

Analogy Generation by Prompting Large Language Models: A Case Study of InstructGPT

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Abstract

We propose a novel application of prompting Pre-trained Language Models (PLMs) to generate analogies and study how to design effective prompts for two task settings: generating a source concept analogous to a given target concept (aka Analogous Concept Generation or ACG), and generating an explanation of the similarity between a given pair of target concept and source concept (aka Analogous Concept Explanation or ACE). We found that it is feasible to prompt InstructGPT to generate meaningful analogies and the best prompts tend to be precise imperative statements especially with low temperature setting. We also systematically analyzed the sensitivity of the InstructGPT model to prompt design and temperature and found that the model is particularly sensitive to certain variations (e.g., questions vs. imperative statements). Further, we conducted human evaluation on 1.3k of the generated analogies and found that the quality of generations varies substantially by model size. The largest InstructGPT model can achieve human-level performance at generating meaningful analogies for a given target while there is still room for improvement on the ACE task.¹

1 Introduction

Large Pre-trained Language Models (PLMs) such as BERT(Devlin et al., 2018) and GPT(Brown et al., 2020) have been applied to many tasks of text generation (e.g., summarization, dialogue system) with promising results (Li et al., 2021). However, no existing work has studied how to apply PLMs to generate different kinds of textual analogies, such as conceptual metaphors (e.g., “Life is a journey²”), and instructional analogies (e.g., “A red blood cell is like a truck in that they both transport essential supplies”(Newby et al., 1995))

¹Our code and datasets are available for public use: <https://anonymous.4open.science/r/InstructGPT-Analogies-7EC6>.

²https://en.wikipedia.org/wiki/Conceptual_metaphor

Table 1: Selected prompts and InstructGPT-generated analogies for *natural selection*

Prompt (P7):	<i>What is analogous to natural selection?</i>
InstructGPT Output:	The analogous process to natural selection is artificial selection. (9 words)
Prompt (P2):	<i>Explain natural selection using a well-known analogy.</i>
InstructGPT Output:	Imagine that you have a jar of mixed nuts ... If you shake the jar ...the big nuts will fall out first ... analogy is that natural selection is like a sieve that separates the fit from the unfit... (136 words)

Generating analogies has a wide range of applications, such as explaining concepts and scientific innovation, and analogies play a crucial role in human cognition. Analogical matching and reasoning enables humans to understand and learn unfamiliar concepts (aka target concepts) by means of familiar ones (aka source concepts) and to make scientific innovations. Unsurprisingly, computing analogies has been a long-standing goal of AI (Mitchell, 2021). This is a challenging problem because it often requires computing structural similarities that are beyond the surface-level similarity. For example, the Bohr’s atom model and the solar system are analogous due to their *relational* similarities (i.e., atoms *orbit* around the nucleus like planets around the sun).

Much work has been done to compute such analogical similarities between concepts. However, existing approaches generally rely on structured representations, thus they can only work on limited domains where such representations already exist. Moreover, they cannot generate analogies in natural language. For example, one of the most popular models is Structural Mapping Engine (SME) (Forbus et al., 2017), which aligns *structured representations* of the target and source concepts using

predicate logic.

Inspired by the recent success in applying PLMs to many NLP tasks (see, e.g., (Li et al., 2021)), we propose and study the application of PLMs to analogy generation. We consider two typical application scenarios of analogy generation: 1) Analogous Concept Generation (ACG): Given a target concept (e.g., bohr’s model), generate a source concept analogous to the target concept (e.g., solar system) possibly with an explanation of the similarity of the two concepts. 2) Analogy Explanation Generation (AEG): Given a target concept and an analogous source concept, generate an explanation of their similarity.

We note the similarity of the two tasks defined above and other text generation problems, thus inspired by the recent success of using prompted PLMs for text generation, we hypothesize that analogy generation can also be solved by using a PLM with appropriately designed prompts. Table 5.1 shows examples of prompts and PLM-generated outputs for ACG.

Prompting language models (Liu et al., 2021) is a promising emerging paradigm that uses textual prompts with unfilled slots, and directly leverages the language models to fill those slots and obtain the desired output. Our problem setup is similar to the use of PLMs for text generation (Li et al., 2021), but the task of analogy generation (particularly for novel analogies) is challenging and different from the existing text generation tasks in multiple ways:

Firstly, analogical reasoning and explanation require deep knowledge of the attributes, functions and relations of both source and target concepts. Secondly, analogies are most useful when they explain target concepts using everyday-life scenarios. Both commonsense reasoning and creativity are required to generate plausible yet interesting analogical texts (e.g., electrical resistance is like cats blocking mice). It is unclear whether PLMs are capable of such tasks.

In this paper, we those challenges and study the following main research questions: RQ1) How effective is a modern PLM such as InstructGPT in generating meaningful analogies? RQ2) How sensitive are the generated analogies to prompt design and other hyperparameters? RQ3) How does model size impact the quality of generated analogies?

To study these questions, we design several experiments on analogies generated from the InstructGPT (Ouyang et al., 2022) model. First, we man-

ually validate whether InstructGPT can generate meaningful analogies for ten well-known analogies in the science domain. Next, we design and systematically vary prompt variants (e.g., imperative statements vs. questions) and temperature, and investigate the corresponding variations in the generated text by comparing them to a reference dataset of science analogies. Finally, we study the impact of model size on the quality of generated analogies both by automatically comparing against the reference data and using human evaluation.

