Inspired by the analysis of several empirical online social networks, we propose a simple reaction-diffusion-like coevolving model, in which individuals are activated to create links based on their states, influenced by local dynamics and their own intention. It is shown that the model can reproduce the remarkable properties observed in empirical online social networks; in particular, the assortative coefficients are neutral or negative, and the power law exponents $c$ are smaller than 2. Moreover, we demonstrate that, under appropriate conditions, the model network naturally makes transition(s) from assortative to disassortative, and from sparse to dense in their characteristics. The model is useful in understanding the formation and evolution of online social networks.

Massive websites – Facebook, Twitter, MySpace, LinkedIn, Flickr, Orkut, Google+, Weaklink, just to name a few – are booming in the past few years, where millions of users and their interactions naturally form the so called online social networks (OSNs)\(^1\). For OSNs, one important characteristic is the strong interplay between the user behaviour and the network topology\(^4\). On the one hand, the user behaviour is affected by the topology-dependent information flowing in the networks\(^5\)–\(^8\); on the other hand, the network topology continually evolves as a natural consequence of network dynamics\(^8\)–\(^10\). Due to this feature, OSNs exhibit certain correlation patterns during evolution, such as the highly skewed degree distributions\(^11\)–\(^13\), the generalized Gibrat’s Law\(^14\), assortativity/disassortativity\(^11\),\(^12\), etc, which are of great importance for us to understand the possible generic laws governing the organization and evolution in networked systems\(^15\).

Recently, two interesting phenomena in OSNs have attracted much attention. The first one is related to the assortativity/disassortativity property of the network, which is an important structural measure characterizing the degree correlation between pairwise nodes. Mathematically, the assortative coefficient can be defined as the Pearson correlation coefficient averaged for all pairs of adjacent nodes in the network. As shown in Table I, it is reported that some OSNs (e.g., Twitter and Cyworld) show negative or neutral assortative coefficients\(^11\)–\(^13\),\(^16\)–\(^19\), and some OSNs, such as Weaklink\(^11\) and Google+ (G+)\(^12\), even convert from being assortative to being disassortative during evolution. These findings challenge our traditional knowledge\(^20\),\(^21\) that biological and technical networks (e.g., financial networks\(^22\)) are disassortative, while social networks (e.g., acquaintance networks\(^23\)) are assortative. Secondy, the scale-free property is of great importance for a network, which can be characterized by a power law exponent $\gamma$ as in $p(k) \sim k^{-\gamma}$, where $k$ and $p(k)$ are node degree and the distribution of degree, respectively. Under the thermodynamical limit, i.e., the network size $N \rightarrow \infty$, the mean degree of a scale-free network will diverge when $\gamma \leq 2$. Therefore, $\gamma = 2$ is an important boundary, and scale-free networks can be classified into dense ($\gamma = 2$) and sparse ($\gamma > 2$) accordingly. Previously, many scale-free networks are found to be sparse\(^24\). However, as shown in Table I, some large OSNs, e.g., YouTube (YT), Digg, and LiveJournal (LJ), turn out to be dense scale-free networks with $\gamma < 2$\(^13\),\(^19\),\(^25\).

In Table I, the basic statistical properties for 14 popular OSNs are listed. It is found that these OSNs basically share common properties observed in real world networks, such as power-law distribution of degrees, large
clustering coefficient, and small average shortest path. However, two features, i.e., negative or neutral assortative coefficients and $\gamma < 2$, also turn out to be typical. In order to obtain insights into the evolution patterns of real OSNs, it is desirable to set up a dynamical model which could reproduce the properties and dynamics observed in real OSNs. Previously, the power law distribution of degrees $1,2,26,28$ and which could reproduce the properties and dynamics observed in real OSNs are directional. The empirical data sets analyzed in this paper are also listed here, i.e., Flickr, FriendFeed (FF), aNobii, and Epinions

$$\text{Table I} | \text{Properties of typical OSNs, including the number of nodes } N, \text{the average degree } \langle k \rangle, \text{the average shortest path } \langle d \rangle, \text{the exponent of power law for out-degree (in-degree) } \gamma_{\text{out(in)}}(\langle k \rangle), \text{the average clustering coefficient } \langle c \rangle, \text{and the assortative coefficient } r, \text{which is defined as the correlation between out-degree and in-degree as the links in OSNs are directional. The empirical data sets analyzed in this paper are also listed here, i.e., Flickr, FriendFeed (FF), aNobii, and Epinions.}$$

