lab07

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```
spotify <- read_csv("spotify.csv")</pre>
## New names:
## * '' -> ...1
## Rows: 2017 Columns: 17
## -- Column specification -------
## Delimiter: ","
## chr (2): song_title, artist
## dbl (15): ...1, acousticness, danceability, duration_ms, energy, instrumenta...
## i Use 'spec()' to retrieve the full column specification for this data.
## i Specify the column types or set 'show_col_types = FALSE' to quiet this message.
glimpse(spotify)
## Rows: 2,017
## Columns: 17
## $ ...1
                    <dbl> 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15,~
## $ acousticness
                    <dbl> 0.010200, 0.199000, 0.034400, 0.604000, 0.180000, 0.0~
                    <dbl> 0.833, 0.743, 0.838, 0.494, 0.678, 0.804, 0.739, 0.26~
## $ danceability
                    <dbl> 204600, 326933, 185707, 199413, 392893, 251333, 24140~
## $ duration_ms
                    <dbl> 0.434, 0.359, 0.412, 0.338, 0.561, 0.560, 0.472, 0.34~
## $ energy
## $ instrumentalness <dbl> 2.19e-02, 6.11e-03, 2.34e-04, 5.10e-01, 5.12e-01, 0.0~
                    <dbl> 2, 1, 2, 5, 5, 8, 1, 10, 11, 7, 5, 10, 0, 0, 9, 6, 1,~
## $ key
## $ liveness
                    <dbl> 0.1650, 0.1370, 0.1590, 0.0922, 0.4390, 0.1640, 0.207~
## $ loudness
                    <dbl> -8.795, -10.401, -7.148, -15.236, -11.648, -6.682, -1~
## $ mode
                    <dbl> 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0,~
                    <dbl> 0.4310, 0.0794, 0.2890, 0.0261, 0.0694, 0.1850, 0.156~
## $ speechiness
## $ tempo
                    <dbl> 150.062, 160.083, 75.044, 86.468, 174.004, 85.023, 80~
## $ time_signature
                    ## $ valence
                    <dbl> 0.286, 0.588, 0.173, 0.230, 0.904, 0.264, 0.308, 0.39~
```

<chr> "Future", "Childish Gambino", "Future", "Beach House"~

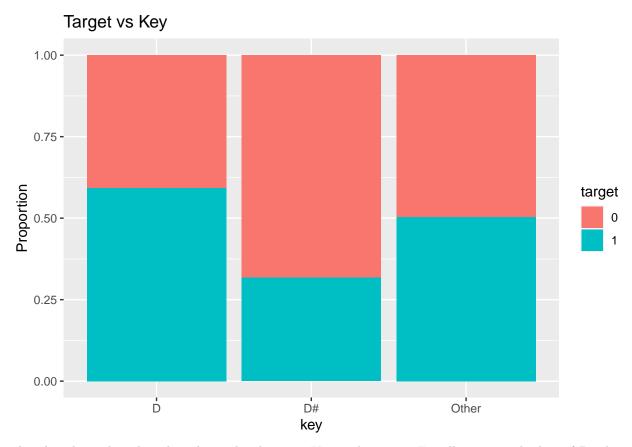
\$ target

\$ song_title
\$ artist

Part 1: Data Prep & Modeling

Exercise 1

