Persuasion through content design

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Abstract

We consider a model of strategic communication between a content creator (*sender*) and a decision-maker, DM (*receiver*). The content creator designs content that has both informational value and a communication value for the DM. The DM decides whether to engage with the content or opt for an outside option. The content provides a utility value to the DM and changes her belief. Following this stage, the DM chooses to pay further attention to uncover the state. We find that there exists a cutoff point for the DM's prior belief (about the content creator's type) below which the CC maximally uses the communication value and above which he chooses the minimum value. Furthermore, the information content decreases with the level of prior belief of DM about the content creator's type. The communication value allows content creators to manipulate the belief of the DM even when the prior belief is sufficiently low. Thus, the communication value introduces a new channel through which the CC can manipulate the DM's strategy and payoff.

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1 Introduction

Effective communication that allows a DM to act on the content creator's information typically requires the content creator to first capture the DM's attention. Tools such as making emotional and empathetic appeals, using storytelling, vivid examples, or even humor to spark curiosity, and employing an energetic delivery combined with using vocal variety, movement, or visual aids are often suggested to engage a disinterested audience. These techniques, often independent of the actual informational content, are frequently employed by political and business leaders, social media influencers, journalists, teachers, scientists, marketers, and advertisers to communicate their ideas and influence decision-making. We aim to study how a content creator can effectively communicate by exploiting such tools.

Historical figures such as Hitler (infamously) and Martin Luther King Jr. (heroically) are known to have made strong emotional appeals and built powerful narratives with mass appeal to effect change. Currently, many social media influencers organize "giveaways" and offer specialized discount coupons to attract viewers. Such techniques, which we model as providing additional payoffs to the DM and call communication value, are commonplace in real-world persuasion settings. We are specifically interested in determining how a content creator optimally designs its content, a combination of the informational value and the communication value, to persuade a decision-maker to first pay attention to its content and, second, to choose its preferred action. Moreover, we are interested in the content design problem when two or more content creators compete to persuade the decision-maker in opposite directions.

To answer these questions, we construct a theoretical model (currently) comprising two players, a content creator (he) and a decision-maker (DM, she). We augment a standard communication game, where the creator privately knows the realization of a state, with two new features. First, the creator designs the content, comprising an informational strategy and a communication value to the DM, to encourage her to engage with the content and ultimately choose the preferred action. And second, if the DM engages with the creator's content, she decides whether to pay further attention to uncover the state before making her decision.

The DM may choose to take a risky or safe action based on her own research. The risky option generates a positive payoff only if the action matches the state, and the safe option generates a fixed (intermediate) payoff. The DM can choose to not engage with the creator's content and receive an outside option payoff. The DM's final payoffs are a combination of the payoff from decision-making and the communication value, net of the (entropy) cost of paying further attention to uncover the state.

Our framework reveals a unique cutoff point on the prior belief, above which the content creator minimally utilizes the communication value and below which he extensively uses it. This result implies that the content creator can induce the DM to choose his preferred action with a positive probability even for arbitrarily small but positive priors.

When the prior belief about the state is sufficiently high, if the DM engages with the content, she does not find it worthwhile to pay more attention to refining her belief before making her decision. The information strategy in the content is therefore uninformative as the DM will choose the creator's preferred action. Thus, the content creator only needs to induce the DM to engage with his content. This purpose can be attained by offering a communication value that makes it just worthwhile to reject the outside option at the prior belief.

When the prior belief is lower than the cutoff, then if the DM were to engage with the creator's content, the strategy must be informative so that the DM is induced to learn further and take the creator's preferred decision at least some time. However, the creator must then utilize the communication value more aggressively to compensate for the costly attention required for further learning and for rejecting the outside option. This result implies that there is a range of prior beliefs such that if zero communication value were provided, as in the standard setting of a communication game, then the DM would choose the outside option. In contrast, in our setting, the communication value can be used to offset the expected value from further attention and decision-making. Thus, the DM can be induced to choose the creator's preferred decision with a positive probability.

When we interpret the communication value as arising from the costly effort of the content creator or simply as a transfer of utility from the content creator to the DM, the result can be reinterpreted as follows: First, under certain prior beliefs, the content creator gains from transferring utility to the DM, i.e., from creating costly but engaging content for the DM rather than saving on this cost. Second, this transfer or effort decreases in the prior belief. So, with a given transfer budget, a content creator can utilize this budget only for some intermediate ranges of prior beliefs.

