they *responded with*. Colored circles that are larger and more saturated reflect codes with more frequent self-connections.

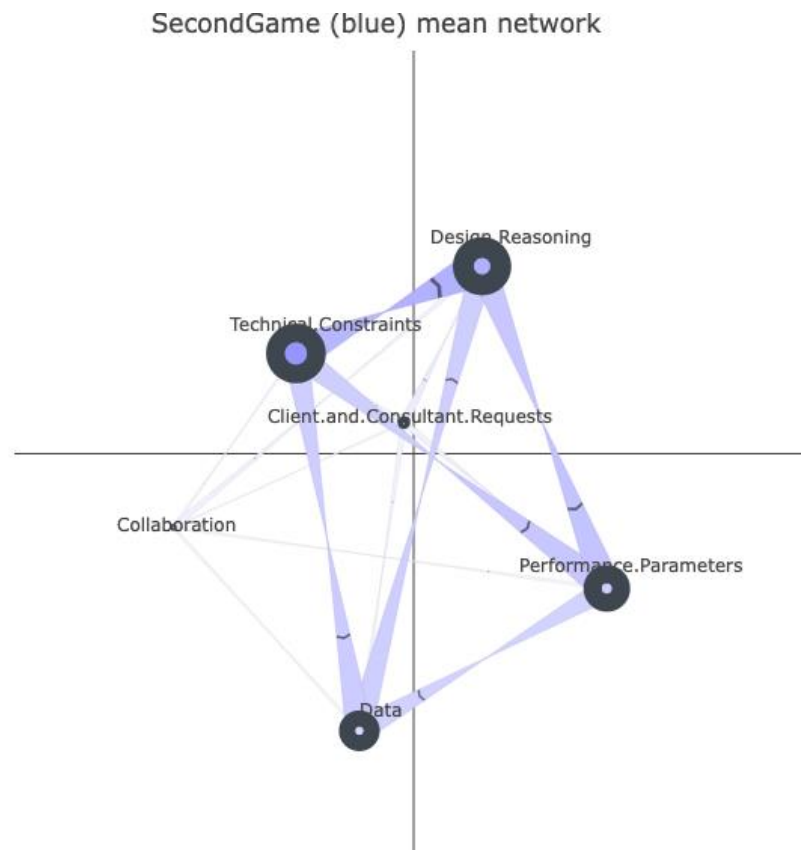
Edges: Note that unlike most directed network visualizations, which use arrows or spearheads to indicate direction, ONA uses a “broadcast” model, where the source of a connection (what students responded to) is placed at the apex side of the triangle and the destination of a connection (what students responded with) is placed at its base.

Chevrons on edges: The chevrons point in the direction of the connection. Between any pair of nodes, if there is a bidirectional connection, the chevron only appears on the side with the stronger connection. This helps viewers differentiate heavier edges in cases such

as between Technical.Constraints and Data, where the connection strengths from both directions are similar. When the connection strengths are identical between two codes, the chevron will appear on both edges.

Now, plot the mean network for SecondGame.

```
plot(set.ona, title = "SecondGame (blue) mean network") |>
  edges(
    weights = set.ona$line.weights$Condition$SecondGame,
    edge_size_multiplier = edge_size_multiplier,
    edge_arrow_saturation_multiplier = edge_arrow_saturation_multiplier,
    node_position_multiplier = node_position_multiplier,
    edge_color = c("blue")) |>
  nodes(
    node_size_multiplier = node_size_multiplier,
    node_position_multiplier = node_position_multiplier,
    self_connection_color = c("blue"))
```



Then, plot the subtracted network to show the differences between the mean networks of the FirstGame and SecondGame conditions.

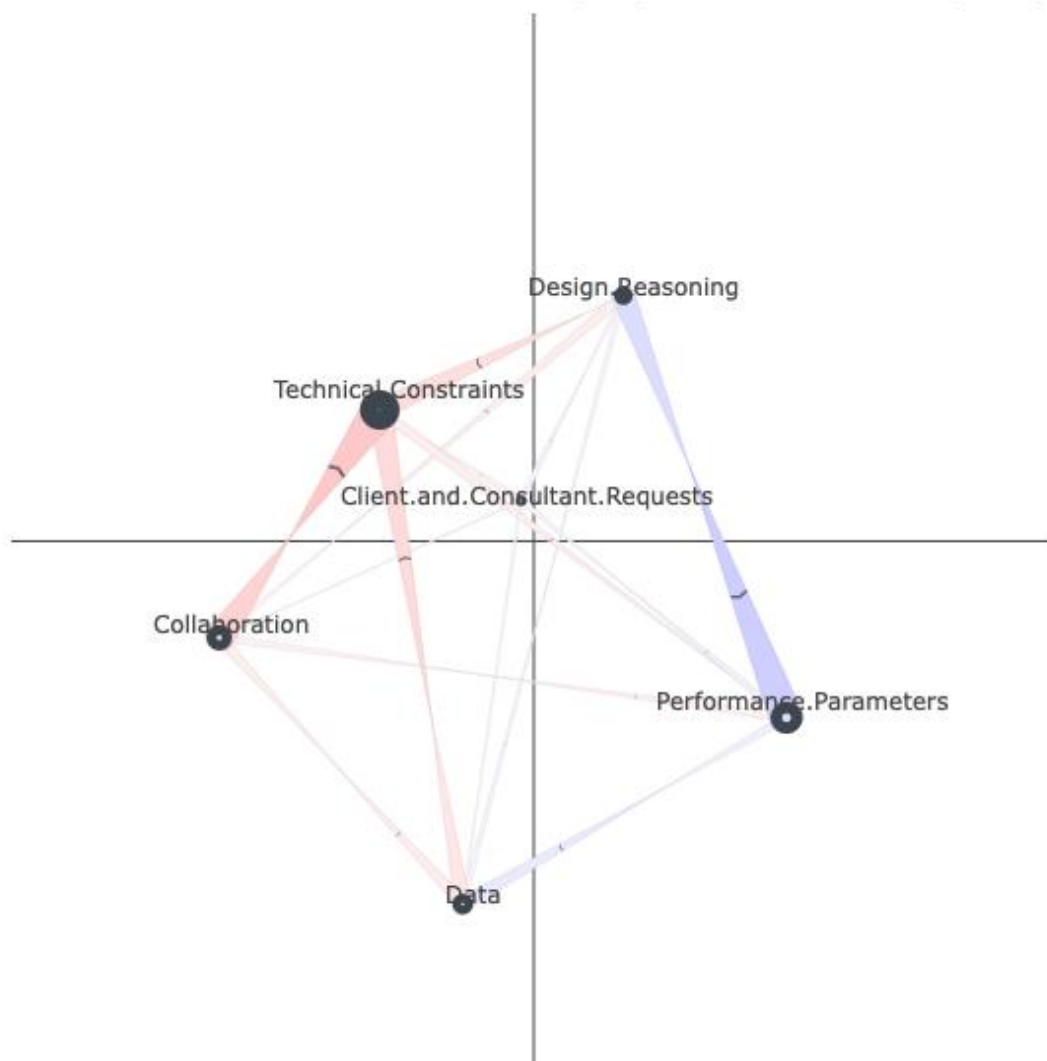
```
plot(set.ona, title = "Subtracted mean network: FirstGame (red) vs SecondGame (blue)") |>
```

```

edges(
  weights = (colMeans(set.ona$line.weights$Condition$FirstGame) - colMeans(
set.ona$line.weights$Condition$SecondGame))*4, # optional weights multiplier
to adjust readability
  edge_size_multiplier = edge_size_multiplier,
  edge_arrow_saturation_multiplier = edge_arrow_saturation_multiplier,
  node_position_multiplier = node_position_multiplier,
  edge_color = c("red","blue")) |>
nodes(
  node_size_multiplier = node_size_multiplier,
  node_position_multiplier = node_position_multiplier,
  self_connection_color = c("red","blue"))

```

Subtracted mean network: FirstGame (red) vs SecondGame (blue)



