

An Explainable Knowledge Graph-Based News Recommendation System

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Keywords: Explainability, Recommendation System, Knowledge Graphs, News.

Abstract: The paper outlines an explainable knowledge graph-based recommendation system that aims to provide personalized news recommendations and tries to explain why an item is recommended to a particular user. The system leverages a knowledge graph (KG) that models the relationships between items and users' preferences, as well as external knowledge sources such as item features and user profiles. The main objectives of this study are to train a recommendation model that can predict whether a user will click on a news article or not, and then obtain the explainable recommendations for the same purpose. This is achieved with three steps: Firstly, KG of the MIND dataset are generated based on the history and, the clicked information of the users, the category and subcategory of the news. Then, the path reasoning approaches are utilized to reach explainable paths of recommended news/items. Thirdly, the proposed KG-based model is evaluated using MIND News data sets. Experiments have been conducted using the MIND-demo and MIND-small datasets, which are the open-source English news datasets for public research scope. Experimental results indicate that the proposed approach performs better in terms of recommendation explainability, making it a promising basis for developing transparent and interpretable recommendation systems.

1 INTRODUCTION

In recent years, knowledge graphs have emerged as a powerful tool for representing and organizing large amounts of structured and unstructured data. One of the domains in which knowledge graphs can be used are explainable recommendation systems, which aim at providing personalized recommendations to users based on their preferences and transactions in a more transparent and interpretable way than traditional recommendation systems. They allow users to understand how recommendations are generated and provide insights into why certain recommendations are proposed, thereby improving transparency, persuasiveness, effectiveness, trustworthiness, and user satisfaction with recommendations (Zhang, 2020).

Traditional news recommendation systems have relied on various techniques, such as collaborative filtering (Das, 2007, Lian 2018), content-based filtering (Joseph, 2019, Huang, 2013), and hybrid

recommendation methods (Meguebli, 2014). However, these methods often face limitations in capturing the complex relationships and nuances present in news articles. Furthermore, these methods disregard the sequential information in the user's browsing history, making it difficult to learn users' changing interests, and ignoring the importance of entities in the news article (Zeng, 2022).

To address these challenges, knowledge embeddings can be considered as an effective tool in the field of news recommendation. One of the key advantages of knowledge embeddings is their ability to capture both the explicit and implicit semantic relationships between news articles. By incorporating various contextual concepts, such as word co-occurrence patterns, syntactic structures, and semantic similarities, knowledge embeddings can effectively connect the news articles, even in the absence of explicit relations. Furthermore, knowledge embeddings facilitate the integration of external knowledge sources, such as knowledge

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graphs and ontologies, into the recommendation process. By leveraging the structured information encoded in these knowledge sources, the embeddings can enrich the semantic representation of news articles, enabling more accurate and context-aware recommendations (Liu, 2020, Sheu, 2021). This integration opens up possibilities for incorporating additional information, such as news article metadata, user profiles, and social network connections, to generate explainable recommendations.

To enhance the quality and accuracy of the knowledge embedding based recommendations, path reasoning models have emerged as a promising approach. These models leverage the rich contextual information embedded in users' browsing histories to infer their interests and preferences. However, these path reasoning models encounter significant challenges due to the dynamic nature of news consumption patterns, the need to balance serendipity and user preferences, and the ever-present risk of filter bubbles (Tai, 2021, Zheng, 2018). In this study, we will examine the complexities and obstacles associated with path reasoning models in news recommendation systems, exploring the limitations they encounter and the potential solutions that can enhance their performance in delivering diverse, more precise, and reliable recommendations.

As traditional media platforms struggle to keep up with the proliferation of online content, news recommendation systems have emerged as essential tools for personalized news delivery. These systems aim to tailor news recommendations to users' preferences and provide them with news articles of interest. However, while news recommendation systems offer convenience and customization, they also face numerous challenges. From the filter bubble effect to information overload and algorithmic bias, these systems encounter complex obstacles that affect the diversity, accuracy, and reliability of the news individuals receive. In this context, understanding and addressing the challenges of news recommendation systems is crucial to promote a well-informed society and responsible news consumption. From filter bubbles and echo chambers to bias and ethical considerations, navigating the complex landscape of news recommendation presents obstacles that require careful attention. Recent studies have explored these challenges faced by news recommendation systems and shed light on the importance of balancing between personalization and diversity in providing accurate and unbiased news recommendations (Qi, 2022, Bernstein, 2020 and Chen 2023).

