

Semantic Information Retrieval in Wireless Networks

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Abstract—Motivated by recent success of Machine Learning (ML) tools in wireless communications, the idea of semantic communication by Weaver from 1949 has received considerable attention. It breaks with the classic design paradigm of Shannon by aiming to transmit the meaning of a message, i.e., semantics, rather than its exact copy and thus allows for savings in channel uses or information rate. In this work, we extend the fundamental approach from Basu et al. for modeling semantics from logical to probabilistic entailment relations between meaning and messages. Thus, we model semantics by means of a hidden random variable and define the task of semantic communication as transmission of messages over a communication channel such that semantics is best preserved. We formulate the semantic communication design either as an Information Maximization or as an Information Bottleneck optimization problem. Finally, we propose the ML-based semantic communication system SINFONI for a distributed multipoint scenario: SINFONI communicates the meaning behind multiple messages that are observed at different senders to a single receiver for semantic retrieval. We analyze SINFONI by processing images as an example of messages. Numerical results reveal a tremendous rate normalized SNR shift up to 20 dB compared to classically designed communication systems.

Index Terms—Semantic communication, wireless communications, wireless networks, infomax, information bottleneck, information theory, machine learning.

I. INTRODUCTION

WHEN Shannon laid the theoretical foundation of the research area of communications engineering back in 1948, he deliberately excluded semantic aspects from the system design [1], [2]. In fact, the idea of addressing semantics in communications arose shortly after Shannon’s work in [2] but it remained largely unexplored. Since then the design focus of communication systems has been on digital error-free symbol transmission. In recent years, it has become clear that semantics agnostic communication limits the achievable efficiency in terms of bandwidth, power and complexity trade-offs. Notable examples include wireless sensor networks and broadcast scenarios [3].

Owing to the great success of Artificial Intelligence (AI) and in particular its subdomain Machine Learning (ML), ML tools have been recently investigated for wireless communications [4], [5], [6]. Now, ML with its ability to extract features appears to be a proper means to realize a semantic design. Further, we note that the latter design is supported and possibly

enabled by the 6G vision of integrating AI and ML on all layers of the communications system design, i.e., by an ML-native air interface.

Motivated by these new ML tools and driven by high bandwidth and latency demands of the next wireless communication standard 6G, the idea of semantic communication has received considerable attention. It breaks with the existing classic design paradigms by including semantics into the design. Semantics is equal to the meaning defined by the human or application behind. More precisely, semantic communication aims to transmit the meaning of a message rather than its exact copy and hence allows for compression to the actual semantic content. Thus, savings in bandwidth, power and complexity are expected.

A. Related Work

The notion of semantic communication traces back to Weaver [2] who reviewed Shannon’s information theory [1] in 1949 and amended considerations w.r.t. semantic content of messages. Since then semantic communication was mainly investigated from a philosophical point of view, see, e.g., [7], [8].

In [9], [10], the authors extend the propositional logic-based approach from one of the earliest works [11] into a model-theoretical framework and define semantic information source and semantic channel. In particular, the authors consider a semantic source that “observes the world and generates meaningful messages characterizing these observations” [10]. The source is equivalent to conclusions, i.e., “models” of the world, that are unequivocally drawn following a set of known inference rules based on observation of messages. By this means, the authors are able to derive semantic counterparts of the source and channel coding theorems. However, as the authors admit, these theorems do not tell how to develop optimal coding algorithms and the assumption of a model-theoretical description leads to “many non-trivial simplifications” [9].

In [12], the authors define semantic similarity as a semantic error measure to quantify the distance between meanings of two words. Based on this metric, communication of a finite set of words is modeled as a Bayesian game from game theory and optimized for improved semantic transmission over a binary symmetric channel.

Recently, enabled by the rise of ML in communications research, semantic communication has been reinvented in the context of Natural Language Processing (NLP). Deep learning based NLP techniques were introduced in [13], [14], [15],

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[16] to learn compressed hidden representations for the task of text and speech transmission. This leads to performance improvements especially at low SNR compared to classical digital transmissions.

As a result, semantic communication is still a nascent field: It remains still unclear what this term exactly means and especially its distinction from Joint Source Channel Coding (JSCC) [13], [17]. As a result, many survey paper aim to provide an interpretation, see, e.g., [18], [19], [20], [21]. We will revisit this issue in Sec. II.

B. Main Contributions

The main contributions of this article are:

- Inspired by Weaver’s notion of semantic communication [2], we extend the fundamental approach from Basu et al. [9], [10] for modeling semantics from logical to probabilistic entailment relations between meaning and messages. Thus, we explicitly model semantics by means of a semantic hidden Random Variable (RV).
- We define the task of semantic communication as reliable and bandwidth-efficient transmission of messages over a communication channel such that the semantic RV is best preserved. We formulate the semantic communication design either as an Information Maximization or as an Information Bottleneck optimization problem and consider important implementation aspects, e.g., application of Deep Neural Networks (DNNs). We solve the problems approximately by minimizing the cross entropy that upper bounds the negative mutual information.
- Finally, we propose the ML-based semantic communication system SINFONI for a distributed multipoint scenario: SINFONI communicates the meaning behind multiple messages that are observed at different senders to a single receiver for semantic retrieval.
- We analyze SINFONI by processing images as an example of messages. Notably, numerical results reveal a tremendous bandwidth normalized SNR shift up to 20 dB compared to classically designed communication systems.

In the following, we reinterpret Weaver’s philosophical considerations in Sec. II-A paving the way for our proposed theoretical framework in Sec. II. Finally, in Sec. III and IV, we provide one numerical example of semantic communication, i.e., SINFONI, and summarize the main results, respectively.

II. A FRAMEWORK FOR SEMANTICS

A. Philosophical Considerations

Despite much renewed interest, research on semantic communication is still in its infancy and recent work reveals a differing understanding of the word *semantics*. In this work, we contribute our interpretation. To motivate it, we shortly revisit the research birth hour of communications from a philosophical point of view: Its theoretical foundation was laid by Shannon in his landmark paper [1] in 1948.

He stated that *“Frequently the messages have meaning; that is they refer to or are correlated according to some system with*

certain physical or conceptual entities. These semantic aspects of communication are irrelevant to the engineering problem.” In fact, this viewpoint abstracts all kinds of information one may transmit, e.g., oral and written speech, sensor data, etc. and lays also the foundation for the research area of Shannon information theory. Thus, it found its way into many other research areas where data or information is processed including Artificial Intelligence (AI) and especially its subdomain Machine Learning (ML).

Weaver saw this broad applicability of Shannon’s theory back in 1949. In his comprehensible review of [1], he first states that *“there seem to be [communication] problems at three levels”* [2]:

- A. How accurately can the symbols of communication be transmitted? (The technical problem.)
- B. How precisely do the transmitted symbols convey the desired meaning? (The semantic problem.)
- C. How effectively does the received meaning affect conduct in the desired way? (The effectiveness problem.)

These levels are quoted in recent works where Level C is oftentimes referred to as goal-oriented communication instead [19].

But we note that in his concluding section, he then questions this segmentation: He argues for the generality of the theory at Level A for all levels and *“that the interrelation of the three levels is so considerable that one’s final conclusion may be that the separation into the three levels is really artificial and undesirable”*.

We think it is important to emphasize this point. We share the view that the separation is rather arbitrary. The important point is that semantics or context is introduced. By doing so, we are able to introduce meaning, i.e., to reduce uncertainty and hence Shannon entropy, and thus to save information rate. (The meaning is reflected in “models” as in [9], [10].) In fact, we are able to add arbitrarily many levels of semantic details to the communication problem and optimize communications for a specific semantic background, e.g., an application or human.

