IPR: Integrative Policy Recommendation Framework Based on Hybrid Semantics

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Abstract. Policy recommendations aim to inform people who are faced with policy decisions on specific issues about how research and evidence can assist them in making the best decisions possible. This paper proposes an ontology-focused semantical driven integrative system for policy recommendation. The recommendation is user query-centric and uses Structural Topic Modelling to find topics that can be correlated. The semantic similarities are computed using Resnik and concept similarity methods to achieve ontology alignment, and for the alignment of principle classes, three models, normalized compression distance, Twitter semantic similarity, and Hiep's Evenness Index, are used. The IPR achieves the best-in-class accuracy of 94.72% and precision of 93.14% for a wide range of recommendations over the other baseline models, making it an efficient and semantically compliant system for the policies recommendation.

Keywords: Twitter semantic similarity · Resnik and concept similarity · Hiep's Evenness Index · RDF · NCD · Structural topic modelling

1 Introduction

Policies are guidelines or principles that govern decisions and lead to positive outcomes that benefit the community or unit. That leads to the development of procedures and protocols to ensure that policies are executed appropriately. Public policies are based on balancing individual and social values. Policy analysis helps us find the solutions to practical problems brought to the government's plan. Understanding how public policy works can help us better resolve problems. Since the amount of content available on the internet has increased dramatically after the internet's inception. This overabundance has resulted in a spot of bother for the end-user, who generally ends up with a handful of data

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that may or may not suit his needs. Thus arises the need to recommend accurate and relevant data to the user's needs. A recommender system is a filtration solution that provides relevant and necessary data to a user based on the user's input queries and data.

The lack of knowledge about these policies can create multiple losses or problems. One spends an intemperate amount of time finding the proper documents for the government policy. The system proposed in this paper enables a semantic approach to recommend such government policies.

The policy recommendation is quite crucial in the present-day time because policies are required to implement irrespective of the domain. Policies serve as standard guidelines to ensure that specific rules and regulations are followed. To implement rules and regulations, policies have to be met, and to do this the existing policies have to be recommended for which recommendation systems are required sometimes it is very difficult to find the policy document for specialized specific instances because of the large amount of policies documents but lack of relevant policy documents.

There is always a need for a semantically inclined approach to policy recommendation which would not only try to identify the documents containing policies but also be able to relate existing policies through the query and moreover give a crisp answer. Structuring documents for recommending policies is the need of the hour such that the external existing intelligent information system is able to relate the query with existing policies and rephrase and reframe the policies in accordance with the query that has been input. To know that a semantically inclined strategic approach for knowledge-centric policy recommendation is the need of the hour and semantically inclined models based on semantic rules-based inference with preferential learning and differential hybrid semantics ensure an integrative collective intelligence driven model for recommending the policies.

Motivation: With the web's current structure, namely the Web 3.0 or the semantic web, there emerges a need for Semantically Infused recommendation strategies. Recommendations involving highly specialized domains like the judicial domain are challenging using traditional means, mainly because a lot of domain knowledge is needed. Moreover, the judicial aspects differ from country to country in the socio-legal judicial domain. Hence, it is generally difficult to generalize such systems; specific domain knowledge from different countries is essential for the system's support. This bolsters the need for the semantically inclined recommendation of socio-legal judicial documents.

Contribution: A semantically inclined recommender system IPR is proposed for the recommendation of government policies. The model incorporates generated Resource Description Framework (RDF). Structural Topic Modelling (STM) is used for topic modelling and is subjected to RNN and deep learning classifiers. The auxiliary knowledge is provided through government policy portals, Wikidata, and government policy blogs. The semantic similarities are computed using Resnik and concept similarity methods to achieve ontology alignment, and for the alignment of principle classes, three models, normalized compression distance, Twitter semantic similarity, and Hiep's Evenness Index, are used.

Organization: The remaining paper is organized as follows: Section 2 depicts related works, Sect. 3 depicts the proposed system architecture, Sect. 4 depicts results and the whole paper is concluded in Sect. 5.

