Social Media Influence Analyzer

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In a time where online social media has a significant influence on both individuals and groups of people in our modern societies, there is a need to have a digital tool that helps gather and construct data from online social media, then use this data to detect influence between individual users by detecting, measuring, and classifying the strength and topic field of influence in the process. This project proposes a method for influence detection, then build a technical solution on top of it to enable analyzers of online social media to have a visual and scientific understanding of the influence flow in social media network.

Keywords: Social-media, influence-detection, influence-topic-classification, text-classification, graph-centrality, graph-node-ranking, IT-system-architecture, logging, caching, HTTPS-Basic-Authentication.

Motivation

Upon the rise of the digital revolution through the last two decades, people around the world are no longer limited to the constraints of place and time to socialize with each other. The newly introduced concept of digital media has transformed the way our society function and socializing no longer requires the physical presence of society members. As a result of the introduction of multiple social media platforms, people from all over the world can now engage in local, national, and global events, participating in society and expressing themself in an open arena where physical boundaries do not stand in the way.

Today and after a very short time of experiencing the advantages of social media platforms, our society has become almost totally dependent on such platforms, and most social events and happenings does not pass away from being recorded and discussed in the wide arena of social media. This effect generates a huge amount of valuable data that has a big potential of revealing the type and strength of social influence between society members and opens for many useful applications in multiple fields.

The most obvious application from social data is understanding how social media is used as a tool to mobilize groups of people in controversial social events such as political elections. The serious allegation of Russian interference in the US presidential election in 2016 is one application of analyzing social influence on social media.

Furthermore, by mapping and visualizing social influence between users on social media, we can speed up and improve the detection of fake news and other illegal activities on social media, and by removing their damaging effects on multiple social environments, we can create a healthier society that benefits all its members.

Social influence is also highly valuable for commercial use, as many companies are interested in detecting different types of social influence to reveal new marketing trends and allow businesses to develop more specialized marketing strategies and customized products which often increase the competition in economy and generate more values for companies and their surrounding societies.

These were some applications that can benefit from analyzing influence between users on social media, and there is still both uncovered and undiscovered areas where understanding social influence is highly crucial for the purpose of the application.

# **Introduction**

Data from social media has a great potential in revealing how strong the influence is between different users, just like in real life every action a user commit and how society members react to this action can serve as an object for analysis which helps in drawing a big but rather detailed picture of how users influence each other across many societies and fields.

The aim of this research is to establish a ground foundation for extracting information about user activities on social media and use such information to detect social influence between network users. Such foundation is desired to make up the core of a future technical solution that enables social media analyzers with little or no technical experience in data processing and visualization to perform social media analysis on regular periods with a continuous timeline.

To serve this purpose, we start by determining the common characteristics in available user functionalities on the most popular social media platforms, then produce a model for data structure based on these similarities in user functionality, and by taking a starting point of common user functionalities, we increase the flexibility of this research to be applied to as many social media platforms as possible, and perhaps combine results from several platforms in one single analysis if needed.

After establishing an agreement on the data model to be used for collecting and storing crawled data from social media, we dive into the main core functionality of detecting social influence between network users. Multiple techniques of detecting and scoring social influence will be implemented to fit the different needs of a final analysis. The desired result is a user-oriented influence graph where each node represents a participating user, while each edge between two given users represents the influence between them with respect to direction of influence, and holding the score of influence strength along with its classified field of influence whether it is in sports, politics, or economy etc.

Following the previous effort, we evaluate the performance of the influence graph model and go through test results from both dummy and real-life data using crawled data from a rising social media platform called “Reddit”. We will then try to highlight the most interesting and useful features of the produced influence graph and push its power of detecting influencers and their area of influence to the limit. The final two processes of test and evaluation are together a vital step to confidently rely on the quality of the produced model of the influence graph by ensuring its informative capabilities in social analysis.

Furthermore, a technical solution is to be designed and implemented to work hand in hand with the theoretical approach and function as a possible practical implementation used as a proof of concept and as a helping tool in testing and evaluation. During the process of designing and building this technical solution, many important aspects of data protection, reliability and availability are discussed and dealt with to improve the ecosystem of this application.

This was a brief introduction of the upcoming research in a nutshell, but first let’s take notes and learn from some interesting pre-attempts in studying influence between users of online social media.

# **Related Works**

Among the community of data science, a wide variety of studies has focused on extracting information from online social media, and a great amount of effort has been dedicated to studying social influence between users to better understand the behaviour of individuals for many purposes. Research of social influence takes different forms and vary in size and scope, while some researchers take on the very fundamentals of detecting social influence, others dive through it to reveal details such as a specific influence or hidden behaviour patterns on different levels. In this section, we explore some related work in the field of social activity on online social media and try to get an inspiration that helps direct the effort of this research in the right path.

## **Measuring Influence Between Users of Online Social Media.**

A good fundamental approach is described by a social network analysis carried out by Y. Guo, J. Cao & W. Lin. The fellow researchers divide the influence evaluation models into 2 main categories; the first category is based on network topology which measures social influence between different users by considering the user degree, shortest path, and some random walk characteristics, while the second category bases the influence between users on their interactions through different activities organized in a tree-like structures containing submissions and multilevel comments. However, and despite the reasonably good classification and overview, the published paper of this research lacks some proven results of an experimental approach. [1]

## **Data-driven Influence Learning.**

A short but rather interesting experimental and mathematical approach is introduced by a paper on Data-driven Influence Learning in Social Networks published by F. Wang, W. Jiang, G. Wang & D. Xie. In this paper, the process of influence diffusion is divided into two parts: the launcher (influence strength) and the receiver (influence threshold) which can generate an accurate and finer grained influence diffusion model according to this research. [2]

Furthermore, the researchers highlight the importance of having a solid criterium when scoring the strength and threshold properties of social influences. Another important acknowledgment is the difficulty and complexity associated with detecting influence relationships between users as a by-product of big datasets that usually include a considerable amount of noisy or less important datapoints, making it essential for any algorithm used in learning and testing the influence models to perform a minimal scan over the data in the most efficient way possible.

## **Alternatives of Information Gathering.**

Most well-known providers of social media platforms assist developers and data scientists with instructions on how to crawl their platforms by offering multiple endpoints and methods that can be used for gathering data for analysis.

Multiple researchers spot the light on this initial aspect of gathering data from social media platforms. A significant research is one that mainly describes the alternative of Pushshift Reddit Dataset by J. Baumgartner, S. Zannettou, B. Keegan, M. Squire and J. Blackburn. [3] This research paper offers an undirected but also claimed to be a more efficient and flexible way to gather data from the “Reddit” social media platform, in comparison to using the official Reddit API endpoint.

It also gives an excellent brief description of the FAIR data[[1]](#footnote-1) principles which is highly relevant when choosing the source of data especially when it comes to accessibility and findability.

Another advantage of this research is its extension in discussing a series of the other major alternatives for gathering data from “Reddit”, highlighting their strengths and weaknesses in a constructive manner.

## **Topic Detection in Socical media platforms.**

As mentioned in the introduction, we are set to determine the category of a detected influence between users, this opens for the use of artificial intelligence for the purpose of classification between different topics where a certain user activity might fit in. Inspiration on possible solutions for this task can be obtained from a research about annotating and detecting topics in social media forum and modelling the annotation to derive directions carried out by B. Athira, J. Jones, S. M. Idicula, A. Kulanthaivel and E. Zhang. [4]

A practical case study from an online health community was represented to give a good introduction of data pre-processing and cleaning, then preceding to construct a reasonable mathematical approach in the training and testing of a machine learning model to be used for the purpose of topic classification.

Another contribution of this research is the use of various deep learning algorithms to classify posted content such as CNN[[2]](#footnote-2), LSTM[[3]](#footnote-3) and BiLSTM[[4]](#footnote-4), all in which enable the researchers to achieve a promising F1-score[[5]](#footnote-5) of about 0.75 to 0.80 in topic classification accuracy.

Furthermore, the above research offers a solution for a much-needed ability to minimize the amount of training data and dealing with the negative effects of label imbalance in a training dataset, then constructing a convincing conclusion after carrying out a process of well-performed testing and evaluation, where metrics of evaluation are carefully examined and explained in a good scientific approach [4].

## **Study Case Alternatives of Online Social Media.**

Determining which social media platform to crawl under testing and evaluation of a new modelling approach is important to produce a flexible influence model that can be used for analysis of as many social media platforms as possible, this is why it is desirable to work with real-life datasets gathered from a digital media platform that shares common user functionalities with as many popular social media platforms as possible, examples of such functionalities are posts or submissions, comments, and upvotes or commonly known as likes.

