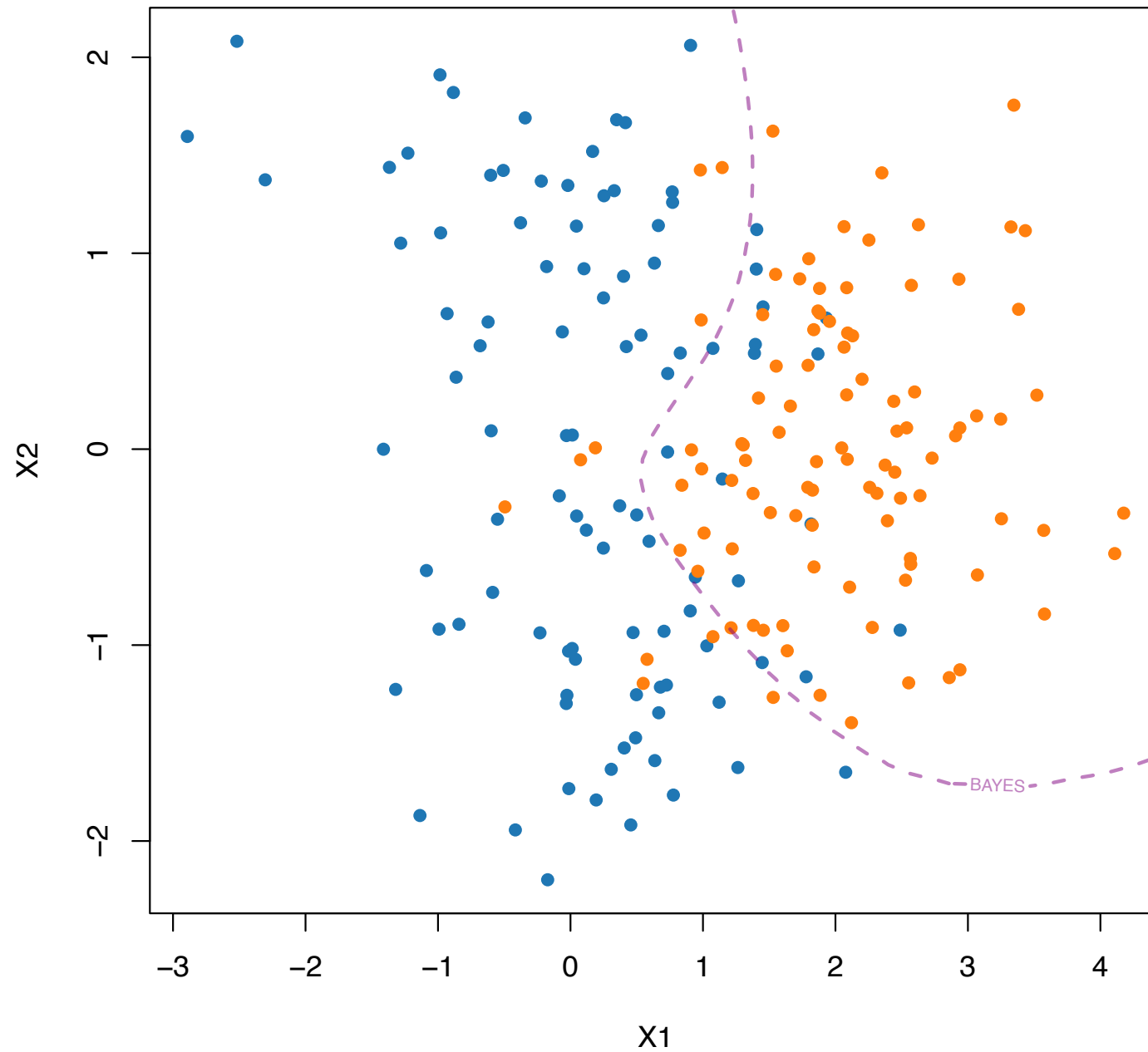
