A Survey on Self-supervised Pre-training for Sequential Transfer Learning in Neural Networks

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Abstract

Deep neural networks are typically trained under a supervised learning framework where a model learns a single task using labeled data. Instead of relying solely on labeled data, practitioners can harness unlabeled or related data to improve model performance, which is often more accessible and ubiquitous. Self-supervised pre-training for transfer learning is becoming an increasingly popular technique to improve state-of-the-art results using unlabeled data. It involves first pre-training a model on a large amount of unlabeled data, then adapting the model to target tasks of interest. In this review, we survey self-supervised learning methods and their applications within the sequential transfer learning framework. We provide an overview of the taxonomy for self-supervised learning and transfer learning, and highlight some prominent methods for designing pre-training tasks across different domains. Finally, we discuss recent trends and suggest areas for future investigation.

1. Introduction

Deep learning has led to significant improvements in state-of-the-art performance across many domains (LeCun et al., 2015) and has become the dominant approach in building intelligent systems over the last decade. Traditionally, deep networks are trained under a supervised learning framework where a model is trained \textit{tabula rasa} (from scratch) to optimize the performance on a single task with the hopes of generalizing to unseen test examples. A task is typically provided as a set of labeled data with the assumption that the training and test set are drawn from the same underlying distribution. While effective when labeled data is abundant, the paradigm of learning a single task in isolation is limited when human-annotated data is lacking for tasks of interest, leading to poor model generalization (Pan and Yang, 2010).

In contrast to the supervised learning framework, humans are able to learn priors about our environment without labels and adapt our knowledge to new tasks with only a few examples (Dubey et al., 2018). For instance, learning how to play piano can help us learn music fundamentals, which, subsequently, makes learning how to play violin easier. When an infant learns how to recognize faces, they can apply this knowledge to recognize other objects (Wallis and Bülthoff, 1999). Ideally, a similar approach could be applied to machine learning. Instead of relying solely on labeled data, practitioners can leverage unlabeled or related data, which is often more accessible and ubiquitous. Knowledge from a large corpus of unlabeled data can be extracted and transferred to improve performance on a target task where labeled data is either limited or unavailable.

There is a large amount of literature on unsupervised and transfer learning. In this paper, we focus on surveying self-supervised learning methods for sequential transfer learn-
ing. Self-supervised learning is a type of unsupervised learning where a model is trained on labels that are automatically derived from the data itself without human annotation (Erhan et al., 2010; Hinton et al., 2006). Self-supervised learning methods enable a model to learn useful knowledge about an unlabeled dataset by learning useful representations and parameters. Transfer learning focuses on how to transfer or adapt this learned knowledge from a source task to a target task (Pan and Yang, 2010). Specifically, we focus on a specific type of transfer learning called sequential transfer learning (Ruder, 2019) which adopts a “pre-train then fine-tune” paradigm. Self-supervised learning and transfer learning are two complementary research areas that, together, enable us to harness a source task with a large amount of unlabeled examples and transfer the learned knowledge to a target task of interest. These methods have grown in popularity due to their success and scalability in improving state-of-the-art results across domains. Finding useful self-supervised learning algorithms and transfer learning methods are areas of active investigation.

Compared to other surveys that focus primarily on either computer vision (Schmarje et al., 2020; Jing and Tian, 2019) or natural language processing (NLP) (Ruder, 2019), we provide a broad review of self-supervised learning across domains in computer vision, natural language and audio/speech. This can, hopefully, provide a birds eye view of self-supervised research in deep learning and highlight areas for further investigation.

We first provide a background overview of self-supervised pre-training and transfer learning in section 2 and 3. We then review self-supervised learning methods organized under the following categories: bottleneck-based methods (sec. 4) and prediction-based methods (sec. 5). Bottleneck-based methods drive learning by imposing an information bottleneck through a model’s architecture. Prediction-based methods learn by asking a model to predict or generate relevant data with respect to the input. Finally, we provide a discussion of research trends and frontiers for future work in section 6.

2. Transfer Learning

We provide a more formal definition of transfer learning, following the definitions from Pan and Yang (2010); Ruder (2019). Transfer learning is a collection of techniques that focus on adapting knowledge between tasks and involves two concepts: a domain and a task. A domain $\mathcal{D} = \{\mathcal{X}, P(X)\}$ has a feature space $\mathcal{X}$ and a marginal distribution $P(X)$ over the feature space where $X = \{x_1, \ldots, x_n\} \in \mathcal{X}$. For image classification, $\mathcal{X}$ is the space of all images, $x_i$ corresponds to some image and $X$ is a sample of images used for training.

A task $\mathcal{T}$ is defined with respect to some domain $\mathcal{D}$ and consists of a label space $\mathcal{Y}$, a prior distribution $P(Y)$ and a learned conditional probability distribution $P(Y|X)$. $P(Y|X)$ is typically learned from a training set of $\{x_i, y_i\}$ where $x_i \in X, y_i \in \mathcal{Y}$. For image classification, $\mathcal{Y}$ is the set of possible image classes.

The aim of transfer learning is to learn the target task $\mathcal{T}_t$ using knowledge learned from a source task $\mathcal{T}_s$. Specifically, we want to learn the target conditional probability distribution $P_t(Y_t|X_t)$ in $\mathcal{D}_t$ from information learned from $\mathcal{T}_s$ and $\mathcal{D}_s$ where $\mathcal{D}_s \neq \mathcal{D}_t$ and/or $\mathcal{T}_s \neq \mathcal{T}_t$.

2.1 Transfer Learning Scenarios

Following the taxonomy from Pan and Yang (2010), we can categorize transfer learning into three broad settings depending on the tasks in the source and target domain (Figure
1). When source and target tasks are the same $\mathcal{T}_s = \mathcal{T}_t$ with labels only available in the source domain, we call it transductive transfer learning. A specific example of transductive transfer learning is domain adaptation (Wang and Deng, 2018), where a model could be trained on the source task of predicting sentiment on Amazon reviews and needs to be adapted to predict sentiment in news. When the tasks are different and labeled data is provided in the target domain $\mathcal{T}_s \neq \mathcal{T}_t$, we refer to this as inductive transfer learning. An example of inductive transfer learning is training a model on (optionally labeled) data to classify many images of natural scenery, then adapting the model to classify images of cats. When no labels are provided in either case, we refer to this setting as unsupervised transfer learning.

Ruder (2019) further refines inductive transfer learning into two subcategories: multi-task learning (Caruana, 1997) and sequential transfer learning. In multi-task learning, tasks $\mathcal{T}_s$ and $\mathcal{T}_t$ are learned simultaneously, typically through the joint optimization of multiple objective functions. In sequential transfer learning, $\mathcal{T}_s$ is first learned, then the downstream task $\mathcal{T}_t$ is learned. The first stage is often called pre-training while the second stage of learning is often called fine-tuning in the context of neural networks. The primary difference between these two types of transfer learning is when the target task is learned. More generalized schemes can define a multi-tasking schedule that interpolates between learning the source and target task (Liang and Shu, 2017) or contain multiple source tasks (Mao et al., 2019).

Sequential transfer learning is our primary focus in this paper. Sequential transfer learning is more popular in practice as it is simple to set up a two-phase training pipeline and easy to distribute pre-trained models without needing to disclose the pre-training dataset. Most of the self-supervised learning techniques we review can be categorized under sequential transfer learning.

**Related Areas** There are other related research areas to transfer learning that are beyond the scope of this paper, that we briefly mention here. Lifelong learning (Parisi et al., 2019) can be seen as form of sequential transfer learning of many tasks, with the additional goal of learning without forgetting previous tasks (e.g., catastrophic forgetting). Few shot learning (Wang et al., 2019) focuses on the general problem of learning with few labels and is achievable in certain extents with transfer learning. Meta learning (Vilalta and Drissi, 2002) focuses on algorithms that enable us to learn how to learn and can be considered a form of transfer learning where meta-knowledge is transferred to task-specific knowledge.
2.2 Why Does Sequential Transfer Learning Work?

In order to understand the success of sequential transfer learning it is useful to consider some theoretical arguments as to why it works.

