COMP5329 Deep Learning

A neural network approach to the researcher recommender system

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Abstract

The Hierarchical Word Movers Distance has been recently proposed to find potential matches for research collaborations using a sample of journals extracted from the Faculty of Engineering and Information Technologies. However, this approach does not take social relations into account. For instance, a researcher may prefer to collaborate with others from the same school. Using a calculated distance metric from the Hierarchical Word Movers Distance as a predictor variable along with other social relations extracted from researcher profile pages, we use the Neural Network to compute a similarity metric among pairs of researchers. Because the similarity metric is a latent variable, we use a co-authorship count as a proxy. Higher similarity scores are; the more co-authorship counts should be. This paper simply extends the capstone project we previously worked on when we used the generalised linear model to predict the co-authorship count. The neural network relaxes a linearity assumption that imposes on the generalised linear model. In this paper, we describe the neural network from the frequentist perspective, and compare its performance with the generalised linear model. We also introduce a framework of Bayesian neural network. That is, we allocate credibility across all possible co-authorship counts.

1 Introduction

The ever-increasing research collaboration activities are commonly seen in the same research group or the same school. However, this trend has also started emerging when researchers from academia and non-academia work together [7]. Researchers specialising one or two areas can often complement others when it comes to research collaborations. Knowledge sharing helps understanding a research of interest from various perspectives. Unfortunately, the Faculty of Engineering and Information Technologies has always been difficult to find relevant researchers when it comes to this space. When searching for researchers, people often look for those who have close proximity, or have high research impacts. However, in other cases, people seek out others in a completely different area.

1.1 Objectives

We previously examined this domain from the semantic perspective by proposing the Hierarchical Word Movers Distance [13, 12]. However, this approach does not take social relations into account. We then extended the scope to capture social relations using the generalised linear model [12]. The generalised linear model relies on a linearity assumption to hold, which in practice it is often not the case. The neural network relaxes this assumption. Therefore, using a calculated distance metric from the Hierarchical Word Movers Distance as a predictor variable along with others extracted from researcher profile pages, we use the neural network to determine whether any predictor variables affect the co-authorship counts and estimate their magnitudes, if any.

Thus far we have learned the neural network mainly from the frequentist perspective. Surely, regularisation techniques [5] such as L^1 and L^2 do mimic Bayesian statistics by penalising θ to prevent over-fitting. However, it is widely conceived as pseudo-Bayesian. It is hard to convince making predictions based on a single value of θ because a different sample will almost always yield a different θ [10]. Clearly, there is a flaw in the frequentist view. For instance, say, a image recognition problem where you are required to classify either a cat or dog image, randomly inserting a leopard image would surely mess up the classifier. Sometimes, we are not only interested in predictions themselves, but also how confident predictions are. Therefore, we introduce a framework of Bayesian neural network by considering all possible values of θ. In other words, the neural network outputs credibility [1] across all the possible co-authorship counts. All in all, we effectively measure uncertainty. The Bayesian Neural Network is chosen for the following reasons:

- We are not only interested in predictions themselves, but also how confident predictions are.
- We avoid over-fitting when we have a smaller dataset, and dataset itself is very skewed (See the Section 3.1).

1.2 Research Questions

This paper simply extends the work we previously worked on and attempts to answer the following questions:

- While semantic analysis is a critical factor for the researcher recommender system, arguably, social relations are equally important. By integrating the two using the neural network, can we improve researcher recommendations? How does it compare with the generalised linear model?
- Can we turn the neural network from frequentist to Bayesian? Is it possible to output credibility of the co-authorship counts?

2 Related Work

In an era of information overload, searching for researchers or publications related to researchers' area of interest is a difficult task. Hence, many institutes implemented such collaborative networks on researcher project pages based on historical publications and grants [11]. However, such visualisation does not show much value to researchers because they already know whom they have previously collaborated with. An alternative approach is to suggest relevant researchers based on keywords provided by users. For instance, Gollapalli et al. [4] computed similarity by using the Named-Entity Recognition on journals as well as researcher profile pages. The Named-Entity Recognition annotates names of entities in journals in which users search for. Unfortunately, this approach does not consider a document semantic structure. On the contrary, Haruna et al. [6] suggested a collaborative approach when journals are not publicly accessible. Provided that journals are accessible, we recently proposed the Hierarchical Word Movers Distance [13, 12] to find potential matches for research collaborations. The Hierarchical Word Movers Distance first applies the Word Movers Distance to journals, and subsequently to researchers who have published them.

[1] Some authors, noticeably Chris Bishop [2], refer to predictive distribution.

The journal similarity is one of many factors that fosters research collaborations. Arguably, social relations such as researchers of the same research group, researchers from the same school, researcher rank differences and so on also play a critical role when it comes to research collaborations. Xu et al. [14] concluded researcher collaboration systems had been thus far broadly classified into two categories for the past few years – Semantic Analysis and Social Relations. They recommended a two-layer network approach that integrates the two together. Previously, we proposed to integrate the two by means of the generalised linear model [12]. The generalised linear model relies on a linearity assumption to hold, which in practice it is often not the case.

3 Techniques

In this section, we detail dataset before diving into the proposed architecture.

3.1 Dataset

Dataset for the study is extracted from both Scopus [8] for journals, and researcher profile pages for social relations. In the sample dataset, because we have 74 researcher profiles, we have 2,701 pairs, mathematically $C_2^{74} = 2,701$. Due to privacy reasons, the researcher identities such as names, employment histories and so on have been deleted from the sample. The sample instead records either differences or similarities between pairs of researchers. The Table 1 shows the first 10 pairs of researchers. The full sample is shown in the Section 6.2.

`distance`	`is_same_title`	`is_same_department`	`duration_difference`	`coauthorship`
0.344081887	0	1	84	25
0.506936579	1	1	1290	15
0.652820559	0	1	3279	31
0.667356028	1	1	2495	41
0.675607872	1	0	4606	8
0.701469131	0	0	4690	9
0.713546647	1	1	1282	3
0.745227537	1	1	4922	44
0.745956446	0	1	434	15
0.74975835	0	1	2929	24

Table 1: The first 10 pairs of a sample dataset

The `distance` metric that has been calculated from the Hierarchical Word Movers Distance measures similarity between a pair of researchers in term of semantic analysis. The `is_same_title` is a boolean that indicates if a pair shares the same title (i.e. fellow, professor and etc.). It is important to note that the title has been preprocessed before computing the `is_same_title`. For instance, “Senior Lecturer”, “Lecturer” or “Associate Lecturer” is mapped to “Lecturer”. The `is_same_department` is a boolean that indicates if a pair shares the same school (i.e. civil engineering, electrical & information engineering and etc.). The `duration_difference` is days in term of employment history differences. For instance, `duration_difference`=84 means one researcher of a pair has been employed 84 days more than another one in the same pair. The `coauthorship` is a count that indicates a pair has co-authored this many times. The `distance`, `is_same_title`, `is_same_department` and `duration_difference` are predictor variables. The `coauthorship` is a response variable that models have to predict.

The sample has an excess of zero counts, precisely 2593 pairs. It is possible these pairs may have collaborated, but no observations are recorded in this sample.

3.2 Proposed Architecture

The `coauthorship`, which is a response variable, is a non-negative integer. Statistically speaking, this kind of data is often assumed to follow the Poisson distribution [1]. Hence, the generalised linear model should satisfy with the exponential relationship

$$\mu = e^{b+w_{\texttt{distance}}x_{\texttt{distance}}+w_{\texttt{is\_same\_title}}x_{\texttt{is\_same\_title}}+w_{\texttt{is\_same\_department}}x_{\texttt{is\_same\_department}}+w_{\texttt{duration\_difference}}x_{\texttt{duration\_difference}}} \tag{1}$$

where $w_{\texttt{distance}}$, $w_{\texttt{is\_same\_title}}$, $w_{\texttt{is\_same\_department}}$, $w_{\texttt{duration\_difference}}$, and b are weights and bias respectively. μ is always guaranteed to produce a non-negative value. Unfortunately, the exponential activation function does not provide a reasonable accuracy. Alternatively, we simply do not "transform" μ. In other words, we use an identity link, but it sometimes produces negative values as a side-effect. In this case, a negative value is mapped to 0, so the ReLU activation (σ) function is used in the output layer. No hidden layers are used in the proposed architecture.

