SCoT: Sense Clustering over Time – a tool for analysing lexical change

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Abstract

We present Sense Clustering over Time (SCoT), a novel network-based tool for analysing lexical change. SCoT represents the meanings of a word as clusters of similar words. It visualises their formation, change, and demise. There are two main approaches to the exploration of dynamic networks: the discrete one compares a series of clustered graphs from separate points in time. The continuous one analyses the changes of one dynamic network over a time-span. SCoT offers a new hybrid solution. First, it aggregates time-stamped documents into intervals and calculates one sense graph per discrete interval. Then, it merges the static graphs to a new type of dynamic semantic neighbourhood graph over time. The resulting sense clusters offer uniquely detailed insights into lexical change over continuous intervals with model transparency and provenance. SCoT has been successfully used in a European study on the changing meaning of 'crisis'.

1 Introduction

Most real-world networks change over time. So do dynamic networks of word similarities that can be used to infer the meanings of a word. The noun 'crisis', for example, used to be strongly linked to the religious word 'doom' in English-language books in the early modern period. However, in the modern age 'crisis' has become more closely associated with terms denoting economic problems such as 'unemployment', 'depression' or 'inflation' (Biemann et al., 2020).

In the recent decade, the interest in dynamic networks has increased. (Rosetti and Cazabet, 2018). This has also stimulated new graph-based approaches to analysing vocabulary change (Mitra et al., 2015; Riedl et al., 2014). Such research is a key interest of linguists (Tahmasebi et al., 2018; Nulty, 2017) and scholars in the humanities (Koselleck, 1989; Mueller and Schmieder, 2016; Friedrich and Biemann, 2016).

Traditionally, scholars have determined such changes through close reading. However, the growing availability of ever larger digital corpora (Goldberg and Orwant, 2013) and the increasing speed of sense changes in social media (Stilo and Velardi, 2017) have boosted the significance of new research (Nulty, 2017).

Of particular importance in the research on lexical change is the unsupervised approach of word sense induction (WSI). WSI enables the development of data-driven hypotheses. The approach induces meaning from the bottom upwards and can be used with a diachronic angle. Several implementations for diachronic WSI exist (Tahmasebi et al., 2018). While many of them represent word meaning by dense vector embeddings, sparse models with network representations still play an important role. The use of sparse, human-readable models enables a better interpretation of meaning hypotheses by linguists and other researchers.

There are two main approaches to implement diachronic network-based WSI. Discrete approaches compare several networks that relate to discrete points in time. Continuous approaches analyse when specific nodes, edges or clusters appear in a single dynamic network that changes continuously over time (Rosetti and Cazabet, 2018).

Many applications in the field of diachronic network-based WSI fall into the discrete category. Mitra et al. (2015), for example, reduce the number of measuring points to single intervals, build one graph per discrete interval, cluster it and track the resulting sense clusters over intervals. While this approach is considered as less complex than the continuous one (Rosetti and Cazabet, 2018), it brings up complexity problems of its own. The clustering of graphs can namely lead to different

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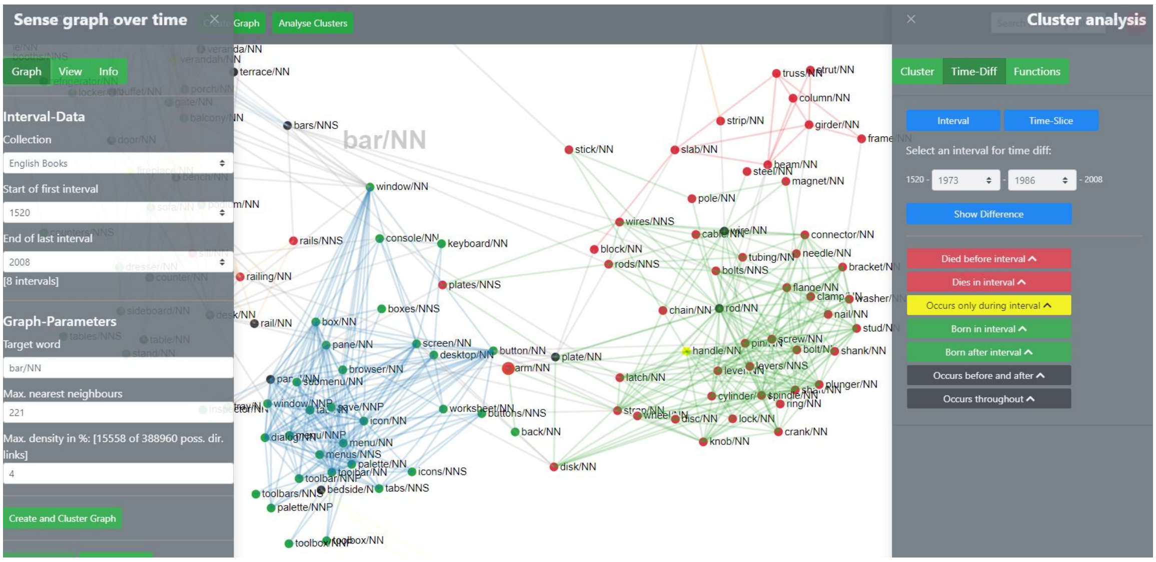
Interval-Data