Related literature Our theoretical model is built on two strands of literature, namely Bayesian Persuasion models and Rational Inattention. We model our communication game following the Bayesian Persuasion literature a la (Kamenica and Gentzkow, 2011,). In these models, the *sender* manipulates the information that the *receiver* obtains by designing information strategies. In (Kamenica and Gentzkow, 2011,), the receiver does not have access to any information other than that which the sender provides. In an extension of this model (Matyskova and Montes, 2023,) consider a model where, after obtaining information from the sender, the receiver can learn on their own. However, (Matyskova and Montes, 2023,) finds that the receiver would never find it optimal to learn on her own. One crucial assumption in these models is that while designing the information structure, the sender does not know the true state. In contrast, in this model, the sender knows the true state before designing the content. This puts a limit on what information can be conveyed. We find that the sender only manipulates the receiver's belief to make her pay attention to his content and not take the outside option. Thus, it is optimal for the receiver to learn on her own after interacting with the sender's content.

In addition to modeling the communication value as independent of the informational value, these results crucially rely on the entropy cost of further learning. We borrow this concept from the Rational Inattention literature, as presented in (Matějka and McKay, 2015,) and (Caplin et al., 2019,). One crucial feature of the entropy cost of learning is given by the property of likelihood invariant posterior (LIP). As shown in (Caplin et al., 2022,), LIP implies that the learning strategy of the receiver can be expressed as consideration sets, where, for extreme beliefs, it is optimal for the receiver not to learn, and for any intermediate belief, the optimal posterior is independent of the prior. This result implies that, in our model, once the sender manipulates the belief to the extent that the receiver is willing to pay further attention, further manipulation by the sender is not necessary. This generates the structure of the equilibrium obtained in our model.

2 A model of communication through content creation

We present below a model with only one content creator who does not face the cost of creating engaging content. However, this framework can be easily extended to include both of these possibilities.

Primitives. We consider a strategic communication model between a content creator (he) and a DM (she) over two stages. In the first stage, the content creator communicates with the DM and the DM decides whether to *engage* with the content or choose an outside option. We assume that if the DM decides to opt for the outside option, then she gets a payoff of u_{out}, the content creator gets zero, and the game ends in stage 1.

Alternatively, if the DM chooses to engage with the content creator, then his payoff depends on the type of the creator and the subsequent action chosen by the DM in the second stage. There are two possible types of creators $\omega \in \{\omega_0, \omega_1\}$ and two possible actions $\{a_0, a_1\}$ the DM can take. The type-dependent payoff function for the DM is given by,

$$u(a_1, \omega_1) = \overline{u} > 0; \quad u(a_1, \omega_0) = \underline{u} < 0; \quad u(a_0, \omega_1) = u(a_0, \omega_0) = 0.$$

Thus, the DM prefers to match the action and the type, i.e., choose action a_i with type ω_i content creator, for $i \in \{0, 1\}$.[1] We assume the creator's payoff function is not state-dependent and is given by,

$$u_C(a_1) = 1, u_C(a_0) = 0.$$

Thus, the content creator always wants the DM to choose the action a_1. We assume that the creator knows her type perfectly. The DM does not know the content creator's type perfectly and has a prior belief $\mu(\omega_1)$ that he is the "high" type.

The communication game. In the first stage, the content creator designs *content* to try to capture the DM's attention. A content is defined by vector (v, s_i) where v determines whether the content will capture the attention of the DM and s_i denotes the probability of sending a signal a_1 by type ω_i.[2]

Formally, the component v enhances the DM's utility of engaging with the content and thus generates $u(a_i, \omega_j) + v$ for all $i, j \in \{0, 1\}$, i.e. for all action-type pairs for the DM. Let us assume that v can take any value between 0 and $\overline{v} > 0$, i.e., $v \in [0, \overline{v}]$.

The component (s_0, s_1) allows the creator of the content to manipulate the DM's belief through the content when the DM engages with the content. If the DM chooses to pay attention to the content, then at the end of stage 1, he updates his belief from prior $\mu(\omega_1)$ to intermediate belief $\mu_C(\omega_1)$ using Bayes' rule given the strategy (s_0, s_1).

[1] Precisely, the DM prefers action a_1 when the state is ω_1, and action a_0 otherwise. These preferences could be interpreted as "risky" and "safe" options, respectively, such that when choosing a_1, matching the state is crucial and not when choosing the safe action a_0.

[2] So, in this formulation, s_1 captures truthful revelation and s_0 the probability of lying about the type. Note that, following (Kamenica and Gentzkow, 2011,) we assume that the sender can commit to a mixed strategy for s_i. In our model, if creating a more informative s_i is costly for the low bias type sender, this assumption can be supported.