B. Semantic System Model

1) *Semantic Source and Channel*: Now, we will define our information-theoretic system model to convey the meaning of messages in the wireless transmission. Fig. 1 shows the schematic of our model. We assume the existence of a semantic source, described as a hidden target multivariate Random Variable (RV) $\mathbf{z} \in \mathcal{M}_z^{N_z \times 1}$ from domain \mathcal{M}_z of dimension N_z distributed according to a probability density or mass function (pdf / pmf) $p(\mathbf{z})$. To simplify discussion, we assume it to be discrete and memoryless.¹

¹For the remainder of the article, note that the domain of all RVs \mathcal{M} may be either discrete or continuous. Further, we note that the definition of entropy for discrete and continuous RVs differs. For example, the differential entropy of continuous RVs may be negative whereas the entropy of discrete RVs is always positive [22]. Without loss of generality, we will thus assume all RVs either to be discrete or to be continuous. In this work, we avoid notational clutter by using the expected value operator: Replacing the integral by summation over discrete RVs, the equations are also valid for discrete RVs and vice versa.

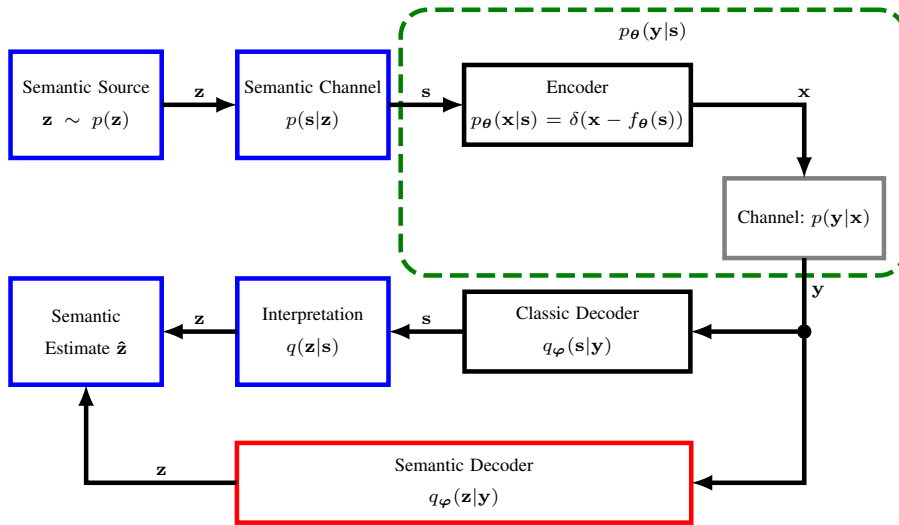


Fig. 1. Block diagram of the considered semantic system model.

This approach is similar to that of [9], [10] and extends models as in [15]: In [9], [10], the semantic source² is described by "models of the world". In [10], a semantic channel³ then generates messages through entailment relations between "models" and "messages". We will call these "messages" source signal and define it to be a RV $s \in \mathcal{M}_s^{N_s \times 1}$ as it is usually observed and enters the communication system. In classic Shannon design, the aim is to reconstruct the source s as accurate as possible at the receiver side. Further, we note that the authors in [10] defined a semantic channel as deterministic entailment relations between z and s based on propositional logic. In this article, we go beyond this assumption and consider probabilistic semantic channels modeled by distribution $p(s|z)$ that include the entailment in [10] as special cases, i.e., $p(s|z) = \delta(s - f(z))$ where $\delta(\cdot)$ is the Dirac delta function and $f(\cdot)$ any generic function. Our viewpoint is motivated by recent success of pattern recognition tools which advanced the field of AI in the 2010s and may be used to extract semantics [5].

We now provide an example to explain what we understand under a semantic source z and channel $p(s|z)$: Let us assume a biologist who has an image of a tree. The biologist wants to know what kind of tree it is by interpreting the observed data (image). In this case, the semantic source z is a multivariate RV composed of a categorical RV with M tree classes. For any realization (sample value) z_i of the semantic source, the semantic channel $p(s|z)$ then outputs with some probability one image s_i of a tree conveying characteristics of z , i.e., its meaning. Note that the underlying meaning of the same sensed data can be different for other recipients like humans/AI or applications, i.e., in other semantic contexts. Imagine a child, i.e., a person with different characteristics (personality,

expertise, knowledge, goals and intentions) than the biologist, who is only interested in climbing on this tree or whether or not the tree provides shade.

Compared to [9], we therefore argue that we also include level C by semantic source and channel since context can be included on increasing layers of complexity. First, a RV z_1 might capture the interpretation like the classification of images or sensor data. Moving beyond the first semantic layer, then a RV z_2 might expand this towards a more general goal like keeping a constant temperature in power plant control. In fact, we can add or remove context, i.e., semantics and goals, arbitrarily often according to the human/AI or application behind and we can optimize the overall (communication) system w.r.t. z_1, z_2, \dots, z_i , respectively.

As a last remark, we note that we basically defined probabilistic semantic relationships and it remains the questions how exactly they might look like. In our example, the meaning of the images needs to be labeled into real-world data pairs $\{s_i, z_i\}$ by experts/humans since image recognition lacks precise mathematical models. This is also true for NLP [15]: How can we measure if two sentences have the same meaning, i.e., how does the semantic space look like? In contrast, in [10], the authors are able to solve their well-defined technical problem (motion detection) by a model-driven approach. We can thus distinguish between model and data-driven semantics which both can be handled within Shannon's information theory.

2) *Semantic Channel Encoding*: After the semantic source and channel in Fig. 1, we extend upon [9] by differentiating between "message"/source signal s and transmit signal $x \in \mathcal{M}_x^{N_{Tx} \times 1}$. Our challenge is to encode the source signal s onto the transmit signal vector x for reliable semantic communication through the physical communication channel $p(y|x)$ where $y \in \mathcal{M}_y^{N_{Rx} \times 1}$ is the received signal vector. We assume the encoder $p_\theta(x|s)$ to be parametrized by a parameter vector $\theta \in \mathbb{R}^{N_\theta \times 1}$. Note that $p_\theta(x|s)$ is probabilistic here but assumed to be deterministic in communications with $p_\theta(x|s) = \delta(x - f_\theta(s))$.

In summary, the Markov chain reads $z \leftrightarrow s \leftrightarrow x \leftrightarrow y$.

²Note that in [10] the semantic information source is defined as a tuple $(z, s, p(z, s), L)$. In this original notation, z is the model, s the message, $p(z, s)$ the joint distribution of z and s , and L is the deterministic formal language.

³In contrast to [9], the semantic channel in [10] and here does not include the transmission channel.

In the following, we summarize encoder and communication channel into distribution $p_\theta(\mathbf{y}|\mathbf{s})$ for better readability. The Markov chain thus reduces to $\mathbf{z} \leftrightarrow \mathbf{s} \leftrightarrow \mathbf{y}$.

At the receiver side, maximum a-posteriori decoding w.r.t. variable \mathbf{s} uses the posterior $p_\theta(\mathbf{s}|\mathbf{y})$ that can be deduced from prior $p(\mathbf{s})$ and likelihood $p_\theta(\mathbf{y}|\mathbf{s})$ by application of Bayes law. Based on the estimate of \mathbf{s} , then the application interprets the actual semantic content \mathbf{z} by $p(\mathbf{z}|\mathbf{s})$.

