Abstract

In this work, we use a transformer-based pretrained multimodal model, CLIP, to shed light on the mechanisms employed by human speakers when referring to visual entities. In particular, we use CLIP to quantify the degree of descriptiveness (how well an utterance describes an image in isolation) and discriminativeness (to what extent an utterance is effective in picking out a single image among similar images) of human referring utterances within multimodal dialogues. Overall, our results show that utterances become less descriptive over time while their discriminativeness remains unchanged. Through analysis, we propose that this trend could be due to participants relying on the previous mentions in the dialogue history, as well as being able to distill the most discriminative information from the visual context. In general, our study opens up the possibility of using this and similar models to quantify patterns in human data and shed light on the underlying cognitive mechanisms.

1 Introduction

During a conversation, speakers can refer to an entity (e.g., the girl in Fig. 1) multiple times within different contexts. This has been shown to lead to subsequent referring expressions that are usually shorter and that show lexical entrainment with previous mentions (Krauss and Weinheimer, 1967; Brennan and Clark, 1996). This trend has been confirmed in recent vision-and-language (V&L) datasets (Shore and Skantze, 2018; Haber et al., 2019; Hawkins et al., 2020): referring utterances become more compact (i.e., less descriptive), and yet participants are able to identify the intended referent (i.e., they remain pragmatically informative).

Several approaches (Mao et al., 2016; Cohn-Gordon et al., 2018; Schüz et al., 2021; Luo et al., 2018, i.a.) have tackled the generation of image captions from the perspective of pragmatic informativity; Coppock et al. (2020) have compared the informativity of image captions and of referring expressions; and Haber et al. (2019); Hawkins et al. (2020) have explored how dialogue history contributes to discriminativeness. However, no work to date has investigated how these two dimensions, descriptiveness and discriminativeness or pragmatic informativity, interact in referring expressions uttered in dialogue.

In this work, we use a transformer-based pretrained multimodal model to study the interplay between descriptiveness and discriminativeness in human referring utterances produced in dialogue. Due to their unprecedented success in numerous tasks, pretrained V&L models—such as LXMERT (Tan and Bansal, 2019), VisualBERT (Li et al., 2019), UNITER (Chen et al., 2020) and ALIGN (Jia et al., 2021)—have recently attracted a lot of interest aimed at understanding the properties and potential of their learned representations as well as the effect their architectures and training setups have (Bugliarello et al., 2021). These include probing such models in a zero-shot manner, i.e., without any specific fine-tuning (Hendricks and Nematzadeh, 2021; Parcalabescu et al., 2021); quantifying the roles of each modality (Frank et al., 2021); inspecting attention patterns (Cao et al., 2020); and evaluating their learned multimodal representations against human judgments (Pezzelle et al., 2021).

We focus on one model: Contrastive Language-
Image Pre-training (CLIP, Radford et al., 2021), which learns via contrasting images and texts that can be aligned or unaligned with each other. This contrastive objective makes CLIP particularly suitable for modelling referential tasks that inherently include such comparisons. Here, we use CLIP to gain insight into the strategies used by humans in sequential reference settings, finding that although the descriptiveness of referring utterances decreases significantly, the utterances remain discriminative over the course of multimodal dialogue. The code to reproduce our results is available at https://github.com/ecekt/clip-desc-disc.

2 Data

We focus on PhotoBook (PB; Haber et al., 2019), a dataset of multimodal task-oriented dialogues where players aim to pick the images they have in common without seeing each other’s visual contexts (which consist of 6 images coming from the same domain). The game is played over several rounds in which the previously seen images reappear in different visual contexts, giving the players an opportunity to refer to such images again. As a result, chains of utterances referring to a single image are formed over the rounds as the players build common ground. See Fig. 1 for a simplified representation of a chain. In total, PB consists of 2,500 games, 165K utterances, and 360 unique images from COCO (Lin et al., 2014).

All our experiments are conducted on a subset of 50 PB games with manually annotated referring utterances, which contains 364 referential chains about 205 unique target images. We refer to this subset as PB-GOLD. Although a dataset of automatically-extracted chains using all PB data is also available (Takmaz et al., 2020), as reported by the authors these chains may contain errors. We therefore opt for using the smaller but higher-quality PB-GOLD subset since we are interested in analysing human strategies. Given that we use a pretrained model without fine-tuning, experimenting with large amounts of data is not a requisite.

