Recommendations from Cold Starts in Big Data

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Keywords: Recommender Systems, Information Retrieval, Data Mining, Sparse Data, Partially Labelled Data.

Abstract: In this paper, we introduce Transitive Semantic Relationships (TSR), a new technique for ranking recommendations from cold-starts in datasets with very sparse, partial labelling, by making use of semantic embeddings of auxiliary information, in this case, textual item descriptions. We also introduce a new dataset on the Isle of Wight Supply Chain (IWSC), which we use to demonstrate the new technique. We achieve a cold start hit rate @10 of 77% on a collection of 630 items with only 376 supply-chain supplier labels, and 67% with only 142 supply-chain consumer labels, demonstrating a high level of performance even with extremely few labels in challenging cold-start scenarios. The TSR technique is generalisable to any dataset where items with similar description text share similar relationships and has applications in speculatively expanding the number of relationships in partially labelled datasets and highlighting potential items of interest for human review. The technique is also appropriate for use as a recommendation algorithm, either standalone or supporting traditional recommender systems in difficult cold-start situations.

1 INTRODUCTION

New Big Data recommendation systems face a high barrier to entry due to the large labelled data requirement of most existing recommendation techniques such as collaborative filtering and bespoke deep learning models such as Suglia et al., (2017). Obtaining this labelled data, such as user interactions or human judgements, is particularly problematic in highly specialised or commercially competitive domains where this labelling may not yet exist or not be freely available, often requiring an expensive expert or crowd-sourced labelling. As such, techniques that function well with few labels are highly desirable.

The cost of labelling is highly dependent on the complexity of the task, specifically the time needed per human annotation and the expertise required. Snow et al., (2008) find that for tasks such as textual entailment and word sense disambiguation approximately four non-expert labels have similar quality to one expert label. Grady and Lease (2010) investigate crowdsourcing binary relevance labelling tasks and find that tasks where annotators must use item descriptions achieve poorer accuracy and require greater time per judgement than tasks using titles.

In some cases, datasets may be too large for comprehensive manual labelling and may only be viable to label by observing user behaviour, which requires a system able to function with very few labels without exclusively preferencing the already labelled subset of the data. Such systems can be used to bootstrap a recommendation platform where user interactions can then be observed to enhance the model or train an alternative model which performs well with many labels. This is also related to the cold-start problem where newly added items have no past interaction data.

Content based and hybrid recommender systems reduce the requirement for user-item interaction labels by making use of item content, such as descriptions. Many such systems rely on either knowledge bases and ontologies (Zhang et al., 2016), which do not avert the requirement of experts for new or commercially guarded domains, or tags and

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Ralph, D., Li, Y., Wills, G. and Green, N.
Recommendations from Cold Starts in Big Data.
DOI: 10.5220/0007798801850194
In *Proceedings of the 4th International Conference on Internet of Things, Big Data and Security (IoTBDS 2019)*, pages 185-194
ISBN: 978-989-758-369-8

categorisation (Xu et al., 2016), which requires either many labels or distinct groupings in the data.

2 ISLE OF WIGHT SUPPLY CHAIN DATASET

We examine the case of supply chain on the Isle of Wight. We introduce a new dataset for this task, which we name the Isle of Wight Supply Chain (IWSC) dataset. The data consists of varying length text descriptions of 630 companies on the Isle of Wight taken via web scraping from the websites of IWChamber (2018), IWTechnology (2018), and Marine Southeast (2018).

HTML tags and formatting have been removed, but the descriptions are otherwise unaltered and are provided untokenized, without substitutions, and complete with punctuation. Some descriptions contain product codes, proper nouns, and other non-dictionary words.

Most of the descriptions are a few sentences describing the market role of the company, or a general description of the company's activities or products. Several but not all the descriptions also contain a list of keywords, but this is included as part of the descriptive text and not as an isolated feature. The mean description length is 61 words, or 412 characters (including whitespace). The distribution of description lengths is shown in Figure 1.

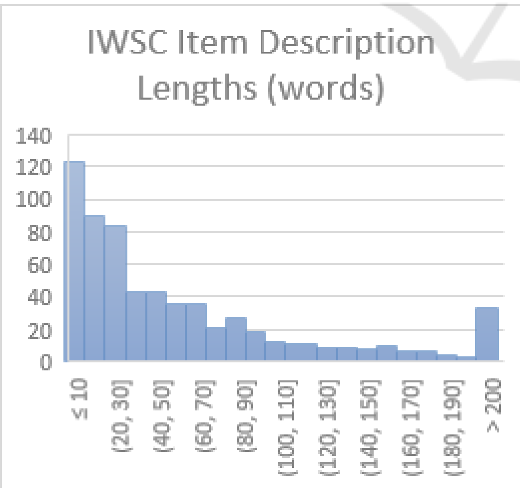


Figure 1: Histogram of item description lengths in the IWSC dataset.

