Document embedding centroids: new and versatile semantic descriptors for compounds

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Abstract

Language embedding models facilitate learning on unstructured text by encoding entities of interest in a vector space. Here we demonstrate how document embedding models applied to Pubmed abstracts can be used to generate descriptors for compounds. These descriptors facilitate tasks such as nearest neighbor retrieval. We demonstrate that semantic embeddings encode orthogonal information when compared to traditional chemical topological and biological descriptors and posit that the integration of semantic embeddings into ligand-based virtual screening pipelines will enable future lead identification in early drug discovery.

Introduction

Biomedical data is being generated at unprecedented scale. This poses a challenge for the evidencebased prioritization of therapeutic, disease, and/or target relationships in early drug discovery. Though pharmacogenomic databases facilitate the cataloguing of scientists' accumulated knowledge, their utility and accuracy are limited by several factors. First, all databases rely on ontologies, which do not always capture relevant entities/relationships and may not translate across applications. Furthermore, some databases rely on manual curation, which can be expensive, time-intensive, and subject to human interpretations and errors. Finally, gaps in data incorporation may lead to missing or incorrect information. One way to address these limitations and improve evidence integration is to learn entity associations directly from the unstructured text of primary research articles and experimental records.

The development of word and document embedding models has facilitated rapid, automated knowledge extraction and downstream learning from unstructured text [1,2]. These techniques work by encoding texts as numeric vectors based on semantic content and/or contexts. Subsequent similarity and analogy relationships between text entities can then be gleaned using simple algebraic and arithmetic operations, while classification learning can be facilitated using the reduced dimensionality of vector representations. Semantic embeddings have been applied to answer diverse biomedical research questions, such as learning disease-drug and disease-disease relationships from research articles and clinical notes [3, 4], predicting compound-protein, protein-protein, and gene-disease interactions [5, 6], and predicting material functional properties [7].

The automated generation and comparison of descriptive fingerprints for compounds can facilitate diverse classification tasks for drug discovery. For example, calculated similarity in chemical feature space can help identify new target modulators in quantitative structure activity relationship (QSAR) modeling [8], and similarity between assay performance profiles can facilitate mechanism-of-action deconvolution [9]. Previous work has demonstrated that augmenting traditional chemical structural fingerprints with semantic occurrence information can benefit classification performance [10]. We expand upon this idea, creating and comparing several different methods for generating semantic descriptors of compounds. We demonstrate that chemical semantic fingerprints can be generated rapidly from public biomedical literature and have utility for compound nearest neighbor retrieval. We also show that the document centroid method captures partially orthogonal information in comparison to existing biological and chemical fingerprints.

Methods

Semantic modeling

Abstracts from NCBI/Pubmed through March 2020 were assembled into a joint corpus for semantic modeling. Document embeddings were also generated using the Universal Sentence Encoder Multilingual Model [11]. In order to assess model quality, we developed an information retrieval task similar to that of Le & Mikolov [2]. We assembled query sets of the top 10 NCBI Pubmed search results for random Medical Subject Heading (MESH) terms. For each query a triplet was assembled containing two abstracts from the query and a random third abstract. Pairwise relatedness was then calculated within triplets.

Fingerprint generation, similarity calculation, and clustering

Compound semantic fingerprints generated using the document embedding centroid method were calculated by summing the vectors of documents in which the compounds occur, followed by L2 normalization. Semantic fingerprints using the TFIDF method were calculated as reduced 300 dimensional vectors by principal component analysis of the TFIDF matrix, performed using the python package delayedsparse [12]. Similarity for each method was calculated using the cosine metric. Normalized pointwise information (nPMI) between two compounds, *A* and *B* was calculated using the following formula:

$$
nPMI = \frac{\ln(coccur(A,B)*N/(occur(A)*occur(B)))}{-\ln(coccur(A,B)/N)}
$$
 [13]

Compound occurrences in Pubmed articles were obtained using a combination of public and private curation tools, including Pubtator and Leadmine [\(https://www.nextmovesoftware.com/leadmine.html\)](https://www.nextmovesoftware.com/leadmine.html) [14]. Chemical similarity was calculated using the tanimoto metric from Morgan fingerprints of radius 2 generated using RDKit (fpsize=2048 bits). Biological similarity was calculated using pearson correlations of 722-dimensional compound vectors comprising normalized z-scores of activities in Novartis highthroughput assays, as previously described [9].