Collection

English Books

Start of first interval

1520

End of last interval

2008

[8 intervals]

Graph-Parameters

Target word

bar/NN

Max. nearest neighbours

221

Max. density in %: [15558 of 388960 poss. dir. links]

4

Select an interval for time diff:

1520 - 1973 - 1986 - 2008

Figure 1: Analysis of the sense shifts of 'bar/NN' in Google Books (Goldberg and Orwant, 2013) with SCoT: the clusters of the neighbourhood graph over time show that the sense "a rigid piece of metal used as a fastening or obstruction" [top right] loses traction, while the sense "computer-menu" [bottom left] gains significance. The coloring is relative to the interval "1973-1986". Red indicates the disappearance of a node before 1986. Green indicates the emergence of a node after 1986.

solutions. Thus, the number of clustering combinations in a time-series of sense graphs can grow unpredictably. Another issue is the identification of corresponding clusters across time points.

Continuous representations are more fine-grained, but can lead to other issues. Since the clustering in such scenarios is mostly done in an incremental way, problems of costly reclusterings or very large clusters can emerge.

The application Sense Clustering over Time (SCoT) offers a new hybrid approach to network-based WSI that reduces complexity. SCoT works in two steps. In a first, 'discrete' step, the time-stamped documents are aggregated into intervals. Static graphs are built per interval. Then SCoT merges the static graphs to a new type of dynamic neighbourhood graph over time (NGoT). The encoded time-based information from the underlying continuous series of graphs enables a time-coloring of the sense clusters.

Haase (2020) has shown that there are different approaches to constructing such semantic NGoTs. The best known method for creating such a dynamic network consists of the merging of a series of equally-sized graphs from each interval, but it is also possible to aggregate nodes and links in different ways. These approaches exhibit different strengths and are explained in more detail below.

Figure 1 shows how such a NGoT looks like. The graph shows sense clusters for the target word *bar*. It shows that words such as "button", "desktop" and "icon" became increasingly similar to each other and to the target *bar* in the 1990s, thereby forming the new sense of 'computer-menu'.

SCoT can be used for various tasks such as linguistic studies of polysemic words or research into the history of concepts, but also offers a general and new solution to the analysis of dynamic networks with the neighbourhood graph over time.

2 System description

The system enables an analysis of the lexical change of words in an interactive web-interface based on metrics calculated from large time-sliced corpora. This requires a division of the system into a web-front-end and a back-end that accesses the databases with the similarity scores. In addition, the system offers the user additional information on the syntagmatic features that have been used to calculate the similarity scores.

2.1 Computing distributional thesauri for time-sliced corpora

The calculation of the similarity scores that inform the graph is steeped in the de Saussurian notion of paradigms and syntagmatic contexts as implemented in JoBimText (Biemann and Riedl, 2013). The nodes represent the paradigms. The more syn-

