Visualization of the Occupational Therapy Researcher Database

For Assignment #1-10

Working Draft - 4/18/2016

Authorship

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Project Description and Goals

For several years, the American Occupational Therapy Foundation, in partnership with the American Occupational Therapy Association, has built up a researcher database to track research on Occupational Therapy techniques and practices. The intent of this is to create a comprehensive understanding of the scientific community for building scientific networks, identifying scientific leaders for specific initiatives, and summarizing capacity to external stakeholder groups.

The goal of this project is to turn that data into insights to help realize this vision, and provide guidance for larger analysis of research data.

Planned Visualizations

As requested by the project client, several visualizations are planned to understand different aspects of the data. Additionally, as we improve our understanding of the data and the project objectives, this team will suggest additional approaches, such as the “data explorer” tool.

Data Preparation (Lead Mahesh Suravajjala & Helen)

Research Project table is used as a base, and there is one field in each of the other tables that is joined with this table using Project ID and Profile ID. More details below:

On Research Project Table:

1. Total Funding Amount is calculated by summing up NIH Funding Amount, Fed Funding Amount, and Non Fed Amount

2. Total Cost is calculated by adding up Fed Direct cost, Non Fed direct cost, and NIH Direct Cost

3. Funding Division is calculated by using the below, and all the names are converted to lower case for ease of use

```
IF [FED_Funding_DIVISION] != "NULL" Then
        Lowercase([FED_Funding_DIVISION])
ELSE
        IF [NIH_Funding_DIVISION] != "NULL" Then
                Lowercase([NIH_Funding_DIVISION])
        ELSE
                IF [NON_FED_Funding_DIVISION] != "NULL" THEN
                        Lowercase([NON_FED_Funding_DIVISION])
                ELSE
                        "No Funding division name found"
                ENDIF
        ENDIF
ENDIF
```

Join with Research Profile table to include Institution Name (Assumption - one to one mapping between Profile ID and Institution Name)

4. JOIN Research Profile table using Profile ID, and pull Institution Name

5. Convert Institution name to lowercase

Join with Diagnosis table to include Diagnosis Areas

6. Each project has many diagnosis areas. So, a simple join of the tables will bloat the Funding amounts as there will be multiple entries for each project with multiple diagnosis areas.

7. So, a new column is created joining (separated ;) all the diagnosis areas for each Project and Profile combination. [Query - Group by Project ID, Profile ID and concatenate Diagnosis Areas]

Join with Ages table

8. Followed a similar logic as explained above. A new column, Age Brackets, to concatenate all the age groups (separator - ,)

9. If the age bracket contains "Across all ages", Age bracket is defaulted to "Across all ages", otherwise left as is.

E.g "Young Adult (19-25);Adult (26-44);Middle Age (45-64);Older Adult (65-79);Oldest Old (80+);Across all ages/Population-based" is stored as "Across all ages/Populated-based"

If Contains([Concat_Age Brackets], "Across all ages",1) Then

"Across all ages/Population-based"

Else

Lowercase([Concat_Age Brackets])

ENDIF

10. Convert Age brakcet to Lowercase

Join with ICF table

11. Followed a similar logic as explained above. A new column, ICF Description, is created to concatenate all ICF Areas (separator ,)

12. Convert ICF Descriptions to Lowercase

Join with Agenda table

12. Followed a similar logic as explained above. A new column, Agenda Description, is created to concatenate all Agenda Descriptions (separator - ,)

13. Convert Agenda Descriptions to Lowercase

Join with Project Setting table

14. Followed a similar logic as explained above. A new column, Project Setting Description, is created to concatenate all Project Settings (separator - ,)

15. Convert Project Setting Description to Lowercase

Temporal Analysis (lead: Mahesh Suravajjala)

Main objective of temporal analysis is to highlight the topics funded by AOTF over a period of time. Data points like ACF Area descriptions, Diagnosis descriptions, and Agenda Categories could be normalized/tokenized and used for temporal analysis to represent various topics funded over a period of time (using funding start date). Each topic will be represented as a horizontal bar graph with a specific start and end date. Area of each bar code will represent amount of funding granted by AOTF for a particular topic.

Related work: There is no specific burst analysis visualization created using diagnosis and ACF information of AOTF funded projects. The approach here will re-apply techniques learned in the IVMOOC class.

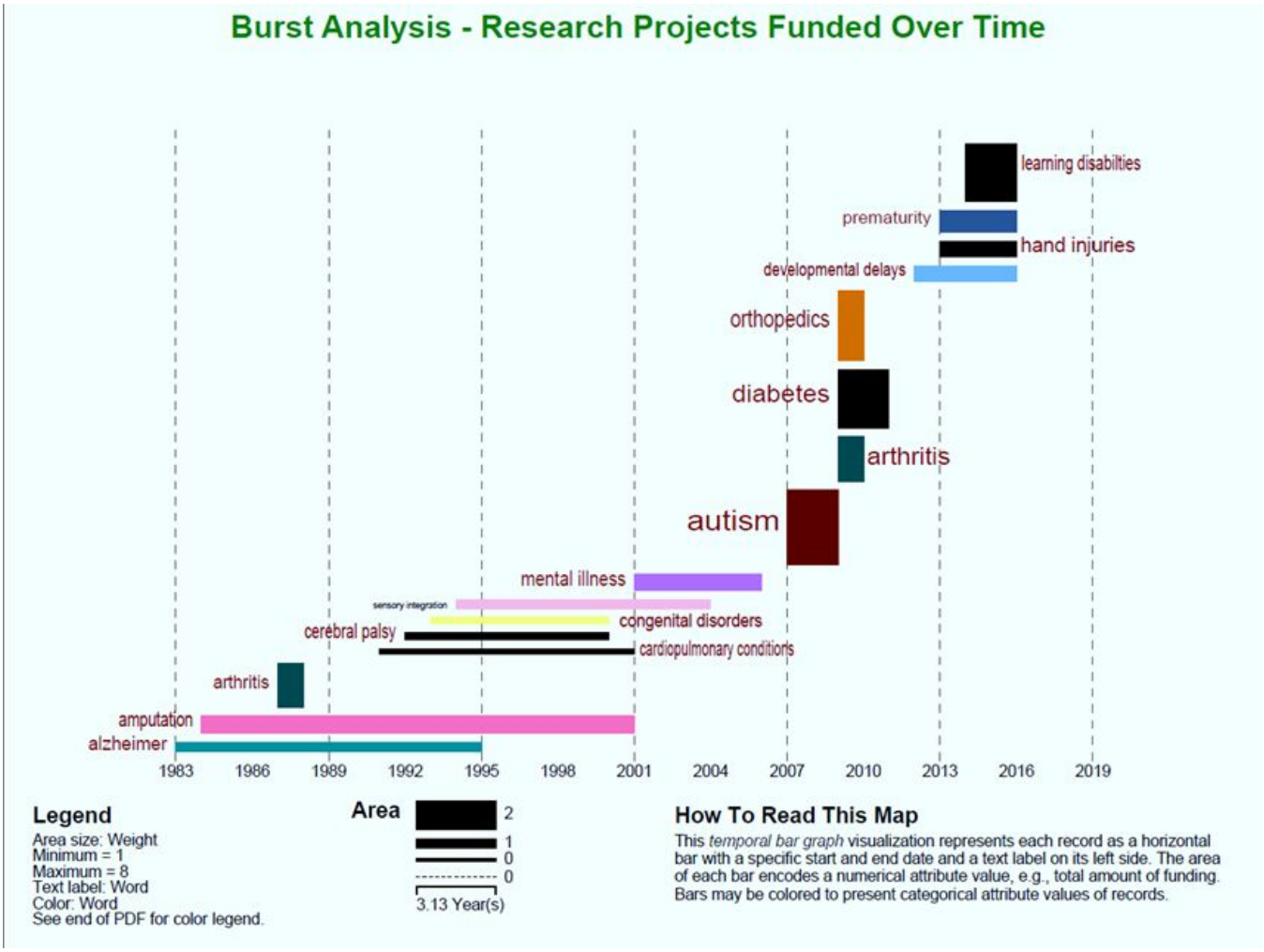
First & Second Visualizations:

Project Analysis based on Diagnosis description:

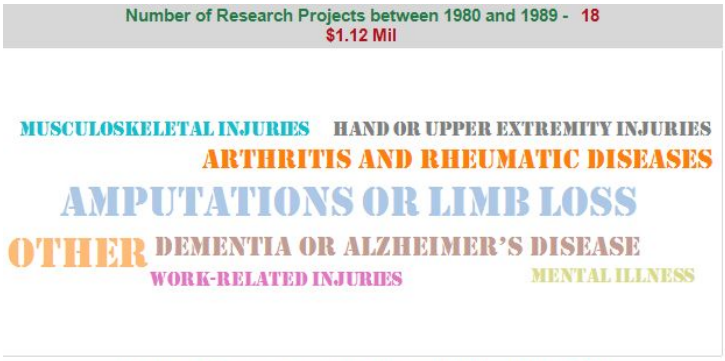
Data Cleaning:

Burst analysis based on diagnosis description. Diagnosis Area descriptions is joined with Project Research data. Given that each research project covers multiple diagnosis area descriptions, all the diagnosis areas are concatenated and joined with project research table. Below is how a simple burst analysis looks based on diagnosis areas between 1985 to 2015. Output of burst detection algorithm via Sci2 had to be cleaned up to data the end year, 2015, and change the words to make diagnosis descriptions a little more meaningful.