We propose to include the semantic hidden target RV \mathbf{z} into the design by processing $p_\theta(\mathbf{z}|\mathbf{y})$. If calculation of the posterior is intractable, we can replace $p_\theta(\mathbf{z}|\mathbf{y})$ by the approximation $q_\varphi(\mathbf{z}|\mathbf{y})$, i.e., the semantic decoder, with parameters $\varphi \in \mathbb{R}^{N_\varphi \times 1}$. We expect the following benefit: Given the Markov chain $\mathbf{z} \leftrightarrow \mathbf{s} \leftrightarrow \mathbf{x} \leftrightarrow \mathbf{y}$, the entropy $\mathcal{H}(\mathbf{z}) = \mathbb{E}_{\mathbf{z} \sim p(\mathbf{z})}[-\ln p(\mathbf{z})]^4$ of the semantic RV \mathbf{z} is expected to be less or equal to the entropy $\mathcal{H}(\mathbf{s})$ of the source \mathbf{s} , i.e., $\mathcal{H}(\mathbf{z}) \leq \mathcal{H}(\mathbf{s})$. Consequently, by transmitting the relevant, i.e., semantic, RV rather than \mathbf{s} , we can compress more. Note that in semantic communication the relevant variable is \mathbf{z} , not \mathbf{s} . Thus, processing $p_\theta(\mathbf{s}|\mathbf{y})$ without taking \mathbf{z} into consideration resembles the classical approach. Instead of using (and transmitting) \mathbf{s} for inference of \mathbf{z} , we now want to find a compressed representation \mathbf{y} of \mathbf{s} containing the relevant information about \mathbf{z} .

C. Semantic Communication Design via Infomax Principle

After explaining the system model and the basic components, we are able to approach a semantic communication system design: We first define an optimization problem to obtain distribution $p_\theta(\mathbf{y}|\mathbf{s})$ following the Infomax principle from an information theoretic perspective [22]. Thus, we like to find the distribution $p_\theta(\mathbf{y}|\mathbf{s})$ that maps \mathbf{s} to a representation \mathbf{y} such that at most information of the relevant RV \mathbf{z} is included in \mathbf{y} , i.e., we maximize the Mutual Information (MI) $I(\mathbf{z}; \mathbf{y})$ w.r.t. $p_\theta(\mathbf{y}|\mathbf{s})$ [23]:

$$\arg \max_{p_\theta(\mathbf{y}|\mathbf{s})} I_\theta(\mathbf{z}; \mathbf{y}) \quad (1)$$

$$= \arg \max_{p_\theta(\mathbf{y}|\mathbf{s})} \mathbb{E}_{\mathbf{z}, \mathbf{y} \sim p_\theta(\mathbf{z}, \mathbf{y})} \left[\ln \frac{p_\theta(\mathbf{z}, \mathbf{y})}{p(\mathbf{z})p_\theta(\mathbf{y})} \right] \quad (2)$$

$$= \arg \max_{p_\theta(\mathbf{y}|\mathbf{s})} \mathcal{H}(\mathbf{z}) - \mathcal{H}(p_\theta(\mathbf{z}, \mathbf{y}), p_\theta(\mathbf{z}|\mathbf{y})) \quad (3)$$

$$= \arg \max_{p_\theta(\mathbf{y}|\mathbf{s})} \mathbb{E}_{\mathbf{z}, \mathbf{y} \sim p_\theta(\mathbf{z}, \mathbf{y})} [\ln p_\theta(\mathbf{z}|\mathbf{y})] . \quad (4)$$

There, $\mathcal{H}(p(\mathbf{x}), q(\mathbf{x})) = \mathbb{E}_{\mathbf{x} \sim p(\mathbf{x})}[-\ln q(\mathbf{x})]$ is the cross entropy between two pdfs / pmfs $p(\mathbf{x})$ and $q(\mathbf{x})$. Note independence from θ in $\mathcal{H}(\mathbf{z})$ and dependence in $p_\theta(\mathbf{z}|\mathbf{y})$ and $p_\theta(\mathbf{z}, \mathbf{y})$ through the Markov chain $\mathbf{z} \rightarrow \mathbf{s} \rightarrow \mathbf{y}$. It is worth mentioning that we so far have not set any constraint on the variables we deal with. Hence, the form of $p_\theta(\mathbf{y}|\mathbf{s})$ has to be constrained to avoid learning a trivial identity mapping $\mathbf{y} = \mathbf{s}$. We indeed constrain the optimization by our communication channel $p(\mathbf{y}|\mathbf{x})$ we assume to be given.

If calculation of the posterior $p_\theta(\mathbf{z}|\mathbf{y})$ in (4) is intractable, we are able to replace it by a variational distribution $q_\varphi(\mathbf{z}|\mathbf{y})$

with parameters φ . Similar to the transmitter, Deep Neural Networks (DNNs) are usually proposed [15], [24] for design of the approximate posterior $q_\varphi(\mathbf{z}|\mathbf{y})$ at the receiver. To improve the performance complexity trade-off, the application of *deep unfolding* can be considered, a model-driven learning approach that introduces model knowledge of $p_\theta(\mathbf{s}, \mathbf{x}, \mathbf{y}, \mathbf{z})$ to create $q_\varphi(\mathbf{z}|\mathbf{y})$ [6], [25]. With $q_\varphi(\mathbf{z}|\mathbf{y})$, we are able to define a Mutual Information Lower Bound (MILBO) [23] similar to the well-known Evidence Lower Bound (ELBO) [5]:

$$I_\theta(\mathbf{z}; \mathbf{y}) \geq \mathbb{E}_{\mathbf{z}, \mathbf{y} \sim p_\theta(\mathbf{z}, \mathbf{y})} [\ln q_\varphi(\mathbf{z}|\mathbf{y})] \quad (5)$$

$$= -\mathbb{E}_{\mathbf{y} \sim p(\mathbf{y})} [\mathcal{H}(p_\theta(\mathbf{z}|\mathbf{y}), q_\varphi(\mathbf{z}|\mathbf{y}))] \quad (6)$$

$$= -\mathcal{L}_{\theta, \varphi}^{\text{CE}} . \quad (7)$$

The lower bound holds since $-\mathcal{H}(p_\theta(\mathbf{z}, \mathbf{y}), p_\theta(\mathbf{z}|\mathbf{y}))$ itself is a lower bound of the expression in (3) and $\mathbb{E}_{\mathbf{z}, \mathbf{y} \sim p_\theta(\mathbf{z}, \mathbf{y})} [\ln p_\theta(\mathbf{z}|\mathbf{y}) / \ln q_\varphi(\mathbf{z}|\mathbf{y})] \geq 0$. Now, we can calculate optimal values of θ and φ of our semantic communication design by minimizing the amortized cross entropy $\mathcal{L}_{\theta, \varphi}^{\text{CE}}$ in (6), i.e., marginalized across observations \mathbf{y} [6].

If we consider classical communication design approaches, we would solve the problem

$$\arg \max_{p_\theta(\mathbf{y}|\mathbf{s})} I(\mathbf{s}; \mathbf{y}) \quad (8)$$

which relates to Joint Source Channel Coding (JSCC). There, our aim is to find a representation \mathbf{y} that retains a significant amount of information about the source signal \mathbf{s} . Again we can apply the lower bound (7). In fact, Eq. (8) shows that approximate maximization of the mutual information justifies the minimization of the cross entropy in the Auto Encoder (AE) approach [4] oftentimes seen in recent semantic communication literature [15], [24].

