

Linear Models

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Introduction

One of the most basic approaches towards learning a classifier is using Linear Models. Linear models for classification separate the input vectors (data points) into various classes using linear decision boundaries. In this assignment, we study and implement four different types of classifiers based on Linear Models.

POCKET Algorithm (Modified Perceptron Algorithm)

The Perceptron learning algorithm learns a decision boundary given some linearly separable data. In case of non separable data, a modified version of the algorithm is used known as the POCKET Algorithm.

Algorithm: Perceptron Learning Algorithm

```
P ← inputs with label 1;  
N ← inputs with label 0;  
Initialize w randomly;  
while !convergence do  
    Pick random x ∈ P ∪ N ;  
    if x ∈ P and w.x < 0 then  
        | w = w + x ;  
    end  
    if x ∈ N and w.x ≥ 0 then  
        | w = w - x ;  
    end  
end  
//the algorithm converges when all the  
inputs are classified correctly
```

In POCKET algorithm, we randomly initialize the separating hyperplane parameters and keep updating them, storing the best parameters found till each iteration in a 'pocket'.

Hypothesis function

$$h_w(x_i) = \operatorname{sgn}(w^T x_i + w_0)$$

Loss function

$$J(w) = \sum_{i=1}^n \max(-y_i h_w(x_i), 0)$$

The class labels are assumed to be {-1, 1} in this case.

Linear Least Squares

In this algorithm, we try to minimize the total squared error. We can augment the input vectors, (i.e append 1 to each input vector) for ease of computation.

Hypothesis function

$$\begin{aligned} h_w(x_i) &= 1 \quad w^T x_i + w_0 > t \\ &= 0 \quad \text{otherwise} \end{aligned}$$

Where t is some threshold value.

Loss function

$$J(w) = \frac{1}{n} \sum_{i=1}^n (w^T x_i + w_0 - y_i)^2$$

The solution to \mathbf{W} is given by:

$$\mathbf{W} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{Y}$$

Where both \mathbf{X} and \mathbf{W} are augmented.

Shape of \mathbf{W} : $(d+1, 1)$ and Shape of \mathbf{X} : $(n, d+1)$

Logistic Regression

Hypothesis function

$$\begin{aligned} h_w(x_i) &= 1 \quad \sigma(w^T x_i + w_0) > t \\ &= 0 \quad otherwise \end{aligned}$$

where:

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

Loss function

$$J(w) = -\frac{1}{n} \sum_{i=1}^n y_i \log(a(x_i)) + (1 - y_i) \log(1 - a(x_i))$$

Where:

$$a(x) = \sigma(w^T x + w_0)$$

Q1: Classification on Synthetic dataset

We observed the performance of various algorithms for different prior probabilities. We chose 3 different prior probabilities for class 0: 0.05 (extreme imbalance), 0.3 (moderate imbalance), 0.5 (no imbalance). The metrics we use for comparing the algorithms are accuracy and f1-score.

Terminology:

- acc: test accuracy of our implemented classifier
- Train_f1, Train_acc: train f1 score and train accuracy
- sk_acc: Accuracy of sklearn classifier
- f1 : f1 score of our classifier, sk_f1: f1 score of sklearn classifier

10-dimensional data

We generated 10-dimensional 2000 training examples and 1000 testing examples for both classes. The mean of the data was 0 across all dimensions for class 0 and 1 across all dimensions for class 1. The covariance matrices were identity for both classes.

Performance of each algorithm was as follows:

Bayes Decision Boundary				weights
	prior	bayes_acc	bayes_f1	
	0.05	0.981	0.990047	[1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, -2.06]
	0.30	0.938	0.955903	[1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, -4.15]
	0.50	0.933	0.933860	[1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, -5.0]

POCKET algorithm								weights	sk_weights
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	prior		
0.05	0.978	0.975	0.969	0.989	0.987	0.984	[0.32, 0.14, 0.24, 0.22, 0.04, 0.46, 0.4, 0.25, 0.27, 0.21, -0.02]	[3.68, 1.03, 3.82, 4.99, 4.63, 1.52, -0.73, 1.06, 3.97, 1.83, -4.0]	
0.30	0.952	0.936	0.916	0.967	0.955	0.939	[0.45, 0.6, 0.52, 0.47, 0.22, 0.41, 0.32, 0.48, 0.47, 0.24, -1.5]	[3.94, 5.26, 3.42, 2.8, 4.71, 7.33, 4.28, 3.37, 0.1, 2.5, -18.0]	
0.50	0.941	0.916	0.922	0.941	0.917	0.924	[0.44, 0.25, 0.41, 0.52, 0.31, 0.62, 0.25, 0.4, 0.43, 0.22, -1.89]	[3.27, 5.4, 5.19, 1.47, 3.65, 5.01, 2.72, 7.5, 4.43, 6.92, -20.0]	

LeastSquares algorithm								weights	sk_weights
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	prior		
0.05	0.982	0.979	0.954	0.990	0.989	0.976	[0.03, 0.03, 0.03, 0.04, 0.03, 0.04, 0.03, 0.04, 0.04, 0.03, 0.64]	[0.03, 0.03, 0.03, 0.04, 0.03, 0.04, 0.03, 0.04, 0.04, 0.03, 0.64]	
0.30	0.957	0.942	0.937	0.969	0.958	0.955	[0.06, 0.07, 0.08, 0.07, 0.06, 0.06, 0.08, 0.07, 0.07, 0.06, 0.22]	[0.06, 0.07, 0.08, 0.07, 0.06, 0.06, 0.08, 0.07, 0.07, 0.06, 0.22]	
0.50	0.945	0.935	0.929	0.945	0.935	0.930	[0.09, 0.07, 0.06, 0.06, 0.06, 0.08, 0.06, 0.08, 0.09, 0.07, 0.14]	[0.09, 0.07, 0.06, 0.06, 0.06, 0.08, 0.06, 0.08, 0.09, 0.07, 0.14]	