| Network | $N$ | $\langle k \rangle$ | $\langle d \rangle$ | $\gamma_{\text{out(in)}}(\langle k \rangle)$ | $\langle c \rangle$ | $r$ |
|---------|-----|------------------|----------------|--------------------------------|----------------|---|
| Flickr  | 2302925 | 14.4 | 5.7 | 1.75(1.74) | 0.11 | 0.02 |
| FF      | 204458 | 20.6 | 4.0 | 2.29(2.17) | 0.19 | -0.10 |
| aNobii  | 94238  | 8.07 | 5.3 | 2.71(2.70) | 0.13 | -0.05 |
| Epinions| 114467 | 5.63 | 4.9 | 1.75(1.72) | 0.08 | -0.06 |
| Twitter16 | 470040 | 87.1 | - | 2.42(2.85) | 0.11 | -0.26 |
| Cyworld17 | 12048186 | 31.7 | 3.2 | - | 0.17 | -0.13 |
| Nioki18  | 50259 | 8.07 | 4.1 | 2.2(2.4) | 0.01 | -0.10 |
| Wealink11 | 223482 | 2.53 | 2.91 | - | -0.07 |
| YT13    | 1157827 | 4.29 | 5.1 | 1.63(1.99) | 0.14 | -0.03 |
| Digg19  | 685719 | 9.8 | 5.6 | 1.6(1.5) | -0.03 |
| G+12    | 30000000 | 16 | 6.9 | - | 0.25 | -0.02 |
| Tianya26 | 411554 | - | 1.66 | - | 0.07 | 0.03 |
| Orkut13 | 3072441 | 106 | 4.3 | 1.50(1.50) | 0.17 | 0.07 |
| UI13    | 5284457 | 17 | 5.6 | 1.59(1.65) | 0.33 | 0.18 |

different types of degrees. In this paper, we focus on the dynamical origin of the transition from assortative to disassortative, and from sparse to dense in the OSNs characteristics. In addition, in the current model, we introduce the general Fermi function to simulate the diversity of user dynamics, which should be more reasonable than the random connection in Ref. 33.

**Results**

**Empirical analysis.** The mechanism of link formation is the central dynamical process during network evolution. In the seminal work, Barabási and Albert proposed a general rule governing the growth of networks, the preferential attachment (PA), which can explain the scale-free properties observed in many real world networks.$1-3$ Since then, much attention has been paid to the investigation of possible microscopic mechanisms underlying the PA phenomenon.$1-3$ So far, this important question is still open and challenging. In this paper, we first carry out empirical study on four typical OSNs, including Flickr, FriendFeed (FF), aNobii, and Epinions.$19$ (see Methods for data description). Our particular interest is on the patterns of link creation during network evolution.

To facilitate the analysis, we divide the new links into two mutually-exclusive types: the balance links and the distant links based on the topological distance.$30$ If a new link is formed between a user and one of his second neighbours, i.e., the user who is two hops apart from him in the network, it is regarded as a balance link.$30$ Otherwise, it belongs to the distant links. Obviously, generating a balance link always contributes a triangle in the network. By distinguishing between these two types of new links, we can investigate the dependence of new links on the topological distance.

The main method we use to analyze the pattern of link growth is to measure the conditional probability that nodes acquire (create) new links with respect to their existing in-degree (out-degree)$41,42$ (see Methods for details). The main empirical results for the four OSNs are summarized in Table II and illustrated in Fig. 1. Interestingly, the relative probabilities of acquiring or creating new links satisfy a power law with respect to the existing degrees, indicating that the users with larger out-degree (in-degree) are more likely to create (acquire) new links. Moreover, it is found that the exponents $\alpha$ for the balance links are significantly larger than that for the distant links, as shown in Figs. 1(a) and 1(b). This suggests that the balance links depend on the local topological structure more than the distant links. We attribute this preferential formation of balance links in the OSNs to the locality of information in such networks, i.e., usually users within a neighbourhood tend to influence each other.
To further examine the micro-dynamics in the process of link formation, we measure the probability of forming balance links with respect to the number of common neighbours between the source node and the destination node. As shown in Table II and Fig. 1(c), the probability is (approximately) linearly proportional to the number of common neighbours. Thus the preferential formation of balance links can be understood as a two-step random walk in the network. Here, by carefully examining the four OSNs mentioned above, we obtain empirical evidence that the preferential formation of triadic closure, i.e., the formation of balance links, can be one possible micro-dynamical process leading to the PA phenomenon in OSNs.

