Prediction and overfitting

Data Science in a Box

datasciencebox.org

Modified by Tyler George

Prediction

Goal: Building a spam filter

- Data: Set of emails and we know if each email is spam/not and other features
- Use logistic regression to predict the probability that an incoming email is spam
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- Building a model to predict the probability that an email is spam is only half of the battle! We also need a decision rule about which emails get flagged as spam (e.g. what probability should we use as out cutoff?)
- A simple approach: choose a single threshold probability and any email that exceeds that probability is flagged as spam

A multiple regression approach

Output Code

```
## # A tibble: 22 x 5
##    term         estimate std.error statistic  p.value
##    <chr>           <dbl>     <dbl>     <dbl>    <dbl>
##  1 (Intercept) -9.09e+1   9.80e+3  -0.00928 9.93e- 1
##  2 to_multiple1 -2.68e+0   3.27e-1  -8.21    2.25e-16
##  3 from1       -2.19e+1   9.80e+3  -0.00224 9.98e- 1
##  4 cc           1.88e-2   2.20e-2   0.855   3.93e- 1
##  5 sent_email1 -2.07e+1   3.87e+2  -0.0536  9.57e- 1
##  6 time         8.48e-8   2.85e-8   2.98    2.92e- 3
##  7 image       -1.78e+0   5.95e-1  -3.00    2.73e- 3
##  8 attach       7.35e-1   1.44e-1   5.09    3.61e- 7
##  9 dollar      -6.85e-2   2.64e-2  -2.59    9.64e- 3
## 10 winneryes    2.07e+0   3.65e-1   5.67    1.41e- 8
## 11 inherit      3.15e-1   1.56e-1   2.02    4.32e- 2
## 12 viagra       2.84e+0   2.22e+3   0.00128 9.99e- 1
## 13 password    -8.54e-1   2.97e-1  -2.88    4.03e- 3
## 14 num_char     5.06e-2   2.38e-2   2.13    3.35e- 2
## 15 line_breaks -5.49e-3   1.35e-3  -4.06    4.91e- 5
## 16 format1     -6.14e-1   1.49e-1  -4.14    3.53e- 5
## 17 re_subj1    -1.64e+0   3.86e-1  -4.25    2.16e- 5
## 18 exclaim_subj  1.42e-1   2.43e-1   0.585   5.58e- 1
## 19 urgent_subj1  3.88e+0   1.32e+0   2.95    3.18e- 3
## 20 exclaim_mess  1.08e-2   1.81e-3   5.98    2.23e- 9
## 21 numbersmall -1.19e+0   1.54e-1  -7.74    9.62e-15
## 22 numberbig   -2.95e-1   2.20e-1  -1.34    1.79e- 1
```

