

Test-Time Matching: Unlocking Compositional Reasoning in Multimodal Models

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Code: <https://github.com/yinglunz/test-time-matching>

Abstract

Frontier AI models have achieved remarkable progress, yet recent studies suggest they struggle with *compositional reasoning*, often performing at or below random chance on established benchmarks. We revisit this problem and show that widely used evaluation metrics systematically *underestimate* model capability. To address this, we introduce a *group matching score* that better exploits group structure and reveals substantial hidden capability in both contrastive vision-language models (VLMs) and multimodal large language models (MLLMs). Moreover, simply overfitting to the induced group matchings at test time transfers this hidden capability into higher scores under standard evaluation metrics, closing much of the reported gap. This adjustment enables SigLIP-B16 to surpass all previous results and GPT-4.1 to *yield the first result surpassing estimated human performance on Winoground*.

Building on this insight, we propose *Test-Time Matching* (TTM), an iterative, self-improving algorithm that further bootstraps model performance without any external supervision. TTM delivers additional, non-trivial improvements: for example, **TTM enables SigLIP-B16 to surpass GPT-4.1 on MMVP-VLM, establishing a new state of the art**. Importantly, TTM remains broadly effective even on benchmarks without metric-induced effects or group structures, **achieving relative gains up to 85.7%** on challenging datasets such as WhatsUp. Across 16 dataset variants spanning diverse setups, our experiments demonstrate that TTM consistently improves model performance and advances the frontier of compositional reasoning.

1 Introduction

Compositional reasoning provides a stringent test of frontier AI models, assessing their ability to systematically combine primitive elements—such as objects, attributes, and relations—to interpret or reason about novel configurations (Lake et al., 2017; Bahdanau et al., 2019). Recent benchmarks evaluate this capability by organizing examples into small groups of images and captions that differ in subtle yet systematic ways (Thrush et al., 2022; Hsieh et al., 2023; Kamath et al., 2023; Tong et al., 2024; Burapachee et al., 2024). For example, Winoground consists of 2×2 groups where both captions contain the same words but in different orders, such that each caption correctly describes only one of the two images.

Despite the impressive practicality of modern multimodal systems, both contrastive vision-language models (VLMs) and multimodal large language models (MLLMs) have been reported to perform at or below random guessing on these benchmarks (Thrush et al., 2022; Diwan et al., 2022; Tong et al., 2024; Burapachee et al., 2024; Li et al., 2025). On Winoground, even frontier AI models still fall far short of the estimated human performance of 85.5 (Thrush et al., 2022), with the previous state of the art reaching only 58.75, achieved through scaffolding and prompt tuning GPT-4V (Wu et al., 2023; Vaishnav and Tammet, 2025).

We revisit this conclusion and show that standard evaluation metrics systematically *underestimate* model capability. We introduce a *group matching score* (GroupMatch) that better exploits group structure by

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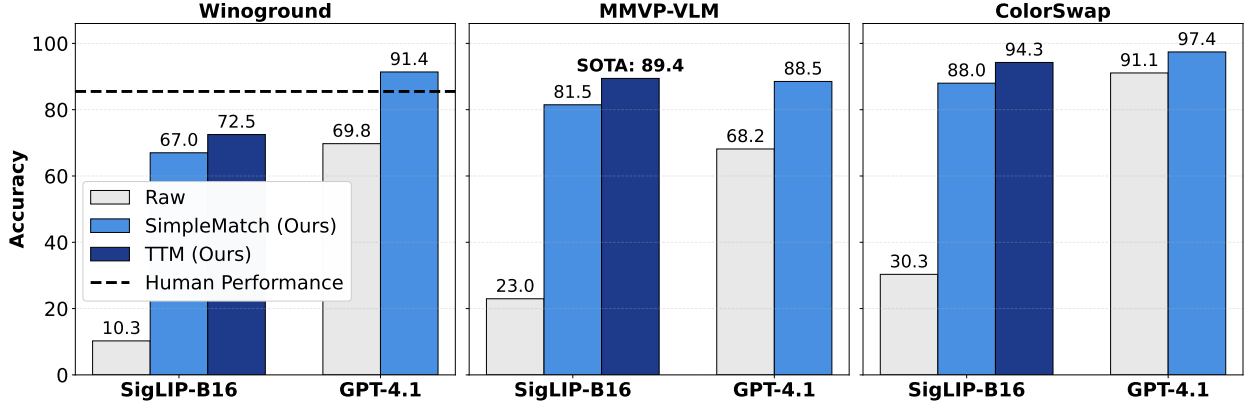


Figure 1: SimpleMatch and TTM substantially improve VLM and MLLM performance on compositional reasoning benchmarks Winoground, MMVP-VLM, and ColorSwap, achieving new performance records. We highlight: (1) SimpleMatch enables GPT-4.1 to surpass human performance on Winoground (*left*), and (2) TTM enables SigLIP-B16 to surpass GPT-4.1 on MMVP-VLM, establishing a new state of the art (*middle*).

evaluating the *best overall matching* rather than isolated pairwise comparisons, as in the widely used group score metric (GroupScore) (Thrush et al., 2022; Tong et al., 2024; Burapachee et al., 2024). Simply overfitting to the matchings induced by GroupMatch transfers the gains to performance under the standard metric GroupScore; we refer to this approach as SimpleMatch (see Section 3.1). This adjustment alone reveals substantial hidden capability: as shown in Fig. 1, SigLIP-B16 improves from 10.25 $\rightarrow$ 67 on Winoground, 22.96 $\rightarrow$ 81.48 on MMVP-VLM, and 30.33 $\rightarrow$ 88 on ColorSwap, surpassing all previous results without access to additional data (Wu et al., 2023; Vaishnav and Tammet, 2025; Zhang et al., 2024c; Burapachee et al., 2024). GPT-4.1 also improves dramatically, from 69.75 $\rightarrow$ 91.38 on Winoground, 68.15 $\rightarrow$ 88.52 on MMVP-VLM, and 91.08 $\rightarrow$ 97.42 on ColorSwap—*yielding the first result to surpass the estimated human performance of 85.5 on Winoground* (Thrush et al., 2022).¹

Building on this insight, we introduce *Test-Time Matching* (TTM), an iterative, self-improving algorithm that further bootstraps model performance without any external supervision. TTM selects matching-induced pseudo-labels for self-training and progressively relaxes the selection threshold to expand coverage over the test set. This yields *additional, non-trivial* gains on top of SimpleMatch: SigLIP-B16 reaches 72.5 on Winoground, 89.44 on MMVP-VLM, and 94.25 on ColorSwap. Remarkably, TTM elevates SigLIP-B16 to the level of GPT-4.1 on ColorSwap (Table 1) and **enables SigLIP-B16 to surpass GPT-4.1 on MMVP-VLM, establishing a new state of the art**. See Fig. 1 and Table 1 for details. Crucially, TTM is broadly effective even where metric changes cannot help—on $1 \times k$ benchmarks such as SugarCrepe (Hsieh et al., 2023) and WhatsUp (Kamath et al., 2023), where GroupScore and GroupMatch coincide, TTM still delivers substantial test-time improvements, including **up to 85.7% relative gains** on challenging datasets such as WhatsUp (Fig. 3).

Finally, we extend TTM beyond group-structured datasets by formulating a single global matching across all images and captions. Even a one-shot global matching outperforms raw GroupScore, and applying the global variant of TTM yields further improvements, demonstrating that the test-time matching principle generalizes robustly beyond benchmarks with group structures.

Contributions. We summarize our main contributions below:

1. **Revisiting evaluation metrics.** We introduce a group matching score (GroupMatch) that better exploits group structure and reveals hidden capability masked by standard evaluation metrics. We further develop a simple matching procedure (SimpleMatch) that transfers these gains to performance under the widely used metric GroupScore, enabling GPT-4.1 to achieve the first Winoground result surpassing human performance.

¹We use GPT-4.1-2025-04-14, the latest GPT model that provides log probabilities, enabling more accurate computation of similarity scores (Lin et al., 2024). As of October 2025, GPT-5 does not support log probability outputs.