**Multi-tasking Perspective**  We briefly summarize an analysis from Ruder (2017) on why multi-task learning is beneficial since it is highly related to sequential transfer learning. Multi-task learning (Caruana, 1997) has been shown to serve as a form of regularization as it reduces the Rademacher complexity of the model (the ability to fit random noise) (Søgaard and Goldberg, 2016). It biases the model to prefer representations that other tasks would likely prefer (Baxter, 2000) and allows the model to learn a task better through hints from another task (Abu-Mostafa, 1990). While multi-task and sequential transfer learning are not strictly the same, it is useful to consider these related effects especially when hybrid sequential and multi-task transfer learning approaches are used.

**Regularization**  To understand why sequential transfer learning works, we summarize an early work that provides useful insights in unsupervised pre-training. Erhan et al. (2010) analyzed a special case of unsupervised pre-training applied to deep belief networks (Hinton et al., 2006), but the arguments presented there are more broadly applicable to sequential transfer learning. Erhan et al. (2010) hypothesizes that pre-training serves as a form of implicit regularization through parameter initialization by constraining the minima that the supervised objective can optimize to. Pre-training restricts learning to a subset of the parameter space bound by a basin of attraction achievable through fine-tuning the supervised target task. This hypothesis is supported experimentally by observing the training dynamics of MNIST filters (Erhan et al., 2010). Recent work has also shown some evidence to suggest that fine-tuning pre-trained language models does not deviate from the pre-trained weights significantly (Sanh et al., 2020). In other words, the final weights are mostly predetermined by pre-training, especially if the pre-training task dominates the total training time of the sequential transfer learning process.

**Inducing Priors**  Treating sequential transfer learning as simply a form of regularization underestimates its benefits. Similar to multi-task learning, sequential transfer learning also induces a prior on the model. Practitioners who use similar source and target tasks encode a prior on what knowledge is likely useful, thus the effects are akin to selecting good neural architectures and better hyperparameters.

**Implicit Meta Learning**  Another perspective we can consider is that pre-training, when given an appropriate and sufficiently large source task, can perform implicit meta learning (Brown et al., 2020a). This provides a similar effect as meta-learning algorithms such as MAML (Finn et al., 2017) that explicitly aim to learn an initialization that easily adapts to various problems.

3. Self-supervised Learning

Unsupervised learning is a family of approaches that learn from data without any supervision. A particular form of unsupervised learning of growing interest is self-supervised learning. The terms unsupervised and self-supervised have been, historically, used interchangeably in the literature, but recent work has preferred the term self-supervised learning
for its specificity. In this review, we refer to self-supervised learning as any unsupervised learning approach that can be easily reduced into a supervised problem by generating labels. Thus, self-supervised learning can reap the advancements and breakthroughs from supervised learning. Self-supervised learning still requires labels, but it is unsupervised in the sense that these labels are derived from the data itself rather than annotated by humans.

Early work in self-supervised pre-training for deep neural networks aimed to effectively train stacked auto-encoders (Bengio et al., 2007) and deep belief networks (DBN) (Hinton et al., 2006) without labels. These techniques train deep networks one layer at a time in a greedy fashion in order to circumvent poor local minima that prevented successful end-to-end gradient descent (Bengio and Lecun, 2007). Once trained, the neural network is fine-tuned, where the model with pre-trained weights switches from unsupervised learning to supervised learning objective of the target task. This can lead to improved performance on the target task as opposed to simply learning the target task from scratch. In the last decade, greedy layer-wise unsupervised learning has fallen out of fashion in favor of end-to-end learning where an entire deep network is trained in one operation. This shift is partly due to the architectural innovations (He et al., 2015), normalization (Ioffe and Szegedy, 2015) and better activation functions (Nair and Hinton, 2010) that enable training of very deep networks (Bachlechner et al., 2020) while avoiding local minima.

In contrast to classic work on greedy self-supervised learning (Ackley et al., 1985; DeMers and Cottrell, 1993), modern approaches focus on end-to-end learning. Self-supervised learning constructs a pre-training or “pretext” task that is used to extract knowledge from unlabeled data (Jing and Tian, 2019). After training a model on the pretext task, it can then be adapted to the target task through transfer learning. Pre-training tasks come in many forms. They usually involve transforming or imputing the input data with the goal of forcing the model to predict missing parts of the data or through introducing some information bottleneck, which we will review in later sections.

**Downstream Tasks** Self-supervised learning has been used to transfer knowledge into a variety of target tasks. In this review, we do not focus on any specific downstream task since we are primarily concerned with pre-training methods. Instead, we briefly highlight some common tasks used to benchmark self-supervised learning algorithms. For computer vision, image classification is typically the downstream task of interest for self-supervised learning of still images (Chen et al., 2020) and action recognition benchmarks are used to evaluate video self-supervised learning methods (Srivastava et al., 2015). For natural language, a popular benchmark, GLUE (Wang et al., 2018), has been used to test self-supervised learning approaches on a bag of tasks including natural language inference, sentiment analysis and paraphrase identification. For speech, automatic speech recognition, phoneme identification and speaker identification are downstream tasks of interest (Chi et al., 2020).

**Information Content in Learning** It is useful to consider the amount of information content that can be derived from different learning frameworks (Ruder, 2019). Yann LeCun has referred to the hierarchy of information given to learning algorithms metaphorically as a “cake”: Reinforcement learning gets the cherry on top (a single scalar value per episode, (Williams, 1992)); supervised learning the frosting (10-10k bits per sample); and unsupervised and self-supervised learning is the foundation of the cake (millions of bits per example
depending on the domain). Hence, in many cases, self-supervised learning can provide significantly more information per example for learning.

3.1 Generative verses Discriminative Learning

A critical decision when designing pre-training schemes is to consider whether we want to perform generative or discriminative learning. In this section we outline the differences between the two approaches. These approaches are somewhat orthogonal to the choice of pre-training tasks and either option can be used for a given task.

3.1.1 Generative Approaches

Generative approaches for self-supervised learning involve the process of producing all or parts of the training data as part of the model’s output (Jing and Tian, 2019). For instance, we can take a frame in a video and ask the model to generate future frames (Srivastava et al., 2015). The labels, in this case, are typically in the feature space of the training data. Generative approaches have the advantage that the output is qualitatively interpretable as we can inspect samples from the model. In addition, generative models have other applications beyond self-supervised learning (Goodfellow et al., 2014). The drawback of generative learning is that it requires learning how to produce every single detail in the input feature space, which could be a substantial amount of dedicated computation and modeling resources. For example, generating an image requires predicting every single pixel in the output space of the model and the process of decoding an image is not necessarily helpful for transfer learning to downstream tasks.

For continuous domain applications such as images or raw audio, generation is challenging when there are multiple “correct” answers (e.g., predicting the future audio frames spoken), sometimes leading to the model predicting the mean of all futures (which qualitatively results in blurry predictions). To avoid generating the average prediction, researchers have adopted alternative generative techniques using adversarial learning (GANs) (Goodfellow et al., 2014), which can lead to sharper generations. For a detailed survey on GANs, we refer the reader to Jabbar et al. (2020).

3.1.2 Discriminative Approaches

On a high level, discriminative approaches for self-supervised learning involve the process of determining positive samples from negative samples. When labels are provided, as in supervised learning, this is simply called classification. Discriminative approaches eschew the challenge of generation by asking the model to simply differentiate between pairs of input samples. In self-supervised learning, a common interpretation of discriminative learning without labels is mutual information maximization (Hjelm et al., 2018).

The mutual information (MI) (Bell and Sejnowski, 1995) of two random variables $X, Y$ measures the reduction in uncertainty of one variable when the other is observed. For instance, knowing that the background of an image contains grass $x$ can make us less uncertain about the location $y$ in which the image was photographed. For the purpose of self-supervised learning, it may be desirable to maximize the mutual information between certain features of the data (Hjelm et al., 2018).
More formally, mutual information is defined as:

$$I(X,Y) = \mathbb{E}_{p(X,Y)} \left[ \log \frac{p(x,y)}{p(x)p(y)} \right]$$  

(1)

It is intractable to compute $I$ and sample-based estimators that maximize lower bounds on MI are used in practice. The most commonly used lower bound that has been shown to work well is Information Noise Contrastive Estimation (InfoNCE) (van den Oord et al., 2018). InfoNCE is a probabilistic contrastive loss (Chopra et al., 2005) that tries to separate positive examples from negative examples. Following the formulation and notation in Kong et al. (2019), the InfoNCE lower bound is defined as:

$$I(A,B) \geq \mathbb{E}_{p(A,B)} \left[ f_\theta(a,b) - \mathbb{E}_{q(\tilde{B})} \left[ \log \sum_{\tilde{b} \in \tilde{B}} \exp f_\theta(a,\tilde{b}) \right] \right] + \log |\tilde{B}|,$$

(2)

where $a$ and $b$ are the positive example pairs, $\tilde{B}$ is a set of samples drawn from some proposal distribution $q(\tilde{B})$, and $f_\theta \in \mathbb{R}$ is a learned comparison function with parameters $\theta$. $\tilde{B}$ contains positive samples $b$ and $|\tilde{B}| - 1$ negative samples. There are many ways to construct $f_\theta$. For instance, we can construct it as the dot product of features produced by two identical encoders, commonly known as Siamese Networks (Hadsell et al., 2006).

In practice, training $f_\theta$ involves sampling a pair of positive samples and $|\tilde{B}| - 1$ negative samples, then minimizing the cross entropy loss of the positive example over all samples. This is equivalent, in expectation, to maximizing Eq. 2.

Contrastive learning can be used in self-supervised learning by trying to predict certain samples from negative samples, such as predicting future audio frames against random frames or image patches within the same images against random patches (details in section 5). This works well for various continuous domain tasks as shown in van den Oord et al. (2018). A challenge with contrastive learning is choosing proposal distribution $q(B)$, which determines how negative samples are selected. Having a large number of negative samples can be helpful in certain domains (He et al. 2020).

For discrete domain tasks such as natural language, Kong et al. (2019) show that language modeling and generation tasks that maximize cross entropy loss also maximizes InfoNCE. Indeed, cross entropy loss is a special case of InfoNCE when $\tilde{B} = B$. For instance, language modeling predicts the next token by comparing against all possible tokens in the model’s vocabulary. This is equivalent to performing a “negative sampling” scheme where all possible outputs are sampled at all times.

Mutual information maximization alone is insufficient for learning good representations as suggested in Hjelm et al. (2018) and demonstrated empirically in Tschannen et al. (2020). Instead, good representations also depend on the choice of architecture, task and parametrization of the MI estimators.

4. Architectural Bottleneck Methods

We categorize self-supervised learning approaches that primarily rely on an information bottleneck induced through a model’s architecture as bottleneck-based methods. Bottleneck-based methods attempt to learn a low dimensional or constrained representation of the data
typically by learning to reconstruct the input data (DeMers and Cottrell, 1993). Bottleneck-based methods are sometimes categorized in the literature as unsupervised rather than self-supervised learning.

By learning a constrained representation, a model must discard irrelevant information and retain useful information. A direct application of bottleneck-based methods is in their learned representations, which can be used as feature extractors for downstream target tasks (Fleming and Cottrell, 1990; Cottrell and Fleming, 1990; Cottrell and Metcalfe, 1991). Alternatively, the model’s weights (usually the encoder) can also be transferred to target tasks via fine-tuning or learned jointly in a multi-task setting. We present a summary of bottleneck-based methods in this section.

4.1 Dimensionality Reduction

We first briefly review classical approaches to dimensionality reduction. The most well known technique for dimensionality reduction in machine learning is principal component analysis (PCA) (Wold et al., 1987). Given a dataset of \( d \)-dimensional vectors represented as a matrix \( X \), PCA aims to find a low dimensional representation of the data by eliminating correlations between variables. In practice, PCA can be solved by using singular value decomposition. The low dimensional feature can then be used as input to other machine learning algorithms.

4.1.1 Latent Semantic Analysis

In natural language, inputs are often sequences of discrete tokens, which can be represented as one-hot vectors over some vocabulary. It is useful to extract low-dimensional representation of words, known as word embeddings, because one-hot vectors are large in dimensionality and do not contain semantic meaning of the words they represent.

Latent semantic analysis (LSA) (Deerwester et al., 1990) is a classic technique used to extract low dimensional distributed representations of words based on the co-occurrence of words within a document context. First, a word-document matrix \( A \) is constructed by counting the occurrence of words that appear in each document. Then, we apply dimensionality reduction on \( A \) using singular value decomposition to factorize it into the product of three matrices.

\[
A = U \Sigma V^T
\] (3)

Word embeddings \( E \) of dimension \( d \) can be extracted by truncating matrices \( U \) and \( \Sigma \) by retaining only the top \( d \) rows, resulting in \( U_d \) and \( \Sigma_d \). Then, word embeddings can be computed by the product:

\[
E = U_d \Sigma_d
\] (4)

LSA can be considered as PCA applied to matrix \( A \).

4.2 Deep Autoencoders

Approaches such as PCA and LSA extract low dimensional representations of data, but are linear approaches. Deep autoencoders (DeMers and Cottrell, 1993; Hinton and Salakhutdinov, 2006) with non-linearity are more expressive approaches that can extract better low-dimensional features from data. In the most high level definition, deep autoencoders
can be formulated as two neural networks that contain an encoder $\text{enc}$ and decoder $\text{dec}$. The encoder produces a latent representation from input $x$,

$$h = \text{enc}(x).$$

While the decoder reconstructs the input $x$ from the latent representation $h$,

$$\hat{x} = \text{dec}(h).$$

Autoencoders are trained to minimize the reconstruction error between $x$ and $\hat{x}$. Thus, autoencoders are considered as generative approaches.

There are a variety of methods to impose an information bottleneck in the autoencoder and we summarize some prominent approaches in the following subsections. Once an autoencoder has been trained, depending on the task, the decoder may be discarded and the encoder can be transferred to downstream tasks. We also highlight how some of these techniques have been applied for fine-tuning.

4.2.1 Compression-based Autoencoders

In order to learn a non-trivial mapping, the dimensionality of $h$ is typically constrained to be less than the dimensionality of $x$, thus the model must learn what information to keep. Early work (Cottrell et al., 1987) demonstrated that this bottleneck, after quantization, can learn effective image compressors.

Compression-based autoencoders have been successfully applied to natural language for self-supervised learning. In Dai and Le (2015), a sequence-to-sequence autoencoder is trained to take an input sequence $x$, produce a single latent vector $h$, which is then used to generate the original sequence $x$. The authors demonstrated improvements on sentiment analysis tasks through pre-training.

4.2.2 Sparse Autoencoders

Alternatively, $h$ can be overcomplete (dimensionality of $h$ is greater than dimensionality of $x$) but constrained by other means (Bengio et al., 2013). One popular constraint is by imposing a sparsity prior on the latent representation typically by minimizing the L1 loss of $h$. Sparsity prior has been motivated biologically by the human visual cortex (Olshausen and Field, 1997). Ranzato et al. (2008) suggests that this acts as a soft way of restricting “the volume of the input space over which the energy surface can take a low value”.

Makhzani and Frey (2013) introduced k-sparse autoencoders, where the latent representation is constrained to only have top $k$ largest activations active and the rest are set to zero. They demonstrated experimentally that k-sparse autoencoders can be used as a pre-training step, then fine-tuned on image classification tasks for improved performance. One drawback of this technique is that it could lead to dead hidden units, which can be addressed by scheduling the sparsity level.

4.2.3 Variational Autoencoders

Another method to impose a constraint on the latent variables is by treating the latent variable as a stochastic variable, as introduced in variational autoencoders (VAE) (Kingma
and Welling, 2013). VAEs impose a regularization term in addition to the reconstruction loss to minimize the KL divergence between the latent representation and a prior distribution, typically a multivariate Gaussian. One issue with VAE approaches in sequence models is the posterior collapse problem, where the latent variable is completely ignored when more powerful sequence decoders are used (Roberts et al., 2018). This can be mitigated by using hierarchical decoders. We have found that, generally, Gaussian VAEs have been less explored for the purpose of transfer learning.

