# Massachusetts Unemployment During COVID-19: Using Classification Models to Find Increases in Employment by Industry in the State of Massachusetts

MIS 587: Business Applications in Machine Learning
December 10, 2020

# Business Memo

Unemployment rates are continuing to stagnate through the Fall of 2020 with claims being either constant or rising since late September to December 10 (U.S. Department of Labor, 2020). This model will be focusing on predicting whether or not there will be an increase in employment for the next future month based on the industries available. From this, a positive result indicating increase will notion a recovery in that specific industry while a negative result will indicate that the employment rate is staying the same or decreasing. Knowing in advance if employment will be increasing for certain industries will allow the Massachusetts government to then prepare for the additional employment. This increase could be marked partly by workers being able to go back to work, but it could also see an overall increase due to workers changing professions which could result in higher employment in some industries than even before the start of the shut down due to the COVID-19 Pandemic.

Using DataRobot, this problem is addressed using the Extreme Gradient Boosted Trees Classifier as it performed the best overall. This showed mostly false positives values however meaning that the falsely predicted were those that actually did not increase but were predicted to. This would result in funding not given to industries that are still experiencing either a lag or decrease in employment.

The most important feature used in the project is the employment data of previous months. These data are immutable features because they have already happened and cannot be changed. This kind of feature is suitable for modeling and making predictions but may not be interesting to management. Because the actions of the management team are not able to have influence on these features.

Looking through the ideal model distribution, the recommended threshold would be at .65. Although higher thresholds would eliminate the false positives, it would result in many false negatives indicating that many industries would receive funding when it is not required. Monetary support can be one of the most important solutions for unemployment issues. The state government has applied the Unemployment Insurance (UI) and Pandemic Unemployment Assistance (PUA) to financially support people who lose their jobs due to COVID-19.

The total value of the payoff is vastly growing when the threshold is higher than 0.7. According to the research in the previous section, we can know it is due to the increase of the False Negative prediction. But the increase of the threshold can also reduce the False Positive predictions, which is harmful to the industries which really need help. Hence, if the government wants to adjust the value of the threshold to provide support to all the industries which are in a difficult time, the cost brought by False Negative prediction is an important problem they have to consider.

The model does have potential to help especially as the Pandemic will still continue to affect the United States into 2021. In conclusion, the Massachusetts Government should not implement this directly for decisions but use it for now for comparison to the actual result and rely mainly on additional expertise to make an informed decision.

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# Business Problem and Project Objectives

Unemployment rates are continuing to stagnate through the Fall of 2020 with claims being either constant or rising since late September to October 15 (U.S. Department of Labor, 2020). The Paycheck Protection Program (PPP) provided by the federal government has been administered but only to cover 2.5 months of payroll costs which will not be sufficient as unemployment rates stagnate. There is also not much specific support from the state of Massachusetts but instead based on what their employers can do on a case-by-case basis (Maura, 2020). Researchers at Cornell University are already underway with mapping out which occupations are deemed "at-risk" for furloughs and for loss of health benefits where the biggest sector at risk is the service industry at 48% of all deemed at-risk (Cornell, 2020). This will help the state of New York to determine which areas will require more support than others. The current data available for this project is limited to the employment by industry for the months through September of 2020. This model will be focusing on predicting whether or not there will be an increase in employment for the next future month based on the industries available. From this, a positive result indicating increase will notion a recovery in that specific industry while a negative result will indicate that the employment rate is staying the same or decreasing.

The main goal of the Department of Labor is to "support workers' safety/health, wages, and working conditions" (Commonwealth of Massachusetts, 2020). Knowing in advance if employment will be increasing for certain industries will allow the Massachusetts government to then prepare for the additional employment. This increase could be marked partly by workers being able to go back to work, but it could also see an overall increase due to workers changing professions which could result in higher employment in some industries than even before the start of the shut down due to the COVID-19 Pandemic.

Machine Learning is suitable for this problem as the machine is predicting the increase in employment for months that are still unknown. This utilizes previous data to compare based on months that are known and then uses this knowledge to predict future months. Machine Learning then is appropriate for making an educated prediction to give time to prepare for increases in employment.

## Data Decisions

The dataset our team is using for this project comes from the Massachusetts Department of Labor Statistics that contains monthly employment data from September 2019 to September 2020. The dataset has been adjusted to remove certain attributes which will be discussed in the Feature Engineering section but was reduced to showing the three previous months employment with a final calculated column of whether or not there was an increase in the last three months. Because there is a two-month delay in obtaining the data, the first of the previous months start two months back from the month for prediction. For example, if the model were to predict whether or not September would have an increase, the three previous months to compare would be June, May, and April.

The final column is the target variable which is a Boolean variable indicating yes if there was an increase in employment in the last three months and no if there was not an increase, namely that it stayed the same or decreased. With this target variable, the prediction type for this problem is classification.