```
spotify <- spotify %>%
 drop_na() %>%
 mutate(target = as.factor(target),
        key = case_when(
          key == 2 \sim "D",
          key == 3 \sim "D#",
          TRUE ~ "Other"
        ))
glimpse(spotify)
## Rows: 2,017
## Columns: 17
## $ ...1
                     <dbl> 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15,~
## $ acousticness
                     <dbl> 0.010200, 0.199000, 0.034400, 0.604000, 0.180000, 0.0~
                     <dbl> 0.833, 0.743, 0.838, 0.494, 0.678, 0.804, 0.739, 0.26~
## $ danceability
## $ duration ms
                     <dbl> 204600, 326933, 185707, 199413, 392893, 251333, 24140~
## $ energy
                     <dbl> 0.434, 0.359, 0.412, 0.338, 0.561, 0.560, 0.472, 0.34~
## $ instrumentalness <dbl> 2.19e-02, 6.11e-03, 2.34e-04, 5.10e-01, 5.12e-01, 0.0~
                     <chr> "D", "Other", "D", "Other", "Other", "Other"~
## $ key
                     <dbl> 0.1650, 0.1370, 0.1590, 0.0922, 0.4390, 0.1640, 0.207~
## $ liveness
## $ loudness
                     <dbl> -8.795, -10.401, -7.148, -15.236, -11.648, -6.682, -1~
                     <dbl> 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0,~
## $ mode
## $ speechiness
                     <dbl> 0.4310, 0.0794, 0.2890, 0.0261, 0.0694, 0.1850, 0.156~
## $ tempo
                     <dbl> 150.062, 160.083, 75.044, 86.468, 174.004, 85.023, 80~
                     <dbl> 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 3, 4, 4, 4, 4, 4, 4, 4, **.
## $ time_signature
## $ valence
                     <dbl> 0.286, 0.588, 0.173, 0.230, 0.904, 0.264, 0.308, 0.39~
                     ## $ target
## $ song_title
                     <chr> "Mask Off", "Redbone", "Xanny Family", "Master Of Non~
                     <chr> "Future", "Childish Gambino", "Future", "Beach House"~
## $ artist
ggplot(data = spotify, aes(x = key, fill = target)) +
```



The plot above describes the relationship between Key and Target. For all songs in the key of D, about 60% of them have a target value of 1. For all songs in the key of D#, about 30% of them have a target value of 1. For all other songs, about half of them have a target value of 1.

Exercise 2

```
model <- glm(target ~ acousticness + danceability + duration_ms + instrumentalness + loudness + speeching
tidy(model, conf.int = TRUE, exponentiate = FALSE) %>%
   kable(format="markdown", digits = 5)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	-2.95548	0.27640	-10.69288	0.00000	-3.50377	-2.41978
acousticness	-1.72231	0.23982	-7.18155	0.00000	-2.19743	-1.25678
danceability	1.63040	0.34421	4.73664	0.00000	0.95847	2.30841
$duration_ms$	0.00000	0.00000	4.22500	0.00002	0.00000	0.00000
instrumentalness	1.35291	0.20659	6.54883	0.00000	0.95236	1.76298
loudness	-0.08744	0.01727	-5.06219	0.00000	-0.12160	-0.05383
speechiness	4.07238	0.58302	6.98493	0.00000	2.94695	5.23420
valence	0.85638	0.22326	3.83573	0.00013	0.41997	1.29551

```
model_with_key <- glm(target ~ acousticness + danceability + duration_ms + instrumentalness + loudness
summary(model)$aic</pre>
```

[1] 2534.517

```
summary(model_with_key)$aic
```

[1] 2525.16

Adding key to the model lowers the model's AIC, making it better at predicting target. Therefore, we will continue to use the model with key.

