

COINs2010

Towards “Honest Signals” of Creativity – Identifying Personality Characteristics Through Microscopic Social Network Analysis

Peter A. Gloor^{a*}, Kai Fischbach^b, Hauke Fuehres^a, Casper Lassenius^c, Tuomas Niinimäki^c, Daniel Olguin Olguin^a, Sandy Pentland^a, Arttu Piri^c, Johannes Putzke^b

^aMIT, Cambridge MA, USA

^bUniversity of Cologne, Germany

^cAalto University, Helsinki

Abstract

This paper presents preliminary results on predicting individual creativity based on interpersonal interaction patterns. We combine insights from analyzing communication in an E-mail student network of a distributed course with measurements of interaction by sociometric badges for 23 programmers in Northern Europe. In the first case study we measure communication patterns of 23 software developers in a Nordic country through sociometric badges over a period of 4 weeks, associating it with creativity and productivity collected by a daily questionnaire. At the same time we collected individual trust through another questionnaire. We found that the more central people are in the network, the more trusting they are, and the less they oscillate between low and high states of energy, the more trusting they are.

The second case study is based on a sample of 17 students from a German university participating in a multinational course. We show that e-mail behavior is associated with personality type as measured by the FFI personality test. We found that the larger degree and betweenness centrality of students in the e-mail course network is, the more agreeable and less neurotic they are. The faster students respond to e-mail, the more open and agreeable they are. The smaller the contribution index of students is, i.e. the less e-mails they send relative to other team members, the more neurotic they are.

We speculate that there might be two different types of creativity, “lonely genius” - feeling most creative when on his/her own with lower trust in others, and “swarm creative” - most creative when in the midst of other people, and with higher trust.

Keywords: sociometric badges, social network analysis, creativity, trust

* Corresponding author. Tel.: 001-617-253-7018;
E-mail address: pgloor@mit.edu.

1. Introduction

Sandy Pentland (2008) defines “honest signals” as indicators that humans unknowingly exchange and that convey their intent, emotional state, and characteristics. Frequently humans might not even be aware of what their true intent is: “they don’t know what they know”. Honest signals, however, make this information clear to the sender of the signal.

In this paper we focus on honest signals expressing personality characteristics associated with creativity as described by Mihaly Csikszentmihalyi. According to (Csikszentmihalyi 1997) there are three different types of creativity. The first one is applied to any person that expresses interesting and novel ideas. A bright conversationalist, a person with varied interests, who appears highly intelligent, is commonly called “creative”. Csikszentmihalyi calls these people “brilliant”. The second group according to Csikszentmihalyi are the “personally creative” people, people with insightful judgments who might make important discoveries that only they know about. Most interesting, however, are the Creative people with the capital “C”, people like Leonardo, Edison, or Picasso who have changed our culture in some important aspect. In this paper we focus on the later two categories. While not everybody can be a Leonardo, Edison, or Picasso, groups, companies and organizations rely on creativity that is recognized by others.

Creativity is defined by Csikszentmihalyi as an act, idea, or product that changes an existing domain – which can be anything from nursing to nuclear physics – or that transforms an existing domain into a new one. Creative processes happen in a state of flow. Flow experiences can emerge in many different situations. The interesting point, however, is that it always takes other people for a person to reach the state of flow. Whether it is in sports, music, conversation, sex, or creating a new product, the state of flow is immensely rewarding: the individual is not looking for any external rewards anymore, just the fact of being immersed into the activity is reward enough. Ultra creative people share some contradicting common traits according to Csikszentmihalyi:

- high physical energy, but also often quite at rest
- smart but naïve, with an IQ of at least 120
- playfulness and discipline combined
- fantasy and rooted in reality combined
- combine extroversion and introversion
- humble and proud at the same time
- masculine and feminine
- rebellious and independent
- passionate but objective
- suffering and pain, yet also a great deal of enjoyment

In this paper we are trying to put these qualitative insights onto a more measureable footing by studying these traits through the lens of dynamic social network analysis by mining e-mail archives and face-to-face interaction tracked by sociometric badges invented at the MIT Media lab (e.g. Olguin et. al 2009). In the remainder of this paper we use the different “honest signals” available from e-mail interaction and the sociometric badges to identify the conditions that might get individuals into the state of flow. In particular, we speculate that there might be two types of creativity, the “personal creativity” and “Creativity” with the capital “C” distinguishable by different types of honest signals.

In the first project we studied the flow-experience of software developers by looking at their self-rated productivity and creativity. Software development, particularly applying the agile development methodology, is a creative activity (Crawford et. al 2008), as the programmer creating new code is creating a new product according to the definition of Csikszentmihalyi. In the second project we analyze the e-mail archive of a graduate level distributed course where teams of students solved a creative task.

2. Measuring Creativity and Trust with Sociometric Badges

In our first project, face-to-face interaction is measured through sociometric badges, which are worn around the neck (Olguin et. al 2009). Through an accelerometer these sociometric badges measure energy of the wearer, through a microphone speaking activity, and through an infrared and radio sensor the badges collect mutual interaction.

