Keep the Caption Information: Preventing Shortcut Learning in Contrastive Image-Caption Retrieval

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ABSTRACT
To train image-caption retrieval (ICR) methods, contrastive loss functions are a common choice for optimization functions. Unfortunately, contrastive ICR methods are vulnerable to learning shortcuts: decision rules that perform well on the training data but fail to transfer to other testing conditions. We introduce an approach to reduce shortcut feature representations for the ICR task: latent target decoding (LTD). We add an additional decoder to the learning framework to reconstruct the input caption, which prevents the image and caption encoder from learning shortcut features. Instead of reconstructing input captions in the input space, we decode the semantics of the caption in a latent space. We implement the LTD objective as an optimization constraint, to ensure that the reconstruction loss is below a threshold value while primarily optimizing for the contrastive loss. Importantly, LTD does not depend on additional training data or expensive (hard) negative mining strategies. Our experiments show that, unlike reconstructing the input caption, LTD reduces shortcut learning and improves generalizability by obtaining higher recall@k and r-precision scores. Additionally, we show that the evaluation scores benefit from implementing LTD as an optimization constraint instead of a dual loss.

1 INTRODUCTION
Image-caption retrieval (ICR) is the task of using an image or a caption as a query and ranking a set of candidate items in the other modality. Both the images and captions are mapped into a shared latent space by two encoders, which correspond to the two modalities. These encoders are typically optimized with contrastive loss functions [4, 11, 12, 22, 27, 29, 34, 38, 39, 54, 55, 59].

Shortcut learning. How well an ICR method generalizes beyond the specific training setup depends on the features that the method has learned during training. Contrastive loss functions are prone to learning shortcuts [30, 49], which are rules that perform well on standard benchmarks but fail to generalize to other testing conditions [13]. In the context of ICR, a shortcut is a latent representation of either the image or the caption that does not contain all the aspects mentioned in a caption that describes that scene. If a caption describes certain aspects of a scene that are ignored by either the image or the caption encoder, these aspects cannot be used for retrieval (i.e., the encoder has learned a shortcut to match certain images and captions). Features extracted during training depend on the difficulty of the discrimination task, i.e., how difficult it is for the model to discriminate positive and negative candidates [49]. Shortcut feature representations are problematic from a generalization perspective: if certain features are not learned during training, even though this information is present in the training data, this information cannot be used during evaluation (i.e., for retrieval).

Avoiding shortcut learning. The two benchmark datasets that are widely used for training and evaluating ICR methods, MS-COCO Captions (COCO) [32] and Flickr30k (F30k) [58], are relatively small in terms of training samples compared to the training data of state-of-the-art pre-trained ICR or image-text matching methods [22, 60]. One general approach to improve the difficulty of a contrastive discrimination task is to increase the batch size during training [6, 44]. This results in a higher probability of having difficult in-batch negative samples for a query. However, when an ICR method is trained from scratch using these benchmark datasets only, scaling-up the size of a batch is not a feasible solution to prevent shortcut features due to the limited data size of F30k and COCO.

Another approach to increase the difficulty of the discrimination task during training is to directly mine hard negative examples for each query, rather than relying on an increased batch size to include difficult negative examples. The disadvantage of hard negative mining is that it can be computationally expensive [5]. Moreover, the COCO dataset contains many visually similar images [41]. When a similar image is mined as a hard-negative, it will be considered as a negative w.r.t. the query, while in practice this image is a false negative. This will create conflicting and incorrect supervision signals that will not be beneficial to the training process.

The autoencoding paradigm [17] provides an alternative solution by learning latent data representations that contain as much of the input information as possible. A logical step to reduce shortcut features would be to add an extra decoder to the contrastive learning algorithm that decodes the original input from either the caption or image representation (or both). By applying the bottle-neck principle, the encoder should compress all input information into a low-dimensional representation while preserving as much as possible of the input information. However, adding a decoder on top of the image representations, as has been done in [30], is sub-optimal for the ICR task. The provided captions for each image are already a dense summary of the image. However, there is a big gap between the objective to encode the high-level semantics of an image and the reconstruction of individual pixels. Reconstructing pixels results in image representations that contain too much local (pixel) information, which is irrelevant for the ICR task. A more natural choice to reduce shortcut features is to decode the input caption rather than the image, but adding a decoder on top of the caption representations might not reduce shortcut features as expected. Strong textual decoders can reduce a reconstruction loss by mainly relying on the learned language model [36]. The input for this decoder (the latent caption representation) can mostly be ignored while still correctly decoding the input sequence. Therefore, the latent caption representation can still contain shortcut features while the reconstruction loss is reduced.
Our proposed solution. To address the disadvantages of current approaches for reducing shortcut feature representations, viz. (1) high costs (in terms of compute and data), and (2) reconstruction of the input caption and images in the input space, we introduce the latent target decoding (LTD) framework. For each caption in the training set, we generate a latent target representation that contains all the (semantic) information of the input caption. We decode the information of the caption in a latent space. Thus, the decoder cannot rely on a language model to decode the input, and the caption representation learned by the caption encoder should contain all input information to decode the latent target. LTD only requires an additional target representation for each caption and a simple feed-forward decoder network. LTD does not depend on (1) additional training data, (2) extra manual data annotation or (hard) negative mining, or (3) significantly more computational resources.