4.5.2 Plot a mean network and its points

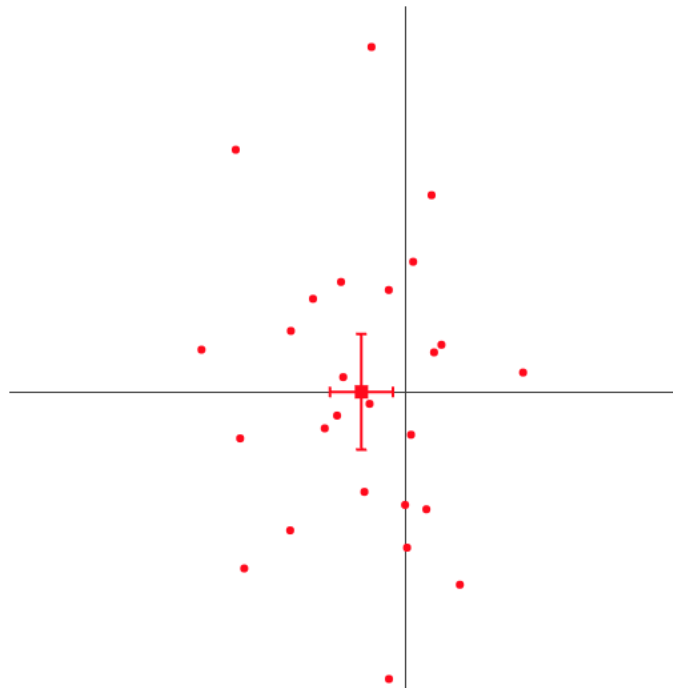
Besides plotting the mean network for each condition and the subtracted network, we can also plot the individual units within each condition.

Use `set.ona$points` to subset the rows that are in each condition and plot the units in each condition as a different color.

The points are specified in the `units` function. The `edges` and `nodes` functions remain the same as above.

```
plot(set.ona, title = "points (dots), mean point (square), and confidence interval") |>
  units(
    points=set.ona$points$Condition$FirstGame,
    points_color = c("red"),
    show_mean = TRUE, show_points = TRUE, with_ci = TRUE)
```

points (dots), mean point (square), and confidence interval



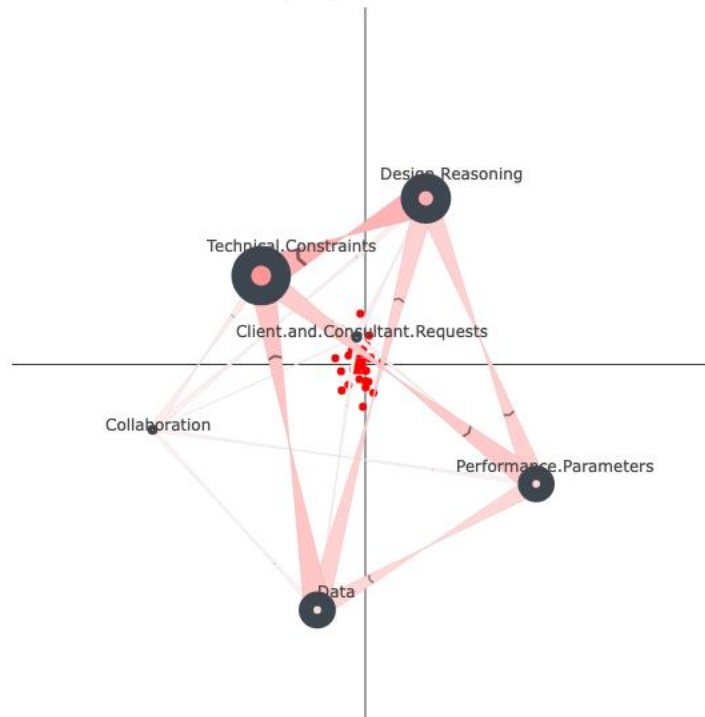
```
plot(set.ona, title = "FirstGame (red) mean network") |>
  units(
    points=set.ona$points$Condition$FirstGame,
    points_color = c("red"),
    show_mean = TRUE, show_points = TRUE, with_ci = TRUE) |>
  edges(
    weights =set.ona$line.weights$Condition$FirstGame,
    edge_size_multiplier = edge_size_multiplier,
    edge_arrow_saturation_multiplier = edge_arrow_saturation_multiplier,
    node_position_multiplier = node_position_multiplier,
    edge_color = c("red")) |>
```

```

nodes(
  node_size_multiplier = node_size_multiplier,
  node_position_multiplier = node_position_multiplier,
  self_connection_color = c("red"))

```

FirstGame (red) mean network

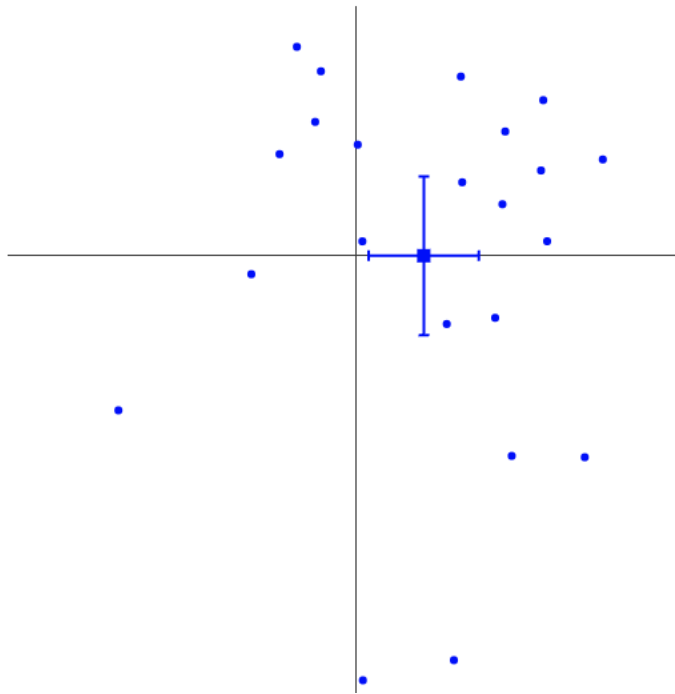


```

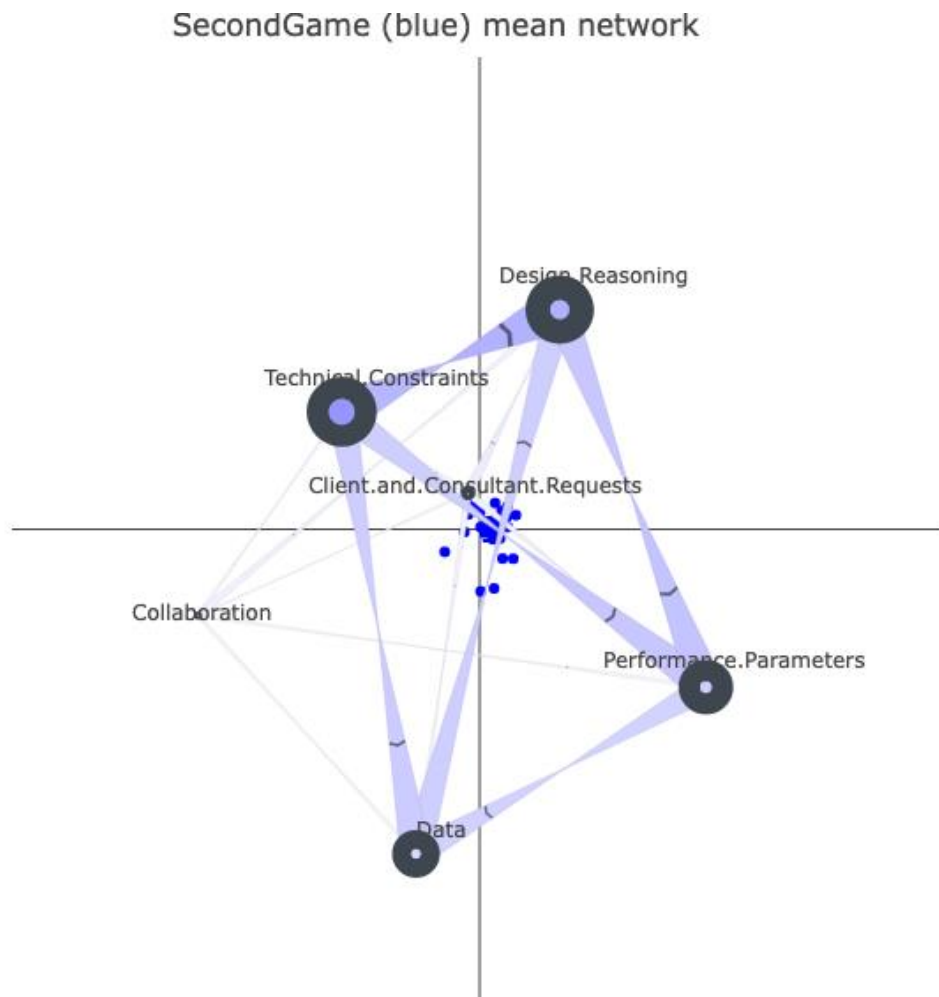
plot(set.ona, title = "points (dots), mean point (square), and confidence interval") |>
  units(
    points=set.ona$points$Condition$SecondGame,
    points_color = c("blue"),
    show_mean = TRUE, show_points = TRUE, with_ci = TRUE)

