INM363 Project Proposal

Enhancing Music Discovery through a Knowledge-Graph-and Deep-Learning-Based Music Recommendation System

By Ratna Pathak, **220046535,**
Ratna.Pathak@city.ac.uk

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1. Introduction and Project Objective

1.1 Problem Statement

The current challenge is to develop a music recommendation system that is both intelligent and contextually aware while leveraging knowledge graphs (KGs) to their fullest potential. The aim is to meet the growing demand for transparent recommendations, where users seek a deeper understanding of how the system operates. Additionally, it is crucial to ensure that the system remains explainable, thereby allowing for ongoing performance enhancements. By recognizing the ability of KGs to capture semantic relationships and utilizing the underlying factors and relationships within the knowledge graph, the objective is to refine and adjust the system to improve the accuracy and relevance of its music recommendations.

1.2. Research Questions

- How can the integration of knowledge graphs enhance the effectiveness and accuracy of music recommendation systems?
- What design considerations can ensure that music recommendation systems using knowledge graphs and deep learning approaches provide fair, inclusive, diverse, and explainable recommendations while also enhancing their effectiveness and accuracy?

1.3. Objectives

- Generate a music knowledge graph in the RDF/OWL file format by creating a new one or selecting an existing one and adhering to standard formatting guidelines for saving and future utilization. The criterion is to produce at least one music knowledge graph that meets these specifications.
- Preprocess the knowledge graphs and dataset by cleaning, filtering, and transforming them into a usable format. The criterion is to produce at least one pre-processed knowledge graph that is readable by the model.

- Develop models that not only offer music recommendations but also provide clear and intelligible explanations of why those recommendations were made. This can be accomplished using propagation-based, embedding-based, or connection-based methods. The criterion is to produce at least one model that incorporates one of these approaches and can explain its recommendations in an understandable manner.
- Use the pre-trained recommendation models to generate a list of top-n music recommendations for a given user.
- Generate a curated list of top-n music recommendations for a particular user utilizing a pre-trained recommendation model .The criterion is to produce a list of top-n music recommendations that are based on the user's preferences and align with the user's music tastes and interests, as determined by the recommendation models.
- Evaluate the effectiveness of the recommendation system by employing traditional evaluation metrics, such as Normalized Discounted Cumulative Gain (NDCG), to gauge the quality and relevance of the recommended items' ranking. The criterion is to achieve a high NDCG score, indicating that the recommendation system is successfully providing accurate and relevant recommendations to the users.
- Produce textual explanations for the top-n recommendations and evaluate the explanation quality using state-of-the-art offline evaluation metrics, such as interaction recency, shared entity popularity, and explanation type diversity. The criterion is to generate high-quality textual explanations and assess them using these metrics to ensure that the explanations are effective and diverse in nature.
- Evaluate and compare the explanations generated by the models and analyze how these explanations affect the quality and effectiveness of the recommendations. The criterion is to conduct a comprehensive analysis of the explanations provided by the models, including their impact on the recommendation outcomes, and present the findings in a clear and concise manner.
- Identify and evaluate the trade-offs associated with using different recommendation models, considering factors such as the balance between recommendation accuracy and explanation quality. The criterion is to assess the impact of these trade-offs and determine the most appropriate model to use based on the specific requirements of the music recommendation system.

1.4 Generated Products and Outputs

- Pre-processed knowledge graphs in a standard format that is readable by the recommendation models. And pre-processed datasets will be created to be used by the models to optimize and generate recommendations effectively.
- Trained recommendation models that not only provide top-n recommendations for a given user but also explain the reasons for their recommendations.
- A list of top-n music recommendations for a given user generated by the trained models.

- Evaluation metrics such as Normalized Discounted Cumulative Gain (NDCG) to measure the effectiveness of the generated recommendations.
- Textual explanations for the top-n recommendations that assess the quality of the explanations using offline evaluation metrics such as linking interaction recency, shared entity popularity, and explanation type diversity, among others.
- Analysis of the impact of the explanations on the quality and effectiveness of the recommendations, including the trade-offs involved in generating recommendations with different models.
- Report with insights into the effective approaches for generating music recommendations with high accuracy and providing understandable explanations for those recommendations.