The IWSC dataset is provided with two discrete sets of labels intended to evaluate algorithmic performance in different scenarios. In both cases, the labels are binary, directed, human judgements of market relatedness based on the company descriptions. The number and distribution of labels is shown in Table 1. These labels are speculative potential relationships, not necessarily real existing relationships. We choose to provide binary labels as real-world supply chain relationships are typically multi-class binary relationships. i.e. any two companies either are or are not in each possible type of supply chain relationship.

Table 1: Labels in the IWSC dataset.

Label Name	Total Labels	Labelled Items	Unique Targets
SL_suppliers	142	15	75
SL_not_suppliers	563	16	120
SL_consumers	376	17	117
SL_not_consumers	712	16	157
SL_competitors	82	15	49
SL_not_competitors	396	17	99
ES_suppliers	92	48	76
ES_consumers	207	51	171
ES_competitors	95	53	82
ES_unrelated	431	75	299

The first label set we denote IWSC-SL. It is comprised of the labels 'SL_consumers', 'SL_not_consumers', 'SL_suppliers', 'SL_not_suppliers', 'SL_competitors, and 'SL_not_competitors. These labels are concentrated on a small number of labelled items, relating them to a random distribution of other items (both labelled and unlabelled). These labels are intended for evaluation in the case that we only have records for a small subset of items and must extrapolate from this to perform inferences on many unseen items. We refer to this scenario as "Subset Labelling" (SL).

The second label set we denote IWSC-ES. It is comprised of the labels 'ES_suppliers', 'ES_consumers', 'ES_competitors', and 'ES_unrelated'. The labels are randomly distributed across all labelled items with no intentional patterns (random pairs were selected for labelling). These labels are intended for evaluation in the case that known items have very few labels and many are entirely unlabelled, in contrast to common recommender system datasets such as Movie Reviews (MR) (Pang and Lee, 2004), Customer Reviews (CR) (Hu and Liu, 2004), and MovieLens (Harper and Konstan, 2015), where most items have many recorded interactions. While in those examples the labels are sparse as most possible item pairs are unlabelled, in our scenario, which we refer to as "extremely sparse" (ES) labelling, there is the additional condition that most items in the dataset do not occur in any of these pairs.

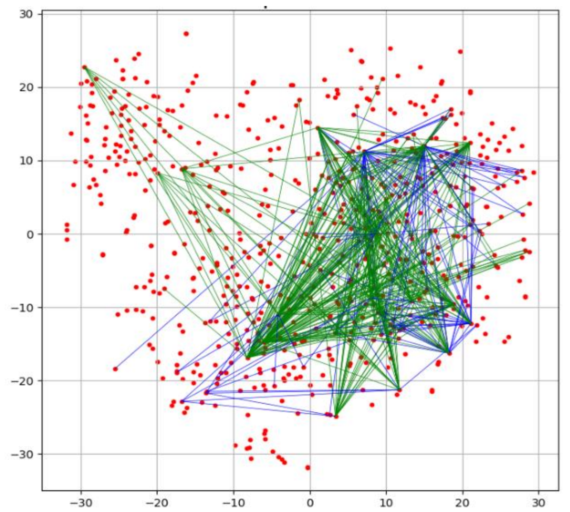


Figure 2: A 2D t-SNE plot of ISWC item description embeddings showing labels for the SL tasks.

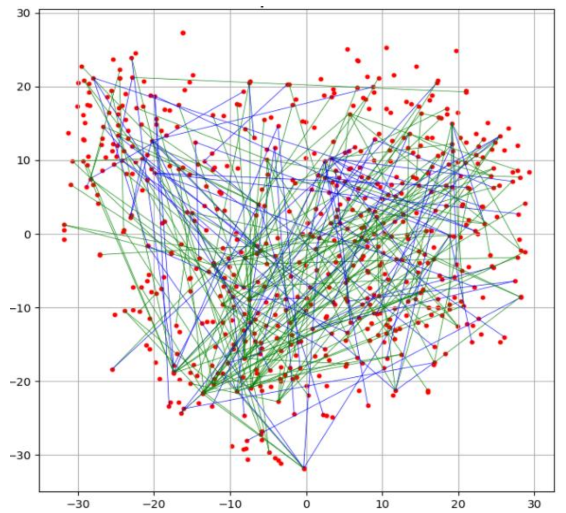


Figure 3: A 2D t-SNE plot of ISWC item description embeddings showing labels for the ES tasks.