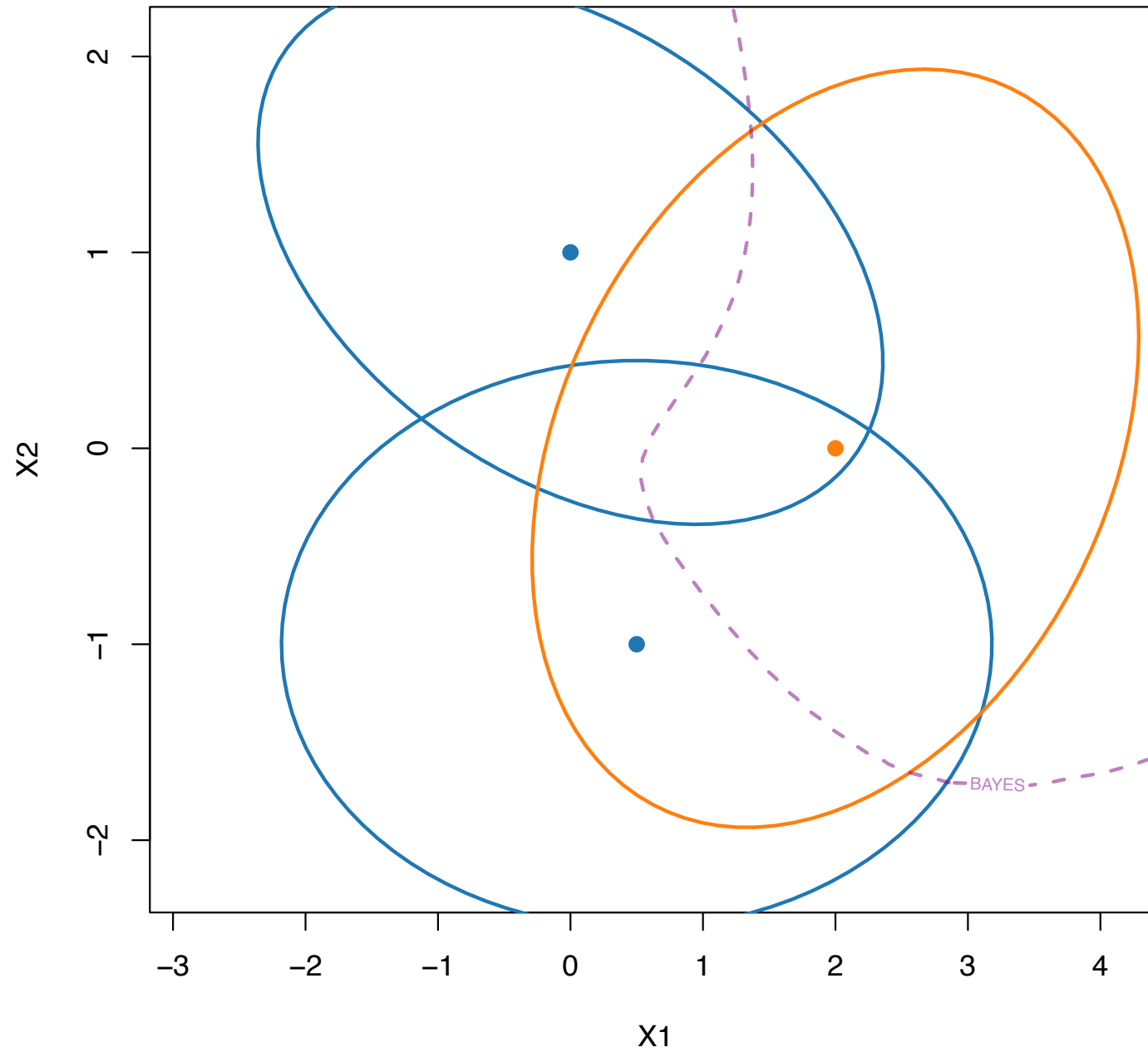