Figure 1 illustrates correlating accelerometer readings with different activities. Figure 1 shows the energy levels collected by the accelerometer of one of the co-authors during one morning, where the co-author was delivering a talk from 9:30 to 10:30 at a scientific conference.

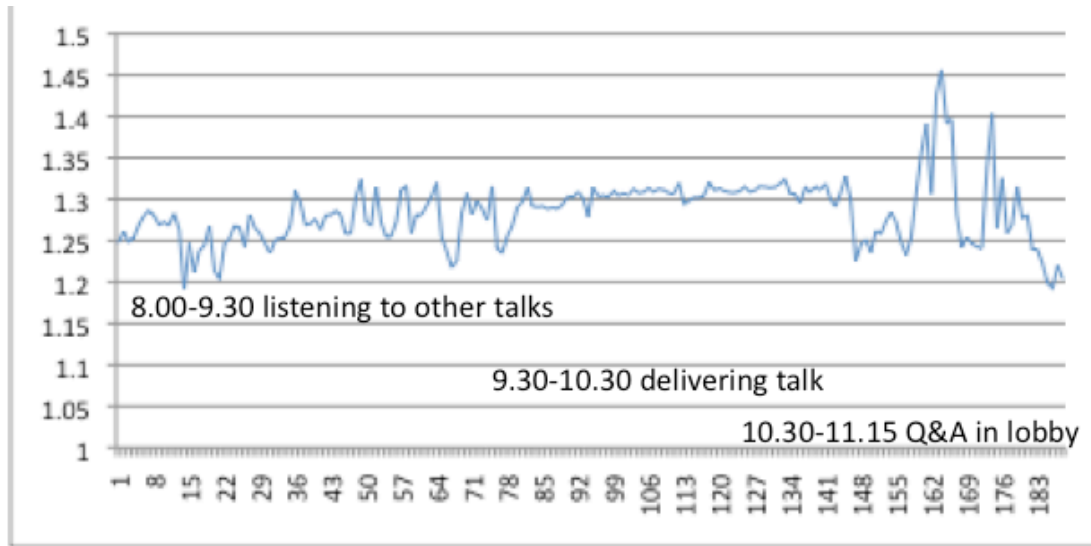


Figure 1 Energy levels during one morning in the life of one of the co-authors

As the talk went well, from 9.30 to 10.30 the co-author was in a state very similar to flow as described by Csikszentmihalyi, recognizable through the accelerometer readings. As the energy curve shows, the co-author was at a consistently high energy level with very low variance during the talk, after the talk his energy readings switched to very high oscillations particularly during informal Q&A in the hotel lobby.

Figure 2 gives a second example of interpreting honest signals of team members. It depicts the accelerometer readings of three members of our research team involved in identical activities during one morning. It illustrates that two members act frequently in synch as indicated through their energy levels (the green and red lines), while the third team member operates independently (the blue line). One of the two coordinated team members (the one with the green line) expends significantly more energy than the other two.

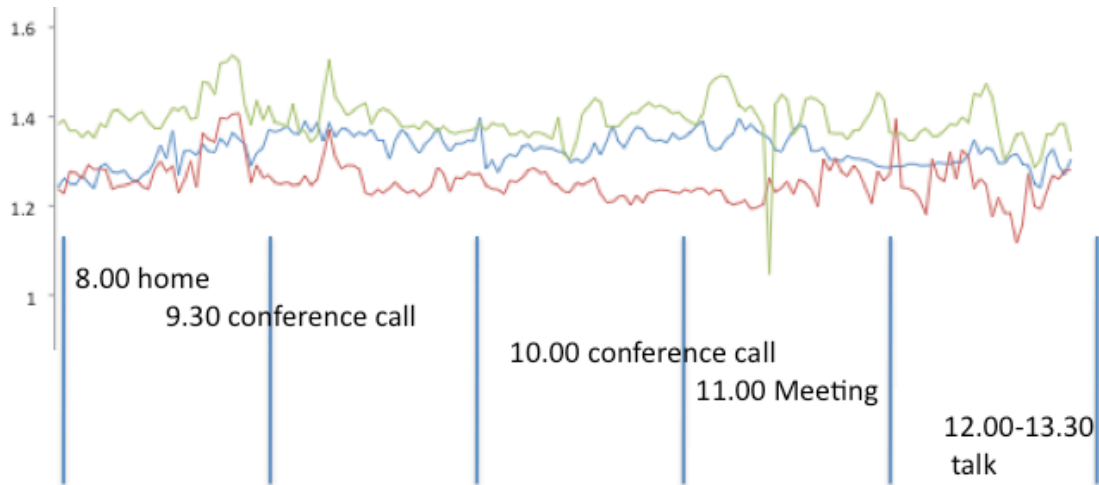


Figure 2. Energy levels during one morning of three members of our research team

The energy lines in figure 2 seem to indicate that at multiple times during the morning, one member appears to mirror the energy levels of a second team member, triggered by some as yet unknown signal of the other person. Motivated by these observations, we decided to investigate these interpersonal signaling mechanisms in more detail by tracking interpersonal face-to-face communication in small teams of co-located software developers.

