Vision-and-Language Pretraining: Methods, Applications, and Future Challenges

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Abstract

With the burgeoning amount of data of image-text pairs and diversity of Vision-and-Language (V&L) tasks, scholars have introduced an abundance of deep learning models in this research domain. Furthermore, in recent years, transfer learning has also shown tremendous success in Computer Vision for tasks such as Image Classification, Object Detection, etc., and in Natural Language Processing for Question Answering, Machine Translation, etc. Inheriting the spirit of Transfer Learning, research works in V&L have devised multiple pretraining techniques on large-scale datasets in order to enhance the performance of downstream tasks. The aim of this article is to provide a comprehensive revision of contemporary V&L pretraining models. In particular, we categorize and delineate pretraining approaches, along with the summary of state-of-the-art vision-and-language pretrained models. Moreover, a list of training datasets and downstream tasks is supplied to further polish the perspective into V&L pretraining. Lastly, we decided to take a further step to discuss numerous directions for future research.

Keywords: vision-and-language pretraining, deep learning, survey
1 Introduction

Humans have a tendency to process information in a multimodal manner. In particular, when we read texts, the neocortex and thalamus regions imagine related images, and as we observe objects, our broca’s areas produce associated words. As a result, in order to equip humans’ capabilities for machines, there is a need to provide them with the ability to process information in various modalities, typically in both vision and language in most situations.

In recent years, there has been a surge of research interests in constructing models that can process both visual and textual information, known as Vision-and-Language (VL) models. In general, VL models take images and texts as input, encode them into computable representations, then learn their mutual correlations to produce the target output. Conceptually, VL models are categorized as single-stream and dual-stream systems based upon the manner of learning vision-and-language correlations.

At the moment, with the steep development of computation power, deep learning has gained an increasing level of popularity. Researchers have accomplished widespread success when adapting deep learning to a wide range of applications. As a result, deep learning has been a revolution in both NLP and CV fields, especially thanks to the contribution of the transfer learning technique, notably with the pretraining-finetuning paradigm. Since the advent of Transformer model (Vaswani et al, 2017) with the prominent variant BERT (Devlin et al, 2018), people have begun to leverage the existence of huge amount of data on the internet via devising self-supervised learning tasks to pretrain the Transformer model. This has been shown to help the model achieve fast learning progress and arrive at impressive performance when researchers continue to finetune it on manually annotated target datasets of smaller scales. Generally, people have pointed this success to the hypothesis that self-supervised training allows Transformer to capture intrinsic relationships within the data and learn beneficial general knowledge from them.

Prevalence and ubiquity of pretraining in Vision-and-Language models

From the industry perspective, vision-and-language works play a fundamental role in the functions of myriad real-life systems. For example, big-tech companies such as Google, Baidu, and Amazon employ Image Retrieval models to build Google Image Search, Baidu Image Search, and Fashion Product Searching systems whose scales are up to millions of users. Additionally, (Guo and Wu, 2019) presented a Visually Grounded based dialog system for Image Retrieval software of Slack and IBM Watson Assistant. (Paluri et al, 2020) proposed hashtag-based transfer learning paradigm for Facebook and Instagram’s Image Captioning applications, starting by weakly supervised pre-training and proceeding with fine-tuning. All of these models have surpassed the performance of conventional methods and verified the efficiency of the pre-training scheme for Vision-and-Language models. Hence, we can claim that pre-trained Vision-and-Language models have been revolutionizing themselves in industrial applications.

From the research perspective, witnessing the triumph of pre-trained unimodal models, researchers have sought to adapt self-supervised learning approaches to Vision-and-Language models. As a result, the quantity of research publications on Vision-and-Language pretrained models has burgeoned exponentially. Since 2019, the number
of submissions of Vision-and-Language papers has always been around 100 to ACL, and 200 to CVPR conference. These academic events have made an enormous impact in promoting the research in Vision-and-Language pretrained models.

The success of Vision-and-Language pretrained models both in academia and industry demands an encyclopedic summary and review for future researchers and practitioners to assist deep understanding in the strengths, weaknesses, and applicability of these models in different scenarios.

**What marks the distinction between this survey and previous ones?** As it can be seen, there has been ample research performed which is related to Vision-and-Language pretrained models. Unfortunately, to the best of our knowledge, little attention has been paid to conduct systematic reviews which produce a thorough and clear view of current research progress. Even though a number of works have explored self-supervised training in Vision-and-Language models, an in-depth review of contemporary efforts is still missing. This survey endeavors to supply such an exhaustive summary of modern research on Vision-and-Language pretrained approaches, with a view to encouraging a discussion of present issues constraining the power of those models and identifying potential directions for future research.

Lately, there are some publications surveying the integration of vision and language signals. For instance, (Stefanini et al, 2021; Amaresh and Chitrakala, 2019; Perez-Martin et al, 2021; Li et al, 2019c; Bai and An, 2018; Bernardi et al, 2016; Hossain et al, 2019) introduced comprehensive surveys on the Image (or Video) Captioning task. (Khurana and Deshpande, 2021; Kafle and Kanan, 2017; Wu et al, 2017) re-examined Visual Question Answering (VQA). Nonetheless, most of them only focused on a subset of downstream tasks. Moreover, there were attempts to produce a revision of challenges in training Vision-and-Language models (Zhang et al, 2020; Kafle et al, 2019; Guo et al, 2019) as well. Furthermore, (Bitton et al, 2021) contemplated cross-modal architecture concepts. These works yield myopic perspectives on a specific aspect, while our survey covers the whole Vision-and-Language pretraining field. To the extent of our knowledge, only two short surveys (Du et al, 2022; Chen et al, 2022) are published which are mostly related to our work. Particularly, both (Du et al, 2022) and (Chen et al, 2022) introduced descriptions of Vision-and-Language pretrained models, examining input encoding, architectures, self-supervised objectives, and corresponding datasets. However, these surveys only deliver adequate material, whereas we advance one step further to dig deeper into intuition, motivations, and extensions of Vision-and-Language pretraining approaches. We also carried out analysis from divergent perspectives and demonstrated novel insights in this area. To achieve our goal, we collected and organized over 100 works in this survey. **How do we gather the papers?** This survey is based upon the content of a hundred of associated papers. Choosing Google Scholar as the main search engine, we leveraged auxiliary tools such as ScienceDirect, Emerald, and artificial Github paper repositories to discover related publications. Additionally, we scrutinize prestigious top-tier conferences such as ICML, ICLR, NeurIPS, EMNLP, ACL, AAAI, ICCV, CVPR, etc., to diversify our paper database. Our fundamental keywords comprised: vision-and-language, self-supervised learning, multimodal learning, language grounding, single-stream model, dual-stream model, etc.
Contributions of this survey: This survey can be considered as a literature review on the evolution of Vision-and-Language pretrained models. Our main purpose is to assist readers in rapidly grasping the field of Vision-and-Language and corresponding methods pursuing to polish vision-based language grounding. To this end, we establish the foundations and basis in Vision-and-Language Pretraining (VLP) and subsequently delve into the diversity of this research direction. On top of that, we hope to give scientists and engineers who are excited about VLP a suitable perspective when they make a decision to ascertain VLP models for their projects. To sum up, our core contributions are three-fold:

• We produce a methodical summary for VLP approaches and propose a scheme to categorize the current work.
• We present an organized view of state-of-the-art models up to date.
• We clarify open dilemmas in the VLP field and discuss prospective directions for future research as a means to exhibit our vision and horizons of VLP models.

The rest of this article is organized as follows: Section 2 briefs the basic building blocks of VLP methods and explains the necessity of VLP. Section 3 gives the details of our organization framework and fine-grained introduction to state-of-the-art models. Section 4 investigates challenges and novel research quandaries. Section 5 concludes this survey.

We incorporate into this survey a repository 1 of the mentioned paper resources to provide easy access for researchers.

2 Overview of Vision-and-Language Pretraining

We start our investigation with the presentation of elementary concepts regarding Vision-and-Language models and deep pretraining techniques. In addition, we go over the motives and directions of Vision-and-Language pretraining approaches.

2.1 Vision-and-Language Pretraining

Vision-and-Language models are capable of processing input from both vision and language modalities in order to produce the output. Theoretically, assume we have a text sequence consisting of $N$ tokens $X = \{x_1, x_2, \ldots, x_N\}$, and an image input $I$. The model’s goal is to predict the target output, which can possess the form of a scalar $y$ or a tensor $Y$. To this end, the model strives to learn joint representations of vision and language, and capture their correlations which can benefit tasks demanding the co-operation of visual and textual signals.

Vision-and-Language models can be optimized in the two following manners: direct finetuning and pretraining-finetuning paradigm. During the training process, direct finetuning methods straightly update the model parameters according to the discrepancy between model computation and the value of target label. Performance of this approach relies on the efficiency of core modules such as Bilinear Attention (Kim et al, 2018), Graph Attention (Li et al, 2019a), and Object Detection models (Anderson et al, 2018). On the contrary, pretraining-finetuning paradigm initially trains the models to learn general features and then fine-tunes them for specific tasks.

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1 https://github.com/nguyentthong/Paper-VLP
model on self-supervised learning tasks with a view to providing models with universal knowledge. After the pretraining stage, model designers finetune the model on the final downstream task. Inspired by the success of Transformer and its variant BERT, which pretrains the Transformer encoder on two objectives Masked Language Modeling (MLM) and Next Sentence Prediction (NSP), continuous efforts have followed to inherit Transformer-based architecture and adopt BERT’s pretraining-finetuning framework for Vision-and-Language models (Tan and Bansal, 2019; Zhang et al, 2021b; Chen et al, 2020).

2.2 Revisit Transformers - BERT

In this section, we revise the Transformer-based model, and its key technique self-attention mechanism. We also offer details in the BERT pre-training framework. These would form the basis for future enlightenment of Vision-and-Language pretrained models.

Let \( X = \{ x_1, x_2, \ldots, x_N \} \) be the input sequence of length \( N \) to the Transformer model. Each of the tokens in the sequence is first embedded via an embedding matrix \( E \in \mathbb{R}^{|V| \times e} \) to become \( \{ h^{(0)}_1, h^{(0)}_2, \ldots, h^{(0)}_N \} \), where \( V \) is the vocabulary and \( e \) is the embedding size. Sequentially, the embedded elements are passed through \( L \) encoder layers, each of which estimates the hidden states of every token as follows:

\[
\begin{align*}
\tilde{k}^{(l+1)}_i &= \sum_{m=1}^{M} \text{Linear} \left( \sum_{j=1}^{N} A^{(m)}_{i,j} \cdot V^{(l+1)}_m \cdot h^{(l)}_j \right) \\
A^{(m)}_{i,j} &= \text{Softmax} \left( \frac{(Q^{(l+1)}_m \cdot h^{(l)}_i)^T (K^{(l+1)}_m \cdot h^{(l)}_j)}{\sqrt{d_k}} \right), \quad \text{Multi-head Attention}, \\
k^{(l+1)}_i &= \text{LayerNorm}(h^{(l)}_i + \tilde{k}^{(l+1)}_i), \quad \text{Residual Connection}, \\
\tilde{h}^{(l+1)}_i &= \text{Linear}(\text{RELU}(\text{Linear}(k^{(l+1)}_i))), \quad \text{Feed-forward}, \\
h^{(l+1)}_i &= \text{LayerNorm}(k^{(l+1)}_i + \tilde{h}^{(l+1)}_i), \quad \text{Residual Connection},
\end{align*}
\]

where \( m \) indexes over the attention heads; \( d_k \) denotes the hidden size; \( Q^{(l+1)}_m, K^{(l+1)}_m \), and \( V^{(l+1)}_m \) are trainable weights for the \( m \)th attention head; Linear is a fully-connected layer. The decoder of the Transformer model adds one sub-layer to relate the decoder outputs with the encoder ones. Figure 1 illustrates the overall architecture of the Transformer.

One caveat worth noting is that Transformer inserts positional encoding of sinusoidal function to the token embedding, since the self-attention computation is position-invariant. With the self-attention calculating the hidden representations in
the above manner, the Transformer model is capable of grasping fine intrinsic relationships among elements, thus leading to an enhanced understanding of the input information.