Thus, the idea is to learn parametrizations of the transmitter discriminative model and of the variational receiver posterior, e.g., by AEs or reinforcement learning. Note that in our semantic problem (1), we do not auto encode the hidden \mathbf{z} itself, but encode \mathbf{s} to obtain \mathbf{z} by decoding. This can be seen from Fig. 1 and by rewriting the amortized cross entropy (6), (7):

$$\mathcal{L}_{\theta, \varphi}^{\text{CE}} = \mathbb{E}_{\mathbf{y} \sim p(\mathbf{y})} [\mathcal{H}(p_\theta(\mathbf{z}|\mathbf{y}), q_\varphi(\mathbf{z}|\mathbf{y}))] \quad (9)$$

$$= \mathbb{E}_{\mathbf{z}, \mathbf{y}, \mathbf{s} \sim p_\theta(\mathbf{z}, \mathbf{y}, \mathbf{s})} [-\ln q_\varphi(\mathbf{z}|\mathbf{y})] \quad (10)$$

$$= \mathbb{E}_{\mathbf{s}, \mathbf{z} \sim p(\mathbf{s}, \mathbf{z})} [\mathbb{E}_{\mathbf{y} \sim p_\theta(\mathbf{y}|\mathbf{s})} [-\ln q_\varphi(\mathbf{z}|\mathbf{y})]] . \quad (11)$$

We can further proof the amortized cross entropy to be decomposable into

$$\begin{aligned} & \mathcal{L}_{\theta, \varphi}^{\text{CE}} \\ &= \mathbb{E}_{\mathbf{y} \sim p(\mathbf{y})} [\mathbb{E}_{\mathbf{z} \sim p_\theta(\mathbf{z}|\mathbf{y})} [-\ln q_\varphi(\mathbf{z}|\mathbf{y}) + \ln p(\mathbf{z}|\mathbf{y}) \\ & \quad - \ln p(\mathbf{z}|\mathbf{y})]] \end{aligned} \quad (12)$$

$$= \mathbb{E}_{\mathbf{y} \sim p(\mathbf{y})} [D_{\text{KL}}(p_\theta(\mathbf{z}|\mathbf{y}) \parallel q_\varphi(\mathbf{z}|\mathbf{y}))] + \underbrace{\mathcal{H}(\mathbf{z}|\mathbf{y})}_{=-I_\theta(\mathbf{z}; \mathbf{y}) + \mathcal{H}(\mathbf{z})} \quad (13)$$

$$= \mathcal{H}(\mathbf{z}) - \underbrace{I_\theta(\mathbf{z}; \mathbf{y})}_{\text{enc. objective}} + \underbrace{\mathbb{E}_{\mathbf{y} \sim p(\mathbf{y})} [D_{\text{KL}}(p_\theta(\mathbf{z}|\mathbf{y}) \parallel q_\varphi(\mathbf{z}|\mathbf{y}))]}_{\text{dec. objective}} . \quad (14)$$

To the end, maximization of the MILBO w.r.t. θ and φ balances maximization of the mutual information $I_\theta(\mathbf{z}; \mathbf{y})$ and

⁴There, $\mathbb{E}_{\mathbf{x} \sim p(\mathbf{x})}[f(\mathbf{x})]$ denotes the expected value of $f(\mathbf{x})$ w.r.t. both discrete or continuous RVs \mathbf{x} .

minimization of the KL divergence $D_{\text{KL}}(p_{\theta}(\mathbf{z}|\mathbf{y}) \parallel q_{\varphi}(\mathbf{z}|\mathbf{y}))$. The former objective can be seen as a regularization term that favors encoders with high mutual information for which decoders can be learned that are close to the true posterior.

D. Information Bottleneck View

It should be stressed that we have not set any constraints on the variables in the Infomax problem so far. However, in many applications compression is needed because of limited information rate. Therefore, we can formulate an optimization problem where we like to maximize the relevant information $I_{\theta}(\mathbf{z}; \mathbf{y})$ subject to the constraint to limit the compression rate $I_{\theta}(\mathbf{s}; \mathbf{x})$ to a maximum information rate I_C :

$$\arg \max_{p_{\theta}(\mathbf{x}|\mathbf{s})} I_{\theta}(\mathbf{z}; \mathbf{y}) \quad \text{s.t.} \quad I_{\theta}(\mathbf{s}; \mathbf{x}) \leq I_C. \quad (15)$$

Problem (15) is called the Information Bottleneck (IB) problem [19], [26], [27], [28], [29], [30]. Note that we aim at an encoder that compresses \mathbf{s} into a compact representation \mathbf{x} for discrete RVs by clustering and for continuous RVs by dimensionality reduction.

To solve the constrained optimization problem (15), we can use Lagrangian optimization and obtain

$$\arg \max_{p_{\theta}(\mathbf{x}|\mathbf{s})} I_{\theta}(\mathbf{z}; \mathbf{y}) - \beta I_{\theta}(\mathbf{s}; \mathbf{x}) \quad (16)$$

with Lagrange multiplier $\beta \geq 0$. The Lagrange multiplier β allows to define a trade-off between the relevant information $I_{\theta}(\mathbf{z}; \mathbf{y})$ and compression rate $I_{\theta}(\mathbf{s}; \mathbf{x})$ which indicates the relation to rate distortion theory [29]. With $\beta = 0$, we have the InfoMax problem (1) whereas for $\beta \rightarrow \infty$ we minimize compression rate. Calculation of the mutual information terms may be computational intractable as in the InfoMax problem (1). Approximative approaches can be found in [31], [32]. Notable exceptions include if the RVs are all discrete or Gaussian distributed.

In this article, we follow a different strategy to solve (15). First, let us assume the RVs to be discrete. Indeed, this is true if the RVs are processed discrete with finite resolution on digital signal processors as in the numerical example of Sec. III. Then, we can upper bound compression rate $I(\mathbf{s}; \mathbf{x})$ by the sum of entropies of any output x_n of the encoder $p_{\theta}(\mathbf{x}|\mathbf{s})$:

$$I(\mathbf{s}; \mathbf{x}) = \mathcal{H}(\mathbf{x}) - \underbrace{\mathcal{H}(\mathbf{x}|\mathbf{s})}_{\geq 0} \leq \mathcal{H}(\mathbf{x}) \leq \sum_{n=1}^{N_{\text{Tx}}} \mathcal{H}(x_n) \quad (17)$$

$$= I_C. \quad (18)$$

Note that the entropy sum in (17) grows with N_{Tx} . By choosing dimension N_{Tx} , we can thus set the constraint I_C higher or lower.

To the end, we set constraint I_C by fixing N_{Tx} . With fixed constraint I_C , we then need to maximize the relevant information $I_{\theta}(\mathbf{z}; \mathbf{y})$. As in the InfoMax problem, we can exploit the MILBO to use the amortized cross entropy $\mathcal{L}_{\theta, \varphi}^{\text{CE}}$ in (9) as the optimization criterion.