If we were to add LTD to the learning algorithm, the overall training objective would become a multi-task loss: a contrastive and reconstruction loss. Multi-task losses are difficult to optimize [37], however, and the reconstruction loss should serve as an extra regularizer rather than as the main learning objective. Therefore, we implement LTD as an optimization constraint instead of an additional loss. The main training objective is to minimize the contrastive loss, given the constraint that the reconstruction loss is below a certain threshold value. Similar to [48, 51], we implement this reconstruction loss constraint using a Lagrange multiplier [43]: the two losses are scaled automatically, which avoids manual tuning of the scaling hyper-parameter and simplifies optimizing the overall training objective.

Our main findings. (1) LTD reduces shortcut features and improves the generalizability of learned representations, as it outperforms a contrastive baseline; (2) Implementing LTD as constraint-based optimization makes it easier to optimize LTD with a contrastive loss function, resulting in higher evaluation scores.

2 RELATED WORK

2.1 Image-caption retrieval

Neural architectures for ICR. We focus on ICR methods that compute a global representation for both the image and caption. In general, an ICR method consists of two encoders: one to encode the image into a latent representation and one to encode the caption [10, 12, 22, 29]. Most work on ICR focuses on new architectures to learn multi-modal feature representations. State-of-the-art results have been obtained using graph neural networks [11, 29, 34, 54] to represent visual relations in scenes as a graph, or attention mechanisms to align words in the caption with specific regions in the input image [4, 27, 55, 59]. Li et al. [29] add a caption encoder-decoder on top of the image encoder to add extra training signals to the learning algorithm. These methods are only trained and evaluated on the COCO and F30k datasets.

Recently, there has been a shift to transformer-based [52] network architectures for both the image and caption encoder. Messina et al. [38, 39] introduce a transformer-based network architecture solely trained for the ICR task. Since then, several transformer-based methods have been introduced [8, 22, 28, 31, 35]; some of them combine the image and caption encoder into one unified architecture. Align [22] and Oscar [31] significantly improve the performance on the COCO and F30k benchmark test sets. These methods are all (pre-)trained on a large amount of additional training data and most of the methods are not trained for the ICR task specifically, but for multiple vision-text tasks.

Hard negative mining. Few publications have looked into the improvement of contrastive optimization for ICR methods. Faghri et al. [12] introduce a new formulation of the triplet loss, which only considers the hardest negative candidate in the training batch instead of all negative candidates, which significantly improved the evaluation scores on the ICR benchmarks. Since then, many ICR methods [4, 11, 27, 29, 34, 38, 39, 54, 59] have used this loss function for optimization. Chen et al. [5] introduce an offline hard-negative mining approach for ICR in order to overcome the limitations of in-batch negative mining. Instead of mining an in-batch hard-negative, they mine negative candidates, for each query, over the entire training set to learn from so-called harder-to-distinguish negatives.

One-to-many problem. Chun et al. [10] focus on the one-to-many problem in ICR. An image can be described by many different captions but most methods in ICR learn one representation for the image, which should match with a number of different captions. They propose a probabilistic ICR method, where images and captions are represented as probability distributions in a shared latent space instead of a point representation. Although their method does not specifically focus on contrastive optimization, it addresses shortcut features by learning a distribution over features instead of a point prediction of features. Chun et al. also propose the plausible match metric, which is a heuristic for identifying missing positive examples by finding images that contain similar objects (i.e., plausible matches) and considering these in the evaluation.

Unlike previous work, we do not focus on the network architecture to improve the ICR performance. Similar to [10], we focus on small-scale learning set-ups and use relatively simple architectures to train an ICR method from scratch to show the strength of our method. Our proposed approach incorporates autoencoding into the learning algorithm in order to reconstruct the input caption.

2.2 Generalizability of contrastive losses

Contrastive learning losses are used to learn discriminative representations of the input data that can be used to contrast positive and negative pairs of information. These loss functions have made a big impact in representation learning, whether self-supervised [6, 19, 40, 53] or supervised [25, 45]. Although ICR is a supervised learning task, some of the theoretical findings about contrastive self-supervised learning can be used for supervised settings as well.