# Feature Engineering Techniques

The project team has gathered different data of Massachusetts employment in 2020. Because the problem that we encounter with this project is a current concern among the country, specifically for the state, there is no prebuilt dataset that the team can use. Thus, the employment data was mostly collected from the official website of Massachusetts government named mass.gov.

Figure 1 shows the sample data of the Monthly Employment dataset by different industries in Massachusetts.

| CES Series Cod | Description | Sep-19 | Oct-19 | Nov-19 | Dec-19 | Jan-20 | Feb-20 | Mar-20 | Apr-20 | May-20 | Jun-20 | Jul-20 | Aug-20 | Sep-20 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 06-000000 | Goods-producing | 407,500 | 406,500 | 406,900 | 405,400 | 406,000 | 409,600 | 406,100 | 325,000 | 346,800 | 369,800 | 373,300 | 373,500 | 377,500 |
| 07-000000 | Service-providing | 3,286,300 | 3,286,600 | 3,294,200 | 3,293,000 | 3,303,000 | 3,303,000 | 3,262,700 | 2,697,100 | 2,730,300 | 2,801,900 | 2,869,300 | 2,931,600 | 2,964,500 |
| 08-000000 | Private service-providing | 2,829,400 | 2,829,200 | 2,836,400 | 2,836,300 | 2,845,400 | 2,844,900 | 2,803,800 | 2,267,400 | 2,307,900 | 2,375,800 | 2,438,000 | 2,485,100 | 2,530,300 |
| 10-000000 | Mining and logging | 1,000 | 1,000 | 1,100 | 1,000 | 1,000 | 1,100 | 1,000 | 800 | 900 | 800 | 800 | 800 | 800 |
| 15-000000 | Mining, Logging, and Construction | 164,200 | 162,900 | 163,000 | 162,900 | 163,700 | 164,400 | 162,800 | 106,200 | 121,900 | 141,400 | 142,800 | 142,700 | 144,700 |
| 20-000000 | Construction | 163,200 | 161,900 | 161,900 | 161,900 | 162,700 | 163,300 | 161,800 | 105,400 | 121,000 | 140,600 | 142,000 | 141,900 | 143,900 |
| 30-000000 | Manufacturing | 243,300 | 243,600 | 243,900 | 242,500 | 242,300 | 245,200 | 243,300 | 218,800 | 224,900 | 228,400 | 230,500 | 230,800 | 232,800 |
| 31-000000 | Durable goods | 157,400 | 157,000 | 157,000 | 156,900 | 156,600 | 158,400 | 156,800 | 145,400 | 147,800 | 147,400 | 149,300 | 150,400 | 150,800 |

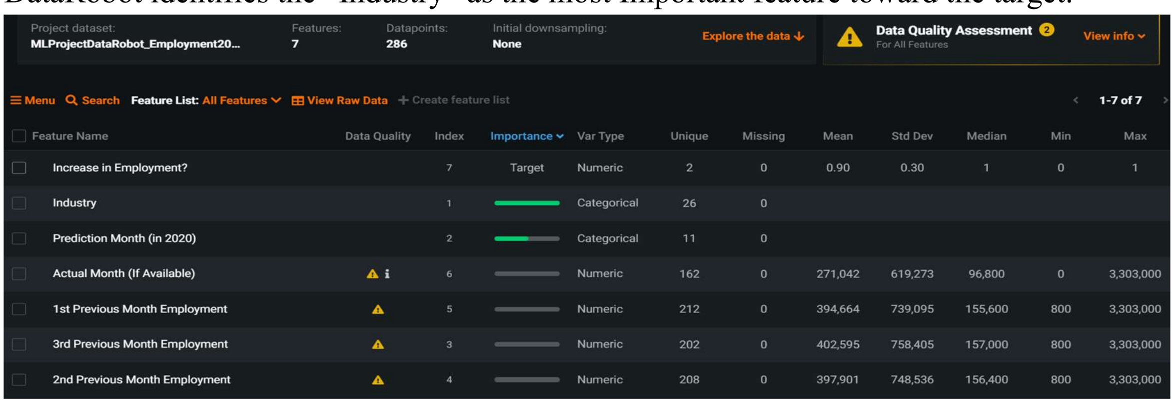
*Figure 1. Original data*

Next, the data set above is featured as presented in the figure 2 below, which the industry employment data is grouped by the Prediction Month. The feature engineered dataset consists of 7 columns, referred as 7 features: Industry, Prediction Month (in 2020), 3rd Previous Month Employment, 2nd Previous Month Employment, 1st Previous Month Employment, Actual Month, and Increase in Employment is used as a target variable. The target is labelled with binary code of 0 or 1, which respectively depicts the trend of decrease or increase in employment for the prediction month.