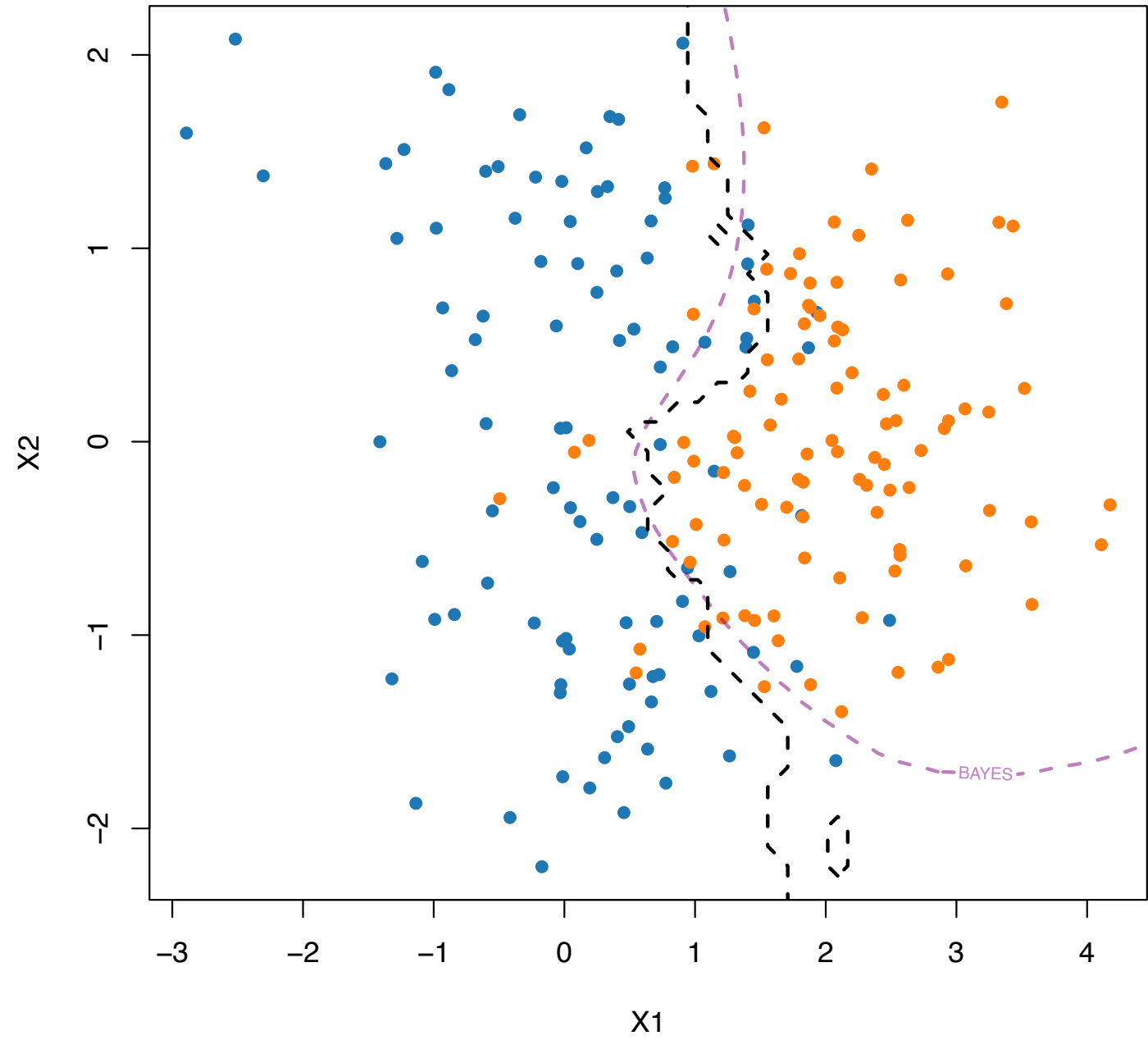
Bayes decision boundary



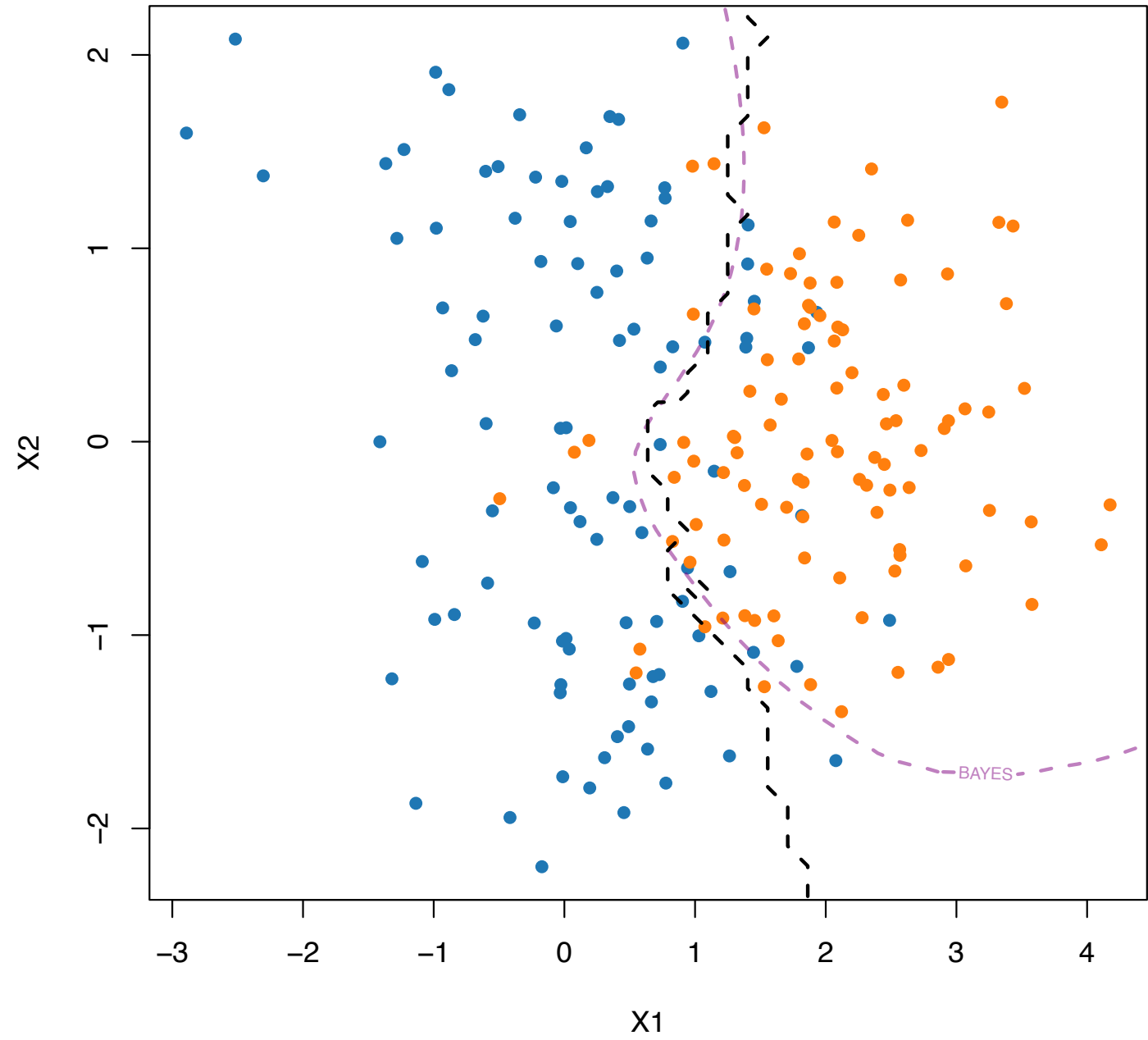
