

# Strategy finder

Augmented Qualitative Analysis  
(AQA) with Strategyfinder

by Prof Dr Mike Yearworth, March 2025

**Strategyfinder**  
**Consulting Software GmbH**  
FN 623983y, ATU80524309  
Muenichreiterstrasse 25  
A-1130 Vienna Austria

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Author Copyright © Prof Dr Mike Yearworth

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## Augmented Qualitative Analysis (AQA)

Augmented Qualitative Analysis (AQA) with Strategyfinder provides a semi-automated means of analysing a very large document set (a corpus) pertaining to a project or similar coordinating or planning activity with a view to generating putative Causal Maps (CM) or Hierarchical Process Models (HPM) suitable for import into the Strategyfinder platform as a preliminary to working with a group of stakeholders.

## Background

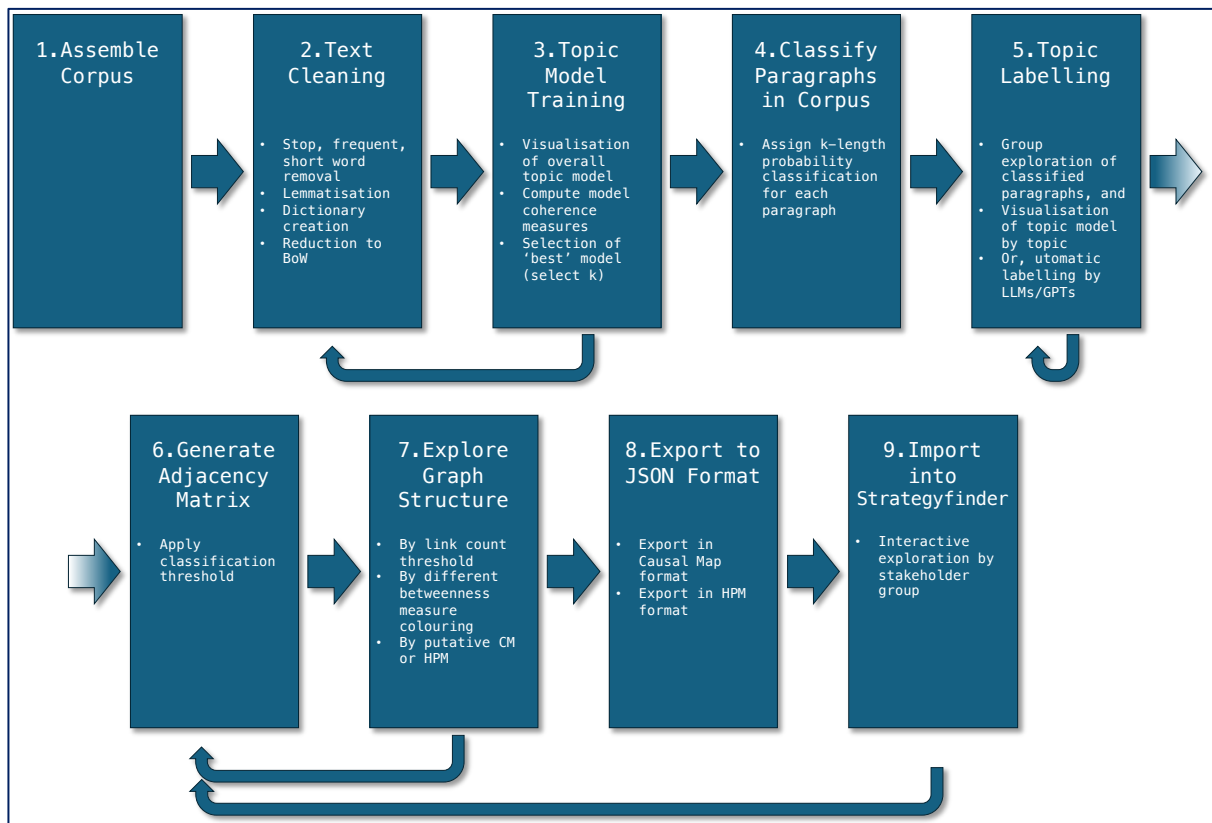
Advanced computational techniques are beginning to have an impact on social science research and have placed approaches such as automated content analysis on the threshold of a major transformation (Nelson, 2020). With the support of new computational techniques, it is possible for the qualitative researcher to move back-and-forth in an “hermeneutic circle” between the text, coding, and higher-order concepts (Mantere & Ketokivi, 2013). A probabilistic topic modelling technique using the Latent Dirichlet Allocation (LDA) is described in outline by Blei, Ng and Jordan (2003). Analysing a corpus to examine context and to generate themes for a theoretical model of concepts using a probabilistic topic model is demonstrated in recent work by Hannigan et al. (2019). The technique to be deployed is ideally suited to data sets that sit at the ‘top end’ of the scale of a ‘conventional’ qualitative analysis by a small group of researchers, even if supported by current Computer-Assisted Qualitative Data Analysis Software (CAQDAS) tools, but still modest compared to what topic modelling is able to handle – this is an ‘Augmented Qualitative Analysis’ (AQA) technique.