PB-GOLD’s chains contain 1,078 utterances, i.e., 2.96 utterances per chain on average (min 1, max 4). We henceforth use the term ‘rank’ to refer to the position of an utterance in a chain. The average token length of utterances is 13.34, 11.03, 9.23, and 7.82, respectively, for ranks 1, 2, 3, and 4. This decreasing trend, which is statistically significant at p < 0.01 with respect to independent samples t-tests between the ranks, is in line with the trend observed in the whole dataset (Haber et al., 2019). PB-GOLD’s vocabulary consists of 926 tokens.

3 Model

We use CLIP (Radford et al., 2021), a model pretrained on a dataset of 400 million image-text pairs collected from the internet using a contrastive objective to learn strong transferable vision representations with natural language supervision. In particular, we employ the ViT-B/32 version of CLIP, which utilizes separate transformers to encode vision and language (Vaswani et al., 2017; Dosovitskiy et al., 2021; Radford et al., 2019, 2021).

As the model learns to align images and texts, this enables zero-shot transfer to various V&L tasks such as image-text retrieval and image classification and even certain non-traditional tasks in a simple and efficient manner (Radford et al., 2019; Agarwal et al., 2021; Shen et al., 2021; Cafagna et al., 2021; Hessel et al., 2021). This makes it an intriguing tool to investigate the properties of visually grounded referring utterances. In this work, we freeze CLIP’s weights and do not fine-tune the model or perform prompt engineering, since we aim to exploit the model’s pretrained knowledge for the analysis of human referring strategies.

4 Descriptiveness

In our first experiment, we investigate the degree of descriptiveness exhibited by referring utterances in the PhotoBook game, i.e., the amount of information they provide about the image out of context. We consider each target image and corresponding referential utterance at a given rank in isolation, i.e., without taking into account the other competing images nor the dialogue history. We quantify descriptiveness as the alignment between an utterance and its image referent using CLIPS (Hessel et al., 2021), assuming that a more descriptive utterance will attain a higher score. For all the target image-utterance pairs in the chains of PB-GOLD, we use CLIP to obtain a vector t representing the utterance and a

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1 Only 1 player’s perspective for 1 context is represented.
2 We use the gold set of the utterance-based chains v2 available at https://dmg-photobook.github.io/.
3 We use TweetTokenizer: https://www.nltk.org/api/nltk.tokenize.html
4 https://github.com/openai/CLIP
Figure 2: Set of captions from COCO (Lin et al., 2014), the order of captions is arbitrary.

Figure 3: Sequential description from Image Description Sequences (Ilinykh et al., 2019).

vector \( v \) representing the image. CLIPScore is then computed as the scaled cosine similarity between these two vectors, with range \([0, 2.5] \): 
\[
\text{CLIPScore}(t, v) = 2.5 \times \max(\cos(t, v), 0).
\]
We compute the average CLIPScore per rank over the whole PB-GOLD dataset.

Results. We find that earlier utterances are better aligned with the target image features and that there is a monotonically decreasing trend over the 4 ranks (Fig. 4, blue bars). The differences between all pairs of ranks are statistically significant (according to independent samples t-tests, \( p < 0.01 \)), except for the comparison between the last 2 ranks (\( p > 0.05 \)). Since earlier referring utterances tend to be longer (see Sec. 2), we check to what extent length may be a confounding factor. We find that there is only a weak correlation between token length and CLIPScore (Spearman’s \( \rho = 0.29, p < 0.001 \)).

We compare these results on PhotoBook with text-to-image alignment computed with the same method on two other datasets: (1) COCO (Lin et al., 2014), which includes 5 captions per image provided independently by different annotators as shown in Fig. 2; here we do not expect to find significant differences in the level of descriptive-ness across the captions, and (2) Image Description Sequences (IDS, Ilinykh et al., 2019) where one participant describes an image incrementally as shown in Fig. 3, by progressively adding sentences with further details; here we do expect a similar pattern to PhotoBook, albeit for different reasons (because participants add less salient information; Ilinykh et al., 2019).

Fig. 4 shows that these expectations are confirmed. According to CLIP, COCO captions (green bars) are more descriptive than IDS descriptions and PB referring utterances, and are equally aligned with the image across ‘ranks’ (the order is arbitrary in this case). In contrast, IDS incremental descriptions (yellow bars) are intrinsically ordered and show a significant decreasing trend similar to PB.