BERT architecture inherits the encoder module of the Transformer model. In the original paper, (Devlin et al, 2018) proposed two pretraining tasks that bear a huge impact on BERT’s performance. The first task is Masked Language Modeling (MLM). This task randomly chooses a word to mask with a probability of 15%. If chosen, the word will be replaced with a special token [MASKED] 80% of the time, with another normal word 10%, and will remain intact 10% of the time. The model’s aim is to predict the masked token given the unmasked ones. The objective function of this task is formulated as follows:

$$L_{MLM}(\theta) = -\mathbb{E}_{X \sim D}(\log P_{\theta}(x_m|x_{\not=m}))$$  \hspace{1cm} (5)

where $X$ denotes a text in dataset $D$, $x_m$ and $x_{\not=m}$ denote the masked and unmasked tokens, respectively, and $\theta$ denotes BERT’s parameters. Intuitively, MLM enables the model to learn the linguistic context in a bidirectional manner, which has been shown to have a vast effect on downstream natural language understanding objectives such as question answering, sentiment analysis, etc.

The second task, Next Sentence Prediction (NSP), dictates the model to learn the alignment between two sentences. Specifically, given two sentences, BERT will seek to determine whether the second sentence is the successor of the first one. To this end, the authors insert two specialized tokens [CLS] and [SEP] to the beginning and the middle of the first and second sequences. The hidden vector of the [CLS] token is...
\[ \hat{y} = p_\theta(y = 1|X_1, X_2) = \text{Softmax}(\text{Linear}(h_{CLS})) \] (6)

where \( X_1 \) and \( X_2 \) are two consecutively concatenated sequences. The task will 50% of the time select two truly successive sentences, and 50% of the time select uncorrelated ones. The NSP objective upon which the model is optimized is defined as follows:

\[ L_{\text{NSP}}(\theta) = -\mathbb{E}_{(X_1, X_2, y) \sim D}(y \cdot \log(\hat{y}) + (1 - y) \cdot \log(1 - \hat{y})) \] (7)

By being optimized on the NSP task, BERT has the capability of reasoning about the relationship of two sentences. This property has been shown to play a significant role in Natural Language Inference tasks.

### 2.3 Vision-and-Language Pretraining Approaches

Inspired by the notable achievement of unsupervised pretraining in unimodal frameworks (Devlin et al, 2018; Radford et al, 2019; Lewis et al, 2020), Vision-and-Language research community has started to explore adapting pretraining to Vision-and-Language modules. In this work, we study the Vision-and-Language pre-trained models which are able to process both textual and visual input and follow the two-stage approach of pretraining-then-finetuning. We look into the motives of their contributions to classify these works.

- **First Moves:** these works are the pioneers that initiate the research interest in Vision-and-Language pretrained models. Their aim is to provide models with general knowledge involving visual and textual modalities to construct commonsense reasoning capacity.
- **Pretraining Diversification:** the main idea is to devise a group of pretraining tasks so that the model is able to adapt to as various downstream tasks as possible. These tasks, also called pretext tasks, are often learned in a multi-task fashion. As a result, a model can attain all advantages of the tasks, advocating parameter saving and efficient computation.
- **Vision and Language Representation Polishing:** a research area that conducts Vision-and-Language Pretraining to enhance unimodal performance before turning to the multimodal case. Particularly, these research will seek to utilize textual representations to embellish the visual ones or vice versa.
- **End2End Pretraining:** because both image and text encoding modules’ scales are extremely large, most systems decide to freeze one of the aforementioned modules or both of them during the training process. Research projects in this area propose solutions to tackle this problem, with typical methods including image patch embedding, grid feature utilization, etc.
- **Vision-and-Language Pretraining Application:** these works investigate the application of Vision-and-Language pretrained models. They make downstream-task-catered adjustments in pretraining schemes in order to optimize the downstream performance. The range of studied downstream tasks is extensive, ranging
from Vision-Language Navigation, to Visual Dialog, to Novel Object Captioning, etc.

- **Risk Assessment:** despite impressive efficiency, Vision-and-Language pretrained models still contain flaws that make the model prone to potential predicaments such as adversarial examples or bias compounding. As a result, these works pursue to mitigate the severity of these problems and help the model perform better in case they encounter risks.

- **Model Compression:** Vision-and-Language pretrained models’ scales of millions or billions of parameters limit their implementation in industry. As an attempt to resolve this usage issue, Model Compression approaches concentrate on constraining the models’ scale and increasing the computation speed. There are numerous techniques, *e.g.* Network Pruning, Knowledge Distillation, and Quantization.

- **Multilinguality in Vision-and-Language Pretraining:** A tremendous percentage of research efforts of Vision-and-Language pretraining works in English contexts. Hence, research in this subarea attempts to extend the scope of VLP research, integrating the capacity to process multiple languages into the Vision-and-Language pretrained models.

### 2.4 Why Pretraining for Vision-and-Language models?

In the last few years, research in Neural Architecture has been proliferating. Generally, most of them tackle the prime problem that is how to train deep neural models in order to obtain reasonable predictions. One dominant method in Vision-and-Language research is conducting Vision-and-Language pretraining. An increasing amount of research in the Vision-and-Language field has adapted pretraining frameworks to train Vision-and-Language models. Hence, there is a need to understand the rationale behind the prevalence of Vision-and-Language pretraining. It is undoubted that Vision-and-Language pretraining brings immense performance improvement. Nevertheless, we still need to further investigate the foundation leading to such improvement. In overall, the two most popular hypotheses are that (1) they provide profitable universal inductive biases and (2) they have the capacity to work on large-scale unannotated datasets. Theoretically, inductive biases offered by pretraining tasks enable Vision-and-Language models to form intuitions about visual and textual contexts. Those intuitions play a role as prior knowledge which has been shown to improve the efficiency of the finetuning process (Zhang et al, 2021; Diligenti et al, 2017). Moreover, because most of the pretraining tasks do not require supervision signals, researchers can directly adopt them to train the model on unlimited resources of unannotated data on the internet.

Furthermore, certain Vision-and-Language pretraining schemes benefit specific groups of downstream tasks. For example, Image-Text Matching and Cross-modal Contrastive Learning are beneficial for Visual Commonsense Reasoning (VCR), Natural Language for Visual Reasoning (NLVR²), etc. Cloze-based pretraining tasks like Masked Language Modeling (MLM) and Masked Region Modeling (MRM) are advocates for downstream tasks such as Vision-and-Language Machine Translation, Vision-and-Language Document Summarization, etc. Researchers are aware of these
correspondences between pretraining and downstream tasks. Therefore, they tend to choose particular pretraining tasks to optimize the target performance. Before the advent of Vision-and-Language pretraining, deep learning engineers are forced to tune specific architectures for their Vision-and-Language tasks, since there does not exist such a universal pretraining scheme that works well in diverse circumstances. It is worth noting that Vision-and-Language pre-trained models can also exploit the strengths of multiple pretraining tasks at once if we undertake pretraining in the multi-task fashion (Lu et al, 2020), or leverage prompt-based techniques (Cho et al, 2021). These mechanisms create unified frameworks which help to shrink memory costs and bring parameter saving.

Vision-and-Language Pretraining has also been shown to improve generalizability. (Tsimpoukelli et al, 2021) demonstrate the capability of learning vocabulary for novel objects and novel visual categories via only pretraining a vision encoder while still freezing the language module. For the text-to-image generation task, (Ramesh et al, 2021) contend that by training to autoregressively model the joint distribution of the text and image tokens, Vision-and-Language models are able to earn sensible performance under zero-shot evaluation settings. Therefore, in some scenarios, people can even omit the finetuning stage in the pretraining-finetuning paradigm for Vision-and-Language pre-trained models.

To sum up, we recapitulate the fortes of Vision-and-Language pretraining techniques that academic researchers and industrial engineers might take into consideration for their problems:

- **Foundation Establishment.** Unsupervised Vision-and-Language pretraining has led to the establishment of overlapping schemes. Most contemporary solutions adapt frameworks that include a certain set of common pre-training techniques. Not only do these frameworks bring an upgrade to the performance, but they also minimize designing cost. Before 2019, when pretraining remains as a subarea in Vision-and-Language research (Bommasani et al, 2021), Vision-and-Language models operate with mechanisms specifically crafted based on authors’ motivations. Bilinear Attention Network (Kim et al, 2018) uses bilinear attention distribution to manage cross-modal alignment of textual words and visual regions in which visual concepts are represented by multiple words. (Li et al, 2019a) introduced Graph Relation Network to model interactive dynamics among objects in the image. The main contribution of Pythia (Jiang et al, 2018) is a Bottom-Up-Top-Down network (Anderson et al, 2018) whose hyperparameters are being intricately tuned. Meticulousness to the desired tasks limits the extension of these methods to a wide variety of circumstances. In addition, with sufficiently massive amount of data, Vision-and-Language pre-trained models can surpass such manually designed building blocks.

- **Representation Learning.** One of the first goals of unsupervised Vision-and-Language pretraining is to capture contextualized representations (Tan and Bansal, 2019; Lu et al, 2019; Li et al, 2019b). Currently, there is a myriad of texts and images on online platforms. Implementing human understanding of online multimodal contexts can lead to better Vision-and-Language models. As such, researchers have been pushing to make models comprehend joint
Vision-and-Language contexts by studying Vision-and-Language pretraining. The representations that Vision-and-Language pretrained models learn to capture are dubbed as contextualized representations. Moreover, we humans also have the ability to reason by drawing an analogy among semantically related images and texts and differentiating semantically separate ones. Thus, research projects have proposed Cross-modal Contrastive Learning to mine mutual information of visual and textual signals.

• **Robustness and Calibration:** Latest works have verified the virtues of Vision-and-Language pretraining by the metrics of accuracy, precision, and recall. In detail, extensive experiments have proved that Vision-and-Language pretrained models are more robust to noise than traditional task-specific methods (Li et al., 2020b). Pretraining has also been shown to raise adversarial robustness of Vision-and-Language models (Hendrycks et al., 2019). Other than robustness, (Hendrycks et al., 2019) declare that Vision-and-Language pretraining polishes model calibration with reliable uncertainty estimates. These advantages play a fundamental role in practice since real-world deployments not only rely on accuracy but also adversarial robustness and model calibration.

• **Flexibility:** Thanks to the invention of deep learning libraries, the development and engineering of large-scale Vision-and-Language pretraining frameworks have become faster than ever. Particularly, well-known libraries such as Tensorflow and PyTorch all have interfaces for developers to execute and modify Vision-and-Language pretraining schemes. Those modifications can be in the form of technical advancement or a hybrid combination of pretraining techniques. Further expansion of deep learning libraries are proposed as well (e.g. PyTorch Lightning) to provide speedup in Vision-and-Language pretraining through parallelization. All of them have fueled the brisk growth of research works of Vision-and-Language pretraining.

2.5 About Prospective Shortcomings

Despite the abundance of merits, Vision-and-Language Pretraining methods still carry some drawbacks under certain circumstances. We give a description of prevalently claimed arguments against pretraining in the realm of Vision-and-Language research.

• **Data Demand:** Vision-and-Language Pretraining is well-known to require a massive size of data so as to achieve favorable performance. Nonetheless, since almost all of the pretraining approaches are unsupervised, there is no need to gather data that must be annotated and undergo assiduous quality control. Hence, research works often leverage the availability of online texts and their associated images to gather training datasets for Vision-and-Language models. These datasets are often publicly available without rigorous access control.

• **Training Time Expansion:** Pretraining-finetuning prototype causes the overall training time to increase. Research has devised several approaches to ameliorate this dilemma. In particular, (Lu et al., 2020) proposed a 12-in-1 pretraining strategy to create a general model that has the capability of adapting to various downstream tasks. Multiple Vision-and-Language pretrained models display high performance under zero-shot settings (Ramesh et al., 2021; Li et al., 2022;
Kim et al, 2021; Radford et al, 2021), suggesting that the finetuning stage can be pruned with only incremental performance loss.

- **Consequences of Homogenization:** A third potential limitation of Vision-and-Language pretraining originates from the fact that Vision-and-Language models have been implemented to solve a wide range of problems. In consequence, defects of a single model can be transferred to a broad group of implementations. Researchers have begun to conduct investigation to resolve the problem.

3 Vision-and-Language Pretraining

In this section, we introduce the categories of Vision-and-Language pretraining works. In each category, we delineate research prototypes, strategies, and objectives of representative articles.