Although the modelling can be largely automated there is still an important role for the qualitative researcher. Analysis proceeds inductively, by interpreting the term lists within the raw topics to generate first order concepts. A suggestion, following Charmaz (2006) and Glaser (1978), is that gerunds are used for the coding in order to focus interpretation on the identification of enacted processes rather than static topics. This aligns rather well with Hierarchical Process Modelling (HPM) (Yearworth, 2025, pp. 139-140).

Probabilistic topic modelling to support AQA affords approaches to analysis not available to the conventional qualitative researcher. In this case, having classified the data at the paragraph level with the equivalent of a CAQDAS coding strip then it is possible to derive an adjacency matrix by counting for each topic pairs the number of times the pair co-code a paragraph of text. Following the method described by Yearworth and White (2013) this generated adjacency matrix can be interpreted as a graph or map of the corpus being analysed. Further information about the origins and use of this technique can be found in (Yearworth, 2024a; Yearworth, 2025, pp. 239-244).

## Workflow

The overall schema is shown in Figure 1. The workflow requires iteration to refine the technique and is thus not completely automatic. The production of topic models using LDA from very large corpora is achieved as a consequence of the significant reduction in the size of texts by the use of ‘Bag of Words’ (BoW) representation. Here, positional information is discarded, and each document is instead coded by a vector of length of the dictionary and frequency of occurrence of each term in the dictionary. Iteration between steps #2 and #3 is required to achieve the ‘best’ model. Topic labelling, step #5, is also iterative, although it is also possible to automate this by the use of LLMs/GPTs. The density and structure of the putative Causal Maps (CM) or Hierarchical Process Models (HPM) requires iterative exploration of classification thresholds in step #6, link count thresholds in step #7, and overall model structure as imported into Strategyfinder at step #9.