5 Discriminativeness

In order for a listener to select the target image among distractor images, a referring utterance should be discriminative in its visual context. Our results in the previous section show that descriptive-ness decreases over time—what is the trend regarding discriminativeness? To address this question, in our second experiment we use CLIP from the perspective of reference resolution.

We focus on local text-to-image alignment, initially ignoring the previous dialogue history. To this end, we feed CLIP a single referring utterance together with the visual context of the speaker who produced that utterance. CLIP yields softmax probabilities for each image contrasted with the single text. As a metric, we use accuracy: 1 if the target image gets the highest probability; 0 otherwise.

Results. The overall accuracy is 80.15%, which is well above the random baseline of 16.67%. In Fig. 5, we break down the results per rank (blue bars). A \( 4 \times 2 \) chi-square test (4 ranks vs. correct/incorrect) did not yield significant differences
in accuracy between the ranks, $p > 0.05$. Thus, although descriptiveness decreases over time, discriminativeness is not significantly affected. An analysis of the entropy of the softmax distributions reveals that entropy increases monotonically over the ranks (this difference is statistically significant according to an independent samples t-test between ranks 1 and 4; $H_1 = 0.62, H_4 = 0.79, p < 0.01$). That is, the model is more uncertain when trying to resolve less descriptive utterances. There is indeed a negative correlation between entropy and CLIPScore computed between the target image and the corresponding utterance (Spearman’s $\rho = -0.5, p < 0.001$).

6 Analysis

How do participants manage to maintain discriminativeness while decreasing descriptiveness? Do they rely on the previous mentions present in the dialogue history? Do they refine their referring strategy by distilling the most discriminative information in a given context?

6.1 Dialogue history

The results of our experiment in the previous section show that the utterances in isolation are effective at referring; yet, uncertainty increases when the less descriptive utterances are considered out of context. To reduce such uncertainty, participants may rely on the dialogue history (Brennan and Clark, 1996; Shore and Skantze, 2018; Takmaz et al., 2020). We consider a scenario where participants keep in memory the previous mention when processing the current referring utterance. We model this scenario by prepending the previous referring utterance in the chain to the current utterance and feeding this into the reference resolution model described in Section 5. As shown in Fig. 5, the resulting discriminativeness is similar to the one obtained earlier (the differences are not significant; chi-square test, $p < 0.05$) and, as before, remains stable across ranks (chi-square test, $p > 0.05$). However, taking into account the previous mentions leads to a significant reduction of the entropy in general: e.g., at the last rank $H_4 = 0.79$ vs. $H'_4 = 0.62$ (t-test, $p < 0.05$). This suggests that relying on the dialogue history allows speakers to use less descriptive utterances by reducing discriminative uncertainty.

6.2 Most discriminative information

Besides exploiting the dialogue history, participants may refine their referring strategy by distilling the most discriminative information in a given context. To gain insight into this hypothesis, we explore what is discriminative in the images: we compute the discriminative features $v_d$ of a target image by taking the average of the visual representations of distractor images to obtain the mean context vector and then subtracting this vector from the visual representation of the target image. We encode all 926 words in the vocabulary of PB-GOLD using CLIP, and retrieve the top-10 words whose representations are the closest to $v_d$ in terms of cosine similarity (amounting to 1% of the vocabulary). We take these words to convey the most discriminative properties of an image in context. We analyse whether at least one of these retrieved words is mentioned exactly in the referring utterance, finding that this is indeed the case for a remarkable 60% of utterances.\footnote{Randomly sampling 10 words from the vocabulary for each utterance yields 11% (average of 5 random runs).}

As an illustration, for the example in Fig. 1, the words walking (mentioned at rank 1)
and blue (used at ranks 1, 2, 3, 4) are among the top-10 most discriminative words, while the word water (mentioned at ranks 1, 2, 3, 4) is close to the word beach, which is also retrieved as one of most discriminative words in this case.

The most discriminative words are likely to be reused in later utterances, even though the visual context changes from rank to rank. For instance, the most discriminative words mentioned at rank 1 constitute 60% of the discriminative words at rank 2, indicating that entrainment is likely for words that have high utility across contexts. We also find a significant increase in the proportion of discriminative content words to all the content words per utterance (only between ranks 1 and 4, 14% vs. 19%, p < 0.01).

