SEMI: Self-supervised Exploration via Multisensory Incongruity

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Abstract: Efficient exploration is a long-standing problem in reinforcement learning since extrinsic rewards are usually sparse or missing. A popular solution to this issue is to feed an agent with novelty signals as intrinsic rewards. In this work, we introduce SEMI, a self-supervised exploration policy by incentivizing the agent to maximize a new novelty signal: multisensory incongruity, which can be measured in two aspects, perception incongruity and action incongruity. The former represents the misalignment of the multisensory inputs, while the latter represents the variance of an agent’s policies under different sensory inputs. Specifically, an alignment predictor is learned to detect whether multiple sensory inputs are aligned, the error of which is used to measure perception incongruity. A policy model takes different combinations of the multisensory observations as input, and outputs actions for exploration. The variance of actions is further used to measure action incongruity. Using both incongruities as intrinsic rewards, SEMI allows an agent to learn skills by exploring in a self-supervised manner without any external rewards. We further show that SEMI is compatible with extrinsic rewards and it improves sample efficiency of policy learning. The effectiveness of SEMI is demonstrated across a variety of benchmark environments including object manipulation and audio-visual games.

Keywords: Self-supervised Reinforcement Learning

1 Introduction

Efficient exploration is a major bottleneck in reinforcement learning problems. In many real-world scenarios, rewards extrinsic to an agent are extremely sparse or completely missing, leading to nearly random exploration of states. A common remedy to exploration is adding intrinsic rewards, i.e., rewards automatically computed based on the agent’s model of the environment. Existing formulations of intrinsic rewards include maximizing “visitation count” [1, 2, 3] of less-frequently visited states, “curiosity” [4, 5, 6] where future prediction error is used as reward signal and “diversity rewards” [7, 8] which incentivizes diversity in the visited states. These rewards provide continuous feedback to the agent when extrinsic rewards are sparse, or even absent. However, it is challenging to deploy these methods in practice. For “visitation count” based method, it is hard to count in a continuous space. And for “predictive model” based method, the key challenge is to model and interact with a stochastic world where multiple futures are available.

As humans, we experience our world through a number of simultaneous sensory streams, such as vision, audition and touch. The novel feedback from these sensory streams motivate us to explore the world and gain knowledge actively. In modern robot design, sensors with different modalities are ubiquitous in order to augment the performance of the robot perception. However, few exploration policies are designed around multimodal feedback for reinforcement learning agents. The difficulties are mainly reflected in two aspects: how to leverage multiple modalities with very different dimensions, frequencies and characteristics; and how to measure novelty with multimodal feedback.

In this work, we introduce SEMI, a self-supervised exploration method by incentivizing the agent to maximize multisensory incongruity, including perceptual incongruity and action incongruity, as shown in Figure 1.

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Figure 1: SEMI: a self-supervised exploration policy by incentivizing the agent to maximize multisensory incongruity, including perceptual incongruity and action incongruity. Perceptual incongruity indicates the misalignment between the multisensory perceptual inputs, and action incongruity refers to the discrepancy of actions under different perceptual inputs.

Perceptual incongruity is defined as the misalignment between multisensory inputs. As humans, the coincidence of senses gives us strong evidence that they were generated by a common, underlying event [9], since it is unlikely that they co-occurred across multiple modalities merely by chance. Thus, the misalignment or incongruity between multisensory streams can be used as a strong signal of novelty. Researches in psychology suggested that this incongruity can attract human’s attention and trigger further exploration [10, 11], which has been widely used in product design [12, 13]. In SEMI, we use such novelty to guide robot exploration. Specifically, an alignment predictor is trained to detect misalignment between multisensory inputs. The model observes raw sensory streams — some of which are paired, and some have been shuffled — and we task it with distinguishing between the two. This challenging task forces the model to fuse information from multiple modalities and meanwhile learn a useful feature representation. The prediction error of the sensor fusion model serves as a metric of perceptual incongruity, which is further used as an intrinsic reward to guide the agent’s exploration.