The prior distribution of VAEs could also be categorical. Vector quantized variational autoencoders (VQ-VAE) (van den Oord et al., 2017) and probabilistic variants (Sønderby et al., 2017) are a type of autoencoder with a discrete bottleneck. The learned discrete bottleneck provides several advantages such as enabling latent discrete modeling.

Discrete latent autoencoders have been used in speech for unsupervised phoneme discovery. For example, Eloff et al. (2019) trained autoencoders to quantize speech and found that the learned discrete codes can be used for speech synthesis. Quantizing speech is a reasonable prior, since spoken words in raw wave forms often have corresponding discrete phonemes that represent them. Discrete latent models have also been combined with prediction-based methods for self-supervised speech recognition (Baevski et al., 2019b). In these scenarios, the extracted discrete latent code can be further processed using NLP pre-training techniques, such as BERT (Devlin et al., 2018), to learn even better representations. Dhariwal et al. (2020) extended this line of work to learn discrete latent codes for music generation.

4.3 Other Approaches

Autoencoders are not the only way to impose bottleneck learning. Wu et al. (2018) demonstrate that one can perform unsupervised learning by simply treating each data point as its own class, and to maximally scatter all data points onto a 128 embedding space using contrastive learning. By trying to compress the entire dataset into a low dimensional space similar inputs must cluster together. They show that this method can lead to competitive results on ImageNet when compared to other self-supervised techniques. This is similar to the bottleneck-based approaches in autoencoders except learning is performed using a contrastive loss without a decoder.

In Donahue et al. (2016) the authors train a bidirectional GAN (BiGAN) for self-supervised representation learning. GANs typically employ a generator and a discriminator, which learns a latent to data space mapping. For self-supervised learning, we ideally want a data to latent mapping for downstream tasks (e.g. image classification). Thus, the authors propose a bidirectional GAN learning framework where an encoder is also learned jointly with a generator and discriminator. This model is not explicitly an autoencoder, but the adversarial constraint forces the encoder to invert the generator. The authors show that BiGAN is closely related to autoencoders with an $l_0$ loss.

4.4 Limitations

As mentioned in previous sections, bottleneck-based methods have shown success in various domains, especially when realized as autoencoders. However, bottleneck approaches have generally been found to be inferior to prediction-based methods (Zhang et al., 2017)
and current state-of-the-art techniques are mostly prediction-based methods. This may stem from the fact that bottleneck approaches need to trade off between information content and representational capacity. Critics claim that autoencoders are an unsupervised learning approach, which, by definition, cannot be tailored to downstream tasks without additional priors (Rasmus et al., 2015). That is not to say that bottleneck approaches cannot be combined with prediction-based methods for improved performance and, indeed, many prediction-based methods have built upon bottleneck-based approaches.

5. Prediction-Based Methods

Prediction-based methods aim to learn useful representations of data through learning a relevant predictive task such as asking the model to predict the missing parts of an input given its related context. These techniques range from asking a model to predict the future given the present, predict missing patches of an image or missing words in a sentence. Intuitively, prediction forces a model to learn relationships between the global and local parts of the data. In this section, we review methods for continuous and discrete domains separately since they tend to have different methods.

5.1 Pre-training for Continuous Domains

In this section, we focus on self-supervised learning methods for continuous domain tasks such as vision and speech. An overarching theme among these approaches is to create self-supervised tasks that learn high level features while discarding low level information and noise. Here, we summarize various commonly used pre-training tasks.

5.1.1 Spatial Prediction

Spatial prediction aims to learn representations by removing patches of an image and predicting the masked patches. When posed as a generative task, this technique is also known as image in-painting. In Context Encoders (Pathak et al., 2016), the authors train a convolutional neural network (CNN) autoencoder by blanking-out the center patch of an input image and ask the model to generate contents within the missing square. This is similar to a denoising autoencoder (Vincent et al., 2008), but differs in that the input mask is a contiguous block instead of random noise, and only the masked segments are predicted. An issue raised by the paper is that pixel-level prediction creates blurry in-paintings, since L2 loss encourages learning the average of all possible completions. Using an adversarial loss can mitigate this issue.

Alternative spatial masking approaches perform self-supervised learning by using a discriminative loss where the ground truth patch must be correctly identified from negative samples. Hjelm et al. (2018) proposes to maximize mutual information between local and global features of an image. This is done by encoding an image into feature vectors for each patch, forming low-level features. A separate network summarizes the low-level features into high-level features. These low and high level features are grouped together but some high-level features are grouped with low-level features from another random image. A discriminator is trained to assign correct groupings with a higher score than random groupings.
van den Oord et al. (2018) segments an image into overlapping patches, imposes a top-left to bottom-right ordering of all patches, then uses an auto-regressive model to predict “future” patches of the image using InfoNCE loss. “Future” is defined as the next patch in the imposed ordering. Follow up work demonstrated that adding more model capacity and increasing the task difficulty (e.g., predicting several steps into the future) improves performance (Hénaff et al., 2019). Trinh et al. (2019) proposes a similar approach but avoids imposing an ordering of patches by randomly masking input image patches and training the model to predict the masked patches.

5.1.2 Channel Prediction

Color or channel prediction methods perform self-supervised learning by removing channel information from an image and asking the model to predict the missing channel. Several work (Zhang et al., 2016; Larsson et al., 2017, 2016) has shown that using colorization as a pre-training task can lead to improvements on ImageNet classification without labels. In Split-Brain Autoencoders (Zhang et al., 2017), the authors split a traditional autoencoder into two disjoint sub-networks with each sub-network receiving a subset of the input channels. The disjoint autoencoders are then trained to predict the missing channels of the other encoder.

5.1.3 Temporal Prediction

Temporal prediction focuses on exploiting temporal information to learn representations. Many work in this area are based on ideas from early work on slow feature analysis (SFA) (Wiskott and Sejnowski, 2002), which suggests that a good prior for feature extraction is to learn features that vary slowly with time. Learning to extract information that move slowly with time can naturally lead to higher-level representations and discard low-level noise. A modern realization of this idea in deep learning is found in Jayaraman and Grauman (2016), where temporally close representations are encouraged to exhibit small differences.

Temporal prediction for computer vision focus on learning how to predict different perspectives of an image by leveraging either the camera movement or the motion of objects in the image. A motivation for this type of learning is that motion in video helps identify objects, since pixels of the same moving object will likely move together (Wertheimer, 1938). In Srivastava et al. (2015), the authors predict future frames in a video using an LSTM. Alternatively, a contrastive loss can be used to avoid modeling low level information (Han et al., 2019). Instead of learning directly to predict future frames, the motion of objects can be extracted as synthetic labels for training static images (Pathak et al., 2017).

Temporal prediction has also been applied for self-supervised learning for speech. Schneider et al. (2019) trains a self-supervised model from raw audio waves to predict future speech features against negative samples from the same audio clip, similar to van den Oord et al. (2018). Chi et al. (2020) proposes to mask random speech frames (represented a spectrograms) and to predict those masked frames. These approaches have many commonalities with those in section 5.1.1.
5.1.4 Order Prediction

Order prediction approaches aim to train a model to predict the position of image patches. In Doersch et al. (2015), random pairs of image patches are sampled from one of 8 positions in the image. The model is asked to predict the relative position of one patch to another. In Noroozi and Favaro (2016), image patches are randomly shuffled and the model has to predict the permutation of the shuffle as a classification task. A follow up work increased the difficulty (Kim et al., 2018) of the task by randomly deleting an image patch and asking the model to also predict the color of the image. Misra et al. (2016) applies this principle of order prediction to videos to predict the ordering of frames given shuffled frames.

5.1.5 Hybrid Approaches

When choosing a self-supervision task, it is not necessary for us to choose only a single predictive learning task. Recent work (Chen et al., 2020) has shown that a combination of different self-supervision tasks can yield much better results, rivaling the results of purely supervised learning for image classification.

5.2 Pre-training for Discrete Domains

In this section, we survey approaches that enable self-supervised learning in the discrete domain such as natural language processing (NLP). Natural language treats text as a sequences of discrete symbols (also called tokens). Although we primarily focus on self-supervised learning applied to NLP, techniques presented here are likely applicable to other forms of discrete sequences or non-natural languages (e.g., modeling music (Donahue et al., 2019) or programming languages (Lachaux et al., 2020)).