2. **Test-time matching for self-improvements.** We propose *Test-Time Matching* (TTM), an iterative, self-improving algorithm that selects matching-induced pseudo-labels for self-training and progressively relaxes the selection threshold to expand coverage. TTM delivers additional, non-trivial gains on top of SimpleMatch, enabling SigLIP-B16 to surpass GPT-4.1 on MMVP-VLM and establishing a new state of the art.
3. **Broad applicability of TTM.** We conduct extensive experiments across 16 dataset variants spanning 2×2 , $1 \times k$, and non-grouped settings, demonstrating that TTM consistently improves model performance across diverse scenarios, including those without metric-induced effects or predefined group structures.

Paper organization. In Section 2, we review group-structured evaluation for compositional reasoning. In Section 3, we revisit evaluation metrics, introduce a new group matching score (GroupMatch), present our test-time matching (TTM) algorithm, and extend it to global (non-grouped) settings. In Section 4, we report results on benchmarks with 2×2 groups, $1 \times k$ groups, and non-grouped structures, together with ablations and analysis. We discuss related work in Section 5 and conclude in Section 6. Formal proofs, additional experimental details, and extended results are provided in the Appendix.

2 Preliminaries

We study compositional reasoning in multimodal models. Benchmarks for this task are typically organized into *groups* of images and captions, often of shape $k \times k$ or $1 \times k$. Within each group, the images and captions differ in subtle yet systematic ways. For example, the widely used Winoground dataset consists of groups with two images and two captions, where both captions contain the same set of words but in different orders, such that each caption correctly describes only one of the two images (Thrush et al., 2022).

To succeed on these benchmarks, a model must correctly align images and captions within each group. Let $s_{ij} := s(I_i, C_j)$ denote the similarity score between image I_i and caption C_j . For contrastive vision-language models such as CLIP (Radford et al., 2021) and SigLIP (Zhai et al., 2023), s_{ij} is typically computed as the inner product of image and text embeddings. For multimodal large language models, similarity can instead be estimated using metrics such as VQAScore (Lin et al., 2024). We collect all scores into a similarity matrix s , which shares the same shape as the group.

The GroupScore metric for $k \times k$ groups. Consider a group of k images and k captions with ground-truth pairings $\{(I_i, C_i)\}_{i=1}^k$ hidden from the learner. The most widely used evaluation metric is the GroupScore (Thrush et al., 2022; Tong et al., 2024; Burapachee et al., 2024). The GroupScore equals 1 if the model’s similarity scores admit a bijection such that (i) each image is assigned to its correct caption and (ii) each caption is assigned to its correct image; otherwise it equals 0. Mathematically, we have

$$\text{GroupScore}(s) := \begin{cases} 1 & \forall i: s_{ii} > \max_{j \neq i} s_{ij} \quad \text{and} \quad s_{ii} > \max_{j \neq i} s_{ji}, \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

Evaluation metrics for $1 \times k$ groups. Without loss of generality, we assume each group consists of 1 image and k captions (Kamath et al., 2023; Hsieh et al., 2023). In this case, the GroupScore reduces to the TextScore, which equals 1 if the model selects the correct caption and 0 otherwise.

Scope and extensions. In this paper, we primarily focus on $k \times k$ and $1 \times k$ groups as they are the most common configurations in compositional reasoning benchmarks. We defer discussion of general rectangular groups of shape $m \times k$ to Appendix A.2.

3 Methods

Our approach begins with a re-examination of evaluation metrics for compositional reasoning. We introduce an alternative group matching score (GroupMatch) that better exploits group structure and reveals substantial

hidden model capability (Section 3.1). Building on this insight, we develop an iterative, self-improving *Test-Time Matching* (TTM) algorithm that bootstraps model performance without external supervision (Section 3.2). Finally, we extend TTM beyond group-structured datasets to a global matching formulation applicable to general settings (Section 3.2.1).

3.1 Revisiting evaluation metrics: from random guessing to group matching

Most compositional reasoning benchmarks use the **GroupScore** metric described in Section 2. Despite the broad practical success of frontier AI models, reported results on established benchmarks—particularly those with $k \times k$ groups—are often *at or below random guessing* (Thrush et al., 2022; Diwan et al., 2022; Tong et al., 2024; Burapachee et al., 2024; Li et al., 2025).²

Revisiting evaluation metrics. Such counter-intuitive results motivate us to re-examine evaluation metrics for $k \times k$ groups. To calibrate their behavior, we analyze a *random guessing model* under each metric. Consider a group of k images $\{I_i\}_{i=1}^k$ and k captions $\{C_i\}_{i=1}^k$, with ground-truth pairings $\{(I_i, C_i)\}_{i=1}^k$ hidden from the learner (Thrush et al., 2022; Tong et al., 2024; Burapachee et al., 2024). For each pair (I_i, C_j) , the random guessing model assigns a similarity score $\text{sim}(I_i, C_j) \sim \text{unif}([0, 1])$, producing a similarity matrix $s \in \mathbb{R}^{k \times k}$ with entries $s_{ij} := \text{sim}(I_i, C_j)$.

Under the widely used **GroupScore** metric, achieving a score of 1 requires the similarity matrix s to satisfy $2k^2 - 2k$ constraints (see Eq. (1)). Equivalently, each diagonal entry s_{ii} must be the largest element in both its row and column—a highly restrictive condition. The probability of achieving a group score of 1 under random guessing is given below (see Appendix A.1 for proofs).

Proposition 1. *For random similarity scores $s \in \mathbb{R}^{k \times k}$, $\mathbb{P}(\text{GroupScore}(s) = 1) = \frac{(k-1)!}{(2k-1)!}$.*

Group matching score: an alternative metric. We propose an alternative evaluation metric that evaluates the *best overall matching* rather than isolated pairwise comparisons. We consider *bijective matchings* (one-to-one and onto) from images to captions. Let π denote such a matching, where $\pi(i)$ is the caption assigned to image i . We define the **GroupMatch** as

$$\text{GroupMatch}(s) := \begin{cases} 1 & \text{if } \sum_{i=1}^k s_{i, \pi^*(i)} > \sum_{i=1}^k s_{i, \pi(i)}, \quad \forall \pi \neq \pi^*, \\ 0 & \text{otherwise,} \end{cases}$$

where $\pi^* : i \mapsto i$ denotes the ground-truth matching. Intuitively, the **GroupMatch** equals 1 if the *total similarity* of the ground-truth matching exceeds that of all other possible matchings. For $k = 2$, this reduces to the simple condition $s_{11} + s_{22} > s_{12} + s_{21}$. Since there are $k!$ distinct matchings (permutations) and, under random guessing, each is equally likely to maximize the total score, we obtain the following result.

Proposition 2. *For random similarity scores $s \in \mathbb{R}^{k \times k}$, $\mathbb{P}(\text{GroupMatch}(s) = 1) = \frac{1}{k!}$.*

Remark 1. *The **GroupMatch** naturally extends to general rectangular groups of shape $m \times k$ (with $m < k$) by considering all injective matchings (one-to-one). In these cases, it also improves over the **GroupScore**, increasing the expected random guessing score from $1/k^m$ to $(k-m)!/k!$ (see Appendix A.2 for details). In the special case of $1 \times k$ groups, the **GroupMatch** and the **GroupScore** coincide.*

Simple test-time matching: exploiting evaluation gaps. While there is nothing wrong with evaluating models using **GroupScore**, two key observations emerge:

- $\mathbb{P}(\text{GroupMatch}(s) = 1) > \mathbb{P}(\text{GroupScore}(s) = 1)$ for all integers $k > 1$.
- If the correct matching π^* is selected, overfitting to π^* at test time guarantees a group score of 1.

Together, these observations reveal an *arbitrage opportunity*: one can improve model performance under **GroupScore** by (i) selecting the most likely matching under **GroupMatch** and (ii) overfitting to that matching

²These benchmarks are widely adopted; for example, as of October 2025, Winoground (Thrush et al., 2022) has over 500 citations and MMVP-VLM (Tong et al., 2024) has nearly 500 citations.

Algorithm 1 Test-Time Matching (TTM)

Input: Pretrained f_0 ; test set of groups $\mathcal{D} = \{G_i\}_{i=1}^n$; number of iterations T ; thresholds $\{\tau_t\}_{t=1}^T$.

