DATA CONSIDERATIONS

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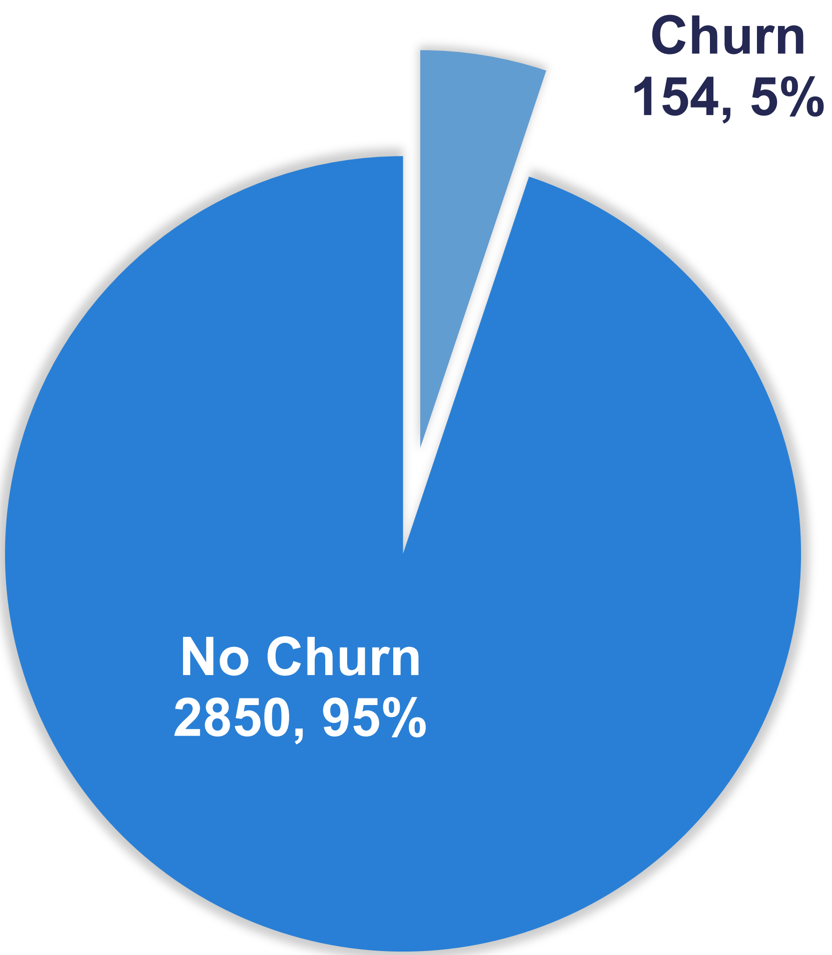
RARE EVENT MODELING

Rare Event Modeling

- 5% or smaller in a category can lead to classification problems.
- Common Situations:
  - Fraud
  - Default
  - Marketing Response
  - Weather Event

Telecomm Churn Data Set

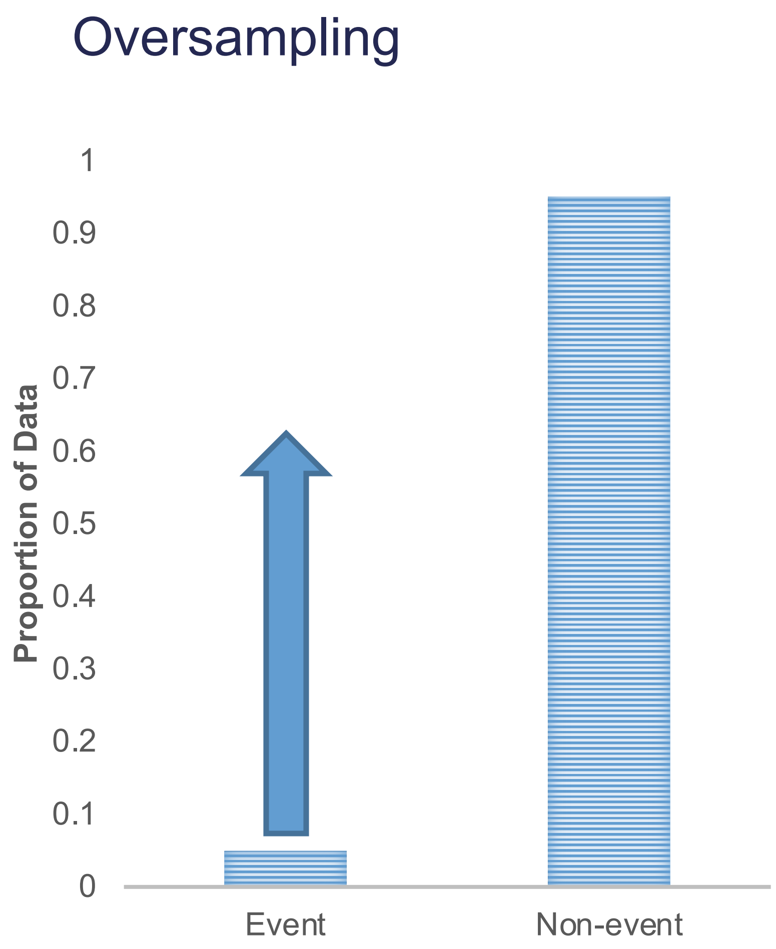
- Model the association between various factors and a customer churning (leaving the company)
- 3004 observations in the data set

