

Preregistering NLP research

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Abstract

Preregistration refers to the practice of specifying what you are going to do, and what you expect to find in your study, before carrying out the study. This practice is increasingly common in medicine and psychology, but is rarely discussed in NLP. This paper discusses preregistration in more detail, explores how NLP researchers could preregister their work, and presents several preregistration questions for different kinds of studies. Finally, we argue in favour of *registered reports*, which could provide firmer grounds for *slow science* in NLP research. The goal of this paper is to elicit a discussion in the NLP community, which we hope to synthesise into a general NLP preregistration form in future research.

1 Introduction

Scientific results are only as reliable as the methods that we use to obtain those results. Recent years have seen growing concerns about the reproducibility of scientific research, leading some to speak of a ‘reproducibility crisis’ (see Fidler and Wilcox 2018 for an overview of the debate). Although the main focus of the debate has been on psychology (e.g. through Open Science Collaboration 2015) and medicine (Macleod et al., 2014), there are worries about the reproducibility of Natural Language Processing (NLP) research as well (Fokkens et al., 2013; Cohen et al., 2018; Moore and Rayson, 2018; Branco et al., 2020). The reproducibility debate has led to Munafò et al.’s (2017) *Manifesto for reproducible science*, where the authors discuss the different threats to reproducible science, and different ways to address these threats. We will first highlight some of their proposals, and discuss their adoption rate in NLP. Our main observation is that preregistration is rarely used. We believe this is an undesirable situation, and devote the rest of this paper to argue for preregistration of NLP research.

Munafò et al. recommend **more methodological training**, so that e.g. statistical methods are

applied correctly. In NLP, we see different researchers picking up the gauntlet to teach others about statistics (Dror et al., 2018, 2020), achieving language-independence (Bender, 2011), or best practices in human evaluation (van der Lee et al., 2019, 2021). Moreover, every *ACL conference offers tutorials on a wide range of different topics. While efforts to improve methodology could be more systematic (e.g. by actively encouraging methodology tutorials, and working towards community standards),¹ the infrastructure is in place.

Munafò et al. also recommend to **diversify peer review**. Instead of only having journals, that are responsible for both the evaluation and dissemination of research, we can now also solicit peer feedback after publishing our work on a platform like ArXiv or OpenReview. The NLP community is clearly ahead of the curve in terms of the adoption of preprints, and actively discussing ways to improve peer review (ACL Reviewing Committee 2020a,b; Rogers and Augenstein 2020). To improve the quality of the reviews themselves, ACL2020 featured a tutorial on peer reviewing (Cohen et al., 2020).

Another advice from Munafò et al. is to **adopt reporting guidelines**, so that papers include all relevant details for others to reproduce the results. The NLP community is rapidly adopting such guidelines, in the form of Dodge et al.’s (2019) reproducibility checklist that authors for EMNLP2020 need to fill in. Beyond reproducibility, we are also seeing more and more researchers adopting Data statements (Bender and Friedman, 2018), Model cards (Mitchell et al., 2019), and Datasheets (Geburu et al., 2018) for ethical reasons.

Munafò et al.’s final recommendation, **preregistration**, means that authors should specify what they are going to do, and what they expect to find, before carrying out their studies (Nosek et al.,

¹A more radical proposal would be to *always* host methodology-focused tutorials, and to invite researchers to teach specific modules, similar to keynote talks.