The mean square error is the loss function with the weights being set to 10. Because of the excess of zero counts, without setting the weights, the neural network almost always returns zeros. The optimisation method is the Adam Optimisation [3]. The epoch is set to 100,000. Smaller epoch could result the neural network being less accurate. Again, it is the excess of zero counts issue. The proposed architecture is then shown as follows:

$$\begin{aligned}\mu = b + w_{\texttt{distance}}x_{\texttt{distance}} + w_{\texttt{is\_same\_title}}x_{\texttt{is\_same\_title}}+ \\ w_{\texttt{is\_same\_department}}x_{\texttt{is\_same\_department}} + w_{\texttt{duration\_difference}}x_{\texttt{duration\_difference}}.\end{aligned} \tag{2}$$

The activation function becomes

$$\sigma = max(0, \mu). \tag{3}$$

3.3 Bayesian Neural Network

Purposefully, the Bayesian statistics is to compute the posterior distribution of σ by considering all possible values of θ. In our case, θ refers to b, $w_{\texttt{distance}}$, $w_{\texttt{is\_same\_title}}$, $w_{\texttt{is\_same\_department}}$, and $w_{\texttt{duration\_difference}}$.

To compute the posterior distribution, we need the prior as well as the likelihood. When the prior and the likelihood combine, the posterior distribution has the same form as the prior distribution. The prior is then called a conjugate prior [10]. In practice, it seldom takes place, and the posterior distribution can often get very complicated. In this situation, we employ numerical methods such as Markov Chain Monte Carlo [10] or Variational inference [9] to compute the posterior distribution. Due to time constraints, we attempt to avoid such situation by choosing the uniform distribution for the prior. In other words, we believe every value in θ is equally likely. In other words, the likelihood is effectively the posterior distribution.

To list down all possible values of θ, we have to perform sampling. Unfortunately, optimisation methods commonly used in the neural network such as gradient descent, AdaGrad, RMSProp and so on [3] do not always guarantee to reach a global optimum point. That is to say, it is possible $w_{\texttt{distance}}$ has two or more very likely values, or statistically speaking multi-modal distribution. Such situation could have a potential impact to the posterior distribution, or in other words, every co-authorship count is possible.

4 Experiments

We have two experiments in this study – Model Comparisons and Bayesian Neural Network. Let us start with model comparisons.

4.1 Model Comparisons

The experiment is set up in a way the sample is fed into the models, including a baseline, which we will get into it very shortly. Using the 10-fold cross validation, the experiment is conducted, and performances are measured on a validation set. The mean square error (MSE) is the only criteria to assess performances.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2, \tag{4}$$

where y_i is a truth count for the ith observation and $\hat{y}$ is a predicted count for the ith observation. We have three possible models, which are the Poisson Regression, Negative Binomial Regression, and Neural Network. The first two are generalised linear models. Given 96% of sample that has zero counts, the baseline is to always output zeros. The goal is to find the best model that approximates the co-authorship counts. This is a supervised learning in which the ground truth (i.e. the co-authorship counts) is provided when training the models.

4.1.1 Results

When we compare the neural network with others including the baseline, this model is better than the most except the negative binomial (See the Table 2 and Figure 1). The poisson regression always over-predicts when the truth count is at least 1; the negative binomial consistently outperforms others with the MSE at most 0.1% across all the experiments. However, the average MSE for the neural network is around 2.4%. The MSE indicates the negative binomial is the best model overall.

Experiment	**Poisson**	**Negative Binomial**	**Neural Network**	**Baseline**
1	6.638376384	0.003690037	1.483394834	0.442804428
2	105.4148148	0.051851852	4.218518519	6.674074074
3	55.56666667	0.011111111	3.266666667	3.266666667
4	4.066666667	0.014814815	0.448148148	0.337037037
5	126.4740741	0.014814815	2.637037037	7.318518519
6	217.9481481	0.103703704	4.57037037	13.95185185
7	33.42222222	0.040740741	0.637037037	2.074074074
8	175.7037037	0.014814815	4.7	18.12857143
9	8.162962963	0.025925926	0.518518519	0.507407407
10	109.9259259	0.1	1.540740741	7.314814815
Average	**84.33235616**	**0.038146781**	**2.402043187**	**6.00158203**

Table 2: Performance of all the models

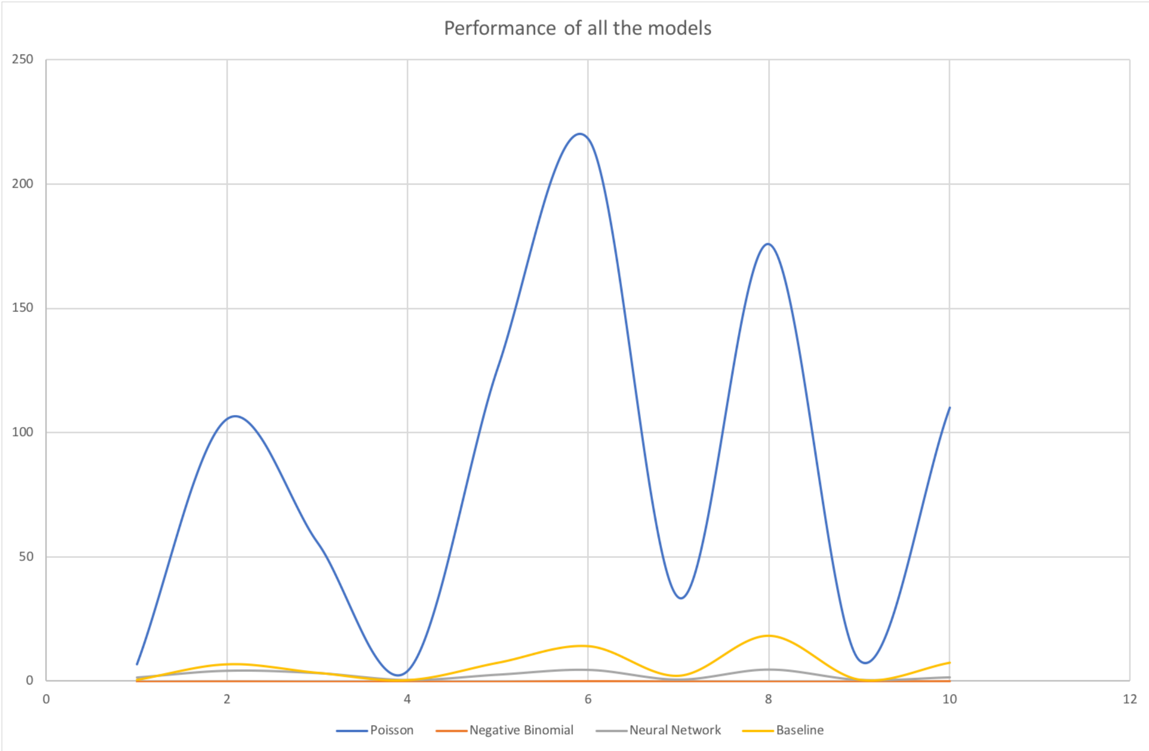
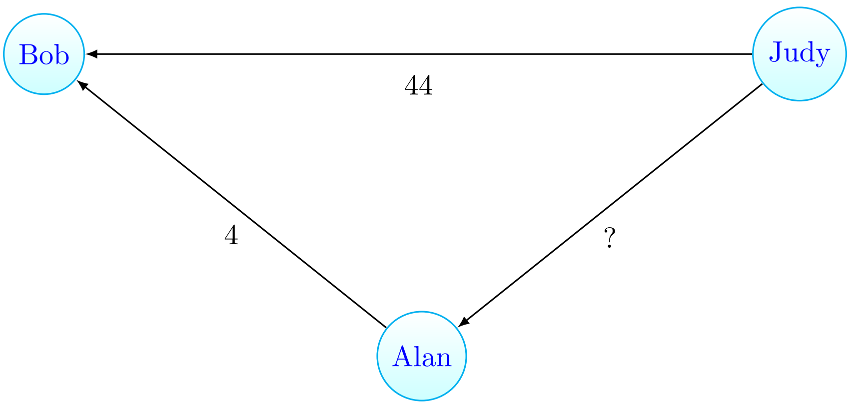


Figure 1: Performance of all the models

4.1.2 Analysis

Given the negative binomial being the lowest MSE by some margins, the results are not conclusive.