Figures 2 and 3 illustrate the label distributions using 2d t-SNE (Maaten and Hinton, 2008) plots of IWSC item description embeddings generated using Universal Sentence Encoder (USE) (Cer et al., 2018), annotated with the labels from IWSC-SL and IWSC-ES respectively.

For the problem of effective recommendations from few labels, we set the four following tasks:

1. Prediction of "SL_consumers" labels using IWSC-SL labels and item descriptions
2. Prediction of "SL_suppliers" labels using IWSC-SL labels and item descriptions
3. Prediction of "ES_consumers" labels using IWSC-ES labels and item descriptions
4. Prediction of "ES_suppliers" labels using IWSC-ES labels and item descriptions

These tasks could also be expressed as two multi-class classification problems (one each for IWSC-SL and IWSC-ES), but in this paper we look at the four single-class recommendation tasks set out above.

The full IWSC dataset is available for download from https://github.com/DavidRalph/TSR-Public/tree/master/datasets

3 TRANSITIVE SEMANTIC RELATIONSHIPS

We introduce a novel approach to approach the problems of extremely sparse labelling and subset labelling previously described, that we call "Transitive Semantic Relationships" (TSR). TSR uses auxiliary item information for unsupervised comparison of items to expand the coverage of the few available labels. This is conceptually similar to other embedding based hybrid recommenders such as Vuurens et al. (2016) and He et al. (2017), but we implement a novel approach which combines item content embeddings with inferential logic instead of learned or averaged user embeddings, making it suitable for datasets with fewer labels and producing provenance that is both intuitively understandable and easy to visualise.

3.1 Theory

Transitive Semantic Relationships are based on an apparent transitivity property of many types of data items, where it is the case that items which are described similarly are likely to have similar relationships to other data items. Take for example, the supply chain: if company A, a steel mill and company B, a construction firm are known to have the relationship A supplies (sells to) B, it is likely that some other companies C, another steel mill, and D, another construction firm, would have a similar relationship. Given auxiliary information about each company, such as a text description of their product or market role, and the example relationship A->B, we can infer the potential relationships C->D, A->D, and C->B. We illustrate this example in Figure 4.

It follows that the greater the similarity between an item of interest and an item in a known relationship, the greater confidence we can have that the relationship is applicable. Given some fixed length vector representation of the auxiliary information about each item, we can use cosine

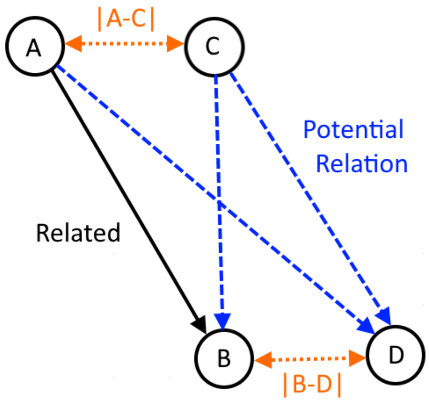


Figure 4: Illustration of Transitive Semantic Relationships.

similarity to measure similarity between the items. The vector representation should ideally capture semantic features of the auxiliary information that indicate whether the items they describe are similar in function in terms of the known relationship. If the vector representations fulfil this criterion, then the cosine similarity between two items is their semantic similarity. It then follows that we can determine the confidence that two items share a relationship by measuring the cosine similarity of the semantic vector for each item with another pair of items that share the same relationship. Cosine similarity values range from 0 (no similarity) to 1 (completely similar), so to keep confidence scores in the range 0 to 1, we take the sum of the similarity values over 2.

Continuing from the prior example illustrated in Figure 4, if the semantic similarity of A and C is |A-C|, and the similarity of B and D is |B-D|, we can calculate the confidence for each inferred relationship to be as shown in equations 1, 2, and 3.

$$A \rightarrow D = \frac{1 + |B - D|}{2} \quad (1)$$

$$C \rightarrow B = \frac{|A - C| + 1}{2} \quad (2)$$

$$C \rightarrow D = \frac{|A - C| + |B - D|}{2} \quad (3)$$

To further illustrate this, if C is very similar to A, for example |A-C|=0.8, but D was only slightly similar to B, |B-D|=0.2, then we can calculate A->D=0.6, C->B=0.9, C->D=0.5, indicating that there is a good chance that C could share a similar relationship with B as A does, but other new relations are unlikely. In another example, if C remains very similar to A, |A-C|=0.8, and we make D highly similar to B, |B-D|=0.7, then we calculate A->D=0.85, C->B=0.9, C->D=0.75, showing that while all relationships are likely, higher confidence scores are awarded when there is less uncertainty (due to dissimilarity with the known items).