Knowledge embeddings are a means to that end, providing rich information of users and items that can be exploited to generate intuitive and more suitable explanations for the recommended items. In this study, we will explore the concept of explainable recommendation systems based on knowledge graphs, outlining some key terms, and benefits and challenges regarding their development and implementation for the domain of news recommendations.

- In Section 2, we delve into the existing approaches that augment traditional models with KGs for the explainable news recommendations.
- In Section 3, we will provide an initial overview of the recommendation pipeline, to characterize how explanations can be enabled at several stages, namely, data acquisition and storage, data preprocessing, model training, model prediction, model evaluation, and recommendation delivery.
- Then, the details of the proposed model that relies on path reasoning models are given to access high-level relationships between users and products, according to the KG structure, in Section 3.
- Finally, we show how different types of explanations can emerge from a news recommendation system via KGs.

2 KG FOR EXPLAINABLE NEWS RECOMMENDATIONS

Knowledge embeddings are learned over the graph to reach the embeddings from each user, item, relation, and entity, then the recommendations are generated for a particular user to find the most preferable item under the main relation of the recommendation system. The main relations can be used for that purpose are 'purchase', 'watch' and 'click' etc., and recommendations can be yielded using the shortest path from the user to the respective item through the knowledge graph (KG). Furthermore, to also address the demand for explainability, several approaches can be applied, including embedding-based, connection-based, and propagation-based methods (Baloccu, 2022). That includes connection-based explainable KG-based models, which utilize path embedding approaches, and Policy Guided Path Reasoning (PGPR) and CoArse-to-FinE neural symbolic reasoning method (CAFÉ), which represent the current state-of-the-art: PGPR can be considered an adaptation of Reinforcement Learning (RL), in which an agent starts from a given user, and learns to

navigate to the potential items of interest, such that the path history can provide an explanation for why the item is recommended to the user (Xian, 2019). CAFÉ, on the other hand, represent a commonly used path reasoning model that is based on finding a coarse sketch of past user behaviour, and then conducting path reasoning to derive recommendations based on the user model for fine-grained modelling (Xian, 2020). The effectiveness of PGPR and CAFE approaches have been evaluated for several Amazon e-commerce domains, obtained explainable reasoning paths in (Xian, 2019 & 2020). However, utilizing the KG path reasoning algorithms for news recommendation has not been fully examined, while existing studies are utilizing KG try to improve news recommendation accuracy.

Another path reasoning algorithm for news recommendation via KG is Anchor-KG, which has been proposed in (Liu, 2021). The main purpose of this algorithm is to develop a policy network to generate a subgraph from the KG for each news article. Each subgraph needs to include key entities from the news article and some necessary neighbouring entities which connect the article entities via multi-hop relational paths. The knowledge subgraph is called “anchor graph” since it only uses the most essential knowledge entities from the exponential growth of multi-hop relations and produces a footprint for each news article over the KG. Hence, the knowledge-aware reasoning of any two news articles can be conducted simply using the interactions of their corresponding anchor graphs. Anchor-KG utilizes an RL-based optimization framework for training, and experiments are applied on two real-world news datasets. However, while this approach can be utilized for enhancing document representation and providing knowledge reasoning between news documents, it cannot generate explainable recommendations.

Being inspired by the success of leveraging KGs, deep knowledge-aware network (DKN) has also been proposed for recommendation (Wang, 2018). DKN is a content-based recommendation model for click-through rate (CTR) predictions that utilizes users’ click history as input, and generates outputs based on the probability of the user clicking the news. This model is trying to take advantage of external knowledge for news recommendation, especially generating the KG by associating each word in the news content with a relevant entity in (Wang, 2018). The set of contextual entities of each entity is searched and used to provide more complementary and distinguishable information. After the user’s embeddings and the candidate news’ embeddings are

generated based on the entities, a deep neural network (DNN) is applied on these embeddings for CTR prediction in the DKN model.

