A Social Network Study of the Apple vs. Android Smartphone Battle

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Abstract—**In this paper we measure and quantify how consumer's choice of smartphones are related to their peers' smartphone choices. Specifically, we study and compare this 'social component' of product adoption for two competing classes of smartphones: iPhone and Android. This is done by constructing a proxy of a social network by using anonymous phone log data from Norwegian mobile phone users, and then coupling adoption data to this social network. We find that smartphone adoption is dependent on the underlying social network both for Android and for iPhone users. Comparing the two, we see that the effect is strongest for the latter. In addition, we measure that the core social network is larger for iPhone users than for Android – Measured by telecom communication, Apple users have more friends than android users. We also present results showing urban/rural differences in smartphone usage.**

Social Network Analysis;Viral Marketing; iPhone; Android; Telecom, product diffusion

I. Introduction

It has long been known among marketers that our social network matters when we make purchasing decisions, and that having positive word of mouth about a product can be a key to success; see e.g. [1] for a review of studies on social networks within marketing. Traditionally, data on social networks have been difficult to collect, but in recent years researchers have gained access to massive social network data from e.g. online instant messaging services [8][5] and phone log data [2][4][3][6][9]. Such data has made it possible to study e.g. social churn [3], service uptake [2] among telecom customers, and product adoption on an Instant Messaging network [8].These studies confirm that consumer behavior is dependent on the communication network. We have in a recent study [6] shown how the structure of the *adopter network*—the social network of adopters—develops over time, and how social spreading can be measured by studying this network. In this paper, we do a comparative study of social spreading effects for two competing types of smartphones - the Apple iPhone, and smartphones based on Google's Android OS.

II. Method

Our social network is built by collecting anonymized call data records, aggregated over a 3-month period, and then using the communication links (voice and sms) as proxy for the social relationships. To remove error sources due to 'non-personal' relationships we have applied some filtering of the dataset. E.g. we see that some customers have thousands of contacts during the three months period. This can be machines set up to automatically send SMSs, company call-centers or other forms of extreme calling behavior. Such outlier nodes are filtered out based on combinations of extreme usage and degree (number of unique contacts). Only traffic between Telenor customers is used, calls to other operators are excluded. For this study we have also included weak links – we also want to include relations with limited SMS/voice traffic in the period. In total we end up with a network containing around 2.5 million nodes and 45 million edges.

Other studies have shown that mobile phone activity is a good way to measure real social relationships [5]. We also use handset type data to associate a handset type with each node in the social network. With these data we can define the 'adoption network' – the social network among adopters [6]. This is simply the sub network consisting of adopters and their common links. We can then study the development of the adoption network for iPhones (viewed as a single 'product')—as seen in [6]—and, here, for Android phones, over time (again making no distinction among the various models of Android phones). These same data allow us to measure conditional adoption probabilities between neighbors on the network, which we use as an indicator of social effects. Finally, we use postcode information—very coarse-grained geographic information— on subscribers to map smartphone adoption to geographical areas in Norway.

III. Results

In a previous paper [6], we looked at the growth of the iPhone adoption network over time, showing clearly the development of a 'social monster'—a giant connected component of the adoption network which shows the fastest growth. We equated the strength of this monster with the presence of iPhone adopters in the 'dense core' of highly central subscribers—a sign of success of the product in taking off. Presence in the dense core is also inevitably associated with a high density of adopter-adopter links—a sign that the product adoptions is 'social'. Here, in using the term 'social adoption', we do not attempt to distinguish homophily effects from true inter-customer influence: we simply seek to measure the tendency for those who talk together to adopt together.

In Figure 1, we compare the growth of the Apple adoption network with that of the Android adoption network, on a quarterly basis. In each case, we start with the quarter in which the 'product' was first launched. While we see no dramatic difference in the first–quarter picture (Fig 1(a)), it is clear that already, two quarters later (Fig 1(c)), the Apple 'monster' (Largest Connected Component - LCC) is growing much more rapidly than the Android monster. This holds not only for total number of adopters in the LCC, but also in terms of their percentage of all adopters: two quarters after launch, the Apple LCC has ca 38% of all adopters, while the Android LCC has around 28%.

For another indicator of social adoption, we look at the number of inter-adopter links (adoption pairs) in each adoption network, over time. Figure 2 tracks the number of adoption pairs for each product, versus the total number of adopters. The black dotted curve in Figure 2 gives the number of adopter pairs expected, for the given total number of adopter pairs on the fixed call network, if adoption was purely random. We see that both products generate many times the number of adopter pairs expected from this random reference model. Thus, both products show significant social adoption—but, again, the effect is clearly weaker for Android. (The ratio between the empirical number of adopters, and that number found in the random reference model, was studied in Ref. [6] and termed 'kappa'.)

