Slot Contrastive Networks: A Contrastive Approach for Representing Objects

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Abstract

Unsupervised extraction of objects from low-level visual data is an important goal for further progress in machine learning. Existing approaches for representing objects without labels use structured generative models with static images. These methods focus a large amount of their capacity on reconstructing unimportant background pixels, missing low contrast or small objects. Conversely, we present a new method that avoids losses in pixel space and over-reliance on the limited signal a static image provides. Our approach takes advantage of objects’ motion by learning a discriminative, time-contrastive loss in the space of slot representations, attempting to force each slot to not only capture entities that move, but capture distinct objects from the other slots. Moreover, we introduce a new quantitative evaluation metric to measure how “diverse” a set of slot vectors are, and use it to evaluate our model on 20 Atari games.

1. Introduction

Understanding a scene from low-level sensory data is an important aspect of human intelligence. One way humans are able to do this is by explicitly learning representations of objects in the scene. Effectively encoding objects is emerging as an important subfield in machine learning because it has the potential to lead to better representations, which accelerates the learning of tasks requiring understanding or interaction with objects and can potentially allow transfer to unseen tasks. Furthermore, these structured object-like representations can be used as input to and are often a pre-requisite to structured downstream systems like graph-based relational techniques (Battaglia et al., 2016), casual modelling (Pearl, 2009), physics-based simulators (Sanchez-Gonzalez et al., 2020), and reinforcement learning from low-dimensional state vectors. There are many existing approaches for representing objects in computer vision with bounding boxes (Redmon et al., 2016); however, these approaches all require external supervision in the form of large numbers of human-labelled bounding box coordinates, which are expensive to obtain. To avoid the reliance on labels, many impressive unsupervised object representation approaches have been developed. However, most of these techniques involve generative models, which have two issues: wasted capacity on modelling spurious background pixels (Oord et al., 2018) and inability to capture small objects (Anand et al., 2019). As a promising alternative to generative models for representation learning, discriminative, self-supervised techniques have emerged, which can be divided into two subcategories: pretext-task based techniques (Weng, 2019) and contrastive techniques (Anand, 2020; Arora et al., 2019). Indeed, many of the recent state of the art models for unsupervised pretraining on static image datasets involve these contrastive techniques (Bachman et al., 2019; Hénaff et al., 2019; Chen et al., 2020; He et al., 2019). While these results are impressive, they are designed to work with static images and not sequential visual datasets, like videos or transition tuples in reinforcement learning. This means that these methods miss out on the helpful signal that time provides, like the fact that interesting entities in a scene are often the ones that move or change with time. As a result, many self-supervised pretext approaches (Misra et al., 2016; Aytar et al., 2018) and contrastive approaches (Hyvärinen & Morioka, 2017; Oord et al., 2018; Anand et al., 2019) have begun to harness time in their self-supervised signal. However, these approaches are often unstructured in the sense that they model the scene with just one global vector instead of a set of representation vectors of separate entities. As a result, we aim to learn structured, object-centric slot representations harnessing time and using a self-supervised time-contrastive signal similar to (Anand et al., 2019; Hyvärinen & Morioka, 2017) to force each object’s representation, but also a “slot contrastive” signal as an attempt to force each slot to capture a unique object compared to the other slots.
2. Slot Contrastive Networks

2.1. Architecture

The architecture of slot contrastive networks, as shown in Figure 1, is structured as a standard convolutional neural network, but where instead of the network encoding a single frame into one vector representation, it encodes the frame, \( x_t \) into \( K \) slot vectors, \( s^i_t \), \( i \in \{1, 2, 3, ..., k \} \). It does this by splitting up the feature maps from the CNN into \( K \) sets of feature maps, which we call “slot maps”, each separately encoded into a different slot vector by a small sub-network (convolutional layer followed by MLP) with shared weights.

2.2. Losses

The losses of SCN are computed by separately encoding frames from consecutive time steps into slot vectors and then computing relationships between the slot vectors. The loss has two terms that attempt to enforce two constraints on the slot representation: slot saliency and slot diversity.