| Industry | Prediction Month (in 2020) | 3rd Previous Month Employment | 2nd Previous Month Employment | 1st Previous Month Employment | Actual Month (If Available) | Increase in Employment? |
|---|---|---|---|---|---|---|
| Accommodation and I | December | 188000 | 199000 | 208700 | 0 | 1 |
| Administrative and Su | December | 159400 | 162200 | 163200 | 0 | 1 |
| Arts, Entertainment, a | December | 30200 | 32700 | 33800 | 0 | 1 |
| Construction | December | 142000 | 141900 | 143900 | 0 | 1 |
| Educational Services | December | 146800 | 153000 | 155600 | 0 | 1 |
| Finance and Insuranc | December | 174100 | 173100 | 175000 | 0 | 1 |
| Health Care and Socia | December | 588200 | 596300 | 604800 | 0 | 1 |
| Information | December | 89900 | 90000 | 90800 | 0 | 1 |

*Figure 2. Feature-engineered Data*

The data is then processed through DataRobot and yielded the following result in figure 3 DataRobot identifies the "Industry" as the most Important feature toward the target.




| Feature Name | Data Quality | Index | Importance | Var Type | Unique | Missing | Mean | Std Dev | Median | Min | Max |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Increase in Employment? | | 7 | Target | Numeric | 2 | 0 | 0.90 | 0.30 | 1 | 0 | 1 |
| Industry | | 1 | | Categorical | 26 | 0 | | | | | |
| Prediction Month (in 2020) | | 2 | | Categorical | 11 | 0 | | | | | |
| Actual Month (If Available) | i | 6 | | Numeric | 162 | 0 | 271,042 | 619,273 | 96,800 | 0 | 3,303,000 |
| 1st Previous Month Employment | | 5 | | Numeric | 212 | 0 | 394,664 | 739,095 | 155,600 | 800 | 3,303,000 |
| 3rd Previous Month Employment | | 3 | | Numeric | 202 | 0 | 402,595 | 758,405 | 157,000 | 800 | 3,303,000 |
| 2nd Previous Month Employment | | 4 | | Numeric | 208 | 0 | 397,901 | 748,536 | 156,400 | 800 | 3,303,000 |

*Figure 3. DataRobot data*

The Feature Impact shows in figure 4 will help us define how the features impact the target variable of "Increase in Employment". It is noticeable that the employment numbers in the 1st, 2nd and 3rd previous month are the most important features that have affected the target, which predict whether the employment in an industry would increase or not in the upcoming month. To be more specific, the Employment data of the 2nd Previous Month can affect 100% the prediction, and the data of 1st and 3rd months may affect 91% and 77%, respectively (figure 5).

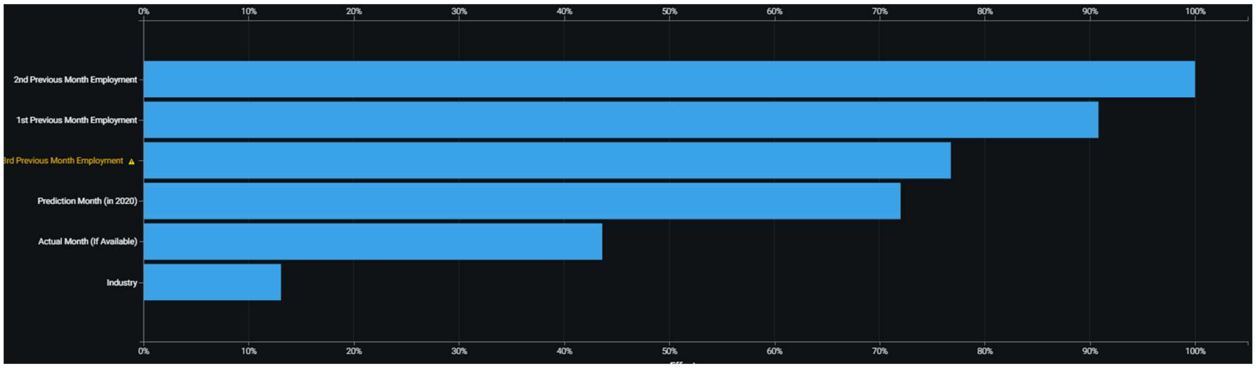



*Figure 4. Feature Impact*

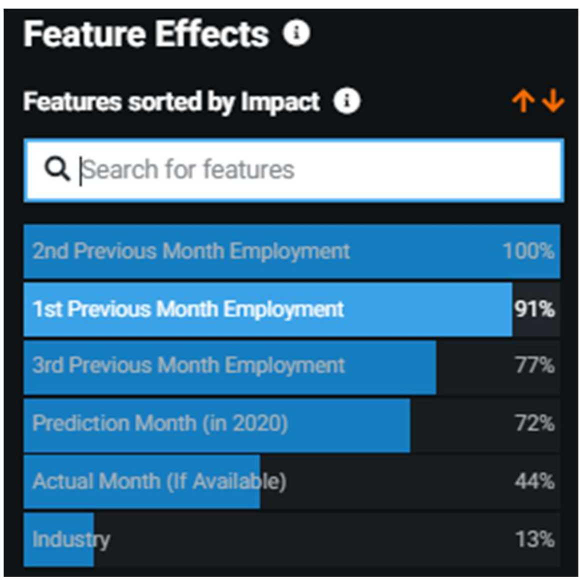



*Figure 5. Feature Effects*

Those features are believed to be useful for the model performance to predict on which industries that have the employment increase in the next month. The model will be processed with different algorithms to train and test the data. The detailed performance of the model using the best algorithms will be delivered in the following section of the report.