In Figure 3 we plot yet another indicator of social adoption. Here we look at $p_X(k)$—the conditional probability that, given that a node has k neighbors adopting product X, the node in question has also adopted product X.

Since random adoption gives a flat $p_X(k)$, the positive slope of the results in Figure 3 are again taken as evidence for social effects (of some kind) in adoption—for both products. The difference between Apple and Android is seen here in that the Android curve has more weight at small k—flattening out at large k—while the Apple curve has less weight at small k, but grows steeply, and almost perfectly linearly, all the way to *k*=10. These data were taken in Q3/2011. In this period, the Apple and Android penetration were approximately equally (around 18% each). Hence we see that p(k) is *under*represented at small k (compared to the random case, ie, a flat line at p(k) = 18%), and *over*represented at large k, for both products—but the skew is greater for Apple than for Android. Taking this skew as an indicator of social adoption, we find again that Apple is 'more social' than Android.

Figure 4 shows the two-dimensional conditional probability $p_W(k_X,k_Y)$ that a node has adopted product W = (Apple or

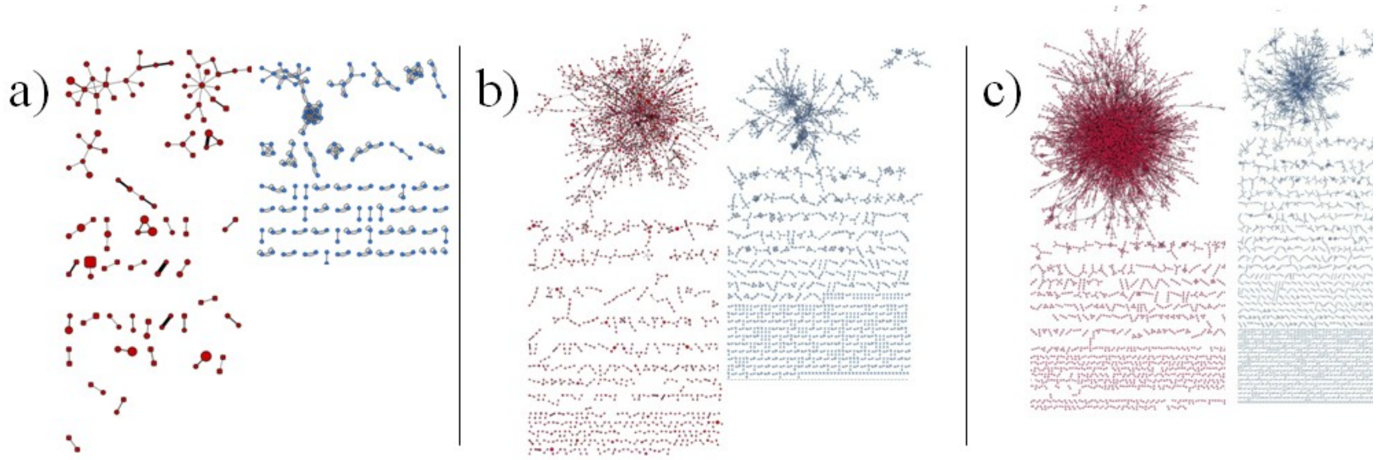

Figure 1
The figure shows the evolution of the iPhone (Red/Left) and Android (Blue/Right) adoption networks during the 3 first quarters after launch of the first respective brands. The nodes are customer with iPhone(red) and Android (blue). Links indicate communication between the nodes. Figure a) is the quarter when the handset first appears in the market, b) is the next quarter and c) is third quarter after product launch. Isolated nodes are not shown – i.e iPhone customers that do not know other iPhone buyers or Android Customers that do not call other Android customers will not appear in this visualization.

