1.) a.) Normal distribution (Probit model) 6400641046

$p(y=1|x) = \Phi(x_1, x_2, x_3, x_4)$

```
probit y x1 x2 x3 x4

Iteration 0:   log likelihood = -248.43455
Iteration 1:   log likelihood = -150.03919
Iteration 2:   log likelihood = -147.48531
Iteration 3:   log likelihood = -147.46882
Iteration 4:   log likelihood = -147.46881

Probit regression                               Number of obs     =        400
                                                LR chi2(4)        =     201.93
                                                Prob > chi2       =     0.0000
Log likelihood = -147.46881                     Pseudo R2         =     0.4064
```

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
x1	.3590739	.0371539	9.66	0.000	.2862536	.4318941
x2	-.8525746	.144481	-5.90	0.000	-1.135752	-.569397
x3	-.5735764	.2202882	-2.60	0.009	-1.005333	-.1418195
x4	-1.248569	.226762	-5.51	0.000	-1.693014	-.8041238
_cons	1.45664	.2037279	7.15	0.000	1.057341	1.85594

```
fitstat

Measures of Fit for probit of y

Log-Lik Intercept Only:       -248.435   Log-Lik Full Model:           -147.469
D(395):                        294.938   LR(4):                         201.931
                                         Prob > LR:                       0.000
McFadden's R2:                   0.406   McFadden's Adj R2:               0.386
Maximum Likelihood R2:           0.396   Cragg & Uhler's R2:              0.557
McKelvey and Zavoina's R2:       0.640   Efron's R2:                      0.446
Variance of y*:                  2.775   Variance of error:               1.000
Count R2:                        0.818   Adj Count R2:                    0.416
AIC:                             0.762   AIC*n:                         304.938
BIC:                         -2071.691   BIC':                         -177.966
```

Overall test $p < \alpha = 0.05$ jointly significant

Individual test significant at $\alpha = 0.05$

pseudo R^2 : 0.4064

Count R^2 : 0.818 > 0.5 but adj count R^2 is < 0.5 so, the model is not accurately project y

6.) logistic distribution

$\hat{p}_i = P_r[y=1|X] = \Lambda[X_1, X_2, X_3, X_4]$

```
. logit y x1 x2 x3 x4

Iteration 0:   log likelihood = -248.43455
Iteration 1:   log likelihood = -154.06753
Iteration 2:   log likelihood = -148.00091
Iteration 3:   log likelihood = -147.90887
Iteration 4:   log likelihood = -147.90869
Iteration 5:   log likelihood = -147.90869

Logistic regression                             Number of obs     =        400
                                                LR chi2(4)        =     201.05
                                                Prob > chi2       =     0.0000
Log likelihood = -147.90869                     Pseudo R2         =     0.4046

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          x1 |   .6299401   .0708979     8.89   0.000     .4909828    .7688974
          x2 |  -1.488248   .2597744    -5.73   0.000    -1.997396   -.9790992
          x3 |  -.9562902   .3882611    -2.46   0.014    -1.717268   -.1953124
          x4 |  -2.155321   .4055058    -5.32   0.000    -2.950097   -1.360544
       _cons |      2.5165   .3714373     6.78   0.000     1.788496    3.244503
------------------------------------------------------------------------------

. fitstat

Measures of Fit for logit of y

Log-Lik Intercept Only:     -248.435     Log-Lik Full Model:          -147.909
D(395):                      295.817     LR(4):                       201.052
                                         Prob > LR:                     0.000
McFadden's R2:                 0.405     McFadden's Adj R2:             0.385
Maximum Likelihood R2:         0.395     Cragg & Uhler's R2:            0.555
McKelvey and Zavoina's R2:     0.622     Efron's R2:                    0.445
Variance of y*:                8.707     Variance of error:             3.290
Count R2:                      0.818     Adj Count R2:                  0.416
```

overall test $p < \alpha = 0.05$

Individual test significant at 5%

pseudo R^2 : 0.4064

count R^2 : 0.818 > 0.5 However adj count $R^2 < 0.5$, The model is not accurately predict y

(6.) Both models pseudo R^2, count R^2, and log are similar. So, both models don't have a significant difference goodness of fit

(c)