Bayes decision boundary



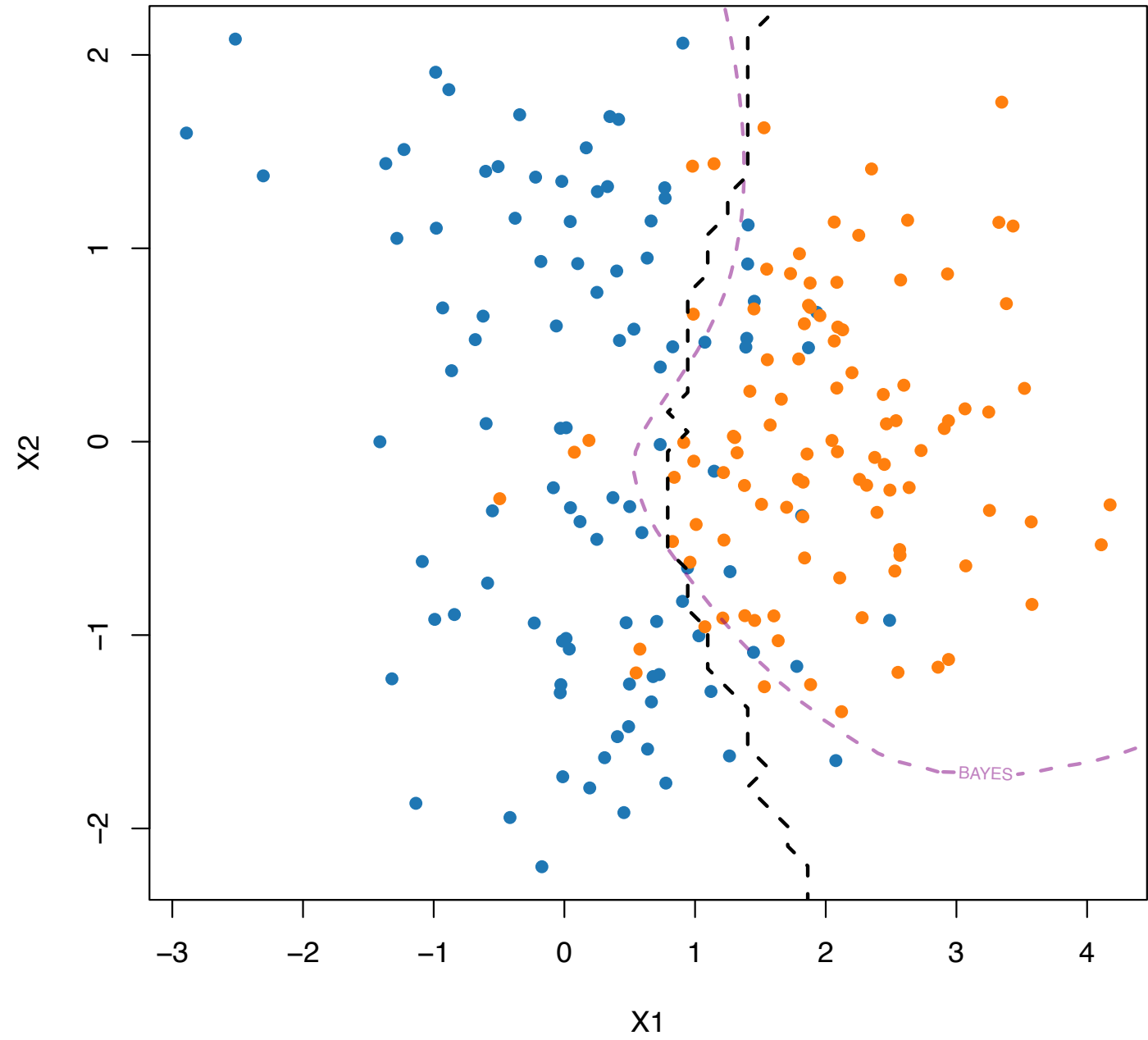
k-NN with k = 05

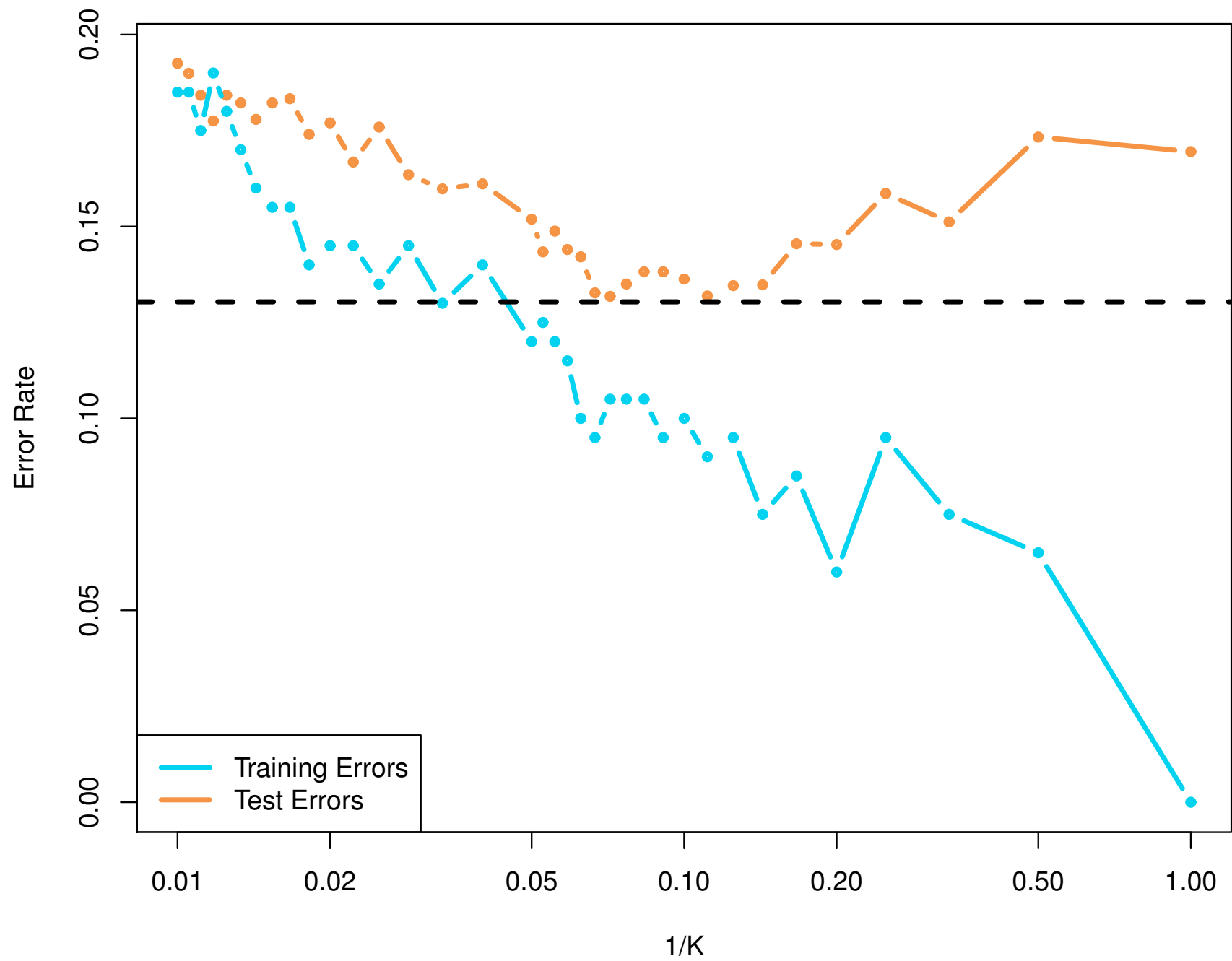