A multiple regression approach

Output Code

```
logistic_reg() %>%
  set_engine("glm") %>%
  fit(spam ~ ., data = email, family = "binomial") %>%
  tidy() %>%
  print(n = 22)
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

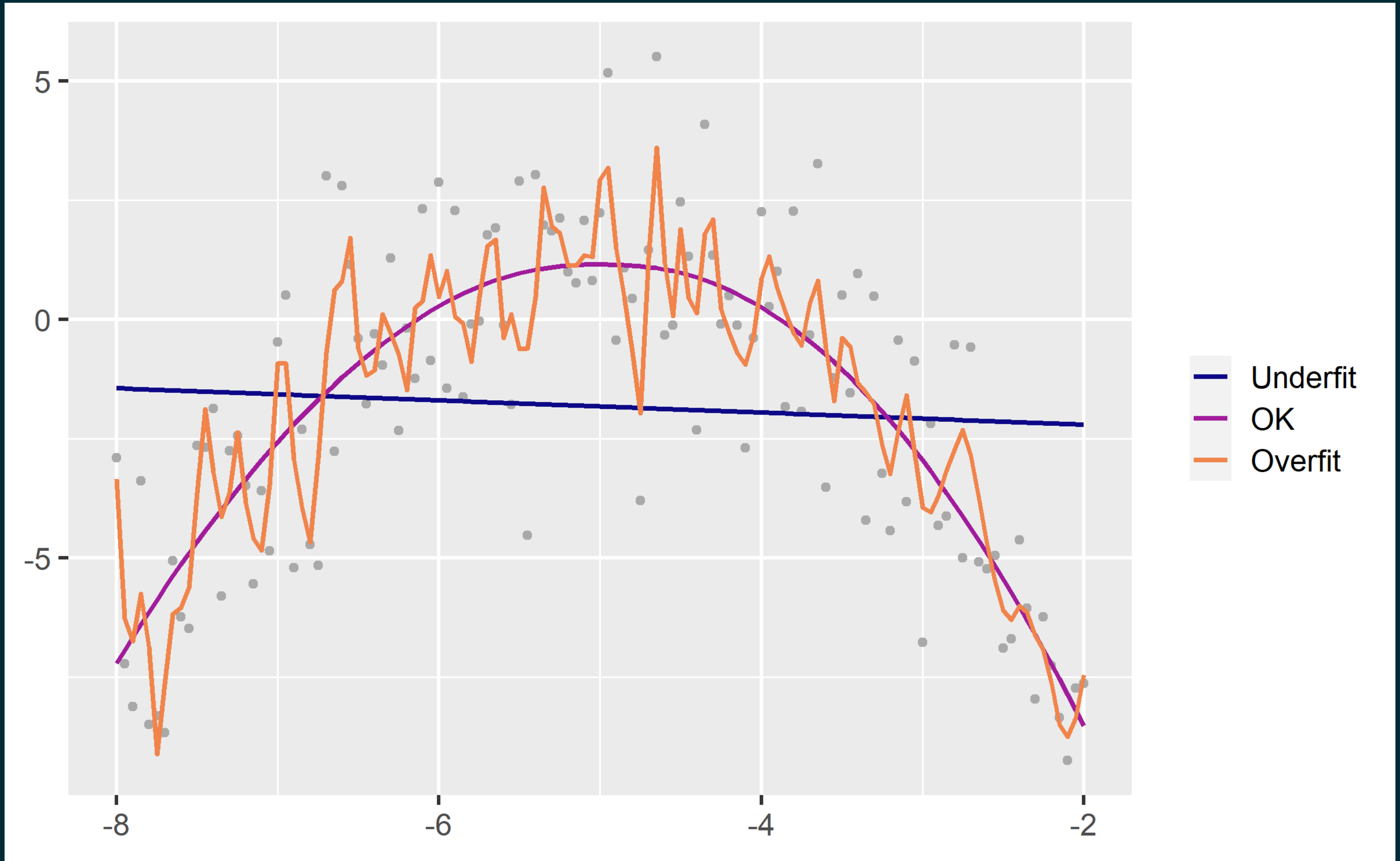
Prediction

- The mechanics of prediction is **easy**:
  - Plug in values of predictors to the model equation
  - Calculate the predicted value of the response variable, $\hat{y}$

Prediction

- The mechanics of prediction is **easy**:
  - Plug in values of predictors to the model equation
  - Calculate the predicted value of the response variable, $\hat{y}$
- Getting it right is **hard**!
  - There is no guarantee the model estimates you have are correct
  - Or that your model will perform as well with new data as it did with your sample data

Underfitting and overfitting



Spending our data

- Several steps to create a useful model: parameter estimation, model selection, performance assessment, etc.

- Doing all of this on the entire data we have available can lead to **overfitting**

- Allocate specific subsets of data for different tasks, as opposed to allocating the largest possible amount to the model parameter estimation only (which is what we've done so far)

Splitting data

Splitting data

- **Training set:**
    - Sandbox for model building
    - Spend most of your time using the training set to develop the model
    - Majority of the data (usually 80%)
- **Testing set:**
    - Held in reserve to determine efficacy of one or two chosen models
    - Critical to look at it once, otherwise it becomes part of the modeling process
    - Remainder of the data (usually 20%)

Performing the split