To provide meaningful news recommendations, it is also necessary to incorporate additional KG information (Wang, 2018). Several academic studies are utilized such as NELL and DBpedia, as well as commercial ones such as Google Knowledge Graph and Microsoft Satori to generate KGs from a dataset (Wang, 2018, Zhang, 2016). These KGs have been successfully implemented in text classification, machine reading, and word embedding research areas but not yet for recommendation systems. To combine user behaviour and news content information to generate a KG, the News Graph (NG) model was proposed (Liu, 2019), which include topic entities and collaborative relations that are relevant for news recommendations, while removing news-irrelevant relations. User behaviours are incorporated, and three types of collaborative relations are constructed depending on the co-occurrence in the same news, clicked by the same user, or clicked by the same user in the same browsing session. The extraction of news-relevant relations and enhancement of collaborative information provides increased capabilities for representing news articles and users’ reading behaviours as a result. Hence, applications include not only news recommendations, but also news category classification, news popularity prediction and local news detection.

Based on the above, an explainable news recommendation system utilizing a KG graph model is presented in this study. Firstly, conceptual foundations are introduced, and the real-world examples is described to understand how the KGs can be integrated into the recommendation pipeline, also for the aim of providing explanations. Using an example algorithmic solution to model, integrate, train, and evaluate a recommendation system with KGs based on explainability perspective, we aim at training a recommendation model that can predict whether a user would click on a news article or not. The implementation can be split in three domains: (1) generation of metadata and KG of the MIND News dataset based on (a) user history, (b) user clicks and (c) news categories and subcategories. (2) PGPR and CAFÉ approaches are utilized to reach the explainable paths of recommended items/lists (3) the proposed KG-based model is evaluated using two real-world public MIND-News data sets.

3 THE PROPOSED KG-BASED RECOMMENDATION MODEL

The following presents a new explainable KG-based algorithm for personalized recommendations. With its ability to incorporate a large amount of knowledge from various sources and represent it in a comprehensible and transparent manner, it can provide users with recommendations that are not only accurate but also easy to understand. It can be especially useful in domains where trust and transparency are crucial. We use the publicly available MIND News datasets which vary in domain, extensiveness, and sparsity. For scalability purposes, the reduced version of this dataset is utilized and obtained with the following steps:

In the first step, the raw news data is cleaned and pre-processed to generate explainable recommendations. The raw dataset is composed by the following files and illustrated in Figure 1(a):

- behaviours.tsv: List of users and some demographical data.
- news.tsv: the catalog of news and the entities.

A dataset reduced to its K-cores (i.e., dense subsets) is a subset with removed items and users, such that each of the remaining users and items have k reviews each. Hence, these datasets are reduced to its 5-cores and transformed to the standardized format. Then, simple time-based data and knowledge graph embeddings are obtained for training stage and finally, the proposed Explainable Knowledge Graph-Based Recommendation Model (EKG-RM) is evaluated on this metadata. The standardized KG model is composed by 4 different main files and generated as in (Balloccu, 2022) and illustrated in Figure 1(b):

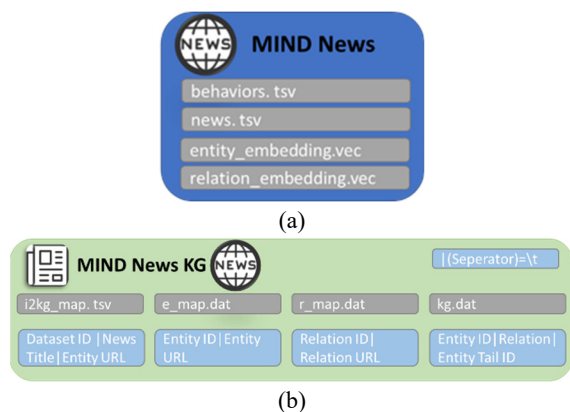


Figure 1: a) The raw data and b) the standardized KG model of the Mind News Dataset (Balloccu, 2022).

- Item to KG (i2kg_map.tsv) includes the mapping between the News dataset and the corresponding entity in the KG.
- Entity map (e_map.dat) includes the set of entities and contains all the unique entities present in the triplets including item entities.
- Relation map (r_map.dat) includes set of relations and contains all the unique relations present in the triplets.
- KG (kg.dat) includes set of triplets (the graph itself) and contains all the triplets of the form (entity_head, relation, entity_tail).