- 1: **for** iteration $t = 1$ to T **do**
- 2: Initialize pseudo-labeled set $\mathcal{S}_t \leftarrow \emptyset$.
- 3: **for** each group $G_i \in \mathcal{D}$ **do**
- 4: Induce matching $\pi_{f_{t-1}}(G_i) \leftarrow \arg \max_{\pi} s(\pi; G_i, f_{t-1})$.
- 5: Compute margin $\Delta(G_i; f_{t-1})$ as
$$\Delta(G_i; f_{t-1}) \leftarrow s(\pi_{f_{t-1}}(G_i); G_i, f_{t-1}) - \max_{\pi \neq \pi_{f_{t-1}}(G_i)} s(\pi; G_i, f_{t-1}).$$
- 6: **if** $\Delta(G_i; f_{t-1}) \geq \tau_t$ **then**
- 7: $\mathcal{S}_t \leftarrow \mathcal{S}_t \cup \{(G_i, \pi_{f_{t-1}}(G_i))\}$.
- 8: Finetune model on $\mathcal{S}_t$ to obtain f_t . *// Self-improving with no external supervision.*

Output: Test-time adapted model f_T .

at test time to transfer gains.³ We refer to this approach as **SimpleMatch** with **GroupMatch**. In the commonly studied case with $k = 2$, the expected group score of a random guessing model increases from $1/6$ to $1/2$.

Empirical validation. We evaluate **SimpleMatch** on SigLIP (Zhai et al., 2023) and GPT-4.1 across three established compositional reasoning benchmarks with $k \times k$ group structures: Winoground (Thrush et al., 2022), MMVP-VLM (Tong et al., 2024), and Colorswap (Burapachee et al., 2024). Results are presented in Fig. 1. **SimpleMatch** reveals substantial hidden capability: SigLIP-B16 improves from $10.25 \rightarrow 67$ on Winoground, $22.96 \rightarrow 81.48$ on MMVP-VLM, and $30.33 \rightarrow 88$ on ColorSwap, surpassing all previous results without access to additional data (Wu et al., 2023; Vaishnav and Tammet, 2025; Zhang et al., 2024c; Burapachee et al., 2024). GPT-4.1 also improves dramatically, from $69.75 \rightarrow 91.38$ on Winoground, $68.15 \rightarrow 88.52$ on MMVP-VLM, and $91.08 \rightarrow 97.42$ on ColorSwap—*yielding the first result to surpass the estimated human performance of 85.5 on Winoground* (Thrush et al., 2022).

3.2 Test-Time Matching: iterative bootstrapping of model performance

The alternative metric **GroupMatch** introduced in Section 3.1 reveals hidden model capability. To push performance further, we introduce a test-time matching algorithm that iteratively bootstraps model performance, yielding new state-of-the-art results. Our method applies to groups of general shapes: we consider bijective matchings for square groups and injective matchings for rectangular groups. We also extend test-time matching to datasets without group structures (Section 3.2.1).

High-level idea. Our test-time matching algorithm (Algorithm 1) proceeds iteratively for T iterations. At each round $t \in [T]$, the current model f_{t-1} induces candidate matchings for all groups, which serve as pseudo-labels. The algorithm then retains only those matchings it is most confident about, and finetunes on them to obtain the next model f_t . By repeating this process, the model progressively self-improves directly at test time, without any external supervision.

The core of Algorithm 1 lies in two design choices: (1) how pseudo-labels are induced within each group, and (2) how the confidence thresholds are scheduled across iterations. We discuss both below.

Group matching and pseudo-labeling. For a group G and model f_{t-1} , we define the induced matching

$$\pi_{f_{t-1}}(G) := \arg \max_{\pi} s(\pi; G, f_{t-1}),$$

where $s(\pi; G, f_{t-1}) := \sum_u s_{u, \pi(u)}(G; f_{t-1})$ denotes the total similarity of matching π on G under f_{t-1} . For example, in a 2×2 group, $\pi_{f_{t-1}}(G) = (1 \mapsto 1, 2 \mapsto 2)$ if $s_{11} + s_{22} > s_{12} + s_{21}$, and $(1 \mapsto 2, 2 \mapsto 1)$ otherwise.

³Since overfitting to matchings induced by **GroupMatch** achieves the same level of performance under **GroupScore**, throughout the paper, we report raw model performance under **GroupScore** and our algorithms’ performance under **GroupMatch**. The latter can always be converted to equivalent **GroupScore** performance with an additional overfitting step.

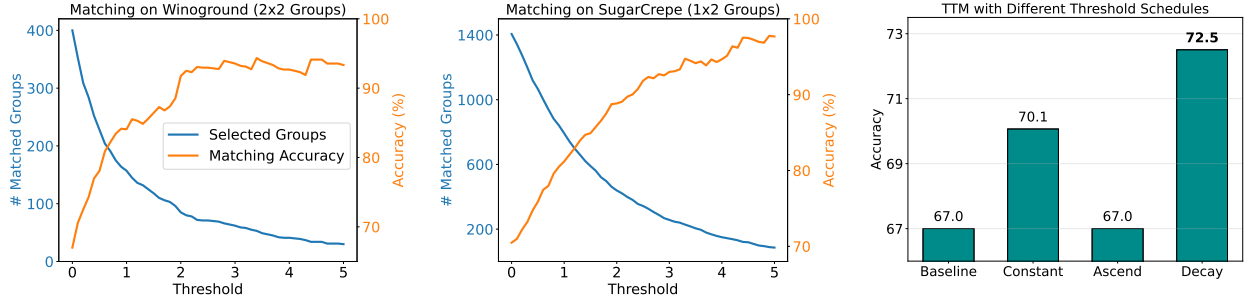


Figure 2: *Left and middle*: Matching results across different thresholds on Winoground and SugarCrepe (the Replace Relation subset) with SigLIP-B16. *Right*: Performance of TTM under different threshold schedules on Winoground with SigLIP-B16. *Baseline* denotes model performance without TTM (under GroupMatch). *Constant* applies TTM with a fixed threshold $\tau_t = 2.0$. *Ascend* applies TTM with a linearly increasing schedule from $\tau_1 = 0$ to $\tau_T = 2.0$, but yields no gains as the model quickly overfits to all pseudo-labels in the first iteration. *Decay* applies TTM with a linearly decreasing schedule from $\tau_1 = 2.0$ to $\tau_T = 0$, yielding the best performance.

For a $1 \times k$ group, the induced matching is $(1 \mapsto \arg \max_{j \in [k]} s_{1j})$. We convert $\pi_{f_{t-1}}(G)$ into a pseudo-label $(G, \pi_{f_{t-1}}(G))$ and add it to the training set $\mathcal{S}_t$ only when its *margin*

$$\Delta(G; f_{t-1}) := s(\pi_{f_{t-1}}(G); G, f_{t-1}) - \max_{\pi \neq \pi_{f_{t-1}}(G)} s(\pi; G, f_{t-1})$$

is greater than or equal to a threshold τ_t . By controlling the threshold, we ensure that the model retains pseudo-labels it is sufficiently confident about.

Iterative threshold scheduling. Lower thresholds τ_t yield more pseudo-labels but at lower precision, while higher thresholds produce fewer but cleaner labels. This trade-off is illustrated in the left and middle plots of Fig. 2, which show the number of matched groups (blue) and the accuracy among matched groups (orange) across different thresholds. To balance quality and coverage, we adopt a decaying schedule $\tau_{t+1} < \tau_t$, allowing the model to first learn from high-precision pseudo-labels before gradually expanding coverage over the test set. The right plot of Fig. 2 confirms this intuition: the decaying threshold schedule outperforms all other threshold schedules. In practice, we find it effective to set the initial threshold τ_1 such that roughly 15%–30% of the groups are matched, and the final threshold τ_T such that more than 90% of the test set is covered. Both cosine and linear decay schedules perform well. Further analyses and ablations are provided in Section 4.5.