Action incongruity is defined as the discrepancy of an agent’s decisions when it perceives different senses of the same underlying event. This is inspired from the fact that humans are able to integrate multimodal sensory information in a near-optimal manner for decision making [14, 15], and are even robust to the loss of some senses [16, 17]. Sensory compensation empowers humans to make similar decisions when different senses are used [18, 19, 20]. Thus, the incongruity of decisions which are made under different combinations of senses is also a signal of novelty for robots, and can be utilized for exploration. In SEMI, a policy network is learned with multi-modal dropout during multisensory fusion. Concretely, we randomly drop one or several modalities during multisensory fusion to imitate loss of senses. The variance of actions suggested by the policy network under different dropout states is used to measure action incongruity, which is also used as an intrinsic reward for better exploration.

SEMI is evaluated in two challenging scenarios: object manipulation (vision and depth) and audio-visual games (Gym Retro). We show that SEMI outperforms “predictive model” based exploration policy by a large margin in both scenarios.

The contributions of this paper can be summarized as follows. Inspired by psychology, we propose SEMI, a novel self-supervised exploration policy through discovering multisensory perceptual and action incongruity; SEMI enables agents to learn compact multimodal representation from hard examples; we demonstrate the efficacy of this formulation across a variety of benchmark environments including object manipulation and audio-visual games; furthermore, we show that SEMI is complementary to other intrinsic and extrinsic rewards.

2 Related Works

Explore with Intrinsic Rewards. Consider an agent that sees an observation, takes an action and transitions to the next state. We aim to incentivize this agent with a reward relating to how informative the transition was, so that the agent can explore the complicated environment more efficiently. One simple approach to encourage exploration is to use state visitation counts [1, 21, 22], where one maximizes visits on less frequent states. However, counting in the continuous space is
Figure 2: SEMI pipeline overview: at time step $t$, an agent takes action $a_t$ given a multisensory observation $O_t$ as input and ends up in a new state. The multisensory fusion model takes a new observation $O_{t+1}$ as input and predicts whether these sensory inputs are aligned. The prediction loss is used as the measure of perceptual incongruity. The variance of actions suggested by the policy network given different combination of multisensory inputs is used to measure action incongruity. Both incongruities are used as intrinsic rewards to train the policy $\pi$.

A concurrent work from Dean et al. [27] has also demonstrated the effectiveness of using multisensory signals as intrinsic rewards. Specifically, they focus on the association of audio and visual signals as intrinsic rewards for reinforcement learning exploration. Different from them, our multisensory incongruity contains both perceptual incongruity and action incongruity.

Multimodal Self-supervised Learning. Self-supervised methods learn features by training a model to solve a pretext task derived from the input data itself, without human labeling. A variety of pretext tasks have been proposed to learn representations from different modalities. Several works leverage the natural correspondence [28, 29] and synchronization [30, 31] between the audio or tactile and RGB streams to learn representations. Others use a modality distillation framework to learn video [32] and sound [33] representations. Recent works have also found that multi-modal learning can lead to more robust representations as they can partly account for the different learning speeds of the different modalities [34].

Noise-contrastive Estimation. Noise-contrastive estimation [35, 36, 37] measures the compatibility between sample pairs in a representational space and is at the core of several recent works on unsupervised feature learning [38, 39, 35, 29, 40]. It reduces a density estimation problem into a simpler probabilistic classification problem, circumventing the need to design handcrafted tasks in the raw signal space. Contrastive learning has recently been shown to yield good performance for image and video representation learning [41, 39, 42]. Prominently, Chen et al. [40] demonstrated that proper combination of data augmentation strategies and noise-contrastive re-identification achieves superior unsupervised learning results.

3 Method

SEMI is a self-supervised exploration policy that incentivizes agents to maximize multisensory incongruities, which we formulate as two aspects: perceptual incongruity (Section 3.1) and action incongruity (Section 3.2). Both incongruities are fed to the agent as intrinsic rewards to encourage its exploration. Figure 2 gives an overview of the pipeline of SEMI, and we will detail each sub-module in the following.
**Notation.** Given an agent’s current observation \(O_t\) at time \(t\), our goal is to generate intrinsic curiosity reward \(r_t\), so that the agent learns a policy \(\pi\) to explore unknown and difficult environment. In this paper, we focus on the multisensory setting, where the agent observes a set of perceptual inputs \(O_t = \{o^1_t, o^2_t, ..., o^M_t\}\), where \(M\) is the number of modalities, which could represent vision, audio, touch, etc. By executing an action \(a_t\) produced by the policy, the agent further observes the next state, which we denote as \(O_{t+1} = \{o^1_{t+1}, o^2_{t+1}, ..., o^M_{t+1}\}\).