In the second stage, given her intermediate belief μ_C, the DM decides whether to pay further attention to uncover the type of content creator. If the content creator chooses $v = 0$, then the DM chooses her strategy according to his prior belief μ about the content creator. We assume that the DM faces an entropy (or UPS) cost of attention. For simplicity, we assume that in stage 2, the content creator cannot manipulate the DM's attention strategy.

WLOG, let us define the DM's attention strategy as choosing a recommendation strategy a_0 or a_1 given the type of content creator. Formally, an attention strategy is the choice of a signal structure $\pi : \{\omega_0, \omega_1\} \to \{a_0, a_1\}$, where given signal a_i, the DM chooses action a_i. Following (Caplin et al., 2019,), (Matějka and McKay, 2015,), we can assume that the DM chooses Bayes plausible posteriors $\gamma \equiv (\gamma^0, \gamma^1)$ instead of choosing a recommendation strategy. The following function gives the cost of paying attention,

$$K(\mu_C, \gamma) = \lambda(F(\mu) - E(F(\gamma)))$$

for some convex function $F(.)$ and $\lambda \geq 0$. If $F(p) = \sum_p p \ln p \equiv H(p)$, then we obtain the standard Shannon mutual entropy cost. For the remainder of the paper, we will assume the Shannon mutual entropy cost,

$$K(\mu_C, \gamma) = \lambda(H(\mu) - E[H(\gamma)])$$

The parameter λ denotes the marginal cost of paying attention. We assume that both the creator of the content and the DM know λ.

Timeline. The timeline of the communication game is as follows.

1 Nature chooses the type of content creator ω and reveals it only to him. The content creator chooses (v, s).[3]

2 DM pays attention or chooses the outside option given (v, s).

3 If the DM pays attention, she updates her belief given μ and s using Bayes' rule.

4 Given an updated belief, the DM decides whether to pay further attention and update his belief to (γ^0, γ^1).

5 The DM chooses her optimal action given the posterior belief.

[3] The content creator is committed to the strategy s such that if the DM pays attention to the content, he cannot revert to always recommending a_1.

3 Persuasion through content design

To understand how optimal content design can persuade the DM to take the creator's preferred action, we begin by solving the DM's attention problem in the second stage of the game.

3.1 The DM's problem

For any belief μ at the beginning of stage 2, we want to solve for the optimal posterior beliefs (γ^0, γ^1) chosen by the DM given his attention cost function.[4]

The DM's learning problem can be described as follows.

WLOG, let the DM's learning generate a recommendation to either choose action a_1 or a_0. Let $P(a_i, \omega_i)$ denote the probability of obtaining a_i recommendation in state ω_i and $P(a_i)$ denote the unconditional probability of obtaining a_i across all states. Following MM(2015) we get,

$$P(a_i, \omega_j) = \frac{z(a_i, \omega_j)P(a_i)}{z(a_1, \omega_j)P(a_1) + z(a_0, \omega_j)(1 - P(a_1))},$$

where $z = \exp \frac{u(a,\omega)}{\lambda}$.

And the posterior belief $\gamma^i(\omega_j)$, i.e., the posterior belief about the type of the content creator being ω_j given the recommendation a_i is given by,

$$\gamma^i(\omega_j) = \frac{P(a_i, \omega_j)\mu(\omega_j)}{\sum_k P(a_i, \omega_k)\mu(\omega_k)}.$$

Our first lemma outlines the DM's attention and learning strategy.

Lemma 1 *There exist thresholds on beliefs, $\underline{\mu} = \frac{1-z_2}{z_1-z_2}$ and $\overline{\mu} = \frac{z_1(1-z_2)}{z_1-z_2}$ where $z_1 = \exp \frac{\overline{u}}{\lambda} > 1$ and $z_2 = \exp \frac{\underline{u}}{\lambda} < 1$, such that*

(a) if $\mu < \underline{\mu}$, the DM chooses not to learn, takes action a_0 with probability 1 and obtains zero payoff $V(\mu) = 0$;

(b) if $\mu > \overline{\mu}$, the DM chooses not to learn, takes action a_1 with probability 1 and obtains an expected payoff of $V(\mu) = \mu\overline{u} + (1 - \mu)\underline{u}$; and

[4]The DM's belief after the first stage is given by μ_C, i.e., the belief after observing the content designed by the content creator. However, since that belief is arbitrary when solving for the second stage, we subdue the subscript C notation for ease of exposition.

