VIEWMAKER NETWORKS: LEARNING VIEWS FOR UNSUPERVISED REPRESENTATION LEARNING

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ABSTRACT

Many recent methods for unsupervised representation learning involve training models to be invariant to different "views," or transformed versions of an input. However, designing these views requires considerable human expertise and experimentation, hindering widespread adoption of unsupervised representation learning methods across domains and modalities. To address this, we propose *viewmaker* networks: generative models which learn to produce input-dependent views for contrastive learning. We train this network jointly with an encoder network to produce adversarial ℓ_p perturbations for an input, which yields challenging yet useful views without extensive human tuning. Our learned views, when applied to CIFAR-10, enable comparable transfer accuracy to the the well-studied augmentations used for the SimCLR model. Our views significantly outperforming baseline augmentations in speech (+9% absolute) and wearable sensor (+17% absolute) domains. We also show how viewmaker views can be combined with SimCLR views to improve robustness to common image corruptions. Our method demonstrates that learned views are a promising way to reduce the amount of expertise and effort needed for unsupervised learning, potentially extending its benefits to a much wider set of domains.

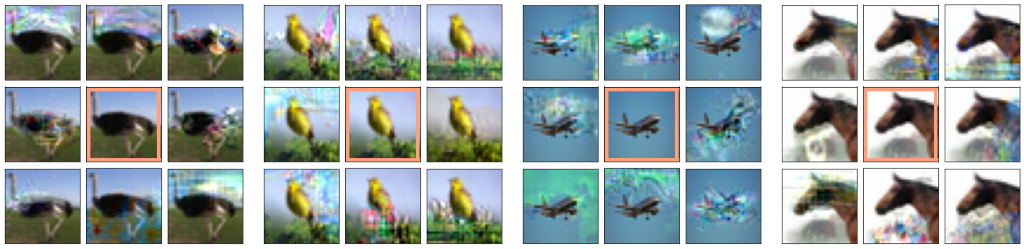


Figure 1: **Viewmaker networks generate complex and diverse input-dependent views for unsupervised learning.** Examples shown are for CIFAR-10. Original image in center with pink border.

1 INTRODUCTION

Unsupervised representation learning has made significant recent strides, including in computer vision where view-based methods have enabled strong performance on benchmark tasks (Wu et al., 2018; Oord et al., 2018; Bachman et al., 2019; Zhuang et al., 2019; Bachman et al., 2019; Misra & Maaten, 2020; He et al., 2020; Chen et al., 2020a). *Views* here refer to human-defined data transformations which target capabilities or invariances thought to be useful for transfer tasks. In particular, in contrastive learning of visual representations models are trained to maximize the mutual information between different views of an image, including cropping, blurring, noise, and changes to color and contrast (Bachman et al., 2019; Chen et al., 2020a). Much work has investigated the space of possible image views (and their compositions) and understanding their effects on transfer learning (Chen et al., 2020a; Wu et al., 2020; Tian et al., 2019; Purushwalkam & Gupta, 2020).

The fact that views must be hand designed is a significant limitation: while views for image classification have been refined over years, new views must be developed from scratch for new modalities.

Making matters worse, even *within* a modality different domains may have different optimal views (Purushwalkam & Gupta, 2020). Previous studies have investigated the properties of good views through the lens of mutual information (Tian et al., 2020; Wu et al., 2020), but a broadly-applicable approach for learning views remains unstudied.

In this work, we present a general method for learning diverse and useful views for contrastive learning. Rather than searching through possible compositions of existing view functions (Cubuk et al., 2018; Lim et al., 2019), which may not be available for many modalities, our approach produces views with a generative model, called the *viewmaker* network, trained jointly with the encoder network. This enables learning a very broad set of possible view functions, including input-dependent views, without resorting to hand-crafting or expert domain knowledge. The viewmaker network is trained adversarially to create views which increase the contrastive loss of the encoder network. Rather than directly outputting views for an image, the viewmaker instead outputs a stochastic perturbation that is *added* to the input. This perturbation is projected onto an ℓ_p sphere, controlling the effective strength of the view, similar to methods in adversarial robustness. This constrained adversarial training method enables the model to reduce the mutual information between different views while preserving useful features of the input data for the encoder to learn from.