Data collection	Have any data been collected for this study already?
Hypothesis	What's the main question being asked or hypothesis being tested in this study?
Dependent variable	Describe the key dependent variable(s) specifying how they will be measured.
Conditions	How many and which conditions will participants be assigned to?
Analyses	Specify exactly which analyses you will conduct to examine the main question/hypothesis.
Outliers and Exclusions	Describe exactly how outliers will be defined and handled, and your precise rule(s) for excluding observations.
Sample Size	How many observations will be collected or what will determine sample size?
Other	Anything else you would like to pre-register?
Research aim	Specify the overall aim of the research.
Use of literature	Specify the role of theory in your research design.
Rationale	Elaborate if your research is conducted from a certain theoretical perspective.
Tradition	Specify the type of tradition you work in: grounded theory, phenomenology, ...
Data collection plan	Describe your data collection plan freely. Be as explicit as possible.
Type of data collected	Select the type(s) of data you will collect.
Type of sampling	Indicate the type of sampling you will rely on: purposive, theoretical, convenience, snowball...
Rationale	Indicate why you choose this particular type of sampling.
Sort of sample	Pick the ideal composition of your sample: heterogenous, homogenous, ...
Stopping rule	Indicate what will determine to stop data collection: saturation, planning, resources, other.
Data collection script	Upload your topic guide, observation script, focus group script, etc.

Table 1: Top: preregistration form from AsPredicted (<https://aspredicted.org>) for quantitative research. Bottom: additional items from Haven and Grootel (2019) for qualitative research. All text is quoted verbatim.

2018). The goal of preregistration is to ensure that all hypotheses and research methods are made explicit before researchers are confronted with the data. Otherwise, researchers end up in a *garden of forking paths*, where all research decisions are made implicitly, based on common sense and the available data (Gelman and Loken, 2013). This negatively impacts the reliability and generalisability of any study. In other words: preregistration allows us to distinguish between exploratory and confirmatory research. Exploratory research does not require preregistration, because the goal is to get a sense of what is possible. Any pattern you come across during exploratory research, allows us to draw up hypotheses. For a subsequent confirmatory study you could/should preregister to test those hypotheses. By explicitly marking (parts of) your study as exploratory or confirmatory, it is easier to understand the status of your results.

Compared to the work on reporting quality, there has been little talk of preregistration in the NLP literature; the terms ‘preregister’ or ‘preregistration’ are hardly used in the ACL Anthology.² For this reason, we will focus on preregistration and its application in NLP research. The next sections discuss how preregistration works (§2), propose preregistration questions for NLP research (§3), discuss the idea of ‘registered reports’ as an alter-

²Looking for these terms, we found four papers that mention preregistration: Cao et al. (2018) and van der Lee et al. (2019) mention it, and van Miltenburg et al. (2018) and Futrell and Levy (2019) share their own preregistration.

native pathway to publication (§4) and the overall feasibility of preregistrations in NLP (§5).

2 How does preregistration work?

Before you begin, you enter the hypotheses, design, and analysis plan of your study on a website like the *Open Science Framework*, *AsPredicted*, or *ResearchBox*. These sites provide a time stamp; evidence that you indeed made all the relevant decisions before carrying out the study. During your study, you follow the preregistered plans as closely as possible. In an ideal world, there would be an exact match between your plans and the actual study you carried out. But there are usually unforeseen circumstances that force you to change your study. This is fine, if the changes are clearly specified (including the reasons for those changes) in your final report (Nosek et al., 2018).

A typical preregistration form. Table 1 shows questions from the preregistration form from AsPredicted.³ This form is geared towards hypothesis-driven, experimental research where human participants are assigned to different experimental conditions. Simmons et al. (2017) note that answers should state exactly how the study will be executed, but also that it should be short and easy to read.

Data collection, hypothesis, dependent variable. The form first asks whether data collection has been carried out yet (ideally the answer should be *no*, but see Appendix §A.1), and then asks researchers to

³See <https://osf.io/zab38/wiki/home/> for an overview of different forms.

What are your hypotheses/key assumptions?
What is the independent variable? (e.g. model architecture)
What is the dependent variable (e.g. output quality)
How will you measure the dependent variable?
Is there just one condition (corpus/task), or more?
What parameter settings will you use?
What data will you use, and how is it split in train/val/test?
Why this data? What are key properties of the data?
How will you analyse the results and test the hypotheses?

Table 2: Questions for analysis, experiments, and re-production papers (expanded in Appendix A).

make their main hypothesis explicit so that it cannot be changed after the fact. Following the hypothesis, researchers should describe their key dependent variables (i.e. the main outcome variables) and how they will be measured. This includes cutoff points that will be used to discretise continuous variables (e.g. to divide participants in different groups).

