

# Discovering Good Links Between Objects in the Internet of Things

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**Abstract:** The Internet of Things is an emerging paradigm allowing the control of the physical world via the Internet protocol and both human-to-machine and machine-to-machine communication. In this scenario, one of the most challenging issues is how to choose links among objects in order to guarantee an effective access to services and data. In this paper, we present a new selection criterion that improves the classical approach. To reach this goal, we extract knowledge coming from the social network of humans as owners of objects, and we exploit a recently proven property called interest assortativity. The preliminary experimental results reported in this paper give a first evidence of the effectiveness of our approach, which performs better than classical strategies. This is achieved by choosing only not redundant links in such a way that network connectivity is reserved and power consumption is reduced.

## 1 INTRODUCTION

The Internet of Things refers to a new paradigm composed of networked interconnection of everyday objects which are often smart (e.g. equipped with bits) into intelligence. This innovative scenario will increase the ability of the Internet by integrating every object for interaction via embedded systems. Moreover, it will lead to a highly distributed network of devices where machine-to-machine and human-to-machine communication will be possible.

One of the basic problems to face is how to build the Internet of Things. Indeed, the choice of a strategy to drive the formation of communities of objects has a direct impact on different aspects relevant from the application point of view. First desiderata is that the network of objects has a sufficient connectivity degree to guarantee that the potential benefits arising from the communication among objects are not inhibited. According to this principle, one could think of a highly connected network, ideally a complete graph. However, the trade-off to solve regards the limited computational and power capabilities of smart objects for which the number of connections should be minimized.

The typically adopted approach to establishing a direct connection between two objects is mainly based on proximity (Nixon 2005; Hang et al. 2011; Vangelos et al. 2011). Instead, we define a new

strategy leveraging the properties of the objects and estimating how much similar properties should enforce a direct link between two objects. This is done by matching object properties to human interests and by measuring the assortativity degree of such interests in the human social network of owners (used to be Twitter) (Buccafurri et al. 2015a). The claim is that the higher such an interest assortativity (Buccafurri et al. 2015b), the higher the potential benefit of directly connecting the corresponding objects. This process allows us to *discover* good links between objects which guarantee good network connectivity among *similar* objects by limiting the node degree and then the related inefficiencies. We tested the above strategy experimentally and obtained very promising results. According to a number of social-network-analysis measures (Buccafurri et al. 2015c), we conclude that the network of objects created by means of our approach is much better than the network obtained by using the classical one.

### 1.1 Motivating Example

To better explain our goal, we present the following real-life situation.

Francis is a runner who likes to measure his performance and is especially interested in knowing his speed during his activity. He is used to measure his advancement by a smart bracelet in conjunction to his

smart phone. Both ensure him a full tracking of his personal activity data. He has a Twitter account and he is follower of many sportive man. Personal coach instructor because he wants to stay well informed about all news in the field.

Lucy is always watching her weight. She likes to be in fit and to eat biologic food. She likes read about nutrient information on food, herbs, properties, cosmetics, etc. and so on. To accomplish her goal, she is used to adopt a series of mobile apps to track about food, sports and to stay informed about these topics. On Twitter, for instance, she follows famous actresses, personal trainers and nutritionists to get well informed about these topics.

Steven is a student. He spends a lot of time staying sit and working on the laptop. He is worried about missing a right posture then he had bought a machine to give a vibration whenever his posture is wrong or he is staying too long. He has a Twitter account and he is follower of healthy products in general from posture to food to sports and so on. He does not like to practice sports.

By following the interest assortativity approach we found out health like a common macro-interest. Sharing on this topic of interest, we are able to suggest friendship between these components supporting their owners in achieving their goals, however they look like totally different. In fact, Francis and Lucy have never considered the importance of a right posture for the wellbeing, conversely, Steven does not take care enough about sports and food while he is a very sedentary person. What the new approach allows is the establishment of friendship between this series of devices to allow the full accomplishment of personal goals of everybody suggesting them new ones and novel ways to accomplish the same results.