Word	Level	Weight	Length	Start	End
cardiopulmonary conditions	1	3.060652	1	1991	1991
cardiopulmonary conditions	1	1.953084	1	2001	2001
cardiopulmonary conditions	1	1.822058	1	2009	2009
diabetes	1	3.128309	1	2011	2011
limb loss	1	13.27927	12	1985	1996
polytrauma	1	2.497206	1	2013	2013
developmental delays	1	2.192905	1	1993	1993
work-related injuries	1	1.813374	1	2010	2010
premature	1	3.184623	4	2013	2015



The second graph is a word network based on diagnosis descriptions and their occurrences. Size of the words is defined by amount of funding received for those diagnosis areas. Tableau is used for second visualization.



9. What problems surfaced during validation and how does your redesign resolve them?

Burst analysis of the various diagnosis areas gets skewed as more and more research areas were funded over time. Burst analysis had to be re-created multiple times by adjusting Gamma & Density in order to make sure all the important diagnosis areas have been highlighted and persistence of funding is appropriately visualized. In order to further substantiate various diagnosis areas that were funded, and highlighted, a word cloud by decade has been created, using Tableau. This word cloud along with the burst analysis should clearly articulate how various various research areas have been funded over the decade, and also highlights how research areas evolved over time.

10. Discussion of challenges and opportunities. Address complexity and scaling issues, desirable modifications and extensions of your work. You have only four weeks for this project restricting the amount of work that can be done considerably. I would like to know what promising avenues you see for future work.

Challenges:

1. Most of the research projects covered multiple diagnosis areas. There are no specific fields to highlight how much of the funding went towards which area. So, it was difficult to use funding amount in temporal analysis.
2. Tokenization and Normalization of health care jargons is a big complex. Different set of stopwords had to be created.

Opportunities:

1. Results of temporal analysis should be overlayed with various diseases that primarily hit during this period. Overlaying this disease information with AOTF research areas could explain if AOTF research projects were reactive or proactive in nature. Also, it will highlight how relevant research areas have been with the conditions/health care issues prevalent during those times.
2. Peer comparison could be interesting. Comparing AOTF research areas and funding amounts to other organizational funded research areas will explain if there is funding overload in some areas, or lack of funding. Such analysis will also highlight if the research areas are complementary or supplementary in nature with the industry.

Topical Analysis (lead: Shahzad Saleem)

Goal: Complete a topical analysis using text associated with projects and researchers and map the evolving topic space.

Need: Topical analysis will extract the set of unique words and their frequency from text associated with projects and researchers in occupational therapy research dataset. We will be creating a word co-occurrence network visualization for this dataset. Extract Word Co-Occurrence Network will create a weighted network where each node is a word and edges will connect words to each other, where the strength of an edge will represent how often two words occur in the same body of text together. Stop words, such as 'the' and 'of' are removed, and stemming will be applied. Once done this visualization will highlight the important words/text for occupational therapy research.

Related work: There has not been any Topical analysis done on Text associated with projects and researchers involved in occupational therapy research. The approach here will re-apply techniques learned in the IVMOOC class

First and 2nd Iteration of Visualizations

In order to do the Topical analysis on Keywords associated with projects and researchers in occupational therapy research dataset. Excluded word “Null” and combined all three keyword fields (USR_KEYWORD_1, USR_KEYWORD_2, USR_KEYWORD_3) in to one called “ALL_KEYWORDS”. Converted xls file into csv and loaded in Sci2 tool.

Applied Pre-Processing step “Lowercase, Tokenize, Stem, and Stopword” to standardize text. Once standardized explored data and found out there are total of 470 unique keywords, which got referred from 1 to 59 times. Breakdown is shown in following table,

Words Count	Count of appearance	Words Count	Count of appearance
228	1	1	16
81	2	1	17
42	3	2	18
30	4	2	19
13	5	3	20
15	6	1	23
6	7	2	24
11	8	1	25
4	9	2	26
3	10	1	37
2	11	1	45
3	12	1	46
6	13	1	48
1	14	1 (Stroke)	59
5	15		

From above can be seen the most frequent word was Stroke which was encountered 59 times in keywords field.

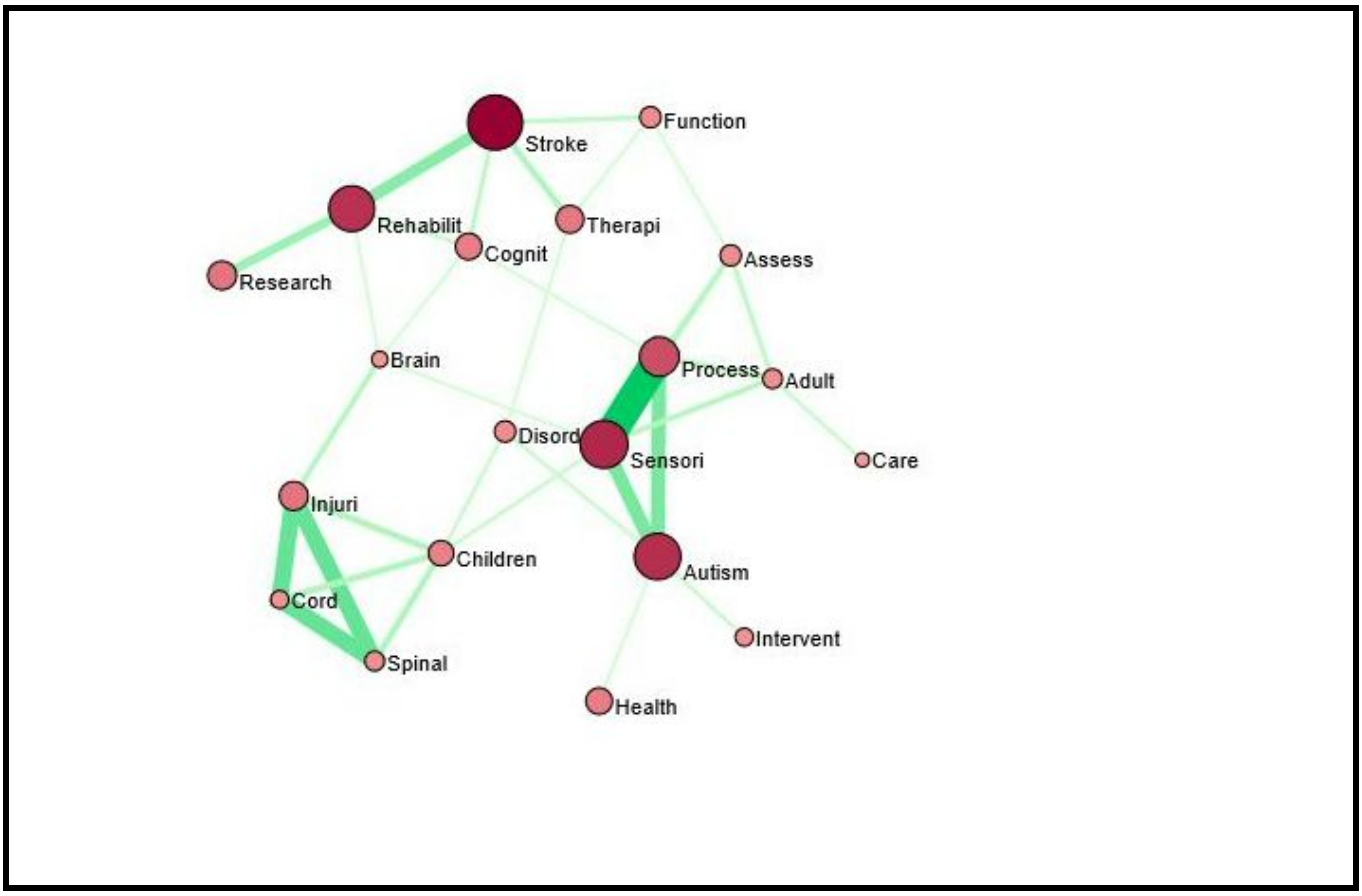
Applied “Extract Word Co-Occurrence Network” algorithm with “ALL_KEYWORDS” as input parameter. Using “Extract Nodes Above or Below Value” step, selected only nodes (Keywords) which got referred at least 6 times in the text, Used “Extract Edges Above or Below Value” algorithm to select edges (relationships among keywords) with the value at-least 3. Executed “Network Analysis Toolkit” and “Remove Isolates” procedures to get rid of 15 isolates.