Self-supervised contrastive learning. A common approach in self-supervised representation learning is to create two (matching) views of the same (or similar) data point(s) by applying different augmentations [6] or by splitting the data into parts [40] (i.e., predicting the future). The two positive views are contrasted with other negative samples in the training batch. The goal is to learn encoders that are invariant under these augmentations and that can discriminate between positive and negative pairs. How well self-supervised representations generalize to different settings, after training, is often assessed using a down-stream evaluation task, such as object classification [6] or speaker identification [40].
Shortcut feature representations. Robinson et al. [49] show that the features learned by the InfoNCE [40] loss depend on the difficulty of instance discrimination during training. If the instance discrimination task is easy to solve during training, the model will learn shortcut features. However, when the task becomes more difficult, by using hard negatives, shortcut features become less effective. Preventing shortcut features. Some work examines data augmentation to learn strong feature representations. Good augmentations retain task-relevant information while removing task-irrelevant nuisances [50]. The main purpose of removing task-irrelevant nuisances is to prevent encoders from using this information as a shortcut. Xiao et al. [56] show that the features needed to learn good representations depend on the down-stream task. ICR does not depend on augmentations to generate positive and negative pairs. These pairs are given by the annotations of the benchmark datasets [32, 58]. The difficulty of the discrimination task mainly depends on which candidates are present in the training batch.

The generalizability of contrastive learning methods is also influenced by the number of (hard) negatives present in a training batch. In general, the larger the number of in-batch negatives, the higher the down-stream evaluation performance [6]. Some work has focused on methods to increase the number of negatives during training [15] or on applying hard-negative mining strategies to increase the number of hard negatives in the batch [20, 33, 57].

A different approach to increase the generalizability of learned representations is autoencoding [17]. Autoencoding can be combined with a contrastive learning loss and reduces shortcut features without depending on sampling (hard) negative candidates. To learn high-quality text sequence embeddings for the dense passage retrieval task, Lu et al. [36] add a weak decoder on top of a document encoder to reconstruct the original document. To make image encoders more robust against shortcut features, Li et al. [30] add a decoder on top of the image encoder to decode the input image.

To reduce shortcut feature representations for the ICR task, we introduce latent target decoding (LTD). LTD reduces shortcut features without focusing on the difficulty of the contrastive discrimination task. LTD requires neither a large number of negative samples nor hard negative mining strategies. Unlike other methods that reconstruct the input data, we reconstruct the input information of the caption in a latent space instead of the input space.

3 METHOD

We start with preliminaries and then discuss the InfoNCE [40] contrastive loss and why autoencoding captions in the input space is not a solution to reduce shortcut features. Finally, we introduce latent target decoding (LTD) to reduce shortcut features for ICR.

3.1 Preliminary and notation

Notation. We follow the notation introduced in [3, 6]. For the ICR task we use a multi-modal dataset \( D = \{(x_I^j, x_C^j, \ldots, x_C^k)\}_{i=1}^N \). This dataset consists of \( N \) image-caption tuples. Each tuple contains one image \( x_I^j \) and \( k \) captions \( x_C^j \), where \( 1 \leq j \leq k \), that describe the scene depicted in the image. At each training iteration, we randomly sample a batch \( B \) of image-caption pairs from \( D \). Per image, one of the \( k \) captions is sampled per training iteration; together, this image and caption form a positive (or matching) image-caption pair. Each caption is used only once during a training epoch.

The image and caption encoder are trained for two tasks: image-to-text (i2t) and text-to-image (t2i) retrieval. Thus, each image and caption in \( B \) is used as a query \( q \). We denote the matching items in the other modality as \( v^+ \). All other candidates in \( B \), in the other modality, are considered as negative candidates \( v^- \). The set of all negative candidates for query \( q \) in batch \( B \) is \( S_q \), where \( v^- \in S_q \).

Baseline model. The baseline ICR model (BL) in this work consists of two encoders. We use an image and caption encoder relatively similar to [10, 12]. The image encoder \( f \) takes an image \( x_I^j \) as input and encodes this image into a latent representation \( z_I^j \). The caption encoder \( g \) takes a caption as input and encodes this caption into a latent representation \( z_C^j \). \( z_I^j \) and \( z_C^j \) have the same dimensionality and are normalized on the unit sphere. The encoders are optimized by minimizing a contrastive learning loss \( L_{con} \). Our goal is not to obtain the highest possible evaluation performances, but to show the strength of LTD on small-scale training setups.