```
# Fix random numbers by setting the seed
# Enables analysis to be reproducible when random numbers are used
set.seed(1116)

# Put 80% of the data into the training set
email_split <- initial_split(email, prop = 0.80)

# Create data frames for the two sets:
train_data <- training(email_split)
test_data  <- testing(email_split)
```

Peek at the split

```
glimpse(train_data)
```

```
## Rows: 3,136
## Columns: 21
## $ spam         <fct> 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, ~
## $ to_multiple  <fct> 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, ~
## $ from         <fct> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, ~
## $ cc           <int> 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 35,~
## $ sent_email   <fct> 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ time         <dttm> 2012-01-25 16:46:55, 2012-01-02 23:28:28,~
## $ image        <dbl> 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ attach       <dbl> 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ dollar       <dbl> 10, 0, 0, 0, 0, 0, 13, 0, 0, 0, 2, 0, 0, 0~
## $ winner       <fct> no, no, no, no, no, no, no, yes, no, no, n~
## $ inherit      <dbl> 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ viagra       <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ password     <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ num_char     <dbl> 23.308, 1.162, 4.732, 42.238, 1.228, 25.59~
## $ line_breaks  <int> 477, 2, 127, 712, 30, 674, 367, 226, 98, 6~
## $ format       <fct> 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, ~
## $ re_subj      <fct> 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, ~
## $ exclaim_subj <dbl> 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, ~
## $ urgent_subj  <fct> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ exclaim_mess <dbl> 12, 0, 2, 2, 2, 31, 2, 0, 0, 1, 0, 1, 2, 0~
## $ number       <fct> small, none, big, big, small, small, small~
```

