Facilitating Creativity in Collaborative Work with Computational Intelligence Software

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Abstract:

The use of computational intelligence for leveraging social creativity is a relatively new approach that allows organizations to find creative solutions to complex problems in which the interaction between stakeholders is crucial. The creative solutions that come from joint thinking—from the combined knowledge and abilities of people with diverse perspectives—contrast with traditional views of creativity that focus primarily on the individual as the main contributor of creativity. In an effort to support social creativity in organizations, in this paper we present computational intelligence software tools for that aim and an architecture for creating software mashups based on the concept of affinity space. The affinity space defines a digital setting to facilitate specific scenarios in collaborative business environments. The solution presented includes a set of free and open source software tools ranging from newly developed brainstorming applications to an expertise recommender for enhancing social creativity in the enterprise. The current paper addresses software design issues and presents reflections on the research work undertaken in the COLLAGE project between 2012 and 2015.

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I. Introduction

The complex problems faced by organizations today require creative solutions that come from joint thinking—the combined knowledge and abilities of people with diverse perspectives. While traditional views of creativity have mostly focused on the individual as the main contributor of creativity, recent findings suggest that most scientific and business innovations come from interactions with others and from joint thinking, thus emphasizing the social dimension of creativity [1], [2]. The knowledge relevant to a problem is often distributed among many stakeholders who have different perspectives and background knowledge [3]. Bringing together different points of view and trying to create a shared understanding among all stakeholders are key underpinnings of creative collaborative work that can lead to new insights, ideas, and artifacts [4]. Creativity in collaborative work usually springs from collaboration and conversation [5]. Working together in collaboration can stimulate individual creativity due to the unique perspectives that the individual brings to the tackled problem [6]. In the early stages of idea generation, the individual shares knowledge while at the same time receives information from others that might build on ideas suggested by others [7]. Opportunities for discovering more creative solutions can be found by collaborating with others and, in so doing, by making use of the various individuals' different perspectives, knowledge and expertise.

Computational creativity has focused on applying technologies to assist humans in thinking outside the box and expanding their exploration boundaries [8, 9]. Applications of computational creativity range from the arts (e.g., [10], [11]) and science (e.g., [12]) to everyday activities such as cooking—generating new ingredient combinations and finding new flavors [13]. Researchers have often tried to pair machine creativity with the creative capabilities of individuals to generate the best possible outcomes and results. Still, existing computational creativity approaches have mostly focused on supporting or imitating individuals in being creative. Computational support for social creativity has been limited, primarily addressing computer media and technologies for helping people work together and share knowledge. However, more can be achieved in helping users interact with artifacts and tools, facilitating access to novel perspectives, and providing opportunities for serendipitous encounters that have the potential to stimulate new ideas [7]. For example, social media have been shown to leverage social creativity by acting as conversation enablers [6] and as a source of information and stimulation [14]. Having loose ties to many other individuals in different social circles provides access to a large variety of information and diverse perspectives, which act as sources of creative inspiration.

Computational intelligence (CI) [15] can enhance social creativity software by enabling users to be aware of and draw on the experiences of others, by discovering, shaping and rendering inspirational resources, by harnessing diversity, and by providing mechanisms to contribute the results of creative work back to the community. For example, CI software can analyze social networks and recommend inspirational content from like-minded friends or from influential thinkers. In this paper, we introduce a set of free and open source CI software and describe how this software has been applied to enhance creativity in collaborative work. We focus on software design issues such as architectural choices for a seamless mashup of CI software into applications and user-friendly interfaces for delivering end-to-end social creativity support software. To this end, we introduce the concept of the affinity space that defines a digital setting to facilitate specific scenarios in collaborative business environments.

We organize the rest of this paper as follows: First, the design method that was used to develop creativity support software and the specific tools developed are presented in Section II. Then, Section III introduces the architecture being able to integrate the latter tools. Section IV presents a use-case-specific application to show how the presented tools and the mashup architecture considered enhance social creativity. Finally, Section V contains the main conclusions and lines of future research.

II. Developing Computational Intelligence Software tools for Social Creativity

The design of social creativity software is driven strongly by user needs that are latent and therefore difficult to elicit using traditional requirements elicitation approaches. In this section, we outline the design method that was used to develop creativity support software by working with users on the case studies of the COLLAGE research project (www.projectcollage.eu). The main goals of COLLAGE project were to design, develop, and validate innovative software services and tools to support social creativity processes. We followed a user-centric software design approach in which user needs and requirements were elicited and refined in an iterative and cooperative manner, including phases of divergent thinking and of harmonization of perspectives. We proceeded iteratively with more structured refinement of the requirements. In each cycle, we sought to understand, describe, and define the scope of the work contexts of our case studies in terms of relevant software, human actors, information resources, and systems that interact with elements of the new socio-technical system. Derived context models were used in creativity workshops with the aim of leveraging users' input to generate and select ideas by combining needs and solutions. Selected ideas were represented as storyboards from which key requirements were extracted and corresponding software prototypes were built. As a result, we developed six free and open source CI tools with different objectives for social creativity (**Table 1**).

Table 1. Free and open source CI software for social creativity.

