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Human-as-a-Service: An Empirical Study of Growth in Human Service Ecosystem

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Abstract— **With the sweeping progress of services technology and crowdsourcing, individuals are offering their capability as a service and companies are orchestrating them for problem solving over the web. As a consequence, recent years have witnessed a rapid development of a human service ecosystem. In contrast to web service ecosystem, human service ecosystem is more complicated by the fact that humans grow capability overtime and their collaborations typically imply human involvement. It is thus worthy to understand the modeling of evolution of human capabilities and collaborations for optimization and more effective management. This paper proposes a three-layer time-aware heterogeneous network model, and based on it, a novel method is developed to *study how human service providers and consumers develop their service provision and orchestrating capabilities as well as how they collaborate with each other*. Exploratory analysis uncovers some evolution patterns which open a gateway for building possible applications such as human service recommendation for consumers, human capability development, and mechanism design for platform management.**

Keywords- Human as a Service, Heterogeneous Network, Service Provision/Orchestrating Capability, Collaboration Pattern

I. INTRODUCTION

With the sweeping progress of web technologies, individuals are no longer just passive browsers but active contributors who can proactively participate into different procedures to offer their expertise [1]. More and more individuals are now offering their capability as a service through the web [2][3]. Additionally, crowdsourcing has been considered as an effective model for many commercial companies as well as non-profit institutions to outsource tasks to a generally large network of people for problem solving [4]. As a consequence, several online human service platforms, such as Fiverr[1], Upwork[2], and Freelancers[3], have emerged to create the opportunity for any individual or organization to leverage *Human as a Service*, leading to a rapid development of an unprecedented human service ecosystem.

Many efforts have been conducted to study the online web service ecosystem such as mashup-service ecosystem [5]–[9] and scientific workflow-service ecosystem [10]–[12], crowdsourcing including its applications in different situations and for different purposes [4], motivation and behavior people to participate in crowdsourcing activities [13], and reputation evaluation [14]. However, the following two unique characteristics make the human services different from web services:

1) Growth of Human Capability: A human service itself rarely stays constant but evolves during its life cycle [15]. Furthremore, in the human service domain, the capabilities of servers (i.e., humans) who provide the services are growing so that they may offer more human services to the ecosystem as time goes by. Additionally, the consumers who use human services are improving their abilities for service orchestration that they may use services in a more complex and reliable way.

2) Different Collaboration Methodology: The collaboration between web services is achieved through their fixed interoprational APIs. On the contrary, the collaboration between human services is achieved through interpersonal communications oriented to consumers. In other words, human involvement is usually unavoidable. As a result, the web service orchestration approaches based on the services' interface may not be always applicable to human service orchestration.

Therefore, the goal of this project is to conduct an empirical study of the two characteristics in the contemporary human service ecosystem. Specially, a three-layer time-aware heterogeneous network model are presented, consisting of servers, services, consumers and their time-aware relations. Such an instrument is used to scrutinize the historical data gathered from human service platforms. Among popular human service platforms, we chose Fiverr.com to conduct our study due to the richness of the its publicly available data and its simple yet extensible business model. The substantial findings from our study have demonstrated that, human service provisioning and collaboration behaviors can be tracked and leveraged to enable and facilitate human service composition and recommendation. To our best knowledge, this project is the first effort, and paves a new way of examining human service ecosystem from the services computing perspective.

The main contribution of this paper is summarized in two-fold:

- A network-based method is developed to formally define the evolution of human's capability in service

[1] www.fiverr.com
[2] www.upwork.com
[3] www.freelancers.com

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provision and orchestration, as well as the collaboration patterns between human services.

- The exploratory empirical study is reported to uncover the evolution of the human service capability and collaboration patterns, which open a gateway for building possible human service applications, including human service recommendation, personal skill expansion strategy, and systematic support at human service platform.

The rest of this paper is organized as follows. Section 2 proposes the network model and formally defines the research problem. Section 3 presents our data collection methodology. Section 4 reports the empirical study and analyzes the results. Section 5 discusses some possible applications based on the network study. Section 6 compares with related work and Section 7 draws the conclusion.