3.2 Contrastive loss

To train the image and caption encoder, we use the InfoNCE contrastive loss [6, 40]. The InfoNCE loss is a popular loss function for self-supervised representation learning [6, 15], multi-modal representation learning [45], and ICR [22, 60]. To keep the notation simple and intuitive, we use \( q \) and \( \sigma \) for the latent representations computed by the caption and image encoder and not \( z_C^j \) and \( z_I^j \). The InfoNCE loss is defined as follows:

\[
L_{con} = \frac{1}{|B|} \sum_{(q, v^+) \in B} -\log \frac{\exp(q^Tv^+/\tau)}{\exp(q^Tv^+/\tau) + \sum_{v^- \in S_q} \exp(q^Tv^-/\tau)}. \tag{1}
\]

\( L_{con} \) in Eq. 1 is minimized when, given a query \( q \), the cosine similarity score with the positive candidate \( v^+ \) is high (i.e., \( \approx 1 \)), while the similarity scores with the negative candidates \( v^- \) in the batch are as low as possible; \( \tau \) serves as a temperature parameter. The main objective of a contrastive learning loss is to learn data representations that can be used to discriminate between similar and dissimilar image-caption pairs. However, there is no constraint that enforces the encoders to learn representations that contain all available input information to make this discrimination, which is what we add.

3.2.1 Gradient w.r.t. the input representations. To show some important properties of the InfoNCE loss and why this loss function is prone to result in shortcut features, we provide the derivative of
- $L_{\text{con}}$ w.r.t. the input in Eq. 2 [6]:

$$ \frac{\partial L_{\text{con}}}{\partial q} = (1 - Z(q, \sigma^+)) \sigma^+ \tau^{-1} - \sum_{\sigma^- \in S_q} Z(q, \sigma^-) \sigma^- \tau^{-1} \quad (2a) $$

$$ \frac{\partial L_{\text{con}}}{\partial \sigma^+} = (1 - Z(q, \sigma^+)) \sigma^+ q^{-1} \quad (2b) $$

$$ \frac{\partial L_{\text{con}}}{\partial \sigma^-} = -Z(q, \sigma^-) \sigma^- q^{-1} \quad (2c) $$

$$ Z(q, \sigma) = \frac{\exp(q^T \sigma / \tau)}{\exp(q^T \sigma / \tau) + \sum_{\sigma^- \in S_q} \exp(q^T \sigma^- / \tau)}. \quad (2d) $$

$Z(q, \sigma)$ returns the similarity score of candidate $\sigma$ w.r.t. the query $q$, normalized by the sum of similarity scores of all candidates in the batch. Based on Eq. 2, we infer the following properties:

1. The update w.r.t. the query $q$ (Eq. 2a), is a weighted sum over the positive candidate $\sigma^+$ and all negatives $\sigma^-$. Hence, the query representation $q$ will be pulled closer to $\sigma^+$, while being pushed away from all $\sigma^-$. The weight value of each candidate, $Z(q, \sigma)$ (Eq. 2d), depends on the similarity score with the query.

2. $\sigma^+$ (Eq. 2b) will be pulled closer to the query representation (and the other way around).

3. All negatives $\sigma^-$ (Eq. 2c) will be pushed away from the query representation (and the other way around).

Importantly, the query and candidate representations are in different modalities and therefore generated by different encoders. Hence, the update of the query and candidate representations is based on “fixed” representations in the other modality. Without contrasting with negative candidates, the encoders will learn a trivial solution where latent representations collapse to a single point in the latent space [23]. If we combine this fact with Eq. 2, it is clear that the learned representations mainly depend on (the representations) of negative candidates in the training batch. The learned representations depend on which positive and negative candidates are presented in the training batch [49]. If certain information that is present in the input caption or image is not needed to solve the contrastive training objective, it will be suppressed by the learned caption and image encoder, which results in shortcut features. The problem is especially acute if the training data is limited, since there will never be enough positive-negative comparisons to robustly learn which parts of the input matter. Also, the optimal number of negative samples during training for NLP tasks should scale with the number of underlying concepts in the data, which, in theory, consists of all concepts in natural language for the ICR task [1].

### 3.3 Autoencoding reconstruction objective

Autoencoding [17] is a natural choice for learning latent data representations that contain the full input information (i.e., no shortcuts) without relying on hard negative samples. To reconstruct the input caption from the encoded latent representation $z_{CJ}$, we introduce a decoder network $h_o$:

$$ \hat{x}_{CJ} = h_o(z_{CJ}). \quad (3) $$

The decoder network $h_o$ takes the latent caption representation as input and outputs a reconstruction of the input caption $\hat{x}_{CJ}$. To decode the input sequence from the latent representation, this latent representation should be a dense representation of the entire input sequence. The reconstruction loss, $L_{\text{rec}}$, of a sequence of tokens, $x_i, \ldots, x_n$ of length $n$, is the negative log-likelihood of the observed data:

$$ L_{\text{rec}} = -\sum_{i=1}^{n} \log p(x_i | x_{i-1:1}, z_{CJ}^i). \quad (4) $$

Based on Eq. 4 it is clear that each predicted token $x_i$ in the sequence is conditioned on: (1) the latent caption representation $z_{CJ}^i$, and (2) the already predicted sequence $x_{i-1:1}$.