Conditions, analyses, outliers and exclusions. Next, the form asks about the design of the study, the analyses, and the process of determining outliers (and whether those should be excluded). The answer needs to be detailed enough so that other researchers are able to reproduce the study.

Sample size and other. The form then asks how much data will be collected, so as to prevent *optional stopping* (where researchers keep collecting data until the results are in line with their preferred hypothesis).⁴ Finally, the form allows researchers to specify other aspects of the study they would like to preregister, such as “secondary analyses, variables collected for exploratory purposes, [or] unusual analyses.”

Qualitative research. Preregistration is not only suitable for quantitative research; [Haven and Grootel \(2019\)](#) present a proposal to preregister qualitative studies as well. Their suggestions are also presented in Table 1. The authors argue that, although qualitative research differs in its goals from quantitative research (developing theories rather than testing them), it is still valuable to make your assumptions and research plans explicit before carrying out your planned study. Because qualitative research is more flexible than quantitative research, [Haven and Grootel](#) view qualitative preregistrations as living documents; continuously updated to track the research progress. This stimulates conscientiousness, and avoids sloppy research. Public preregistrations also allow for immediate feedback.

⁴Although it is not necessary for the form, at this point it is good to justify the sample size, e.g. by using a power analysis.

What do you aim to learn from the error analysis?
What do you know from the literature about system errors?
What kinds of errors do you expect to find?
How will you sample the outputs to analyse?
Do you also consider the input in your sampling strategy?
How do you plan to analyse the output?
How many judges will assess the output? Are they trained?
How is the reliability of the judges assessed?
Is there a fixed error categorisation scheme or not?

Table 3: Questions to ask before an error analysis.

3 Preregistration in NLP research

To determine what a preregistration for NLP research should look like, we need to consider the different kinds of research contributions in NLP. For this, we use the paper types proposed for COLING 2018.⁵ These are: Computationally-aided linguistic analysis; NLP engineering experiment paper; Reproduction/Resource/Position/Survey Paper. Of these, position papers are less suitable for preregistration, since these are more opinion/experience-driven, and the process of writing them cannot be formalised. We treat the others below.

Analysis, experiments, and reproduction papers typically have one or more hypotheses, even though they may not always be marked as such.⁶ This means we can ask many of the same questions for these studies as for experimental research. Table 2 provides a rough overview of important questions to ask before carrying out your research.

If your study contains an error analysis, then you could ask the more qualitatively oriented questions in Table 3. They acknowledge that you always enter error analysis with some expectation (i.e. researcher bias) of what kinds of mistakes systems are likely to make, and where those mistakes may be found. The questions also stimulate researchers to go beyond the practice of providing some ‘lemons’ alongside cherry-picked examples showing good performance.

The main benefit of asking these questions beforehand is that they force researchers to carefully consider their methodology, and they make researchers’ expectations explicit. This also helps to identify unexpected findings, or changes that

⁵<https://coling2018.org/paper-types/>

⁶Taking the best papers from COLING 2018 as an example, [Ruppenhofer et al. \(2018, analysis\)](#) test assumptions from the linguistics literature about affixoids, [Thompson and Mimno \(2018, experiment\)](#) test which subsampling methods improve the output generated by topic models, and [Lan and Xu \(2018, reproduction\)](#) test whether the reported performance for different neural network models generalises to other tasks.

were made to the research design during the study.

Resource papers are on the qualitative side of the spectrum, and as such the questions from [Haven and Grootel \(2019\)](#), presented at the bottom of Table 1, are generally appropriate for these kinds of papers as well. Particularly 1) the original purpose for collecting the data, 2) sampling decisions (what documents to include), and 3) annotation (what framework/perspective to use) are important. Because the former typically influences the latter two, it is useful to document how the goal of the study influenced decisions regarding sampling and annotation, in case the study at some point pivots towards another goal.