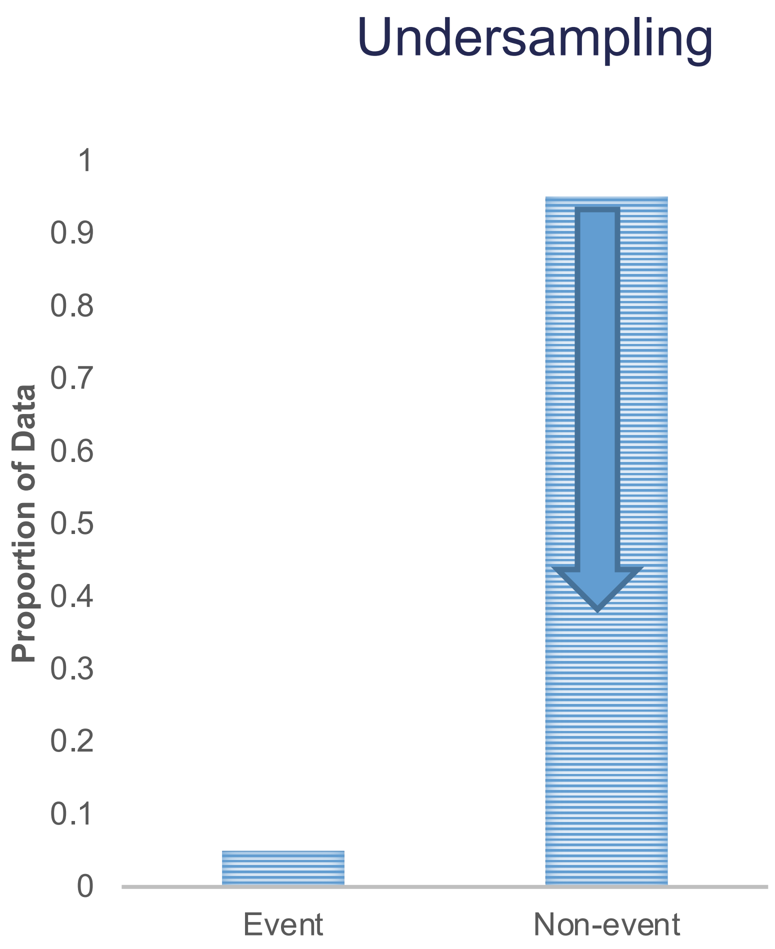


Telecomm Churn Data Set

- Model the association between various factors and a customer churning (leaving the company)
- Predictors:
  - **account_length:** length of time with company
  - **international_plan:** yes, no
  - **voice_mail_plan:** yes, no
  - **customer_service_calls:** number of service calls
  - **total_day_minutes:** minutes used during daytime
  - **total_day_calls:** calls used during daytime
  - **total_day_charge:** cost of usage during daytime
  - Same as previous three for evening, night, international

Rare Event Sampling Correction





Rare Event Sampling Correction

Oversampling

- Duplicate current event cases in training set to balance better with non-event cases.
- Keep test set as original population proportion.

Undersampling

- Randomly sample current non-event cases to keep in the training set to balance with event cases.
- Keep test set as original population proportion.

