hosts over 20,000 datasets with over 50,000 associated machine learning tasks. Working with these datasets can provide a great opportunity to practice your machine learning skills. A disadvantage of competitions is that they already provide a particular metric to optimize, and usually a fixed, preprocessed dataset. Keep in mind that defining the problem and collecting the data are also important aspects of real-world problems, and that representing the problem in the right way might be much more important than squeezing the last percent of accuracy out of a classifier.

Conclusion

We hope we have convinced you of the usefulness of machine learning in a wide variety of applications, and how easily machine learning can be implemented in practice. Keep digging into the data, and don't lose sight of the larger picture.

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