Firstly, the excess of zero counts causes the neural network longer to train when the epoch is set to 100,000, and the learning rate is set to 0.001. It is argued the neural network would achieve better results if the epoch was set even higher. Secondly, because the poisson regression always over-predicts, it hints the sample may suffer over-dispersion [1]. Our model only uses `distance`, `is_same_title`, `is_same_department`, and `duration_difference` as predictor variables. We believe other variables that are not recorded also influence the co-authorship counts. Nevertheless, the negative binomial has an additional hyper-parameter α to cater for this situation. Thirdly, the sample also suffers under-dispersion. To illustrate this issue, let us say Bob and Judy co-authored 44 times; Bob and Alan co-authored 4 times. If the sample was truly independent, we would not be able to work out the co-authorship counts between Alan and Judy. From the sample, it turns out they co-authored 5 times. The memoryless neural network cannot manage this situation.



Lastly, we attempt to make a level playing field among the models. In other words, the models all have single layer. However, the proposed neural network architecture is too simple to capture any useful information. Other activations may also work better.

4.2 Bayesian Neural Network

Using a hold-out method, more precisely 90% of sample for training and the remaining 10% of the sample for testing, the experiment is conducted 1,000 times to capture distributions for θ. In our case, θ refers to b, $w_{\texttt{distance}}$, $w_{\texttt{is\_same\_title}}$, $w_{\texttt{is\_same\_department}}$, and $w_{\texttt{duration\_difference}}$. We use the uniform distribution for the prior. In other words, we believe every value in θ is equally likely.

Once distributions of θ are calculated, the posterior distribution of σ is computed by plugging them into the Equation 2. Statistically speaking, it is not correct. When you have a non-uniform prior, you will almost always need either Markov Chain Monte Carlo [10] or Variational inference [9] to compute the posterior distribution. However, in our case, we make the likelihood as the posterior distribution by choosing a non-informative prior.

4.2.1 Results

The distributions for θ are shown in the Figure 2. Each sub-plot is a histogram with 100 bins. The top left sub-plot shows the bimodal distribution for b when majority falls around 26 and a few centres around 0. The top middle sub-plot shows the bimodal distribution for $w_{\texttt{distance}}$. Again, the bulk falls around -60 whereas a few sits between 0. The top right sub-plot shows the uni-modality for $w_{\texttt{is\_same\_title}}$. However, the distribution is rather flat, which indicates it is less confident. The bottom left sub-plot displays the bi-modal distribution for $w_{\texttt{is\_same\_department}}$. The shape peak is around 36 whereas a few is close to 0. The bottom middle sub-plot displays the multi-modal distribution for $w_{\texttt{duration\_difference}}$.

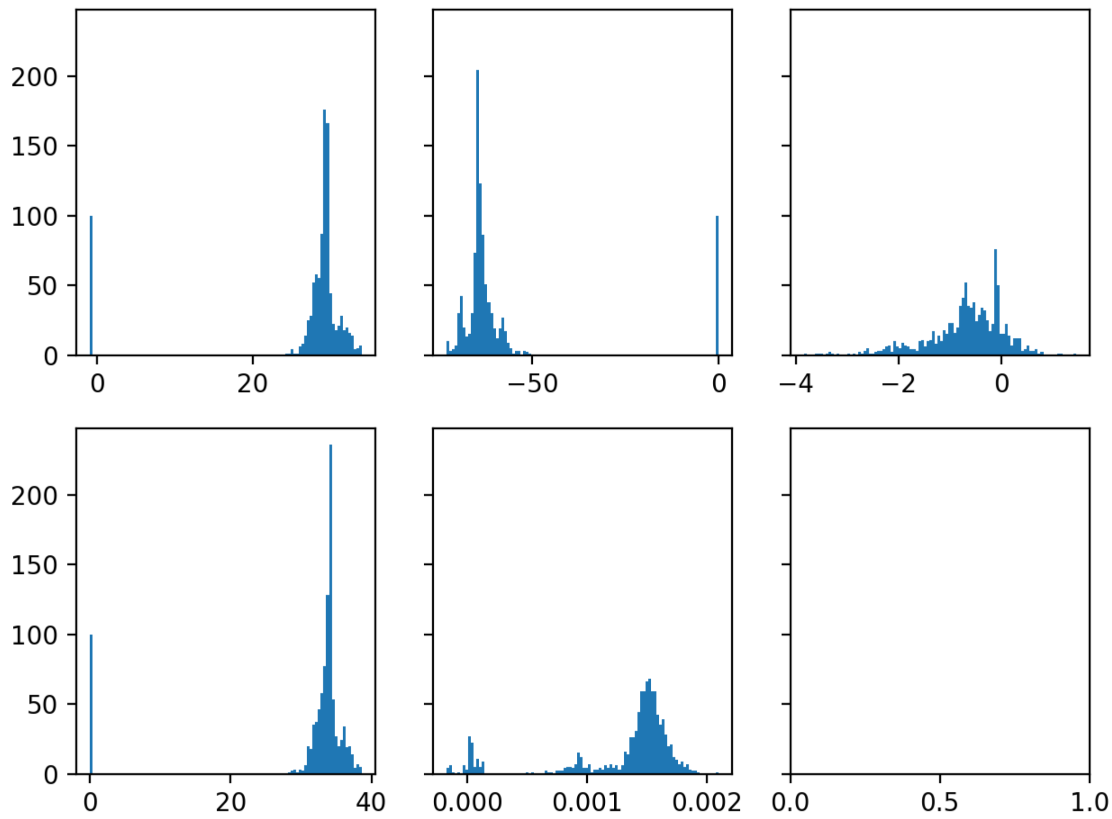


Figure 2: Distributions for b, $w_{\texttt{distance}}$, $w_{\texttt{is\_same\_title}}$, $w_{\texttt{is\_same\_department}}$, and $w_{\texttt{duration\_difference}}$

The posterior distributions of σ for the first four unseen observations are shown in the Figure 3. The truth co-authorship counts, from the top left to bottom right order, are 25, 2, 15, and 16 respectively. The posterior distributions seem to have well captured the top left and bottom right sub-plots only. It hints the proposed architecture may not be right.

