

Semantics-Empowered Communication for Networked Intelligent Systems

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Abstract

Wireless connectivity has traditionally been regarded as a content-agnostic data pipe; the impact upon receipt and the context- and goal-dependent significance of the conveyed messages have been deliberately ignored. Nevertheless, in emerging cyber-physical and autonomous intelligent networked systems, acquiring, processing, and sending excessive amounts of distributed real-time data, which ends up being stale, irrelevant, or useless to the end user, will cause communication bottlenecks, increased response time, and safety issues. We envision a communication paradigm shift that makes the *semantics of information*, i.e., the importance and the usefulness of information generated and transmitted for attaining a certain goal, the underpinning of the communication process. We advocate for a goal-oriented unification of data generation/active sampling, information transmission, and signal reconstruction, by taking into account process and source variability, signal sparsity and correlation, and semantic information attributes. We apply this structurally new joint approach to a communication scenario where the destination is tasked with real-time source reconstruction for the purpose of remote actuation. Capitalizing on semantics-aware metrics, we explore the optimal sampling policy, which significantly reduces the number of samples communicated and the reconstruction error in ways that are not possible by today's state-of-the-art approaches.

I. INTRODUCTION

Today's communication technology offers a cornucopia of wireless connectivity and is the foundation of our hyperconnected society and automated economy. The unprecedented mobile traffic growth, the insatiable demand for ubiquitous connectivity, and the generation of abundant data are aftermaths of the digital information revolution we are undergoing. Remarkably, this is

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just the beginning as we are entering the era of connected intelligence. The interconnection of myriad autonomous devices (robots, vehicles, drones, etc.) with advanced sensing, computing, and learning capabilities, is forecast to generate a staggering amount of data (in the order of zettabytes). For example, data gathered by an autonomous car starts from at least 750 MB per second. A swarm of mobile robots may involve transmission of 1 GB aggregated data per second for target tracking or collaborative sensing. In this expanding ecosystem, wireless communication is becoming a commodity that caters to a plethora of socially useful services, such as autonomous transportation, consumer robotics, environmental monitoring, and telehealth.

The envisioned use cases and applications will put future networks under pressure to deliver on an unprecedented number of highly demanding requirements. Next-generation communication systems should efficiently and effectively handle massive volumes of data, which comes from multimodal sensors (visual, auditory, haptic cues) and is often high dimensional. Data should be gathered from different geographical locations, exchanged over the air, and fused/processed at remote destinations for computationally intensive decision making, actuation, or inference. What is more, emerging networked control systems push wireless communication into real-time operating regimes, entailing timely state updates, ultra-fast response time, and on-time delivery of valuable information. In this context, simply generating and communicating large amounts of distributed data, which might often end up being stale, redundant, irrelevant, or useless to the end user/application, could cause severe communication bottlenecks. These bottlenecks, if left unresolved, will inevitably jeopardize the functioning of wireless networks; they will result in unnecessary network congestion and excessive resource/energy consumption, and will violate the stringent real-time and safety requirements imposed by autonomous mission-critical systems.

A. The End of Current Communication Paradigm?

Practically all contemporary wireless systems are built upon fundamental principles of reliable communications over noisy channels, first developed in the *locus classicus* of information theory [1]. Following Shannons mantra, the content of an information stream, as well as its impact upon receipt and its goal-dependent importance, have been deliberately considered as irrelevant at both physical and data link layers. Application-driven packet prioritization and information content-centric networking are deferred to the upper network layers [2]. In existing communication paradigms, the main objective is to optimize performance metrics, such as throughput, delay, or packet loss, and quality of service (QoS) is provisioned through network over-provisioning

and resource reservation control. Moreover, state-of-the-art systems have adopted - not always unjustifiably - prevailing separation principles, which often decouple data acquisition, sampling, and/or computation from communication and application-dependent reconstruction.

The information-impact/meaning dichotomy was a conceptual advance, which has been suitable for classical human-centric data communication, whose goal is to reliably transmit a given information stream in its entirety as fast as possible. In sharp contrast, conventional, separated approaches overlooking the content of the exchanged information, its context of use, and its significance in achieving a specific goal are highly inefficient, come short of meaningfully scaling, and are inadequate for networked autonomous systems and time-sensitive communication. A major roadblock therein is how to jointly acquire, communicate, fuse, and reconstruct relevant and impactful multi-source multimodal information, in particular under real-time constraints. This is not simply a question of understanding the throughput-reliability-delay tradeoff or moving sequences of random bits from one point to another. Moreover, maximizing throughput or minimizing delay are neither necessary nor sufficient for optimal operation in applications based on timely status updates, remote computations, and/or real-time event detection.

B. Towards Goal-oriented Semantic Communication

Looking beyond the aforementioned confined view of wireless connectivity, we place ourselves in a setting where communication is not an end in itself but a means to achieving specific *goals*. We advocate for a radically new communication paradigm that directly connects the application objectives with the physical and medium access control layers and adapts the entire communication process - from data acquisition to source reconstruction and information exploitation - to the semantic value of information. Differently from its use in linguistics, logic, and computer science (e.g., Semantic Web, databases, ontologies, etc.), semantics is employed here with its etymological meaning, that of significance, which posits that the semantic value of information is its usefulness in attaining a certain goal (pragmatics). *Semantics of information is the data importance and the information usefulness/value with respect to a communication goal*. Our approach capitalizes on the largely untapped innate and contextual attributes of information, which influence the relevance and effectiveness of the information communicated, depending on the applications objectives. Considering a simple actuation-oriented causal reconstruction scenario, we show that this paradigm shift has the potential to entirely transforming several prevailing design principles. We showcase its potential to significantly reduce the data volume

generated (i.e., the number of valuable samples), the real-time reconstruction error and the cost of actuation error, in ways that are not possible by today's state-of-the-art approaches.

II. SEMANTICS-EMPOWERED COMMUNICATION: A PARADIGM SHIFT

A. Defining the Semantics of Information

A first natural question is how to define and quantify the semantics of information. As stated before, the semantics of information is associated to the goal-dependent data importance and usefulness/value and capitalizes on the innate and contextual information attributes. We advocate for measuring the semantics of information at three different granularity levels.

1) *Microscopic scale*: At the source level, semantics is related to the relative importance that different equiprobable outcomes/events/observations from stochastic sources and processes/signals have. Those primary information sources could represent data from sensor measurements, trajectories or patterns of a physical phenomenon (e.g., vehicles mobility), or in general the state of the system. Imagine two equally rare events, occurring with probability $p \ll 1$, one of which carries a major safety risk while the other is just a peculiarity. Formally, they provide the same high amount of information ($-\log p$), but the information conveyed by the first event is evidently of higher significance. This disparity in importance can be incorporated into key information measures (e.g., entropy rate, mutual information) and statistical similarity metrics (e.g., f -divergences) using weight functions. These functions should capture potential spatio-temporal evolution of the information utility and depend on the application objectives. To its simplest form, we can define a context-dependent entropy defined as $H(P) = -\sum_{y \in \mathcal{Y}} \varphi(y) P(y) \log P(y)$, for a probability mass function P on a discrete set \mathcal{Y} and a function $\varphi(\cdot)$ that weights the different outcomes with respect to their utility for a specific goal. Another direction to capture information semantics is through Rényi entropy [3], i.e., $H_\beta = \frac{1}{1-\beta} \log \sum_{i=1}^n p_i^\beta$ in the discrete case, and its relatively unexplored operational interpretation of the order β (when $\beta > 1$) as observer-based information gain efficiency in decision making. Rényi's information measures seem to be instrumental in quantifying “novelty”, compressability/sparsity, trackability of stochastic processes, as well as signal complexity. In general, semantic information measures could be incorporated as reward functions or in information gain expressions in a wide spectrum of communication, sequential decision making, and learning problems, such as robotic exploration, multimodal fusion, multi-goal reinforcement learning, and feature extraction to name a few. For instance, many autonomous multi-agent control applications or multi-task active learning problems can be modeled as a

partially observable Markov decision process. Reward functions adapted to the semantics-based requirements posed by the application/end-user could transform how exploration, learning, and control under uncertainty are performed, as well as the associated data collection and information exchange processes.