Survey papers should follow the PRISMA guidelines for structured reviews ([Moher et al., 2009](#); [Liberati et al., 2009](#)). According to these guidelines, researchers should state exactly where they searched for existing literature, what search terms they used, and what criteria they used to select relevant papers. This increases reproducibility, allows readers to find any gaps in the survey, and avoids a biased presentation of the literature (i.e. only citing researchers you know, or work that fits your preferred narrative). A recent NLP example of a structured review is provided by [Reiter \(2018\)](#).

4 Registered reports

Registered reports “[split] conventional peer review in half” ([Chambers, 2019](#)). First, authors submit a well-motivated research plan for review, before carrying out the study (similar to a preregistration). This plan may go back-and-forth between the authors and the reviewers, but once the plan is accepted, the authors receive the guarantee that, if they carry out the study according to plan, their work will be published. As with preregistration, deviations from the original plan are allowed, but these should be identified in the final report. The main advantage of registered reports is that they provide a means to avoid publication bias. Because studies aren’t judged on the basis of their results, positive results are equally likely to be published as negative results. As long as the study is deemed valuable *a priori*, it should get published. An additional benefit of registered reports is that reviews may actually correct flaws in the research design, meaning that we reduce the chance of running an expensive study all for nothing. In the case of NLP research, this may save a lot of energy (cf. [Strubell et al. 2019](#)). We are not aware of any NLP journals

that offer registered reports, but strongly encourage the NLP community to take steps in this direction.⁷

5 Feasibility

[Gelman and Loken \(2013, 2014\)](#) touch upon the feasibility of preregistration, noting that:

“[f]or most of our own research projects this strategy hardly seems possible: in our many applied research projects, we have learned so much by looking at the data. Our most important hypotheses could never have been formulated ahead of time.”

This certainly rings true for NLP as well. However, we should be careful about conclusions that are drawn on the basis of pre-existing data. [Gelman and Loken \(2013\)](#) note that in such cases, if it is feasible to collect more data, it is good to follow up positive results with a pre-registered replication to confirm your initial findings. One way to do this is to collect and evaluate your model on a new test set (cf. [Recht et al. 2019](#)). This tells us to what extent trained models generalise to unseen data. Another idea could be to preregister the human evaluation (or error analysis) of the model output.

We believe that preregistration, and especially registered reports, could ease the pressure to publish as soon as possible. If your analysis plan is accepted for publication, you can take as long as you want to actually carry out the study, without having to worry about being scooped. This provides new opportunities for *slow science* in NLP (also see Min-Yen [Kan’s](#) keynote at [COLING 2018](#)).

6 Questions about preregistration

Below we address some common questions about preregistration. We thank our anonymous reviewers for raising some of these questions.

Is preregistration more work? In our experience, preregistration adds little overhead to a research project. Especially if a project requires approval by an Institutional Review Board (IRB), you need to write a description along similar lines anyway. For projects not requiring IRB approval, it is good practice to provide a model card ([Mitchell et al., 2019](#)), data sheet ([Geburu et al., 2018](#)) or data statement ([Bender and Friedman, 2018](#)) with your model or resource. Given the ethical aspects of NLP research, it is advisable to consider all dimensions of your study before you carry it out. Moreover, preregistration is a good way to start writing the paper before carrying out the research, a practice

⁷Cf. [Mannarswamy and Roy \(2018\)](#) regarding AI research.

advocated by [Eisner \(2010\)](#) to maximise the impact of your work. Finally, it may be more work to prepare a registered report, but this comes with the benefit of having a pre-approved methodology. Once the project is completed, reviewers will not reject your paper based on methodological choices.

Should I worry about being scooped? There is no need to worry. We already discussed registered reports, where research proposals are provisionally accepted before data collection starts. Otherwise, this worry has been addressed through the existence of both public and private preregistrations. A researcher can choose to keep a preregistration private until the research is completed. They can make their preregistration public whenever they like, for example to invite feedback from the community. In addition, preregistrations are also time-stamped, and you can use these time stamps during the review phase to show that you have had these ideas before similar work was published.⁸

What about citing preregistrations? In some regards, the discussion about preregistrations is similar to the discussion about preprints (i.e. papers on ArXiv), thus similar questions arise. Both preregistrations and published studies are being cited. For example, medical journals like BMC Public Health also publish study protocols (similar to preregistrations), without any results, that are also cited by others (e.g. work using a similar protocol).