2.1. Methodology

This work is part of a larger project where we study communication among software developers by combining different communication channels such as e-mail, phone, wiki, chat, and face-to-face interaction. In this paper we focus on measuring face-to-face interaction through sociometric badges. We analyze face-to-face interaction among co-located programmers working on software development projects in a shared group office. We correlate social network metrics such as betweenness centrality, degree centrality, and contribution index (Gloor et. al 2003) with individual daily ratings collected through an online survey from the developers. In particular, we ask on a Likert scale of one to five how creative, productive, communicative, and stressed the developers felt on each particular day. The daily survey questions are listed in table 1.

Productivity	Subjective personal productivity compared to normal day	{1 much less productive...5}
Creativity	Subjective personal creativity compared to normal day	{1 much less creative...5}
Stress	Subjective personal stress level compared to normal day	{1 much lower stress...5}
Communication	Amount of communication needed compared to normal day	{1 much less communication...5}
Mng_Interact_Prod	Managerial interactions' affect on productivity compared to normal day	{1 much more negative... 5 much more positive}
Clig_Interact_Prod	Collegial interactions' affect on productivity compared to normal day	{1 much more negative... 5}
Clnt_Interact_Prod	Client interactions' affect on productivity compared to normal day	{1 much more negative... 5}
Demnt_Availabl_Prod	Document availability and productivity compared to normal day	{1 much more negative... 5}

Table 1. Self-rating questions submitted daily

We study interaction among two groups of developers: team A is a co-located team of 10 developers applying the SCRUM software development methodology working in a Nordic country and team B, consisting of 8 co-located people in a Nordic country, and 5 people in an Eastern European country.

Figure 3 illustrates the social network measured over four weeks through the sociometric badges with radio-based proximity sensors and IR sensors of team A. The IR network measures physical interaction of the programmers facing each other.

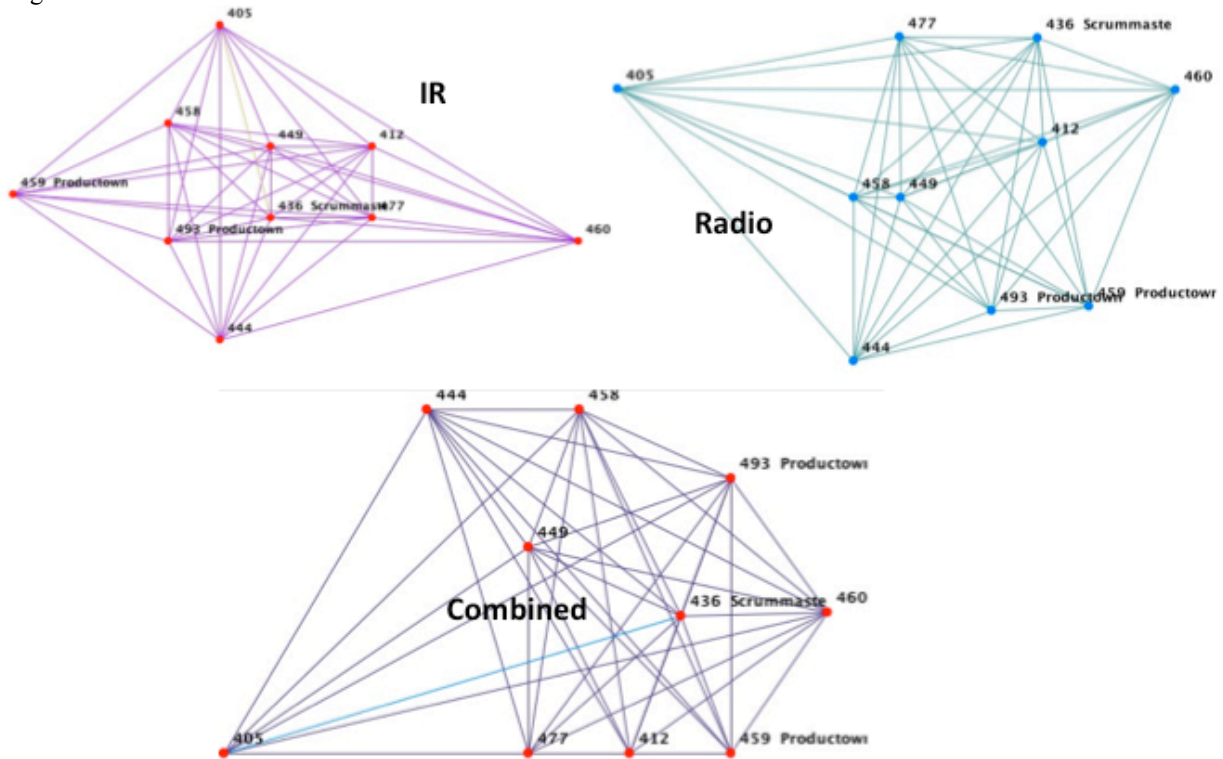


Figure 3. Interaction network of 10 programmers in team A measured with IR (top left), radio (top right), and IR and radio combined (bottom) over duration of 49 days (25 work days).