```

points (dots), mean point (square), and confidence interval



```
plot(set.ona, title = "SecondGame (blue) mean network") |>
  units(
    points=set.ona$points$Condition$SecondGame,
    points_color = "blue",
    show_mean = TRUE, show_points = TRUE, with_ci = TRUE) |>
  edges(
    weights = set.ona$line.weights$Condition$SecondGame,
    edge_size_multiplier = edge_size_multiplier,
    edge_arrow_saturation_multiplier = edge_arrow_saturation_multiplier,
    node_position_multiplier = node_position_multiplier,
    edge_color = c("blue")) |>
  nodes(
    node_size_multiplier = node_size_multiplier,
    node_position_multiplier = node_position_multiplier,
    self_connection_color = c("blue"))
```



Plot the subtracted network as follows.

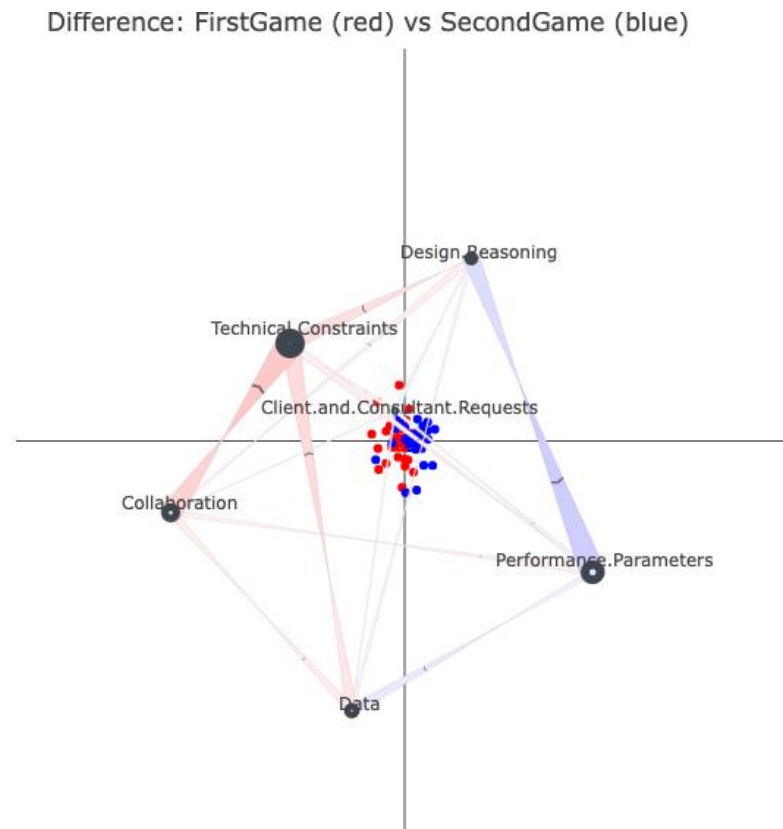
```
# FirstGame and SecondGame subtracted plot
plot(set.ona, title = "Difference: FirstGame (red) vs SecondGame (blue)") |>
  units(
    points = set.ona$points$Condition$FirstGame,
    points_color = "red",
    show_mean = TRUE, show_points = TRUE, with_ci = TRUE) |>
  units(
    points = set.ona$points$Condition$SecondGame,
    points_color = "blue",
    show_mean = TRUE, show_points = TRUE, with_ci = TRUE) |>
  edges(
    weights = (colMeans(set.ona$line.weights$Condition$FirstGame) - colMeans(
set.ona$line.weights$Condition$SecondGame))*4, # optional multiplier to adjust
t for readability
    edge_size_multiplier = edge_size_multiplier,
```



```

edge_arrow_saturation_multiplier = edge_arrow_saturation_multiplier,
node_position_multiplier = node_position_multiplier,
edge_color = c("red","blue")) |>
nodes(
  node_size_multiplier = node_size_multiplier,
  node_position_multiplier = node_position_multiplier,
  self_connection_color = c("red","blue"))

```



4.5.3 Plot an individual network and its points

To plot an individual student's network and ONA point, use `set.ona$points`.

Here, we choose the same two units we compared in the ENA analysis (Section 3.5.3).

```

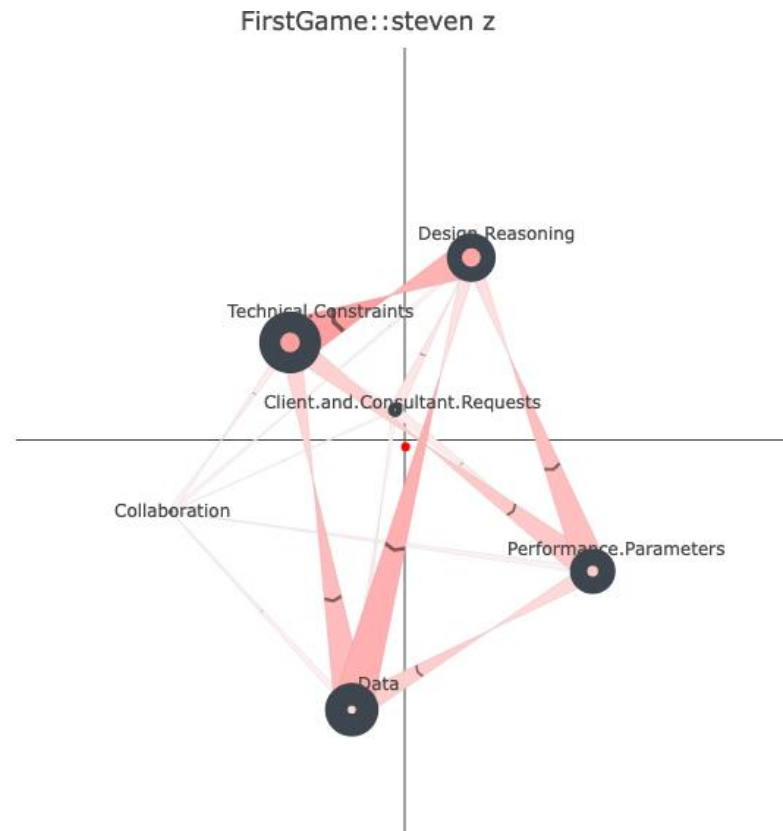
# first game
plot(set.ona, title = "FirstGame::steven z") |>
  units(
    points=set.ona$points$ENA_UNIT`FirstGame::steven z`,
    points_color = "red",
    show_mean = FALSE, show_points = TRUE, with_ci = FALSE) |>
  edges(
    weights = set.ona$line.weights$ENA_UNIT`FirstGame::steven z`,
    edge_size_multiplier = edge_size_multiplier,
    edge_arrow_saturation_multiplier = edge_arrow_saturation_multiplier,

