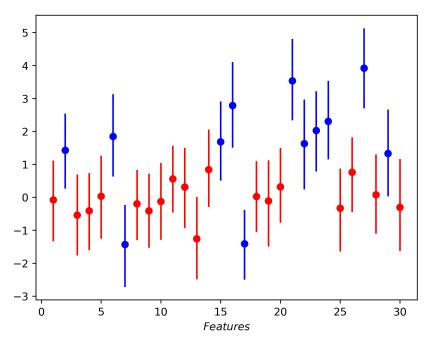
## Question 1

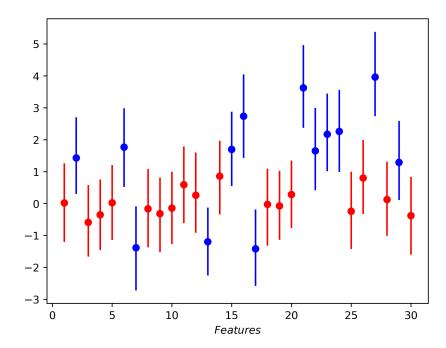
a



Screenshot of code here: 0.1.

- i. C is a hyperparameter used for regularization to prevent overfitting of the Logistics Regression model. This is inversely proportional to the penalty constant  $\lambda$  and penalises models that have a lot of features and therefore the effect is that it reduces each feature importance.
- ii. The effect that this has on the Bootstrap graph is that it increases the variance of each feature, therefore making the 90% confidence intervals larger and more reliable since their largeness means they are more likely to include the true value.

At C=0.1, most of the features have their average at 0 with a very small confidence interval. Because I know how the data was generated and I know that the mean for each feature *should* be 0, I know that this is a reliable estimate. However in the real world when I don't know how the data was generated, a model with C=0.1 would probably be overfit on the data and not contain a true mean.



Screenshot of code here: 0.2.

## **Appendix**

## 0.1 q1a

```
def q1a():
23
         data = import_data(Q1_DATA_DIR)
         Xtrain = data.iloc[:, :30].to_numpy()
         Ytrain = data.Y.to_numpy()
         np.random.seed(12)
         B = 500
         C = 1000
         p = Xtrain.shape[1]
         coef_mat = np.zeros(shape=(B,p))
         for b in range(B):
             b_sample = np.random.choice(np.arange(Xtrain.shape[0]), size=Xtrain.shape[0])
             Xtrain_b = Xtrain[b_sample]
             Ytrain_b = Ytrain[b_sample]
             mod = LogisticRegression(penalty="l1", solver="liblinear", C=C).fit(Xtrain_b, Ytrain_b)
             coef_mat[b,:] = mod.coef_
         means = np.mean(coef_mat, axis=0)
         lower = np.quantile(coef_mat, 0.10, axis=0)
         upper = np.quantile(coef_mat, 0.90, axis=0)
         colors = ["red" if lower[i] <= 0 and upper[i] >= 0 else "blue" for i in range(p)]
         plt.vlines(x=np.arange(1,p+1), ymin=lower, ymax=upper, colors=colors)
         plt.scatter(x=np.arange(1,p+1), y=means, color=colors)
         plt.xlabel("$Features$")
         plt.savefig("./outputs/NPBootstrap.png", dpi=400)
```

## 0.2 q1b

plt.xlabel("\$Features\$")

plt.savefig("./outputs/NPParameterisedBootstrap.png", dpi=400)

```
def q1b():
     data = import_data(Q1_DATA_DIR)
     Xtrain = data.iloc[:, :30].to_numpy()
     Ytrain = data.Y.to_numpy()
    np.random.seed(20)
    B = 500
    C = 1000
    p = Xtrain.shape[1]
    mod = LogisticRegression(penalty="l1", solver="liblinear", C=C).fit(Xtrain, Ytrain)
     B0 = mod.intercept_[0]
     coefs = mod.coef_[0]
     coef_mat = np.zeros(shape=(B,p))
     for b in range(B):
          b_sample = np.random.choice(np.arange(Xtrain.shape[0]), size=Xtrain.shape[0])
          Xtrain_b = Xtrain[b_sample]
          Ytrain_b = np.zeros(shape=(1,Xtrain.shape[0]))
          idx = 0
          for i in Xtrain_b:
               prob = math.exp(B0 + coefs.T @ i) / (1 + math.exp(B0 + coefs.T @ i))
              prob = math.exp(B0 + coefs.T @ i) / (1 + math.exp(B0 + coefs.T @ i))
              response = np.random.binomial(n=1, p=prob, size=1)
             # Add to ytrain data
Ytrain_b[0, idx] = response[0]
          mod_b = LogisticRegression(penalty="l1", solver="liblinear", C=C).fit(Xtrain_b, Ytrain_b[0])
          coef_mat[b,:] = mod_b.coef_
      means = np.mean(coef_mat, axis=0)
lower = np.quantile(coef_mat, 0.10, axis=0)
upper = np.quantile(coef_mat, 0.90, axis=0)
      colors = ["red" if lower[i] \le 0 and upper[i] \ge 0 else "blue" for i in range(p)]
      \label{pll.vlines} $$ plt.vlines(x=np.arange(1,p+1), ymin=lower, ymax=upper, colors=colors) $$ plt.scatter(x=np.arange(1,p+1), y=means, color=colors) $$
```