1.1.1 Whitepaper 42: Modeling and Analysis of Information Flow in Networks

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Thrust

QoI-SAN; 2a

Technical Abstract
In this task we examine the flow of information through multi-genre networks. We consider both the quality of the information as it propagates, and the quantity of information supportable by different network structures and types. The problem arises in social networks – e.g., rumor/information propagation through social media, in communications networks – e.g. exchange of data such as images and video in a tactical wireless network, as well as multi-genre networks – e.g. collaborative decision making by military personnel connected over a multi-hop wireless network.

We propose to develop foundational models, analytical tools and experimental studies for characterizing information flow in multi-genre networks. We will focus on: (a) models for information flow at the node, community and network levels to characterize the effects of information load, its quality, structural attributes and congestion bottlenecks; (b) impact of different types of social media modalities (text message, voice, twitter) and constraints (e.g., time to communicate) on QoI; (c) modeling the effect of collaborative memory on information flow; and (d) experimental studies with human subjects and analysis of data sets such as Twitter and the military Singapore data set to validate our models.

Research Issue/Technical Approach

Key Research Questions and Initial Hypotheses

Q1: How is the quality of the information affected as it flows through a multi-genre network, for instance by node characteristics, capacity, memory of prior interactions, etc.?

As information flows through a multi-genre network, each node has to make decision on what to do with it, if it should be merged (fused) with past knowledge, etc. Each node may modify the information in some way, even if inadvertently. What are good models that capture this flow in communication, social and multi-genre networks?

Q2: How does the ability of the network to handle the information flow depend upon the network structure and type of network? Where are the bottlenecks (nodes, links), and how do the bottlenecks change with flow patterns and between single- and multi-genre networks?

There are a variety of network structural models. Some of these structures may be more scalable than others as the magnitude of information is increased. Of particular interest is the role of bottlenecks, their effect on information flow patterns, e.g. how does the congestion at the bottleneck scale as a function of structural models and their parameters?

H1: Models for information flow and quality considerations thereof can be adapted to a social and multi-genre context.

In years 1-5, we developed "symptotic" models that capture the relationship between node capacity, network load, information quality, mobility, network structure, and protocol overhead largely for communication networks. Many aspects of social communications are analogous, yet some are very different. By developing node processing models, notions of quality, and influences of memory, we can extend our models to a social and multi-genre context.

Research Problem Background

The capacity of wireless communication networks has been well studied [GK2000], from an asymptotic viewpoint. Recently, as part of the NS-CTA, we have studied the *symptotic* scalability, which is a framework for the non-asymptotic analysis of real-world wireless networks [RABFJKLRSF2010, RSL2012]. We have characterized tradeoffs of different QoI metrics against the amount of data that must be transferred to achieve a desired QoI [EBJCL2013]. This allowed us to determine QoI-sensitive capacities. The information carrying capacity of social networks has not been analytically studied to our knowledge, and is arguably much more challenging.

To understand information flow in a social network, we must consider how individuals process and alter information (in isolation and as a group), and how information propagates. Indeed, cognitive and social psychology have shown that the accuracy of information processing in a collaborative, social network is not necessarily just the sum of the knowledge of each individual node [HE2012, RP2010, SP2000]. For example, social biases, often called "audience tuning" in social cognition, influence what information is propagated forward, which can then can have feedback effects on the communicator's own memory and situation awareness [HE2012].

Information propagation models and influence maximization have been extensively studied in the literature. [KKT2003] and its follow-ups proposed various kinds of effective algorithms that could maximize the spread of influence through a social network. Unlike our proposed work, these studies assume that information is directly copied through propagation and the propagation rate at each node is fixed and given beforehand.

The works described above have largely been restricted to single-genre networks. For this task, we shall bring together our understanding and results from social and communication networks and create models for multi-genre networks.

Technical Approach

In this section we outline the challenges in our task, and then present our approach.

Our first challenge is understanding the impact of social structure, which may be influenced by the communication network structure, and the memory capabilities of individual nodes on what information (and quality) transformations may take place in a social network. We must address the impact of conversation on memory, determine social structures that enable remembering (without inhibition), understand how social contagion degrades accurate memory (and perhaps how to prevent it), and consider the impact of audience tuning in communication.

