Disability Rights Promotion International

Developing a Global Methodology for Monitoring Human Rights in Media Depictions of Disability

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1. Description of methods used to monitor media coverage of disability

a. Neural networks analysis

Perhaps the largest body of data available to the social scientist is text. The analysis of text, however, is particularly difficult. Two generic methods generally define text analysis.

The first type of text analysis involves careful study of text by skilled interpreters. Discourse and content analysis are generally assumed to produce the deepest and most detailed understanding of text, but is by their labor-intensive nature limited to relatively small texts. Although software to assist content analysis exists, it is mainly to aid the analyst in her/his analysis, and does no analysis itself. Although such software can indeed be extensive and useful, it is mainly a way to search for concepts, phrases, keywords in context (KWIK), and other linguistic structures that must be provided in advance by human analysts who know what they are looking for.

Proximity analysis

A second type of computer software, however, actually performs analysis with little or no guidance by human analysts. These algorithms generally work by calculating the proximities of words in the text. The simplest of these, and the most common, utilize a simple co-occurrence algorithm. In the co-occurrence model, the text is divided into discrete parts (called "cases" in the Catpac model). These cases could be linguistic units, such as sentences or paragraphs, or arbitrary units, such as pages, chapters, articles, or even arbitrary chunks. Co-occurrence software counts the number of times each pair of words co-occurs in the cases, and these numbers of co-ocurrences are used as a measure of the similarity of the words – the higher the co-occurrence, the more similar the words are judged to be.

More powerful proximity models add a "sliding window" instead of the discrete parts or cases. In such models a "window" of several words "slides" through the text. With a three-word window, for example (the size most commonly used by Danowski, 2008) the program will begin with the first three words of a text in the window. Each of these three words will be counted as co-occurring, since they are in the window simultaneously. The window will then slide one word, and words 2, 3 and 4 will now co-occur in the window. When the window has slid through the entire text, the result is a word-by-word matrix of similarities based on co-occurrences in the sliding window.

Neural text analysis

The most powerful model – the one employed in Catpac and Katmandu (Chen, et. al., 2008) adds an artificial neural network (Woelfel, 1993) to the proximity system. Catpac and its larger sibling Katmandu can utilize either a simple case based or window based co-occurrence model, but differ fundamentally from other proximity models. Catpac does not count co-occurrences. Rather, each unique word[1] in the text is assigned an artificial neuron. A neuron, however complicated in actual organic nervous systems, can be considered a simple unit which can be dormant or active. In Catpac, the level of activity for any neuron can vary continuously between zero (dormant) and 1.1.

As in an organic system, these neurons may or may not be interconnected in a way that allows them to share their activation. Thus, if two neurons are interconnected, when one becomes active, it can communicate its activation to the other. If the connection between the two is strong, a large portion of the activation can be communicated; if the connection is weak, proportionally less activation can be communicated. The system of interconnected neurons is referred to as a "neural network."

The operation of the network

When any neuron is in a window (or a case) its activation is set to 1.0. Catpac's window size can be set by the user, but its default value is 7, so, in general, seven words will be in the window at all times. When the program begins, these will, of course, be the first seven words of the text, so the activation of each of the first seven words will be set to 1.0.

In an actual organic brain, when some neurons are activated, they will communicate their activation to other neurons to which they are connected. But when Catpac is reading the first seven words of the text, none of the neurons are yet connected and *only* the first seven words will be active. The program then polls all neurons, determines their levels of activation, and increments the connection between all pairs of active neurons proportionally to their activations. Obviously, the first seven words in the window – and *only* those words -- will all be active, and the connections among them will all be incremented.

The window then slides one word to the right, so words 2 through 8 are now in the window, and the process is repeated. As the window continues to move through the text in this manner, it is likely that some of the words in the window may be connected to other words not in the window. Thus, activation of the words in the window may lead to the activations of other words as well. Again, the connection among all active words is strengthened proportionally to their co-activation.

At each cycle all connections are weakened by a small amount to simulate a constant rate of forgetting, which is natural to all organisms. Due to the forgetting, only those words that are frequently co-active will be tightly connected. Casual connections due to chance or other minor factors are forgotten. Also, at each cycle, the matrix of connection strengths is centered by subtracting the mean connection strength from each cell and normalized so that the largest connection strength is 1.0.

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[1] Multiple occurrences of the same word are considered one "unique" word.