```

```

node_position_multiplier = node_position_multiplier,
edge_color = c("red")) |>
nodes(
  node_size_multiplier = node_size_multiplier,
  node_position_multiplier = node_position_multiplier,
  self_connection_color = c("red"))

```

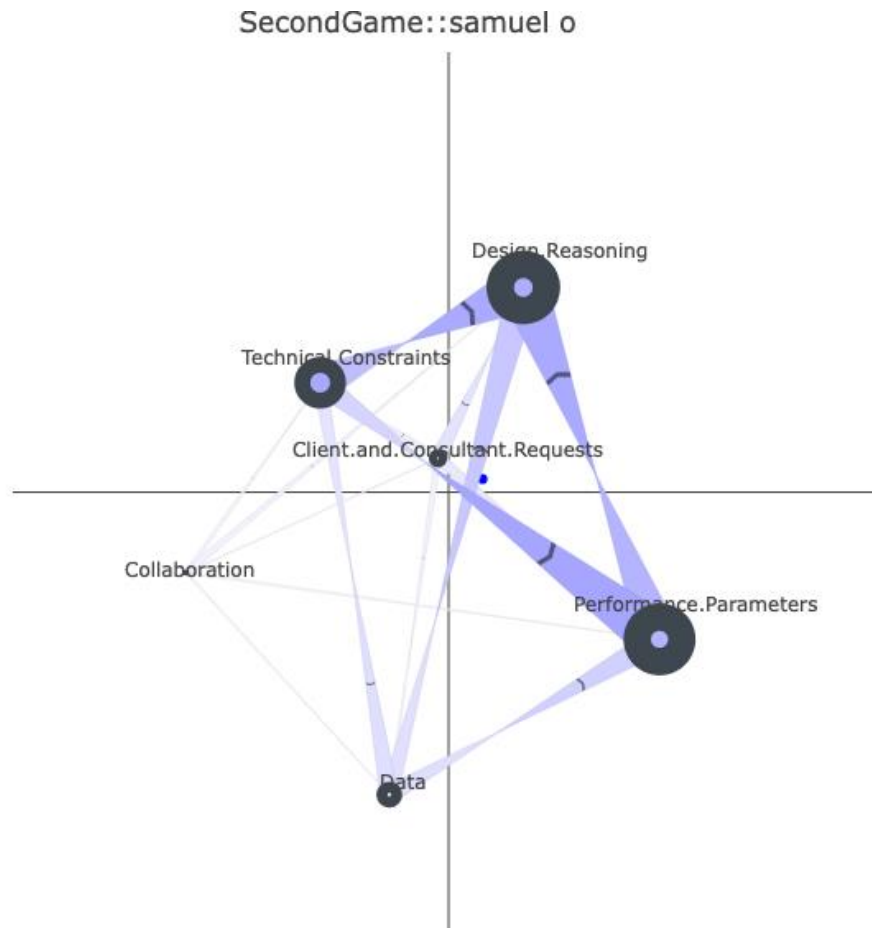


```

# second game
plot(set.ona, title = "SecondGame::samuel o") |>
units(
  points=set.ona$points$ENA_UNIT`SecondGame::samuel o`,
  points_color = "blue",
  show_mean = FALSE, show_points = TRUE, with_ci = FALSE) |>
edges(
  weights = set.ona$line.weights$ENA_UNIT`SecondGame::samuel o`,
  edge_size_multiplier = edge_size_multiplier,
  edge_arrow_saturation_multiplier = edge_arrow_saturation_multiplier,
  node_position_multiplier = node_position_multiplier,
  edge_color = c("blue")) |>
nodes(
  node_size_multiplier = node_size_multiplier,

```

```
node_position_multiplier = node_position_multiplier,
self_connection_color = c("blue"))
```



In this case, both units make relatively strong connections between Design.Reasoning and Data. However, for Unit A (red), the connection is relatively more *from* Design.Reasoning to Data than the other way around. This indicates that more often this unit responded with Data. In contrast, Unit B (blue) responded more frequently to Data with Design.Reasoning.

A subtracted network can make such differences more salient.

```
# units difference
mean1 = as.vector(as.matrix(set.ona$line.weights$ENA_UNIT$`FirstGame::steven
z`))
mean2 = as.vector(as.matrix(set.ona$line.weights$ENA_UNIT$`SecondGame::samuel
o`))

subtracted.mean = mean1 - mean2

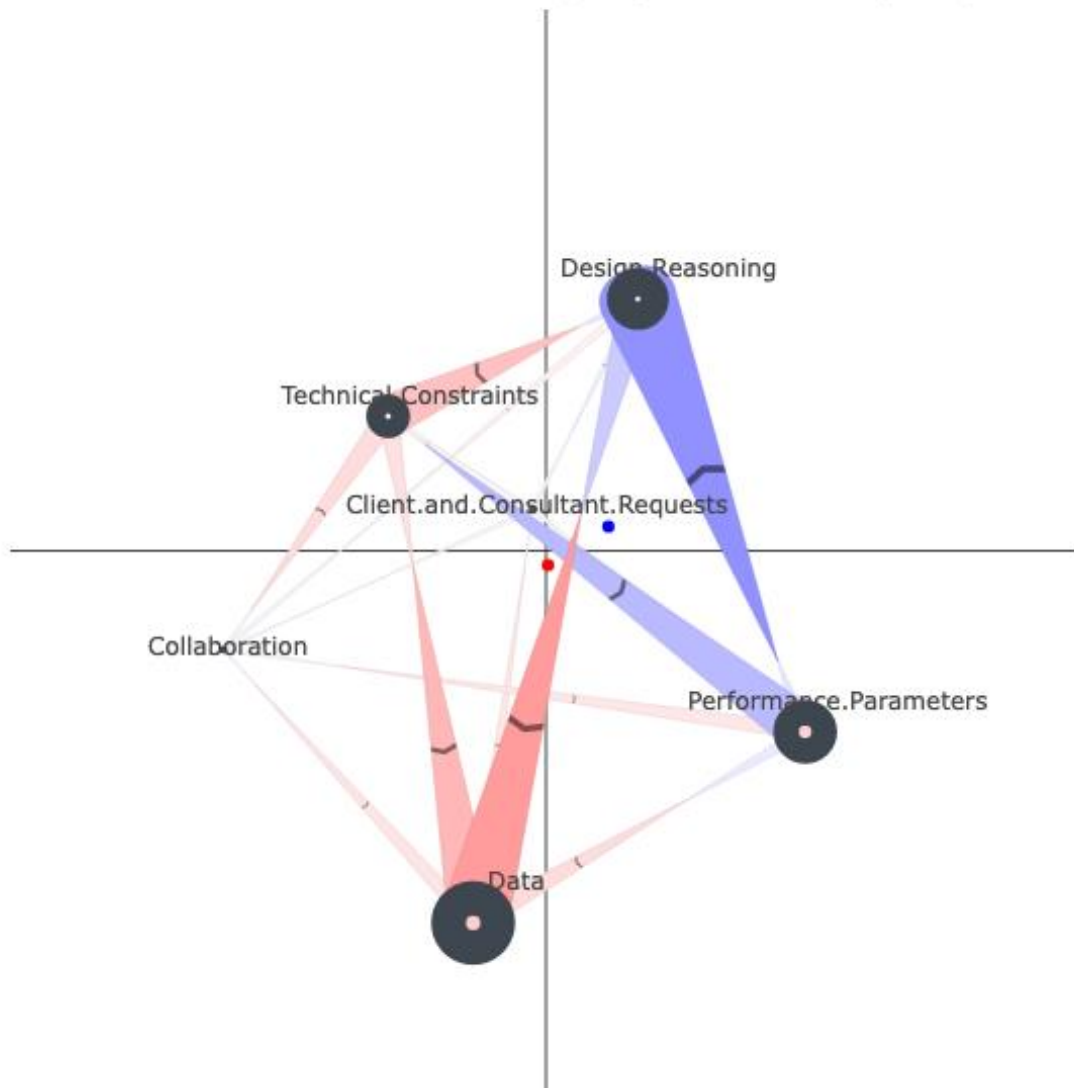
plot(set.ona, title = "subtracted network of steven z.FirstGame.Electric and
SecondGame.luke u") |>
units(
```

```

    points = set.ona$points$ENA_UNIT$`FirstGame::steven z`, points_color = "red",
    point_position_multiplier = point_position_multiplier,
    show_mean = FALSE, show_points = TRUE, with_ci = FALSE) |>
units(
  points = set.ona$points$ENA_UNIT$`SecondGame::samuel o`, points_color = "blue",
  point_position_multiplier = point_position_multiplier,
  show_mean = FALSE, show_points = TRUE, with_ci = FALSE) |>
edges(
  weights = subtracted.mean*2,
  edge_size_multiplier = edge_size_multiplier,
  edge_arrow_saturation_multiplier = edge_arrow_saturation_multiplier,
  node_position_multiplier = node_position_multiplier,
  edge_color = c("red", "blue")) |>
nodes(
  node_size_multiplier = node_size_multiplier,
  node_position_multiplier = node_position_multiplier,
  self_connection_color = c("red", "blue"))