A social media platform that satisfies all these user functionalities is “Reddit” which is examined by the research with the title “Information and Social Analysis” carried out by T. Steinbauer at the University of California, Santa Barbara. [5]

Steinbauer starts off with a brief but very constructive comparison between the most popular sites for social news with Reddit included. The core of Steinbauer’s research lays in his analysis of subreddits, submissions and comments on the virtual platform of Reddit, this analysis helps explaining why Reddit should be used in evaluating the performance of an influence model and its ability to view the most influencing users in a social media platform. The reason for this is Steinbauer’s detailed analysis on which subreddits seems to have the most of user’s activity, and in addition his further construction of an example user-oritened influence graph that helps showing which user has the highest influence based on the user’s interactions through comments.

However, submission authors are not included in the dataset of the constructed influence graph, making this influence model less reliable if ignoring the often-significant role of posters in generating discussions on social media. Another downside of Steinbauer’s modelling of an influence graph is the limitation of not using any other criteria than user interaction through comments, such as the upvote score or number of thread or descendant comments posted on other comments or submissions.

Although Steinbauer has introduced a detailed result overview of his evaluations and analysis, there is still a question mark on the technical details because algorithms that has been used for producing the model of the influence graph are not provided to the reader in satisfying details.

# **Reddit as a case study social media**

There exist a wide variety of popular social media platforms and most of them are constantly gaining popularity among users from all over the world.

The following figure shows the market share of the top 7 most popular social media platforms during the last decade from 2010 to 2019, where market share data is obtained from statcounter.com which claims to base its statistics about digital market shares on a sample exceeding 10 billion pageviews per month. [6]



Figure 1, Worldwide market share of top popular social media platforms from the beginning of 2010 to the end of 2019 [7]

Although Facebook is the definite leading social media platform, it is still possible to observe a competition in popularity when looking at the next 6 platforms below Facebook, with Reddit having a popularity corresponding to all other social media platforms that are less popular than Reddit.

A normal side effect of a more popular social media is the large amount of data users generate on such platforms, which slows the process of extracting data from such platforms, and although data from a more popular media often has a higher integrity, it is important to keep a balance between data integrity and easiness in findability and accessibility. In this research, we try to compensate between these two factors by choosing a medium-sized social media platform for use during testing and evaluation of the influence graph model.

The market share of Reddit does nearly equal as the sum of at least 14 other social media platforms and all of these are reported to be below reddit in popularity including well established platforms such as LinkedIn and Instagram. This makes Reddit a suitable candidate to be used as a case study social media in this research, as Reddit offers our desired moderate balance between network size and easiness to crawl.

In addition, many of the most popular social media platforms tends to specialize in a certain area or field of social activities such as LinkedIn for professional life, and Facebook on the other hand mostly used for private and personal socializing, some digital platforms combine aspects from both areas such as the so-called digital news platforms that offers its users an opportunity to interact with each other in many aspects of socializing like professional and personal life combined. Reddit is considered as one those digital news platforms which is still gaining popularity and increasing in content since its launch in 2005.[[6]](#footnote-6)

A user on Reddit can create or join a group, make a submission on any group and comment on any submission or comment made by other users. A user can join a group, but it is not obligatory to join a group to be active in them or read their content. These groups are called subreddits and tend to specialize in a certain topic of interest in society, and for many users it is seen in a way that is somehow like reading the newspapers which is often divided into pages for multiple areas of concern such as politics, economy, or sports. The high separation between topics of interest in Reddit makes this platform ideal for testing how well an influence detecting algorithm can discover and classify different types of influence between users.

Reddit differs from other social media platforms in the sense that Reddit attracts users by their interest in topics and events in their social surroundings, while other social media often relays on the social affiliation of a future user. However, and on the other hand, many other social media platforms share a lot of common user functionalities with Reddit, such as groups, submissions, and comments.

This high similarity between Reddit and most popular social media platforms, along with Reddit’s ability to separate users into multiple different social groups, makes Reddit very suitable as an evaluation study case for this research as common functionality increases the modelling flexibility to be used on other social media platforms in future analysis, and its separation of social environments in groups serves the purpose of comparing the predicted type of social influence between users to the actual definition of the group where the interaction between users has occurred to give us an idea of how well our influence model is classifying topics of social influence.

Although Reddit is a user-oriented platform, its users often prefer to be anonymous, which is useful when presenting results without having to worry about neutrality issues, but Reddit’s users can also choose a username that can be used to identify them personally if they desire.

Another good reason for choosing Reddit as a study case is the highly developed endpoint crawling API which is very object-oriented and offers a wrapper library for the Python language. This eliminates the bother of dealing with HTTP requests and latency issues, as all of this is taken care off in the background of the Python Reddit API Wrapper. The Wrapper is free to use but it requires a registration which once done offers no restrictions on how often Reddit is crawled, unlike crawling by adding “.json” to the URL which have its downsides such as limitation for under 100 submissions at a time, and the blockage of multiple requests from the same IP address as a prevention measure from Reddit to stop denial of service attacks. All these downsides are escaped by using the Python Reddit API Wrapper which increases the reliability and stability of data streams from reddit. In other word the PRAW[[7]](#footnote-7) python module satisfies the following FAIR data principles:

* Findability:

Once using PRAW, it is easy to find and retrieve data from Reddit no matter how detailed the data is.

* Accessibility:

As mentioned earlier a programmer does not have to deal with HTTP requests and latency issues as when using a traditional API endpoint, this makes the programming experience much easier allowing programmers to focus on the objective of their work.

* Interoperability:

A good documentation and maintaining history of the PRAW module [8], along with its popularity between programmers which gives it an excellent record of ability to integrate with different products and systems that uses it.

* Reusability:

PRAW is highly object-oriented in both query language and retrieval results. This is helpful for the usability for integration in different projects and technical solutions both in present and future technologies.

Based on the above four FAIR data principles and the previous analysis of user habits and possibilities on Reddit and other social media platforms, Reddit makes a good case study in the testing and evaluation process when we are seeking to detect user influence and their area of influence. We shall than design our ground data structure to adapt for the common functionality between Reddit and the most popular social media platforms as we will go through in the upcoming section on the ground data structure.

# **Definiing a ground data structure**

Flexibility of design is an important requirement of this research, as we aim for a future application of the influence modelling developed in this research on as many other social media platforms as possible, and although this might be difficult to achieve as a result of the wide variety of available social media and the different user-functionalities in them, we can still notice some common user functionalities between the most popular social media platforms such as LinkedIn, Facebook and Reddit, this common functionality is no accident, as these social media platforms most likely inspired from real life social interactions to begin with, which in turn is a natural advantage for our application.

After studying the available user functionalities in Reddit compared with these same functionalities on the most popular social media platforms, it is easy to see a big potential for developing a generalized data model that can be used to structure data crawled from any of the applying social media platforms. It is therefore important to consider the desired results of this research before establishing a ground model for data structure.

Social influence can be defined to be the ability of one society member to change the thoughts or behavior of another society member, and although this definition is simple, the complexity is hidden in the way social influence plays out in real life society. Some people get influenced without any big significant reaction that can be recorded and studied, such influence is said to be of a passive type of influence, an example of passive influence is reading a newspaper where the reader gets influenced without adding any additional comments to the content.

The main goal of this research is to use recorded data from social media to visualize the influence flow between a group of people in a social interaction. For this reason, we are going to look at active social influence where we would expect the person who get influenced to react by submitting an activity on the content of influence. This requires an activity-based model, where activities such as submissions and comments are considered as indicators for social influence.

The second requirement of this research is the importance of visualizing the flow and direction of influence between members in a social media interaction. For this purpose, we will be building an interaction-based model that is able to retain the origin and target of each detected and measured influence, which benefits the storage of influence direction and in the big picture can be used to visualize the entire flow of social influence between society members.

The model can initially be based on four different entities a user can create and interact to; these entities are:

1. Network

Which holds information about the crawled social media platform or a smaller segment of it, having this entity, makes it possible to study multiple social media platforms at the same time which increases the flexibility of design.

1. Group

A group contains a bundle of submissions posted by users of the group. It also contains information about a certain group in form of identification and other attributes such as the group ID and name.

1. Submission

A submission is posted by one user and is assumed to be in text format with the possibility of further extension to multiple other formats like images and links in future improvements. The submission entity has multiple useful information stored in its attributes such as the current number of- comments, and -upvotes on this submission, along with information about the author of this submission and other identity attributes.

1. Comment

The comment entity is very similar to the submission entity containing a body text, identification of author and information about the location of a comment in the comment thread. And therefore, it has an additional feature which its ability to be a parent and/or a child of other comments. This means that comments can be modelled as a tree data structure that can grow unlimited.