II. NETWORK-BASED METHODOLOGY

A. Network Model for Human Service Ecosystem

Human service ecosystem is typically organized around human service platforms, represented by Fiverr.com, upWork.com and Freelancers.com. Operating under a similar fashion, these platforms serve as service market places to link service providers and requesters togethertypically. Take Freelancers.com as an example. Consumers post projects at the platform, with clear definition of the task, time frame, and price. Freelancers (a.k.a. servers) create worker accounts in the platform with profiles that describe the services they can provide, and bid for posted projects. After communications, a freelancer is selected and begins to work on the project. After finished, the freelancer will deliver the outcome via the platform and the consumer will make the payment and rate the quality of the service. The platform charges a small portion of the earnings of the freelancer as an introduction fee. Throughout this paper, the three terms *server, worker*, and *human service provider* will be used interchangeably.

We model such operational model as a three-layer time-aware heterogeneous network:

Definition 1 (Heterogeneous Network Model for Human Service Platform, G ***)****: A human service platform is formally defined as a three-layer heterogeneous network* $G = \{P, S, C, R_{ps}, R_{cs}\}$*, where* P *refers to the servers,* S *refers to the hunter services, and* C *refers to the consumers who purchase the human services.* $R_{ps} = \{r_{ps} =< p_i, s_j, t_{ij} >| p_i \in P, s_j \in S\}$ *refers to service provision relations where each triple* $< p_i, s_j, t_{ij} >$ *represents that server* p_i *offers human service* s_j *at the* t_{ij} *time interval.* $R_{cs} = \{r_{cs} =< c_k, s_j, t_{kj} >| c_k \in C, s_j \in S\}$ *refers to service purchase history where each triple* $< c_k, s_j, t_{kj} >$ *represents that consumer* c_k *uses human service* s_j *at the* t_{kj} *time interval.*

Each human service is represented as a two-layer instrument based on its functionality, comprising a root category and a sub category. A root category refers to a general functional service set such as "*Advertising,*" "*Business,*" "*Gifts,*" and "*Lifestyle.*". A sub category refers to a specific service set with finer-grained functionality under root category such as "*Banner Advertising,*", "*Human Billboards,*" "*Career Advice,*" "*Market Research,*" "*Cooking Recipe,*" and "*Animal Care & Pet.*" Therefore, each service can be further defined as a triple $s_j =< fs_j, rc_m, sc_n >$ where fs_j refers to the service index, rc_m refers to the root category, and sc_n refers to the sub category.

B. Growth of Human Capability

As discussed above, in the human service ecosystem, the human's capability, both for the servers and the consumers, is not stable but growing as time goes by.

1) Service Provision Capability

Human servers may enhance their skills and keep on publishing new services at the platform. To study a human server's service provisioning history, we use *service provision capability* to represent her provided services. Given server p_i and a time interval t_j, her service provision capability is divided using the following metrics:

- Ever Provided Services (*EPS*): all the services provided by p_i before or during t_j.

$$EPS(p_i, t_j) = \{r_{ps} \to s \mid r_{ps} \to p = p_i, r_{ps} \to t \le t_j\} \quad (1)$$

- Newly Provided Services (*NPS*): the services firstly provided by p_i during t_j.

$$NPS(p_i, t_j) = EPS(p_i, t_j) - EPS(p_i, t_j - 1) \quad (2)$$

Here $r_{ps} \to s \mid p \mid t$ refers to the service, server and time interval for the service provision triple r_{ps}.

In order to understand the growth of the service provision over the server's lifespan, for each server p_i, given a metric $PC = \{EPS, NPS\}$, we can sort her provision capability by the time interval:

$$\{PC(p_i, t_{i,1}), PC(p_i, t_{i,2}) \ldots PC(p_i, t_{i,n_i})\}, t_{i,1} < \ldots < t_{i,n_i} \quad (3)$$

Then we can consider $t_{i,1}$ as the first active time interval that p_i begins her career as a human service provider. Its provision capability growth can be defined as:

$$\{PC(p_i, lt_{i,1}), PC(p_i, lt_{i,2}) \ldots PC(p_i, lt_{i,n_i})\}, lt_{i,j} = t_{i,j} - t_{i,1} \quad (4)$$

Therefore, we define the growth of the provision ability in the human service ecosystem as follows:

Definition 2 (Growth of Provision Capability)*: Given a human service ecosystem* G*, its service provision capability is defined as the average of the service provision capability of all servers in the platform:*

$$APC(lt_i) = \frac{\sum_{p_j \in P} | PC(p_j, lt_i) |}{| \{p_j \mid p_j \in P, PC(p_j, lt_i) > 0\} |} \quad (5)$$

Where $PC = \{EPS, NPS\}$ refers to the two different metrics developed above.

