### Logistic regression

Predict binary outcomes (success/failure) from numerical or categorical predictors.

### Linear vs. logistic regression

Linear regression:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n + \varepsilon$$

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Logistic regression:

$$Pr(success) = \frac{e^t}{1 + e^t}$$
$$t = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n + \varepsilon$$

### Linear vs. logistic regression

Linear regression:

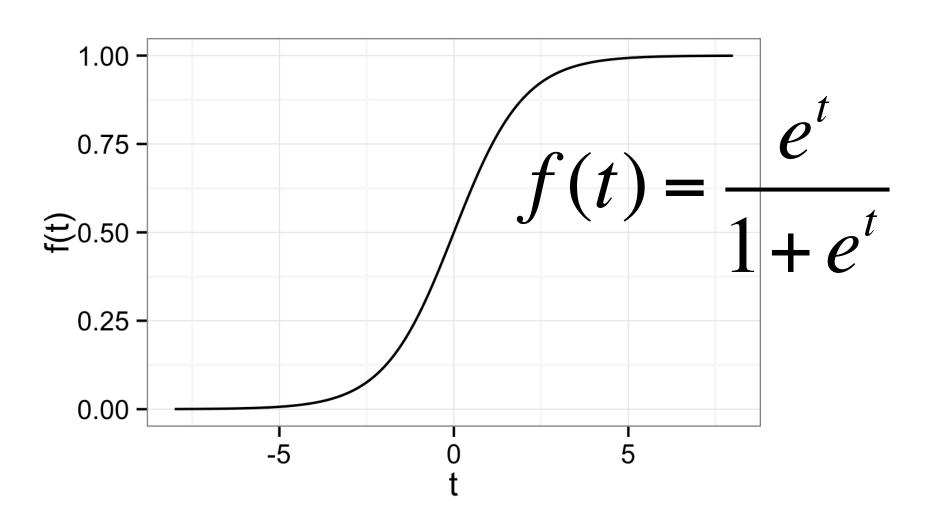
$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n + \varepsilon$$

Logistic regression:

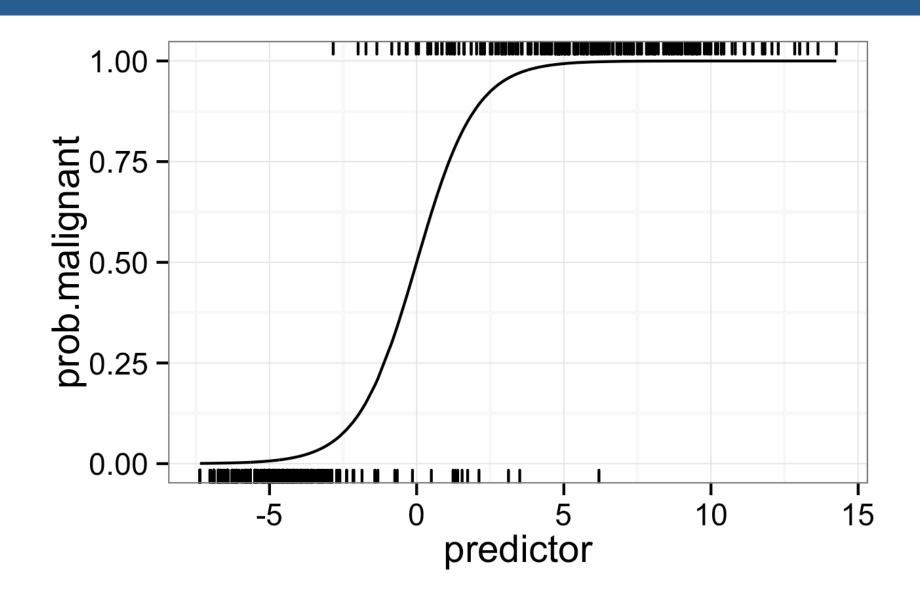
$$Pr(success) = \frac{e^{t}}{1 + e^{t}}$$
$$t = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n + \varepsilon$$

(generalized linear model, GLM)

### The logistic equation



### Example: Pr(malignant) in biopsy data set



### Let's do this step by step...

### Recall the biopsy data set

```
> biopsy <- read.csv("http://wilkelab.org/classes/SDS348/data_sets/biopsy.csv")</pre>
> head(biopsy)
  clump_thickness uniform_cell_size uniform_cell_shape marg_adhesion
1
2
5
                                   10
                                                        10
  epithelial_cell_size bare_nuclei bland_chromatin normal_nucleoli mitoses
                                                    3
1
                                   1
                                                                              1
                                                                      2
2
                                  10
5
                                  10
    outcome
     benign
     benign
     benign
     benign
     benign
6 malignant
```