E. Implementation Considerations

Now, we will provide important implementation considerations for optimization of (7)/(10) and (15). We note that computation of the MILBO leads to similar problems like for the ELBO [22]. If calculating the expected value in (10) cannot be solved analytically or is computational intractable, we can approximate it using Monte Carlo sampling techniques. For Stochastic Gradient Descent (SGD) - based optimization like, e.g., in the AE approach, the gradient w.r.t. φ can then be calculated by

$$\frac{\partial}{\partial \varphi} \mathcal{L}_{\theta, \varphi}^{\text{CE}} = \frac{\partial}{\partial \varphi} \mathbb{E}_{\mathbf{z}, \mathbf{s}, \mathbf{y} \sim p_{\theta}(\mathbf{y}|\mathbf{s})p(\mathbf{s}|\mathbf{z})p(\mathbf{z})} [-\ln q_{\varphi}(\mathbf{z}|\mathbf{y})] \quad (19)$$

$$\approx -\frac{1}{N} \sum_{i=1}^N \frac{\partial \ln q_{\varphi}(\mathbf{z}_i|\mathbf{y}_i)}{\partial \varphi} \quad (20)$$

and by application of the backpropagation algorithm to $\frac{\partial}{\partial \varphi} \ln q_{\varphi}(\mathbf{z}_i|\mathbf{y}_i) = \frac{\partial}{\partial \varphi} q_{\varphi}(\mathbf{z}_i|\mathbf{y}_i)/q_{\varphi}(\mathbf{z}_i|\mathbf{y}_i)$ in Automatic Differentiation Frameworks (ADF), e.g., TensorFlow and Pytorch. Computation of the so called Reinforce gradient w.r.t. θ leads to high variance of the gradient estimate since we sample w.r.t. the distribution $p_{\theta}(\mathbf{y}|\mathbf{s})$ dependent on θ [22].

Typically, the reparametrization trick is used to overcome this problem as in the VAE approach [22]. Here it is applicable if the latent variable $\mathbf{y} \sim p_{\theta}(\mathbf{y}|\mathbf{s})$ can be decomposed into a differentiable function $f_{\theta}(\mathbf{n}, \mathbf{s})$ and a RV $\mathbf{n} \sim p(\mathbf{n})$ independent of θ . Fortunately, the typical forward model of a communication system $p_{\theta}(\mathbf{y}|\mathbf{s})$ fulfills this criterion. Assuming a deterministic DNN encoder $\mu_{\theta}(\mathbf{s})$ and additive noise \mathbf{n} with covariance Σ , we can thus rewrite into $f_{\theta}(\mathbf{n}, \mathbf{s}) = \mu_{\theta}(\mathbf{s}) + \Sigma^{1/2} \cdot \mathbf{n}$ and accordingly the Monte Carlo approximation of the amortized cross entropy gradient into:

$$\frac{\partial}{\partial \theta} \mathcal{L}_{\theta, \varphi}^{\text{CE}} = -\mathbb{E}_{\mathbf{z}, \mathbf{s}, \mathbf{y} \sim p_{\theta}(\mathbf{y}|\mathbf{s})p(\mathbf{s}|\mathbf{z})p(\mathbf{z})} \left[\frac{\partial}{\partial \theta} \ln q_{\varphi}(\mathbf{z}|\mathbf{y}) \right] \quad (21)$$

$$= -\mathbb{E}_{\mathbf{s}, \mathbf{n} \sim p(\mathbf{n})p(\mathbf{s}|\mathbf{z})p(\mathbf{z})} \left[\frac{\partial f_{\theta}(\mathbf{n}, \mathbf{s})}{\partial \theta} \cdot \frac{\partial \ln q_{\varphi}(\mathbf{z}|\mathbf{y})}{\partial \mathbf{y}} \right] \quad (22)$$

$$\approx -\frac{1}{N} \sum_{i=1}^N \frac{\partial f_{\theta}(\mathbf{n}_i, \mathbf{s}_i)}{\partial \theta} \cdot \frac{\partial \ln q_{\varphi}(\mathbf{z}_i|\mathbf{y})}{\partial \mathbf{y}} \Big|_{\mathbf{y}=f_{\theta}(\mathbf{n}_i, \mathbf{s}_i)}. \quad (23)$$

The trick is easy to implement in ADFs by adding a simple noise layer after (DNN) function $\mu_{\theta}(\mathbf{s})$. The noise layer is usually used for regularization in ML literature. Thus, in recent works, e.g., [4], unsupervised optimization of AEs is treated like a supervised learning problem.

III. EXAMPLE OF SEMANTIC INFORMATION RETRIEVAL

In this section, we provide one numerical example of data-driven semantics to explain what we understand under a semantic communication design and to show its benefits: It is the task of image classification. In fact, we consider our example of the biologist from Sec. II-B who wants to know of which type the tree is.

For the remainder of this article, we will thus assume the hidden semantic RV to be a one-hot vector $\mathbf{z} \in \{0, 1\}^{M \times 1}$

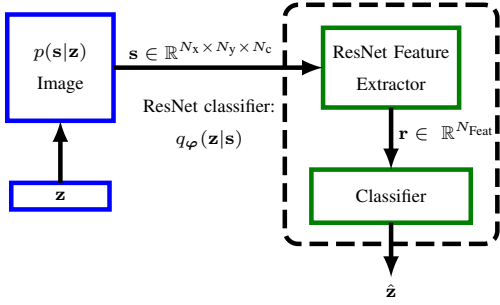


Fig. 2. Central image processing: Based on the images, ResNet extracts semantics by classification.

where all elements are zero except for one element representing one of M image classes. Then, the semantic channel $p(\mathbf{s}|\mathbf{z})$ (see Fig. 1) generates images belonging to this class, i.e., the source signal \mathbf{s} .

Note that for point-to-point transmission we could first classify the image based on the posterior $q_\varphi(\mathbf{z}|\mathbf{s})$ as shown in Fig. 2 and transmit the estimate $\hat{\mathbf{z}}$ (encoded into \mathbf{x}) through the physical channel since this would be most rate or bandwidth efficient.

But if the image information is distributed across multiple agents, all (sub) images may contribute useful information for classification. We could thus lose information when making hard decisions at each transmitter side. In the distributed setting, transmission and combination of features, i.e., soft information, is crucial to obtain high classification accuracy.

Further, we note that transmission of full information, i.e., raw image data \mathbf{s} , through a wireless channel from each agent to a central unit for full image classification would consume a lot of bandwidth. This case is also shown in Fig. 2 assuming perfect communication links between output of the semantic channel and the input of the ResNet Feature Extractor.

Therefore, we investigate a distributed setting shown in Fig. 3. There, each of four agents sees its own image $\mathbf{s}_1, \dots, \mathbf{s}_4 \sim p(\mathbf{s}_i|\mathbf{z})$ being generated by the same semantic RV \mathbf{z} . Based on these images, a central unit shall extract semantics, i.e., perform classification. We propose to optimize the four encoder $p_{\theta_i}(\mathbf{x}_i|\mathbf{s}_i)$ with $i = 1, \dots, 4$, each consisting of a bandwidth efficient feature extractor (ResNet Feature Extractor i) and transmitter (Tx i) **jointly** with a decoder $q_\varphi(\mathbf{z}|\mathbf{y})$, consisting of a receiver (Rx) and concluding classifier (Classifier), w.r.t. cross entropy (10) of the semantic labels (see Fig. 3). To the end, we maximize the system's overall semantic measure, i.e., classification accuracy. Note that this scenario is different from [33]: We include a physical channel (Channel i) since we aim to transmit and not only to compress. The IB is addressed by limiting the number of channel uses which defines constraint I_C in (15).