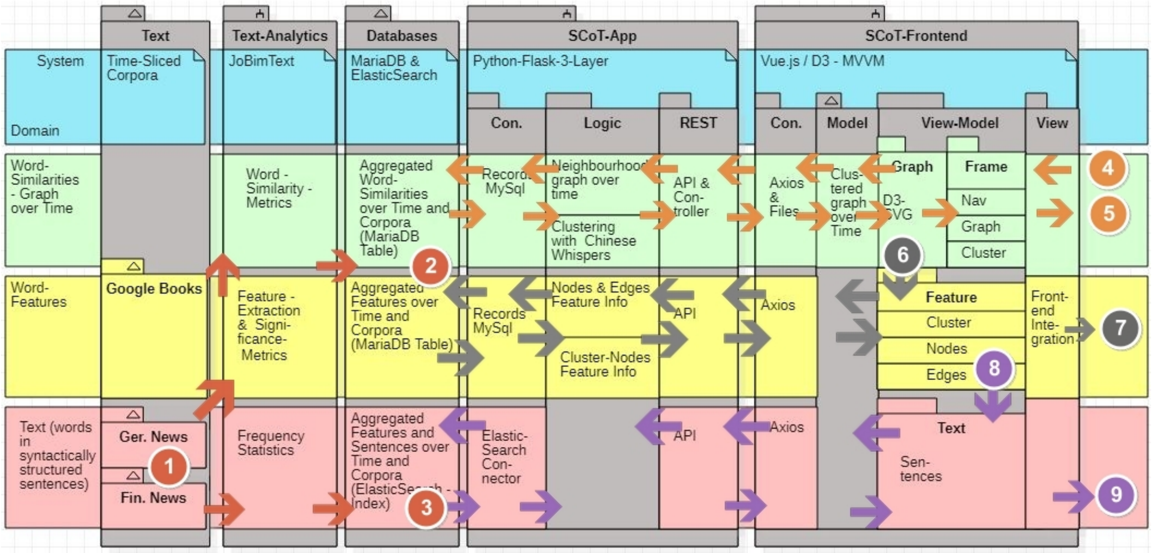
Text
Text-Analytics
Databases
SCoT-App
SCoT-Frontend
System
Domain
Time-Sliced Corpora
JoBimText
MariaDB & ElasticSearch
Python-Flask-3-Layer
Vue.js / D3 - MVVM
Con.
Logic
REST
Con.
Model
View-Model
View
Word-Similarities - Graph over Time
Word - Similarity - Metrics
Aggregated Word-Similarities over Time and Corpora (MariaDB Table)
Records MySql
Neighbourhood graph over time
Clustering with Chinese Whispers
API & Con-troller
Axios & Files
Clus-tered graph over Time
Graph
D3-SVG
Frame
Nav
Graph
Cluster
4
5
6
Word-Features
Google Books
Feature - Extraction & Signi-ficance-Metrics
Aggregated Features over Time and Corpora (MariaDB Table)
2
Records MySql
Nodes & Edges Feature Info
Cluster-Nodes Feature Info
API
Axios
Feature
Cluster
Nodes
Edges
8
Front-end Inte-gration
7
Text (words in syntactically structured sentences)
Ger. News
1
Fin. News
Frequency Statistics
Aggregated Features and Sentences over Time and Corpora (ElasticSearch - Index)
3
Elastic-Search Con-nector
API
Axios
Text
Sen-tences
9

Figure 2: The SCoT-system consists of multiple layers and domain-specific components relating to the similarity graph (green), the underlying syntagmatic features (yellow) and the corpus (red). The system's four key processes are highlighted with numbers: the preprocessing (1-3), the graph-analysis (4-5), the feature-analysis (6-7) and the querying of example sentences for research (8-9). Arrows indicate the data-flow direction.

tagmatic contexts two paradigms share, the more similar they are (Miller and Charles, 1991). The contexts and words are extracted from the sentences of documents.

The raw texts, the syntagmatic features and the network representation of the relations between the paradigms require very different processing steps. They are thus handled by different groups of components of the SCoT application that constitute so-called sub-domains. They have been color-coded in Figure 2.

The current online demonstration version of SCoT uses three corpora. These include a large dataset of syntactic n-grams from Google Books (Goldberg and Orwant, 2013), a corpus of Finnish magazines and newspaper articles (University of Helsinki, 2017), and a corpus of German newspapers articles as described by (Biemann et al., 2007; Benikova et al., 2014). These corpora have been sliced into 7 to 9 time-based intervals which roughly contain the same amount of data.

The semantic similarity of words can be computed with different methods. For SCoT, we have opted for distributional thesauri (DT) due to their flexibility. They can be based upon different types of context features such as word n-grams, part-of-speech n-grams and syntactic dependencies. We have used syntactic dependencies.

We have calculated the DTs with the software JoBimText (Biemann and Riedl, 2013). It uses the Lexicographer's Mutual Information (LMI) to rank words and their context features. We have limited the computation to the top ranked 1000 features.