7 Conclusion

We used a pre-trained multimodal model claimed to be a reference-free caption evaluator, CLIP (Radford et al., 2021), to quantify descriptiveness and discriminativeness of human referring utterances within multimodal dialogues. We showed that (i) later utterances in a dialogue become less descriptive in isolation while (ii) remaining similarly discriminative against a visual context.

We found that the addition of dialogue history helps decrease and control the entropy of resolution accuracy even when the speakers produce less descriptive referring utterances. In addition, we found that the proportion of discriminative words increases over the ranks. These suggest that participants playing the PhotoBook game (Haber et al., 2019) show a tendency towards distilling discriminative words and utilize the dialogue history to keep task performance stable over the dialogue. This outcome resonates with the findings by Giulianelli et al. (2021) who observe that PhotoBook dialogue participants tend to limit fluctuations in the amount of information transmitted within reference chains, in line with uniform information density principles (e.g., Genzel and Charniak, 2002; Jaeger and Levy, 2007).

Interestingly, future work could explore novel ways of incorporating the CLIP model or its representations into a reference resolution or generation model embedding dialogue history and visual context to obtain human-like outcomes.

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References

Sandhini Agarwal, Gretchen Krueger, Jack Clark, Alec Radford, Jong Wook Kim, and Miles Brundage. 2021. Evaluating clip: Towards characterization of broader capabilities and downstream implications.

Susan E. Brennan and Herbert H. Clark. 1996. Conceptual pacts and lexical choice in conversation. Journal of Experimental Psychology: Learning, Memory, and Cognition, 22:1482–1493.

Emanuele Bugliarello, Ryan Cotterell, Naoaki Okazaki, and Desmond Elliott. 2021. Multimodal pretraining unmasked: A meta-analysis and a unified framework of vision-and-language BERTs. Transactions of the Association for Computational Linguistics.

Michele Cafagna, Kees van Deemter, and Albert Gatt. 2021. What vision-language models ’see’ when they see scenes. ArXiv, abs/2109.07301.

Jize Cao, Zhe Gan, Yu Cheng, Licheng Yu, Yen-Chun Chen, and Jingjing Liu. 2020. Behind the scene: Revealing the secrets of pre-trained vision-and-language models. ECCV Spotlight.

Yen-Chun Chen, Linjie Li, Licheng Yu, Ahmed El Kholy, Faisal Ahmed, Zhe Gan, Yu Cheng, and Jingjing Liu. 2020. UNITER: Universal image-text representation learning. In European Conference on Computer Vision, pages 104–120. Springer.

Reuben Cohn-Gordon, Noah Goodman, and Christopher Potts. 2018. Pragmatically informative image captioning with character-level inference. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers), pages 439–443, New Orleans, Louisiana. Association for Computational Linguistics.

Elizabeth Coppock, Danielle Dionne, Nathanial Graham, Elias Ganem, Shijie Zhao, Shawn Lin, Wenxing Liu, and Derry Wijaya. 2020. Informativity in image captions vs. referring expressions. In Proceedings of the Probability and Meaning Conference (PaM 2020), pages 104–108, Gothenburg. Association for Computational Linguistics.

Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai,
Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, and Neil Houlsby. 2021. An image is worth 16x16 words: Transformers for image recognition at scale.

Stella Frank, Emanuele Bugliarello, and Desmond Elliott. 2021. Vision-and-language or vision-for-language? On cross-modal influence in multimodal transformers. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing (EMNLP 2021). Association for Computational Linguistics.

Dmitriy Genzel and Eugene Charniak. 2002. Entropy rate constancy in text. In Proceedings of the 40th annual meeting of the Association for Computational Linguistics, pages 199–206.

Mario Giulianelli, Arabella Sinclair, and Raquel Fernández. 2021. Is information density uniform in task-oriented dialogues? In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 8271–8283. Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Janosch Haber, Tim Baumgartner, Ece Takmaz, Lieke Gelderloos, Elia Bruni, and Raquel Fernández. 2019. The PhotoBook dataset: Building common ground through visually-grounded dialogue. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1895–1910. Florence, Italy. Association for Computational Linguistics.

Robert Hawkins, Minae Kwon, Dorsa Sadigh, and Noah Goodman. 2020. Continual adaptation for efficient machine communication. In Proceedings of the 24th Conference on Computational Natural Language Learning, pages 408–419. Online. Association for Computational Linguistics.