**Modelling.** The above empirical analysis has shown that in the OSNs studied, user behaviour is essentially influenced by each other within the neighbourhood, and such an interplay in turn regulates the global evolution of the network. This suggests that local dynamics plays a leading role in the formation of new links during evolution. Based on this finding, in the following we set up a coevolving model, which is only driven by local interactions at the microscopic level, i.e., preferential formation of triadic closures and influence within the neighbourhood. For simplicity, we neglect the link directions in the modelling, i.e., we only consider an undirected network.

In order to describe the dynamics of the users, we introduce a state function $\phi(i, t)$ for each user in the network. Here $i$ and $t$ denote the nodes and time, respectively. The values of the state functions describe the willingness of the users to create links. For each user in the network, we assume that his state function satisfies the following reaction-diffusion-like equation:

$$\phi(i, t + 1) - \phi(i, t) = \phi_0 + \mu \sum_j a_{ij} [k_j(t + 1) - k_j(t)],$$  \hspace{1cm} (1)

where two parameters $\mu$ and $\phi_0$ are constants; $k_j(t)$ is the degree of user $j$ at time $t$. The LHS of the equation is the change of state function with time, which is driven by two "forces": reaction and diffusion. The first term on the RHS, i.e., $\phi_0$, is a source term denoting the reaction, which means that a user can change his state on his own. The second term describes the diffusion process, i.e., how the interplay in the neighbourhood of the user $i$ changes his state function. Basically, if the neighbours of user $i$ build new links, his state function will be increased as a result of this influence. We set a threshold $\Theta$ for the state function of each user. If the state function exceeds the threshold, the user will be activated, and has a probability $F(k_i)$ to actively create a new link. Once a user has built a new link or his state function has exceeded the threshold, his state $\phi(i, t)$ is reset to zero at the next time step. Essentially, the model simulates the user logins and activities in the OSNs in terms of the state functions.

As shown in Fig. 1(b), users with more friends, i.e., with larger degrees, turn out to be more active in generating new links. To characterize the diversity of users’ activities, we adopt a general Fermi function, which has been extensively used in evolutionary games models as the adaptive acceptance probability for each activated user:

$$F(k_i) = \frac{1}{1 + 20e^{-0.001(k_i - \langle k \rangle)}}.$$  \hspace{1cm} (2)

Here $k_i$ is the degree of user $i$, $\langle k \rangle = 2(m + 1)$ is determined by the parameter $m$ in the model, representing the average degree of the whole network, and 0.001 denotes the intensity of selection. $F(k_i)$ monotonically saturates to 1 with the increase of $k_i$, modulating the acceptance probability of nodes with different degrees. The parameter values (20 and 0.001) do not affect the qualitative behaviour of the model. In this paper, we choose the parameter values to allow the assortative coefficient vary in a relatively wide range. We emphasize that the acceptance probability $F(k_i)$ may take other forms as long as it has similar behavior as the Fermi function.

Specifically, the algorithm to realize the model works as follows:

1. At the very beginning, the initial network consists of a few users ($N_0$, forming a small connected random network. The state functions of users in the network evolve according to Eq. (1). (2) Adding users: at every time step, one new user is added to the network and randomly connects to an existing user. (3) Adding links: at each time step, $m$ users are randomly selected from the activated users with the acceptance probability $F(k_i)$ (Eq. (2)), and each connects to one of his second neighbours if they are not connected. If the number of activated users is less than $m$, the remaining users are randomly chosen.