```
glimpse(test_data)
```

```
## Rows: 785
## Columns: 21
## $ spam         <fct> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ to_multiple  <fct> 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, ~
## $ from         <fct> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, ~
## $ cc           <int> 0, 1, 0, 1, 4, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ sent_email   <fct> 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ time         <dttm> 2012-01-01 11:55:06, 2012-01-01 13:38:32,~
## $ image        <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ attach       <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, ~
## $ dollar       <dbl> 0, 0, 5, 0, 0, 0, 0, 5, 4, 0, 0, 0, 21, 0,~
## $ winner       <fct> no, no, no, no, no, no, no, no, no, no, no~
## $ inherit      <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, ~
## $ viagra       <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ password     <dbl> 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, ~
## $ num_char     <dbl> 4.837, 15.075, 18.037, 45.842, 11.438, 1.4~
## $ line_breaks  <int> 193, 354, 345, 881, 125, 24, 296, 13, 192,~
## $ format       <fct> 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, ~
## $ re_subj      <fct> 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, ~
## $ exclaim_subj <dbl> 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ urgent_subj  <fct> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ exclaim_mess <dbl> 1, 10, 20, 5, 2, 0, 0, 0, 6, 0, 0, 1, 3, 0~
## $ number       <fct> big, small, small, big, small, none, small~
```

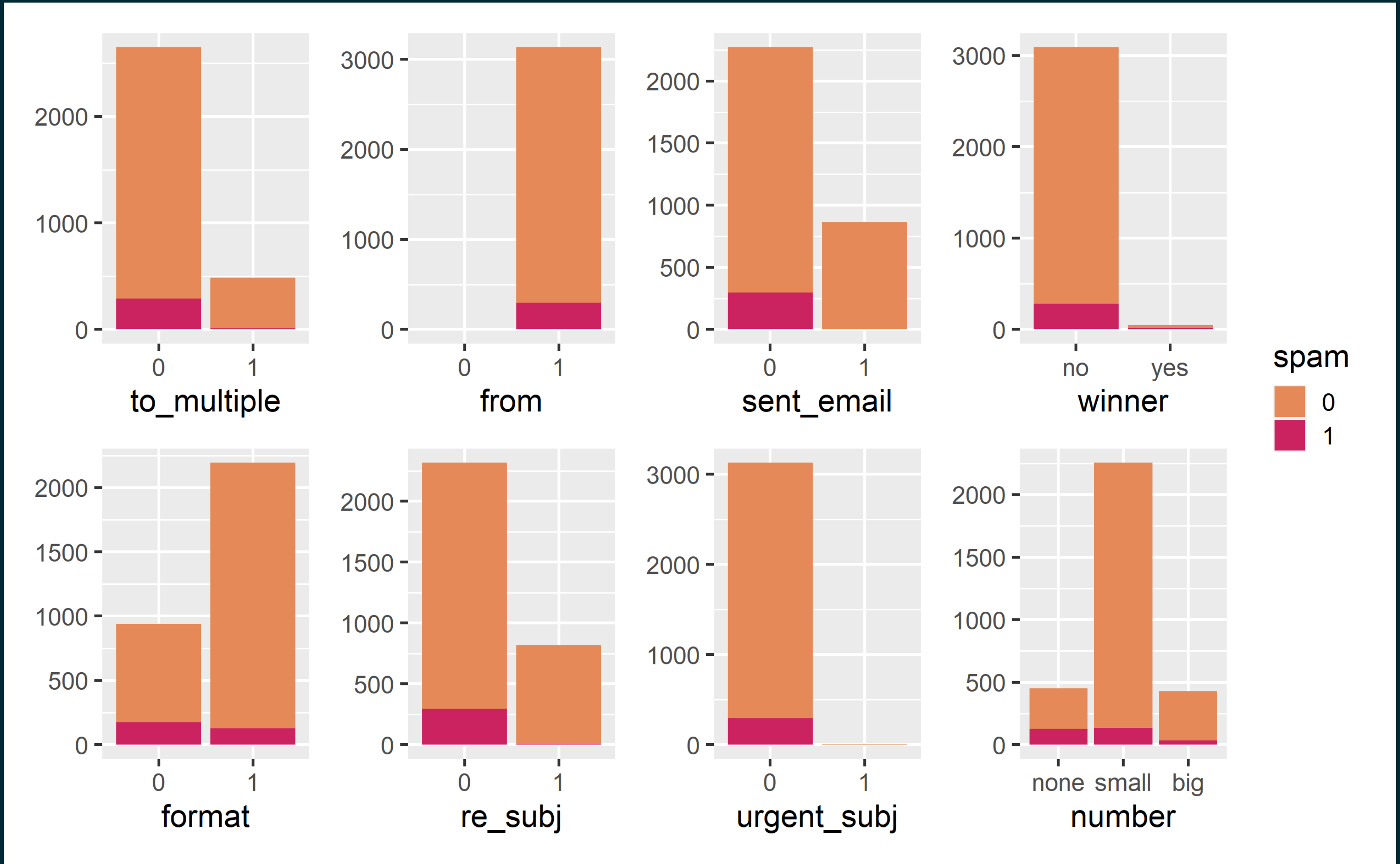
Modeling workflow

Fit a model to the training dataset

```r
email_fit <- logistic_reg() %>%
  set_engine("glm") %>%
  fit(spam ~ ., data = train_data, family = "binomial")
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

Categorical predictors



from and sent_email

- from: Whether the message was listed as from anyone (this is usually set by default for regular outgoing email)

```
train_data %>%
  count(spam, from)
```

```
## # A tibble: 3 x 3
##   spam  from      n
##   <fct> <fct> <int>
## 1 0     1      2837
## 2 1     0         3
## 3 1     1       296
```

- sent_email: Indicator for whether the sender had been sent an email in the last 30 days

```
train_data %>%
  count(spam, sent_email)
```

```
## # A tibble: 3 x 3
##   spam  sent_email     n
##   <fct> <fct>      <int>
## 1 0     0           1972
## 2 0     1            865
## 3 1     0            299
```