Loss Term 1 (\( \mathcal{L}_1 \)): Encouraging Slot Saliency  
With slot saliency we want each slot vector to capture an important part of the scene, namely an object. To enforce that objective, we take advantage of our main assumption that objects and other important parts of a scene change in time, while spurious parts like backgrounds do not. Thus, we formulate a loss that tries to ensure that the slot representations capture “time dependent” features (i.e. capture things that move). This is the intuition that motivates time-contrastive losses (Hyvarinen & Morioka, 2017; Anand et al., 2019; Sermanet et al., 2018): learning state representations that make it easy to predict the temporal distance between states, will potentially ensure that these representations capture time dependent features. We adapt this type of loss to slot-structured representations by designing an InfoNCE loss (Oord et al., 2018) to contrast similar or positive pairs (the same slot at two consecutive time steps) with dissimilar or negative pairs (the same slot at random, likely nonconsecutive, time steps). The loss shown in Equation 1 ends up looking similar to a standard softmax multiclass classification loss, so we can describe it as classifying a positive pair among many negative pairs.

\[
\mathcal{L}_1 = \sum_{x_t, x_{t+1} \in X} \sum_{j=1}^{K} \left[ -\log \frac{\exp f_{jj}(x_t, x_{t+1})}{\sum_{i=1}^{K} \exp f_{ij}(x_t, x_{t+1})} \right]
\]

where \( X = \{(x_t, x_{t+1}) \}_{i=1}^{N} \) is a minibatch of consecutive pairs of frames that are randomly sampled from collected episodes and \( X_{t+1} = X[:1] \) is the second element of the pair from the set of pairs in the minibatch. In addition, \( f_{ij}(X_1, X_2) \) is a function of the \( i \)-th slot from frame \( X_1 \) and the \( j \)-th slot from frame \( X_2 \). In our case it is a bilinear map: \( f_{ij}(X_1, X_2) = \phi_i(X_1) \phi_j(X_2) \), where \( \phi_j(X_2) \) is the function that extracts the \( j \)-th slot from frame \( X_2 \) and \( W \) is a matrix of size \( |s^i| \times |s^j| \), where \( |s^i| \) is the length of a slot vector.

Loss Term 2 (\( \mathcal{L}_2 \)): Encouraging Slot Diversity  
To encourage diversity between slots, we try to incentivize each slot representation to be different from the others. We achieve this by implementing a “slot contrastive” loss, where we train a classifier to predict whether a pair of slot representations consists of the same slot at consecutive time steps or if the pair consists of representations from two different slots. We again implement this as a contrastive loss using InfoNCE as shown in Equation 2 and Figure 2.

\[
\mathcal{L}_2 = \sum_{x_t, x_{t+1} \in X} \sum_{j=1}^{K} \left[ -\log \frac{\exp f_{jj}(x_t, x_{t+1})}{\sum_{i=1}^{K} \exp f_{ij}(x_t, x_{t+1})} \right]
\]

3. Related Work

There have been many previous approaches for unsupervised learning of object-centric representations. Most previous works have involved various latent generative models.
The approaches differ in the structure and assumptions they impose on their models. The first type is spatial attention models which attend different locations in the scene to extract objects (Kosiorek et al., 2018; Eslami et al., 2016; Crawford & Pineau, 2019a; Lin et al., 2020; Jiang et al., 2019) and the second is scene-mixture models, where the scene is modelled as a Gaussian mixture model of scene components (Nash et al., 2017; Greff et al., 2016; 2017; 2019; Burgess et al., 2019). The third major form of object-centric models are keypoint models (Zhang et al., 2018; Jakab et al., 2018), which extract keypoints (the spatial coordinates of entities) by fitting 2D Gaussians to the feature maps of an encoder-decoder model. In addition, some works have begun to use video-like datasets, so that objects can be extracted by harnessing their movement. For example, several works have jointly extracted objects and computed their interactions with each other to predict their future state for: scene mixture models (Van Steenkiste et al., 2018; Engelcke et al., 2019), spatial attention models (Kossen et al., 2019), and keypoint models (Kulkarni et al., 2019; Minderer et al., 2019). All of these models are trained to reconstruct the input scene in pixel space. In contrast, a few works have begun using discriminative models for learning objects including (Ehrhardt et al., 2018), which uses a temporal self-supervised pretext task to learn objects and constrastive structured world models (CSWM) (Kipf et al., 2019), which predicts future object representations with a contrastive training loss.