In summary, we contribute:

1. Viewmaker networks: to our knowledge the first modality-agnostic method to *learn* views for unsupervised representation learning
2. On image data, where expert-designed views have been extensively investigated, our viewmaker-models achieve transfer performance comparable to state of the art contrastive methods, while being more robust to common corruptions.
3. On speech data, our model significantly outperform existing human-defined views on a range of speech recognition transfer tasks.
4. On time-series data from wearable sensors, our model significantly outperforms baseline views on the task of human activity recognition (e.g. cycling, running, jumping rope).

2 Related work

Unsupervised representation learning Learning useful representations from unlabeled data is a fundamental problem in machine learning (Pan & Yang, 2009; Bengio et al., 2013). A recently successful framework for unsupervised representation learning of images involves training a model to be invariant to various data transformations (Bachman et al., 2019; Misra & Maaten, 2020), although the idea has much earlier roots (Becker & Hinton, 1992; Hadsell et al., 2006; Dosovitskiy et al., 2014). This idea has been expanded by a number of contrastive learning approaches which push embeddings of different views, or transformed inputs, closer together, while pushing other pairs apart (Tian et al., 2019; He et al., 2020; Chen et al., 2020a;b;c). Related but more limited setups have been explored for speech, where data augmentation strategies are less explored (Oord et al., 2018; Kharitonov et al., 2020).

Understanding and designing views Several works have studied the role of views in contrastive learning, including from a mutual-information perspective (Wu et al., 2020), in relation to specific transfer tasks (Tian et al., 2019), with respect to different kinds of invariances (Purushwalkam & Gupta, 2020), or via careful empirical studies (Chen et al., 2020a). Outside of a contrastive learning framework, Gontijo-Lopes et al. (2020) study how data augmentation aids generalization in vision models. Much work has explored different handcrafted data augmentation methods for supervised learning of images (Hendrycks et al., 2020; Lopes et al., 2019; Perez & Wang, 2017; Yun et al., 2019; Zhang et al., 2017), speech (Park et al., 2019; Kovács et al., 2017; Tóth et al., 2018; Kharitonov et al., 2020), or in feature space (DeVries & Taylor, 2017).

Adversarial methods Our work is related to and inspired by work on adversarial methods, including the ℓ_p balls studied in adversarial robustness (Szegedy et al., 2013; Madry et al., 2017; Raghunathan et al., 2018) and training networks with adversarial objectives (Goodfellow et al., 2014; Xiao et al., 2018). Our work is also connected to the vicinal risk minimization principle (Chapelle et al., 2001) and can be interpreted as producing amortized virtual adversarial examples (Miyato et al.,

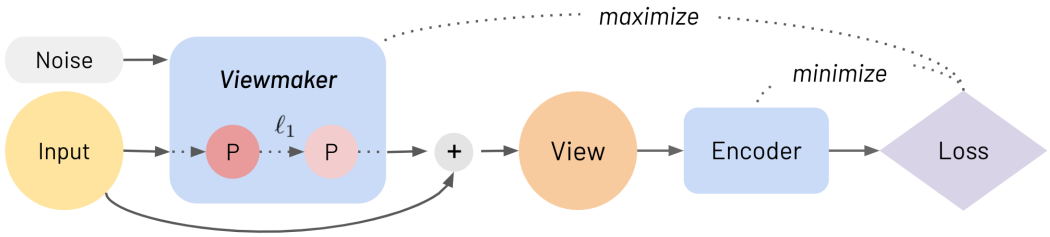


Figure 2: **Diagram of our method.** The viewmaker network is trained to produce adversarial views restricted to an ℓ_1 sphere around the input.

2018). Previous adversarial self-supervised methods add adversarial noise on top of existing human-defined transformations (Kim et al., 2020); in contrast, we do away entirely with human-defined views, using only learned adversarial ones. Outside of multi-view learning paradigms, adversarial methods have also been used for representation learning with GANs (Donahue & Simonyan, 2019) or choosing harder negative samples (Bose et al., 2018), as well as for data augmentation (Antoniou et al., 2017; Volpi et al., 2018; Bowles et al., 2018). Adversarial networks that perturb inputs have also been investigated to improve GAN training (Sajjadi et al., 2018) and to remove "shortcut" features (e.g. watermarks) for self-supervised pretext tasks (Minderer et al., 2020).