The relations are extracted from behaviors and the news files of the MIND dataset. The history, the non-clicked and clicked information from behaviors file used to define history and clicked relations. The category, and subcategory information from the news file used to define same category relations. Hence three different relations are defined in the KG model of MIND dataset which are history, clicked and same category. The detailed of the relations and KG model is given in Section 3.1.

In the second step, the path reasoning models for KG-based recommendation systems are applied on the proposed model. A path-reasoning algorithm starts from specific user and proceeds through the graph to discover the preferable items in the graph for the target user. The objective is that if the system bases its results on an explicit reasoning path, it is easy to interpret the reasoning process leading to each recommendation, i.e., providing the relevant reasoning paths in the graph as interpretable evidence for why a particular recommendation is made. For instance, considering the user A, the proposed model is trying to find candidate News B and News C, along with their explainable paths in the graph, as shown in Figure 2, e.g., $\{User A \rightarrow News A \rightarrow Clicked \text{ by } \rightarrow User B \rightarrow Also_Clicked \rightarrow News B\}$ and $\{User A \rightarrow News A \rightarrow Belong \text{ to Same Category } \rightarrow News D\}$.

The path-based approaches implement a path selection algorithm or define a set of meta-patterns to constrain the path search space due to the large number of nodes and edges in the KG, (Balloccu, 2022). The path-based approaches rely on pre-computed paths (tuples) that model high-order relationships between users and items/news or perform path reasoning to conduct recommendation and path retrieval simultaneously according to the KG structure. The path-based reasoning approaches can extract one or multiple explainable paths between the recommended item and already experienced items. These paths can be translated into textual explanations for the end users. For instance, in the news domain, a path between the news already

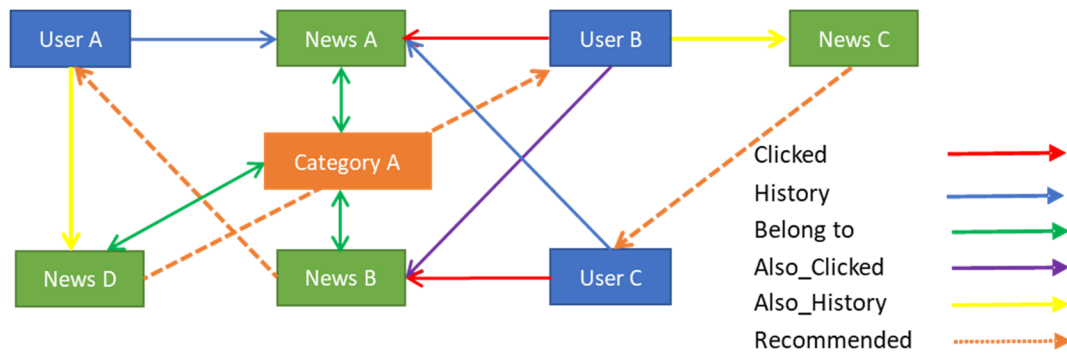


Figure 2: A sample of KG-based structure for Mind News Dataset (Balloccu, 2022).

clicked by the user (news1) and a news recommended to that user (news2), shaped in the form of user1 clicked news1 belongs to same category1 of the news2, can be used to provide the explanation “news2 is recommended because you clicked another news1 belongs to same category1 of news2”.

Unfortunately, the path generation and selection are not optimized for the recommendation purpose and lead to sub-optimal recommendations and explainable paths. Hence, path reasoning models, more specifically connection-based explainable KG-based approaches are proposed to overcome this issue and to optimize the recommendation model while searching for paths in the KG. The most recent path-based reasoning algorithms that enable textual explanations, such as PGPR and CAFÉ models, are utilized for this purpose. These models depend on RL framework to optimize recommendations by navigating paths between users and recommended items in the KG, (Balloccu, 2022).

The PGPR model relies on an RL agent that is conditioned to the user and trained to navigate to potentially relevant items. The RL agent can be performed an explicit multi-step path reasoning over the graph with starting from a given user node to find out appropriate items in the graph for the target user. Then, the path from the user u to the item i can be used to explain the recommendation (Balloccu, 2022 & Xian, 2019).