1.5. Beneficiaries

- Music Streaming Platforms: Online music streaming platforms can benefit from this recommendation system by integrating it into their services to enhance user engagement, increase user satisfaction, and drive personalized content discovery. The system will help platforms retain users by providing them with relevant and engaging content tailored to their musical preferences.
- Users: Music enthusiasts will benefit from personalized and accurate song recommendations that align with their musical tastes and preferences. They will discover new songs, artists, and genres that they might not have encountered otherwise, enhancing their overall music listening experience.
- Artists and Labels: The recommendation system can help promote lesser-known artists or songs that align with a user's preferences. This can potentially boost the exposure and popularity of emerging artists and contribute to a more diverse music ecosystem.
- Music archives and libraries: The recommendation system can help music archives and libraries by making it easier for users to discover and access a wide range of music content. This can help to preserve and promote music heritage and culture.
- Musicologists and other music researchers: The system can provide valuable insights into music trends, user preferences, and emerging genres, which can be useful for musicologists and other music researchers. The system can also help researchers identify gaps and areas for further exploration in the music landscape.

1.6. Project Scope

The project scope encompasses the entire process of developing a knowledge graph and deep learning-based music recommendation system, which can not only recommend music but also give a textual explanation of the recommendation. This is done by processing available music knowledge graphs and using the above mentioned algorithms to train the model. The scope also involves evaluating the system's effectiveness through various metrics such as NDCG and analyzing the impact of the system's explanations.

2. Critical Context

To get a broader range of ideas about the topics related to knowledge-based music recommendation, including models, algorithms, and exploratory search the doctoral dissertation "Knowledge-based Music Recommendation: Models, Algorithms and For initiating the project, can be found in Lisena's work on "Exploratory Search."

Going forward the idea of using knowledge graphs and deep learning for recommendation systems was derived from the need for personalized and explainable recommendations in the music domain. Various paper used this concept, one that discusses the use of knowledge graphs and deep learning for recommendation systems in the music domain in detail is "Unifying Knowledge Graph Yixin Cao and colleagues' paper titled "Towards a Better Understanding of User Preferences: Learning and Recommendation" can be restated as, "A study on Learning and Recommendation for Improved Comprehension of User Preferences" by Yixin Cao and team.[2].

The LFM-1b dataset for music retrieval and recommendation (Schedl, 2016) [1] was used as a benchmark dataset for music recommendation research.

Storti, E. (2019) [12] presents an ontological model for a FAIR (Findable, Accessible, Interoperable, and Reusable) digital library of music documents. The paper highlights the challenges in extending existing model schemas to represent other music traditions beyond western music notation. Future work involves developing the application layer on top of the model, which will include graphical user interfaces for browsing and exploring the graph, annotation of scores, analysis, and sharing.

To integrate knowledge graph learning with recommendations, Ai et al. (2018) [3] proposed a heterogeneous knowledge graph embedding approach that aimed to improve the interpretability of recommendations. Also, Cao et al. (2019) [4] proposed a novel approach that unifies knowledge graph embeddings with collaborative filtering methods, resulting in a better understanding of user preferences. The proposed model learns embeddings for users, items, and their attributes taking inspiration from Zhang et al. (CIKM 2017) [5] who proposes a joint representation learning approach for top-N recommendation with heterogeneous information sources.

The idea of using different methods in knowledge graph-based music recommendation systems was inspired by several papers.

- The propagation-based approach for recommendation systems involves using reinforcement learning (RL) agents to navigate a knowledge graph (KG) and optimize recommendations. The approach uses knowledge graph embeddings (KGE) to generate recommendations by providing the RL agents with a low-dimensional representation of the entities and their relationships in the KG.The propagation-based approach for recommender systems utilizes reinforcement learning (RL) agents to navigate the knowledge graph (KG) and optimize recommendations. Papers that use this approach are "RippleNet: Propagating User Preferences on the Knowledge Graph for Recommender Systems" by Wang et al. (2018) [5] and "Attention-Enhanced Knowledge-Aware User Preference Model for Recommendation" by Tang et al. (2019).[16] Both papers use KGE models, such as TransE and DistMult, to generate entity embeddings and train RL agents to navigate the KG and optimize recommendations.