2) *Mesoscopic scale*: At the link/data transmission level, the semantics of information is a non-linear multivariate function of qualitative innate (objective) and contextual (subjective) attributes of information. The former attributes are inherent in information regardless of its use, such as freshness and precision. They depend on the data/information generated by a source and on its transformations (e.g., compression). The latter are attributes that depend on the particular use of information and the context, with timeliness and completeness, being the most relevant ones. An attribute of particular applicability, which can be perceived as both intrinsic and contextual, is accuracy. It is related with distortion, i.e., the distance between the measured or estimated value/state and the true value/state. Formally, the information semantics $\mathcal{S}_t = \nu(\psi(\mathcal{I}, \mathcal{C}))$, where $\psi(\mathcal{I}, \mathcal{C})$ is a multidimensional, non-linear function of the vector of innate (\mathcal{I}) and contextual (\mathcal{C}) attributes, and $\nu(\cdot)$ is a context-dependent, cost-aware function that maps qualitative information attributes to their application-dependent semantic value. For example, in a simple scenario, $\mathcal{S}_t = w_1\mathcal{A} + w_2\mathcal{T}$, i.e., a weighted sum of accuracy \mathcal{A} and timeliness \mathcal{T} , where $\mathcal{T} = e^{-\gamma A_t}$, an exponential function of AoI and γ a parameter capturing the latency sensitivity [4]. The path towards finding meaningful contextual functions goes through characterizing the non-trivial interplays and fundamental tradeoffs among different attributes, which in turn depend on source dynamics, data transformations, and network characteristics. It is important to highlight the following dualism; information may have a value *per se*, in addition to its “utilitarian”, context-dependent value. For instance, the precision of a sensor measurement has an intrinsic value related to the quality of how accurately it represents a phenomenon, whereas this same measurement has different value depending on its context of use and the application requirements (e.g., whether it monitors temperature in a smart home or in a nuclear plant).

3) *Macroscopic scale*: At the system/network level, semantics is related to the end-to-end distortion and time mismatch between information (state) X_{t_1} , generated at space-time point (\vec{x}_1, t_1) (e.g., physical world), and its estimate \hat{X}_{t_2} at space-time point (\vec{x}_2, t_2) (e.g., virtual world), factoring in all sources of variability and latency (sensing latency and accuracy, data gathering, transmission latency, etc.). Optimizing the semantics of information flow would result in synchronizing/aligning \hat{X}_{t_2} to the evolution/variability of X_{t_1} , in an analogous manner as

dynamic time warping, while maximizing their closeness. Roughly speaking, for some functional $\psi(\cdot)$, we would like that $\|\psi(\hat{X}_{t_2}) - \psi(X_{t_1})\|^2 \rightarrow 0$ and $|t_2 - t_1| \rightarrow 0$. That will allow minimizing the time duration a remote system (e.g., control unit) remains in an erroneous and/or time mismatched state, compensating for the system state/time dilation (to draw an analogy with relativistic clock synchronization). This holds the promise to provide the theoretical foundations for applications targeting real-time experience, such as extended reality, tactile internet, remote control/actuation, and holographic communication.

B. Shifting the Communication Paradigm

Despite various endeavors to develop a theory of semantic/pragmatic information [5]–[9] and its potential applications into wireless protocol design [10], the information content/impact agnostic communication model has remained virtually unchallenged. Recent work on status updates systems has considered that information is valuable when it is fresh, as assessed by the age of information (AoI), which quantifies the freshness of an information flow or of the systems knowledge about a process observed remotely. Let ν_t the generation time of the newest sample that has been delivered to the receiver by time instant t . The AoI is defined as $A_t = t - \nu_t$, $t \in \mathbb{R}$, i.e., the time elapsed since the newest sample was generated. AoI and its recent variants [11] can be viewed as simple, concrete proxy metrics for semantics. Information importance has also been associated with the concepts of value of information (VoI) [12], [13] in decision/control theory, and of quality of information in sensor networks [14]. Data prioritization mechanisms using AoI and/or VoI [15]–[18] are first steps towards importance-aware communication. Nevertheless, these metrics represent only one of the multiple facets of semantics; they also fail to simultaneously account for the information dynamics and variability during data generation, processing, and communication in their initial definitions. Wireless networks have predominantly been designed based on several separation principles, such as data acquisition and communication decoupling, layer separability, and computation-communication isolation. In the prevalent sample-then-compress-and-encode paradigm, time- or event-driven acquired signals are first sampled, and then compressed to remove the inherent redundancy, followed by encoding for transmission. Despite reducing the design complexity, this separation principle can be highly sub-optimal in our setting. It may result in the collection of a large amount of raw data during the acquisition stage, which is then thrown away during