Service	Description and URL	Participants
Cruise	CRUISE (Creative User Centric Inspirational Search), http://cruise.imuresearch.eu/ui, is a search tool that lets users interactively explore the available information space, and relate concepts, ideas and elements in order to provide them with surprising or inspirational information. One can use it to uncover unexpected information, visualize relevant information from the social chatter (e.g. Twitter), and use it as clues for exploring the Web, or to receive personalized recommendations for inspirational information and exploration actions.	1 or more
HatParty	HatParty, http://hatparty.eu/, is an application to challenge different teams to find new ideas to solve a problem. This gamified brainstorm does not stop there because the ideas each team submits are then evaluated by the other teams in order to filter and get the bost ones. HatParty uses game mechanics such as timed sessions, goals, reputation points, rating, racing, and social recommender such as inspirational search to help groups of 3 to 8 people generate a large number of ideas and rank them in record time.	3 to 8
StarQuest	StarQuest, http://starquest.eu/, improves group activity through the use of social constructs and game mechanisms such as turn-taking, stretch-goals, nudging, competition, cooperation, social points, and loss aversion. It encourages peer assessment, reflection and feedback, and reduces social loafing. StarQuest is presented as an asynchronous multi-player idea development platform for helping teams research, gather and relate existing artifacts, create new artifacts, log their social creativity process, provide peer assessment, and improve their connections and knowledge.	2 to 20
Creative	BeCreative, http://becreative.city.ac.uk/, is a creativity toolbox that provides advice on many different problem-solving techniques, from problem definition to idea generation, selection and implementation. Users of BeCreative can describe their problem and retrieve relevant techniques completed with descriptions, step-by-step guides and usage information to help organize and run workshops or team-working sessions.	1 to 15
BrightSparks	Sometimes your point of view is not the one needed to find a solution to a problem. Have you ever wondered how a genius or a historical figure would solve something you are struggling with? BrightSparks, http://brightsparks.city.ac.uk/, searches the web to provide problem solvers with support from famous and relevant characters. Just let the application select a random character, learn about him or her with the charts BrightSparks provides and gets a new focus on your problem. The tool is suitable for unstructured problem solving with open questions and answers, and can be used effectively in just a few minutes.	1
CER	The COLLAGE Inspirational Expertise Recommender (CER), http://www.htstats.com/collage/, service recommends collaborators based on an appropriate mixing and an optimal matching of their characteristics and the user's preferences. It relies on several dimensions, according to the availability of data in the profiles of the candidates such as areas of candidates' expertise, tools the candidate is familiar with, etc. CER can get the user requirements from a user's profile and utilizes fuzzy aggregators to compute the match between the user requirements and the candidates' profiles.	1

In the next subsections we describe three of the said software tools in more detail. These three tools have been selected to give an overview of the most significant COLLAGE outcomes. Moreover, these three tools are used in an affinity space mashup application serving the needs of a use case described in Section III.

A. CRUISE: Search for Inspirational Content

CRUISE supports the discovery of inspirational resources through a collective intelligence approach that uses clues from social chatter (e.g., Twitter) and uses them to enable users to explore information available in specific repositories, such as intranets, and the Web at large. The exploration starts with the user entering a set of terms as an initial entry point to their exploration. The tool uses these terms and queries Twitter for the most recent popular tweets. Then, it constructs a cloud of high frequency terms found in recent popular tweets as well as tweets from the user's social networks (see Figure 1). It can also retrieve linked images and videos. Users can click any of the items for more details or can make multiple selections of items appearing on the word cloud and add them into their 'collection'. We use collections as new queries, giving users the capability to continue their exploration in a new browser window by selecting more items from the cloud to restrict their search or to relax it by removing items.

Figure 1. Creative User-Centric Inspirational Search (CRUISE).

CRUISE combines diversification of content and sources with a newly developed algorithm for filtering content in order to enhance serendipity, i.e., the unexpectedness yet relevance and usefulness of results [16]. We *diversify* the results using an algorithm that re-ranks results with the goal to boost in the top ten results content that is related to all possible aspects of the query. For this purpose, we use the canonical version of Maximal Marginal Relevance (MMR) framework [17]:

$$MMR = \text{Arg} \max_{D_i \epsilon \mathrm{R} \backslash S} [\lambda Sim(D_i, Q) - (1 - \lambda) \max_{D_j \epsilon S} Sim(D_i, D_j)] \quad (1)$$

where S is the set of documents, $R \backslash S$ is the set of as yet unselected documents, $Sim(D_i,Q)$ is the similarity of the document with respect to the query Q, $Sim(D_i, D_j)$ is the similarity between the current document and a document in previous ranks and λ is a parameter that optimizes a linear combination of the criteria of relevance and diversity. When $\lambda=1$ then the original relevance-ranked list is produced, whereas when $\lambda=0$ a maximal-diversity list of documents is generated. We consider the snippet of each result item as a document. Since we rely on public search Application Programming Interfaces (APIs) when searching the Web and hence do not know the native similarity scores of the results with respect to the query, we compute them by exploiting the documents' positions in the result list as follows [18]:

$$Sim(D_i, Q) = \frac{N - Pos(D_i)}{N}, \qquad (2)$$

where *Pos*(D_i) is the position of document *d* in the query result list returned by the public search API and *N* is the size of the list. The document ranked first gets a value of *Sim*(D_i,*Q*)=1 while the last one gets a value of *Sim*(D_i,*Q*)= 1/*N*. In order to compute the similarity between the documents in the result set *R* we use cosine similarity:

$$Sim(D_i, D_j) = \cos(\theta) = \frac{D_i\, D_j}{||D_i||\, ||D_j||}, \qquad (3)$$

Where θ is the angle between the vectors of documents. We use the Vector Space Model (VSM) [19] to represent each document as a vector, the components of which represent the importance of a term using TF-IDF metrics, given a bag of words that derives from the documents in *R* [20]. For the lexicographic analysis (tokenization, stop words removal and stemming) of the documents in *R*, we use the Apache Lucene Standard analyser.