Connection to prior arts. Our TTM algorithm can be viewed as a form of test-time training, a paradigm that has gained significant attention with the advent of powerful pre-trained models (Sun et al., 2020; Gandelsman et al., 2022; Hardt and Sun, 2024; Hübottter et al., 2025; Akyürek et al., 2025). Most prior approaches, however, treat each test instance in isolation, producing instance-specific finetuned models and often relying on instance-specific in-context examples (Akyürek et al., 2025). In contrast, TTM leverages pseudo-labels across the entire test set to iteratively update a single model under an adaptive thresholding schedule. A key feature of our approach is the use of matching—either locally (Section 3.2) or globally (Section 3.2.1)—to improve pseudo-label quality and supervision. Our adaptive thresholding schedule also resonates with classical ideas in active learning (Castro and Nowak, 2007; Balcan et al., 2007; Dasgupta et al., 2009; Hanneke, 2014; Krishnamurthy et al., 2019; Puchkin and Zhivotovskiy, 2021; Zhu and Nowak, 2022a,b), though with a reversed logic: whereas active learning queries the most uncertain data for annotation, our method begins with the most confident pseudo-labels and gradually relaxes thresholds to expand coverage. This confidence-first perspective is central to the effectiveness of TTM, enabling consistent performance gains without any external supervision.

3.2.1 Test-Time Matching without group structures

While Algorithm 1 is designed for datasets organized into local groups, the same principle extends naturally to settings without any predefined group structure. In this case, we treat the entire dataset as a single global matching problem between all images and all captions.

Let $\mathcal{S}_I$ denote the set of images and $\mathcal{S}_C$ the set of captions. We assume $|\mathcal{S}_I| \leq |\mathcal{S}_C|$ and each image has a unique corresponding caption (one-to-one assignment). Let $s \in \mathbb{R}^{|\mathcal{S}_I| \times |\mathcal{S}_C|}$ be the similarity matrix produced by a model f . We consider all injective matchings $\pi : \mathcal{S}_I \rightarrow \mathcal{S}_C$ from images to captions. The model-induced global matching is then defined as

$$\pi_f := \arg \max_{\pi: \mathcal{S}_I \rightarrow \mathcal{S}_C} \sum_{i \in \mathcal{S}_I} s_{i, \pi(i)}, \quad (2)$$

which maximizes the total similarity over image-caption pairs. Eq. (2) corresponds to the classical *assignment problem*, which can be efficiently solved by strongly-polynomial time algorithms such as the Hungarian algorithm (Kuhn, 1955).

Analogous to Algorithm 1, we adopt an iterative schedule with pseudo-labeling. At iteration t , let $\pi_{f_{t-1}}$ be the global matching induced by model f_{t-1} . Because the entire dataset is treated as a single group, group-level margin thresholding loses granularity: the model would either accept all matches or none. To address this, we apply thresholding at the level of individual pairs. Specifically, the pseudo-label set at iteration t is

$$\mathcal{S}_t := \{(i, \pi_{f_{t-1}}(i)) : s_{i, \pi_{f_{t-1}}(i)} \geq \tau_t\},$$

where τ_t is the threshold at iteration t . The threshold can be set either as an absolute value or relative to the distribution of similarity scores (i.e., the p -th percentile). Following the same principle as in Algorithm 1, we begin with a relatively high threshold to ensure high-precision pseudo-labels and gradually decay it over iterations to expand coverage and bootstrap performance over the test set.

4 Experiments

We describe experimental setups in Section 4.1, present main results in Sections 4.2 to 4.4, and provide analyses and ablations in Section 4.5. Additional experimental details and results are deferred to Appendix B.

4.1 Experimental setups

Datasets. We evaluate on five challenging compositional reasoning benchmarks: Winoground (Thrush et al., 2022), MMVP-VLM (Tong et al., 2024), Colorswap (Burapachee et al., 2024), SugarCreme (Hsieh et al., 2023), and WhatsUp (Kamath et al., 2023). Winoground, MMVP-VLM, and Colorswap consist of 2×2 groups; we also construct their non-grouped variants by discarding group structures (Section 3.2.1). SugarCreme consists of 1×2 groups and WhatsUp consists of 1×4 groups; we evaluate on 4 different subsets of SugarCreme and all 2 subsets of WhatsUp. Following Li et al. (2025), we further convert WhatsUp into 4 different variants with 2×2 groups. In total, our evaluation spans 16 dataset variations covering diverse structures and evaluation settings.

Models. We test both contrastive vision-language models and multimodal large language models. For contrastive models, we use SigLIP (Zhai et al., 2023) and CLIP (Radford et al., 2021) at multiple scales, including SigLIP-B16, SigLIP-L16, CLIP-B16, and CLIP-B32. For multimodal large language models, we use GPT-4.1, where image-text similarity is computed based on VQAScore (Lin et al., 2024).

Evaluation metrics. For GPT-4.1, we report raw GroupScore and GroupMatch-induced performance via SimpleMatch (Section 3.1). For CLIPs and SigLIPs, we additionally include results with TTM (Algorithm 1). Specifically: on 2×2 datasets we report (i) raw GroupScore, (ii) GroupMatch-induced performance, and (iii) TTM-boosted performance; on $1 \times k$ datasets we report (i) raw GroupScore and (ii) TTM-boosted performance, since GroupScore and GroupMatch coincide in this case; and on datasets without group structures we report

Table 1: Performance on Winoground, MMVP-VLM, and ColorSwap. Raw model performance is reported under GroupScore. SimpleMatch corresponds to the performance under GroupMatch (Section 3.1), and TTM corresponds to the performance of Algorithm 1. We report absolute gains (Δ), relative gains, and relative error reductions of TTM over SimpleMatch. Cells highlighted in indicate results obtained with TTM, while cells in denote the SOTA performance for each dataset.

Dataset / Model	Raw	SimpleMatch	TTM	Δ	Error Red.
Winoground					
GPT-4.1	69.75 $\pm$ 0.56	91.38 $\pm$ 0.80	—	—	—
CLIP-B16	7.25	60.00	65.44 $\pm$ 1.10	+ 5.4 (9.1% $\uparrow$)	13.6% $\downarrow$
SigLIP-B16	10.25	67.00	72.50 $\pm$ 0.64	+ 5.5 (8.2% $\uparrow$)	16.7% $\downarrow$
SigLIP-L16	13.00	69.50	72.75 $\pm$ 0.64	+ 3.3 (4.7% $\uparrow$)	10.7% $\downarrow$
MMVP-VLM					
GPT-4.1	68.15 $\pm$ 0.00	88.52 $\pm$ 0.83	—	—	—
CLIP-B16	5.19	72.59	80.19 $\pm$ 0.81	+ 7.6 (10.5% $\uparrow$)	27.7% $\downarrow$
SigLIP-B16	22.96	81.48	89.44 $\pm$ 0.96	+ 8.0 (9.8% $\uparrow$)	43.0% $\downarrow$
ColorSwap					
GPT-4.1	91.08 $\pm$ 0.28	97.42 $\pm$ 0.14	—	—	—
CLIP-B16	12.00	77.67	85.75 $\pm$ 0.64	+ 8.1 (10.4% $\uparrow$)	36.2% $\downarrow$
SigLIP-B16	30.33	88.00	94.25 $\pm$ 0.43	+ 6.3 (7.1% $\uparrow$)	52.1% $\downarrow$
SigLIP-L16	37.00	91.33	96.08 $\pm$ 0.43	+ 4.8 (5.2% $\uparrow$)	54.8% $\downarrow$

(i) raw GroupScore (with known groups), (ii) global assignment accuracy under Eq. (2), and (iii) TTM-boosted performance via the global variant introduced in Section 3.2.1. In all cases, we highlight performance gains from TTM—over GroupMatch for 2×2 datasets, over GroupScore for $1 \times k$ datasets, and over global assignment accuracy under Eq. (2) for datasets without group structures. All results are averaged over four random runs, with standard deviations reported.

4.2 TTM achieves new SOTAs

We evaluate on three established compositional reasoning benchmarks—Winoground, MMVP-VLM, and ColorSwap—all consisting of 2×2 groups and considered challenging for frontier AI models. Previous state-of-the-art results include 58.75 on Winoground (GPT-4V with prompt tuning (Wu et al., 2023; Vaishnav and Tammet, 2025)), 70.7 on MMVP (via a GPT-4o multi-agent system with tool use (Zhang et al., 2024c)),⁴ and 87.33 on ColorSwap without training-set access (95.33 with finetuning on the training set (Burapachee et al., 2024)).

Simple matching reveals hidden capabilities. Applying SimpleMatch (Section 3.1) to CLIP, SigLIP, and GPT-4.1 already yields striking improvements (Table 1). SimpleMatch enables SigLIP-B16 to surpass all prior state-of-the-art results without access to additional data, and enables GPT-4.1 to set new records across all three benchmarks. Notably, GPT-4.1 improves from 69.75 to 91.38 on Winoground, *yielding the first result to surpass the estimated human performance of 85.5* (Thrush et al., 2022). These findings confirm that the GroupMatch metric can reveal substantial hidden compositional reasoning capabilities.