Taking the inverse of this TSR confidence can be described as the combined-cosine-distance, or more generally the combined-semantic-distance. When explaining algorithms for recommendation using TSR confidence, we generally use this combined distance metric as we consider it easier to interpret when results are visualised and when distance values are weighted.

3.2 Application

The previous scenarios suppose that we have already pre-determined the items of interest for comparison. However, we can extend this principle to selection of items for comparison, given an input item to use as a query. Note that this is not a query in the sense of traditional search engines but is auxiliary information for an item for which we want to find relations (e.g. an item description).

First, we must make the distinction between cases where relationships map from one space to some other non-overlapping space, for example separate document collections, and the alternative case where items on either side of the relationship co-exist in the same space. A practical example of the former might be a collection of resumes and a collection of job adverts, while an example of the later might be descriptions of companies looking for supply chain opportunities, as in the IWSC dataset on which we evaluate TSR later in this paper. The TSR scoring does not differentiate between these two dataset types, but in the former case, with separate item collections, it is only necessary to make similarity comparisons between items in the same collection and irrespective of the total number of collections, we need only examine the collections featuring items on either end of at least one example of the relationship type of interest; this may be a useful filtering criteria in datasets featuring many types of relationships across many non-overlapping collections.

Having identified the collections that are of interest, we can optionally apply additional filtering of items before similarity comparison, such as by using item meta-data or additional auxiliary information, for example, only considering recent information, or limiting by language or region. This filtering could be done to the list of known relationships, if, for example historical trends are not of interest, or could be applied to potential targets, for example, ignoring adverts in a different language to the query item.

The next stage is to calculate similarity between the query item and other items in the same collection which are members of relationships of the type we are looking to infer, items not in such relationships are not of interest. We then calculate the similarity between the query and each of these, we refer to these items as “similar nodes” and call the similarity for each S1.

We then look at all items pointed to by the known relationships of each similar node, we refer to these collectively as “related nodes”. If the number of similar nodes is large we can choose to only follow relationships for a maximum number of similar nodes, preferring ones most similar to the query, in the results section we denote this parameter as L1. We then calculate the similarity between each related node and every other node in that space, which we call the “target nodes” and the similarity S2. An item can be both a related node and a target node, but an item cannot be both the query and a target node. If the number of target nodes is large, we can limit the number of comparisons in the next stage by considering only a maximum number of targets for each related node, preferring the most similar, we denote this parameter as L2.

We discuss alternative scoring approaches in section 5.3, but a simple scoring metric equivalent to the pre-selected items examples in the previous section is to determine the score for each target node by finding the largest value for (S1+S2)/2 that creates a path to it from the query item, where S1 is the similarity between the query and an item in the query’s space (the similar node), which shares a relationship with an item in the target’s space (the related node) which is of similarity S2 to the target node. This scoring system ranks items by the minimum combined-semantic-distance from a known relationship of the desired type.

In Figure 5 we show a visualised example of several TSR routes for a query. Due to the number of relationships considered for a query a 2d plot is not an ideal visualisation. While not shown in this publication, the evaluation software can also produce interactive 3d plots which allow inspection of individual routes and the relevant nodes and labels, allowing some insight into the behaviour of the scoring algorithm.

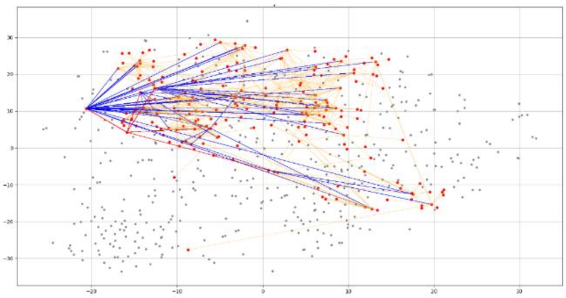


Figure 5: A 2D t-SNE plot of IWSC item descriptions showing labelled and inferred relationships for a query. Each route is comprised of three lines: query node→similar node, similar node→related node, related node→target node.