LogisticRegression algorithm									
	train_acc	acc	sk_acc	train_f1	f1	sk_f1		weights	sk_weights
prior									
0.05	0.982	0.978	0.978	0.991	0.988	0.988	[1.01, 0.63, 0.75, 1.08, 0.9, 0.77, 0.75, 1.2, 1.14, 1.06, -1.93]	[0.96, 0.61, 0.73, 1.03, 0.86, 0.75, 0.73, 1.13, 1.08, 1.0, -1.8]	
0.30	0.955	0.936	0.936	0.968	0.955	0.955	[1.06, 1.04, 1.07, 1.12, 0.88, 1.14, 1.06, 1.18, 1.21, 1.01, -4.57]	[1.03, 1.01, 1.04, 1.09, 0.86, 1.1, 1.03, 1.14, 1.17, 0.98, -4.43]	
0.50	0.938	0.930	0.931	0.938	0.931	0.931	[1.23, 0.97, 0.97, 0.82, 0.91, 1.15, 0.81, 1.13, 1.26, 1.01, -5.32]	[1.19, 0.95, 0.95, 0.81, 0.89, 1.12, 0.8, 1.11, 1.22, 0.98, -5.19]	

FisherLDA algorithm									
	train_acc	acc	sk_acc	train_f1	f1	sk_f1		weights	sk_weights
prior									
0.05	0.982	0.976	0.979	0.991	0.987	0.989	[0.94, 0.81, 0.8, 1.24, 1.03, 1.11, 0.87, 1.26, 1.14, 0.92, -2.6]	[0.94, 0.81, 0.8, 1.24, 1.03, 1.11, 0.87, 1.26, 1.14, 0.92, -2.18]	
0.30	0.958	0.940	0.935	0.969	0.957	0.954	[0.93, 1.06, 1.17, 1.03, 0.95, 0.94, 1.2, 1.13, 1.07, 0.97, -4.86]	[0.93, 1.06, 1.17, 1.03, 0.95, 0.94, 1.2, 1.12, 1.07, 0.97, -4.41]	
0.50	0.946	0.928	0.929	0.945	0.927	0.930	[1.22, 1.01, 0.89, 0.91, 0.85, 1.17, 0.87, 1.1, 1.22, 0.95, -5.8]	[1.22, 1.01, 0.89, 0.91, 0.85, 1.17, 0.87, 1.1, 1.22, 0.95, -5.18]	

2-dimensional data

Different mean, same identity covariance

In this case, we generate the 2-dimensional data with the same no. of train and test data points with identity covariance matrices.

Bayes classifier

$$\ast \mu_0 = [0, 0 \dots]^T = \bar{0}, \mu_1 = [1, 1 \dots]^T = \bar{1}, \Sigma_0 = \Sigma_1 = I_d.$$

here $\mu_0, \mu_1 \in \mathbb{R}^d$ $d=2$ or 10 according to question.

Predict C_1 if $g_1(x) > g_0(x)$

$$\text{ie, } \log \frac{P_1}{P_0} - \frac{1}{2} [\|x - \bar{1}\|^2 - \|x\|^2] > 0.$$

$$\log \frac{P_1}{P_0} - \frac{1}{2} \left[-2 \sum_{i=1}^d x_i + d \right] > 0$$

we get the boundary as linear boundary.

$$\left[\sum_{i=1}^d x_i + \log \frac{P_1}{P_0} - \frac{d}{2} = 0 \right]$$

Without feature transformation:

Bayes Decision Boundary				
	bayes_acc	bayes_f1	weights	
prior				
0.05	0.954	0.976337	[1.0, 1.0, 1.94]	
0.30	0.820	0.877049	[1.0, 1.0, -0.15]	
0.50	0.763	0.762763	[1.0, 1.0, -1.0]	

POCKET algorithm									
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	weights	sk_weights	
prior									
0.05	0.954	0.954	0.951	0.976	0.976	0.974	[0.19, 0.24, 0.39]	[1.45, 0.65, 1.0]	
0.30	0.799	0.809	0.317	0.868	0.874	0.047	[0.19, 0.21, 0.05]	[0.55, 0.62, -3.0]	
0.50	0.757	0.763	0.711	0.760	0.764	0.762	[0.07, 0.07, -0.07]	[0.86, 0.5, 0.0]	

LeastSquares algorithm									
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	weights	sk_weights	
prior									
0.05	0.904	0.923	0.950	0.948	0.959	0.974	[0.04, 0.05, 0.87]	[0.04, 0.05, 0.87]	
0.30	0.792	0.813	0.811	0.859	0.874	0.873	[0.15, 0.15, 0.5]	[0.15, 0.15, 0.5]	
0.50	0.759	0.770	0.767	0.764	0.775	0.764	[0.17, 0.16, 0.32]	[0.17, 0.16, 0.32]	

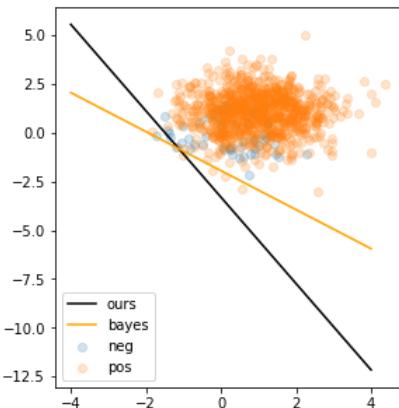


LogisticRegression algorithm									
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	weights	sk_weights	
prior									
0.05	0.952	0.954	0.954	0.975	0.976	0.976	[1.01, 1.05, 2.0]	[1.0, 1.04, 2.0]	
0.30	0.789	0.818	0.817	0.857	0.877	0.876	[0.99, 0.98, -0.11]	[0.98, 0.97, -0.11]	
0.50	0.755	0.770	0.770	0.753	0.768	0.768	[1.05, 0.98, -1.06]	[1.04, 0.97, -1.05]	

FisherLDA algorithm									
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	weights	sk_weights	
prior									
0.05	0.909	0.922	0.954	0.951	0.958	0.976	[0.99, 1.06, 0.23]	[0.99, 1.06, 1.99]	
0.30	0.792	0.813	0.818	0.859	0.874	0.876	[0.98, 0.99, -0.05]	[0.98, 0.99, -0.12]	
0.50	0.760	0.770	0.767	0.765	0.775	0.764	[1.04, 0.97, -0.94]	[1.04, 0.97, -1.06]	