k-NN with k = 20

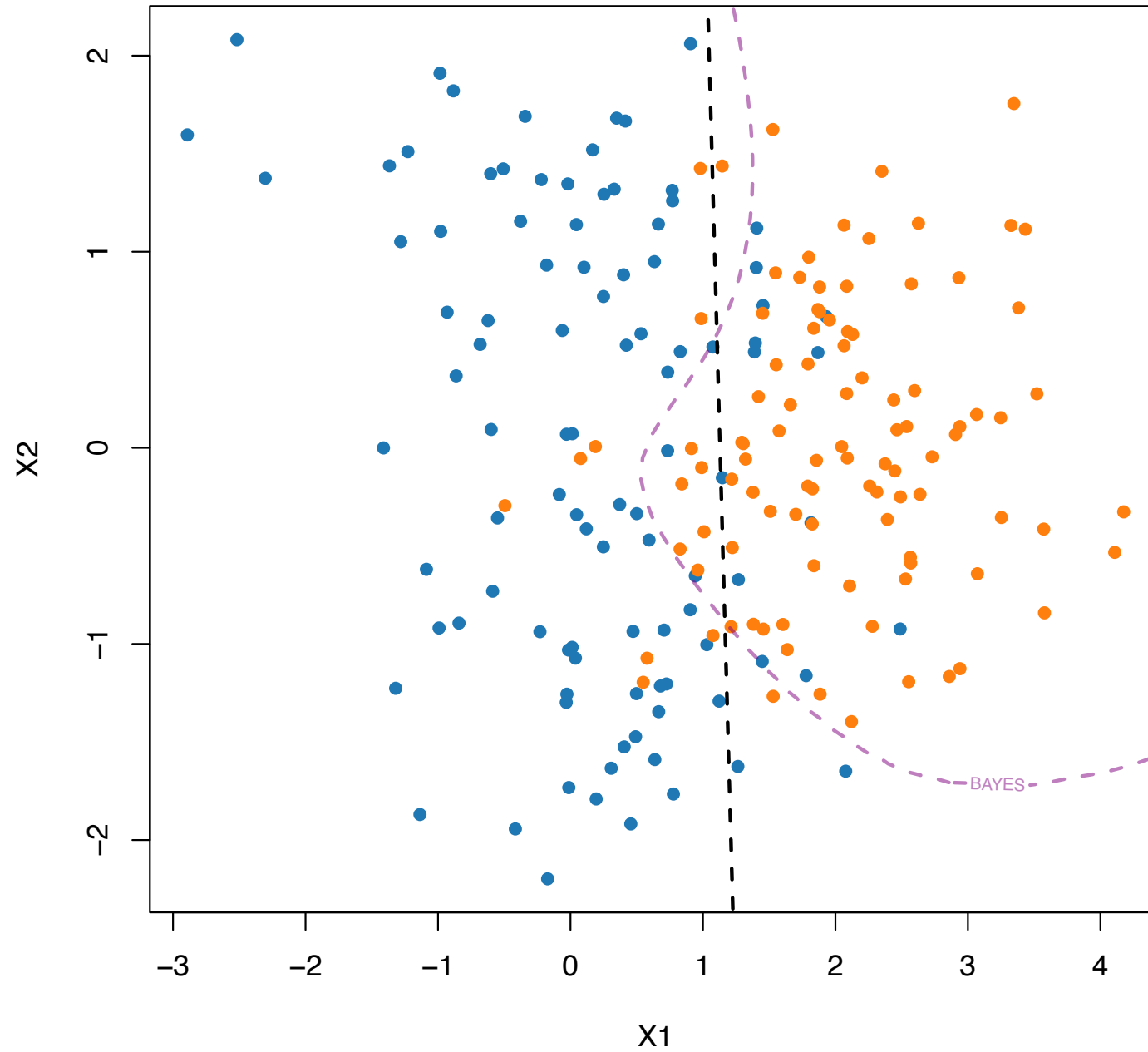


k-NN with k = 50





Logistic Regression




```
# estimating the logistic regression classifier for this data  
logreg <- glm(y ~ ., data=df_train, family=binomial)
```