Lisa Anne Hendricks and Aida Nematadeh. 2021. Probing image-language transformers for verb understanding. In Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021, pages 3635–3644. Online. Association for Computational Linguistics.

Jack Hessel, Ari Holtzman, Maxwell Forbes, Ronan Le Bras, and Yejin Choi. 2021. CLIPScore: A reference-free evaluation metric for image captioning. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 7514–7528. Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Nikolai Ilinykh, Sina Zarrieß, and David Schlangen. 2019. Tell me more: A dataset of visual scene description sequences. In Proceedings of the 12th International Conference on Natural Language Generation, pages 152–157. Tokyo, Japan. Association for Computational Linguistics.

T. Florian Jaeger and Roger P. Levy. 2007. Speakers optimize information density through syntactic reduction. In Advances in neural information processing systems, pages 849–856.

Chao Jia, Yinfei Yang, Ye Xia, Yi-Ting Chen, Zarana Parekh, Hieu Pham, Quoc V. Le, Yun-Hsuan Sung, Zhen Li, and Tom Duerig. 2021. Scaling up visual and vision-language representation learning with noisy text supervision. In ICML.

Robert M. Krauss and Sidney Weinheimer. 1967. Effect of referent similarity and communication mode on verbal encoding. Journal of Verbal Learning & Verbal Behavior, 6(3):359–363.

Liunian Harold Li, Mark Yatskar, Da Yin, Cho-Jui Hsieh, and Kai-Wei Chang. 2019. VisualBERT: A simple and performant baseline for vision and language. arXiv preprint arXiv:1908.03557.

Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C. Lawrence Zitnick. 2014. Microsoft coco: Common objects in context. In Computer Vision – ECCV 2014, pages 740–755. Cham. Springer International Publishing.

Ruotian Luo, Brian L. Price, Scott D. Cohen, and Gregory Shakhnarovich. 2018. Discriminability objective for training descriptive captions. In 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 6964–6974.

Jinhua Mao, Jonathan Huang, Alexander Toshev, Oana Camburu, Alan L. Yuille, and Kevin Murphy. 2016. Generation and comprehension of unambiguous object descriptions. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 11–20.

Letitia Parcalabescu, Albert Gatt, Anette Frank, and Iacer Calixto. 2021. Seeing Past Words: Testing the Cross-Modal Capabilities of Pretrained V&L Models. In Proceedings of the First Workshop on Multimodal Semantic Representations (MMSR), Groningen. To appear.

Sandro Pezzelle, Ece Takmaz, and Raquel Fernández. 2021. Word representation learning in multimodal pre-trained transformers: An intrinsic evaluation. Transactions of the Association for Computational Linguistics, 9:1563–1579.

Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. 2021. Learning transferable visual models from natural language supervision. In ICML.

Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners. Technical report, OpenAI.
Simeon Schüz, Ting Han, and Sina Zarrieß. 2021. Diversity as a by-product: Goal-oriented language generation leads to linguistic variation. In Proceedings of the 22nd Annual Meeting of the Special Interest Group on Discourse and Dialogue, pages 411–422, Singapore and Online. Association for Computational Linguistics.

Sheng Shen, Liunian Harold Li, Hao Tan, Mohit Bansal, Anna Rohrbach, Kai-Wei Chang, Zhewei Yao, and Kurt Keutzer. 2021. How Much Can CLIP Benefit Vision-and-Language Tasks? arXiv, abs/2107.06383.

Todd Shore and Gabriel Skantze. 2018. Using lexical alignment and referring ability to address data sparsity in situated dialog reference resolution. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 2288–2297, Brussels, Belgium. Association for Computational Linguistics.

Ece Takmaz, Mario Giulianelli, Sandro Pezzelle, Arabella Sinclair, and Raquel Fernández. 2020. Refer, Reuse, Reduce: Generating Subsequent References in Visual and Conversational Contexts. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 4350–4368, Online. Association for Computational Linguistics.

Hao Tan and Mohit Bansal. 2019. LXMERT: Learning cross-modality encoder representations from transformers. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 5100–5111, Hong Kong, China. Association for Computational Linguistics.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In Advances in Neural Information Processing Systems, volume 30. Curran Associates, Inc.

Bolei Zhou, Hang Zhao, Xavier Puig, Sanja Fidler, Adela Barriuso, and Antonio Torralba. 2017. Scene parsing through ade20k dataset. In 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 5122–5130.