Our second challenge is to examine the impact on quality as information spreads across a social network. Quality may be impacted differently, for example, if a person receives information that they already have a portion or all of, or have context for the information, or if they are hearing the information for the first time. It may also be influenced by the available communication networks and messaging modalities (text, tweet, email, conversation). We focus on accuracy, precision and completeness.

Third, we must understand the impact of the structure of networks on the scalability and quality. This is not straightforward, because in a social network bandwidth and load may not be the only, or primary factors in a finding a bottleneck node. Instead it might be memory, past knowledge and access to different types of media. Also, the structure of social networks is intrinsically tied to the underlying communication network, so for multi-genre models, both must be considered together.

The problem is challenging enough that we need to address it in two parts: (1) fully understand and characterize information flow in communications and social networks; (2) extend and integrate our models to capture information flow in multi-genre networks. We shall do the first part largely in Year 6, and the second part in Year 7. Over the last few years of the NS-CTA, we have had great success characterizing the capacity of communication networks, thus, the main challenge in the first year is to understand information flow on social networks, while consolidating our results on communication networks.

Modeling information flow in a social or multi-genre network comprises of three broad models: node-level, community-level and network-level. Each model “feeds into” or is “incorporated within” the higher level model.

Node level model

When a person (node) receives a piece of information, the user has multiple options: ignore, modify, and transmit. Her response might be influenced by many factors: interest, prior knowledge, information overload, time constraint, etc. Her behavior may also be impacted by the type of available networks. This process may be roughly mapped to the *capacity* of a node, the *mutations* of information, and the *routing* of the node. Note that all of these aspects are related.

<u>Capacity.</u> One important characteristic limiting a node’s ability to process information in the network is its working memory capacity. Because working memory represents a limited resource for the maintenance and manipulation of information [MHB2014], individuals should optimally bias this resource selectively toward the information most relevant to task goals. This selectivity will influence not only what is encoded into long-term memory, but also what information is later retrieved and propagated. Thus, the information encoded and retrieved by any individual will typically represent only the subset of the available information consistent with their goals [MPC2001, MBLGD06, SM2007]. These restrictions will be more salient when there is greater overall memory load, time stress, arousal or related pressures [MPC2001, MGWMD12]. Even expert nodes in isolation can be overwhelmed by information and may exhibit pervasive ordering

biases (i.e., serial position effects where by the first and last pieces of information in a stream are preferentially remembered) and confirmation biases (i.e., where information that confirms schemas is encoded at the expense of disconfirming evidence).

We propose to develop models of individuals and groups in terms of their capacity to receive process and transmit data. These models will largely be driven by empirical studies (see Validation section).

Mutation. The second issue is information mutation at nodes. The selection of information to be propagated is subject to biases that can recursively impact the memory of the node. Specifically, because communicators typically must select only some information to propagate (i.e., the audience tuning memory bias), audience congruent information is reinforced through retrieval and propagation, whereas the suppressed information is inhibited through retrieval inhibition. The effects of audience tuning are particularly salient in situations where the information received by the communicator is ambiguous and/or conflicting and the communicator has foreknowledge of the audience's disposition [EKH2013].

We can also resort to the evolution theories in population genetics and use genome mutation as an analogy to study information modification when it goes through nodes. [ALAN2014] has demonstrated the possibility of studying information evolution in social networks using the Yule process [Y1925], which was previously used to model the number of species per genus. In military command and control networks, we expect such models shall be modified to accommodate regularity and constraints.

This model development will be driven by both experiments with humans, as well as the analysis of data traces of information propagation.

Forwarding. Information forwarding is a function of both the individual nodes and the structure of the network. We address the structure of the network in a subsequent sub-task. Each node might unicast or broadcast the messages it receives or creates. Given the audience tuning effects described previously, the type of broadcast could also influence choices of what information to broadcast. It is important to model what kind of information a node might choose to transmit, and its destinations. A probabilistic model could be built on the type of information, the previous owner of the information, the group of nodes this node has been frequently communicating with before, and the messages they commonly receive. In [SSTLKTY2014] we show that the expertise difference between a sender and a receiver follows a log-normal distribution. We plan to apply a similar approach to studying the forwarding behaviors of different genre networks and investigate if there exists a similar law in these networks.