```

subtracted network of steven z (red) and Samuel (blue)



The connection between Design.Reasoning and Data consists of two triangles, one in blue pointing from Data to Design.Reasoning, the other in red pointing from Design.Reasoning to Data. This indicates that although both units made strong connections between these two codes, the relative directed frequencies are different. Recall that in the ENA subtracted network for the same two units, the connections between Data and Design.Reasoning were basically the same. ONA, by accounting for the order of events, shows that while the undirected relative frequencies were similar, there was a difference in the order in which the two students made the connection.

4.6 Compare groups statistically

In addition to visual comparison of networks, ENA points can be analyzed statistically. For example, here we might test whether the patterns of association in one condition are significantly different from those in the other condition.

To demonstrate both parametric and non-parametric approaches to this question, the examples below use a Student's t test and a Mann-Whitney U test to test for differences between the FirstGame and SecondGame condition.

First, install the `lsr` package to enable calculation of effect size (Cohen's d) for the t test.

```
install.packages('lsr')
library(lsr)
```

Then, subset the points to test for differences between the points of the two conditions.

```
ona_first_points_d1 = as.matrix(set.ona$points$Condition$FirstGame)[,1]
ona_second_points_d1 = as.matrix(set.ona$points$Condition$SecondGame)[,1]

ona_first_points_d2 = as.matrix(set.ona$points$Condition$FirstGame)[,2]
ona_second_points_d2 = as.matrix(set.ona$points$Condition$SecondGame)[,2]
```

Conduct the t test on the first and second dimensions.

```
parametric tests
t_test_d1 = t.test(ona_first_points_d1, ona_second_points_d1)
t_test_d1

##
##  Welch Two Sample t-test
##
## data:  ona_first_points_d1 and ona_second_points_d1
## t = -3.7729, df = 41.001, p-value = 0.0005111
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.18227713 -0.05517572
## sample estimates:
##  mean of x    mean of y
## -0.05441628  0.06431015

t_test_d2 = t.test(ona_first_points_d2, ona_second_points_d2)
t_test_d2

##
##  Welch Two Sample t-test
##
## data:  ona_first_points_d2 and ona_second_points_d2
## t = -6.9301e-16, df = 45.45, p-value = 1
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
```

```
## -0.1008208 0.1008208
## sample estimates:
##      mean of x      mean of y
## -1.727628e-17  1.742362e-17
```

Compute any other statistics that may be of interest. A few examples are given below.

```
mean(ona_first_points_d1)
## [1] -0.05441628
mean(ona_second_points_d1)
## [1] 0.06431015
mean(ona_first_points_d2)
## [1] -1.727628e-17
mean(ona_second_points_d2)
## [1] 1.742362e-17
sd(ona_first_points_d1)
## [1] 0.09754142
sd(ona_second_points_d1)
## [1] 0.1171941
sd(ona_first_points_d2)
## [1] 0.1784777
sd(ona_second_points_d2)
## [1] 0.1679372
length(ona_first_points_d1)
## [1] 26
length(ona_second_points_d1)
## [1] 22
length(ona_first_points_d2)
## [1] 26
length(ona_second_points_d2)
## [1] 22
cohensD(ona_first_points_d1, ona_second_points_d1)
```

```
## [1] 1.109985
```

```
cohensD(ona_first_points_d2, ona_second_points_d2)
```

```
## [1] 1.997173e-16
```

Here, along the x axis (MR1), a two-sample t test assuming unequal variance shows that the FirstGame (mean=-0.05, SD=0.09, N=26) condition is statistically significantly different for $\alpha=0.05$ from the SecondGame condition (mean=0.06, SD=0.12, N=22; $t(41.001) = -3.77$, $p=0.00$, Cohen's $d=1.1$). Along the y axis (SVD2), a two-sample t test assuming unequal variance shows that the FirstGame condition (mean=-1.73, SD=0.17, N=26) is not statistically significantly different for $\alpha=0.05$ from the SecondGame condition (mean=1.74, SD=0.17, N=22; $t(45.45) = 0$, $p=1.00$, Cohen's $d=0.00$).

The Mann-Whitney U test is a non-parametric alternative to the independent two-sample t test.

First, install the `rcompanion` package to calculate the effect size (r) for a Mann-Whitney U test.

```
# install.packages('rcompanion')
library(rcompanion)
```

Then, conduct a Mann-Whitney U test on the first and second dimensions.

```
# non parametric tests
w_test_d1 = wilcox.test(ona_first_points_d1, ona_second_points_d1)
w_test_d2 = wilcox.test(ona_first_points_d2, ona_second_points_d2)

w_test_d1

##
## Wilcoxon rank sum exact test
##
## data:  ona_first_points_d1 and ona_second_points_d1
## W = 130, p-value = 0.0009533
## alternative hypothesis: true location shift is not equal to 0

w_test_d2

##
## Wilcoxon rank sum exact test
##
## data:  ona_first_points_d2 and ona_second_points_d2
## W = 264, p-value = 0.6593
## alternative hypothesis: true location shift is not equal to 0
```

Compute any other statistics that may be of interest. A few examples are given below.

```
median(ona_first_points_d1)
```

```
## [1] -0.04307778
```



```

median(ona_second_points_d1)
## [1] 0.09596238
median(ona_first_points_d2)
## [1] 0.001753116
median(ona_second_points_d2)
## [1] 0.05862436
length(ona_first_points_d1)
## [1] 26
length(ona_second_points_d1)
## [1] 22
length(ona_first_points_d2)
## [1] 26
length(ona_second_points_d2)
## [1] 22
abs(wilcoxonR(ona_first_points_d1, ona_second_points_d1))
## r
## 0
abs(wilcoxonR(ona_first_points_d2, ona_second_points_d2))
## r
## 0.707

```

Here, along the x axis (MR1), a Mann-Whitney U test shows that the FirstGame condition (Mdn=-0.04, N=26) was statistically significantly different for $\alpha=0.05$ from the SecondGame condition (Mdn=0.10, N=22 $U=130$, $p=0.001$, $r=0.00$). Along the y axis (SVD2), a Mann-Whitney U test shows that the FirstGame condition (Mdn=0.001, N=26) is not statistically significantly different for $\alpha=0.05$ from the SecondGame condition (Mdn=0.00, N=22, $U=264$, $p=0.66$, $r=0.71$). The absolute value of r value in Mann-Whitney U test varies from 0 to close to 1. The interpretation values for r commonly in published literature is: $0.10 - < 0.3$ (small effect), $0.30 - < 0.5$ (moderate effect) and ≥ 0.5 (large effect).

4.7 Model evaluation

4.7.1 Variance explained

Briefly, variance explained (also called explained variation) refers to the proportion of the total variance in a dataset that is accounted for by a statistical model or set of predictors.

In ONA, to represent high-dimensional vectors in a two-dimensional space, ONA uses either singular value decomposition or means rotation combined with SVD. For each of the reduced dimensions, the variance in patterns of association among units explained by that dimension can be computed.

```
head(set.ona$model$variance,2)
```

```
##          MR1          SVD2
## 0.1367940 0.2736079
```

In our example above, since we used means rotation method, the first dimension is labeled as MR1 and the second dimension is labeled as SVD2. The two dimensions in combination explained more than 40% of the variance.