# Model Selection Process

After running the dataset through DataRobot, the top two models considered were the Extreme Gradient Boosted Tree Classifier and the Gradient Boosted Tree Classifier. The blender results were ignored since they are combinations of the models considered. For this problem, the focus remained on the Extreme Classifier. Below in Figure 6, it can be seen that the difference in validation is over .01 so this one was not as heavily considered.

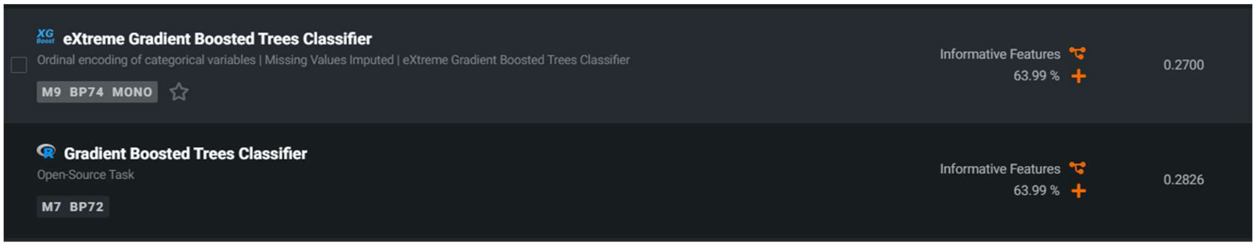



*Figure 6. Top Two Leaderboard for Model Selection of Employment Dataset*

## Model Quality Metrics

The confusion matrix and relative scores provide great metrics for how the model performs. The confusion matrix will be viewed and explained first which can be found in Figure 7 below. This model utilizes 100% of the data for these metrics after deciding this was the proper model. The results of the validation, cross validation, and holdout can be viewed in Figure 8 below. These show to be a bit better than the original with 63.99% above.

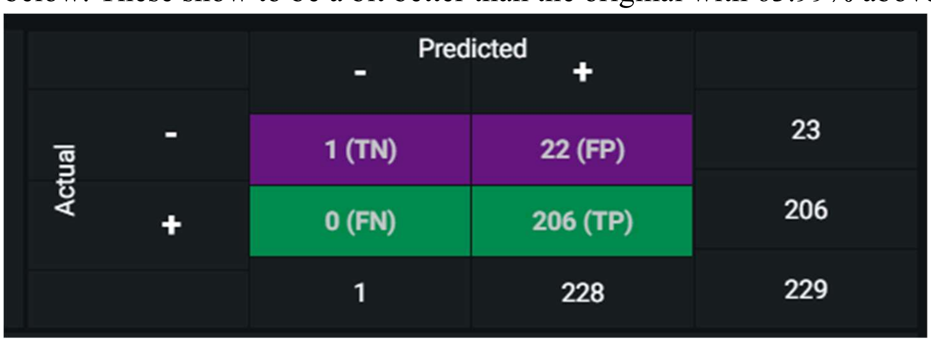



*Figure 7. Confusion Matrix for Extreme Gradient Boosted Trees Classifier*

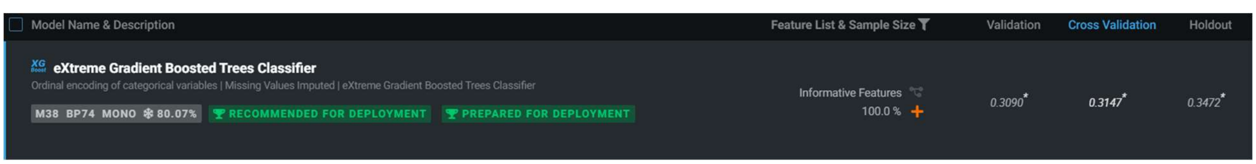



*Figure 8. Model Selected for Final Evaluation*

Looking at the confusion matrix, there are 207 out of the 229 data points that are predicted correctly with the remaining 22 not resulting in an accuracy of about .904. This is considered okay but the focus shifts now to the False Positives as those hold all of the wrongly predicted values. For this problem, false positives indicate that the model predicted there was an increase in employment for an industry when there actually wasn't. The other aspect of false negatives indicates that the model predicted no increase in employment when there actually was in fact. For this case, the false positives are much more detrimental to the problem as this means industries with an increase will not receive support as this indicates recovery, when they actually do need support. However, it is important to note that there were only 23-month points where there was not an increase compared to the remaining 206 that did have an increase. This indicates that the model is struggling only with predicting when there is not an increase in employment.