2 Related Works

Tong et al. [1] present a model based on text mining which consists of Policy structure division; Attribute extraction; Matching, and recommendation. Their approach suggestion results cover policy text pieces, related legislative organizations, quality substances, legitimate relations, and connections to the whole policy text. Alessandra et al. [2] put forward two approaches firstly, an ontology-driven approach that heavily relies on the expressive features of Description Logic (DL) languages. The second approach is a rule-based system that encodes policies as Logic Programming (LP) rules. They also describe a hybrid approach that exploits the expressive capabilities of both DL and LP approaches. Olga et al. [3] have put forth a recommendation system that can add adaptive navigation support to existing learning management systems to overcome the current limitations of organizing training systems in terms of personalization and accessibility. Hyunsook et al. [4] have discussed In-depth curriculum and syllabus ontologies that were created. They also propose a method for syllabus integration and classification based on the definition of the syllabus's semantic model, claiming that this approach aids adaptive concept sequencing and syllabus sharing. Joshi et al. [5] proposed a semantic-based machine-processable structure to observe digital security strategy and populate an information diagram that effectively captures various consideration and prohibition terms and rules inserted in the approach They depict this system using Natural Language Processing, Modal/Deontic Logic, and Semantic Web as well as AI innovations. Ge et al. [6] have proposed a model for instance matching using concept similarity and semantic distance in a highly cohesive environment like the Web 3.0. Lu et al. [7] have put forth a hybrid model which is semantically inclined for recommendations personalization in support of e-government businesses. The personalization was with respect to e-services rendered based on business to business model for a government linked scheme in support of semantic techniques. Deepak et al. [8] proposed an intelligent system for webpage recommendation encompassing semantics using ontologies. Ontologies served as indicators and provisioned Knowledge Map in support of recommendations for a Web 3.0 environment. Adithya [9] an ontology focused collective knowledge approach for requirement traceability modelling. In European, Asian, Middle Eastern, North African Conference on Management Information Systems. Fernando et al. [10]

have proposed a framework for improving electronic communication for government agencies targeting several ethic groups using ontologies in multi-faceted dialect encompassing Language Processing Techniques. Deepak et al. [11] have put forth a differential semantic algorithm for recommending web pages where differential vibrational thresholds on Adaptive Pointwise Mutual Information measure was applied. Fernando et al. [12] put forth an approach for sharing, retrieval and exchange of Legal Documents in support of e-governmental policies using Ontology Driven Methods. Panchal et al. [13] have proposed a framework which is an Ontology Driven Semantic Model in support of higher education in public universities. Sanju et al. [14] have formulated methodologies for representing domain knowledge focusing on Web of Things. In [15] Tiwari et al., have formalized the study of knowledge graph construction and put forth their opinion in building knowledge graphs across several interrelated domains in the real-world Web. Yethindra et al. [16] proposed a fashion recommendation model in support of Web 3.0 and its dense Open Linked Format by integrating auxiliary knowledge, domain based fashion experts opinion, personalized information from Browsing History and Machine Intelligence Incorporation through Logistic Regression, Variational Inferencing and Ontologies.

3 Proposed System Architecture

The proposed system architecture is the government policy recommendation model, which is ontology-focused semantical driven, in correlation with standards of Web 3.0. Figure 1 illustrates the architecture diagram for the proposed government policies recommendation system from web data and input queries provided by the user. Initially, the input user query is analyzed, and information for the policies recommendation is taken and sent for pre-processing; the input query obtained is too subject to pre-processing. The pre-processing of the query data entails Lemmatization, Tokenization, named entity recognition and stop word removal.

These processes are performed using the python natural language toolkit. To yield the individual query words, many people seek different ways. The user query results in the individual informative query words, which are visualized as a set; these query words are subject to ontology alignment. Ontology alignment is the mapping of concepts and the sub concept as well as individuals with each other, which is achieved by computing similarity between the concepts and sub-concepts; however, the semantic similarity between individuals has not been computed to avoid ambiguity and to ensure that the proposed model is computationally less complex.

The ontology used here is the enhanced government policy ontology used for matching, which is obtained by modeling government policy ontology based on human cognition. Manually modeled ontology based on human cognition is initially used as a seed ontology, the ontology of government policy. This is further subjected to the enrichment of term aggregation and ontology enhancement by gathering information specifically from several blogs, government policy portals,