**Table II** | Exponents $\alpha$ for empirical networks, characterizing the dependence of balance links and distant links (in the parentheses) on the degree and the number of common neighbours, i.e., $\kappa(x) \sim x^{\alpha}$. Here $\alpha_F$ for PA, $\alpha_C$ for preferential creation, and $\alpha_N$ for common neighbours. For comparison, exponents $\alpha$ for balance links in the model networks are also listed in the brackets.

| $\alpha$   | Flickr | FF   | aNobii | Epinions |
|-----------|--------|------|--------|----------|
| $\alpha_F$ | 1.0 [0.48][0.98] | 0.97 [0.5][0.99] | 1.13 [0.70][0.96] | 1.22 [0.84][0.97] |
| $\alpha_C$ | 1.0 [0.5][1.19] | 0.9 [0.55][0.96] | 1.11 [0.73][0.94] | 1.13 [0.56][1.11] |
| $\alpha_N$ | 0.9 [1.14] | 1.12 [1.13] | 1.0 [0.95] | 0.95 [1.13] |

![Figure 1](https://www.nature.com/scientificreports/)

**Figure 1** | The influence of the current topological status on the formation of balance links and distant links in the aNobii and FF (in the insets) networks. (a) The cumulative functions of the relative probability $\kappa^b(k_{in})$ for PA versus the in-degree of the destination nodes; (b) $\kappa^c(k_{out})$ for preferential creation versus the out-degree of the source nodes; (c) The cumulative functions of the relative probability $\kappa^u(u)$ for a pair of users to build a social link given that they have already shared $u$ common neighbours for all balance links. The exponents are obtained by fitting the curves of $\kappa(k)$ averaged over different initial snapshots. The straight lines are guide to the eye throughout this paper.
from the network. The above procedure is schematically illustrated in Fig. 2, where the states and the topology coevolve for one step driven by the local dynamics. As shown in Figs. 2(d)–2(f), with the increase of $k$, the period of the state $w(i,t)$ for a user could become smaller, indicating that the users with larger degrees are more frequently activated.

Verifications. In our model, although we consider only simple local rules as the force driving network evolution, numerical experiments have shown that the model can exhibit the main properties observed in empirical OSNs, such as the large clustering coefficient, small average shortest path, and the power-law distributions of degrees, etc. In order to verify our model, we first compare the degree distributions of the model network with that of the empirical networks in Fig. 3. It is found that the distributions are qualitatively consistent with each other under appropriate parameters. In empirical networks, the probability to build a new link depends on the existing degrees, as shown in Fig. 1 and Table II. To compare the dynamics of our model with that of the empirical networks, we also applied the same analysis to the model under the same parameters of Fig. 3 and summarized the results in Table II (in the brackets). It is seen that the characteristic exponents $z$ are qualitatively consistent with the empirical ones.

We now focus on the two major properties of the model network: the power-law exponent $\gamma$ and the assortative coefficient $r$. First, we investigate how the exponent $\gamma$ varies with respect to the model parameter $m$. In this work, the best power-law exponents $\gamma$ are calculated using the maximum likelihood method. As shown in Fig. 4(a), for small parameter $m$, the distribution of degrees follows a stretched power law with the exponents $\gamma$ larger than 2; while for large $m$, the exponent $\gamma$ turns out to be smaller than 2. As we know, many real world OSNs are characterized by $\gamma < 2$. The present model can produce this important feature in flexible parameter regimes. In Fig. 4(a), we show the degree distributions for different network sizes. It is found that they are almost the same, indicating that the statistical properties of the model network are stable after long-time evolution. We further find that, as parameter $m$ increases, the exponents $\gamma$ go down across 2, as shown in Figs. 4(b) and 4(c), indicating that the generated network makes a transition from a sparse scale-free network to a dense network. To justify the power law fitting, we compute the $p$-value for the power law model, which measures how good the power law fitting is suitable for the data. As shown in the insets of Figs. 4(b) and 4(c), the $p$-values are generally larger than 0.25 and the averages are 0.60 and 0.63, respectively, indicating the power law model is a plausible fit to the data. We then investigate the assortative coefficient $r$ in the model. Since the links in the model are undirected, the assortative coefficient $r$ is defined as the correlation between degrees of pairwise nodes. As shown in Figs. 5(a) and 5(b), with the increase of parameter $m$, $r$ changes from positive to negative, indicating that the model...
networks convert from being assortative to being disassortative. There are two important points to emphasize. First, as shown in Fig. 5(a), the change of the sign of \( r \) occurs at larger \( m \) as parameter \( w_0 \) increases. Second, as shown in Fig. 5(b), the value of \( H \) has significant influence on \( r \).