In order to understand how a server expands his/her skill set over the lifespan, for each $s_i \in NPS(p_j, lt_i)$, three expansion patterns are identified:

- ***Same Sub Category***: refers to the case where one improves his/her new service in the same sub category, for example, new services in the ever provided sub category "*data base admin.*"
- ***Cross Sub Category***: refers to the case where one provides new services in the neighboring fields, for example, in a newly created sub category "*coding*" but under the ever provided root category "*programming & tech.*"
- ***Cross Root Category***: refers to the case that one develops a new capability in a totally different domain, e.g., in another root category "*Business*" in which she is never involved before.

2) Service Orchestrating Capability

Unlike web service composition, the composition of human services is typically not based on services' interoperation, but the orchestration of the consumers. Therefore, the growth of the service orchestrating capability is important for the human service ecosystem. Note that for a consumer, the more complex the human services that she can purchase in a process are, the more skillful she is in the service orchestrating. In this paper, we consider the services purchased by the same consumer in the same time interval are for the same transaction. Therefore, given the consumer c_k and the time interval t_j, we can define the following metrics to represent her orchestrating capability:

- Orchestrating Services (*OS*): the services purchased by c_k during t_j.

$$OS(c_k, t_j) = \{r_{cs} \to s \mid r_{cs} \to c = c_k, r_{cs} \to t = t_j\} \quad (6)$$

- Ever Orchestrating Services (*EOS*): all the unique services purchased by c_k before or during t_j.

$$EOS(c_k, t_j) = \{r_{cs} \to s \mid r_{cs} \to c = c_k, r_{cs} \to t \le t_j\} \quad (7)$$

- New Orchestrating Services (*NOS*): the new unique services purchased by c_k during t_j.

$$NOS(c_k, t_j) = EOS(c_k, t_j) - EOS(c_k, t_j - 1) \quad (8)$$

To represent the growth of a consumer's orchestrating capability, given a metric $OC = \{OS, EOS, NOS\}$, for each consumer c_k, we can sort her orchestrating capability by the time interval:

$$\{OC(c_k, t_{k,1}), OC(c_k, t_{k,2}) \ldots OC(c_k, t_{k,n_k})\}, t_{k,1} < \ldots < t_{k,n_k} \quad (9)$$

$t_{k,1}$ is considered as the first time interval that c_k begins to use the human service over the platform. Therefore the growth of its orchestrating capability can be defined as:

$$\{OC(c_k, lt_{k,1}), OC(c_k, lt_{k,2}) \ldots OC(c_k, lt_{k,n_k})\}, lt_{k,j} = t_{k,j} - t_{k,1} \quad (10)$$

Hence, we can obtain the growth of the orchestrating capability in the human service ecosystem as follow:

Definition 3 (Growth of Orchestrating Capability)*: Given a human service ecosystem G, its service orchestrating capability can be formally defined as the average of the service orchestrating capability of all consumers in the platform:*

$$AOC(lt_i) = \frac{\sum_{c_k \in C} |OC(c_k, lt_i)|}{|\{c_k \mid c_k \in C, OC(c_k, lt_i) > 0\}|} \quad (11)$$

Here $OC = \{OS, EOS, NOS\}$ refers to the three different metrics developed above.

Similarly, for each $s_i \in NOS(c_k, lt_i)$ three expansion patterns are identified:

- ***Same Sub Category***: refers that the consumers will purchase the services in the same sub category, for example, the consumers can purchase another new services in the ever purchased sub category "*data base admin.*"
- ***Cross Sub Category***: refers that the consumers use the new services in the neighboring fields, for example, new orchestrating sub category "*coding*" but remaining under the ever orchestrating root category "*programming & tech.*"
- ***Cross Root Category***: refers to the case that the consumers may use the human services in a totally different domain, e.g., new orchestrating root category "*Music & Audio*" in which she is never involved before.

