Beyond Bags of Words: Inferring Systemic Nets

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Abstract—Textual analytics based on representations of documents as bags of words have been reasonably successful. However, analysis that requires deeper insight into language, into author properties, or into the contexts in which documents were created requires a richer representation. Systemic nets are one such representation. They have not been extensively used because they required human effort to construct. We show that systemic nets can be algorithmically inferred from corpora, that the resulting nets are plausible, and that they can provide practical benefits for knowledge discovery problems. This opens up a new class of practical analysis techniques for textual analytics.

I. MOTIVATION

Sets of documents represent one of the largest sources of “big data”, with web search engines indexing tens of billions of pages. For information retrieval, where the key problem is to identify the content of a document, the bag-of-words model of text has proven extremely successful, even for languages such as English where word order is crucial to meaning. Sentences such as “the criminal shot the officer” and “the officer shot the criminal” are equally plausible responses to queries about criminals and officers, but much less equivalent from the perspective of, say, the media.

Many textual analytics tasks assess documents based not just on what they contain, but how they were built – their significance depends on properties that derive from the author, the author’s goals or intent, and the situation or context in which the document was created. Examples include: determining a document’s authorship, an author’s gender or age, an author’s opinions (polarity, sentiment), an author’s intention, and whether the author is being knowingly deceptive.

Such tasks are key to domains such as e-discovery (finding significant emails in a corporate archive), intelligence (finding meaningful threats in a set of forum posts), measuring the effectiveness of a marketing campaign (in online social media posts), or predicting an uprising (using Twitter feed data).

Although bag-of-words approaches have been moderately successful for such problems, they tend to hit a performance wall (80% prediction accuracy is typical) because the representation fails to capture sufficient subtleties [13]. There have been attempts to increase the quality of representations, for example by extracting parse trees (that is, context-free grammar representations) but this focuses entirely on (somewhat artificial) language structure, and not at all on mental processes [6]. Other approaches leverage syntactically expressed semantic information, for example by counting word bigrams, by using Wordnet [11], or using deep learning [12].

Fig. 1. A simple example of a systemic net

One approach that shows considerable promise is systemic functional linguistics [9], [4], [3], a model of language generation with sociological origins and an explicit focus on the effect of the creator’s mental state and social setting on a created document. In this model, the process of generating an utterance (a sentence, a paragraph, or an entire document) is conceived of as traversing a systemic net, a set of structured choices. The totality of these choices defines the created utterance. At some nodes, the choice is disjunctive: continue by choosing this option or by choosing that one. At others, the choice is conjunctive: choose a subset of these options and continue in parallel down several paths.

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A systemic net is explanatory at three different levels. First, the existence of a net organizes constructions into categories and so explains some aspects of how the pieces in a text fit together.

Second, the choices made by individuals traversing a net are not typically unique; rather, they cluster into common choice patterns that reflect particular kinds of textual targets. This is because there are social rules that govern acceptable end-products. Each individual can write with an individual style, but we can also say that some set of documents by different authors are written in a down-to-earth style, and another set in a flowery style. This idea of a consistent set of choices in a net, leading to detectable consistencies in the resulting documents is called a register. Thus the set of registers associated with a net are also explanatory.

Third, for any particular document we can list the choices made in its construction, and this becomes a record that describes that document at a higher level of abstraction than as a bag of words. This level of explanation is most directly useful for knowledge discovery – such a description of choices can be used for clustering or for prediction.

Thus the advantages of a systemic functional approach to textual analytics are:

- The choices within the net are a smaller, more abstract, and more structured set than the choice of individual words, and therefore provide a stronger foundation for knowledge discovery – a kind of structured attribute selection; and
- These choices reflect, and make accessible, the mental state of the author/speaker and his/her perception of the social situation for which the text was constructed. This enables a kind of reverse engineering of how the text came to be, that is knowledge discovery about authors and settings.

