(a) T(0)=1: if P(x=x)=I we are certain of the outcome and there is no more info to learn,

-I() is monotonic decreasing: We begin with a finite amount of information that can be learned so as we learn I train the amount of remaining information must less than or equal to its past value, implying monotonic decreasing.

-I(.) > 0: The concept of negative information abord not make sense so we need the range of I(.) to be greater than or equal to 0.

-I(P(X; X,)) =

IP(X,)+P(Xz)): for indepen RVs $P(x_1,x_2)=P(x_1)P(x_2)$ log(ab)=log(a)+log(b) so $log(P(X_1,x_2))=log(P(X_1))+log(P(X_2))$

1b) I(1)=0: logz (p(x=x)) > p(x=x)=1 > logz(1)=0 /

I(.) monotonic decrease: as we approach P(X=x)=1+

the value of log2 (1/p(x=x)) approaches 0

That is

 $\log_2(\overline{p(x=x)=0.1}) > \log_2(\overline{p(x=x)=0.5}) > \log_2(\overline{p(x=x)=1})$

which is equivalent to I(0.1) > I(0.5) > I(1) so as more info is learned

I(.) =0: since P(X=x) is on range [0 1]

log_z(P(X=x)) is on range [0 00) so always

Non negative

16) For independent X, Xz 1092 (P(X,=X, X,=X2)) = 1092 (P(X,=X1)P(X2=X2)) = log_2(P(X,=x,))+log_2(P(X2=X2)) -> I(P(X1))+I(P(X2)) Z) $H(\hat{y}) + H(X|\hat{y}) = H(x) + H(\hat{y}|x)$ when yeis a function completly dependent on X Such that y= g(x) we know H(y|x)=0 as x explains all the entropy of y. Here $\hat{y} = f(x) \le 0$ $H(\hat{y}|x) = 0 \rightarrow H(\hat{y}) = H(x) - H(x|\hat{y})$ So if $H(x|\hat{y}) = 0$: $H(\hat{y}) = H(x)$ if H(x19) \$0: H(9) < H(x) 3a) See attatched code 3b) $X_1 | X_2 = 0$ $\Sigma = \begin{bmatrix} 0, & 0, & 0 \\ 0, & 0, & 0 \end{bmatrix}$ $P = \frac{3}{\sqrt{7}\sqrt{2}} = 0.802$ P(X, 1X=0) ~ N(µ1+ 01 p(0-µ2), (1-p2) 0,2) P(X, 1 X2=0) ~ N(4.5, 2.5) 3c) $p(x_2) = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \times A = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$ / P(X2) ~ N(Aμ, AΣAT) = N(-1, 2)

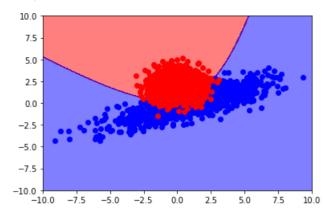
 $MAP = p(x|y) \cdot p(y)$ $p(x) = \frac{1}{2} \sum_{i=1}^{n} p(x|y=i)$ $p(x|y=0) = \frac{1}{2\pi |\Sigma|^{1/2}} e^{\left(-\frac{1}{2}(x-\mu_0)\Sigma_0^{-1}(x-\mu_0)\right)^{-1}}$ 40 $\left(-\frac{1}{2}(x-\mu_1)^{\dagger}\Sigma^{-1}(x-\mu_1)\right)$ $p(x|y=1) = \frac{1}{2\pi |x|^{1/2}}$ £Ν(μο.Σ.) p(y=01x)= #(N(y0, \S.)+N(y, \S.)) lag(p(y=01x)) = log(N(μο, Σ.))-log(N(μο, Σ.)+N(μ, Σ.)) log(p(y=11x))= log(N(p,, E,1)-log(N(p., E.)+N(p,, E.)) $\frac{p(y=0|x)}{p(y=1|x)} \ge 1 \rightarrow \log\left(\frac{p(y=0|x)}{p(y=1|x)}\right) \le 0$ \$0 log(ply=0|x))-log(ply=1|x)) ≥0 log(ply=olx)) 5 log(ply=1/x)) which simplifies to = log | Zo | - = (x-16) Z. (x-10) = = log | E, 1- = (x-11) [X. (x-11)]