C. Human Service Collaboration

The collaboration of the human services is not based on the interface of the services but the consumer's orchestrating. As we consider the services $OS(c_k, t_j)$ purchased by the same consumer c_k in the same time interval t_j are for a process, we can further consider the sequence of these services and get the orchestrating log for services:

$$ols_i = \{s_{i,1}, s_{i,2}, \ldots s_{i,n_i}\}, s_{i,m_i} \in OS(c_k, t_j), m_i = 1, \ldots n_i \quad (12)$$

Here the order of s_{i,m_i} in ols_i represents the sequence that these services are purchased in the transaction. For example, $s_{i,1}$ is firstly used and then $s_{i,2}$.

Each orchestrating log comprises a series of service collaboration pairs $< s_{i,j}, s_{i,j+1} >, s_{i,j} \in OS(c_k, t_j)$, $j = 1, \ldots n_i - 1$. Hence we can form the service collaboration network as follows:

Definition 4 (Human Service Collaboration Network)*: The collaboration between human services is modeled as a homogeneity network $G_s = \{S, R_{ss} = \{r_{ss} =< s_i, s_j, w_{ij} >\}\}$: where each node s_i represents a human service, each edge r_{ss} represents the collaboration between two services s_i, s_j and the weight w_{ij} refers to the frequency of the service collaboration pair $< s_i, s_j >$.*

Furthermore, based on the sub category and root category each service belongs to, three types of collaborations are identified in the human service ecosystem:

- ***Type 1: Same sub-category composition***, the consumer composes services in the same sub-category to work on her project(s). Since matching capabilities are provided in those services, a plausible scenario for this case is to divide a single task into pieces which will be distributed among all the workers for better performance.

$$s_i \rightarrow sc = s_j \rightarrow sc \tag{13}$$

- ***Type 2: Cross sub-category composition***, composing services in the same root-category but in different sub-categories. Similar capabilities are provided by the services, a likely scenario for this case is to hire workers to develop related aspects of the project(s).

$$s_i \rightarrow sc \neq s_j \rightarrow sc, s_i \rightarrow rc = s_j \rightarrow rc \tag{14}$$

- ***Type 3: Cross root-category composition***, composing services in the different root-categories. In this case, very different capabilities are provided by the services. A likely scenario is that workers are hired to work on different components of the projects(s).

$$s_i \rightarrow rc \neq s_j \rightarrow rc \tag{15}$$

As each sub category represents a basic skill in the ecosystem, we can get the sub category network to represent how different skills collaborate with each other:

Definition 5 (Sub Category Collaboration Network)*: The collaboration between different sub categories can be modeled as a network $G_{sc} = \{SC, R_{sc} = \{r_{sc} =< sc_i, sc_j, w_{ij} >\}\}$: where each node sc_i represents a sub category, each edge r_{sc} represents the collaboration between two sub categories sc_i, sc_j and the weight w_{ij} refers to the frequency of the sub-category collaboration pair $< sc_i, sc_j >$.*

III. Data Collection and Overview

A. Data Collection

In our study, we choose Fiverr.com as our subject platform for studying human services. Fiverr.com is one of the most popular freelancer platforms, similar to Upwork.com and Freelancers.com. The critical reason for choosing Fiverr.com is due to the richness of its publicly available data regarding service descriptions and historical transactions.

To avoid extreme sparseness in the data set, we downloaded the descriptions and the transactional histories of all the top rated services on Fiverr.com in the past 12 months. This approach filters out all the services that have few activities and transactions, and helps us to focus on the group of services and service providers which are the major contributors to the entire activities on the platform.

As elaborated in Section 2, the human service platform consists of three key entities, namely, the server (the freelancer), the service (called "gig" on Fiverr.com) and the consumer (the purchaser of the service). The data set we downloaded has the description and category tags for each service. The transaction history R_{cs} of a particular service is inferred using the comments and rating given by the users. Fiverr allows a user to rate and comment a service only after a purchase transaction is finished, i.e., the freelancer has finished the task a user hired her to undertake. Therefore, the comments and ratings are a direct indication of the transactions, the timestamps of which are used as $t_{k,j}$.

B. Fake-purchase Cleansing

Like many other social platforms, Fiverr relies on a user rating system to recommend services and servers. Apparently, there is a strong connection between the rating and the financial gains of the freelancers, therefore it is desirable for one to have many good reviews as well as good comments. However, such a rating system is subject to many types of attacks as reported in [16][17]. One example of an often used attack is called self-promoting [14], which refers to the case where a freelancer herself or hires another person to make fake transactions and leave good rating and comments. In this paper, we will leave the detailed study on this attack as future work, but we made a best effort attempt to minimize the impact of such attacks.