Exercise 4

```
tidy(model_with_key, conf.int = TRUE, exponentiate = FALSE) %>%
kable(format="markdown", digits = 5)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	-2.50934	0.31102	-8.06817	0.00000	-3.12416	-1.90422
acousticness	-1.70210	0.24091	-7.06521	0.00000	-2.17930	-1.23436
danceability	1.64880	0.34536	4.77417	0.00000	0.97468	2.32911
$duration_ms$	0.00000	0.00000	4.18744	0.00003	0.00000	0.00000
instrumentalness	1.38316	0.20745	6.66741	0.00000	0.98104	1.79505
loudness	-0.08662	0.01726	-5.01848	0.00000	-0.12075	-0.05301
speechiness	4.03380	0.58491	6.89650	0.00000	2.90456	5.19917
valence	0.88094	0.22434	3.92682	0.00009	0.44248	1.32224
keyD#	-1.07319	0.33497	-3.20385	0.00136	-1.74517	-0.42805
keyOther	-0.49390	0.16898	-2.92288	0.00347	-0.82793	-0.16468

If the key of the observation is D#, the target value's prediction will increase, by a value of exp(-1.07319).

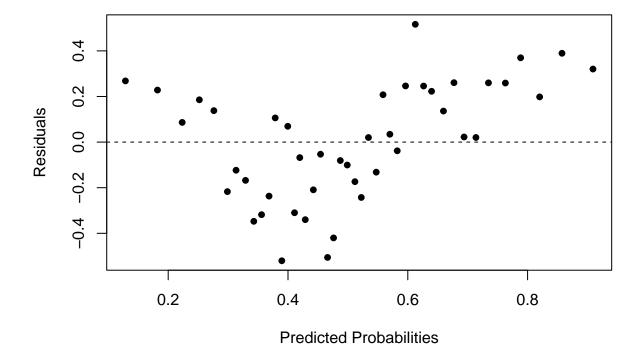
Part 2: Checking Assumptions

Exercise 5

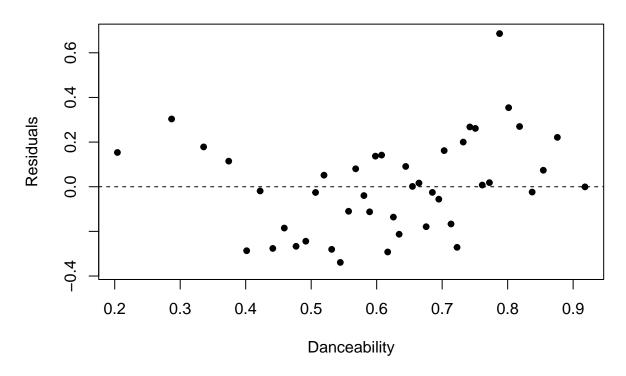
```
df <- augment(model_with_key, type.predict = "response",type.residuals = "deviance")
glimpse(df)</pre>
```

```
<dbl> 0.010200, 0.199000, 0.034400, 0.604000, 0.180000, 0.0~
## $ acousticness
## $ danceability
                      <dbl> 0.833, 0.743, 0.838, 0.494, 0.678, 0.804, 0.739, 0.26~
## $ duration ms
                      <dbl> 204600, 326933, 185707, 199413, 392893, 251333, 24140~
## $ instrumentalness <dbl> 2.19e-02, 6.11e-03, 2.34e-04, 5.10e-01, 5.12e-01, 0.0~
                      <dbl> -8.795, -10.401, -7.148, -15.236, -11.648, -6.682, -1~
## $ loudness
## $ speechiness
                      <dbl> 0.4310, 0.0794, 0.2890, 0.0261, 0.0694, 0.1850, 0.156~
## $ valence
                      <dbl> 0.286, 0.588, 0.173, 0.230, 0.904, 0.264, 0.308, 0.39~
                      <chr> "D", "Other", "D", "Other", "Other", "Other", "Other"~
## $ key
## $ .fitted
                      <dbl> 0.9015924, 0.6379788, 0.7829667, 0.4223972, 0.8489462~
                      <dbl> 0.4551764, 0.9481036, 0.6995214, 1.3128664, 0.5722926~
## $ .resid
## $ .std.resid
                      <dbl> 0.4567745, 0.9493120, 0.7028629, 1.3163187, 0.5733889~
                      <dbl> 0.006985200, 0.002544191, 0.009485687, 0.005238444, 0~
## $ .hat
                      <dbl> 1.117466, 1.117311, 1.117402, 1.117126, 1.117439, 1.1~
## $ .sigma
                      <dbl> 7.731894e-05, 1.451076e-04, 2.679972e-04, 7.238900e-0~
## $ .cooksd
```

Binned Residual vs. Predicted Values



Binned Residual vs. Danceability



Exercise 8

```
df %>%
  mutate(key_resid = if_else(.resid > 1 | .resid < -1, "High Residual", "Low Residual")) %>%
  group_by(key, key_resid) %>%
  summarise(n = n()) %>%
  kable(format="markdown")
```

'summarise()' has grouped output by 'key'. You can override using the '.groups' argument.

key	key_resid	n
D	High Residual	98

key	key_resid	n
D	Low Residual	86
D#	High Residual	21
D#	Low Residual	42
Other	High Residual	1039
Other	Low Residual	731

The linearity assumption is not satisfied because there is no clear linear relationship between our fitted values and our predictors, as shown by the plot in exercise 6.