Learning views Outside of adversarial approaches, our work is related to other studies that seek to learn data augmentation strategies by composing existing human-designed augmentations (Ratner et al., 2017; Cubuk et al., 2018; Zhang et al., 2019; Ho et al., 2019; Lim et al., 2019; Cubuk et al., 2020) or by modeling variations specific to the data distribution (Tran et al., 2017; Wong & Kolter, 2020). By contrast, our work requires no human-defined view functions, does not require pretraining a generative model, and can generate perturbations beyond variation observed in the training data.

3 Method

In contrastive learning, the objective is to push embeddings of positive views (derived from the same input) close together, while pushing away embeddings of negative views (derived from different input). We focus mainly on the successful SimCLR contrastive learning algorithm (Chen et al., 2020a), but our method is general and we also consider a memory bank-based algorithm (Wu et al., 2018) in Section 4. Formally, given positive views i, j the SimCLR loss is

$$\mathcal{L} = \frac{1}{2N}\sum_{k=1}^{N}[\ell(2k-1,2k)+\ell(2k,2k-1)] \quad \text{where} \quad \ell(i,j) = -\log\frac{\exp(s_{i,j}/\tau)}{\sum_{k=1}^{2N}\mathbb{1}_{[k\neq i]}\exp(s_{i,k}/\tau)}$$

and $s_{a,b}$ is the cosine similarity of the embeddings of views a and b.

We generate views by perturbing examples with a *viewmaker* network V, trained jointly with the main *encoder* network M. There are three attributes that are desirable for useful perturbations, each of which motivate an aspect of our method:

1. **Challenging:** The perturbations should be complex and strong enough that an encoder must develop useful representations in order to perform the self-supervised task. We accomplish this by generating perturbations with a neural network that is trained adversarially to increase the loss of the encoder network. Specifically, we use an neural network which ingests the input X and outputs a view $X + V(X)$.
2. **Faithful:** The perturbations must not make the encoder task impossible, being so strong that they destroy all features of the input. For example, perturbations should not be able to zero out the input, which would make learning impossible. We accomplish this by constraining the perturbations to an ℓ_p sphere around the original input. ℓ_p constraints are common in the adversarial robustness literature where perturbations are expected to be indistinguishable. In our experiments, we find the best results are achieved with an ℓ_1 sphere, which grants the viewmaker a *distortion budget* which it can spend on a small perturbation for a large part of the input or a more extreme perturbation for a smaller portion.

3. **Stochastic:** The method should be able to generate a variety of perturbations for a single input, as the encoder objective requires contrasting two different views of an input against each other. To do this, we inject random noise into the viewmaker, such that the model can learn a stochastic function that produces a different perturbed input each forward pass.

Figure 2 summarizes our method. The encoder and viewmaker are optimized in alternating steps to minimize and maximize $\mathcal{L}$, respectively. We use an image-to-image neural network as our viewmaker network, with an architecture adapted from work on style transfer (Johnson et al., 2016). See the Appendix for more details. This network ingests the input image and outputs a perturbation which is constrained to an ℓ_1 sphere. The radius of this sphere is determined by the volume of the input tensor times a hyperparameter ϵ, the *distortion budget*, which determines the strength of the applied perturbation. This perturbation is added to the input image, and optionally clamped in the case of images to ensure all pixels are in $[0, 1]$. Algorithm 1 describes this process precisely.