What should we do with concurrent work? It may of course happen that multiple researchers have similar ideas around the same time. We believe that it is still valuable to publish multiple independent studies with similar results. Even if they don't provide any new insights (which is rare), they do provide evidence towards the robustness of the findings. Where and how those findings should be published is a separate discussion.⁹

How should we teach preregistration? Preregistration is already being incorporated into Psychology courses (see, for example, [Blincoe and Buchert 2020](#)). It is relatively straightforward to implement as part of student research proposals during applied courses in NLP: specify what you plan to do

⁸The public/private distinction has been implemented by both the Open Science Foundation and AsPredicted.org. The Open Science Foundation allows for a 4-year embargo, during which the preregistration is kept private. Aspredicted allows for preregistrations to be private indefinitely.

⁹However, if there is value in publishing the 'first' paper, there is probably also value in publishing the 'second' one. The same holds for the question of whether both studies should be cited; good scholarship considers *all* the available evidence.

exactly, and what you expect to find. It is often useful for students to have an explicit format to think through their research plans, to make sure that they make sense.

7 Limitations

Although preregistration is offered as a solution to improve our work, it does not solve all of our problems. [Van 't Veer and Giner-Sorolla \(2016\)](#) mention three limitations: 1. *Flexibility*. It may be difficult or infeasible for authors to foresee all possible outcomes, and as such there may be gaps in the preregistration, which still allow for flexibility in the analysis. 2. *Fraud*. There is no way to prevent fraudulent researchers from, e.g., creating multiple preregistrations, or falsely 'preregistering' studies that were already run. At some point we just have to trust each other to do the right thing, but increased transparency does make it harder to commit fraud. 3. *Applicability*. Preregistration may not be possible for all kinds of studies. As discussed above, it has mainly been developed for quantitative studies (particularly experiments), and there are proposals for the preregistration of qualitative research ([Haven and Grootel, 2019](#)), although we have yet to see whether this idea will catch on. Finally, [Szollosi et al. \(2020\)](#) argue that, although preregistration might offer greater transparency, it does not by itself improve scientific reasoning and theory development. Since large parts of NLP are pre-theoretical (we have observed effects but do not have any theoretical explanations for why these effects occur), one might reasonably argue that we should focus on theory development first, before we can carry out any meaningful experiments.

8 Conclusion

We have discussed how preregistration could benefit NLP research, and how different kinds of contributions could be preregistered. We have also proposed an initial list of questions to ask before carrying out NLP research (and see Appendix A for example preregistration forms). With this paper, we hope to encourage other NLP researchers to consider preregistering their work, so that they will no longer get lost in the garden of forking paths. Still, there is no silver bullet to cure sloppy science. Although preregistration is certainly helpful, it does not guarantee high-quality research, and we do need to stay critical about preregistered studies, and the way they are carried out.

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A Preregistration forms

This appendix provides preregistration forms for different kinds of paper types. These forms are preliminary, and they are mainly meant as a starting point for discussions of preregistration in NLP. We are happy to admit that there may be flaws in this appendix (either in the forms or in our reasoning). Future work should investigate whether these forms are complete (i.e. limit *researcher degrees of freedom* as much as possible) and appropriate for different kinds of NLP research.

A.1 Preface: data availability in NLP

Preregistration is a means to avoid hindsight bias, because you have to specify your expectations upfront, when your perspective is not yet colored by your experience with the data. But for NLP studies it is unclear what ‘the data’ is. We can distinguish three kinds of data: 1. The training/validation/test sets, 2. The model output, 3. Human judgments.