Our study confirms that PLMs (specifically, InstructGPT) offer a promising general approach to generate analogies with properly designed prompts. Furthermore, the InstructGPT model is found to be sensitive to the prompt design and temperature for this task, particularly to the prompt style (i.e., question vs. imperative statement). Precise imperative statements in low temperature setting are found to be the best prompts. Finally, the quality of the generated analogies depends heavily on the model size. While the largest model can achieve human-level performance on the ACG task, the smallest model barely generates any meaningful analogies. The ACE task proved to be more challenging based on human evaluation and could be a better test of the analogical reasoning capabilities of PLMs.

2 Related Work

2.1 Computational Models of Analogies

There has been a lot of work on computational modeling of analogies (Mitchell, 2021). The SME model (Forbus et al., 2017) is one of the most popular symbolic model that finds the *mapping*, or connections between structured representations of source and target concepts and their attributes. However, such methods cannot generate new analogous source concepts with analogical explanation.

The recent deep learning-based approaches, including using pre-trained language models (Mikolov et al., 2013; Rossiello et al., 2019; Ushio et al., 2021), are able to *generate* analogies to some extent, but are currently limited to simple word-level and proportional analogies, such as (ostrich:bird :: lion:?). In contrast, we aim to generate longer analogies of concepts, e.g. instructional analogies (Newby et al., 1995) to help explain those concepts to readers and assist creative writing.

Another line of work is on finding analogous documents for scientific innovation, such as product descriptions and research papers, based on their

semantic similarities (Kittur et al., 2019). In contrast, we operate in a generative task setup.

To the best of our knowledge, none of the existing work has studied the problem of automatically generating complex analogies. (Mitchell, 2021) recommended research on more generative tasks for progress on developing AI systems for analogy-making. Along this direction, we believe that our proposed task is challenging and more practically useful than the existing text-based generative analogical tasks including letter-string (e.g., if “abc” changes “abd”), what does “pqrs” change to?) and word-level analogies.

2.2 Prompting Language Models

Recently, prompts have been either manually created or learned to successfully leverage PLMs for several natural language tasks (Liu et al., 2021). Our work is closest to prompting for Question Answering using prompting, which has recently shown great promise (Khashabi et al., 2020; Tafjord and Clark, 2021). Analogy generation could be considered as a special and challenging case of question answering. For example, two questions in the Challenge300Dataset (Tafjord and Clark, 2021) require comparing the relation between two entities (e.g., how do pandas and parrots differ). But, none of the existing work has performed an in-depth study on prompting PLMs for both generating analogous concepts and explaining the analogies.

3 Problem Formulation

Motivated by the practical applications of this task (e.g., explaining concepts), we study analogy generation in the following settings.

1. **Analogous Concept Generation (ACG) or No Source (NO_SRC)**: Here, only the target concept is provided as the input. The goal is to generate an analogous source concept or scenario, along with some explanation to justify the analogy. For example, “Explain natural selection using an analogy”.

2. **Analogy Explanation Generation (AEG) or With Source (WSRC)**: Here, in addition to the target, the source concept is also a part of input. The goal is to generate an explanation of how the target and source are analogous. For example, “Explain how natural selection is analogous to artificial selection”.

4 Experiment Setup

In this section, we discuss the data sets and the InstructGPT PLM used in our experiments.

Dataset: As the task of analogy generation, as defined in this paper, has not been previously studied, there is no existing data set available to use directly for evaluation. We thus opted to create new data sets for evaluation. Table 2 shows sample data from these datasets.

Standard Science Analogies (STD): As far as we could find, the closest dataset consisting of conceptual analogies is from (Turney, 2008). It consists of ten standard science analogies. However, these do not contain any explanation in nature language, but only the source and target concepts.

Science analogies from academic Q&A sites
SAQA: We searched for quiz questions that asked to create analogies on academic Q&A sites like Chegg.com, Study.com³ by using search queries like ‘create an analogy’, ‘analogy to explain’, and manually downloaded the relevant questions and answers. After manually removing irrelevant data, 75 unique question-answer pairs were obtained. Next, we manually extracted the analogies from answers, i.e., target and source concepts, and the explanation of the analogical similarity.

There are total 109 concepts with 148 analogies. The average word length of analogies is 62.25 words. The analogies are mostly about high school science and few basic computer science concepts in English.

Table 2: Sample analogies from STD and SAQA.

Dataset	Target	Source	Explanation
STD	atom	solar system	-
SAQA	ligase	sewing machine	... Ligase is similar to a sewing machine, as it binds two elements ... (25 words)

InstructGPT Model: Recently, several PLMs have been developed and trained on massive web data (Devlin et al., 2018; Brown et al., 2020; Raffel et al., 2019). In this study, we probe the aligned GPT-3 models, InstructGPT. These are GPT-3 models that have been optimized to follow instructions better (Ouyang et al., 2022). InstructGPT has four variants depending on the model size (number of parameters), namely Ada (350 M), Babbage (1.3

³<https://chegg.com/>, <https://study.com/>. We manually inspected the data and found no personal identifiers or offensive content. We manually compiled the datasets, no scraping was done.

B), Curie (6.7 B) , and Davinci (175 B)⁴. Unless otherwise mentioned, we use the Davinci model for the experiments as it is expected to have the best performance.

We used the Open AI API⁵ to generate all analogies. Main hyperparameters are described in Section 5.2.2 and rest in the Appendix A

5 Experiment Results

5.1 Feasibility Analysis

We first investigate whether InstructGPT is capable of generating analogies with simple prompts by looking at the results on the smaller STD dataset which contains well-known analogies. Here, we seek standard analogies, so we designed prompts with keywords such as "well-known analogy", "often used to explain", etc. The full list of prompts is in Table 16, Appendix C).

