HW 1
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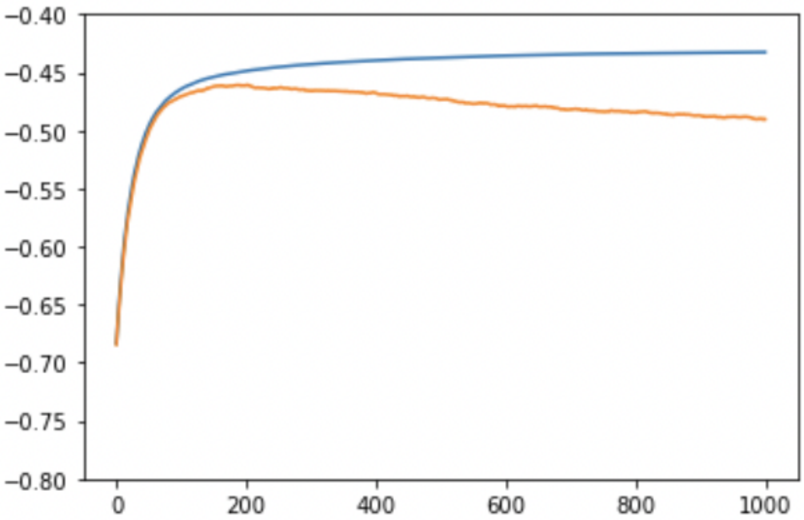
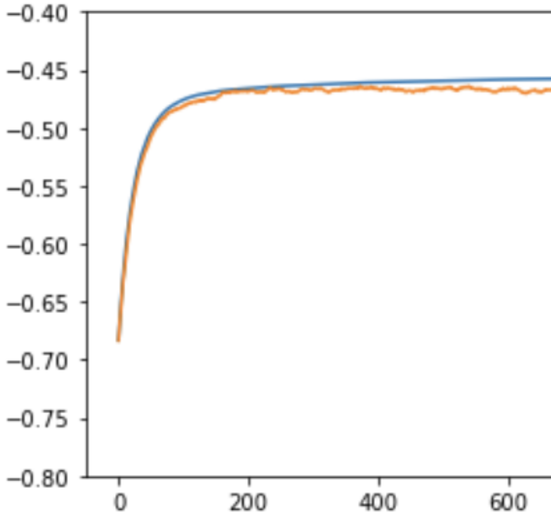
Problem 1:

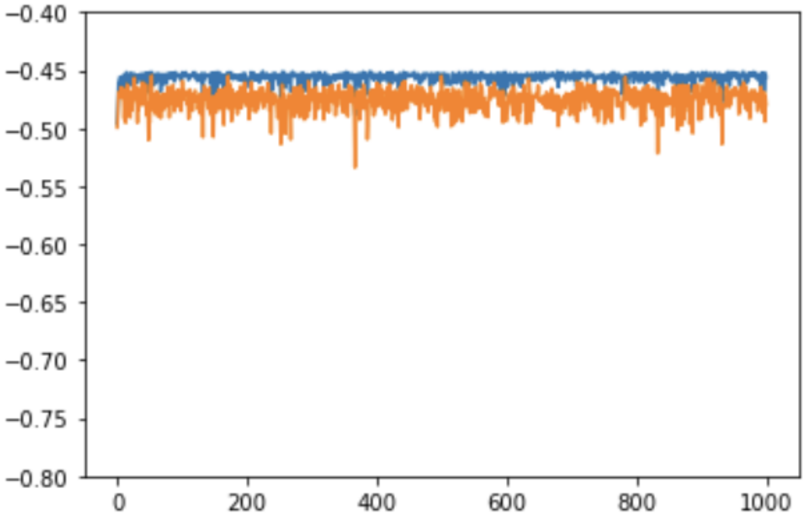
For this problem, I implemented Bayesian logistic regression on a dataset of Starbucks union elections from August 2021- August 2023. I got the data on their locations, dates, and results from the unionelections.org website, and modified the dataset to include attributes that I thought could be relevant or interesting to study. The inputs included: whether or not the union election took place in a "Right to Work" state, the median household income of the town where the election took place in the 2020 census, the minimum wage of the state, the Gini coefficient for the state (measuring income inequality), the percentage union membership in the state, the percentage of Democratic votes from the state in the 2020 presidential election, the margin shift from Republican to Democrat in the 2020 presidential election, the percent of immigrants in the state, whether the ballot was the initial vote or revised vote, the percentage of eligible workers that voted in the election, the total number of eligible voters in the election, the relative date filed (measured from the first date a union election was filed for), the relative tally date (also measured from the first file date), the number of days between filing and voting, and the number of elections that had taken place in that state so far. I found most of this information from the census, though most of the data was limited by the fact that it was much harder to get local data on the town, and so generalized state demographic were used despite clear variances in the social context of different locations within each state. I scaled the features to a mean of 0 and variance of 1 in order to make the results of the regression more interpretable and to improve the results of stochastic gradient descent. This resulted in 451 total observations. The response variable measured the success of the election, or whether the number of votes to join the union was greater than the number of votes to not join the union. The pre-scaled data is attached in the files here:)