(c) if $\mu \in [\underline{\mu}, \overline{\mu}]$, the DM learns and takes action a_1 with a positive probability and obtains an expected payoff of $V(\mu) = \lambda[\mu \ln \mu + (1-\mu)\ln(1-\mu) - \mu \ln \frac{1-z_2}{z_1-z_2} - (1-\mu)\ln \frac{z_1-1}{z_1-z_2}]$.

Thus, the expected payoff $V(\mu)$ is continuous and increases in belief μ.

Proof. By the Likelihood Invariant Posterior (LIP) property, we know $P(a_1) = 1$ for $\mu > \gamma^1(\omega_1)$ and $P(a_1) = 0$ for $\mu < \gamma^0(\omega_1)$. Using the belief update rules in the main text, and Bayes' plausibility, we get

$$\sum_{\omega} \mu(\omega_i) \frac{z(a_i, \omega_j)}{\sum_k P(a_k) z(a_k, \omega_j)} \leq 1$$

Solving them jointly we get,

$$\begin{aligned}
P(a_1, \omega_1) &= \frac{z_1(\mu z_1 + (1-\mu)z_2 - 1)}{\mu(z_1 - z_2)(z_1 - 1)}; \quad P(a_0, \omega_1) = \frac{(1-\mu)z_1 + \mu z_2 - z_1 z_2}{\mu(z_1 - z_2)(z_1 - 1)} \\
P(a_1, \omega_0) &= \frac{z_2(\mu z_1 + (1-\mu)z_2 - 1)}{(1-\mu)(z_1 - z_2)(1 - z_2)}; \quad P(a_0, \omega_0) = \frac{(1-\mu)z_1 + \mu z_2 - z_1 z_2}{(1-\mu)(z_1 - z_2)(1 - z_2)} \\
P(a_1) &= \frac{\mu z_1 + (1-\mu)z_2 - 1}{(z_1 - 1)(1 - z_2)}; \quad P(a_0) = \frac{(1-\mu)z_1 + \mu z_2 - z_1 z_2}{(z_1 - 1)(1 - z_2)}
\end{aligned}$$

where

$$\begin{aligned}
z_1 = \exp \frac{u(a_1, \omega_1)}{\lambda} &= \exp \frac{\overline{u}}{\lambda} > 1; \quad z_2 = \exp \frac{u(a_1, \omega_0)}{\lambda} = \exp \frac{\underline{u}}{\lambda} < 1 \\
\exp \frac{u(a_0, \omega_1)}{\lambda} &= \exp \frac{u(a_0, \omega_0)}{\lambda} = 1
\end{aligned}$$

and,

$$\begin{aligned}
\gamma^1(\omega_1) &= \frac{z_1(1 - z_2)}{z_1 - z_2}; \quad \gamma^1(\omega_0) = \frac{z_2(z_1 - 1)}{z_1 - z_2} \\
\gamma^0(\omega_1) &= \frac{1 - z_2}{z_1 - z_2}; \quad \gamma^0(\omega_0) = \frac{z_1 - 1}{z_1 - z_2}
\end{aligned}$$

Again, by LIP, if $\mu > \frac{z_1(1-z_2)}{z_1-z_2}$ then the DM chooses not to learn, takes action a_1 with probability 1 and obtains an expected payoff of $\mu\overline{u} + (1-\mu)\underline{u}$. Similarly, if $\mu < \frac{1-z_2}{z_1-z_2}$, the DM chooses not to learn, takes action a_0 with probability 1 and obtains zero payoff.

For $\mu \in [\frac{1-z_2}{z_1-z_2}, \frac{z_1(1-z_2)}{z_1-z_2}]$, we now solve for the net expected payoff. Plugging in the values of the prior and the posterior belief, the cost of attention is given by,

$$\begin{aligned}K(\mu,\gamma) = \lambda[&\mu\ln\mu + (1-\mu)\ln(1-\mu)\\&- P(a_1)[\frac{z_1(1-z_2)}{z_1-z_2}\ln\frac{z_1(1-z_2)}{z_1-z_2} + \frac{z_2(z_1-1)}{z_1-z_2}\ln\frac{z_2(z_1-1)}{z_1-z_2}]\\&- P(a_0)[\frac{z_1-1}{z_1-z_2}\ln\frac{z_1-1}{z_1-z_2} + \frac{1-z_2}{z_1-z_2}\ln\frac{1-z_2}{z_1-z_2}]]\end{aligned}$$