We observed that all the prompts were successful in retrieving natural language analogies to some extent but they differed in several aspects. Table 1 shows sample analogies generated by two of our prompts (P7 and P2, Table 16) for the target concept "natural selection." In this case, the reference answer in the STD dataset is "artificial selection," which P7 successfully retrieved, while P2 generated a different but also valid analogy. Such variations indicate both the potential of using different prompts to generate (multiple) different analogies and the model sensitivity to prompt design, which we further investigate in Section 5.2.

To quantify the effectiveness of different prompts, we manually evaluated the source concepts mentioned in the generated analogies (if any). Table 3 shows the number of exact matches of generated source concepts to those in the reference STD dataset, along with the number of "valid" source concepts generated. Valid means a reasonable analogy that is either commonly known (e.g., easily available on the internet⁶) or contains a meaningful justification. All prompts generated valid analogies in most cases, even if they didn't exactly match the reference source concept further suggesting the promise of InstructGPT for generating meaningful analogies.

⁴<https://blog.eleuther.ai/gpt3-model-sizes/>

⁵<https://beta.openai.com/docs/api-reference/completions/create>

⁶Note that commonly known does not necessarily mean available on the internet. We use it only as a proxy here since there is no good way to determine what is common knowledge.

Table 3: Number of analogies that match the ground truth or are otherwise meaningful, out of the total ten analogies generated for STD target concepts by the seven prompts (P1-P7).

	P1	P2	P3	P4	P5	P6	P7
# Match	3	3	6	4	3	5	3
# Valid	6	9	9	8	7	10	10

5.2 Comparative analysis of prompts and temperature

As observed in many other applications of prompted PLMs, the performance of a task tends to be sensitive to the prompts used and the temperature parameter (Lu et al., 2021; Zhao et al., 2021). Thus, it is important to experiment with variations of both the prompts and the temperature parameter (with frequency_penalty, Section 5.2.2) and study how they impact the generated analogy.

For these analyses, we need to compare the model performance in a large number of configurations, which makes human evaluation impossible. Thus, we rely on automatic metrics. Automatic evaluation of natural language generation is known to be challenging (e.g., long-form question answering (Krishna et al., 2021)) as automatic metrics do not accurately reflect semantic similarity or correlation with human judgement (Callison-Burch et al., 2006; Raffel et al., 2019). Evaluation of analogies is even more challenging especially because a target concept could have several valid analogies with seemingly different meanings (e.g., "artificial selection" vs. "sieve" from Section 5.1). Thus, before using existing methods, we designed sanity checks and found that methods behave as we expect (e.g., analogies have higher score than non-analogies, see Appendix B). We note that our sanity checks are only the necessary and not the sufficient requirements of a good metric for evaluating analogies as they do not evaluate creativity or reasoning. However, we use them as an approximation only for relative comparison between methods on the same task as they are unlikely to favor any single method.

We use three representative measures of automatic evaluation of generated text: BLEURT (Selam et al., 2020) (B), METEOR (Lavie and Agarwal, 2007) (M), ROUGE-L (R)⁷ (Lin, 2004)⁸. BLEURT (B) is used as the primary metric for evaluation since it is a recent machine learning-based metric that has been shown to capture semantic similarity

⁷<https://pypi.org/project/rouge-score/>

⁸https://www.nltk.org/api/nltk.translate.meteor_score.html

ties between texts.

Similar average BLEURT values would indicate that the prompts are equally good (or bad) on a task, but not necessarily in the same way. On the other hand, Kendall’s Tau (Kendall, 1938) indicates how well the ranks of two variables are correlated. This would suggest that those prompts have similar strengths and weaknesses. Thus, we analyze both scores to get a more complete picture of hyperparameter sensitivity.

5.2.1 Analysis of prompts

To study the effectiveness and robustness of different prompts for analogy generation in the unsupervised setting, we manually designed several prompts for all the problem settings. The different prompt variants are all paraphrases, such that they are semantically similar. The main ways they differ are: 1. *Questions vs. Imperative Statements* (e.g., P5 vs. P2, Table 5); 2. *Synonyms* (e.g., P2 vs. P3, Table 5); 3. *Word Ordering* (e.g., P1 vs. P3, Table 4). We only study the zero-shot setting mainly because the choice/number of examples in few-shot could significantly impact the results.

Table 4: Prompts for NO_SRC

Id	Prompt
P1	Explain <target> using an analogy.
P2	Create an analogy to explain <target>.
P3	Using an analogy, explain <target>.
P4	What analogy is used to explain <target>?
P5	Use an analogy to explain <target>.

Prompts for the NO_SRC and WSRC settings are in tables 4, 5, respectively. Here, <target>, <src> are target and source concept placeholders.

Table 5: Prompts for WSRC

Id	Prompt
P1	Explain <target> using an analogy involving <src>.
P2	Explain how <target> is analogous to <src>.
P3	Explain how <target> is like <src>.
P4	Explain how <target> is similar to <src>.
P5	How is <target> analogous to <src>?
P6	How is <target> like <src>?
P7	How is <target> similar to <src>?

Results: We discuss our major findings below.

Questions and statements are significantly different: The question prompts are P4, Table 4 and

P5-P7, Table 5. From tables 6 and 7, questions have significantly different and lower scores than statements. This could be an artifact of how the InstructGPT models are trained and should be further investigated.