Figure 3 shows the IR network in the upper left, illustrating that there is a core team – an inner circle – consisting of scrum master 436, developers 412, 458, 477, 449, and product owner 493. The upper right shows the radio network, measuring physical proximity, where programmers 448, 449, and 412 are most central, which could just be because of their office layout. The bottom graph shows the combined network illustrating both types of ties captured by IR and radio. In this network the scrum master 436 is most central, together with 449, while 412 and 477 are quite central also. Combination was done by merging the individual ties over the entire time period by IR and radio between two individuals.

Figure 4 shows the temporal social surface (Gloor 2005) of team A. The x-axis of figure 4 is time, the y-axis is the individual actors (n=10), and the z-axis is the actor betweenness centrality of each of the programmers sorted by decreasing betweenness centrality for each day.

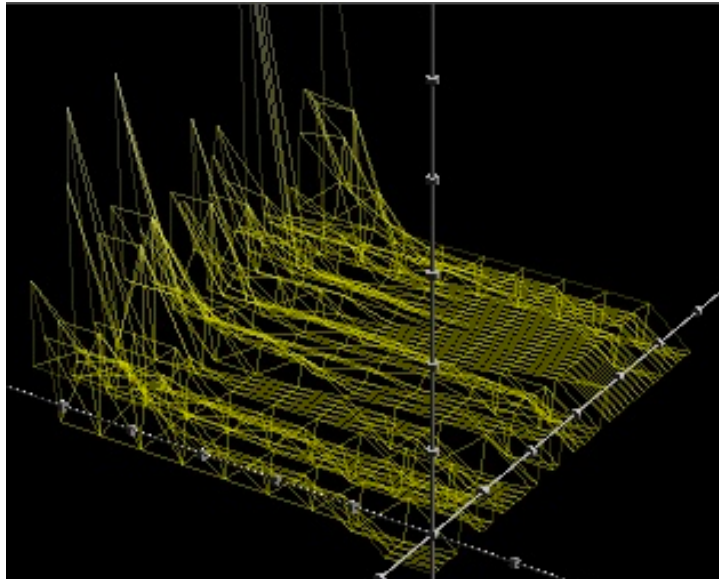


Figure 4. Temporal social surface of combined network illustrating changes in actor betweenness centrality over 49 days of the entire team of 10 programmers

Based on previous research (Kidane & Gloor, 2007), figure 4 is indicative of highly creative work. We therefore decided to compare social networking structure and position of each programmer for each day with her/his creativity, productivity, communication and stress level self-rating.

In addition to betweenness centrality, we also include degree centrality, i.e. the number of direct interaction partners for each developer, as well as contribution index into our analysis. Contribution index ci_k of actor k is

defined as $ci = \frac{\# messages_sent - \# messages_received}{\# messages_sent + \# messages_received}$. (Gloor et. al. 2003) In the case of IR readings this

means that $ci = -1$ for an actor who is only looked at, while he/she never looks at anybody, i.e. his/her badge picks up a lot of signals, but his/her badge's IR signal is never picked up by anybody else. $ci = +1$ for an actor who only looks at others, i.e. his/her badge only sends signals to other badges, but never picks up any from somebody else's badge. In particular this means that the interaction can be asymmetric. If programmer A is facing programmer B, A's signal will be picked up by B's sociometric badge. If B is not looking at A at this time, B's signal will not be picked up by A's sociometric badge. The radio signal, on the other hand, measures physical proximity, which means if A is close to B, B is also close to A – or to put it in other words, the signal is symmetric between A and B.

Figure 5 illustrates the contribution index of the different members in team A. As can be clearly seen, there is a group of high activity developers (493, 436, 449, 477) who also show well-balanced communication behavior (with y-values close to 0).



Figure 5. Aggregated actor contribution index of 10 developers in team A over 49 days of IR network

Based on the sensor readings of the sociometric badges we therefore calculated the variables listed in table 2.

BC – betweenness centrality	The higher BC, the more central is a programmer in the team, i.e. the more information flows through him.
CI – contribution index	The more positive the contribution index, the more an actor is looking at other people. The more negative it is, the more the actor is being looked at while not looking at other people.
DC – degree centrality	The higher degree centrality, the more a developer interacts with many different people on the same day.
Audio_sum	The daily sum of audio is a proxy for speaking time, the larger it is, the more time per day the developer spends speaking.
Audio_mean	The daily average of audio corresponds to the average volume, i.e. the larger it is, the louder on average the developer speaks
Energy_stdv	the daily standard deviation of the minute-by-minute energy. Low standard deviation means high consistency or "flow", i.e. the lower the standard deviation, the more consistent and less fluctuating in his bodily activity the developer is.
Energy_mean	daily average of the minute-by-minute energy, the higher it is, the more energy the developer spends, i.e. the more bodily active he is.