Finally, the scores for this matrix will be viewed along with the accompanying probability distribution. The scores for this matrix and the accompanying charts can be found in Figure 9 below. The F1 Score of .9493, which is a weighted average of the precision and fallout, shows to do well between the two. However, the precision is of more worry in this case as there are not any false negatives which results in a higher fallout score. The precision of .9035 is not really ideal for this model. Looking at the distributions below, the prediction distribution shows this by having the green indicating frequency for increases or positives to be to the far right. But the purple seen at the very bottom in the middle which should be more to the left in the chart shows this discrepancy that no increase values are not predicted well. The ROC curve also shows this as it increases pretty close to a straight line which is not ideal for the model. Further changes to features will be addressed in the next sections, but for now the model did okay for the initial and pretty small dataset.


*Figure 9. Model Scores for Confusion Matrix and Accompanying Curves and Distribution*

## Areas of Struggle for the Model

The Lift chart provided in figure 10 is developed by all of the Cross-validation industries by their probability of employment increase. DataRobot uses 10% bins, which means each bin consists of 23 industries. In brief, the blue and orange lines represent the Predicted and Actual results, respectively. The ideal situation is when the two lines overlap on each other, which indicate the accuracy of the model.

It is noticeable from the figure that the model quite struggles to produce predictions. The chart reports the big gaps between the Predicted and Actual values, especially in the beginning and the end of the bin points. In details, the model under-predicts the employment increase mostly in bins two, nine and ten, where the actual percentage of employment increase seems to be much higher than 95%. However, the model made two over prediction points at bin one and eight, where the probability of employment increase is around 75 and 90%.

The model seems to be more accurate with the industries that are categorized in bins three, five, six and seven, those have prediction percentage ranges around 85 to 90%.

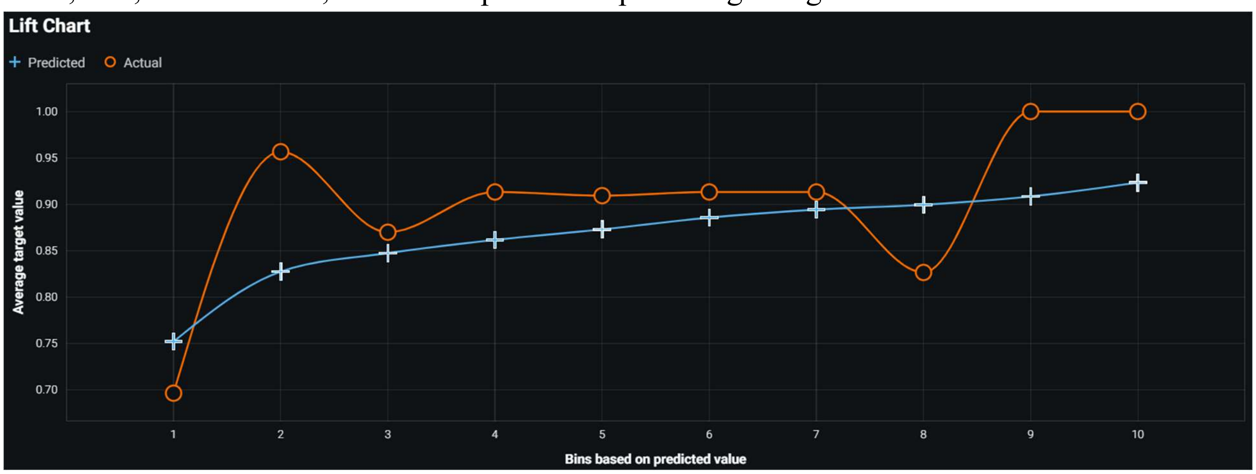



*Figure 10. Lift chart shows where the model struggles*

## Predictive Features

Some related features would be used to train the model to predict whether the employment will increase in the upcoming months. The effects of each feature on the target variable will be illustrated below. The model users-the Massachusetts government-can pay more attention to those critical points when they consider applying the model.

In figure 11, the employment data from the three previous months are the most predictive information to determine whether the employment would increase in the upcoming months or not. It can be seen in the figure; the prediction would be more accurate for the industries that have the number of employments less than 500,000 or more than 2,500,000.