3.1 Categories of Vision-and-Language Pretraining

This section presents a comprehensive view of the field, clustered based upon the motives and characteristics of Vision-and-Language Pretraining works. We further classify Vision-and-Language Pretraining approaches into two categories. Figure 2 gives the summary of our categorization scheme.

Fig. 2: Clusters of Vision-and-Language Pretraining approaches. There are two main branches, i.e. performance optimization and probing analysis

- **Vision-and-Language Pretraining for Performance Optimization.** The main aims of works in this cluster are to maximize the veracity in predictions and extend the implementation of Vision-and-Language pretrained models. The aim can be subdivided into smaller goals that determine the structure of this section: first moves, pretraining diversification, vision and language representation polishing, end2end pretraining, vision-and-language pretraining application, risk assessment, model compression, multilinguality in vision-and-language. These groups enlighten the outcomes that Vision-and-Language pretraining researchers seek to accomplish in these years. For instance, publications in the End2End Pretraining branch concentrate on enabling the model to optimize both heavyweight text and image
| Type                                | Publications                                                                 |
|-------------------------------------|-----------------------------------------------------------------------------|
| First Moves (FM)                    | Tan and Bansal (2019); Lu et al (2019); Li et al (2020a); Chen et al (2020); Zhou et al (2020); Li et al (2019b); Su et al (2019) |
| Pretraining Diversification (PD)    | Cho et al (2021); Sun et al (2021); Li et al (2020d); Lu et al (2020); Yu et al (2020); Gan et al (2020); Shi et al (2020) |
| Vision and Language Representation Polishing | Zhang et al (2021b); Li et al (2020); Sariyildiz et al (2020); Desai and Johnson (2021); Tan and Bansal (2020); Jia et al (2021); Radford et al (2021) |
| End2End Pretraining (E2E)           | Huang et al (2020); Kim et al (2021); Huang et al (2021b); Xu et al (2021) |
| Vision-and-Language Pretraining Application (VLPA) | Wang et al (2020b); Hao et al (2020); Hu et al (2020b); Yang et al (2021b); Zhuge et al (2021); Murahari et al (2020); Shevchenko et al (2021) |
| Risk Assessment                     | Li et al (2020b); Yang et al (2021a); Li et al (2021b); Srinivasan and Bisk (2021) |
| Model Compression (MC)              | Wang et al (2020a); Fang et al (2021); Gan et al (2021)                      |
| Multilinguality in Vision-and-Language (MVL) | Zhou et al (2021); Ni et al (2021); Huang et al (2021a)                      |
| Probing Analysis (PA)               | Cao et al (2020); Li et al (2020c); Hendricks et al (2021); Xue et al (2021) |

We list all approaches in Table 1, following the previous categorization scheme. We provide an abstract table of Vision-and-Language approaches from the perspective of pretraining tasks in Table 2. Many publications appear in more than one group since almost all of the works combine two to three unsupervised techniques. In addition, we also group approaches according to the type of textual and visual encoders in Table 3 and 4. Most of them rely on prevalent neural building blocks proposed lately, for instance self-attention or region proposal networks.

### 3.2 First Moves in Vision-and-Language Pretraining

These works establish initial steps as the basis for ensuing Vision-and-Language Pretraining research. To this end, they propose methodology with novel ideas in input encoding, model architecture, and upstream tasks.
Table 2: Vision-and-Language Pretraining arranged based on their specific pretraining tasks.

| Pretraining task                               | Publications                                                                 |
|------------------------------------------------|-------------------------------------------------------------------------------|
| Masked Language Modeling                       | Li et al (2019b); Chen et al (2020); Li et al (2020); Lin et al (2020); Lu et al (2019); Tan and Bansal (2019); Su et al (2019); Huang et al (2020); Zhou et al (2020); Li et al (2020e); Huang et al (2021b); Cho et al (2021); Xia et al (2021); Xue et al (2021); Li et al (2021a); Kim et al (2021); Wang et al (2021a) |
| Masked Region Classification                   | Chen et al (2020); Lin et al (2020); Su et al (2019); Li et al (2020e)        |
| Masked Region Feature Regression               | Chen et al (2020); Tan and Bansal (2019); Li et al (2020e); Xia et al (2021) |
| Image-Text Matching                            | Li et al (2019b); Chen et al (2020); Li et al (2020); Lin et al (2020); Lu et al (2019); Tan and Bansal (2019); Huang et al (2020, 2021b); Cho et al (2021); Xue et al (2021); Li et al (2021a); Kim et al (2021); Wang et al (2021a); Singh et al (2021) |
| Cross-Modal Learning                           | Li et al (2020e, 2021a); Huo et al (2021); Radford et al (2021); Jia et al (2021); Wang et al (2021a); Singh et al (2021) |

Table 3: Vision-and-Language pretrained models with their associated text encoder.

| Text Encoder | Publications |
|--------------|--------------|
| BERT         | Li et al (2019b); Chen et al (2020); Li et al (2020); Lin et al (2020); Lu et al (2019); Tan and Bansal (2019); Huang et al (2020); Li et al (2020e); Xue et al (2021); Li et al (2021a) |
| UniLM        | Zhou et al (2020) |
| RoBERTa      | Li et al (2020e); Huo et al (2021) |
| GPT-2        | Radford et al (2021) |

Table 4: Lookup table based on the model’s image encoders.

| Image Encoder | Publications |
|---------------|--------------|
| Faster R-CNN  | Li et al (2019b); Chen et al (2020); Li et al (2020); Lin et al (2020); Su et al (2019); Li et al (2020e); Cho et al (2021); Xue et al (2021); Huo et al (2021) |
| ResNet        | Huang et al (2020, 2021b) |
| ViT           | Li et al (2021a); Wang et al (2021b) |

3.2.1 Vision-and-Language model architecture

Most existing Vision-and-Language pretraining approaches fall into two families, single-stream and dual-stream. Each family upholds a separate manner to capture cross-modal interactions between language and vision.

**Single-stream architecture.** The single-stream architecture leverages a single Transformer encoder to extract the representations of the concatenation of textual and visual tokens. In most cases, auxiliary embeddings are added to the original
embedding in order to clarify the modality of the input tokens. Representatives of Vision-and-Language pretrained models in the single-stream approach group are VL-BERT (Su et al, 2019), B2T2 (Alberti et al, 2019), VisualBERT (Li et al, 2019b), etc. Let $X^T = \{x^T_1, x^T_2, \ldots, x^T_L\}$ and $X^V = \{x^V_1, x^V_2, \ldots, x^V_L\}$ be the textual and visual input sequences, respectively. The encoding formulation is defined as follows

$$h^T_1, h^T_2, \ldots, h^T_L, h^V_1, h^V_2, \ldots, h^V_L = \text{TransformerEncoder}_\theta([X^T, X^V]) \quad (8)$$

where $\theta$ denotes the parameters of the Transformer encoder; $L^T, L^V$ denote the lengths of visual and linguistic input sequences; $[;:]$ denotes the concatenation operator. Intuitively, self-attention has been shown to exhibit expressiveness in modeling interactions among cross-modal elements. As a result, it is rational to utilize the prowess of the self-attention mechanism to seize both intra-modal and inter-modal alignments. Moreover, some works make modifications to advance the single-stream architecture. (Li et al, 2020f) insert object tags in the middle of the textual and visual tokens. Those tags are capable of alleviating the burden of learning the alignments between two modalities. (Hu et al, 2020a) append the embeddings of detected tokens from the Optical Character Recognition (OCR) module to aid the Scene Text Visual Question Answering task.

**Dual-stream architecture.** Different from single-stream architecture, dual-stream one employs disparate Transformer encoders for encoding separate modalities, then implements a cross-modal module to catch the intra-modal relationships. The encoding formulation of dual-stream design is executed as follows

$$H^T = h^T_1, h^T_2, \ldots, h^T_L = \text{TransformerEncoder}^T(X^T) \quad (9)$$

$$H^V = h^V_1, h^V_2, \ldots, h^V_L = \text{TransformerEncoder}^V(X^V) \quad (10)$$

$$k^T_1, k^T_2, \ldots, k^T_L, k^V_1, k^V_2, \ldots, k^V_L = \text{CrossModule}_\phi([H^T, H^V]) \quad (11)$$

where $\phi$ denotes the parameters of the cross-modal module. Generally speaking, there are three types of cross-modal alignment, alignment by self-attention-based, co-attention-based modules, and task-based alignment. Self-attention-based module (Li et al, 2021a; Zhou et al, 2020; Hong et al, 2021) concatenates visual and linguistic hidden representations, and progressively passes the resulting sequence through a standard Transformer encoder to get the fusion output. Co-attention-based module (Lu et al, 2019; Murahari et al, 2020) fuses visual and linguistic signals by exchanging their roles as key, query, and value in two cross-modal text-to-image and image-to-text attention modules. For task-based alignment, (Jia et al, 2021) and (Jain et al, 2021) associated vision and language representations via exploiting the text-text and image-text contrastive learning losses. In the same vein, XGPT model (Xia et al, 2021) learns the vision-language correspondence through Image-conditioned MLM, Image-conditioned Denoising Autoencoding, and Text-conditioned Image Feature Generation.
3.2.2 Input Encoding for Vision-and-Language Pretraining

Before extracting intra-modal and inter-modal relations, Vision-and-Language pretrained models have to embed the input into real-valued tensors upon which neural building blocks can undertake computations. For both visual and textual signals, there is a diversity of embedding methods.

**Visual Embedding.** For Image Encoding, Vision-and-Language Pretrained Models initially break an image into objects, grids, or patches. In all three styles, the embedding can be added auxiliary information, for instance, segment embedding, to indicate that the input signals are from the visual modality.

- **Region-based embedding.** Region-based image embedding consists of two components: an image encoder and a projection operator. Image Encoder is an off-the-shelf object detector like Faster R-CNN that extracts objects from an image, where each object is a region indicated by position coordinates and high-dimensional features of Regions of Interest (ROI). After object detection, the proceeding component is a computation taking hitherto mentioned representations of objects as input to produce position-sensitive visual understanding that shares the dimension with the textual one. The formal estimation can be written as follows

\[ r^V_i = f(v_i, c_i) \]  

where \( f \) denotes the projection function; \( v, c \) denote the ROI feature and position coordinate vector, respectively. Customarily, object-detection-based embedding tunes the size of the position coordinate to gain the highest performance, for example, (Tan and Bansal, 2019) merely use four coordinates of the bounding boxes, whereas (Chen et al, 2022) insert the ratio of the bounding area to the image area to obtain 5-dim coordinate vectors.

The above generic formulation sanctions Vision-and-Language pretrained models to install their own approach to calculate the visual embedding. In one case, OSCAR's (Li et al, 2020f) projection function is the linear mapping computed on the concatenated vector of the ROI features and bounding box's coordinates. LXMERT (Tan and Bansal, 2019) uses two distinct linear projections to map \( v_i \) and \( c_i \), then sum the results to attain the final embedding. Hypothetically, it could be claimed that \( f \) is one of the tunable components in Vision-and-Language pretrained models.

- **Grid-based embedding.** Despite decent performance, region-based embedding still holds several drawbacks. Firstly, region extractors pay attention to objects but forget to consider contextual information, or relationships among objects. For example, cropping out a box of the giraffe does not betray what their current behavior is (Huang et al, 2020). Secondly, the prowess of extracted features are constrained by the pre-defined object categories and attributes of the image encoder. Lastly, the overall system performance might be harmed in situations the image encoder does not perform soundly, which is not infrequent since it is trained on large-scale data filled with noise and poorly annotated bounding boxes.

As a consequence, to resolve those issues, some pioneering works propose to encode images into grid-based representations. A convolutional neural network (CNN) pretrained on a colossal dataset is widely used as the feature extractor, some popular of
which are ResNet or ResNeXt trained on ImageNet dataset. Procedurally, an image $I \in \mathbb{R}^{H \times W \times C}$ will be downsampled and flattened to become a vector $v \in \mathbb{R}^{d}$ where $H$, $W$, $C$, and $d$ denote the height, width, number of channels, and the hidden dimension.

As a typical Vision-and-Language pretrained model deploying grid-based embedding, PixelBERT (Huang et al., 2020) puts a CNN backbone into use to acquire the visual embedding, and thereafter takes the sum of the feature vector and the segment embedding as the ultimate visual embedding of the image $I$: $\hat{v} = v + s^V$. All of the pixels in the visual modality will share the segment embedding which is considered as a bias term. By applying the aforementioned formulation, PixelBERT compresses the spatial size of the image 64 times totally.