The figure below shows a diagram of an entity-relationship model that will make the base of our data structure further on in this research. In addition to the four entities explained earlier in this section, four relationships bind these entities together defining their relations to each other. A network can contain multiple groups, and a group can contain multiple submissions or posts, where users can either comment on those submissions or on other comments that is a child descendant of the comment tree of a certain submission.



Figure 2, The Entity-Relationship model which represents the ground datastructure of this research.

Most of the popular social media platforms contains the four identified entities in this ER-model[[8]](#footnote-8), although they might have a different name, form, or purpose such as a company page on LinkedIn or a user profile on Facebook, but both can be treated as groups just like Reddit groups as well.

The attributes of entities open for more flexibility as we might have the need to extend or shrink our ER-model in the future i.e., by not including an upvote attribute or by adding a reaction attribute to submissions and comments. But also, attributes are generalized to match the very common details about of these entities in between the most popular social media platforms.

Now that we have a ground Entity-Relationship model to base our data structure on, we can proceed into discovering influences between users based of the interactions between them using these entities and relationship roles established in this section. In the next steps, we will elaborate the different stages of our influence modelling process for detecting and extracting social influence from online social media, the algorithms of the upcoming influence modelling are expected to have multiple dimensions for revealing the strength and types of social influence between different users online.

# **Influence Graph Modelling**

## **The Activity Thread.**

The previously established model of the ground data structure in figure 2 provides the required entities of detecting activity- and interaction-based social influence, we can observe a clear hierarchy between the following four entities: network, group, submission, and comment. This hierarchy enables us to model the data from a social network as a tree structure where network contains multiple groups that in turn contain a series of submissions which can contain multiple branches of comments, comments can have their own comments resulting in a tree that can grow endlessly as users add more comments on previous comments.

The figure below shows a small example of an activity thread tree of just one submission, which contains the activity of the submission in the root position and its several branches of comments each in its respective hierarchy level, we can call this thread the activity thread as each single node in this thread represents an activity object that a certain user had performed.



Figure 3, A set of submissions and comments is modelled as an activity tree by taking advantage of its natural thread hierarchy.

In the activity thread drawn in figure 3 above, we have 2 participating authors, the arrows indicate that the target activity was an interaction on the source activity, where a red arrow indicates an interaction from “User D” to the activity of “User A”, and a blue arrow indicates an interaction from “User A” to the activity of “User D”. In the next steps of influence modelling, we will investigate how we can use this activity thread to give birth to a weighted and directed activity-oritened graph that shows the interaction flow between users performing these activities, along with other details such as influence type and score magnitude.

Before we head further into more details, we should control the endless grow of the activity thread by defining comments based on their level in the activity tree to avoid any confusion when referring to different types of comments. As comments can have their own thread comments, we can establish a categorization of comments based on their level position in the thread hierarchy tree, where we can use two types of comments:

* Top Level Comments

Which are comments made directly on a submission.

* Sub Level Comments

Which are comments made on top comments or other sub comments.

The distribution of comments between top comments and sub comment can give us a picture of how involved members are in each submission, because observing more sub comments than top comments can indicate that authors are taking their time to read and react to top comments in addition to the submission which is an indication of a greater engagement from authors than if they just keep themselves to writing top level comments.

## **Scoring Influence.**

Since every tree is naturally a graph, we can take benefit from our hierarchical activity thread to construct a directed graph where each edge in this graph is directed from a parent activity to one of its child activities. And each edge represents one interaction between 2 submitters where target and source nodes are represented by their authors, showing that the author of the target activity has reacted to an activity submitted by the source author, which in turn can be considered as an influence indication directed from the source author towards the author of the child or target activity.

Knowing the direction of influence helps us detect influence between users, but it is not satisfying enough to give an idea of how strong a certain influence is, therefore we aim to grade all detected influence between users, so we can determine how strong a certain influence is in comparison to other influences in the influence graph topology. For this reason, we will give each influence edge a score that shows its strength.

Many techniques can be used to perform the scoring of influence; however, each technique have its strengths and weaknesses, and one way to reinforce the analysis system is by offering multiple scoring techniques to be used in analysis, to accomplish this, three different scoring techniques are used, each having some strengths and weaknesses depending on the use case of final influence analysis.

1. Interaction

This scoring technique measures how many times a studied user has reacted to activities performed on another user. The strength of this measure is in its ability to detect each interaction between users and differentiate them using the number of interactions as a score. But depending on the network, many users tend to interact one or two times in most cases, this is despite that the topic might be very interesting users who does interact that much. To accommodate such cases of low interaction influence, the following two scoring techniques can be applied in analysis.

1. Upvotes

By using the difference between upvotes or likes and downvotes or dislikes on a parent activity, we rely on the audience opinion on the parent activity given by other users. The submitting author of this activity is the influencer, and its influence takes the score calculated as the difference between upvotes and downvotes, this influence is then directed towards those users who comment on this parent activity, and thus they get influenced from the author of this activity having this influence score.

This scoring method gives a democratic approach that enables us to know whether an influence activity is supported or downvoted by a group of interested audience. At the same time, it is important to notice that in some networks such as Facebook, it is not possible for users to downvote an activity, which leave us without knowing for sure whether the influence is most likely to support an activity or not. However, it is still possible to accommodate this by counting the number of upvotes as a measure where 0 is the lowest score of an influence.

A downside of this upvotes-based scoring technique is that all child activities will get the same score, which can result in low differentiating effect between influence edges in the influence graph model.

1. Activity

The activity scoring technique scores influences based on how many edges of influence are found in the full branch of influence started from a parent activity.

Central people in society like politicians tends to influence the most people by triggering a great number of response activities. This scoring measure is based on the general extended impact of an influencer and can therefore help identify the central influencers and which users do they have an influence on.

The upside of this activity-based scoring technique is its ability to include the impact of all activities in an influence branch and still be able to differentiate between influence edges on child activities because of its branch oritened calculation, and it does not take in account all descendant activities of the parent activity.

The figure below contains a graph built on the skeleton of the previous activity thread in figure 3. It converts nodes from representing an activity object to represent the author of that activity, while preserving the hierarchical structure as it is in edges and their directions, it also introduces the three scores of interaction, upvotes and activity as separate weights calculated for each influence edge.



Figure 4, The activity graph is constructed by representing the nodes of activities using their authors, and applying the scoring techniques of interaction, upvotes and activity to score the individual influence edges.

When examining the activity graph example in figure 4, we can count 4 influence edges, half of these are directed from “User A” to “User D” and the others two are oritened in the opposite direction. We can digest the structure of this directed and weighted activity-oritened graph by merging all nodes and influence edges having the same unique pair of source and target authors of activities, while performing a simple addition of the respective scores for each of the three scoring measures. The final produced graph is to be called the influence graph with more details and examples on how to construct this graph model presented in the next section.

## **The Influence Graph.**

After going through the activity thread tree and its transformation to a directed and weighted activity graph, it is now easier to digest such a graph to produce the desired output of a person-oriented influence graph, where each node represents a unique author in this graph, and where edges are used to indicate a particular scored influence between two persons with respect to the direction of influence.

Looking at the previous activity thread in figure 3 and the activity graph in figure 4, we can count 2 submitters who are “User A” and “User D”, and together they submit 5 nodes of activity objects. To find out how much influence does “User A” have on “User D” and vice versa, we go through the following steps:

1. Creating a person node for each unique author in the activity graph.
2. Listing all influence edges stretched from “User A” to “User D” in the activity graph.
3. Merging all influence edges in step 2 by summing the values in each scoring measure to produce the respective score of each measure for this influence edge.
4. Step 2 and 3 above is to be repeated to find the influence in the direction from “User D” to “User A”, and the same goes for finding influence between any possible pair of two persons in the graph.

To further clarify the merging calculations of influence scores, we notice that an interaction score from “User A” to “User D” would be the number of edges going from activities submitted by “User A” and interacted to in activities submitted by “User D”, while the upvotes score is the sum of upvotes values recorded on these unmerged edges in the activity-oritened graph and the same goes for the activity score.

Following the four steps above, a new person-oritened graph is born with a unique node for each person, and with its influence edges having three scoring attributes that measure the strength of each represented influence. This resulted new influence graph visualizes the flow of influence between persons, how strong each influence is, and in which direction between them it is observed. An example of the previous four steps transformation from the activity graph in figure 4 to a person-oritened influence graph is presented in figure 5 below.

The example user-oritened influence graph below does have two users with two influence edges between them; according to the interaction score, both users does have equal influence in each other, while using the upvotes scoring technique, tells us that “User D” has a little more influence on “User A”, and the opposite is observed when using the activity scoring technique.