compression or unnecessarily consumes communication resources despite being useless and/or irrelevant.

C. Semantics-aware Communication Model

In sharp contrast to the prevailing communication model with exogenous traffic arrivals, the basic semantics-empowered communication model, depicted in Fig. 1, starts from data generation and acquisition. This radical departure capitalizes on the autonomous smart devices ability to control their traffic via active sampling, in which samples are generated at will according to the source/signal variability and the innovation rate of the underlying process.

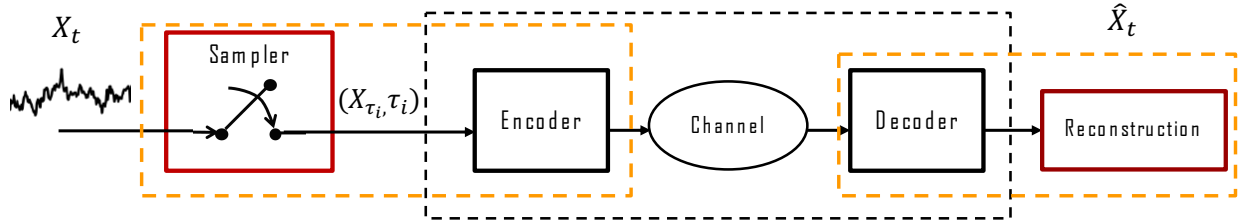


Fig. 1: Semantics-aware communication model.

The entire communication process extends up to goal-oriented signal reconstruction and information exploitation as follows.

- A continuous-time signal (stochastic process) X_t , $t \in \mathbb{R}_+$, which represents a physical phenomenon/event distributed in space and evolving in time, is observed by a smart node. A noisy version of the physical signal is commonly acquired, which is then conditioned (e.g., amplified, filtered).
- The transmitter sends information updates to a destination (e.g., fusion center, control unit). The updates are generated using process-aware, non-uniform active sampling, adapted to both the signal variability (e.g., innovation, sparsity, autocorrelation, self-similarity) and communication link characteristics, and tailored to the semantics-aware application requirements. That way, only the most valuable/informative samples are generated and prioritized for transmission.
- Data samples can be preprocessed prior to being encoded and scheduled for transmission over a noisy and delay/error-prone channel. The encoding process includes quantization and compression of semantically valuable samples.

- The signal is finally reconstructed at the destination from causally received samples in order to obtain measurements/estimates \hat{X}_t . The reconstruction/estimation quality is measured by a distortion metric, such as the mean squared error (MSE) $\delta(X, \hat{X}) = \frac{1}{T} \mathbb{E} \left[\int_0^T (X_t - \hat{X}_t)^2 \right]$, averaged over a given time window T .

The reconstructed signal may alter the recipient's state and initiate specific actions at the receiving end (actionable intelligence).

The above point-to-point model could be extended to a multi-node wireless network of interconnected spatially distributed devices, which collect multimodal information of different quality (e.g., precision, freshness) from one or multiple sources. The nodes may have heterogeneous sensing, computational, and learning/inference capabilities. Data - raw or preprocessed - generated from different, possibly correlated, sources is then scheduled for transmission to a destination(s) according to its semantic importance and value to serve its purpose collision avoidance, remote state estimation, control and actuation, situation awareness, learning model training, to name a few. For example, edge devices (robots) observe a moving vehicle and collect, process, and transmit data to a fusion unit, which is in charge of tracking this vehicle. Note that in this setting, sensing, sampling, and signal recovery can be performed in a joint or distributed manner.

