Programming Report

Question 1

I extract links to 14 topics (stored in *TopicsLinks*) and 128 papers that have been de-duplicated (stored in *PaperLinks*) and placed them in the preparation area. Three steps comprise my design proposal for this question.

The purpose of the first step is to traverse all the paper links to find the title and corresponding citation number for each paper. I begin by locating a *div* element with a style attribute of '*color:orange*'. It is assumed that this is a unique identifier for a paper's citation number and impact factor. The *citation* variable is then set to the text of this *div* element.

I use an if function to check if the word 'Citation' appears in the citation variable, and if it does, it splits the string over the word 'Citation:' and takes the final portion of the string (i.e., the citation number). Then, I erase the last two # characters from the string by removing the final two characters. I then append the paper's title (using *soup.find('h1').text* or *soup.find('title').text). text.split(' |')[0]*) to the *Titles* list and the citation number (stored as an integer) to the *Citations* list.

The second step is to merge the titles and corresponding citation numbers via the zip function and sorted function, store them in 'results' and sort them in descending order.

The third step is to build a data frame named 'table' to store the first 25 rows of the 'result', set the column names, adjust the attributes, and then show the 'table'.

	Citation Number	Title
0	228	A Quadruple Diffusion Convolutional Recurrent Network for Human Motion Prediction
1	201	Interaction Patches for Multi-Character Animation
2	150	Real-Time Posture Reconstruction for Microsoft Kinect
3	112	Simulating Multiple Character Interactions with Collaborative and Adversarial Goals
4	112	Simulating Competitive Interactions using Singly Captured Motions
5	102	Simulating Interactions of Avatars in High Dimensional State Space
6	98	Kinect Posture Reconstruction based on a Local Mixture of Gaussian Process Models
7	88	Interaction-based Human Activity Comparison
8	79	Environment-aware Real-Time Crowd Control
9	68	Real-time Physical Modelling of Character Movements with Microsoft Kinect
10	62	Posture Reconstruction Using Kinect with a Probabilistic Model
11	61	Interactive Formation Control in Complex Environments
12	60	Bi-projection based Foreground-aware Omnidirectional Depth Prediction
13	60	A Two-Stream Recurrent Network for Skeleton-Based Human Interaction Recognition
14	55	Interpreting Deep Learning based Cerebral Palsy Prediction with Channel Attention
15	55	Filtered Pose Graph for Efficient Kinect Pose Reconstruction
16	51	Emulating Human Perception of Motion Similarity
17	50	Motion Adaptation for Humanoid Robots in Constrained Environments
18	50	Differential Evolution Algorithm as a Tool for Optimal Feature Subset Selection in Motor Imagery EEG
19	48	Spatio-temporal Manifold Learning for Human Motions via Long-horizon Modeling
20	45	Validation of an Ergonomic Assessment Method using Kinect Data in Real Workplace Conditions
21	45	Arbitrary View Action Recognition via Transfer Dictionary Learning on Synthetic Training Data
22	44	SkillVis: A Visualization Tool for Boxing Skill Assessment
23	44	Multi-layer Lattice Model for Real-Time Dynamic Character Deformation
24	44	DurLAR: A High-fidelity 128-channel LiDAR Dataset with Panoramic Ambientand Reflectivity Imagery for Multi-modal Autonomous Driving Applications

Fig 1 Titles and Citation numbers of the top 25 cited papers

Question 2

Part A

The first step is to traverse the webpages of all papers, calculate the number of LDOs and the corresponding years, and record them. For each paper, I find the title, year, and find all LDO items (YouTube videos: *'youtube-player'*, other: *'ImgThumbnailDiv'*), storing this information in the *mydict* dictionary. The year is the key and the number of LDOs and YTBs is the value. *PaperLDOs* records the number of LDO items per paper.

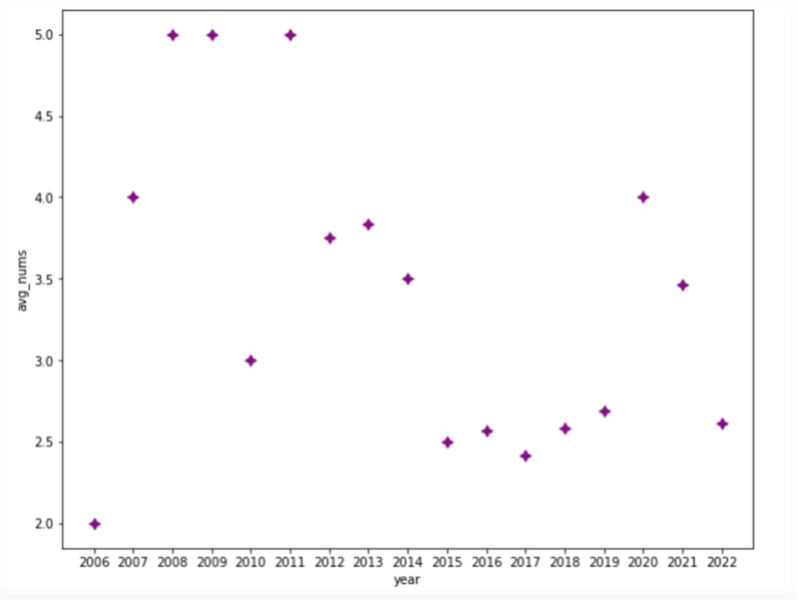
The second step is to count simultaneously in the storage procedure.

Table 1 Average number of LDO per year

2006	2007	2008	2009	2010	2011	2012	2013	2014
2.0	4.0	5.0	5.0	3.0	5.0	3.75	3.83	3.5
2015	2016	2017	2018	2019	2020	2021	2022	/
2.5	2.57	2.416	2.583	2.692	4.0	3.467	2.611	/

The third step generates a scatter plot using the data stored in the list *Years* and *LDONums*.