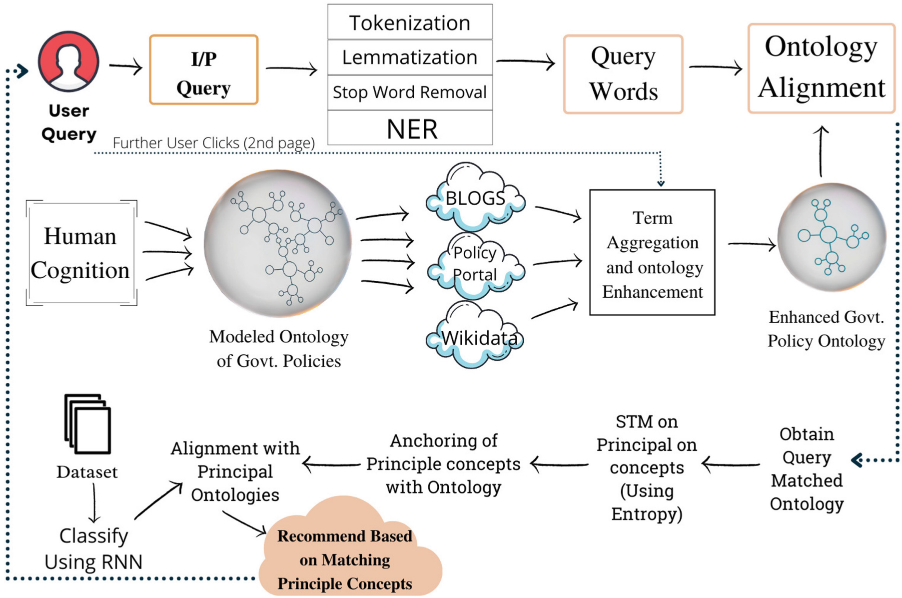

Fig. 1. Proposed system architecture design for the IPR model

and the scraped relevant data from the World Wide Web. We are also using wikidata as a knowledge store in these cases. The wikidata knowledge store was also used before term aggregation and ontology enhancement which further yields the enhanced government policy ontology, which is used for ontology alignment based on the concept and sub concept alignment with that of the preprocessed query terms.

Ontology alignment is achieved by computing the semantic similarity using two models. The first model is Resnik similarity, and the second similarity is concept similarity. These two similarities are used here to work with the large volume and size of enhanced government policy ontology. Both Resnik and concept similarities are used at the threshold of 0.75, which is called ontology alignment. Aligned ontology with that of query words further used for Structural Topic Modeling (STM).

Resnik presents a new measure of semantic similarity based initially on an English lexical database of concepts and relations, WordNet. The measures include three augmenting path-based measures and two path-based measures with corpora information content statistics.

The Concept Similarity matching method based on semantic distance comprehensively takes into account the inheritance and semantic distance relationships among concepts, and uses semantic similarity to determine the degree of matching between concepts. The algorithm calculates semantic similarity between concepts using various macro steps and gains human intuition similarity. The whole concept similarity matching method is proposed in [6]. Here, the weight allocation is to the edge between concepts and for the two concepts C1 and C2, the weight allocation function is:

$$W[sub(C_1, C_2)] = 1 + \frac{1}{k^{depth(C_2)}} \tag{1}$$

where depth(C) is the depth of concept C in the ontology hierarchy from the root concept to node C, and k is a predefined factor.

The predefined factor, k is greater than 1 and indicates the rate at which weight values decrease along the ontology hierarchy.

For two concepts (E_1, I_1) and (E_2, I_2) the concept similarity (Sim) is defined as:

$$Sim((E_1, I_1), (E_2, I_2)) = \frac{|E_1 \cap I_1|}{r} * w + \frac{M(I_1, I_2)}{m} * (1 - w) \tag{2}$$

here, $M(I_1, I_2)$ is the set where sum of ics (Information content similarity) of the pairs of attributes is maximum, r is maximum of cardinalities of E_1 and E_2, m is maximum of cardinalities of I_1 and I_2, $w(0 \leq w \leq 1)$ is a weight can be calculated using Eq. (1).

The Structural Topic Model (STM) is a type of topic modeling that allows us to include metadata in our model and see how different documents could discuss the same underlying topic using different word choices. It is part of the Bayesian generation topic model, which assumes that each topic is a set of words and that each document is a combination of topics within the corpus. The STM allows for quick, transparent, and repeatable analyses with few a priori assumptions about the texts being studied. Researchers can use the STM algorithm to find topics that can be correlated and estimate their relationships to document metadata using the STM algorithm.

Here, STM is identified as the principal concept. This principal concept is determined by computing the entropy randomly on the obtained query-matched ontology. However, the entropy between the query word and the query matched ontology subset is computed and noted with the highest entropy considered the principal concept and structure topic modeling. This principal concept is subjected to STM and then encored with other concepts in the enhanced government policy ontology.

