## 1 Introduction

#### • Group members

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#### • Team name

The Breakfast Club

• Division of labour

### 2 Overview

- Models and techniques tried
  - Bullet: Bullet text.
- Work timeline
  - Bullet: Bullet text.

## 3 Approach

- Data processing and manipulation
  - Bullet: Bullet text.
- Details of models and techniques
  - Bullet: Bullet text.

#### 4 Model Selection

#### Scoring

Due to the binary output classification, we chose to do scoring by classification accuracy (as opposed to loss measure).

#### • Validation and Test

We used cross-5 validation for all model selection and choosing semi-finalists of the neural-network models, except for choosing the finalists in the neural network models, where we used cross-10 validation. By generating these cross validations, we were able to select the optimal learning parameters, such as regularization terms, early stopping (max iterations), and loss functions. This was done by manually fixing all parameters except for one, optimizing that parameter, then moving on to optimizing another parameter, before circling back to the same parameter. In a way, we performed a manual

step-wise gradient-like descent on parameters. The results of cross validation for various models can be seen in Table # in the Appendix. The parameters variables refer to the API SKlearn's definition of parameters.

## 5 Conclusion

- Discoveries
- Challenges
- Concluding Remarks

# 6 Appendix

Table 1: With data normalization, without de-categorization of data (does not include all tests)

| Туре                | K-Folds | Parameters   | Classification Accuracy |
|---------------------|---------|--|-------------------------|
| SVM                 | 5       | 4-degree polynomial kernel   | 0.7568                  |
| SVM                 | 5       | RBF kernel   | 0.7568                  |
| Logistic Regression | 5       | SAG solver, 25 iterations (converged), $10^{-5}$ regularization strength                 | 0.774                   |
| Logistic Regression | 5       | SAG solver, 25 iterations (no convergence), $C=10^{0}$ regularization strength           | 0.773                   |
| Logistic Regression | 5       | SAG solver, 100 iterations (no convergence), $C=10^{0}$ regularization strength          | 0.773                   |
| Logistic Regression | 5       | SAG solver, 100 iterations (no convergence), $C=10^5$ regularization strength            | 0.773                   |
| Logistic Regression | 5       | SAG solver, 400 iterations (no convergence), $C=10^{0}$ regularization strength          | 0.773                   |
| Logistic Regression | 5       | Liblinear solver, 100 iterations (no convergence), $C=10^{0}$ regularization strength    | 0.774                   |
| Ridge Regression    | 5       | $\alpha=20$ regularization strength, (optimal alpha found by plotting CV vs. alpha)      | 0.7738                  |
| Lasso Regression    | 5       | $\alpha=10^{-3}$ regularization strength, (optimal alpha found by plotting CV vs. alpha) | 0.7718                  |

**SGD** 

**SGD** 

5

5

0.7737

0.7727

| MLP* Classifier     | 5           | Hidden layers=(200,100), iterations=5 (optimal iterations found by plotting CV vs. iter.)     | 0.7711 |
|---------------------|-------------|---|--------|
| MLP* Classifier     | 5           | Hidden layers=(100), iterations=3 (optimal iterations found by plotting CV vs. iter.)         | 0.7726 |
| MLP* Classifier     | 5           | Hidden layers=(100, 50, 10), iterations=4 (optimal iterations found by plotting CV vs. iter.) | 0.7725 |
| MLP* Classifier     | 5           | Hidden layers=(20), iterations=10 (optimal iterations found by plotting CV vs. iter.)         | 0.7734 |
| MLP* Classifier     | 5           | Hidden layers=(20, 20), iterations=15 (optimal iterations found by plotting CV vs. iter.)     | 0.7733 |
| MLP* Classifier     | 5           | Hidden layers=(20, 20,20), iterations=10 (optimal iterations found by plotting CV vs. iter.)  | 0.7730 |
| MLP* Classifier     | 5           | Hidden layers=(200,100), iterations=5 (optimal iterations found by plotting CV vs. iter.)     | 0.7711 |
|                     | Table 1: Wi | ithout data normalization, with de-categorization of  | data   |
| SVM                 | 5           | RBF kernel  | 0.7707 |
| Logistic Regression | 5           | Liblinear solver, 50 iterations (converged) $C=1$ regularization strength                     | 0.7725 |
| Logistic Regression | 5           | Liblinear solver, 100 iterations (converged) $C=1 \ {\rm regularization \ strength}$          | 0.7725 |
| SGD                 | 5           | Hinge loss, 1000 iterations,  | 0.7748 |

Table 1: Finalists from 43 cross validations of various layer dimensions and iterations (bounded cross validation by iterations on both sides, such that an increase or decrease in iterations increased validation significantly):

 $\alpha = 0.001$  regularization strength

Hinge loss, 500 iterations,

 $\alpha = 0.001$  regularization strength Hinge loss, 100 iterations,

 $\alpha = 0.001$  regularization strength

| MLP* Classifier | 10 | Hidden layers=(50, 50), iterations=4 (optimal iterations found by plotting CV vs. iter.) | 0.7775 |
|-----------------|----|--|--------|
|-----------------|----|--|--------|

| MLP* Classifier | 10 | Hidden layers=(100, 50, 10), iterations=9 (optimal iterations found by plotting CV vs. iter.) | 0.7782 |
|-----------------|----|---|--------|
| MLP* Classifier | 10 | Hidden layers=(150, 50), iterations=5 (optimal iterations found by plotting CV vs. iter.)     | 0.7776 |
| MLP* Classifier | 10 | Hidden layers=(150, 50, 10), iterations=6 (optimal iterations found by plotting CV vs. iter.) | 0.7781 |

Table 1:  ${}^*MLP = Multilayered Perceptron. {}^*SGD = Stochastic Gradient Descent. We saw de-categorization improve performance significantly in neural network models, whereas linear models performed slightly worse.$