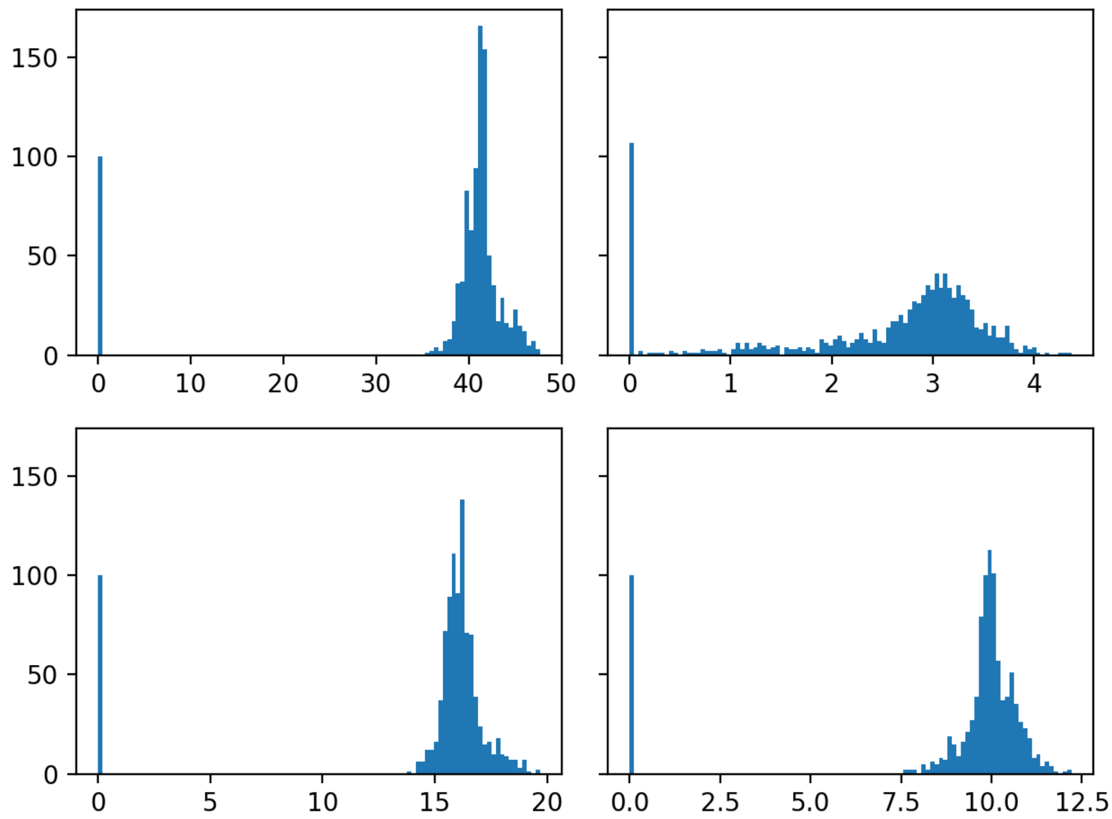


Figure 3: Posterior distributions of σ for the first four unseen observations

4.2.2 Analysis

Visually, the top right and bottom middle sub-plots in the Figure 2 are relatively flat compared with others. We are less confident about $w_{\texttt{is\_same\_title}}$ and $w_{\texttt{duration\_difference}}$. In other words, we are not certain if $w_{\texttt{is\_same\_title}}$ and $w_{\texttt{duration\_difference}}$ influence the co-authorship counts. Furthermore, we believe glitches that occur around 0 in the top left, top middle and bottom left sub-plots respectively are numerical issues rather than proper estimates. For the top middle sub-plot, shorter $w_{\texttt{distance}}$ between a pair is; higher the co-authorship counts it should be. Similarly, in the bottom left sub-plot, a pair who works in the same department $w_{\texttt{is\_same\_department}}$ yields more co-authorship counts.

Admittedly, this neural network architecture is rather simple, so interpreting the network will not be a problem. However, a multi-layer neural network would require more efforts.

5 Conclusions

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6 Appendix

6.1 Hardware and Software

The software is developed in the macOS High Sierra using Python 3.6.4. The required packages for Python are the following:

- `from patsy import dmatrices`
- `import statsmodels.api as sm`
- `import tensorflow as tf`
- `import matplotlib.pyplot as plt`
- `import pandas as pd`
- `import numpy as np`
- `import csv`
- `import h5py`

The software consists of several modules:

- `glm.py` is a class that details generalised linear models - Poisson and Negative Binomial regressions.
- `neuralnetwork.py` is a class that defines the neural network.
- `recommender.py` is a main module.

To run the software, the following command should be entered in the terminal:

`python3 -W ignore recommender.py`.

It is expected the software should also run in a Linux or Windows environment.

6.2 Dataset

distance	is_same_title	is_same_department	duration_difference	coauthorship
0.344081887	0	1	84	25
0.506936579	1	1	1290	15
0.652820559	0	1	3279	31
0.667356028	1	1	2495	41
0.675607872	1	0	4606	8
0.701469131	0	0	4690	9
0.713546647	1	1	1282	3
0.745227537	1	1	4922	44
0.745956446	0	1	434	15
0.74975835	0	1	2929	24
0.768221345	0	1	3171	29
0.785957016	1	1	747	4
0.791505181	0	1	3230	24
0.814178807	1	1	300	14
0.825873767	1	1	182	16
0.828363592	1	0	0	16

distance	is_same_title	is_same_department	duration_difference	coauthorship
0.829718071	0	1	736	2
0.830670631	1	1	729	4
0.833719254	1	0	21	16
0.837085708	0	1	2873	26
0.837536625	0	1	3587	41
0.840943137	1	1	144	29
0.850871566	0	1	4569	15
0.852772841	0	1	546	1
0.85367489	1	0	2719	21
0.877569836	0	1	3582	9
0.887522771	1	1	2037	4
0.891481245	0	1	3602	15
0.903393	1	1	197	3
0.924793515	0	1	6265	18
0.927923218	1	1	1015	7
0.929938415	1	1	129	0
0.942231299	0	1	352	9
0.944441805	0	1	3944	9
0.945684075	1	1	314	3
0.947352519	0	1	848	3
0.947568961	1	1	21	2
0.949071245	1	1	3230	9
0.957291068	0	1	1681	11
0.960424095	1	1	0	0
0.961204619	0	1	666	9
0.974332739	1	1	3192	5
0.974588511	1	0	3664	5
0.977421672	0	0	735	0
0.978164225	1	1	1876	2
0.981834051	1	0	3230	0
0.982567355	0	1	5316	4
0.983915035	1	0	3230	1
0.985942893	1	0	5106	0
0.987989598	1	1	2177	5
0.988742993	1	0	5106	0
0.989108175	0	0	119	5
0.989390209	0	0	2124	0
0.990592023	0	0	129	0
0.991127348	1	0	3101	0
0.991728968	1	0	0	11
0.991858884	1	0	2401	0
0.9936999	0	0	2305	4
0.993913935	1	0	3230	0
0.995629714	0	1	1767	5
0.996704722	1	0	3230	0
0.99855752	0	1	1487	2
1.000156057	0	0	0	0
1.004885433	0	1	2124	0
1.005585069	1	0	2719	0
1.006778246	1	0	1767	1

distance	is_same_title	is_same_department	duration_difference	coauthorship
1.007161646	0	1	2103	0
1.008016643	1	1	129	0
1.008487909	1	0	2698	4
1.008736911	1	1	28	0
1.009802559	0	1	56	3
1.011051839	1	1	4922	4
1.011941689	1	0	4977	0
1.012609701	0	1	5106	0
1.012863653	0	0	2159	0
1.013847344	0	0	3279	0
1.01456835	1	0	3048	0
1.0174944	0	0	2593	0
1.017788403	1	1	0	5
1.019773377	0	1	3258	0
1.020442724	1	0	2086	0
1.020835405	1	0	1463	1
1.021310597	1	1	3333	1
1.021712533	0	1	77	3
1.021800317	0	0	595	0
1.023763779	1	1	2891	0
1.02531359	1	0	2215	0
1.025355869	0	0	0	0
1.026064728	1	1	5106	1
1.026078013	0	1	3202	3
1.026186817	1	0	1169	0
1.026466434	1	1	1192	2
1.026644562	1	0	3048	0
1.027105321	0	1	3230	0
1.027111137	1	1	2678	0
1.027654423	0	0	77	2
1.027871123	1	0	3048	0
1.029786088	1	1	2058	1
1.029997534	1	0	3048	0
1.03050658	0	0	560	0
1.0308459	1	1	444	8
1.032885196	1	0	3101	0
1.033043893	0	1	627	2
1.033442735	1	1	86	4
1.033570792	0	1	2223	1
1.034244071	0	1	1524	1
1.035056008	1	1	0	0
1.03618247	1	0	2215	0
1.036209345	1	0	280	0
1.036789239	0	0	5088	0
1.037090466	1	0	6345	0
1.037118715	1	1	1876	0
1.037318342	0	1	1648	1
1.037491639	1	0	5512	4
1.038392829	1	0	3230	0
1.039026564	0	0	5088	0