Straightforwardly, as we known, in the practice, it is extremely unlikely for one to hire more than 30 freelancers in a month given that the average job delivery time frame is 2 to 3 days. While it might be too early to draw the conclusion that these transactions are self-promoting attacks, it is a reasonable presumption. In order to reduce the potential impact of such attacks while preserving the integrity of the data set, we chose to filter out all the transactions that have used more than 30 services monthly. This strategy retained 98.94% of the recorded transactions and removed the obviously suspicious ones. Actually, we found that the distribution of transactions with different service length fits the power-law distribution with a very long tail, which means a very small group of transactions use many services monthly.

C. Data Overview

As reported in Table I, after removing the fake purchase transactions, the data set we managed to download contains 40,049 servers, who provide 95,835 services. The number of transactions occurred between January 2015 and January 2016 is 2,288,255, involving 726,926 consumers. In average, each server provides 2.39 services, each of which has been used for 23.88 times on average. A consumer averagely incurs 3.15 transactions in a 12-month time frame.

TABLE I. Overview of Dataset

Metric	Value
Number of Servers	40,049
Number of Services	95,835
Number of Consumers	726,926
Number of Purchases	2,288,255
Number of Root Category	11
Number of Sub Category	117

IV. Empirical Results

A. Capability Growth

1) Service Provision Capability

In a live service network, the services offered are a dynamic collection of the capabilities of the servers. A server will over time, expand her skills so that new services could be offered and effectively grow her potential customer group and in turn, increase her revenue. An example could be a server offering C programming service firstly and then Java programming service later.

New freelancers may join the platform all the time. To study the pattern of such a growth, we removed all the servers who ever offered services before January 2015 to get 32,607 servers joining the platform during our study period. Based on the method presented in Section 2 B.1, we obtain the growth of the provision capability for these servers.

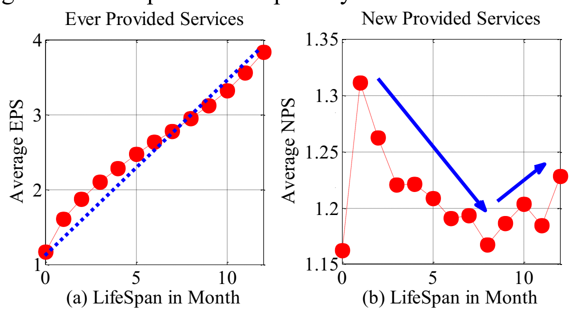

Figure 1. Growth of the service provision capability in the ecosystem.

As shown in Figure 1, it is interesting to note that the growth of the services slows down at the beginning, which is consistent with *the law of diminishing marginal utility*. However, afterwards that we can observe a decreasing marginal utility, leading to an increase of new services. The possible intuition behind this pattern is that, eventually a server would publish all the services under her current capabilities and then it becomes more and more difficult to expand them further, where non-trivial learning will be needed for them to do so. However, as time goes by, these servers become more and more senior that they can cross the first-stage of the learning curve and become professional to develop more new services for the platform.

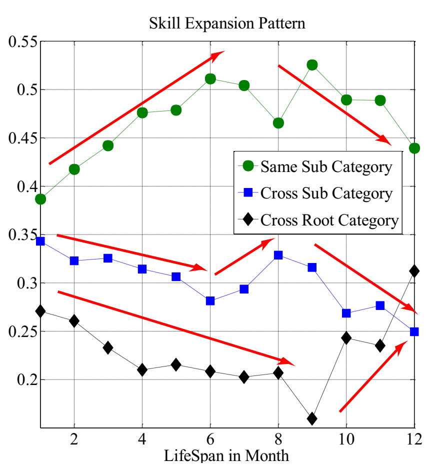

Figure 2. Expansion Pattern for New Provided Services

Obviously, expanding one's capability over a new sub category or root category is difficult. This pattern is clearly presented in Figure 2. It can be seen that the percentage of the "*same sub category*" is much higher than the other two over our study period. More significant is that, we can separate the skill expansions into three phases:

1) At the beginning (1~6 months), the percentage of the "same sub category" is increasing while the other two are decreasing. This means that more services in the same sub category are developed.