D. Joint sampling, communication, and reconstruction under real-time constraints

A foundational element of the proposed paradigm is the cohesion between data generation, transmission, and source/process reconstruction, which have to be optimized jointly under the prism of the semantics of information. Let us highlight this with an example from networked robotics. A mobile robot generates updates of a continuous stochastic process (e.g., vehicles mobility trajectory) and sends them to a remote server for real-time estimation from causally received samples. The conventional approach decouples sampling from transmission, resulting in a simple yet suboptimal solution. Sampling is optimized based on the signals changes; samples can become stale before being successfully received. Transmission is optimized based on some metric (e.g., delay, timeliness) ignoring the source variability; hence samples are received on time but they contain no useful information or are misleading on the system's state. This simple tracking scenario reveals the structural links between sampling and communication, which are generally non-separable in our setting. This means that one cannot just take the best sampling algorithm, place it before the best communication scheme, and expect to get the best out of both.

The optimal solution calls for semantics-aware joint non-uniform sampling and transmission prioritization, tailored to both the signal/process characteristics and the channel quality, as a means to efficiently meet the application's requirements.

E. Key Semantic Operations

The semantics-aware communication system has to be armed with key functionalities, which enable *reliable communication and timely delivery of concisely represented valuable information*. This entails goal-driven information representation and data prioritization mechanisms, which allow to perform:

- ***Semantic filtering and censoring*** for removing redundancy during data acquisition and encoding. That way, only useful and relevant information is generated and transmitted. Moreover, semantic data generation can significantly reduce the sampling frequency (sub Nyquist regime) and the channel utilization while improving the reconstruction accuracy.
- ***Semantic computation***, such as feature extraction and labeling, which enables concise information representation and value distillation through preprocessing. For example, a robot could compute local estimates of the state (tracked target's velocity and location) from visual features or scene labeling extracted from an image. In distributed learning scenarios, only data samples that are semantically representative (core set selection, gradient alignment) or important ("distance" between local gradient vector and global model) are processed and/or transmitted.
- ***Semantic processing and reconstruction*** for fast partial/approximate source reconstruction and goal-dependent information fusion and distillation. The reconstruction quality is conventionally measured by a distortion (error) performance metric, some function of MSE. However, depending on the application requirements, approximate outputs with different distortion or perceptual quality could be sufficient for their purpose. A simple example is that of a low quality video for surveillance during non-alert mode. Moreover, there are cases (e.g., images, patterns, learning) where "low distortion" does not necessarily mean "high perceptual quality". For that, the reconstruction performance can also be assessed by a *semantic quality indicator*, such as a divergence function $\mathcal{D}(p_X||p_{\hat{X}})$ or a statistical distance function $d_X : \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}_+$ on a sample space \mathcal{X} (e.g., Wasserstein metric), where X (\hat{X}) is the input (output) signal with distribution p_X ($p_{\hat{X}}$).

- **Semantic control** for agilely orchestrating multi-source multi-quality information gathering and for efficient resource utilization.

III. AN ILLUSTRATIVE EXAMPLE

We consider an end-to-end communication system, in which a device monitors a two-state random process as depicted in Fig. 2. The source initiates certain actions to the robotic object (in the left side) and the goal is to have a digital twin of that robotic object at the right end. The monitoring device performs sampling and transmission of the status updates regarding the evolution of the source. Transmission takes place over an erasure wireless channel. Each transmission is successful with a probability, which captures key propagation phenomena, e.g., fading, attenuation, etc. The application objective is to maintain the actions of the original object in a real-time manner. For that, the receiver performs real-time reconstruction of the source at the end point, upon receipt of status updates.