Closer investigation reveals that compared with region-based one, grid-based approach models visual features in a denser mode. This property might lead to the vision-language discrepancy since language word tokens are managed discretely. To bridge the cross-modal gap, (Huang et al., 2021b) present Visual Dictionary (VD) in their SOHO model to discretize visual semantics. In more detail, VD is an embedding matrix $D \in \mathbb{R}^{k \times c}$ of $k$ embedding vectors whose dimension length is $c$. For a visual feature, SOHO pulls out the index of the row whose distance with the feature is the minimum

$$p_i = \arg\min_j ||d_j - v_i||_2$$

(13)

$$f(v_i) = d_j$$

(14)

In the beginning, the whole dictionary is initialized randomly and gradually updated with Momentum Learning as follows

$$\hat{d}_j = \gamma \cdot d_j + (1 - \gamma) \cdot \sum_{p_i = j} v_i / |f^{-1}(j)|$$

(15)

where $\gamma$ denotes the coefficient in range $[0, 1]$, $|f^{-1}(j)|$ denotes the cardinality of the inverse mapping group. The VD mechanism clusters visual components into groups, for example elements of a car, tree groups, etc., and represents each group with a vector. For each group, its index can be regarded as the self-generated semantic label.

Instead of Visual Dictionary, a simpler solution is to combine the benefits of region-based and grid-based representations. (Su et al., 2019) uses Faster-RCNN and its ResNet-101 module to attain both grid-based and region-based features for an image, and chronologically aggregates them to form visual content embedding for the VL-BERT model.

Patch-based Embedding A majority of visual encoders implement the CNN architecture. Nonetheless, CNN is a bias model that only performs efficaciously when the amount of data is limited. On the other hand, Transformer does not make any assumptions and is well-known to be a general model. The more abundant the data is, the more performance gain Transformer is able to obtain. Although several works have sought to mix CNN and Transformer, the performance is still some points behind pure CNN models such as ResNet. Consequently, novel publications decide to adapt
Transformer completely to image encoding. Because Transformer works on sequential signals, there is a need to firstly preprocess the input into become a sequence. Given an image \( I \in \mathbb{R}^{H \times W \times C} \), the model initially divides and flattens it into patches \( S = \{s_i\}_{i=1}^{N_S} \), where \( N_S, H, W, C \) denote the sequence length, height, width, and the number of channels of the image, respectively; \( s_i \in \mathbb{R}^{N \times (P^2 \times C)} \), and \( N = \frac{HW}{P^2} \). Procedurally, the visual embedding is extracted by multiplying each patch with the linear projection matrix \( V \in \mathbb{R}^{(P^2 \cdot C) \times D} \) and then added the position embedding to become \( V = \{v_i\}_{i=1}^{N_S} \), where \( D, P \) denote the hidden dimension, the patch size, and \( v_i \in \mathbb{R}^D \). Afterward, the embedding is passed through the Transformer encoder in the same fashion with the textual tokens as follows

\[
\mathbf{h}_1^V, \mathbf{h}_2^V, \ldots, \mathbf{h}_{N_S}^V = \text{VisionTransformer}(\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_{N_S}) \tag{16}
\]

The formulation has been initiated by (Dosovitskiy et al, 2020) as the Vision Transformer. Since its advent, a continuous stream of research has shifted attention to studying the effect of Vision Transformer image encoding on Vision-and-Language pretrained models. While ALBEF (Li et al, 2021a) and ViLT (Kim et al, 2021) preserve the above-mentioned encoding approach, SimVLM (Wang et al, 2021b) introduces a slight modification that after the division step, it leverages ResNet to attain visual contextualized patches before pushing them through self-attention layers.

**Textual Embedding.** Following advances and trends in NLP domains, nearly all of Vision-and-Language pretrained models encode texts using the self-attention mechanism. Firstly, every word is forwarded towards a word embedding (WE) layer. Subsequently, the model will continue to process the word embedding through a stack of self-attention blocks, each of which consists of a self-attention, a feed-forward (FF) layer, and a Layer Normalization operator. Let \( W = \{w_1, w_2, \ldots, w_{N_L}\} \) be the sequence of text tokens, the textual representation calculation takes the formulation as follows

\[
e_1, e_2, \ldots, e_{N_L} = \text{WE}(w_1, w_2, \ldots, w_{N_L}) \tag{17}
\]

\[
\mathbf{h}_1^L, \mathbf{h}_2^L, \ldots, \mathbf{h}_{N_L}^L = \text{LayerNorm}(\text{FF}(\text{SelfAttn}(e_1, e_2, \ldots, e_{N_L}))) \tag{18}
\]

where \( N_L \) denotes the textual sequence length. Predominantly, BERT model is designated as the architecture of the text encoders of innumerable Vision-and-Language pretrained models (Li et al, 2019b; Chen et al, 2020; Li et al, 2020f; Lin et al, 2020; Lu et al, 2019; Tan and Bansal, 2019; Su et al, 2019; Xue et al, 2021; Li et al, 2021a; Cho et al, 2020). Other options also exist including T5 or BART (Cho et al, 2021). Apart from the architecture, differences among research works might lie in the loaded weights at the beginning of pretraining stages. (Tan and Bansal, 2019) found training upstream tasks from pretrained weights of BERT model is incompetent compared with training from scratch, which authors of the XGPT model agree with (Xia et al, 2021). Despite this, a quantity of Vision-and-Language pretraining works favor pretrained language models, for instance, textual encoders of ViLBERT (Lu et al, 2019), UNITER (Chen et al, 2020), and OSCAR (Li et al, 2020f) are initialized from BERT-base weights; VL-T5 and VL-BART from T5-base and BART-base ones, respectively.
3.2.3 Vision-and-Language Pretraining Objectives

There are three styles of upstream tasks, generation, classification, and regression. Masked Language Modeling (MLM) and Masked Vision Modeling fall under the generation group, Image-Text Matching classification group, Contrastive Learning regression one. Vision-and-Language pretrained models are often optimized upon a range of objectives. Interested readers can refer back to Table 2 for a summarization of Vision-and-Language pretrained models and their corresponding upstream tasks.

**Masked Language Modeling (MLM).** Equivalent to BERT, MLM objective in VLP schemes randomly masks a word and attempts to produce the masked tokens from unmasked ones. However, distinct from BERT, the unmasked contexts comprise both vision and language modalities. Let \( T = \{ w_1, w_2, \ldots, w_N \} \) be the sequence of textural tokens, \( V = \{ v_1, v_2, \ldots, v_N \} \) be the sequence of visual patches or visual regions. Vision-and-Language pretrained models optimize the objective function as follows:

\[
\mathcal{L}_{\text{MLM}}(\theta) = -\mathbb{E}_{(T,V) \sim D} \log P_{\theta}(T_m | T_\text{\neg m}, V) \tag{19}
\]

where \( T_m, T_\text{\neg m} \) denote masked and unmasked words, \( D \) denote the whole dataset space. OSCAR (Li et al, 2020f) extends MLM framework as it inserts object tags detected by Faster R-CNN to the middle of the textual and visual tokens. Hypothetically, this can provide Vision-and-Language pretrained models with more contexts to predict the masked elements, thus ameliorating the burden of the MLM pretraining process.

**Masked Vision Modeling (MVM).** MVM paradigm masks a percentage of visual tokens in the input sequence and assigns the model to predict those masked tokens given both unmasked visual and textual ones. In most cases, the percentage is set equal to 15 (Chen et al, 2020; Tan and Bansal, 2019; Li et al, 2020e; Lu et al, 2019), while for some exception it is designed to be 10% (Lin et al, 2020). It is worth noting that the nature of textual and visual signals are different, as documents are made up of discrete elements while image pixels are continuous and high-dimensional. Hence, scholars have taken into consideration this discrepancy and devised adjustments for the MVM framework. The main ingredient of the adjustments lies in two variants of MVM tasks, Masked Region Feature Regression and Masked Region Classification.

**Masked Region Feature Regression (MRFR)** is a task that forces Vision-and-Language pretrained models to learn to regress visual features of image regions. The prediction will be the output of the FC layer taking the hidden representations associated with the masked region as the input. In general, \( L_2 \) is chosen as the loss function, since MRFR involves computation upon continuous real values

\[
\mathcal{L} = \sum_{i=1}^{M} \left\| \text{FC}(h^V_i) - r(v_i) \right\|_2^2 \tag{20}
\]

where \( M \) denotes the cardinality of the masked regions. \( v_i \) is usually the ROI pooled feature generated by the object detection model. Nonetheless, this variant relies on the assumption that language understanding can assist the generation of low-level image features. In many situations, this is unsatisfying because language is more appropriate to depict high-level semantics. For instance, the sentence “the dog is running on the
stadium” only mentions two objects “dog” and “stadium” without relating to their fine-grained properties. Therefore, another variant of MVM is essential to devise to pretrain Vision-and-Language models.

Masked Region Classification is a discriminative task which endeavors to infer the semantic class of the masked region. Since the annotated bounding boxes are typically non-existent, output classes of the object detector play a role as the groundtruth labels. Dependent upon the format of the aforementioned class, the loss function is adapted so that the computation can be conducted smoothly. In particular, the loss formulation for scalar label owns the following fashion:

$$L = \sum_{i=1}^{M} \text{CE}(c_i, o_i)$$ (21)

whereas the formulation for the normalized class label is as follows:

$$L = \sum_{i=1}^{M} \text{KL}(c_i, o_i)$$ (22)

where CE, KL denote cross-entropy and KL Divergence, respectively. (Chen et al, 2020) implement both of the above-mentioned versions as upstream objective functions for their UNITER model.

Image-Text Matching (ITM). ITM is an upstream task that models the cross-modality relationship at a coarse-grained level. Given an image-text pair, the goal is to train the model to predict the alignment correctly. Analogous to other binary classification tasks, the Vision-and-Language model is optimized towards the negative log-likelihood as follows:

$$L = -\sum_{i=1}^{M} (y \cdot \log(\hat{y}) + (1 - y) \cdot \log(1 - \hat{y}))$$ (23)

The strategy to output \(\hat{y}\) may vary among different Vision-and-Language pretrained approaches. Single-stream architectures such as SOHO (Huang et al, 2021b) or UNITER (Chen et al, 2020) consider the hidden vector of the [CLS] token as the fused representation of the language and vision inputs and proceedingly feed the vector through a linear layer and sigmoid function to obtain the logit. Meanwhile, approaches to dual-stream models are quite divergent. For instance, because LXMERT (Tan and Bansal, 2019) seizes the intra-modal attention of vision and language separately, it uses a distinctive stack of cross-modal attention blocks to correlate representations of the two modalities and decides to designate the hidden vector of the [CLS] token from the linguistic sequence as the input for the image-text alignment prediction layer. In the same vein, VilBERT (Lu et al, 2019) allocates two distinct tokens [IMG] and [CLS] to indicate visual and linguistic information and multiplies two corresponding hidden vectors in the element-wise demeanor, subsequently learning a linear layer to estimate the matching probability.
Contrastive Learning. There are diverse frameworks to discern contrastive learning approach in Vision-and-Language pretraining. First of all, contrastive learning can be interpreted as learning useful image representations with Natural Language Supervision, where models should infer images possessing the same captions to belong to a similar class (Radford et al, 2021). Second of all, contrastive learning can be considered to dictate Vision-and-Language pretrained models to manufacture dynamic dictionaries. In those dictionaries, a query is supposed to be analogous to its matching key and distinct from mismatched ones (Huo et al, 2021). Third of all, some hypothesize that contrastive learning assists models in capturing universal representation of texts and images as they align them on a common embedding space (Jia et al, 2021). Regardless of interpretation manners, one goal that they all share is that they suppose elements with cognate semantics to be pulled together, and those with unrelated semantics to be pushed away. To this end, Vision-and-Language pretrained models are trained upon contrastive losses of two directions as follows:

\[
L_{i2t} = - \frac{1}{N^V} \sum_{i=1}^{N^V} \frac{\exp \left( \frac{s(h_i^V, h_i^L)}{\tau} \right)}{\exp \left( \frac{s(h_i^V, h_i^L)}{\tau} \right) + \sum_{j=1}^{M^L} \exp \left( \frac{s(h_i^V, h_j^L)}{\tau} \right)} + \sum_{j=1}^{M^L} \exp \left( \frac{s(h_i^V, h_j^L)}{\tau} \right) \tag{24}
\]

\[
L_{t2i} = - \frac{1}{N^L} \sum_{i=1}^{N^L} \exp \left( \frac{s(h_i^L, h_i^V)}{\tau} \right) + \sum_{j=1}^{M^V} \exp \left( \frac{s(h_i^L, h_j^V)}{\tau} \right) \tag{25}
\]

where \( N^L, N^V, M^L, M^V \) denote the number of texts, images, negative text and negative image samples, respectively; \( L_{i2t}, L_{t2i} \) denote contrastive losses in image-to-text and text-to-image directions; \( \tau \) denotes learnable temperature; \( s \) denotes the similarity function, which is often chosen as the dot product operation.