As with the other propinquity based methods, the result of Catpac analysis is a word-by-word matrix. But instead of counts of co-occurrences in the text's cases or moving windows, Catpac's matrix contains connection strengths among the neurons and thereby, the words they represent; these connections may vary in strength and are not just on or off, connected or not. Accordingly, the patterns of connections among the neurons in the network are simulacra of the patterns the network encountered in the text. As in an organic brain, connections among the neurons form the network's memory of what it has encountered. Also, as in an organic brain, the memories represent only the systematic patterns of experience; for the most part, minor or infrequent relationships have been forgotten. The connections strengths, then, represent the core concepts in the text.

Data presentation

Whatever method is used to obtain the square words-by-words matrix, the matrix needs to be represented in a simple and graphic way. The most common procedure is cluster analysis, in which the matrix is analyzed to find out how the words group together or "cluster." Catpac provides the option for 7 different cluster analysis algorithms; the default algorithm is Ward's Method. The output of the cluster analysis is arrayed in a dendogram (sometimes spelled "dendrogram"), which is illustrated in Table 1.

Words are written vertically across the top of the dendogram. Underneath the words, patterns of carets underlie the words that go together. The higher the structure of the carets, the more closely the words above it are connected. At the extreme right of the dendogram, the highest part of the structure occurs under the words "people" and "disabilities", indicating that these are the two most closely connected words in the text. To the left, a slightly lower structure underlies the words "special" and "education." At the highest level, "people" and "disabilities" form one cluster, and "special" and "education" form another.

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WARDS METHOD

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Table 1: Dendogram for the term “disabilities”

To the left and slightly lower, “learning” and “disability” form a third cluster. Slightly lower and to the right, we can see that “students” joins the “special education” cluster. As we continue to move downward in the dendogram, we can see new clusters forming, and previously distinct clusters merging into more complex clusters. To the left of the dendogram, a large cluster contains the terms “provide”, “support”, “state”, “child”, “needs”, “parent”, “home,” “care”, and “center”. To the right of this cluster there is a “public school” cluster, including also “first”, “time”, “help”, “life” and “work”. To the right of this is a cluster including “disabled”, “children”, “community”, “services”, “learning”, and “disabilities.” To the right of this is a cluster concerning “special”, “education”, and “students.” Last, there is the very strong cluster, “people” and “disabilities.” These clusters represent the most important concepts which underlie the text.

A second, more precise method of presenting the same information is the perceptual map. Since the connections among the words can be interpreted as “distances,” it is possible to calculate the coordinates of the words in a visual map. Catpac uses the Galileo™ algorithm (Woelfel & Fink, 1980) to compute these coordinates, which are displayed by the program ThoughtView (Woelfel, 1993) in Figure 1.