Generalized
Linear
Model

because we consider **categorical** variables

Take a look at Section 4.6.3 of James et al. if you're curious

```
# estimating the logistic regression classifier for this data
logreg <- glm(y ~ ., data=df_train, family=binomial)
```

```
> summary(logreg)
```

Call:

```
glm(formula = y ~ ., family = binomial, data = df_train)
```

Deviance Residuals:

	Min	1Q	Median	3Q	Max
	-2.53908	-0.47746	0.01229	0.46460	2.81335

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-2.71826	0.43988	-6.179	6.43e-10 ***
X1	2.40805	0.33359	7.219	5.26e-13 ***
X2	0.09884	0.23342	0.423	0.672

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

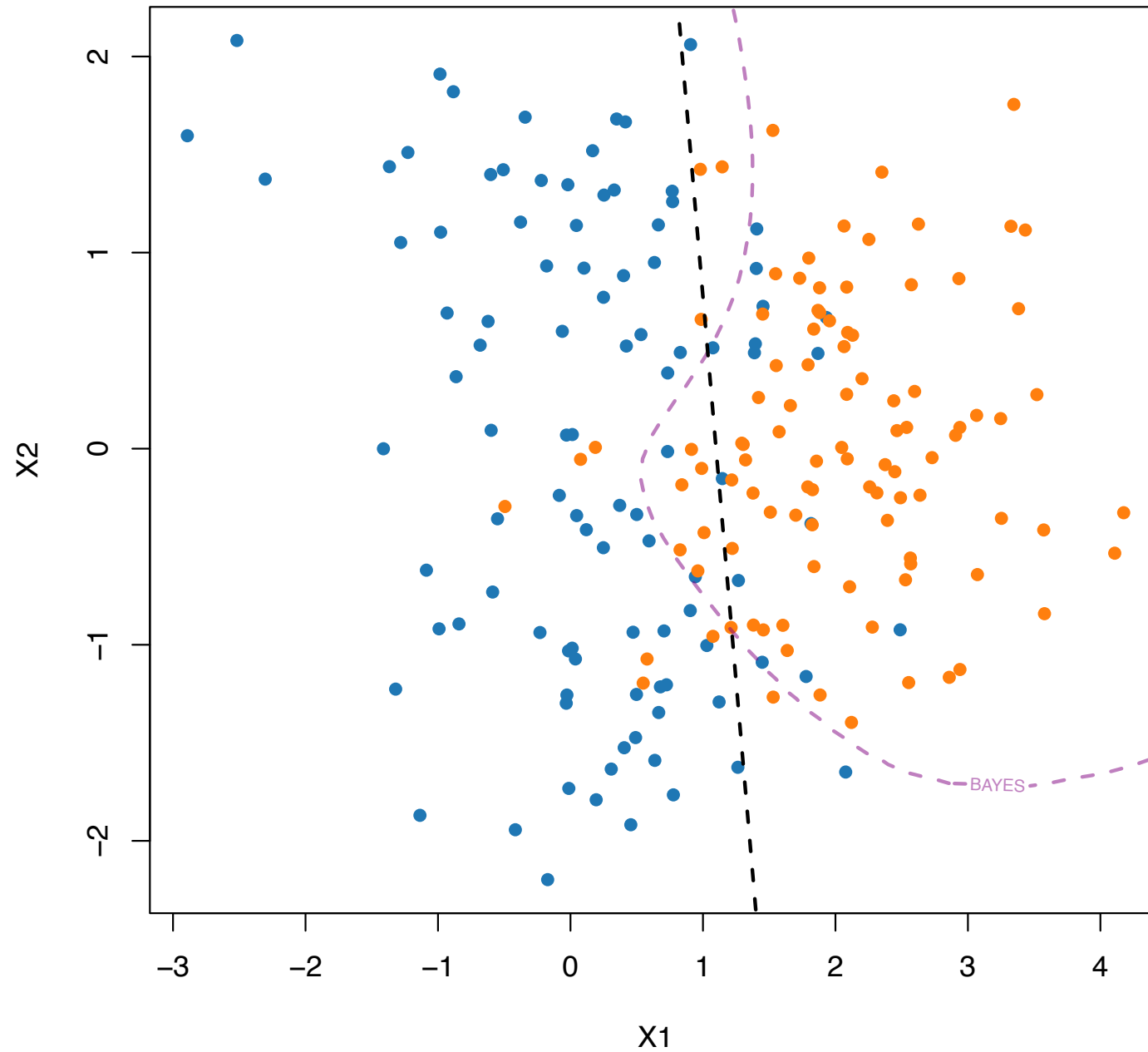
Null deviance: 277.26 on 199 degrees of freedom
Residual deviance: 135.80 on 197 degrees of freedom
AIC: 141.8