5.2.1 Word Embeddings

Skip-gram and Continuous Bag of Words (CBOW) (Mikolov et al., 2013a b) are popular approaches developed in 2013 for learning high quality word embeddings. Skip-gram learns word embeddings by forcing words to predict nearby surrounding words within a given context. Given a context of word embeddings $S = (s_{t-c}, ..., s_t, ..., s_{t+c})$ with context length $c$, Skip-gram predicts $s_{t+i}, i \in [-c, c], i \neq t$ from $s_t$.

CBOW involves a similar idea to Skip-gram, but instead learns to predict $s_t$ using the sum of its surrounding embeddings,

$$\hat{s}_t = \sum_{i \in [-c, c], i \neq t} s_i.$$  (7)

Once these embeddings are learned they can be used as input or fine-tuned as lower layers of other models.

5.2.2 Contextual Embeddings

Word embeddings are scalable and fast to train, but are limited in their representative power since they are usually learned using a linear model. Furthermore, words in isolation provide limited information for which features can be extracted. A natural extension to word embeddings is to learn deeper networks with contextual embeddings.
Early work explored learning contextual representations by predicting contiguous sentences of an input using a recurrent neural network (Kiros et al., 2015). Contextual Word Vectors (McCann et al., 2017) provided embeddings based on a word and its entire sentence by leveraging the attention learned from machine translation. These models have shown some success in text classification tasks and question answering.

5.2.3 Language Models

Core to the recent surge in transfer learning in NLP arises from the success of self-supervised learning from language modeling tasks and their variants. Language modeling, in this context, is a pre-training task that learn to predict the probability of the next word or token given a historical context for an input sequence \( X = \{x_1, ..., x_n\} \).

\[
p(x_i|x_1, ..., x_{i-1})
\]

A seminal work that demonstrates the general transferability of language modeling is the paper *Embeddings from Language Models* (ELMo) (Sun et al., 2019a). ELMo learns a bidirectional LSTM (Hochreiter and Schmidhuber, 1997) language model and demonstrated strong improvements to a variety of downstream GLUE tasks with less labeled data.

**Transformer Language Models** Since ELMo, researchers have transitioned to focus on training self-attention models instead of recurrent neural networks. Transformers (Vaswani et al., 2017) are a type of deep neural network that contain stacked layers of self-attention and feed-forward layers. When compared to recurrent neural networks, Transformers are more efficient to train and enable gradients signals to easily propagate to all positions of the input. The General Pre-trained Transformer (GPT) (Radford et al., 2018) is the first successful attempt at pre-training a Transformer and achieving strong target task performance for a variety of tasks. GPT learns a unidirectional language model on a large corpus of text. Follow up work (Brown et al., 2020b) scaled GPT to larger models and bigger datasets, observing strong generative capabilities and zero-shot performance on a variety of natural language tasks.

**Masked Language Modeling** A major limitation with GPT is that it learns a unidirectional language model in which every token can only attend to the tokens left of it. Bidirectional Encoder Representations for Transformers (BERT) (Devlin et al., 2018; Baevski et al., 2019a) proposes to learn bidirectional Transformers using a masked language modeling (MLM) pre-training task. MLM randomly removes input tokens to the model and trains the model to predict the removed tokens. At every iteration, BERT masks 15% of its input tokens. The downside of BERT is the pre-training procedure is expensive (only 15% of positions are trained per iteration) and it does not explicitly learn conditional generation akin to language models. Several extensions of BERT have been proposed, such as SpanBERT (Joshi et al., 2020), a training procedure that masks out contiguous spans instead of individual tokens, and ERNIE (Sun et al., 2019b), which masks out full entities or phrase-level units. These strategies propose smarter masking strategies for better performance.

**Permutation Language Models** XLNet (Yang et al., 2019) harnesses the benefits of language model conditioning with bidirectional training by introducing a permutation lan-
guage modeling objective. However, BERT, with more training and better hyperparameters, can outperform XLNet (Yang et al., 2019). It is later shown that permutation language modeling can be seen as a masked language model with stochastic attention masks (Kong et al., 2019).

5.2.4 Sequence to Sequence Pre-training

BERT has shown a lot of success in natural language inference tasks, but it is less well suited for sequence to sequence tasks. Pre-training for sequence to sequence learning is explored T5 (Raffel et al., 2019), BART (Lewis et al., 2019) and MASS (Song et al., 2019). Raffel et al. (2019) provides an extensive analysis of various sequence to sequence pre-training tasks including prefix language modeling, masking and deshuffling. They found that masking input spans and asking the model to generate these masked spans leads to the best performance. Interestingly, learning how to deshuffle an input sequence performs the worse, which contradicts some of the success of order prediction techniques found in vision.

5.2.5 Discriminative Pre-training Tasks

An alternative to the popular approach of learning a generative language model is to consider discriminative pre-training tasks. Indeed, in the original BERT (Devlin et al., 2018) implementation the authors proposed to jointly perform masked language modeling and next sentence prediction. Next sentence prediction is a task where segments of text (specifically, sentences) are randomly swapped 50% of the time and the model must predict whether or not the swap occurred. This task has later been found to be not useful given masked language modeling (Liu et al., 2019b).

Electra (Clark et al., 2020) proposes to pre-train a model by classifying whether or not a token in the input sequence was randomly replaced by a small BERT model. This focuses the model to learn how to differentiate real sequences from plausible alternatives. The authors demonstrated that learning a discriminator yields strong results on downstream tasks with much better sample efficiency, since every single position is trained per iteration.

6. Discussion

Throughout this review, we have seen a variety of approaches to enable self-supervised learning. The following are some general tips for self-supervision based on our observations of previous work.

Pre-training should be challenging Choosing a pre-training task that is sufficiently difficult is desired and the difficulty should scale as models becomes larger. It is also critical to prevent models from exploiting shortcuts and cheating (Minderer et al., 2020) or leak statistical information from normalization (Chen et al., 2020). Combining pre-training tasks can be much better than using any single pre-training task alone (Chen et al., 2020). Ideally, pre-training tasks should be similar to the target task or subsume it. For example, language modeling have shown to implicitly perform few shot learning when the dataset and model is sufficiently large (Brown et al., 2020b), likely because the patterns that appear in a text
corpus naturally contain relevant tasks. Designing better and more universal\footnote{Universal can be defined as beneficial to all conceivable tasks that humans care about, which does not contradict the “No Free Lunch Theorem” (Wolpert 2012).} pre-training tasks should be an active area for future investigation.

**More data and larger models are better** Unsurprisingly, having more data and larger models lead to better results (Kolesnikov et al., 2019). This is even more important in self-supervised learning where a lot of information needs to be absorbed for fine-tuning. Furthermore, as seen in the trend of moving from word embeddings to contextual embeddings in NLP, the more parameters of a model that are pre-trained the better. Even under computational constraints, training a larger model with more parameters for fewer iterations on a sufficiently large dataset is better than training a small model (Li et al., 2020). These large models can be subsequently pruned if fast inference is required (Frankle and Carbin 2018).

**Choose flexible architectures** Choosing model architectures that have more flexibility (trading off priors and bias) can be advantageous in the context of self-supervised learning. More flexible models enable a form of soft architectural search (Elsken et al., 2018). We see this example in NLP where Transformers have the advantage of having no positional bias as opposed to the recency bias of recurrent neural networks (Ravfogel et al., 2019). This lack of positional bias likely provides more opportunities for gradient descent to mold its learning, which explains Transformer’s tendency to be more data hungry and appropriate for large scale self-supervised training. In computer vision, most self-supervised work has focused on ResNet (He et al., 2015) and it would be interesting to see if this trend holds across domains.

### 6.1 Future Work

There are many future directions to further explore self-supervised learning. Simply scaling existing approaches to larger models and datasets have diminishing returns (Kolesnikov et al., 2019) and even 175 billion parameter language models cannot learn commonsense physics and lack world knowledge (Brown et al., 2020b). Most self-supervised learning approaches have been focused on a single domain and it would be interesting to extend these techniques to multi-modal scenarios. After all, humans are multi-modal learners. Several work (Chen et al., 2019; Arandjelovic and Zisserman, 2017) have shown promising results in this direction by performing contrastive learning of audio and visual information or masked “language” modeling between images and text.