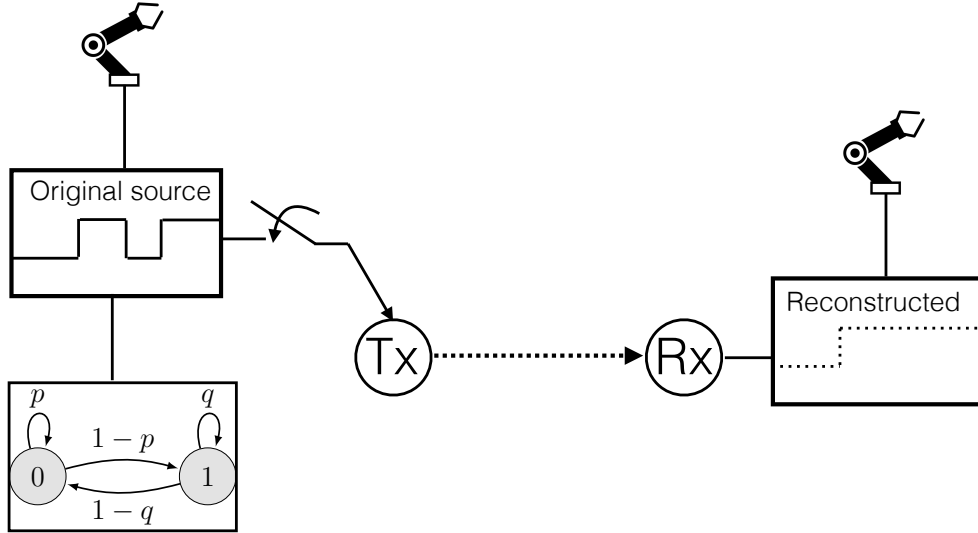


Fig. 2: The setup for the considered example.

We consider four different policies for sampling the source (information generation) and transmitting the acquired updates. The first one is uniform sampling (or source-agnostic), in which samples are generated periodically; in case of a transmission error, the most recently acquired measurement (sample) is communicated. The second one is an age-aware policy, in which the acquisition and the transmission of a new sample is triggered once the AoI reaches a predefined threshold; in case of transmission/decoding error, the receiver tries to anticipate the

update based on the statistics of the source. Note that since AoI can be viewed as a simple, quantitative proxy for information semantics, age-aware policy can be considered as a first, very simple semantics-aware scheme. Finally, we consider two main semantics-empowered schemes, which are based on a change-triggered information generation, i.e., sampling is performed according to the process variability/innovation. The first method represents the case where changes occur (and are tracked) at the source only. The second method tracks the process variability or changes based on the information discrepancy between the two communication ends. In the performance plots, the previously described policies are coined as uniform, age-aware, semantics-aware, and end-to-end (E2E) semantics, respectively.

Performance is assessed using the following metrics of interest: real-time reconstruction error and cost of actuation error. The reconstruction error describes the discrepancy in real-time of the values between the original and the reconstructed source as time evolves. The cost of actuation error captures the significance of the error at the actuation point given the fact that some errors may have higher impact than others. In our example, we consider two cases when an error occurs: when the original source is in state zero but the reconstructed source believes that is in state one, the cost is equal to one, while in the opposite case the cost equals five. When the sources are in the same state, there is no actuation error.

For the communication channel, we consider two cases, one with low channel quality, in which the success probability is $P_s = 0.4$, and one with high channel quality with success probability $P_s = 0.9$. Furthermore, we consider two cases regarding the source variability; the first being when the source is slowly changing ($p = 0.95$, $q = 0.9$) depicted in Fig. 3, and the second being when the source is rapidly changing ($p = 0.8$, $q = 0.3$), which is depicted in Fig. 4. We observe that in the case of low source variability, the age-aware scheme outperforms the semantics-aware one when the communication channel quality is poor. This is due to the fact that if a transmission error occurs and the receiver fails to anticipate the right state, this leads to a large reconstruction error. This is the case where a uniform sampling scheme could perform better. However, the performance in terms of cost of actuation error is different, as the semantics-aware scheme outperforms the uniform sampling one.