In the above, we have shown that \( r \) in the model could convert from positive to negative when parameter varies. As reported in Refs. 11, 12, some OSNs convert from being assortative to being disassortative during evolution. How does \( r \) in the model behave with the increase of time in our model? First we note that the final network size \( N \) is proportional to the total evolution time. As shown in Fig. 5(c), the coefficients \( r \) become almost stationary when the model evolves for sufficiently long time. In particular, in certain parameter regimes, the generated networks evolve from the initial assortativity to the subsequent disassortativity with the increase of time. Therefore, the current model can characterize the distinct dynamical stages observed in the OSNs such as Weaklink and Google+

The assortative to disassortative change in our model can be heuristically understood based on Eq. (1). Basically, it is the result of the competition between two factors in our model: the reaction factor denoted by parameter \( \phi_0 \), and the diffusion factor denoted by parameter \( \mu \). Parameter \( m \) is important because it controls the diffusion and thus can change the ratio of these two factors. When \( m \) is small, i.e., the number of new links formed at each time step is small, the local influence is weak due to the small average degree, i.e., \( \langle k \rangle = 2(m + 1) \). In this case, the factor of reaction is relatively more important, and the user’s own motive plays a dominant role in the evolution of the state function. Consequently, the activation probability of a user is almost independent of the degree. Users thus have almost equal chance to be activated and connect to others, leading to the assortative mixing pattern. This may correspond to the situations in some OSNs where users tend to establish links with people they know in real life, resulting in assortativity in the acquaintance network during the initial stage. On the other hand, when \( m \) is large, according to Eq. (1), the local influence, i.e., the diffusion, then plays a dominant role in the evolution of state function. In this case, users with larger degrees have more chance to be activated and connect to others, leading to the disassortative mixing pattern. In real situations, this may correspond to certain OSNs where the celebrities attract their fans to connect to them.

To further illustrate how parameter \( m \) regulates the assortative mixing pattern in the model network, we calculate the average degree distribution for different values of \( m \) and \( \phi_0 \). The results are shown in Fig. 4(a) for \( m = 3 \) and \( m = 25 \), and in Fig. 4(b) for different values of \( \phi_0 \) and \( \Theta \). The insets are the p-values from the maximum likelihood method. If not specified, the parameters in our simulations are \( N = 500,000, \mu = 1, \phi_0 = 0.1, \Theta = 100 \) throughout the paper. Results are averaged over 10 realizations.

Figure 3 | Comparing the degree distributions of the empirical networks with that of the model network. Since the model network is undirected, we ignored the direction of links in the empirical networks for comparison. (a) Flickr, where the parameters of the model are \( m = 25, N = 500,000, \mu = 1, \phi_0 = 0.01, \Theta = 100 \). (b) FriendFeed, where the parameters of the model are \( m = 8, N = 200,000, \mu = 1, \phi_0 = 0.02, \Theta = 200 \). (c) aNobii, where the parameters of the model are \( m = 7, N = 100,000, \mu = 1, \phi_0 = 0.02, \Theta = 180 \). (d) Epinions, where the parameters of the model are \( m = 25, N = 100,000, \mu = 1, \phi_0 = 0.01, \Theta = 100 \).

Figure 4 | Transition from sparse to dense in the model network. (a) Degree distribution for \( m = 3 \) and \( m = 25 \) with different size \( N \). (b)–(c) Power law exponents \( \gamma \) with respect to parameter \( m \) for different values of \( \phi_0 \) (b), and for different values of \( \Theta \) (c). The insets are the p-values from the maximum likelihood method. If not specified, the parameters in our simulations are \( N = 500,000, \mu = 1, \phi_0 = 0.1, \Theta = 100 \) throughout the paper. Results are averaged over 10 realizations.
increases with time. This roughly corresponds to the increase of ‘Acquaintances’ in Google consisting of the acquaintance social network and a virtual online network. The former subnetwork viewpoint of competition between reaction and diffusion factors. of parameter being disassortative with the increase of time. Similarly, the decrease dominant, and the network may convert from being assortative to model in Fig. 5(c), this will cause the diffusion factor gradually to be different values of and negative assortativity, as in some real OSNs. Similarly, the decreases when the degree is large enough, corresponding to neutral for increasing coefficients are 0.21, 0.15, 0.12, 0.09, 0.07, 0.007, —0.10, —0.23, and —0.41 for increasing m, respectively.