Numerical predictors

```
##
## -- Variable type: numeric ------------------------------------------------------------------------
## # A tibble: 22 x 11
##     skim_variable spam  n_missing complete_rate      mean       sd    p0     p25      p50     p75  p100
##   * <chr>         <fct>     <int>         <dbl>     <dbl>    <dbl> <dbl>   <dbl>    <dbl>   <dbl> <dbl>
##   1 cc            0             0             1   0.393     2.62   0       0        0       0      68
##   2 cc            1             0             1   0.388     3.25   0       0        0       0      50
##   3 image         0             0             1   0.0536    0.503  0       0        0       0      20
##   4 image         1             0             1   0.00334   0.0578 0       0        0       0       1
##   5 attach        0             0             1   0.124     0.775  0       0        0       0      21
##   6 attach        1             0             1   0.227     0.620  0       0        0       0       2
##   7 dollar        0             0             1   1.56      5.33   0       0        0       0      64
##   8 dollar        1             0             1   0.779     3.01   0       0        0       0      36
##   9 inherit       0             0             1   0.0352    0.216  0       0        0       0       6
##  10 inherit       1             0             1   0.0702    0.554  0       0        0       0       9
##  11 viagra        0             0             1   0         0      0       0        0       0       0
##  12 viagra        1             0             1   0.0268    0.463  0       0        0       0       8
##  13 password      0             0             1   0.112     0.938  0       0        0       0      22
##  14 password      1             0             1   0.0201    0.182  0       0        0       0       2
##  15 num_char      0             0             1  11.4      14.9    0.003   1.97     6.83   15.7    190.
##  16 num_char      1             0             1   5.63     15.7    0.001   0.468    0.999   3.55   174.
##  17 line_breaks   0             0             1 247.      326.     2      42      138     318     4022
##  18 line_breaks   1             0             1 108.      321.     1      14       23      66.5   3729
##  19 exclaim_subj  0             0             1   0.0783    0.269  0       0        0       0       1
##  20 exclaim_subj  1             0             1   0.0769    0.267  0       0        0       0       1
##  21 exclaim_mess  0             0             1   6.68     50.2    0       0        1       5     1236
##  22 exclaim_mess  1             0             1   8.75     88.4    0       0        0       1     1209
```

Fit a model to the training dataset

```
email_fit <- logistic_reg() %>%
  set_engine("glm") %>%
  fit(spam ~ . - from - sent_email - viagra, data = train_data, family = "binomial")
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
email_fit
```

```
## parsnip model object
##
## Fit time:  31ms
##
## Call:  stats::glm(formula = spam ~ . - from - sent_email - viagra, family = stats::binomial,
##     data = data)
##
## Coefficients:
##  (Intercept)  to_multiple1            cc          time         image        attach        dollar
##   -9.867e+01    -2.505e+00     1.944e-02     7.396e-08    -2.854e+00     5.070e-01    -6.440e-02
##    winneryes       inherit      password      num_char   line_breaks       format1      re_subj1
##    2.170e+00     4.499e-01    -7.065e-01     5.870e-02    -5.420e-03    -9.017e-01    -2.995e+00
## exclaim_subj  urgent_subj1  exclaim_mess   numbersmall     numberbig
##    1.002e-01     3.572e+00     1.009e-02    -8.518e-01    -1.329e-01
##
## Degrees of Freedom: 3135 Total (i.e. Null);  3117 Residual
## Null Deviance:        1974
## Residual Deviance: 1447     AIC: 1485
```

Predict outcome on the testing dataset

```
predict(email_fit, test_data)
```

```
## # A tibble: 785 x 1
##   .pred_class
##   <fct>
## 1 0
## 2 0
## 3 0
## 4 0
## 5 0
## 6 0
## # ... with 779 more rows
```

Predict probabilities on the testing dataset

```r
email_pred <- predict(email_fit, test_data, type = "prob") %>%
  bind_cols(test_data %>% select(spam, time))

email_pred
```

```
## # A tibble: 785 x 4
##    .pred_0 .pred_1 spam  time
##      <dbl>   <dbl> <fct> <dttm>
## 1    0.993 0.00709 0     2012-01-01 11:55:06
## 2    0.998 0.00181 0     2012-01-01 13:38:32
## 3    0.981 0.0191  0     2012-01-01 23:42:16
## 4    0.999 0.00124 0     2012-01-02 09:12:51
## 5    0.988 0.0121  0     2012-01-02 10:45:36
## 6    0.830 0.170   0     2012-01-02 15:55:03
## # ... with 779 more rows
```