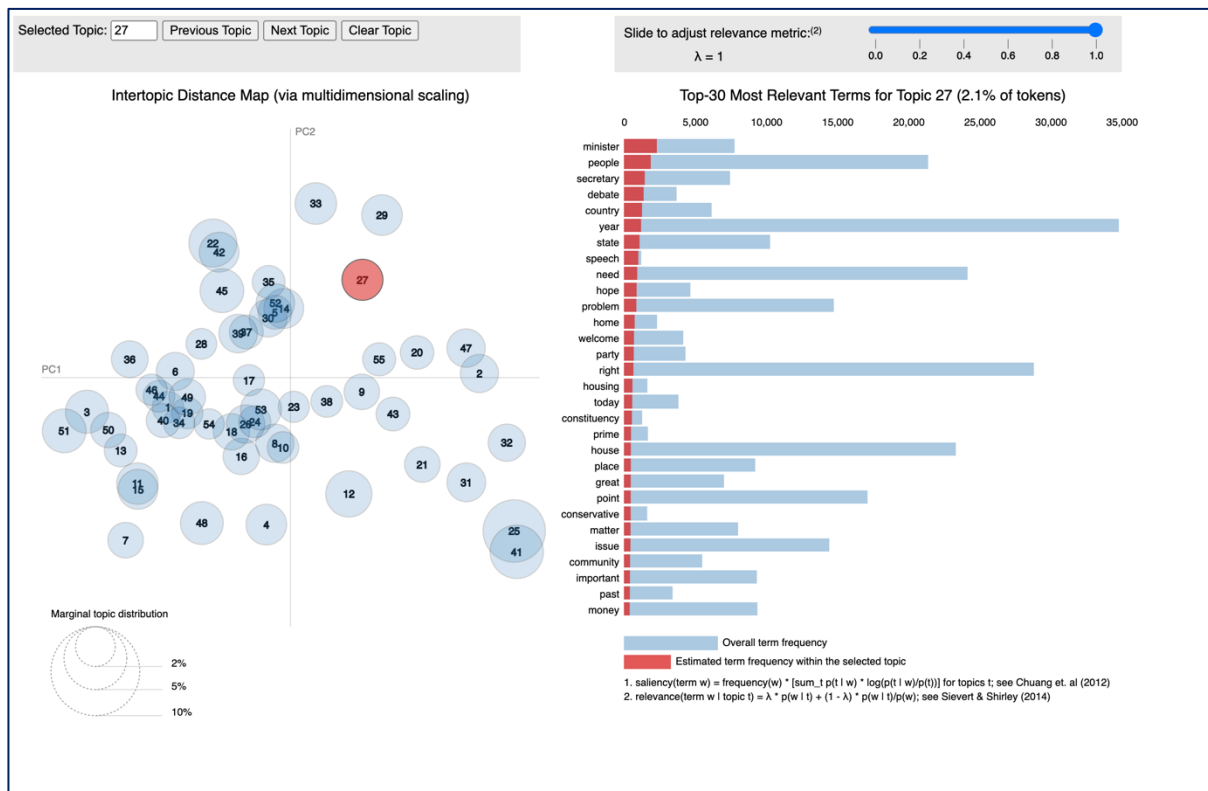


**Figure 1. AQA workflow schematic.**

## Example application

A small corpus of 229 documents was assembled concerning the planning and parliamentary scrutiny of the CrossRail project, a new underground line for London that had long been under consideration that was approved for construction in 2007 and opened in 2022 as the Elizabeth Line. The corpus comprised of 10.6 million words that was eventually reduced to 5.05 million words after stop, short, and common words had been removed and yielded a dictionary of 31,281 unique tokens for the probabilistic topic modelling. A heuristic search over model parameters eventually yielded a 'useful' model<sup>1</sup> with 55 topics. The LDA model is visualised in Figure 2.

<sup>1</sup> There is no objective measure of 'useful' or 'best' model. This will be determined by the participants in the process and the purpose of the modelling.



**Figure 2. Visualisation of the probabilistic topic model with Topic #27 highlighted using LDAvis (Sievert & Shirley, 2014).**