We have stored the scores in one SQL-database per corpus. Each database includes three tables: a table of intervals, a table of word pairs with their similarity scores and references to the intervals in which they occurred, and a table of words and their features with interval information. In addition, we have stored example sentences in an ElasticSearch server. This calculation and storage is highlighted with the numbers 1, 2 and 3 in Figure 2.

2.2 Creating the neighbourhood-graph over time

The system offers the user the possibility to select a target word and to enter parameters for building the NGoT. This is highlighted as number 4 in Figure 2. The user can select between three different types of NGoTs. These have repercussions for the resulting sense clusters (Haase, 2020). We have implemented the interval-, the dynamic and a mixed global/dynamic approach. The user can fine-tune them with three parameters: the number of intervals i, the number of nearest neighbour nodes n and the density d.

The interval-approach creates one static graph with n words and the density d per interval and then merges these. This results in a dynamically sized graph, which is often larger than a static single interval graph. This creates a very clear distinction between clusters and nodes that occur frequently over time and those that do not. The approach is optimal for getting an analytical overview of sense-shifts. We, thus, use it as a starting point for the analysis.

The dynamic approach fixes the number of unique words n and the density d of the resulting graph and expands the underlying data-points of the static graphs across intervals. This usually only creates partial graphs per interval. Since the dynamic approach fixes the number of links and nodes of the resulting graph it is better suited for comparisons across different graphs than the interval-approach.

The global approach fixes the number of static single word-nodes and edges in total across all intervals based on maximal values. The significance of the approach lies in the ability to tweak the number of single edges, which has an effect on the number of resulting clusters. For ease of use, we have implemented it as a mixed approach: the nodes are allocated according the dynamic approach. The edges can be tweaked globally.

The number of the edges in relation to the nodes is the key to creating a useful graph for clustering and the analysis of lexical change. In order to enhance the dynamic allocation of edges over time, we have relaxed the condition that each node in the resulting graph has a fixed limit of connected edges. This is the standard implementation in many neighbourhood graphs. In sum, SCoT offers a new type of neighbourhood graph that is different to all known implementations of neighbourhood or so-called ego graphs (Mitra et al., 2015).

The variants are implemented with a similar pattern: each algorithm first searches for the nodes and then for the edges. Then, the algorithm merges those nodes and edges that refer to the same words in different intervals. It encodes the time-based scores in the nodes and edges.

2.3 Sense clustering

The advantage of NGoTs is that they need to be clustered only once. For this, we use the Chinese Whispers algorithm (Biemann, 2006). The key characteristics of the algorithm are that it is non-deterministic, has a linear time-complexity and runs with a fixed number of iterations that result in a stable partition of the graph. We set the number of iterations to 15 in order to increase the chances of the algorithm of reaching a stable plateau. However, there may be more than one stable solution. We have thus implemented the possibility to recluster the graph in order to see whether multiple solutions exist. If one wants to break a tie, it is recommended to slightly reduce the density of the graph and to cluster again. This should remove less significant edges and thus provide a more nuanced clustering.

2.4 Displaying the sense clusters over time

During the creation process of the NGoT, the interval information is encoded in the nodes and edges. This information is used for the subsequent coloring of the nodes in the time-difference analysis in the front-end.

The front-end is based on a modern Model-View-View-Model (MVVM) framework, namely Vue. In MVVM frameworks, the main view of the web-page is rendered by several dynamic model-view components. SCoT has four main components. They render the navigation and side-bars, display the graph, show additional syntagmatic features and exhibit exemplary sentences. The graph-component uses the D3.js library to render the graph. In addition, the front-end includes a connection-layer that communicates with the RESTful SCoT API of the back-end.

2.5 Diachronic analysis with time-colouring

Since the sense clusters over time are the most important feature of SCoT and provide the starting point for the research, they are displayed by default when the graph has been created. In the cluster-view, the clusters are ordered by size.

The tool offers a wide range of advanced functions to analyse the sense clusters. One can use a hovering function over nodes and links to display the development of similarity scores over time for each node and edge. Furthermore, network metrics such as the betweenness centrality can be used to enlarge central nodes. Such central nodes play a significant role as centres of the clusters and bridges between clusters. Nodes between clusters, which can exhibit ambivalence, can also be highlighted.