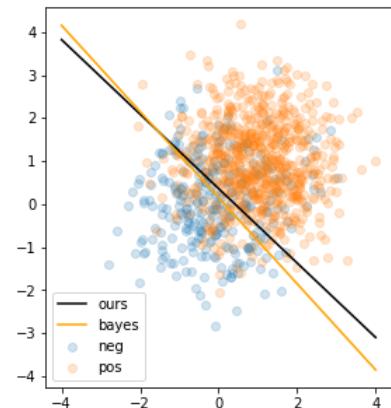
We plotted the decision boundaries for the algorithms:

Prior=0.05

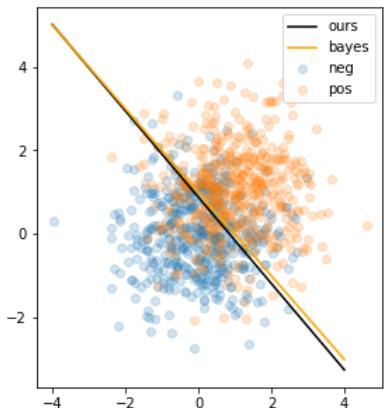


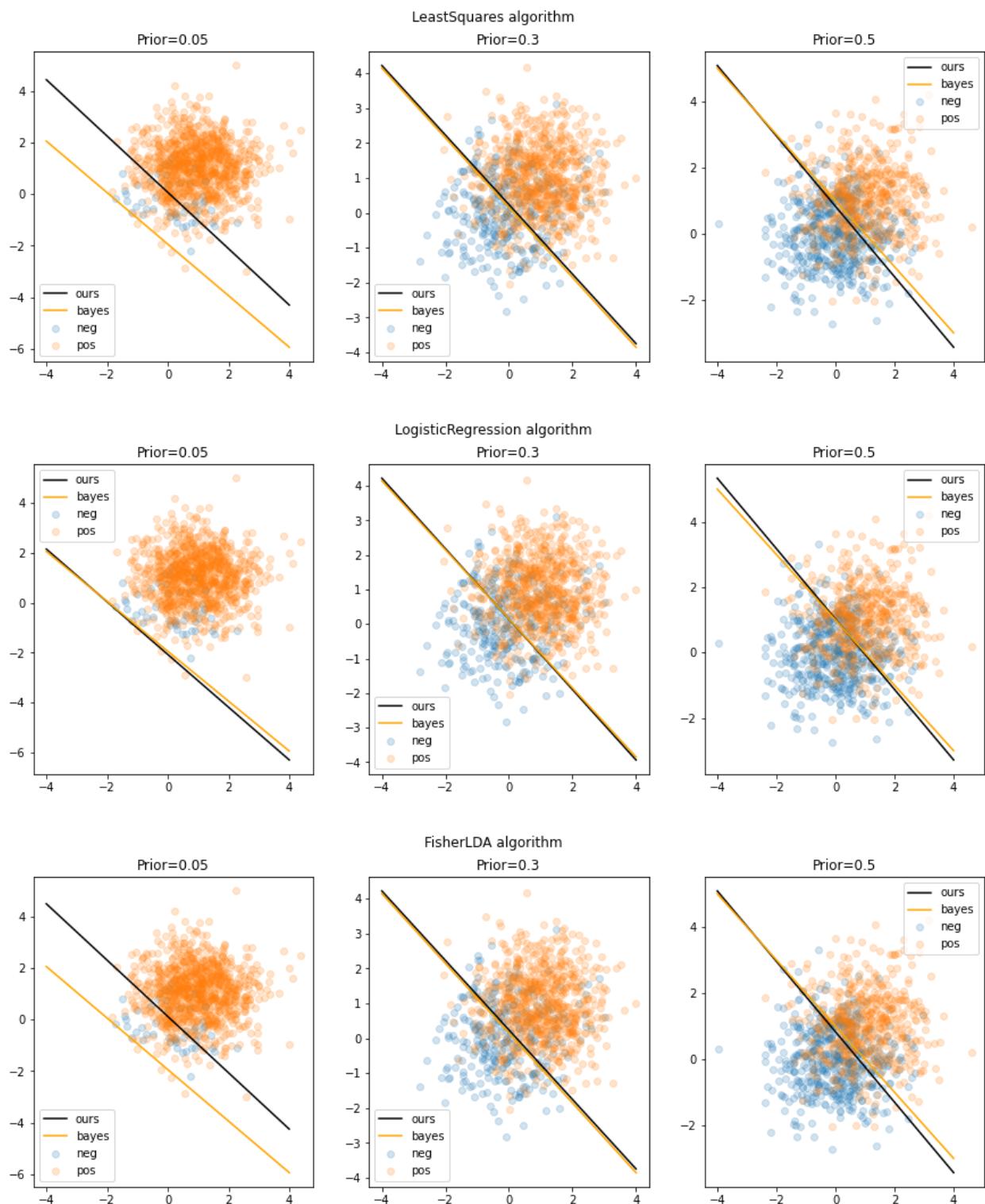
POCKET algorithm

Prior=0.3



Prior=0.5





Applying Feature Transformation

We transformed the input data features into a polynomial with degree=2, hoping to improve the performance. That is, initially we had (x_1, x_2) . Now, after feature transformation, we have non-linear features: $(1, x_1, x_2, x_1x_2, x_1^2, x_2^2)$.