As a first demonstration example, we use the grayscale MNIST and colored CIFAR10 datasets with $M = 10$ image classes [34]. We assume that the semantic channel generates an image that we divide into four equally sized quadrants and each agent observes one quadrant $\mathbf{s}_1, \dots, \mathbf{s}_4 \in \mathbb{R}^{N_x \times N_y \times N_c}$ where N_x and N_y is the number of image pixels in the x - and y -dimension, respectively, and N_c is the number of color

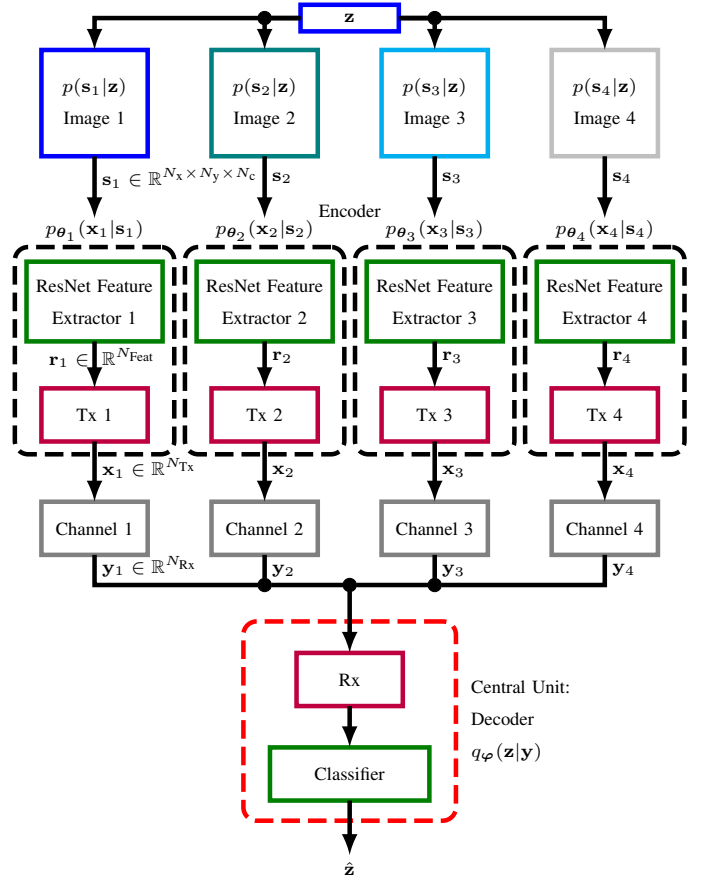


Fig. 3. Semantic INFORMATION traNsmission and retrIeval (SINFONI) for distributed agents. Each agent extracts features for bandwidth efficient transmission. Based on the received signal, the central unit extracts semantics by classification.

channels. Albeit this does not resemble a realistic scenario, note that we can still show the basic working principle and ease implementation.

A. ResNet

For design of the overall system, we rely on a famous DNN approach for feature extraction breaking records at the time of invention: ResNet [34], [35]. The key idea of ResNet is that it consists of multiple residual units: Each unit's input is fed directly to its output and if the dimensions do not match, a convolutional layer is used. This structure allows for fast training and convergence of DNNs since the training error can be backpropagated to early layers through these skip connections. From a mathematical point of view, usual DNNs have the design flaw that using a larger function class, i.e., more DNN layers, does not necessarily increase the expressive power. However, this holds for nested functions like ResNet which contain the smaller classes of early layers.

Each residual unit itself consists of two Convolutional NNs (CNNs) with subsequent batch normalization and ReLU activation function, i.e., $\rho_1(\cdot) = \max(\cdot, 0)$, to extract translation invariant and local features across two spatial dimensions N_x and N_y . Color channels like in CIFAR10 add a third dimension $N_c = 3$ and additional information. The idea behind stacking

TABLE I
SEMANTIC INFORMATION TRANSMISSION AND RETRIEVAL (SINFONI) -
DNN ARCHITECTURE FOR DISTRIBUTED IMAGE CLASSIFICATION.

Component	Layer	Dimension
Input	Image (MNIST, CIFAR10)	(14, 14, 1), (16, 16, 3)
4×	Conv2D	(14, 14, 14), (16, 16, 16)
Feature	ResNetBlock (2/3 res. un.)	(14, 14, 14), (16, 16, 16)
Extractor	ResNetBlock (2/3 res. un.)	(7, 7, 28), (8, 8, 32)
	ResNetBlock (2/3 res. un.)	(4, 4, 56), (4, 4, 64)
	Batch Normalization	(4, 4, 56), (4, 4, 64)
	ReLU activation	(4, 4, 56), (4, 4, 64)
	GlobalAvgPool2D	(56), (64)
4× Tx	ReLU	N_{Tx}
	Linear	N_{Tx}
	Normalization (dim.)	N_{Tx}
Channel	AWGN	N_{Tx}
Rx	ReLU (4× shared)	(2, 2, N_w)
	GlobalAvgPool2D	N_w
Classifier	Softmax	10

multiple layers of CNNs is that features tend to become more abstract from early layers (e.g., edges and circles) to final layers (e.g., beaks or tires).

In this work, we use the preactivation version of ResNet without bottlenecks from [34], [35] implemented for classification on the dataset CIFAR10. In Tab. I, we show its structure for the distributed scenario from Fig. 3. There, ResNetBlock is the basic building block of the ResNet architecture. Each block consists of multiple residual units (res. un.) and we use 2 for MNIST and 3 for CIFAR10 which means we use ResNet14 and ResNet20, respectively. We arrive at the architecture of central image processing from Fig. 2 by removing the components Tx, (physical) Channel, Rx and increasing each spatial dimension by 2 to contain all quadrants of the original image. For further implementation details, we refer the reader to the original work [35].

B. Distributed Semantic Communication Design Approach

Our key idea here is to modify ResNet w.r.t. the communication task by splitting it at a suitable point where a representation $\mathbf{r} \in \mathbb{R}^{N_{Feat} \times 1}$ of semantic information with low-bandwidth is present (see Fig. 2 and 3). ResNet and CNNs in general can be interpreted to extract features: With full images, we obtain a feature map of size $8 \times 8 \times N_{Feat}$ after the last ReLU activation (see Tab. I). These local features are aggregated by the global average pooling layers across the 2 spatial dimensions into \mathbf{r} . Based on these N_{Feat} global features in \mathbf{r} , the softmax layer finally classifies the image. We note that the features contain the relevant information w.r.t. the semantic RV \mathbf{z} and are of low dimension compared to the original image or even its sub images, i.e., 64 compared to $16 \times 16 \times 3 = 768$ for CIFAR10.

Therefore, we aim to transmit each agent's local features $\mathbf{r}_i \in \mathbb{R}^{N_{Feat} \times 1}$ ($i = 1, \dots, 4$) instead of all sub images \mathbf{s}_i and add the component Tx in Tab. I to encode the features $\mathbf{r}_i \in \mathbb{R}^{N_{Feat} \times 1}$ into $\mathbf{x}_i \in \mathbb{R}^{N_{Tx} \times 1}$ for transmission through the wireless channel (see Fig. 3). We note that $\mathbf{x}_i \in \mathbb{R}^{N_{Tx} \times 1}$ is

analog and that the output dimension N_{Tx} of \mathbf{x}_i defines the number of channel uses per agent/image. Note that the less often we use the wireless channel (N_{Tx}), the less information we transmit but the less bandwidth we consume and vice versa. Hence, the number of channel uses defines the IB in (15). We implement the Tx module by DNN layers. To limit the transmit power to one, we constrain the Tx output by the norm along the training batch or the encode vector dimension (dim.), e.g., $\mathbf{x}_i = \tilde{\mathbf{x}}_i / \|\tilde{\mathbf{x}}_i\|_2$ where $\tilde{\mathbf{x}}_i \in \mathbb{R}^{N_{Tx} \times 1}$ is the output of the layer Linear from Tab. I. For numerical simulations, we choose all Tx layers to have width N_{Tx} .