(Huo et al, 2021) contrive Contrastive Learning under the dynamic dictionary frameworks. Because the amount of semantics that a model can capture depends on the size and the quality of the dictionary, the authors decide to make dictionaries as large and consistent as possible. A large dictionary means that it encompasses numerous relevant entries to the query, and a dictionary is claimed to perform consistent comparisons if their keys are represented by the same encoder for the query. To this end, they create a queue to store negative keys that are generated by a Momentum Encoder. The queue is considered as a dictionary that satisfies the aforementioned two conditions.

(Li et al, 2021a) present Momentum Distillation mechanism to abet their contrastive learning process. To explain in more detail, the main model will be optimized to match the prediction of the momentum model whose parameters are updated according to the main model’s ones following the Exponential-Moving-Average rule, in addition to optimizing the contrastive loss. The mechanism is intended to mitigate the phenomenon that in some cases, positive images and texts do not correspond bijectively.
### 3.3 Vision-and-Language Pretraining Diversification

A variety of approaches to variegate Vision-and-Language pretraining have been proposed: (1) Adversarial Training; (2) Contrastive Learning; (3) Knowledge-aided Training; (4) Efficiency Optimization; (5) Framework Unification; and (6) Unsupervised Vision-and-Language Pretraining. We will give a description of each approach, covering the methodology and motivations. Table 5 summarizes works outlined in this section.

**Adversarial Training.** Although research has been repeatedly reporting high performance, deep neural networks, especially Vision-and-Language pretrained models, are still vulnerable to adversarial inputs. Those inputs are so slightly perturbed that they are unrecognizable to humans, but still capable of distorting model outputs. Hence, to deal with those inputs, numerous works have expanded the research in the adversarial direction. In general, there are two fundamental sub-topics in this domain, Adversarial Attack (AA) and Adversarial Defense (AD).

**Adversarial Attack (AA).** AA research aims to invent better procedures to generate adversarial samples that are able to fool Vision-and-Language pretrained models without being detected. (Chen et al., 2018) focused on the Image Captioning task, presenting Targeted Caption and Targeted Keyword method for their attack. They arrange their framework under a general optimization problem as follows

\[
\min_{\delta} \quad c \cdot \text{loss}(I + \delta) + ||\delta||^2_2 \\
\text{s.t.} \quad I + \delta \in [-1, 1]^n
\]

(26)

(27)

where \(\delta\) denotes the adversarial perturbations to the input I, loss denotes the function that if loss is minimal, the quality of the attack will be maximal, which means that the model is successfully fooled. For Targeted Caption approach, the objective is to maximize the likelihood of the word sequence in the desired caption. Let \(S_t\) be the target token at position \(t\), the model will be trained to minimize the difference between the maximum logit in the vocabulary and the one of \(S_t\)

\[
\text{loss}(I + \delta) = \sum_{t=2}^{N-1} \max_{k \neq S_t} (-\epsilon \cdot \max_{k \neq S_t} \{ z_t^{(k)} \} - z_t^{(S_t)})
\]

(28)

where \(z_t^k\) denotes the logit of word \(k\), \(N\) denotes the length of the target caption, and \(\epsilon > 0\) denotes the margin level beyond which, the gradient will be turned off. For
targeted keyword task, since the target word $K_j$ in the keyword list $[K_1, K_2, \ldots, K_M]$ can appear at any position in the caption, (Chen et al, 2018) leverage the hinge-like objective over all positions $1 \leq t \leq N$ to capture that intuition

$$\text{loss}(I + \delta) = \sum_{j=1}^{M} \min_{t \in [N]} \max \{ -\epsilon, \max_{k \neq K_j} \{ z_t^{(k)} \} - z_t^{(K_j)} \}$$ (29)

The two loss terms are rightly integrated into equation (27). Empirically, Show-and-Fool attacks are able to attain 95.8% success rate for Targeted Caption method, and the rate is claimed to be even higher for Targeted Keyword one (Chen et al, 2018).

**Adversarial Defense (AD).** In order to help Vision-and-Language pretrained models defend such adversarial attacks, (Gan et al, 2020) proposed VIvision-and-Language Large-scale ADversarial training (VILLA), which takes into account adversarial training in the Vision-and-Language pretraining process. The goal of VILLA is to prevent the output from Vision-and-Language pretrained models for adversarial samples from deviating those for benign samples. In particular, not only the discrete outputs but also the distribution ones must be matched. To this end, VILLA simulates adversarial scenarios by adding perturbations to the embedding space of the text input and the region feature space of the image input. Hence, for each word token $x_i$ and region feature vector $r_i$, we can define its noise injection process as follows:

$$e_i = \delta_{\text{txt}} + \text{WordEmb}(x_i)$$ (30)

$$v_i = \delta_{\text{img}} + r_i$$ (31)

where $\delta_{\text{txt}}, \delta_{\text{img}}$ denotes the perturbation for linguistic and visual modalities, respectively. For optimization, the authors define three loss terms to train their VILLA model. The first loss $L_{\text{std}}$ is the standard supervised loss function on clean data. The second loss $L_{\text{at}}$ measures the preserving level of the model output when VILLA is fed adversarial samples. The last term is to make the model maintain the fine-grained class distribution when we give the adversarial input. Thus, the final term is formulated as the KL Divergence between the clean and noisy output distributions. The whole optimization framework is defined as follows:

$$L_{\text{std}}(\theta) = \text{CE}(f_\theta(x^{\text{img}}, x^{\text{txt}}), y)$$

$$L_{\text{at}}(\theta) = \max_{||\delta_{\text{img}}|| \leq \epsilon} \text{CE}(f_\theta(h^{\text{img}}(x^{\text{img}}, \delta_{\text{img}}), x^{\text{txt}}), y) + \max_{||\delta_{\text{txt}}|| \leq \epsilon} \text{CE}(f_\theta(x^{\text{img}}, h^{\text{txt}}(x^{\text{txt}}, \delta_{\text{txt}})), y)$$ (32)

$$L_{\text{kl}}(\theta) = \max_{||\delta_{\text{img}}|| \leq \epsilon} \text{KL}(f_\theta(h^{\text{img}}(x^{\text{img}}, \delta_{\text{img}}), x^{\text{txt}}), f_\theta(x^{\text{img}}, x^{\text{txt}})) + \max_{||\delta_{\text{txt}}|| \leq \epsilon} \text{CE}(f_\theta(x^{\text{img}}, h^{\text{txt}}(x^{\text{txt}}, \delta_{\text{txt}})), f_\theta(x^{\text{img}}, x^{\text{txt}}))$$ (33)

$$L = L_{\text{std}}(\theta) + \alpha \cdot L_{\text{at}}(\theta) + \beta \cdot L_{\text{at}}(\beta)$$ (34)
where $f_{\theta}, \theta$ denote model and its corresponding parameters; $h^{\text{txt}}, h^{\text{img}}$ denote the noise injection function hitherto defined; $\epsilon$ denotes the radius of the ball constraint for the perturbations; CE, KL denote the cross-entropy loss and KL Divergence; $\alpha, \beta$ denote the hyperparameter coefficients assigned to the respective loss terms. From an optimization perspective, VILLA can be considered as inserting regularization effects to Vision-and-Language pretraining through the introduction of $L_{\text{at}}$ and $L_{\text{kl}}$. The motivation is to raise the robustness of Vision-and-Language pretrained models against adversarial attacks. Unfortunately, (Gan et al, 2020) merely emphasizes their work on discriminative tasks such as VQA, VCR, and NLVR$^2$. Hence, one potential future research direction is to delve into Adversarial Defense for Vision-and-Language generative tasks.

**Knowledge-aided Training.** Vision-and-Language pretraining works which address image-text correspondence rely on the assumption that high-level semantics of the textual and visual information can be mapped one-to-one on each other. Nevertheless, in some situations, this is not the case. For instance, the caption may fail to mention smaller objects, properties of objects, or the relationship among them in the image (Guo et al, 2020). Therefore, one approach to resolve such missing links is to supply exterior knowledge to assist the pretraining process. Given a piece of text, (Yu et al, 2021) parse its scene graph, which consists of nodes indicating Objects and their accompanying Attributes, and edges representing Relationships among the objects. Based upon the extracted elements, they propose three novel pretraining tasks, Object Prediction (OP), Attribute Prediction (AP), and Relationship Prediction (RP). For OP, an object in the scene graph is selected randomly and its subwords in the text will be masked for the model to predict. Similar settings are applied to AP and RP. They pretrain their Vision-and-Language models on those three upstream tasks, in addition to MLM, MRP, and ITM.

To inform the models of objects not mentioned in the caption, (Guo et al, 2020) gather labels output by the object detection models. Those labels will be interleaved with the region features, and the result is called the object-label scheme. Two novel pretraining tasks are invented for the scheme, Masked Object Regression (MOR) and Masked Object Classification (MOC). In MOR, some region feature vectors will be replaced with 0 vector, and the model’s goal is to regress the features. Different from MOR, MOC tasks the model to produce the label going with the region. Those object-label alignment tasks offer models with more fine-grained semantic details, sharpening image-text alignment which is essential for downstream tasks such as VQA, NLVR$^2$, and Text or Image Retrieval.

**Efficiency Optimization.** Most Vision-and-Language pretrained models are heavy-weighted, as their scales usually span from millions to billions of parameters. This not only calls for huge memory storage but also leads to high latency as the input must pass through such parameters before the output can be produced. On average, each query requires 48 seconds for a model with 110 millions of parameters to complete (Yu et al, 2021). These features limit implementation scenarios of Vision-and-Language pretrained models as they might exceed storage limits or exhibit high computation time when being forced to work with hundreds of thousands of requests per second. As such, ample research has been developed to deal with the issue. (Sun et al, 2021)
investigate inference acceleration in Image-Text Retrieval task in their LightningDOT framework. They introduce two contributions that involve replacing time-consuming cross-modal attention with plainer operators such as addition and dot product. First of all, they propose to modify conventional MLM task with the updated objective as follows:

\[ \mathcal{L}_{\text{updated-MLM}} = - \log P_{\theta}(w_{m}^{L} | h_{m}^{L} + h_{0}^{V}) \] (36)

where \( w_{m}^{L} \) denotes the masked language word, \( h_{m}^{L} \) hidden representations of unmasked words, and \( h_{0}^{V} \) hidden representation of [CLS] token from visual modality. The formulation can be derived accordingly for the MVM task. One point worth noting is that instead of depending upon implicit cross-modal fusion of attention layers, LightningDOT explicitly produces visual-guided textual information as the basis to predict masked linguistic token, and vice versa for the MVM task. Second of all, LightningDOT does not learn the image-text alignment score using non-linear multi-layer perceptrons, but utilizes the dot product of the hidden vectors of visual and linguistic [CLS] tokens. These two contributions lead to computation time reduction of approximately 23000 times without sacrificing model accuracy.

For shrinking memory overhead, one solution is to train a single model that can perform adeptly on multiple tasks and datasets at once. To achieve that goal, (Lu et al, 2020) present a multi-task learning Vision-and-Language pretraining approach 12-in-1 which jointly pretrains ViLBERT (Lu et al, 2019) on 6 tasks and 12 datasets. Their target task groups are Visual Question Answering (VQA), Information Retrieval (IR), Referring Expression Comprehension (REC), and Multimodal Verification (MV). To deftly synchronize sensible performance among tasks, 12-in-1 takes advantage of the novel Dynamic Stop-and-Go strategy. To delineate, during training if one task’s validation performance improvement is less than 0.1% for 2 epochs, the model will terminate optimizing that task, in other words set the task’s state to Stop. While in Stop state, if the validation performance degrades by more than 0.5%, the optimization process will restart, or set its state to Go. Analysis exhibits not only total memory reduction, from 3 billions to 270 millions, but also overall performance burgeoning.

Framework Unification. Related to model unification such as 12-in-1 (Lu et al, 2020), framework unification is an interesting research direction as well. The crucial purpose is to create a general model that shows adroitness in various settings. This approach alleviates the burden of designing specific architectures and is more intuitive to human behavior since we humans are able to perform efficiently in a wide range of circumstances involving both vision and language information processing.

(Cho et al, 2021) adapt BART and T5 model to Vision-and-Language settings, and call their models as VL-BART and VL-T5. They manage both training tasks under a generative framework. Particularly, models are delegated to generate labels in text sequence format. Table 6 reviews input-output format of VL-BART and VL-T5 models. In all cases both of them can be implemented as one language model architecture, thus enjoying generative universality in both upstream and downstream domains.

Former research has shown that Vision-and-Language pretrained models are not efficaciously adaptable to both single-modal and multi-modal settings. To cope with this issue, (Li et al, 2021d) propose their resolution of learning universal mapping space
Table 6: Input-output formats of VL-BART and VL-T5 models (Cho et al, 2021)

| Tasks          | Input                                      | Output Text     |
|----------------|--------------------------------------------|-----------------|
| **Pretext tasks:** |                                            |                 |
| - VQA          | [image] + vqa: [question]                  | [answer]        |
| - ITM          | [image] + image text match: [caption]      | [true/false]    |
| - Visual grounding | [image] + visual grounding: [object subwords] | [visual false]  |
| - Grounded captioning | [image] + caption region: [visual token] | [object token]  |
| **Downstream tasks:** |                                            |                 |
| - VQA          | [image] + vqa: [question]                  | [answer]        |
| - VCR Q → A    | [image] + vcr qa: question [question] answer [answer] | [true/false]  |
| - VCR QA → R   | [image] + vcr qar: question [question] answer [answer] rationale: [rationale] | [true/false]  |
| - En-De translation | [image] + translate English to German: [English text] | [German text]  |

for textual and visual inputs. Apparently, they pursue their goal by leveraging Cross-modal Contrastive Learning (CMCL), training their model on CMCL beside MLM, MRFR, MRC, and Seq2Seq Generation tasks. The authors further present solutions to increase the performance of their contrastive learning framework. The first solution is to adopt Image-Text Retrieval for sampling positive images and texts. The second one is to employ text rewriting for positive/negative text sampling. Whereas positive texts are produced by back translation process, negative ones are pieces of texts with the most equivalent TF-IDF representation to the one of the prototype.

**Unsupervised Vision-and-Language Pretraining.** Datasets of annotated aligned image-text pairs are hard to collect. On the other hand, raw texts and image data are publicly available on the internet. For that reason, it is natural for researchers to favor reachable resources, composing pretraining approaches that ameliorate the dependence upon such expensively labeled datasets. This motivation has formed the unsupervised Vision-and-Language pretraining research direction. (Li et al, 2020d) and (Su et al, 2019) introduce their Vision-and-Language pretraining frameworks that completely train the model on unsupervised datasets. Challenging the prevalent notion that aligned data are indispensable for Vision-and-Language pretraining, (Li et al, 2020d) pretrain their model on three tasks, MLM, MVM, and Tag Reconstruction. For Tag Reconstruction, an object detection will extract regions as visual tokens, along with respective object tags for each image. Those tags and visual tokens are concatenated to form the input sequence. During training, certain tags are masked for the model to predict based upon remaining tags and visual tokens. Initial embedding of each tag is the summation of the linguistic and spatial coordinate embedding. Details of MLM and MVM pretraining follow original variants. For (Su et al, 2019), the focus of their VL-BERT work is not to develop unsupervised Vision-and-Language
Pretraining. Despite that fact, they also take a step to advance this research branch, since they construct their pretraining scheme with two pretext unsupervised tasks: Masked Language Modeling and Masked ROI Classification only.

3.4 Vision-and-Language Pretraining for Representation Polishing

One of the most important factors that ascertain the success of Vision-and-Language is the quality of the information stored in the hidden representations output by the Vision-and-Language models. Hidden representations that comprise meaningful information are termed as refined representations. Inherently, the more refined the representations are, the more likely that Vision-and-Language pretrained models enjoy higher performance. Understanding this property, Vision-and-Language pretraining research has put effort into polishing Vision-and-Language semantics in three elements: visual, textual representations, and cross-modal alignments.

Enhancing Visual Representations. Research works approach to burnish visual representations in two manners. The first group initially focuses on involving textual signals to embellish visual encoding, as they usually leverage text as the guidance signal to pretrain visual presentations. After finishing pretraining, they preserve only the vision module and continue to finetune it on target tasks. (Desai and Johnson, 2021) propose a dual model VirTex which is made of a ResNet-50 visual backbone and a Transformer decoder textual head. They initially train their architecture on the Image Captioning task which assigns the model to generate the associated captions of images word by word, conditioned on visual cues. Caption generation training is conducted bidirectionally, using two separate left-to-right and right-to-left decoders. After the pretraining stage, the left visual backbone is progressively finetuned on downstream tasks with two strategies. In the first scheme only the linear-output layer on top of the backbone is updated. In the second one, both visual encoder and such layer’s parameters are optimized. Analogous to (Desai and Johnson, 2021; Sariyildiz et al, 2020) propose to exploit caption-image data to pretrain their model ICMLM. Nonetheless, distinct from VirTex’s authors, they design a novel Tag Prediction (TP) pretraining framework, besides MLM pretext task. To explain, in the beginning, the authors define frequent nouns, adjectives, and verbs in the captions to be concept words. In the first variant of TP, ICMLM attempts to learn to infer POS tags of those concepts. The POS tag labels are created by leveraging off-the-shelf language parser Spacy (Honnibal and Montani, 2017). In the second variant, [CLS] representation of each caption is extracted, then the K-means clustering algorithm is applied to group captions into K clusters. Afterwards, the model is trained to predict the cluster label of the respective caption to the input image.

Enhancing Textual Representations. Language representation learning seldom correlates language to external signals in a fine-grained fashion, especially visual modality. Therefore, even though prominent works, such as BERT, GPT, etc., have gained outstanding natural language understanding, they lack connections of language to external visual world. With a view to building such connections to hone linguistic representations, (Tan and Bansal, 2020) propose to construct explicit language grounding in the vision. To put it simply, they attempt to relate each word to a corresponding
image, dubbed as “voken”. To accomplish the goal, first of all, the authors introduce a vokenization process to annotate words in huge language corpora with their vokens. The core of the annotation process is a token-image matching model that takes a sentence \( S = \{w_1, w_2, \ldots, w_N\} \) and image \( I \) as input, then outputs the relevance score \( f_\theta(w_i, I, S) \). Because there is no dense annotation available to train the model, (Tan and Bansal, 2020) align all textual tokens in the caption with its image to form positive pairs \( (w_1, I), (w_2, I), \ldots, (w_N, I) \). In a different vein, other images \( I' \neq I \) are drawn to obtain negative pairs. Based upon those positive and negative samples, a hinge-loss objective function is formulated to optimize the matching model so as to maximize the relevance scores of positive pairs while minimizing those of negative pairs

\[
L(S, I, I') = \sum_{i=1}^{N} \max(0, \alpha - f_\theta(w_i, I, S) + f_\theta(w_i, I', S))
\]

(37)

where \( \alpha \) denotes the margin beyond which the gradient update is unnecessary. After being trained, the matching model is employed to infer the voken \( v_i \) for every token \( w_i \). Tan and Bansal (2020) proceed to propose the Voken Classification task. The policy is to make the Vision-and-Language model learn to classify the correct vokens for all textual tokens. The cost function is the negative log-likelihood calculated on all tokens

\[
L(S) = -\sum_{w_i \in S} \log p(v_i | w_i, S)
\]

(38)

The above objective is trained besides MLM, which is a renowned pretraining task for Vision-and-Language models. 

**Enhancing Cross-modal Alignments** Because high performance in Vision-and-Language tasks demands the model to conduct reasoning on two modalities efficiently, it is essential to pay attention to cross-modal alignment operation when brainstorming proposals to improve Vision-and-Language pretrained models. Enhanced cross-modal alignment can be achieved through scaling up Vision-and-Language alignment pretraining (Jia et al, 2021; Radford et al, 2021) or making use of ancillary information (Li et al, 2020f).

**Scaling up pretraining to burnish Vision-and-Language alignment.** Both (Jia et al, 2021) and Radford et al (2021) make capital out of large noisy image-text data on the internet to pretrained their Vision-and-Language models. While (Radford et al, 2021) collect 400 million (image, text) pairs, (Jia et al, 2021)’s data even scales up to 1.8 billion samples. Those two works have validated the usefulness of Contrastive Learning when applying the mechanism on such tremendous datasets. It is worth noting that they leverage Contrastive Learning as a productive scheme to connect visual and textual inputs, without tuning to perfect the performance as works described in Section 3.3.

**Ancillary signal to sharpen Vision-and-Language alignment.** (Li et al, 2020f) propose to insert object tags inferred by the object detector to the middle of visual and textual token sequences so that the input format is transformed into [image regions] [object tags] [text tokens]. With that input modification, a particular pretraining scheme is presented to adapt to the change, according to two ways to interpret the
input, the modality view and the dictionary view. The essence of the dictionary view is that all input elements lie upon two semantic spaces, where image regions are from the visual space, while textual tokens and object tags from the linguistic one. From this perspective, the model is pretrained on masked token loss, in which some tokens from the text and tag sequence are masked and to be predicted conditioned on unmasked tokens and visual cues. The modality view is to differentiate the genesis of input elements. Apparently, visual regions and object tags emerge from the visual modality, whereas linguistic tokens from textual one. For this scheme, a contrastive objective is characterized to contrast textual with positive and negative visual modalities. The authors specify negative modality as (visual regions, object tags) sequence, matched tags are randomly replaced with those from other images.

3.5 End2End Pretraining

Previous works utilize ready-made object detectors trained on Visual Genome Dataset to extract region-based visual features and use them as visual tokens. However, those approaches have a number of disadvantages: (1) Regions focus on items within bounding boxes while ignoring contextual information beyond the boxes and the surroundings, which is critical for comprehending and reasoning (2) Although the number of objects appearing in captions or questions may be unlimited, pre-defined categories for areas of annotations in the dataset are limited. Recently, some Vision-and-Language research steps out of the box of the region-based extractor to apply the trainable visual encoder to create end-to-end models. These approaches help the visual encoder adapt to vision and language dataset domains, and not depend on other object detection models.

**Grid-based encoding** The details of this visual encoder have been described clearly in the Section 3.2.2. To be more precise, PixelBERT (Huang et al, 2020) applies the Pixel Random Sampling technique that randomly takes a subset of 100 from a set feature map after extracting it from the CNN model. This would help the model reduce the computation cost of self-attention and decrease the training time of each sample. Moreover, PixelBERT (Huang et al, 2020) and SOHO (Huang et al, 2021b) use the same CNN-based ResNet architecture as the visual encoder and also fit the model with mentioned objectives. However, in PixelBERT, the visual feature vectors are then input directly into the transformer model, while SOHO maps each visual feature vector with the nearest visual embedding in the Visual Dictionary.

**Patch-based encoding** The details of this visual encoder have been also described clearly in Section 3.2.2. ViLT (Kim et al, 2021) and E2EVL (Xu et al, 2021) encode the image in a way which is similar to ViT (Dosovitskiy et al, 2020). SimVLM (Wang et al, 2021b) feeds image patches into the very first layers of the ResNet model to

| Visual Encoder                  | Publications                                      |
|---------------------------------|---------------------------------------------------|
| Grid-based encoding             | Huang et al (2020, 2021b)                         |
| Patch-based encoding            | Li et al (2021a); Wang et al (2021b); Xu et al (2021); Kim et al (2021) |
extract visual features before passing them to the linear transformation. In contrast, ALIGN (Jia et al, 2021) fuses visual features only after pushing the image to the ViT model.

### 3.6 Applications of Vision-and-Language Pretraining

A huge variety of tasks in vision and language demand overlapping techniques, for example, intra-modality, inter-modality reasoning, visual grounding in textual tokens, etc. In consequence, VLP can be ubiquitously adapted to an abundance of down-stream tasks. Typical use cases include visual dialog (Murahari et al, 2020; Wang et al, 2020b), object captioning (Hu et al, 2020b; Yang et al, 2021b), and other elaborate circumstances (Hao et al, 2020; Zhuge et al, 2021).

#### Vision-and-Language Pretraining for Visual Dialog Systems.

(Murahari et al, 2020) substantiate the superiority of VLP for visual dialog. They propose a VLP framework with a dual-stream architecture taking an image $I$, a dialog history $\{(Q_1, A_1), (Q_2, A_2), \ldots, (Q_{t-1}, A_{t-1})\}$, where $Q_i$ and $A_i$ denote the question and answer of the $i^{th}$ turn, and the present question $Q_t$, as input. The whole framework is pretrained upon three uptext tasks Masked Language Modeling (MLM), Next Sentence Prediction (NSP), and Masked Image Region Prediction (MIRP). Inheriting (Murahari et al, 2020)’s perspective, (Wang et al, 2020b) present a pretraining scheme for multi-turn visual dialog modeling. Their distinct factors lie in the fact that they leverage a single-stream architecture to implicitly align linguistic and visual elements, training the neural module on MLM and NSP objectives.

In practice, visual dialog datasets incorporate both sparse and dense annotations. Dense mode integrates fine-grained probability distribution for each answer, for instance, for the query “How old are you?” asked to a 5-year-old boy, the answer “5” and “five” would be assigned equivalent logits of 0.5. In a different vein, sparse mode indicates the most relevant response in the one-hot format. Wang et al (2020b) and (Murahari et al, 2020) make use of both classes of annotations to finetune their models.

#### Vision-and-Language Pretraining for Object Captioning.

(Hu et al, 2020b) design an image-tag-based pretraining paradigm for novel object captioning research. During pretraining, instead of image-caption pairs, they work upon image-tag ones, where textual tags are inferred by a pretrained object detector on the Open Images dataset (Kuznetsova et al, 2020). In detail, they conduct MLM on those tags. (Hu et al, 2020b) realize that the sequence of tags is unordered, as such for instance, if “dog” and “hound” are masked simultaneously, the inferences of two words can be placed in positions of one another. To resolve this ambiguity, the authors propose a strategy to ascertain the optimal permutation for predictions on masked positions, depending upon minimizing the Hungarian matching loss function (Carion et al, 2020). (Yang et al, 2021b) extend their research domain to Scene Text Captioning. They finetune the hitherto delineated polished vision-and-language pretrained model on TextCaps dataset (Sidirov et al, 2020), which is catered for Scene Text scenarios, and achieve state-of-the-art CIDEr score.

#### Intricate Applications of Vision-and-Language Pretraining.

Other applications of VLP consist of involved tasks including Vision-and-Language Navigation (VLN) (Hao et al, 2020) or Vision-and-Language for Fashion E-commerce (Zhuge et al, 2021).
Hao et al. (Hao et al., 2020) explore the generalization of VLP to multimodal inputs which are highly variable, particularly VLN where visual signals repeatedly change after every action is undertaken, and textual instructions sustain ambiguity. Their exploration comes up with a **PRE-trained Vision-And-Language basEd NavigaTor**, as known as PREVALENT, to attain multimodal generic joint representations to reason fluctuating image and text signals. The navigator is pretrained upon two tasks, Action Prediction (AP) and Masked Language Modeling (MLM). For AP, after sampling a state-action pair, where a state is defined to be an RGB image, the model will determine the next action without being conditioned on the trajectory history. On the other hand, MLM is performed on textual tokens of the instruction inputs in an equivalent manner to previous VLP research works.

(Zhuge et al., 2021) propose a pretrained model in the fashion domain, KaleidoBERT, with three original strategies in order to capture details that benefit fashion Vision-and-Language tasks: Kaleido Patch Generator (KPG), Alignment Guided Masking (AGM), and Aligned Kaleido Patch Modeling (AKPM) pretraining. First of all, KPG passes the image forward to a saliency network, such as EGNet Zhao et al. (2019a), to obtain foreground mask, crop the input with respect to the mask, and then split the cropped image into five levels, 1x1, 2x2, and so on to 5x5. Afterwards, a CNN-based backbone will compute visual embedding on each of 55 patches. Second of all, AGM strategy applies Show, Attend, and Tell model (Xu et al., 2015) to produce tokens describing the image and their visual heatmap. Based upon the heatmap, the aforementioned patches in KPG step which hold high weights will be paired with their associated tokens. In consequence, the MLM scheme is able to mask either textual or one of aligned patches, and commission the model to predict masked tokens. Third of all, AKPM pretraining framework is divided into five subtasks—Rotation Recognition, Jigsaw Puzzle Solving, Camouflage Prediction, Grey-to-Color Modeling, and Blank-to-Color Modeling—to learn fruitful representations in terms of not only spatial context structure knowledge but also classification and generation capacity.

### 3.7 Risk Assessment in Vision-and-Language Pretraining

Large-scale vision-and-language pretrained models have established splendid generalizability across different tasks. However, despite high empirical results, potential risks, notably adversarial attacks, intrinsic, and extrinsic biases, do have the capacity to inhibit their applicability for practical deployments.

It is noteworthy that deep vision-and-language models are prone to scenarios involving adversariality as even negligible perturbations can alter model predictions (Goodfellow et al., 2014). (Li et al., 2020b) mitigate this issue of vision-and-language pretrained models for the VQA task from the model perspective. Their system incorporates an Adversarial Noise Generator (ANG) $g$ that corrupts visual and textual token embeddings $v, w$ as follows

$$\alpha \sim \mathcal{N}(0, 1)$$

$$\delta_v = g_v(\alpha), \delta_w = g_w(\alpha)$$

$$v_{\text{adv}} = v + \delta_v, w_{\text{adv}} = w + \delta_w$$
where $g$ is implemented with a neural network. During training, the generator $g$ is updated to maximize VQA-based and adversarial loss. In particular, the adversarial objective, consisting of both label classification and distribution divergence terms, is able to gain knowledge from both hard-label and soft-label matching. In addition to ANG, (Li et al, 2020b) adopt Random Masking strategy to randomly mask image representations as well as inserting [MASK] tokens to visual and textual sequences, further burnishing model robustness. From the data perspective, (Li et al, 2021b) evolve adversarial VQA benchmarks through presenting Adversarial VQA, a dataset constructed from Human-And-Model-in-the-Loop Enabled Training (HAMLET) pipeline. Their benchmarks possess three merits over previous baselines: (1) The questions from Adversarial VQA are constructed by humans, rather than by heuristics; (2) Images sustain diversity as they stem from a wide variety of domains, instead of solely VQA v2 dataset; (3) Their collected dataset prepares vision-and-language models for sundry adversarial attacks, because the collection process does not curb workers on certain robustness types.

Besides adversarial samples, because exterior and interior trends, dubbed as biases, can bend models’ predictions towards undesirable directions, they can cause substantial harm to overall performance as well. (Srinivasan and Bisk, 2021) investigate gender bias in VLBERT (Su et al, 2019), identifying three inherent bias sources in vision-and-language models - language context, visual context, and visual-linguistic context. Their research discerns that gender information is capable of influencing vision-and-language pretrained models. For instance, the model is more likely to generate words like “purse” and “apron” for female agents, and “briefcase” and “beer” for male ones. On another note, Yang et al (2021a) confront dataset bias that vision-and-language pretrained models might memorize when making inferences. Concretely, when seeing overwhelming evidence of “men ride horses”, the models have the likelihood to interpret that “men only ride”, thus they tend to refrain from connecting “men” to other vehicle-related terms such as “drive”, “run”, or “go”. Their proposed solution is to integrate information from other samples into the attention computation—cross-sample attention—rather than bank on traditional in-sample attention. In reality, their module combines both kinds of attention layers in order to make use of the most virtues. Nevertheless, because hidden representations output by two attention groups might turn out to lie upon two disparate distributions, they propose to leverage a unified set of parameters for both cross-sample and in-sample attention.

### 3.8 Multilinguality in Vision-and-Language Pretraining

A large portion of vision-and-language pretraining research is conducted in English-only settings. To open the ability to comprehend more than one language, much research aims to furnish pre-trained Vision-and-Language models with the capacity to process several languages. **M3P** Ni et al (2021) (Multitask Multilingual Multimodal Pre-trained) is the first multilingual Vision-and-Language pre-trained model. It builds two basic data streams: Multilingual Monomodal and Monolingual Multimodal; the model is pre-trained on multimodal English-only corpus and the multilingual corpus - Wikipedia without corresponding image. To learn the alignment between different languages and
visual features, M3P utilizes Multimodal Code-switched Stream that works upon multilingual data and multimodal data at the same time. Given a pair of English text and image \((w_{\text{EN}}, v) = (w_1^{\text{EN}}, w_2^{\text{EN}}, ..., w_M^{\text{EN}}), (v_1, v_2, ..., v_N))\), the set of code-switched languages \(C = \{c_1, c_2, ..., c_k\}\), and bilingual dictionaries which can translate a word from English to any language \(c_i\), for each word \(w_i^{\text{EN}}\) in English text \(w^{\text{EN}}\), the Code-switched Stream replaces it with a translated word with a probability of \(\beta\) to create a multilingual input sequence \((w^{[C]}, v) = (w_1^{[C]}, w_2^{[C]}, ..., w_M^{[C]}), (v_1, v_2, ..., v_N))\).

To learn the representation of different languages and visual modality together, M3P mixes this Code-switched Stream with original pre-training tasks to form Multimodal Code-switched Training tasks.

**UC2** Unlike M3P (Ni et al, 2021) where English is used as the focal point to create a bridge between visual modality and different languages, UC2 (Zhou et al, 2021) (Universal Cross-lingual Cross-modal) augments English-only datasets with non-English languages via machine translation (MT) API, and leverage the augmented datasets for pre-training. UC2 provides two new pretraining tasks to adapt to multilingual problems: Masked Region-to-Token Language Modeling (MRTM) and Visual Translation Language Modeling (VTLM). While original Masked Region Modeling predicts the masked image region via an index in the range of the number of pre-defined object annotations (0-1600), MRTM uses extra semantic association between object labels and captions to capture semantic alignment between vision and language. In addition, VTLM is a cross-lingual cross-modal pretraining task that directly and simultaneously learns the alignment between visual and textual context in multiple languages.

### 3.9 Model Compression

Deep neural models have grown in size as a result of the introduction of deep learning to tackle sophisticated computer vision and natural language processing jobs. But while a greater size is generally related to greater performance, supersizing comes at a cost: longer training time, longer inference time, and more memory requirements. Computational resources are restricted; thus, a network that demands too much will either train too slowly or won’t be able to be stored at all; moreover, many deep learning applications are used on devices with limited resources. As a result, model compression is very important, it tries to reduce the costs involved with large model sizes (such as those stated above), while still performing in a more efficient way with hardly any performance effect. In recent research, various techniques have emerged as especially important (and interesting) strategies for model compression, for example, Low-Rank Approximation, Network Pruning, Knowledge Distillation, and Quantization. In Vision and Language pretraining fields, Knowledge Distillation and Network Pruning are two of the above techniques that have been applied to achieve the aforementioned goal.

**Knowledge Distillation** Knowledge Distillation is the process of transferring knowledge from a huge model or group of models to a single smaller model. MiniVLM is the first work belonging to this direction. In MiniVLM (Wang et al, 2020a), both the region feature extractor and the transformer for alignment are much smaller compared to the normal VLP model but they can still retain 94 - 97% accuracy compared to large
state-of-the-art models on multiple VL downstream tasks, the whole model reduces
the number of parameters to 27% and FLOPS to 1% in total compared to OSCAR.
Moreover, the "student" MiniVLM also mimics the larger model by learning behavior
through much more captions generated by the "teacher" model. DistillVLM (Fang
et al, 2021) applies distillation in both the pre-training and fine-tuning stages. How-
ever, there is a difference between the region feature of the lightweight detector and
the original detector in the teacher. Thus, to tackle this problem, the region proposals
from the student model are injected into the feature extractor of the larger detector
to conserve the alignment. Additionally, the compressed model can mimic at 3 levels:
the logits (before softmax output), the hidden state, and the attention matrix.