The results are as follows:

							weights	sk_weights
	train_acc	acc	sk_acc	train_f1	f1	sk_f1		
prior								
0.05	0.953	0.951	0.950	0.976	0.975	0.974	[0.73, 0.43, 0.54, 0.56, -0.2, 0.11, -0.19]	[1.0, 1.83, 5.83, 2.99, -3.37, 11.0, 1.0]
0.30	0.792	0.801	0.518	0.857	0.865	0.536	[-0.17, 0.45, 0.43, 0.01, -0.06, -0.09, 0.1]	[-1.0, -2.89, 3.34, -4.79, 3.52, 1.62, -1.0]
0.50	0.778	0.759	0.756	0.780	0.761	0.752	[-0.25, 0.34, 0.43, 0.13, -0.0, -0.04, -0.17]	[-2.0, 2.56, 4.69, 1.41, 3.83, -0.2, -2.0]

							weights	sk_weights
	train_acc	acc	sk_acc	train_f1	f1	sk_f1		
prior								
0.05	0.936	0.940	0.953	0.966	0.968	0.976	[0.42, 0.12, 0.11, -0.02, -0.04, -0.02, 0.42]	[0.0, 0.12, 0.11, -0.02, -0.04, -0.02, 0.85]
0.30	0.800	0.798	0.800	0.862	0.862	0.867	[0.25, 0.21, 0.18, -0.01, -0.04, -0.01, 0.25]	[0.0, 0.21, 0.18, -0.01, -0.04, -0.01, 0.49]
0.50	0.781	0.764	0.763	0.778	0.761	0.762	[0.16, 0.17, 0.17, -0.0, -0.0, 0.01, 0.16]	[0.0, 0.17, 0.17, -0.0, -0.0, 0.01, 0.33]

							weights	sk_weights
	train_acc	acc	sk_acc	train_f1	f1	sk_f1		
prior								
0.05	0.953	0.952	0.952	0.976	0.975	0.975	[1.02, 1.12, 1.12, -0.14, -0.04, 0.06, 1.02]	[-0.0, 1.1, 1.1, -0.14, -0.03, 0.07, 2.04]
0.30	0.798	0.798	0.798	0.860	0.862	0.862	[-0.15, 1.01, 0.9, 0.08, 0.04, 0.11, -0.15]	[-0.0, 1.01, 0.89, 0.08, 0.05, 0.11, -0.3]
0.50	0.777	0.763	0.763	0.777	0.763	0.763	[-0.55, 1.11, 1.08, -0.01, -0.05, 0.04, -0.55]	[-0.0, 1.1, 1.07, -0.0, -0.04, 0.04, -1.09]

							weights	sk_weights
	train_acc	acc	sk_acc	train_f1	f1	sk_f1		
prior								
0.05	0.943	0.946	0.946	0.970	0.972	0.972	[0.0, 2.94, 2.75, -0.56, -0.93, -0.42, 2.3]	[0.0, 2.95, 2.76, -0.56, -0.93, -0.43, 2.31]
0.30	0.800	0.798	0.797	0.862	0.862	0.864	[0.0, 1.42, 1.23, -0.1, -0.28, -0.04, -0.38]	[0.0, 1.42, 1.23, -0.1, -0.28, -0.04, -0.16]
0.50	0.782	0.758	0.763	0.777	0.754	0.762	[0.0, 1.05, 1.06, -0.0, -0.02, 0.03, -1.17]	[0.0, 1.05, 1.06, -0.0, -0.02, 0.03, -1.07]

As can be observed from the tables, applying feature transformation did not improve test accuracy/f1 score much. This is because the Bayes decision boundary itself is linear.

Also, adding complexity to the model has increased train_acc and train_f1, which is an example of a small amount of overfitting.

Same means, different covariance1

Here, we used $\mu_0 = \mu_1 = [0, 0]^T$, $\sigma_0 = I$ and $\sigma_1 = [(1, .9), (.9, 1)]$ to generate data

Bayes classifier

We notice that the bayes classifier has quadratic terms in its decision boundary.

Bayes Decision boundary

* for same mean (origin) diff covars Σ_0, Σ_1

Predict C_1 if $g_1(x) > g_0(x)$
ie, $P_1 f_1(x) > P_0 f_0(x)$

$$\log \frac{P_1}{P_0} + \log \frac{f_1(x)}{f_0(x)} > 0$$

$$\log \frac{P_1}{P_0} - \frac{1}{2} \log \frac{|\Sigma_1|}{|\Sigma_0|} - \frac{1}{2} x^T (\Sigma_1^{-1} - \Sigma_0^{-1}) x > 0$$

Set $Q = \frac{1}{2} (\Sigma_1^{-1} + \Sigma_0^{-1}) = \begin{bmatrix} q_{00} & q_{01} \\ q_{10} & q_{11} \end{bmatrix}$

$b = \log \frac{P_1}{P_0} - \frac{1}{2} \log \frac{|\Sigma_1|}{|\Sigma_0|}$

$x = [x_1 \ x_2]^T$

we get the boundary as

$b + (q_{10} + q_{01})x_1 x_2 + q_{00}x_1^2 + q_{11}x_2^2 = 0$
↙ quadratic boundary

