1. It is not possible to predict next day movement following earnings release because there are a lot more factors in play driving stock movements than just earnings results in that short time frame.

2. Empirical study shows that -1d-to-1d returns are uncorrelated with 1d-to-30d returns.

3. The first two points combined can explain why the 1d-to-30d returns are so uncorrelated to the model inputs even when the same set of inputs have much success predicting the returns of -1d-to-30d.

4. When doing classification, filter away those predicted values that are closer to 0.5. This improves the overall classification success rate massively with the remaining points

5. When doing classification, it is possible to show that the success rate is higher at both ends.

This may not be true. Somehow I am not seeing this again. I need to show it.

This is important because if I can improve the accuracy by simply filtering away the middle points I will be able to align this technique with my other discoveries in item 8.

For Q4 2018 10d, I can improve the -1d-to-10d forecast accuracy to 72% by really using the handful of forecasted numbers on both sides.

6. When doing classification using regression results, I am able to show that, if I were only using those stocks whose -1d-to-30d movement directions have been correctly predicted, I am able to predict the 1d-to-30d movement direction with very high accuracy by checking if the real -1d-to-1d movement has been in contrast to the predicted -1d-to-30d movement.

7. Although the objective function and evaluation criteria are different between the classification and regression runs, for Q3 2018 there is still an 80.9% that both tests have produced the same prediction on the direction of movements.

8. When doing classification, I also see that when I use all the data points whose prediction is correct to deduce the direction of 1d-to-30d returns, I achieve even better results, seemingly 100% success rate. This discovery again shows that we can transform the problem of predicting 1d-to-30d returns to increasing the prediction accuracy of -1d-to-30d returns as much as possible.

Note that there are two filtering conditions involved: a correct -1d-to-30d prediction and real -1d-to-1d return is in an opposite direction as the predicted -1d-to-30d return. Without the first condition, the success rate of correcting deducing the 1d-to-30d direction is still poor.

9. I can seemingly only improve the classification rate up to 60% by using the largest and smallest classification output values. But this not-so-exciting situation doesn't change my claim that future improvements will make my discovery useful and meaningful and actionable.

10.

In Q4 2018,

When the -1d-to-10d prediction accuracy is 100%, it corresponds to a **65.7%** of accuracy for 1d-to-10d prediction.

When the -1d-to-30d prediction accuracy is 100%, it corresponds to a **70.1%** of accuracy for 1d-to-30d prediction.

In Q3 2018,

When the -1d-to-10d prediction accuracy is 100%, it corresponds to a **62.9%** of accuracy for 1d-to-10d prediction.

When the -1d-to-30d prediction accuracy is 100%, it corresponds to a **79.8%** of accuracy for 1d-to-30d prediction.

On 25 Oct 2018,

When the -1d-to-30d prediction accuracy is 100%, it corresponds to a **82.1%** of accuracy for 1d-to-30d prediction.

11. I have shown that if I run feature selection for a long time I will converge a number of chromosomes to the same fitness value. This effectively means all these different chromosomes are the 'best' feature combinations. This supports my earlier discovery that there is really no best feature selection per se, and instead the best features are only best when working with the associated model, in a way much the same as tuning a particular model parameter

12. It is entirely possible to tune model parameters and do feature selection at the same time. This is because selecting a combination of features can be effectively treated as just tuning a particular parameter of the model