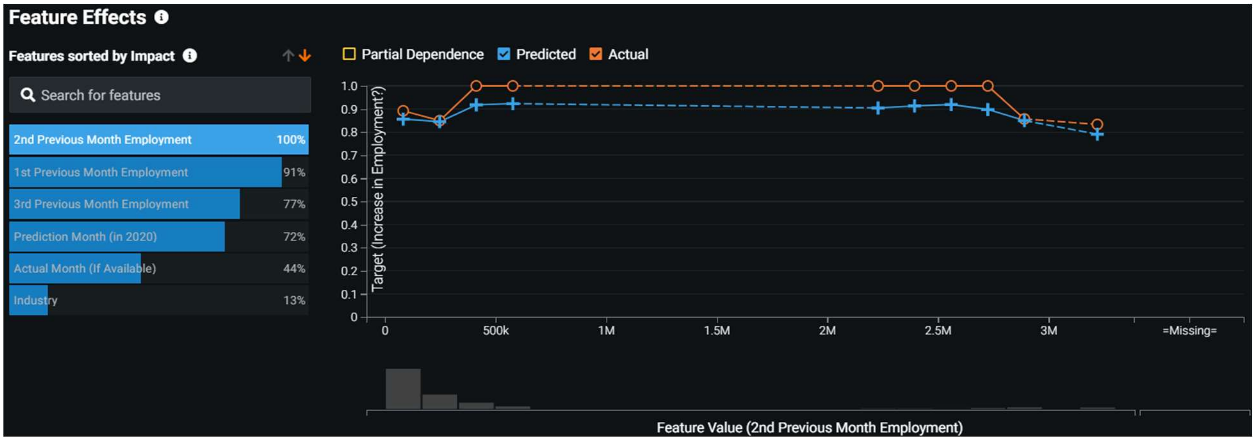



*Figure 11. Feature Effects of "2nd Previous Month Employment"*

In addition, besides the numeric features above, the categorial feature as 'Industry' also indicates the prediction. Briefly, according to figure 12, the "Educational Services" and "Mining and Logging" industries tend to be less likely to have the employment increases, which means the unemployment number in those two may be significant. Besides, there are six industries that have the actual number of employment increases, which are "Accommodation and Food services", "Good producing", "Professional and Technical services", "Federal", "Merchant Wholesalers", and "Retail Trade".


*Figure 12. Feature Effects of "Industry"*

## Feature Types

The most important feature used in the project is the employment data of previous months. These data are immutable features because they have already happened and cannot be changed. This kind of feature is suitable for modeling and making predictions but may not be interesting to management. Because the actions of the management team are not able to have influence on these features.

"Industry" is a mutable feature in the project. Now there are 26 different industries in the dataset. According to the research, the employment condition can be very different in these industries. Some of them have an increase in the employment data and others may have a decrease. If the management team wants to find out the reason behind the increase and decrease, they can regroup the industry by the prediction result. In this way, it is easier to find out the common points of these industries and make suggestions.

The “Increase in Employment” is the feature requiring further examination. The managers are most likely to ask follow-up questions about this feature. What is the reason behind the increase and decrease in employment data? Which reason has the biggest effect on it? To answer these questions, we can seek help from subject matter experts. The team can also add more features to the dataset like education level, salary and other related features to make the prediction more comprehensive and convincing. Because 2020 is a special year, there is infection of COVID-19. The condition may have a big difference when employment is compared with previous years. If the team adds these factors into the dataset, the suggestions come from the prediction maybe more practical for this year.

# Business Recommendations

## Business Decisions at Probability Thresholds

Looking at the final results for the probability thresholds, the distribution shows to have a very strong predictive power towards the positives results or indicating when there is an increase and very little to almost none for the negative cases. Below in Figure 13 is the first chart of the chosen threshold from DataRobot which was at .6347. Following these two are charts with the threshold at .2 and .9. The values tried in between didn't show a large difference for analysis of what threshold should be decided.

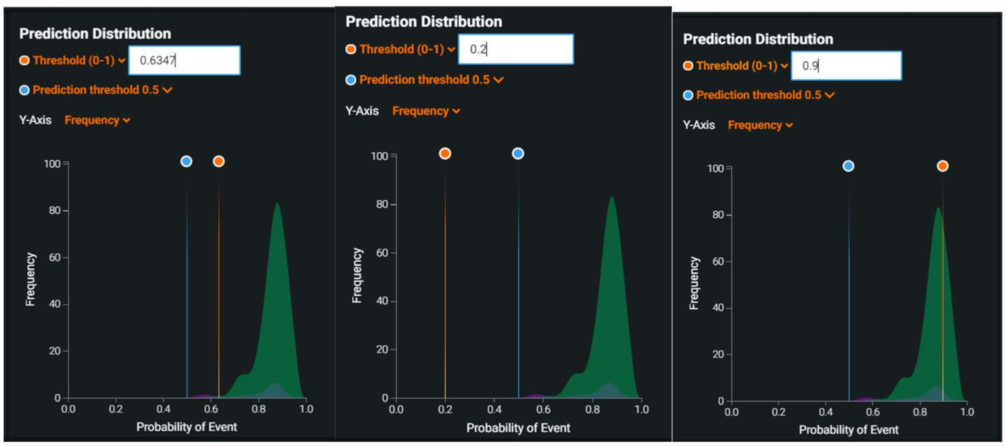



*Figure 13. Probability Distribution for Ideal Threshold through DataRobot*

| | | Predicted - | Predicted + | |
|---|---|---|---|---|
| Actual | - | 0 (TN) | 23 (FP) | 23 |
| | + | 0 (FN) | 206 (TP) | 206 |
| | | 0 | 229 | 229 |

| | | Predicted - | Predicted + | |
|---|---|---|---|---|
| Actual | - | 23 (TN) | 0 (FP) | 23 |
| | + | 151 (FN) | 55 (TP) | 206 |
| | | 174 | 55 | 229 |