### We do logistic regression with the glm() function

```
> summary(glm.out)
```

#### Call:

```
glm(formula = outcome ~ clump_thickness + uniform_cell_size +
    uniform_cell_shape + marg_adhesion + epithelial_cell_size +
    bare_nuclei + bland_chromatin + normal_nucleoli + mitoses,
    family = binomial, data = biopsy)
```

#### Deviance Residuals:

```
Min 1Q Median 3Q Max -3.4841 -0.1153 -0.0619 0.0222 2.4698
```

#### Coefficients:

|                      | Estimate  | Std. Error | z value | Pr(> z ) |     |
|----------------------|-----------|------------|---------|----------|-----|
| (Intercept)          | -10.10394 | 1.17488    | -8.600  | < 2e-16  | *** |
| clump_thickness      | 0.53501   | 0.14202    | 3.767   | 0.000165 | *** |
| uniform_cell_size    | -0.00628  | 0.20908    | -0.030  | 0.976039 |     |
| uniform_cell_shape   | 0.32271   | 0.23060    | 1.399   | 0.161688 |     |
| marg_adhesion        | 0.33064   | 0.12345    | 2.678   | 0.007400 | **  |
| epithelial_cell_size | 0.09663   | 0.15659    | 0.617   | 0.537159 |     |
| bare_nuclei          | 0.38303   | 0.09384    | 4.082   | 4.47e-05 | *** |
| bland_chromatin      | 0.44719   | 0.17138    | 2.609   | 0.009073 | **  |
| normal_nucleoli      | 0.21303   | 0.11287    | 1.887   | 0.059115 | •   |
| mitoses              | 0.53484   | 0.32877    | 1.627   | 0.103788 |     |
|                      |           |            |         |          |     |

> summary(glm.out)

#### Call:

glm(formula = outcome ~ clump\_thickness + uniform\_cell\_size +
 uniform\_cell\_shape + marg\_adhesion + epithelial\_cell\_size +
 bare\_nuclei + bland\_chromatin + normal\_nucleoli + mitoses,
 family = binomial, data = biopsy)

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|                      |           |            |         |          |     |

```
> summary(glm.out)
Call:
glm(formula = outcome ~ clump_thickness + uniform_cell_shape +
   marq adhesion + epithelial cell size + bare nuclei +
bland chromatin +
   normal nucleoli + mitoses, family = binomial, data = biopsy)
Deviance Residuals:
           10 Median
   Min
                          30
                                 Max
-3.4823 -0.1154 -0.0620 0.0222 2.4694
Coefficients:
                  Estimate Std. Error z value Pr(>|z|)
                 -10.09765
                            1.15546 - 8.739 < 2e-16 ***
(Intercept)
clump thickness
                 0.53456 0.14125 3.784 0.000154 ***
uniform cell shape 0.31816 0.17424 1.826 0.067847 .
marg adhesion
              0.32993 0.12115 2.723 0.006465 **
epithelial_cell_size 0.09612 0.15564 0.618 0.536876
bare nuclei
                   bland chromatin
                   normal nucleoli
                   0.21255 0.11174 1.902 0.057149 .
mitoses
                   0.53406 0.32761 1.630 0.103064
```

```
> summary(glm.out)
```

#### Call:

#### Deviance Residuals:

| Min     | 1Q      | Median  | 3Q     | Max    |
|---------|---------|---------|--------|--------|
| -3.4823 | -0.1154 | -0.0620 | 0.0222 | 2.4694 |