Overall test H_0 ; $\beta_2 = \beta_3 = \cdots = \beta_4 = 0$

H_1 ; otherwise

```
2 . probit y x1 x2 x3 x4

Iteration 0:   log likelihood = -248.43455
Iteration 1:   log likelihood = -150.03919
Iteration 2:   log likelihood = -147.48531
Iteration 3:   log likelihood = -147.46882
Iteration 4:   log likelihood = -147.46881

Probit regression                                 Number of obs     =        400
                                                  LR chi2(4)        =     201.93
                                                  Prob > chi2       =     0.0000
Log likelihood = -147.46881                       Pseudo R2         =     0.4064

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          x1 |    .3590739   .0371539     9.66   0.000     .2862536    .4318941
          x2 |   -.8525746    .144481    -5.90   0.000    -1.135752   -.569397
          x3 |   -.5735764   .2202882    -2.60   0.009    -1.005333   -.1418195
          x4 |   -1.248569    .226762    -5.51   0.000    -1.693014   -.8041238
       _cons |    1.45664    .2037279     7.15   0.000     1.057341    1.85594
------------------------------------------------------------------------------

4 . probit y, nolog

Probit regression                                 Number of obs     =        400
                                                  LR chi2(0)        =       0.00
                                                  Prob > chi2       =          .
Log likelihood = -248.43455                       Pseudo R2         =     0.0000

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |    .4887764   .0654634     7.47   0.000     .3604706    .6170822
------------------------------------------------------------------------------
```

test stat $= 2(\ln L_{UR} - \ln L_R) \sim \chi^2_{(k-1)}$

$= 201.93$

(d)

```
. mfx, predict(xb)

Marginal effects after logit
      y  = Linear prediction (log odds) (predict, xb)
         =     1.32418

------------------------------------------------------------------------------
variable |      dy/dx   Std. Err.      z    P>|z|  [    95% C.I.   ]       X
---------+--------------------------------------------------------------------
      x1 |    .6299401     .0709     8.89   0.000   .490983  .768897   .454973
      x2 |   -1.488248     .25977    -5.73   0.000  -1.9974 -.979099   .809344
      x3 |   -.9562902     .38826    -2.46   0.014 -1.71727 -.195312   .556712
      x4 |   -2.155321     .40551    -5.32   0.000  -2.9501 -1.36054  -.119684
------------------------------------------------------------------------------

. mfx

Marginal effects after logit
      y  = Pr(y) (predict)
         =    .7898763

------------------------------------------------------------------------------
variable |      dy/dx   Std. Err.      z    P>|z|  [    95% C.I.   ]       X
---------+--------------------------------------------------------------------
      x1 |    .1045522     .01146     9.12   0.000   .082083  .127022   .454973
      x2 |    -.247007     .04388    -5.63   0.000  -.333011 -.161003   .809344
      x3 |   -.1587171     .06397    -2.48   0.013    -.2841 -.033334   .556712
      x4 |   -.3577223     .06679    -5.36   0.000  -.488633 -.226812  -.119684
------------------------------------------------------------------------------
```

(e)

```
mfx

Marginal effects after logit
      y  = Pr(y) (predict)
         =   .7898763
```

variable	dy/dx	Std. Err.	z	P>|z|	[95% C.I.]		X
x1	.1045522	.01146	9.12	0.000	.082083	.127022	.454973
x2	-.247007	.04388	-5.63	0.000	-.333011	-.161003	.809344
x3	-.1587171	.06397	-2.48	0.013	-.2841	-.033334	.556712
x4	-.3577223	.06679	-5.36	0.000	-.488633	-.226812	-.119684

```
mfx, at(median)

Marginal effects after logit
      y  = Pr(y) (predict)
         =  .84127022
```

variable	dy/dx	Std. Err.	z	P>|z|	[95% C.I.]		X
x1	.0841188	.00961	8.76	0.000	.065292	.102946	.655749
x2	-.1987326	.03349	-5.93	0.000	-.264373	-.133093	.692745
x3	-.1276979	.04944	-2.58	0.010	-.224597	-.030799	.488768
x4	-.28781	.05616	-5.12	0.000	-.397881	-.177739	-.109732

(f)

```
mfx, at(0.5 1 0.5 0)

Marginal effects after logit
      y  = Pr(y) (predict)
         =  .70372027
```

variable	dy/dx	Std. Err.	z	P>|z|	[95% C.I.]		X
x1	.1313413	.01481	8.87	0.000	.102307	.160376	.5
x2	-.3102967	.0596	-5.21	0.000	-.427116	-.193478	1
x3	-.1993846	.07892	-2.53	0.012	-.354074	-.044695	.5
x4	-.4493802	.09126	-4.92	0.000	-.628243	-.270517	0

(g)

```
. predict pr
(option pr assumed; Pr(y))

. g yhat1=0 if pr<=0.5
(300 missing values generated)

. replace yhat1=1 if pr>0.5
(300 real changes made)

. tabulate y yhat1
```

y	yhat1 0	1	Total
0	76	49	125
1	24	251	275
Total	100	300	400

Correct R^2 : $\frac{76+251}{400}$: 0.8175

(h)

```
18. g yhat2=0 if pr<=0.7
  (241 missing values generated)

19. replace yhat2=1 if pr>0.7
  (241 real changes made)

20. tabulate y yhat2
```

y	yhat2 0	1	Total
0	101	24	125
1	58	217	275
Total	159	241	400

Correct R^2 : $\frac{101+217}{400}$: 0.795