### 3.1 Multisensory Perceptual Incongruity

The synchrony of multiple senses is a fundamental property of natural event perception. We humans are extremely sensitive to the incongruity between these senses, which is a strong signal of novelty. For example, if a common object makes an uncommon sound, we are motivated to further interact with this object to gain better knowledge about it. Inspired by this observation, we aim to use such novel association signals as curiosity to drive an RL agent to explore unfamiliar states.

To guide an agent to explore novel states, we propose an alignment predictor to discover the perceptual incongruity. Alignment prediction can take various forms, one possible design is to predict one sensory stream from other streams. For example, we could generate sounds from a corresponding visual input, or generate images from its sounds. However, generating data in the raw signal space suffers from overfitting to trivial details or noises [5].

A better idea is to predict the compatibility of multisensory streams in the latent space. Along the idea of contrastive learning [41, 40], our design of alignment predictor directly maximizes the agreement between different modalities of the same event. This is achieved by predicting positive (aligned) modality streams from negative ones via a contrastive loss penalty in the latent space. The predicted alignment score can then be used as an indicator of perceptual incongruity.

Concretely, the alignment predictor comprises the following two major components.

- A set of neural network base encoders \((f_1(\cdot), ..., f_M(\cdot))\) that extracts representation vectors from each modality. Our framework is agnostic to the choices of neural network architectures. In the following experiments, we use a 2D ConvNet to extract RGB visual features, another 2D ConvNet to obtain depth features, and a Short Time Fourier Transform (STFT) followed by a 1D ConvNet to extract the audio features.

- A contrastive loss function defined for a contrastive learning. Given one sensory stream \(o^i\) from a multisensory observation \(O = \{o^i\}_{i=1}^{M}\) (we omit time \(t\) in the following for brevity), we define the other \(M-1\) simultaneous observation streams \(\{o^j\}_{j \neq i}\) as positive examples. In a minibatch of \(N\) observations, there are \(M \times (N-1)\) sensory streams from other modalities, which can be used to build misaligned examples. The contrastive prediction task aims to identify aligned sensory streams from these misaligned examples.

The similarity of a pair of multimodal observation \((o^i, o^j)\) are measured by the cosine distance, i.e.

\[
\text{sim}(o^i, o^j) = \cos(f_i, f_j) = \frac{f_i^T \cdot f_j}{\|f_i\| \cdot \|f_j\|},
\]

where \(f_i = f_i(o^i)\), \(f_j = f_j(o^j)\) are features from different modalities. Then the contrastive loss function for a pair of positive observation \((o^i_k, o^j_k)\) is defined as

\[
L(o^i_k, o^j_k) = -\log \left( \frac{\exp(\text{sim}(o^i_k, o^j_k)/\tau)}{\sum_{n=1}^N \sum_{m=1}^M \exp(\text{sim}(o^i_k, o^m_n)/\tau)} \right),
\]

where \(\tau\) denotes a temperature parameter.

The multisensory perceptual incongruity of an observation \(O_k\) is then defined numerically as the sum of losses of all possible multisensory pairs from the same timestep, which can be used as an intrinsic reward \(r^p\) as follows:

\[
r^p = \sum_{i=1}^{M} \sum_{j=i+1}^{M} L(o^i_k, o^j_k).
\]

### 3.2 Multisensory Action Incongruity

Congruity in actions is inspired from the fact that human perception is robust to the partly loss of senses, and humans have an exceptional ability to compensate for the loss with other senses. For
example, an experienced driver can predict if cars are coming up from nearby lanes just from sound
oise, without turning his/her head to look. If we make different decisions with different sensory
inputs, it suggests we have low confidence of the event we experienced, e.g. an inexperienced driver
might change lane recklessly without a good understanding of the distance of cars from the sound
noise. Inspired by the above observation, we further aim to use the action incongruity as an indicator
of novelty in RL exploration.