Our diversification algorithm starts with the representation of each document as a vector of all words included in the index and the calculation of the similarity of each document with the query. It then proceeds with applying MMR that starts by placing the first document in the final list of documents, which will be the diversified bucket of documents. It iterates through the remaining documents and calculates the MMR score for each one summing its similarities with each of the documents that are already in the final bucket. The document with the maximum MMR value will occupy the place of the next element in the final bucket of documents. The process continues until all documents are placed in the bucket. A detailed description of the algorithm is provided in [21].

We tackle *unexpectedness* primarily by focusing on 'unexpectedness from the source' [22]: a balancing act between relevance of content to the query and distance from the profile of the content source. In our case, we ensure relevance by searching for tweets relevant to the query. To evaluate distance, we require the followees' profiles. We do so by following the bag of words model [23] by constructing a dictionary with related frequencies per user. In addition, we apply a custom filter to the results in order to filter out redundant words. Finally, each bag contains the words included in the user's tweets, alongside how many times they have been used. Each profile is represented by an *n*-entry vector containing the term frequency of each of the *n* distinct words in the bag. Similarly, queries are also represented as vectors of terms. In order to measure similarity, we apply cosine similarity on the two vectors to assess divergence or closeness:

$$Sim(U_i, T_j) = \cos(\theta) = \frac{U_i \cdot T_j}{||U_i||\,||T_j||}, \tag{4}$$

where U_i is the vector of the user profile, T_j is the vector of the query, θ is the angle between the two vectors.

We have experimented with several similarity values as a threshold for the filtering of unexpected yet related content. Our tests showed that a similarity value less than 0.15 produced quite unexpected yet related results. We filter the set of relevant tweets based on this value and further proceed with the ranking of the results. This threshold, though, is dependent on each user's perception and thus evaluation with a large number of users is needed to come up with a definitive value recommendation.

Finally, we address *usefulness* primarily by focusing on social power, which can affect the user perception of usefulness as pointed out in information diffusion theory [24]. We define the content that derives from those users followed by a large number of followers or those tweets re-tweeted many times as socially powerful. The number of followers of a user indicates how trustworthy and useful he/she is perceived by the remaining users as a source of information [25]. We sort the tweets according to the number of followers favouring those that derive from the users with a higher number of followers and boosting up to higher positions.

B. "BrightSparks": Transformational Creativity Using Personas

BrightSparks implements an adapted version of the Hall of Fame creativity technique that allows a problem-solver to explore how well-known personas (social roles or a characters played by an actor either fictional or real) would solve a particular problem thanks to their more extreme characteristics and traits. Unlike the original Hall of Fame, it does not use quotes but rather creative clues applied to the personas for use during creative design tasks. BrightSparks invokes a computational service that supports transformational creativity (encouraging problem-solvers to think about the space of possible ideas in a different, and often larger, way) and exploratory creativity (enabling problem-solvers to explore new spaces more effectively with simple guidelines) by combining and mixing a problem or idea with extreme personas selected from a static list of more than 150 personas or from the web.

BrightSparks implements two types of codified knowledge: (i) knowledge about the types of information about a persona to present during creative problem-solving, and (ii) knowledge about the clues to use to prompt creative thinking about a persona. The following types of information about each persona were externalized as important during a creative problem-solving process: (i) the name and a photograph of the persona, e.g., Jonathan Ive; (ii) the role of the persona, e.g., product designer; (iii) important defining characteristics of the persona described in less than 100 words, e.g., "he believes in the importance of materials and making them part of the design process"; (iv) the broader persona type, to enable the classification of personas in categories such as design and art.

Similarly, BrightSparks externalizes four types of codified clues specified for users with personas during creative design tasks. Firstly, the persona as stakeholder: Imagine that the persona is a stakeholder in the design process and explores what needs and knowledge the stakeholder would contribute. Secondly, the persona as an inspiration or role model for the product or service: Imagine that the persona has characteristics and/or qualities that the product or service should have. Thirdly, the persona as emotional inspiration: Imagine that the persona is a source of emotional engagement in the design process and evokes different emotions in the designers and other stakeholders. Fourthly, combining personas to generate new personas: Imagine that the persona is combined with another persona to generate new combinations of characteristics and qualities that can then provide a new persona as a stakeholder or an inspiration or role model for the product or service.

The software architecture of BrightSparks is depicted graphically in Figure 2. The current version of the repository has stable, codified knowledge about 160 fictional and real personas.

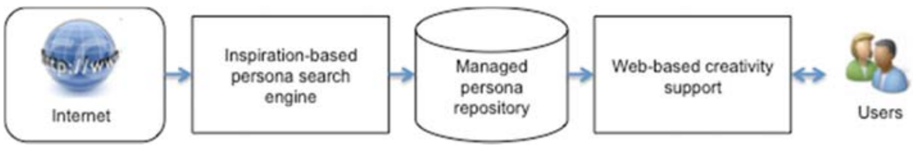


Figure 2. The software architecture of the BrightSparks web-based software tool.

The BrightSparks creative problem-solving web page, with the demonstration persona *Jonathan Ive*, is shown in Figure 3. The web page presents stored, codified knowledge about each persona: name, role, type, characteristics, and image. The page is divided into two parts. The left side presents information about each retrieved persona and features for manipulating personas, and the right side presents the codified creative clues instantiated for the persona currently shown on the left side of the page.