This is discussed in the next section in which we show that, in the cases like those described above, the knowledge typically used to establish a connection between objects would produce unsatisfactory results. More amenable by considering proximity, i.e. the fact that the objects meet each other a given number of times with a sufficient frequency, we should conclude that there is no reason to connect the above objects. Indeed, probably the above objects never meet

## 1.2 Structure of the Paper

The plan of this paper is as follows. In Section 2 we present our approach to choose links in a IoT environment. Section 3 describes the preliminary experimentation carried out to study the effectiveness of our technique. Section 4 deals with literature related to our work. Finally, in Section 5 we draw our conclusions.

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## 2 DISCOVERING GOOD LINKS

According to the Internet-of-Things paradigm, an entity on a network has to be notified of the availability of desirable services or devices on the network in order to form a link. Typically, the fact that two objects get in touch somewhere and sometimes, maybe because the corresponding owners meet in a certain location, is enough to trigger, with a given threshold, the establishment of a link between the two objects. Nion (2005), Hang et al. (2011), Vangelos et al. (2011). This property is called *proximity*. The aim of this section is to identify possible enhanced ways to discover potentially beneficial links. To do this, preliminarily, we consider which are the candidate properties existing in the literature: we can see to build a more complete model. They are: (i) proximity, (ii) homogeneity, i.e. they are the same kind of object created by the same manufacturer, (iii) ownership, i.e. they belong to the same user, (iv) friendship, i.e. owners are mutual friends in a social network.

Regarding that the decision regarding the insertion of a link between two objects could rely on a mix of the above properties, we define a decision function to decide whether a link between two objects  $\langle x, y \rangle$  has to be inserted or not.

Observe that all the above properties give some information about the direct relationship between two objects. Our proposal aims to use also some indirect knowledge coming from the social network of owners to support the computation of the above decision function. Baccafri et al. (2016b). In addition, besides the classical selection criteria that are based on the sole proximity, we use all the above direct properties. Therefore, we introduce two measures which we combine to compute the aimed decision function. These are:

- 1  $T_{x,y}^{dir}$  which derives from the *direct* knowledge about objects and owners, and
- 2  $T_{x,y}^{ind}$  which encodes some *indirect* knowledge.

Using indirect knowledge, we exploit a recently proven property occurring in online social networks called *interest assortativity* (Baccafri et al. 2016a). According to this result, it is possible to have a measure of the correlation between a given human interest and the presence of links between humans.

To exploit the above indirect property, we need to match objects to humans in such a way that interests are somehow reserved. To do this, we define a taxonomy on top of the properties and/or aims of objects.

This taxonomy allows us to associate each object  $x$  with a set of human interests  $I_x$  belonging to a given domain  $I$  derived from the owners' social network. Clearly the following reasoning is valid only if all the involved humans have a social network account. To build this taxonomy we consider how many times a user with a certain interest say  $i$  owns a given object  $x$ . This way we can define an *occurrence degree*  $O_i^x$  of  $i$  w.r.t.  $x$  as the ratio between the number of users with interest  $i$  owning  $x$  and the total number of occurrences of the interest  $i$  in the network.

Therefore given two objects  $\langle x, y \rangle$  we compute the overlapping set of associated interests as  $I_{x,y} = I_x \cap I_y$  and for each common interest  $i \in I_{x,y}$  we compute the assortativity level  $IA_i$  of  $i$  in the considered social network and the common occurrence degree  $O_i^{x,y}$  defined as the mean between  $O_i^x$  and  $O_i^y$ .

At this point we are ready to define how  $T_{x,y}^{ind}$  is computed. In article [14]

$$T_{x,y}^{ind} = \sum_{i \in I_{x,y}} \frac{O_i^{x,y} \cdot IA_i}{|I_{x,y}|}.$$

In words  $T_{x,y}^{ind}$  is obtained as a mean between assortativity degrees of common interests weighted by the common occurrence degrees. Since objects  $\langle x, y \rangle$  are both related to  $I_{x,y}$  we expect that the higher the value  $T_{x,y}^{ind}$  the higher the linking power of interests in  $I_{x,y}$  should be also for objects  $\langle x, y \rangle$ .

Finally we combine the two values  $T_{x,y}^{dir}$  and  $T_{x,y}^{ind}$  to obtain our boolean function to decide whether to add a link between the two objects. Specifically given two objects  $\langle x, y \rangle$  a new link is established if

$$F(T_{x,y}^{dir}, T_{x,y}^{ind}) \geq th$$

where  $th$  is a suitable threshold value and  $F$  is a parameter of our model to set by experiments.