Simplifying, we get,

$$\begin{aligned}K(\mu,\gamma) = \lambda[&\mu\ln\mu + (1-\mu)\ln(1-\mu) - \mu\ln\frac{1-z_2}{z_1-z_2} - (1-\mu)\ln\frac{z_1-1}{z_1-z_2}\\&- \frac{\mu z_1 + (1-\mu)z_2 - 1}{z_1-z_2}[\frac{z_1}{z_1-1}\ln z_1 + \frac{z_2}{1-z_2}\ln z_2]]\end{aligned}$$

The expected payoff from this strategy is given by,

$$\begin{aligned}E_\gamma u(a,\omega) &= P(a_1)[\gamma^1(\omega_1)u(a_1,\omega_1) + \gamma^1(\omega_0)u(a_1,\omega_0)] + P(a_0)[\gamma^0(\omega_1)u(a_0,\omega_1) + \gamma^0(\omega_0)u(a_0,\omega_0)]\\&= \lambda\frac{\mu z_1 + (1-\mu)z_2 - 1}{z_1-z_2}[\frac{z_1}{z_1-z_2}\ln z_1 + \frac{z_2}{1-z_2}\ln z_2]\end{aligned}$$

Thus the net expected payoff from the strategy is given by,

$$\begin{aligned}V(\mu) &= E_\gamma u(a,\omega) + K(\mu,\gamma)\\&= \lambda[\mu\ln\mu + (1-\mu)\ln(1-\mu) - \mu\ln\frac{1-z_2}{z_1-z_2} - (1-\mu)\ln\frac{z_1-1}{z_1-z_2}]\end{aligned}$$

Note that, at $\mu = \frac{1-z_2}{z_1-z_2}$ we get, $V(\mu = \frac{1-z_2}{z_1-z_2}) = 0$ and at $\mu = \frac{z_1(1-z_2)}{z_1-z_2}$ we get,

$$\begin{aligned}V(\mu = \frac{z_1(1-z_2)}{z_1-z_2}) &= \lambda[\mu\ln\frac{z_1(1-z_2)}{z_1-z_2} + (1-\mu)\ln\frac{z_2(z_1-1)}{z_1-z_2} - \mu\ln\frac{1-z_2}{z_1-z_2} - (1-\mu)\ln\frac{z_1-1}{z_1-z_2}]\\&= \lambda[\mu\ln z_1 + (1-\mu)\ln z_2] = \mu\overline{u} + (1-\mu)\underline{u}\end{aligned}$$

Thus, $V(\mu)$ is continuous and increases in μ. ■

Thus, paying attention and engaging with the content creator's content in stage 1 is optimal if

$$V(\mu_0) + v \geq u_{out}.$$

Let us assume, for the rest of the analysis that $\overline{v}$ is such that $\overline{v} > u_{out} - \overline{u}$, i.e., for all $\mu_0 \in (0,1)$, there exits a value of v where paying attention is optimal for the DM.

3.2 The content creator's problem

Given the attention strategy and action choice of the DM, the type ω_i content creator chooses (v, s_i) to maximize his expected payoff. Given the optimal choice of the DM, for any belief μ_0, the content creator should choose at least $v(\mu_0) = u_{out} - V(\mu_0)$ to make the DM pay attention to the content. Given the prior belief μ_0 and the content creator's strategy (v, s_i), the intermediate belief of the DM μ_C can be derived using Bayes' rule as follows

$$\mu_C = \begin{cases} \mu_0 \quad \text{if} \quad v = 0, \\ \mu_C^1 \equiv \frac{s_1\mu_0}{s_1\mu_0 + s_0(1-\mu_0)} \quad \text{w.p.} \quad s_i \quad \text{for } v \geq v(\mu_0), \text{ and} \\ \mu_C^0 \equiv \frac{(1-s_1)\mu_0}{(1-s_1)\mu_0 + (1-s_0)(1-\mu_0)} \quad \text{w.p.} \quad 1 - s_i \quad \text{for } v \geq v(\mu_0), \end{cases}$$

where, μ_C^i denotes the intermediate belief of the content creator being type ω_1 given the recommendation of a_i by the content creator in the first stage. Thus, the expected payoff from choosing (v, s_i) is given by

$$V_C(v \geq v(\mu_0), s_i|\mu_0) = \max\{s_i P(a_1(\mu_C^1)) + (1 - s_i)P(a_1(\mu_C^0)), P(a_1(\mu_0))\},$$

where the probability of choosing action a_1 given intermediate belief μ_C is given by,

$$P(a_1(\mu_C)) = \begin{cases} \frac{\mu_C z_1 + (1-\mu_C)z_2 - 1}{(z_1-1)(1-z_2)} \quad \text{for } \mu_C \in [\frac{1-z_2}{z_1-z_2}, \frac{z_1(1-z_2)}{z_1-z_2}], \\ 0 \quad \text{for } \mu_C < \frac{1-z_2}{z_1-z_2}, \text{ and} \\ 1 \quad \text{for } \mu_C > \frac{z_1(1-z_2)}{z_1-z_2}. \end{cases}$$