Table 2. Independent variables based on sociometric badge readings

Unfortunately the data basis for our analysis was limited, because a few sociometric badges did not collect data on all days, meaning that some programmers do not appear in the daily networks on some days. Also it was not possible to properly align the timestamps of the badges. We therefore were not able to conduct a fine-grained temporal analysis, but aggregated all data for the 7 independent variables in table 2 over the four weeks into one value per day per developer (for the days where the badges worked), and an aggregated value over the entire four week period.

2.2. Networking and Creativity Characteristics of Individual Developers

In this section we analyze the individual developers, in the next section we will look at the combined readings and compare them with aggregated actor creativity and productivity ratings. 412 is a core developer of the inner

circle in the IR network in figure 3. Figure 6 shows 412's betweenness over the entire duration of 49 days, out of which daily survey data for 25 days was available.

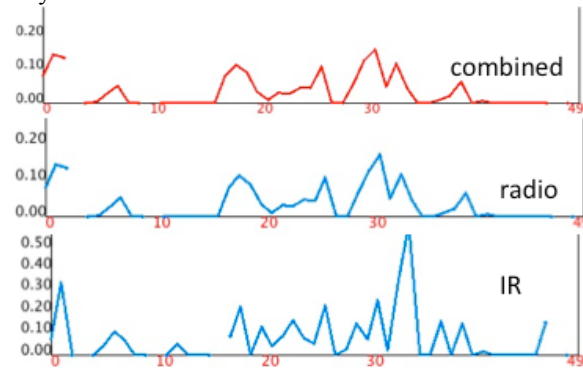


Figure 6. Betweenness curves for IR, radio, and combined network of developer 412

As figure 6 illustrates, the united betweenness curve where IR and radio readings are combined is very close to the radio betweenness curve, while the IR curve is distinctly different. In most of the analysis in this paper we use combined network statistics, combining the radio-sensor-measured proximity network and the IR-sensor-measured face-to-face network because we speculate that both physical proximity and who is facing whom matters. For 412 there is a negative correlation between contribution index and creativity (-0.517^*) and productivity (-0.42^*). This means that the more developer 412 looks at other people, the less creative and productive he feels. And put the other way: the more he is being looked at by others while not looking at them, the more creative and productive he feels. There is also negative correlation between creativity and betweenness centrality (-0.700^{**}), meaning that he feels most creative when not in the center.

The negative correlations between creativity and productivity on the one hand, and betweenness and contribution index on the other hand illustrate that 412 feels most creative and productive when he is least between and has lowest contribution index, i.e. when he is at the fringe of the network, and he does not look at other people. We can therefore reasonably assume that he feels creative and productive when he is on his own, not interacting with others, and in the periphery, i.e., his behavior is that of a *lonely genius*.

Interestingly, developer 458 shows a different behavior. While productivity and creativity are again strongly correlated (0.725^{**}), betweenness and degree centrality are insignificantly positively correlated with productivity, while contribution index is also positively correlated with communication. This means that 458 feels most productive when he interacts with as many developers as possible and is in the center of the group. Communication is negatively correlated with contribution index, which means that he feels he needed a lot of communication when everybody looks at him while he does look less at other people – that is others were communicating with him. 458 therefore offers the picture of a *swarm creative*.

Developer 477 only filled out 10 daily surveys, which reduces the confidence interval of his results. As table 1 shows, his degree centrality and creativity are negatively correlated with communication and betweenness centrality. This means that he feels the need for a lot of communication on the days when he is isolated, while he feels more creative on the days when he communicates with fewer people. Similarly to 412, 477 therefore seems to be a *lonely genius*.

Scrum master 436 unfortunately only filled out 8 daily surveys. There is insignificant correlation (0.642) between contribution index and productivity, which means that the scrum master is productive when he looks at other people, meaning he is the initiator of contacts, a behavior which is expected from a project manager.

While the betweenness and degree correlations with productivity and creativity are not significant, they are also positive, which seems to indicate that the scrum master is *swarm creative*.

Table 3 resumes these findings for the six developers who filled out the most daily surveys. As the table shows, the correlations are weak, and frequently non-significant, so these results are only indications of a possible trend that need to be verified or rejected in further work. But we still believe that this pattern is interesting enough to merit mention.