*Figure 14. Confusion Matrix for Threshold of 0.2 and 0.9*

Looking at the confusion matrices for the two thresholds chosen (figure 14), it is seen that the .2 threshold does not show a large difference from the .6347 threshold. This seems to make sense as there is not much change in the distribution between those values. However, the .9 threshold shows a large shift with only false negatives summing to 151 out of the 229-month points. This threshold scores a perfect precision of 1 but then has a fallout of 0. For the sake of this problem, having a higher threshold may be helpful to ensure all of the actual negatives are predicted correctly, but it would result in a large chunk predicted to have no increase that actually did. Because the number of falsely predicted negatives is so large, this would result in a lot of funding going to industries that do not really need it. With that, it would still be better to have a much threshold closer to .6 to .65 similar to the idea depicted by DataRobot as only 23 of the 229 points were falsely predicted. The payoff of these different thresholds and value of having false positives and negatives will be covered in the future section.

## Organization Actions of Implementation

The prediction model is believed to support Massachusetts state government to proactively prepare for the industries that have low rates of employment in the upcoming months. Especially in the current COVID-19 pandemic time, if the model predicts the employment for an industry will not increase, it means the industry employment may be constant or tends to decrease. Then, it requires monetary support from the government.

Monetary support can be one of the most important solutions for unemployment issues. The state government has applied the Unemployment Insurance (UI) and Pandemic Unemployment Assistance (PUA) to financially support people who lose their jobs due to the COVID-19. Besides, the current federal regulation named CARES Act, also provides benefits for unemployed people, in which they can receive up to $600 per week (mass.gov, 2020). Thanks to the machine learning model, if any specific industries are identified to have the tendency of unemployment by the end of 2020 to the early of 2021, Massachusetts government can consider targeting their budget to support those predicted industries than others. This can help the state wisely spend the money and support the at-risk industries more efficiently.

Besides financial support, the state government can also generate some more realistic and practical approaches to tackle the unemployment risk. Investing in education is believed to be the most effective solution to address unemployment in the long term. Specifically, according to Amadeo (2020), $1 billion spent for hiring teachers can add up to $1.3 billion to the country's economy. Each billion spent can create 17,687 jobs, which are much higher than defense spending, as she asserted.

Additionally, providing career-focused training programs on community colleges would also help foster the labor force to meet the high demand in the job markets (Eyster & Spaulding, 2020). Those targeted training can help the unemployed to prepare various skill sets to transition into different positions in the same industry or shift to other expertise sectors. Assuming that the government may invest around $60 million to $125 million a year, which means for the first quarter of 2021, they may spend $15 to $31. Thus, if the proposed ML model can help them narrow down to some urgent-need industries, the cost can be reduced, which can eventually enhance employment by developing the high-skilled labor force to fulfill the in-demand industries.