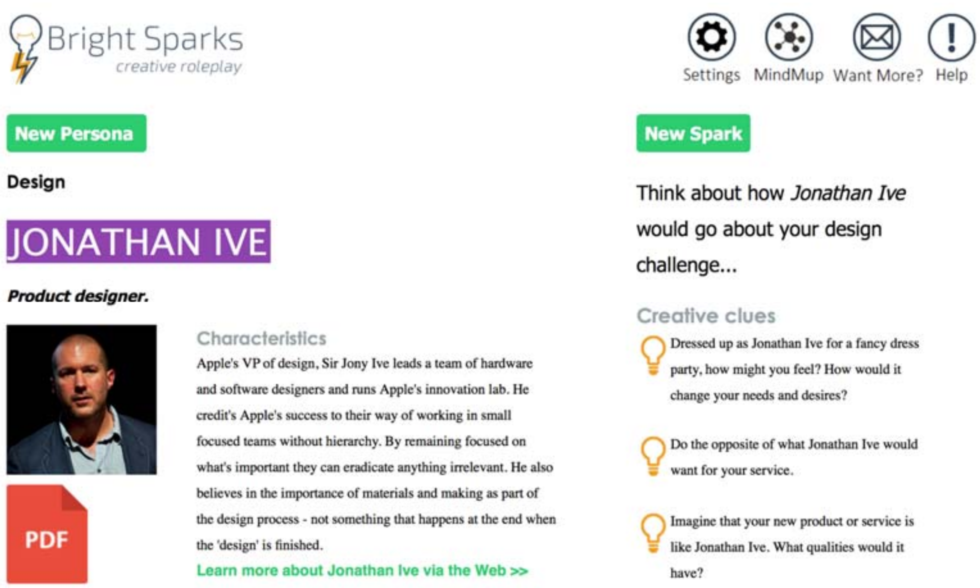


Figure 3. The BrightSparks web page for creative problem-solving showing the Jonathan Ive persona.

C. "CER": Finding the Right Expert

Finding expertise effectively helps organizations identifying collaborators in order to unlock knowledge, solve interdepartmental problems, and accelerate processes of creativity and innovation. For organizations, finding an expert can be challenging because experts are disperse and vary in level of knowledge on a topic. Their knowledge is difficult to qualify and changes frequently [26]. In addition, experts can be culturally isolated when business units are disconnected from one another [27]. Social creativity is leveraged by interaction among users with different backgrounds, opinions and levels of expertise, ultimately leading to higher creativity and inspiration.

Collage Expertise Recommender (CER) uses linguistic descriptions of candidates and a fuzzy aggregation function to summarize the information obtained. Fuzzy systems and in particular fuzzy aggregations are used in a wide range of problems in different application fields. A detailed overview of freely available and open source fuzzy systems software can be found in [28]. The CER uses four dimensions to suggest people based on their expertise, qualifications, proximity, and availability. It focuses on three main features:

1. The strength of the relationship between a candidate and a specific knowledge area.

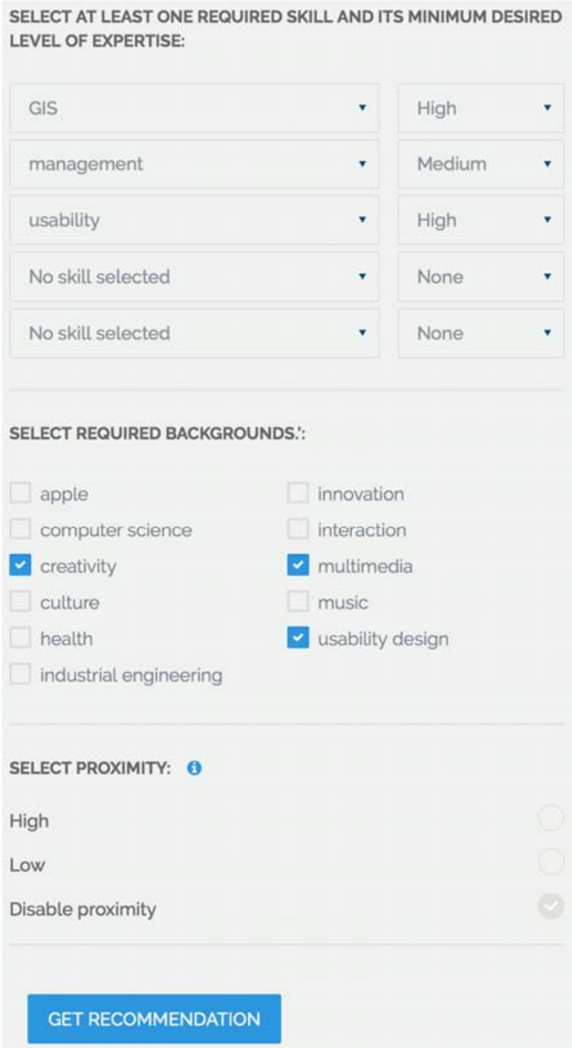
2. The candidate’s suitability and availability to provide information.

3. The development of personal profiles based on qualifications.

CER assesses candidates’ profiles according to the user’s preferences by determining a partial assessment of different attributes. These attributes consider not only the candidate’s level of expertise in different knowledge areas but also other cognitive aspects obtained from the interaction between the candidate and the system. In addition, CER considers the candidate's current availability and location as attributes.