	<i>Creativity</i>						<i>Communication</i>					
	412	419	477	436	438	458	412	419	477	436	438	458
CI	-.52*	-.5	-.2	.45	.43	.07	.29	-.1	-.62	-.17	.26	-.25
BC	-.70*	-.5	-.3	.27	.34	.19	.03	-.1	0	-.28	-.2	-.53*
audio_sum		-.96**										
audio_mean		-.92**		.6								
energy_stdv		-.83*		.5								

Table 3. Pearson correlations between badge metrics and self-assessed individual creativity (left) and communication (right) ratings (* p<0.1 ** p<0.05)

To resume the results of table 3, the *swarm creatives* (left three individuals 412, 419, 477 of table 3) feel most creative when they

- are in the center of the people, i.e. have high betweenness centrality
- look at other people, i.e. have high contribution index
- talk a lot, i.e. have high audio mean
- move around a lot, i.e. have high energy standard deviation.

On the other hand they feel they communicate most when *others* communicate with them.

The *lonely geniuses* (right three individuals 436, 438, 458 of table 3) feel most creative when they

- are left alone, i.e. have low betweenness centrality
- do not have to look at other people, i.e. have low contribution index
- talk with a lower voice, i.e. have low audio mean
- sit very quiet, i.e. have low energy standard deviation.

They feel they communicate most when they are the *active* part in the communication process.

2.3. Aggregated Team Evaluation

For our team evaluation we have combined all daily network metrics and surveys into one virtual actor. The first finding is the strong correlation between creativity and productivity, which means that software developers feel creative and productive at the same time. This also fits the self-image of a software developer, who sees the software development process as a creative process.

	<i>Productivity</i>	<i>energy_stdv</i>	<i>energy_mean</i>	<i>audio_mean</i>	<i>audio_sum</i>
Creativity	.683* (N=144)			0.360* (N=67)	
Flow		0.251 (N=144)			
Communication				-.25 (N=77)	-.19 (N=144)
Stress			0.374* (N=67)		
Mgmt_Interact				-.28* (N=77)	

Table 4. Correlations between badge metrics and self-assessed combined ratings on the group level (* p<0.1)

As our teams are made up by a mix of lonely geniuses and swarm creatives, we do not find a correlation between creativity and betweenness on the team level. Creativity of programmer teams therefore seems to be more dependent on individual characteristics of a programmer. One interesting correlation on the team level however is between the average volume of speaking of the team and creativity: the louder on average team A speaks, the more creative the team feels (0.360*). On the other hand the less management interaction team B experiences, the louder it speaks. Not surprisingly, a high level of physical activity predicts a high subjective feeling of stress. Finally we also defined flow as creativity/stress for each day, i.e. the more creative and the less stressed a programmer feels on any given day, the higher the flow experience. Quite surprisingly, we find positive, although non-significant correlation between flow and *energy_stdv*. This means that our group of programmers feels more in flow when they have a varied activity pattern during the day.

2.4. Measuring Trust and Social Network Position

Besides creativity we also asked programmers about the trust they placed in the organization and into each other. Programmers answered the questions shown in table 5 once during the project.

TEAM_TRUST_Honesty	I trust that the people in my team are completely honest with me.	{1 I strongly disagree...5}
TEAM_TRUST_OrgInterests	I trust that the people in my team put the organization's interests before their own.	{1 I strongly disagree...5}
TEAM_TRUST_CaringPersonal	I trust that the people in my team care about my well-being.	{1 I strongly disagree...5}
TEAM_TRUST_Expectations	I trust that the people in my team have consistent expectations of me.	{1 I strongly disagree...5}
TEAM_TRUST_Sacrifices	I trust that the people in my team would make sacrifices for our organization.	{1 I strongly disagree...5}
TEAM_TRUST_AcknowledgingMistakes	I trust that the people in my team would acknowledge their own mistakes.	{1 I strongly disagree...5}

Table 5. Trust-related survey questions

We then associated the results of this survey to the sociometric badge related metrics introduced in table 2. Table 6 displays our findings.

	contribution index	betweenness centrality	energy_stdv	audio_mean	audio_sum
TEAM_TRUST_Honest	-.692**	.674**	-.610*	-.120	-.535*
TEAM_TRUST_OrgInterests	-.027	.056	-.164	.618*	.268
TEAM_TRUST_CaringPersonal	-.360	.332	-.543*	-.248	-.383
TEAM_TRUST_Expectations	-.129	-.056	-.777**	.014	-.176
TEAM_TRUST_Sacrifices	-.132	.031	-.567*	.275	.043
TEAM_TRUST_AcknowledgingMistakes	-.218	.290	-.693**	-.402	-.594*

Table 6. Pearson correlations between trust survey and social badge readings (N=14) (* p<0.1 ** p<0.05)

The more people trust that other team members are completely honest with them, the more central they are in the social team network (0.674**) and the more they are being looked at, i.e. the more negative is their contribution index (-.692**). Also, the less people talk, the more they trust that others are honest with them (-.535*). Finally, the more they are in a stable energy state, i.e. the less they oscillate between low and high states of energy, the more they trust in other people's honesty (-.610*). The same correlations also exist for the belief of one person into the others caring about them, although only the energy_stdv correlation is significant.

Combining these results – the most trusting people are the most central ones, with the creativity results of the previous section, where we found indications for two types of creatives, the swarm creatives, and the lonely geniuses, we therefore speculate that the swarm creatives might be more trusting, while the lonely geniuses might harbor some mistrust against their collaborators, further causing them to prefer working in self-imposed isolation.