Another area to explore is better ways to extract information from these pre-trained models. In this survey, we primarily focused on the popular fine-tuning approach, but other knowledge adaptation techniques exist (Ruder, 2019). For example, Liu et al. (2019a); Raffel et al. (2019) explored learning multiple tasks in a multi-task learning framework while fine-tuning pre-trained language models, leading to better downstream performances. One interesting approach for pre-trained language models adopted by Brown et al. (2020b) is few-shot probing. This technique involves using natural language itself to specify the desired downstream task along with a few examples and requires no fine-tuning. It would
be interesting to see if this type of probing works for other domains such as vision and speech.

7. Conclusion

Supervised learning’s primary bottleneck is the availability of labeled data. Self-supervised learning is a powerful technique to extract knowledge from a large unlabelled corpus of data. After a model is trained in a self-supervised manner, it can attain significantly improved performance on tasks that have few labels and even on tasks that have plenty of labels. The value of self-supervision comes from its scalability with virtually unlimited data in certain domains and its ability to be fine-tuned to a variety of tasks. In the long term, self-supervision approaches are likely to outperform more task-specific approaches as computational resources become more ubiquitous (Sutton, 2019; LeCun et al., 2015).

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References

Y. S. Abu-Mostafa. Learning from hints in neural networks. *Journal of complexity*, 6(2):192–198, 1990.

D. H. Ackley, G. E. Hinton, and T. J. Sejnowski. A learning algorithm for boltzmann machines. *Cognitive science*, 9(1):147–169, 1985.

R. Arandjelovic and A. Zisserman. Look, listen and learn. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 609–617, 2017.

T. Bachlechner, B. P. Majumder, H. H. Mao, G. W. Cottrell, and J. McAuley. Rezero is all you need: Fast convergence at large depth. *arXiv preprint arXiv:2003.04887*, 2020.

A. Baevski, S. Edunov, Y. Liu, L. Zettlemoyer, and M. Auli. Cloze-driven pretraining of self-attention networks. *arXiv preprint arXiv:1903.07785*, 2019a.

A. Baevski, S. Schneider, and M. Auli. vq-wav2vec: Self-supervised learning of discrete speech representations. *arXiv preprint arXiv:1910.05453*, 2019b.

J. Baxter. A model of inductive bias learning. *Journal of artificial intelligence research*, 12:149–198, 2000.

A. J. Bell and T. J. Sejnowski. An information-maximization approach to blind separation and blind deconvolution. *Neural computation*, 7(6):1129–1159, 1995.

Y. Bengio and Y. Lecun. *Scaling learning algorithms towards AI*. MIT Press, 2007.

Y. Bengio, P. Lamblin, D. Popovici, and H. Larochelle. Greedy layer-wise training of deep networks. In *Advances in neural information processing systems*, pages 153–160, 2007.
Y. Bengio, A. Courville, and P. Vincent. Representation learning: A review and new perspectives. *IEEE transactions on pattern analysis and machine intelligence*, 35(8):1798–1828, 2013.

T. B. Brown, B. Mann, N. Ryder, M. Subbiah, J. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell, S. Agarwal, A. Herbert-Voss, G. Krueger, T. Henighan, R. Child, A. Ramesh, D. M. Ziegler, J. Wu, C. Winter, C. Hesse, M. Chen, E. Sigler, M. Litwin, S. Gray, B. Chess, J. Clark, C. Berner, S. McCandlish, A. Radford, I. Sutskever, and D. Amodei. Language models are few-shot learners. *CoRR*, abs/2005.14165, 2020a.

T. B. Brown, B. Mann, N. Ryder, M. Subbiah, J. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell, et al. Language models are few-shot learners. *arXiv preprint arXiv:2005.14165*, 2020b.

R. Caruana. Multitask learning. *Machine learning*, 28(1):41–75, 1997.

T. Chen, S. Kornblith, M. Norouzi, and G. Hinton. A simple framework for contrastive learning of visual representations. *arXiv preprint arXiv:2002.05709*, 2020.

Y.-C. Chen, L. Li, L. Yu, A. E. Kholy, F. Ahmed, Z. Gan, Y. Cheng, and J. Liu. Uniter: Learning universal image-text representations. *arXiv preprint arXiv:1909.11740*, 2019.

P.-H. Chi, P.-H. Chung, T.-H. Wu, C.-C. Hsieh, S.-W. Li, and H.-y. Lee. Audio albert: A lite bert for self-supervised learning of audio representation. *arXiv preprint arXiv:2005.08575*, 2020.

S. Chopra, R. Hadsell, and Y. LeCun. Learning a similarity metric discriminatively, with application to face verification. In *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR’05)*, volume 1, pages 539–546. IEEE, 2005.

K. Clark, M.-T. Luong, Q. V. Le, and C. D. Manning. Electra: Pre-training text encoders as discriminators rather than generators. *arXiv preprint arXiv:2003.10555*, 2020.

G. W. Cottrell and M. Fleming. Face recognition using unsupervised feature extraction. *ICNN’90*, 1990.

G. W. Cottrell and J. Metcalfe. Empath: Face, emotion, and gender recognition using holons. In *Advances in neural information processing systems*, pages 564–571, 1991.

G. W. Cottrell, P. Munro, and D. Zipser. Learning internal representations from gray-scale images: An example of extensional programming. pages 461–468, 1987.

A. M. Dai and Q. V. Le. Semi-supervised sequence learning. In C. Cortes, N. D. Lawrence, D. D. Lee, M. Sugiyama, and R. Garnett, editors, *Advances in Neural Information Processing Systems 28: Annual Conference on Neural Information Processing Systems 2015, December 7-12, 2015, Montreal, Quebec, Canada*, pages 3079–3087, 2015.

S. C. Deerwester, S. T. Dumais, T. K. Landauer, G. W. Furnas, and R. A. Harshman. Indexing by latent semantic analysis. *J. Am. Soc. Inf. Sci.*, 41(6):391–407, 1990. doi:10.1002/(SICI)1097-4571(199009)41:6<391::AID-ASI1>3.0.CO;2-9.
D. DeMers and G. W. Cottrell. Non-linear dimensionality reduction. In *Advances in neural information processing systems*, pages 580–587, 1993.

J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.

P. Dhariwal, H. Jun, C. Payne, J. W. Kim, A. Radford, and I. Sutskever. Jukebox: A generative model for music. *arXiv preprint arXiv:2005.00341*, 2020.

C. Doersch, A. Gupta, and A. A. Efros. Unsupervised visual representation learning by context prediction. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 1422–1430, 2015.

C. Donahue, H. H. Mao, Y. E. Li, G. W. Cottrell, and J. McAuley. Lakhnes: Improving multi-instrumental music generation with cross-domain pre-training. *arXiv preprint arXiv:1907.04868*, 2019.

J. Donahue, P. Krähenbühl, and T. Darrell. Adversarial feature learning. *arXiv preprint arXiv:1605.09782*, 2016.

R. Dubey, P. Agrawal, D. Pathak, A. A. Efros, and T. L. Griffiths. Investigating human priors for playing video games. In *6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 - May 3, 2018, Workshop Track Proceedings*. OpenReview.net, 2018.

R. Eloff, A. Nortje, B. van Niekerk, A. Govender, L. Nortje, A. Pretorius, E. Van Biljon, E. van der Westhuizen, L. van Staden, and H. Kamper. Unsupervised acoustic unit discovery for speech synthesis using discrete latent-variable neural networks. *arXiv preprint arXiv:1904.07556*, 2019.

T. Elsken, J. H. Metzen, and F. Hutter. Neural architecture search: A survey. *arXiv preprint arXiv:1808.05377*, 2018.

D. Erhan, Y. Bengio, A. C. Courville, P. Manzagol, P. Vincent, and S. Bengio. Why does unsupervised pre-training help deep learning? *J. Mach. Learn. Res.*, 11:625–660, 2010.