2) After that (6~8 months), we can see an increase for the "cross sub category" which means that the freelancer is turning to develop services in the neighboring fields.

3) Finally (9~12 months), the servers in the platform are developing services in different root categories so that the percentage of "cross root category" is increasing.

This is consistent with our observation of the growth of the new provided services because they both show how the server goes through the "learning curve" for the human service provision, growing from novice to mature enough to provide diverse human services for the ecosystem.

2) Service Orchestrating Capability

In the human service ecosystem, the complexity of the services purchased for a transaction represents the consumer's orchestrating capability. As we mention above, there may exist some fake-purchase in the platform. Therefore, we removed all the fake-purchase records from the original data set and then based on the method we discuss in Section 2 B.2, we can calculate these metrics to illustrate the growth of the orchestrating capability.

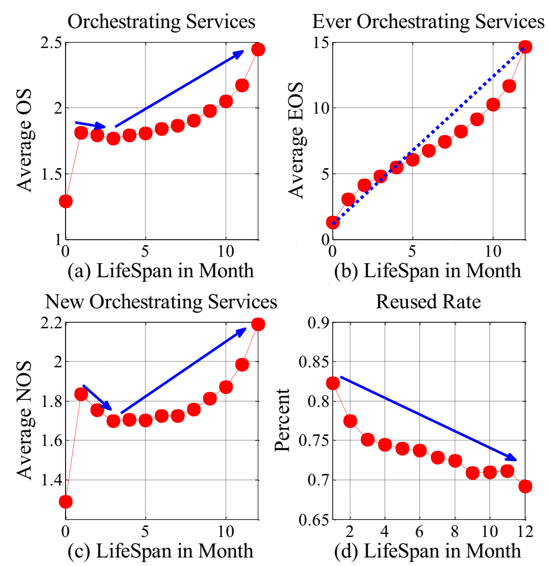

Figure 3. Expansion Pattern for the service orchestrating capability

As shown in Figure 3, after a slight decrease, the average number of services used in each transaction is increasing more and more rapidly, which means that consumers are using the outside human services to deal with more complex task. Similar to the provision capability, the new orchestrating services decrease firstly and then increase. However, it can be seen that the length of the "diminishing marginal utility" effect is much shorter than the service provision capability, which means that comparing with the servers; it is much easier for the consumers to grow their skills to use the human services in their business. Additionally, it can be seen that the reuse rate remains higher than 65%, which means that most purchased services are new for the consumers. However, as the consumers grow their capability to use human services, they intend to use the new services.

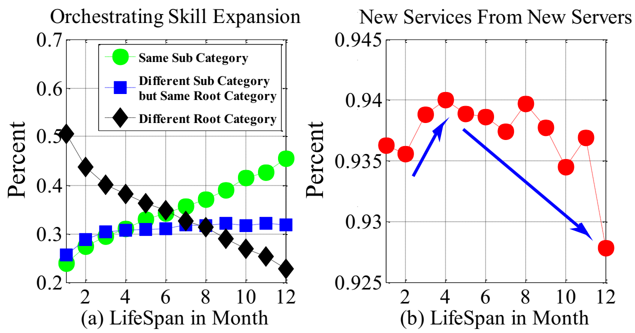

Figure 4. Expansion Pattern for New Orchestrated Services

Figure 4 shows how the consumers purchase new services over time. It can be seen that different from the expansion of the provision skills, the percentage of the "*same sub category*" is increases and the "different root category" is decreases. This means that as time goes by, the consumers are able to separate their tasks into different sub jobs for different human services with similar functionality to run their business in a parallel way. Also they may realize the uncertainty of the human services, so that they increase the redundancy to guarantee the reliability of their business.

Furthermore, as the consumers purchase more and more human services on the platform, they may build trust to some servers so that they may purchase new services from same the servers with whom they collaborate. Therefore, for the new orchestrating services, we can calculate the percentage from the servers with whom consumers never collaborate.

As shown in Figure 4 (b), more than 90% of new services come from new servers, which means that the consumers need to collaborate with new servers to solve their problems. How to evaluate the reputation of a server is an extremely important issue for consumers. However, we can see that such a percentage increases firstly because the consumers just join the platform so that they need to collaborate with new servers to solve their new problems. As time goes by, the consumers can build the trust with some servers so that if their requirements can be fulfilled by these servers, they will have a higher possibility to continue the collaboration.