#### Coefficients:

|                      | Estimate  | Std. Error | z value | Pr(> z ) |     |
|----------------------|-----------|------------|---------|----------|-----|
| (Intercept)          | -10.09765 | 1.15546    | -8.739  | < 2e-16  | *** |
| clump_thickness      | 0.53456   | 0.14125    | 3.784   | 0.000154 | *** |
| uniform_cell_shape   | 0.31816   | 0.17424    | 1.826   | 0.067847 | •   |
| marg_adhesion        | 0.32993   | 0.12115    | 2.723   | 0.006465 | **  |
| epithelial cell size | 0.09612   | 0.15561    | 0.618   | 0.536876 |     |
| bare_nuclei          | 0.38308   | 0.09384    | 4.082   | 4.46e-05 | *** |
| bland_chromatin      | 0.44648   | 0.16986    | 2.628   | 0.008578 | **  |
| normal_nucleoli      | 0.21255   | 0.11174    | 1.902   | 0.057149 | •   |
| mitoses              | 0.53406   | 0.32761    | 1.630   | 0.103064 |     |
|                      |           |            |         |          |     |

```
> summary(glm.out)
Call:
glm(formula = outcome ~ clump thickness + uniform cell shape +
   marg adhesion + bare nuclei + bland chromatin +
normal nucleoli +
   mitoses, family = binomial, data = biopsy)
Deviance Residuals:
            10 Median
   Min
                             30
                                    Max
-3.5235 -0.1149 -0.0627 0.0219 2.4115
Coefficients:
                 Estimate Std. Error z value Pr(>|z|)
                            1.12610 -8.865 < 2e-16 ***
                 -9.98278
(Intercept)
clump thickness
               0.53400 0.14079 3.793 0.000149 ***
uniform cell shape 0.34529 0.17164 2.012 0.044255 *
marg adhesion
              0.34249 0.11922 2.873 0.004068 **
bare nuclei
            0.38830 0.09356 4.150 3.32e-05 ***
bland chromatin 0.46194 0.16820 2.746 0.006025 **
normal nucleoli 0.22606 0.11097 2.037 0.041644 *
mitoses
                  0.53119
                            0.32446 1.637 0.101598
```

```
> summary(glm.out)
Call:
glm(formula = outcome ~ clump thickness + uniform cell shape +
   marg adhesion + bare nuclei + bland chromatin +
normal nucleoli +
   mitoses, family = binomial, data = biopsy)
Deviance Residuals:
   Min
             10 Median
                              30
                                     Max
-3.5235 -0.1149 -0.0627 0.0219
                                  2.4115
Coefficients:
                 Estimate Std. Error z value Pr(>|z|)
                            1.12610 - 8.865 < 2e-16 ***
                 -9.98278
(Intercept)
clump thickness
                0.53400
                            0.14079 3.793 0.000149 ***
                            0.17164 2.012 0.044255 *
uniform cell shape 0.34529
marg adhesion
               0.34249 0.11922 2.873 0.004068 **
bare nuclei
                0.38830
                            0.09356 4.150 3.32e-05 ***
bland chromatin 0.46194
                            0.16820 2.746 0.006025 **
normal nucleoli
               0.22606
                             0.11097 2.037 0.041644 *
```