A user may be better able to define the level of expertise required in relative terms such as “low”, “medium” and “high”. Therefore, a linguistic approach to describing the user requirements is considered. We use these linguistic terms to match user requirements with candidate profiles. The user—the seeker of expertise—can therefore define the skill and level of expertise desired.

Figure 4 depicts the CER user interface that allows the seeker to specify her preferences in order to get a proper recommendation.



Fi 4. CER web page (requirements selection).

To aggregate the partial assessments into a global index that reflects the overall adequacy of the candidate's profile with respect to the user requirements, we consider a fuzzy ordered weighted averaging (OWA) aggregation operator. OWA operators [29] are a type of weighted mean that enables the weights of each variable to be tuned according to their relative importance for each candidate. The computation of these weights is guided by a linguistic quantifier [30]. More specifically, the quantifier 'most of', represented via a Regular Increasing Monotone (RIM) function Q is considered: $Q(r)=r^{1/2}$. Then, the weights are computed by the following expression: $w_i = Q\left(\frac{i}{n}\right) - Q\left(\frac{i-1}{n}\right)$, i=1,$\cdots$,n where n is the number of values to be aggregated. For each possible candidate, variable values are ordered before being weighted. Based on the user requirements, the system should recommend experts according to a ranking of individuals' similarities and differences. In addition, the recommendation output shows the selected candidates in rows and their adequacy for each requirement in columns (Figure 5).

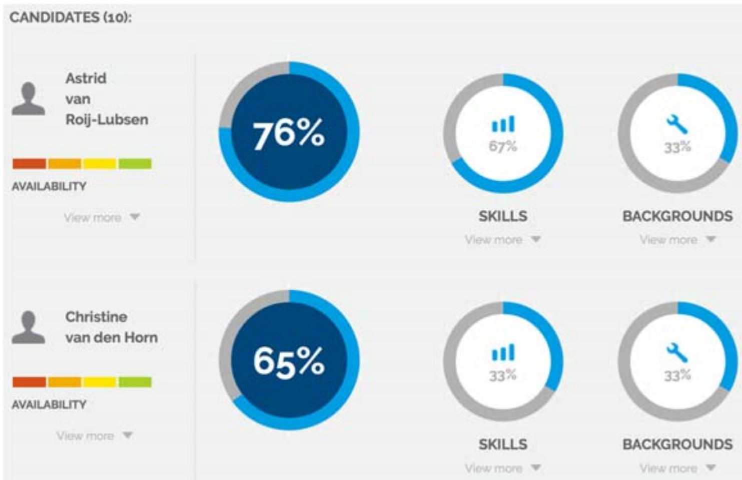


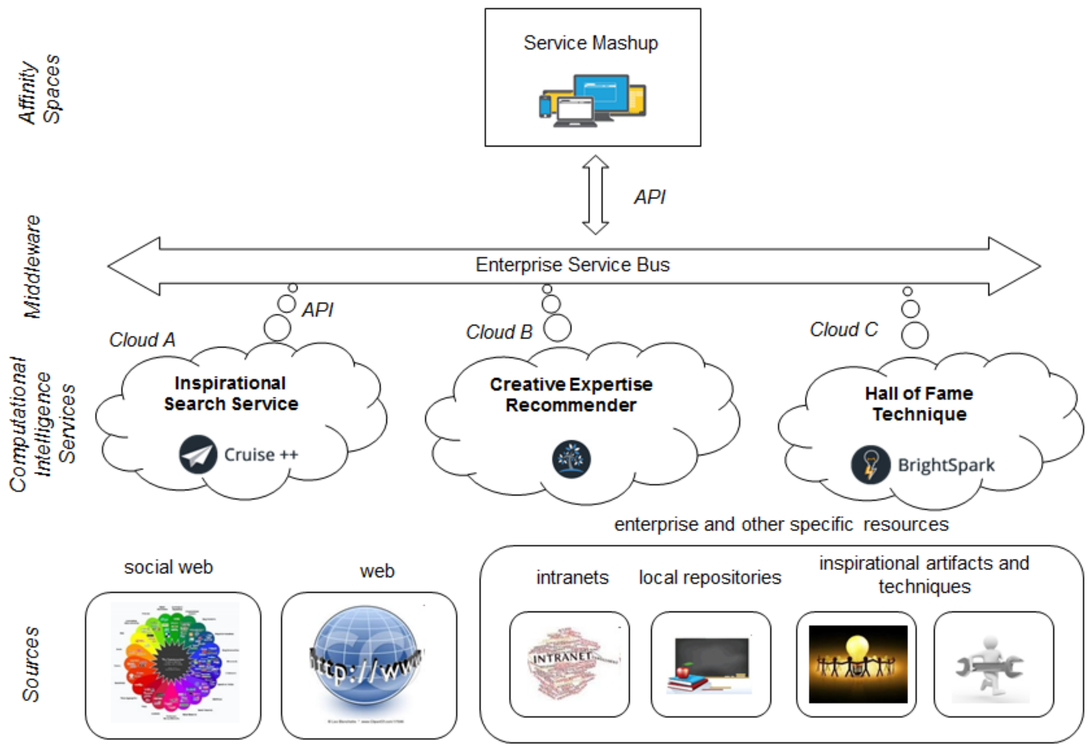
Figure 5. Example of a final ranking of recommended candidates in CER.

A more exhaustive description of the methodology employed by CER is detailed in [31].