### 3 EXPERIMENTS

In this Section we describe our experimental campaign carried out in order to validate our approach. In article [14] we started from a set of humans and objects and we built two networks:

- 1 a network of objects obtained by adding links according to our approach based on interest assortativity
- 2 a network of objects formed through the classical proximity-based criterion

The obtained results showed that the quality of the first network is better in terms of efficiency than the second one. In the following we will explain which

is the measurement adopted to evaluate the network efficiency.

#### 3.1 Testbed and Dataset

Our experiments were carried out on a machine equipped with a 2nd-Gen Intel Core i7-5500U processor and 16 GB of RAM. The operating system was Ubuntu Server 14.04.4 LTS with kernel version 4.2.0-35-ava-rt-amd64 Machine version 1.0.45-64-bit. We wrote our code in Java by also exploiting some features of Neo4j Neo4j 2016 a graph database management system.

Our experiments used a Neo4j graph dataset called *GraphofThings* consisting of nodes categorized by one or more labels and connected by instances of directed relationships. We obtained it from a GitHub repository maintained by the GraphLchemist group [15].

Figure 1 shows an instance of the graph model representing interactions, i.e. arcs between entities, i.e. nodes used in our experiments.

Our experimental campaign we needed only some of the entities showed in the above schema. In article [14] the nodes we took into consideration are:

- *Human*. user identified with a device
- *User*. node representing a social network role, i.e. Facebook, LinkedIn, Twitter, etc. Observe that not all the users are humans.
- *Machine*. node that indicates any wearable or mobile device. It possesses a tag *type* that indicates the family which it belongs to.
- *Interest*. node that holds a single *interest* category.
- *Location*. node that indicates a physical place. It can be identified with a number of attributes indicating for example an event, an activity, a store, a park, etc.

The main relationships involved in our dataset are:

- *Uses*. directed relationship between a human and any number of devices he wears.
- *Located*. action taken by a device implying that a user was in a specific location.
- *Friend*. implicitly bi-directional relationship implying a connection in a given social network.
- *Has*. relationship implying that a user has a specific interest.

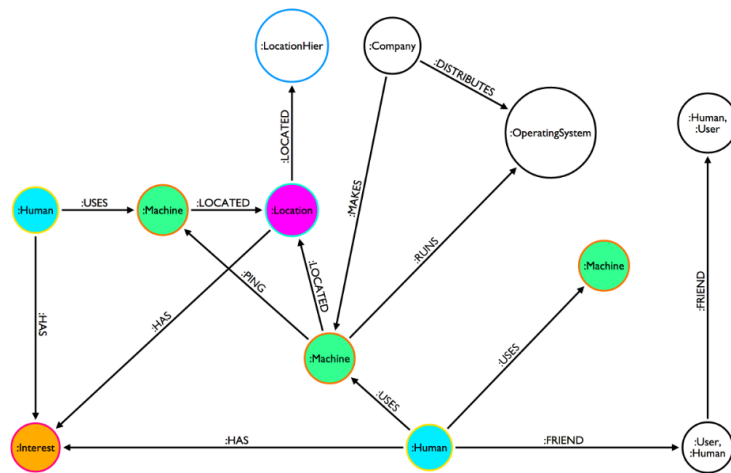


Figure 1: Graph representation of the *Graph of Things* nodes and relationships

### 3.2 Results and Analysis

In the first step we generated the network of humans and objects according to the classical proximity criterion. Specifically we added a link between two machines if they had got in touch at least once in a certain location.

Secondly we generated the network of objects by following our criterion. This task required some more complex steps. Indeed for two objects  $\langle x, y \rangle$  we added a link between them only if  $T_{x,y}^{dir} \cdot T_{x,y}^{ind} \geq th$  where  $T_{x,y}^{dir}$  is a boolean function returning 1 if  $x$  and  $y$  had got in touch in a given location at least once or their owners have a friendship relation in the corresponding social network. Otherwise, in other words for this first investigation we consider only proximity and friendship as direct properties and we set the function  $F$  by the simple product between  $T_{x,y}^{dir}$  and  $T_{x,y}^{ind}$ .