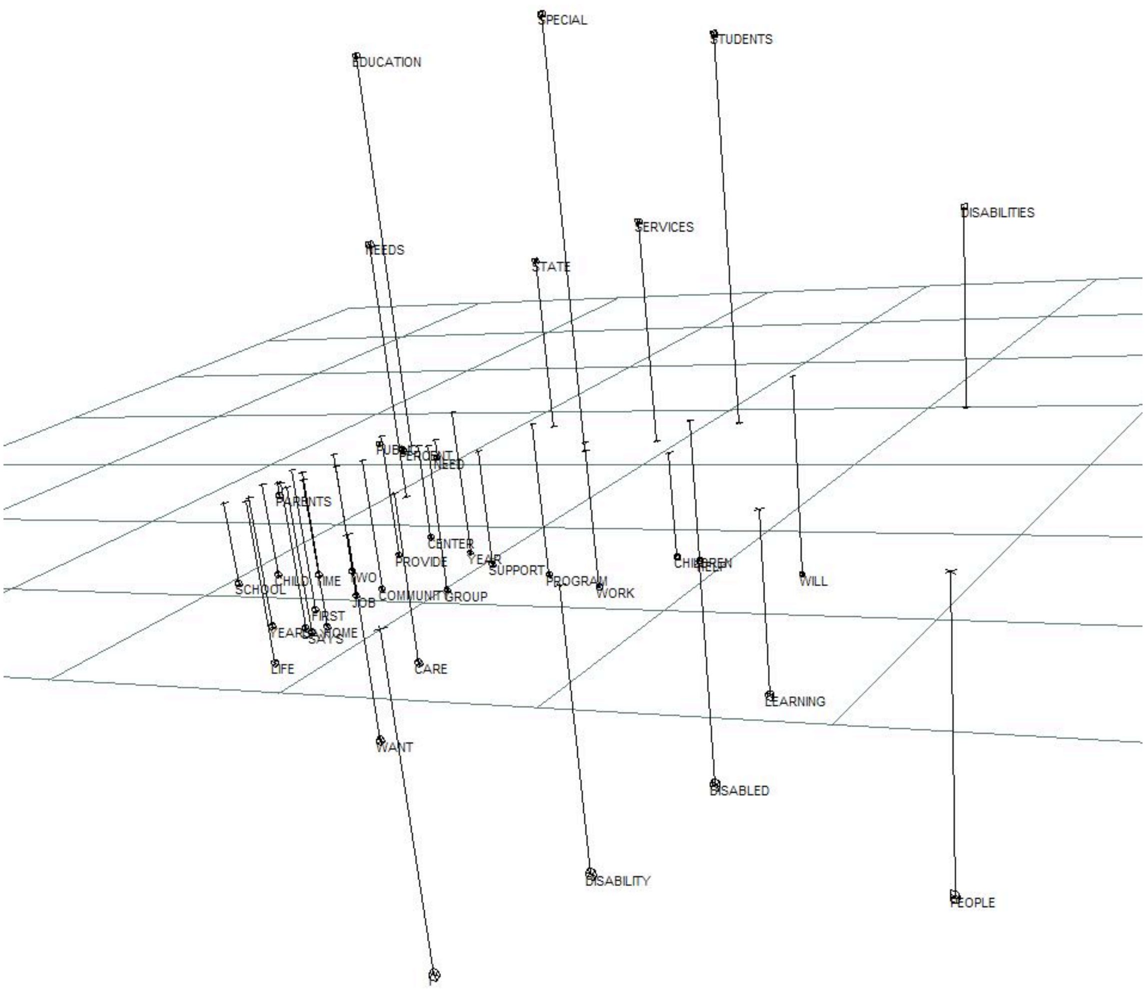

Figure 1. ThoughtView Plot of Disabilities

The “People” and “disabilities” cluster is shown by these two terms standing off to the right of the picture. The “school” cluster is tightly grouped at the left side of the picture, while the “special education” cluster is at the top. To the right of the “school” cluster the “learning”, “disabled”, “children”, “community”, “services” cluster can be seen to the right of the “school” cluster.

ThoughtView allows real time interaction with the picture – it can be rotated, zoomed, panned and otherwise manipulated to help understand the structure. It is also possible to magnify the plot using the zoom feature in a typical word processor. By doing this, and referring back to the dendogram, it is possible to get a good visual understanding of how the concepts relate to each other.

Statistics

Catpac also presents extensive quantitative information to aid in analysis, most importantly the frequencies of occurrences[2] of the words. Table 2 shows that the “disabilities” text contained 9,711 words, followed by lists of the top 40 words in order of frequency of occurrence and in alphabetical order. Catpac allows the user to specify how many unique words to analyze; in this analysis the maximum number of words to analyze was set at 40. The frequency of occurrences for each unique word is listed as both a count and as a percentage of all word occurrences. (“Case freq” and “case pct” refer to the percentages of all cases in which the words occurred if casewise analysis was used; in this study only the sliding windows method was employed.) Thus the most frequently occurring word is “disabilities”, which occurred 1063 times and represented 10.9% of all occurrences. The least frequently occurring words of the top 40 words were “child”, “day”, and “want”, each of which occurred 113 times, for 1.2% of all occurrences.

[2] Catpac offers the option of excluding certain words from analysis. These are generally articles, prepositions and other words that experience has indicated have no significance, yet occur frequently enough to distort analysis. Often, for example, the most frequently occurring word in a text is “the”. A default list of excluded terms is included in a file called default.exc, but this file may be edited or substituted by the user.