The pre-processed categorical government policy dataset is classified using the RNN. Artificial recurrent neural networks (RNNs) are a broad and diverse class of computational models inspired by biological brain modules in some way. RNN is a neural network with hidden states that allows previous outputs to be used as inputs. RNN is a deep learning algorithm that works with time series or sequential data. In an RNN, the information cycles through a loop. It considers the current input and what it has learned from the previous inputs and makes its decision. The reason for using RNN is that it is a deep learning model. Second, the recurrent neural network incorporates automatic feature selection so that a large volume dataset can easily be classified using RNN (Fig. 2).

$$h_{(t)} = \sigma_{(h)}(U_{(h)}.x_{(t)} + W_{(h)}.h_{(t-1)} + b_{(y)}) \tag{3}$$

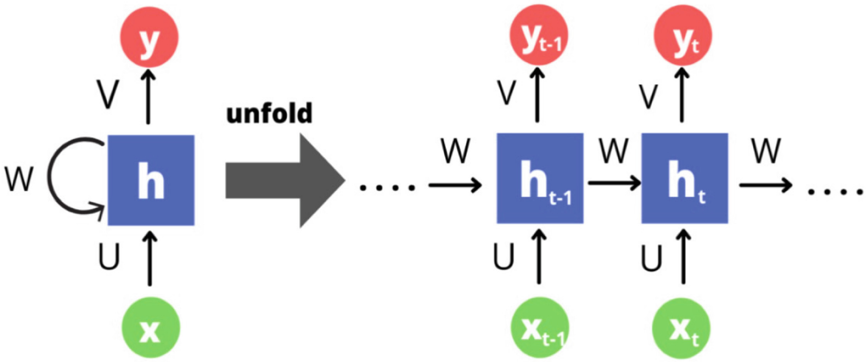

Fig. 2. Structure of Recurrent Neural Network (RNN)

$$y_{(t)} = \sigma_{(y)}(V_{(h)}.h_{(t)} + b_{(y)}) \tag{4}$$

$x_{(t)}$: Input Vector, $y_{(t)}$: Output Vector, $\sigma_{(h)}$ and $\sigma_{(y)}$: Activation Functions, W and U : Parameter matrices, $b_{(h)}$ and $b_{(y)}$: Bias Vector

The principal classes are aligned again with the anchored principal concepts in the ontology cluster. For this alignment, we use three models: normalized compression distance (NCD), Twitter semantic similarity, and Hiep's Evenness Index.

The normalized compression distance (NCD) is a method of determining object similarity. The NCD is a set of distances that have been parametrized using the compressor Z. The higher Z is, the nearer the NCD approaches the NID, and also the better the results are. With Kolmogorov complexity function C(x), normalized compression distance NCD (x, y) is defined as:

$$NCD(x, y) = \frac{C(xy) - min(C(x), C(y))}{max(C(x), C(y))} \tag{5}$$

Twitter Semantic Similarity (TSS) is a semantic similarity measure supported social network Twitter that is time-dependent with static similarity measure. But it's a high temporal resolution for detecting real-world events and induced changes within the distributed structure of semantic relationships across the whole lexicon.

The Hiep's Evenness Index outperforms other evenness indices statistically in a low-diversity neighborhood of copepods with in benthos of shallow saline water habitat; it is the only index that shows no significant deviation from normality. Hiep's Evenness Index is defined as:

$$HE(Hiep'sEvennessIndex) = 1 + \frac{e^H - 1}{S - 1} \tag{6}$$

here H represents the Shannon's index of diversity and S represents species richness. The index ranges from 0 to 1 and measures how similarly the species extravagance adds to the all-out overflow or biomass of the local area.

Both normalized compression distance (NCD) and Twitter semantic similarity are computed with the threshold of 0.75. However, the Hiep's Evenness Index is calculated with a step deviation of 0.25 to recommend the ontology based on principal concepts.

Only the principal concept is first recommended along with the ontology; however, the computation of this semantic similarity happens only when the principal concept is matching. The increasing order of Twitter and semantic similarity is prioritized and rearranged and is recommended to the user. Based on the user clicks further captured, it is fed into the term aggregation and ontology enhancement phase such that this process continues until the user is satisfied with the information needs and there are no further clicks captured.