For Visualizations, Tried multiple visualizations and selected following

1: TreeMap, This visualization is showing Keyword names and number of times they got referred in the keywords field, selected only keywords which got referred at- least 6 times. Color scheme lighter to darker is based on number of references for those keywords. (Used Tableau)Geo

2: Second Visualization is Kambada Kawai Layout using GUESS, through which we can see Keywords and their relationships, For better understanding and readability Picked top twenty keywords based on their reference count (Ranging from reference count 16 to 59), node size and color is reflecting reference count.

Edge (relationship among nodes) is reflected with color and relationship strength (ranging from count 3 to 33).



9. What problems surfaced during validation and how does your redesign resolve them?

In order to do topical analysis, multiple visualizations were tested: Word Cloud, Tree Map, Network with many different layouts, GEM, Circular, Radial Tree, Kambada Kawai. Preprocessing step on keywords caused issues because stemming caused use to lose meaning in some of the terms. For example, the word “injury” became “injuri”, “Early Intervention” was one word but after tokenization became two words: “earli” and “intervent”. Similarly, “Spinal Cord” became Spinal and Cord . Due to this a lot of edges arose between the nodes which should not have been if we would have preserved the space between these kinds of words. I manually modified network file after executing Word Co Occurrence network so that word reflection is appropriate as encountered in the input file.

10. Discussion of challenges and opportunities.

THe word cloud was prefect where I was able to show all 470 keywords and frequency of words was being displayed through font size. However, it was challenging to show all those keywords in any other layouts. As a trade off- for the network analysis, I picked only keywords which showed up in the text at least 6 times for the Kambada Kawai layout.

I gound a lot of spelling mistakes and related issues in data due to which Word Co-occurrence algorithm was not producing correct results and had to manually review all keywords. Use of existing stop words list along with standard tokenization technique with this healthcare dataset was a challenge so edited the network file multiple times

Not having an Undo capability in GUESS made things much more time consuming too, one single mistake made me redo all again. As a consolation, it was kind of a blessing in disguise in that I discovered a lot of its features. Down the road I see a need for industry specific stop words list and tokenization technique, GUESS tool improvement.

Geospatial Analysis (lead: Rose Rahman)

Goal: Complete a geospatial analysis and map to identify potential collaboration links between institutions.

Title of planned visualization: Proportional Symbol Map of Potential Collaboration Links Among Institutions in Occupational Therapy Research, YYYY – YYYY

The proportional symbol map is necessary to map out the institutions with scientific leaders in Occupational Therapy research as to visualize the potential collaboration links among them. The nodes may represent the institution mapped on the U.S. map based on states/zip codes. The size of the nodes may represent the total amount of funding received by the institutions. The color of the nodes may represent the number of researchers within each institution. Discussion will be held among group members to reach decisions on mapping details.

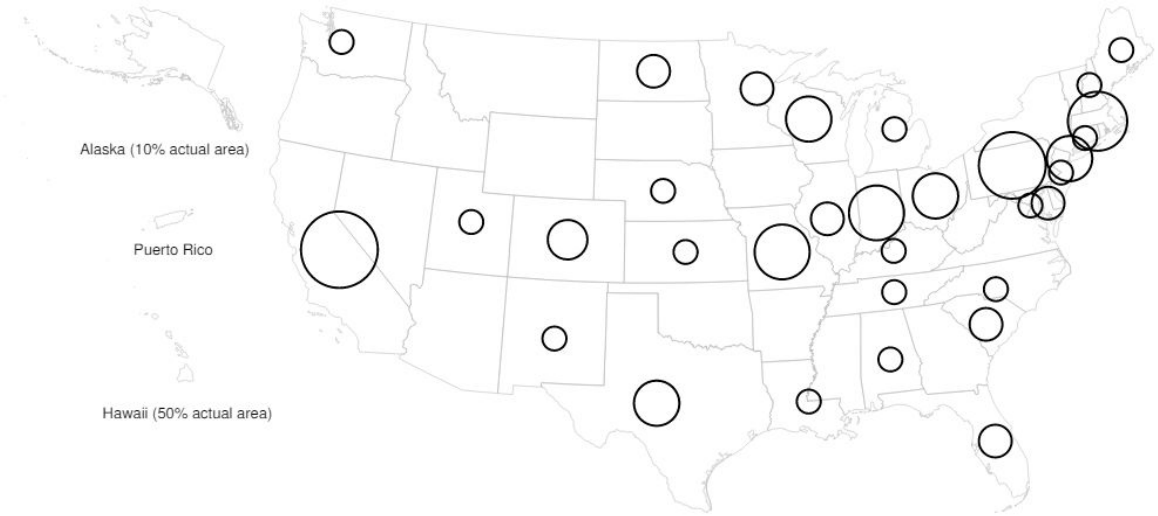
Related work: There has not been any geospatial analysis done on institutions conducting research occupational therapy, particularly proportional symbol map. There has been some analysis done on mapping the literature of occupational therapy however, there is no actual geospatial visualization.

Mock-Up of Visualization

Geospatial Visualization (Proportional Symbol Map)

Potential Collaborations Among Institutions in Occupational Therapy Research

Mar 27, 2016 | 01:45:22 PM -06:00



Legend

Area (Linear)

Count

12

6.5

1

How to Read this Map

This *proportional symbol map* shows 52 U.S. states and other jurisdictions using the Albers equal-area conic projection with Alaska, Puerto Rico, and Hawaii inset. Each dataset record is represented by a circle centered at its geolocation. The area, interior color, and exterior color of each circle may represent numeric attribute values. Minimum and maximum data values are given in the legend.

CNS (cns.iu.edu)

The cleaned data set is aggregated by zip code (unique to institutions) and sum the total funding amount, number of researchers and number of projects. The resulting data set contains 29 rows of unique institutions. Five existing attributes were retained to create the data set for geospatial analysis. An additional of seven attributes were created in geocoding process to extract longitude and latitude markers.

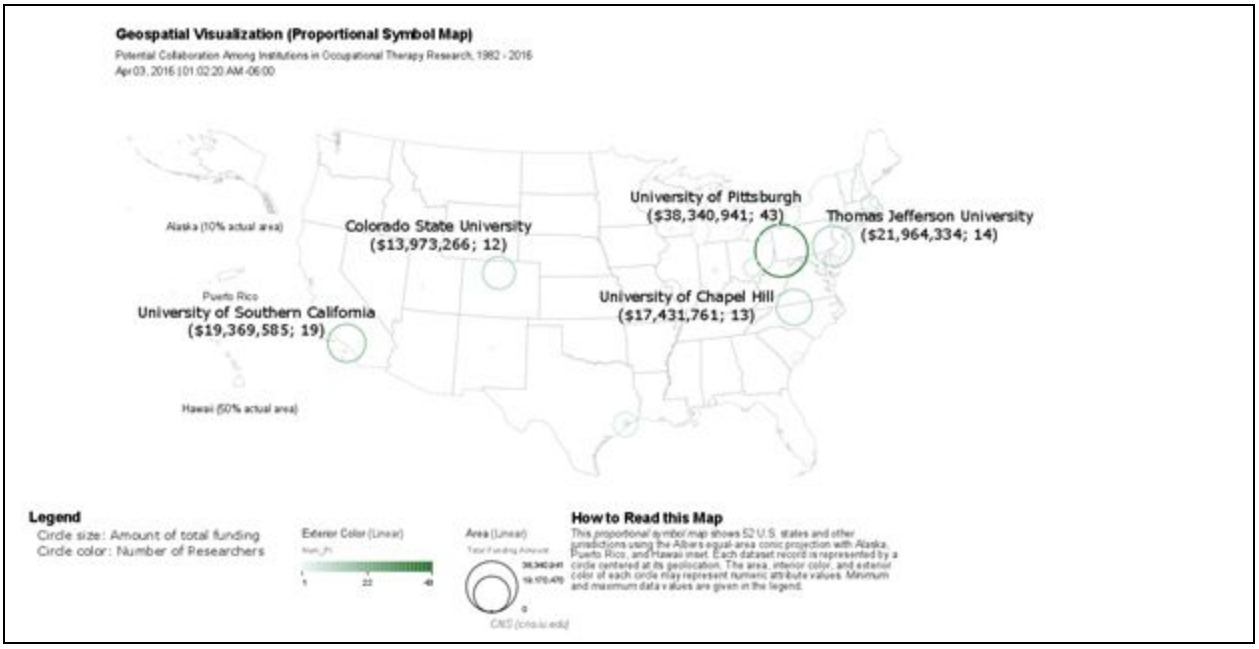
The geospatial analysis was run using Congressional District Geocoder. There were five zip codes which could not been given a congressional district. The longitude and latitude markers were located using GPS Visualizer online tool for the five zip codes. The data was then visualized using proportional symbol map with the size of the edges represents the total amount of funding and the color of the circles represents the number of researchers in sample 1, while in sample 2, the size of the edges represents the number of projects and the color of the circles represent the number of researchers.

The proportional symbol maps clearly show the top five players in the occupational therapy research – The University of Pittsburgh, Thomas Jefferson University, University of Southern California, University of Chapel Hill, and Colorado State University. These institutions have the most researchers who have conducted the most research projects from 1982 until recent year (based on the earliest funded project). The two maps showing different attributes did not differ as much. The map, however, will not be a good visualization to show the topics researched by these institutions.