Oversampling

```
library(tidyverse)

set.seed(12345)
train_o <- churn %>%
  sample_frac(0.70)

train_o_T <- train_o %>%
  filter(churn == TRUE) %>%
  slice(rep(1:n(), each = 10))

train_o_F <- train_o %>%
  filter(churn == FALSE)

train_o <- rbind(train_o_F, train_o_T)

test_o <- churn[-train_o$id,]
```

```
table(train_o$churn)

FALSE  TRUE
 1996  1070
```

```
table(test_o$churn)

FALSE  TRUE
  854    47
```

Undersampling

```
set.seed(12345)

train_u <- churn %>%
  group_by(churn) %>%
  sample_n(104)

test_u <- churn[-train_u$id,]
```

```
table(train_u$churn)

FALSE  TRUE
  104   104
```

```
table(test_u$churn)


FALSE  TRUE
 2746    50
```

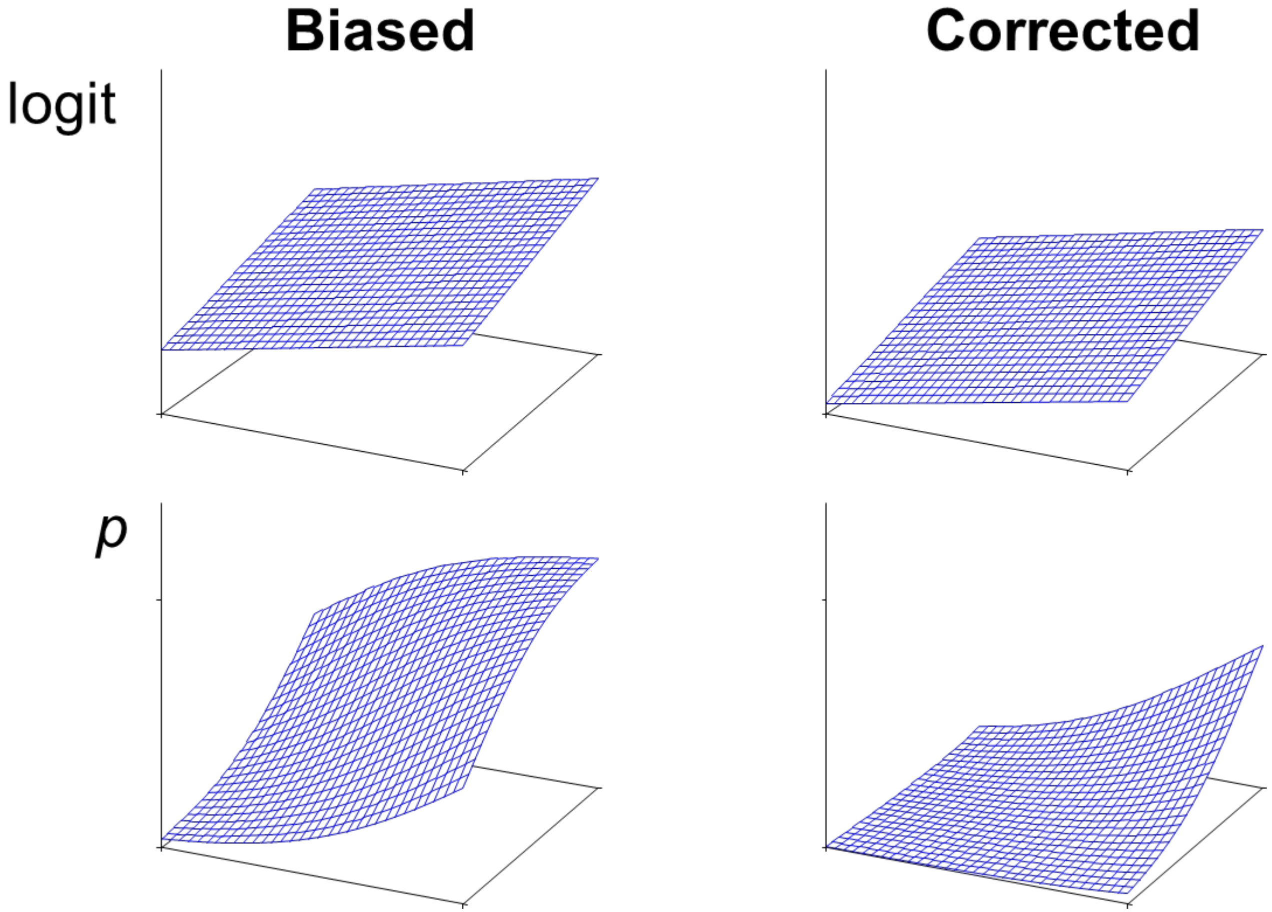
Telecomm Model

```
logit.model <- glm(churn ~ factor(international.plan) +
                           factor(voice.mail.plan) +
                           total.day.charge +
                           customer.service.calls,
                   data = train_u, family = binomial(link = "logit"))

summary(logit.model)
```