We could also do statistical inference
on the coefficients of the classifier

Number of Fisher Scoring iterations: 6

Mostly related to the non-convex optimization
of the loss function for logistic regression

Linear Discriminant Analysis



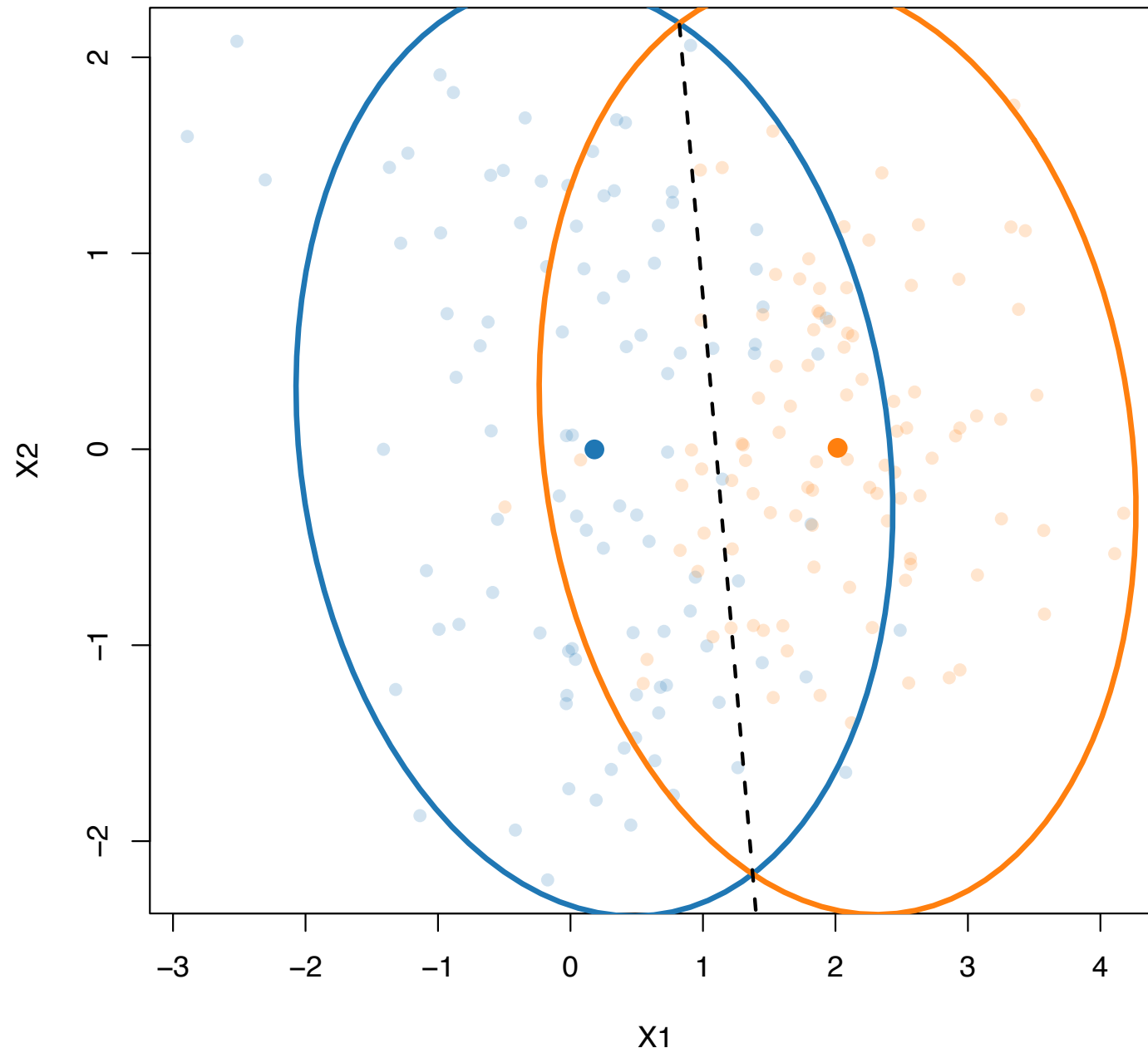
```
# estimating the LDA classifier for this data  
library("MASS")  
ldac1f <- lda(y ~ ., data=df_train)  
y_pred <- predict(ldac1f, newdata=df_test)
```

data structure containing the results of the LDA fitting

```
> y_pred$
```

◆	class
📊	posterior
📊	x

LDA



Naive Bayes classifier