Test-time matching further boosts performance. We next apply TTM (Algorithm 1) to CLIP and SigLIP, enabling additional performance gains without external supervision. As shown in Table 1, TTM *consistently improves over SimpleMatch across datasets and model scales, with relative gains up to 10.5% and relative error reduction up to 54.8%*.⁵ Crucially, TTM elevates SigLIP-L16 to the level of GPT-4.1 on

⁴This result is on MMVP, a variant of MMVP-VLM formulated as binary-choice question answering. In this paper, we focus on MMVP-VLM, which is better suited for contrastive models. Prior work has shown that model performance on the two variants is positively correlated (Tong et al., 2024; Li et al., 2025).

⁵While the absolute boosts may appear modest compared to GroupMatch-induced gains, they are *highly significant*: for comparison, scaffolding GPT-4V yields only a 1.25-point gain on the Winoground dataset, improving performance from 50.75 (Zhang et al., 2024a) to 52 (Vaishnav and Tammet, 2025).

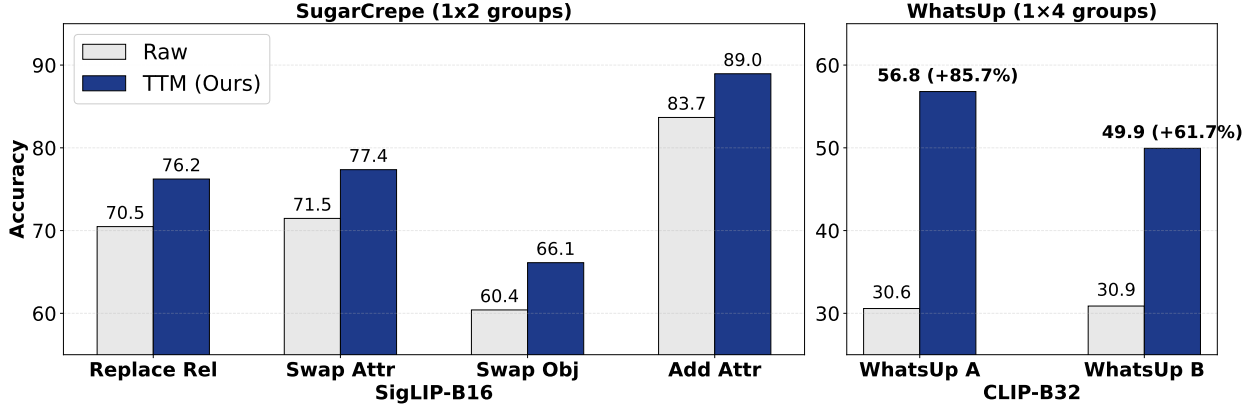


Figure 3: TTM results on benchmarks without metric-induced boosts: for $1 \times k$ groups, GroupMatch (and thus SimpleMatch) coincide with GroupScore. *Left*: results on four SugarCrepe subsets consisting of 1×2 groups. *Middle*: results on both WhatsUp subsets consisting of 1×4 groups.

Table 2: Performance on non-grouped variants of Winoground, MMVP-VLM, and ColorSwap. Raw model performance is reported under GroupScore, SimpleMatch corresponds to the performance of global assignment defined in Eq. (2), and TTM corresponds to the performance of the global variant of Algorithm 1. We report absolute gains (Δ), relative gains, and relative error reduction of TTM over SimpleMatch.

Datasets	SigLIP-B16	SimpleMatch	+ TTM	Δ	Error Red.
Winoground	10.25	44.38	46.78 $\pm$ 1.05	+ 2.4 (5.4% $\uparrow$)	4.3% $\downarrow$
MMVP-VLM	22.96	39.63	44.54 $\pm$ 2.02	+ 4.9 (12.4% $\uparrow$)	8.1% $\downarrow$
ColorSwap	30.33	88.00	92.00 $\pm$ 1.24	+ 4.0 (4.5% $\uparrow$)	33.3% $\downarrow$

ColorSwap and enables **SigLIP-B16 to surpass GPT-4.1 on MMVP-VLM, establishing a new state of the art**. These results demonstrate that TTM is a powerful and practical approach for enhancing model performance through self-improvement at test time.

4.3 TTM improves models without metric-induced boosts

To evaluate the effectiveness of Algorithm 1 beyond cases where alternative metrics can inflate performance, we consider benchmarks with $1 \times k$ group structure, where GroupScore and GroupMatch coincide and thus provide no metric-induced boost.

We experiment on 4 SugarCrepe subsets (1×2 groups) and all 2 WhatsUp subsets (1×4 groups), reporting results in Fig. 3. Even without metric-induced gains, Algorithm 1 consistently delivers substantial test-time improvements. The gains are especially striking on the WhatsUp datasets, where **performance improves by up to 85.7%**, turning these previously challenging tasks into tractable ones.

Following Li et al. (2025), we further convert the WhatsUp datasets into 4 directional variants with 2×2 group structures. As shown in Table 8 (in Appendix B.2), Algorithm 1 again yields significant improvements—**up to 135.1% relative gains and 95.5% relative error reduction**—on top of SimpleMatch. Together, these results demonstrate that TTM is broadly effective across both $k \times k$ and $1 \times k$ groups, even when metric-induced effects are absent, as in the case of $1 \times k$ groups.

4.4 TTM improves models without group structures

To further assess the generality of Algorithm 1, we evaluate its global variant introduced in Section 3.2.1 on datasets *without any predefined group structures*. Specifically, we flatten Winoground, MMVP-VLM, and ColorSwap by removing local $k \times k$ groups, resulting in a general dataset with an image set $\mathcal{S}_I$ and a caption set $\mathcal{S}_C$.

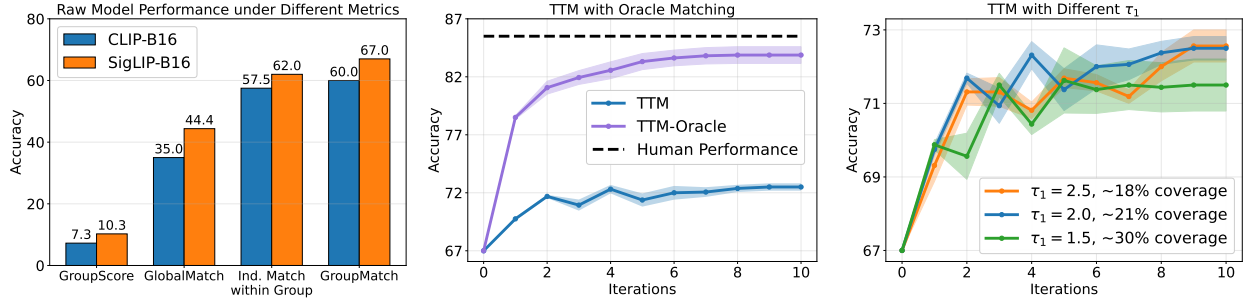


Figure 4: *Left*: Raw performance of CLIP-B16 and SigLIP-B16 on Winoground under different evaluation metrics. *Middle*: Skyline performance of TTM with oracle matching on Winoground with SigLIP-B16, illustrating the upper bound achievable by TTM. *Right*: Effect of the initial threshold τ_1 on TTM performance, evaluated on Winoground with SigLIP-B16.

We report three metrics: (i) raw **GroupScore** (with the extra knowledge of the group structure), (ii) global assignment accuracy obtained via **SimpleMatch** under Eq. (2), and (iii) TTM-boosted performance achieved using the global variant introduced in Section 3.2.1. Results show that even global assignment without group structures substantially outperforms the vanilla **GroupScore**, demonstrating the effectiveness of using *matching-based supervision* to generate high-quality pseudo-labels. More importantly, applying the iterative global TTM algorithm yields further gains over global assignment alone, with especially large relative error reductions on **ColorSwap**, i.e., **33.3% relative error reduction on ColorSwap** (see Table 2). This demonstrates that the test-time matching principle generalizes effectively beyond group-structured datasets.