4 Results

The proposed IPR (integrative Policy Recommendation) framework is in comparison with two baseline modes, namely BizSeeker [7] and TMPR [1]. Since there is a lacune of models which recommend government policies. Experiments have been conducted by combining SVM, KNN with cosine similarity, and Adaboost with K-means clustering. Precision-recall accuracy, F-measure percentages, and the false discovery rate (FDR) are used as potential matrix precision-recall accuracy. F measure computes the relevance of the result. In contrast, FDR quantifies for several false positives discovered by the model. It is indicative in Table 1 that the proposed IPR yields the highest precision, recall, and accuracy of 93.14%, 96.29%, 94.72%, respectively, with the average F-measure of 94.69 with a very low FDR of 0.07.

The BizSeeker results average precision, recall, and accuracy of 78.68%, 80.44%, 79.56%, respectively, with average F-measure and FDR of 79.55, 0.22 respectively. TMPR yields average precision, recall, and accuracy of 88.24%, 90.18%, 89.21%, respectively, with an average F-measure of 89.20 and FDR of 0.12. SVM along with KNN and Cosine similarity results average precision, recall, and accuracy of 82.12%, 86.77%, 88.45%, respectively, with average F-measure and FDR of 84.38, 0.18 respectively, whereas Adaboost along with K-means clustering yields average precision, recall, and accuracy of 84.45%, 86.33%, 85.39%, respectively, with average F-measure of 85.38 and FDR of 0.16 (Table 2).

Table 1. Performance comparison of the proposed IPR with other baseline methods.

Models	Precision %	Recall %	Accuracy %	F-measure
BizSeeker [7]	78.68	80.44	79.56	79.55
TMPR [1]	88.24	90.18	89.21	89.20
SVM + KNN	82.12	86.77	88.45	84.38
Adaboost + K-means	84.45	86.33	85.39	85.38
Proposed IPR	93.14	96.29	94.72	94.69

Table 2. FDR values of the proposed IPR with other baseline methods.

Models	FDR
BizSeeker [7]	0.22
TMPR [1]	0.12
SVM + KNN	0.18
Adaboost + K-means	0.16
Proposed IPR	0.07

The proposed IPR yields the highest accuracy, average precision, average recall, F measure, and the lowest FDR mainly because it is semantically enriched and empowered. It is the hybrid model which uses strong semantics. Ontology alignment is the core of the model, along which structural topic modeling is selected using entropy. RNN and deep learning classifiers are used for the automatic classification of the dataset. Auxiliary knowledge is provided through government policy portals, Wikidata, and government policy blogs. Concept similarity, Resnik similarity, and Twitter semantic similarity are used for computing the semantic similarity at several stages, sometimes standing alone for ontology alignment with using concept similarity or computing the relevance they use hybridized with various differential thresholds. Combining three different semantic similarity models ensures that the relevance computation is much more at a higher rate. As a result, the proposed IPR yields the highest F measure, precision-recall accuracy with the lowest FDR rate.

The Bizseeker model is a very traditional renowned model that uses collaborating filtering. Collaborating filtering is lacking because item-based similarity item-item similarity has to be computed wherein the rating plays a vital role. Every government policy need not be read, and who raises government policies first of all the policy seekers are a very few and it is not very acting in seeking rating for government policy. It is not an eCommerce book store wherein every item might be rated. Government policy getting the rating for the policy itself is a very controversial phenomenon. As a result, collaborating filtering does not work practically; it is not feasible. Moreover, it does not yield any relevant results.

TMPR uses the text mining natural language processing methodologies for policy structure segment fragmentation, policy structure division, attribute extraction, attribution matching, elementary discourse, units' analysis, matching, and NER and other NLP methods constitute the text mining methods TMPR. Though the TMPR attempts to integrate text mining with NLP, it yields above-average results; however, it lacks auxiliary knowledge. As a result, the model does not perform up to the mark. It has to perform in a completely cohesive environment like Web 3.0.

SVM and KNN, and Cosine similarity hybridization use ensure that two naive classifiers and the conventional similarity measures have been used. It yields results, but the results are inappropriate because of the outdated classifier, and auxiliary knowledge is not included.

Although the classifier is robust in Adaboost and K-means clustering, ambiguity with K-means clustering improves the results. However, the classifier's lack of auxiliary knowledge and the lack of power ensure the model does not perform up to the mark.

The dataset used for experimentation is collected from multiple sources. It is a customized and curated dataset. The first dataset in this Combined Government Policy Dataset (CGPD) is the Australian government indigenous program and policy location, AGIL dataset. The AGIL metadata and the AGIL.csv file are taken; it is used as it is. However, the AGIL dataset is also annotated by using the RDF distiller. Specific crawlers are used to crawl online web documents relevant to the annotation, which are generated based on the metadata of the AGIL dataset.

The second curated dataset is based on documents which are based on several themes, namely the Aayushman Bharat Yojna, Skill India Scheme, Smart Cities Mission, Amrut, Pradhan Mantri Avas Yojana, Heritage city development and augmentation Yojna, Deen Dayal Upadhyay Gramin Kaushal Yojna, Gramin Bandara Yojna, JNNURM, Nipun Bharat Mission. These policies are based on the categories like agriculture, education, health. The policies like Digital India for urbanization, Atal Pension Yojna for pension, Bharat Maa Ki Suraksha Beema Yojna for insurance are considered. All the policy documents on the world wide web are crawled, directly or indirectly, and further indexed using an RDF distiller. This is an indigenous dataset specific to India.

The third one is from national portal of India. Policy for .in internet domain registration, auto policy, Kerla state women policy, web policy for Haryana, Industrial promotion policy, schemes - micro, small and medium enterprise government institute Goa, Information on Jammu and Kashmir Industrial Policy, Information on State Home for Women, Himachal Pradesh, Information on Mother Teresa Ashaya Matri Sambal Yojna, Himachal Pradesh, Logistics, Warehousing & Retail Policy, Haryana Textile Policy, Haryana Pharmaceutical Policy 2019, Information on Electric Vehicles Policy 2021, Assam, Information on Handloom Policy 2017–18, Assam, Information on Tourism Policy 2017, Assam, Bihar Industrial Investment Promotion Policy, 2016, Information on Industrial Policy 2019–2024, Chhattisgarh all these policies and related websites are crawled. Apart from the data crawled, 7864 documents comprising these policies were curated, out of which 44892 tags were generated for annotation.

The model is executed for 4481 queries, out of which 2681 queries are single-word queries, and the remaining queries are multiword. The ground truth has been validated by voting from 611 users based on the queries. Each user gave around 50 to 60 queries; however, only 30–40% of the total number of queries were collected for the remaining queries, the ground truth was assumed based on the dataset.

Implementation was conducted using the latest python version with Google Collaboratory as an online development platform.

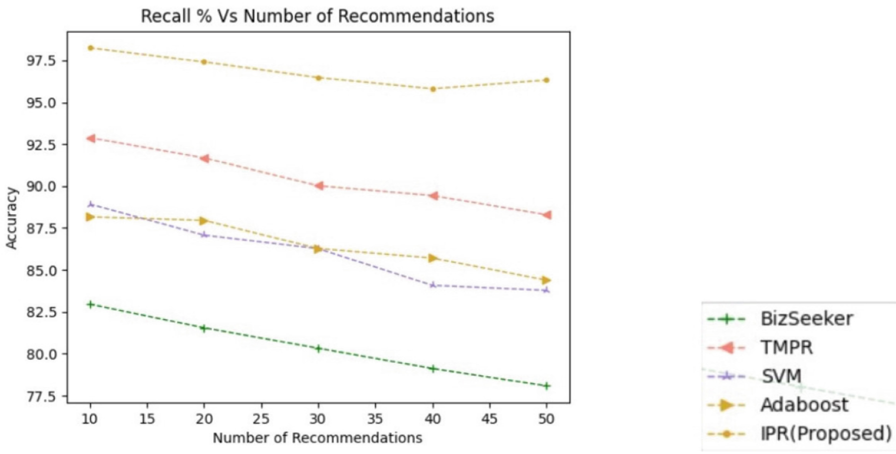

Fig. 3. Recall % vs Number of recommendations of the proposed IPR and other baseline models.

The accuracy at different number of recommendations of each baseline model is shown in Fig. 2. It is evident from the figure that the proposed Integrative Policy Recommendation (IPR) Framework has higher accuracy for the number of recommendations when compared to other baseline models.

5 Conclusion

A model with semantic infused artificial intelligence-driven skills, IPR, is proposed to recommend policies. The model is based on RDF and incorporates user queries web utilization statistics for policy recommendation. The Combined Government Policy Dataset (CGPD), different semantic similarity methods are used at several stages is used, along with it, using ontology alignment and STM results are obtained which are validated by ground truth too. As the proposed IPR is semantically enriched and empowered, it results average accuracy of 94.72% and yields much better results than the other baseline models and makes it an efficient and semantically compliant system for the policies recommendation.