Fig 2 Scatter plot of average LDO numbers per year



Part B

As the name of the LDO item cannot be found via soup, I have defined a function *find_LDO_name* which takes a URL as input and returns a string indicating the type of LDO resource. If none of the conditions are met, the function returns 'other'. The result is that a total of two ‘other’ appear in all papers with LDO items. One of the ‘other’ is in Fig.3, line 20.

Next, I iterate through all the webpages of the paper, extracting the links to LDOs (except YouTube) and YouTube videos. The *‘find_LDO_nam’* function is then used to divide the LDOs into categories. The URLs containing LDOs were de-duplicated, the number of LDOs in each category was calculated via a dictionary, the number of YouTube videos was calculated separately, and this information was added to the ‘*LDONameSet*’. Finally, sorted and zipped to create it in a new data frame.

Fig 3 Names and Numbers of LDO projects in the top 25 papers

	LDOnumber	Title	Url	LDOSet
0	10	Angular Momentum Guided Motion Concatenation	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_siggraphasia2008interaction5478.htm	[("DOI - Publisher's Page", 1), ('Paper', 1), ('Presentation Slides', 1), ('Program', 1), ('YouTube', 3), ('video', 3)]
1	7	STGAE: Spatial Temporal Graph Auto-encoder for Hand Motion Denoising	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_casa2020hand1816.htm	[("DOI - Publisher's Page", 1), ('Paper', 1), ('Program', 1), ('YouTube', 2), ('video', 2)]
2	7	Preparation Behaviour Synthesis with Reinforcement Learning	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_tvcg2012interaction1595.htm	[("DOI - Publisher's Page", 1), ('Paper', 1), ('Presentation Slides', 1), ('YouTube', 2), ('video', 2)]
3	7	Interaction Patches for Multi-Character Animation	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_i3d2008interaction5368.htm	[("DOI - Publisher's Page", 1), ('Paper', 1), ('Presentation Slides', 1), ('YouTube', 2), ('video', 2)]
4	6	Facial Reshaping Operator for Controllable Face Beautification	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_icpr2020makeup8430.htm	[("DOI - Publisher's Page", 1), ('Paper', 2), ('Presentation Slides', 1), ('YouTube', 1), ('video', 1)]
5	6	Bi-projection based Foreground-aware Omnidirectional Depth Prediction	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_wscg2020depth2109.htm	[("DOI - Publisher's Page", 1), ('Paper', 2), ('Presentation Slides', 1), ('YouTube', 1), ('video', 1)]
6	6	An Intelligent Mobile-Based Automatic Diagnostic System to Identify Retinal Diseases using Mathematical Morphological Operations	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_vr2022depth8426.htm	[('Paper', 1), ('Presentation Slides', 1), ('YouTube', 2), ('video', 2)]
7	6	A New Method to Evaluate the Dynamic Air Gap Thickness and Garment Sliding of Virtual Clothes During Walking	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_mig2019prior7507.htm	[("DOI - Publisher's Page", 1), ('Paper', 1), ('Presentation Slides', 1), ('Program', 1), ('YouTube', 1), ('video', 1)]
8	5	Spatio-temporal Manifold Learning for Human Motions via Long-horizon Modeling	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_tcsvt2021prediction7122.htm	[("DOI - Publisher's Page", 1), ('Paper', 1), ('Presentation Slides', 1), ('YouTube', 1), ('video', 1)]
9	5	Simulating Interactions Among Multiple Characters	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_casa2009angular3290.htm	[("DOI - Publisher's Page", 1), ('Paper', 1), ('Presentation Slides', 1), ('YouTube', 1), ('video', 1)]
10	5	Semantics-STGCNN: A Semantics-guided Spatial-Temporal Graph Convolutional Network for Multi-class Trajectory Prediction	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_cgf2018multitouch1252.htm	[("DOI - Publisher's Page", 1), ('Paper', 1), ('Presentation Slides', 1), ('YouTube', 1), ('video', 1)]
11	5	Resolving Occlusion for 3D Object Manipulation with Hands in Mixed Reality	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_ijvr2011accelerometer1736.htm	[("DOI - Publisher's Page", 1), ('Paper', 1), ('Presentation Slides', 1), ('YouTube', 1), ('video', 1)]