In an ideal situation, preregistration would occur before any kind of data has been obtained. The problem is that this is often not the case; there are many canonical datasets for which the data is publicly available. Of course one could collect an additional test set (as we suggested above), but the community often judges new approaches based on their performance for established datasets. So what should we do? Still preregister! Arguably the training, validation, and test data is usually not central to the work. What matters is how a particular system performs. So even if we don’t usually find ourselves in the ideal situation where none of the data is available yet, it is typically fine to preregister your study if the train/eval/test data is available but system outputs and evaluation scores are not. When authors are transparent in their data sharing policy, we can reconstruct the timeline of events before and after the preregistration, to see how much their knowledge about the data may have influenced them.

A.2 Computationally aided linguistic analysis

This paper type corresponds to several different setups, ranging from experiments with human subjects, to corpus analyses to see if particular generalisations from the literature hold up. Preregistration has been discussed from a linguistics perspective by [Roettger \(2020\)](#). For experiments with human participants, readers may refer to the standard preregistration forms from [AsPredicted](#) (see our Table 1),

OSF, or the questions from Roettger’s Figure 1.

For more corpus-oriented studies (e.g. Ruppenhofer et al. 2018), we should consider a mix of the quantitative and qualitative questions from our Table 1. Usually these kinds of studies do require some data collection, so authors should ask:

1. What is the goal of this study?
2. What are the main questions/hypotheses?
3. What kind of data will be collected?
4. How will this data be collected?
5. What sampling strategy will be used? Why?
6. How much data are you planning to collect? (Is there any target or stopping criterion?)
7. How will the data be analysed?
 - (a) If automatic: what analysis tool will you use, and how will it be configured?
 - (b) If manual: what is the background of the annotators? How will you ensure reliability and validity of the analysis?
8. What statistical tests will be used, if any?
9. Anything else you’d like to preregister?

A.3 NLP Engineering experiment paper

NLP engineering experiments are like experiments in the social sciences, except that the subjects are NLP models and the performance data is model output. So the standard social science questions do not need to be modified that much to fit NLP experiments.

1. What is the goal of your study?
2. What are your hypotheses/key assumptions?
3. What are the (in)dependent variables?
4. How will these variables be measured?
5. Is there just one condition, or more?
6. What software libraries will you use?
7. What hardware will you use?
8. What parameter settings will you use?
9. What data set will you use?
10. If the data set does not already exist, see §A.6. If it does:
 - (a) How familiar are you with the data?
 - (b) To what extent are your hypotheses informed by yourself or others interacting with this data? To what extent does this hinder the generalisability of your approach?
 - (c) Are you planning to collect additional data to validate your approach?
11. Why this data? What are its key properties?
12. How is the data split in train/val/test?
13. How will you analyse the results and test the hypotheses?
 - (a) If automatic: what metric(s) (including implementation) will you use, and how will they be configured?
 - (b) If human judgments: see §A.8.1.

14. Will you carry out an error analysis? If so, see §A.8.2.
15. Anything else you’d like to preregister?

A.4 Position paper

Position papers typically do not need to be preregistered, since they often do not provide any new data, but rely on the author’s experience. These kinds of papers also usually signal that they are more opinionated than other kinds of papers.

A.5 Reproduction paper

For a reproduction paper, the questions are a mix of the questions above (§A.3) with reproduction-specific questions.

1. What results do you aim to reproduce?
2. What kinds of experiments does this involve?
3. What is the goal?
 - (a) What constitutes a successful reproduction?
 - (b) What constitutes an unsuccessful reproduction?
 - (c) What is the margin of error?
4. Do you expect to be successful? Why (not)?
5. How are you planning to reproduce the original results?
 - (a) Will you use the same soft/hardware?
 - (b) Will you use the same data?
 - (c) Will you use the same codebase?
 - (d) If human participants are used: will you target the same demographic, and use the same experimental settings?
 - (e) Will you contact the authors?
 - (f) How much time do authors have to respond to your queries?
 - (g) How much time/effort are you willing to spend?
6. Will you carry out an error analysis? If so, see §A.8.2.
7. Anything else you’d like to preregister?