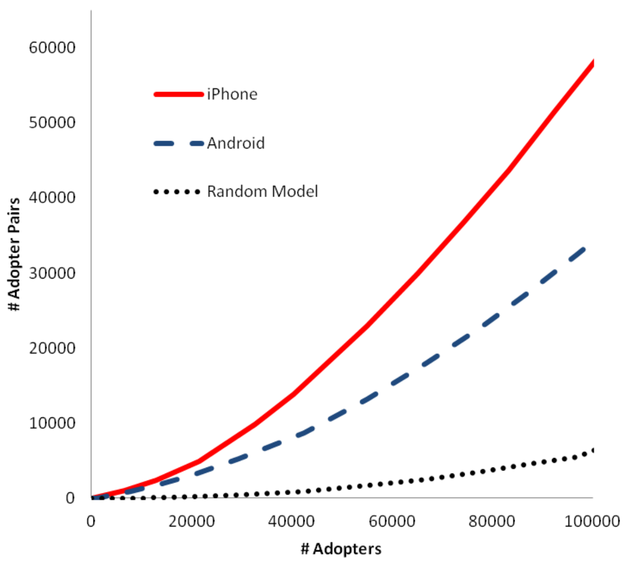

Figure 2
The plot shows the number of adoption pairs (Connected customers adopting same type of handset) vs. the total number of customers having the brand (x-axis). Red solid line is iPhone, blue stipled line is Android and black dotted line is the random simulation model.

Android), given that the node has k_X neighbors who have adopted W, and k_Y neighbors who have adopted the competing product. The upper part of Figure 4 shows this for W = Apple, and the lower part for W = Android. In each case, the x axis gives the number of neighbors having adopted product W. Thus we expect (and find) highest weight in the lower right-hand corner: lots of W neighbors, and few or no competing neighbors, giving high probability of adopting W.

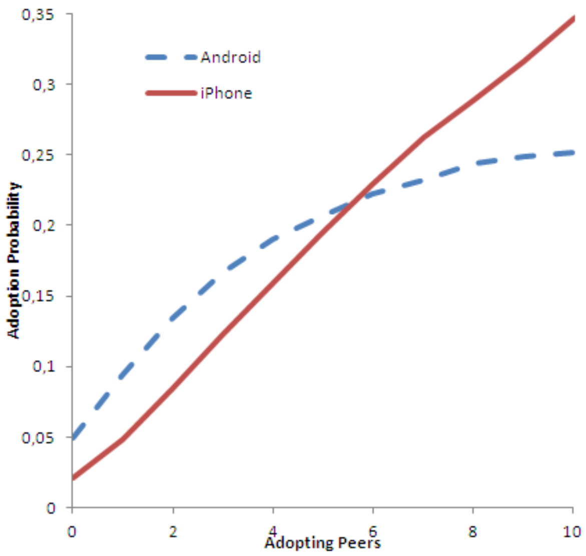

Figure 3
The plot shows ego's handset adoption probability given *x* number of alters with same handset. Red solid line is iPhone adoption probability and blue stippled line is Android. Note that adoption probability increases strongly with the number of adopting peers.

Hence, qualitatively, neither part of Figure 4 gives a surprise—and, once again, the observed 'biasing' effects on neighbors are clearly stronger for Apple than for Android.

Inspired by these results, we have examined the geographic distributions of these two products. Our method here was to first aggregate Apple and Android adoption totals over Norwegian postal codes, and then we take the ratio of the two. Figure 5 shows the results superimposed on a map of Norway. What we find, very simply, is that Apple is dominating in Norway's cities. Since these results are also from Q3/2011, there are roughly equal numbers of Apple and Android phones—so that Apple cannot win everywhere. Thus we see a rather stark urban/rural dichotomy, with Apple dominating the cities and Android turning up as scattered blue spots in the countryside.

We conjecture (but have not yet tested) that the high-centrality users (as measured by eigenvector centrality) are concentrated geographically in the cities (just as they are concentrated, by definition, in the dense core of the social network). In any case, all of the above results give a picture of Apple users as being more attracted to other Apple users than are Android users to other Android users—but also, more social in general. To test this idea, we show in Figure 6 the average degree centrality of three groups: Apple users, Android users, and the whole population. The result is clear: while Android users have slightly higher degree centrality than the whole population, Apple users have around 50% higher degree centrality—they are more social, by this definition.

Results from an earlier period confirm this picture. We measured the number of Apple-Apple links and Android-Android links (as in Figure 2), but also the number of Apple-