Since it is never in the interest of the content creator to induce a belief that leads to the DM choosing a_0 w.p. 1, the relevant question is whether and how the content creator induces a belief $\mu_C \in [\frac{1-z_2}{z_1-z_2}, \frac{z_1(1-z_2)}{z_1-z_2}]$ that gets the DM to learn or $\mu_C > \frac{z_1(1-z_2)}{z_1-z_2}$ that gets the DM to choose the creator's preferred action a_1 w.p. 1. The proposition below breaks down these possibilities for different prior beliefs.

Proposition 1 *For $\mu_0 > \frac{z_1(1-z_2)}{z_1-z_2}$, both types of creators choose $s_i^* = 1$, and the optimal choice of v is given by*

$$v^* = \begin{cases} 0 \text{ if } u_{out} < \frac{z_1(1-z_2)}{z_1-z_2}\overline{u} + \frac{z_2(z_1-1)}{z_1-z_2}\underline{u} \text{ or if } u_{out} \in [\frac{z_1(1-z_2)}{z_1-z_2}\overline{u} + \frac{z_2(z_1-1)}{z_1-z_2}, \overline{u}] \text{ then } \mu_0 > \mu_0^v, \\ v(\mu_0) \equiv u_{out} - V(\mu_0) \text{ otherwise,} \end{cases}$$

for some $\mu_0^v > \frac{z_1(1-z_2)}{z_1-z_2}$.

For all $\mu_0 \in (0, \frac{z_1(1-z_2)}{z_1-z_2})$*, the optimal choice of* v *is* $v^* \geq v(\mu_0)$*. Furthermore, the creator type* ω_1 *chooses* $s_1^* = 1$ *for all priors* μ_0 *and the type* ω_0 *chooses* $s_0^* = \min\{\frac{\mu_0}{1-\mu_0}(\sqrt{\frac{z_1-z_2}{1-z_2}} - 1), \frac{\mu_0}{1-\mu_0}\frac{z_2(z_1-1)}{z_1(1-z_2)}\}$*.*

Proof. Let us first consider the case where, $\mu_C \in [\frac{1-z_2}{z_1-z_2}, \frac{z_1(1-z_2)}{z_1-z_2}]$. Plugging in the value of $P(a_1)$, we get for $v = \overline{v}$, the expected payoff of the content creator will be,

$$\begin{aligned}
V_C(v \geq v(\mu_0), s_i) &= s_i \frac{\mu_C^1(z_1-z_2)}{(z_1-1)(1-z_2)} - s_i \frac{1}{z_1-1} + (1-s_i)\frac{\mu_C^0(z_1-z_2)}{(z_1-1)(1-z_2)} - (1-s_i)\frac{1}{z_1-1} \\
&= \frac{(z_1-z_2)}{(z_1-1)(1-z_2)}(s_i \frac{s_1\mu_0}{s_1\mu_0 + s_0(1-\mu_0)} + (1-s_i)\frac{(1-s_1)\mu_0}{(1-s_1)\mu_0 + (1-s_0)(1-\mu_0)}) - \frac{1}{z_1-1}
\end{aligned}$$

Thus, for the high type content creator, we get

$$V_C(v \geq v(\mu_0), s_1) = \frac{(z_1-z_2)}{(z_1-1)(1-z_2)}(\frac{s_1^2\mu_0}{s_1\mu_0 + s_0(1-\mu_0)} + \frac{(1-s_1)^2\mu_0}{(1-s_1)\mu_0 + (1-s_0)(1-\mu_0)})) - \frac{1}{z_1-1}$$

