**Machine Breakdown Predictions**

**Harrison Howze, Sam Schmall, Omar Abdelsalam, Daniel Byerly**

1. **Problem Statement and Background (15%)**

Our goal is to use a generated dataset to minimize costs and downtime of a business by predicting machine failures and finding the primary factors that contribute to those failures.

We found the initial dataset from Kaggle. The data includes rotational speed, air and process temp, torque of the machines, tool wear in minutes. There are 2 target variables, whether the machine fails and what specific failure type it is if it does fail. Our goal is to create a model of the data that can accurately predict when a machine is going to break before it does.

We believe that machine owners and operators would benefit from having a model like our intended one, as it would potentially reduce downtime and lost product due to misaligned, broken, or worn machine parts as we could better predict when the machine is to fail.

Should our work be successful, there could be practical application to the manufacturing industry as well as further incentive to collect accurate machine data to create a model like ours with real recorded data for specific machines and entire production lines.

As for related work, there have been several attempts to make predictive machine failure algorithms and of the ones we found, several were successful in predicting failures, giving us a basis to work from and potential future work in

1. **Data and Exploratory Analysis (15%)**

We have potentially unnecessary columns, the UID and product ID which allow the algorithm to learn which items in the training set always fail, as such we removed them from the dataset for training and testing purposes. We also are not going to use failure type, as our focus is predicting whether the machine will fail or not regardless of type. Our focus at the start is binary classification, failure or not. There is no missing data, tool wear has a large amount of variance but is standardized. As for issues with the data, we examined the data thoroughly and searched for outliers, anomalies, and missing data, all of which came up as none.

For the specific code, we removed these unnecessary rows by creating a new dataset – a subset of the original data – that omitted these rows.

updated <- subset(master, select = -c(UDI, Product.ID, Failure.Type))

1. **Methods (10%)**

*[Describe the methods you explored (usually algorithms, or data cleaning or data wrangling approaches). Justify your methods in terms of the problem statement. What did you consider but \*not\* use? In particular, be sure to include every method you tried, even if it didn't "work". When describing methods that didn't work, make clear how they failed and any evaluation metrics you used to decide so.]*

1. **Tools (10%)**

*[Describe the tools that you used and the reasons for their choice. Justify them in terms of the problem itself and the methods you want to use. Tools will probably include machine learning, and possibly data wrangling and visualization. Please discuss all of them. How did you employ them? What features worked well and what didn't? What could be improved? Describe any tools that you tried and ended up not using. What was the problem?]*

1. **Results (35%)**

*[Give a detailed summary of the results of your work. Here is where you specify the exact performance measures you used. Usually there will be some kind of accuracy or quality measure. There may also be a performance (runtime or throughput) measure. Please use visualizations whenever possible. Include links to interactive visualizations if you built them. You should attempt to evaluate a primary model and in addition a "baseline" model. The baseline is typically the simplest model that's applicable to that data problem, e.g. Naive Bayes for classification, or K-means on raw feature data for clustering. If there isn't a plausible automatic baseline model, you can e.g. compare with human performance by having someone hand-solve your problem on a small subset of data. You won’t expect to achieve this level of performance, but it establishes a scale by which to measure your project's performance. Compare the performance of your baseline model and primary model and explain the differences.]*

1. **Summary and Conclusions (10%)**

*[In this section give a high-level summary of your results. If the reader only reads one section of the report, this one should be it, and it should be self-contained. You can refer back to the "Results" section for elaborations. This section should be less than a page. In particular, emphasize any results that were surprising.]*

1. **Appendix (5%)**

Include the link to your github/gitlab repository (that I can access) containing your R programs/scripts, and link to the data.