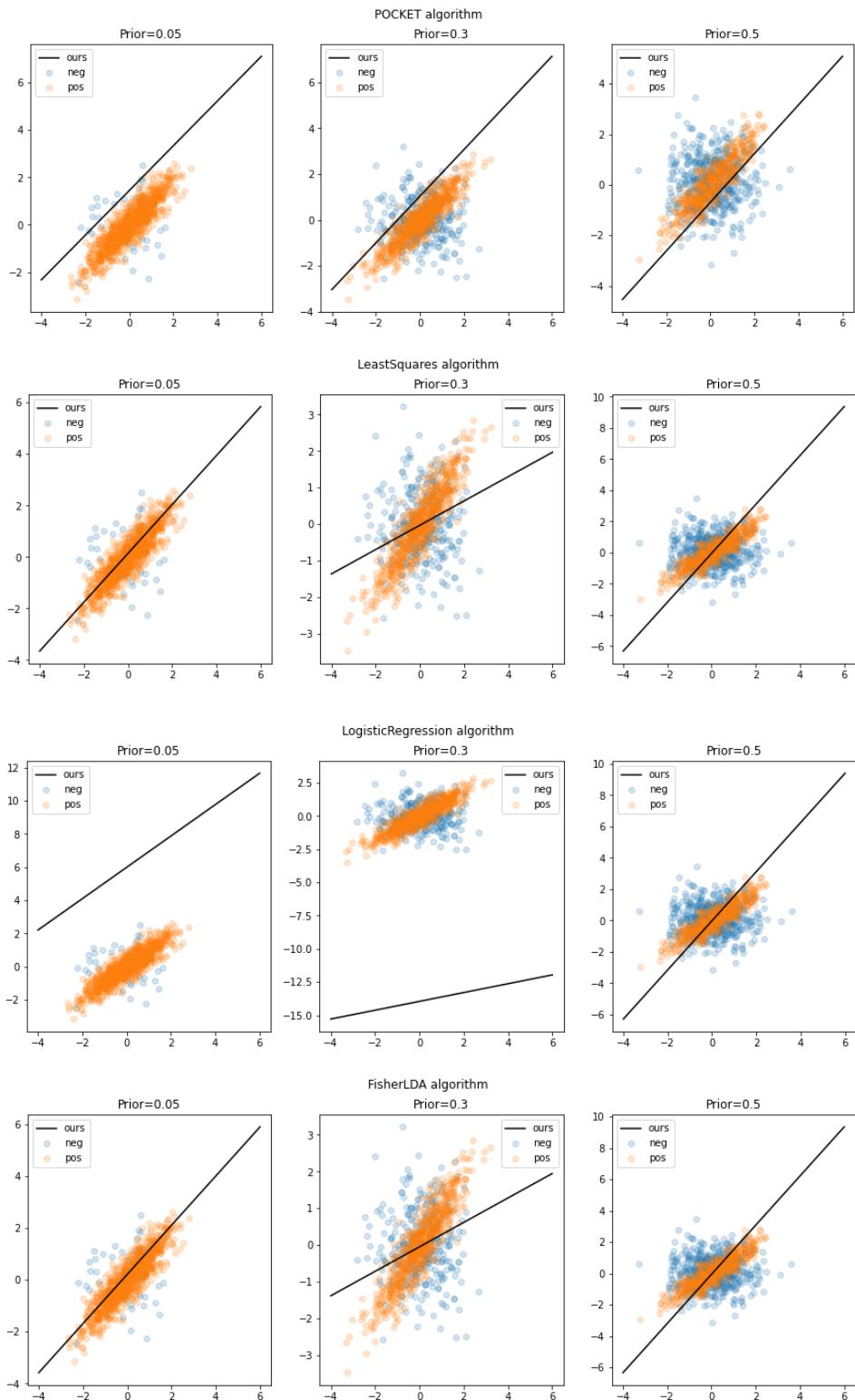
Without Feature transformation

POCKET algorithm								
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	weights	sk_weights
prior								
0.05	0.960	0.961	0.947	0.979	0.980	0.973	[0.2, -0.21, 0.3]	[0.39, 0.01, 1.0]
0.30	0.766	0.750	0.712	0.856	0.846	0.829	[0.19, -0.19, 0.2]	[0.35, -0.46, 1.0]
0.50	0.642	0.610	0.505	0.727	0.707	0.024	[-0.12, 0.12, 0.08]	[0.59, 0.36, -2.0]

LeastSquares algorithm								
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	weights	sk_weights
prior								
0.05	0.626	0.629	0.950	0.762	0.765	0.974	[0.02, -0.03, 0.95]	[0.02, -0.03, 0.95]
0.30	0.520	0.524	0.700	0.607	0.608	0.824	[-0.0, 0.01, 0.7]	[-0.0, 0.01, 0.7]
0.50	0.532	0.477	0.473	0.539	0.481	0.470	[-0.01, 0.01, 0.5]	[-0.01, 0.01, 0.5]

LogisticRegression algorithm								
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	weights	sk_weights
prior								
0.05	0.950	0.950	0.950	0.974	0.974	0.974	[0.47, -0.5, 2.98]	[0.44, -0.47, 2.97]
0.30	0.700	0.700	0.700	0.824	0.824	0.824	[-0.02, 0.06, 0.85]	[-0.02, 0.06, 0.85]
0.50	0.524	0.473	0.474	0.525	0.470	0.472	[-0.06, 0.04, 0.0]	[-0.06, 0.04, 0.0]

FisherLDA algorithm								
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	weights	sk_weights
prior								
0.05	0.687	0.686	0.950	0.809	0.808	0.974	[0.51, -0.53, 0.11]	[0.51, -0.53, 2.98]
0.30	0.520	0.527	0.700	0.611	0.612	0.824	[-0.02, 0.06, 0.0]	[-0.02, 0.06, 0.85]
0.50	0.535	0.481	0.473	0.545	0.489	0.470	[-0.06, 0.04, 0.0]	[-0.06, 0.04, 0.0]



Applying feature transformation degree = 2

A function was written to calculate the numerical values of the coefficients from the above image. Using the same decision boundary, we get the following performance metrics

Bayes Decision Boundary						
	bayes_acc	bayes_f1	weights			
prior						
0.05	0.969	0.983929	[3.77, 0.0, 0.0, -2.13, 4.74, -2.13]			
0.30	0.815	0.878847	[1.68, 0.0, 0.0, -2.13, 4.74, -2.13]			
0.50	0.735	0.768559	[0.83, 0.0, 0.0, -2.13, 4.74, -2.13]			

POCKET algorithm									
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	weights	sk_weights	
prior									
0.05	0.967	0.967	0.963	0.983	0.983	0.981	[0.38, 0.12, -0.01, -0.18, 0.6, -0.13, 0.0]	[2.0, 2.65, 2.13, 1.07, 14.16, -0.99, 2.0]	
0.30	0.834	0.807	0.793	0.888	0.871	0.861	[0.75, 0.14, -0.13, -0.42, 1.16, -0.57, -0.46]	[1.0, 2.78, 0.4, -2.36, 16.92, -5.94, 1.0]	
0.50	0.771	0.729	0.624	0.803	0.770	0.493	[0.33, -0.13, 0.16, -0.61, 1.42, -0.6, -0.03]	[0.0, -0.07, -1.44, -7.32, 15.59, -7.06, 0.0]	

LeastSquares algorithm									
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	weights	sk_weights	
prior									
0.05	0.970	0.969	0.962	0.984	0.984	0.980	[0.49, 0.0, -0.0, -0.14, 0.29, -0.14, 0.49]	[0.0, 0.0, -0.0, -0.14, 0.29, -0.14, 0.99]	
0.30	0.834	0.811	0.778	0.889	0.874	0.863	[-763326545046.74, 0.03, -0.02, -0.1, 0.26, -0.11, 763326545047.48]	[0.0, 0.03, -0.02, -0.1, 0.26, -0.11, 0.74]	
0.50	0.769	0.726	0.722	0.801	0.768	0.774	[2880729406525.78, -0.01, 0.01, -0.06, 0.22, -0.07, 2880729406525.23]	[0.0, -0.01, 0.01, -0.06, 0.22, -0.07, 0.54]	