As discussed in Section 1, a strong decoder will mainly rely on the learned language model and language patterns to decode the input sequence [36]. This implies that the input sequence can be decoded correctly while mainly ignoring $z_{CJ}^i$, especially when $t$ is large. Therefore, decoding the caption sequence in the input space is not guaranteed to reduce shortcut features.

### 3.4 Latent target decoding

In Section 3.2 we argued why the contrastive loss is prone to learn shortcut features, and in Section 3.3 we discussed why decoding a caption in the input space will not prevent shortcut features. In this section we introduce latent target decoding (LTD). LTD decodes the semantics of the input caption in a latent space to reduce shortcut features, which can be used in combination with a contrastive loss. LTD addresses the issues of decoding the caption in the input space. See Fig. 1 for a high-level overview of LTD.

For each caption $C^i$ in the training dataset we generate $y_{CJ}^i$: a latent target representation. $y_{CJ}^i$ is a dense vector representation and we assume that this vector contains all the (semantic) information of the caption, captured by a general purpose language encoder. We use our decoding network $h_o$ to decode $y_{CJ}^i$ instead of the input caption. By reconstructing a vector representation instead of the original input sequence, the reconstruction is not conditioned on the already predicted sequence of tokens. The latent target decoder assumes conditional independence of each feature in the latent target. Therefore, the decoder cannot rely on conditional (language model) patterns in the data to reconstruct the input semantics. This implies that we force the decoder to rely completely on $z_{CJ}^i$ to decode the latent target representation.

**Decoding network.** To decode $y_{CJ}^i$, we use a three layer feed-forward decoder network:

$$ h_o(z_{CJ}^i) = W^{(3)} \sigma \left( W^{(2)} \sigma \left( W^{(1)} z_{CJ}^i \right) \right), \quad (5) $$

where $\sigma$ is the ReLU non-linearity; $h_o$ takes the latent caption representation as input and maps it to a reconstruction of the latent target representation $\hat{y}_{CJ}^i$.

**Loss function.** To train $h_o$, we use the negative cosine similarity between $\hat{y}_{CJ}^i$ and $y_{CJ}^i$ as reconstruction loss $L_{\text{rec}}$:

$$ L_{\text{rec}} = 1 - \frac{\hat{y}_{CJ}^i}{\|y_{CJ}^i\|_2} \cdot \frac{y_{CJ}^i}{\|y_{CJ}^i\|_2}. \quad (6) $$

Minimizing negative cosine similarity is equivalent to minimizing the mean squared error of two vectors normalized on the unit sphere [7, 14]. By introducing an extra loss criterion, the overall
We can implement this optimization constraint in combination with 

\[ L = \min_{\theta, \psi, \omega} \mathcal{L}_{\text{con}} + \lambda \mathcal{L}_{\text{rec}} \]

where \( \lambda \) serves as a scaling parameter to scale the two losses.

**Constraint-based optimization.** By adding LTD to the learning framework, we introduce an extra loss component \( \mathcal{L}_{\text{rec}} \). To effectively minimize \( \mathcal{L}_{\text{dual}} \), we have to find the right value for the balancing parameter \( \lambda \) in Eq. 7. This may require a considerable amount of manual tuning, and often one specific value for \( \lambda \) does not generalize to different training settings. Besides that, \( \mathcal{L}_{\text{rec}} \) is not the main training objective for the ICR tasks. The main reason we add \( \mathcal{L}_{\text{rec}} \) to the learning algorithm is to reduce shortcut features learned by the contrastive loss. We therefore argue that implementing LTD as an optimization constraint [48, 51], as opposed to an optimization objective, might be more effective. Our goal, then, is to minimize the contrastive loss \( \mathcal{L}_{\text{con}} \) given the constraint that the reconstruction loss is lower than or equal to a certain threshold value \( \eta \):

\[ \min_{\theta, \psi, \omega} \mathcal{L}_{\text{con}} \text{ such that } \mathcal{L}_{\text{rec}} \leq \eta. \]  

We can implement this optimization constraint in combination with gradient descent by using the method of Lagrange multipliers:

\[ \max_{\lambda} \min_{\theta, \psi, \omega} \mathcal{L}_{\text{lag}} = \mathcal{L}_{\text{con}} + \lambda \left( \frac{\mathcal{L}_{\text{rec}}}{\eta} - 1 \right). \]  

The optimization objective is to minimize \( \mathcal{L}_{\text{lag}} \) w.r.t. the model parameters \( \theta, \psi, \omega \), while maximizing \( \mathcal{L}_{\text{lag}} \) w.r.t. to the multiplier \( \lambda \). The multiplier \( \lambda \) is tuned automatically by using stochastic gradient ascent with momentum. By optimizing \( \lambda \) with stochastic gradient ascent, the two losses will be balanced automatically during training such that the reconstruction constraint is met, while the contrastive loss is minimized by gradient descent.