Table 6: Comparison of performances of different prompts and temperatures in NO_SRC. * and ** mean statistically significant at $p < 0.1$ and $p < 0.05$ respectively based on a two-tailed t-test.

	B	R	M
P1 _{tl}	0.46	0.187	0.154
P1 _{th}	0.448**	0.181**	0.167
P2 _{tl}	0.451	0.193	0.154
P2 _{th}	0.45*	0.184	0.161
P3 _{tl}	0.462	0.196	0.164
P3 _{th}	0.452	0.188	0.171
P4 _{tl}	0.427**	0.170**	0.126**
P4 _{th}	0.431**	0.179**	0.156
P5 _{tl}	0.451	0.188	0.154
P5 _{th}	0.449*	0.183*	0.163

Impact of synonyms and word order: Prompt performances vary based on synonyms and word order. For example, some synonymous prompt pairs (e.g., P2-P4, P5-P7 in WSRC) are more correlated than others (e.g., P2-P3, P5-P6 in WSRC). This could be because “analogous to” and “similar to” share a word unlike the other synonym “like”. As expected, prompts with the most different meanings (e.g., P1 in WSRC – involving <src> is not necessarily the same as analogous to <src>) are least correlated with others. However, from Table 7, the average performances of synonymous prompts (e.g., P2_{tl} and P3_{tl}, P2_{th} and P5_{th}) are not significantly different. Overall, this suggests that InstructGPT is more robust to synonyms/word-order than to the prompt style (question/imperative statements) for this task. The overall winning prompts (P3 in NO_SRC, P2 in WSRC) contain some form of the word “analogy” rather than its synonyms, confirming that precise and direct prompts are better.

5.2.2 Analysis of temperature

Higher temperature increases the randomness in the generated text and is often suggested for creative tasks (Lucy and Bamman, 2021). Since some analogies require creativity, we are especially interested in studying the impact of this hyperparameter.

We explore two settings. **Low Temperature (tl):** this is a deterministic setting, where temperature = frequency_penalty = presence_penalty = 0. **High Temperature (th):** Here temperature is set to 0.85.

Table 7: Comparison of performances of different prompts and temperatures in WSRC. * and ** mean statistically significant at $p < 0.1$ and $p < 0.05$ respectively based on a two-tailed t-test.

	B	R	M
$P1_{tl}$	0.504	0.223	0.187**
$P1_{th}$	0.497**	0.212**	0.199
$P2_{tl}$	0.515	0.217	0.203
$P2_{th}$	0.502*	0.210**	0.208
$P3_{tl}$	0.504	0.229	0.191
$P3_{th}$	0.504	0.216	0.203
$P4_{tl}$	0.506	0.214	0.197
$P4_{th}$	0.497**	0.206**	0.2
$P5_{tl}$	0.499*	0.217	0.18**
$P5_{th}$	0.496**	0.211**	0.191*
$P6_{tl}$	0.500*	0.216	0.176**
$P6_{th}$	0.494**	0.212**	0.183**
$P7_{tl}$	0.497**	0.208**	0.179**
$P7_{th}$	0.492**	0.204**	0.186**

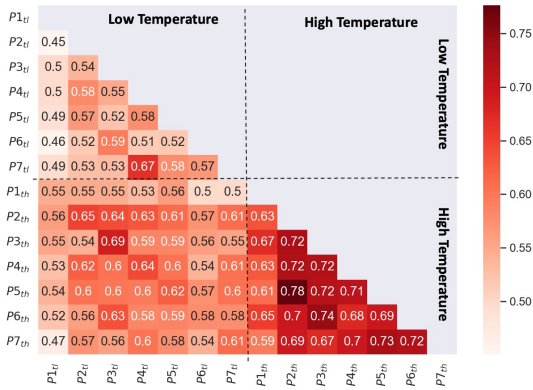


Figure 1: Kendall’s Tau correlation between BLEURT scores of various prompts and temperatures in WSRC

To avoid repetition of words and topics, we set frequency_penalty = 1.24 and presence_penalty = 1.71. These hyperparameters were selected based on initial qualitative exploration. To account for the randomness, we set best_n = 3, i.e., select the best response out of three generated responses, and generate 5 such best responses. In all experiments, we report the average performance of all 5 responses.

Results: Firstly, at high temperature, prompts are generally well-correlated with each other (lower right, figures 1, 3) suggesting lesser sensitivity to prompt design at high temperatures. This requires further investigation because we expect higher randomness to generate a variety of different analogies, and thus have lower correlations in general.

Secondly, the overall performances of the high temperature variants are generally lower than their low temperature counterparts. To investigate when

high temperature could help, we further looked into a case in the WSRC setting where the high temperature version of the best prompt, ($P2_{th}$), performed much better. The results are shown in Table 8. In this case, unlike $P2_{hl}$, $P2_{tl}$ fails on identifying the target and also generates incorrect facts, (“rubber of your lungs”). This shows some evidence of high temperature prompts working better for more complex and creative analogies, which should be investigated further in the future.

5.3 Analysis of model size

Model size or the number of model parameters is generally correlated with performance. We now study whether the same holds for this task and how much the model size impacts the performance.

5.3.1 Automatic evaluation

Figure 2 shows the BLEURT scores of various models on both the task setups. As expected, the performance increases significantly with model size in both WSRC and NO_SRC, suggesting that larger models are better at generating analogy-like text for the given targets. Further, the biggest improvement is seen as the number of parameters increases from 0.3B to 1.3 B in both the settings (19.17% and 15.34% relative improvements, respectively).