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Figure 5, The user-oriented influence graph contains a unique node for each person, and the edges of this graph indicate the weights and directions of influence between the persons in this influence graph.

## **Testing & Evaluation of The Influence Scoring Techniques.**

So far, we have proposed a staged method that is meant to detect influence between users who submits various activities such as submissions and comments on social media platforms. The output of this method is an influence graph where each node represents a person, and each edge indicates an influence from its source person into its target influenced person.

We are primally interested in the overall capability of the influence graph to visualize the flow of influence between activity authors in a dataset. For this reason, we are going to focus on the edges of influence between users as they hold score values obtained by using different influence scoring techniques that were detailed previously in this research.

We hereby plan to test the score distribution in the user influence graph after observing the effects of applying each scoring measure (i.e., Interaction, Activity, and Upvotes) to the same dataset, which is crawled from Reddit, and contains the top 3 newest submissions taken from each of the top 3 most popular subreddits according to internal Reddit.com statistics by using the python Reddit API wrapper on the 12th of July 2021 between 12 to 12:30 O’clock.

The following figure shows 3 box plots and 3 histograms that shows the score value distribution of each scoring measure recorded in edges of the person-oritened influence graph.

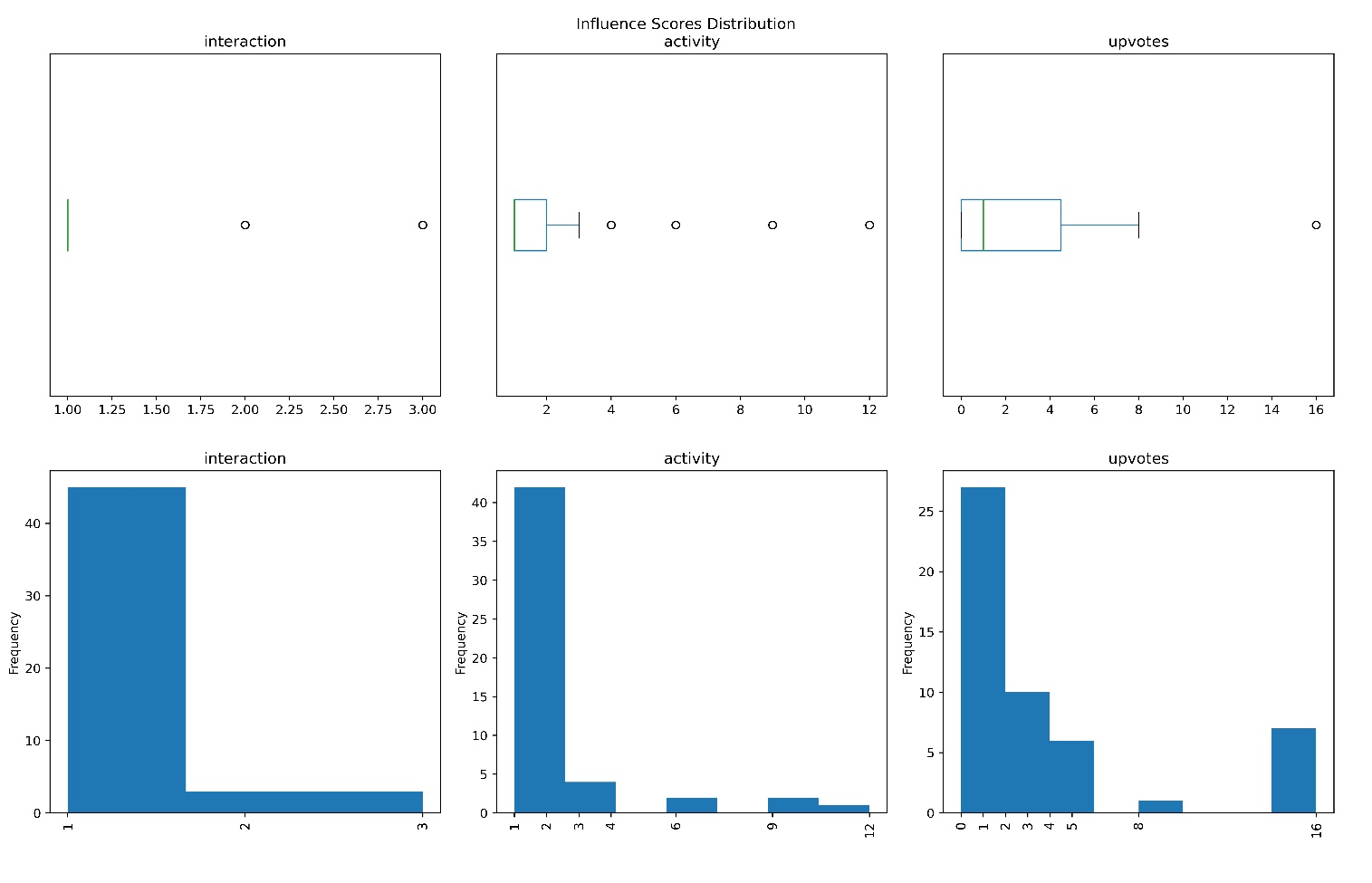


Figure 6, The single score distributions recorded in the edges of the influence graph, constructed on a dataset containing the top 3 newest submissions posted inside the top 3 most popular subreddits on the 12th of July 2021 between 12 to 12:30 O’clock.

Examining the distribution of interaction-based score values in the left box- and histogram plots in figure 6 above, gives a clear observation of low variance between score values which reduce the differentiating capability of the interaction scoring technique. However, a relatively good number of influences were successfully detected from the crawled dataset.

Moving on to the examination of activity-based score values in the middle of figure 6 above, we notice a slight decrease in the number of influences having the lowest score in comparison with the interaction-based score values on the left side. In addition, there is a noticeable extend in variance as the range of recorded values has increased from 1 to 3 in the interaction-based score values to a range between 1 to 12 using the activity score values. Four outliers on the right side of the box plot of activity scores also tells us that this scoring measure has more potential to differentiate between influences and present the detected influences that are having more significance than others.

Finally, we examine the upvotes-based score values to discover a higher achieved variance and a smaller number of outliers in the distribution of obtained score values. This result shows us the effectiveness of using the upvotes-based scoring technique for differentiating between detected influences.

Because each scoring technique might have its strengths and weaknesses in accordance with the purpose and motivation of the performed analysis, an analyzer might also wish to combine multiple scoring techniques and look on the distribution outcome of score values. In this research, the single scoring techniques are combined by performing an addition operation on all possible combination of the 3 scoring techniques in each edge in the influence graph. This results in the following four new scoring techniques:

* Interaction + Activity
* Activity + Upvotes
* Interaction + Upvotes
* Total = Interaction + Activity + Upvotes

Figure 7 below does plot the distribution of score values obtained from the double combined scoring techniques. An increase of variance is observed on all double combinations of scoring measures, especially when combining the activity and upvotes scoring techniques, which gives the highest achieved variance and therefore the best capability of differentiating between detected influences based on their scores, and independent of the purpose and motivation of analysis.



Figure 7, The double score distributions recorded in the edges of the influence graph, constructed on a dataset containing the top 3 newest submissions posted inside the top 3 most popular subreddits on the 12th of July 2021 between 12 to 12:30 O’clock.

Furthermore, it is also possible to examine the results of combining all scoring techniques to produce a single total score where the distribution of its scoring values is plotted in figure 8 below. This total score measure gives us an even wider range of possible score values, but with a nearly as equal variance as the combination of activity and upvotes scores, reasonably because of the low differentiating capability and low variance of the interaction score values.



Figure 8, The total score distribution recorded in the edges of the influence graph, constructed on a dataset containing the top 3 newest submissions posted inside the top 3 most popular subreddits on the 12th of July 2021 between 12 to 12:30 O’clock.

Based on the previous testing results, we can conclude that each scoring technique is mostly dependent on the nature of raw data generated by users on a social media platform who may have different ways of using the social media platform and therefore different ways of influencing each other. However, it is possible to mitigate the effect of how users use the network to influence each other by using a combined scoring technique which can have either an advanced formula or be as simple as an addition of the single scores in each influence edge of the user influence graph.

## **Testing & Evaluation of The Activity & Influence Graph Models.**

An important desire in any graph is to be informative, easy to read, and easy to visualize, we hereby wish to test how informative the activity and influence graphs in visualizing the picture of influence flow in the studied dataset.

We start by drawing the activity graph on a dataset crawled from Reddit and contains the top 3 newest submissions taken from each of the top 3 most popular subreddits according to internal Reddit.com statistics by using the python Reddit API wrapper on the 12th of July 2021 between 12 to 12:30 O’clock.