12	5	PyTorch-based Implementation of Label-aware Graph Representation for Multi-class Trajectory Prediction	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_smc2021trajectory8283.htm	[("DOI - Publisher's Page", 1), ('Paper', 1), ('Presentation Slides', 1), ('YouTube', 1), ('video', 1)]
13	5	Posture Reconstruction Using Kinect with a Probabilistic Model	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_tcyb2013kinect6747.htm	[("DOI - Publisher's Page", 1), ('Paper', 1), ('Presentation Slides', 1), ('YouTube', 1), ('video', 1)]
14	5	Interpreting Deep Learning based Cerebral Palsy Prediction with Channel Attention	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_tvcg2020interaction9753.htm	[("DOI - Publisher's Page", 1), ('Paper', 1), ('Program', 1), ('YouTube', 1), ('video', 1)]
15	5	Human-centric Autonomous Driving in an AV-Pedestrian Interactive Environment Using SVO	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_icpr2020interaction3707.htm	[("DOI - Publisher's Page", 1), ('Paper', 1), ('Presentation Slides', 1), ('YouTube', 1), ('video', 1)]
16	5	Human Motion Variation Synthesis with Multivariate Gaussian Processes	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_pg2013topology5337.htm	[("DOI - Publisher's Page", 1), ('Paper', 1), ('Presentation Slides', 1), ('YouTube', 1), ('video', 1)]
17	5	Foreground-aware Dense Depth Estimation for 360 Images	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_grapp2020car6252.htm	[("DOI - Publisher's Page", 1), ('Paper', 1), ('Presentation Slides', 1), ('YouTube', 1), ('video', 1)]
18	5	Finding Repetitive Patterns in 3D Human Motion Captured Data	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_tmm2020mesh9359.htm	[("DOI - Publisher's Page", 1), ('Paper', 1), ('Program', 1), ('YouTube', 1), ('video', 1)]
19	5	DSPP: Deep Shape and Pose Priors of Humans	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_eswa2022formation2257.htm	[("DOI - Publisher's Page", 1), ('Paper', 1), ('YouTube', 1), ('other', 1), ('video', 1)]
20	5	Cerebral Palsy Prediction with Frequency Attention Informed Graph Convolutional Networks	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_bhi2021cerebral8050.htm	[("DOI - Publisher's Page", 1), ('Paper', 1), ('Presentation Slides', 1), ('YouTube', 1), ('video', 1)]
21	5	A Hybrid Metaheuristic Navigation Algorithm for Robot Path Rolling Planning in an Unknown Environment	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_mig2010physically2702.htm	[("DOI - Publisher's Page", 1), ('Paper', 1), ('Presentation Slides', 1), ('YouTube', 1), ('video', 1)]
22	4	Validation of an Ergonomic Assessment Method using Kinect Data in Real Workplace Conditions	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_cag2017visualization4134.htm	[("DOI - Publisher's Page", 1), ('Paper', 1), ('YouTube', 1), ('video', 1)]
23	4	Usability of Corrected Kinect Measurement for Ergonomic Evaluation in Constrained Environment	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_mig2016visualization9440.htm	[("DOI - Publisher's Page", 1), ('Paper', 1), ('YouTube', 1), ('video', 1)]
24	4	Unsupervised Abnormal Behaviour Detection with Overhead Crowd Video	https://sitescrape.awh.durham.ac.uk/comp42315/pbl_cgf2016crowd5730.htm	[("DOI - Publisher's Page", 1), ('Paper', 1), ('YouTube', 1), ('video', 1)]

Question 3

Counts the total number of citations for each author and all articles he has written plus the topic. The 149 authors were ranked according to the total number of citations. I found that the highest ranked author was **Shum, Hubert P. H.**, who had written 128 papers on 14 topics. The top 10 most cited authors wrote on the most cited topic of **character animation**.

Table 2 Top 10 most cited authors

1	Shum, Hubert P. H.	3266
2	Ho, Edmond S. L.	1140
3	Komura, Taku	1052
4	Leung, Howard	655
5	Yamazaki, Shuntaro	527
6	Men, Qianhui	369
7	Morishima, Shigeo	261
8	Aslam, Nauman	260
9	Yang, Longzhi	236
10	Takagi, Shu	220

Fig 4 Top 10 most cited authors by topics

	topic	num
0	characteranimation	26
1	motionanalysis	20
2	interactionmodelling	20
3	biomedicalengineering	17
4	3dreconstruction	16
5	actionrecognition	15
6	surfacemodelling	11
7	crowdmodelling	9
8	facemodelling	9
9	virtualreality	9
10	robotics	8
11	biometrics	8
12	computationalintelligence	7
13	handandgesture	7

I reconstructed a data frame with all URLs, titles, LDO numbers, topic, author names, citations, impact factors, article type, pages, year, publisher, volume number. We looked at the names of the authors in the new pd and found a total of 11 sets of co-authors appearing twice or more, counting the topics on

which these 11 sets of authors collaborated. **'Feng, Qi', 'Shum, Hubert P. H.', 'Morishima, Shigeo'** have worked together most often. The most popular topic for collaboration between authors is **character animation**.