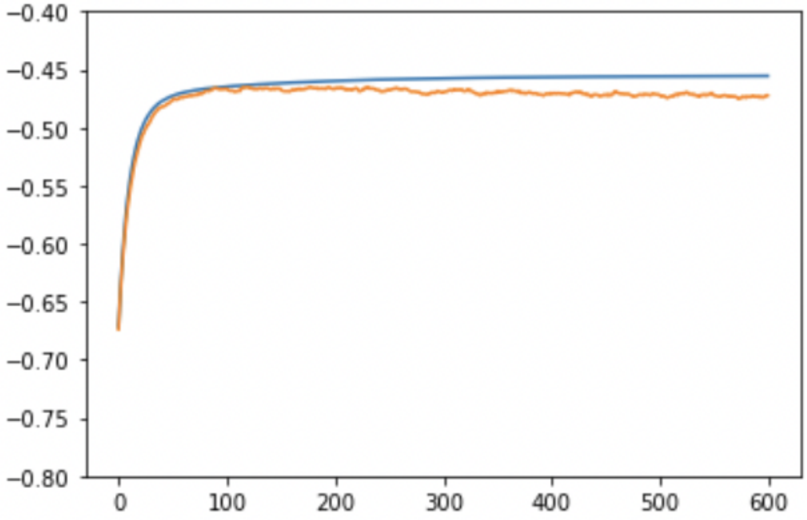
I chose a large prior variance for the Gaussian prior within the model because I didn't know the effects of the parameters well. Small variances promoted more overfitting to the test data, wheras larger variances generalized better but performed worse on the train data. Below are graphs with a prior of 10^{-2} vs 10^{2}.