A closer look at predictions

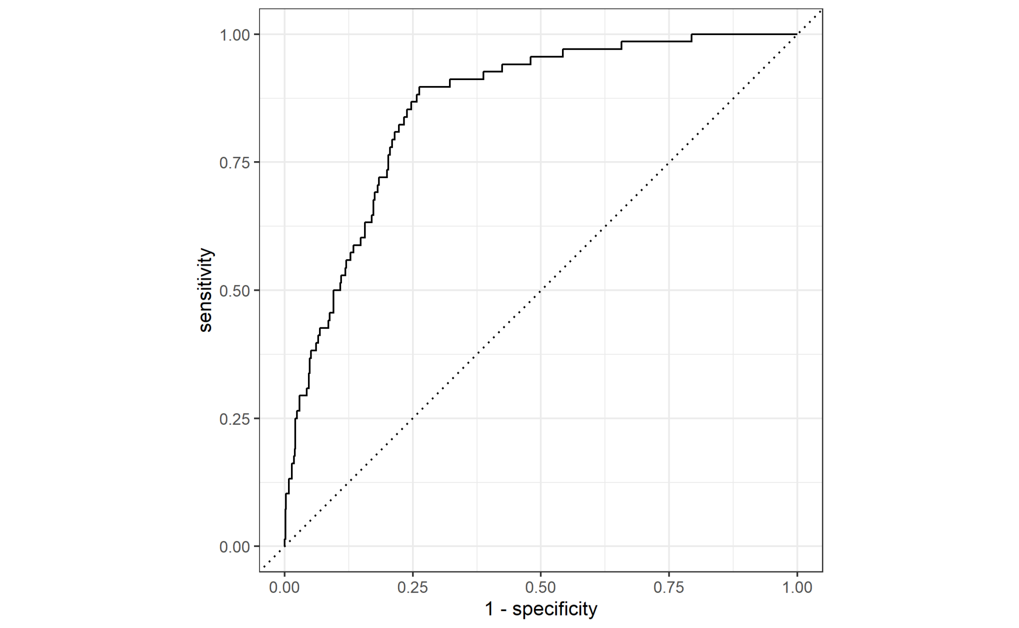
```r
email_pred %>%
  arrange(desc(.pred_1)) %>%
  print(n = 10)
```

```
## # A tibble: 785 x 4
##    .pred_0 .pred_1 spam  time
##      <dbl>   <dbl> <fct> <dttm>
##  1  0.0972   0.903 1     2012-02-13 06:15:00
##  2  0.167    0.833 0     2012-01-27 14:05:06
##  3  0.175    0.825 1     2012-02-29 23:40:27
##  4  0.267    0.733 1     2012-03-17 05:13:27
##  5  0.317    0.683 1     2012-03-21 07:33:12
##  6  0.374    0.626 1     2012-02-08 02:00:05
##  7  0.386    0.614 0     2012-01-30 08:20:29
##  8  0.403    0.597 1     2012-01-07 10:11:49
##  9  0.462    0.538 1     2012-03-06 05:46:20
## 10  0.463    0.537 0     2012-02-17 16:54:16
## # ... with 775 more rows
```

Evaluate the performance

Receiver operating characteristic (ROC) curve+ which plot true positive rate vs. false positive rate (1 - specificity)

```
email_pred %>%
  roc_curve(
    truth = spam,
    .pred_1,
    event_level = "second"
  ) %>%
  autoplot()
```



+Originally developed for operators of military radar receivers, hence the name.

Evaluate the performance

Find the area under the curve:

```
email_pred %>%
  roc_auc(
    truth = spam,
    .pred_1,
    event_level = "second"
  )
```

```
## # A tibble: 1 x 3
##   .metric .estimator .estimate
##   <chr>   <chr>          <dbl>
## 1 roc_auc binary         0.857
```