

# Notes on RMSD inference

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## 1 Overview

We consider a quantity, the Root-Mean-Squared Distance, denoted by  $y$ , and a set of quantities called “features”, denoted by  $x$ . A value of RMSD  $y$  and values for the features  $x$  can be associated with each target-ligand pair, which I’ll call a “datapoint”.

Our problem is to infer  $y_0$  given:  $x_0$  for a new datapoint, known pairs  $(\bar{y}, \bar{x}) := ((y_1, x_1), (y_2, x_1), \dots, (y_N, x_N))$  for other  $N$  datapoints, and additional facts and hypotheses  $H$ . Additional hypotheses are unavoidable since we are making an extrapolation. Our uncertainty about  $y_0$  is expressed by a probability (density)

$$p(y_0 | x_0, \bar{y}, \bar{x}, H), \quad (1)$$

which we want to quantify.

The first question we must ask in approaching this problem is how much our uncertainty about  $y_0$  depends on the relative frequencies for previous datapoints  $(\bar{y}, \bar{x})$ . For example, if  $y_0$  is hand-picked by someone, then knowledge of the frequencies for  $(\bar{y}, \bar{x})$  is irrelevant. But even in such a case it might be that the reversed probability  $p(x_0 | y_0, \bar{y}, \bar{x}, H)$  *does* depend on the frequencies of previous datapoints, and it can be used to calculate (1) as

$$p(y_0 | x_0, \bar{y}, \bar{x}, H) = \frac{p(x_0 | y_0, \bar{y}, \bar{x}, H) p(y_0 | H)}{\sum_{y_0} p(x_0 | y_0, \bar{y}, \bar{x}, H) p(y_0 | H)}. \quad (2)$$

The important difference between eqs (1) and (2) is that in the latter we must also quantify  $p(y_0 | H)$  using extra-data facts or hypotheses.

In technical terms we are asking whether  $y_0$  is *exchangeable* given  $x_0$ , or vice versa. Or using Fisherian (1956 §§ II.4, IV.1) parlance we are

asking whether  $y_0$  should be considered as belonging to a *subpopulation* determined by  $x_0$  or vice versa. (Or neither, in which case our study would simply end here, so we won't consider this third possibility.) Another way of seeing our question is whether the “causal connections” mainly go in the direction  $x_0 \rightsquigarrow y_0$  or  $y_0 \rightsquigarrow x_0$  (cf. Pearl 1988 §§ 2.1.2, 2.2.5).

This question is discussed in a brilliant paper by Lindley & Novick (1981), who show with examples its fundamental importance for making correct inferences.

In this study we'll consider both possibilities.

## 2 Direct case: methodology

For the direct case (1) we shall consider the RMSD  $y$  as a continuous variable, mapped to a log-scale.

The assumption in this case is that  $y_0$  is exchangeable given  $x_0$ , but  $x_0$  is not exchangeable given the known datapoints  $\bar{x}$ . This is a sensible assumption – a fact indeed – if we are actually *choosing* the specific value of  $x_0$ , as we do in testing for example.

The calculation of  $p(y_0 | x_0, \bar{y}, \bar{x}, H)$  is actually done via the calculation of the joint probability  $p(y_0, x_0 | \bar{y}, \bar{x}, H)$  through

$$p(y_0 | x_0, \bar{y}, \bar{x}, H) = \frac{p(y_0, x_0 | \bar{y}, \bar{x}, H)}{p(x_0 | \bar{y}, \bar{x}, H)} \quad (3)$$

with the assumption that the marginal probability for  $x_0$  is independent of the datapoints and equal to unity:  $p(x_0 | \bar{y}, \bar{x}, H) = p(x_0 | H) = 1$ , which is a sensible assumption if we are actually *choosing* the specific value of  $x_0$ , as we for example do in testing.

## 3 Reverse case: methodology

For the reverse case (2) we shall consider a binned RMSD, divided into the three categories “good”, “uncertain”, “bad”.

## Bibliography

(“de  $X$ ” is listed under D, “van  $X$ ” under V, and so on, regardless of national conventions.)

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