The reason why systemic net approaches have not been more widely used in textual analytics is primarily because they have, so far, been constructed by computational linguists, often requiring several person-years to build, even when modestly sized. Some substantial systemic nets have been built, but usually within the context of projects where they have been kept confidential; those that are public, like the Appraisal Net above, are usually small.

The contribution of this paper is twofold:

- We show that it is possible to infer systemic nets from corpora using Non-Negative Matrix Factorization (NNMF), and that these nets are plausibie. Thus we are able to construct systemic nets for any corpus, and for any set of relevant words. This creates a new path to representing corpora at a deeper level, but without the need (and cost) for substantial human input.
- We show that the resulting systemic nets organize corpora more strongly than the corresponding bags of words, and that this organization improves both clustering and prediction tasks, using authorship prediction as a demonstration task.

This removes the bottleneck to the widespread use of systemic-network approaches, which opens up large, variable corpora to new, deeper levels of analysis.

Section 2 describes some of the related work leveraging systemic nets for knowledge discovery tasks. In Section 3 we introduce the process for inducing systemic nets from data and show the results on a modest corpus of novels. In Section 4, we demonstrate some of the benefits of using the resulting nets.

II. RELATED WORK

There have been several applications of predefined systemic nets to textual prediction problems. For example, Whitelaw et al. [13] show improvement in sentiment analysis using the...
Appraisal Net mentioned above. Argamon et al. show how to predict personality type from authored text, again using systemic functional ideas [14]. Herke-Couchman and Patrick derive interpersonal distance from systemic network attributes [5].

The most successful application of systemic functional techniques is the Scamseek project. The goal of this project was to predict, with high reliability, web pages that represented financial scams and those that represented legitimate financial products. This is a challenging problem – the differences between the two classes are small and subtle, and even humans perform poorly at the margins. The fraction of documents representing scams was less than 2% of the whole. This project’s predictive model was successfully deployed on behalf of the Australian Securities and Investments Commission [10]. However, the effort to construct the registers corresponding to normal and (many varieties of) scam documents was substantial.

Kappagoda [7] shows that word-function tags can be added to words using conditional random fields, in the same kind of general way that parsers add part-of-speech tags to words. These word-function tags provide hints of the systemic-functional role that words carry. This is limited because there is no hierarchy. Nevertheless, he is able to show that the process of labelling can be partially automated and that the resulting tags aid in understanding documents.

III. INDUCTIVE DISCOVERY OF SYSTEMIC NETS

The set of choices in a systemic net lead eventually, at the leaves, to choices of particular (sets of) words. One way to conceptualize a systemic net, therefore, is as a hierarchical clustering of words, with each choice representing selection of a subset. We use this intuition as a way to inductively construct a systemic net: words that are used together in the same document (or smaller unit such as a sentence or paragraph) are there because of a particular sequence of choices. An inductive, hierarchical clustering can approximate a hierarchical set of choices.

Our overall strategy is to build document-word matrices (where the document may be as small as a single sentence), and then cluster the columns (that is, the words) of such matrices using the similarity of the documents in which they appear. The question then is: which clustering algorithm(s) to use.

In this domain, similarity between a pair of documents depends much more strongly on the presence of words than on their absence. Conventional clustering algorithms, for example agglomerative hierarchical clustering and other algorithms that use distance as a surrogate for similarity, are therefore not appropriate, since mutual absence of a word in two different documents is uninformative, but increases their apparent similarity.

Singular value decomposition is reasonably effective (J.L. Creasor, unpublished work) but there are major issues raised by the need to normalize the document-word matrix so that the cloud of points it represents is centered around the origin. Typical normalizations such as z-scoring confute median frequencies with zero frequencies and so introduce artifacts that are difficult to compensate for in subsequent analysis.