## Topic Labelling

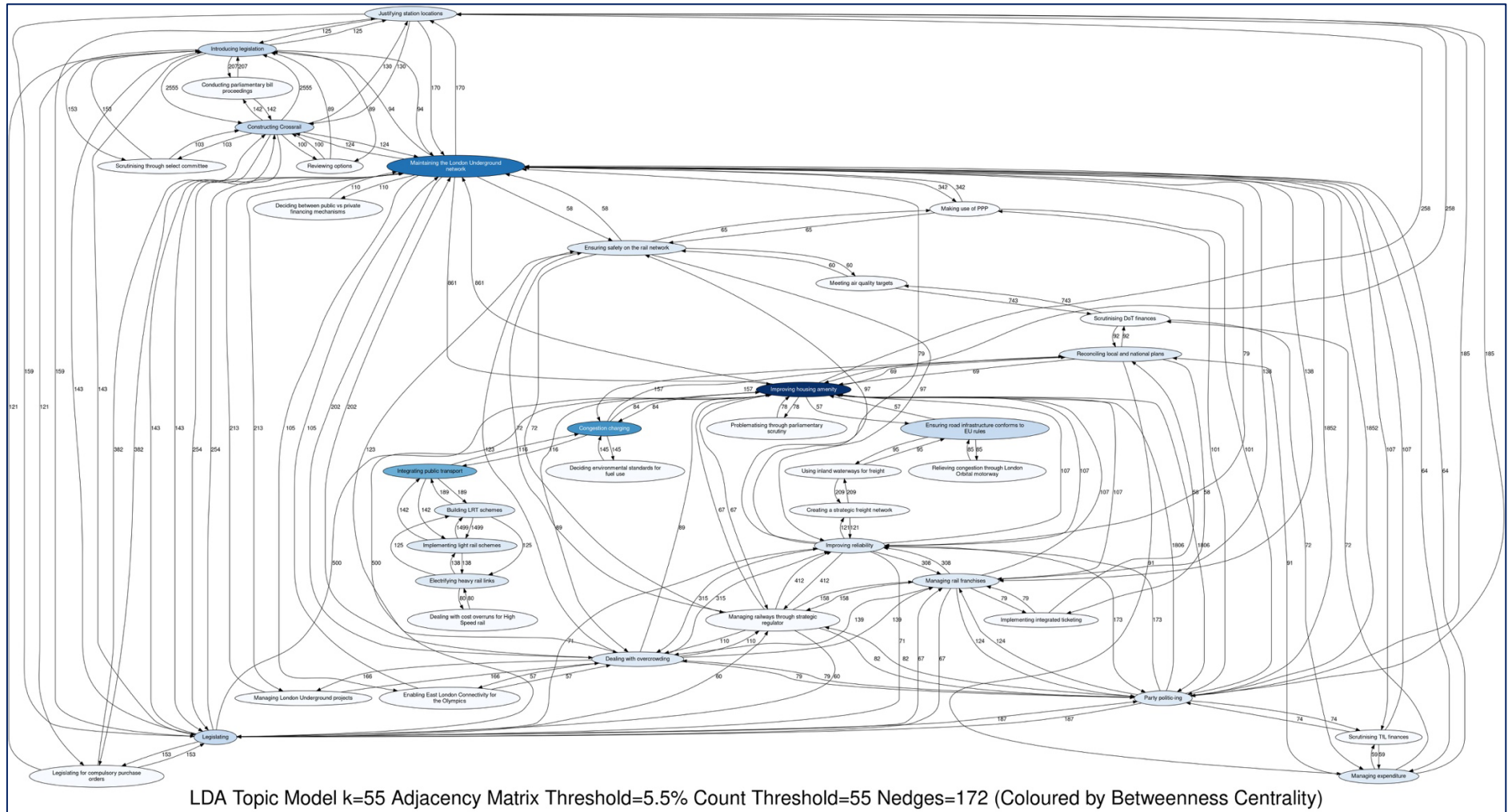
From a qualitative research perspective, topic labelling is ideally conducted in a group setting by stakeholders with familiarity of the subject material. Access can be arranged to an interactive tool to explore text at the paragraph level that has been classified by the topic model. When used in conjunction with the topic model visualisation (as shown in Figure 2) to view term lists for each topic it is possible to quickly arrive at agreed topic labels.

An alternative option is available relying on a GPT/LLM to automatically generate topic labels based on the term lists and a selection of the highest classified paragraphs for each topic. This is potentially useful for speed and/or very large topic models although there are also some drawbacks too (Yearworth, 2024b).