Another interesting observation is that in the high source variability case, both semantics-empowered schemes exhibit similar performance regarding the reconstruction error; the end-to-end method significantly outperforms the semantics-aware scheme that considers changes only at the source. Interestingly, the end-to-end semantics-aware method provides the lowest

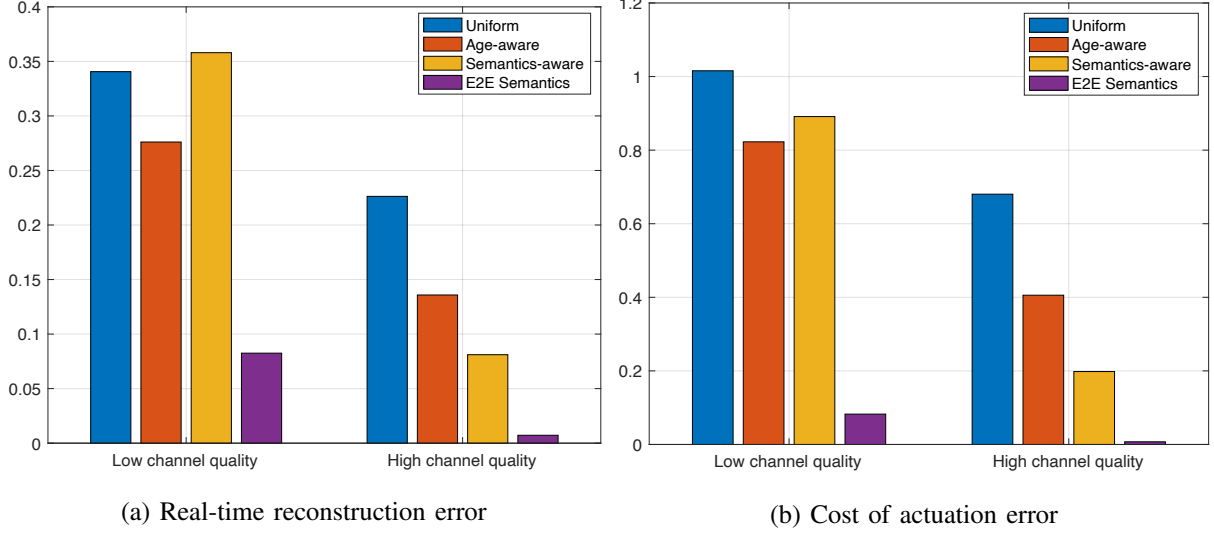


Fig. 3: The case of a slowly varying source with $p = 0.95$ and $q = 0.9$.

reconstruction and actuation errors for a rapidly varying source.

In a nutshell, semantics-empowered schemes are mainly generating samples that contain the most useful information for real-time reconstruction and actuation, in particular since the timing when this information is acquired is of cardinal importance. Note that learning the patterns of the source evolution, for instance using reinforcement learning, and exploiting this knowledge in the semantics-empowered schemes could lead in additional performance gains, mainly in terms of savings in communication load and number of samples generated.

IV. FUTURE CHALLENGES

We discuss now several key open problems in this area. Our hope is that this section will be useful for researchers aiming to explore this promising avenue of research.

Semantics-aware metrics: A key challenge is to establish new, concrete, and amenable to analysis metrics, which incorporate the qualitative attributes and the importance of information in the existing communication theoretic edifice. These metrics may evolve according to the source and network dynamics and should capture potential multivariate dependencies. They will serve as the foundations for the algorithmic design and the network performance optimization, and will inspire novel communication technologies.