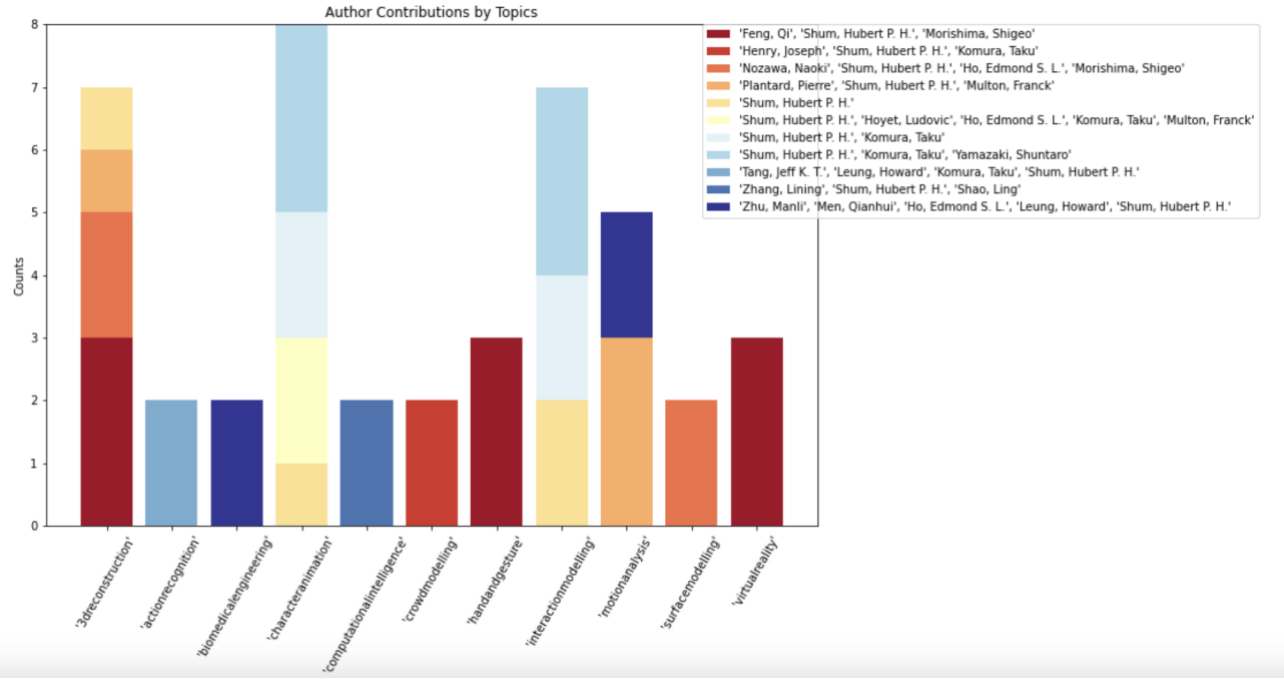


Fig 5 A collaborative topic by 11 groups of authors

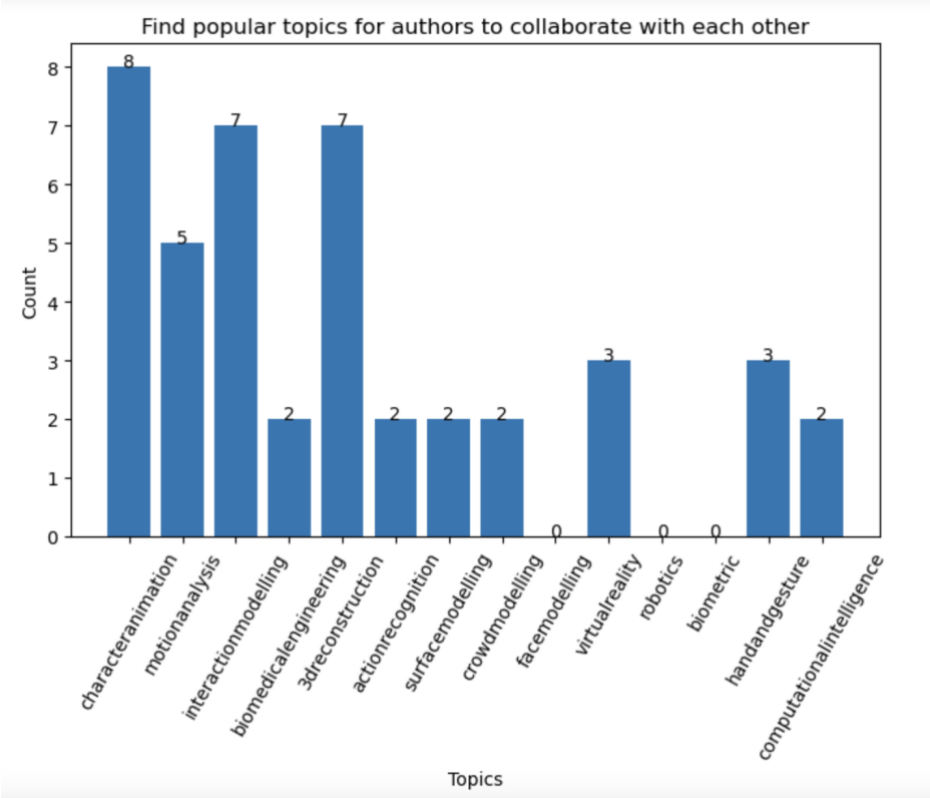


Fig 6 Find popular topics for authors to collaborate with each other

There are 8 features that influence citation, 5 numerical variables: impact factor, year, number pages, volume number, LDO number, and 3 categorical variables: publisher, type of venue, topics. I initially considered multiple regression but found the results to be unsatisfactory based on the regression line images. I then considered a decision tree model, which fit very well, and identified the three features that had the greatest influence on the 'citation' count: **LDO number**, **volume number**, and **impact factor**.

Fig 7 Multiple linear regression fit plots

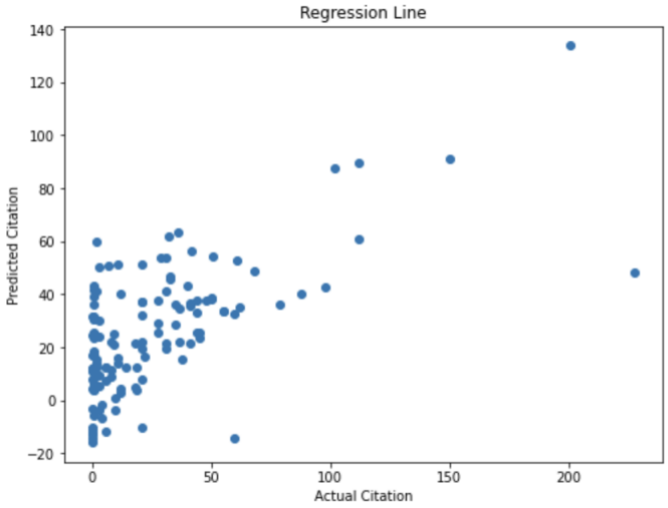
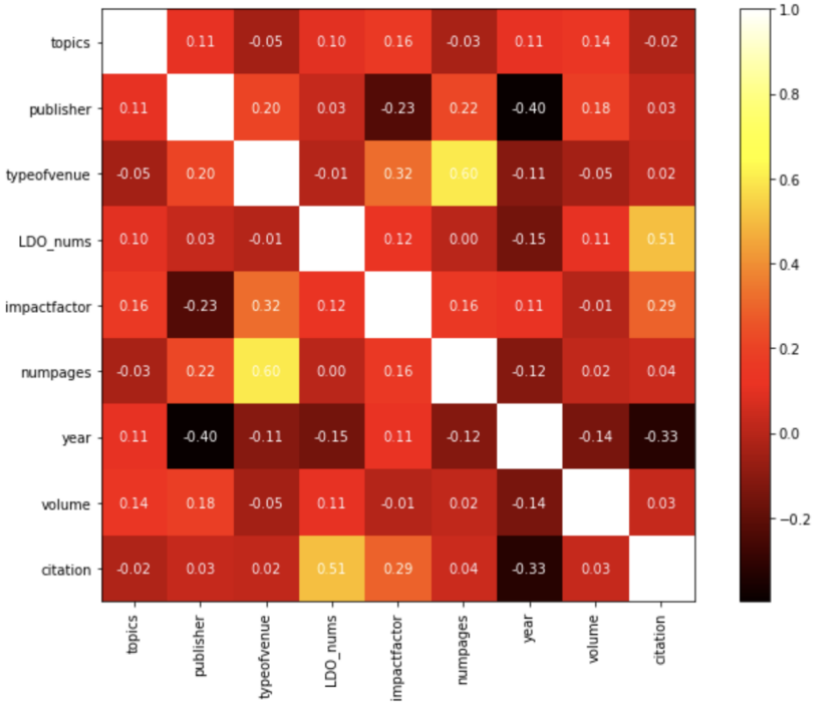