- The connection-based approach in KG-based recommender systems involves using deep learning models that can model both user-item interactions and the semantic relationships between items in the KG. One such model is Zhao et al. (2017) [15], the authors propose a meta-graph based fusion approach that combines NCF and CKGE models for improved recommendations on heterogeneous information networks. They combine these models using a meta-graph based approach that considers item similarity and the recommendation performance of each method.
- The embedding-based approach combines collaborative filtering and KGE techniques to generate recommendations. Yang et al. (2018) [13], a two-stage deep learning model with a GAN-based generator and discriminator is proposed to generate item embeddings used in a collaborative filtering approach. The authors also use a KGE model to generate entity embeddings and combine them with the item embeddings to improve recommendation performance. Hongwei Wang et al. (2018) [14], a multi-task learning approach is used to jointly train a KGE model and a sentiment analysis model for sentiment link prediction. Both methods outperform state-of-the-art methods on their respective tasks.

The concept of evaluating recommendation models with standard evaluation metrics like NDCG or precision to improve model performance is mentioned in "Explainable knowledge graph-based recommendation via deep reinforcement learning" by Song et al.(2019) [6],

Using standard evaluation metrics like Precision and Recall, Mean Average Precision (MAP),Normalized Discounted Cumulative Gain (NDCG), Area Under the Receiver Operating Characteristic Curve (AUC-ROC) and Root Mean Squared Error (RMSE) is a common practice in the field of recommender systems, as it allows researchers to compare the performance of different recommendation models on the same datasets.For instance, Wang et al. (2018) [5] and Tang et al. (2019) [16] used these standard evaluation metrics to show that their methods outperform state-of-the-art KG-based recommender systems on benchmark datasets.

3. Approaches

1. The benchmark dataset for this project will be LastFM [1], which includes user-generated data such as music listening histories, user profiles, and social network information. Other datasets with similar characteristics, such as KKBox and the Million Song Dataset, will also be considered. These datasets provide information about music, including user listening histories and song metadata.

2. Developing or using an existing domain-specific knowledge graph (KG) will be done : [12].

- Create a domain-specific knowledge graph (KG): To create a domain-specific KG, one must first identify the entities and relationships relevant to the domain, and then design a schema to represent them. Populating the KG with instances of entities and relationships can be a complex and time-consuming task.
- Find an existing domain-specific KG that meets the project's requirements : to use an existing one that contains relevant information requires evaluating available KGs to find the one that best fits the project's needs. Modifications or extensions may be necessary to adapt the chosen KG for the project.

3. Preprocess the KG and domain-specific data by cleaning wrong-formatted triplets, threshold discarding, etc. Preprocessing of a knowledge graph (KG) and domain-specific data involves several steps to ensure that the data is ready for use in the deep learning model. This step is critical because the quality of the input data can directly impact the performance and accuracy of the model. One important step in preprocessing is cleaning the data, which involves removing or correcting incorrect or incomplete data. For example, some triplets in a KG may be wrong-formatted or contain incorrect or irrelevant information. These errors can lead to inconsistencies in the KG and negatively impact the accuracy of the model. Therefore, it is important to clean the data by removing these incorrect triplets and ensuring that the remaining triplets are correctly formatted and relevant to the domain. Another preprocessing step is threshold discarding, which involves removing triplets that occur infrequently or are not relevant to the domain. This can be done by setting a threshold for the minimum number of times a triplet must occur in the data or by manually filtering out irrelevant triplets. This step can help reduce noise in the data and improve the accuracy of the model.

Guo et al.[11] provide an overview of various techniques used in knowledge graph-based recommender systems, including data preprocessing, which involves cleaning and filtering the data to remove noise and improve its quality. They discuss different methods such as entity resolution, data integration, data normalization, and feature extraction, which can be used to preprocess the data.

4.Map the KG and data into a standard format that can be read by the chosen recommendation algorithm.In order to effectively utilize knowledge graphs (KGs) for music recommendation, the KG and music data need to be transformed into a standard format that can be read by the chosen recommendation algorithm. This format can vary depending on the type of recommendation algorithm being used, such as propagation-based, connection-based, or embedding-based. In general, this mapping process involves converting the entities and relationships in the KG into numerical or categorical representations that can be fed into the recommendation algorithm. This is an important step in building effective music recommendation systems that leverage the rich information contained in.Guo et al. (2020) paper includes a discussion of mapping of data into a standard format for recommendation.