## Generating a graph from the adjacency matrix

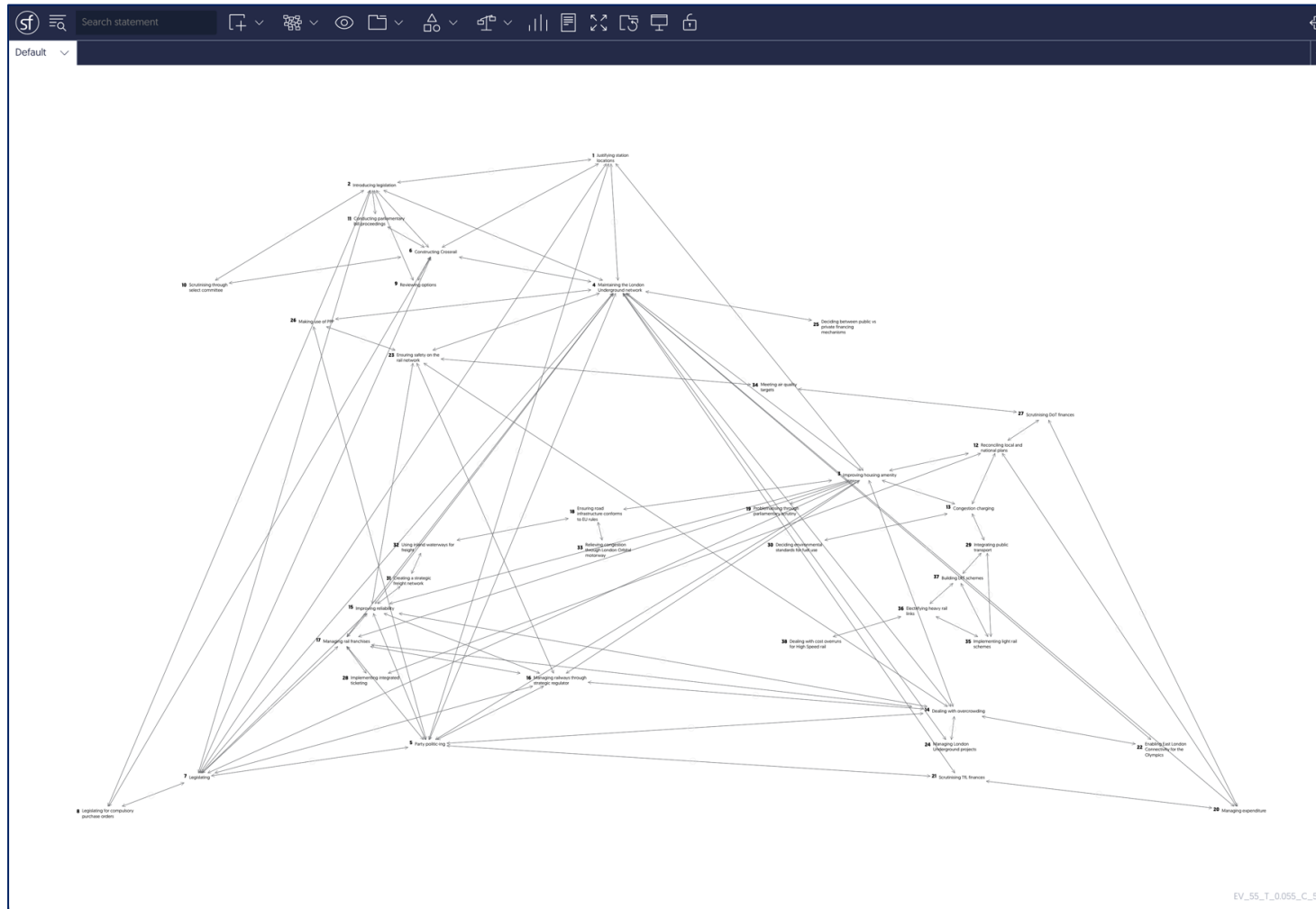
An adjacency matrix is generated by first using the topic model to classify the source documents at the paragraph level and then by counting the number of times a paragraph is co-coded by each possible pairing of topics. An example adjacency matrix is shown in Figure 3. Note that the matrix is symmetric and thus the links between topics in graphs will be bi-directional.