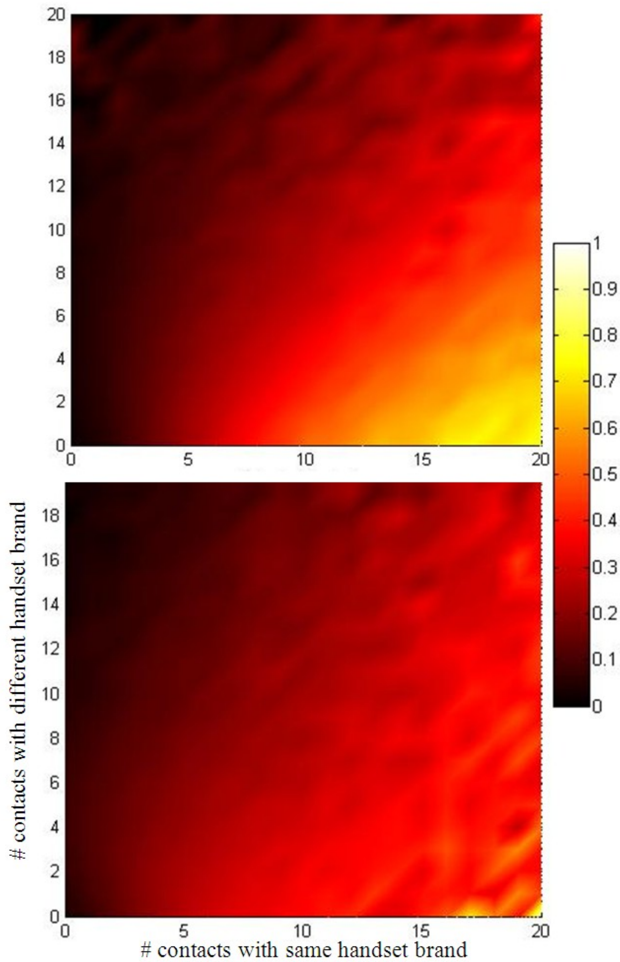

Figure 4
The plots show the adoption probability for iPhone and Android versus the number of contacts with iPhone and number of contacts with Android. Top plot: *x*-axis is the number of iPhone contacts, *y*-axis is number of Android contacts and color intensity is iPhone adoption probability for ego (Dark is low probability).
Lower plot: Color intensity is ego's Android adoption probability given *x* number of Android contacts and *y* number of iPhone contacts. At the time of measurement, market share of iPhones roughly equals that of Android smartphones.

Android links. From these data we can get the average number of Apple and Android friends an Apple user has—and the same for an Android user. The result was clear: the average Apple user had over two times as many Apple friends as statistically expected from no preference—while all other results (number of Apple friends of Android users, and number of Android friends of Apple and Android users) were statistically consistent with no Apple/Android preference. In short: restricted to smartphone users, we again find that Apple users have more friends, and a stronger preference for their 'own kind'.

Using our geographic information on subscribers, we have displayed the results in Figure 6 in terms of three broad geographic categories—"urban", "small town", and "rural". Here we see a clear result that is counterintuitive: for all three groups of nodes (Apple, Android, all), we find that the average degree centrality *increases* steadily as one moves from urban to small town to rural. This result is not understood. We leave this question (and the measurement of eigenvector centrality for these groups) to future work.

IV. SUMMARY AND FUTURE WORK

In previous work [6], we showed strong social effects on the adoption of iPhones. Our aim in this work was to perform similar measurements on Android phones, in such a way that we could compare the two types of Smartphones on the dimension of social adoption effects. We have looked at: (i) the growth of the social monster in the dense core of the social network; (ii) the number of adoption pairs; (iii) the conditional probabilities for adopting Apple or Android, conditioned on the adoption numbers for adopting neighbors; (iv) the distribution of Apple and Android over the Norwegian geography; and (v) the average degree centrality of each group. Without exception, our results in all these tests support the conclusion that social adoption effects are considerably stronger for Apple than for Android. Furthermore, our degree centrality results imply that Apple users in general are more socially active than Android users. It seems that Apple appeals to this type of very social user; and that Apple users in turn interact strongly, and preferentially, with one another.