B. Human Service Collaboration

Service collaboration here refers to the service compositions the consumers have used together in a 30-day time frame. Although it is arguable that one may hire different services at the same time to serve different projects, it is reasonable to assume such projects are more or less correlated. Following this intuition, the servers hired by the consumer at a particular moment form a team of workers who collaborate with each other. The consumer thus becomes the team leader who orchestrates the efforts of the individual team members and weaves them together.

In order to understand how human services collaborate with each other, as discussed in Section 2.C, we can build the *service collaboration network* in which each edge represents the service collaboration pair and the weight represents the frequency. Fiverr provides the specific date only for transactions happened in the past 30 days. Beyond that, only the month is provided. Therefore we use the transactions happened in one month and report the statistics in Table II.

TABLE II. COLLABRATION BETWEEN HUMAN SERVICES

	All Edges	**Top 10% Edges**
No. of occurrences	91,195	65,505
Same root-category	61,187 (67%)	55,971 (85%)
Same sub-category (type 1)	45,078 (49%)	44,776 (68%)
Cross sub-category (type 2)	16,109 (18%)	11,195 (17%)
Cross root-category (type 3)	30,008 (33%)	9,534 (15%)

It is interesting to note that the top 10% most popular edges account for 72% of all the occurrences of the edges in the month. Certain popular edges can occur thousands of times, while some edges may occur only once. This in a way implies the validity of the top popular edges, as they are widely adopted within the ecosystem. From the table, we can see that the majority of the edges occurred in the month is the same sub-category composition. This pattern applies to both edges as well as the top popular ones, which suggests that the type 1 composition is the most frequently used one among the three. This means that the consumers will employ different services with the same functionality to guarantee the reliability of their processes due to the dynamicity of the human services. Intuitively, it is simpler to outsource a single task than a project with many aspects and components.

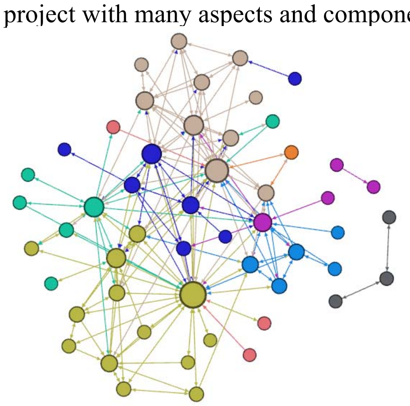

Figure 5. Human Skill Collaboration Patterns

As elaborated earlier, unlike Web services, the composition of the human services are not limited to the service interfaces. Usually, there is no service interface; instead interpersonal communications are used. In theory, each human service can be composed with any other human services. However, in the real practice, these human services are collaborated to solve the same problem that certain patterns are emerging as time goes by. As the correlations between different sub categories can represent the relations between different human skills as well as the patterns in the consumers' requirements, we build the sub category collaboration network G_{sc} following the discussion in Section 2.C. Figure 5 shows the network diagram weaved using the top 10% most popular edges in G_{sc}. Each node represents a sub-category, each color represents a root-category, and each directional edge represents the compositions between the sub categories. The direction represents the sequencing between two sub-categories. The size of the node reflects the in/out degrees of that node: the bigger the node, the bigger the number of other nodes it is connected to via in/out edges. Apparently, some root-categories are more popular than the others, and the same happens to the sub-categories. In fact, the top 10% most popular edges only include nine root-categories (81%) and 52 sub-categories (49%). This implies that the excluded root/sub-categories are not often used in the compositions.

Another important observation is that, many more collaborations happen within the same root-category than cross-root-category. An excellent example of such an observation is the 3-services composition at the very right hand-side of the diagram. Those 3 nodes are all under the root-category of "*Lifestyle*" and they are not connected to any other node with a different root-category. Considering the observation that consumers intend to build reputation with servers during the collaboration. If a server can offer services in these three sub categories, she can build a strong relationship with the consumers and gain more earnings over the ecosystem.

V. HUMAN SERVICES ADAPTATION

The observations from our study have uncovered the evolution in the human service ecosystem, which suggests some possible applications for the human services.