C. Finn, P. Abbeel, and S. Levine. Model-agnostic meta-learning for fast adaptation of deep networks. In *Proceedings of the 34th International Conference on Machine Learning-Volume 70*, pages 1126–1135. JMLR. org, 2017.

M. K. Fleming and G. W. Cottrell. Categorization of faces using unsupervised feature extraction. In *1990 IJCNN International Joint Conference on Neural Networks*, pages 65–70. IEEE, 1990.

J. Frankle and M. Carbin. The lottery ticket hypothesis: Finding sparse, trainable neural networks. *arXiv preprint arXiv:1803.03635*, 2018.

I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio. Generative adversarial nets. In *Advances in neural information processing systems*, pages 2672–2680, 2014.
R. Hadsell, S. Chopra, and Y. LeCun. Dimensionality reduction by learning an invariant mapping. In *2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR’06)*, volume 2, pages 1735–1742. IEEE, 2006.

T. Han, W. Xie, and A. Zisserman. Video representation learning by dense predictive coding. In *Proceedings of the IEEE International Conference on Computer Vision Workshops*, pages 0–0, 2019.

K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. *corr abs/1512.03385* (2015), 2015.

K. He, H. Fan, Y. Wu, S. Xie, and R. Girshick. Momentum contrast for unsupervised visual representation learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9729–9738, 2020.

O. J. Hénaff, A. Srinivas, J. De Fauw, A. Razavi, C. Doersch, S. Eslami, and A. v. d. Oord. Data-efficient image recognition with contrastive predictive coding. *arXiv preprint arXiv:1905.09272*, 2019.

G. E. Hinton and R. R. Salakhutdinov. Reducing the dimensionality of data with neural networks. *science*, 313(5786):504–507, 2006.

G. E. Hinton, S. Osindero, and Y. W. Teh. A fast learning algorithm for deep belief nets. *Neural Computation*, 18(7):1527–1554, 2006. doi: 10.1162/neco.2006.18.7.1527.

R. D. Hjelm, A. Fedorov, S. Lavoie-Marchildon, K. Grewal, P. Bachman, A. Trischler, and Y. Bengio. Learning deep representations by mutual information estimation and maximization. *arXiv preprint arXiv:1808.06670*, 2018.

S. Hochreiter and J. Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.

S. Ioffe and C. Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. *arXiv preprint arXiv:1502.03167*, 2015.

A. Jabbar, X. Li, and B. Omar. A survey on generative adversarial networks: Variants, applications, and training. *arXiv preprint arXiv:2006.05132*, 2020.

D. Jayaraman and K. Grauman. Slow and steady feature analysis: higher order temporal coherence in video. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3852–3861, 2016.

L. Jing and Y. Tian. Self-supervised visual feature learning with deep neural networks: A survey. *CoRR*, abs/1902.06162, 2019.

M. Joshi, D. Chen, Y. Liu, D. S. Weld, L. Zettlemoyer, and O. Levy. Spanbert: Improving pre-training by representing and predicting spans. *Transactions of the Association for Computational Linguistics*, 8:64–77, 2020.
D. Kim, D. Cho, D. Yoo, and I. S. Kweon. Learning image representations by completing damaged jigsaw puzzles. In 2018 IEEE Winter Conference on Applications of Computer Vision (WACV), pages 793–802. IEEE, 2018.

D. P. Kingma and M. Welling. Auto-encoding variational bayes. arXiv preprint arXiv:1312.6114, 2013.

R. Kiros, Y. Zhu, R. R. Salakhutdinov, R. Zemel, R. Urtasun, A. Torralba, and S. Fidler. Skip-thought vectors. In Advances in neural information processing systems, pages 3294–3302, 2015.

A. Kolesnikov, L. Beyer, X. Zhai, J. Puigcerver, J. Yung, S. Gelly, and N. Houlsby. Big transfer (bit): General visual representation learning. arXiv preprint arXiv:1912.11370, 2019.

L. Kong, C. d. M. d’Autume, W. Ling, L. Yu, Z. Dai, and D. Yogatama. A mutual information maximization perspective of language representation learning. arXiv preprint arXiv:1910.08350, 2019.

M. Lachaux, B. Rozière, L. Chamussot, and G. Lample. Unsupervised translation of programming languages. CoRR, abs/2006.03511, 2020.

G. Larsson, M. Maire, and G. Shakhnarovich. Learning representations for automatic colorization. In B. Leibe, J. Matas, N. Sebe, and M. Welling, editors, Computer Vision - ECCV 2016 - 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part IV, volume 9908 of Lecture Notes in Computer Science, pages 577–593. Springer, 2016. doi: 10.1007/978-3-319-46493-0\_35.

G. Larsson, M. Maire, and G. Shakhnarovich. Colorization as a proxy task for visual understanding. In 2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017, pages 840–849. IEEE Computer Society, 2017. doi: 10.1109/CVPR.2017.96.

Y. LeCun, Y. Bengio, and G. Hinton. Deep learning. nature, 521(7553):436–444, 2015.

M. Lewis, Y. Liu, N. Goyal, M. Ghazvininejad, A. Mohamed, O. Levy, V. Stoyanov, and L. Zettlemoyer. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. arXiv preprint arXiv:1910.13461, 2019.

Z. Li, E. Wallace, S. Shen, K. Lin, K. Keutzer, D. Klein, and J. E. Gonzalez. Train large, then compress: Rethinking model size for efficient training and inference of transformers. arXiv preprint arXiv:2002.11794, 2020.

D. Liang and Y. Shu. Deep automated multi-task learning. arXiv preprint arXiv:1709.05554, 2017.

X. Liu, P. He, W. Chen, and J. Gao. Multi-task deep neural networks for natural language understanding. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4487–4496, Florence, Italy, July 2019a. Association for Computational Linguistics. doi: 10.18653/v1/P19-1441.
Y. Liu, M. Ott, N. Goyal, J. Du, M. Joshi, D. Chen, O. Levy, M. Lewis, L. Zettlemoyer, and V. Stoyanov. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*, 2019b.

A. Makhzani and B. Frey. K-sparse autoencoders. *arXiv preprint arXiv:1312.5663*, 2013.

H. H. Mao, B. P. Majumder, J. McAuley, and G. W. Cottrell. Improving neural story generation by targeted common sense grounding. *arXiv preprint arXiv:1908.09451*, 2019.

B. McCann, J. Bradbury, C. Xiong, and R. Socher. Learned in translation: Contextualized word vectors. In *Advances in Neural Information Processing Systems*, pages 6294–6305, 2017.

T. Mikolov, K. Chen, G. Corrado, and J. Dean. Efficient estimation of word representations in vector space. In Y. Bengio and Y. LeCun, editors, *1st International Conference on Learning Representations, ICLR 2013, Scottsdale, Arizona, USA, May 2-4, 2013, Workshop Track Proceedings*, 2013a.

T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean. Distributed representations of words and phrases and their compositionality. In C. J. C. Burges, L. Bottou, Z. Ghahramani, and K. Q. Weinberger, editors, *Advances in Neural Information Processing Systems 26: 27th Annual Conference on Neural Information Processing Systems 2013. Proceedings of a meeting held December 5-8, 2013, Lake Tahoe, Nevada, United States*, pages 3111–3119, 2013b.

M. Minderer, O. Bachem, N. Houlsby, and M. Tschannen. Automatic shortcut removal for self-supervised representation learning. *arXiv preprint arXiv:2002.08822*, 2020.

I. Misra, C. L. Zitnick, and M. Hebert. Shuffle and learn: unsupervised learning using temporal order verification. In *European Conference on Computer Vision*, pages 527–544. Springer, 2016.

V. Nair and G. E. Hinton. Rectified linear units improve restricted boltzmann machines. In *Proceedings of the 27th international conference on machine learning (ICML-10)*, pages 807–814, 2010.

M. Noroozi and P. Favaro. Unsupervised learning of visual representations by solving jigsaw puzzles. In *European Conference on Computer Vision*, pages 69–84. Springer, 2016.

B. A. Olshausen and D. J. Field. Sparse coding with an overcomplete basis set: A strategy employed by v1? *Vision research, 37(23):3311–3325*, 1997.