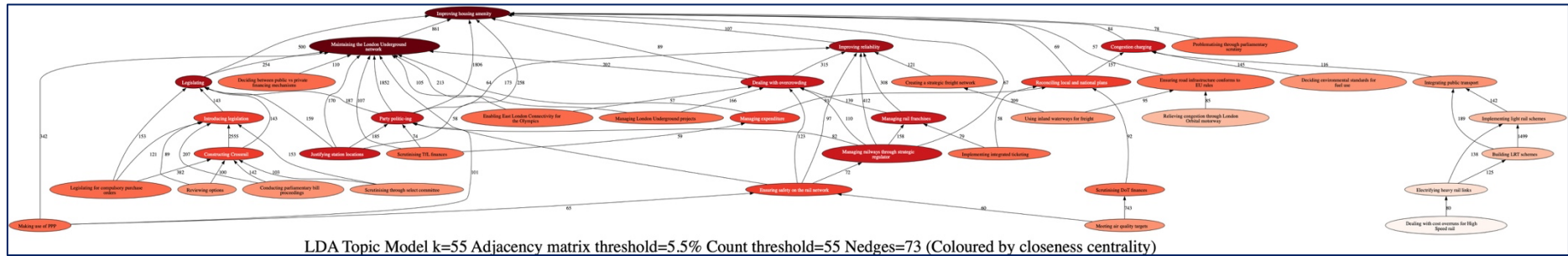
**Figure 5. Visualisation of the adjacency matrix. The classification threshold is 5.5% and the link count threshold is 55 resulting in a graph with 172 edges. The graph has been coloured by betweenness centrality.**





EV\_55\_T\_0.055\_C\_55

**Figure 6. The graph shown in Figure 5 exported to the Strategyfinder JSON format and imported into the Strategyfinder platform as a possible Causal Map.**



**Figure 7.** The graph of the adjacency matrix has been pruned by a custom algorithm to produce a directed acyclic graph based on the closeness centrality measure. The same thresholds have been used as in Figure 5, but this time the edges have been reduced to 73 and the graph can now be interpreted as a possible HPM.