References

1. Zhang, T., Liu, M., Ma, C., Tu, Z., Wang, Z.: A text mining based method for policy recommendation. In: 2021 IEEE International Conference on Services Computing (SCC), pp. 233–240. IEEE (2021)
2. Toninelli, A., Bradshaw, J., Kagal, L., Montanari, R.: Rule-based and ontology-based policies: toward a hybrid approach to control agents in pervasive environments. In: Proceedings of the Semantic Web and Policy Workshop (2005)
3. Santos, O.C., Boticario, J.G.: Requirements for semantic educational recommender systems in formal e-learning scenarios. Algorithms **4**(2), 131–154 (2011)

4. Chung, H., Kim, J.: An ontological approach for semantic modeling of curriculum and syllabus in higher education. Int. J. Inf. Educ. Technol. **6**(5), 365 (2016)
5. Joshi, K., Joshi, K.P., Mittal, S.: A semantic approach for automating knowledge in policies of cyber insurance services. In: 2019 IEEE International Conference on Web Services (ICWS), pp. 33–40. IEEE (2019)
6. Ge, J., Qiu, Y.: Concept similarity matching based on semantic distance. In: 2008 Fourth International Conference on Semantics, Knowledge and Grid, pp. 380–383. IEEE (2008)
7. Lu, J., Shambour, Q., Xu, Y., Lin, Q., Zhang, G.: BizSeeker: a hybrid semantic recommendation system for personalized government-to-business e-services. Internet Research (2010)
8. Deepak, G., Ahmed, A., Skanda, B.: An intelligent inventive system for personalised webpage recommendation based on ontology semantics. Int. J. Intell. Syst. Technol. Appl. **18**(1–2), 115–132 (2019)
9. Adithya, V., Deepak, G.: OntoReq: an ontology focused collective knowledge approach for requirement traceability modelling. In: Musleh, A.-S., Abdalmuttaleb, M.A., Razzaque, A., Kamal, M.M. (eds.) EAMMIS 2021. LNNS, vol. 239, pp. 358–370. Springer, Cham (2021). https://doi.org/10.1007/978-3-030-77246-8_34
10. Ortiz-Rodriguez, F., Tiwari, S., Panchal, R., Medina-Quintero, J. M., Barrera, R.: MEXIN: multidialectal ontology supporting NLP approach to improve government electronic communication with the Mexican Ethnic Groups. In: DG. O 2022: The 23rd Annual International Conference on Digital Government Research, pp. 461–463 (2022)
11. Deepak, G., Priyadarshini, J.S., Babu, M.H.: A differential semantic algorithm for query relevant web page recommendation. In: 2016 IEEE International Conference on Advances in Computer Applications (ICACA), pp. 44–49. IEEE (2016)
12. Ortiz-Rodriguez, F., Medina-Quintero, J. M., Tiwari, S., Villanueva, V.: EGODO ontology: sharing, retrieving, and exchanging legal documentation across e-government. In: Futuristic Trends for Sustainable Development and Sustainable Ecosystems, pp. 261–276. IGI Global (2022)
13. Panchal, R., Swaminarayan, P., Tiwari, S., Ortiz-Rodriguez, F.: AISHE-Onto: a semantic model for public higher education universities. In: DG. O2021: The 22nd Annual International Conference on Digital Government Research, pp. 545–547 (2021)
14. Tiwari S., Garcia-Castro R.: A Systematic Review of Ontologies for the Water Domain. In: ISTE Book, ISBN 9781786307644, Wiley (2022)
15. Tiwari, S., Gaurav, D., Srivastava, A., Rai, C., Abhishek, K.: A preliminary study of knowledge graphs and their construction. In: Tavares, J.R.S., Chakrabarti, S., Bhattacharya, A., Ghatak, S. (eds.) Emerging Technologies in Data Mining and Information Security. LNNS, vol. 164, pp. 11–20. Springer, Singapore (2021). https://doi.org/10.1007/978-981-15-9774-9_2
16. Yethindra, D.N., Deepak, G.: A semantic approach for fashion recommendation using logistic regression and ontologies. In: 2021 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES), pp. 1–6. IEEE (2021)