**Choice of latent target representation.** To generate the latent target \( y_{Cj} \), we use a Sentence-BERT transformer model [47]. Sentence-BERT is a general purpose sentence encoder that is trained on a large amount of data to capture the semantic input information. The Sentence-BERT model we use in this work is trained on a dataset of 1 billion sentence pairs. Thus, we expect these embeddings to be more general than those we learn for the ICR task, which makes them a suitable choice for the latent target representations \( y_{Cj} \).

## 4 EXPERIMENTAL SETUP

We design experiments aimed at showing: (1) a reduction of shortcut feature representations by using LTD; (2) the advantages of LTD over reconstructing the caption in the input space to reduce shortcut feature representations; and (3) the benefit of constraint-based optimization of LTD over dual loss optimization. The facilitate the reproducibility of the work, our code is available at https://github.io/MauritsBleeker/keep-the-caption-info.

**Datasets.** For training and evaluating our ICR method, we use the two common ICR benchmark datasets: MS-COCO Captions (COCO) [32] and Flickr30k (F30k) [58]. The F30k dataset contains 31,000 images. We use the train, validate and test split from [24], with 29,000 images for training, 1,000 for validation, and 1,000 for testing. COCO consists of 123,287 image-caption tuples. We use the train, validate and test split from [24]; we do not use the 1k test setup. Both F30k and COCO come with \( k = 5 \) captions per image.

We also use the CrissCrossed Captions (CxC) dataset, which extends COCO with additional annotations of similar captions and images [41], so as to evaluate whether LTD improves the recall scores by retrieving semantically similar candidates.

**Implementation details.** For the image and caption encoder we use, except some minor details, the same encoders as in [10, 12]. To show the strength of LTD, we choose network architectures that can easily be trained without multi-modal pre-training on the ICR benchmark datasets [32, 58]. In Appendix A (Supplementary materials), we compare our contrastive baseline with the VSE++ method [12], to show that our contrastive baseline performs as expected.

**Image encoder.** For the image encoder we use a ResNet-50 [16] network. We apply average pooling on the last convolutional layer followed by a projection head to map the image feature vector into a shared multi-modal latent space; the projection head has two feed-forward layers and a ReLU non-linearity.

**Caption encoder.** For the caption encoder we use a bi-directional, single-layer, GRU [9] network. We use pre-trained GloVe [42] embeddings as word embeddings. We use a similar projection head

1https://huggingface.co/sentence-transformers/all-MiniLM-L6-v2
While we cannot measure the presence of shortcut features directly, with a contrastive ICR baseline; we ask if similar results can be achieved with ITD as with LTD; we then investigate the role of the optimization constraint, whether LTD generalizes to a different contrastive loss function, and use the target generator directly as caption encoder instead of training a caption encoder from scratch.

5.1 Baseline vs. LTD
In Table 1 we compare LTD with the baseline ICR method, which is optimized by using the contrastive loss $L_{\text{con}}$ defined in Eq. 1. Based on Table 1, row 1.1, 1.4, 2.1.1, 2.4.1, and 2.4.2, 2.4.2, we observe that LTD optimized as a dual loss ($L_{\text{dual}}$) with $\beta = 1$ does not convincingly (or only with a small margin) outperform the baseline ICR method, which is optimized solely in a contrastive manner, in terms of recall@k and r-precision for both datasets and both tasks.

In contrast, when we implement LTD as an optimization constraint, by using $L_{\text{lag}}$ with $\eta = 0.2$ (see Section 5.3 for a motivation for the value of $\eta$), row 1.5, 2.1.5, and 2.2.5, we observe that LTD consistently outperforms the baseline ICR methods on both F30k and COCO for both tasks (i2t and t2i) with a large margin. Constraint-based LTD results in the highest relative improvement for F30k, which suggests that smaller datasets benefit more from constraint-based LTD. Moreover, an increase in recall also comes with an increase in the r-precision scores. Hence, features learned by constrained LTD optimization generalize better to the evaluation task, which is an indication of the reduction of shortcut features.

5.2 Latent vs. Input space reconstruction
As argued in Section 3.3, decoding the caption in the input space will probably not result in a reduction of shortcuts due to overfitting of the learned language model. To empirically show this, we also implemented a decoder (ITD) that decodes tokens of the input captions, which is an indication of the reduction of shortcut features. Based on row 1.2, 2.1.2 and 2.2.2 in Table 1 we conclude that implementing ITD as a dual loss does not
What is the role of the optimization constraint when minimizing \( \eta \)?

1. ITD does not prevent shortcut feature representations for ICR, and implementing ITD as an optimization constraint even hurts performance.