Fig 8 Heat map between 8 variables and citation



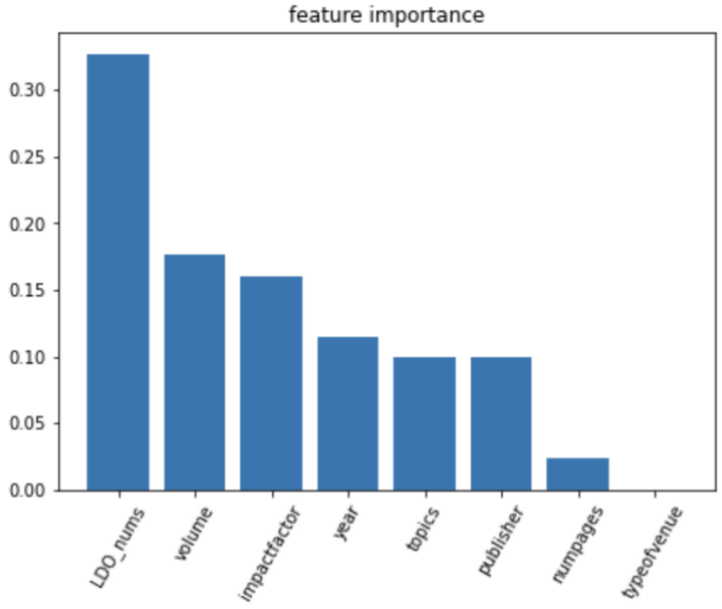


Fig 9 Feature importance under decision tree model

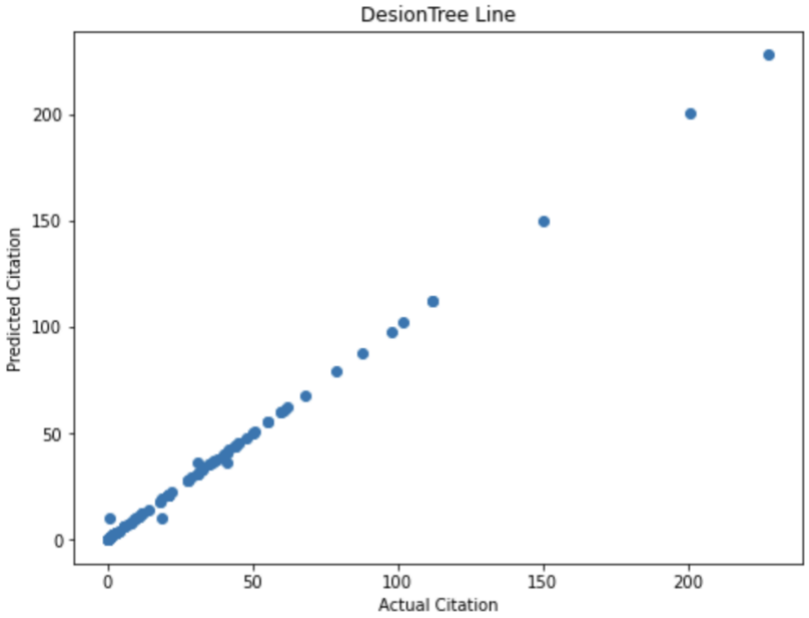


Fig 10 Decision Tree Model Fit Plots

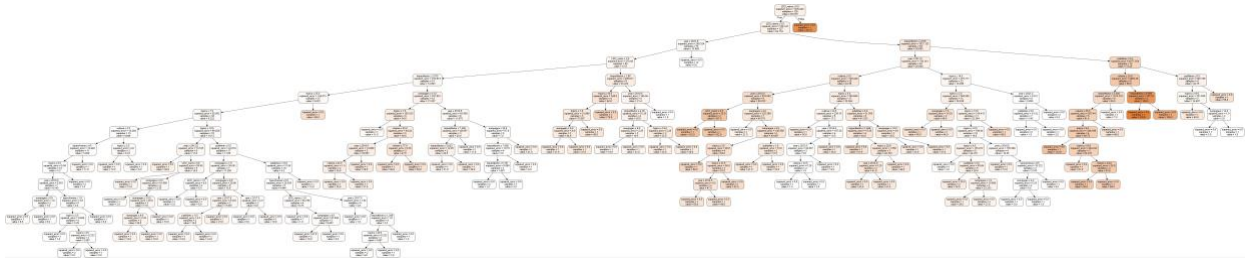


Fig 11 Decision Tree

Direct observation of numerical variables through scatter plots and categorical variables through violin plots. We can reach the same answer.