Question 3a

```
In [ ]: | import numpy as np
            import matplotlib.pyplot as plt
In [ ]: sig = np.array([[7,3],[3,2]])
           L = np.linalg.cholesky(sig)
In [ ]: | x1 = []
           x2 = []
           for i in range(1000):
    x = np.random.randn(2,1)
              temp = L@x
              x1.append(temp[0]+3)
              x2.append(temp[1]-1)
In [ ]: plt.scatter(x1,x2)
    plt.ylim((-10,8));
    plt.xlim((-6,12));
              6
             4
              2
             0
            -2
            -6
            -8
           -10
                                                                  10
                                                                         12
                           -2
In [ ]:
```

Question 4

```
import numpy as np
  In [1]:
           import matplotlib.pyplot as plt
  In [2]: | # Vector Means
           mu0 = np.array([[1],[0]])
           mu1 = np.array([[0],[2]])
           # Vector Covariance Matrices
           sig0 = np.array([[8,3],[3,2]])
           sig1 = np.array([[1,0.1],[0.1,1]])
           # Inverse Covariance Matrices
           inv_sig0 = np.linalg.inv(sig0)
           inv_sig1 = np.linalg.inv(sig1)
           # Covariance Matrix Determinants
           det0 = np.linalg.det(sig0)
           det1 = np.linalg.det(sig1)
           # Linear Transformations
           A0 = np.linalg.cholesky(sig0)
           A1 = np.linalg.cholesky(sig1)
  In [3]: def classify(x):
             dx0 = (x-mu0)
             y0 = (-0.5*np.log(det0))-(0.5*dx0.T@inv_sig0@dx0)
             dx1 = (x-mu1)
             y1 = (-0.5*np.log(det1))-(0.5*dx1.T@inv sig1@dx1)
             if y0 >= y1:
               return True
             else:
               return False
  In [4]: xy0 = np.zeros((1000,2))
           xy1 = np.zeros((1000,2))
           misclass = 0
           for i in range(1000):
             x = np.random.randn(2,1)
             temp = (A0@x) + mu0
             xy0[i] = [temp[0], temp[1]]
             if classify(temp):
              misclass+=1
             x = np.random.randn(2,1)
             temp = (A1@x)+mu1
             xy1[i] = [temp[0], temp[1]]
             if not classify(temp):
               misclass+=1
          <ipython-input-4-ba9f797bb53b>:7: DeprecationWarning: setting an array element with a sequence. This was supporte
          d in some cases where the elements are arrays with a single element. For example `np.array([1, np.array([2])], dt
          ype=int)`. In the future this will raise the same ValueError as `np.array([1, [2]], dtype=int)`.
             xy0[i] = [temp[0], temp[1]]
           <ipython-input-4-ba9f797bb53b>:12: DeprecationWarning: setting an array element with a sequence. This was support
          ed in some cases where the elements are arrays with a single element. For example `np.array([1, np.array([2])], d
          type=int)`. In the future this will raise the same ValueError as `np.array([1, [2]], dtype=int)`.
            xy1[i] = [temp[0],temp[1]]
  In [5]: nn = 400
           x1g = np.linspace(-10, 10, nn)
           x2g = np.linspace(-10, 10, nn)
           decisions = -1*np.ones((nn,nn))
           for i, x1 in enumerate(x1g):
             for j, x2 in enumerate(x2g):
               x = np.array([[x1],[x2]])
               if (classify(x)):
                 decisions[j,i] = 1
           plt.figure()
  In [6]:
           nlt.contourf(x1g. x2g. decisions.colors=['red','blue'],alpha=0.5)
Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js | blue')
           plt.scatter(xy1[:,0],xy1[:,1],color='red')
```



In [7]: | print("Misclassification Rate: %f" %(1-(misclass/2000)))

Misclassification Rate: 0.084500

In []: