Professional profiles matching: What keywords to display on one's profile

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Abstract

Getting in contact with new people is not easy for everyone. Being successful and efficient may depend on the manner, the context and the content. In a professional field, networking can become a key element in a career. Nowadays, several applications try to organize potential connections between people to help match, but then what kind of information is the best, how and how precise should it get? Based on categories and degrees of precision of information, we try to get a better understanding about the type of information can offer the best chances to match and thus, get in contact in a professional context.

Introduction

Problem of meeting new people

Over the last decades, Social Networking through Websites or mobile applications has taken a role increasingly important. Many different devices propose various networking platforms based on common specifications like interests, professions or research fields. The aim is to find the best kind of information to get in order to promote meetings. As a parallel, doing Curriculum Vitae is a way to introduce oneself in order to get collaborators or employees. As we know, the reception one can get from the view of a profile depends partly on what is written inside but is also the result of a way to describe it. Getting a good Curriculum Vitae or doing a good presentation of oneself can become a tough task.

Proposition: technology allow to increase and ease the possibilities

The development of social networking environment has allowed today's society to enhance their possibility of meeting professionally related people and to make it more efficient. Mobile Social Networks (MSNs) grabbed these years an increasing importance in the efficiency of meetings partly due to the fact that it's a "live" common device. Despite the remaining use of paper during such events, MSNs could give all the information one's need about what is happening where and with who (Ball, 2013). As in API's Future Watch Survey (FutureWatch, 2013), the use of Smartphone in a

business manner has become a nearly standard as 80% of meeting professional get to use them in their careers.

The increasing performance of technology has enhanced the possibility of cutting and systemizes certain processes as meetings in this kind of context. Therefore, it is important that participants get an effective way to communicate and to exchange information during the mean time. In an experiment around information displayed on social media (Evans, Gosling, & Carroll, 2008) Evans & al. experiment the gap between intra and interpersonal perception. Some information or categories of information are more relevant than others. On a profile on Social or professional medias like Facebook or LinkedIn, the quantity of information displayed can be chosen but an overload of information can dismiss the global appreciation of a profile.

The experiences we make about a person, an environment are directly organized by the brain. The inputs are filtered, simplified and categorized by it in order to avoid a processing overload (Smith & Medin, 1981). Catching each piece of information separately would overwhelm the brain and thus get us unable to remember more than a second what we encounter. The necessity of classing notions and experiences allows us to base our environment on passed experiences and to have a better understanding of what is expected or unexpected, to get the way things works and how to act with it (Macrae & Bodenhausen, 2000). In general, some introduce themselves based mainly on their personality, their past experiences or their qualifications. The degree of specification or direct pertinence of these categories may vary. For example, a person that talks about his football team could be seen as rather distant from a standard presentation in a professional manner. But it can become rather rich if he is looking for a job where cohesion of a team work is important.

We then need to categorize and organize the profile. On these types of Social Networks, there is a relatively big amount of retrievable data. In an elevator talk (Pincus, 2007), the situation allows a restricted time and thus, implies an optimization of speech we can do to get a meeting. the principal aims of a short meeting is to get a second one, to construct the speech according to the person in front of you and to be as efficient in a few words as possible.

Having an affinity with someone based on common interest or similar background can also play a great role in the choice of getting new contacts (Miller M., 2001). In different social platforms, homophily can represent a big part of the networking in the way to find people that seem similar but also in a deeper degree (Ido G., 2010). The spreading context can be enhanced by people known in common, communities, interest or participation in different discussions. We know that at a starting point, finding someone similar is more likely to lead to a meeting.

How to test the efficiency of a profile?

The EPFL start-up, Nowy Connect, proposes to display information about participant to a specific professional event. In the same manner, we will experiment the rating one can get from a profile based on criteria as pertinence, precision and different categories. In order to optimize these "first impressions" or profiles, we will organize and observe what kind of profile can be more efficient.

In an experiment on the concept of love (Regan, Kocan, & Whitlock, 1998), people were asked to sum up prototypes or names related to the notion of Love. They were then asked to relate these words according to the definition of Romantic Love. In the same manner, we will try to understand

what keywords people use to describe themselves in a professional manner and how these keywords are perceived, related to the concept of Professional Networking. In this discussion, we will observe and try to demonstrate the different impacts that these categories can have in a self-presentation and focus on the different degrees of pertinence and precision of the keywords.

Method

We made the experiment with two different groups. First one was with Psychology student and PhDs (10 participants) and the second one with Bioengineering Master Students (15 participants). Every participant was put in the context of a professional event in order to meet new people in a professional manner.

They filled profile sheets in which they were asked to write from 2 to 10 keywords to describe themselves. They were told that these keywords would decide whether they would get a meeting or not. It was important that all the keywords remained condensed and that each participant filled his sheet separately.

We then took all the profiles and redistributed all of them to every participant. They had to look at each profile individually, to evaluate the profiles and to give it a grade from 1 to 6 based on whether they would like to meet this person or not.

The third step was for them to choose 3 profiles considered as the preferred ones and 3 least preferred. This step was meant to avoid exceeding an overload of choices to do for the following. For these 6 profiles, they had to look at every keyword and to rate them on a scale of pertinence and a scale of precision, from 1 to 7, "7" meaning really pertinent or really precise.

This exercise was lead to correspond to a realistic situation like filling a profile on LinkedIn or another professional network platform.

After the experiment, we gathered all the profiles and organized every keyword by type: Skill (technical skills and language), background (past experience), interest (interest in field of research, domain), hobby (sports and occupations), future (future projects, research field or position) and personality.

The categorization in this way can be seen as subjective in the sense that it was operated by the organizers of the experiment, but the remaining aim was to compare the different types of elements rather than work empirically on each category.

All the data were treated separately and then gathered after the categorization.

Results

Introduction

In the following, we will analyze the impact of pertinence and precision in the appreciation and the grade of a profile. By doing two experiments, we can compare the types of profiles made by two different fields and what is the difference in efficiency of each of them.

Experience

On the 25 profiles, one condensed several keywords on one line making the pertinence and precision confusing for the "judges". This profile was excluded from the data.

One participant selected his own profile as preferred, which was excluded in a purpose of "matching" data.

One participant did not evaluate the pertinence and precision of 2 profiles which were not counted.

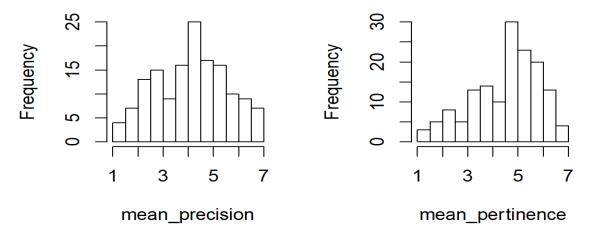


Figure 1: Mean pertinence and precision appearing in both experiments

Pertinence and precision

Firstly, for the main focus of the experiment, we wanted to see the correlation that can exist between the average grade and other elements. By computing the correlation between pertinence, precision, the number of keywords and the main category that participant were likely to use, the fig.1 shows that there is a strong influence of all the factors on the average grade obtained by the subjects.

| Parameter | p-value |
|--------------------|---------------|
| pertinence | 3.178e-13 *** |
| precision | 0.005 ** |
| number of keywords | 1.700e-08 *** |
| main category | 3.230e-05 *** |

Figure 2: ANOVA results of the influence of the keywords parameter on the grades obtained by each subject. Significance of codes: 0 '***' 0.001 '**' 0.05

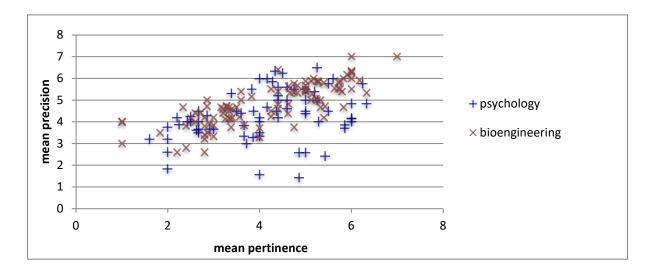


Figure 3: Pertinence and precision for each keyword

In this figure, we see that globally, pertinence and precision are correlated. Writing elements that are more distant from a standard professional description will tend more to be vague. By comparing the 2 kinds of participants, we can see that Psychology subjects have an irregular distribution while Bioengineers are rather strict on the correspondence between pertinence and precision.

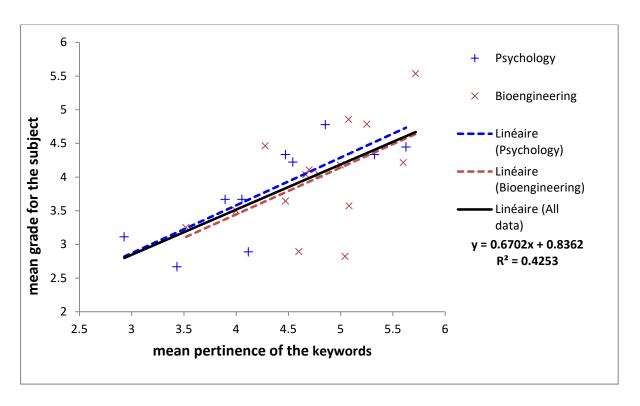


Figure 4: Profile grades and mean pertinence of keywords.

As opposed to the last figure, here we can see Bioengineering participants have a vaguer tendency between the pertinence and the average grade.

<u>**Iudges**</u>

To understand the relevance of this study, we need to observe the subjects as judges in their choices of profiles. This gives an indication on the reliability of the grades given. In other words, do the results depend on who is judging or not, in their own characteristics like precision or main category.

| Parameter | p-value |
|--|---------------|
| Judge's precision | 1.037e-12 *** |
| Keyword precision | 0.0011543** |
| Judge precision* keyword precision | 0.1667946 |
| Judge's main category | 4.366e-05 *** |
| Keyword's category | 0.0002857 *** |
| Judge's main category * keyword category | 8.256e-08 *** |

Figure 5: ANOVA results of the influence of the judge's profiles on the grade given to each profile. Significance of codes: 0 '***' 0.001 '**' 0.05. The "judge's main category" represents the category that appears the most often in the judge's profile.

If we look at the judge specifically, we can see that the grade obtained after judging a profile depends on who is judging as seen in fig.3. If the judge is globally precise in his profile, he will tend to rate more positively other profiles. But the correlation between a precise judge and a precise keyword doesn't occur.

The main difference between the two experiments was the position of the participants in their respective professions. Bioengineers were all in Master year in the same school, but Psychologists included first year students and PhDs.

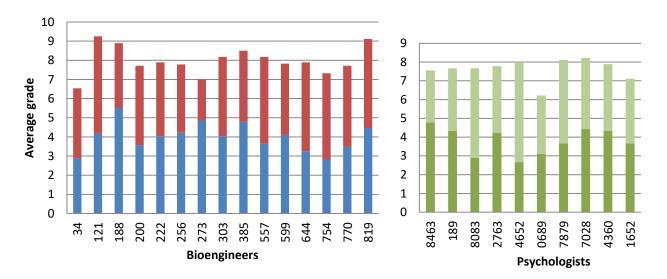


Figure 6: Average grade given and received by all subjects. The bottom corresponds to the grade they received for their profiles. The upper one corresponds to the average grade each participant gave.

By superposing the two columns, we can perceive that the results are more regular for Psychologists than for Bioengineers. In the case of Psychologists, it basically means that a participant having a general good profile will tend to rate other profiles with a lower grade.

Impact of pertinence and precision on keywords of each category

After the experiment, the three of us gathered all the keywords and split them into 6 categories that define the type of indication the keyword gives. By doing so, we can see that on 1069 keywords, the participants used different ways to describe themselves.

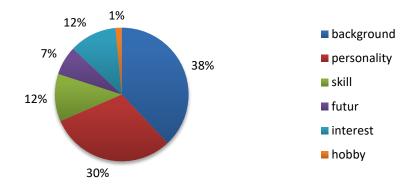


Figure 7: Frequency of each keyword's category appearance

68% (732 keywords) were based on Background or Personality.

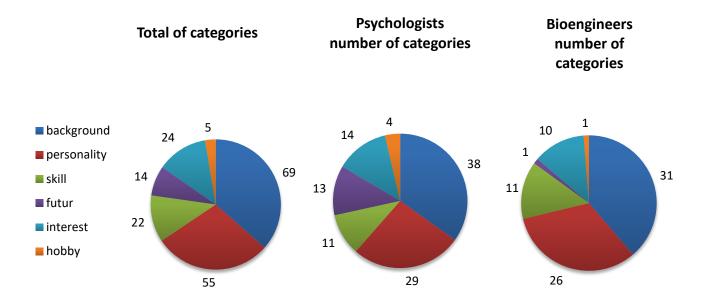


Figure 8: Number of appearance of each category

To bring back the pertinence and precision of the keywords, we can now compare the data but by comparing these keywords through their categories.

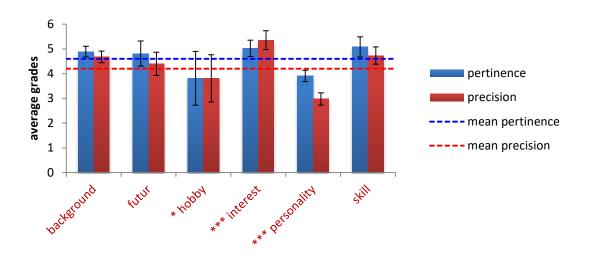


Figure 9: Overall pertinence and precision per keyword category.

Each keyword category has a seemingly coordinated level of precision and pertinence. In the two main categories that have an impact on the average grade, we can see that the levels of precision of keywords are significantly different. The keywords based on Hobbies and Personalities tend to be less precise.

The pertinence of categories (with some gap due to the method of classification of categories) shows the relevancy of such elements in professional self-description. We then see Hobbies and Personality seem to be considered as less correlated to a standard profile scheme.

| note~moy_prec*moy_pert+skill+background+interest+hobby+futur+personality | | | | |
|--|---------------------------------|--|--|--|
| Response: note | | | | |
| | Sum Sq Df F value Pr(>F) | | | |
| moy_prec | 18.209 1 10.6801 0.0013668 ** | | | |
| moy_pert | 104.725 1 61.4244 1.115e-12 *** | | | |
| skill | 2.652 1 1.5555 0.2144401 | | | |
| background | 11.268 1 6.6091 0.0112055 * | | | |
| interest | 14.073 1 8.2545 0.0047083 ** | | | |
| hobby | 3.411 1 2.0007 0.1594761 | | | |
| future | 20.774 1 12.1846 0.0006474 *** | | | |
| personality | 4.635 1 2.7188 0.1014448 | | | |
| moy_prec:moy_pert | 0.001 1 0.0007 0.9791453 | | | |
| Residuals | 235.281 138 | | | |

Table 1: Influence of each category on the grade of the profile

In table 1, we can see that the impact of some categories such as interest and future is significantly positive on the final grade of a profile. We can say that the presence of these elements in profiles is positive while the others may be significant more by their content.

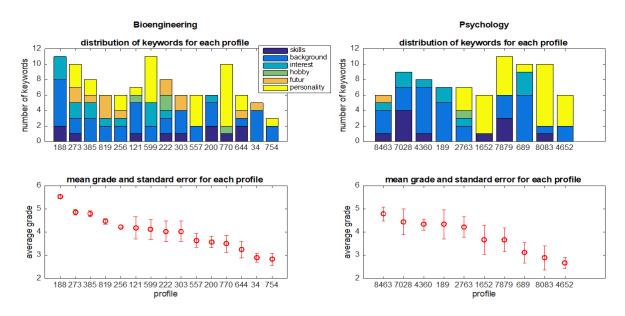


Figure 10: Number of keywords per category and their correspondence with their average grade and standard error.

By comparing the two experiments, we can see that Bioengineering Students talk more about their future. We have a tendency between the number of keywords used and the average grade of the profile concerning the *best* and *worst* grades while the distribution for the Psychology participants is more regular.

We can note that, by looking at the categories, Psychology subject that included personality in their profiles are in the lower part of the average grade. Almost none of them integrated their future in their profiles.

The 5 fives best rated profiles in Engineering Students show that the range of error in their grades is very small. The grade given was then more unanimous than the other profiles.

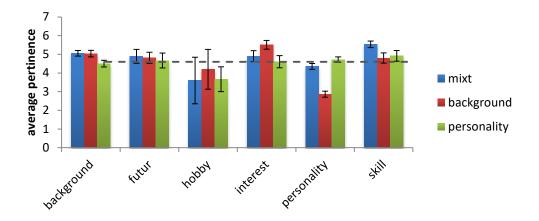


Figure 11: Average pertinence given by each judge category

There is a difference in the pertinence grade given depending on which type of judge rated it. The "hobby" participants tend to rate the different categories of keywords lower.

An interesting gap is between the "interest" and "personality" type of participants. We can see that people that use to describe themselves mostly on personality will find background elements to be less pertinent in a profile than the rest. The opposite occurs with "interest" type of participants.

We will now compare the number of appearance of each category of keyword with the average grade of the profile.

| Factor | Coefficient | p-value |
|---------------------|-------------|--------------|
| | | |
| Skills | 4.3946 | 0.037840 * |
| Background | 2.2321 | 0.137406 |
| Interest | 5.0742 | 0.025829 * |
| Hobby | 1.4531 | 0.230044 |
| Future | 9.2234 | 0.002847 ** |
| Personality | 0.9508 | 0.331191 |
| Skills * Background | 11.3817 | 0.000958 *** |

Table 2: Results for multifactorial ANOVA of the grades given to each profile by each judge. The factor tested is the number of keywords per categories for each profile.

Here we can see that having skill or background keywords barely affects the average grade of the profile. But when combined, we can see that having the two elements in a description.

Matches

The following results put in evidence the characteristics and correlation between two profiles that matched. The next figure shows the profiles that were selected by participants as being the "preferred" ones.

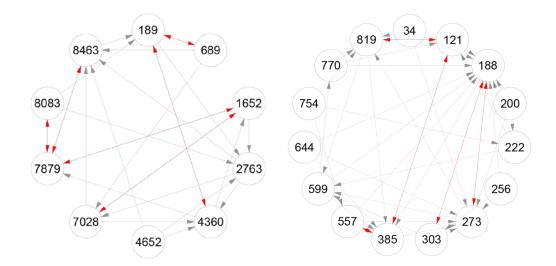


Figure 12: Results of the selected profiles of each participant. The lines in red show the double sided selection which represent a "match". On the left are the profiles from the Psychology participants. On the right are the profiles from the Bioengineering participants.

The first observation is the irregular distribution of arrows. Some profiles were often selected and others, not at all.

To understand and enhance the "matching" possibility between profiles, we will focus on these selected profiles.

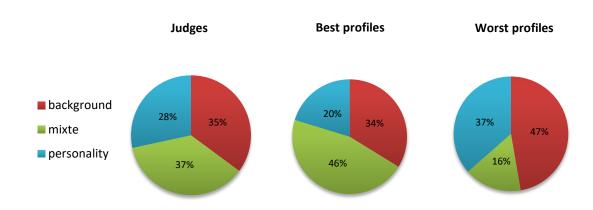


Figure 13: Main categories prevalently identifying the selected profiles. The "mixt" category represents profiles that have an equal number of different categories.

Even though the diagrams show a tendency on "mixt" main category in the best profiles, it is not significant enough to say that one category works better than others. We saw that a mix between categories offer statistically better results in profile grades.

After having looked on what makes a good profile grade, we will now concentrate on the matches. As every participant is different, the elements that can match them together can be diverse. On the next figure, we see the correspondence between two matching profiles in their number of keywords and categories.

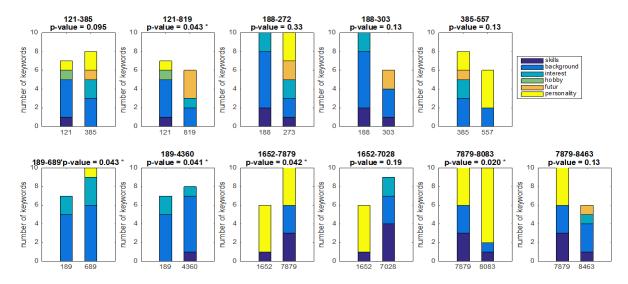


Figure 14: Comparison of the categories of keywords between profiles that matched.