At the receiver side, we use a single Rx module only with shared DNN layers and parameters φ for all inputs \mathbf{y}_i : This setting would be optimal if any feature is reflected in any sub image and if the statistics of the physical channels are the same. Exploiting the prior knowledge of location-invariant features and assuming Additive White Gaussian Noise (AWGN) channels, this design choice seems reasonable. In our experiments, all layers of the Rx module have width N_w . A larger layer width N_w is equivalent to more computing power.

The output of the Rx module can be interpreted as a representation of the image features \mathbf{r}_i with index i indicating the spatial location. Thus, we have a representation of a feature map of size $(2, 2, N_w)$ that we aggregate across the spatial dimension according to the ResNet structure. Based on this semantic representation, a softmax layer with 10 units finally computes class probabilities $q_\varphi(\mathbf{z}|\mathbf{y})$ whose maximum is the maximum a posteriori estimate \hat{z} . In the following, we name our proposed approach Semantic INfOrmation TraNsmission and RetrIeval (SINFONI).

C. Optimization Details

We evaluate SINFONI in TensorFlow 2 [36] on MNIST and CIFAR10. We split the data set into 60k/50k training data and 10k validation data samples, respectively. We do not make use of data augmentation in contrast to [34], [35] yielding slightly worse accuracy. The ReLU layers are initialized with uniform distribution according to He and all other layers according to Glorot [37].

In case of CIFAR10 classification with central image processing and original ResNet, we need to train $N_\theta + N_\varphi = 273,066$ parameters. We like to stress that although we divided the image input into four smaller pieces, this number grows more than four times to $4N_\theta + N_\varphi = 1,127,754$ with $N_{Tx} = N_{Feat} = 64$ for SINFONI. The reason lies in the ResNet structure with minor dependence on the input image size and that we process at four agents with additional Tx module. Only $N_\varphi = 4,810$ parameters amount to Rx module and classification, i.e., the central unit. We note that the number of added Tx and Rx parameters of 33,560 and 3,192 is relatively small. Since the number of parameters only weakly grows with N_w in our design, we choose $N_w = N_{Feat}$ as default.

For l_2 regularization, we use a weight decay of 0.0001 as in [34], [35]. For optimization of the cross entropy (10), we use the reparametrization trick from II-E and Stochastic Gradient Descent (SGD) with momentum of 0.9 and a batch size of 64.

The learning rate of 0.1 is reduced to 0.01 and 0.001 after 100 and 150 epochs for CIFAR10 and after 3 and 6 for MNIST. In total, we train for 200 epochs with CIFAR10 and for 10 with MNIST. In order to optimize the transceiver for a wider SNR range, we choose the SNR to be uniformly distributed within $[-4, 6]$ dB where $\text{SNR} = 1/\sigma_n^2$ with noise variance σ_n^2 .

D. Numerical Results

In the following, we will investigate the influence of specific design choices on our semantic approach SINFONI. Then, we compare a semantic with a classical Shannon-based transmission approach. The design choices are as follows:

- **Central:** Central and joint processing of full image information by ResNet classifier, see Fig. 2. It indicates the maximum achievable accuracy.
- **SINFONI - perfect comm.:** The proposed distributed design SINFONI with perfect communication links and without channel encoding, i.e., Tx and Rx module, but with Tx normalization layer. Thus, the plain and power constrained features are transmitted with $N_{\text{Tx}} = N_{\text{Feat}}$ channel uses. It serves as the benchmark since it indicates the maximum performance of the distributed design.
- **SINFONI - AWGN:** SINFONI perfect comm. evaluated with AWGN channel.
- **SINFONI - AWGN + training:** SINFONI perfect comm. trained with AWGN channel.
- **SINFONI - Encoding ($N_{\text{Tx}} = N_{\text{Feat}}$):** SINFONI with channel encoding, i.e., Tx and Rx module, and $N_{\text{Tx}} = N_{\text{Feat}}$ channel uses.
- **SINFONI - Encoding ($N_{\text{Tx}} < N_{\text{Feat}}$):** SINFONI with channel encoding and $N_{\text{Tx}} < N_{\text{Feat}}$ channel uses for feature compression.
- **SINFONI - Classic digital comm.:** SINFONI - perfect comm. with classic digital communications (Huffman coding, LDPC coding with belief propagation decoding and BPSK modulation) as additional Tx and Rx modules. For details see Sec. III-D4.
- **SINFONI - Classic analog AE:** SINFONI - perfect comm. with ML-based analog communications (AE for any element in \mathbf{r}_i) as additional Tx and Rx modules. For details see Sec. III-D4.

Since meaning is expressed by the RV \mathbf{z} , we use classification accuracy to measure semantic transmission quality. For illustration in logarithmic scale, we show the opposite of accuracy in all plots, i.e., classification error rate.

1) *MNIST dataset:* The numerical results of our proposed approach SINFONI on MNIST are shown in Fig. 4 for $N_w = 56$. First, we observe that the classification error rate of 0.5% of the central ResNet unit with full image information (Central) is smaller than that of 0.9% of SINFONI - perfect comm. Note that we assume ideal communication links. However, the difference seems negligible considering that the local agents only see the quarter of the full images and learn features independently based on it.

With noisy communication links (SINFONI - AWGN), the performance degrades especially for $\text{SNR} < 10$ dB and we can avoid degradation just partly by training with noise (SINFONI

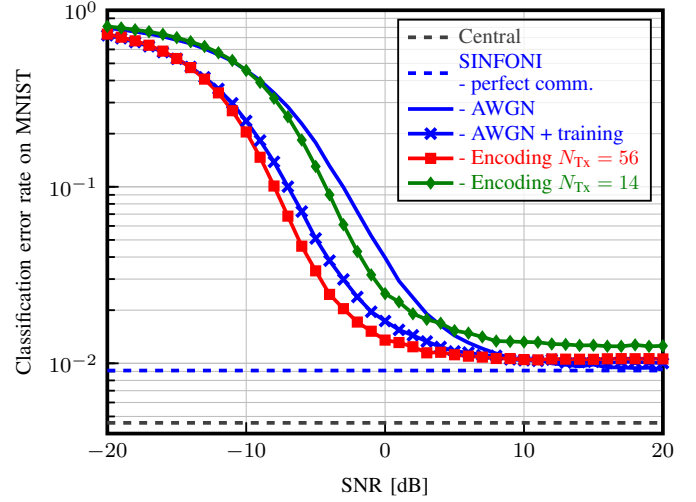


Fig. 4. Classification error rate of central image processing and SINFONI (distributed setting) on MNIST as a function of SNR.

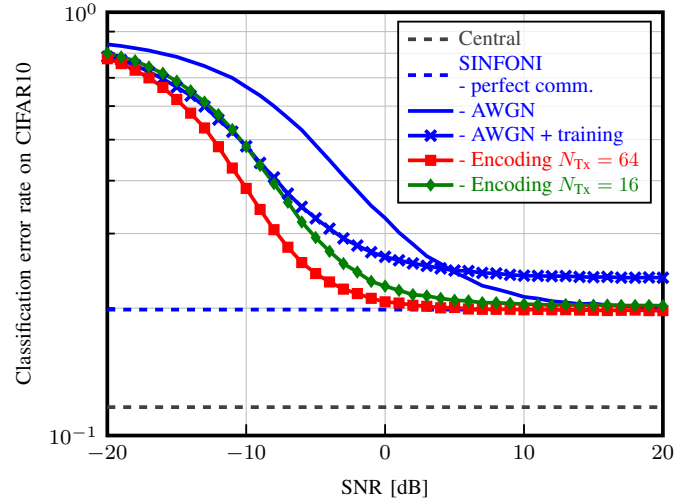


Fig. 5. Classification error rate of central image processing and SINFONI (distributed setting) on CIFAR10 as a function of SNR.