5. Apply knowledge graph embedding (KGE) techniques to represent entities and their relationships as low-dimensional embeddings, using methods such as TransE, DistMult, or ComplEx. These embeddings capture the semantic meaning of entities and their relationships, and allow for more efficient processing and analysis of large knowledge graphs.

The most common KGE techniques include TransE, which represents entities and relationships as vectors in the same space and learns to map entities to their corresponding relationships; DistMult, which models each relationship as a diagonal matrix and computes the similarity between entities and relationships using dot products; and ComplEx, which uses complex numbers to represent relationships and captures both symmetric and asymmetric relationships.

6. Develop a recommendation model based on one of the following approaches [11] :

- The first approach, propagation-based, utilizes reinforcement learning (RL) agents to navigate the knowledge graph and optimize recommendations. In this method, KGE embeddings are used to generate recommendations by providing the RL agents with a low-dimensional representation of the entities and their relationships in the KG. Used in paper [5] [16]
- The second approach, connection-based, involves the use of deep learning models such as Neural Collaborative Filtering (NCF) or Collaborative Knowledge Graph Embedding (CKGE) to model the interactions between users and items in the KG. These models consider both the user-item interactions and the semantic relationships between the items in the KG.[15]
- The third approach, embedding-based, involves the use of two-stage joined models or multi-task learning approaches to combine collaborative filtering and KGE techniques to generate recommendations. This approach seeks to combine the strengths of both collaborative filtering and KGE methods to provide more accurate and explainable recommendations.[13] [14]

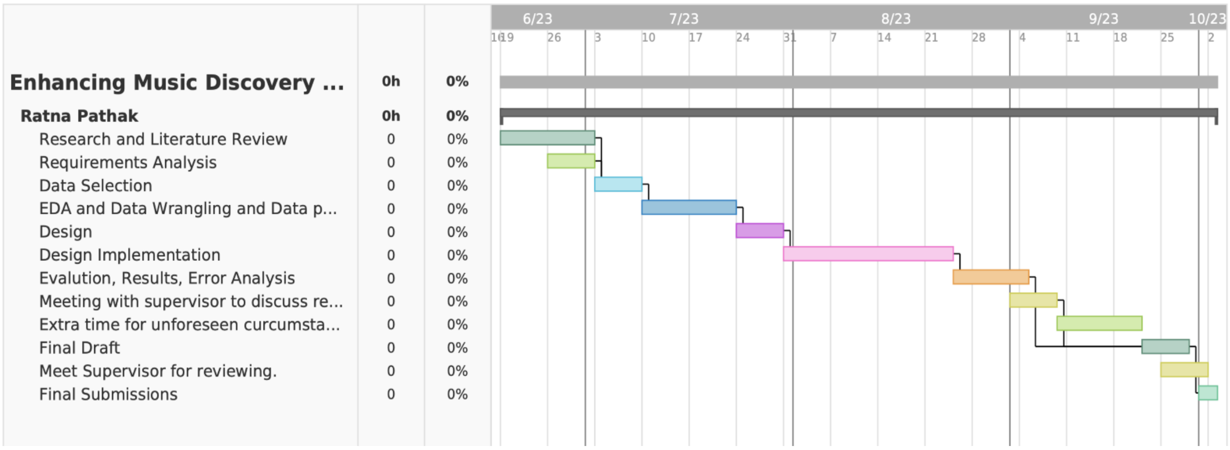
7. Extract paths from the KG using propagation-based, connection-based, or embedding-based techniques such as random walk, meta-path, or attention-based methods.

8. Train a machine learning model (e.g., neural network) using the extracted paths and labels (e.g., user-item interactions) to learn a specified policy or set of rules to generate recommendations.

9. Evaluate the effectiveness of the recommendation models using standard metrics such as NDCG or precision, experimenting with different model architectures and hyperparameters to optimize performance.

10. If time permits, develop methods for providing textual explanations for the recommendations generated by the models by leveraging the KG structure to generate path-based explanations or using attention mechanisms in the deep learning models to highlight the content features that led to the recommendations.