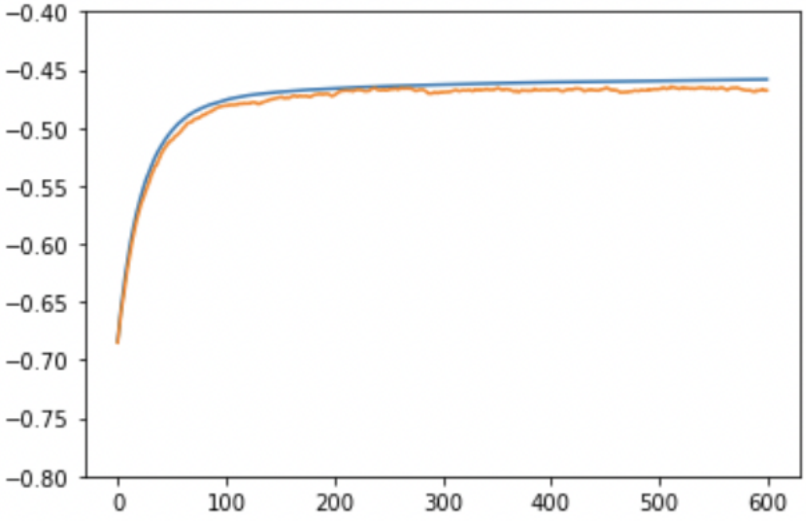




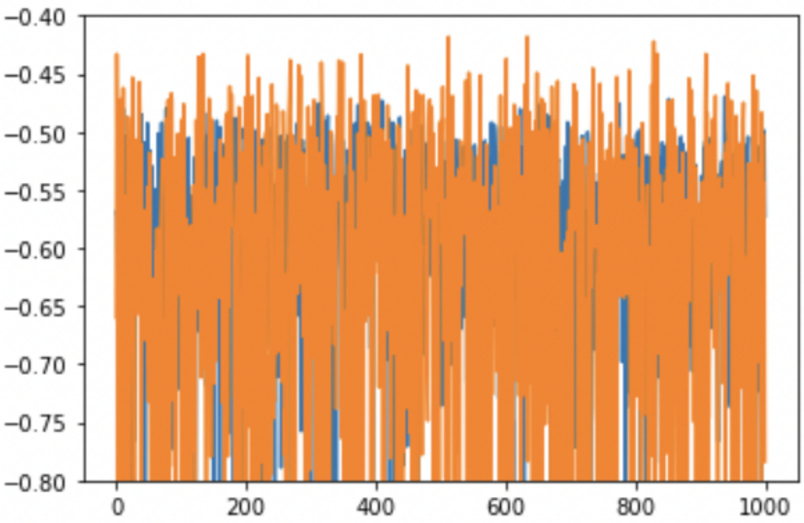
I adjusted batch size, but since my dataset was small used a small batch size for the stochastic gradient descent. Very small batches were unstable (see below, batch sizes of 6, 48, and 128) but large batches took longer to improve. I ultimately chose a batch size of 48 for this reason