Here, the first dimension is MR1 and the second dimension is SVD2. The two dimensions in combination explained more than 40% of the variance.

As with any statistical model, greater explained variance does not necessarily indicate a better model, as it may be due to overfitting, but it provides one indicator of model quality.

3.7.2 Goodness of fit

Briefly, a model's goodness of fit refers to how well a model fits or represents the data. A model with a high goodness of fit indicates that it accurately represents the data and can make reliable predictions.

In ONA, a good fit means that the positions of the nodes in the space—and thus the network visualizations—are consistent with the mathematical properties of the model. In other words, we can confidently rely on the network visualizations to interpret the ONA model. The process that ONA uses to achieve high goodness of fit is called co-registration, the same as the one used in ENA. The mathematical details of co-registration are beyond the scope of this chapter and can be found in Bowman et al., (2022).

To test a model's goodness of fit, use `ona::correlations`. The closer the value is to 1, the higher the model's goodness of fit is. Most ENA models have a goodness of fit that is well above 0.90.

```
ona::correlations(set.ona)
```

```
##      pearson  spearman
## 1 0.9801173 0.9801799
## 2 0.9801431 0.9759160
```

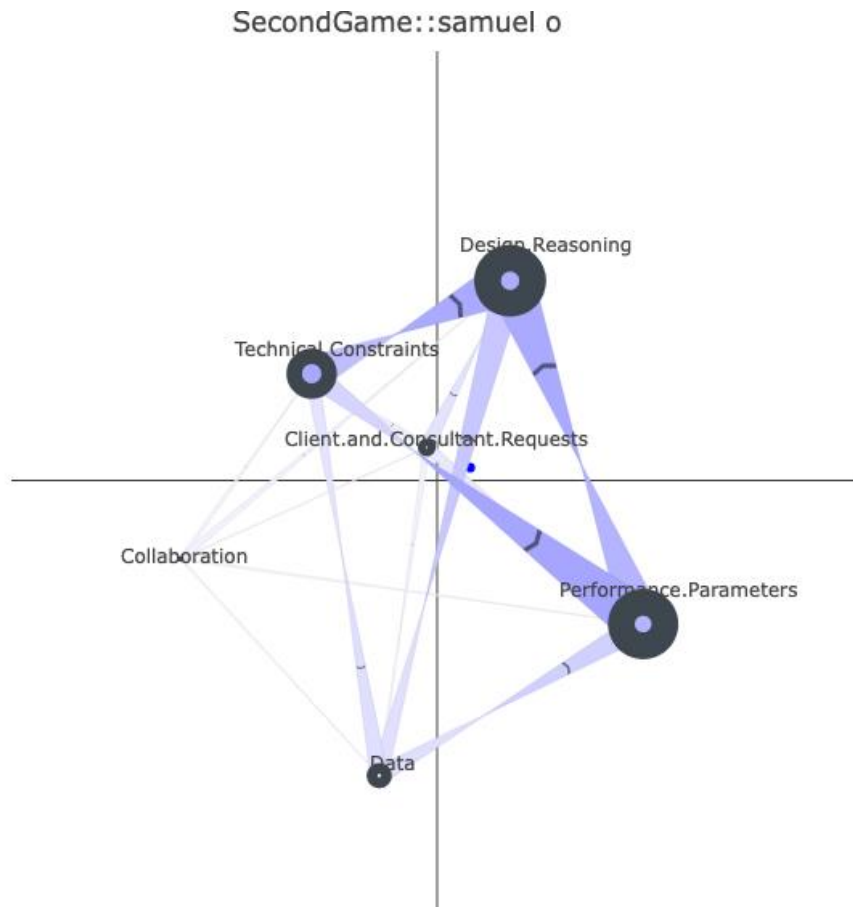
4.7.3 Close the interpretative loop

Another approach to evaluate an ONA model is to confirm the alignment between quantitative model (in our case, our ONA model) and the original qualitative data. In other words, we can return to the original data to confirm that quantitative findings give a fair representation of the data. This approach is an example of what's called as closing the interpretative loop in Quantitative Ethnography field (Shaffer, 2017).

For example, based on our visual analysis of the network of "SecondGame::samuel o" in previous section, we are interested in what the lines are in the original data that contributed to the connection *from* Performance.Parameters *to* Design.Reasoning.

Let's first review what "SecondGame::samuel o" ONA network looks like. Based on the connection direction and strength from Technical.Constraints to Performance.Parameters, we would expect to see more examples of Samuel responded with "Design.Reasoning" to "Performance.Parameters", than the other way around.

```
plot(set.ona, title = "SecondGame::samuel o") |>
  units(
    points=set.ona$points$ENA_UNIT$`SecondGame::samuel o`,
    points_color = "blue",
    show_mean = FALSE, show_points = TRUE, with_ci = FALSE) |>
  edges(
    weights = set.ona$line.weights$ENA_UNIT$`SecondGame::samuel o`,
    edge_size_multiplier = edge_size_multiplier,
    edge_arrow_saturation_multiplier = edge_arrow_saturation_multiplier,
    node_position_multiplier = node_position_multiplier,
    edge_color = c("blue")) |>
  nodes(
    node_size_multiplier = node_size_multiplier,
    node_position_multiplier = node_position_multiplier,
    self_connection_color = c("blue"))
```



To do so, we use `view()` function and specify required parameters as below.

This is going to activate a window shows up in your Viewer panel. If it is too small to read, you can click on the “Show in new window” button to view it in your browser for better readability.

In the Viewer panel, hover over your cursor on any of the lines that are in bold, a size of 7 lines rectangle shows up, representing that in a moving stanza window of size 7, the referent line (the line in bold) and its preceding 6 lines. The 1 and 0 in Technical.Constraints column and Design.Reasoning column shows where the connections happened.

QEID	Condition	UserName	GroupName	ActivityNumber	text	Performance.Parameters	Design.Reasoning
2464	SecondGame	jackson p	Hydraulic	5	I would look at the numbers and saw how good each power source or control sensor was at each	1	1
2465	SecondGame	samuel o	Hydraulic	5	I had to weigh the pros and cons of each power source and sensor	0	0
2466	SecondGame	shane t	Hydraulic	5	So what did you guys choose as the best battery and sensor?	0	1
2467	SecondGame	brandon f	Hydraulic	5	The area covered by the NiCd graph really stood out to me as the clear front runner	0	0
2468	SecondGame	jackson p	Hydraulic	5	The graphs gave us an approximation by showing the area that each individual battery type took	0	0
2469	SecondGame	samuel o	Hydraulic	5	The helped illustrate which devices were good and bad with different attributes	1	1
2471	SecondGame	shane t	Hydraulic	5	They gave us a visual of the data, made it easier to compare them and see the best choice	0	1
2472	SecondGame	casey f	Hydraulic	5	@Brandon: I agree. It covers the most area on the graph.	0	0
2473	SecondGame	jackson p	Hydraulic	5	I agree with NiCd too	0	0
2474	SecondGame	samuel o	Hydraulic	5	@Brandon: I agree, I like the NiCd also	0	0
2475	SecondGame	jackson p	Hydraulic	5	when it came to the different attributes, i think that all were important in their own way but i think	1	0
2476	SecondGame	casey f	Hydraulic	5	Well not one source/sensor can be the best in every area so we had to sacrifice certain attributes.	1	1
2477	SecondGame	samuel o	Hydraulic	5	No, I just was mindful of the how one device scores relative to other ones	0	1
2478	SecondGame	shane t	Hydraulic	5	I also chose the NiCd battery	0	1
2479	SecondGame	brandon f	Hydraulic	5	to agree on which power source and control sensor we should use	0	0
2480	SecondGame	brandon f	Hydraulic	5	to agree on which power source and control sensor we should use	0	0
2481	SecondGame	jackson p	Hydraulic	5	Test the battery out with an actual prototype	0	1
2482	SecondGame	casey f	Hydraulic	5	@Shane: I agree	0	0
2483	SecondGame	jackson p	Hydraulic	5	do more research on the nickel cadmium battery and see how we can optimize it	0	1
2484	SecondGame	samuel o	Hydraulic	5	design prototype	0	1

Notice that here we are viewing the same qualitative example as in section 3.7.3 in ENA. In line 2477 Samuel shared his [Design.Reasoning] about “mindful of (the) how one device scores relative to other ones”, **as a response to** what Casey said in line 2476 about [Performance.Parameters] “not one source/censor can be the best in every area so we had to sacrifice certain attributes”, as well as what Jackson said in line 2475 about safety as one of the [Performance.Parameters] “when it came to the different attributes, i think that all were important in their own way but i think safety is one of the most important”.