LogisticRegression algorithm									
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	weights	sk_weights	
prior									
0.05	0.968	0.969	0.969	0.983	0.984	0.984	[2.01, -0.12, 0.05, -2.43, 5.06, -2.4, 2.01]	[-0.0, -0.13, 0.06, -1.93, 4.07, -1.91, 3.77]	
0.30	0.837	0.818	0.813	0.892	0.880	0.878	[0.84, 0.17, -0.16, -2.26, 5.12, -2.3, 0.84]	[-0.0, 0.15, -0.14, -2.0, 4.57, -2.03, 1.59]	
0.50	0.774	0.737	0.734	0.798	0.768	0.768	[0.44, -0.11, 0.1, -2.35, 5.41, -2.44, 0.44]	[-0.0, -0.11, 0.1, -2.06, 4.76, -2.12, 0.8]	

FisherLDA algorithm									
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	weights	sk_weights	
prior									
0.05	0.970	0.969	0.971	0.984	0.984	0.985	[0.0, 0.04, -0.07, -4.01, 8.36, -4.18, 6.4]	[0.0, 0.04, -0.07, -4.04, 8.43, -4.21, 7.7]	
0.30	0.834	0.813	0.783	0.889	0.876	0.866	[0.0, 0.21, -0.13, -0.59, 1.6, -0.67, 0.37]	[0.0, 0.21, -0.13, -0.59, 1.61, -0.67, 1.38]	
0.50	0.770	0.727	0.722	0.802	0.769	0.774	[0.0, -0.03, 0.05, -0.33, 1.13, -0.37, 0.13]	[0.0, -0.03, 0.05, -0.33, 1.13, -0.37, 0.22]	

Different means, different covariances

Data was drawn from 2 normal distributions with $\mu_0 = (3, 6)$, $\mu_1 = (3, -2)$, $\text{cov}_0 = [[0.5, 0], [0, 2]]$, $\text{cov}_1 = [[2, 0], [0, 2]]$

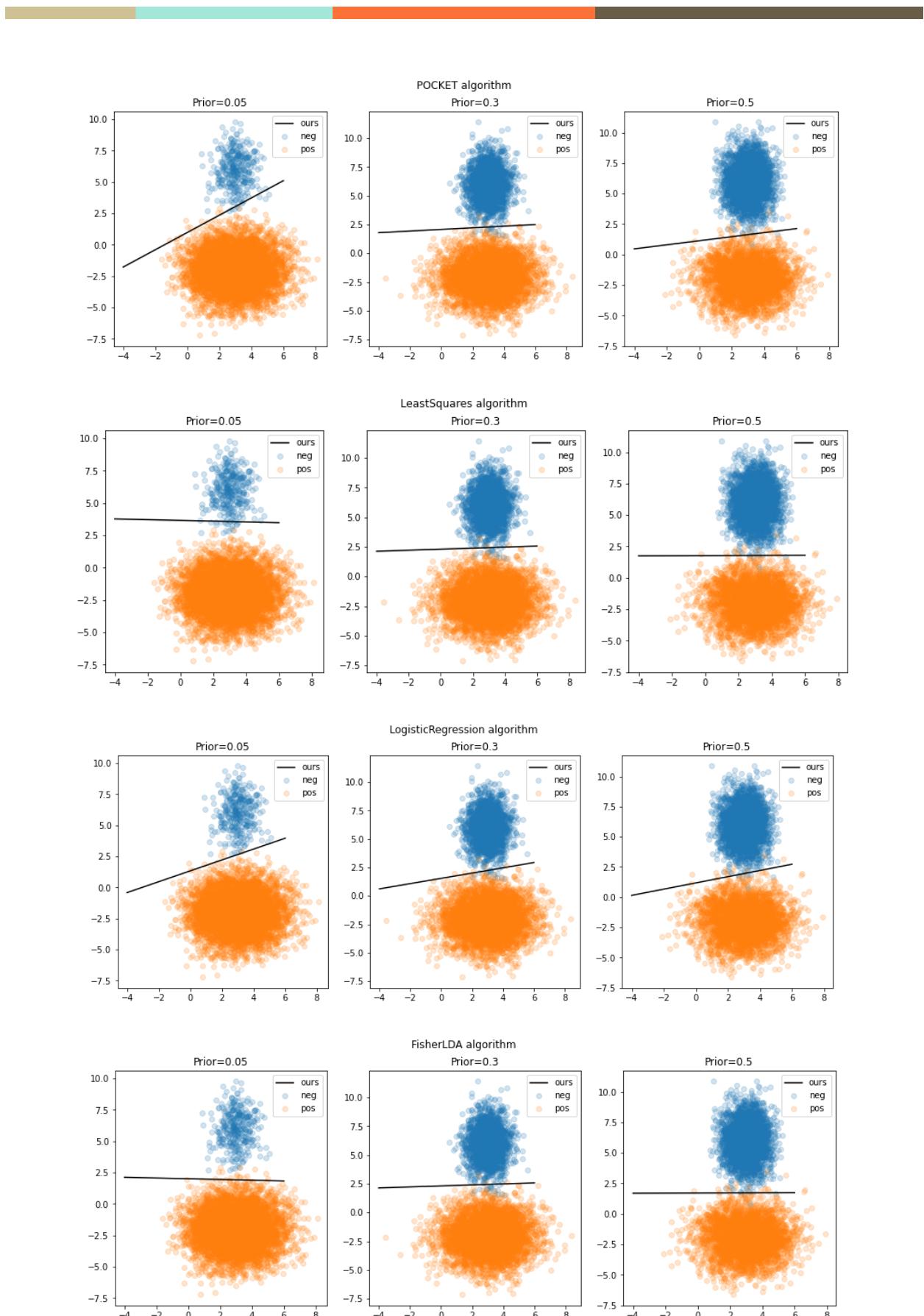
Without feature transformation

POCKET algorithm									
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	weights	sk_weights	
prior									
0.05	0.999	0.997	0.999	0.999	0.999	0.999	[0.42, -0.61, 0.6]	[5.27, -11.57, 16.0]	
0.30	0.998	0.997	0.996	0.999	0.998	0.997	[0.07, -0.97, 2.01]	[0.5, -10.82, 17.0]	
0.50	0.996	0.996	0.994	0.996	0.996	0.994	[0.17, -1.01, 1.15]	[0.91, -13.95, 15.0]	