We therefore chose to use Non-Negative Matrix Factorization, since a document-word matrix naturally has non-negative entries. An NNMF decomposes a document-word matrix, \( A \), as the product of two other matrices:

\[
A = WH
\]

If \( A \) is \( n \times m \), then \( W \) is \( n \times r \) for some chosen \( r \) usually much smaller than either \( m \) or \( n \), and \( H \) is \( r \times m \). All of the entries of \( W \) and \( H \) are non-negative, and there is a natural interpretation of the rows of \( H \) as ‘parts’ that are ‘mixed’ together by each row of \( W \) to give the observed rows of \( A \).

Algorithms for computing an NNMF are iterative in nature, and the results may vary from execution to execution because of the random initialization of the values of \( W \) and \( H \). In general, the results reported here are obtained by computing the NNMF 10 times and taking the majority configuration. We use a conjugate gradient version of NNMF, using Matlab code written by Pauca and Plemmons.

There are two alternative ways to use an NNMF, either directly from the given data matrix, or starting from its transpose. If we compute the NNMF of the transpose of \( A \), we obtain:

\[
A' = WH
\]

and, in general, it is not the case that \( \bar{H} = W' \) and \( \bar{W} = H' \). Experiments showed that results were consistently better if we applied the NNMF to \( A' \), that is to the word-document matrix. The textual unit we use is the paragraph. A single sentence might, in some contexts, be too small; a whole document is too large since it reflects thousands of choices.

We extracted paragraph-word matrices in two ways. A parts-of-speech-aware tagger made it possible to extract the frequencies of, for example, all pronouns or all determiners [2]. For larger word classes, such as adjectives, it was also possible to provide the tagger with a given list and have it extract only frequencies of the provided words. Frequency entries in each matrix were normalized by the total number of words occurring in each paragraph, turning word counts into word rates. This compensates for the different lengths of different paragraphs.

Superior results were obtained by choosing only \( r = 2 \) components. In the first step, the \( W \) matrix has dimensionality \( \text{number of words} \times 2 \), with non-negative entries. Each word was allocated to the cluster (column) with the largest entry in the corresponding row of \( W \), and the process repeated with the two submatrices obtained by splitting the rows of \( A' \) based on this cluster allocation. This process continued until the resulting clusters could not be cleanly separated further. These clusters therefore form a binary tree where each internal node contains the union of the words of its two children.

Each NNMF was repeated 10 times to account for the heuristic property of the algorithm. We were able to leverage...
this to estimate the confidence of each clustering. For example, there were occasionally particular words whose membership oscillated between two otherwise stable clusters, and this provided a signal that they didn’t fit well with either. We were also able to use this to detect when to stop the recursive clustering: either clusters shrunk until they contained only a single word (usually a high-frequency one), or their subclusters began to show no consistency between runs, which we interpreted to mean that the cluster was being over-decomposed.

The result of applying this recursive NNMF algorithm to a word-paragraph matrix is a hierarchical binary tree whose internal nodes are interpreted as choice points, and whose leaves represent the “outputs” that result from making the choices that result in reaching that leaf. A leaf consists of a set of words that are considered to be, in a sense, equivalent or interchangeable from the point of view of the total set of words being considered. However, this view of leaves contains a subtle point. Suppose that a leaf contains the words “red” and “green”. These are clearly not equivalent in an obvious sense, and in any given paragraph it is likely that an author will select only one of them. In what sense, then, are they equivalent? The answer is that, from the author’s point of view, the choice between them is a trivial one: either could serve in the context of the document (fragment) being created. Thus a leaf in the systemic net contains a set of words from which sometimes a single word is chosen and sometimes a number of words are chosen – but in both cases the choice is unconstrained by the setting (or at least undetectably unconstrained in the available example data).

We have remarked that choices at internal nodes in a systemic net can be disjunctive or conjunctive. However, in our construction method each word in a particular document is allocated to exactly one cluster or the other. We estimate the extent to which a choice point is conjunctive or disjunctive by counting how often the choice goes either way across the entire set of documents, that is we treat conjunction/disjunction as a global, rather than a local, property. (It would be possible to allocate a word to both clusters if the entries in the corresponding row of \( W \) had similar magnitude, and therefore detect conjunctive choices directly. However, deciding what constitutes a similar magnitude is problematic because of the variation between runs deriving from the heuristic nature of the algorithm.)