Algorithm 1: Generating viewmaker views

Input: Viewmaker network V, $C \times W \times H$ image X, ℓ_1 distortion budget ϵ, noise δ
Output: Perturbed $C \times W \times H$ image X
$P \leftarrow V(X, \delta)$ `// generate perturbation`
$P \leftarrow \frac{\epsilon CWH}{|P|_1} P$ `// project to` ℓ_1 `sphere`
$X \leftarrow X + P$ `// apply perturbation`
$X \leftarrow \text{clamp}(X, 0, 1)$ `// clamp (images only)`

4 Images

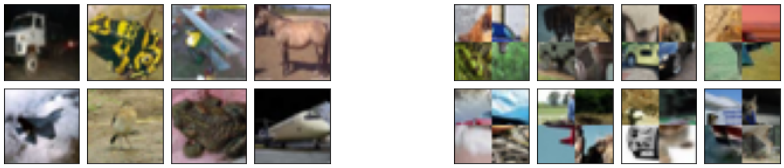
We begin by applying the viewmaker to contrastive learning for images. In addition to SimCLR (Chen et al., 2020a), we also consider a memory bank-based instance discrimination framework (Wu et al., 2018, henceforth InstDisc), and note that our method can be naturally extended to other contrastive algorithms such as MoCo (He et al., 2020) and Local Aggregation (Zhuang et al., 2019).

We pretrain Resnet-18 (He et al., 2015) models on CIFAR-10 (Krizhevsky, 2009) for 200 epochs with a batch size of 256. We train a viewmaker-encoder system with a distortion budget of $\epsilon = 0.05$. We tried distortion budgets $\epsilon \in \{0.1, 0.05, 0.02\}$ and found 0.05 to work best, however we anticipate that further tuning would yield additional gains. As we can see in Figure 1, the learned views are diverse, consisting of qualitatively different kinds of perturbations and affecting different parts of the input. We compare the resulting encoder representations with a model trained with the *expert views* used for SimCLR, comprised of many human-defined transformations targeting different kinds of invariances useful for image classification: cropping-and-resizing, blurring, horizontal flipping, color dropping, and shifts in brightness, contrast, saturation, and hue (Chen et al., 2020a).

4.1 Transfer results on image classification tasks

	SimCLR		InstDisc			SimCLR		InstDisc	
Dataset	Expt	Ours	Expt	Ours	Dataset	Expt	Ours	Expt	Ours
CIFAR-10	**86.2**	84.5	**82.4**	80.1	MNIST	97.1	**98.7**	98.7	**98.9**
MSCOCO	49.9	**50.4**	48.6	**50.2**	FaMNIST	88.3	**91.5**	89.2	**91.4**
CelebA (F1)	51.0	**51.8**	**57.0**	53.7	CUBirds	**11.2**	8.7	**13.7**	9.4
LSUN	**56.2**	55.0	**56.0**	55.6	VGGFlower	53.3	**53.6**	**61.5**	54.8
Aircraft	**32.5**	31.7	**37.7**	33.5	TrafficSign	**96.6**	94.9	**98.9**	94.3
DTD	**30.4**	28.8	**29.8**	**29.8**	Fungi	**2.2**	2.0	**2.6**	2.1

Table 1: **Our learned views enable comparable transfer performance to human-engineered views on CIFAR-10.** Suite of transfer tasks using pretrained representations from CIFAR-10 for both the SimCLR and InstDisc pretraining setups. Numbers are percent accuracy with the exception of CelebA which is F1. FaMNIST stands for FashionMNIST.



(a) CIFAR-10 (b) CIFAR-10-Corners

Figure 3: Our learned views are still able to yield useful information even when the inter-patch mutual information in a dataset is low, as in Figure 3b.

We evaluate our models on CIFAR-10, as well as eleven transfer tasks including MetaDataset (Triantafillou et al., 2019), MSCOCO (Lin et al., 2014), MNIST (LeCun et al., 1998), and Fashion-MNIST (Xiao et al., 2017). We use the standard linear evaluation protocol which trains a logistic regression on top of representations from a frozen model. During transfer training we apply the same views as in pretraining, freezing the final viewmaker when using learned views; we apply no views during validation. Table 1 shows our results, indicating comparable overall performance with SimCLR and InstDisc, all without use of human-crafted view functions. This is noteworthy as our ℓ_1 views cannot implement cropping-and-rescaling, which was shown to be the most important view function in Chen et al. (2020a). We speculate that the ability of the viewmaker to implement partial masking of an image may enable a similar kind of spatial information ablation as cropping.