# Strategyfinder

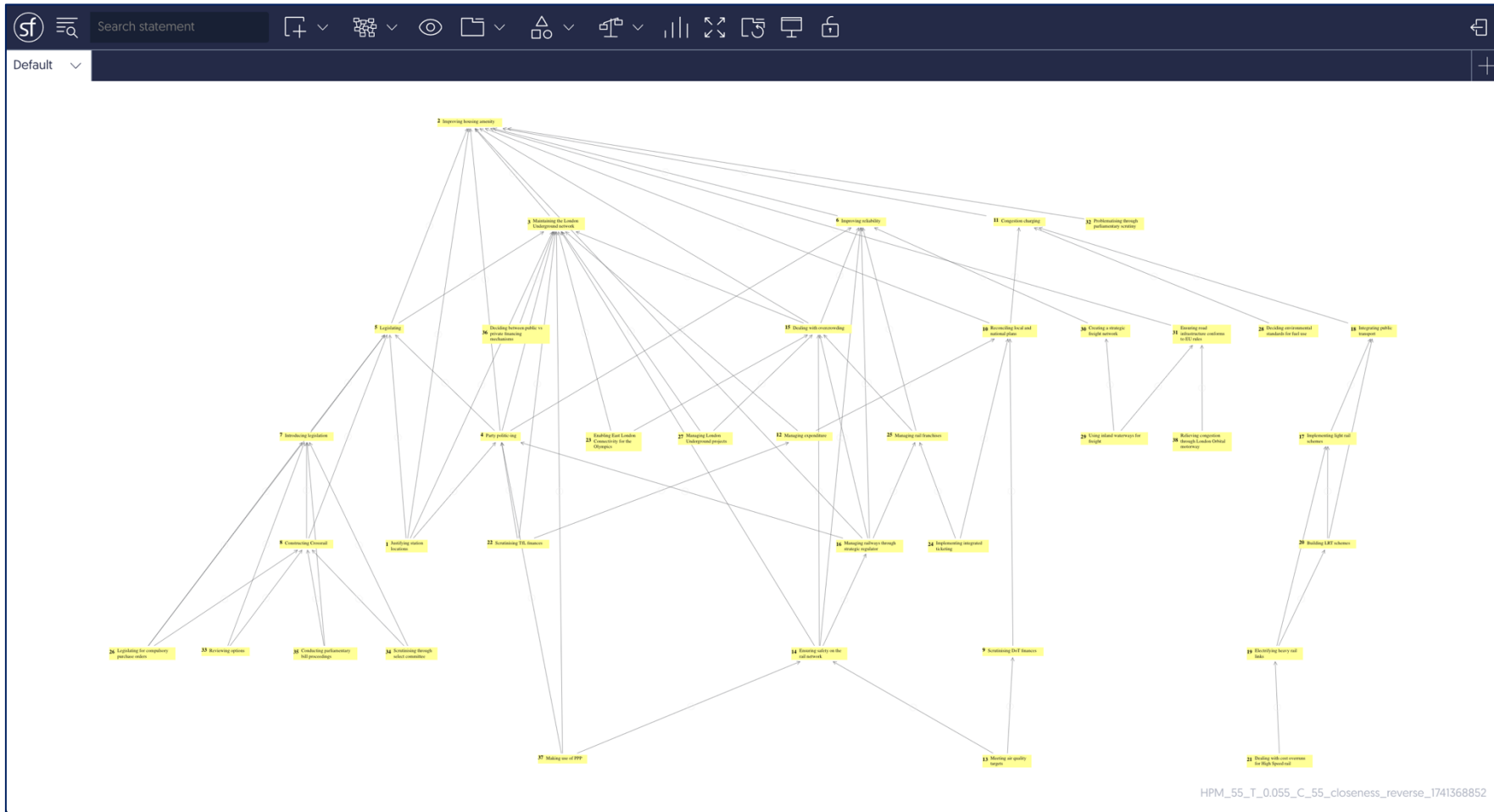


Figure 8. The graph shown in Figure 7 exported to the Strategyfinder JSON format and imported into the Strategyfinder platform HPM Module .

## Deployment

The specific deployment of this module depends on customer requirements over the confidentiality of the documents used for training the probabilistic topic model and should be discussed with Strategyfinder Consulting Software GmbH.

## Pruning a graph to a directed acyclic graph for HPM

The following algorithm removes cycles in a graph and produces a hierarchical DAG based on a centrality metric.

### Requirement

Let  $G = (V_G, E_G)$  be a directed graph (digraph), where  $V_G$  represents the set of vertices (nodes) and  $E_G \subseteq V_G \times V_G$  represents the set of directed edges (arcs) between nodes. The function used generates a Directed Acyclic Graph (DAG)  $H = (V_H, E_H)$  based on the input graph  $G$ , ensuring that the new graph  $H$  has no cycles and that the edges are directed based on the specified centrality metric and link direction and where  $centrality\_metric \in \{\text{'degree'}, \text{'betweenness'}, \text{'closeness'}\}$ .

### Method

Create a new graph  $H = (V_H, E_H)$  where  $V_H = V_G$ , and initialize  $V_H = \emptyset$ .

For each edge  $(u, v) \in E'_G(u, v)$ , perform the following steps:

1. If  $arrow\_direction = \text{'normal'}$ , add the edge  $(u, v)$  to  $E_H$  if adding it does not create a cycle:  $\neg \exists$  a path from  $v$  to  $u$  in  $H$ .
2. If  $arrow\_direction = \text{'reverse'}$ , add the edge  $(v, u)$  to  $E_H$  if adding it does not create a cycle:  $\neg \exists$  a path from  $u$  to  $v$  in  $H$ .
3. After adding each edge, if multiple edges point to the same node (i.e., there are multiple incoming edges to a node  $v$  or multiple outgoing edges from a node  $u$ ), remove all but the highest-weighted edge:
  - Let  $E_{in}(v) = \{(u, v) \mid u \in V_G\}$  be the set of incoming edges to node  $v$ , and  $E_{out}(u) = \{(u, v) \mid v \in V_G\}$  be the set of outgoing edges from node  $u$ .
  - Retain only the edge with the highest weight in each set.

## The Strategyfinder Website

<https://www.Strategyfinder.com>

The web site provides a variety of video support.

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**Strategyfinder**  
**Consulting Software GmbH**  
FN 623983y, ATU80524309

Dr Anita Reinbacher  
Muenichreiterstrasse 25  
A-1130 Vienna Austria  
Mail@Strategyfinder.com

ISBN: 978-3-903556-94-2