Once both the networks were created we measured some quality parameters to compare them. Table 1 shows the results of our analysis carried out by exploiting CIN Tici 2016, a well-known software package for the analysis of social network data. From the results reported above we can observe that the network built by using the assortativity-based approach shows a lower average degree and thus a lower density level. Although in general high values of *density* imply a higher probability of reaching target nodes, this has also a negative impact on the network efficiency. Indeed the higher the value of density, the higher the traffic level and duplication in broadcast communications.

We can make a similar reasoning for all parameters that have a direct relationship with the number of point-to-point communications that nodes have to

maintain, such as *average degree*. Observe that network efficiency is a very important aspect in an Internet-of-Things scenario in which smart objects have to reserve the battery consumption. Obviously in this context what we have to minimize is the number of contacts per object, provided that the efficiency of the network, also in terms of cohesion, is reserved.

By considering *degree centralization* of our network achieves slightly better results, allowing us to conclude that it is more inclined to have information accumulation points that can be used as seeds to start the information propagation (Mislove et al., 2007). Moreover, better results are achieved for *component ratio* and *connectedness*. These parameters measure the cohesion of the network and show us that our network has a single connected component, so all the nodes are reachable, and that the connectivity is higher than the classical network. The latter property means that the expected number of hops to reach a given target is reduced in our network wrt the classical one, hence also for the *compactness* and *fragmentation* point of view we can conclude that the strategy based on assortativity chooses only not redundant links that allow a full connectivity. We observe that this has not a cost in terms of network resilience. Indeed, according to the definition of fragmentation, as it is 0.676 vs 0.776 of the classical network, we obtain a network that is more resilient.

In summary, the obtained results allow us to state that the approach based on interest assortativity has been able to build a network showing better efficiency in terms of both node reachability and cohesion level. An important achievement is that nodes exhibit a reduced average degree wrt the classical network. This aspect has a deep impact on the traffic level and duplication in broadcast communications, which is

Table 1 Statistics of our dataset

	homophily-based	Heterophilous
<i>Avg Degree</i>	12.017	10.075
<i>Density</i>	0.101	0.05
<i>Deg. Centralization</i>	0.265	0.273
<i>Component Ratio</i>	0.52	1
<i>Connectedness</i>	0.224	0.324
<i>Compactness</i>	0.162	0.10
<i>Fragmentation</i>	0.776	0.676