The activity graph has 3 types of nodes: the submissions, top level comments and sub level comments. In figure 8 below, we view the activity graph of this Reddit dataset and notice a little higher concentration of top-level comments having the red color in comparison to sub level comments with the blue color, which tells us that people in this dataset have a medium engagement in the threads of submissions, this engagement benefits the process of detecting social influence in the dataset when constructing the final person-oritened influence graph.



Figure 9, The activity graph, having the colors; yellow for submissions, red for top level comments, and blue for sub level comments. The graph is constructed on a dataset containing the top 3 newest submissions posted inside the top 3 most popular subreddits on the 12th of July 2021 between 12 to 12:30 O’clock.

The nodes of the activity graph in Figure 9 represents 69 activities in the crawled dataset from Reddit, having the count of 9 submissions, 38 top level comments and 22 sub comments. Since the percentage of sub comments is around 32%, it can be used as an indication of good social engagement from the participating persons in the dataset. This result is also highly visible by taking a quick look at the colored activity graph in figure 9 without having to calculate the exact number of each activity type. This highlights the importance of defining the types of activities to be used under the visualization of the activity graph.

By digesting this previous activity graph and merging its influence edges to transform it to a person-oriented graph, we obtain the influence graph shown in figure 10 below. The visualization of this graph takes advantage of the total combined score values to adjust the thickness of each influence edge, indicating its high or low score value in an intuitive display that allows analyzers to identify and focus on the high score influence.



Figure 10, The influence graph. The graph is constructed on a dataset containing the top 3 newest submissions posted inside the top 3 most popular subreddits on the 12th of July 2021 between 12 to 12:30 O’clock

In addition to visualizing the strength of each influence, the type on influence is also used as a label on each influence, where only one influence type is possible for each influence edge in the activity graph, but due to the merging into the influence graph some edges will accumulate multiple influence types as viewed in the right bottom of the influence graph in figure 10, this tells us that this influence is most likely to be in politics and technology.

Another important feature of the influence graph is the use of unweighted outdegree centrality to identify central influencers and distinguish them from other less influencing persons in the graph, which can be visualized using their calculated centrality value to be reflected on the size and opacity of the person node as in figure 10.

The use of unweighted centrality measures allows the analyzer to have a view that is dependent from the score of influence edges, as we observe in the influence graph in figure 10, where 3 significantly bigger person nodes are shown in the middle of the graph where no thick edges is to be found. But in the case of having the combination of a series of thick edges connected by a big sized person node in the graph, then it is a good indication of the high influence this person has on other connected persons. An example of this case is to be observed at the left bottom area of the graph on figure 10 above.

Looking at the overall collection of different features and tools provided by the final influence graph, it is clear to observe its beneficial capabilities under the process of social influence detection and analysis. Many applications can then benefit from easiness of interpreting the influence graph to determine the strength of influence, its predicted field of influence along with the centrality ranking of persons in the dataset.

## **Influence Field Classification.**

Being able to identify influencers on a social media platform is one objective of this research, another objective is to classify detected influence in multiple distinct topics such as politics, sports or economy. Knowing the type of influence between people enriches the process of analysis and gives it a topic-specific dimension that helps the analyzers to focus on the topics of interest during influence analysis. In this section, a classification method is proposed by integrating a text classification machine learning model into the process of building the activity and influence graphs.

Due to the normally large number of influences detected between people on online social media, a manual classification between different fields of influence is hard to perform and proof its reliability as topics can be perceived differently from one person to another. This is where artificial intelligence can come in handy by building a machine learning model with the task of classifying influences into multiple topics learned from a training dataset.

This training dataset can be static over time or continuously changing, the advantage that can be gained be having a dynamic training dataset is its ability to stay updated with the newest details that differs different fields of influence, while a static dataset will be frozen in time and might give false classification results in future use. For this reason, a dynamic process of updating the training dataset before being fed into a text classification model is implemented in this research. More details are included in some of the upcoming sections about the process of crawling dynamic training datasets and building the text classifier used to determine the field of influence based on texts from submissions and comments.

We hereby assume that we have a trained text classifier ready to be used to classify influence edges in the activity graph in between different fields of influence. Then when transforming the activity thread tree into an activity graph, we classify the influence type of each edge in the activity graph by constructing a combined text from the submission activity at the root of the activity thread tree, along with the texts from the source parent and target child activities of an edge, then input this constructed text into the text classifier to have an estimate about which influence field a particular influence edge is most likely to belong in.

Adding the text of the submission activity to each classification trial increases the chances of having a more correct classification as the submission text tends to have a clear indication to the topic of discussion in its activity thread. However, using only the submission text as an input for classification of each activity edge leads to a sterile and little informative classification as all edges between activities in the activity thread will have the same classification, therefore the source parent and target child activities are also added to the input of the classification trial, which also helps detect any derailment between topics under the user discussion in the activity thread.

An overview of this process is drawn in figure 11 below, where 4 classifications had been performed on the 4 edges in the activity thread tree shown on the right of this figure, then labeling the corresponding 4 edges with the respective classification output results in the activity graph at the middle of this figure.

An example of such classification process is the edge between the comment “SC\_2” and “SC\_3” in the activity thread, here we construct an input text from the following activities:

* Submission activity: “Tech giant invests 30 billions in renewable energy”
* Parent activity: “But if invested in the right way, it should pay off”
* Child activity: “I fully agree”.

After adding spaces between these 3 texts, the classification method of our trained text classifier is used, which classify the influence edge into the sport category, and then store this output value in its respective edge between users in the activity graph at the middle of figure 11.



Figure 11, An example overview showing the process of influence field detection integrated in the skeleton of building an activity graph and its final transformation to an influence graph.

Finally, we gather the distinct classified fields of influence in each respective edge in the influence graph during the merging process from an activity graph to an influence graph. Noticing that an edge in the activity graph can only have one classified field of influence, but when constructing the influence graph, multiple edges having the same combination of source and target persons would be merged, and in result all distinct classified fields of influence will accumulate in the respective merged edge in the final influence graph.

When examining the texts submitted by authors in the activity thread, we might want to manually conclude that the influence constructed from this thread is to be reasonably related to technology, and although the used text classifier has classified some influences in the sport category, a final look at the influence graph confirms that the technology category is also included in the respective edges in the influence graph. This tells us that our implementation of influence field detection can investigate and capture any derailments of discussion under the activity thread, which represents a strength that enable this method to look beyond what the human eye can assume about a certain written discussion.

This classification process is very similar to the process of influence detection, as it has the same three staged skeleton which plays out by transforming the activity thread tree into an activity graph, then into a final influence graph. This similarity makes it easier to merge the three processes of influence detection, influence scoring and influence field detection, which can have the effect of reducing the runtime of a practical algorithm that implements these three processes all at once, so the need for multiple iterations over records in the dataset is eliminated. However, this can have a moderate increase on the complexity of such implementation, but this complexity can be dealt using best practices under programming.

## **Testing of Influence Field Classification.**

Performing a reliable process of text classification is the core challenge in detecting different types of social influence, as there is a need to have a reliable well tested and tuned text classifier for more accurate helping in classifying between influence fields.

In this research, we will be using a well-documented text classifier inspired from the “scikit-learn.org” community website [9], which is a highly optimized model that combines the use of multiple machine learning algorithms for the purpose of text classification. This classifier has a pipeline architecture that starts with text vectorization which maps each unique n-gram[[9]](#footnote-9) term in the provided training records to its occurrence count, followed by a transformation process that can benefit from using the measure of Term Frequency-Inverse Document Frequency [11], the last part of this pipeline is a text classifier that is to be built on top of vectorization and transformation to produce a text classifier that can be used to categorize given text into different topics after learning from the provided training dataset.

To solve this challenge of providing training records, it is possible to have a training dataset made up of categorized text which enables supervised learning and allow to predict or classify the topic of a new unclassified text. And as most traditional machine learning models, the model’s ability to classify text with high accuracy is highly affected by the quality of its training dataset, and the different key parameters for the algorithms used in building the model. In the following steps, we will describe the process of gathering training data, testing its initial quality, and tuning the text classifier for optimal classification.

* Gathering training data

We start by gathering training data from different subreddits that is having a name which matches one of our target categories that we are interested in under analysis, an example of a category collection can include politic, economy, sport, entertainment, and technology.

The top 100 newest submissions on these subreddits are crawled from “Reddit.com” if available, meaning that we can have up to 100 texts from each subreddit, and every group of 3 subreddits can be trusted as a text provider for a certain topic, labeling text from these subreddits with the target topic name as shown in table 1 below.