IV. INFERRED SYSTEMIC NETS

The data used for proof of concept of this approach is a set of 17 novels downloaded from gutenberg.org and lightly edited to remove site-specific content. These novels covered a period of about a century from the 1830s to the 1920s and represent well-written, substantial documents. For processing they were divided into paragraphs; because of the prevalence of dialogue in novels, many of these paragraphs are actually single sentences of reported speech. The total number of paragraphs is 48,511. The longest novel contained 13,617 paragraphs (Les Miserables) and the shortest 736 (The 39 Steps).

We selected six different categories of words for experiments as shown in Table I.

| Group type          | Words                                                                 |
|---------------------|----------------------------------------------------------------------|
| Personal Pronouns   | I, me, my, mine, myself, we, us, our, ours, ourselves, you, your, yours, yourself, yourselves, they, their, theirs, them, themselves, he, him, his, himself, she, her, hers, herself, it, its, itself, one, one’s |
| Adverbs             | afterwards, already, always, immediately, last, now, soon, then, yesterday, above, below, here, outside, there, under, again, almost, ever, frequently, generally, hardly, nearly, never, occasionally, often, rarely |
| Auxiliary verbs     | was, wasn’t, had, were, hadn’t, did, didn’t, been, weren’t, are, is, does, am, has, don’t, haven’t, doesn’t, aren’t, do, isn’t, have, be, hasn’t |
| Positive auxiliary verbs | was, had, were, did, been, is, does, are, am, has, do, have, be |
| Adjectives          | good, old, little, own, great, young, long, such, dear, poor, new, whole, sure, black, small, full, certain, white, right, possible, large, fresh, sorry, easy, quite, blue, sweet, late, pale, pretty |
| Verbs               | said, know, see, think, say, go, came, make, come, went, seemed, made, take, looked, thought, saw, tell, took, let, going, get, felt, seen, give, knew, look, done, turned, like, asked |

![Fig. 3. Systemic net inferred for pronouns](image)

TABLE I
LIST OF WORDS USED TO CREATE THE SYSTEMIC NETWORKS

Figure 3 shows the systemic net of pronouns. In all of these figures, the thickness of each line indicates how often the corresponding path was taken as the result of a choice. Lines in blue represent the “upper” choice, red the “lower” choice, and black the situation where both choices occurred with approximately equal frequency.

The top-level choice (1) in this net is between pronouns where the point of view is internal to the story, and where the point of view is of an external narrator. This seems plausible, especially in the context of novels. Choice point 2 is largely between first-person and second-person pronouns, with apparently anomalous placement of “me” and “we”. Choice point 4 is between masculine pronouns and others, again entirely plausible given the preponderance of masculine protagonists in novels of this period. The remaining choices in this branch separate feminine, impersonal, and third-person plural pro-
nouns. All of these choices are strongly disjunctive, weakening down the tree with choice point 7 the least disjunctive. It might be expected that, after the choice at point 1, choices might become more conjunctive as two or more people are mentioned. However, reported speech by one person is the most common paragraph structure in these novels, and many of these do not contain another pronoun reference (“He said ‘What’s for dinner?’”).

Figure 4 shows the systemic net for auxiliary verbs. These might have separated based on their root verb (to be, to have, to do) but in fact they separate based on tense. Choice point 1 is between past tense forms and present tense forms. Choices between verb forms are visible at the subsequent levels. Of course, auxiliary verbs are difficult to categorize because they occur both as auxiliaries, and as stand-alone verbs.

The set of auxiliary verbs is also difficult because many of them encapsulate a negative (“hadn’t”), and negatives represent an orthogonal category of choices. Figure 5 shows that systemic net when only the positive auxiliary verbs are considered. Again, tense is the dominant choice.