While both our model and CSWM use a contrastive loss in the space of the slot representations, and use time to provide a notion of similarity, there are a few key differences. For instance, for each slot at a given time step, CSWM predicts that slot’s representation at the next time step using a graph neural network, while our model can be thought of as using a linear layer. Their distance function between pairs is Euclidean distance, while ours is a dot product. CSWM uses a hinge-based formulation to maximize the positive pair distance and minimize the negative pair distance, while we use InfoNCE (Oord et al., 2018). Lastly, while CSWM’s loss is an intra-slot loss, which bears many similarities to our first loss term, we add a novel inter-slot loss term (for encouraging slot diversity) which has no analog in CSWM.

**4. Evaluating Slot Representations**

Traditionally, slot representations have been evaluated by inspecting qualitative reconstructions (Greff et al., 2019) or measuring how similar temporally close slots are in representation space (Kipf et al., 2019). However, there have not been many quantitative measures of slot representations grounded in how well they capture the true state of objects in the scene. Borrowing from the self-supervision and disentangling literature, we propose several evaluation metrics to measure how accurately slots capture objects in the scene and how disentangled each slot is from the others. We use three measures from the disentangling community, which we adapt to slot representations: slot accuracy (sometimes called explicitness), slot modularity, and slot compactness.

**Slot Accuracy** For slot accuracy, we use linear probing, a technique commonly used in self-supervised learning (Anand et al., 2019; Hjelm et al., 2018; Chen et al., 2020) and disentangling (Locatello et al., 2018). We concatenate all the slots into one vector and then input it to multiple linear regressors each trained to regress a particular x or y coordinate of a particular object in the scene. Accuracy values are the $R^2$ score of each linear regressor. Negative values for $R^2$ are possible, which happens when the total squared error of the linear regressor is more than the variance of the ground truth coordinate values.

**Slot Compactness and Slot Modularity** Inspired by (Eastwood & Williams, 2018), we compute a variant of DCI completeness (Locatello et al., 2018), which we call slot compactness. To compute slot compactness, we first take the weights of the linear regressor probes used to compute slot accuracy, then we take their absolute value and normalize them to create a feature importance matrix denoting how “important” each element of each slot vector is to regressing each object’s coordinate. We then average the feature importances across each slot to get a slot importance matrix, which has shape $P \times K$, where $K$ is the number of slots and $P$ is the number of objects. The element at index $(i, j)$ denotes how important the $i$-th slot is for encoding the $j$-th object. We then treat each row as a probability distribution and compute the average of one minus the entropy of each row of the matrix to get the slot compactness. This gives a score between 0 and 1, where the higher score the fewer slots contribute to encoding an object. Slot modularity, which is inspired by DCI disentangling (Eastwood & Williams, 2018; Locatello et al., 2018) is computed by calculating one minus the entropy of each column of the slot importance matrix (after normalizing the columns). This gives a score between 0 and 1, where the higher score the fewer objects are encoded by a slot.

**5. Experiments**

For our experiments we train our slot contrastive networks using full-sized $210 \times 160$ RGB frames from 20 Atari games. For evaluation, we use labels from the AtariARI dataset (Anand et al., 2019), restricting ourselves to labels that correspond to the x or y coordinates of objects. We set $K$ to be equal to the true number of objects in the game, which is a common practice used in (Kipf et al., 2019; Kulkarni et al., 2019). Following (Anand et al., 2019), we train our...
model with 100,000 frames acquired with a random agent on the Atari games; an additional 50,000 frames are used for training and testing the evaluation probes. We compare to several baselines: a randomly initialized model with no training, CSWM (Kipf et al., 2019) and a fully supervised model, where each slot in the model is trained to regress the true position of one of the objects in the scene. The architectural details of all models are similar to (Anand et al., 2019). We use 20 of the 22 games in AtariARI; we skipped Hero because it only contains one object and Qbert because of poor regression performance even for the supervised model (negative $R^2$ values).