III. A Service-Oriented Mashup Architecture

To support the dynamic software design and development approach outlined in Section 2, we need a flexible architecture capable of easily integrating the developed tools with additional third-party software and building affinity spaces that are highly customized for each specific use case. In addition, the architecture should support distributed deployment of tools and loose coupling between them so as to enable quick roll-out of new releases of affinity spaces. The architecture employed is based on the software as a service (SaaS) cloud computing model, in which CI software tools providing specific creativity support functionalities are deployed as services on different cloud providers. Moreover, it exploits the concept of "mashups", web-based applications that combine content or services from more than one source into an integrated experience. Services connect to a mashup via an endpoint, which is the address that a service must use in order to perform "actions" with content such as Create, Retrieve, Update and Delete (CRUD) actions. In our architecture, these actions are mapped to Get/Put/Post/Delete operations.

Our architecture considers two types of mashups. On the one hand, mashups by aggregation that simply assemble sets of information from different sources side by side within a single interface. They do not require advanced programming skills and are often a matter of cutting and pasting from one site to another. On the other hand, we consider mashups by integration that create more complex applications integrating different APIs in order to combine data from different sources.



Fig[illegible]. Architecture for creating service mashups.

Figure 6 details the designed architecture, which consists of the following four main layers:

1. The Affinity Spaces (or presentation layer). Affinity spaces represent the front-end of the architecture and aim to leverage social creativity by facilitating interaction between users and CI services. To this end, affinity spaces leverage the possibility to mashup cloud-enabled tools and services from multiple sources into a user-controlled

space. This ranges from simply juxtaposing content retrieved from different sources (e.g. intranets, Twitter, …) into a single interface (mashup by aggregation) to a more complex remixing of different APIs into an integrated application to create entirely different views or uses of the original data (mashup by integration).

2. Middleware. An Enterprise Service Bus (ESB) is used to integrate and orchestrate mashups of the cloud-enabled services, decoupling services and clients, regardless where the services are dislocated in the cloud, the protocol adopted or used technologies. It also supports secure user management, session control, and user authentication and enabling Single Sign On (SSO).
3. CI Services. These are key architecture components that support people to undertake creative activities. They can be installed potentially everywhere, from the application partners intranet to cloud servers such as Amazon EC2. The installation of the COLLAGE services on cloud servers offers advantages over dedicated, non-virtualized servers including scalability, almost unlimited storage capacity and flexibility.
4. Data Sources. The data sources layer provides access to external (like social web and the Web) and internal (like expert databases, intranet) resources.

Next, we explain in more detail how the proposed architecture makes it possible to mash up CI software into a specific Web-based affinity space. Additional examples of mashups in free and open source platforms, such as WordPress and Moodle, are available at: http://projectcollage.eu/alpha-services/.

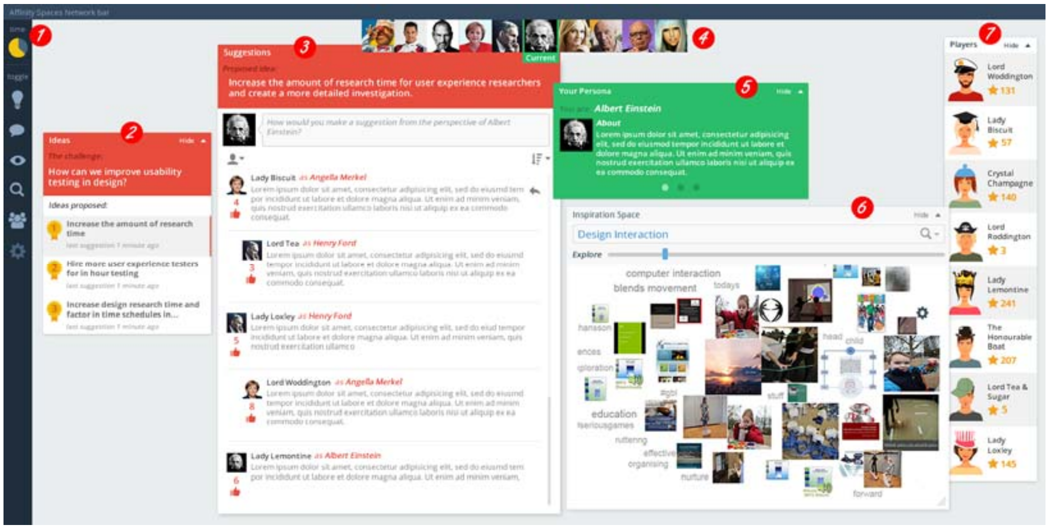
IV. A Case Study in Creative Research

We present a real example of how CI software can be mashed up in a use-case-specific application that exploits synergies between CI services. We worked with a team of professional concept developers from the Waag Society institute for art, science and technology (www.waag.org) to develop an affinity space for enhancing their creative work outcomes. The Waag Society conducts creative research in close cooperation with stakeholders from education, healthcare, culture and other sectors.

The concept developers envisaged an affinity space that would foster an open attitude for reconsidering existing concepts and approaches in a playful way so as to promote engagement. Users needed to be able to collaboratively engage in creative activities with other team members. Moreover, they would need to be able to search for information and receive inspiration for their projects as well as to find existing concepts, ideas and experts that are relevant to their projects. They asked for support in discovering relevant, trending topics from the social web by monitoring users' actions (for example, on social networks), profiling them, and using this information to recommend inspirational information that could assist users in generating new ideas. Finally, the concept developers enjoy reading comments posted by others about their ideas, so they asked for feedback mechanisms that would encourage people to keep submitting comments and suggestions and leverage a sense of ownership for their work.

A. Mashup Development: IdeaFocus

To address the aforementioned requirements, we developed IdeaFocus (Figure 7), an affinity space where concept developers can come together to generate ideas in a funny, collaborative environment, using game mechanics such as goals, reputation points and ratings to help small groups generate a large number of ideas and engage in deep creative debate with colleagues.



Figu IdeaFocus. Item 1: navigation bar (displays the time currently left in the session and buttons to hide/show panels). Item 2: ideas panel. Item 3: suggestion panel (allows users to express their opinions about the ideas in focus using the Hall of Fame technique, which prompts users to respond and debate from the perspective of known personas). Items 4 and 5: persona panels (display the persona that the user has currently become). Item 6: inspirational search (allows users to use the inspirational search service, CRUISE, by entering a term they wish to explore and gain ideas around). Item 7: player panel.

IdeaFocus has been implemented as a server-based mashup, which analyses and reformats the data on a remote server and transmit the data to the user's browser in its final form. A more exhaustive description of IdeaFocus is detailed in [32]. IdeaFocus mashes up several of the CI tools listed in **Table 1**. For example, to help concept developers discover inspirational clues, we mashed up CRUISE with BrightSparks in a way that allows persona-related clues and characteristics to be used to search the web for inspirational content. This mashup exploits the proven effectiveness of the Hall of Fame technique, which prompts users to respond and debate from the perspective of known personas, as well as the rich, far-reaching content-discovery capabilities of the inspirational search tool. To implement the aforementioned example mashup, the following steps should be followed.

1) Authenticating Users: Before embarking on mashingup services, one may want to employ user authentication through the Single Sign-On mechanism. To do so the user authentication service can be programmatically invoked using the following endpoint:

```
Get http://esb.exactls/COLLAGE/cas/user?start=0&ticket=xxx
Returns a JSON object with the currently authenticated users:
{
"users": [
```

```
{ "email": "user@example.com", "firstName": "john", "id": 1, "lastName": "doe", "login": "admin", "roles": [ "admin", "USER_MANAGER", "superadmin" ], "skills": [],"tools":[] }
      ]
}
```

Once users are logged in to IdeaFocus through the central authentication service of the ESB, they are automatically logged in to all services and can visit them seamlessly with no further configuration. In case of authentication failure, the authentication or any of the invoking services will raise one of the following exceptions: AuthenticationException, BadCredentialsException or AuthenticationServiceException.

2) Create a Session (StarQuest mashup): The following endpoint should be used to create a new session (so called 'quest') for enabling users to collaboratively access to linked services and to generate ideas.

```
POST https://private-25c5-gaminomics.apiary-mock.com/quests
RETURN JSON object with the new quest id
```

3) Create a Team Retrieval (CER mashup): The following endpoint should be used to retrieve the creation of a team. The first substep is to get the list of available skills and subskills/tools.

```
GET http://www.htstats.com/collage/er/{skills|tools}&token={token}
RETURN JSON object with the list of skills or subskills
```

Once the available items are clear, the user can ask for translating his/her preferences to specific requirements:

```
POST http://www.htstats.com/collage/er/translate&token={token}
RETURN JSON object with the explicit requirements
```

The final step is to ask for the recommendation by passing the requirements.

```
POST http://www.htstats.com/collage/er/request&token={token}
RETURN JSON object with the list of recommendations
```

All substeps should be run as many times as components of the team we want.

4) Persona Retrieval (BrightSparks mashup): The following endpoint should be used to retrieve one or all persona information pertinent to the search parameter.

```
GET
http://achernar.soi.city.ac.uk/HallOfFame/HallOfFameService/Service1.asmx?op=RetrieveAllPersonas
```

```
RETURN JSON object containing all current personas with image and natural
language statements describing attributes of the personas


GET
http://achernar.soi.city.ac.uk/HallOfFame/HallOfFameService/Service1.asmx?o
p=RetrievePersonaAdvanced
RETURN JSON object about the persona
```

5) Search the Web for Inspirational Content (CRUISE mashup): The following endpoint should be used to invoke CRUISE to search the Web or specific company sources for inspirational content:

```
GET http://esb.exactls.com/COLLAGE/iccs/is?ticket={ticket}&query={term}
RETURN JSON array of objects
[
{ "id": 0, "source": "twitter", "term": "streaming report", "data": [
"Canadians doubling time online with mobile devices, video streaming:
http://t.co/XCcRgmRj3a", ], "frequency": 0.06778420507907867 },
{ ... }
]
```

Note that the frequency count can be used by the user interface rendering code to size the scale of the fonts used to display results, effectively creating a tag cloud effect (see Figure 1). Results may be text-based, images, or videos. Also note that as query terms for this service one can use the JSON object retrieved using the BrightSparks service in the previous step so that persona clues and characteristics to be used to trigger CRUISE to search for inspirational content.