Here we implement the action incongruity via drop of senses. Proposed by Srivastava et al. [43],
dropout has been widely used to prevent neural networks from overfitting [44, 45]. Gal et al. [46, 47]
further cast dropout training in deep neural networks as approximate Bayesian inference in deep
Gaussian processes, which offers a mathematically grounded framework to reason about model
uncertainty.

We adopt a similar approach by taking a sensory-wise dropout strategy during sensor fusion for
the policy network. Then multisensory action incongruity is defined as the divergence of actions
suggested by the policy network given different combinations of multisensory observations.

Specifically, we combine features of different modalities with dropout to obtain a fused perceptual
feature \( z \),

\[
    z = \frac{1}{\sum_{i=1}^{M} \mathbb{1}^i (\sum_{i=1}^{M} \mathbb{1}^i f_i)}, \tag{3}
\]

where \( \mathbb{1}^i \in \{0, 1\} \) indicates the existence of \( f_i \). Apparently, different combinations of \( \mathbb{1}^i \) will lead
to different \( z \). We collect the action outputs from the policy network \( \pi_r \) given all possible inputs \( z \)'s
\((2^M - 1 \) possible inputs in total), and define the variance of these actions as the multisensory action
incongruity. The action incongruity is further used as an intrinsic reward \( r^a \) for exploration,

\[
    r^a = \frac{1}{2^M - 1} \sum_{k=1}^{2^M-1} ||\pi_r(z^k) - \frac{1}{2^M - 1} \sum_{k=1}^{2^M-1} \pi_r(z^k)||^2. \tag{4}
\]

### 3.3 Multisensory Incongruities as Intrinsic Rewards

To summarize, we use both multisensory perceptual incongruity and multisensory action incongruity
as intrinsic rewards. It is worth noting that the policy network \( \pi_r \) used to calculate intrinsic reward
\( r^a_t \) is different from that used for exploration \( \pi \). Inspired by Double Q-learning [48] and Dual Policy
Iteration [49], \( \pi_r \), with parameters \( \theta \) being the same as \( \pi \) except that its parameters are copied every
\( \tau \) steps from the \( \pi \). This simple strategy not only reduces the observed overestimations, but also
leads to better convergence.

At time step \( t \), the agent takes action \( a_t \) given multisensory observation \( O_t \) with modality dropout
as input and receives a new observation \( O_{t+1} \) and intrinsic reward in calculated as \( r_t = r^a_t + \gamma \cdot r^a_{t+1} \),
where \( \gamma \) is a weight factor. The agent is optimized using PPO [50] to maximize the expected reward
according to

\[
    \max_\theta \mathbb{E}_{\pi(O_t; \theta)} (\sum_t r_t). \tag{5}
\]

### 4 Experiments

We evaluate the performance of SEMI in two environments, OpenAI Robotics and Atari. Three set-
things are considered and discussed: exploration with multisensory incongruity only (Section 4.1),
combining multisensory incongruity with extrinsic reward (Section 4.2), and combining multisen-
sory incongruity with other intrinsic rewards (Section 4.3).

#### 4.1 Exploration via Multisensory Incongruity

##### 4.1.1 Environment and Setting

**OpenAI Robotics** We evaluate our method on OpenAI Robotics [51], where robot receives RGB
image and Depth image as two modality, and controls the gripper Cartesian movement, gripper
rotation as well as gripper open or close.

**Atari** We also evaluate our method on Atari games, where vision and audio are considered as
multi-modal inputs. We use Gym Retro [52] in order to access game audio.

Further details for the two evaluation environments are described in the supplementary materials.
4.1.2 Training Details

In general, we used 5 convolutional layers to extract RGB features, a similar network to extract depth features or 5 consecutive frames channel-wise spectrum to represent audio feature. We used a 4-layer multi-layer perceptron (MLP) as our policy network and used PPO to maximize the intrinsic reward with an Adam Optimizer. During training, all rewards that are collected in trajectories will be replaced or added by intrinsic reward. Further details in training the agent in OpenAI Robotics and Atari Games are described in supplementary materials.