Community level model

We define a *community* as a group of close-knit nodes, possibly of multiple genres. A community exhibits phenomena distinct from both a single node and an entire network, and therefore benefits from its own model.

When nodes are operating in a collaborative mode, the more similar the goals and memory schema are across nodes, the more similar the encoded and retrieved information about a particular scenario will be. It follows then that one way to maximize accuracy and completeness (and reduce redundancy) is to have individuals who have different schemas and goals retrieve information in isolation and then pool that information (i.e., collaborative facilitation; RP2010). Paradoxically, if the retrieval by dissimilar others occurs in the context of an interactive conversation, conflict between retrieval strategies may cause collaborative inhibition, in which less information is retrieved by each individual node than if the node had operated in isolation [RP2010].

Members in a community or a group could produce information, consume information and modify information. It is interesting to treat the community as a black box and observe information flow-in and flow-out. Developing a model to capture the relationship between what are consumed, produced and transferred in a community can reveal the properties and capacity of each community without looking into activities of individual nodes, which might be quite random and noisy. Such a model will reduce the complexity of analyzing large networks. A community can be viewed as a super node, where the same models aforementioned can be applied. It is expected that models derived at community level shall be more robust and reliable. Relating the models derived at community level with the models at node level and the community structure, will tell us the influence of network structure on the performance of communities.

Network level model

We will use the node- and community-level models along with models of network structure and information sources and sinks to build a network level model for information flow. This model applies to both communication and social networks, but here we discuss the more challenging problem of a social network. There are several aspects of interest: network capacity, information bottlenecks and their dependence on network structure and size, propagation distance and time-to-propagate, differences between unicast and broadcast information, the effect of QoI on social network capacity and multi-genre extensions.

As part of the Symptotics framework in previous NS-CTA years [RSL2012,CRL13], we have modeled the *residual capacity* of a node m as

$$R(m) = W(m) - \Sigma_j\ QRF(Q_j)\ (1 + C_j(m))(1 + T_j(m)) \qquad \text{(Eq. 1)}$$

where $W(m)$ is the available node capacity, j denotes a flow, $C_j(m)$ denotes the *contention factor* which is a rough measure of the capacity taken up due to nodes sharing the same (wireless) channel, $T_j(m)$ is the *transit factor*, which is a measure of the number of flows through a node, and QRF converts a desired QoI vector Q_j to a rate. As the network size (density) grows, $T_j(m)$ $(C_j(m))$ grows, and at some size (density) there is a node whose residual capacity becomes zero or negative. We refer to this limiting size as the symptotic scalability.

We observe that the basic elements of our framework are *genre-agnostic*. We shall begin with the above model, but instantiate each of the elements as appropriate for a social network setting.

There are three particularly challenging aspects to adapting Equation 1 to a social network: the impact of the nodes and community on the overall capacity of the system, $W(m)$, the impact on quality, QRF, and the determination of the bottleneck node and its transit factor, $T_j(m)$.

System capacity. $W(m)$ will be derived based on the node and community models discussed above. The development of this variable, and the node and community models, will be the subject of extensive experimentation as discussed in the Validation section.

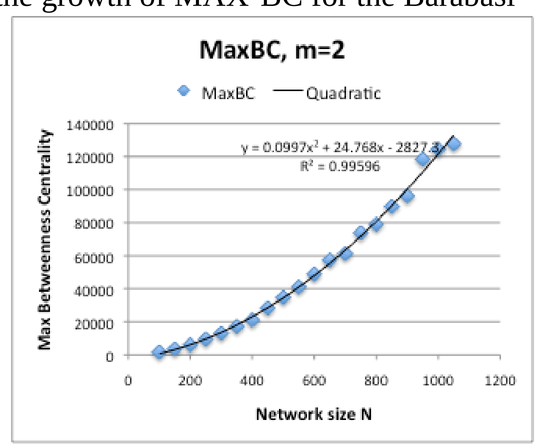
QoI. As information is subject to human memory constraints and mutations, its quality will change. In this task we will consider several QoI metrics that are of interest in a human, social network:

- Accuracy – the correctness of the information being passed; this metric has been explored extensively in the first 5 years of the CTA with respect to communication networks;
- Precision – the detail and degree of accuracy with which information is passed and received; this has also been studied extensively for communication networks;
- Timeliness – the time limit or content limit, if any, on the person conveying the information. We expect the impact of time constraints on the generating and summarization of information to have a dramatic effect on QoI in social networks.
- Completeness – the coverage provided by the information in terms of the request. This has been largely unexplored in the CTA. We will examine this metric with respect to social and communication networks.