4. Work Plan



Task	Start Date	End Date	Duration
Research and Literature Review	18-06-2023	02-07-2023	2 weeks
Requirements Analysis	25-06-2023	02-07-2023	1 week
Data Selection	02-07-2023	09-07-2023	1 week
EDA and Data Wrangling and Data preparation	10-07-2023	23-07-2023	2 weeks
Design	24-07-2023	30-07-2023	1 week
Design Implementation	31-07-2023	23-08-2023	3 and a half weeks
Evaluation , Results And Error Analysis	24-08-2023	04-09-2023	1 and a half weeks
Meeting with supervisor to discuss results	01-09-2023	07-09-2023	1 week
Extra time	08-09-2023	20-09-2023	2 weeks
Final Draft	21-10-2023	27-10-2023	1 week
Meet Supervisor	25-10-2023	29-10-2023	1 week
Final Submissions	30-10-2023	02-11-2023	2 days

5. Risks

Risk Description	Likelihood (1-3)	Consequence (1-5)	Impact (L x C)	Mitigation Strategy
Tasks taking longer to complete than initially thought	3	3	9	Allow enough time to account for this, add 10% to time estimates, and sticking to the plan
Data not sufficient to answer research question	1	3	3	In constructing research make note of other open sources of data available
Interesting, new topics arise and take extra time to research	2	3	6	Add 10% to time estimates, and sticking to the plan
Disruption due to illness or personal reasons	2	4	8	Significant contingency period between planned project end date, encourage self-care
Neural network models are difficult to write	3	5	15	Use pytorch example scripts and modify, test small models on home computer
Neural network models take too long to run	2	5	10	Optimize the model architecture, use of hardware acceleration like GPUs, extra 2 weeks of extra time have been considered, using cloud computing services to access scalable resources
Model Interpretability	2	3	6	Using explainable AI techniques
Existing results cannot be replicated exactly	3	3	9	Ensuring thorough documentation, use of standardized protocols, transparency and openness
Code is lost or accidentally written over	2	5	10	Regular backups and use version control
Ethical considerations - bias and fairness issues	2	5	10	Using techniques such as fairness constraints or incorporating diversity metrics into the model training process.

6. References

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[6] Song, W., Shi, C., Xiao, H., Wang, J., & Jiang, X. (2019). Explainable knowledge graph-based recommendation via deep reinforcement learning. arXiv preprint arXiv:1906.09506.

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[10] Afchar, D., Melchiorre, A. B., Schedl, M., Hennequin, R., Epure, E. V., & Moussallam, M. (2021). Explainability in Music Recommender Systems. IEEE Transactions on Multimedia, 23, 2147-2159.

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[12]Storti, E. (2019). Towards a Knowledge Graph Representation of FAIR Music Content for Exploration and Analysis. Dipartimento di Ingegneria dell'Informazione, via Brecce Bianche 60121, Ancona, Italy.

[13] Yang, D., Guo, Z., Wang, Z., Jiang, J., Xiao, Y., & Wang, W. (2018). A Knowledge-Enhanced Deep Recommendation Framework Incorporating GAN-Based Models. In Proceedings of the IEEE International Conference on Data Mining (ICDM) (pp. 1368-1373).

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[15] Zhao, H., Yao, Q., Li, J., Song, Y., Lee, D. L. (2017). Meta-Graph Based Recommendation Fusion over Heterogeneous Information Networks. In Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD '17) (pp. 635-644).

[16] Tang, X., Wang, T., Yang, H., Song, H., & AKUPM. (2019). Attention-Enhanced Knowledge-Aware User Preference Model for Recommendation. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (KDD '19) (pp. 1891-1899).

7. Ethics Review

Research Ethics Review Form: BSc, MSc and MA Projects

Computer Science Research Ethics Committee (CSREC)

http://www.city.ac.uk/department-computer-science/research-ethics

Undergraduate and postgraduate students undertaking their final project in the Department of Computer Science are required to consider the ethics of their project work and to ensure that it complies with research ethics guidelines. In some cases, a project will need approval from an ethics committee before it can proceed. Usually, but not always, this will be because the student is involving other people ("participants") in the project.

In order to ensure that appropriate consideration is given to ethical issues, all students must complete this form and attach it to their project proposal document. There are two parts:

PART A: Ethics Checklist. All students must complete this part.

The checklist identifies whether the project requires ethical approval and, if so, where to apply for approval.

PART B: Ethics Proportionate Review Form. Students who have answered "no" to all questions in A1, A2 and A3 and "yes" to question 4 in A4 in the ethics checklist must complete this part. The project supervisor has delegated authority to provide approval in such cases that are considered to involve MINIMAL risk.The approval may be ***provisional*** *– identifying the planned research as* likely to involve MINIMAL RISK.In such cases you must additionally seek ***full approval*** from the supervisor as the project progresses and details are established. ***Full approval*** must be acquired in writing, before beginning the planned research.

A.1 If you answer YES to any of the questions in this block, you must apply to an appropriate external ethics committee for approval and log this approval as an External Application through Research Ethics Online - https://ethics.city.ac.uk/		Delete as appropriate
1.1	Does your research require approval from the National Research Ethics Service (NRES)? e.g. because you are recruiting current NHS patients or staff? If you are unsure try - https://www.hra.nhs.uk/approvals-amendments/what-approvals-do-i-need/	NO
1.2	Will you recruit participants who fall under the auspices of the Mental Capacity Act? Such research needs to be approved by an external ethics committee such as NRES or the Social Care Research Ethics Committee - http://www.scie.org.uk/research/ethics-committee/	NO
1.3	Will you recruit any participants who are currently under the auspices of the Criminal Justice System, for example, but not limited to, people on remand, prisoners and those on probation? Such research needs to be authorised by the ethics approval system of the National Offender Management Service.	NO
A.2 If you answer YES to any of the questions in this block, then unless you are applying to an external ethics committee, you must apply for approval from the Senate Research Ethics Committee (SREC) through Research Ethics Online - https://ethics.city.ac.uk/		Delete as appropriate
2.1	Does your research involve participants who are unable to give informed consent? For example, but not limited to, people who may have a degree of learning disability or mental health problem, that means they are unable to make an informed decision on their own behalf.	NO
2.2	Is there a risk that your research might lead to disclosures from participants concerning their involvement in illegal activities?	NO

2.3	Is there a risk that obscene and or illegal material may need to be accessed for your research study (including online content and other material)?	NO
2.4	Does your project involve participants disclosing information about special category or sensitive subjects? For example, but not limited to: racial or ethnic origin; political opinions; religious beliefs; trade union membership; physical or mental health; sexual life; criminal offences and proceedings	NO
2.5	Does your research involve you travelling to another country outside of the UK, where the Foreign & Commonwealth Office has issued a travel warning that affects the area in which you will study? Please check the latest guidance from the FCO - http://www.fco.gov.uk/en/	NO
2.6	Does your research involve invasive or intrusive procedures? These may include, but are not limited to, electrical stimulation, heat, cold or bruising.	NO
2.7	Does your research involve animals?	NO
2.8	Does your research involve the administration of drugs, placebos or other substances to study participants?	NO
A.3 If you answer YES to any of the questions in this block, then unless you are applying to an external ethics committee or the SREC, you must apply for approval from the Computer Science Research Ethics Committee (CSREC) through Research Ethics Online - https://ethics.city.ac.uk/ Depending on the level of risk associated with your application, it may be referred to the Senate Research Ethics Committee.		Delete as appropriate
3.1	Does your research involve participants who are under the age of 18?	NO

3.2	Does your research involve adults who are vulnerable because of their social, psychological or medical circumstances (vulnerable adults)? This includes adults with cognitive and / or learning disabilities, adults with physical disabilities and older people.	NO
3.3	Are participants recruited because they are staff or students of City, University of London? For example, students studying on a particular course or module. If yes, then approval is also required from the Head of Department or Programme Director.	NO
3.4	Does your research involve intentional deception of participants?	NO
3.5	Does your research involve participants taking part without their informed consent?	NO
3.5	Is the risk posed to participants greater than that in normal working life?	NO
3.7	Is the risk posed to you, the researcher(s), greater than that in normal working life?	NO
A.4 If you answer YES to the following question and your answers to all other questions in sections A1, A2 and A3 are NO, then your project is deemed to be of MINIMAL RISK. If this is the case, then you can apply for approval through your supervisor under PROPORTIONATE REVIEW. You do so by completing PART B of this form. If you have answered NO to all questions on this form, then your project does not require ethical approval. You should submit and retain this form as evidence of this.		Delete as appropriate
4	Does your project involve human participants or their identifiable personal data? For example, as interviewees, respondents to a survey or participants in testing.	NO