Telecomm Model

```
Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.19331  -0.74911  -0.01389   0.73301   2.51757

Coefficients:
                              Estimate Std. Error z value Pr(>|z|)
(Intercept)                   -5.81880    0.95939  -6.065 1.32e-09 ***
factor(international.plan)yes  2.97995    0.57057   5.223 1.76e-07 ***
factor(voice.mail.plan)yes    -0.85107    0.41372  -2.057   0.0397 *
total.day.charge               0.12898    0.02234   5.773 7.79e-09 ***
customer.service.calls         0.78520    0.14947   5.253 1.50e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 288.35  on 207  degrees of freedom
Residual deviance: 195.24  on 203  degrees of freedom
AIC: 205.24
```

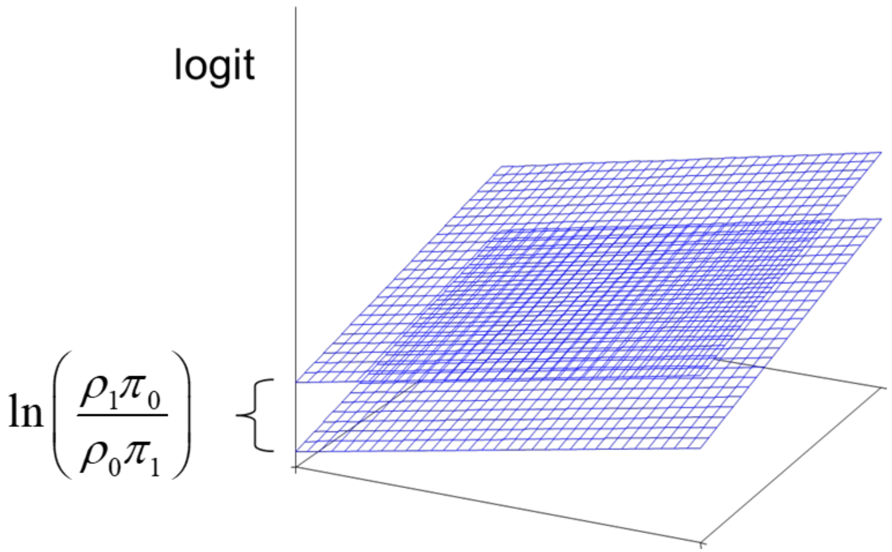
Effect of Oversampling



Adjustments to Oversampling

- When the sample proportion is out of line with the population proportion, adjustments need to be made to correct the bias.
- 2 Methods:
  1. Adjusting the intercept
  2. Weighting observations

Adjusting the Intercept



- Need to correct for the bias created by oversampling.
- Adjustment is only applied to intercept.
- This adjusts the predicted values:

- Population proportion: π_1, π_0
- Sample proportion: ρ_1, ρ_0
- Unadjusted predictions: $\hat{p}_i^*$

$$\hat{p}_i = \frac{\hat{p}_i^* \rho_0 \pi_1}{(1 - \hat{p}_i^*)\rho_1 \pi_0 + \hat{p}_i^* \rho_0 \pi_1}$$

Adjusting the Intercept

```
test_u_p_bias <- predict(logit.model, newdata = test_u, type = "response")
test_u_p <- (test_u_p_bias*(104/208)*(154/3004))/
            ((1-test_u_p_bias)*(104/208)*(2850/3004) +
             test_u_p_bias*(104/208)*(154/3004))

test_u <- data.frame(test_u, 'Pred' = test_u_p)

head(test_u_p)
```

```
         1          2          3          4          5          6
0.04788873 0.00516951 0.03230002 0.91516214 0.56312205 0.29766875
```

Weighting Observations

- Instead of adjusting the model after it is built, weighting observations adjusts while the model is being built.
- Uses **weighted MLE** instead – each observation has potentially different weight to the MLE calculation.
- Need to create a weight variable in the oversampled data set:

$$weight = \begin{cases} 1, & y = 1 \\ \rho_1\pi_0/\rho_0\pi_1, & y = 0 \end{cases}$$

Bigger than 1!

Weighting Observations

- Instead of adjusting the model after it is built, weighting observations adjusts while the model is being built.
- Uses **weighted MLE** instead – each observation has potentially different weight to the MLE calculation.
- Need to create a weight variable in the oversampled data set:

$$weight = \begin{cases} 1, & y = 1 \\ \rho_1 \pi_0 / \rho_0 \pi_1, & y = 0 \end{cases}$$

Need to overweight the 0's, since their effect was reduced in the sampling!