4 EVALUATION TECHNIQUES

Various evaluation metrics are used in recommender system and information retrieval literature. As the IWSC dataset uses binary labels, and the total number of labels is small, we look at evaluation techniques which best reflect this.

Normalised Discounted Cumulative Gain (NDCG) (Järvelin and Kekäläinen, 2002) is a common evaluation metric in information retrieval literature. This is a graded relevance metric which rewards good results occurring sooner in the results list, however it does not penalise highly ranked negative items. As binary labels have no ideal order for positive items, we do not consider this a suitable metric.

Quantitative error metrics such as Root Mean Squared (RMS) error or Median Absolute Error are also common. Error metrics naturally favour scoring systems optimised to minimise loss such as learning-to-rank algorithms and require scores to fit the same range as the label values. For the IWSC dataset, as the labels are binary, the range is 0 to 1. However, scores output from TSR have no guarantee of symmetric distribution over the possible output range and are typically concentrated towards high-middle values due to averaging similarity scores making extreme values uncommon. Figure 6 shows the typical score distribution for the standard TSR algorithm TSR-a.

In section 5.3 we describe some alternative scoring algorithms with unbounded upper values. A scaling function can be applied after scores are calculated to fit them to a specific range, but this still

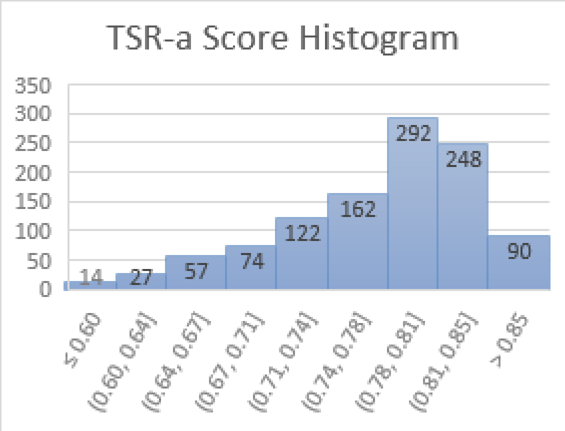


Figure 6: Histogram of item scores produced by TSR-a.

does not guarantee the desired distribution and could be sensitive to outliers, such as unusually high scoring items, distorting error values.

For a binary labelled dataset, it is intuitive to set some threshold on the rankings and produce a confusion matrix, and take precision (P), recall (R), and f1 scores. As scores are not evenly distributed, there is no obvious score value to use as a threshold, so instead we look at some number of the top ranked items.

Due to the sparsity of labels in the dataset, the number and ratio of known positives and known negatives varies significantly between items and in many cases the number of known positives is smaller than typical values of K used for Precision at K. For this reason, we instead use R-Precision, setting the threshold at R, the number of true positives, and take the R most highly rated items to be predicted positive and all remaining to be predicted negative; at this threshold P, R, and f1 are equal. In the results section, we denote scores taken at this threshold as @R. A drawback of this approach is that we can only evaluate using known positives and known negatives, which is a minority of possible pairs in a sparse dataset. The difficulty of this evaluation task also varies with the ratio of known positives and negatives which is undesirable when evaluating datasets such as IWSC where the ratio varies greatly between items.

Finally, we look at techniques from the literature on implicit feedback. Techniques for implicit feedback have the desirable property of allowing us to expand the number of unique evaluation cases by enabling us to use unlabelled pairs of items (which for a sparse dataset is most possible item pairs) as implicit negative feedback. We use the common evaluation framework used by He et al. (2017) and Koren (2008), where we perform leave-one-out cross validation by, for each item, taking one known positive and 100 randomly selected other items (excluding known positives), and judging the ranking algorithm by ability to rank the known positive highly. The typical threshold used is that the known positive must be in the top 10 results, this Hit Ratio (HR) metric is denoted as HR@10. HR@5 refers to the known positive being in the top 5, and HR@1 as it being the highest rated item. We also show the mean and median values for the ranks of the known positives across all test cases.

It is of note that due to the random selection of negative items results may vary between runs. To ensure the results are representative we test each known positive against multiple random pools of implicit negatives. This significantly increases the compute time required for evaluation but minimises variation in scores between runs.

Having a fixed number of items in each evaluation and repeating with different random sets of items makes this metric well suited to datasets with uneven label distribution such as IWSC. We also consider the values to be quite intuitive as the random-algorithm performance for any HR@n is approximately n%, with ideal performance always being 100%. Mean and median positive label rank is in the range 0 to 100.