The CAFÉ model (Xian, 2020) creates a personalized user profile based on transactions of the user in the KG and utilizes a neural symbolic reasoning modules in the path reasoning stage. A layout tree is generated with the modules based on the user profile, then this tree is used by the path reasoning algorithm to generate a set of recommendation paths. The path inference is structured using a layout tree which offers more efficiency compared to PGPR. However, the CAFÉ model is also needed for profile guided path reasoning (Balloccu, 2022, Xian, 2020).

3.1 The Generated KG Model

In particular, the collaborative edges/relations are extracted in four different ways: (1) in history of the same user; (2) clicked by the same user; and (3) clicked by the same user in the same browsing session (4) the news in the same category or subcategory. In this paper, the objective of the KG-based recommendation system is to recommend news to users and explain why the news are recommended. A knowledge base as a set of triplets $T = f(entity_head, entity_tail, relation)$ or recommendation are generated whether the relation denotes the relationship between entity head and entity tail. Then the proposed explainable recommendation has two different purposes, the first one is to find one or a set of items i that are most likely to be clicked by the user u , and the second one is to generate an explanation based on T to explain why the user should click the item. Three types of entities (i.e., `entity_head` or `entity_tail`) for explainable recommendations are considered for MIND News dataset:

- `user`: the users of the recommendation system.
 - `item`: the news in the system to be recommended.
 - `category`: the categories that the news belongs to.
- Furthermore, we consider 5 different types of relationships between entities:
- *History*: the relation from a user to an item/news, which means that the user has already clicked and read that news.
 - *Clicked*: the relation from a user or an item, which means that the user has clicked the item/news.
 - *Belongs_to*: the relation from an item to a category, which means that the item/news belongs to the same category.
 - *Also_History*: the relation from an item to another item, which means these news/items have been already read by the same user.

- *Also_Clicked*: the relation from an item to another item, which means this items/news have been already clicked by the same user.

The relations are extracted from behaviours and the news files of the MIND dataset. The history, the non-clicked and clicked information are reached from behaviours file to define history and clicked relations. The category, and subcategory information are reached from the news file to define belongs to same category relations. The title entities, abstract entities from news file can be also used to extract more relations, but it is considered as a future work. The KG standard format for MIND News dataset is obtained as in (Balloccu, 2022).

To generate explainable news recommendation, firstly the main relation clicked relationship between user u and item i needs to be extracted, secondly explanations for each retrieved user-item (u, i) pair based on the relations and entities related to them needs to be provided. The following explainable recommendations can be deduced from Figure 2:

- The News B is recommended to User A, since the News A is *in the history* of User A and *clicked by* the User B.
- The News D is recommended to User B, since News A and News B *belong to same category* of News D that are already *clicked by* the User B.
- The News C is recommended to User C, since News A is *in the history* of User C and *clicked by* the User B.

Table 1: Detailed statistics of the MIND News dataset.

Dataset	MIND-Demo	MIND-Small
Users	5,000	65,238
News	28,603	94,057
Interactions	80,088	829,162
Relation Types	5	5
Triplets	634,630	4,066,384

4 EXPERIMENTAL ANALYSIS AND EVALUATION METRICS

The proposed algorithm is applied on the open-source English MIND News dataset (MIND website) that was collected from Microsoft News website in 2019. Users were randomly selected who had at least 5 news clicks, and each user is hashed into an anonymized ID to protect user privacy. The news click behaviours of the users were formatted into impression logs and valued as 1 for click and 0 for non-click. In addition, small versions of MIND-Small and MIND-Demo

dataset were released by randomly sampling 50,000 and 5,000 users and their behaviour logs.

Table 2: The experimental results based on the evaluation metrics of the MIND-Demo and MIND-Small datasets.

Datasets	Metrics Methods	Precision (%)	Recall (%)	Hit Ratio (%)	NDCG (%)
		MIND-Demo	PGPR	1.17	3.11
	CAFE	2.85	8.02	5.17	6.28
MIND-Small	PGPR	0.55	2.66	5.22	2.41
	CAFE	1.28	5.88	2.33	3.97

The testing methodology adopted in this study is the same as in a previous study (Balloccu, 2022). The implicit ratings are split by two subsets that are named by training and test sets for each dataset. Each split is consisting of 80% for training and 20% for testing sets. The detailed statistics of the utilized MIND datasets are given in Table 1.