Table 1, A plan for gathering a dynamic training dataset using selected subreddits from Reddit.com

|  |  |  |  |
| --- | --- | --- | --- |
| Shared Topic | Subreddits | Number of training records (Up to) | Example record |
| Politic | politics | 100 | title: "elections is postponed due to security reasons",  label: "Politic" |
| PoliticsPeopleTwitter | 100 |
| elections | 100 |
| Economy | Economics | 100 | title: "The price of oil is at record low",  label: "economy" |
| economy | 100 |
| business | 100 |
| Sport | sports | 100 | title: "3 days until kickoff of FIFA world cup",  label: "sport" |
| olympics | 100 |
| worldcup | 100 |
| Entertainment | movies | 100 | title: "show to be canceled due to bad weather conditions",  label: "comedy" |
| comedy | 100 |
| culture | 100 |
| Technology | technology | 100 | title: "new material used in batteries might revolutionize electric cars",  label: "Technology" |
| science | 100 |
| Futurology | 100 |
|  | | | |
|  | Total | Up to 1500 records if available |  |

Following this crawling plan, we obtain up to 1500 training records, these records would then be fed to the text classifier that is used for influence field classification during the process of building the influence graph.

This way of gathering training data from the same social media platform makes the text classification model up to date in a continuous timeline, where training datasets can be obtained on periodic intervals which provide the text classification model with new text submissions that reveals the latest events happening in the different pre-defined categories, making the text classifier always updated with the latest categorization of topics according to the active community and not in fixed a dataset. However, the downsides of this method are the need to constantly consume system and network resources to crawl new training datasets, and in addition having to tune and evaluate the performance of the new built text classifier after each updating replacement of periodic training datasets. These downsides can be mitigated by keeping a moderate size of the training datasets to enable quick data crawling and tunning of the text classifier.

Before starting to evaluate and tune our text classifier, we shuffle the data randomly to guarantee a fair distribution of categories throughout the dataset and freeze it by using a constant seed in a pseudo-random function, this freezing allows us to have the same results after each run of evaluation, tunning or classification using the same dataset, which comes in handy when trying to document the performance that can be achieved from a certain text classifier.

* Initial Evaluation of the text classification model

We start by testing the initial performance capability that can be obtained with using the crawled training dataset to build a non-tuned text classifier using its default key parameters. The training data is then partitioned into 5 equally sized chunks of data.

A text classifier is then trained and tested N-times where N is equal to the number of data chunks, and 80% or 4 chunks of data are used for training the classifier, while 20% or 1 chunk of data is used for testing the performance of the text classifier. The chunk of dataset that is meant for testing will be different every time a new model is trained, this guarantees that each record in the dataset will participate at least once in the testing process and 4 times in the training process, which increases the representation of every individual record in the dataset, then the we calculated the mean values of measured accuracies, precisions, recalls and F1 scores in the N=5 times the text classifier has been trained and tested, these results are presented in table 2 below and based on a dataset crawl performed on the 13th of July 2021 between 12 to 12:30 O’clock according to the crawling plan in table 1

Table 2, Initial performance evaluation of the text classifier used for influence field detection.

|  |  |
| --- | --- |
| Metric | Measure Value |
| Accuracy | 0.663 |
| Precision | 0.67 |
| Recall | 0.663 |
| F1-score | 0.663 |

* Tuning the text classification model

When examining the results of the previous initial evaluation of the text classifier, we notice very close values of accuracy, Precision and F1-score parameters at about 70% efficiency which can be improved by tunning key parameters of the pipeline algorithms used in this text classifier, these parameters are stated in the table below along with their significance to the text classifier.

Table 3, An overview of the key parameters used for tunning the text classification model.

|  |  |  |
| --- | --- | --- |
| Model Parameter | Test Values | Explanation |
| vect\_\_ngram\_range | (1, 1), (1, 2), (1, 3), (1, 4), or (1, 5) | Whether to use words of unigrams, bigrams, trigrams, 4-gram-sequence or 5-gram sequence in vectorization |
| tfidf\_\_use\_idf | True or False | Whether to use Term Frequency-Inverse Document Frequency or not |
| clf\_\_alpha | 1e-2 or 1e-3 | A penalty parameter used in the SGD classifier |

To find the best parameters for building the text classifier, we run an automated test of cross validation using a split relation of 80% to 20% between training records and test records when forming the 5 data chucks at each possible combination of the test values of tunning parameters in table 3. The result of tuning would then be obtained as a combination of parameter values that gives the highest possible performance in term of the more reliable F1-score. The key parameters that give the highest F-score are those who are most likely to optimize the performance of the text classifier, these optimal values are viewed in table 4 below.

Table 4, Best values of text classification key parameters that gives an optimal and reliable text classification.

|  |  |
| --- | --- |
| Metric | Measure Value |
| Best score | 0.691 |
| vect\_\_ngram\_range | 0.001 |
| tfidf\_\_use\_idf | True |
| clf\_\_alpha | (1, 1) |

Using the these optimal parameters, we manage to increase the F1-score score to 0.715 from 0.663, and although this score might be considered low among the community of artificial intelligence, it is still a good score considering many factors and priorities such as the need of having a dataset that is dynamic and easy to update and use for training a text classifier.

Another important question to ask here, what is a good score under testing in artificial intelligence? This depends on what we are trying to achieve from this text classifier, and as we are only seeking the use of this text classifier to estimate the field of influence between users based on the text in their activities, a score of around 70% is satisfying to proceed into using this text classifier in building the influence graph and perform an evaluation on its ability to distinguish between different categories of topics in the user’s data. A deeper picture is drawn in the upcoming evaluation section where an evaluation will be carried out on the influence graph model to reveal its ability to detect and distinguish as many target categories as possible.

* Detailed information about the performance of the optimized text classification model.

After tuning the text classifier, we repeat the first evaluation step but with using the best score parameters obtained from the tunning process while keeping track of the actual and predicated category of every testing record which is used to produce an informative classification report shown in table 5 below.

Table 5, The classifcation report after tuning of the text classifier.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Category | Precision | Recall | F1-score | Support |
| Sport | 0.878 | 0.865 | 0.872 | 67 |
| Economy | 0.745 | 0.65 | 0.694 | 63 |
| Politic | 0.77 | 0.649 | 0.704 | 57 |
| Technology | 0.583 | 0.688 | 0.631 | 61 |
| Entertainment | 0.61 | 0.692 | 0.648 | 52 |
|  |  |  |  |  |
| Weighted Average | 0.723 | 0.713 | 0.715 | 300 |
| Macro Average | 0.717 | 0.709 | 0.71 | 300 |

The classification report indicates a weighted F1-score average of 0.715 with the highest F1-score for the sport category at 0.872 and lowest score to the technology category at 0.631, the lowest score category might has been affected by the big interference of multiple aspects of the other categories into technology, which can cause the model to falsely classify records that should belong to the technology category and not to other overlapping categories.

The confusion Matrix in table 6 below shows the detailed classification of the 300 testing records where 215 records were classified correctly as expected, while 85 records were classified in the wrong category, 51 records or 60% of those with an incorrect classification stands between the 2 categories of Technology and entertainment on the one side against politic and economy on the other side, leaving 34 incorrect classifications between the others more distinct categories, i.e. sport, economy and politic. This confirms that both the technology and entertainment category are often falsely classified to belong to either politic or economy respectively and vice versa, which tells us that this text classifier perform better when classifying general categories with little in common rather than classifying categories that might overlap.

Table 6, The confusion matrix after tuning the text classifier, green colored cells shows the correctly classified test records, red colored cells shows the falsely classified test records, cells marked with dark red color shows the distribution of falsely classified test records due to the overlapping between technology and entertainment on the one hand, and economy and politic on the other hand due the natural overlapping of these categories.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Predicted (below) / Actual (Right) | Sport | Economy | Politic | Technology | Entertainment |
| Sport | 58 | 0 | 0 | 4 | 5 |
| Economy | 0 | 42 | 0 | 12 | 9 |
| Politic | 3 | 5 | 37 | 4 | 8 |
| Technology | 1 | 8 | 6 | 42 | 4 |
| Entertainment | 3 | 1 | 3 | 9 | 36 |

The objective of analyzing social influence aims to find the most non-overlapping category of influence in society like politic, economy and sport. Each one of these categories are clearly defined on what they are about, this makes our text classifier suitable for use in building a social influence model with good potential of detecting the right category of influence.

In the next section, we will evaluate the performance of this text classifier under the process of forming the influence graph using real life data crawled from “Reddit.com” that is new and unseen to the text classifier. As we aim to investigate how well this classifier is contributing to the objective of identifying different fields of influence in the influence graph.