As the impact on QoI is better understood, we will map the quality to an analogous rate function for social networks.

Bottleneck Node and Transit Factor. In an N node network, we have shown that the transit factor is related to the *betweenness centrality* (BC) of a node i, as $T_i(m) = 2*BC(i)/(N-2)$. Thus, the capacity of such a network is dominated by the node with the maximum betweenness centrality (MAX-BC), which we refer to as the *bottleneck.* In a human network, the bottleneck node is not necessarily a function only of the number of paths transiting it, but also a function of different factors, such as previous experiences. Based on node models we will determine how to determine the bottleneck node in a social, human network. To start we will continue to use MAX-BC.

An important part of studying the capacity and its scalability is to study the scalability of MAX-BC. However, while one can fairly easily derive analytical closed form expressions for MAX-BC for simple networks like line, ring, clique, and at least approximately even for grid [RSL2012], this appears extremely challenging for models of social networks such as scale-free and small-world networks. We will therefore seek to characterize the MAX-BC using numerical methods. In some preliminary work, we have studied the growth of MAX-BC for the Barabasi-Albert (BA) model using randomly generated scale-free networks and using curve-fitting (see Figure to the right). This shows the growth is similar to that of a line or a tree leading to the conclusion that for social networks that follow a scale-free model, the congestion at the bottleneck is asymptotically similar to the situation with clearly non-redundant structures such as the line and the tree. This leads to the question: what information flow processes can relieve congestion, and which structures exhibit least congestion.



We will perform similar analysis for other social network structures such as small world, hierarchical, and other topologies representative of military settings. Approximate closed form expressions will be derived in a manner similar to the above. With complementary models for contention factor, node models, information sourcing and dissemination models, we believe we can build a capacity model for social networks.

Using these models, we will investigate several questions of interest: Given a social collaboration network where each actor generates a certain amount of information that has certain scope, and given a model of resource constraints, which actors are bottlenecks and what is the maximum amount of information that can be handled? Conversely, given a certain information load, what is the maximum size social network that can be supported without information loss? What is the impact of the transmission medium – point-to-point (phone/direct email), broadcast (chat, facebook, group email) on the capacity of the network?

Multi-genre Networks

After developing models for information flow in social networks in Y6, and consolidating communication network models from Y1-Y5, we will address multi-genre networks in Y7.

We define a multi-genre network and information flow thereof using graph terminology, as follows. We are given a graph $G = (V,E)$ where $V = V_c \cup V_s$, V_c is a set of communication nodes and V_s is a set of social nodes[1]. The key difference is in the node models, which as we discussed above is entirely different. The edge set $E = \{(u,v): u, v \in V\}$, that is, edges can be between nodes of the same genre, or between different genres. A *unicast* information flow in a multi-genre network is between two nodes of the same genre, but can pass through any combination of social and communication nodes. Bottlenecks could appear either at a social or at a communication device. In fact, the two networks will interact and may influence the identity of the type and placement of the bottleneck node. A *multicast* information flow in a multi-genre network can have multiple such endpoints.

A key challenge in extending our models to the multi-genre setting is that the assumption of "homogeneity" of nodes that we made is no longer true. We now have two kinds of nodes, and hence concepts such as the contention factor need to be re-visited, and some basic steps in derivations re-evaluated.

While the challenges are substantial at the network level, there are also challenges at the node and community levels. Models of collaboration between neighboring nodes will now have to address the heterogeneity of inputs. A community can consist of a mixture of social and information nodes.

Validation Approach

We drive some of our model development, and validate our results through a combination of human experiments and data trace analysis.

For human experiments, we will perform empirical lab experiments in which we manipulate factors to determine their influence on specific memory behaviors. Because our population of convenience is undergraduate students, the type of information propagated will be calibrated to what is salient in this population. However, we will work with ARL to ensure that these tasks mimic command and control or information gathering applications. These results will drive and validate our models for node capacity and information mutation.