Similar to what we observed in the case of the Davinci model, the performance in WSRC is higher than that in NO_SRC for other models too. This confirms that all models have some capacity to incorporate the source provided in the prompt.

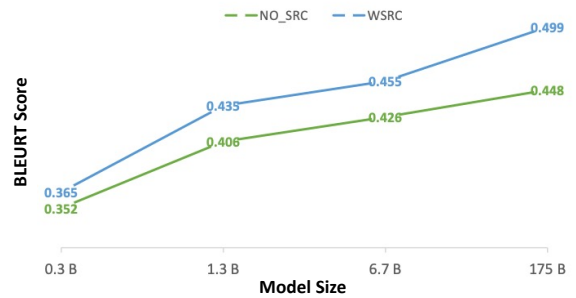


Figure 2: Average performances of various InstructGPT models based on BLEURT scores.

5.3.2 Human evaluation

To further validate the generated results more robustly, we also conducted human evaluation as described below.

Annotation Setup We conducted the study on Amazon Mechanical Turk. Based on manual evalu-

Table 8: Analogies generated in the high and low temperature setting by the prompt: *Explain how breathing mechanism of frogs is analogous to blowing of the balloon.*

Temp.	Generated Analogy
High	... When you blow into a balloon, the air pressure ... The frog’s respiratory system works in a similar way. When you breathe in, you increase the air pressure inside your lungs. This increased air pressure causes the walls ...
Low	When you blow up a balloon, the air inside the balloon is pushing outwards on the rubber of the balloon. This is the same thing that happens when you breathe in: the air inside your lungs is pushing outwards on the rubber of your lungs.

ation of responses to screening tests (Appendix E), we selected 17 workers for the main study.

Further, we created a sample dataset for evaluating analogies generated both in the NO_SRC and WSRC settings. In total, we generated 13k analogies⁹ in NO_SRC and 18k analogies¹⁰ in WSRC. From this data, we randomly selected 42 concepts for the NO_SRC setup and 21 of them were selected for the wsrc setup (to have comparabale number of analogies in both settings). The analogies for the selected concepts, generated by all the models using all the prompts in the low temperature setting were selected for evaluation since low temperature was better based on automatic evaluation.

In total, 1407 unique analogies (576 from WSRC, 770 from NO_SRC, and 61 human-generated from SAQA) were evaluated by 3 workers each. The main study had one question asking workers to evaluate whether the shown candidate analogy was meaningful for the target concept (Yes/No/Can’t decide) and provide a text input for explaining their choice (Figure 6, Appendix F). Please refer to Appendix E for more details of the study design.

Quantitative Results Table 9 shows the percentage of analogies rated as meaningful, based on majority vote, for the various models and the human references from SAQA. There were <2% ties or cases with ‘Can’t decide’ as the majority, which were discarded. The Fleiss’ kappa (Fleiss, 1971) inter-annotator agreement was 0.347 in case of WSRC (plus human references for the selected concepts for wsrc concepts), indicating fair agreement and 0.553 in case of NO_SRC (plus human references for the selected concepts for no_src concepts) indicating moderate agreement.

We observe that the percentage of meaningful analogies increases with model size, again confirm-

ing that larger models have a higher capacity to generate analogies. Interestingly, in the NO_SRC setting, the largest model has comparable performance to humans. We note that this doesn’t necessarily mean that those models are creative or have commonsense reasoning skills as they could have seen those analogies while training. It requires further research to test how often do the models generate novel analogies unseen during training.

Moreover, upon inspection, we found that the human-generated analogies commonly have issues, such as grammatical errors, which could impact their rating by annotators. So, it is possible that analogies written by experts, such as science instructors proficient in English, might be rated higher. Nevertheless, these results are quite encouraging and suggest that future research on building systems for explaining concepts using analogies could be promising.

In the WSRC setting, the performance of Instruct-GPT is lower than human performance. This could be because there is a lesser likelihood of seeing the exact same analogy, i.e the one asked to explain in the prompt, during training, compared to seeing *any* analogies for the target concept as required in the NO_SRC setting. So, WSRC might require more “analogical reasoning” from the models. This highlights the importance of human evaluations for such tasks because otherwise, based on automatic evaluation alone, we would conclude that this is an easier setting. This is because metrics like BLEURT cannot assess the soundness of the generated reasoning, but only that some terms related to the provided source concept are generated.

We also compute the NO_SRC performance on the 21 shared concepts (NO_SRC₂₁, Table 9) for a fair comparison between the two settings. It is interesting to note that the performances of smaller models increase while that of larger models go down in the WSRC setting. This could be because the provided source in the prompt helps provide

⁹6 analogies (5 in high temperature and 1 low temperature)
*109 target concepts*5 prompts*4 models

¹⁰6 analogies (5 in high temperature and 1 low temperature)
*109 target concepts*7 prompts*4 models

some guidance to the smaller models. For example, even by copying parts of the prompt (i.e., source and target), they could generate meaningful analogies (e.g., <source> is like <target>) in a few cases. Since their performance in the NO_SRC setting is very poor, even minor help or “tricks” would lead to performance improvement. On the other hand, the larger models that already performed very well, likely do not have much to gain from such help and in fact perform worse due to the analogical reasoning argument made above.

Overall, this highlights some limitations of the InstructGPT model for analogical reasoning, that requires further research for improvement.

Error Analysis

The annotators were also asked to provide an explanation on their answer choice (i.e., meaningful analogy or not). By inspection, we identified the following major themes based on the workers’ explanations for choosing “not meaningful” across all models/tasks. These themes are not mutually exclusive and multiple themes were often found for one wrong generation.