## **Evaluation of Influence Field Classification**

Now that we have investigated the performance of our text classification model and tested its capabilities in classifying different text submissions from social media into distinct topics, we take in use this text classifier into the previously detailed algorithm of determining the field of influence between two persons based on the combined texts of the main submission, the parent activity, and the child activity.

We start by crawling the 3 most popular subreddits on reddit at the time of this evaluation which are “Home”, “AskReddit” and “PublicFreakout”, then extract information about the 3 newest submissions and their comment threads, along with a training dataset for the text classifier which includes 1500 records distributed between topics according to the crawling plan detailed in table 1. All of the information attributes about the subreddits, submissions and comments are stored in the data structure visualized in the Entity-Relationship model established in figure 2.

After having a real-life dataset to work on, an activity thread is constructed, then transformed to an activity graph that is used as a foundation to detect influences between distinct persons showing both the strength and predicted field of influence.

In this evaluation, we examine the different predicted fields of influence between the participating persons by focusing on the influence edges regardless of which persons are connected to those edges, this is because the influence fields are stored in the influence edges and not directly in the nodes representing the authors in the dataset.

Before preceding into studying the edges of the influence graph, we are interested of knowing how many submissions were crawled from each subreddit or group, which is important to make sure that no one group is overrepresented in the dataset, we will call this distribution measure for “Crawled Groups”. And in addition, we also wish to know how many influence edges are learned from each group, and we call this distribution measure for “Modelled Groups”. Finally, we extract all predicted fields of influence from the edges of the user influence graph and visualize its distribution, this distribution measure is called “Predicted Influence areas”.

The measure of “Modelled Groups” can help us understand the observed distribution of the “Predicted Influence areas”, for example if we have a subreddit or group that have a reputation to be related to a certain topic like for instance sport, then we would expect around the same percentage on this topic in the distribution of both “Modelled Groups and “Predicted Influence areas” assuming all of the crawled and modelled groups are related to different categories.

Now that we have defined our evaluation plan to test the performance of influence field detection in the influence graph, we visualize this information through three pie plots, one for each distribution measure as shown in the next figure



Figure 12, A visualization of the distribution of targeted subreddits (left), the amount of detected influence in each subreddit (middle), and the distribution of detected influence fields (right) in the influence graph. The foundation dataset of the influence graph is based on the 3 newest submissions on the 3 most popular subreddits at the time of this evaluation.

The right plot in figure 12 above proofs that our text classifier has been successfully able to identify 4 out 5 possible topics of influence between persons in the influence graph. The absent topic is economy which may be expected since all the 3 most popular crawled subreddits are not strongly associated with economy but more with the 4 other topics which are technology, politic, sport and entertainment, with relatively higher portion of politic and technology.

The results above are promising for the reliability of our text classifier to be used in building the user influence graph. However, we wish to be sure that our model can distinguish between all the target topics in a training dataset of the text classifier. For this reason, we will crawl the 3 newest submissions from 5 other selected subreddits where each subreddit is strongly associated with one distinct topic of influence, and strongly not associated to the other 4 topics, this means we will be crawling the subreddits; “Finance”, “Cinema”, “worldnews”, “research”, and “NBA” as each of these subreddits is strongly associated with one of the topics; economy, entertainment, politic, technology, and sport respectively. This should enable us to see whether our model can detect all the 5 different categories.



Figure 13, A visualization of the distribution of targeted subreddits (left), the amount of detected influence in each subreddit (middle), and the distribution of detected influence fields (right) in the influence graph. The foundation dataset of the influence graph is based on the 3 newest submissions on 5 selected subreddits that is most likely to be assiciated with one of the targeted influence fields in the training dataset at the time of this evaluation.

As we see from the plot above, 3 submissions were crawled from each of the 5 subreddits, and after building the influence graph, all influence edges were reviewed to know how many influence edges each subreddit has contributed in, then the same process was performed to know the share of each predicated topic between all the influence edges.

This shows that the text classifier has helped identify the 5 different categories with greater share for economy which is expected since Finance is a subreddit that is mainly associated with economy. However, there is only 1.3 % influence edges that is predicted to be in the field of sport, but NBA does have a greater representation in the influence graph than cinema, worldnews and research. Knowing the exact reason for this observation requires digging down into the nature and origin og each individual influence edge. However, some difference and variations between a certain subreddit and the topics of influence extracted from it is not necessarily a downside since most topics tends to overlap in real life scenarios.

## **Introducing Centrality Measures**

In search of identifying the top influential persons in a social network graph, many techniques can be used to distinguish each user’s ability to influence others by assigning each person a certain rank based on his connections to other people in the graph.

Graph centrality is a well-known technique referring to a group of algorithms that gives each node a calculated rank of importance relative to other nodes in the graph, every centrality algorithm differs from other algorithms in how to calculate the ranking of nodes based on the objective of the algorithm whether it favors the direct links between neighboring nodes or goes beyond neighborhood to examine the flow of possible paths throughout the entire graph.

In our case, we have an influence graph, representing users as nodes and influence between them as directed edges, and centrality measures have the potential to identify the power of each person in the this influence graph, both in term of the user’s ability to influence others and his/her contribution into transforming influence from one user to another.

There exist a wide range of available algorithms used to calculate centrality measures, some of these focuses on the direct influence connections to other user nodes while others examine the different paths between nodes that might not have a direct influence connection. In this project we are going to implement 3 different centrality measures, starting with the connection-based outdegree centrality that focuses on the outgoing edges from a certain node, and following with an implementation of the betweenness centrality which looks for the occurrence of each user node in the available shortest paths between any two nodes in the graph, then we will compare the results from each of the previous centrality measures to the Authority and Hub centrality measures of an link-based algorithm called Hyperlink-induced Topic Search (also popular under the name of HITS), this HITS algorithm is considered to be more advanced and complicated than the more simple algorithm of degree and centrality measures.

* Outgoing Degree Centrality

In a directed graph, degree centrality is based on the direction of connected edges to each node, it can be divided into 2 segments of calculations; the first counts the number of outgoing edges from a node, and the second counts the number of ingoing edges from the same node. And although both counts are often summed up to output the node’s rank, in our directed influence graph, influence edges between persons indicate the influence of the source person have on the target person, and because we wish to rank the top influential persons in the graph, the outdegree centrality is a cleaner measure of revealing the power of influence from each person node, regardless of how many other persons does have an influence on an influencer.

The introduction of degree centrality to the influence graph model of this research is inspired from a hands-on approach into the use of centrality measures in the analysis of social media [12], which can be accessed to gain more details about how to apply the measure of degree centrality to the networks of social media.

Figure 14 below shows an example of an influence graph, where degree centrality measures are calculated for each user. We notice that the top influential users according to the outdegree centrality are “user B” and “User C” since both have 2 outgoing influence edges, while all other users except “User E” have a rank of 1 indicating the only outgoing influence each of them has, “User E” on the other hand is only a receiver of influence and does not influence any other persons which gives him the lowest influence score of 0.

* Betweenness Centrality

Betweenness centrality is more concerned of the participating role of each person node in all the possible shortest paths between any given two users in the influence graph. Following this principle allow us to rank each person based on his ability to carry influence from one person to another. The operation of the betweenness algorithm starts by listing all possible shortest paths in the given influence graph, then counts the occurrence of each person in the connecting nodes between the source and target persons, not to include the nodes of the source and target persons in occurrence counting, each person will then have his rank to be equal to the number of times it occurs in connecting nodes of any shortest path in the graph.

More details on how to apply the betweenness centrality measure to social media networks can also be viewed from the hands-on approach into the use of centrality measures in the analysis of social media [12].

The calculation of influence ranking using the betweenness centrality measure is shown in the figure 14 below, and it elects “User F” as the top influential person because this person is located on the shortest paths from both “User C” and “User G” to “User B” and “User E”, and in the second place “User B” and “User C” gets the score of 3, while the rest of 4 non-central users gets the lowest influence rank of 0 because they do not participate in connecting other persons in the influence graph.

* HITS centrality – Auth and Hub with 10 iterations

The process of the HITS[[10]](#footnote-10) algorithm is divided into two symmetric but different calculations that assign two scores to each node in the graph; the first calculation is based on the ingoing edges of nodes and gives each node a score known as the authority score, while the second calculation is based on the outgoing edges of nodes and give each node a score called the hub score. The hub score indicates the ability of one node to point to other nodes in the graph, while the authority score indicates how much a node is pointed to from different hubs.