Thus the optimal choice of s_1 given $v > 0$ would be,

$$\begin{aligned}
\frac{\partial V_C}{\partial s_1} &= \frac{(z_1-z_2)}{(z_1-1)(1-z_2)}(\frac{2s_1\mu_0(s_1\mu_0 + s_0(1-\mu_0)) - s_1^2\mu_0^2}{(s_1\mu_0 + s_0(1-\mu_0))^2} \\
&\quad - \frac{2(1-s_1)\mu_0((1-s_1)\mu_0 + (1-s_0)(1-\mu_0)) - \mu_0^2(1-s_1)^2}{(1-s_1)\mu_0 + (1-s_0)(1-\mu_0))^2}) \geq 0 \\
&= \frac{\mu_0 s_1^2 + 2(1-\mu_0)s_1 s_0}{(s_1\mu_0 + s_0(1-\mu_0))^2} - \frac{\mu_0(1-s_1)^2 + 2(1-\mu_0)(1-s_1)(1-s_0)}{((1-s_1)\mu_0 + (1-s_0)(1-\mu_0))^2} \geq 0
\end{aligned}$$

Simplifying we get,

$$\frac{\partial V_C}{\partial s_1} \geq 0 \Leftrightarrow s_1(1-s_0) \geq s_0(1-s_1)$$

Thus, $s_1 = 1$ is always an optimal choice of high (ω_1) type content creators. Given $s_1 = 1$ we get,

$$\mu_C = \begin{cases} \mu_C^1 \equiv \frac{\mu_0}{\mu_0 + s_0(1-\mu_0)} \quad \text{w.p.} \quad s_0 \quad \text{for } v > 0 \\ \mu_C^0 = 0 \quad \text{w.p.} \quad 1-s_0 \quad \text{for } v > 0 \end{cases}$$

If $\mu_C^1 \in [\frac{1-z_2}{z_1-z_2}, \frac{z_1(1-z_2)}{z_1-z_2}]$, plugging in the $P(a_1)$ in the low (ω_0) type content creator's payoff function we get,

$$V_C(v \geq v(\mu_0), s_0) = \frac{s_0\mu_0}{\mu_0 + s_0(1-\mu_0)}\frac{(z_1-z_2)}{(z_1-1)(1-z_2)} - s_0\frac{1}{z_1-1}$$

Thus, the FOC is given by,

$$\frac{\partial V_C}{\partial s_0} = \frac{(z_1 - z_2)}{(z_1 - 1)(1 - z_2)} \frac{\mu_0(\mu_0 + s_0(1 - \mu_0)) - (1 - \mu_0)\mu_0 s_0}{(\mu_0 + s_0(1 - \mu_0))^2} - \frac{1}{z_1 - 1} = 0$$
$$s_0^* = \frac{\mu_0}{1 - \mu_0}(\sqrt{\frac{z_1 - z_2}{1 - z_2}} - 1)$$

Note that, $\frac{\partial s_0^*}{\partial \mu_0} > 0$ and $s_0^* = 0$ at $\mu_0 = 0$, i.e., the more favorable the prior is, the more likely would be the case that the low (ω_0) type content creator will *lie* and pretend to a higher type content creator. Given the optimal choice of s_0, let us check whether $\mu_C \in [\frac{1-z_2}{z_1-z_2}, \frac{z_1(1-z_2)}{z_1-z_2}]$. Plugging in the values we get,

$$\frac{\mu_0}{\mu_0 + \mu_0(\sqrt{\frac{z_1-z_2}{1-z_2}} - 1)} \geq \frac{1 - z_2}{z_1 - z_2}; \quad \text{and} \quad \frac{\mu_0}{\mu_0 + \mu_0(\sqrt{\frac{z_1-z_2}{1-z_2}} - 1)} \leq \frac{z_1(1 - z_2)}{z_1 - z_2}.$$

Simplifying the first inequality, we get,

$$\sqrt{\frac{1 - z_2}{z_1 - z_2}} \geq \frac{1 - z_2}{z_1 - z_2} \quad \Rightarrow \sqrt{\frac{1 - z_2}{z_1 - z_2}} \leq 1,$$

since $z_1 > 1$, we get, $\mu_C > \frac{1-z_2}{z_1-z_2}$ for all $\mu_0 \in (0, 1)$. For the second inequality, we get,

$$\sqrt{\frac{1 - z_2}{z_1 - z_2}} \leq \frac{z_1(1 - z_2)}{z_1 - z_2} \quad \Rightarrow \quad z_1 \geq \sqrt{\frac{z_1 - 1z_2}{1 - z_2}}.$$

If the condition does not hold, then the content creator will choose s_0^* such that $\mu_C = \frac{z_1(1-z_2)}{z_1-z_2}$,i.e.,

$$s_0^* = \frac{\mu_0}{1 - \mu_0} \frac{z_2(z_1 - 1)}{z_1(1 - z_2)}.$$

Furthermore, if the content creator chooses $v = 0$, then his expected payoff would be

$$V_C(v = 0) = \begin{cases} P(a_1(\mu_0)) & \text{if } V(\mu_0) \geq u_{out} \\ 0 & \text{otherwise.} \end{cases}$$