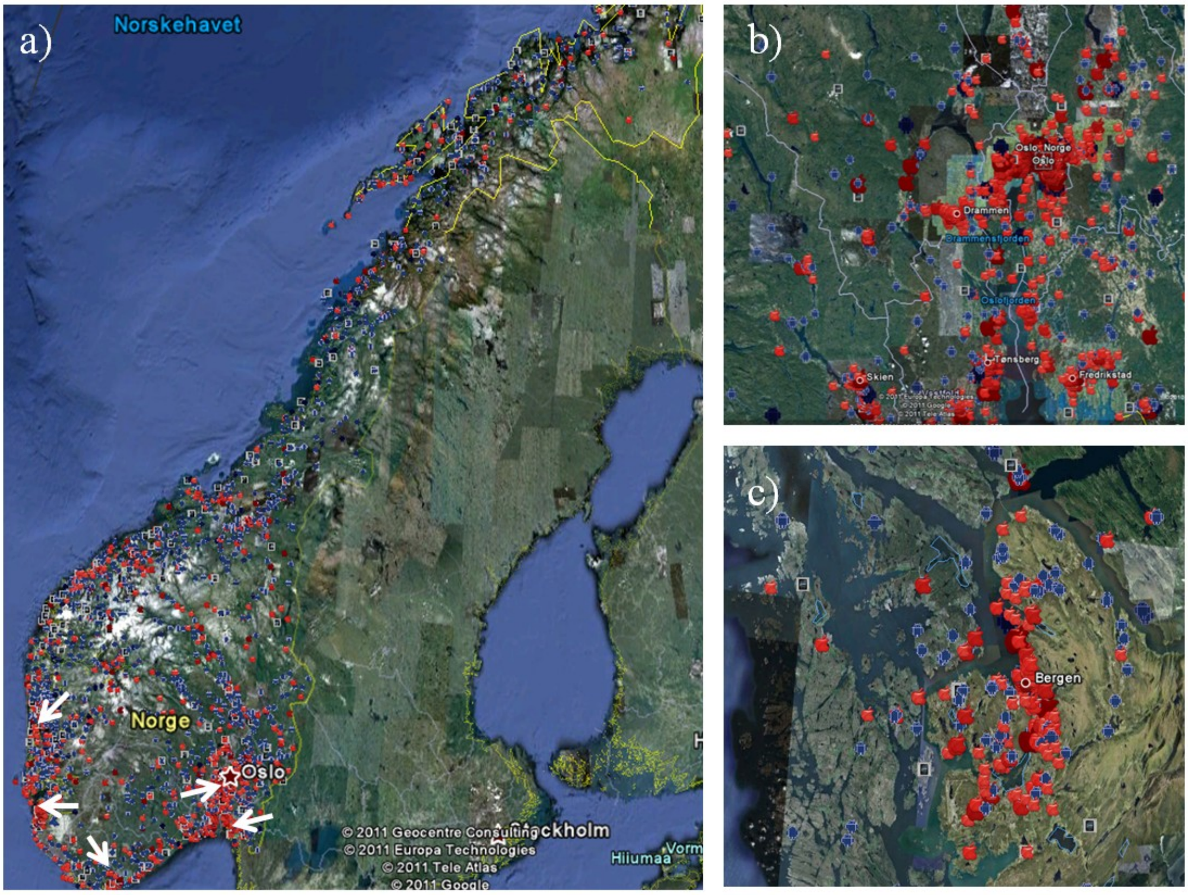

Figure 5

The figure shows iPhone and Android uptake mapped to geography via postcodes: Postcodes with more iPhone users than Android users are colored red. Blue indicates more Android than iPhone in that area. The arrows point at some of the largest cities in Norway. From west to east: Bergen, Stavanger, Kristiansand, Oslo and Fredrikstad. The visualization shows that iPhone 'wins' the cities and Android dominates in rural areas. b) is a close-up of the area around Oslo – the largest city, and c) the area around Bergen – the second largest city. iPhone dominates close to the center and in surrounding suburbs.

These results (especially the 'monster' results) imply [6] that Apple users should have higher (eigenvector) centrality than Android users. We save this question for future work. We also plan to look further at the intriguing result, seen here, showing higher degree centrality in rural areas than in urban areas. We will also look further into if 'peer pressure' effects vary between urban and more rural locations.
Android handsets are manufactured by several producers, with varying features. A study on how the social adoption varies among the different Android brands is reserved for future work.

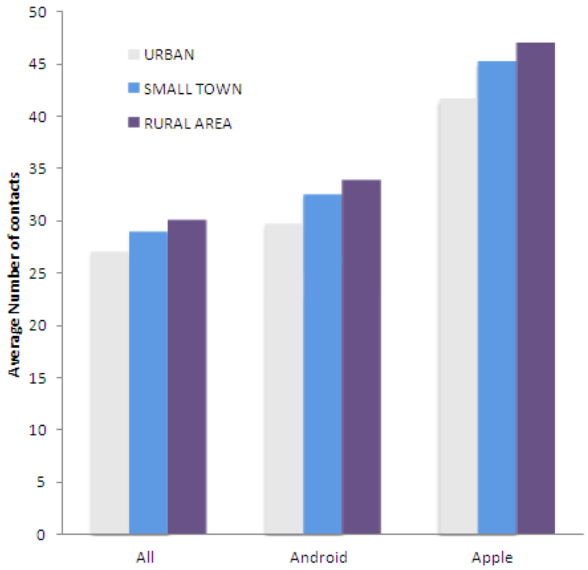

Figure 6
Average number of contacts split by customer groups: All, Android users and Apple Users. The colors indicates location of residency- Urban (grey), Small town (blue) and Rural (violet).

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