Figure 6 shows the systemic net for adverbs from a limited set of three different kinds: time, place, and frequency. This systemic net seems unclear, but note that at least some branches agree with intuition, for example the lower branch from choice 4.

There are a very large number of adjectives used in the corpus, most of them only rarely. However, it is interesting to consider how adjectives might be empirically distinguished in fiction. (Note that this would not be the same net as the Appraisal Net described earlier, which might be inferrable from, say, a corpus of product reviews.) Figure 7 shows the systemic net for a limited set of adjectives of three kinds: appearance, color, and time. This net shows the typical structure for an extremely common word, in this case “good” which appears as one outcome of the first choice. The sets of adjectives at each leaf are not those that would be conventionally grouped, but there are a number of interesting associations: “great” and “large” occur together, but co-occur with “black” which is a plausible psychological association.

These systemic nets look, from a human perspective, somewhere between plausible and peculiar. We now turn to more rigorous validation. Our goal is not so much that these nets should be explanatory from an intuitive perspective, but that they should be useful for knowledge-discovery tasks.

V. Validation

To validate our technique for inferring systemic nets, we use the following methods:

- Face validation. The systemic nets should involve choices that appear sensible and realistic. Note that this does not
Fig. 8. Systemic net inferred for verbs

mean that they should match the hierarchy created to explain English grammar — such a grammar is an artificial construct intended to suggest consistent rules, and owing much to the grammar of Latin, rather than an accurate description of how English actually works.

• Comparison of document clustering based on word choices and based on systemic net choices. If choices reflect deeper structure, then documents should cluster more strongly based on choice structure than on word structure.

• Comparison of the performance of an example prediction task, authorship prediction, using word choices and systemic net choices. If choices reflect deeper structure, it should be easier to make predictions about documents based on choice structure than on word structure.

• Comparison with randomly created choice nets. Hierarchical clusterings with the same macroscopic structure as induced systemic nets should perform worse than the induced systemic nets.

A. Face validation

The systemic nets shown in the previous section are not necessarily what a linguist might have expected, but it is clear that they capture regularities in the way words are used (especially in the domain of novels that was used, with their emphasis on individuals and their high rates of reported speech).

B. Clustering using word choices versus net choices

The difference between the systemic net approach and the bag-of-words approach is that they assume a different set of choices that led to the words that appear in each paragraph. The bag-of-words model implicitly assumes that each word was chosen independently; the systemic net model assumes that each word was chosen based on hierarchical choices driven by purpose, social setting, mental state, and

language possibilities. Clustering paragraphs based on these two approaches should lead to different clusters, but those derived from systemic net choices should be more obvious. In particular, choices are not independent both because of hierarchy and because of the extrinsic constraints of the setting (novels, in this case) — so we expect to see clusters corresponding to registers.

We used two novels for testing purposes: Robinson Crusoe and Wuthering Heights, processed in the same way as our training data. Since these novels were not used to infer the systemic nets, results obtained using them show that the nets are capturing some underlying reality of this document class.

We compute the singular value decomposition of the paragraph-word matrix and the paragraph-choices matrix, both suitably normalized. Plots show the resulting clustering of the paragraphs, with one test novel’s paragraphs in red and the other in blue. In all of Figures 9, 10, 11 and 12 the clustering derived from word frequencies is a single central cluster. In some of them, there appears to be a separation between the two test documents, but these are illusions caused by overlays of points. In contrast, the clustering using choices shows strong clusters. These correspond to paragraphs that resulted from similar patterns of choices, that is to registers.
C. Authorship prediction using word choices versus net choices

We argued that systemic nets are useful for applications where properties other than simple content are significant. To justify this claim we predict authorship at the level of each individual paragraph for our two test novels. This is a difficult task because paragraphs are so short; even humans would find it difficult to predict authorship at this level, especially without access to the semantics of the words used. Our goal is to show that the choice structure of the nets improves performance over simple use of bags of words. There are, of course, other ways to predict authorship, for example word n-grams, but these are not directly comparable to systemic net approaches.