5 RESULTS

We first use a neural language model to generate fixed length embeddings for all descriptions. In this study we use Universal Sentence Encoder (USE). This model was chosen as it shows good performance on a range of existing downstream tasks (Cer et al., 2018). It is also of particular interest that this model was fine-tuned on the SNLI dataset (Bowman et al., 2015), a set of sentence pairs labelled as contradiction, entailment, or unrelated; we speculate that this may require the model to learn similar linguistic features as are likely needed for the supply chain inference task as the ability to discern whether pairs of descriptions are entailed or contradictory is essential to human judgements for this task, in particular, in determining if companies serve similar supply chain roles. As the focus of this paper is in introducing TSR, we leave detailed investigation of the effects of upstream embedding models to future work.

Table 2: Explicit feedback evaluation of TSR-a on the IWSC-SL tasks.

Positive Label Name	Labelled Items	Positive Labels	Negative Labels	F1 @R	RMS Error	Median Absolute Error
SL_consumers	16	375	712	0.520	0.204	0.688
SL_suppliers	15	142	525	0.477	0.234	0.682

Table 3: Implicit feedback evaluation of TSR-a on the IWSC-SL tasks.

Positive Label Name	Labelled Items	Positive Labels	HR @10	HR @5	HR @1	Median Positive Rank	Mean Positive Rank
SL_consumers	17	376	0.752	0.510	0.146	4	7.8
SL_suppliers	15	142	0.663	0.543	0.150	4	14.0

Table 4: Explicit feedback evaluation of TSR-a on the IWSC-ES tasks.

Positive Label Name	Labelled Items	Positive Labels	Negative Labels	F1 @R	RMS Error	Median Absolute Error
ES_consumers	39	115	198	0.549	0.167	0.560
ES_suppliers	46	90	259	0.350	0.177	0.572

Table 5: Implicit feedback evaluation of TSR-a on the IWSC-ES tasks.

Positive Label Name	Labelled Items	Positive Labels	HR @10	HR @5	HR @1	Median Positive Rank	Mean Positive Rank
ES_consumers	51	207	0.221	0.119	0.018	36	43.0
ES_suppliers	48	92	0.197	0.129	0.055	32	47.7

5.1 Results for Subset Labelled Tasks

Table 2 and Table 3 show our results on the two IWSC-SL tasks introduced in section 2. In these experiments we used the least-combined-cosine-distance soring metric described in section 3.2 and evaluate using metrics discussed in section 4. All experiments are cold-start scenarios where the input (query) item is treated as unseen, only the USE embedding of its description is known.

We set the parameters L1=5 and L2=10, for this scoring metric the value of these parameters has little impact on performance as only the best routes contribute to scoring, but it is observable that this inflates the mean positive rank as items lacking good routes are more excluded from the results, which we treat as it being the worst possible rank.

For the implicit feedback evaluations (HR and Positive Rank) we use one known positive, and a random pool of 100 not-known-positive items. We repeat this process 10 times for each label, using different random pools, and calculate the scores across all tests. Therefore, the number of test runs is always 10 times the number of positive labels. The number of labelled items and positive labels used in the implicit feedback tests is higher as we can additionally test items that lack any known negatives.

Our results show good performance on the IWSC-SL tasks, considering how few labels are available, achieving a hit-rate@10 of over 75%. It is notable that we see less than 9% worse performance on the SL_suppliers test despite having less than half the number of labels, showing that the algorithm can achieve good performance on labelled-subset tasks even when extremely few labels are available (142 labels in a dataset of 630 items). For both IWSC-SL tasks the frequency of the top ranked item being the known positive (when competing with 100 randomly selected others) HR@1 appears similar and is 14-15 times better than random.

5.2 Results for Extra Sparse Labelling Tasks

Table 4 and Table 5 show our results on the two IWSC-ES tasks introduced in section 2. The algorithm and parameters are the same as in the IWSC-SL tasks tests. The IWSC-ES tasks each have around half the number of positive labels as the IWSC-SL tasks, so a lower score should be expected.

In the IWSC-ES tasks we show significantly worse hit-rate, but smaller median absolute error and RMS error. We speculate that the lack of dense regions in the labels, due to the extreme sparsity and random distribution, makes identifying a particular

Table 6: Evaluation of alternative TSR algorithms on the IWSC SL_consumers task.