4.1.1 Comparison to Random ℓ_1 noise

Is random noise sufficient to produce domain-agnostic views? To assess how important adversarial training is to the quality of the learned representations, we perform an ablation where we generate views by adding Gaussian noise normalized to the same $\epsilon = 0.05$ budget as used in the previous section. Transfer accuracy on CIFAR-10 is significantly hurt by this ablation, reaching **52.01%** for a SimCLR model trained with random noise views compared to **84.50%** for our method, demonstrating the importance of adversarial training to our method.

4.1.2 The importance of inter-patch mutual information and cropping views

Cropping-and-resizing has been identified as crucial view function when pretraining on ImageNet (Chen et al., 2020a). However, what properties of a pretraining dataset make cropping useful? We hypothesize that such a dataset must have images whose patches have high mutual information. In other words, there must be some way for the model to identify that different patches of the same image come from the same image. While this may be true for many object or scene recognition datasets, it may be false for other important pretraining datasets, including for medical or satellite imagery where features of interest are isolated to particular parts of the image.

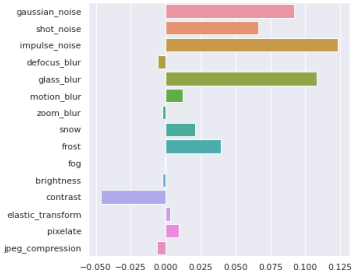
To investigate this hypothesis, we modify the CIFAR-10 dataset to reduce the inter-patch mutual information by replacing each 16x16 corner of the image with the corner from another image in the training dataset (see Figure 3 for an example). Thus, random crops on this dataset, which we call CIFAR-10-Corners, will often contain completely unrelated information. When pretrained on CIFAR-10-Corners, expert views achieve **63.3%** linear evaluation accuracy on the original CIFAR-10 dataset, while viewmaker views achieve **68.8%**. This suggests that viewmaker views are less reliant on inter-patch mutual information than the expert views are.

4.2 Robustness to common corruptions

Image classification systems should behave robustly even in situations where the data distribution is slightly different than seen during training. Does using a viewmaker improve robustness against common types of corruptions not experienced at train time? To answer this, we evaluate both learned views and expert views, as well as their composition, on the CIFAR-10-C dataset (Hendrycks & Dietterich, 2019) which assesses robustness to corruptions like snow, pixelation, and blurring. In this setting, corruptions are applied only at test time, evaluating whether the classification system is robust to some types of corruptions to which humans are robust.

Views	Clean	Corrupted	Diff
Learned	84.5	71.4	-13.1
SimCLR*	**86.2**	77.1	-9.1
Combined*	**86.3**	**79.8**	**-6.5**

(a) Accuracy on CIFAR-10 and CIFAR-C. *Overlap with CIFAR-C corruptions.



(b) Accuracy gain on CIFAR-C by from adding our learned views atop expert views.

Figure 4: **Performance of different views on CIFAR-C corruptions.** Our learned views enable solid performance in the face of unseen corruptions despite not explicitly including any blurring, contrast, or brightness transformations during training, unlike the expert views. Adding our learned views on top of SimCLR yields additional gains in robust accuracy, especially on different kinds of noise corruptions and glass blurring.

As shown in Table 4a, SimCLR augmentations perform quite well, preventing a large drop in accuracy on corrupted data. This is somewhat expected, as the expert views overlap significantly with the CIFAR-C corruptions: both include blurring, brightness, and contrast transformations. Remarkably, however, our learned views, which have no explicit overlap with the CIFAR-C augmentations, also enable significant robustness, though to a slightly lesser degree. More importantly, when we train a viewmaker network while also applying expert augmentations ("Combined," Table 4a), we can further improve the robust accuracy, with notable gains on noise and glass blur corruptions (Figure 4b). We also notice a smaller decline in accuracy on contrast corruptions, possibly due to interactions between changing pixel magnitudes and the ℓ_p constraint. In the Combined setting, we use a distortion budget of $\epsilon = 0.01$ which we find works better than $\epsilon = 0.05$, likely because combining the two augmentations at their full strength would make the learning task too difficult.

These results suggest that learned views are a promising avenue for improving robustness in self-supervised learning models.