4.1.3 Results

OpenAI Robotics  Table 1 shows the exploration performance of object manipulation using the multisensory incongruity, which are measured by the frequency at which our agent interacts (i.e., touches) with the object (i.e., interaction rate). The interaction rate is defined as \( \frac{\text{#trials robot interact with object}}{\text{#total trials}} \).

We evaluate two different versions of our method. We first use only the multisensory perceptual incongruity as our intrinsic reward, as described in Section 3.1. Second, we use both multisensory perceptual incongruity and multisensory action incongruity as our intrinsic reward.

We compare SEMI to Curiosity [5, 23] and Disagreement [53] as our baselines. Also, we compared with a random policy as a sanity check, which samples its action uniformly from the action space.

<table>
<thead>
<tr>
<th>Exploration Strategy</th>
<th>Interaction Rate (1 objects)</th>
<th>Convergence Iteration</th>
<th>Interaction Rate (3 objects)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uni-IR</td>
<td>Curiosity</td>
<td>2.7%</td>
<td>25</td>
</tr>
<tr>
<td></td>
<td>Random</td>
<td>8.4%</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Disagreement</td>
<td>26.3%</td>
<td>23</td>
</tr>
<tr>
<td></td>
<td>SEMI (P)</td>
<td>30.5%</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>SEMI (PA)</td>
<td>34.4%</td>
<td>33</td>
</tr>
<tr>
<td>Multi-IR</td>
<td>Curiosity + SEMI (PA)</td>
<td>35.8%</td>
<td>36</td>
</tr>
<tr>
<td></td>
<td>Disagreement + SEMI (PA)</td>
<td>37.1%</td>
<td>35</td>
</tr>
</tbody>
</table>

Table 1: We measure the exploration quality by evaluating the object interaction frequency of the agent trained with different intrinsic rewards (Row 1-5) and a combination of intrinsic rewards (Row 6-7).

As shown in Table 1, our method outperforms all of these baselines. The method of Disagreement [53] has a performance close to that of our method.

We perform an ablation analysis to quantify the performance of each component of our system (4th and 5th row in Table 1). We see that both multisensory perceptual incongruity and multisensory action incongruity contribute to the robot exploration.

<table>
<thead>
<tr>
<th></th>
<th>MsPacman</th>
<th>Assault</th>
<th>Air Raid</th>
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<tbody>
<tr>
<td></td>
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<td></td>
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</tbody>
</table>

Figure 3: We compare different intrinsic reward formulations across different Atari games. We run three independent runs of each algorithm and show the mean extrinsic reward during training. SEMI far outperforms curiosity-based baseline and disagreement-based baseline, and also learns more efficiently.

Atari  We also test out method in Atari MsPacman, Assault, AirRaider, Alien, Space Invaders, Breakout, and Beam Rider. Figure 3 shows the extrinsic reward of some Atari games during exploration with SEMI in comparison of intrinsic reward via RND, Curiosity and Disagreement. It should be pointed that during training the agent only has access to the intrinsic reward. As illustrated in Figure 3, our method converges faster and achieves better performances comparing with all baseline methods. This result depicts that SEMI can explore the environment more efficiently and
more thoroughly. The reason is that audio signals are always triggered by significant events (e.g. eating pellets). Thus, the multisensory incongruity is more indicative compared with curiosity and disagreement baselines, which are influenced by the stochasticity of the environments.

Figure 4: Comparison of episodic extrinsic rewards of the agent trained with and without multisensory incongruity in the Fetch-Pushing task. Training with SEMI significantly improves the learning efficiency compared with training with only sparse extrinsic reward.

4.2 Combining with Extrinsic Reward

Considering our proposed intrinsic rewards are designed to guide the agent to explore the environment, will they allow the agent to explore well when the extrinsic reward is sparse? To verify this, we conduct additional experiments in OpenAI Robotics and Atari Games. While the network architecture and training schema are exactly the same as Section 4.1, we use the sum of SEMI and extrinsic rewards as training signal,

\[ R_t = r_t + \beta \times r_t^{(e)} \]  

where \( r_t^{(e)} \) is the external reward provided by the environment. We set \( \beta \) to 1 in all the experiments.