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[1] While we contemplated proposing a more general formulation where the number of genres could be arbitrary, we believe the problem is hugely challenging as is, and will defer that to years 8-10.

We expect the data trace analysis to help develop and validate models for information mutation and information spread. We collected data from social networks such as Twitter and military communication networks from simulations including JFE and Singapore data set[2]. For both networks, we will study how information flows through networks, their depth, and possible bottlenecks.

Key Deliverables and Planned Research Outputs

Due	Research Milestones for Y6
Y6-Q1	Define QoI metrics of completeness and precision of human networks (La Porta, Cook, Mangels)
Y6-Q2	Derive approximate expressions for maximum betweenness centrality as a function of size for network structures (Ramanathan, La Porta)
Y6-Q3	Experimental plan for validating network level models using data sets and human-in-the-loop experiments (Yan,Mangels,Ramanathan)
Y6-Q4	Determine other characteristics of nodes that may make them the bottleneck nodes (Mangels, Ramanthan, Yan)
Due	**Research Milestones for Y7**
Y7-Q1	Paper on nature of congestion bottlenecks in QoI-aware social information flow (Ramanathan, La Porta, Cook)
Y7-Q2	Extension of QoI-aware capacity considering time constraints (Mangels, La Porta, Cook)
Y7-Q3	Formulation of model of multi-genre networks (Ramanathan, La Porta)
Y7-Q4	Report/paper that compares and contrasts capacity of social networks based on unicast/broadcast, media type, node model variations using our network level model (Ramanathan,LaPorta,Yan,Mangels)

Impact on Network Science

This task seeks to develop a unified generic formulation of network scalability. This framework will apply to singular networks (social, communications) and multi-genre networks. This task explicitly links social and cognitive networks (node and community models, social network structures), information networks (prior memories, biases) and communications networks (both

[2] Records of collaboration in a joint US-Singapore military simulation in 2004 provided to us by Dr. Norbou Buchler, ARL.

jointly when considering underlying communications infrastructures, and in terms of leading to a generic capacity model).

If successful, this will provide a major advancement in network science. While some aspects of networks have been studied in a generic sense (e.g., topology models), and characterization of network capacity that is generic and may be used for joint networks would be highly novel.

Military Relevance

Collaborative decision making is a critical aspect of tactical networks. This is often done through multi-genre means, i.e., people communicating with people over, say, wireless communication networks. This task will help evaluate the capacity of such networks. In particular, our evaluation will specifically address collaborative decision making applications.

In addition, information gathering, for example to develop intelligence, is often also done via human networks. The quality of this information and the capacity to gather it is of high importance to the military. This task will help characterize information gathering strategies.

Transition Opportunities

The precursor to this task has had excellent success in transitions. A subset of models derived under this task has been transitioned to be part of the Communications Performance Assessment Toolkit (COMPAT), and demonstrated to JPEO staff. Further, symptotics was leveraged by a member of the BBN staff serving on the Air Force Scientific Advisory Board (AF SAB) study panel for Airborne Networking and Communications in Contested Environments (ANCCE). The study is part of a final report to motivate ANCCE recommendations for mid-to-far term technology development. A study for DARPA using the symptotic framework was mentioned in the DARPA C2E BAA, for which BBN will be a performer with Ramanathan as PI. Our hope is to continue to leverage such transition opportunities with results and a possible tool that provides a richer set of multi-genre evaluation capabilities.

Dependencies

This task has nice synergies with Semantic Information Theory (WP# 27) and Semantic Information Delivery (WP#30). SIT explores the semantic capacity of a network in terms of source representation and communication channels. Together with our work on quantifying the amount of data required to achieve a certain quality, we expect to use their results to drive our QRF. SID explores strategies and the execution of strategies for retrieving information in a QoI-aware environment. Their work will also drive the QRF in that they will characterize the amount of information (bits) needed to be transferred. It is also synergistic with Modeling Groups (WP #44), where models for groups are being proposed and relates to the community level models here.

Key Contributors and Their Roles

T. La Porta, PSU:

Role: Task lead, PI with a focus on network capacity and QoI

Area of expertise: Communication networks; Network scalability [RSL2012] and QoI [EBJCL2013].