## Profit Matrices Related to Actions

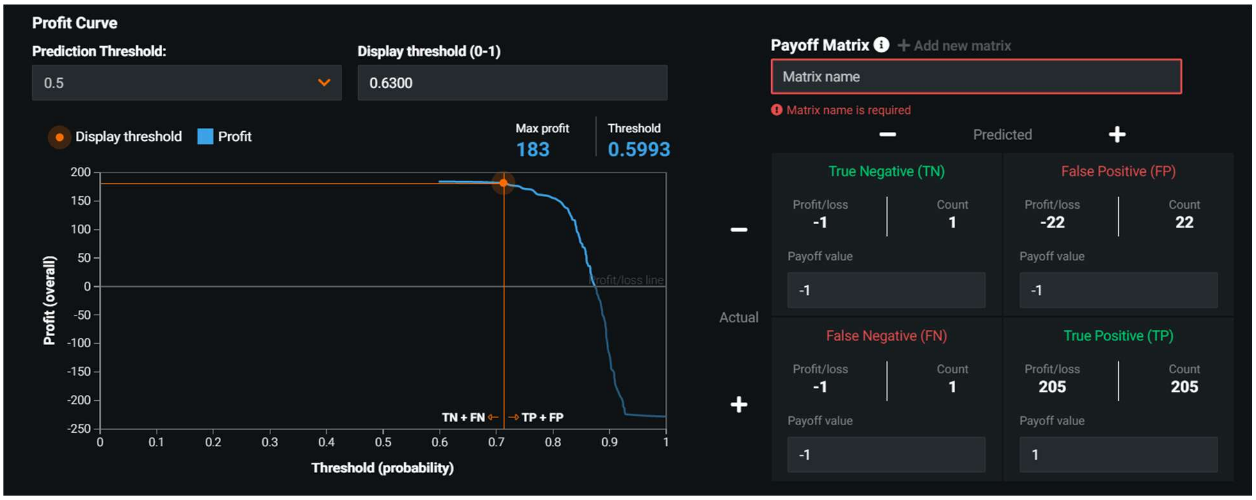



*Figure 15. The original Profit Matrix of the model*

The original profit matrix is shown above in Figure 15 in which we set the value of threshold as 0.63, because the model can have all four kinds of results with this threshold and it is more likely to happen in the real world. In the prediction of 229 industries, 0.4% is true negative, 0.4% is false negative, 9.6% is false positive and 89.6% is true positive. If the government makes plans according to this result, "True Negative" means they will provide help to the industries which really have a rise in the unemployment data. "False Negative" means they will provide support to the industries which actually do not need help, which is a waste of resources. "False Positive" means they will not provide support just in time to those that need it, because there is no problem according to the prediction. "True Positive" means the government doesn't have to provide unemployment help to these industries because their employment rate will rise just as the prediction shows us.

After having a basic understanding, the team made some assumptions to make the profit matrix more realistic. The government does not have to provide support to positive predictions, so the payoff for these predictions is 0. According to the data we have, we can calculate the monthly average decline of employment number in each industry is 5,185. And according to the actions mentioned in the previous section, each unemployed person can get $600 financial support per week. They will at least get $2,400 from the government in a month. So, for the industries which get a negative result in the prediction, the government should prepare to pay about $12 million dollar in the next month to support unemployment workers in these industries to get through the difficult time. And this is also the payoff value for negative predictions.

After we apply the payoff value to the matrix, the result is shown below in Figure 16. If there are 296 industries in Massachusetts, the government has to prepare $24 million dollars each month to deal with the unemployment. But half of them will be wasted because of the false negative predictions. And there are also $264 million which are actually needed but not included in the government's plan because of the false positive predictions. Indeed, there are about 400 industries in MA according to the Labor Market Information from Mass.gov. So according to the model, the government has to cost about $ 384 million each year to deal with the unemployment problem. And $4.2 billion which are actually needed will be ignored.

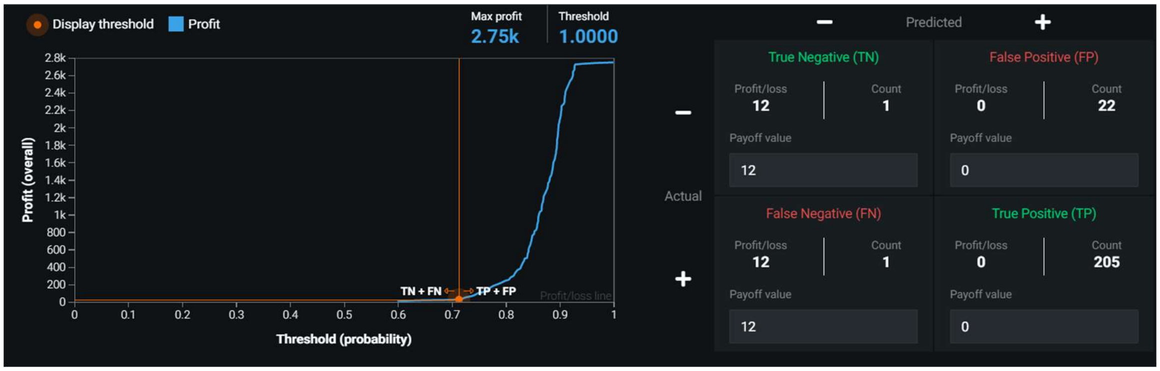



*Figure 16. The Profit Matrix with pay-off value entered*

The total value of the payoff is growing when the threshold is higher than 0.7. According to the research in the previous section, we can know it is due to the increase of the False Negative prediction. But the increase of the threshold can also reduce the False Positive predictions, which is harmful to the industries which really need help. Thus, if the government wants to adjust the value of the threshold to provide support to all the industries which are in a difficult time, the cost brought by False Negative prediction is an important problem they have to consider.

# Final Recommendations for Implementation

Based on the initial goals of this model to predict which industries are increasing employment and therefore recovering from the COVID-19 Pandemic, this model provides a sub-par but still promising result. The resulting false positives and negatives are relatively low overall, but each false positive especially comes at a large cost since it is spending money on an industries that do need it. The final threshold for this model would be to keep at .65 as increasing causes both false positives and negatives to dramatically increase. The final recommendation for this model would be to continue to train the model with further months data. There is also additional data the team was unsuccessful in obtaining publicly that the Massachusetts Government may have that would help improve the precision of the model. These would include aspects like education, salary, and COVID-19 data and policies affecting employment on the daily. These were found to some degree but did not accurately represent the model or the COVID-19 data was not helpful to the model.

The model does have potential to help especially as the Pandemic will still continue to affect the United States into 2021. In conclusion, the Massachusetts Government should not implement this directly for decisions but use it for now for comparison to the actual result and rely mainly on additional expertise to make an informed decision.

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