Thus, the expected payoff of the content creator would be given by,

$$V_C(\mu_0) = \max\{V_C(v = v(\mu_0), s_i^*), V_C(v = 0)\}.$$

The result follows by comparing the payoffs. ■

When the prior on the state is sufficiently high $\mu_0 > \frac{z_1(1-z_2)}{z_1-z_2}$, the content design only has a single purpose to serve – to attract the DM's attention to the creator's content. In this situation, if the outside option were small, the content does not have to be made explicitly attractive to the DM as she is inclined to engage with it and choose the creator preferred action either way. As the outside option increases, whether or not the content has to be made attractive is determined by how high the prior belief is. So, again, it is possible that, despite the outside option being modestly high, if the prior belief is high enough ($\mu_0 > \mu_0^v$), the creator does not have to make the content attractive.

When the prior is lower than this threshold, the content must necessarily be made at least minimally attractive to induce the DM to pay attention to it and consider taking the decision that the content creator wants her to. Moreover, conditional on the content being sufficiently engaging, the low type ω_0 creator would like to lie as frequently as possible. The higher is the prior belief the more likely is it possible to do so. However, the creator must recommend a_0 with a positive probability in this range of beliefs to make his recommendation of a_1 credible. In doing so, the creator may not be able to get the DM to always implement a_1 w.p. 1. Specifically, for all $\mu_0 \in (0, \frac{z_1(1-z_2)}{z_1-z_2})$,

- if $\sqrt{\frac{z_1-z_2}{1-z_2}} < \frac{z_1(1-z_2)}{z_1-z_2}$, then the DM chooses to learn in stage 2, and
- if $\sqrt{\frac{z_1-z_2}{1-z_2}} \geq \frac{z_1(1-z_2)}{z_1-z_2}$, then she chooses to not learn and choose a_1 with probability 1 in the stage 2.

These results have the following key implications:

Corollary 1 *If $u_{out} > 0$, there there exists $\overline{\mu} = V^{-1}(u_{out}) > \frac{1-z_2}{z_1-z_2}$ such that for $\mu \in (\frac{1-z_2}{z_1-z_2}, \overline{\mu})$, if $v = 0$ it is optimal for the receiver to choose the outside option, but for a sufficiently high v, $v > u_{out} - V(\overline{\mu})$, the receiver pays attention to the content in the first stage and chooses action a_1 with strictly positive probability (for all types and for all s) in the second stage.*

4 Discussion and Conclusion

Costly Attention In this model, we assume that the DM faces an entropy cost of attention. This result can be generalized by assuming a uniform posterior separable cost function ((Caplin et al., 2022,)), i.e., all cost functions that are convex in the posterior belief distribution. The key property of the UPS cost function, defined as the likelihood invariant posterior (LIP) property, ensures that the DM never chooses to learn fully, and given any prior, he chooses a learning strategy that generates the same set of posteriors. Such cost functions are commonly used in the Bayesian Persuasion literature ((Gentzkow and Kamenica, 2014,), (Matyskova and Montes, 2023,)). However, a more general cost function would not allow us to obtain a closed-form solution of the communication problem; hence, we have assumed the entropy cost of attention.

Communication Value Another key assumption of the model is that the sender can create content that generates communication value for the DM. Although novel, the assumption is crucial for our model. In the absence of the communication value, if the DM has a low prior belief about the content creator's type, he will never be able to convince the DM, irrespective of his true type. Thus, the communication value creates a new channel for the sender to manipulate the strategy and payoff of the DM. There are several real-world scenarios where the content creator can create communication value for the DM. For example, a social media content creator can provide special access or a discount to their viewers. A political campaigner can create content that boosts the ego utility of the voters, etc.

Information Value We allow the sender to commit to design information content with a mixed strategy. Although ex-post, such a strategy would never be optimal, several real-world environments can sustain such a mixed strategy equilibrium. For example, suppose a high bias type sender faces a strictly positive cost for creating a signal/recommendation that mimics the low bias type sender. In such a context, the high bias type would optimally choose an interior value of s_0.

Moving Forward The next step in this paper would be to consider multiple content creators who are all competing for the attention of the receiver. We want to study under different competition environments, e.g., duopoly or monopolistic competition, how content creators design content, and how competition affects the DM's welfare.

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