DrugBank categories and drug-target association modeling

Category labels for drugs (such as antibiotics or antineoplastics) were retrieved from DrugBank [15]. Human protein associations were obtained from a combination of Chembl, Reaxys, GVK, and Clarivate Integrity databases for 100 random proteins possessing at least 10 unique compounds with association strength >= 3 as defined in [16]. Each fingerprint type was assessed for nearest neighbor retrieval by calculating a leave-one-out, cross-validated ROC AUC metric: 100 ranked nearest neighbors were retrieved for each member of the drug category or target; area under the curve (AUC) was calculated for the sensitivity/specificity curve of retrieval of the remaining category members at each rank threshold; the resulting AUCs were then averaged for each category/target. Nearest neighbors retrieved using the co-occurrence scoring method were ranked using scaled mutual information.

Results

Document embedding models can capture latent semantic content for input corpora. We hypothesized that part of this encoded meaning includes information about compounds mentioned within text, and that we could map a compound into semantic space by calculating the centroid of the document vectors in which it occurs (**Figure 1A**). To first assemble document embeddings, we employed the pre-trained Universal Sentence Encoder multilingual model on ~14.6M Pubmed abstracts [11]. We assessed the quality of the document embeddings using a derived Information Retrieval task, and obtained an accuracy of 90.5%, a 26.4% improvement over a bag-of-words approach (**Supplementary Table 1**). Visual inspection of top document-document cosine scores also revealed highly similar texts (**Supplementary Table 2**). These data gave us confidence in the quality and utility of document embeddings generated for a corpus of Pubmed abstracts, and supported the applicability of the universal sentence encoder algorithm within the technical domain of biomedical literature.

In order to assemble semantic representations of molecules, we next obtained the occurrences of 1.35M compounds within 8.9M Pubmed articles. Compound embeddings were then generated as the unweighted average of the document vectors in which they occurred, resulting in a 512-dimensional representation within the span of the document space. Semantic relatedness between compounds was calculated as a cosine score between their vectors, with a maximum value of 1 representing a compound's similarity with itself. As an example, we applied our document centroid (DC) method for 3 common drugs (**Table 1**). For comparison, we generated results using two alternative measures of compound-compound semantic relatedness: normalized pointwise mutual information (nPMI), and a vector representation of equivalent dimensionality derived from the compound-document TF-IDF matrix (see Methods). We observed overlaps in the nearest neighbors retrieved using each method, supporting the ability of our approach to quantify and rank semantic similarity. We noted for each query that the top neighbors produced using the document centroid method were of related drug class and were among the most co-occurring compounds. In contrast, we noted that the order of retrieval, magnitude of calculated similarity metrics, and number of cooccurrences diverged among the three methods. To quantify this more directly, we considered the distributions of similarity scores (Fig 1B). The cosine similarity metric for document centroids followed a normal distribution centered approximately at 0 with a long right tail, while TFIDF similarity is negatively-skewed with a sharp peak near 1 and nPMI has a sparse distribution with a sharp peak at -1. A nPMI score of -1 is realized when two compounds do not co-occur, and the sharp peak in this score distribution reflects the rarity of co-occurrence between random pairs of compounds in our dataset. In contrast, both TFIDF and DC methods generate similarity measures for compound pairs using the likeness of their textual contexts even if the pair has not explicitly co-occurred in documents. This feature further supports the utility of these methods for discovery hypothesis generation. Finally, in examining the relationship between similarity metrics and compound co-occurrence, we observed a modest correlation (Pearson: DC=0.29 *p*~0, TF-IDF=0.15 *p~*0), supporting that compounds with a high similarity metric share significant semantic relationships.

Figure 1: A) Overview of DC method. A compound is represented as the centroid of all document vectors representing its literature occurrences. B) Similarity score distributions for 120K random compound pairs using three different methods of semantic relatedness.