4.5 Analyses and ablations

Group matching provides strong supervision signals. The key advantage of **GroupMatch** over **GroupScore** lies in its ability to leverage matching within local groups. To assess the benefits of matching and group structure, we examine the raw performance of CLIP-B16 and SigLIP-B16 under different evaluation metrics. In addition to **GroupScore** and **GroupMatch**, we consider (i) *global matching under Eq. (2)*, which performs matching but ignores group structure, and (ii) *individual matching within groups*, which preserves group structure but doesn’t perform matching: it assign captions to images independently within the group. As shown in the left plot of Fig. 4, **GroupMatch** provides the strongest supervision signal among all metrics, making it most effective for guiding pseudo-labeling.

Skyline performance with oracle matching. To study the full potential of TTM, we evaluate an oracle variant that incorporates pseudo-labels into $\mathcal{S}_t$ if and only if they are correct (i.e., with oracle access). As shown in the middle plot of Fig. 4, this oracle variant enables TTM to bootstrap more aggressively, approaching human-level performance on Winoground. This suggests that improving pseudo-label quality—potentially through the incorporation of external supervision—could further enhance the effectiveness of TTM.

Threshold selection for TTM. As discussed in Section 3.2, we generally recommend a decaying threshold schedule that begins with high-quality pseudo-labels and gradually expands coverage. In our experiments, the final threshold τ_T is set to either 0 (full coverage) or 0.1 (typically covering more than 90% of the data). The initial threshold τ_1 is more dataset- and model-dependent. If a training set or hold-out split is available, τ_1 can be selected based on matching results on that data (e.g., see the left and middle plots of Fig. 2). Otherwise, we find it effective to set τ_1 such that roughly 15%–30% of the groups are matched initially. The right plot of Fig. 4 shows TTM results on Winoground with SigLIP-B16 for $\tau_1 \in \{2.5, 2, 1.5\}$, corresponding to roughly {18%, 21%, 30%} initial coverage. While performance varies slightly across these choices, all yield consistent gains, highlighting that TTM robustly improves model performance at test time. For the global matching variant, we find it effective to set τ_1 such that about 50% of the data are pseudo-labeled initially. See Appendix B.1 for further discussion and complete hyperparameter settings used in our experiments.

5 Related work

Compositional reasoning and evaluation metrics. Contrastive vision-language models (VLMs) such as CLIP (Radford et al., 2021) and SigLIP (Zhai et al., 2023), and multimodal large language models (MLLMs) such as the GPT (Achiam et al., 2023; Hurst et al., 2024) and Gemini (Team et al., 2023; Comanici et al., 2025) series, have achieved remarkable progress across a wide range of multimodal tasks. Yet both VLMs and MLLMs struggle on benchmarks specifically designed to test *compositional reasoning*—the ability to systematically combine objects, attributes, and relations to interpret or reason about novel configurations (Lake et al., 2017; Bahdanau et al., 2019; Thrush et al., 2022; Hsieh et al., 2023; Kamath et al., 2023; Tong et al., 2024; Burapachee et al., 2024). These benchmarks are typically organized into small groups of images and captions that differ in subtle but systematic ways (e.g., captions with identical words but different orderings). The prevailing evaluation metric, the **GroupScore**, requires models to correctly assign each image to its corresponding caption and each caption to its corresponding image via isolated pairwise comparisons. While rigorous, this metric is also unforgiving: raw model performance often falls at or below random guessing (Thrush et al., 2022; Diwan et al., 2022; Tong et al., 2024; Burapachee et al., 2024; Li et al., 2025).

Despite recent attempts to improve compositional reasoning in frontier multimodal models (Wu et al., 2023; Zhang et al., 2024c; Vaishnav and Tammet, 2025), progress remains modest. For instance, the previous state of the art on Winoground—achieved by scaffolding and prompt tuning GPT-4V (Wu et al., 2023; Vaishnav and Tammet, 2025)—was only 58.75, still well below the estimated human performance of 85.5 (Thrush et al., 2022).

Our work takes a complementary perspective to prior efforts by revisiting the evaluation metrics used in compositional reasoning. We introduce a *group matching score* (**GroupMatch**) that evaluates the best overall matching rather than isolated pairwise comparisons, revealing substantial hidden capability in both VLMs and MLLMs. Crucially, by simply overfitting to the induced matchings at test time, this hidden capability transfers into higher scores under the original **GroupScore**, closing much of the reported gap. With this adjustment, GPT-4.1 improves from 69.75 to 91.38 on Winoground—*yielding the first result to surpass the estimated human performance of 85.5*. This finding echoes broader observations that measured capability can be highly sensitive to the choice of evaluation metric (Schaeffer et al., 2023), underscoring the need for continued research on evaluation protocols for frontier models.

Test-time training, pseudo-labeling, and adaptive schedules. Test-time training adapts models during inference to improve performance, with roots in early work on local learning and instance-specific adaptation (Cleveland, 1979; Cleveland and Devlin, 1988; Bottou and Vapnik, 1992; Atkeson et al., 1997). The idea has regained attention in the era of large pretrained models, where test-time self-supervision can enhance performance without additional labeled data (Sun et al., 2020; Gandelsman et al., 2022). Recent studies show that finetuning on retrieved data based on test prompts can significantly improve large language models (Hardt and Sun, 2024; Hübötter et al., 2025), and test-time training has become a key component in tackling reasoning-heavy benchmarks such as ARC (Chollet, 2019; Chollet et al., 2024; Akyürek et al., 2025).

Our test-time matching algorithm (TTM) shares this motivation but differs in key aspects. Most prior methods adapt to each test instance independently, producing per-instance finetuned models and often relying on instance-specific in-context examples (Akyürek et al., 2025). In contrast, TTM leverages **GroupMatch**-induced pseudo-labels across the *entire test set*, iteratively updating a single model through an adaptive thresholding schedule. This connects naturally to the literature on self-training (Kumar et al., 2020) and semi-supervised learning (Zhu, 2005; Chapelle et al., 2009; Sohn et al., 2020; Zhang et al., 2021, 2024b), where pseudo-labels drive improvements. A central contribution of our approach is to exploit matching and group structure—both locally and globally—to generate high-quality pseudo-labels.

Finally, our adaptive thresholding schedule resonates with classical ideas in active learning (Castro and Nowak, 2007; Balcan et al., 2007; Dasgupta et al., 2009; Hanneke, 2014; Krishnamurthy et al., 2019; Puchkin and Zhivotovskiy, 2021; Zhu and Nowak, 2022a,b), though with reversed logic: whereas active learning typically queries the most uncertain examples for human annotation, our approach begins with the most confident pseudo-labels and gradually relaxes thresholds to expand coverage. This confidence-first perspective is central to the effectiveness of TTM, enabling consistent performance gains without any external supervision.

6 Discussion

This work revisits the long-standing puzzle of compositional reasoning, where modern multimodal models often appear to perform no better than random guessing (Thrush et al., 2022; Diwan et al., 2022; Tong et al., 2024; Burapachee et al., 2024; Li et al., 2025). We show that this apparent limitation partly arises from the evaluation metrics themselves, which systematically underestimate model capability. By introducing the *group matching score* and a simple test-time matching procedure, we reveal substantial hidden capability in both contrastive vision-language models and multimodal large language models—enough for GPT-4.1 to surpass estimated human performance on Winoground. Building on this insight, we propose *Test-Time Matching* (TTM), an iterative, self-improving algorithm that further bootstraps model performance without external supervision. TTM enables SigLIP-B16 to outperform GPT-4.1 on MMVP-VLM, establishing a new state of the art. Experiments across 16 dataset variants demonstrate that TTM consistently improves performance across diverse settings, including those without metric-induced effects or predefined group structures.

Moving forward, we highlight two promising directions:

- **Rethinking multimodal evaluation.** The same model on the same dataset can yield vastly different results under different metrics. This underscores the need for more robust, transparent, and reliable evaluation protocols for compositional reasoning and beyond (Schaeffer et al., 2023).
- **Extending TTM beyond compositional reasoning.** While developed in the context of compositional reasoning, the core principle of TTM—iterative, matching-based self-training at test time—is general. A natural next step is to explore this idea in broader multimodal or language-only settings.

Author contributions

YZ conceived the project, developed the algorithms, performed the majority of the implementation and experiments, and wrote the manuscript. JZ and FT assisted with the implementation; JZ additionally conducted experiments on the WhatsUp datasets.