Again we use paragraph-word and paragraph-choice matrices as our data, and 5-fold cross-validated support vector machines with a radial basis kernel as the predictors. Results are shown for each of the word sets in Tables II, III, IV, V, VI, and VII.

Across all of these word classes, authorship prediction based on word use hovers close to chance; in contrast, authorship prediction using systemic net choices range from accuracies of around 65% to 75%, that is performance lifts of between 15 and 20 percentage points over prediction from word choices. Clearly, the structural information coded in the systemic nets makes discrimination easier.

### TABLE II
Confusion matrices for personal pronouns; accuracy using words: 69.7%, accuracy using choices: 75.3%

| Actual | Predicted: words and choices |
|--------|-----------------------------|
|        | RobCrusoe | WutHeights | RobCrusoe | WutHeights |
| RobCrusoe | 694 (48%) | 33 (2%)  | 584 (40%) | 143 (10%)  |
| WutHeights | 407 (28%) | 320 (22%) | 216 (15%) | 511 (35%)  |

### TABLE III
Confusion matrices for adverbs; accuracy using words: 51.3%, accuracy using choices: 63.4%

| Actual | Predicted: words and choices |
|--------|-----------------------------|
|        | RobCrusoe | WutHeights | RobCrusoe | WutHeights |
| RobCrusoe | 171 (12%) | 556 (38%) | 387 (27%) | 340 (23%)  |
| WutHeights | 152 (10%) | 575 (40%) | 192 (13%) | 535 (37%)  |

### TABLE IV
Confusion matrices for auxiliary verbs; accuracy using words: 50.6%, accuracy using choices: 72.0%

| Actual | Predicted: words and choices |
|--------|-----------------------------|
|        | RobCrusoe | WutHeights | RobCrusoe | WutHeights |
| RobCrusoe | 435 (30%) | 292 (20%) | 553 (38%) | 174 (12%)  |
| WutHeights | 426 (29%) | 301 (21%) | 233 (16%) | 494 (34%)  |
Fig. 12. SVD using verbs, bag-of-words above, choices below

TABLE V
CONFUSION MATRICES FOR POSITIVE AUXILIARY VERBS; ACCURACY USING WORDS: 51.4%, ACCURACY USING CHOICES: 67.6%

| Actual    | Predicted: words and choices | RobCrusoe | WutHeights | RobCrusoe | WutHeights |
|-----------|------------------------------|-----------|------------|-----------|------------|
| RobCrusoe | 453 (30%)                    | 292 (20%) | 623 (43%)  | 104 (7%)  |
| WutHeights| 415 (29%)                    | 312 (21%) | 367 (25%)  | 360 (25%) |

TABLE VI
CONFUSION MATRICES FOR ADJECTIVES; ACCURACY USING WORDS: 50.1%, ACCURACY USING CHOICES: 70.8%

| Actual    | Predicted: words and choices | RobCrusoe | WutHeights | RobCrusoe | WutHeights |
|-----------|------------------------------|-----------|------------|-----------|------------|
| RobCrusoe | 295 (20%)                    | 432 (30%) | 490 (34%)  | 237 (16%) |
| WutHeights| 294 (20%)                    | 433 (30%) | 187 (13%)  | 540 (37%) |

TABLE VII
CONFUSION MATRICES FOR VERBS; ACCURACY USING WORDS: 50.1%, ACCURACY USING CHOICES: 67.5%

| Actual    | Predicted: words and choices | RobCrusoe | WutHeights | RobCrusoe | WutHeights |
|-----------|------------------------------|-----------|------------|-----------|------------|
| RobCrusoe | 297 (20%)                    | 430 (30%) | 476 (33%)  | 251 (17%) |
| WutHeights| 296 (20%)                    | 431 (30%) | 221 (15%)  | 506 (35%) |