What prevails here is the absence of correspondence. The concept of homophily is here tested as negative. There doesn't seem to be an interaction between any common characteristic in this context.

Discussion

As said before, there are many ways to describe oneself and many factors that can influence the perception of such a profile. This becomes particularly difficult when we try to optimize a profile with a maximum of 10 keywords. As supposed at the beginning of the experiment, the redaction of a precise profile with pertinent key elements is a good way to optimize the quality. But the effect can depend on which category the element of description is part of.

The evaluation of a profile depends on who is watching it. Even if some elements or guide lines can be seen as "universal", every description needs to be put in the right context in order to be effective. We saw for example that on the experiment about Psychologists, people that have in average a good grade profile tend to be more severe in their ratings. We can consider the range of situations and age but it is still an element that needs to be taken in account.

We saw that the type of description keywords is more effective when there is a variety of information. Categories like Skill or Background have barely any effect on the final grade but have a significant correlation when combined.

Categories

In this experiment, we had 3 types of participants. 1st year Bachelor students, Master students and PhDs. We noticed that the elements about projection in a professional future was present for the Master student as opposed for the others even though future keywords seem to have a good effect on a profile grade. It shows how the contextualization can have an effect on the way to introduce oneself. In a same manner, we saw that globally, the use of many keywords lead to a better grade but, as we know, this also depend on the context. Consulting profiles at home to find the best match on LinkedIn or being at an event and having the sight of hundreds of profiles will have a different effect on the number of information displayed. As described before (Smith & Medin, 1981), having fulfilled profiles to inspect in a short time would lead to the same result as an overload of information.

Homophily

The concept of homophily tested in this experiment seem to counteract other researches. This doesn't validate or invalidate any of them but gives a hint on the different levels of common characteristics that can be shared by people. For example, successful match on social media can be based on common interest but could become less relevant in a professional context.

Conclusion and perspectives

This experiment gathered a reduced number of participants that would deserve to be done in a larger scale. The multiplicity of experiments of that kind would allow getting more data based on different degrees of homophily. The results may be different if the candidates share the same position, profession or general field. A further step would be to focus on the precision that enhance a profile when there is a variety of shared factor.

The method used to do this experiment inspired by the experiment on The Concept of Love (Regan, Kocan, & Whitlock, 1998) could easily be adapted to many different platforms. The way we perceive others through social Medias, social networks, and professional networks or even in Curriculum Vitae is a prevalent key element in careers nowadays.

Finally, this study brings and put in evidence some factors that influence description of self in a professional manner. But still, it opens to other studies that could be more specific in the context or type of element that would be displayed.

References

Ball, C. (2013). The Business value of Mobile Applications for Meetings.

Evans, D. C., Gosling, S. D., & Carroll, A. (2008). What Elements of an Online Social Networking Profile Predict Target-.

FutureWatch. (2013). MPI's Future Watch Excutive Summary.

Gabora, L., Rosch, E., & Aerts, D. (2008). Toward an Ecological Theory of Concepts.

Ido G., M. J. (2010). Same places, same things, same people?

Lin, E. L., & Murphy, G. L. (2001). Thematic Relations in Adults' Concepts.

Macrae, N. C., & Bodenhausen, G. V. (2000). Social Cognition: Thinking Categorically about others.

Miller M., L. S. (2001). Homophily in Social Networks.

Pincus, A. (2007). *Perfect Elevator Pitch*. Retrieved from http://www.bloomberg.com/bw/stories/2007-06-18/the-perfect-elevator-pitchbusinessweek-business-news-stock-market-and-financial-advice

Regan, P. C., Kocan, E. R., & Whitlock, T. (1998). Ain't Love Grand! A Prototype Analysis of the Concept of Romantic Love.

Smith, E. E., & Medin, D. L. (1981). Categories and Concepts.