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A Proofs and supporting results from Section 3

A.1 Proofs of Proposition 1 and Proposition 2

Proposition 1. For random similarity scores $s \in \mathbb{R}^{k \times k}$, $\mathbb{P}(\text{GroupScore}(s) = 1) = \frac{(k-1)!}{(2k-1)!}$.

Proof. Because the entries of s are i.i.d. sampled from a continuous distribution (here $\text{unif}([0, 1])$), ties occur with probability 0, so we may use strict inequalities throughout.

Denote $d_i := s_{ii}$ and, for $i \neq j$, set $m_{ij} := \min\{d_i, d_j\}$. By the definition of the **GroupScore**, the event $\{\text{GroupScore}(s) = 1\}$ is equivalent to requiring $s_{ij} < m_{ij}$ and $s_{ji} < m_{ij}$ for every $i \neq j$. Conditioning on the diagonal $d = (d_1, \dots, d_k)$ and using independence of the off-diagonal entries,

$$\mathbb{P}(\text{GroupScore}(s) = 1 \mid d) = \prod_{i < j} \mathbb{P}(s_{ij} < m_{ij}) \mathbb{P}(s_{ji} < m_{ij}) = \prod_{i < j} m_{ij}^2.$$

Let $0 < x_1 < \dots < x_k < 1$ be the order statistics of $(d_1, \dots, d_k)$. We then have $m_{ij} = x_{\min\{r(i), r(j)\}}$, where $r(\cdot)$ is the rank, hence

$$\prod_{i < j} m_{ij}^2 = \prod_{a=1}^k x_a^{2(k-a)}.$$

Since $(x_1, \dots, x_k)$ are the order statistics of i.i.d. $\text{unif}([0, 1])$ samples, their joint density is $k!$ on the ordered region $\{0 < x_1 < \dots < x_k < 1\}$ (and 0 elsewhere). Therefore,

$$\mathbb{P}(\text{GroupScore}(s) = 1) = k! \int_{0 < x_1 < \dots < x_k < 1} \prod_{a=1}^k x_a^{2(k-a)} dx_1 \dots dx_k.$$

For $1 \leq \ell \leq k$ and $y \in (0, 1]$, define

$$I_\ell(y) := \int_{0 < x_1 < \dots < x_\ell < y} \prod_{a=1}^\ell x_a^{2(k-a)} dx_1 \dots dx_\ell.$$

We claim that, for $\ell = 1, \dots, k$,

$$I_\ell(y) = \frac{y^{\ell(2k-\ell)}}{\prod_{r=1}^\ell r(2k-r)}.$$

This is proved by induction on ℓ . For $\ell = 1$,

$$I_1(y) = \int_0^y x^{2(k-1)} dx = \frac{y^{2k-1}}{2k-1}.$$

Assume it holds for $\ell - 1$. Then

$$\begin{aligned} I_\ell(y) &= \int_0^y x_\ell^{2(k-\ell)} I_{\ell-1}(x_\ell) dx_\ell \\ &= \frac{1}{\prod_{r=1}^{\ell-1} r(2k-r)} \int_0^y x_\ell^{2(k-\ell)+(\ell-1)(2k-(\ell-1))} dx_\ell \\ &= \frac{1}{\prod_{r=1}^{\ell-1} r(2k-r)} \cdot \frac{y^{\ell(2k-\ell)}}{\ell(2k-\ell)}, \end{aligned}$$

since $2(k-\ell) + (\ell-1)(2k-(\ell-1)) = \ell(2k-\ell) - 1$. Thus the claim holds. Taking $\ell = k$ and $y = 1$ gives

$$\int_{0 < x_1 < \dots < x_k < 1} \prod_{a=1}^k x_a^{2(k-a)} dx_1 \dots dx_k = I_k(1) = \frac{1}{\prod_{r=1}^k r(2k-r)}.$$

Therefore,

$$\mathbb{P}(\text{GroupScore}(s) = 1) = k! \prod_{r=1}^k \frac{1}{r(2k-r)} = \frac{(k-1)!}{(2k-1)!}.$$

□

Proposition 2. For random similarity scores $s \in \mathbb{R}^{k \times k}$, $\mathbb{P}(\text{GroupMatch}(s) = 1) = \frac{1}{k!}$.

Proof. There are $k!$ distinct injective matchings. Since the random variables $\{s_{ij}\}$ are continuous, ties occur with probability 0. By symmetry, each injective matching is equally likely to achieve the maximum total similarity. Hence, the probability that the ground-truth matching π^* attains the maximum is $\frac{1}{k!}$. □

A.2 Supporting results for general rectangular groups

Without loss of generality, we consider a group of m images $\{I_i\}_{i=1}^m$ and k captions $\{C_i\}_{i=1}^k$ with $m < k$. We assume the ground-truth pairings is $\{(I_i, C_i)\}_{i=1}^m$ (hidden from the learner). As in the main text, we study a random guessing model that assigns i.i.d. similarity scores $s_{ij} := \text{sim}(I_i, C_j) \sim \text{unif}([0, 1])$ for each pair (I_i, C_j) , and collect them into a similarity matrix $s \in \mathbb{R}^{m \times k}$.

GroupScore for $m \times k$ groups. Analogous to the $k \times k$ and $1 \times k$ cases, the GroupScore for $m \times k$ groups can be defined as

$$\text{GroupScore}(s) := \begin{cases} 1 & \forall i \in [m] : s_{ii} > \max_{j \neq i} s_{ij}, \\ 0 & \text{otherwise.} \end{cases}$$

Under the random guessing model, the probability of achieving a GroupScore of 1 for rectangular group is given below.

Proposition 3. For random similarity score $s \in \mathbb{R}^{m \times k}$, $\mathbb{P}(\text{GroupScore}(s) = 1) = \frac{1}{k^m}$.

Proof. Since the random variables $\{s_{ij}\}$ are continuous, ties occur with probability 0. For each row i , by symmetry, the probability that s_{ii} is the largest among the k i.i.d. entries $\{s_{ij}\}_{j=1}^k$ is $1/k$. Since rows are independent, we have

$$\mathbb{P}(\forall i \in [m] : s_{ii} > \max_{j \neq i} s_{ij}) = \prod_{i=1}^m \frac{1}{k} = \frac{1}{k^m}.$$

□

GroupMatch for $m \times k$ groups. We extend GroupMatch to the general rectangular case by considering *injective* matchings $\pi : [m] \rightarrow [k]$ (i.e., $\pi(i) \neq \pi(j)$ for $i \neq j$). With the ground-truth injective matching $\pi^* : i \mapsto i$, we define GroupMatch as

$$\text{GroupMatch}(s) := \begin{cases} 1 & \text{if } \sum_{i=1}^m s_{i, \pi^*(i)} > \sum_{i=1}^m s_{i, \pi(i)}, \quad \forall \pi \neq \pi^*, \\ 0 & \text{otherwise.} \end{cases}$$

Under the random guessing model, the probability of achieving a GroupMatch of 1 for rectangular group is given below.

Proposition 4. For random similarity scores $s \in \mathbb{R}^{m \times k}$, $\mathbb{P}(\text{GroupMatch}(s) = 1) = \frac{(k-m)!}{k!}$.

Proof. There are $\frac{k!}{(k-m)!}$ distinct injective matchings. Since the random variables $\{s_{ij}\}$ are continuous, ties occur with probability 0. By symmetry, each injective matching is equally likely to achieve the maximum total similarity. Hence, the probability that the ground-truth matching π^* attains the maximum is $\left(\frac{k!}{(k-m)!}\right)^{-1} = \frac{(k-m)!}{k!}$. □

GroupMatch helps for rectangular groups. For random similarity scores $s \in \mathbb{R}^{m \times k}$,

$$\mathbb{P}(\text{GroupMatch}(s) = 1) = \frac{(k-m)!}{k!} = \frac{1}{k(k-1) \cdots (k-m+1)} \geq \frac{1}{k^m} = \mathbb{P}(\text{GroupScore}(s) = 1),$$

with strict inequality for any $m \geq 2$ and equality for $m = 1$ (GroupMatch and GroupScore coincide when $m = 1$). Moreover, if the ground-truth injective matching π^* is identified, overfitting to the matching π^* at test time guarantees a GroupScore of 1. Thus, as in the square case, one can improve model performance under GroupScore via SimpleMatch: (i) selecting the most likely matching under GroupMatch and (ii) overfitting to the matching at test time to transfer gains.