TABLE VIII
PERSONAL PRONOUNS: SYSTEMIC NETWORK VERSUS RANDOM NETS

| Number of paragraphs | NNMF systemic network | Random nets |
|----------------------|-----------------------|-------------|
|                      | Accuracy | min   | mean  | max  |
| 1                    | 75.3%    | 69.3% | 75.4% | 82%  |
| 3                    | 84.1%    | 68.1% | 72.1% | 76.2%|
| 6                    | 88.9%    | 66.3% | 70%   | 71.5%|

TABLE IX
ADJECTIVES SYSTEMIC NETWORK VERSUS RANDOM NETS

| Number of paragraphs | NNMF systemic network | Random nets |
|----------------------|-----------------------|-------------|
|                      | Accuracy | min   | mean  | max  |
| 1                    | 70.8%    | 70.2% | 75.2% | 79.4%|
| 3                    | 72.3%    | 66.9% | 71.5% | 73%  |
| 6                    | 74.8%    | 64.5% | 69.4% | 72.3%|

D. Inferred nets versus randomly generated nets

Tables VIII and IX compare the authorship prediction performance of the inferred systemic net and random networks constructed to have the same shape by dividing the words hierarchically into nested subsets of the same sizes as in the systemic net, but at random.

The performance of the random network is approximately the same as the inferred network at the level of single paragraph prediction. This is clearly a small sample size effect: choices that differentiate authors well are also available in the random network by chance. However, as the number of paragraphs available to make the prediction increases, the predictive performance of the systemic net continues to improve while that of the random network remains flat.

E. Combining systemic nets

We have built our systemic nets starting from defined word sets. In principle, a systemic net for all words could be inferred from a corpus. However, such a net would represent, in a sense, the entire language generation mechanism for English, so it is unlikely that it could be reliably built, and would require an enormous corpus.

However, it is plausible that the systemic nets we have built could be composed into larger ones, joining them together with an implied conjunctive choice at the top level. We now investigate this possibility.

One way to tell if such a composition is meaningful is to attempt the authorship prediction task using combined systemic nets. The results are shown in Table X. The combined nets show a lift of a few percentage points over the best single net.

TABLE X
PREDICTION ACCURACY USING COMBINED WORD SETS, BEST SINGLE SYSTEMIC NETWORK, AND COMBINATIONS OF SYSTEMIC NETWORKS.

|               | words | best single | combined |
|---------------|-------|-------------|----------|
| Pronouns + adverbs | 69%   | 75.3%       | 77.4%    |
| Pronouns + adverbs + verbs | 73.1% | 75.3%       | 80.2%    |
| Pronouns + adverbs + verbs + adjectives | 80.37% | 75.3%       | 80.44%   |
These results hint, at least, that complex systemic nets can be built by inferring nets from smaller sets of words, which can be done independently and perhaps robustly; and then composing these nets together to form larger ones. Some care is clearly needed: if the choice created by composing two nets interacts with the choices inside one or both of them, then the conjunctive composition may be misleading. This property is known as selectional restriction, and is quite well understood, so that it should be obvious when extra care is needed. For example, composing a net for nouns and one for adjectives using a conjunctive choice is unlikely to perform well because the choice of a noun limits the choice of adjectives that “match” it.

VI. CONCLUSIONS

For large sets of documents, techniques based on bags of words have been successful for tasks that have the flavor of information retrieval, that is they depend only on the content of each document. However, there are many other tasks where the significance of each document depends not only on its content, but how it was written (the mental states and abilities of the author), and for what purpose (the social context). For these tasks, systemic functional approaches have seemed attractive for some time; but their application has been limited by the difficulty and expense of constructing them. Here, we show that useful systemic nets can be inferred inductively from example corpora; and that the resulting nets, although not matching standard linguistic intuitions, are nevertheless useful for both clustering and prediction.

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