LeastSquares algorithm									
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	weights	sk_weights	
prior									
0.05	1.000	0.998	0.994	1.000	0.999	0.997	[-0.0, -0.08, 0.83]	[-0.0, -0.08, 0.83]	
0.30	0.999	0.997	0.997	0.999	0.998	0.998	[0.0, -0.11, 0.73]	[0.0, -0.11, 0.73]	
0.50	0.997	0.997	0.997	0.997	0.997	0.997	[0.0, -0.11, 0.72]	[0.0, -0.11, 0.72]	

LogisticRegression algorithm									
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	weights	sk_weights	
prior									
0.05	0.999	0.999	0.999	0.999	0.999	1.000	[1.34, -3.06, 4.09]	[-0.18, -2.53, 7.76]	
0.30	0.997	0.997	0.997	0.998	0.998	0.998	[0.64, -2.75, 4.25]	[-0.07, -2.75, 6.53]	
0.50	0.996	0.997	0.997	0.995	0.997	0.997	[0.79, -3.07, 3.62]	[0.18, -2.92, 5.16]	

FisherLDA algorithm									
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	weights	sk_weights	
prior									
0.05	1.000	0.998	0.999	1.000	0.999	1.000	[-0.12, -4.17, 8.4]	[-0.12, -4.17, 11.61]	
0.30	0.999	0.997	0.997	0.999	0.998	0.998	[0.17, -3.98, 9.23]	[0.17, -3.98, 8.3]	
0.50	0.997	0.996	0.997	0.997	0.996	0.997	[0.02, -3.88, 6.61]	[0.02, -3.88, 7.63]	



Bayes Classifier

* Different mean, different covariance

Predict C_1 if $q_1(x) > q_0(x)$

$$\text{ie, } \log \frac{P_1}{P_0} = -\frac{1}{2} \log \frac{|\Sigma_1|}{|\Sigma_0|} - \frac{1}{2} (x - \mu_1)^T \Sigma_1^{-1} (x - \mu_1) + \frac{1}{2} (x - \mu_0)^T \Sigma_0^{-1} (x - \mu_0) > 0$$

$$\text{setting } \Sigma_0 = \begin{pmatrix} 2 & 0 \\ 0 & 2 \end{pmatrix} \text{ and } \Sigma_1 = \begin{pmatrix} 2 & 0 \\ 0 & 2 \end{pmatrix}$$

$$\mu_0 = (3, 6)^T, \mu_1 = (3, -1)^T$$

decision boundary :

↙ quadratic boundary.

$$\left[-\frac{3}{4}x_1^2 + \frac{9}{2}x_1 - \cancel{16}x_2 + \cancel{101} + \log\left(\frac{P_1}{2P_0}\right) = 0 \right]$$

Applying feature transformation degree=2

Bayes Decision Boundary					
	bayes_acc	bayes_f1		weights	
prior					
0.05	0.998143	0.999022	[27.5, 4.5, -16.0, -0.75, 0.0, 0.0]		
0.30	0.996857	0.997755	[25.4, 4.5, -16.0, -0.75, 0.0, 0.0]		
0.50	0.996571	0.996568	[24.56, 4.5, -16.0, -0.75, 0.0, 0.0]		

POCKET algorithm									
	train_acc	acc	sk_acc	train_f1	f1	sk_f1		weights	sk_weights
prior									
0.05	0.998	0.997	0.998	0.999	0.998	0.999	[3.21, 2.02, -4.39, 5.8, -7.01, 1.57, 2.6]	[54.0, 32.04, -41.3, 26.34, -59.13, 6.21, 54.0]	
0.30	0.998	0.997	0.997	0.999	0.998	0.998	[11.26, 8.84, -9.71, 0.88, -5.22, 0.1, 11.59]	[94.0, 67.46, -98.18, 14.09, -45.3, 4.2, 94.0]	
0.50	0.996	0.997	0.995	0.996	0.997	0.995	[7.14, 1.88, -9.05, 3.04, -6.01, -0.07, 6.0]	[79.0, 27.25, -102.85, 45.91, -67.21, 8.2, 79.0]	



LeastSquares algorithm							weights	sk_weights
	train_acc	acc	sk_acc	train_f1	f1	sk_f1		
prior								
0.05	1.000	0.997	0.996	1.000	0.998	0.998	[0.48, -0.01, -0.06, 0.0, -0.0, -0.01, 0.48]	[0.0, -0.01, -0.06, 0.0, -0.0, -0.01, 0.95]
0.30	0.998	0.997	0.995	0.999	0.998	0.996	[0.43, -0.03, -0.09, 0.01, 0.0, -0.01, 0.43]	[0.0, -0.03, -0.09, 0.01, 0.0, -0.01, 0.86]
0.50	0.997	0.998	0.998	0.997	0.998	0.998	[0.4, -0.05, -0.11, 0.01, 0.0, -0.0, 0.4]	[0.0, -0.05, -0.11, 0.01, 0.0, -0.0, 0.79]

FisherLDA algorithm							weights	sk_weights
	train_acc	acc	sk_acc	train_f1	f1	sk_f1		
prior								
0.05	1.000	0.998	0.997	1.000	0.999	0.998	[0.0, -1.34, -8.92, 0.15, -0.16, -1.69, 27.14]	[0.0, -1.34, -8.98, 0.15, -0.16, -1.71, 61.86]
0.30	0.998	0.997	0.995	0.999	0.998	0.996	[0.0, -1.42, -3.94, 0.27, 0.04, -0.24, 11.29]	[0.0, -1.42, -3.94, 0.27, 0.04, -0.24, 15.05]
0.50	0.997	0.997	0.998	0.997	0.997	0.998	[0.0, -1.74, -3.98, 0.3, 0.06, -0.03, 8.8]	[0.0, -1.74, -3.98, 0.3, 0.06, -0.03, 10.24]