- AWGN + training). Introducing channel encoding (SINFONI - Encoding $N_{\text{Tx}} = 56$), we further improve classification accuracy at low SNR. If we encode the features from $N_{\text{Feat}} = 56$ to only $N_{\text{Tx}} = 14$ at the Tx (SINFONI - Encoding $N_{\text{Tx}} = 14$) to have less channel uses/bandwidth (stronger bottleneck), error rate is lower than in a distributed system optimized with ideal links for low SNR. At high SNR, we observe a small error offset which indicates lossy compression. In fact, our system SINFONI learns a reliable semantic encoding to improve classification performance of the overall system with non-ideal links. Every design choice in Tab. I is well-motivated.

2) *CIFAR10 dataset:* Comparing these results to the classification accuracy on CIFAR10 shown in Fig. 5, we observe a similar behavior. But a few main differences become apparent: Central performs much better with 12% error rate than SINFONI - perfect comm. with 20%. We expect the reason to lie in the more challenging dataset with more color channels. Further, SINFONI - AWGN + training with $N_{\text{Tx}} = N_{\text{Feat}} = 64$

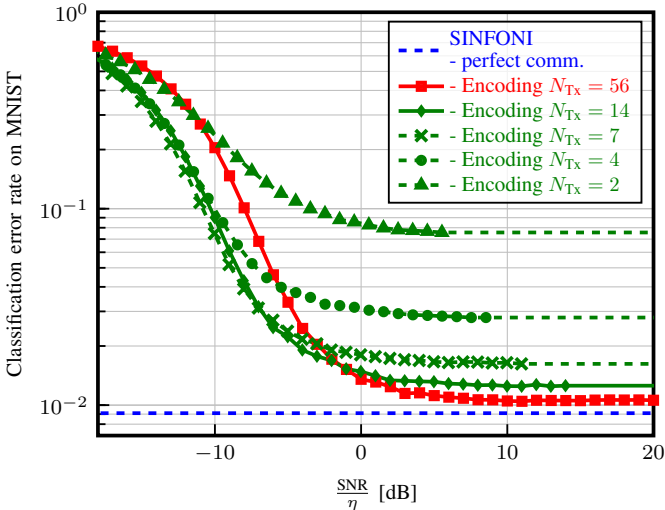


Fig. 6. Classification error rate of SINFONI for different rate/channel uses constraints as a function of normalized SNR.

channel uses runs into a rather high error floor. Notably, even SINFONI - Encoding ($N_{Tx} = 16$) with fewer channel uses performs better than both SINFONI - AWGN and SINFONI - AWGN + training over the whole SNR range and achieves channel encoding with negligible loss. This means adding channel encoding, i.e., Tx/Rx module, is crucial for CIFAR10.

3) *Channel Uses Constraint*: Since one of the main advantages of semantic communication lies in savings of information rate, we finally investigate the influence of the number of channel uses N_{Tx} on MNIST classification error rate shown in Fig. 6. To obtain a fair comparison between transmit signals $\mathbf{x}_i \in \mathbb{R}^{N_{Tx} \times 1}$ of different length N_{Tx} , we normalize the SNR by the spectral efficiency $\eta = N_{Feat}/N_{Tx}$. Decreasing the number of channel uses from $N_{Tx} = 14$ to 2, the gain of channel encoding seen at low effective SNR remains the same. In contrast, the error floor moves higher which hints at increased compression rate. For $N_{Tx} = 56$, almost no error floor occurs at the cost of a smaller channel encoding gain. We conclude that we are able to trade-off channel and source encoding by varying Tx and Rx in dimensions N_{Tx} and N_w .

4) *Semantic vs. Classic Design*: Finally, we compare semantic and classic communication system design. For the classic digital design, it would make sense to assume that the images are compressed lossless and protected by a channel code for transmission and reliable overall image classification by the central unit.

For fair comparison and ease of implementation, we instead replace Tx and Rx modules in Tab. I by a classic design: We first compress each element of the feature vector \mathbf{r}_i that is computed in 32-bit floating-point precision in the distributed setting SINFONI - AWGN to 16-bit. Then, we apply Huffman encoding to a block containing 100 feature vectors of length N_{Feat} . Further, we use a 5G LDPC channel code implementation from [38] with rate 0.25 and long block length of 15360 and modulate the code bits with BPSK. At the receiver, we assume belief propagation decoding where the noise variance is perfectly known for LLR computation.

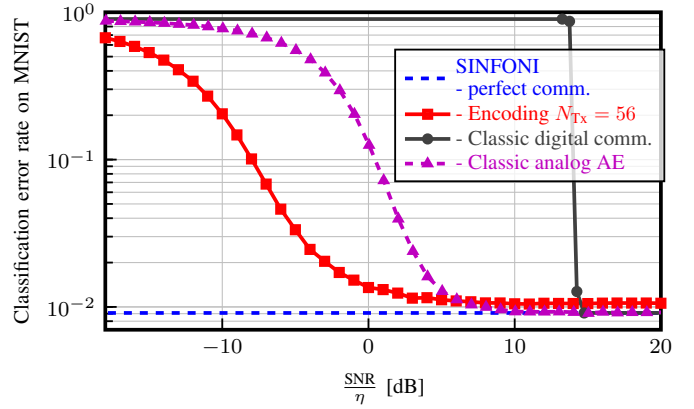


Fig. 7. Classification error rate of SINFONI with semantic, classic digital and ML-based analog communications design on MNIST as a function of normalized SNR.

The results in Fig. 7 reveal tremendous bandwidth savings for the semantic design with SINFONI: We observe an enormous SNR shift of roughly 20 dB compared to the classic digital design (SINFONI - Classic digital comm.). Note that the classic design is already near the Shannon limit and even if we improve it by ML we are only able to shift its curve by a few dB. The reason may lie in overall system optimization w.r.t. semantics and analog encoding of \mathbf{x} .

To distinguish both influences, we also implemented the classic analog approach according to Shannon by AEs. We trained the AE with mean square error criterion for reliable transmission of any element in the feature vector \mathbf{r}_i to replace Tx/Rx modules and provide results (SINFONI - Classic analog AE in Fig. 7): Roughly 15 dB shift are due to analog encoding. By this means, we further avoid the typical thresholding behavior of a classic digital system seen at 14 dB.

In conclusion, this surprisingly clear result justifies an analog semantic communications design and shows its huge potential to provide bandwidth savings.

IV. CONCLUSION

In this article, inspired by Weaver's notion of semantic communication [2], we extended the fundamental approach from Basu et al. [9], [10] for modeling semantics from logical to probabilistic entailment relations between meaning and messages. In particular, we explicitly modeled semantics by means of a semantic hidden Random Variable (RV) and defined the task of semantic communication as reliable and bandwidth-efficient transmission of messages over a communication channel such that the semantic RV is best preserved. We formulated its design either as an Information Maximization or as an Information Bottleneck optimization problem covering important implementations aspects like the reparametrization trick and solved the problems approximately by minimizing the cross entropy that upper bounds the negative mutual information. Finally, we proposed the ML-based semantic communication system SINFONI for a distributed multipoint scenario: SINFONI communicates the meaning behind multiple messages that are observed at different senders to a

single receiver for semantic retrieval. We analyzed SINFONI by processing images as an example of messages. Notably, numerical results reveal a tremendous bandwidth normalized SNR shift up to 20 dB compared to classically designed communication systems.

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