5 Speech

Representation learning on speech data is an emerging and important research area, given the large amount of available unlabeled data and the increasing prevalence of speech-based human-computer interaction (Latif et al., 2020). Compared to images, however, there is considerably less work on self-supervised learning and data augmentations for speech data. Thus, it is a compelling setting to investigate whether viewmaker augmentations are broadly applicable across modalities.

5.1 Self-Supervised Learning Setup

We adapt the contrastive learning setup from SimCLR (Chen et al., 2020a). Training proceeds largely the same as for images, but the inputs are 2D log mel spectrograms. We consider both view functions applied in the time-domain prior to the STFT including noise, reverb, pitch shifts, and changes in loudness (Kharitonov et al., 2020), as well as spectral views, which involve masking or noising different parts of the spectrogram (Park et al., 2019). To generate learned views, we pass the spectrogram as input to the viewmaker. We normalize the spectrogram to mean 0 and variance 1 before passing it through the viewmaker, and do not clip the resulting perturbed spectrogram. See the Appendix for more details. We train on the Librispeech dataset (Panayotov et al., 2015) for 200 epochs, and display some examples of learned views in the Appendix.

5.2 Speech Classification Results

We evaluate on three speech classification datasets: Fluent Speech Commands (Lugosch et al., 2019), Google Speech Commands (Warden, 2018), and spoken digit classification (Becker et al.,

Resnet18, 100hr	Expert		Viewmaker (ϵ)	
	Time	Spec.	0.05	0.1
LibriSpeech Sp. ID	**97.1**	91.6	88.3	84.0
VoxCeleb1 Sp. ID	5.7	7.8	**12.1**	9.1
AudioMNIST	31.7	63.9	**93.3**	87.9
Google Commands	27.1	31.9	**47.4**	41.6
Fluent Actions	29.4	32.0	**41.6**	37.9
Fluent Objects	37.1	40.3	**47.6**	**47.6**
Fluent Locations	59.7	63.3	66.5	**68.3**

Resnet50, 960hr	Spec.	0.05
LibriSpeech Sp. ID	**95.9**	90.0
VoxCeleb1 Sp. ID	8.6	**10.7**
AudioMNIST	80.2	**88.0**
Google Commands	28.3	**32.6**
Fluent Actions	30.5	**42.5**
Fluent Objects	36.2	**50.8**
Fluent Locations	62.0	**68.9**

Table 2: **Our learned views significantly outperform existing views for speech transfer tasks.** Linear evaluation accuracy for SimCLR models trained on LibriSpeech. Left: ResNet18 + Librispeech 100 hour, Right: Resnet50 + Librispeech 960hr. "Time" refers to view functions applied in the time domain (Kharitonov et al., 2020), while "Spec." refers to view functions applied directly to the spectrogram (Park et al., 2019). 0.05 and 0.1 denote viewmaker distortion bounds ϵ.

2018), as well as speaker classification on VoxCeleb (Nagrani et al., 2017) and Librispeech (Panayotov et al., 2015), all using the linear evaluation protocol for 100 epochs. We report results with both the same distortion budget $\epsilon = 0.05$ as in the image domain, as well as a larger $\epsilon = 0.1$, for comparison. Both versions significantly outperform the preexisting waveform and spectral augmentations. The gains for real-world tasks such as command identification are compelling. One notable exception is the task of LibriSpeech Speaker identification. Since LibriSpeech is the same dataset the model was pretrained on, and this effect is not replicated on VoxCeleb1, the other speaker classification dataset, we suspect the model may be picking up on dataset-specific artifacts (e.g. background noise, microphone type) which may make the speaker ID task artificially easier. An interesting possibility is that the worse performance of viewmaker views may result from the model being able to identify and ablate such spurious correlations in the spectrograms.

6 Wearable sensor data

To further validate that our method for learning views is useful across different modalities, we consider time-series data from wearable sensors. Wearable sensor data has a broad range of applications, including health care, entertainment, and education (Lara & Labrador, 2012). We specifically consider whether viewmaker views improve representation learning for the task of human activity recognition (HAR), for example identifying whether a user is jumping rope, running, or cycling.