A.6 Resource paper

It is at least a bit unexpected to promote preregistration for resource papers. After all, if all you do is data collection, then there are no hypotheses to test. But since the goal of this appendix is to provide a starting point for discussion, we are taking the stance that no study is free from biases or initial expectations. As such, it is useful to at least document what you aim to collect, for what reasons, and how you are planning to do so.

1. What is the goal of this study?
2. What kind of data will be collected?
3. How will this data be collected?
4. What is the intended application for the data you plan to collect?
5. What sampling strategy will be used? Why?

6. How much data are you planning to collect? (Is there any target or stopping criterion?)
7. How will the data be analysed?
 - (a) If automatic: what analysis tool will you use, and how will it be configured?
 - (b) If manual: what is the background of the annotators? How will you ensure reliability and validity of the analysis?
8. What properties should the data have?
9. How will you ensure that the data will have those properties?
10. Anything else you'd like to preregister?

A.7 Survey paper

We would recommend that authors follow the PRISMA guidelines (Moher et al., 2009; Liberati et al., 2009) for their surveys. This requires authors to develop a review protocol, which means authors should answer the following questions before initiating their study:

1. What is the goal of this study?
2. What is the rationale behind this study?
3. What questions do you hope to answer?
4. What types of articles are relevant to answer your question?
 - (a) What are the inclusion criteria?
 - (b) What are the exclusion criteria?
 - (c) What languages are included?
5. How will you decide which articles are relevant? (e.g. judging by the title/abstract)
6. What search engines will you use?
7. What search queries will you use?
8. What are the variables of interest?
9. How will you synthesize the results?
10. How will you ensure the reliability and validity of your study?
11. Anything else you'd like to preregister?

A.8 Other kinds of preregistrations

Instead of preregistering a full study, one might also preregister part of a study, e.g. a human evaluation or error analysis.

A.8.1 Human evaluation

Human evaluation studies often do not report all the necessary details to reproduce their work (Howcroft et al., 2020). Thus Shimorina and Belz (2021) developed a datasheet for recording all the necessary details. This datasheet can mostly be filled in before the study is carried out. A selection of their questions is provided below (see the paper for more details and additional questions).

1. What type of input(s) does the system have?
2. What type of output does the system produce?

3. What task is the system supposed to carry out?
4. What languages are involved?
5. How many systems/outputs per system are being evaluated?
6. How are the outputs selected?
7. What is the statistical power of the sample size?
8. What kind of evaluators are being used?
9. What training is given to the evaluators?
10. What is the background of the evaluators?
11. How are responses collected?
12. What quality assurance measures are used?
13. What do evaluators see when carrying out evaluations?
14. How free are evaluators regarding when and how quickly they are supposed to evaluate the results.
15. Can evaluators provide feedback or not?
16. What are the experimental conditions like?
17. What type of quality is assessed in the evaluation?
18. How is this quality assessed?
19. How are the responses processed?
20. What are the ethical implications of your work?

A.8.2 Error analysis

Error analysis is similar to human evaluation, except that it is typically more qualitatively oriented. This does not mean that there cannot be a quantitative component (e.g. counting the number of errors, comparing this number between different systems), but often systems are also just analysed by themselves, and we just want to know what future researchers still ought to improve about the system.

1. What is the goal of the error analysis?
2. What type of input(s) does the system have?
3. What type of output does the system produce?
4. What task is the system supposed to carry out?
5. What languages are involved?
6. What do you know from the literature about system errors?
7. When does something count as an error?
8. What kinds of errors do you expect to find?
9. How many outputs will you analyse?
10. How will you sample the outputs to analyse?
11. Do you also consider the input in your sampling strategy?
12. How do you plan to analyse the output?
13. How many judges will assess the output?
14. What is the background of the judges?

15. What training do the judges receive?
16. How is the reliability of the judges assessed?
17. How will their responses be processed?
18. Is there a fixed error categorisation scheme or not?