distance	is_same_title	is_same_department	duration_difference	coauthorship
1.039032564	1	0	0	0
1.039161649	0	1	424	0
1.039737814	0	0	5988	5
1.040397389	1	0	6474	0
1.040761042	1	0	0	1
1.04154714	1	0	0	2
1.041628082	1	0	2919	0
1.042584098	1	0	2215	0
1.042760875	1	0	3944	2
1.042949037	0	1	651	2
1.043180229	0	0	21	0
1.043219715	1	0	283	0
1.044022022	1	1	2118	0
1.044075753	1	1	3244	0
1.044203227	1	1	4778	0
1.044410514	1	1	2215	0
1.044824788	0	0	0	0
1.045053694	1	1	1155	0
1.045350164	1	0	3230	0
1.046243478	1	0	0	0
1.047621427	1	1	2495	0
1.047713346	1	0	735	0
1.04820041	1	1	833	2
1.048333895	0	1	2587	0
1.048360328	0	0	6013	0
1.048561213	0	0	6296	0
1.048590753	1	1	144	0
1.048661526	1	0	2215	0
1.048969046	1	1	1767	0
1.049162146	1	0	1767	0
1.049306599	0	0	5316	0
1.049500393	1	0	906	0
1.0496847	0	1	1367	1
1.049742172	1	1	0	0
1.049943199	1	0	283	0
1.050083144	0	1	1484	1
1.050816933	1	0	2317	0
1.051018239	1	0	1281	0
1.051188195	1	0	0	0
1.051308708	1	1	3048	0
1.051478415	0	1	2215	0
1.052104115	0	1	5295	1
1.052287187	0	1	6474	0
1.053051161	1	0	144	0
1.053114612	0	1	508	0
1.053151591	0	0	1850	0
1.053375442	0	1	4399	0
1.053707088	0	0	2888	0
1.05381832	1	1	0	0
1.053874212	1	1	3944	0

distance	is_same_title	is_same_department	duration_difference	coauthorship
1.053986422	0	0	2233	0
1.054126342	1	1	129	0
1.054619151	0	0	3322	0
1.054984913	0	0	714	0
1.055067038	0	0	2152	0
1.05513872	1	0	21	0
1.055369762	0	0	3587	3
1.055388321	1	0	3230	0
1.055794261	1	1	129	0
1.056301089	1	0	4172	0
1.056621835	1	0	1854	0
1.056805359	0	1	283	0
1.056886702	1	1	4259	0
1.057313571	0	1	3896	2
1.057335989	0	0	5596	0
1.057468634	0	0	1582	0
1.058474403	1	0	262	0
1.058876507	1	1	0	1
1.059189797	1	0	1767	0
1.059834992	0	1	1210	0
1.060058885	1	0	2611	0
1.060201587	1	0	4922	0
1.060237456	0	1	2331	0
1.060696576	1	0	4200	0
1.060840016	1	0	3045	0
1.060844148	1	0	1638	0
1.060982041	1	0	4922	0
1.061459385	1	1	5561	2
1.061546429	1	1	21	0
1.061695049	1	0	283	0
1.061731206	1	0	1027	0
1.06183747	0	0	5596	0
1.062626081	1	0	129	0
1.06314348	0	0	3135	0
1.063153346	1	0	154	0
1.063207776	0	0	6275	0
1.063236814	0	1	534	0
1.063267039	0	0	943	0
1.063360331	0	1	469	3
1.063376252	1	0	6474	0
1.064058651	0	0	0	0
1.06413445	1	0	144	0
1.064322182	1	0	4823	0
1.064555408	1	0	21	0
1.064599455	1	0	6474	0
1.06486673	0	0	4569	0
1.064925315	0	0	3279	0
1.064946063	0	1	3048	0
1.065261491	0	0	0	0
1.06550365	0	0	1643	0

distance	is_same_title	is_same_department	duration_difference	coauthorship
1.065560078	1	0	5106	0
1.065606811	0	0	5817	0
1.066188123	1	0	2719	2
1.066287047	0	1	1858	0
1.066415708	0	0	2	0
1.066589094	0	0	5313	0
1.066951822	1	0	21	0
1.067158345	1	0	5106	0
1.067311921	1	1	0	0
1.067428154	1	0	5106	0
1.067884859	1	0	129	0
1.068054511	0	1	2047	0
1.068190988	0	1	0	0
1.068269289	0	0	6296	0
1.068279287	0	0	2737	0
1.068448297	0	0	2373	0
1.068646494	1	0	2215	0
1.068763551	1	1	2495	0
1.069433751	0	0	714	0
1.069582108	0	0	2681	0
1.069595357	1	0	0	0
1.069626448	1	0	0	0
1.06970509	1	0	123	0
1.069849402	0	1	4528	0
1.069851115	0	0	5817	0
1.069956119	1	1	0	0
1.070063149	1	0	885	0
1.071022192	0	1	4548	0
1.071253631	1	0	1932	0
1.071460572	1	0	5512	0
1.071553043	1	0	714	0
1.071681718	0	0	3896	0
1.071753127	1	1	3297	2
1.071850054	1	0	906	0
1.072172473	1	1	0	0
1.0723696	0	1	2614	0
1.072589074	1	0	1755	0
1.072637332	0	0	5575	0
1.072864797	0	1	5418	0
1.072971198	1	0	5491	0
1.073000415	1	0	3048	0
1.073029006	0	0	0	0
1.073098733	0	0	2296	0
1.073207591	0	0	1827	0
1.0732678	1	1	2307	4
1.073334975	1	0	283	0
1.073522395	0	1	6152	0
1.07367205	0	0	3279	0
1.073697242	0	0	1652	0
1.073785281	1	0	283	0

distance	is_same_title	is_same_department	duration_difference	coauthorship
1.073927004	1	0	0	0
1.074216318	1	1	2575	0
1.07425103	0	0	1401	0
1.074259311	1	0	0	0
1.074404192	0	0	3454	0
1.074490807	1	0	3979	0
1.074899645	1	0	5106	0
1.075140297	1	0	2215	0
1.075243654	0	1	6296	0
1.07527426	0	1	1424	0
1.075294792	0	0	1841	0
1.075338329	0	0	5817	0
1.075437453	1	1	1368	0
1.075629419	1	1	0	0
1.075634206	1	0	6324	0
1.07576058	1	0	5596	0
1.07579776	0	0	1980	0
1.076186644	1	0	5229	0
1.076491091	1	0	6474	0
1.076611189	0	0	2086	0
1.076637346	1	1	2366	0
1.076738032	0	0	6041	0
1.076845615	0	0	6324	0
1.077090012	0	0	6324	0
1.077408317	0	1	6296	0
1.077433437	1	0	2215	0
1.077437669	1	0	3230	0
1.077611873	0	0	6286	1
1.077904913	0	0	129	0
1.078052731	1	0	283	0
1.07812386	0	0	2642	0
1.078231051	0	0	2597	0
1.078382471	0	0	0	0
1.078658434	1	0	5106	0
1.078744802	1	0	277	0
1.078764006	0	0	175	0
1.078873098	1	0	4901	0
1.078876661	0	0	3454	0
1.079065687	1	1	129	0
1.079403579	0	0	3433	0
1.079551729	0	0	2142	0
1.079730163	1	0	6474	0
1.079766217	0	0	0	0
1.079973232	1	0	0	0
1.080011374	1	1	1921	0
1.08014682	0	0	3325	0
1.080810707	1	1	2235	0
1.080848232	0	0	2996	0
1.080862874	0	0	5688	0
1.081117632	0	1	3381	0

distance	is_same_title	is_same_department	duration_difference	coauthorship
1.081332432	0	0	5512	0
1.081395923	0	0	3663	0
1.081451032	1	0	448	0
1.081552958	1	0	547	0
1.08160849	0	0	2870	0
1.081728195	0	0	1190	0
1.081775374	0	0	3566	0
1.081925579	0	0	3454	0
1.082048562	1	0	6474	0
1.082060692	0	1	1648	0
1.082104583	0	0	0	0
1.082473243	0	0	906	0
1.082485818	1	0	6453	0
1.082586699	0	0	3767	0
1.082751452	1	0	0	0
1.082801274	1	1	3426	0
1.082858693	0	1	3279	0
1.082872504	1	1	0	0
1.082927709	0	0	3587	0
1.083097183	1	1	0	0
1.083469257	0	0	2982	0
1.083518425	1	1	1813	0
1.083549441	0	1	711	0
1.083556388	0	0	3896	0
1.083599342	0	0	1335	0
1.083622388	0	0	3454	0
1.083737991	1	0	6296	0
1.083789608	0	0	3048	0
1.083976533	1	0	283	0
1.084017208	1	0	2215	0
1.08413592	1	0	3017	0
1.084313164	0	0	0	0
1.08435317	0	0	1330	0
1.084378995	0	0	1298	0
1.084411706	0	1	2124	0
1.084444449	0	0	6303	0
1.084776573	0	0	6296	0
1.084817278	0	0	2009	0
1.084826274	1	1	2495	0
1.084841565	0	0	3454	0
1.084994349	0	1	3605	0
1.085162774	0	0	812	0
1.085181186	0	1	3577	0
1.08521317	1	0	5085	0
1.085276218	0	0	674	0
1.085374426	1	1	2719	0
1.085443818	0	0	21	0
1.085474438	1	1	2445	0
1.085704817	1	0	2947	0
1.086068077	1	0	2387	0