1. No Analogy: This is one of the most common cases where the model failed to generate any analogy at all. Instead, it mostly generated a simple description/definition of the target concept. In a few cases, it also generated a tautology or an example. For example, “*The b-lymphocytes are similar to the white blood cells*”.

2. Irrelevant to target: The generated text contained little to none relevant information pertaining to the target. One interesting reason behind this was capitalization for abbreviations. For example, since the targets in the prompt were lowercased (e.g., nadh), smaller models were unable to identify abbreviations, while the larger models succeeded at this. Another reason observed was that of ambiguous target, e.g., computer “mouse” misidentified as a rodent. In more insidious cases, the text looked correct but presented incorrect facts.

3. Incorrect source or explanation: Here, important details about the source concept were either incorrect or missing, or the provided explanation was insufficient, making the analogy completely wrong or weak at best. For example, “*A molecule of DNA is like a drop of water. It has a specific shape and size, and it can carry the genetic instructions for making a particular organism.*”

Some error types found in other natural language generations from GPT-3 (Dou et al., 2021), e.g.,

Table 9: Percentage of meaningful analogies generated by various InstructGPT models and humans based on human evaluation. Highest value per row is underlined.

	Ada	Bbg.	Cur.	Dav.	Hum.
NO_SRC	1.90	15.61	48.29	<u>70.05</u>	66.67
WSRC	8.97	29.05	38.46	53.79	<u>71.88</u>
NO_SRC ₂₁	0	12.0	47.0	66.99	<u>71.88</u>

incoherence, grammar, were also found in our task. Further research is required to quantify them for analogical generation and attempt to fix them.

6 Conclusion

In this study, we proposed and studied the novel task of generating analogies by prompting InstructGPT. Our experiments showed that the InstructGPT is effective on this task when precise prompts are used, thus offering a promising new way to generate analogies, which can break the limitation of the traditional analogy generation methods in requiring a pre-generated structured representation.

By evaluating the performances of the various designed prompts in multiple temperature settings, we found that the InstructGPT model is sensitive to those variations, particularly to the prompt style (question vs. imperative statements) and temperature. Additionally, based on human evaluation, we found that the quality of the generated analogies substantially depends on the model size. The largest model was found to achieve human-level performance at generating analogies for given target concepts. There is still much room for improvement at the challenging task of explaining the analogical similarity between the given target and source concepts. This opens up many exciting opportunities for future work both for application-oriented and foundational research on PLMs for analogy generation.

A major limitation of our study is that we only studied analogies on a small dataset in one domain (high-school science). Its generalizability to other domains and larger datasets should be examined further in the future. Further, the human evaluation was conducted by a small group of people in the US and might not reflect the opinions of a more diverse group.

7 Ethical Considerations

The risks associated with using PLMs for analogy generation are similar to those of NLG tasks, such as bias, toxicity, and misinformation (Bender et al., 2021; Weidinger et al., 2021). Accordingly, these

should be carefully evaluated before deploying the models for any practical applications, such as education.

Furthermore, there is a steep monetary and environmental cost associated with using the GPT-3 models, especially Davinci. The OpenAI API charges \$0.06 /1K tokens. Including early experiments, this study costed a total of about \$240. Since we generated multiple runs in the high temperature settings with best_n=3, the cost rose sharply. Future work should investigate the capabilities of other smaller and more cost-effective models for this task.

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A Hyperparameters

Based on initial explorations, where we varied the number of maximum tokens between 0 and 1000 in increments of 100, and then from 935-955 in increments of 1, we noticed that setting a high number of maximum tokens worked better in generating more comprehensive analogies that were not abruptly cut-off and there was little sensitivity to higher values around 950. So, we randomly chose one value in that range (939). The default value of $\text{top}_p = 1$ was used.

B Suitability of existing evaluation metrics

To first investigate the suitability of existing evaluation metrics for generated analogies before we can trust any evaluation results using them, we designed two testers to examine whether the existing metrics behave as expected: 1) **Ordering Tester OT**: This tester is to see if an evaluation metric can order a set of methods that have known orders

between them correctly as expected. 2) **Random Perturbation Tester RPT**: This tester checks if an evaluation metric responds to a random perturbation to the ground truth data used for evaluation. A reasonable metric is expected to generate lower performance figures after perturbation.

We use those two testers to study the suitability of three popular and representative measures of automatic evaluation of generated text: BLEURT (Sellam et al., 2020), METEOR (Lavie and Agarwal, 2007), ROUGE-L (Lin, 2004).

BLEURT (B) is a recent machine learning-based metric that has been shown to capture semantic similarities between text. ROUGE-L (R)¹¹ measures longest matching subsequence of words. We use its F1-score. METEOR (M)¹² matches word stems and synonyms also.

Design of testers: We design an OT and a RPT based on the following baseline methods:

No Analogy baseline (NO_ANLGY): Here, the prompts instruct the model to generate an explanation or description of the target concept and do not ask for an analogy explicitly. Thus, we expect the generated text to be in a different “style” than analogies and the overall performance to be lower. However, the generation would still contain other relevant keywords describing the target. Thus, it is a good baseline to test if the metrics can distinguish between analogies and other descriptions.

Random baselines: For each of the three setups, we introduced random baselines (NO_ANLGY_RAND, NO_SRC_RAND, and WSRC_RAND, respectively) where a generated string is evaluated against a random analogy (excluding the correct matching analogy) in the reference dataset (i.e., applying a random perturbation to the ground truth). These baselines preserve the “style” of the text but not the content. We expect these methods to perform worse than their non-random counterparts.