B Other details for experiments

B.1 Additional details and hyperparameters

We provide additional experimental details and hyperparameter settings below. For TTM, we set the number of iterations to $T = 10$ and train for 20 epochs per iteration by default, except on Winoground where we train for 30 epochs per iteration. Across all experiments, we use AdamW (Loshchilov and Hutter, 2017) with weight decay 0.05 and $(\beta_1, \beta_2) = (0.9, 0.999)$. The learning rate follows a cosine decay schedule and is restarted at each iteration with a multiplicative factor of 0.95. Optimizer states are reset at each restart, with the exception of SigLIP-B16 on Winoground. We use a batch size of 50 for 2×2 datasets and 100 for $1 \times k$ datasets; the batch size is defined at the group level (e.g., 50 groups of size 2×2 per batch).⁶

By default, we do not apply data augmentation during training, as many datasets are designed to be sensitive to location or color. However, we find it beneficial to apply a simple resizing (factor 1.1) followed by random cropping for the following dataset-model pairs: Winoground with SigLIP-L16, MMVP-VLM with SigLIP-B16, ColorSwap with SigLIP-B16, MMVP-VLM with SigLIP-B16 under global matching, and CLIP-B32 with WhatsUp A-Left-Right.

In Tables 3 to 5, we report, for each dataset-model pair, the initial threshold τ_1 , the final threshold τ_T , the threshold decay schedule (linear or cosine), and the learning rate (lr). For group matching (Tables 3 and 4), we use absolute thresholds. For global matching, we adopt the percentile-based thresholding mentioned in Section 3.2.1: at iteration t , the top $1 - \tau_t$ fraction of pseudo-labels (ranked by similarity) is selected.

In our experiments, the final threshold τ_T is set to either 0 (full coverage) or 0.1 (typically covering more than 90% of the data). The initial threshold τ_1 is more dataset- and model-dependent. For group matching, we find it effective to set τ_1 such that roughly 15%–30% of the groups are matched initially, though in some cases we use thresholds outside this range when they yield better performance (e.g., higher selection fractions for ColorSwap with SigLIP models and lower fractions for WhatsUp 2×2 variants with CLIP-B32). For global matching, performance tends to improve with a larger initial selection fraction—typically around 50%.

Table 3: Hyperparameters used for experiments in Section 4.2.

Dataset	Model	τ_1	τ_T	Schedule	lr
Winoground	CLIP-B16	0.9	0	linear	2.0×10^{-5}
	SigLIP-B16	2.0	0	linear	1.0×10^{-5}
	SigLIP-L16	2.0	0.1	cosine	4.0×10^{-5}
MMVP-VLM	CLIP-B16	2.0	0	linear	1.0×10^{-5}
	SigLIP-B16	2.0	0.1	cosine	2.0×10^{-5}
ColorSwap	CLIP-B16	2.3	0	cosine	4.0×10^{-5}
	SigLIP-B16	1.0	0	cosine	4.0×10^{-5}
	SigLIP-L16	2.5	0	cosine	4.0×10^{-5}

⁶We slightly increase the batch size when the total number of groups is just above a multiple of the default size. For instance, if the dataset contains 102 groups, we set the batch size to 51.

Table 4: Hyperparameters used for experiments in [Section 4.3](#).

Variant	Model	τ_1	τ_T	Schedule	lr
Replace Relation	SigLIP-B16	2.1	0	cosine	1.0×10^{-5}
Swap Attribute	SigLIP-B16	1.8	0	cosine	1.0×10^{-5}
Swap Object	SigLIP-B16	2.0	0	cosine	1.0×10^{-5}
Add Attribute	SigLIP-B16	2.5	0	cosine	1.0×10^{-5}
WhatsUp A (1×4)	CLIP-B32	0.55	0	linear	1.0×10^{-5}
WhatsUp B (1×4)	CLIP-B32	0.80	0	linear	1.0×10^{-5}
A-Left-Right (2×2)	CLIP-B32	0.25	0	linear	1.0×10^{-5}
A-On-Under (2×2)	CLIP-B32	0.85	0	linear	1.0×10^{-5}
B-Left-Right (2×2)	CLIP-B32	0.50	0	cosine	2.0×10^{-5}
B-Front-Behind (2×2)	CLIP-B32	1.30	0	cosine	2.0×10^{-5}

Table 5: Hyperparameters used for experiments in [Section 4.4](#). We adopt percentile-based thresholding: at iteration t , the top $1 - \tau_t$ fraction of pseudo-labels (ranked by similarity) is selected.

Dataset	Model	τ_1	τ_T	Schedule	lr
Winoground	SigLIP-B16	0.50	0	linear	1.0×10^{-5}
MMVP-VLM	SigLIP-B16	0.55	0	linear	2.0×10^{-5}
ColorSwap	SigLIP-B16	0.50	0	linear	4.0×10^{-5}

B.2 Complete results from [Section 4.3](#)

We present complete empirical results for [Fig. 3](#) below in [Tables 6](#) and [7](#). Following [Li et al. \(2025\)](#), we further convert the WhatsUp datasets into four directional variants with 2×2 group structures and present results in [Table 8](#): [Algorithm 1](#) again yields significant improvements—**up to 135.1% relative gains and 95.5% relative error reduction**—on top of SimpleMatch. Together, these results demonstrate that TTM is broadly effective across both $k \times k$ and $1 \times k$ settings, even in cases where evaluation metrics themselves cannot induce gains.

Table 6: Performance on SugarCrep datasets (1×2 groups) without metric-induced boosts: for $1 \times k$ groups, GroupScore and GroupMatch coincide. Raw SigLIP-B16 performance is reported under GroupScore, and TTM corresponds to the performance of [Algorithm 1](#). We report absolute gains (Δ), relative gains, and relative error reductions of TTM over the raw model performance.

Datasets	SigLIP-B16	TTM	Δ	Error Reduction
Replace Relation	70.48	76.23 $\pm$ 0.51	+ 5.8 (8.2% $\uparrow$)	19.5% $\downarrow$
Swap Attribute	71.47	77.36 $\pm$ 0.71	+ 5.9 (8.2% $\uparrow$)	20.6% $\downarrow$
Swap Object	60.41	66.12 $\pm$ 2.06	+ 5.7 (9.5% $\uparrow$)	14.4% $\downarrow$
Add Attribute	83.67	88.95 $\pm$ 0.83	+ 5.3 (6.3% $\uparrow$)	32.3% $\downarrow$

Table 7: Performance on WhatsUp A/B datasets (1×4 groups) without metric-induced boosts: for $1 \times k$ groups, GroupScore and GroupMatch coincide. Raw CLIP-B32 performance is reported under GroupScore, and TTM corresponds to the performance of Algorithm 1. We report absolute gains (Δ), relative gains, and relative error reductions of TTM over the raw model performance.

Datasets	CLIP-B32	TTM	Δ	Error Reduction
WhatsUp A	30.58	56.8 ± 1.84	+ 26.2 (85.7% $\uparrow$)	37.7% $\downarrow$
WhatsUp B	30.88	49.94 ± 2.58	+ 19.1 (61.7% $\uparrow$)	27.6% $\downarrow$

Table 8: Performance on WhatsUp 2×2 directional variants: LR: left-right, OU: on-under; FB: front-behind. Raw CLIP-B32 performance is reported under GroupScore. SimpleMatch corresponds to the performance under GroupMatch (Section 3.1), and TTM corresponds to the performance of Algorithm 1. We report absolute gains (Δ), relative gains, and relative error reductions of TTM over SimpleMatch.

Datasets	CLIP-B32	SimpleMatch	TTM	Δ	Error Reduction
A-LR	0	40.78	95.87 ± 4.42	+ 55.1 (135.1% $\uparrow$)	93.0% $\downarrow$
A-OU	3.88	78.64	99.03 ± 0	+ 20.4 (25.9% $\uparrow$)	95.5% $\downarrow$
B-LR	0	55.88	82.84 ± 0.49	+ 27.0 (48.2% $\uparrow$)	61.1% $\downarrow$
B-FB	0	47.06	66.67 ± 1.30	+ 19.6 (41.7% $\uparrow$)	37.0% $\downarrow$