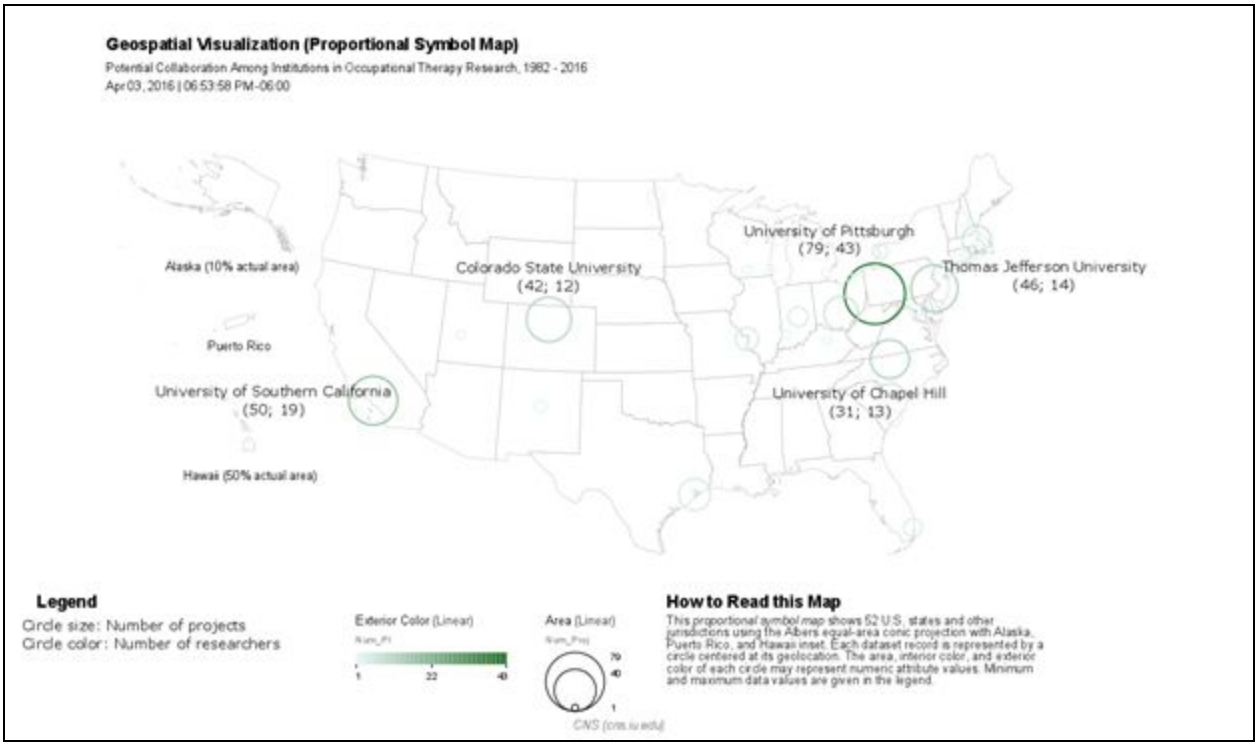
Further work on geospatial analysis and map:

The proportional symbol map function in Sci2 (on my computer) did not show the option to assign the edge color, which will be useful to make the map more readable, visually. I will explore this issue and hoping that the final map will have edge color.

Sample 1: Proportional symbol map showing total amount of funding and number of researchers



Sample 2: Proportional symbol map showing number of research projects and number of researchers



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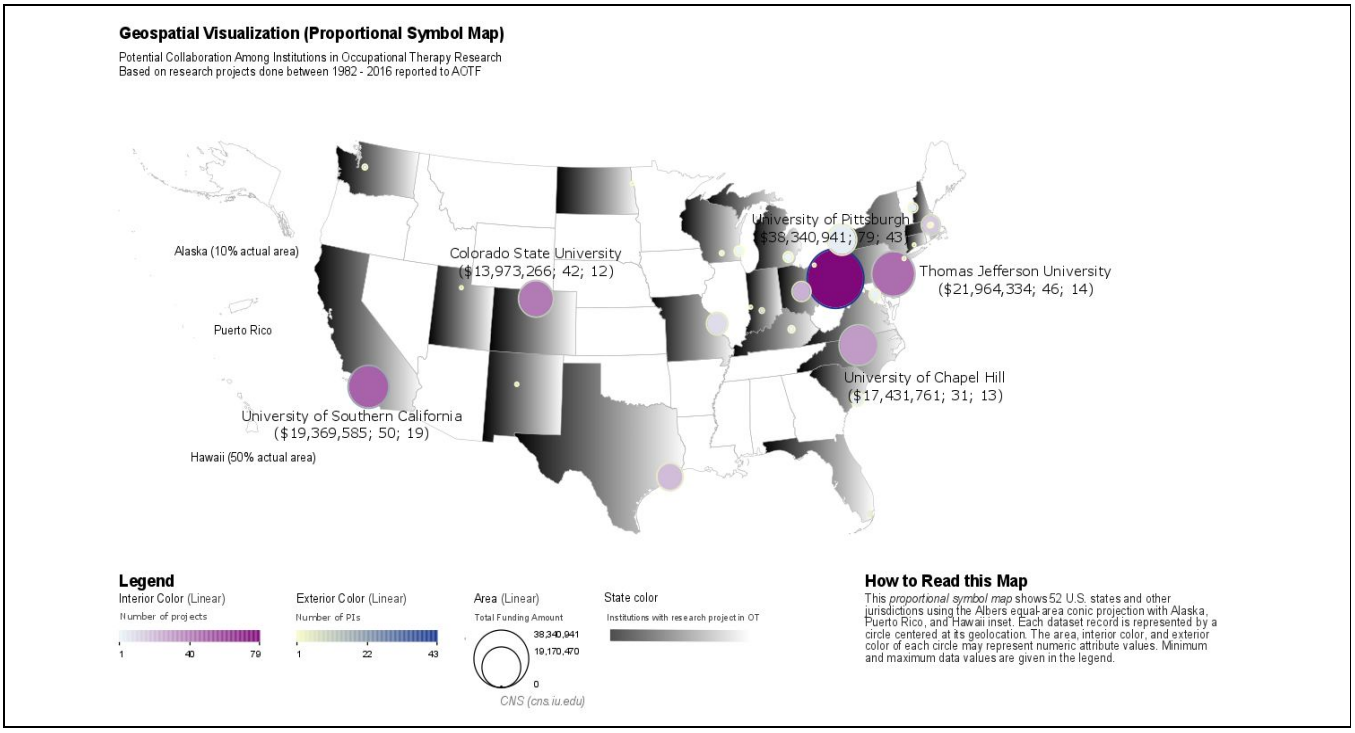
9. What problems surfaced during validation and how does your redesign resolve them?

There were some discrepancies in the locations of the nodes when comparing the geospatial map created using the parameters described earlier in Sci2 and Tableau. The issue seems to stem out from differences in zip codes since zip codes were not provided in the original data set from AOTF. A thorough google search was done to find the best zip codes. Geocoding was rerun on the updated zip codes using the Generic Geocoder. Longitude and latitude information was found on all 29 zip codes. The map was updated to show total funding amount, number of projects and number of researchers.

10. Discussion of challenges and opportunities.

Since the map shows the potential collaboration links among the institutions, it would be helpful to show the network connections based on the keywords. However, trying to create the networks where there are three keyword columns with multiple rows per institution poses some complexities. In addition, the need to use other software like Photoshop, Adobe Illustrator and/or GIMP to overlay the network onto the map also adds to the complexity and is time consuming. The network overlay will certainly be an informational piece to add on the geospatial map for future visualization.



Proportional Symbol Map_2016Apr15.pdf

Network Analysis (lead: Helen Yezerets)

Goal: Complete a network analysis and identify networks of experts and their institutions/expertise areas, projects and diagnosis/ICF/categories then visualize and animate these over time.