These two scores are calculated using what is known as the Authority update rule and the Hub update rule, in both rules every node is initially given an old score of one, then to calculate the new auth scores each node gets the sum values of old auth scores given to the source nodes of ingoing edges. Then, to calculate the hub score, each node is given the sum values of old hub scores given to the target nodes of the outgoing edges, before moving on to the next iteration, and for the purpose of normalization the given new values of auth scores are summed up and each new auth score is divided by the sum of auth scores to output a normalized auth score for each node, the same process is repeated on the new hub scores but by summing up the values of the new hub scores. In the next iteration, the new auth and hub scores will be marked as old scores and the same two processes of auth and hub score calculations is repeated.

In theory the HITS algorithm can carry on for an infinite number of iterations, but in practice both values of auth and hub scores would converge each to its approximate value, then the calculations can be stopped, we are here using a fixed number of iterations set to 10 for simplicity reasons but in future improvements, the number of iterations might dynamically change depending on the given graph by detecting convergence of score values, and to avoid optimization issues an upper number of iterations can override and stop any more iterations.

For more details on how to perform the auth and hub calculations in the HITS algorithm, please refer to pages 7-12 in the journal “Authoritative Sources in a Hyperlinked Environment” by J. M. Kleinberg [13].

The HITS algorithm was originally developed to be used in rating both journals and web pages which can point to each other by using references in their text content. The nature of our user influence graph is very similar to the usual application of the HITS algorithm, as both the nodes and links of our developed influence graph are homogeneous, i.e., nodes does only represent different persons, while directed links between them only represent social influence and nothing else.

Establishing some nodes in the graph as important hubs is an advantage of using the HITS algorithm over the use of the PageRank algorithm, this is because the PageRank algorithm favors older, more established nodes even if more recent nodes are very important. More about the capabilities of the HITS algorithm is investigated in the book titled “Discrete Calculus: Applied Analysis on Graphs for Computational Science” by L. J. Grady and J. R. Polimeni.

Based on the similarity between ranking journals and webpages in comparison with identifying important persons in the influence graph, we can use the HITS algorithm to find the top influential persons, along with those persons with a high role of transforming influence across the graph from one person to another.

Both graphs in the bottom of figure 14 below shows the results of running the HITS algorithm with a limit of 10 iterations to assign each node a hub and auth score. On the right side, both nodes of “User B” and “User C” were given the highest hub score indicating their ability to point to other nodes in graph, while examining the auth scores in the graph on the left side reveals that “User F” is the top scored in the graph, this is highly expected as a good authority in the influence graph is a person that is linked by many different strong Hubs which are “User B” and “User C” in the right graph at the bottom showing the hub centrality scores.



Figure 14, An ranking example using 4 unweighted and direct centrality measures; outdegree centrality (upper left corner), betweenness centrality (upper right corner), HITS Auth (lower left corner), and HITS Hub (lower right corner).

We hereby conclude that the auth scores helps detecting those persons who are more likely to transfer influence between hubs in the influence graph, while the hub scores on the other hand indicate the person’s ability to influence others in the influence graph.

Comparing the results of the hub hits scores to the results gained from the degree centrality on the same influence graph, we notice that both techniques did yield the same ranking for every person in the graph, which confirms that the hub centrality is a measure of how influential a certain person is in the influence graph.

Another comparison can be carried out between the betweenness centrality scores and the HITS auth scores on the same influence graph, where the same person node is elected on top in each measure, however the betweenness algorithm has the tendency to favor nodes of persons at the heart of the graph as they often connect distant persons located at the end of connections, while the HITS authority measure tends to favor those distant persons located at connections ends.

At this point of insight, we notice that each centrality measure has a series of features when used for detecting the most influential users in a social graph, and no one centrality measure can stand out to give the best picture, this makes it essential for the analyzer of the user influence graph to understand the capability of each centrality measure that enables this analyzer to make the best decision on which person is to be considered the most influential. The table below summarizes those previously discovered and discussed features of the various centrality measures.

Table 7, A comparison between 3 types of centrality; outdegree, betweenness, HITS Auth and HITS Hub. This comparison is based on the observations of ranking performed on the example influence graph in figure 14.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Degree | Betweenness | HITS Hub | HITS  Auth |
| Reveals | Direct Influencers | Influence transformers and connectors | Direct Influencers | Influence transformers and connectors |
| Favors | Number of outgoing influence edges | Users at the middle of a connected segment of the graph | Number of outgoing influence edges | Users at the ends of a connected segment of the graph |
| Simplicity | Easy | Medium | High | High |
| Interpretation of results | Easy | Medium | Difficult | Difficult |
| Running time | Low, as it only requires one iteration over the edges in the graph. | Medium, as graph traversal is needed to find the shortest path between every two nodes in the graph | High, as it requires multiple iterations to achieve convergence | High, as it requires multiple iterations to achieve convergence |

##### References

[1] Y. Guo, J. Cao and W. Lin, "Social Network Influence Analysis," 2019 6th International Conference on Dependable Systems and Their Applications (DSA), 2020, pp. 517-518, doi: 10.1109/DSA.2019.00093. J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73.

[2] F. Wang, W. Jiang, G. Wang and D. Xie, "Data-Driven Influence Learning in Social Networks," 2017 IEEE International Symposium on Parallel and Distributed Processing with Applications and 2017 IEEE International Conference on Ubiquitous Computing and Communications (ISPA/IUCC), 2017, pp. 1179-1185, doi: 10.1109/ISPA/IUCC.2017.00177.

[3] Baumgartner, Jason & Zannettou, Savvas & Keegan, Brian & Squire, Megan & Blackburn, Jeremy. (2020). The Pushshift Reddit Dataset.

[4] Balakrishnan, Athira & Jones, Josette & Idicula, Sumam & Kulanthaivel, Anand & Zhang, Enming. (2021). Annotating and detecting topics in social media forum and modelling the annotation to derive directions-a case study. Journal of Big Data. 8. 10.1186/s40537-021-00429-7.

[5] T. Steinbaur, ‘‘Information and social analysis of Reddit,’’ inProc.TROYSTEINBAUER CS. UCSB. EDU, 2012, pp. 1–12. [Online]. Available:http://snap.stanford.edu/class/cs224w-2011/proj/tbower\_Finalwriteup\_v1.pdf

[6] "About Statcounter GlobalStats" https://gs.statcounter.com/about (accessed July. 12, 2021).

[7] Statcounter GlobalStats, Social Media Stats Worldwide, Jan 2010 - Dec 2019. [Online]. accessed from <https://gs.statcounter.com/social-media-stats#monthly-201001-201912-bar>

[8] "PRAW: The Python Reddit API Wrapper." https://praw.readthedocs.io/en/stable/ (accessed July. 12, 2021).

[9] "Working With Text Data" https://scikit-learn.org/stable/tutorial/text\_analytics/working\_with\_text\_data.html (accessed July. 14, 2021).

[10] "n-gram" <https://en.wikipedia.org/wiki/N-gram> (accessed July. 14, 2021).

[11] "Tf-idf" <https://no.wikipedia.org/wiki/Tf-idf> (accessed July. 14, 2021).

[12] J. Golbeck, “Analyzing Networks,” in Introduction to social media investigation : a hands-on approach, 1th ed. Amsterdam, Netherlands: Syngress, 2015, s. 221-235.

[13] J. M. Kleinberg, “Authoritative Sources in a Hyperlinked Environment,” Journal of the ACM, 46, 5, 604, 1999. 10.1145/324133.324140.

[14] L. J. Grady and J. R. Polimeni, “Ranking,” in Discrete Calculus: Applied Analysis on Graphs for Computational Science, 1. Aufl. London: Springer Verlag London Limited, 2010, s. 253-256.

1. FAIR data are data that meet principles of findability, accessibility, interoperability, and reusability, <https://en.wikipedia.org/wiki/FAIR_data> [↑](#footnote-ref-1)
2. Convolutional neural network, <https://en.wikipedia.org/wiki/Convolutional_neural_network> [↑](#footnote-ref-2)
3. Long short-term memory, <https://en.wikipedia.org/wiki/Long_short-term_memory> [↑](#footnote-ref-3)
4. Bidirectional LSTM, <https://paperswithcode.com/method/bilstm> [↑](#footnote-ref-4)
5. A measure of model’s accuracy on a dataset, <https://deepai.org/machine-learning-glossary-and-terms/f-score> [↑](#footnote-ref-5)
6. Reddit is a social news aggregation, web content rating, and discussion website, <https://en.wikipedia.org/wiki/Reddit> [↑](#footnote-ref-6)
7. Python Reddit API Wrapper [↑](#footnote-ref-7)
8. Entity-Relationship model [↑](#footnote-ref-8)
9. An n-gram is a contiguous sequence of n items from a given sample of text. [10] [↑](#footnote-ref-9)
10. Hyperlink-induced Topic Search. [↑](#footnote-ref-10)