6) User Interface Development: The user interface of IdeaFocus has been developed using the iframe Java programming paradigm. Iframes allow services to communicate with the parent page through events: the sender (the CI service inside the iframe) sends a string to the parent window via a JavaScript event such as the following:

```
window.parent.postMessage("my string", "*");
```

Instead of using a simple string, we use a JSON string in order to manage the passing of parameters:

```
var myEvent = {
  event:"search-cruise",
  term: “term to search”
};
window.parent.postMessage(JSON.stringify(myEvent), “*”);
```

The event in the above example is used to open CRUISE with the “term to search” from BrightSparks. The parent window has to register an event handler to capture the events from the COLLAGE applications in the iframe:

```
window.addEventListener('message', function (e) {
  var _event = JSON.parse(e.data);
  if (_event.event == "search-cruise") {
    $(window).trigger("search-cruise", { term: _event.term });
  }
});
```

In this example, the handler for the event type “message” is registered. If the message contains an object structured like the above myEvent, a new “local” event using the jQuery library will start. This local event will show the CRUISE iframe by simply changing the URL of the page:

```
$(window).on('search-cruise', function (e, pram) {
  var h = window.location.href;
  // keep only the server address and path
  var i1 = h.indexOf("#");
  if (i1 > 0) h = h.substring(0, i1);
  window.location.href = h + "#cruise?term=" +
encodeURIComponent(param.term);
});
```

B. *Evaluation*

Concept developers used IdeaFocus and mashed-up CI tools together with end users as part of various projects over a six-month period. For instance, they used it during a two-day workshop about open source materials. In this workshop, they generated ideas about how to design and make their own open materials for the Fablab facility. The project included defining open source materials, brainstorming what could be done with them, experimenting and making materials, and developing two integrated concepts. We asked participants to use IdeaFocus and the mashed-up CI tools as the main idea generation platform.

The software was used with great success, resulting in the generation, in short periods, of more ideas than those generated by concept developers with any related tool previously used in similar assignments. We noticed a quick adoption of the software by the group, as well as positive overall impressions with respect to enhancing the design process and promoting sharing and insights. Positively, users found the software more enjoyable once they were comfortable with it. We used the Creativity Support Index (CSI) to evaluate the quantified increases over the established baseline in the creative process and outcomes resulting from social creative processes supported by the COLLAGE CI tools. The CSI is a survey metric commonly used specifically to evaluate a creativity support tool's ability to support a user's creative process [33]. Once participants in creative sessions finished using the CI tools, they answered the CSI survey, which consisted of two parts: a rating scale section, where participants assessed 12 creativity features of the tools used, and a paired comparison section, which was used to individually assign weights to the features rated. In the 12 rating scale questions, the users assessed six factors: exploration, collaboration, engagement, effort, transparency, and expressiveness.

Table 2. Results from the Waag Society sessions.

Number of Respondents	Mean CSI	Exploration (%)	Collaboration (%)	Engagement (%)	Effort (%)	Transparency (%)	Expressiveness (%)
61	58.7	19%	21%	20%	15%	7%	18%

Table 2 provides details on the average of the results obtained from the various evaluation sessions conducted at the Waag Society. In total, there were 61 responses to the CSI survey. Participants' profiles include creative developers, concept developers, back-end developers, and other participants from the specific sector. The relative contributions of exploration, collaboration, engagement, effort, transparency and expressiveness to the total CSI mean are also depicted in Table 2. Note that the 'collaboration' factor contributes the most among the six factors examined, indicating the capability of the tools to leverage social creativity. The results, CSI index 58.7 (out of 100), indicated a 23% increase over the established collaborative and search tools previously used by Waag Society in the creative process and outcomes. In the real case presented, the users considered that the COLLAGE tools supported their social creative process considerably.

V. Conclusions

We have presented CI software that addresses the needs of social creativity, adopting a mashup architecture that bundles CI software services together to create user-centric collaborative applications focused on specific social creativity needs, such as those of creative research. Evaluation of a specific mashup with a group of concept developers indicated that the software is in line with the creative research approach in which concept developers work together with end users, taking on multiple roles throughout the design process. We saw that CI software can effectively kick-start social creativity by connecting stakeholders, anticipating competencies, and leveraging available information sources. Moreover, CI software can broaden group participation by linking groups with social networks and can facilitate divergent thinking and inspiration by linking users to huge amounts of online information and social media. Still, technology cannot defy cultural barriers to social creativity as long as it is unable to offer the same quality of interaction as face-to-face experiences, which are deeper and richer than their virtual counterparts.

Our experience working with users revealed several implications that the introduction of social creativity software may have for practitioners. Despite the enhanced functionality of CI software, the role of the facilitator cannot be underestimated. A facilitator often acts as a catalyst, enabling the incorporation of new software and practices in collaborative work, supporting users to deal with non-routine or challenging business problems, and helping users overcome possible problems with the use of the software. Facilitators are especially valuable in creating some form of structured reflection about the shared experiences and evaluating whether there are opportunities and challenges for added value creation. Moreover, in our experience, for social creativity to flourish, merging physical tools such as post-its and infographics with computer-based tools may yield the best results, especially in certain stages of the process, such as promoting divergent thinking. Further, creativity support software should be customizable and adaptable to the specific needs and problems to be tackled. A software's usability and fitness to the specific needs and problems are of paramount importance, whereas its cost is relative, depending as it does on the potential long-term impact of the software's use.

Further experimentation is planned in order to assess the impact of software design issues, underlying CI algorithms and architectural issues on the creative process and outcomes. Further studies are needed in order to assess the fitness of the software with more subtle issues underlying creative research, such as leveraging designers' empathy for users' life stories and needs, the subjectivity of interpretation of information, personal intuition, human interaction, and trust. In so doing, we hope to improve our own understanding of creative research and be inspired to provide improved computational support and enhanced creativity support features.

Acknowledgments

The research leading to the results presented in this paper received funding from the European Community's Seventh Framework Programme [FP7-ICT-2011-8] under grant agreement no. GA318536.

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