Here, ONA was able to not only capture the occurrence between code Design.Reasoning and Performance.Parameters as ENA did, but also represent the connection direction *from* Design.Reasoning *to* Performance.Parameters

4.8 Using ONA outputs in other analysis

As with ENA, the outputs of ONA models can be used as inputs in other statistical models. See Section 3.8 for an example using ENA points.

5. Additional features

In the sections above, we demonstrated how to do an ENA analysis and an ONA analysis. In this section, we show how to project new data into a space constructed with different data. This can be done as long as the same codes are used in both sets.

5.1 Projections in ENA

To project the ENA points from one model into a space constructed with different data, replace the `rotation.set` parameter of `ena.make.set`. In the example below, an “expert” model is developed using the SecondGame units and the FirstGame (novice) units are projected into that space. By projecting novice model’s units into expert model’s space, users can interpret the projected novice units’ networks based on the two dimensions defined by expert model’s node positions. In other words, interpreting novice’s networks in the context of experts’ space.

```
data = rENA::RS.data

#expert data
exp.data = subset(data, Condition == "SecondGame")
```

```

#novice data
nov.data = subset(data, Condition == "FirstGame")

#expert model
units_exp = exp.data[,c("Condition", "UserName")]
conversation_exp = exp.data[,c("Condition", "GroupName", "ActivityNumber")]
codes_exp = exp.data[,codeCols]
meta_exp = exp.data[,c("CONFIDENCE.Change",
                       "CONFIDENCE.Pre", "CONFIDENCE.Post", "C.Change")]

set_exp =
  ena.accumulate.data(
    text_data = exp.data[, 'text'],
    units = units_exp,
    conversation = conversation_exp,
    codes = codes_exp,
    metadata = meta_exp,
    window.size.back = 7,
  ) |>
  ena.make.set()

#novice model
units_nov = nov.data[,c("Condition", "UserName")]
conversation_nov = nov.data[,c("Condition", "GroupName", "ActivityNumber")]
codes_nov = nov.data[,codeCols]
meta_nov = nov.data[,c("CONFIDENCE.Change",
                       "CONFIDENCE.Pre", "CONFIDENCE.Post", "C.Change")]

set_nov =
  ena.accumulate.data(
    text_data = nov.data[, 'text'],
    units = units_nov,
    conversation = conversation_nov,
    codes = codes_nov,
    metadata = meta_nov,
    window.size.back = 7,
  ) |>
  ena.make.set(rotation.set = set_exp$rotation)

# plot expert model (what we projected into) Using plotting wrapper to save time
plot_exp = ena.plotter(set_exp,
                       points = T,
                       mean = T,
                       network = T,
                       print.plots = F
)

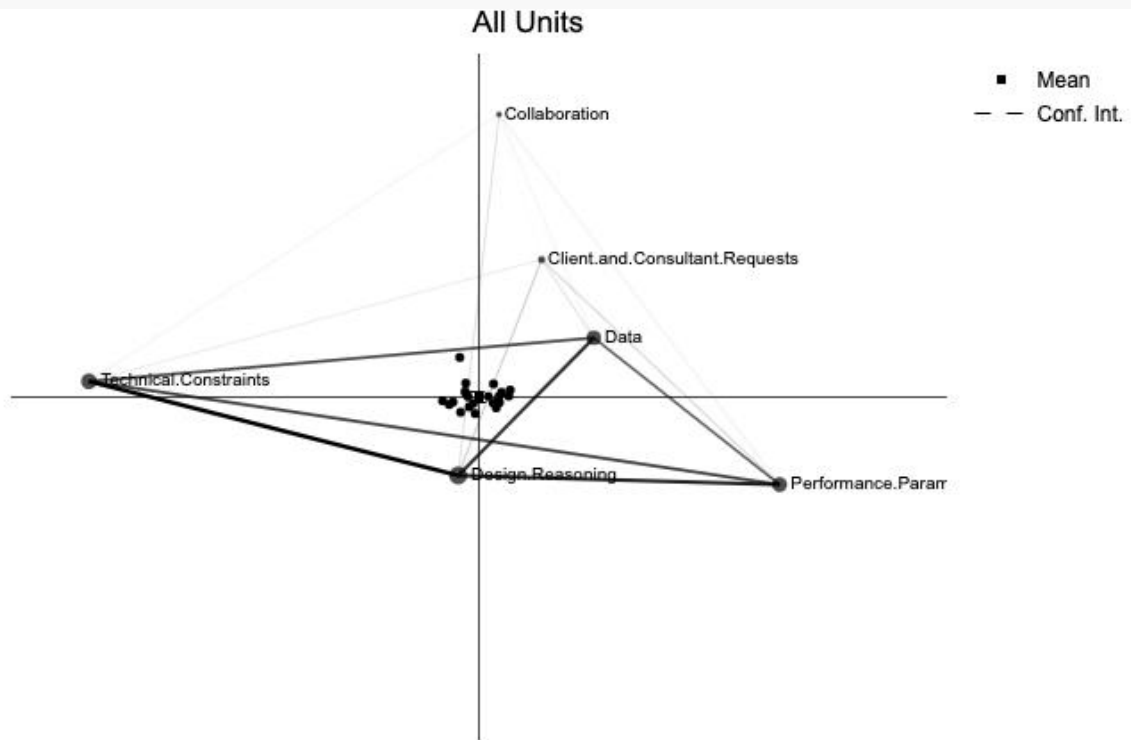
```

```
# plot test model (points from test model in training model space)
```

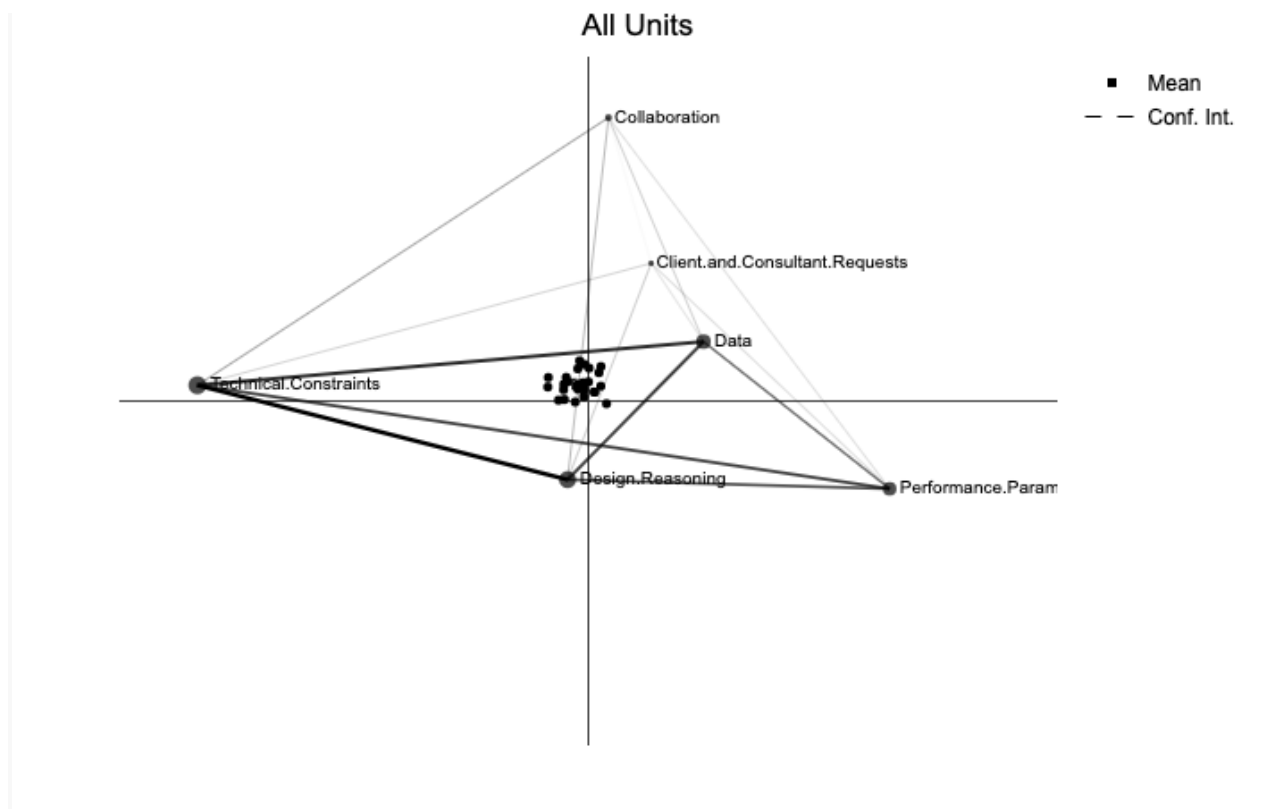
```
plot_nov = ena.plotter(set_nov,  
                        points = T,  
                        mean = T,  
                        network = T,  
                        print.plots = F)
```

```
#compare plots
```

```
plot_exp$plot
```



```
plot_nov$plot
```