S. J. Pan and Q. Yang. A survey on transfer learning. *IEEE Trans. Knowl. Data Eng., 22*(10):1345–1359, 2010. doi: 10.1109/TKDE.2009.191.

G. I. Parisi, R. Kemker, J. L. Part, C. Kanan, and S. Wermter. Continual lifelong learning with neural networks: A review. *Neural Networks*, 2019.
D. Pathak, P. Krähenbühl, J. Donahue, T. Darrell, and A. A. Efros. Context encoders: Feature learning by inpainting. In 2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, Las Vegas, NV, USA, June 27-30, 2016, pages 2536–2544. IEEE Computer Society, 2016. doi: 10.1109/CVPR.2016.278.

D. Pathak, R. Girshick, P. Dollár, T. Darrell, and B. Hariharan. Learning features by watching objects move. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 2701–2710, 2017.

A. Radford, K. Narasimhan, T. Salimans, and I. Sutskever. Improving language understanding by generative pre-training. URL https://s3-us-west-2.amazonaws.com/openai-assets/researchcovers/languageunsupervised/language understanding paper. pdf, 2018.

C. Raffel, N. Shazeer, A. Roberts, K. Lee, S. Narang, M. Matena, Y. Zhou, W. Li, and P. J. Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. arXiv preprint arXiv:1910.10683, 2019.

M. Ranzato, Y.-L. Boureau, and Y. L. Cun. Sparse feature learning for deep belief networks. In Advances in neural information processing systems, pages 1185–1192, 2008.

A. Rasmus, M. Berglund, M. Honkala, H. Valpola, and T. Raiko. Semi-supervised learning with ladder networks. In Advances in neural information processing systems, pages 3546–3554, 2015.

S. Ravfogel, Y. Goldberg, and T. Linzen. Studying the inductive biases of rnns with synthetic variations of natural languages. In J. Burstein, C. Doran, and T. Solorio, editors, Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers), pages 3532–3542. Association for Computational Linguistics, 2019. doi: 10.18653/v1/n19-1356.

A. Roberts, J. Engel, C. Raffel, C. Hawthorne, and D. Eck. A hierarchical latent vector model for learning long-term structure in music. arXiv preprint arXiv:1803.05428, 2018.

S. Ruder. An overview of multi-task learning in deep neural networks. CoRR, abs/1706.05098, 2017.

S. Ruder. Neural transfer learning for natural language processing. PhD thesis, NUI Galway, 2019.

V. Sanh, T. Wolf, and A. M. Rush. Movement pruning: Adaptive sparsity by fine-tuning. CoRR, abs/2005.07683, 2020.

L. Schmarje, M. Santarossa, S.-M. Schröder, and R. Koch. A survey on semi-, self-and unsupervised techniques in image classification. arXiv preprint arXiv:2002.08721, 2020.

S. Schneider, A. Baevski, R. Collobert, and M. Auli. wav2vec: Unsupervised pre-training for speech recognition. arXiv preprint arXiv:1904.05862, 2019.
A. Søgaard and Y. Goldberg. Deep multi-task learning with low level tasks supervised at lower layers. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 231–235, 2016.

C. K. Sønderby, B. Poole, and A. Mnih. Continuous relaxation training of discrete latent variable image models, 2017.

K. Song, X. Tan, T. Qin, J. Lu, and T.-Y. Liu. Mass: Masked sequence to sequence pre-training for language generation. *arXiv preprint arXiv:1905.02450*, 2019.

N. Srivastava, E. Mansimov, and R. Salakhudinov. Unsupervised learning of video representations using lstms. In *International conference on machine learning*, pages 843–852, 2015.

C. Sun, Z. Yang, L. Luo, L. Wang, Y. Zhang, H. Lin, and J. Wang. A deep learning approach with deep contextualized word representations for chemical-protein interaction extraction from biomedical literature. *IEEE Access*, 7:151034–151046, 2019a. doi: 10.1109/ACCESS.2019.2948155.

Y. Sun, S. Wang, Y. Li, S. Feng, X. Chen, H. Zhang, X. Tian, D. Zhu, H. Tian, and H. Wu. Ernie: Enhanced representation through knowledge integration. *arXiv preprint arXiv:1904.09223*, 2019b.

R. Sutton. The bitter lesson. *Incomplete Ideas (blog)*, March, 13, 2019.

T. H. Trinh, M. Luong, and Q. V. Le. Selfie: Self-supervised pretraining for image embedding. *CoRR*, abs/1906.02940, 2019.

M. Tschannen, J. Djolonga, P. K. Rubenstein, S. Gelly, and M. Lucic. On mutual information maximization for representation learning. In *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020*. OpenReview.net, 2020.

A. van den Oord, O. Vinyals, et al. Neural discrete representation learning. In *Advances in Neural Information Processing Systems*, pages 6306–6315, 2017.

A. van den Oord, Y. Li, and O. Vinyals. Representation learning with contrastive predictive coding. *CoRR*, abs/1807.03748, 2018.

A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin. Attention is all you need. In I. Guyon, U. von Luxburg, S. Bengio, H. M. Wallach, R. Fergus, S. V. N. Vishwanathan, and R. Garnett, editors, *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, 4-9 December 2017, Long Beach, CA, USA*, pages 5998–6008, 2017.

R. Vilalta and Y. Drissi. A perspective view and survey of meta-learning. *Artificial intelligence review*, 18(2):77–95, 2002.
P. Vincent, H. Larochelle, Y. Bengio, and P. Manzagol. Extracting and composing robust features with denoising autoencoders. In W. W. Cohen, A. McCallum, and S. T. Roweis, editors, *Machine Learning, Proceedings of the Twenty-Fifth International Conference (ICML 2008), Helsinki, Finland, June 5-9, 2008*, volume 307 of *ACM International Conference Proceeding Series*, pages 1096–1103. ACM, 2008. doi: 10.1145/1390156.1390294.

G. Wallis and H. Bülthoff. Learning to recognize objects. *Trends in cognitive sciences*, 3 (1):22–31, 1999.

A. Wang, A. Singh, J. Michael, F. Hill, O. Levy, and S. R. Bowman. Glue: A multi-task benchmark and analysis platform for natural language understanding. *arXiv preprint arXiv:1804.07461*, 2018.

M. Wang and W. Deng. Deep visual domain adaptation: A survey. *Neurocomputing*, 312:135–153, 2018.

Y. Wang, Q. Yao, J. Kwok, and L. M. Ni. Generalizing from a few examples: A survey on few-shot learning. In *arXiv: 1904.05046*. 2019.

M. Wertheimer. Laws of organization in perceptual forms. 1938.

R. J. Williams. Simple statistical gradient-following algorithms for connectionist reinforcement learning. *Machine learning*, 8(3-4):229–256, 1992.

L. Wiskott and T. J. Sejnowski. Slow feature analysis: Unsupervised learning of invariances. *Neural computation*, 14(4):715–770, 2002.

S. Wold, K. Esbensen, and P. Geladi. Principal component analysis. *Chemometrics and intelligent laboratory systems*, 2(1-3):37–52, 1987.

D. H. Wolpert. What the no free lunch theorems really mean; how to improve search algorithms. In *Santa Fe Institute*, volume 7, 2012.

Z. Wu, Y. Xiong, S. X. Yu, and D. Lin. Unsupervised feature learning via non-parametric instance discrimination. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3733–3742, 2018.

Z. Yang, Z. Dai, Y. Yang, J. Carbonell, R. R. Salakhutdinov, and Q. V. Le. Xlnet: Generalized autoregressive pretraining for language understanding. In *Advances in neural information processing systems*, pages 5754–5764, 2019.

R. Zhang, P. Isola, and A. A. Efros. Colorful image colorization. In B. Leibe, J. Matas, N. Sebe, and M. Welling, editors, *Computer Vision - ECCV 2016 - 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part III*, volume 9907 of *Lecture Notes in Computer Science*, pages 649–666. Springer, 2016. doi: 10.1007/978-3-319-46487-9_40.

R. Zhang, P. Isola, and A. A. Efros. Split-brain autoencoders: Unsupervised learning by cross-channel prediction. In *2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017*, pages 645–654. IEEE Computer Society, 2017. doi: 10.1109/CVPR.2017.76.