Additionally, NO_SRC setting is expected to perform worse than WSRC because in WSRC, the model has more information (i.e., the source concept) and thus has better chances of generating the correct analogical explanation. Thus, the expected order is $\text{NO_ANLGY} < \text{NO_SRC} < \text{WSRC}$.

Metric testing results: Table ?? shows the overall results of experiments on the SAQA dataset using the Davinci model. Each row shows the highest

¹¹<https://pypi.org/project/rouge-score/>

¹²https://www.nltk.org/api/nltk.translate.meteor_score.html

average scores given by a metric in various setups (performances of each prompt are in Section 5.2 and at the end of this section.).

We can see that all the three metrics order the setups as expected, i.e. random baselines are assigned a lower score than non-random setups, and scores for NO_ANLGY < NO_SRC < WSRC. This suggests that all the three metrics have “passed” our two testers and thus can be reasonably used to evaluate whether the automatically generated analogies are similar to those generated by humans. In other words, they should help assess whether the generated text is relevant to the target concept and discuss properties of the concept that could be explained using analogies (because they passed RPT), and written in an analogical style (because they passed OT).

Moreover, the results also indicates that the InstructGPT model is able to follow the prompts in the three settings to some extent and generate non-analogical descriptions, general analogies, and analogies containing the source concepts, in those settings respectively.

In terms of discernment power, all metrics have small gaps between the scores of random and non-random settings. Similar results were previously reported in (Krishna et al., 2021) for ROUGE scores on long-form question-answering. Out of the three metrics, the BLEURT score has the largest gaps in all the settings, both between the random and non-random baselines and also between settings. It is also shown to capture semantic similarity well (Sellam et al., 2020). Thus, we use it as the main metric in the rest of the experiments.

Table 11: Prompts for NO_ANLGY

Id	Prompt
P1	Explain <target>.
P2	What is <target>?
P3	Explain <target> in plain language to a second grader.

Table 12: Comparison of performances of different prompts and temperatures in NO_ANLGY.

	B	R	M
P1 _{tl}	0.434	0.183	0.149
P1 _{th}	0.432	0.18	0.158
P2 _{tl}	0.43	0.175	0.129
P2 _{th}	0.425	0.172	0.136
P3 _{tl}	0.445	0.180	0.132
P3 _{th}	0.444	0.179	0.144

Table 13: Comparison of performances of different prompts and temperatures in NO_SRC_RAND.

	B	R	M
P1 _{tl}	0.375	0.132	0.103
P1 _{th}	0.367	0.123	0.108
P2 _{tl}	0.359	0.116	0.092
P2 _{th}	0.366	0.127	0.105
P3 _{tl}	0.362	0.124	0.099
P3 _{th}	0.364	0.126	0.109
P4 _{tl}	0.338	0.115	0.084
P4 _{th}	0.348	0.121	0.1
P5 _{tl}	0.358	0.121	0.097
P5 _{th}	0.348	0.122	0.107

Table 14: Comparison of performances of different prompts and temperatures in WSRC_RAND.

	B	R	M
P1 _{tl}	0.37	0.120	0.094
P1 _{th}	0.363	0.122	0.107
P2 _{tl}	0.385	0.117	0.096
P2 _{th}	0.381	0.12	0.109
P3 _{tl}	0.358	0.117	0.095
P3 _{th}	0.359	0.115	0.1
P4 _{tl}	0.367	0.113	0.096
P4 _{th}	0.37	0.115	0.105
P5 _{tl}	0.36	0.113	0.09
P5 _{th}	0.356	0.117	0.094
P6 _{tl}	0.346	0.111	0.086
P6 _{th}	0.347	0.113	0.091
P7 _{tl}	0.353	0.114	0.092
P7 _{th}	0.352	0.109	0.093

Table 15: Comparison of performances of different prompts and temperatures in NO_ANLGY_RAND.

	B	R	M
P1 _{tl}	0.346	0.115	0.087
P1 _{th}	0.349	0.122	0.099
P2 _{tl}	0.322	0.116	0.077
P2 _{th}	0.327	0.113	0.081
P3 _{tl}	0.334	0.111	0.079
P3 _{th}	0.336	0.11	0.081

C Experiments on STD dataset

Table 16: Prompts for STD analogies

Id	Prompt
P1	Explain <target> using an analogy.
P2	Explain <target> using a well-known analogy.
P3	What analogy is often used to explain <target>?
P4	Using a well-known analogy, explain <target>.
P5	Using an analogy, explain <target>.
P6	What is a well-known analogy to explain <target>?
P7	What is analogous to <target>?

Table 17: Most common analogies generated for each target concept in the STD dataset. #Pmt. means number of prompts that generated the shown analogy.

Target	Most common src.	# Pmt.
mind	computer	7
atom	solar system	6
heat transfer	fluid/water flow	4
sounds	wave	4
respiration	combustion	3
light	river	3
planet	rock	2
bacterial mutation	game of telephone	3
natural selection	sieve	2
gas molecules	balls	2

D Experiments on SAQA dataset

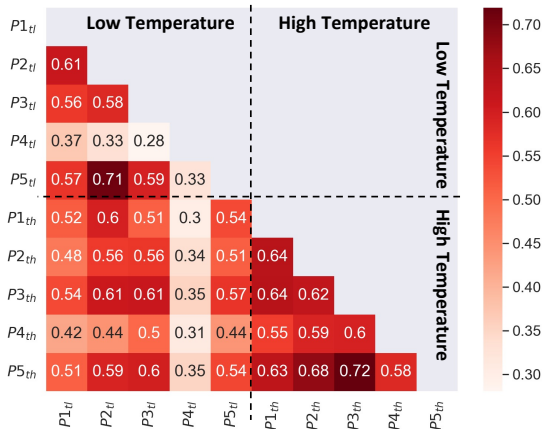


Figure 3: Kendall's Tau correlation between BLEURT scores of various prompts and temperature values in the NO_SRC setting

Table 18: Comparison of lengths of generated responses by question (Q) vs. statement (S) in the WSRC setting. Question versions of the prompts generate fewer words on average, than their statement counterparts.