Approximate time commitment: 1 month and 1 graduate student

Expected research contribution: leading research on quality of information in both social and communication networks, collaborating with Ramanathan and Cook on network scalability.

Cross-institution research rotations: La Porta will visit BBN and ARL 1-2 times per year.

Synergies and collaboration: La Porta will work with Cook and Ramanathan on QoI aspects of information flow, and Ramanathan on network scalability.

J. Mangels, Baruch College, City University of New York:

Role: Principal investigator of experimental human-in-the-loop studies.

Area of expertise: Cognitive psychology, cognitive neuroscience and social cognitive neuroscience, with core strengths in basic research on selective attention [SWEHM07, LM07, SM06], studies of how beliefs and attitudes bias attention [RRCDH13, MGWMD12, MBLGD06, SEGKMH06], and how these attentional biases influence encoding and retrieval from long-term memory [MGWMD12, MMS10, JT08, MBLGD06, BM03, MPC01].

Approximate time commitment: 1 summer month, 1 graduate student.

Expected research contribution: Mangels will use her expertise in experimental research to design and implement one study per year that empirically drive new models, and ultimately validate key factors identified through modeling. She will be able to utilize the undergraduate Baruch College population as a source of human subjects, as well as Amazon Turk.

Cross-institution research rotations: Mangles will make frequent visits to APG to work with T. Cook.

Synergies and collaboration: Mangels will work with Ramanathan and Yan on data sets for on node level models, and experiments. She will explore synergies with TIME tasks.

R. Ramanathan, BBN:

Role: Principal researcher on network level information capacity characterization of social networks.

Area of expertise: Communications Networks, specifically capacity scalability [RSP12, RABFJKLRSF10,CRL13], and network science [RBBJRSZ11,HRS14,YBBR2013]. 50+ publications in this area, including three best paper awards [JR2001,R1996,RL1992]. IEEE Fellow for “contributions to ad hoc networks using topology control and directional antennas”.

Approximate time commitment: 0.2 FTE of PI time

Expected research contribution: Lead the subtask on information flow capacity, and develop new models for social networks and help validate them.

Cross-institution research rotations: Ramanathan will visit ARL 1-2 times each year.

Synergies and collaboration: Ramanathan will work with LaPorta on QoI aspects of information flow, particularly as it relates to capacity, with Yan on data sets for validation, and with Mangels on node level models, and experiments. He will explore synergies with co-EDIN tasks.

T. Cook, ARL:

Role: Ancillary researcher on network level information capacity characterization of social networks.

Area of expertise: Communication networks; Quality of Information Modeling [CT2012,CS2012,MCST12]

Approximate time commitment: 0.3 FTE of investigator's time

Expected research contribution: the modeling of information flow at multiple levels in social and computer networks, and characterizing the relationship to quality.

Cross-institution research rotations: Cook will visit BBN, PSU, and possibly Baruch 1-2 times each year.

Synergies and collaboration: Cook will work with LaPorta and Ramanathan on QoI aspects of information flow, and with Mangels on node level models, and experiments.

X. Yan, UCSB:

Role: Principle researcher in information flow analysis and text mining.

Area of expertise: Information network analysis, topic modeling, text mining, probabilistic models and statistical inference. Publications: [SSTLKTY2014; ZVYK2014; TLSGYBCH2013; LWHHRY2013; MTCMMLY2012; STYAC2010; AKY2011]. ICDE 2013 Best Poster Award, 2012 SIGKDD Best Student Paper Award, and 2011 IEEE ICDM 10-year Highest Impact Paper Award in information network analysis and graph pattern mining.

Approximate time commitment: 1 month, 1 graduate student.

Expected research contribution: Lead the subtask on information flow analysis at node/community levels, and perform text analysis on social and military datasets

Cross-institution research rotations: Yan will visit ARL 1-2 times each year.

***Synergies and collaboration*:** Xifeng Yan is collaborating with Mudhakar Srivatsa (IBM Research), Sue Kase (ARL), and Derya Cansever (Army CERDEC) on WP#55, "Problem Solving in Socio-information Networks." The text mining algorithms and value of information models developed there can be applied to this task. Xifeng Yan is currently collaborating with Jemin George (ARL) on analyzing information flows in social media data for physical event prediction, and Hasan Cam (ARL) on cybersecurity-related flow analysis in information and communication networks.

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