A. Service Recommendation for Consumers

As discussed in Section IV, we can observe growth patterns of the consumers' orchestration capability. As time goes by, consumers are able to purchase more services in a transaction so that it is suitable to offer them more candidates when they post a new project. The consumers are becoming more and more mature in the ecosystem, so that they are able to evaluate the performance of the new human services. Therefore, a recommendation engine can offer them more new human services. However, for the new services, the consumers intend to use them to improve the reliability and capability of their business, so that the new services in the same sub category could be the better candidates. Additionally, they build partnership with the servers based on their collaboration, so that the new services from the partners are more preferred. Furthermore, we are able to identify collaboration patterns in Section V-B. Obviously, these patterns can be employed to recommend the potential service group for the consumers when they design and orchestrate their business processes.

B. Skill Expansion for Servers

Our research shows that the ever provided services / sub category / root category are all increasing as time goes by. Additionally, it can be seen that the consumers tend to purchase new services from the same server, which inspires that the server should try to build long-term partnership with the consumers and continually develop new human services on the platform. However, it can be seen that the ever provided services is still less than 4, the ever provided sub category is no more than 2.5, and the ever provided root category is only 1.526. Therefore, how to help the servers to develop their capability to offer services is an important issue. Good news is that the collaboration patterns identified in Section 4.B, represent the collaboration between different skills as well as the pattern of the consumers' requirement. Therefore, it can be sued to help the servers to understand the relations between different skills and facilitate the process to develop new skills.

C. Mechanism Design for Platform Operator

Based on the analysis of the service provision and orchestrating capability, we can observe that for the service provision capability, the "*diminishing marginal utility*" lasts for almost eight months and then turns to the increment procedure because the servers are able to develop new human services in different root categories. On the other hand, the "*diminishing marginal utility*" lasts for no more than three months for the consumers in service orchestrating. Therefore, the platform should pay more attention to help the servers to develop their skills, for example, to help\ the servers to identify the related skills which is discussed above, or to design some incentives to encourage the servers to offer new services.

VI. RELATED WORK

Human service ecosystem has unique features comparing to web service ecosystem. Many efforts have been presented to study the evolution of the web service ecosystem due to its rapid development in the past years. The network analysis methodology is firstly introduced into scientific service-workflow ecosystem to understand the collaboration patterns [10]. The ReputationNet model is further developed to recommend trustworthy services and workflows [12]. The dynamic patterns in the mashup-service ecosystem are studied [18] and then the link prediction-based methodology is developed to predict the evolution [19]. Some works take this evolution characteristic for further applications. Due to the dynamicity of the execution environment, some invoked services may become unavailable so that they need to be replaced by alternatives one to guarantee the compositions' reliability [20]. A time-aware service recommendation approach is presented for mashup creation, integrating topology, content and temporal information [8]. The dynamicity of the service's functionality is further studied to improve the performance [9].

Crowdsourcing has been considered as an effective model to outsource tasks to a generally large network of people for problem solving [21][4]. Some researchers study the motivation that a server joins crowd sourcing jobs and how they participate in different tasks [13]. Since the server's reputation is very important, some studies focus on the trust evaluation and task recommendation [14]. Because the crowdsourcing will cost the consumers money for each task, some strategies are presented to optimize the task decompose and reduce the total cost [22].

In contrast to related works, this paper studies the human services from services computing perspective. By analyzing the evolution of human services, we study the trend of how people grow skills to provide more services, and how human services collaborate. Our research will lead to direction of building new applications to facilitate human service ecosystem.

VII. CONCLUSIONS

Human service ecosystem is rapidly growing in the recent years triggered by the crowdsourcing strategy. In this paper, we have reported our empirical study over a popular human service platform Fiveer.com, aiming to understand the growth of the capability and collaboration patterns. We have developed a three-layer network model to represent the human service ecosystem and formally calculated the human capability and collaboration based on the network model. Our exploratory empirical study shows that:

- Human service providers go through a "d*iminishing marginal utility and then increasing*" learning curve during the provision capability growth. Specially, they develop the skills with same functionality and then across different domains.
- The consumers own the similar learning curve but take a shorter time to become professional. Additionally, they will build trust with servers during the collaboration.
- Based on the collaboration analysis, the consumers intend to use the services with same functionality to guarantee the reliability of their processes. Also, as time goes by, some collaboration patterns are emerging, representing the relations between different skills.

In the future, we plan to develop applications including recommending services for consumers and for helping servers to expand their skills, and designing monitoring and management mechanism supporting human service platform.

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