5.2 Projections in ONA

Projection works similarly in ONA.

```
data = ona::RS.data

#expert data
exp.data = subset(data, Condition == "SecondGame")

#novice data
nov.data = subset(data, Condition == "FirstGame")

#shared unit cols
units = c("UserName", "Condition", "GroupName")

#shared code cols
codes = c(
  'Data',
  'Technical.Constraints',
  'Performance.Parameters',
  'Client.and.Consultant.Requests',
  'Design.Reasoning',
  'Collaboration')

#shared hoo
```



```

hoo = conversation_rules(
  (Condition %in% UNIT$Condition & GroupName %in% UNIT$GroupName))

#expert accum
accum.exp = contexts(exp.data, units_by = units, hoo_rules = hoo) |>
  accumulate_contexts(codes = codes,
    decay.function = decay(simple_window, window_size = 7),
    return.ena.set = FALSE, norm.by = NULL)

#expert model
set.exp = model(accum.exp)

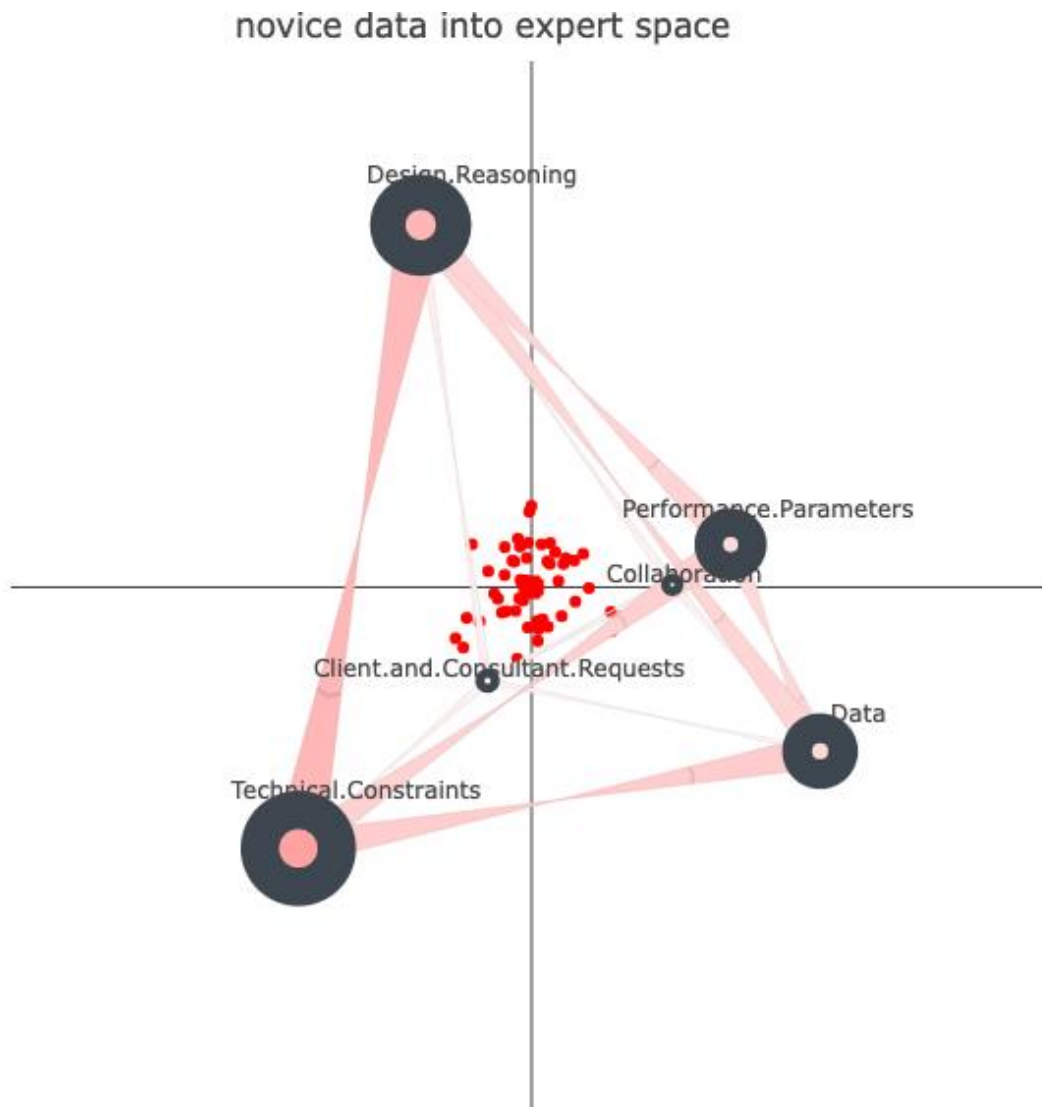
#novice accum
accum.nov = contexts(nov.data, units_by = units, hoo_rules = hoo) |>
  accumulate_contexts(codes = codes,
    decay.function = decay(simple_window, window_size = 7),
    return.ena.set = FALSE, norm.by = NULL)

#novice model
set.nov = model(accum.nov)

# projecting novice data into expert space
set = model(accum.nov, rotation.set = set.exp$rotation)

plot(set, title = "novice data into expert space") |>
  units(
    points = set$points,
    show_mean = TRUE, show_points = TRUE, with_ci = TRUE) |>
  edges(
    weights = set$line.weights) |>
  nodes(
    self_connection_color = "red",
    node_size_multiplier = 0.6)

```



6. Discussion

In this chapter, we introduced two techniques, ENA and ONA, for quantifying, visualizing, and interpreting networks using coded data. Through the use of a demonstration dataset that documents collaborative discourse among students collaborating to solve an engineering design problem, we provided step-by-step instructions on how to model complex, collaborative thinking using ENA and ONA in R. The chapter combines theoretical explanations with tutorials, intended to be of aid to researchers with varying degrees of familiarity with network analysis techniques and R. This chapter mainly showcased the standard and most common use of these two tools. The ENA and ONA R packages, akin to other R packages, offer flexibility to researchers to tailor their analyses to their specific needs. For example, users with advanced R knowledge can supply their own adjacency

matrices and use ENA or ONA solely as a visualization tool rather than an integrated modeling and visualization tool.

Due to the technical and practical focus of this chapter, we omitted detailed explanations of the theoretical, methodological, and mathematical foundations of ENA and ONA that are crucial for informed, theory-based learning analytics research using these techniques. Consult the Further Reading section for papers that explain these aspects of ENA and ONA in greater detail.

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