In the evolution of real OSNs, generally the average degree increases with time. This roughly corresponds to the increase of m in the present model due to (k) = 2(m + 1). As shown by our model in Fig. 5(c), this will cause the diffusion factor gradually to be dominant, and the network may convert from being assortative to being disassortative with the increase of time. Similarly, the decrease of parameter Θ is equivalent to the increase of parameter m, and the behaviour of the model in Fig. 5(c) can also be explained from the viewpoint of competition between reaction and diffusion factors.

To support our argument above, we apply empirical analysis to the aNobii network. Specifically, we regard it as a hybrid of a real world social network and a virtual online network. The former subnetwork consists of the acquaintance links connecting users knowing each other in real life, e.g., their family members and friends, such as “Acquaintances” in Google+ and “Friendship” in aNobii; and the latter comprises the stranger links connecting their online virtual friends, such as “Following” in Google+ and “Neighbourhood” in aNobii. In terms of the reaction-diffusion process, the generation of these two types of links is mainly due to the reaction factor (i.e., user’s personal desire) and the diffusion factor (i.e., the local influence) respectively. Interestingly, we find that the subnetwork consisting of the acquaintance links is assortative with r = 0.06, like real world social networks. On the contrary, the subnetwork consisting of the stranger links is disassortative with r = —0.09. As shown in Fig. 7, the relative probabilities forming stranger links are significantly larger than that forming acquaintance links, implying that the diffusion factor is dominant in aNobii. As a result, the aNobii network as a whole turns out to be disassortative with r = —0.05. The above results provide empirical evidence that the competition between diffusion and reaction might determine the mixing pattern of degrees in an OSN. Reasonably, during the evolution of the OSNs, if the diffusion factor dominates over the reaction factor, a transition from assortativity to disassortativity could be expected as in Weaklink and Google+.

Discussion
In this work, based on some empirical analysis of four typical OSNs, we set up a reaction-diffusion-like model, in which the evolution of the network is governed by both the users’ personal motives and the influence within neighbourhood. As a natural consequence of the coevolution of dynamics and topology, the model is able to qualitatively reproduce the major properties observed in real world OSNs. In particular, the generated networks can convert from being sparse to dense, and from being assortative to disassortative with appropriate parameters. The model provides explanations of these two important features in real world OSNs in terms of the competition between reaction and diffusion factors in network evolution.

We believe that the current work is enlightening in modeling the evolution of the OSNs as well as of other real world networks. For example, other mechanisms of link formation, such as collective action and the structural hole mechanism, etc., can be readily formulated and investigated. The idea of the model might be applicable to a wide range of social networks, and can be easily generalized to treat multi-layer networks, weighted networks, and social-attribute networks, etc. For example, recently, we have carried out a modeling for Flickr, with a typical dual-component and dual-connection OSN, and obtained satisfactory results.

Methods
Data description and notations. Flickr is one of the most famous websites sharing photos. The data set for our study is collected by daily crawling the Flickr network over 2.3 million users from Nov 2, 2006 to Dec 3, 2006, and again daily from Feb 3, 2007 to May 18, 2007. In total, there are 104 days in the time window of data collection. There are more than 2.3 million users and 33 million directed links among them. FriendFeed (FF) is a content aggregation site where users discover and discuss the interesting contents found on
Figure 7 | Characterizing the difference between the acquaintance and stranger links in the aNobii network. (a) The cumulative functions of the relative probability $k^m_\text{out}(k_{\text{out}})$ versus in-degree of destination nodes; (b) $k^m_\text{out}(k_{\text{out}})$ versus out-degree of source nodes. (c) The cumulative functions of the relative probability $u^m$ for a pair of users to build a social link given that they have already shared $u$ common neighbours.
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