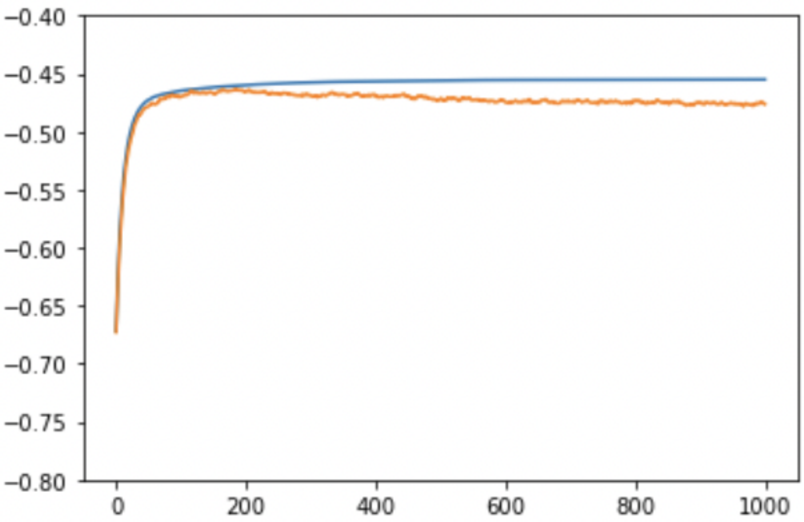




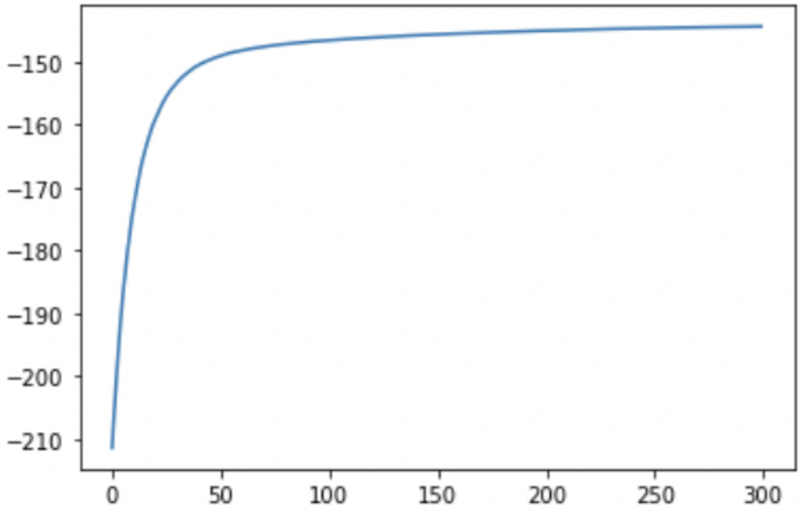


Once I had set these parameters, I decreased the learning rate until I the obective function didnt "jump around" as much. Since I was using a smaller batch size, this made my learning rate smaller as well n order to have a more stable system. I found it was smooth enough at 0.0001 (compared below to 0.01)





I used a number of iterations, under these parameters, where the test cross entropy loss seemed to peak to prevent overfitting. On this graph, that meant setting the number of iterations to 300 (see above). Using that information, we can plot to log liklihood over the iterations:



The resultant beta for the data was [0.27227037, 0.00954723, -0.23437002, 0.54283922, 0.37180527, 0.58296698, 0.48565024, -0.57440793, 0.1693631 , -0.18562403, -0.10718817, 0.08338559, 0.00400394, -0.35841185, -0.14250866] with a bias term of 1.49145598 corresponding to ['RTW', 'MedianIncome', 'MinWage', 'InequalityIndex', 'UnionMembership', 'DemVotes', 'MarginShift', 'IsInitial', 'PercentVoters', 'NumEligibleVoters', 'RelativeDateFiled', 'RelativeTallyDate', 'FileToTallyDays', 'NumElectionsInState'].

This implies the most strong positive correlations between living in a state with more inequality and success in a union election, being in a more Democratic-voting state, being in a state that shifted towards voting more for Democrats than Republicans in the 2020 presidential election. This could be explained by the idea that more exposure to income inequality makes a person more likely to want to join a union or understand class concepts, and the association between the political left and unionism. On the other hand, states with more immigrants, and elections where it took more time between filing for an election were negatively correlated with success. There is some theorizing that immigrant communities are less likely to join unions for fear of reprecussions, which may be reflected here, and an increased time between filing and voting may be related to a more contested election, explaining the negative correlation. Interestingly, the median income of the town and the order of the election (an attempt to measure "momentum") did not seem to have a strong correlation to the outcome of the election.

Problem 2:

a) I'm working on a similar project with a more complete dataset from a series of attempts to organize unions in Walmart stores that I think could be an interesting dataset to work on in the context of this class. The dataset includes demographic data on the site (including racial demographics, percent of male vs female workers at the location and adjusted gross income), campaign data (the length of the campaign, number of organizer conversations, number of workers contacted), and features of the workplace social networks (and I think access to the networks themselves to calculate more features). I would expect there to be correlations within the data, likely positively between the length of the campaign, and the number of organizer conversations/ the number of workers contacted. I would also expected there to be some correlation between the length of the campaign or the number of workers contacted and the number of workers that sign cards, but the number of workers that sign cards could be conditionally independent of the length of the campaing given the number of workers contacted. There could be some correlation between the centrality of the network and the number of cards signed or number of workers contacted, but I dont know what it would be. There also could be a correlation between the mean AGI in the zip code or racial demographics and the number of cards that are signed for unionization but I also dont know which direction this correlation would take.

b) It could be interesting to think of the social or cultural attitudes towards unions in the community as a latent variable in this model, or some latent variables that measure the "closeness" of ties within the network graphs of each of the locations. Latent variables could also be used on the graph data to identify communities within a workplace, leaders of certain communities within each workplace, or people who connect different communities in the workplace. It could also be interesting to study or measure some type of "ability to be convinced to sign a card" latent variable within the context of the dataset.

c) Who are most likely to be important organizers (able to most increase the number of cards signed) in a given workplace network? Which workplaces are mostly likely to be able to successfully sign enough union cards? Which people within a workplace network are most/least likely to be able to be convinced to sign a union card, given their position in the network and workplace features?