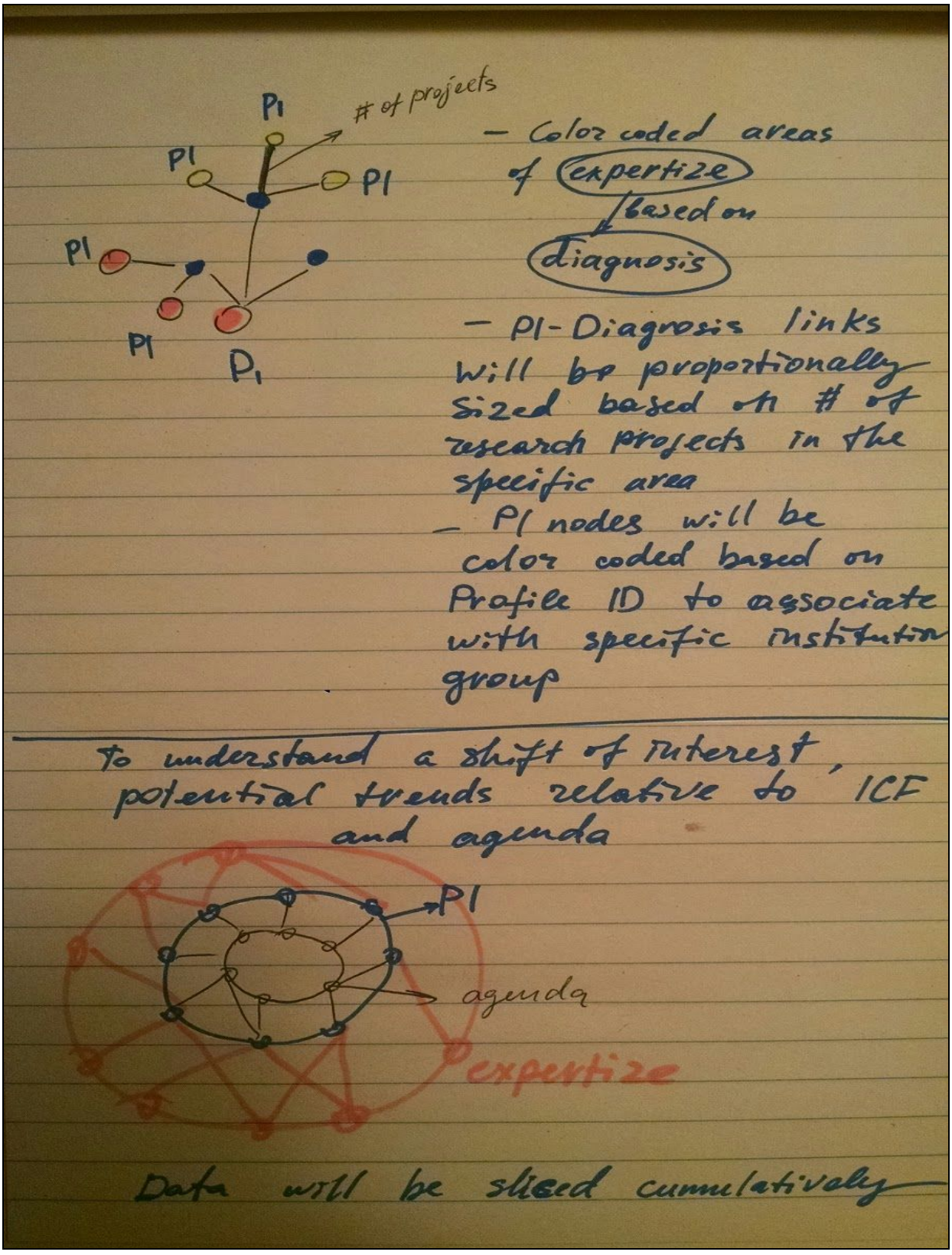
Significance: the network analysis will elicit insights into the existing scientific networks and help to identify scientific leaders for specific expertise areas based on diagnosis/ICF/categories relevant to particular research project.

The following features will be implemented:

- color-coded areas of expertise based on diagnosis description
- PI nodes will be color-coded based on the profile id to associate research projects with specific organizations
- PI-diagnosis links will be proportionally sized based on # of research projects in the specific area.

To understand shift of interest, potential research trend relative to ICF and agenda data will be cumulatively sliced according to the funding date from 1982 to 2016.

Mock-up of visualization



Network Visualizations

#6. Simple statistics of the data sets used, e.g., number of entities, major entity attributes, etc.

The following clean up was performed based on the Julie Bass's feedback:

-Identified projects with duplicate values and deleted projects with highest Project ID number (314, 92, 99, 90, 88, 86, 89, 85, 87, 91)

- assigned ProjectID 9999 to Project ID 1

- reassigned Ellen S Cohn projects to Helen S Cohen

- Updated blank USR_FUNDING_DATE_END with the current date.

Performed crosstab analysis between USR_PRINCIPAL_INVESTIGATOR and number of associated parameters:

USR_PRINCIPAL_INVESTIGATOR (193 unique) vs USR_AGENDA_CATEGORY (7) (excerpt): top 5 PIs depicted in yellow. Complete dataset

USR_PRINCIPAL_INVESTIGATOR	Total Of PROJECT_ID	1	2	3	4	5	6	8
Stephen Page	26	3	12	1	8	1	1	
Kenneth Ottenbacher	25	2	1	1	9	7	3	2
Mary Jane Mulcahey	20	11	3		1	1		4
Patricia Davies	20	9	3		8			
Mary Lawlor	17	9	1	5		1	1	
Scott H. Frey	17	3	2	3	3	3	3	
Roseann Schaaf	15		2		10	1		2
Teresa A. May-Benson	15	8	5		2			
Grace Baranek	14	2	2		9			1
Amanda Jozkowski	12	3	2	2		2	3	
Carolyn Baum	11	1	2	1	4	2		1
Corey McGee	11	6	2		3			
Helen S Cohen	10	2	1	3	2	2		
Joan Rogers	10	1	2		7			
Christine Helfrich	8		2	3		3		
Elizabeth Skidmore	7		5		2			
Fengyi Kuo	7		3	2		2		
Michael Mueller	7	1	1	1	1	1	2	
Olga Solomon	7		2	1		2		2
Arlene Schmid	6		1			1		4
Elizabeth Crais	6		2		1		3	
Elizabeth G. Hunter	6		1	1		3	1	
Erin R. Foster	6		3	3				
Bobbi Pineda	5	1	1	1		2		
Eric Lenze	5	1	3		1			
Ghenet Weldeslassie	5	1	1	1		1	1	
Jan Stube	5		3					2
Shelley D. Portaro	5	2	1		2			
Beth Pfeiffer	4		3		1			
Charles Reynolds	4		1		2		1	
Elicia Dunn Cruz	4	1	1			1	1	
Joseph Piven	4	1			2		1	
Michelle Woodbury	4	1	3					
Naomi Josman	4	3				1		
Christine Arenson	3		1			1		1
Dorothy Edwards	3		2		1			
Eileen S. Auerbach	3	1	1		1			
Jacob J Bloomberg	3	1	1	1				
Jessica Kramer	3	1	2					
Joseph Margolick	3	1		1	1			
Kira Dormann	3				1	1	1	
Linda Watson	3		2		1			
Michael Boninger	3				1		2	
Sharon A. Cermak	3	1	1	1				
Shawn Roll	3	1	1		1			
Steve Cramer	3	1	1	1				
Teresa Damush	3							3
Tracy Chippendale	3		2		1			
Wendy Coster	3	3						
A. Peters	2		1			1		
Aaron M Eakman	2		1	1				
Aaron Steinfeld	2			1			1	
Alexia Metz	2				2			
Alix Sleight	2			1		1		
Amy Wagner	2		2					
Barb Hooper	2				2			
Barbara Bokhour	2		1			1		

USR_PRINCIPAL_INVESTIGATOR vs USR_DIAGNOSIS_AREA(29) (excerpt): top 5 PIs depicted in yellow

Complete dataset

USR_PRINCIPAL_INVESTIGATOR	Total Of PROJECT_ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
Teresa A. May-Benson	41	12									7					8	1						13						
Kenneth Ottenbacher	31				2			1	1			2	1				1		1						4		2	1	
Jeffrey Crabtree	28	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Patricia Davies	26	1			5												1		1	1			12						
Mary Jane Mulcahey	24								2	1														12			3		
Corey McGee	22			4	1									3				3	2					2	2		4		
Elizabeth G. Hunter	21		1	1	2	1	2	1		1			1	1				1	1					2	2		1	1	1
Grace Baranek	20	12																					6						
Roseann Schaaf	20	7																					11						
Christine Helfrich	18			2				2					2				2					3				2	2		2
Stephen Page	18				1									1										1	15				
Mary Lawlor	17	1	13								1																		
Amanda Jozkowski	14	3			1				1	1	1					1		1	1		1		2				1		
Wendy Wood	13	1			1				1		1	1				1	1	1	1			1	1		1	1			
Scott H. Frey	12		3		3									3									3						
Wendy Coster	12	2			1				2	1	2					2					1		1						
Ghenet Weldeslassie	11	1							1		1	1		1		1			1				1		1			1	1
Carla Wilhite	10		1	1									1					1	1					2	1		1		1
Carolyn Baum	10				3							2													2				
Eric Lenze	9							1									3	1	1								2		
Joan Rogers	9			1								1					2	1											
Edward Steinfeld	8		1	1														1				1		1			1		1
Elizabeth Skidmore	8				1																				7				
P.L. Weiss	8				1				1		1	1				1	1		1						1				
Charles Boult	7							1				1	1						1						1		1		
Doris Pierce	7	1			1				1		1					1	1										1		
Elena Volpi	7							1				1						1	1						1		1		
Elizabeth Crais	7	3							1	1	1												1						
Jennie Daplice Feinstein	7	1							1	1	1										1		1					1	
Jessica Kramer	7	1							1	1	3										1								
Kay Wald-Ebbs	7	1			1				1	1	1		1				1												
Kira Dormann	7	1									1					1	1		1							1			
Patricia Fingerhut	7	1							1	1	1					1					1		1						
Jan Stube	6																								3				
Joseph Piven	6	3								1	1						1												
Olga Solomon	6	6																											
Rebecca Edmonson	6	1							1	1	1					1							1						
V. Paquet	6				1									1				1	1								1		1
Arlene Schmid	5																								5				
Beth Pfeiffer	5	4																					1						
Shawn Roll	5													2				2											1
Alexia Metz	4	1									1												2						
Bobbi Pineda	4										1										2		1						
Charles Reynolds	4																3												
Michael Mueller	4										1										1								
Randall Betz	4																	1						1		1			
Shelley D. Portaro	4								2																2				
Yolanda Suarez-Balcazar	4	1									1					1				1									
Aaron M Eakman	3				1																	1							
Craig Velozo	3		1		1																			1					
Ellen Whyte	3																1								2				
Erin R. Foster	3																		3										
Fengyi Kuo	3																2			1									
Helen S Cohen	3																												
Jacqueline Dunbar-Jacob	3			1				1					1																
Kevin D. Evans	3													1				1											1
Kyriakos Markides	3											1	1																
Linda Watson	3	3																											
Michael Munin	3				1																			1	1				
Michelle Woodbury	3																								3				
Naomi Josman	3											1																	
Patrick Kitzman	3				1																			1	1				
S. Logan	3													1				1											1
Teresa Damush	3																								3				
Tracy Chippendale	3																3												
Zeno Franco	3																1					1				1			
Allen Heinlmann	2																							1	1				
Amy Wagner	2				2																								