Figure 5: Comparing the performance of the agent trained with multisensory incongruity against without using intrinsic rewards across different Atari games. We run three independent runs of each algorithm and show the mean extrinsic reward during training. Training with SEMI always leads to a faster convergence.

Figure 4 shows the episodic extrinsic reward of the FetchPush, Pickup and Place, FetchSlide task training with multisensory incongruity against without using intrinsic rewards. The extrinsic rewards are sparse and binary: The agent obtains a reward of 0 if the goal has been achieved (within some task-specific tolerance) and -1 otherwise. Training with SEMI significantly improves the learning efficiency compared with training with only sparse extrinsic reward. By adding action variance in SEMI paradigm (PA), the performance improves further when policy model learns meaningful mapping from observation to action.

We also tested the experiments on Atari MsPacman, AirRaid, Assault, and Alien. Figure 5 shows the effectiveness of our method for efficient exploration in these Games. Training with SEMI always leads to a faster convergence, which indicates that it is able to speed up exploring the environments. Besides, the final performance of the agent does not deteriorate with faster convergence, showing the compatibility of SEMI with any extrinsic rewards.

4.3 Combining with Other Intrinsic Rewards

We further show that exploration via multisensory incongruity is complementary to some other self-supervised exploration methods, e.g. prediction-based curiosity. To demonstrate this, we simply sum the multisensory incongruity with other intrinsic rewards, and use it to train the agents. We evaluate this setup in both OpenAI Robotics and Atari Games. The network architecture and training schema are exactly the same as mentioned in Section 4.1.
Table 1 (5th and 6th row) shows the interaction rate of object manipulation during exploration with a combination of intrinsic rewards, which sums two intrinsic reward directly as the total intrinsic reward for the agent.

The agent maximizing the sum of multiple intrinsic rewards explores better than an agent maximizing single intrinsic rewards, which shows that SEMI is complementary to many existing intrinsic rewards.

Similarly, we combine our method with other intrinsic rewards on MaPacman, Assault and AirRaid. Figure 6 shows the extrinsic reward of Atari during exploration with a combination of intrinsic rewards. On environment such as AirRaid, the extrinsic reward converge significantly faster than trained with only visual prediction or SEMI method. But on environments like Alien and Space Invaders, the performance does not improve compared to the visual prediction baselines no matter whether multisensory incongruity outperforms curiosity. Since it is unclear how the intrinsic rewards will affect each other when trained jointly, it is possible that optimizing some rewards can bring negative impacts on the others, which will lead to a worse exploration efficiency.

4.4 Failure Cases

While SEMI generally shows improvement in exploring the environment and is compatible with training with extrinsic reward, there are still some Atari environments where it does not improve exploration efficiency. We dig into the games and analyze the feature of them to explain why these environments lead to failures.

1) The game presents constant sound patterns. For example in Beam Rider, there is a fixed background sound whenever the agent makes a move. Thus, the multisensory incongruity method will not learn useful patterns to distinguish the incongruity even in the basic situations, therefore the agent cannot learn from any meaningful intrinsic reward signal.

2) The game shows trivial multisensory association. In environments like Breakout, the audio is almost the same when the agent is interacting with the environment, i.e. the sound in Breakout only indicates the ball is making contact with objects in the scene. The multisensory incongruity module could easily distinguish the incongruity in almost all cases in the game. A newly reached game situation will not lead to high intrinsic rewards. Therefore, multisensory incongruity method cannot motivate the agent to explore unseen situations.

5 Conclusion

In conclusion, we proposed SEMI, a self-supervised exploration strategy by incentivizing the agent to maximize multisensory incongruity. We showed that through the use of multisensory perceptual incongruity and multisensory action incongruity, our learned policy can explore the environment efficiently. We also showed the compatibility of our proposed method with extrinsic rewards and other intrinsic rewards.

We hope that our work paves the way towards a direction for intelligent agents to continually develop knowledge and acquire new skills from multisensory observations without human supervision.
References