Among the advanced functions, the time-difference mode is particularly noteworthy. The application offers two functions for the time-diff mode. The first color-codes the nodes in the sense clusters in relation to their occurrence to a set interval. Nodes can disappear before the interval, emerge in the interval or occur after the interval. They can also be stable. The second function offers a slider that highlights all nodes that occur per time-interval (Kempfert et al., 2020).

Furthermore, the front-end offers the opportunity to change several view-parameters. These include charge strength, link distance, and the zoom-factor. It is also possible to drag the graph and individual nodes, add name labels to the clusters and manually change cluster assignments.

2.6 Model transparency

A key aim of SCoT is to enable a transparent interpretation of meaning hypotheses. Therefore, SCoT offers functions to drill into the syntagmatic features utilized in the representation of word meaning here. These are available in a count-based sparse model in the form of the DTs from JoBimText (Biemann and Riedl, 2013). This analysis can be triggered by clicking on a node or an edge. This has been labelled as step 6 in Figure 2. It results in the display syntagmatic contexts per selected word-nodes, including whole clusters, as ranked by LMI. E.g., for the 'rod/stick' sense of 'bar' in Google books, the most salient syntagmatic contexts are "-nn/platinum/NN, -dep/stumbling/NN, -dep/altar/JJ, -dep/electro/NN, -nn/vertebral/NN, -in_pobj/link/NN, -nn/crank/NN, -on_pobj/leaning/VBG, and_conj/key/NN", whereas the same query for the 'menu bar/button' sense yields "-nn/dialog/NN, -nn/edit/NNP, nn/publishing/NN, -nn/options/NNPS, -on_pobj/click/NN, -dobj/clicking/VBG, -on_pobj/button/NN, -nn/cardboard/NN, dep/sill/NN".

The displayed pairs of syntagmatic features and paradigms can serve as a starting point for further analyses: one can retrieve example sentences that include the paradigm and the selected syntagmatic context. This has been labelled as step 8 and 9 in Figure 2.

3 Use case: sense shifts of "crisis"

SCoT can be used in various research fields. Conceptual history is of particular relevance. It is used to produce lexicons of 'basic concepts' and thus encompasses aspects of linguistics and historical research.

Mueller and Schmieder (2016); Friedrich and Biemann (2016) have shown that the growing research field is in need of new unsupervised methods in order to deal with newly available large digital corpora. The research that was established by Koselleck places a particular emphasis on concepts that have changed in the transition to the modern age between 1750 and 1850. (Olsen, 2012)

Within this context, the noun 'crisis' takes centre-stage as the contemporaries perceived the transition into the modern age as a time of different crises. The analysis of the changing meanings of the noun is thus an ideal test case for the applicability of the tool in this interdisciplinary field.

3.1 The 'economic turn' and the changing concept of 'crisis'

The first step in most text-based research projects is the choice of the corpus. We have chosen English Google Books as a suitable corpus.

We start the analysis with a generalized overview over all eight intervals with the graph-type-mode 'interval'. We set the parameters n=100 and d=20 and render the graph. This results in a NGoT with 221 nodes. SCoT analyses three sense clusters over time.

After we have established the overview, we go into the time-diff mode. From the ongoing research, the prominent hypothesis about the changing meaning of 'crisis' between 1750 and 1850 has emerged. We test this hypothesis. We switch to the time-diff mode and color the nodes in relation to the interval 1908-1953. The resulting graph shows that one full sense cluster consists only of 'red' nodes that all disappeared in the first interval. We have thus found a candidate for a first sense shift.

We now follow up the analysis with a more specific look at the nodes. We find that the pre-modern sense of religious "doom" and "juncture of time" was replaced by modern political and economic senses of crisis centred on terms such as 'election', 'law' or 'class'. We then look at individual nodes to deepen the analysis. Each node in the clusters provides an important aspect of the development. The node 'class', for example, relates to Marxist philosophy that viewed the cyclic nature of capitalist 'crises' as the defining characteristic of the modern age.

