Model Info Sheet for Detecting and Preventing Leakage in ML-based Science

**About model info sheets**

Completing this model info sheet requires the researcher to provide precise arguments to justify that predictive models used for making scientific claims do not suffer from leakage. It is inspired by the model cards introduced by Mitchell et al.[[1]](#footnote-1)

Model info sheets are intended to accompany the paper or report that introduces the model: for instance, as an appendix or supplemental material.

This is a beta version of our model info sheet template. We are soliciting feedback and will continue to update the template. For more information about model info sheets and to obtain the latest version of the template, see [reproducible.cs.princeton.edu](https://reproducible.cs.princeton.edu/). For feedback or questions, contact: [sayashk@princeton.edu](mailto:sayashk@princeton.edu)

The model info sheet starts on the next page. After filling it out, save it starting from that page. To cite the paper that introduces the model info sheets, use the bibliography file available at [reproducible.cs.princeton.edu/citation.bib](https://reproducible.cs.princeton.edu/citation.bib)

Model Info Sheet

**Section 1: Information about paper or report**

1) Author(s): Names of the authors of the ­­paper or report

2) Title of the paper or report which introduces the model

3) DOI or permanent link to the paper or report (for example, link to arxiv.org webpage)

4) License: Under which license(s) are the data and/or model shared?

5) Email address of the corresponding author

**Section 2: Scientific claim(s) of interest**

6) Does your paper make a generalizable claim based on the ML model? If yes, what is the scientific claim? For example, “Our ML model can be used to diagnose Covid-19 using chest radiographs of adult patients”.

If there are multiple claims, list each claim in a new line, along with a claim number.

7) Is the scientific claim made about a distribution or population from which you can sample? If yes: (a) what is the population or distribution about which the scientific claim is being made? (b) What is the sample used for the study? For example, “(a) Population: adult patients with symptoms of Covid-19. (b) Sample: We use a random sample of adult patients who present at a U.S. based hospital between April 2020 and June 2020”.

If there are multiple scientific claims, list your answer for each claim in a new line, corresponding to their claim number in Q6.

***Note:*** *A difference between the population and the set from which the sample is drawn could highlight potential generalizability failures, which are related to but distinct from leakage.*

8) Does the scientific claim only apply to certain subsets of the distribution mentioned in Q6? For example, “Our model works on chest radiographs of U.S.-based adult patients and might not generalize to radiographs taken in other places or using different machines.”

If there are multiple claims, list your answer for each claim in a new line, corresponding to their claim number in Q6.

**Section 3: Train-test split is maintained across all steps in creating the model**

9) Train-test split type: How was the dataset split into train and test sets? (For example, cross-validation; separate train and test sets).

*If your model does not have a separate test set, it could suffer from leakage due to overfitting*

10) Are there duplicates in the dataset? If yes, explain how duplicates are handled to ensure the train-test split.

*If duplicates from the training set are included in the test set, your model could suffer from leakage. The higher the percentage of duplicates in the test set, the more severe the leakage.*

11) In case the dataset has dependencies (e.g., multiple rows of data from the same patient), describe how the dependencies were addressed (for example, using block-cross validation).

*If dependencies across the train-test split are not addressed, your model could suffer from leakage. The higher the number of rows in the test set with dependencies, the more severe the leakage.*

12) List all the pre-processing steps used in creating your model. For example, imputing missing data, normalizing feature values, selecting a subset of rows from the dataset for building the model.

13) How was the train-test split observed during each pre-processing step? If applicable, use a separate line for each step mentioned in Q12.

*If the train-test split is not maintained during all pre-processing steps, your model could suffer from leakage.*

14) List all the modeling steps used in creating your model. For example, feature selection, parameter tuning, model selection.

15) How was the train-test split observed during each modeling step? If applicable, use a separate line for each step mentioned in Q14.

*If the train-test split is not maintained during all modeling steps, your model could suffer from leakage.*

16) List all the evaluation steps used in evaluating model performance. For example, cross-validation, out-of-sample testing.

17) How was the train-test split observed during each evaluation step? If applicable, use a separate line for each step mentioned in Q16.

*If the train-test split is not maintained during all evaluation steps, your model could suffer from leakage.*

**Section 4: Test set is drawn from the distribution of scientific interest.**

18) Why is your test set representative of the population or distribution about which you are making your scientific claims?

*If the test set distribution is different from the scientific claim of interest (listed in Q7), your model could suffer from leakage.*

19) Explain the process for selecting the test set and why this does not introduce selection bias in the learning process.

*Selection bias (for example, only choosing data from a given geographic location but expecting your model’s performance to generalize to all locations) can lead to leakage.*

20) In case your model is used to predict a future outcome of interest using past data, detail how data in the training set is always from a date earlier than the data in the test set.

*In predictions about future outcomes of interest, using data from the future to predict in the training set the past in the test set is a form of leakage. Data in the training set should always have timestamps of an earlier time than those in the test set to avoid leakage.*

**Section 5:** **Each feature used in the model is legitimate for the task**

21) List the features used in the model, alongside an argument for their legitimacy. A legitimate feature is one that would be available when the model is used in the real world and is not a proxy of the outcome being predicted. You can also include this list in an appendix and reference the relevant section of your Appendix here.

For example, “Patient age: We include this feature in our ML model for hypertension diagnosis since patient age is easily available in a clinical setting”.

An example of a feature that should not be included (for illustration only; you do not need to include these in your model info sheet): “Anti-hypertensive drugs: We do not include the use of anti-hypertensive drugs as a feature in our ML model for hypertension diagnosis since that information is only available after diagnosis and would not be available when a new patient presents with symptoms of hypertension.”

***Note:*** *You do not need to list each feature used in your model here. However, you must provide an argument for the legitimacy of each feature included in your model to ensure that your model does not suffer from leakage due to illegitimate features. For example, “our model only uses data from the previous year as features. For instance, to predict civil war in 2017, we only use lagged features from the year 2016. Since these features are always available in advance of when we want to make predictions using our model, none of these features can lead to leakage.”*

1. Margaret Mitchell, Simone Wu, Andrew Zaldivar, Parker Barnes, Lucy Vasserman, Ben Hutchinson, Elena Spitzer, Inioluwa Deborah Raji, and Timnit Gebru. "Model cards for model reporting." In *Proceedings of the conference on fairness, accountability, and transparency*, 2019. [↑](#footnote-ref-1)