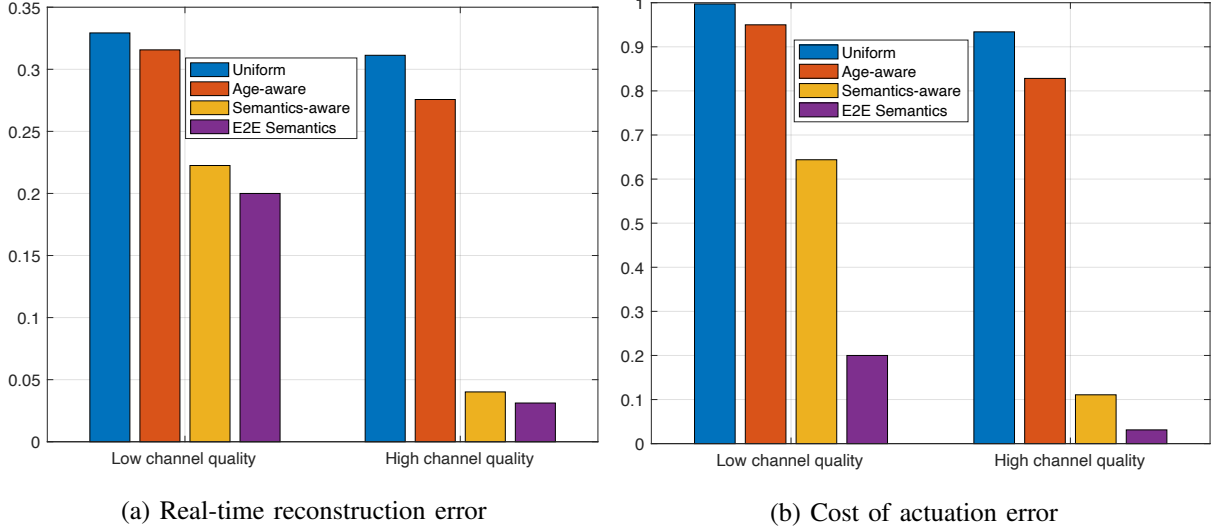


Fig. 4: The case of a rapidly changing source with $p = 0.8$ and $q = 0.3$.

Joint semantic processing, communication, and reconstruction: First results on optimal sampling and scheduling policies consider simple settings, such as single source, i.i.d. communication delays, and Markov processes. We need to come up with a theory of optimal joint, semantics-aware active sampling, communication, and causal reconstruction of multidimensional signals. Signals may come from multiple, possibly correlated, stochastic sources, which can be modeled using general point/counting processes and decomposable stochastic processes (semi martingales).

Semantics-aware multiple access: Consider a (possibly large) number of heterogeneous devices that transmits, either in time-, or event-triggered manner, signals conveying multi-quality information (not necessarily from the same codebook) to a destination. For optimally accessing the shared medium, devices will have to adapt their activation/transmit pattern not only based on exogenous traffic arrivals and the other nodes status, but also based on the sampling rate, the source variability, and the semantic importance of the conveyed information.

Goal-oriented Resource Orchestration: Another unexplored and challenging direction is related to scheduling and resource allocation for gathering information acquired at different semantic quality levels (e.g., in terms of precision, freshness, etc.) by various nodes observing multiple sources. In most relevant scenarios, a goal can be achieved by utilizing one of multiple alternative sets of multi-quality data objects. For example, all sensing data (images) of precision

above $\alpha\%$ and freshness above β could serve a surveillance system in non-alert mode. These problems fall in the realm of real-time and online scheduling with multiple choices. Online algorithms will select which data objects, from where and when, to gather and transmit under communication and processing resource constraints. The problem is exacerbated when causal reconstruction requires a specific ordered sequence of correlated information bearing packets.

Multi-objective stochastic optimization: Importance-based data gathering and prioritization require multi-criteria optimization with semantics based, end user perceived utilities, which assess the relative degree of priority among different information attributes. A multi-objective stochastic optimization framework based on cumulative prospect theory [19], which captures information semantics via risk-sensitive measures and multi-attribute utility functions, and performs rank-dependent weighting through nonlinear transformations of probability, seems to be a promising endeavor. This is a departure from the prevalent risk-neutral expected utility theory in wireless network optimization.

V. EPILOGUE

Supporting autonomous, real-time, and connected intelligence applications in future wireless networks necessitates fundamental theoretical advances in communication, information theory, and signal processing. It requires transforming commonly held design assumptions and prevailing communication paradigms. We proposed a structurally new approach that accounts for the semantics of information and aims at harnessing the high potential benefits of a goal-oriented unification of data generation, information transmission, and signal reconstruction, which have hitherto been treated in separation. A direct gain is the significant reduction in the volume of wireless traffic transported and in required resources and energy in ways that are not possible by today's technology. This importance-centric communication paradigm will enable the *generation of just the right amount of data and the transmission of the right content at the right time*. Such a synergistic design methodology will judiciously augment the current communication edifice to fit for the needs of emerging real-time networked systems. It will pave the way for the design of future wireless networks, which will not simply transport randomized samples of questionable utility or relevance to the application; they will carry around only the most semantically informative samples, hence conveying to the end user only information that is timely, useful, and valuable for achieving its goals.

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