Network Pruning

While Quantization aims to lower the number of bits needed to
store the weights, Pruning is the process of removing parameters from an existing
neural network that are unnecessary, in order to produce a significantly smaller but
effective model. (Gan et al, 2021) apply the lottery ticket hypothesis, which is whether
we can find a (sparse) sub-network in a neural network that can match the performance
of the full model in VLP settings. Accordingly, a sub-network that retains 99% of the
full accuracy can be discovered at 50-70% sparsity of the full model.

3.10 Probing Analysis on Vision-and-Language Pretrained
Models

Due to the advent of superb performances of Vision-and-Language pretrained models,
it has become natural to have a desire to discover how their inner mechanisms induce
empirical success. More concretely, researchers want to interpret factors that bear an
important impact to model predictions (Cao et al, 2020; Hendricks et al, 2021) and
their behavior tendency (Cao et al, 2020; Li et al, 2020c; Xue et al, 2021). Here, we
summarize the latest efforts working in this field, mainly via intermediate estimations
and output observations.

Intermediate Measurement (InM) Probing. IM approaches study models’ ten-
dency and behaviors via looking into intermediate elements, some of which are
attention weights, distribution divergence, or probing metrics. (Cao et al, 2020) inves-
tigate what lies in latent representations of Vision-and-Language pretrained models.
Their framework encompasses probing tasks that extract attention entries falling under
the categories of image-to-image (visual relations), image-to-noun phrase (visual coref-
rence resolutions), and token-to-token in different modalities (modality importance).
Observations from their attention-based experiments are three-fold: (1) Visual modal-
ity plays a more peripheral role than textual one during inference; (2) A specific set of
heads is responsible for cross-modal interactions; (3) Visual relations are encoded in
both single-stream and dual-stream architectures. Comparable with (Cao et al, 2020),
(Li et al, 2020c) reckon on largest attention weights between textual and visual tokens
to pull out the most attended bounding regions, proving the capacity of Vision-and-
Language pretrained models to suitably ground linguistic entities to visual regions.
As well as attention-based probing, (Cao et al, 2020) perform clustering-based prob-
ing, undertaking k-means clustering with $k = 2$ on cross-modal representations, then
estimating the Normalized Mutual Information (NMI) score between inferred and
groundtruth clusters. Apparently, the higher the score, the more analogous the learned
clusters are to the original ones, resulting lower the fusion degree. The clustering technique is also applied by (Xue et al., 2021), particularly while (Cao et al., 2020) leverage the technique to deduce that for single-stream models, multimodal fusion aggravates progressively through deeper layers, (Xue et al., 2021) use it to demonstrate visual encoding with Transformer attention heightens image-text interactions. The authors reinforce their hypothesis by devising an auxiliary metric, dubbed as Inter-Modality Flow (IMF), to measure the level of multimodal interaction.

**Output Observation (OO) Probing.** Research following this approach tweaks prospective choices related to the arrangement of vision-and-language pretraining, trains different variants, and finally observes fluctuations in system predictions or overall performances. In this spirit, (Hendricks et al., 2021) explore the effects of three crucial elements on the pretraining process, data, attention operation, and optimization objectives. They pretrain vision-and-language models with varying options of data (SBU, Conceptual Captions, Visual Genome, Open Images (OI), MSCOCO, and narrative versions of OI and MSCOCO), attention types (co-attention, merged attention, modality-specific attention, asymmetric attention, and no attention at all), and pretraining tasks (MLM, MRM, and ITM). (Cao et al., 2020) take interest in linguistic components in both single-stream and dual-stream architectures, banning vision-related components and finetuning vision-and-language models on SentEval toolkit (Conneau and Kiela, 2018), which is a pure linguistic benchmark. Inherently, OO-based methods express intuitiveness, as they provide immediately practical insights into model operation. Nonetheless, they demand that researchers execute a decent amount of experiment in order to draw sufficiently significant conclusions, thus raising a quandary concerning computation resources.

### 4 Future Directions and Prospective Issues

As it can be seen from our previous discussions, contemporary research works have laid a deep foundation upon vision-and-language pretraining. Nonetheless, there still exists space for future developments. In this section, we elaborate on unresolved predicaments, and based upon that delineate prospective ensuing research directions.

#### 4.1 Enhancing Interpretability of Vision-and-Language Pretrained Models

It is well-known that deep neural models, including vision-and-language pretrained models, operate as a black box that there is no easy explanation for their behaviors (Li et al., 2021e). Indeed, in numerous cases, there is a desire to showcase what factors account for their predictions. The motivation is that users might need explanations in order to trust model outputs. For instance, in healthcare applications, patients would like to know not only the diagnosis but also its support so that they can follow the result. In addition, researchers and engineers may want interpretability as well so as to construe the reasons vision-and-language pretrained models fail to perform as expected, since evaluation metrics do not often provide sufficient evidence for them to draw any conclusions. Existing efforts have been put into interpreting vision-and-language pretrained models, either by diving into hidden weights (Xue et al., 2021;
Cao et al., 2020) or experimenting with model predictions (Hendricks et al., 2021). However, most of them focus on standard datasets of prevalent domains. On that account, one promising approach is to further diversify towards different domains and methodologies.

Intuitively, because salient components will reveal meaningful insights about vision-and-language pretrained models, copious probing research works target model parameters and rising and falling of the outputs. As a class of model parameters, attention layers have led to greater extent of interpretability (Serrano and Smith, 2019; Seo et al., 2017). For vision-and-language pretrained models, attention weights enjoy explainability as researchers plot them to investigate relations between visual regions and textual tokens, extract inter-modal and intra-modal token-token connections of maximal weights, and conduct numerical pooling upon attention weights to infer head-level and layer-level properties (Cao et al., 2020). Another way to look into vision-and-language pretrained models is to observe performance fluctuation with different model variants (Hendricks et al., 2021). Those two lines of research establish a solid foundation and encourage future efforts in developing interpretable vision-and-language pretrained models.

Apparently, vision-and-language pretrained model’s interpretability and explainability depend upon specific domains and tasks. More concretely, whereas restaurant or movie rating demands text-based explanation since consumers often write reviews before providing scores, medical diagnosis offers elucidation in the form of fine-grained scores on each symptom attribute. Unfortunately, the extension of above-mentioned probing works is quite limited, notably to discriminative tasks (Subramanian et al., 2019; Hendricks et al., 2021; Cao et al., 2020). This indicates contemporary restriction upon vision-and-language research for explainability and interpretability. Potential buildup can be considered, particularly investigating explanatory factors for vision-and-language pretrained models on generation tasks, for example, video summarization or image-grounded dialogue generation.

Despite recent achievements, more efforts to progress interpretability in VLP are imperative. Auspicious approaches include integrating prior knowledge into pre-training tasks in order to obtain visual-linguistic interpretable representations, or to produce generative explanations for vision-and-language pretrained models, like (Truong and Lauw, 2019). We believe that such endeavors or correspondent ones will inspire more efficacious VLP frameworks.

4.2 There is a Need for More Rational Evaluation for Vision-and-Language Performances

Until now, there have been myriad proposed VLP frameworks. In spite of the diversity of proposals, little attention has been paid to metrics to evaluate those frameworks. Typically, most research blindly inherits assessment schemes of previous works, or selects the most prevalent ones to judge their hypotheses. This raises several issues, regarding the fact that models in certain tasks are still graded in an improper fashion, the miscorrelation between pretraining and finetuning assessment, and the dearth of specialized experiments.
Different from discriminative tasks, in generative ones there exist a multitude of germane outputs for each input. For example, given the image of the husky dog and the reference: “There is a dog sitting in the image”, both the captions of “A dog is sitting” and “There is a husky dog” are closed to the reference. Thus, it is necessary to devise assessment methods that take into account this phenomenon. At the moment, popular evaluation metrics are based upon word overlapping estimation, which apparently fail in the aforementioned circumstance. Recently, there are BERTScore (Zhang et al, 2019) and MoverScore (Zhao et al, 2019b) that do not rely on word overlapping assumption, and involve hidden states to measure contextual similarity between two sentences. However, a limitation of such metrics is that they are restrained to a pre-defined document length, as such longer documents will be truncated before measurement is conducted. We argue that an improved evaluation suite for vision-and-language generative tasks should be proposed.

Specifically for VLP, it is natural to assess the model quality at the end of the vision-and-language pre-training phase, the purpose being to select a subset of models to pass forward to the fine-tuning phase. The key question is at which pretraining step can the model be passed forward to the fine-tuning stage so as to attain the optimal outcome. Unfortunately, it comes as a surprise that the best results during pre-training do not necessarily generalize to the fine-tuning (Singh et al, 2020). This indicates that either there is a semantic gap between pretraining and finetuning, or the pretraining evaluation has probable space for improvement. We believe that more investigation is imperative for deeper interpretation.

We also note that current evaluation frameworks do not concentrate upon analyzing robustness of Vision-and-Language Pretrained Models. Since adversarial inputs are widespread in real applications, resilience against adversariality should be a fundamental quality of the models. Up to date, although there are several benchmarks judging vision-and-language pretrained models’ resilience (Gokhale et al, 2020; Agarwal et al, 2020; Kervadec et al, 2021), only (Li et al, 2020b) conduct experiments upon these benchmarks, bringing about skepticism about other multimodal pretrained models’ robustness. From our viewpoint, future works are vital to integrate adversarial ingredients with broad aspects into evaluation benchmarks and execution pipeline as well.

4.3 Extending Practical Implementation of Vision-and-Language Pretrained Models

Vision-and-language pretrained models can scale up to millions or billions of parameters, which could incur prodigious memory cost for storage and high latency in computation. Although the research environment does not place stringent constraints upon those storage and computation elements, they would become nettlesome issues when being put into practice in resource-constrained circumstances, notably in industry. Considered in big-data scenarios, when the model pretraining has to endure millions (Radford et al, 2021) or even billions of samples (Jia et al, 2021), the problem would grow more devastating. More future explorations should be undertaken to perform VLP more productively.
Another productivity qualification to evaluate the deployability of vision-and-language pretrained models is whether they could cope with continuous changes. The world keeps moving, hence the scenarios encountered by deep neural models. Inherently, it is exigent to update models’ parameters in order to adapt to new information, borrowing the spirit of (Li et al, 2021b). This elicits a motivation to accelerate the training process, particularly in both pretraining and finetuning phases. Unfortunately, the colossal size of state-of-the-art multimodal pretrained models and cumbersome issues such as catastrophic forgetting exacerbate the dilemma. Contemporarily, broader and deeper research endeavors are warranted in this direction. A feasible solution involves knowledge distillation to train a small student model that absorbs knowledge from both the teacher model and novel data.

Last but not least, the applicability of VLP schemes depends upon their reproducibility. In spite of magnificent performance, if practitioners are unable to reimplement the framework to suit their needs, the framework cannot be put into use, thus hampering its application. Currently, community progress to improve reproducibility level is being hindered by the fact that a number of VLP frameworks do not publish their implementation (Li et al, 2019b; Lu et al, 2019; Li et al, 2020a; Xia et al, 2021; Lin et al, 2020; Huang et al, 2020; Gao et al, 2020; Yu et al, 2021), or release data upon which the models were pretrained (Radford et al, 2021; Jia et al, 2021). We argue that scholars and engineers should pay more attention to polish reproducibility after they have accomplished their research objectives, through providing encyclopedic details concerning their pretraining procedures, or publishing pre-trained weights and training datasets.

5 Conclusion

In this survey, we present a comprehensive review of the latest and most significant research on Vision-and-Language Pretraining. Following that, we outline a categorization disposition for organizing and grouping existing works. Furthermore, we explicate the heterogeneous approaches that vision-and-language pretrained systems have been developed and their miscellaneous applications as well. We recapitulate the article by detailing a number of open predicaments and prospective future research frontiers. In essence, human brain structure enables us to universally process information in multiple modalities, most notably vision and language. As such, advancing VLP in order to provide machines with the multimodal processing ability of humans has been an important research up to date, since it can bridge the gap between human and machine intelligence. We hope that this study gives readers a complete grasp of the key features of this discipline, enlightens the most consequential advancements, and illuminates future horizons.

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