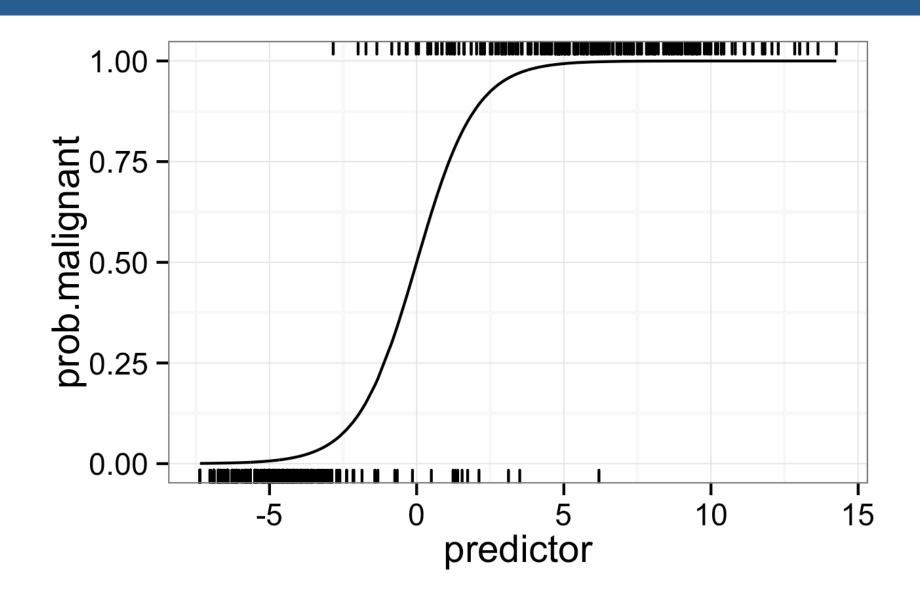
0.32446

0.53110

```
> summary(glm.out)
Call:
glm(formula = outcome ~ clump thickness + uniform cell shape +
   marg adhesion + bare nuclei + bland chromatin +
normal nucleoli,
   family = binomial, data = biopsy)
Deviance Residuals:
            10 Median
   Min
                           30
                                  Max
-3.5201 -0.1186 -0.0570 0.0250 2.4055
Coefficients:
                Estimate Std. Error z value Pr(>|z|)
                          1.08506 -9.001 < 2e-16 ***
                -9.76708
(Intercept)
clump thickness 0.62253 0.13712 4.540 5.62e-06 ***
uniform cell shape 0.34951 0.16503 2.118 0.03419 *
marg adhesion
             0.37855 0.09381 4.035 5.45e-05 ***
bare nuclei
bland chromatin 0.47134 0.16612 2.837 0.00455 **
```

normal nucleoli 0.24317 0.10855 2.240 0.02509 \*

### The fitted logistic model



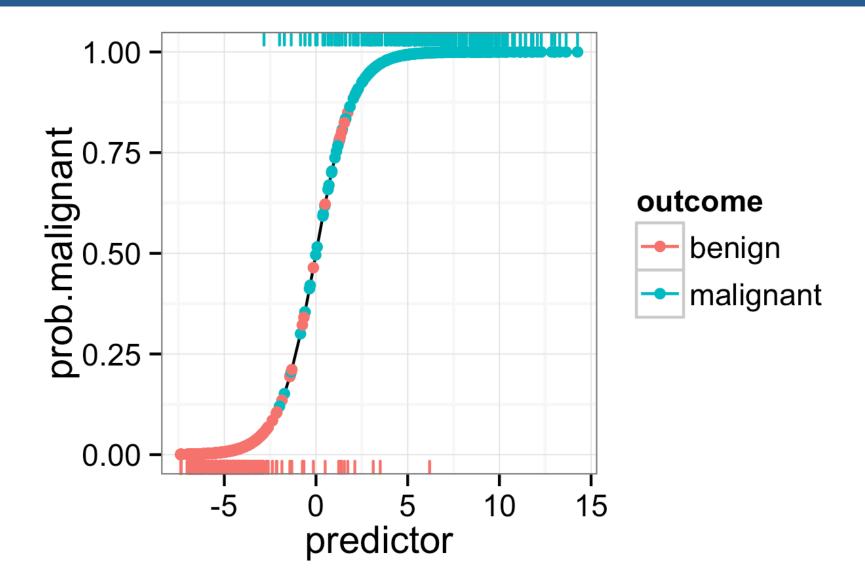
## We can extract fitted probabilities from glm.out\$fitted.values

```
> glm.out$fitted.values
0.0192341317 0.8925583864 0.0081774737 0.8496854505 0.0202506282 0.9999854554
0.0467606911 0.0042790664 0.0011789931 0.0065253423 0.0016231293 0.0018875638
          13
                                    15
                                                 16
0.3544332567 0.0034543023 0.9993353305 0.7371582761 0.0065253423 0.0104135504
                                    21
                                                 22
          19
                       20
                                                               23
0.9989353409 0.0352597948 0.9969203982 0.9994994519 0.0035120154 0.0016231293
                                    27
0.7802514369 0.0035120154 0.0120927435 0.0018875638 0.0012725934 0.0035120154
          31
0.0030206952 0.9977220579 0.0042283384 0.0049740412 0.0018875638 0.9998755391
                                    39
                                                  40
0.1940709471 0.9954253327 0.6691128086 0.9536389392 0.9974078013 0.3002866244
                                                  46
0.9996235802 0.0010137236 0.9583091930 0.0010137236 0.0202506282 0.9836985106
          49
                       50
                                    51
                                                               53
0.7842860362 0.4122043566 0.9956800184 0.9922376046 0.9988895968 0.9870508267
                                    57
                                                  58
                       56
0.9927513406 0.6585108620 0.7534314353 0.8341431018 0.9032183182 0.0014795146
0.9921570845 0.5158282353 0.0010137236 0.7040691331 0.0104135504 0.9498144607
```