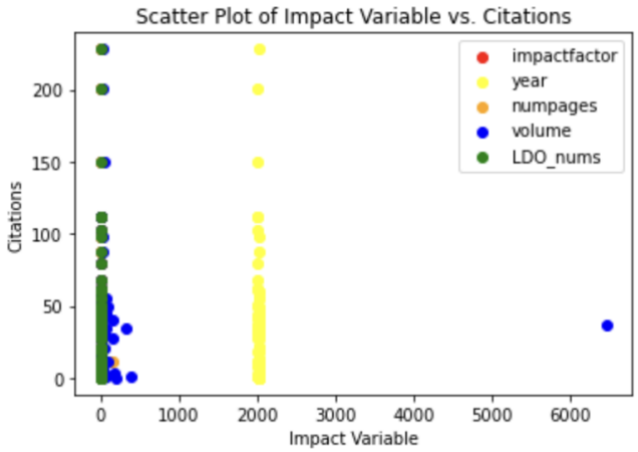


Fig 12 Scatter Plot of Impact Variable vs. Citations

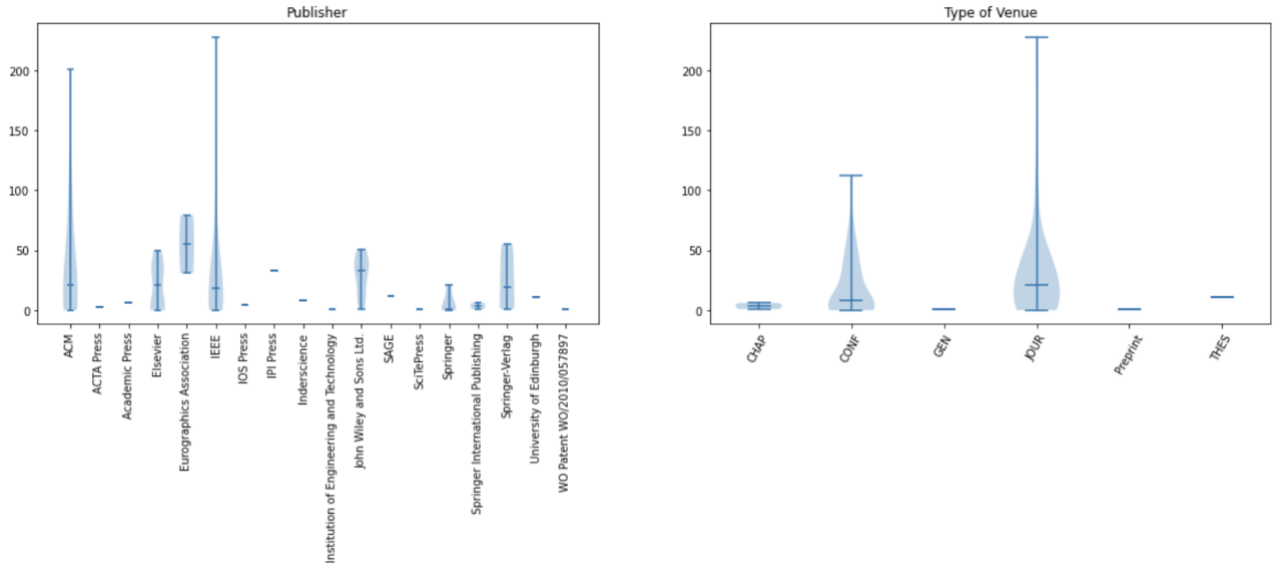


Fig 13 Violin charts for publishers and type of venue

Because categorical variables do not lend themselves to chi-square testing, I used a one-way ANOVA with a p-value significantly less than 0.5 to conclude that there is a significant association between type of venue and impact factor. We discovered that the impact factor was only achievable for journal articles and not for the other five types.

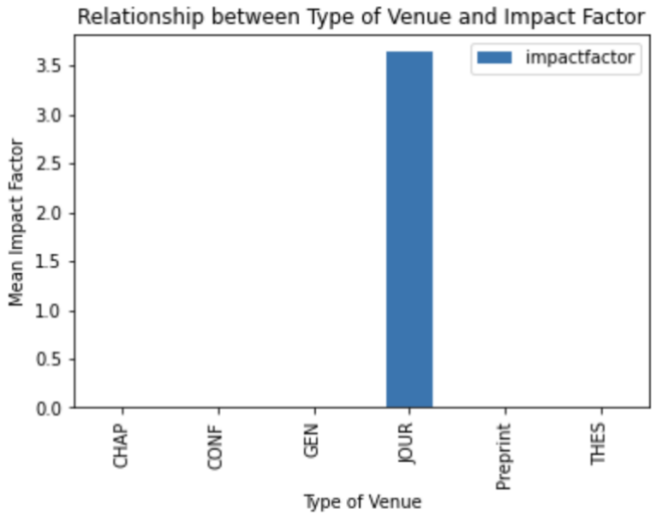


Fig 14 Relationship between type of venue and impact factor

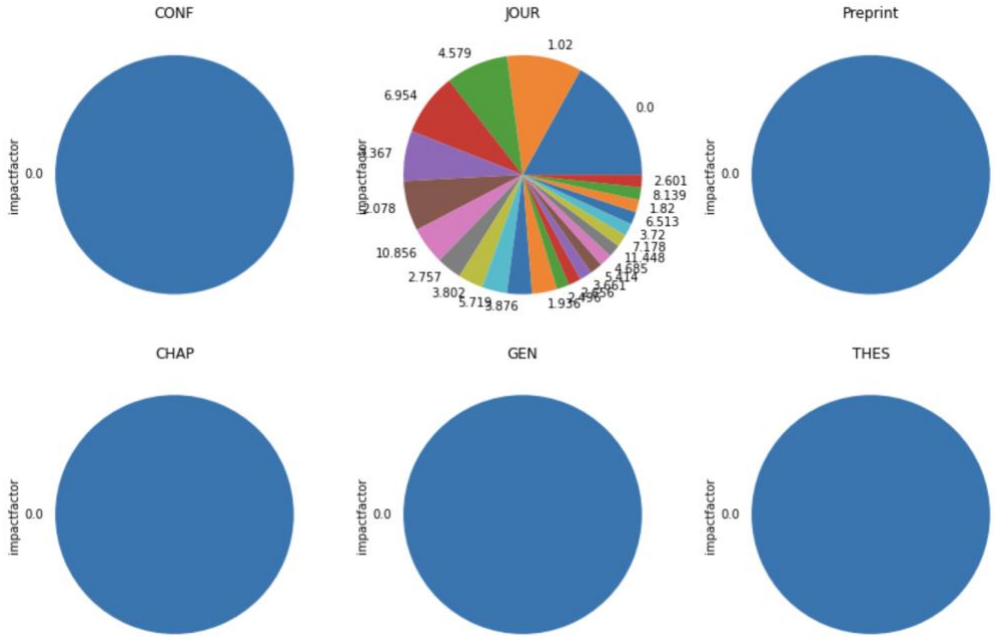


Fig 15 Pie chart between type of venue and impact factor

Question 4

I initially processed the dataset by eliminating the id column and discretizing the level column into four classes: 0. None, 1. Mild, 2. Moderate, and 3. Severe. Separate the training and test sets, establish the structure of climbing search to learn how to make a DAG, and then utilise this DAG to generate a complicated Bayesian network. Based on the scoring, the model is not good enough. I then chose the tree-enhanced naive Bayesian network and found that only the structure score improved by 9 points,

the rest remained essentially the same. According to CPT, it was found that neither of these models had a way of deriving determinants. I tried random forests, with little difference in feature importance.

Fig 16 Complex Bayesian Network

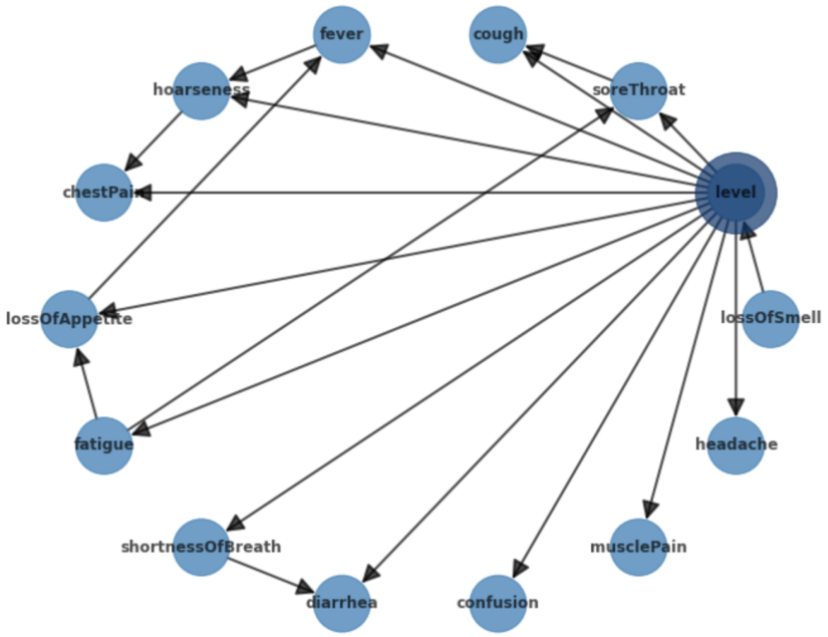
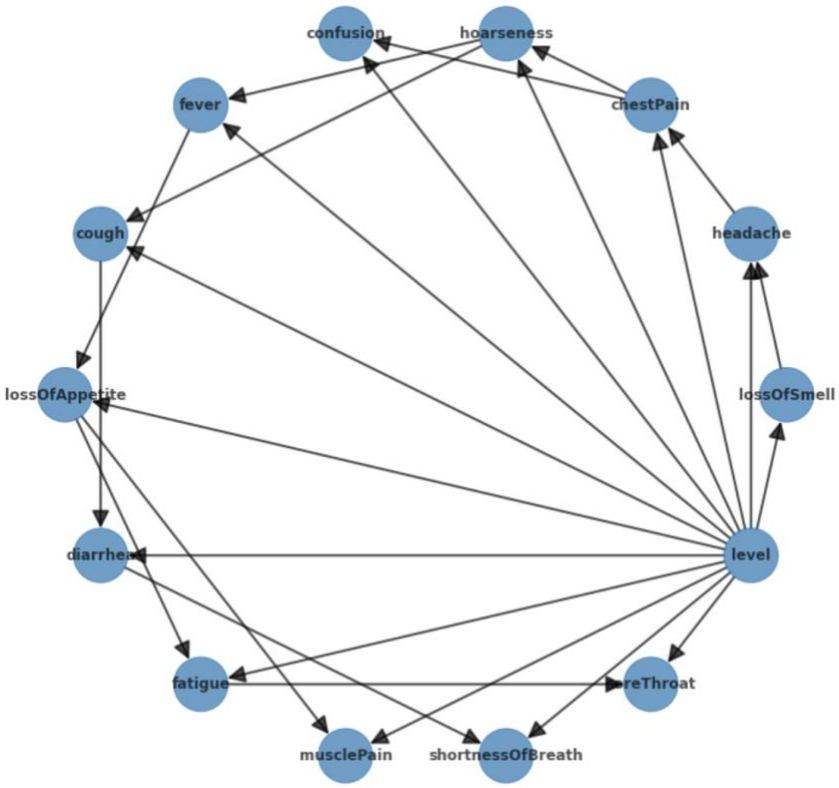


Fig 17 Tree Augmented Naive Bayes Network



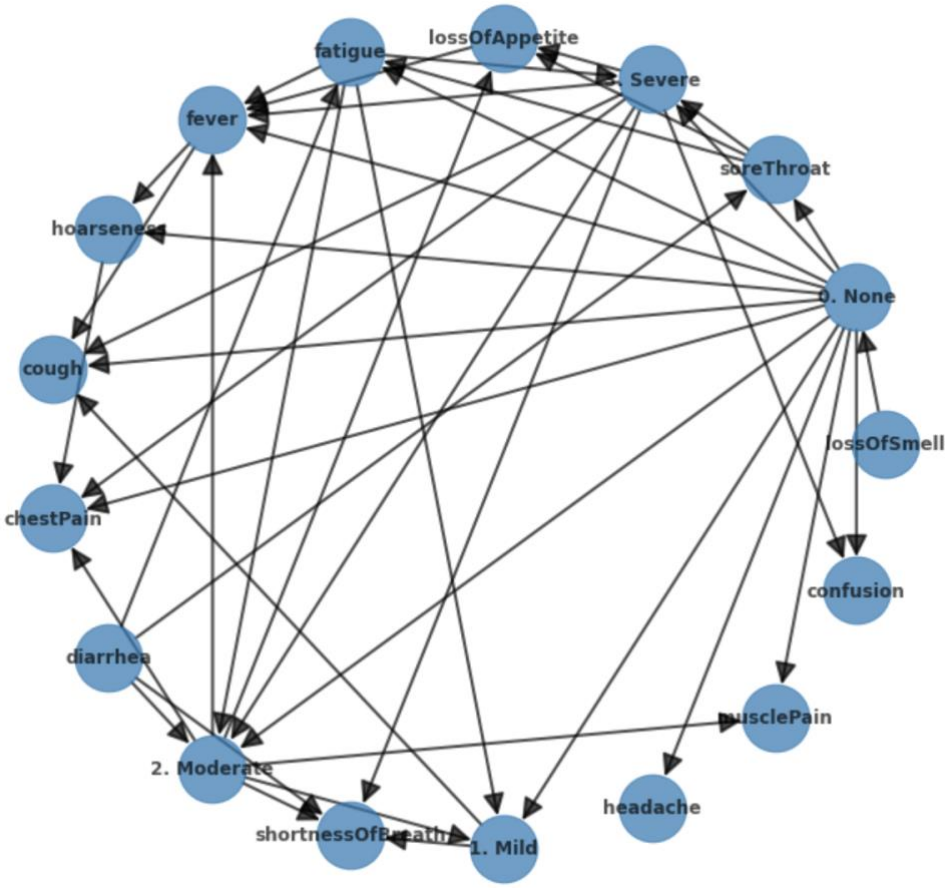


Fig 18 Complex Bayesian networks built with dummy variables

By constructing dummy variables, we can create a complex Bayesian model to improve the model. According to the network diagram,'soreThroat' is significantly associated with 'fatigue', which is associated with 'lossOfAppetite' and 'diarrahea'. From the conditional probability table, we know that fatigue and sore throat account for 99.9% of the variation when the level is severe. When the level is moderate, diarrhea and fatigue are the determining factors with 50% probability. When level is mild, fatigue is the determining factor, 50% probability.

Table 3 Prediction Accuracy Scores for all variables in 3 model

	Complex Bayesian Network	Tree Augmented Naive Bayes Network	Complex Bayesian networks built with dummy variables
headache	0.71235	0.713025	0.71235
lossOfSmell	0.7115	0.713025	0.7115
musclePain	0.711975	0.712625	0.711975
cough	0.7116	0.7135	0.7107
soreThroat	0.714675	0.714675	0.714325
chestPain	0.714225	0.713675	0.714225
fever	0.714125	0.714125	0.712725
hoarseness	0.714225	0.71305	0.714225
lossOfAppetite	0.714125	0.71425	0.714125
diarrhea	0.7138	0.7155	0.7144
fatigue	0.716475	0.71647	0.711175
confusion	0.713125	0.712825	0.713125
shortnessOfBreath	0.714425	0.714425	0.714425
level	0.9998	0.9998	'0. None': 1.0, '1. Mild': 1.0, '2. Moderate': 1.0, '3. Severe': 1.0
Average	0.7340303571428572	0.7343553571428572	0.7805455882352942

Table 4 Structural correlation scores for 3 models

	Complex Bayesian Network	Tree Augmented Naive Bayes Network	Complex Bayesian networks built with dummy variables
F1 score	0.0	0.0	0.35294117647058826
Accuracy score	0.8901098901098901	0.8901098901098901	0.9191176470588235
Precision score	0.0	0.0	1.0
Recall score	0.0	0.0	0.21428571428571427
Log-likilihood score	-264810.9228233893	-264810.47414098127	-264810.1517900896
Strcture score	-265248.8751533862	-265239.5535024299	-265231.0523724723