6. Discussion

Interestingly enough, CSWM and SCN perform similarly in average slot accuracy across all games. CSWM particularly excels at games with a few objects that interact frequently, like Pong and Breakout, which both have a ball bouncing off of a paddle. CSWM also seems perform well at games with very predictable, repeatable motion, like the cars in Freeway and the fish in Seaquest. This is likely because CSWM is trained to learn features that minimize its prediction error. CSWM struggles and SCN performs better in games where the motion is not as regular and predictable, like Boxing and VideoPinball. This may be because SCN trained to find any objects that move regardless of if they are easily predictable. One strange result is CSWM’s negative $R^2$ score for Ms. Pacman. This could be because the diversity of frames one obtains with a random policy on these games is small; for example, the agent in Ms. Pacman will basically stay in one place in expectation and as a result the ghosts, who follow the agent, will not move around much. It is interesting to note from Table 1 that SCN’s slots are not as modular or compact as CSWM. This evidence suggests that potentially the slot diversity loss term in SCN has little actual effect on slot diversity. This is demonstrated more explicitly in Table 2, which shows that removing the slot diversity term of SCN results in almost no noticeable change in modularity and actually a small improvement in compactness. The lack of slot diversity diminishment paired with a decrease in slot accuracy when removing the slot diversity term in SCN suggests it provides a slight regularization benefit, but little else. Perhaps, each slot is focusing on the same object, but different parts of it. Without enforcing any true spatial disentangling between slots, it may be hard to truly coax the slots capturing different objects.

6.1. Future Work

These results suggest that perhaps a simple future direction could be a more careful tuning of a coefficient of the second term of the loss is needed. However, a potentially more elegant solution is to try to force slot diversity through architectural inductive biases instead of loss objectives. For instance, a hard or soft spatial attention or routing module for each slot would be an interesting future direction to pair with the time constrastive objective in slot space. Lastly, exploring ways to enhance this model with the ability to dynamically determine the number of slots. Some of these future directions could be thought of as pairing spatial attention models, like (Crawford & Pineau, 2019b; Jiang et al., 2019; Lin et al., 2020), with a temporal contrastive loss instead of a reconstruction loss.

### Table 1. Slot Compactness and Slot Modularity Scores

| Slot | RANDOM-CNN | SCN | CSWM | SUPERVISED |
|------|------------|-----|------|------------|
| MODULARITY | 0.003 | 0.004 | 0.041 | 0.198 |
| COMPACTNESS | 0.007 | 0.014 | 0.304 | 0.266 |

### Table 2. Ablation Results

| Slot Accuracy | RANDOM-CNN | SCN | CSWM | SUPERVISED |
|---------------|------------|-----|------|------------|
| 0.40 | 0.45 |
| MODULARITY | 0.0041 | 0.0045 |
| COMPACTNESS | 0.0170 | 0.0137 |

### Table 3. Slot Accuracy average $R^2$ score for linear regressors regressing object coordinates trained on all slots concatenated for all 20 games.

| Game | RANDOM-CNN | SCN | CSWM | SUPERVISED |
|------|------------|-----|------|------------|
| ASTEROIDS | 0.14 | 0.11 | 0.11 | 0.39 |
| BERZERK | 0.30 | 0.35 | 0.38 | 0.66 |
| BOWLING | 0.39 | 0.83 | 0.96 | 1.00 |
| BOXING | 0.71 | 0.68 | 0.35 | 1.00 |
| BREAKOUT | 0.21 | 0.55 | 0.70 | 0.75 |
| DEMONATTACK | 0.10 | 0.22 | 0.14 | 0.72 |
| FREEWAY | 0.58 | 0.83 | 0.84 | 0.98 |
| FROSTBYTE | 0.71 | 0.48 | 0.69 | 0.94 |
| MONTEZUMAREVENGE | 0.70 | 0.79 | 0.92 | 0.99 |
| MsPACMAN | 0.13 | 0.11 | -0.04 | 0.82 |
| PITFALL | 0.50 | 0.27 | 0.30 | 0.83 |
| PONG | 0.47 | 0.73 | 0.82 | 0.93 |
| PRIVATEEYE | 0.74 | 0.57 | 0.39 | 0.99 |
| RIVERRAID | 0.11 | 0.38 | 0.59 | 0.94 |
| SEQUEST | 0.36 | 0.39 | 0.54 | 0.83 |
| SPACEINVADERS | 0.41 | 0.42 | 0.21 | 0.92 |
| TENNIS | 0.43 | 0.50 | 0.66 | 0.90 |
| VENTURE | 0.12 | 0.12 | 0.27 | 0.50 |
| VIDEOEINBALL | 0.48 | 0.45 | 0.01 | 0.99 |
| YARSREVENG | 0.17 | 0.11 | 0.11 | 0.81 |
| OVERALL | 0.39 | 0.45 | 0.45 | 0.84 |
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