clearly reduced in our network

## 4 RELATED WORK

In recent years IoT has gained much attention from researchers and practitioners because this new scenario is opening new opportunities for a large number of novel applications [12]. Leavell and Cooper [16], [17], [18], [19]. One of the most challenging issue is how to build the network of objects to access services and data in this new scenario [20]. Some protocols are presented in [21]. [22]. Wang et al. [23]. [24]. [25]. [26]. [27]. [28]. [29]. [30]. [31]. [32]. [33]. [34]. [35]. [36]. [37]. [38]. [39]. [40]. [41]. [42]. [43]. [44]. [45]. [46]. [47]. [48]. [49]. [50]. [51]. [52]. [53]. [54]. [55]. [56]. [57]. [58]. [59]. [60]. [61]. [62]. [63]. [64]. [65]. [66]. [67]. [68]. [69]. [70]. [71]. [72]. [73]. [74]. [75]. [76]. [77]. [78]. [79]. [80]. [81]. [82]. [83]. [84]. [85]. [86]. [87]. [88]. [89]. [90]. [91]. [92]. [93]. [94]. [95]. [96]. [97]. [98]. [99]. [100]. [101]. [102]. [103]. [104]. [105]. [106]. [107]. [108]. [109]. [110]. [111]. [112]. [113]. [114]. [115]. [116]. [117]. [118]. [119]. [120]. [121]. [122]. [123]. [124]. [125]. [126]. [127]. [128]. [129]. [130]. [131]. [132]. [133]. [134]. [135]. [136]. [137]. [138]. [139]. [140]. [141]. [142]. [143]. [144]. [145]. [146]. [147]. [148]. [149]. [150]. [151]. [152]. [153]. [154]. [155]. [156]. [157]. [158]. [159]. [160]. [161]. [162]. [163]. [164]. [165]. [166]. [167]. [168]. [169]. [170]. [171]. [172]. [173]. [174]. [175]. [176]. [177]. [178]. [179]. [180]. [181]. [182]. [183]. [184]. [185]. [186]. [187]. [188]. [189]. [190]. [191]. [192]. [193]. [194]. [195]. [196]. [197]. [198]. [199]. [200]. [201]. [202]. [203]. [204]. [205]. [206]. [207]. [208]. [209]. [210]. [211]. [212]. [213]. [214]. [215]. [216]. [217]. [218]. [219]. [220]. [221]. [222]. [223]. [224]. [225]. [226]. [227]. [228]. [229]. [230]. [231]. [232]. [233]. [234]. [235]. [236]. [237]. [238]. [239]. [240]. [241]. [242]. [243]. [244]. [245]. [246]. [247]. [248]. [249]. [250]. [251]. [252]. [253]. [254]. [255]. [256]. [257]. [258]. [259]. [260]. [261]. [262]. [263]. [264]. [265]. [266]. [267]. [268]. [269]. [270]. [271]. [272]. [273]. [274]. [275]. [276]. [277]. [278]. [279]. [280]. [281]. [282]. [283]. [284]. [285]. [286]. [287]. [288]. [289]. [290]. [291]. [292]. [293]. [294]. [295]. [296]. [297]. [298]. [299]. [300]. [301]. [302]. [303]. [304]. [305]. [306]. [307]. [308]. [309]. [310]. [311]. [312]. [313]. [314]. [315]. [316]. [317]. [318]. [319]. [320]. [321]. [322]. [323]. [324]. [325]. [326]. [327]. [328]. [329]. [330]. [331]. [332]. [333]. [334]. [335]. [336]. [337]. [338]. [339]. [340]. [341]. [342]. [343]. [344]. [345]. [346]. [347]. [348]. [349]. [350]. [351]. [352]. [353]. [354]. [355]. [356]. [357]. [358]. [359]. [360]. [361]. [362]. [363]. [364]. [365]. [366]. [367]. [368]. [369]. [370]. [371]. [372]. [373]. [374]. [375]. [376]. [377]. [378]. [379]. [380]. [381]. [382]. [383]. [384]. [385]. [386]. [387]. [388]. [389]. [390]. [391]. [392]. [393]. [394]. [395]. [396]. [397]. [398]. [399]. [400]. [401]. 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[970]. [971]. [972]. [973]. [974]. [975]. [976]. [977]. [978]. [979]. [980]. [981]. [982]. [983]. [984]. [985]. [986]. [987]. [988]. [989]. [990]. [991]. [992]. [993]. [994]. [995]. [996]. [997]. [998]. [999]. [1000].

aro et al. [2004], Wilson et al. [200]. In [2003], Goh et al. [2003] studies the relationship between assortativity and betweenness centrality correlation for scale-free networks. Newman and Park [2003] analyzes the relation between assortativity and clustering in social communities discovering that these communities are characterized by both high levels of clustering and assortative mixing. By contrast, Catanaro et al. [2004] compares different types of networks (e.g. technological, biological and social networks) showing that only social networks are typically assortative with respect to the degree whereas the others appear in general to be disassortative. Wilson et al. [200] models interaction relationships among users through an interaction graph.

## 5 CONCLUSION

Internet of Things paradigm is an extremely promising scenario that opens new challenging perspectives in terms of interaction between humans and machines. In this context a lot of improvements can be done. For instance, one of the most critical issues is how to choose the links among objects in order to build an efficient network.

In this paper we present a new selection criterion that improves the classical homophily approaches. To do this we relied on the results presented by Baccaferrri et al. [2016a]. This work shows that Twitter is highly assortative in users' interests, i.e. users behave uniformly with respect to different topics and it presents a new social network metric called interest assortativity.

This position paper shows a first experimental evidence of this result by illustrating that our approach performs better than the classical strategies. Indeed, our selection criterion allowed us to pick only non-redundant links. This result is advantageous in terms of network connectivity and battery consumption which are two crucial aspects for smart devices. This encourages us to more deeply analyze this issue in the next future also by testing some different ways to combine direct and indirect knowledge.

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