Scoring Algorithm	HR @10	HR @5	HR @1	Median Positive Rank	Mean Positive Rank	F1 @R	RMS Error	Median Absolute Error
TSR-a	0.754	0.509	0.145	4	7.7	0.520	0.204	0.688
TSR-a*	0.754	0.509	0.145	4	7.7	0.520	0.195	0.481
TSR-b	0.548	0.364	0.115	8	11.5	0.541	0.12	0.319
TSR-c	0.573	0.385	0.133	7	10.9	0.544	0.12	0.309
TSR-d	0.565	0.373	0.124	7	11.1	0.544	0.122	0.322
TSR-e	0.771	0.532	0.163	4	7.6	0.530	0.204	0.584
TSR-f	0.582	0.408	0.158	7	10.5	0.549	0.146	0.456
TSR-g	0.742	0.536	0.185	4	7.8	0.533	0.192	0.523
TSR-h	0.767	0.538	0.152	4	7.5	0.531	0.196	0.508
TSR-i	0.543	0.362	0.112	8	11.5	0.541	0.121	0.32
TSR-j	0.550	0.359	0.117	8	11.6	0.541	0.12	0.318
TSR-k	0.750	0.538	0.179	4	7.9	0.525	0.207	0.605
TSR-l	0.723	0.529	0.189	4	8.1	0.536	0.189	0.525
TSR-m	0.771	0.530	0.151	4	7.5	0.523	0.17	0.433
TSR-n	0.577	0.385	0.135	7	10.7	0.541	0.121	0.32
TSR-o	0.659	0.466	0.181	5	9.2	0.539	0.143	0.452
TSR-p	0.758	0.533	0.158	4	7.5	0.531	0.165	0.456
TSR-q	0.558	0.372	0.119	8	11.2	0.541	0.120	0.325

known positive more difficult, but the better error values and F1 score indicate that the predicted scores are still effective for discerning good and bad results despite being less effective at a ranking a given good result highly.

5.3 Alternative Scoring Algorithms

The TSR-a scoring algorithm described previously, taking the score for a target as simply the minimum combined cosine similarity values over 2 (i.e. shortest combined cosine distance), is relatively simple to calculate and is both intuitive and easy to visualise (see Figure 5). However, as only the shortest route to a target is considered, it does not factor in supporting evidence. For example, in the case of two targets with highly similar shortest distances from the query, if one had multiple high-quality routes and the other had only the one short route, we would intuitively be more confident to recommend the target with greater supporting evidence.

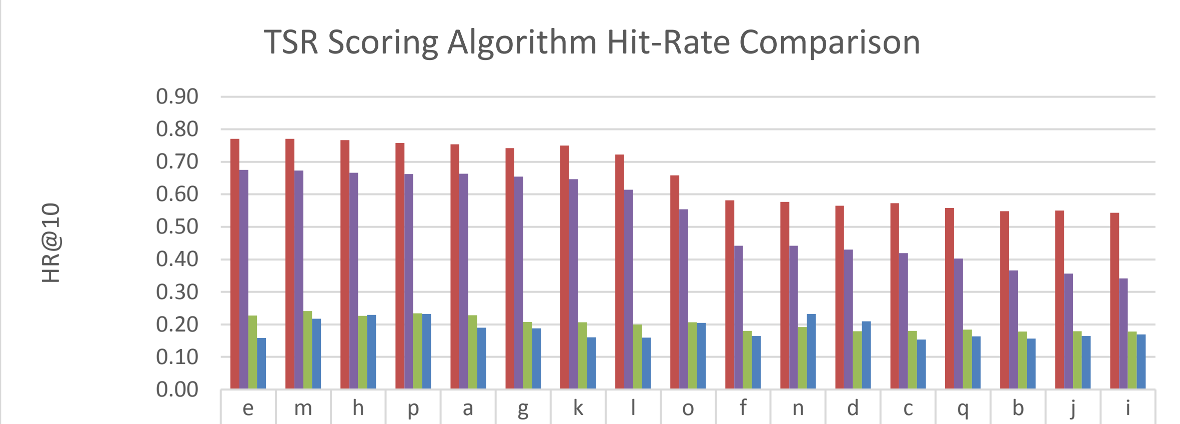
We test several variations of the scoring algorithm which boost the score when multiple good routes to the target are found. These approaches include multiplication of the score based on the number of routes, taking the weighted sum of the scores for each route, and taking the sum of scores for each route but increasing the significance of distance (e.g. distance squared or cubed). The results for some of these tests for the SL_consumers task are shown in Table 6 and a comprehensive comparison across all task is shown in Figure 7. As these algorithms produce scores outside the range 0-1, we apply a simple scaling algorithm shown in equation 4.

$$f(s_i) = \frac{s_i - \min(s)}{\max(s) - \min(s)} \tag{4}$$

The scaling algorithms does not modify the order of results but gives more score values suitable for error measurement. TSR-a produces score in the range 0-1 without scaling, but we include a scaled version TSR-a* for comparison, as TSR-a rarely gives scores close to its bounds (see Figure 6).