Nearest neighbor retrieval performance of document centroids for targets and compound classes

Compound descriptors often have utility in predicting biological activities for compounds. We wondered how the retrieval and classification power of descriptors generated using DC compared to more traditional chemical and biological assay-based descriptors. To investigate this, we devised two common tasks, drug mechanism-of-action and target association categorization, and evaluated the performance of each descriptor by determining how many of the retrieved nearest neighbors of category members reside within the category. We obtained ~140 categorizations of drugs from the Drugbank database and assessed the performance of each descriptor type in random forest modeling (see Methods). We observed that DC descriptors exhibited an average ROC AUC across drug categories of 0.661, far outperforming simple co-occurrence ranking, biological descriptors, and random (ROC AUC=0.5), and performing similar to the chemical descriptor (**Figure 2A**). In investigating individual categories, we observed differing best performing descriptors for each category, and that several classes were best predicted using DC (**Figure 2B**, Supplemental Dataset 1). We next compared descriptor performance in predicting compound-target associations using data for 100 human target proteins obtained from Chembl and other public pharmacogenomic databases (see Methods). DC descriptors achieved a ROC AUC score of 0.695 across all targets, outperforming co-occurrence ranking, chemical and biological descriptors, and random (**Figure 2C**). In investigating individual targets, we again observed that while no individual descriptor was universally optimal, DC performed best for several targets (**Figure 2D**). Though we observed no correlation between ROC AUC metrics and compound occurrence frequency in literature for Drugbank categorizations, we did observe a modest negative correlation (- 0.23, $p=1e^{-307}$) between target ROC AUC scores and the logarithm of occurrence for target associations (**Supplemental Figure 2**). These data support the ability of semantic descriptors, generated using document embedding centroids, to facilitate compound nearest neighbor retrieval tasks.

Figure 2: Classification performance of DC for drug mechanism-of-action and drug target tasks. A) Average ROC AUC of each descriptor method across 100+ Drugbank categories B) Example ROC AUC scores averaged across category members for each descriptor method. C) Average ROC AUC of each descriptor method across 100 random human target proteins D) Example ROC AUC scores averaged across compounds associated with a given target for each descriptor method. Note that illustrated

examples only display the categories that possess compounds with descriptors for all methods. Error bars represent +/-1 standard deviation.

The difference in performance between semantic, biological, and chemical descriptors during the classification tasks is a direct result of differences in calculated similarity between compound class members. To investigate this in more detail, we looked at the correlation between calculated similarity measures among random pairs of compounds (**Figure 3**). We observed no significant correlation between each similarity measure, supporting the orthogonality of these three descriptor types for compounds. We observed distribution outliers and examined several of these compound pairs in further detail (**Table 2**). For example, compounds 1 and 2 have conserved molecular features contributing to their high chemical similarity score, but occur in distinct semantic contexts (the former reported as an anti-allergic [17] and the latter as a component of metallocycles [18]). In contrasts, compounds 3 (Grassofermata) and 4 (Lipofermata) co-occur as identified inhibitors of a fatty acid transporter [19], but have distinct chemical structures and poorly correlated performance in internal Novartis biological assays. Together, our observations on DC nearest neighbor retrieval and orthogonality to other compound similarity metrics suggest that semantic similarity may have utility in scaffold hopping.

Figure 3: Correlogram illustrating the relationships between semantic, chemical, and biological similarity metrics for random compound pairs. Example pairs are described in further detail in **Table 2**.

Conclusions

Numerous fingerprinting methods have been developed to describe compounds and their characteristics. These methods aim to make compound characteristics computable and predictable, in order to facilitate drug discovery, but they often possess orthogonal information in comparison to one another [20]. We propose document centroids as a novel method to generate descriptors for compounds by capturing their semantic contexts. We demonstrated that DC outperforms simple cooccurrence and mutual information standards for semantic relatedness. We also showed that these descriptors facilitate the comparison of compounds to one another. As other entity types can also be extracted automatically from scientific literature, our method may serve as a general framework to embed entities within a common semantic space for cross-domain comparisons.

The construction of semantic descriptors for compounds is inherently dependent on their occurrence in literature. This serves as both a strength and a weakness – as the scientific literature grows, semantic representation of compounds becomes better informed, but literature biases and inaccuracies as well as the ability of automated entity recognition methods to correctly identify occurrences, may limit accuracy. Nevertheless, our methods are widely implementable using current public data and can rapidly integrate newly published articles and compounds in either public or proprietary domains. Alternative literature sources (such as patents or popular chemistry blogs) may also serve to improve the quality and breadth of our semantic space.

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Supplementary Table 1. **Accuracy in a Pubmed search information retrieval task**

Supplementary Table 2. **Example high similarity abstracts from our Pubmed Doc2Vec Model**

Supplemental Figure 1: Scatter plots of ROC AUC scores and log₁₀ occurrence for compound-based nearest neighbor retrieval in Drugbank categorizations (A) and target associations (B).