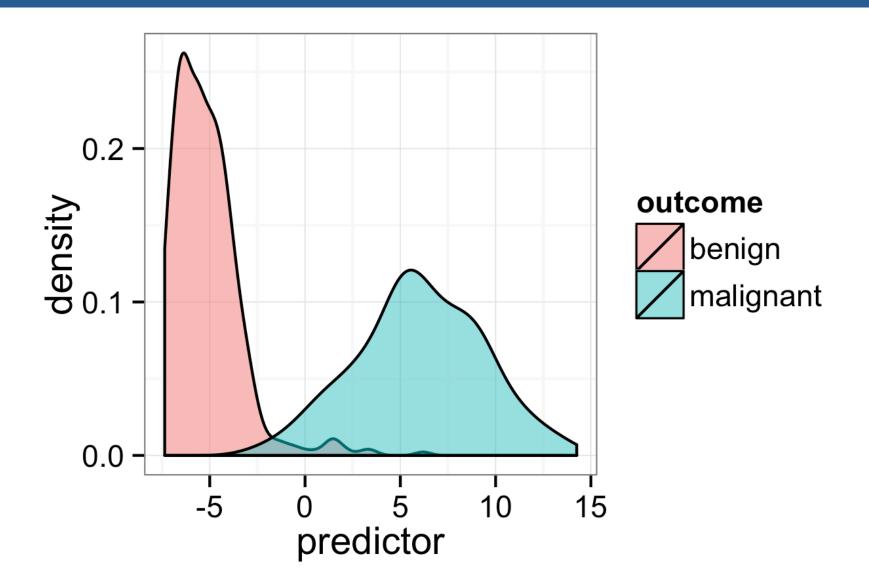
## We can extract linear predictors from glm.out\$linear.predictors

```
> glm.out$linear.predictors
-3.93164737 2.11714436 -4.79816093 1.73213613 -3.87911098 11.13827708
                                  10
-3.01482307 -5.44973218 -6.74191480 -5.02551514 -6.42177489 -6.27057890
          14 15 16 17
      13
-0.59960855 -5.66467448 7.31555568 1.03125059 -5.02551514 -4.55417925
                  21 22
         20
6.84403543 -3.30911549 5.77987063 7.59930618 -5.64804702 -6.42177489
                  2.7
         26
                                  28
1.26713222 - 5.64804702 - 4.40298326 - 6.27057890 - 6.66542501 - 5.64804702
            32
                  33 34 35
-5.79924301 6.08220228 -5.46170888 -5.29853619 -6.27057890 8.99139484
          38
                  39 40
                                           41
-1.42377192 5.38263613 0.70417516 3.02382523 5.95265328 -0.84593335
          44
                         45
                           46 47
7.88442916 -6.89311078 3.13488983 -6.89311078 -3.87911098 4.10006298
                  51 52
                                           53
      49
          50
1.29082051 -0.35486010 5.44017479 4.85067163 6.80192104 4.33368959
                   57
                            58
                56
4.91966368 0.65666514 1.11699791 1.61527962 2.23350656 -6.51456058
                62
                  63 64
4.84027081 0.06333410 -6.89311078 0.86675068 -4.55417925 2.94053974
```

# The linear predictor clearly separates benign and malignant outcomes



## The linear predictor clearly separates benign and malignant outcomes



```
> patient1 <- data.frame(clump thickness = 1,</pre>
                          uniform cell size = 1,
                          uniform cell shape = 1,
                          marg adhesion = 1,
                          epithelial cell size = 4,
                          bare nuclei = 3,
                          bland chromatin = 1,
                          normal nucleoli = 1,
                          mitoses = 1)
> predict(glm.out, patient1) # linear predictor
-6.607346
```

```
> patient1 <- data.frame(clump thickness = 1,</pre>
                          uniform cell size = 1,
                          uniform cell shape = 1,
                          marg adhesion = 1,
                          epithelial cell size = 4,
                          bare nuclei = 3,
                          bland chromatin = 1,
                          normal nucleoli = 1,
                          mitoses = 1)
> predict(glm.out, patient1) # linear predictor
-6.607346
> predict(glm.out, patient1, type="response") # probability
0.00134859
```

```
> patient2 <- data.frame(clump thickness = 4,
                         uniform cell size = 5,
                         uniform cell shape = 5,
                         marg adhesion = 10,
                         epithelial cell size = 4,
                         bare nuclei = 10,
                         bland chromatin = 7,
                         normal nucleoli = 5,
                         mitoses = 8)
> predict(glm.out, patient2) # linear predictor
6.14665
```

```
> patient2 <- data.frame(clump thickness = 4,
                         uniform cell size = 5,
                         uniform cell shape = 5,
                         marg adhesion = 10,
                         epithelial cell size = 4,
                         bare nuclei = 10,
                         bland chromatin = 7,
                         normal nucleoli = 5,
                         mitoses = 8)
> predict(glm.out, patient2) # linear predictor
6.14665
> predict(glm.out, patient2, type="response") # probability
0.9978639
```