distance	is_same_title	is_same_department	duration_difference	coauthorship
1.086090376	1	0	2194	0
1.086166069	1	0	5106	0
1.086483591	0	1	1407	0
1.086540237	0	1	4528	0
1.086747913	1	1	0	0
1.086749755	0	0	206	0
1.086766493	0	0	4569	0
1.087055108	0	0	353	0
1.087107839	1	0	590	0
1.087207496	0	0	5596	0
1.087245127	0	0	0	0
1.087857233	0	0	537	0
1.087877271	0	1	1648	0
1.087890547	0	0	1400	0
1.088150436	1	0	3279	0
1.088187184	1	0	2436	0
1.088237434	0	0	4425	0
1.088427979	1	1	3244	0
1.088435146	0	0	1480	0
1.088539255	0	1	1330	0
1.08860491	1	0	283	0
1.088629069	0	1	1519	0
1.088629309	0	0	1925	0
1.088683707	0	0	743	0
1.088784117	1	0	0	0
1.089131006	1	0	0	0
1.089176498	1	0	3944	0
1.089466275	0	1	305	0
1.089644796	0	0	1648	0
1.089688885	0	0	5596	0
1.08970551	1	1	129	0
1.089782147	0	1	3304	0
1.089797857	0	0	283	0
1.089943654	0	0	1648	0
1.090263546	1	0	283	0
1.090338313	1	0	5512	0
1.090430094	1	0	280	0
1.090441757	0	0	77	0
1.090534566	0	0	1900	0
1.090569696	0	0	578	0
1.091140313	1	1	1946	0
1.091190815	1	0	108	0
1.091251509	1	0	553	0
1.091338008	0	1	221	0
1.091520312	0	1	3454	0
1.091532843	0	0	6324	0
1.091687489	1	0	2215	0
1.091723856	1	0	1155	0
1.091861412	0	0	4410	0
1.09201345	0	0	538	2

distance	is_same_title	is_same_department	duration_difference	coauthorship
1.092078892	0	0	1298	0
1.09234102	1	0	139	0
1.092412145	0	0	3230	0
1.092718024	1	0	2947	0
1.092831913	1	0	0	0
1.092836075	0	0	1074	0
1.093061261	0	0	4569	0
1.093062623	1	0	6191	0
1.093075746	0	0	2842	0
1.093130483	1	0	2324	0
1.093190166	1	0	5368	0
1.093237755	0	0	3699	0
1.093321614	1	0	6474	0
1.093389829	1	0	0	0
1.093812401	1	0	0	0
1.093953271	1	0	2212	0
1.093992691	0	0	4182	0
1.094020551	0	0	5467	0
1.094054115	1	1	1015	0
1.09412369	0	0	2058	0
1.094160635	1	0	0	0
1.094216275	0	0	3896	0
1.094362297	0	0	2124	0
1.094418366	0	0	567	0
1.094440465	1	0	896	0
1.094656219	1	0	2793	0
1.094685727	0	0	6167	0
1.094713058	1	1	0	0
1.094861635	1	0	129	0
1.09495441	0	1	941	0
1.095070653	1	0	3339	0
1.095356208	1	0	129	0
1.095394364	1	1	4228	0
1.095461943	1	0	1767	0
1.095512676	0	0	2877	0
1.095525206	0	0	5596	0
1.095565867	0	0	5596	0
1.095593362	0	1	6180	0
1.095629987	1	0	224	0
1.095746272	1	0	2495	0
1.095830921	1	0	728	0
1.096063165	0	0	2215	1
1.09607486	0	0	196	0
1.09608774	1	0	623	0
1.096155746	1	0	1140	0
1.096217894	0	0	308	0
1.096604622	0	0	1064	0
1.096731535	1	0	2215	0
1.096829073	0	0	3587	0
1.096916787	0	0	6247	0

distance	is_same_title	is_same_department	duration_difference	coauthorship
1.097001387	1	0	3944	0
1.097029501	1	0	21	0
1.097072016	1	1	1389	0
1.097188022	0	0	3310	0
1.09721928	1	1	906	1
1.097298024	1	0	0	0
1.097323847	1	1	182	0
1.097360763	0	0	1767	0
1.097390234	0	0	3377	0
1.09781314	0	0	5452	0
1.097832271	0	0	1239	0
1.097847971	1	0	1284	0
1.097874937	1	0	3048	0
1.098018538	1	1	1106	0
1.098093818	0	0	1280	0
1.098125389	0	0	2313	0
1.098476187	1	0	4962	0
1.09852172	0	1	490	0
1.098533126	1	0	0	0
1.098534861	1	0	6474	0
1.098923756	0	0	6474	1
1.099031334	1	0	4707	0
1.099159074	0	0	318	0
1.099199002	0	0	5596	0
1.099214555	0	0	3587	0
1.099311972	1	1	762	0
1.099505107	0	0	2835	0
1.099529441	0	1	3035	0
1.099576168	0	0	5172	0
1.099611613	1	0	2707	0
1.099680587	0	0	49	0
1.099811802	0	0	3458	0
1.099853247	0	1	0	0
1.099906494	1	0	283	0
1.100038504	1	1	3822	0
1.100150342	1	0	4639	0
1.10027536	1	0	3230	0
1.10055993	1	0	4922	0
1.100872265	1	0	0	0
1.100913157	0	1	5817	0
1.101005074	1	0	5512	0
1.101145405	1	0	3230	0
1.101271861	0	0	0	0
1.101346545	1	0	129	0
1.101397456	0	0	1115	0
1.101461983	1	1	4016	0
1.101515284	0	0	2124	0
1.101535407	1	0	2719	0
1.10161897	0	0	1330	0
1.101840794	0	0	3587	0

distance	is_same_title	is_same_department	duration_difference	coauthorship
1.101850108	0	0	301	0
1.10186251	0	1	3317	0
1.101964987	0	0	3896	0
1.102060624	0	1	1648	0
1.102095567	0	0	3454	0
1.102190992	0	0	2495	0
1.102329449	0	0	1365	0
1.10236889	0	0	885	0
1.102430586	0	1	1330	0
1.102430737	1	0	5106	0
1.102431083	0	0	4528	0
1.102463272	0	0	4134	0
1.102477672	0	1	6324	0
1.102650969	0	0	224	0
1.102723083	1	0	5512	0
1.102818492	1	1	6474	0
1.102854334	0	0	4245	0
1.102878314	1	0	0	0
1.102922942	1	0	1484	0
1.102935214	1	0	5383	0
1.103160836	0	1	2929	0
1.103198037	1	0	1727	0
1.103273498	0	0	4922	0
1.103291942	1	0	3815	0
1.103518965	1	1	0	0
1.103525311	0	1	437	0
1.103553026	1	0	5106	0
1.103718981	1	0	0	0
1.103796464	0	0	6219	0
1.103891377	1	0	0	0
1.10400608	1	0	21	0
1.104071741	0	0	129	0
1.104120216	1	0	1767	0
1.104171579	0	0	3545	0
1.104264761	0	0	4959	0
1.104296662	0	0	3896	0
1.104327044	0	0	91	0
1.104387637	0	0	5596	0
1.104618189	0	0	3454	0
1.104997121	0	1	703	1
1.105069227	0	0	4125	0
1.105565045	0	1	2040	0
1.105589813	0	0	67	0
1.105728686	1	0	5512	0
1.105931506	0	0	5088	0
1.105985741	0	0	0	0
1.106081674	0	0	0	0
1.106153903	1	1	2203	0
1.106171964	0	0	4032	0
1.106480077	0	1	2366	0

distance	is_same_title	is_same_department	duration_difference	coauthorship
1.106537947	0	0	4911	0
1.106569822	0	0	3041	1
1.106678015	0	0	59	0
1.106749961	1	0	184	0
1.106859059	0	0	2548	0
1.106897586	0	0	0	0
1.10691478	1	0	5512	0
1.106956044	0	0	1218	0
1.106972716	0	1	77	0
1.107044235	0	0	6296	0
1.107070285	0	0	4557	0
1.107241209	0	1	2469	0
1.107399003	1	0	0	0
1.107415055	0	1	0	0
1.107415734	0	0	3279	0
1.107418957	0	0	2124	0
1.107474508	1	0	0	0
1.107479288	1	1	707	0
1.107550308	1	0	3198	0
1.107602226	0	0	2719	0
1.107705034	0	1	3896	0
1.107837967	1	0	2495	0
1.107847286	0	1	6324	0
1.107929238	0	0	1204	0
1.107994568	1	0	1001	0
1.108007266	0	0	4528	0
1.108107197	1	0	0	0
1.108200288	1	0	0	0
1.108287295	0	0	3020	0
1.108377294	0	0	3454	0
1.10839303	0	0	6296	0
1.108412727	0	0	2761	0
1.10846568	0	0	2124	0
1.10850499	0	0	5817	0
1.108561587	0	0	3582	0
1.10859861	0	0	967	0
1.108717975	0	0	3279	0
1.108768127	0	0	3454	0
1.108786998	0	0	210	0
1.108937575	0	0	3230	0
1.108954033	1	0	0	0
1.108970795	1	0	5512	0
1.10899482	1	0	906	0
1.109035743	0	0	2124	0
1.109095248	0	0	1068	0
1.109128339	1	0	1729	0
1.109151105	1	1	2282	0
1.109493084	1	0	3230	0
1.109610136	0	0	3454	0
1.109615941	1	0	21	0

distance	is_same_title	is_same_department	duration_difference	coauthorship
1.109696409	0	0	5106	0
1.109730977	0	0	5106	0
1.109850965	1	0	3638	0
1.109870798	0	0	735	0
1.109945087	1	1	2719	0
1.110017155	0	0	1339	0
1.110084387	1	0	0	0
1.110201687	0	0	4528	0
1.110223016	0	0	5596	0
1.110238984	1	1	3230	0
1.110284591	0	0	0	0
1.11035521	1	0	906	1
1.110364192	0	1	5817	0
1.110388418	0	0	3279	0
1.110467113	0	0	6296	0
1.110539947	0	1	2176	1
1.110658749	0	1	4312	0
1.110694076	0	1	1402	0
1.110945407	1	0	3209	0
1.111005467	1	1	5512	0
1.111250345	1	0	511	0
1.111267402	1	0	4473	0
1.1113423	0	0	1796	0
1.111362228	0	0	4266	0
1.111376436	0	0	144	0
1.111400129	0	1	1648	0
1.111541756	1	0	3230	0
1.111598138	1	0	144	0
1.111667149	0	1	4492	0
1.111723862	1	0	4569	0
1.111799089	0	0	2986	0
1.111800561	0	0	2699	0
1.111935859	0	0	77	0
1.112047424	0	0	1946	0
1.112063441	0	0	4286	0
1.112090246	1	0	6296	0
1.112106455	0	1	878	0
1.112165424	0	0	1995	0
1.11216989	0	0	868	0
1.112267823	0	0	3582	0
1.112394244	0	0	1330	0
1.112413893	1	0	504	0
1.112441023	0	0	77	0
1.112573639	0	0	224	0
1.112617931	0	0	3244	0
1.112642027	0	0	4081	0
1.112683285	0	0	863	0
1.112725794	1	1	444	0
1.112801545	1	0	1284	0
1.11287884	1	0	0	0

distance	is_same_title	is_same_department	duration_difference	coauthorship
1.112947596	1	0	2530	0
1.112957147	0	0	1249	0
1.11300363	0	1	5082	0
1.113048042	0	0	959	0
1.11311203	0	0	3587	0
1.113233499	0	1	2366	0
1.113258106	1	0	1289	0
1.113296584	0	1	469	0
1.113307489	1	0	21	0
1.113536725	0	0	3454	0
1.11360243	0	0	3066	0
1.11362524	1	0	3664	0
1.11373936	1	0	3279	0
1.113754703	1	0	2929	0
1.113762306	1	0	2765	0
1.113853444	0	0	5033	0
1.113881478	1	0	144	0
1.113969393	0	1	5596	0
1.113982172	0	1	5316	0
1.114101984	0	0	2124	0
1.114159858	0	0	2177	0
1.114173386	0	1	336	0
1.114260525	1	0	15	0
1.1143479	1	0	0	0
1.114374481	1	0	378	0
1.114498326	0	0	1330	0
1.114526414	1	0	735	0
1.114539717	0	1	2587	0
1.114673468	0	1	133	0
1.114742852	1	0	6474	0
1.114790464	1	0	1648	0
1.114833226	1	1	133	0
1.11495572	1	0	906	0
1.115023787	0	1	1378	0
1.115094271	1	1	4478	0
1.115168671	0	1	847	0
1.115199257	1	0	3510	0
1.115242837	0	0	6397	0
1.115255822	0	0	984	0
1.115257659	0	0	925	0
1.115278525	0	0	1106	0
1.11534066	0	1	2769	0
1.11535109	0	0	0	0
1.115361454	1	0	0	0
1.11540461	0	0	0	0
1.115420126	0	0	2124	0
1.115532108	0	0	4826	0
1.115548849	0	1	666	0
1.115591071	0	1	2305	0
1.115817119	0	0	1165	0

distance	is_same_title	is_same_department	duration_difference	coauthorship
1.115991023	0	0	3582	0
1.116039665	1	1	906	0
1.116099236	0	0	5817	0
1.116114638	1	1	5596	0
1.116147222	0	0	1687	0
1.116238788	0	0	394	0
1.116273384	1	0	2719	0
1.11638446	0	0	3699	0
1.116462814	1	1	2495	0
1.116522637	1	1	406	0
1.11653402	1	1	2282	0
1.116607487	0	1	3587	0
1.116616193	0	1	1284	0
1.116664999	0	1	657	0
1.116694658	1	0	5568	1
1.116878708	0	0	3582	0
1.117026115	0	0	3570	0
1.117102855	0	0	77	0
1.117175872	1	1	462	0
1.117181623	0	0	2354	0
1.117250679	1	0	144	0
1.117345671	1	1	962	0
1.117444509	0	1	4528	0
1.117467502	0	0	1087	0
1.117607771	1	0	728	0
1.117918496	0	1	4569	0
1.118047909	1	1	0	0
1.11811741	0	1	1616	0
1.118138562	1	0	700	0
1.118193729	0	0	21	0
1.118294061	1	0	3230	0
1.118372623	0	0	6265	0
1.118424194	1	0	3230	0
1.118555812	1	0	1692	0
1.118700078	0	0	3230	0
1.118724874	1	0	0	0
1.118739121	1	0	4922	0
1.118804651	1	0	5512	0
1.118867262	1	0	0	0
1.119033665	0	0	2363	0
1.1191106	1	0	3230	0
1.119144387	0	0	3443	0
1.119147192	0	0	357	0
1.119213613	0	0	1809	0
1.119217495	1	0	3230	0
1.119329461	0	0	6324	0
1.119401077	0	0	5316	0
1.119414203	0	0	895	0
1.119429229	0	0	4528	0
1.119469652	0	1	5982	0

distance	is_same_title	is_same_department	duration_difference	coauthorship
1.119537198	0	1	2578	0
1.119539524	1	0	3472	0
1.119559867	1	0	560	0
1.119657488	1	0	6474	0
1.119665721	0	0	3896	0
1.119778288	1	0	2474	0
1.119858441	0	0	3453	0
1.119958842	0	0	6244	0
1.11996428	0	0	1218	0
1.120016142	0	0	3195	0
1.120067502	0	0	4528	0
1.120076746	0	1	5088	0
1.120214811	0	0	3622	0
1.120245999	0	0	2929	0
1.12026114	0	0	4134	0
1.120285022	1	0	6474	0
1.120364211	0	0	669	0
1.120414301	0	1	2929	0
1.120501096	0	0	5534	0
1.120523903	1	0	2071	0
1.120739032	0	0	829	0
1.120787154	1	1	2912	2
1.120890566	1	0	5512	0
1.120906815	0	0	2215	0
1.121002819	0	1	1386	0
1.121044865	0	0	5152	0
1.121083382	0	0	5359	0
1.121112877	0	0	753	0
1.121167126	1	0	1284	0
1.121189944	1	0	283	0
1.121193687	1	0	3230	0
1.121312794	0	0	5596	0
1.121314384	0	0	2521	0
1.121320425	0	0	1201	0
1.121348812	1	0	3230	0
1.121622365	0	1	3582	0
1.121637132	1	0	0	0
1.121641216	0	0	4350	0
1.121653711	0	0	1767	0
1.121656475	0	0	3582	0
1.121680957	1	0	1767	0
1.121896194	1	0	444	0
1.121899389	0	0	1900	0
1.121899642	0	0	5029	0
1.121925883	0	1	2153	0
1.121927254	0	1	455	0
1.121987993	0	1	5512	0
1.122001116	1	0	2124	0
1.12210285	1	0	1284	0
1.122233236	0	0	653	0

distance	is_same_title	is_same_department	duration_difference	coauthorship
1.122336379	1	0	3086	0
1.12240215	1	0	2495	0
1.122422209	1	0	1284	0
1.122475134	0	0	4169	0
1.122476694	0	0	2709	0
1.1226554	1	0	5512	0
1.122667314	1	0	3209	0
1.122674823	0	0	1340	0
1.122682761	0	0	371	0
1.1228528	1	0	1284	0
1.1229173	1	0	1435	0
1.123009964	1	0	4200	0
1.123110213	0	1	1700	0
1.123196932	0	0	144	0
1.12321918	0	1	2929	0
1.123288751	0	0	77	0
1.123291412	0	1	977	0
1.123302577	1	0	5911	0
1.123321429	0	0	0	0
1.123404544	0	0	1468	0
1.123417321	0	0	5088	0
1.123425454	0	0	49	0
1.123436322	1	0	5106	0
1.12348198	0	0	3150	0
1.123485024	0	0	1330	0
1.123490934	0	0	1106	0
1.123537301	0	0	3279	0
1.123576216	0	0	6265	0
1.12360454	0	0	0	0
1.12361865	1	0	777	0
1.12364957	1	0	2719	0
1.123749983	0	0	210	0
1.123846575	0	0	987	0
1.123846827	0	0	4569	0
1.123908622	0	0	6265	0
1.123930612	1	0	734	0
1.123978984	1	0	1767	0
1.124049246	0	0	3388	0
1.124083227	1	0	2566	0
1.124083534	1	0	144	0
1.124085345	0	0	617	0
1.124106015	0	1	4528	0
1.124273519	0	0	3983	0
1.124294204	1	0	3944	0
1.124373851	1	0	980	0
1.124384421	0	0	3587	0
1.124427378	0	0	3098	0
1.124431491	0	0	784	0
1.124473292	1	0	4487	0
1.124489323	0	0	2138	0

distance	is_same_title	is_same_department	duration_difference	coauthorship
1.124567307	0	0	283	0
1.124619919	0	0	784	0
1.124626083	0	0	3066	0
1.124638895	0	0	3454	0
1.12476024	0	0	303	0
1.124859913	0	0	406	0
1.12487269	0	1	5088	0
1.125019273	0	0	5316	0
1.125067433	0	1	1462	0
1.125131833	0	0	5435	0
1.125175517	0	1	18	0
1.125209795	0	0	77	0
1.125220072	0	0	5088	0
1.125226046	0	0	77	0
1.125275689	0	0	5817	0
1.125327582	0	0	5817	0
1.125386181	0	0	4182	0
1.125435912	0	1	5239	0
1.125450685	1	0	5068	0
1.12548151	1	0	0	0
1.125496518	0	1	5390	0
1.125526525	1	0	2124	0
1.125537547	0	0	1330	0
1.125542355	0	0	6195	0
1.125639101	1	0	511	0
1.125674565	1	0	2719	0
1.125809156	0	0	1995	0
1.125829162	0	0	3699	0
1.12583232	1	0	1767	0
1.125948877	0	0	5596	0
1.125990732	1	1	1613	3
1.126010473	1	0	6330	0
1.126020285	0	0	0	0
1.126034344	0	0	3582	0
1.126133675	0	0	0	0
1.126185301	0	1	2800	0
1.126453759	1	0	0	0
1.126498774	1	0	4922	0
1.126536379	1	0	3230	0
1.126584299	1	0	0	0
1.126586707	1	0	3899	0
1.126632507	0	0	1582	0
1.126665602	0	0	3094	0
1.126752924	0	0	5519	0
1.126778744	0	1	352	0
1.12678393	0	1	4528	0
1.126930782	1	0	2215	0
1.126998526	0	1	2811	0
1.127062149	0	0	3699	0
1.127179311	0	0	2793	0

distance	is_same_title	is_same_department	duration_difference	coauthorship
1.127208598	0	0	6296	0
1.127283013	0	0	476	0
1.127299626	0	0	0	0
1.127309429	0	0	1806	0
1.127321338	0	0	4050	0
1.12740135	1	0	1263	0
1.127485989	0	0	5561	0
1.127553839	0	0	3944	0
1.127565996	0	0	0	0
1.127579941	1	0	632	0
1.127651212	0	0	1718	0
1.127659736	0	0	178	0
1.127848298	1	0	1449	0
1.127848519	0	0	6324	0
1.127865995	0	0	5988	0
1.12788643	0	1	1862	0
1.127915507	1	1	1284	0
1.127922883	0	0	5309	0
1.128074061	0	0	2798	0
1.128093287	0	0	2170	0
1.128105359	0	0	357	0
1.128162222	0	0	52	0
1.128273088	1	0	906	0
1.128296388	1	0	3944	0
1.128327187	0	0	3458	0
1.128361821	0	0	5088	0
1.128424443	1	0	3017	0
1.128517476	0	0	6296	0
1.128526101	0	0	3101	0
1.1285333	0	1	2880	0
1.128617572	1	0	3086	0
1.128703211	0	0	2538	0
1.12871074	1	1	2495	0
1.129097923	0	0	4569	0
1.129210225	0	0	31	0
1.129279297	0	0	3587	0
1.129398885	0	0	392	0
1.129403114	0	0	1862	0
1.129534261	1	0	2590	0
1.129547244	0	0	2495	0
1.12963117	1	0	4793	0
1.129642547	1	0	144	0
1.129682093	1	0	906	0
1.129710349	0	0	0	0
1.129761185	0	0	1696	0
1.129859481	0	0	4507	0
1.129939526	1	0	1162	0
1.130063797	0	0	1648	0
1.130122493	0	0	5316	0
1.130172643	0	0	77	0

distance	is_same_title	is_same_department	duration_difference	coauthorship
1.130184106	1	0	1746	0
1.130244373	0	1	2033	0
1.130283846	0	0	3582	0
1.130357241	0	1	2307	0
1.130372813	0	0	1571	0
1.13037319	0	0	4109	0
1.130383653	0	0	5817	0
1.130700391	0	1	1813	0
1.13071941	0	0	5817	0
1.130878766	0	0	4528	0
1.131022915	0	0	2221	0
1.131065252	1	0	129	0
1.13119013	0	0	3279	0
1.131200605	1	1	58	0
1.131235376	0	1	1374	0
1.131313681	1	1	2810	0
1.131407198	1	1	1506	0
1.131495126	0	0	4569	0
1.131571393	0	0	3153	0
1.131662424	0	0	77	0
1.131761452	1	0	3230	0
1.131773233	0	0	3776	0
1.131839985	1	0	906	0
1.131889413	1	0	2495	0
1.132111933	0	0	3587	0
1.132125992	1	0	0	0
1.132167441	0	1	6051	1
1.132361451	1	0	3230	0
1.132395114	0	0	1809	0
1.132454477	1	0	0	0
1.132534103	0	0	3336	0
1.132559461	0	0	4528	0
1.132610837	0	0	6265	0
1.132705728	1	0	3948	0