USR_PRINCIPAL_INVESTIGATOR (193) vs ICF Categories(7) (excerpt) Complete dataset

USR_PRINCIPAL_INVESTIGATOR	Total Of PROJECT_ID	1	2	3	4	5	6	7
Kenneth Ottenbacher	42	6	5	6	9	6	1	9
Teresa A. May-Benson	41	13	11		4	13		
Patricia Davies	34		13	13	1	1	1	5
Stephen Page	29	1	17	3	6	2		
Grace Baranek	26		6	2	5	5	3	5
Mary Jane Mulcahey	24	1	3	7	3	2		8
Mary Lawlor	20	17				3		
Scott H. Frey	18	3	3	3	3	3	3	
Roseann Schaaf	16		11		2			3
Amanda Jozkowski	15	2	2	2	3	3	3	
Corey McGee	15	4	4	2	2	1	1	1
Elizabeth Skidmore	15		7	1	4	3		
Jan Stube	15		1	1	5	4	4	
Joan Rogers	14	1	3	1	3	3		3
Olga Solomon	14	4			4	6		
Carolyn Baum	13	1	2		2	4		4
Erin R. Foster	12		3		3	3	3	
Naomi Josman	11	2	3	2	2	2		
Helen S Cohen	10	3	3	3	1			
Christine Helfrich	9	3			2	3	1	
Tracy Chippendale	9	3	2		2	2		
Mark T. Hegel	8	2			2	2	2	
Michael Mueller	8	1	1	1	1	1	1	2
Arlene Schmid	7	1			1	1		4
Bobbi Pineda	7	2	1		1	2	1	
Fengyi Kuo	7	2	1		1	3		
Barbara Bokhour	6	1	1	1	1	1	1	
Carla Wilhite	6	2		1	1	1	1	
Charles Reynolds	6	1	2		1	1		1
Elizabeth G. Hunter	6				1	2	1	2
Ellen Whyte	6		2	2	1	1		
Jessica Kramer	6				1	3	2	
Michelle Woodbury	6		3		3			
Shawn Roll	6		1	2	2	1		
Shelley D. Portaro	6		2		2	2		
Wendy Coster	6				2	3	1	
Alexia Metz	5		1	1	1	1	1	
Chinghui "Jean" Hsieh	5	1	1	1	1	1		
Elena Volpi	5	1	1	1	1	1		
Elizabeth Schlenk	5	1	1	1	1	1		
Ghenet Weldeslassie	5	1	1		1	1	1	
Leeanne Carey	5		1	1	1	1	1	
Matthew Bair	5		1	1	1	1		1
Rachel Kizony	5	1	1	1		1	1	
Aaron M Eakman	4	1	1		1	1		
Amy Wagner	4		2		1	1		
Beth Pfeiffer	4					4		
Christine Arenson	4	1			1	1	1	
Diane Corman Levy	4	1			1	1	1	
Dorothy Edwards	4		2			2		
Elicia Dunn Cruz	4	1			1	1	1	
Elizabeth Vanderlaan	4		1	1	1		1	
Eric Lenze	4		2			1		1
Gael Orsmond	4				1	2	1	
Janet Poole	4	1	1		1	1		
Kathleen Lyons	4	1			1	1	1	
Kyriakos Markides	4	1	1		1	1		

- Data was sliced by the USR_FUNDING_DATE_START 1982 through 2017 by seven years cumulatively

Number of project was proportionally (times 3) increasing from 18 to 54 to 149 to 406 to 755 in 2016

Properties used:

node.countProjectsperResearcher = PROJECT_ID.count

edge.countProjectsPerDiagnosis=USR_DIAGNOSIS_AREA.count

Network Analysis Toolkit (NAT) was selected.

This graph claims to be directed.

Nodes: 18

Isolated nodes: 0

Node attributes present: label, countProjectsperResearcher, bipartiteType

Edges: 16

No self loops were discovered.

No parallel edges were discovered.

Edge attributes:

Did not detect any nonnumeric attributes.

Numeric attributes:

	min	max	mean
countPr...	1	2	1.125

This network seems to be valued.

Average total degree: 1.7778

Average in degree: 0.8889

Average out degree: 0.8889

This graph is not weakly connected.

There are 3 weakly connected components. (0 isolates)

The largest connected component consists of 9 nodes.

This graph is not strongly connected.

There are 18 strongly connected components.

The largest strongly connected component consists of 1 nodes.

Density (disregarding weights): 0.0523

Additional Densities by Numeric Attribute

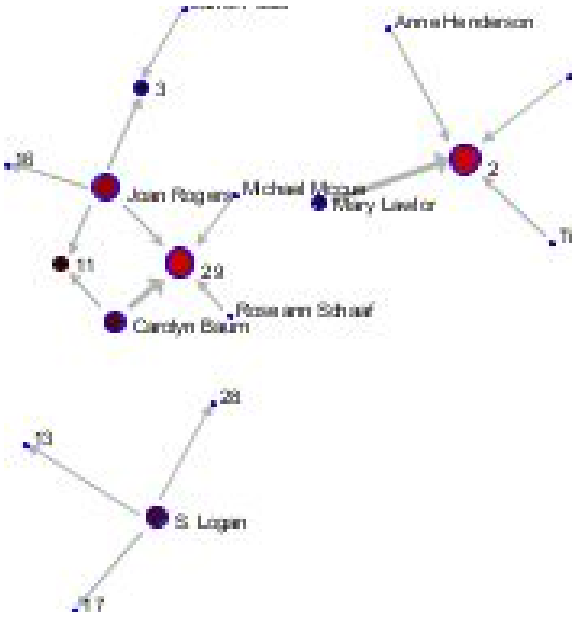
Initial analysis was performed on USR_PRINCIPAL_INVESTIGATOR vs USR_DIAGNOSIS_AREA

#7. Data analysis/visualization (algorithms) applied and resulting visualizations

Two visualization models were created and analyzed based on Network with directed edges from USR_PRINCIPAL_INVESTIGATOR to USR_DIAGNOSIS_AREA.2 visualized using

1)GUESS GEM

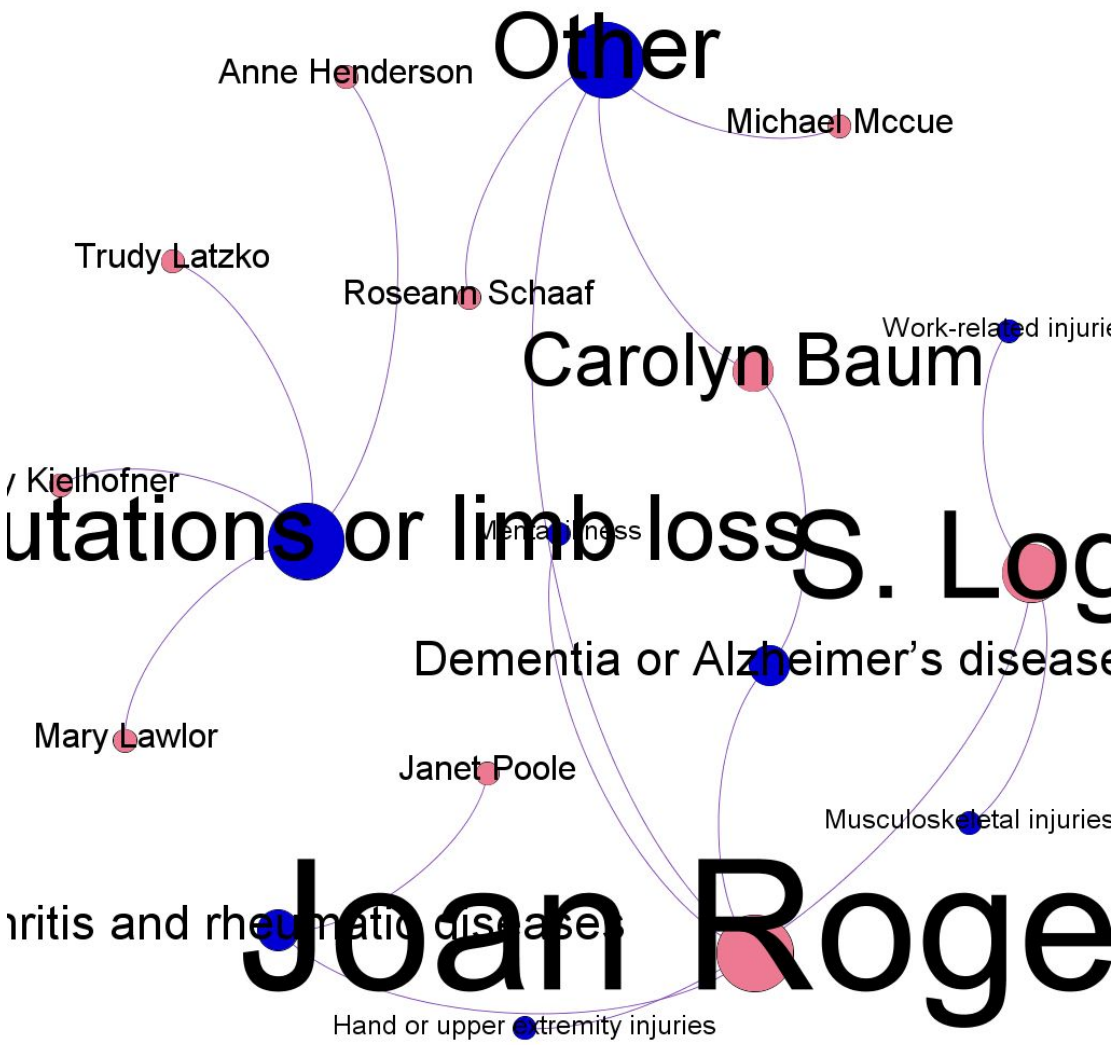
Analyzed time slice 1982 through 1989



Numbers represent the Diagnosis Area ID(1 through 29). Nodes were proportionally sized based on the number of projects per PI. Edges were proportionally sized by number of projects associated with the Diagnosis area

Encountered limitations of the GUESS visualization: cannot easily distinguish between PIs and Diagnosis area.

2)performed viz in GEPHI using Fruchterman Reingold view



- node color by multimode

-label for Researcher sized by out-degree (number of Diagnosis per researcher)

- node sized by degree (number of projects per Diagnosis)

- edges colored by numberProjects perDiagnosisperInvestigator

Preview:default curved

#8. Discussion of key insights gained from the analysis/visualization

For the particular time slice (1982-1989) both types of visualization clearly depicted top players in the OT field being Joan Rogers, S. Logan and Carolyn Baum (nodes and/or labels were sized proportionally to the number of respective projects). In addition, the Diagnosis areas such as 2 - Amputations or limb loss, 29-Other, 3- Arthritis and rheumatic diseases and 11- Dementia or Alzheimer's disease were associated with the most number of research projects.

Even though both algorithms correctly represented the data and the insights, the Gephi algorithm was the most flexible in capturing the types of the nodes used in the bipartite network and allowed to color code PI nodes and diagnosis areas that significantly simplified data analysis. The Gephi algorithm will be used to implement further network visualizations.

9. What problems surfaced during validation and how does your redesign resolve them?

After initial visualization of PI vs Diagnosis in Gephi we realized that coloring nodes based on the bipartite network only depicts major PIs in the field and helps to identify the core types of the diagnoses. At the same time, the essential linkages between individual nodes (PIs and respective diagnoses) become quite obscure. In order to overcome this issue, we decided to provide a Blondel Community Detection analysis that helped to identify additional connections between various diagnosis and researchers.

In order to connect diagnosis descriptions with agenda we tested out several different visualization types including Fruchterman-Reingold with Annotation and Circular Hierarchy, however the Bipartite Network Graph proved to be the most precise and straightforward. The same type of time slicing on the Agenda-Diagnosis data helped to compare PI-Diagnosis with the similar time slice of the Agenda-Diagnosis data and to provide more insights into the nature of OT research during respective time slice.

10. Discussion of challenges and opportunities.

Due to creation of five time slices per network the main challenge was presentation of significant part of the details without compromising the clarity of the images. Since number of the nodes (number of PIs and diagnoses) increased proportionally with every cumulative time slice, in order to minimize crowding of the nodes the last two slices for PI-Diagnosis were restricted to edges with weight >1. Respective isolated nodes were subsequently removed. In addition, we encountered that Gephi cannot provide persistent coloring of the blondel communities by modifying the color based on the percentage of the specific community size in relation to the other communities per time slice. We will continue investigating possibility to use specific colors per community to ensure their color consistency.

Finally, we will work on identifying links between diagnoses and ICF items and will add respective time slices to the previously created network maps.

Network-ppt-slides

Online Data Explorer using Tableau (lead: Peter Annable)

Goal: The intent of this visualization is to provide a simple way for researchers to explore the information available today about Occupational Therapy Research. This can be used in conjunction with the detailed analyses described above to potentially find other connections in the data, or to simply understand the details of research in a given area.

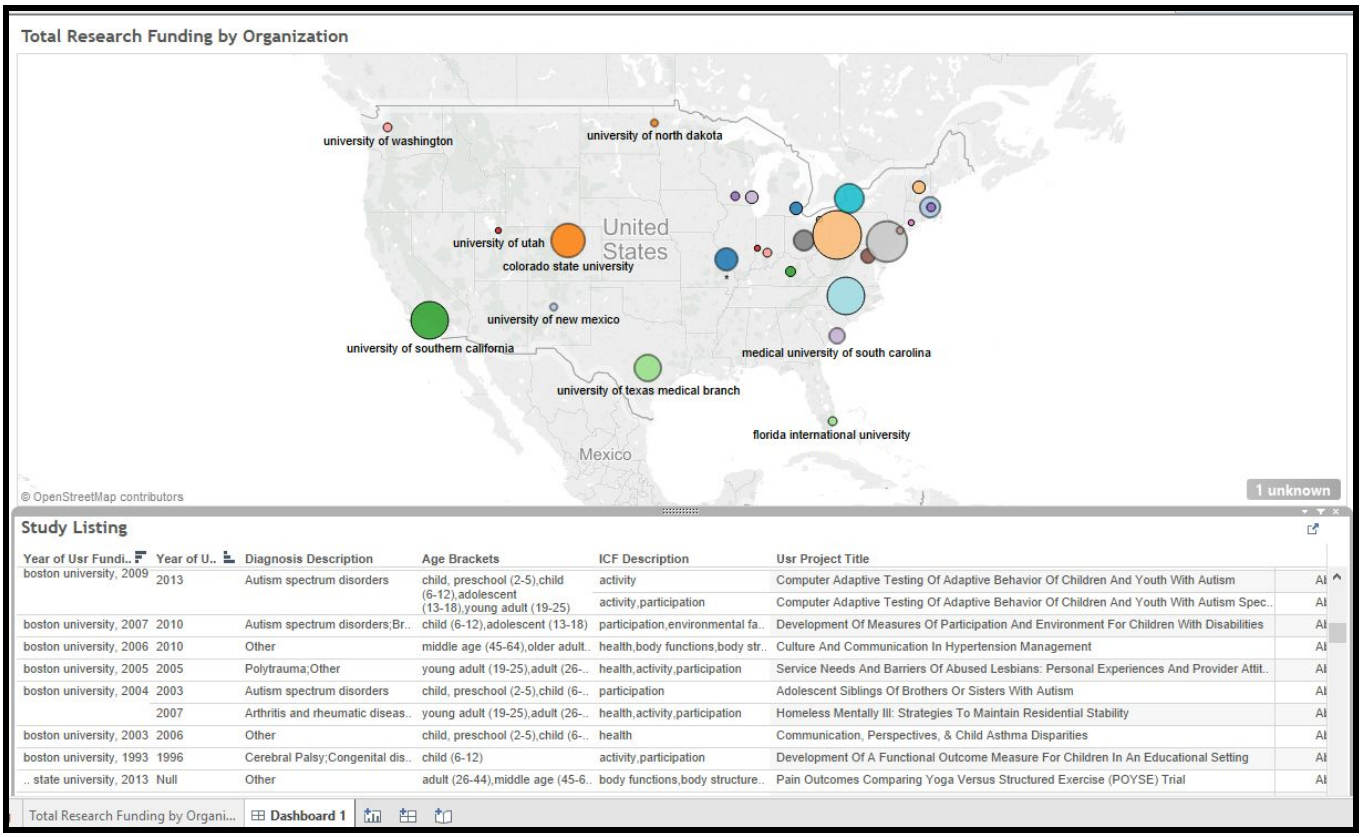
The anticipated visualizations include:

- Use of a tree map and bar graph to understand research concentrations by topic keywords, and ability to click and see what studies make up the included topic.
- Use of a U.S. map to understand research by location
- Research topics organized by amount of funding. Use to understand if certain topics are potentially under represented.
- Note: We are assuming it is permissible to publish these data using Tableau - will verify with the Client

Related work: The AOTF Report to Donors from 2013 and 2014 provide some additional context and examples that the data explorer should connect to. There are no existing visualizations to re-apply.

Visaulization Iterations

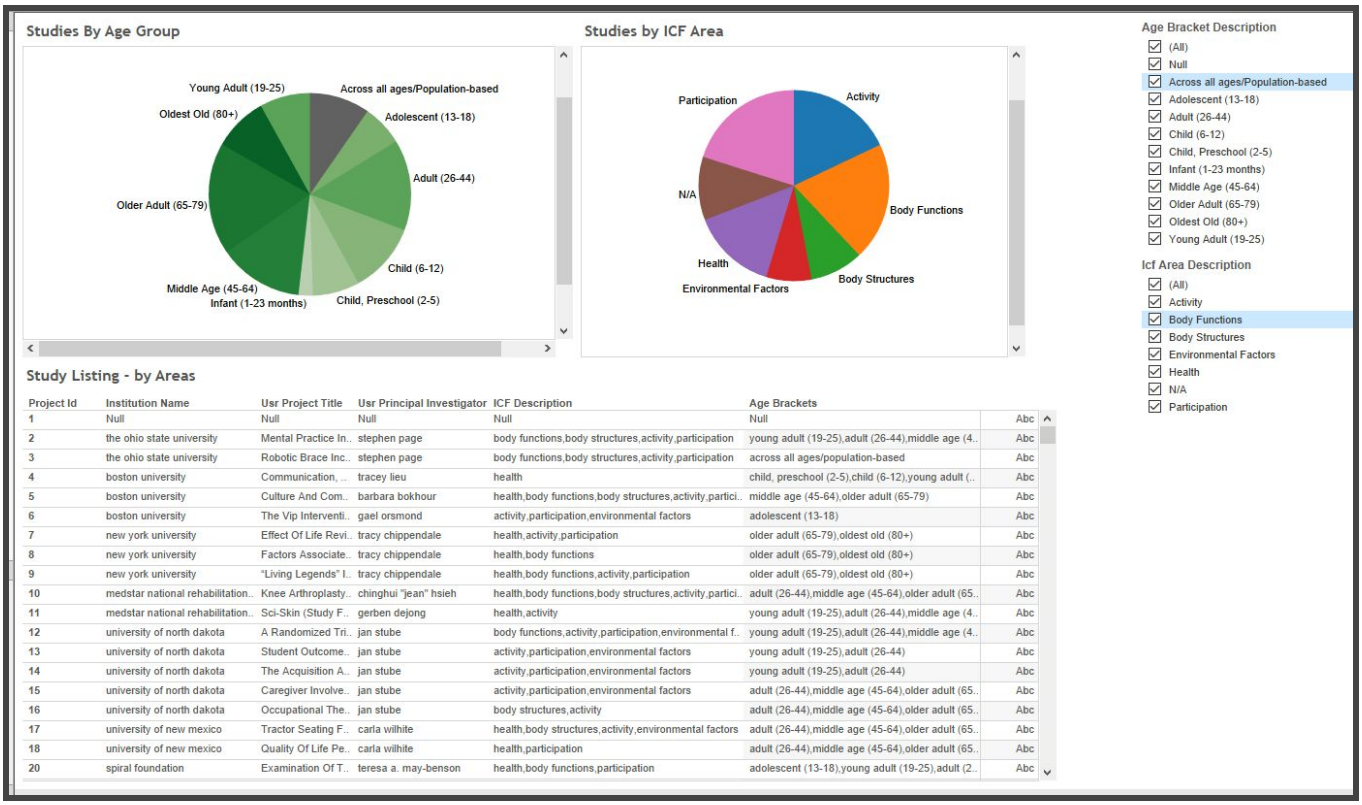
For the first visualization, I will use funding amount to show the total research by each organization. Then allow the user to select from the organization map to see a listing of research projects using Tableau:



For the 2nd Visualization:

This visual allows the user to select and filter a complete list of studies by age group and/or ICF research area. The pie chart shows the relative percentage of studies for each. To produce these charts, I used two versions of the data: in the study listing chart, the Age Brackets and ICF Descriptions are merged value into one cell,this was already done by Mahesh. I then joined this table with the original Age and ICF values listing, which were provided as separate data tables. This allow me to relate the two together.

Both visuals allow the user to interactively make selections and view resulting data.



Project Id	Institution Name	Usr Project Title	Usr Principal Investigator	ICF Description	Age Brackets	
1	Null	Null	Null	Null	Null	Abc
2	the ohio state university	Mental Practice In..	stephen page	body functions,body structures,activity,participation	young adult (19-25),adult (26-44),middle age (4..	Abc
3	the ohio state university	Robotic Brace Inc..	stephen page	body functions,body structures,activity,participation	across all ages/population-based	Abc
4	boston university	Communication, ...	tracey lieu	health	child, preschool (2-5),child (6-12),young adult (..	Abc
5	boston university	Culture And Com..	barbara bokhour	health,body functions,body structures,activity,partici..	middle age (45-64),older adult (65-79)	Abc
6	boston university	The Vip Interventi..	gael orsmond	activity,participation,environmental factors	adolescent (13-18)	Abc
7	new york university	Effect Of Life Revi..	tracy chippendale	health,activity,participation	older adult (65-79),oldest old (80+)	Abc
8	new york university	Factors Associate..	tracy chippendale	health,body functions	older adult (65-79),oldest old (80+)	Abc
9	new york university	"Living Legends" I..	tracy chippendale	health,body functions,activity,participation	older adult (65-79),oldest old (80+)	Abc
10	medstar national rehabilitation..	Knee Arthroplasty..	chinghui "jean" hsieh	health,body functions,body structures,activity,partici..	adult (26-44),middle age (45-64),older adult (65..	Abc
11	medstar national rehabilitation..	Sci-Skin (Study F..	gerben dejong	health,activity	young adult (19-25),adult (26-44),middle age (4..	Abc
12	university of north dakota	A Randomized Tri..	jan stube	body functions,activity,participation,environmental f..	young adult (19-25),adult (26-44),middle age (4..	Abc
13	university of north dakota	Student Outcome..	jan stube	activity,participation,environmental factors	young adult (19-25),adult (26-44)	Abc
14	university of north dakota	The Acquisition A..	jan stube	activity,participation,environmental factors	young adult (19-25),adult (26-44)	Abc
15	university of north dakota	Caregiver Involve..	jan stube	activity,participation,environmental factors	adult (26-44),middle age (45-64),older adult (65..	Abc
16	university of north dakota	Occupational The..	jan stube	body structures,activity	adult (26-44),middle age (45-64),older adult (65..	Abc
17	university of new mexico	Tractor Seating F..	carla wilhite	health,body structures,activity,environmental factors	adult (26-44),middle age (45-64),older adult (65..	Abc
18	university of new mexico	Quality Of Life Pe..	carla wilhite	health,participation	adult (26-44),middle age (45-64),older adult (65..	Abc
20	spiral foundation	Examination Of T..	teresa a. may-benson	health,body functions,participation	adolescent (13-18),young adult (19-25),adult (2..	Abc

9. What problems surfaced during validation and how does your redesign resolve them?

The first issue was getting client approval since the easiest way to share online is via Tableau public. This permission was obtained but with the condition that we not include and funding amounts. Therefore, my data and visuals were updated to use the number of projects to size the proportional symbol map, and not total funding.

The second issue was setting the data up in a way that allowed filtering of multiple data items having multiple values. In our combined data set, we had combined multi-values into one column, which made for easier display of a study details. In order allow for filtering, I added the original mapping tables that mapped each value to its study. Then it took a few attempts to get this relationship set up correctly in Tableau. For example, to preserve all studies and combine with each meta-data item, a LEFT Join is required, not the default INNER join.

10. Discussion of challenges and opportunities.

In Tableau it took quite a while to get the layout of my dashboard in a way I felt was easy to use, and made the most efficient use of screen space. This took several hours. Now that I am more fluent in Tableau, I can more quickly add additional options, and will likely do this before submitting the final version.

Longer term, it would be useful to connect the Tableau template directly to the AOTA database, so that it can be used on an ongoing basis to easily examine submitted research data.

A general overall challenge was coordinating data and visual presentation across the team members. For instance, our Temporal analysis uses time slices by decade, and the network visualizations use 7 year time slices. We didn't realize this issue until it was too late to fix for this submission. This is something we will try to harmonize better for the final presentation. We were able to coordinate a common powerpoint template and color scheme so the final product presentation looks quite professional and should make it easy for our client to understand key insights from our work.