Prompt Pair	Avg. Len. (S)	Avg. Len. (Q)
P2-P5	43.93	34.53
P3-P6	32.55	31.4
P4-P7	42.51	32.72

Table 19: Comparison of lengths of generated responses by low and high temperatures in the NO_SRC setting. High temperature generates consistently longer analogies. Same trend is observed in other settings also.

Prompt	Avg. Length (tl)	Avg. Length (th)
P1	39.74	47.62
P2	32.67	40.71
P3	40.06	46.62
P4	32.51	40.13
P5	36.53	38.50

E Mturk study details

For identifying qualified workers on Amazon Mechanical Turk, we designed a pre-screening test (Mturk Qualification) asking them to identify the meaningful analogy for a target concept (Figure 4, Appendix F). Further, we used the following additional qualifications: workers should have completed at least 5k tasks with >98% approval rate and be located in the US (since the task requires proficiency in english). Those who passed these qualifications worked on a small test batch of analogies asking detailed questions about their quality (Figure 5, Appendix F). The questions consisted of both Likert-style or Binary choice questions and text inputs asking them to explain their choices. We manually assessed their responses, especially paying close attention to their reasoning to identify qualified workers for the main study.

For both the main study and the screening, a simple definition of the target from sites like Simple English Wikipedia¹³ was provided to workers as reference and they were encouraged to refer to the internet to learn more about the shown concepts. We also provided several sample annotations as part of the instructions to guide workers. Moreover, we were available to answer clarification questions via a shared chatroom.

Annotators were paid at the rate of \$50/hr. The rate was decided based on open discussions with them and is above the minimum wage. They were

¹³https://simple.wikipedia.org/wiki/Main_Page

informed that the data generated would be used for research purposes.

We consulted with our university ethics board and found that IRB was not required for this study.

We did not collect any additional demographic or geographic information about the workers (except the US qualification requirement).

F Interface and questions used for human evaluation

NADH stands for "nicotinamide adenine dinucleotide (NAD) + hydrogen (H)." This chemical occurs naturally in the body and plays a role in the chemical process that generates energy.

Which of the following options contains a good analogy to explain NADH? You may refer to the internet to learn more about NADH.

- ☐ NADH plays a role in the chemical process that generates energy.
- ☐ I always drink the energy drink NADH while playing video games with my friends.
- ☐ NADH is an important molecule in the body. NADH is kind of like a battery that stores energy until it is needed.
- ☐ NADH is like a blood vessel. It helps to carry oxygen and nutrients to your cells.
- ☐ The word "nadh" is derived from the an Egyptian word. The analogy used to explain nadh is that between a population and a tribe.

Figure 4: Pre-screening question for identifying qualified workers.

1. Do you think the text is more likely written by a human or a computer?
Please also precisely explain in a complete sentence why you chose the answer below.

☐ Human
☐ Computer
☐ Can't decide

I chose this answer because ...

2. Does the text mention any concept as being analogous to "golgi"?

☐ Yes
☐ No

3. If you answered "yes" to question 2, please write down the analogous concept.

Analogous concept

4. If you answered "yes" to question 2, does the analogy make sense to you? If you don't know about golgi or the analogous concept, please make sure to look them up on the internet to learn more about them. Please also precisely explain in a complete sentence why you chose the answer below.

☐ Yes
☐ No
☐ Can't decide even after looking up information on the internet

I chose this answer because ...

5. If you answered "no" to question 2, please write an analogy (in ~2-3 complete sentences) for explaining golgi. Please refer to the internet if you can't think of any suitable analogies.

Analogy for golgi ...

6. To what extent does the text help explain golgi to a reader?

☐ Very Helpful
☐ Somewhat Helpful
☐ Not so helpful
☐ Not helpful at all

Figure 5: Sample interface for screening qualified workers.

Background on "specialization and communication in a cell": Cell specialization is the process wherein "general" or "common" cells evolve to form specific cells that have specific functions. Cell communication is the ability of a cell to receive, process, and transmit signals with its environment and with itself.

Please carefully read the text about "specialization and communication in a cell" in the box below and answer the following questions. Pay very close attention to all the details in the text as it might contain factual errors that are hard to spot.

You are encouraged to refer to the internet if you need any additional information about "specialization and communication in a cell" or other concepts in the text.

Text:

A cell is a small, complex system that produces and receives energy. It is a part of our body and helps us to survive and thrive. A specialist in a given area, a cell can do things like make new blood or energy.

1. Does the text mention any meaningful analogy for "specialization and communication in a cell"? If you don't know about specialization and communication in a cell or the analogous concept (if any), please make sure to look them up on the internet to learn more about them. Please also precisely explain in a complete sentence why you chose the answer below.

☐ Yes
☐ No
☐ Can't decide even after looking up information on the internet

I chose this answer because ...

Figure 6: Sample interface for human evaluation of the analogies.