The four different top-N recommendation measurements are utilized for evaluation as in (Balloccu, 2022). The precision can be defined as the percentage of correctly recommended items in the test set that are also presented in a user's the top-N recommendation list. The precision of the recommendation system can be indicated as:

$$Precision(N) = \frac{\#hits}{|T| \cdot N}$$

where $|T|$ is the number of test ratings, N is the length of the recommendation list.

The recall can be defined as the percentage of items in the test set that are also presented in a user's the top-N recommendation list. The recall of the recommendation system can be represented as:

$$Recall(N) = \frac{\#hits}{|T|}$$

where $|T|$ is the number of test ratings.

The NDCG takes into consideration the position of correctly recommended items in the list of top-N recommendations and is evaluated as the average of all test users of the NDCG.

The hit-ratio is measured by looking at the number of hits, i.e., the number of items in the test set that are also presented in the top-N recommendation item list returned for each user. Then, the hit-ratio of the recommendation system can be represented as:

$$Hit - Ratio(N) = \frac{\#hits}{n}$$

where n is represented the total number of users, $\#hits$ is symbolized as the overall hit of the recommendation system. The top-N recommendation

list is generated for each user in the testing set, where N is selected 10.

The experimental results based on the evaluation metrics of the MIND-Demo and MIND-Small datasets are given in Table 2. The experimental results demonstrate that the CAFÉ model performs better than PGPR model on the MIND News datasets. It can be concluded from the experiments results that are encouraging; however, it needs to be further improved in the future works. For example, these datasets can be reduced to its 10-cores in the pre-processing stage and transformed to the standardized format as in (Balloccu, 2022).

4.1 The Case Study of the Explainable Recommendation Generation

The generated predicted path file from the KG-based recommendation system is constructed as in the tutorial (Balloccu, 2022). Firstly, the explainable recommendation is extracted for a random User #ID: U8619 via path reasoning approaches. Then the meta-path is extracted for the same user #ID: U8619 as illustrated in Figure 3. Furthermore, the case study for a random User #ID: 2683 is also given in Table 3.

Path User U8619 Clicked - N26320:NFL Week 9 Odds SubCategory Football_NFL Same SubCategory N27894
Meta-path User U8619 Clicked - N26320 Belongs to Football Recommended N27894

Figure 3: The extracted meta-path for the random User #ID: U8619.

To show the ability of the proposed model to generate knowledge-enhanced explanations, a case study for a random test user is conducted from MIND-Small Dataset, for whom we have examined that the first recommendation provided by the system is correct. The top-5 explainable recommendation list for the User #ID:2683 are listed along with their probabilities computed based on PGPR models in Table 3.

Table 3: The top-5 explainable recommendation list for a random User #ID: 2683.

Probability	Entity Head	Relation Type	Entity Tail	Relation Type	Recommendation
0.572	User 2683	clicked	User 1336	clicked	News 12289
0.527	User 2683	clicked	User 3530	clicked	News 6216
0.498	User 2683	clicked	User 2791	clicked	News 10022
0.424	User 2683	clicked	User 2200	clicked	News 21667
0.186	User 2683	belongs_to	News 2322	belongs_to	News 9718

5 CONCLUSIONS

Explainable recommendation systems based on KGs have emerged as a promising approach to address the challenges of traditional recommendation systems. By leveraging KGs, such systems can model complex relationships between entities and provide personalized recommendations that are more accurate and diverse. Moreover, the explainability aspect of these systems enables users to understand the underlying reasoning behind the recommendations, thereby improving their trustworthiness.

In this paper, an explainable KG-based news recommendation model was proposed. The approach applies KG graph generation combining extracted news metadata and five different relationships, and state-of-art PGPR and CAFE algorithms to find explanation paths between a user and the recommended items in the KG to explain the recommendations. Experimental results on real-world MIND-Small and MIND-Demo datasets indicate flexibility of the model to incorporate multiple relation types and show that the proposed approach offers a promising solution for explainable news recommendations to users. As for directions for future work, the explainable recommendation quality needs further improvement by extending the KG and the selecting appropriate parameters for the MIND-News dataset. Another objective as a future work is to advance the development and implementation of privacy-preserved news explainable recommendation systems that prioritize user privacy and provide enhanced user control over their personal data.

ACKNOWLEDGEMENTS

This work was supported by European Union's Horizon 2020 research and innovation programme under grant number 951911.

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