We find that most of these approaches perform either similarly to, or significantly worse than scoring by only the best route as in TSR-a. The scoring metrics that do perform better show slight improvement.

The best performing algorithm for the IWSC-SL tests is TSR-e, where we calculate the target score as the sum of score for the best route and half the score of the second-best route. This produced an improvement to HR@10 of 1.7% for the SL_consumers task and 1.2% for SL_suppliers but has the disadvantage of having a score distribution concentrated towards middle values, as extreme values would require either all routes to be very poor, or both routes to be very good, which is less common than only the best route being very good or bad. This may account for its comparatively high error values as error measurements will be high even for a correct



	e	m	h	p	a	g	k	l	o	f	n	d	c	q	b	j	i
SL_consumers	0.77	0.77	0.77	0.76	0.75	0.74	0.75	0.72	0.66	0.58	0.58	0.57	0.57	0.56	0.55	0.55	0.54
SL_suppliers	0.68	0.67	0.67	0.66	0.66	0.66	0.65	0.61	0.55	0.44	0.44	0.43	0.42	0.40	0.37	0.36	0.34
ES_consumers	0.23	0.24	0.23	0.23	0.23	0.21	0.21	0.20	0.21	0.18	0.19	0.18	0.18	0.18	0.18	0.18	0.18
ES_suppliers	0.16	0.22	0.23	0.23	0.19	0.19	0.16	0.16	0.20	0.16	0.23	0.21	0.15	0.16	0.16	0.16	0.17

Figure 7: Comparison of Hit rate of alternative TSR algorithms on all four IWSC tasks.

ordering if values are concentrated towards the mid-range.

Another well performing algorithm is TSR-m, as given in equation 5, where r is the number of routes to the target and d is the combined-semantic-distance of each route. We omit the scaling function for clarity as it is already given in equation 4. Scaling is applied once all score values have been calculated.

$$S = \sum_{i=0}^{r} \left(\frac{1}{d_i (i+1)^3} \right) \quad (5)$$

The algorithms TSR-o and TSR-p are the same as TSR-m except that the exponent of the route's rank, which the score is divided by, is 1 and 2 respectively; these variations perform significantly worse. It is interesting that when penalising the contribution of additional routes, we see sub-standard performance when the penalty is small, but above-standard performance when it is large. This would suggest that some ideal penalty function exists where additional routes do not overpower the normal scoring but still provide support in closely scored cases. It is possible that the best scoring penalty is a property of the distribution of the data and labels, and that the ideal penalty function may be dependent on the dataset. Testing of this property on other datasets, and alternative penalties for this dataset are left to future research.

5.4 Reproducibility

We have made available for download the full suite of evaluation tools and TSR implementation used in generating these results, along with the full set of experimental results and IWSC dataset at https://github.com/DavidRalph/TSR-Public.

In section 5.3 we describe only the best performing scoring algorithms. The full implementation of each can be found in the publicly available TSR implementation.

6 CONCLUSIONS AND FUTURE WORK

We have demonstrated the Transitive Semantic Relationships technique as an effective recommendation algorithm on datasets with very few labels and from cold-stats. In particular we see good performance on the subset-labelling task of the Isle of Wight Supply Chain dataset also introduced in this paper. We show that supporting evidence in the form of additional high-quality routes to a target can have a positive impact on performance, but that the weighting used can have a large impact on performance. Additionally, we find that the inclusion of additional routes in the scoring can have a negative effect if the labels are extremely sparse and not concentrated. Using TSR we set the baseline performance on the four recommendation tasks for the IWSC dataset. Our best performing algorithm TSR-e showing a hit-rate@10 of 77% on the SL_consumers task.

The focus of this paper has been on introducing the TSR technique and IWSC dataset and tasks. Both contributions open new avenues for further investigation into the properties of extra sparse, and subset labelled datasets. Future work could examine the effects of different embedding models on TSR and prediction of supply chain competitors and test if different fine-tuning of these models would further improve results.

Additional future work could include a comprehensive analysis of the performance of the TSR technique on other datasets and how it compares to or could be used in conjunction with other recommender systems, particularly as the number of labels is increased. TSR could also be applied to expand the number of relationships in a partially labelled dataset to allow the use of algorithms that struggle with cold starts or require many training examples.

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