TOTAL WORDS	9711	THRESHOLD	0.000
TOTAL UNIQUE WORDS	40	RESTORING FORCE	0.100
TOTAL EPISODES	123938	CYCLES	1
TOTAL LINES	7889	FUNCTION	Sigmoid (-1 - +1)
		CLAMPING	Yes

DESCENDING FREQUENCY LIST

WORD	FREQ	PCNT	CASE FREQ	CASE PCNT
DISABILITIES	1063	10.9	7398	6.0
PEOPLE	919	9.5	6378	5.1
I	568	5.8	3808	3.1
WILL	454	4.7	3157	2.5
DISABILITY	366	3.8	2529	2.0
DISABLED	335	3.4	2323	1.9
SCHOOL	323	3.3	2223	1.8
SERVICES	308	3.2	2143	1.7
STUDENTS	298	3.1	2067	1.7
CHILDREN	266	2.7	1856	1.5
YEAR	259	2.7	1785	1.4
WORK	249	2.6	1729	1.4
EDUCATION	244	2.5	1685	1.4
SPECIAL	242	2.5	1684	1.4
STATE	232	2.4	1614	1.3
HELP	217	2.2	1512	1.2
YEARS	215	2.2	1493	1.2
PROGRAM	203	2.1	1415	1.1
COMMUNITY	189	1.9	1321	1.1
GROUP	173	1.8	1201	1.0
LEARNING	172	1.8	1197	1.0
TIME	159	1.6	1113	0.9
NEEDS	145	1.5	1015	0.8
CENTER	143	1.5	1001	0.8
FIRST	141	1.5	987	0.8
NEED	139	1.4	971	0.8
SUPPORT	138	1.4	965	0.8
LIFE	134	1.4	927	0.7
PUBLIC	133	1.4	931	0.8
HOME	125	1.3	871	0.7
PARENTS	123	1.3	850	0.7
SAYS	119	1.2	825	0.7
PERCENT	117	1.2	755	0.6
CARE	116	1.2	808	0.7
JOB	116	1.2	803	0.6
PROVIDE	115	1.2	805	0.6
TWO	114	1.2	787	0.6
CHILD	113	1.2	781	0.6
DAY	113	1.2	768	0.6
WANT	113	1.2	786	0.6

ALPHABETICALLY SORTED LIST

WORD	FREQ	PCNT	CASE FREQ	CASE PCNT
CARE	116	1.2	808	0.7
CENTER	143	1.5	1001	0.8
CHILD	113	1.2	781	0.6
CHILDREN	266	2.7	1856	1.5
COMMUNITY	189	1.9	1321	1.1
DAY	113	1.2	768	0.6
DISABILITIES	1063	10.9	7398	6.0
DISABILITY	366	3.8	2529	2.0
DISABLED	335	3.4	2323	1.9
EDUCATION	244	2.5	1685	1.4
FIRST	141	1.5	987	0.8
GROUP	173	1.8	1201	1.0
HELP	217	2.2	1512	1.2
HOME	125	1.3	871	0.7
I	568	5.8	3808	3.1
JOB	116	1.2	803	0.6
LEARNING	172	1.8	1197	1.0
LIFE	134	1.4	927	0.7
NEED	139	1.4	971	0.8
NEEDS	145	1.5	1015	0.8
PARENTS	123	1.3	850	0.7
PEOPLE	919	9.5	6378	5.1
PERCENT	117	1.2	755	0.6
PROGRAM	203	2.1	1415	1.1
PROVIDE	115	1.2	805	0.6
PUBLIC	133	1.4	931	0.8
SAYS	119	1.2	825	0.7
SCHOOL	323	3.3	2223	1.8
SERVICES	308	3.2	2143	1.7
SPECIAL	242	2.5	1684	1.4
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TIME	159	1.6	1113	0.9
TWO	114	1.2	787	0.6
WANT	113	1.2	786	0.6
WILL	454	4.7	3157	2.5
WORK	249	2.6	1729	1.4
YEAR	259	2.7	1785	1.4
YEARS	215	2.2	1493	1.2

Table 2: Frequency counts of words for Disabilities

The greatest virtue of neural network analysis of text is that it gives the deepest level of analysis that can be achieved automatically, that is, without the intervention of human analysts. This makes it ideal for use in scanning very large bodies of text early, as a screening device to detect areas of interest that might warrant deeper scrutiny via discourse or content analysis.

This capability to provide relatively deep analyses of very large amounts of text without expert intervention suggests two effective ways to implement the technology. First, a very small non-technical staff would be sufficient to monitor worldwide flows of disability rights information and post results to a website on an ongoing basis. Participating researchers could then access these data from anywhere in the world and quickly be apprised of emerging trends. Second, the technology is suitable for use by non-technical personnel whose expertise lies in areas other than computing and text analysis. This means that stand-alone neural analysis kits could be provided to participating researchers around the world to allow local analysis of media on demand.

These references come from the draft for all sections of *Developing a Global Methodology for Monitoring Human Rights in Media Depictions of Disability:*

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