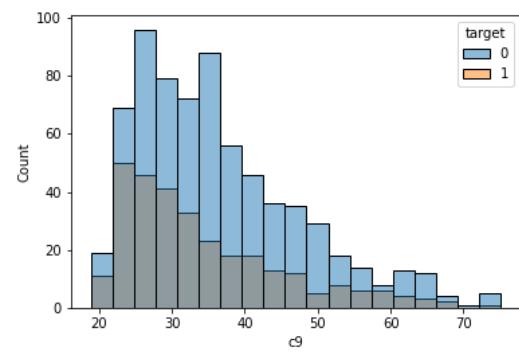
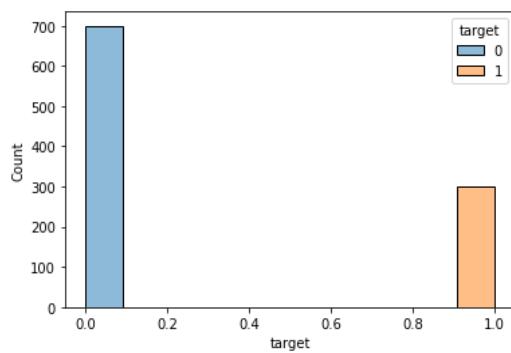
Q2: German Credit Data

This dataset contains attributes of different people (numerical and categorical) and a target (binary) denoting good/bad credit risk.

EDA

For the remaining graphs, please refer to the colab notebook

c0	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	c15	c16	c17	c18	c19	c20	c21	c22	c23	target
0	1	6	4	12	5	5	3	4	1	67	3	2	1	2	1	0	0	1	0	0	1	0	0	
1	2	48	2	60	1	3	2	2	1	22	3	1	1	1	0	0	1	0	0	1	0	0	1	
2	4	12	4	21	1	4	3	3	1	49	3	1	2	1	1	0	0	1	0	0	1	0	0	
3	1	42	2	79	1	4	3	4	2	45	3	1	2	1	1	0	0	0	0	0	0	0	1	
4	1	24	3	49	1	3	3	4	4	53	3	2	2	1	1	0	1	0	0	0	0	0	1	



Without transformation

Without transforming POCKET algorithm							
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	
test_size							
0.2	0.772	0.740	0.690	0.500	0.447	0.597	
0.3	0.776	0.687	0.687	0.529	0.338	0.113	

LeastSquares algorithm							
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	
test_size							
0.2	0.795	0.765	0.765	0.627	0.569	0.535	
0.3	0.796	0.733	0.733	0.619	0.500	0.500	

LogisticRegression algorithm							
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	
test_size							
0.2	0.780	0.760	0.77	0.562	0.529	0.540	
0.3	0.786	0.717	0.73	0.595	0.459	0.484	

FisherLDA algorithm							
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	
test_size							
0.2	0.786	0.755	0.770	0.647	0.574	0.566	
0.3	0.793	0.700	0.723	0.660	0.536	0.497	

Transformation degree=4

POCKET algorithm							
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	
test_size							
0.2	0.781	0.770	0.57	0.615	0.596	0.552	
0.3	0.793	0.707	0.75	0.625	0.494	0.586	
LeastSquares algorithm							
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	
test_size							
0.2	1.0	0.460	0.515	1.0	0.341	0.340	
0.3	1.0	0.503	0.553	1.0	0.433	0.407	
LogisticRegression algorithm							
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	
test_size							
0.2	0.742	0.750	0.775	0.376	0.444	0.587	
0.3	0.760	0.717	0.737	0.458	0.351	0.533	
FisherLDA algorithm							
	train_acc	acc	sk_acc	train_f1	f1	sk_f1	
test_size							
0.2	0.3	0.350	0.625	0.462	0.444	0.490	
0.3	0.3	0.437	0.557	0.462	0.470	0.453	

XGboost classifier

```
Test size: 0.2
  F1 score: 1.000(train), 0.544(test)
  Acc score: 1.000(train), 0.765(test)
Test size: 0.3
  F1 score: 1.000(train), 0.522(test)
  Acc score: 1.000(train), 0.743(test)
```

Q3: Porto Seguro's Safe Driver

Kaggle competition: use features in the data to predict whether an auto insurance policy holder files a claim.

The dataset has 58 features, the suffixes of the name denote if the feature is categorical or not. This indicator has been used to encode those columns into one-hot vectors.

It was noted that there was very high class imbalance - only 3% of the examples belonged to the positive class. It is important to note that a model predicting zero all the time would get 97% accuracy.

Here, we have set out to maximize the f1_score as our performance metric, which is independent of the class imbalance.

We first divide the whole dataset into training and the test set. To tackle the class imbalance problem, we resample the training set to contain an equal number of positive and negative examples. This under-sampled training set is fed to all of the training algorithms below.

POCKET algorithm		
	acc	f1
test_size		
0.2	0.823	0.086
0.3	0.921	0.079

LeastSquares algorithm		
	acc	f1
test_size		
0.2	0.716	0.093
0.3	0.708	0.100

LogisticRegression algorithm		
	acc	f1
test_size		
0.2	0.035	0.068
0.3	0.964	0.000

FisherLDA algorithm		
	acc	f1
test_size		
0.2	0.763	0.098
0.3	0.737	0.101

Xgboost classifier

We make an ensemble model as follows: repeatedly sample training set as mentioned above, train a model on it. Average the test predictions over all the models to measure performance over the test set.

```
Test size: 0.2
Training:
  Fold0: Acc: 0.781, f1:0.763
  Fold1: Acc: 0.789, f1:0.777
  Fold2: Acc: 0.774, f1:0.762
  Fold3: Acc: 0.775, f1:0.763
  Fold4: Acc: 0.777, f1:0.760
Testing:
  Acc: 0.703, f1:0.099
Test size: 0.3
Training:
  Fold0: Acc: 0.794, f1:0.786
  Fold1: Acc: 0.801, f1:0.795
  Fold2: Acc: 0.796, f1:0.794
  Fold3: Acc: 0.796, f1:0.790
  Fold4: Acc: 0.785, f1:0.778
Testing:
  Acc: 0.687, f1:0.101
```