6.1 Self-supervised learning setup

We consider the Pamap2 dataset (Reiss & Stricker, 2012), a dataset of 12 different activities performed by 9 participants. Each activity contains 52 different time series, including heart rate data, as well as accelerometer, gyroscope, and magnetometer data collected from sensors on the ankle, hand, and chest (all sampled at 100Hz, except heart rate which is sampled at approximately 9Hz). We linearly interpolate missing data, then take random 10s windows from subject recordings, using the same train/val/test splits as prior work (Moya Rueda et al., 2018). To create inputs for our model, we generate a multi-channel image composed of one 32x32 log spectrogram for each sensor time-series window. Unlike speech data, we do not use the mel scale when generating the spectrogram. We then normalize the training and validation datasets by subtracting the mean then dividing by the standard deviation of the training dataset.

We train with both our learned views and the spectral views (Park et al., 2019) that were most successful in the speech domain (for multi-channel spectral masking, we apply the same randomly chosen mask to all channels). We also compare against a variant of these views with spectrogram noise removed, which we find improves performance of this baseline.

	Spectral		Viewmaker (ϵ)				
Dataset	With Noise	Without Noise	0.02	0.05	0.2	0.5	2.0
Pamap2	71.0	74.6	83.0	87.4	88.6	**91.3**	9.1

Table 3: **Our learned views significantly outperform existing views for activity recognition on wearable sensor data.** Our method learns superior representations across a large range of distortion budgets ϵ, although budgets that are too strong prevent learning. Linear evaluation accuracy for ResNet18 models trained on Pamap2 with SimCLR. "Spectral" refers to view functions applied directly to the spectrogram (Park et al., 2019).

6.2 Sensor-based activity recognition results

We train a linear classifier on the frozen encoder representations for 50 epochs, reporting accuracy on the validation set. We sample 10k examples for each training epoch and 50k examples for validation. Our views significantly outperform spectral masking by 12.8% absolute when using the same $\epsilon = 0.05$ as image and speech, and by 16.7% absolute when using a larger $\epsilon = 0.5$ (Table 3). We also find that a broad range of distortion budgets produces useful representations, although overly-aggressive budgets prevent learning (Table 3). These results provide further evidence that our method for learning views has broad applicability across different domains.

6.3 Semi-supervised experiments

An especially important setting for self-supervised learning is domains where labeled data is scarce or costly to acquire. Here, we show that our method can enable strong performance when labels for only a single participant (Participant 1) out of seven are available. We compare simple supervised learning on Participant 1's labels against linear evaluation of our best pretrained model, which was trained on unlabeled data from all 7 participants. The model architectures and training procedures are otherwise identical to the previous section. As Figure 4 shows, pretraining with our method on unlabeled data enables significant gains over pure supervised learning when data is scarce, and even slightly outperforms the hand-crafted views trained on all 7 participants (Cf. Table 3).

	Supervised Learning		Pretrain (Ours) & Transfer	
Dataset	1 Participant	7 Participants	1 Participant	7 Participants
Pamap2	58.3	97.1	75.1	91.3

Table 4: **Our method enables superior results in a semi-supervised setting where labels for data from only one participant are available.** Validation accuracy for activity recognition on Pamap2. Supervised Learning refers to training a randomly initialized model on the labeled data until convergence. Pretrain & Transfer refers to training a linear classifier off of the best pretrained model above. 1 or 7 Participants refers to the number of participants comprising the training set.

7 Conclusion

We introduce a method for learning views for contrastive learning, demonstrating its effectiveness across image, speech, and wearable sensor modalities. Our novel generative model—viewmaker networks—enables us to efficiently learn views as *part of* the representation learning process, as opposed to relying on domain-specific knowledge or many costly pretraining runs. There are many interesting avenues for future work. For example, while the ℓ_1 constraint is simple by design, there may be other kinds of constraints that enable richer spaces of views and better performance. In addition, viewmaker networks may find use in supervised learning, through the lens of data augmentation and robustness. Finally, it is interesting to consider what happens as the viewmaker networks increase in size: do we see performance gains or robustness-accuracy trade-offs (Raghunathan et al., 2019)? Ultimately, our work is a step towards reducing the amount of expertise, time, and compute needed to make unsupervised learning work for a much wider variety of domains.

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