In the next section we extend the analysis of personality characteristics from face-to-face interaction archives to e-mail archives. The aim is to predict personality characteristics even from non-face-to-face communication patterns.

3. Measuring personality characteristics through e-mail exchange

In a distributed course with students from three different countries (Italy, Germany, Finland) students formed seven small teams of three to five students, where participants of each team were non-co-located, i.e each team had members from all three countries. The task each team had to solve was highly creative: it consisted of analyzing an online community or communication archive, and coming up with recommendations of how the online community could improve its work. One team, for example, analyzed communication and leadership structure of a 50 people software company through its e-mail network. Another team identified IT trends through Web Coolhunting (Gloor & Cooper 2007), one team participated in the Netflix collaborative filtering competition, yet another one identified large-scale communication patterns by looking at a countrywide archive of mobile phone records. To measure inter- and intra-team communication, all e-mail traffic was recorded by cc'ing the messages to dummy e-mail boxes, which were then analyzed with the dynamic social network analysis tool Condor (Gloor & Zhao 2004).

To compare personality characteristics with in-class e-mail communication behavior, 17 German participants also completed an FFI personality test (Hough 1992). We then compared the personality test with their e-mail behavior by analyzing the e-mail class network of all 34 students participating in the course plus instructors and external advisors. As one of the objectives of this course was to teach online communication, students were encouraged to communicate a lot. Some student teams had extensive outside contact to companies, as they did projects in collaboration with these companies. Other students reached out to course participants of prior years for technical and tool advice, leading to a very rich communication network (figure 7).

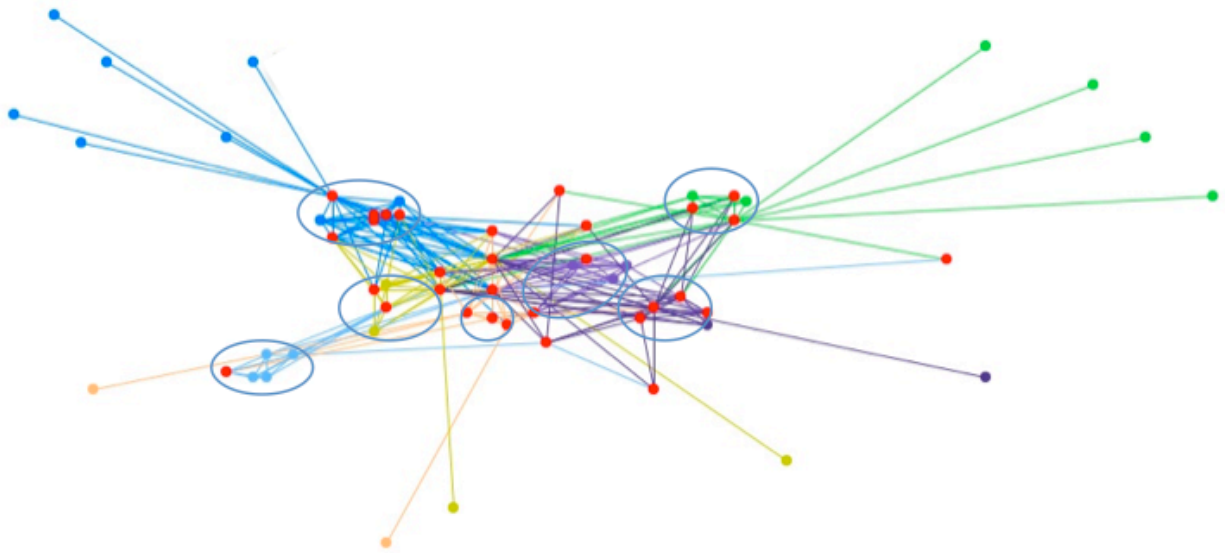


Figure 7. E-Mail Network of 7 student teams.

As figure 7 illustrates, the student teams are clearly recognizable, marked by the blue circles. The instructors are the non-marked red circles in the center, while the external advisors and outside project partners of each team are also clearly visible, e.g. the blue dots in the upper left of figure 7 communicating with the blue team in the upper left circle. Actors are marked in red if they communicate with more than one team. As figure 7 depicts, most team members of the seven teams are red dots, which shows that they communicate over team boundaries with members from other teams.

3.1. Findings

Table 7 displays our results. As the table shows, not all students filled out the FFI survey completely, and we also were not able to compute ART (the average response time to an e-mail) for all students because of inconsistencies in their e-mail headers and timestamps.

