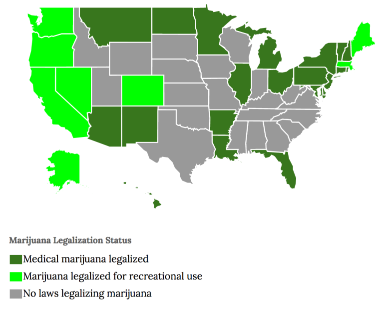
THE UNIVERSITY OF TEXAS AT AUSTIN
McCOMBS SCHOOL OF BUSINESS

Logistic Regression 2

Lecture 16

STA 371G

Should pot be legal?



(Map source)

- The General Social Survey is an annual survey of attitudes and behaviors that has been conducted since the 1970s
- Let's use the GSS to examine the question of whether Americans think pot should be legalized
- An increasing number of states have done so already!

Response variable:

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Predictor variables:

- **year**: The year of the survey (1975-2014)
- **age**: The age of the respondent
- **schooling**: Number of years of schooling (e.g., 12 = HS degree, 16 = bachelor’s)
- **philosophy**: Political philosophy (on the spectrum of liberal to conservative)

Let's start by building a model using only the `year` variable:

```
model1 <- glm(legal ~ year, data=pot, family=binomial)
summary(model1)
```

```
Call:
glm(formula = legal ~ year, family = binomial, data = pot)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.1202  -0.8596  -0.7330   1.3005   1.8827

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -75.022369   2.368408  -31.68   <2e-16 ***
year          0.037183   0.001187   31.34   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 34665  on 28335  degrees of freedom
Residual deviance: 33646  on 28334  degrees of freedom
AIC: 33650

Number of Fisher Scoring iterations: 4
```

Evaluating model fit: Take 1

Our baseline prediction percentage is 69.9% (this is how many cases we'd predict correctly if we just predicted legal $= 0$ for everyone).

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How well do we do by using the model?

```
predicted.legal <- (predict(model1, type='response') >= 0.5)
actual.legal <- (pot$legal == 1)
sum(predicted.legal == actual.legal) / nrow(pot)

[1] 0.6990401
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No better than a naive model that just predicts the same for everyone!

Evaluating model fit: Take 2

Let's also try computing McFadden's pseudo-R^2:

$$\text{Pseudo-}R^2 = 1 - \frac{\text{residual deviance}}{\text{null deviance}} = 1 - \frac{33645.96}{34664.87} = 0.03$$

Evaluating model fit: Take 2

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Both metrics show us that year does not help us predict attitude towards legalization very well (but we wouldn't expect it to — why not?)

Improving the model

Let's add more predictors to the model:

- Years of schooling
- Age of respondent
- Political philosophy
- Gender

Interpreting the coefficients

Let's interpret the coefficients:

```
model2 <- glm(legal ~ year + age + schooling + philosophy
                      + gender, data=pot, family=binomial)
```

```
                                Estimate Std. Error z value Pr(>|z|)
(Intercept)                       -80.24       2.56  -31.34     0.00
year                                0.04       0.00   30.66     0.00
age                                -0.02       0.00  -20.96     0.00
schooling                           0.06       0.00   12.52     0.00
philosophyExtremely liberal         1.73       0.08   20.41     0.00
philosophyExtrmly conservative     -0.01       0.10   -0.09     0.93
philosophyLiberal                   1.41       0.06   25.64     0.00
philosophyModerate                  0.60       0.05   13.05     0.00
philosophySlghtly conservative      0.37       0.05    6.95     0.00
philosophySlightly liberal          0.97       0.05   17.99     0.00
genderMale                         -0.02       0.03   -0.55     0.58
```

Interpreting the coefficients

	Estimate	Std. Error	z value	Pr(>|z|)
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year	0.04	0.00	30.66	0.00
age	-0.02	0.00	-20.96	0.00
schooling	0.06	0.00	12.52	0.00
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All else being equal, being a year older decreases the predicted *odds* that you will support marijuana legalization by 1.8% (since $e^{-0.018} = 0.982$ and $1 - 0.982 = 0.018$).

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How well do we do by using the model?

```
predicted.legal <- (predict(model2, type='response') >= 0.5)
actual.legal <- (pot$legal == 1)
sum(predicted.legal == actual.legal) / nrow(pot)

[1] 0.721
```

Evaluating model fit: Take 2

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Is it surprising that our measures of model fit are fairly low?

Testing the overall null hypothesis

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We first have to define a null model (with no predictors), just like we did for stepwise regression:

```
null <- glm(legal ~ 1, data=pot, family=binomial)
```

Testing the overall null hypothesis

Now we can test our current model against the null model:

```
library(lmtest)
lrtest(null, model2)

Likelihood ratio test

Model 1: legal ~ 1
Model 2: legal ~ year + age + schooling + philosophy + gender
  #Df LogLik Df Chisq Pr(>Chisq)
1   1 -17332
2  11 -15797 10  3071     <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
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```

Since $p < 2 \times 10^{-16}$, we can reject the overall model null hypothesis (not surprising since we had many significant coefficients).