2. The contrastive loss converges to the value of \( \lambda \) during training (Fig. 2c).

3. The trajectory of the contrastive loss over training (Fig. 2b).

4. The trajectory of the reconstruction loss over training (Fig. 2a).

5. The trajectory of the evaluation score (recall sum) over the validation set during training on the COCO dataset. We also provide (1) the trajectories of the reconstruction loss and contrastive loss for different values of \( \eta \) and when optimized without using a constraint (Fig. 2c), and (3) the trajectory of the contrastive loss for different values of \( \eta \) (Fig. 2d). Based on Fig. 2 we observe:

   (1) \( \lambda \) increases until the optimization constraint is met. The closer the reconstruction loss is to the bound, the slower the increase. When the reconstruction constraint is met, \( \lambda \) decreases to 0 (Fig. 2b).

   (2) \( \lambda \) is positive again when the reconstruction loss becomes higher than the bound \( \eta \) (Fig. 2b).

   (3) The reconstruction loss converges to the value of \( \eta \) (Fig. 2c). However, it is not possible to meet every value of \( \eta \). E.g., \( \eta = 0.05 \) is too low to achieve for the model.

   (4) A lower reconstruction loss does not necessarily result in higher evaluation scores (Fig. 2a). E.g., the recall sum is higher for \( \eta = 0.2 \) than for \( \eta = 0.1 \) or \( \eta = 0.05 \). The reconstruction loss, when optimizing with \( L_{\text{dual}} \), is lower than with \( L_{\text{lag}} \eta = 0.2 \), but \( L_{\text{lag}} \eta \) yields higher evaluation scores.

   (5) The value and the development of the contrastive loss do not depend on the value of the reconstruction loss (Fig. 2d). E.g., a model optimized with \( L_{\text{con}} \) has the same contrastive loss trajectory as a model that is optimized with \( L_{\text{lag}} \) as a constraint. Hence, the contrastive loss on its own does not provide a good indication of the performances on the evaluation task. Similar trajectories of the contrastive loss result in different evaluation scores (hence different learned representations).

### 5.4 Generalizability w.r.t. contrastive loss

In Section 3.2 we argue that the InfoNCE loss is prone to learn shortcut feature representations. A popular choice of contrastive loss function for ICR methods is the triplet loss with in-batch hard-negative mining [12]. The triplet loss is a special case of the InfoNCE loss, where the number of positives and negatives are each one [26]. So our line of reasoning in Section 3.2 holds for the triplet loss too.

To show the strength and generalizability of LTD to other contrastive losses, we run the same experiments as in Section 5.1, with the triplet loss [12] instead of the InfoNCE loss as \( L_{\text{con}} \). To make the triplet loss work, we added a batch normalization layer after the projection head, for both the image and caption encoder and disabled SWA; we use a margin value of \( \alpha = 0.2 \).

Table 2 provides the recall@k scores for the F30k and COCO datasets. For both F30k and COCO the triplet loss with constraint-based LTD (see rows 3.1.3 and 3.2.3) results in a higher evaluation performance than the InfoNCE loss with constraint-based LTD (see Table 1, rows 1.5 and 2.5). Our goal here is not to identify the best contrastive loss for ICR or LTD, but to show the generalizability of LTD to different contrastive losses. Moreover, using the triplet loss as \( L_{\text{con}} \) (see row 3.2.1), results in expected evaluation performance on the COCO dataset (given the reproducibility work in [2]). Surprisingly, however, the evaluation scores for the F30k dataset while using the triplet loss as \( L_{\text{con}} \) (see row 3.1.1) are lower than expected (when compared to Table 1, row 1.1). It is unclear why we observe these low evaluation scores for the F30k dataset when only using the triplet loss. In contrast, we observe that constraint-based LTD in combination with the triplet loss drastically improves the evaluation scores for the F30k dataset, which shows the strength of constraint-based LTD for improving ICR evaluation scores.

### 5.5 Directly using the target generator

Why train a caption encoder if you can use the caption targets directly as representations for the input caption? In this case, the target generator is directly used to generate fixed caption representations and the image encoder is optimized to match with these representations. The image encoder is then optimized by minimizing the negative cosine similarity with the fixed caption targets. Since the caption representations are fixed, we do not have to use a contrastive loss. The evaluation scores using this training setup are given in Table 2 (rows 4.1.1 and 4.2.1). If we compare these results against the baseline method in Table 1 (rows 1.1 and 2.1.1), we conclude that using the target representations directly as caption representations does not result in good evaluation performance.
The representations are optimized using the InfoNCE loss. Based on Table 2 (rows 4.1.2 and 4.2.2), we observe that fine-tuning the representations improves the evaluation scores, especially for the i2t task. When optimizing with \( \mathcal{L}_{\text{lag}} \) (close to) zero for the majority of the training after the constraint is met, the evaluation scores on the validation set remain higher than when optimizing with \( \mathcal{L}_{\text{dual}} \), with \( \beta = 1 \) (Fig. 2a). This suggests that a constant gradient from the reconstruction loss does not benefit the training process, which is the case if LTD is implemented as a dual loss. We plan future research into the role of the optimization constraint, and its benefits for evaluation performance.