Subsequently, we want to find out which changes occurred within the modern political and economic clusters in the subsequent intervals. With the help of the time-slider-mode and the individual graphs that are depicted in Figure 2, we can show that that the sense transformation of the term 'crisis' continued after the breakthrough of the modern age. An ever growing cluster with economic words can be observed. Terms, such as 'depression', 'boom', 'inflation' and 'unemployment' dominate the cluster,

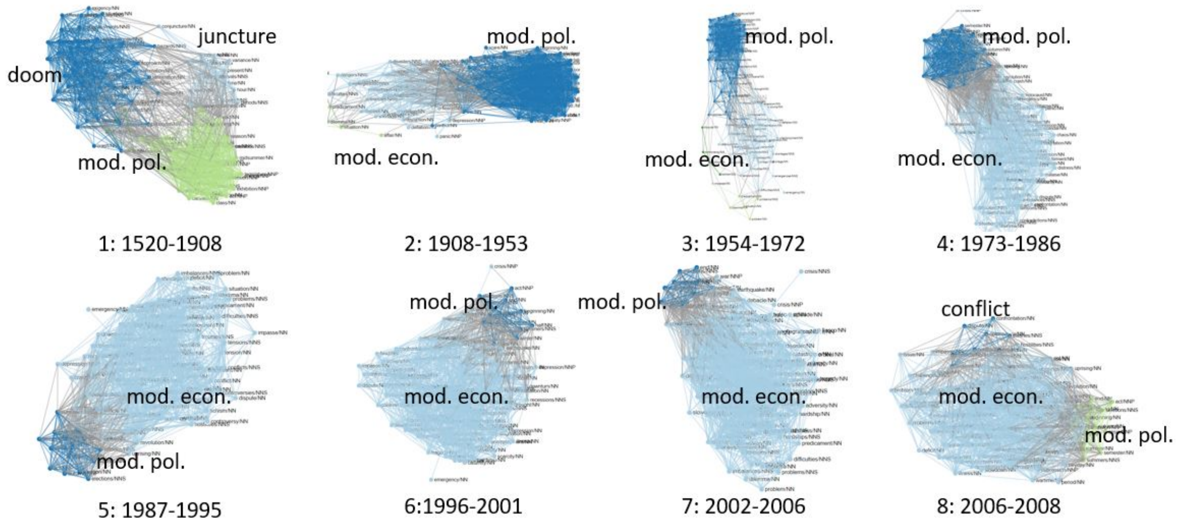

Figure 3: Analysis of sense-shifts of crisis/NN: The neighbourhood graph merges graphs from each interval. The underlying time-series shows that "crisis/NN" developed a modern political and an economic sense with an increasing dominance of economics between 1520 and 2008. Parameters: n=100, d=30, i=1, corpus: Google Books (English).

increasingly so after the 1950s, and in particular after the oil crisis in the 1970s.

This tallies with the research on the so-called "economic turn" in the 1950s and beyond. The argument by economic historians such as Nützenadel is that the cornerstone of the Western postwar-order was the diffusion of new economic and democratic thought, centred on the so-called consensus liberalism that was seen as the antidote to the 'crisis' of the great depression and the following political chaos. (Haase and Schildt, 2007) SCoT advances these findings by adding new details to them in a transparent and scientific manner.

The results of SCoT always need to be contextualised within the limits of the underlying corpus. Google Books contains primary and secondary material and has a strong "thematic" orientation. Since Google Books contains many books from libraries that serve universities, we need to test whether the 'economic turn' of the term 'crisis' has shown up so dramatically in the data due to the underlying basis of vast specialist economic literature stored in university libraries.

In order to check against the possible bias, we use a second corpus, namely German web-news. We find in this corpus a similar development and conclude that the 'economic turn' can be regarded as a wider phenomenon in Western countries after the 1950s. We have arrived at this analysis by the research steps of generalisation, specialisation and comparison that are well supported by SCoT.

4 Conclusion and future directions

This article describes SCoT, a new tool for the analysis of the changes of sense clusters in dynamic networks. SCoT reduces the complexity of this task through interval-aggregation and neighbourhood graphs over time. The dynamic network retains the time-based information. This enables advanced analyses that can be well visualised. The usage of a sparse approach to distributional semantic modeling provides model transparency and provenance.

We have demonstrated the applicability of the solution in the domain of lexical and conceptual change. However, the general nature of the application make it transferable to other domains that use dynamic networks for analysis.

Future directions in the development of SCoT lie in the further refinement of neighbourhood graphs over time, the broadening of the usage of SCoT in various domains, including conceptual change, as well the research on the wider implications of the application for diachronic distributional semantics.

ScoT is available open source under the MIT license[1] and as an online demo[2]. A video demonstrating many of the functionalities can be found at https://youtu.be/SbmfA4hKjvg.

[1] https://github.com/uhh-lt/SCoT

[2] http://ltdemos.informatik.uni-hamburg.de/scot/

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