		ABC	ART	ADC	ACI
Neuroticism	Pearson Correlation	-.472	-.035	-.379	-.551*
	Sig. (2-tailed)	.088	.918	.182	.041
	N	14	11	14	14
Extroversion	Pearson Correlation	.421	-.136	.359	.094
	Sig. (2-tailed)	.092	.659	.157	.718
	N	17	13	17	17
Openness	Pearson Correlation	.572*	-.439	.605*	.005
	Sig. (2-tailed)	.016	.134	.010	.983
	N	17	13	17	17
Agreeability	Pearson Correlation	.544*	-.459	.539*	.170
	Sig. (2-tailed)	.029	.134	.031	.530
	N	16	12	16	16
Conscientiousness	Pearson Correlation	.353	-.276	.336	.067
	Sig. (2-tailed)	.180	.384	.203	.807
	N	16	12	16	16

*. Correlation is significant at the 0.05 level (2-tailed).

Table 7. Correlation between big five FFI personality characteristics and social network metrics of e-mail network. (ABC:actor betweenness centrality, ART: average response time to an e-mail, ADC: actor degree centrality, ACI: actor contribution index)

With the exception of conscientiousness, we get significant results for all big five personality characteristics. This means, that the e-mail behavior of a person indeed predicts her personality. In this case study, we find that the bigger betweenness centrality of a student is in the course network, the more agreeable she is (.544*). Agreeability is also positively correlated with degree centrality (.539*). This means that the more communication partners a student has, the more agreeable she is. The same is true for openness, which is also positively associated with betweenness centrality (0.572*) and degree centrality (0.605*). If we assume that creative people are open for new things, it seems as if centrality in the e-mail network might go along with creativity. Contribution index is negatively correlated with neuroticism, which means that the more somebody is a sender of messages (sending more than they receive), the smaller is his neuroticism. Additionally, although non-significant, the speed with which a person answers her e-mails within the team also predicts high agreeability and openness.

In sum, these e-mail based results deliver further arguments to support our hypothesis of swarm creative people, who combine high openness and agreeability and low neuroticism, and are recognizable through central position in the e-mail network and high responsiveness.

4. Further Work and Conclusions

Based on analyzing personality characteristics through mining electronic interaction archives, we found first indications that there might be two different types of knowledge worker creativity, the “lonely genius” - feeling most creative when on his/her own with lower trust in others, and the “swarm creative” - most creative when in the midst of other people, and with higher trust. Swarm creatives are recognizable both through their face-to-face interaction and their e-mailing behavior.

This project therefore motivates further work towards identifying which personality characteristics associated with creativity might be predicted by social networking and interpersonal interaction behavior.

References

- Back, M.D. Stopfer J.M. Vazire, S. Gaddis, S. Facebook Profiles Reflect Actual Personality, Not Self-Idealization *Psychological Science* 21(3) 372–374, 2010.
- Crawford, B. Claudio León de la Barra. C.L. Letelier, P. Communication and Creative Thinking in Agile Software Development, in IFIP International Federation for Information Processing Volume 277, Computer-Aided Innovation (CAI), Gaetano Cascini (Boston, Springer). pp. 205-216. 2008.
- Csikszentmihalyi, M. *Creativity: Flow and the Psychology of Discovery and Invention*. New York: Harper Perennial. 1997
- Gloor, P. Laubacher, R. Dynes, S. Zhao, Y. Visualization of Communication Patterns in Collaborative Innovation Networks: Analysis of some W3C working groups. ACM CKIM International Conference on Information and Knowledge Management, New Orleans, Nov 3-8, 2003.
- Gloor, P. Capturing Team Dynamics Through Temporal Social Surfaces, Proceedings of 9th International Conference on Information Visualisation IV05, London, 6-8 July 2005.
- Gloor, P. Cooper, S. *Coolhunting – Chasing Down The Next Big Thing*. AMACOM, NY, 2007.
- Gloor, P. Zhao, Y. TeCFlow - A Temporal Communication Flow Visualizer for Social Networks Analysis, ACM CSCW Workshop on Social Networks. ACM CSCW Conference, Chicago, Nov. 6. 2004.
- Gloor, P. Oster, D. Raz, O. Pentland, A. Schoder, D. The Virtual Mirror - Reflecting on Your Social and Psychological Self to Increase Organizational Creativity, *Journal on International Studies of Management & Organization*, M.E Sharpe. vol. 40, no. 2. 2010.
- Hough, L. M. The “big five” personality variables - construct confusion: Description versus prediction. *Human Performance* 5(1):139–155. 1992.
- Olguin Olguin, D. Waber, B. Kim, T. Mohan, A. Ara, K. Pentland, A. Sensible Organizations: Technology and Methodology for Automatically Measuring Organizational Behavior. *IEEE Transactions on Systems, Man, and Cybernetics-Part B: Cybernetics*, Vol. 39. No. 1, February 2009. pp 43-55.
- Kidane, Y. Gloor, P. Correlating temporal communication patterns of the Eclipse open source community with performance and creativity, *Computational & Mathematical Organization Theory*. Volume 13, Issue 1 (March 2007), ISSN:1381-298X, 17 - 27, 2007.
- Pentland, A. *Honest Signals: How They Shape Our World*, MIT Press, Cambridge MA. 2008.