### Measuring shortcut features.

Similar to [30, 49], we measure the reduction of shortcut features by the improvement on a downstream evaluation task, in our case retrieval. What the definition of shortcut feature representations is, and how to properly evaluate the reduction of shortcut features is still an open problem and might be task-specific. For future work, we would recommend investigating task-specific metrics that can measure the reduction of shortcut feature representations.

#### The optimization constraint.

In Section 5.3 we examine the role of the optimization constraint when training the image and caption encoder. When the optimization constraint \( \eta \) is met, \( \lambda \) (i.e., the balancing parameter of the two losses) drops to zero and the reconstruction loss no longer provides a gradient (Fig. 2b). Although \( \lambda \) is (close to) zero for the majority of the training after the constraint is met, the evaluation scores on the validation set remain higher than when optimizing with \( \mathcal{L}_{\text{dual}} \), which confirms that LTD should be implemented as an optimization constraint, and not as an extra loss component.

### Conclusion

In this work, we present latent target decoding, a novel approach to reduce shortcut features for the ICR task. LTD reconstructs the input caption in a semantic latent space, instead of in the input space, and does not depend on additional training data or hard-negative mining strategies. We show that LTD should be implemented as an optimization constraint, and not as an extra loss component.

Our empirical results show that constraint-based LTD reduces shortcut features and improves the generalizability of the learned feature representations by obtaining higher recall at k and r-precision scores than a contrastive baseline. Furthermore, implementing LTD as a dual loss does not result in better evaluation performances, which confirms that LTD should be implemented as an optimization constraint. Next to that, reconstructing the input caption in the input space is not a solution to reduce shortcut feature representations. Finally, LTD does not depend on a specific choice of the contrastive loss function and that the latent target representations can not be used directly as caption representations.

### Acknowledgments

We thank Maartje ter Hoeve, Sarah Ibrahimi, Ana Lucic and Julien Rossi for their valuable feedback and discussions. This research was...
APPENDIX

A COMPARISON WITH VSE++

In this work, we use a convolutional neural network (ResNet-50 [16]) as image encoder, a bidirectional GRU [9] with GloVe [42] word embeddings as caption encoder, and the same training set-up as in [10].

We have chosen light-weighted encoder models that are easy to optimize, given a modest amount of training data [32, 58], to show the strength of constraint-based LTD in a situation where more training data or more computational resources are not a solution to improve the evaluation scores.

The code-base (and therefore the models as well) of this work is mainly based on the code introduced in [10]. However, the image and caption encoder used in [10] are optimized as probabilistic cross-modal embeddings (which come with different loss functions than a contrastive loss function) and are mainly evaluated with the plausible matches metric [10], which we do not use in this work. Therefore, we cannot directly compare our results with the evaluation scores reported in [10].

Another ICR method that is similar to our baseline method is the method introduced by Faghri et al. [12]. If we change the backbone of the image encoder to a ResNet-152, use the same learning rate schedule as in [12] and optimize the models with the triplet loss, the baseline method in this work can be compared with the results reported in [12].

However, there are still some minor differences:

1. we use a bidirectional GRU instead of a single directed GRU,
2. we use GloVe embeddings instead of training the word embeddings from scratch,
3. we use a two-layer projection head instead of a single layer projection head,
4. we use the data augmentations as used in [10].

We argue that these differences should not result in major differences in performances. The goal of this experiment is not to compare our method with other ICR methods to show which method performs best, but primarily to show that our contrastive baseline performs as expected and that the differences in evaluation performances are due to changes in the model architecture and learning algorithm.

Table 3: Our results when training our baseline ICR method in a similar fashion as [12], and the results reported in [12]. Evaluated on the COCO 5k test set. † represents results reported in the original work.

|       | R@1 | R@5 | R@10 | R@1 | R@5 | R@10 |
|-------|-----|-----|------|-----|-----|------|
| Ours  | 38.9| 68.5| 79.9 | 29.9| 59.1| 71.7 |
| VSE++ [12] † | 41.3| 71.1| 81.2 | 30.3| 59.4| 72.4 |

In Table 3 we compare the evaluation score we obtain when training our baseline method in a similar fashion as in [12] with the results reported in [12] on the COCO dataset. Given Table 3, we can observe that our reported results are slightly lower than the results reported in [12]. However, given that there are still minor differences in training setup, and the fact that results can differ given the random seed for training [46], we argue that our baseline model performs as expected.