Weighted Observations

```
train_u$weight <- ifelse(train_u$churn == 'TRUE', 1, 18.49)

logit.model.w <- glm(churn ~ factor(international.plan) +
                             factor(voice.mail.plan) +
                             total.day.charge +
                             customer.service.calls,
                     data = train_u, family = binomial(link = "logit"),
                     weights = weight)

summary(logit.model.w)
```

Weighted Observations

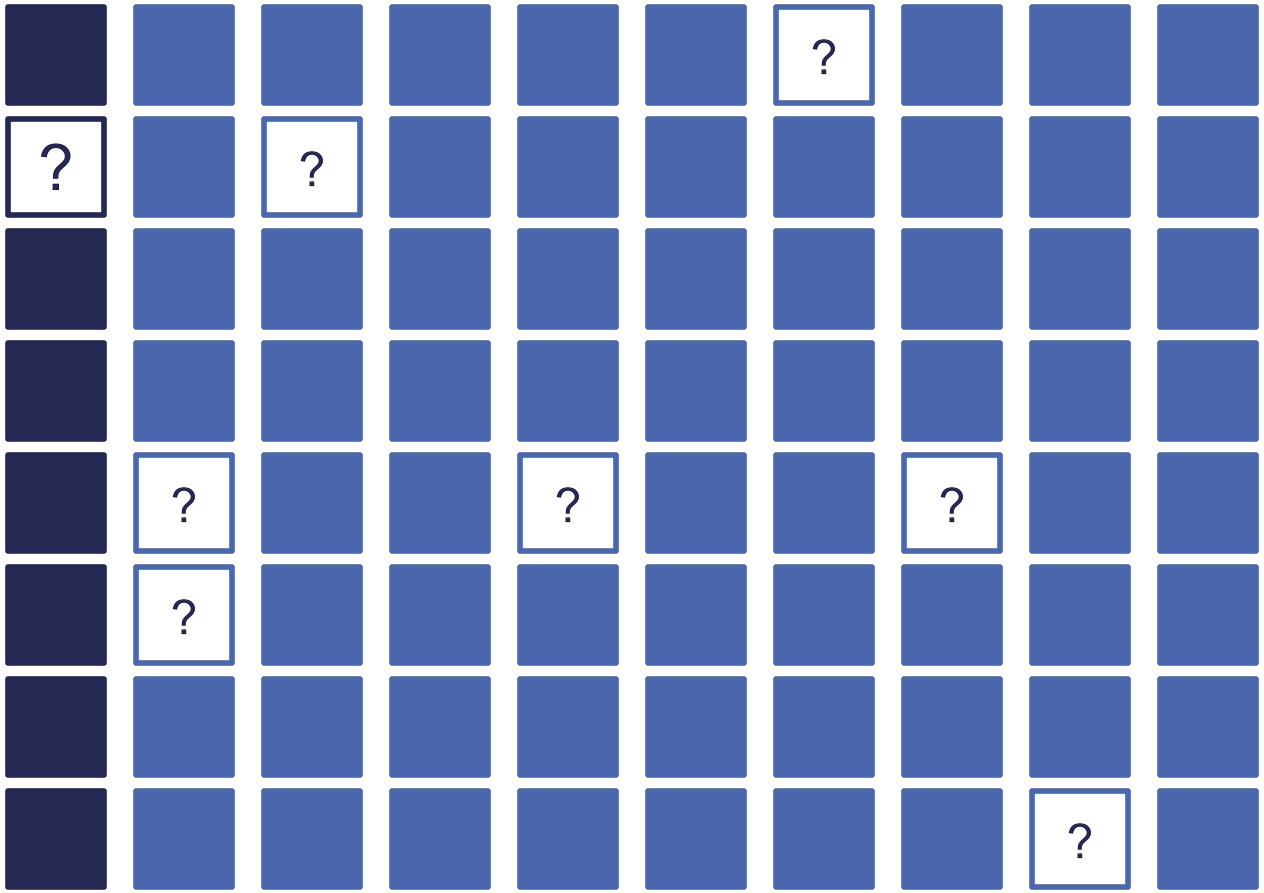
```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-4.5172  -0.7988   0.0717   1.8224   3.7129

Coefficients:
                              Estimate Std. Error z value Pr(>|z|)
(Intercept)                   -9.76831    0.69648 -14.025  < 2e-16 ***
factor(international.plan)yes  3.33560    0.32429  10.286  < 2e-16 ***
factor(voice.mail.plan)yes    -1.07451    0.27107  -3.964 7.37e-05 ***
total.day.charge               0.16320    0.01647   9.911  < 2e-16 ***
customer.service.calls         0.72693    0.08810   8.251  < 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: 820.31  on 207  degrees of freedom
Residual deviance: 585.33  on 203  degrees of freedom
AIC: 590.92
```

When to Use Which Technique?

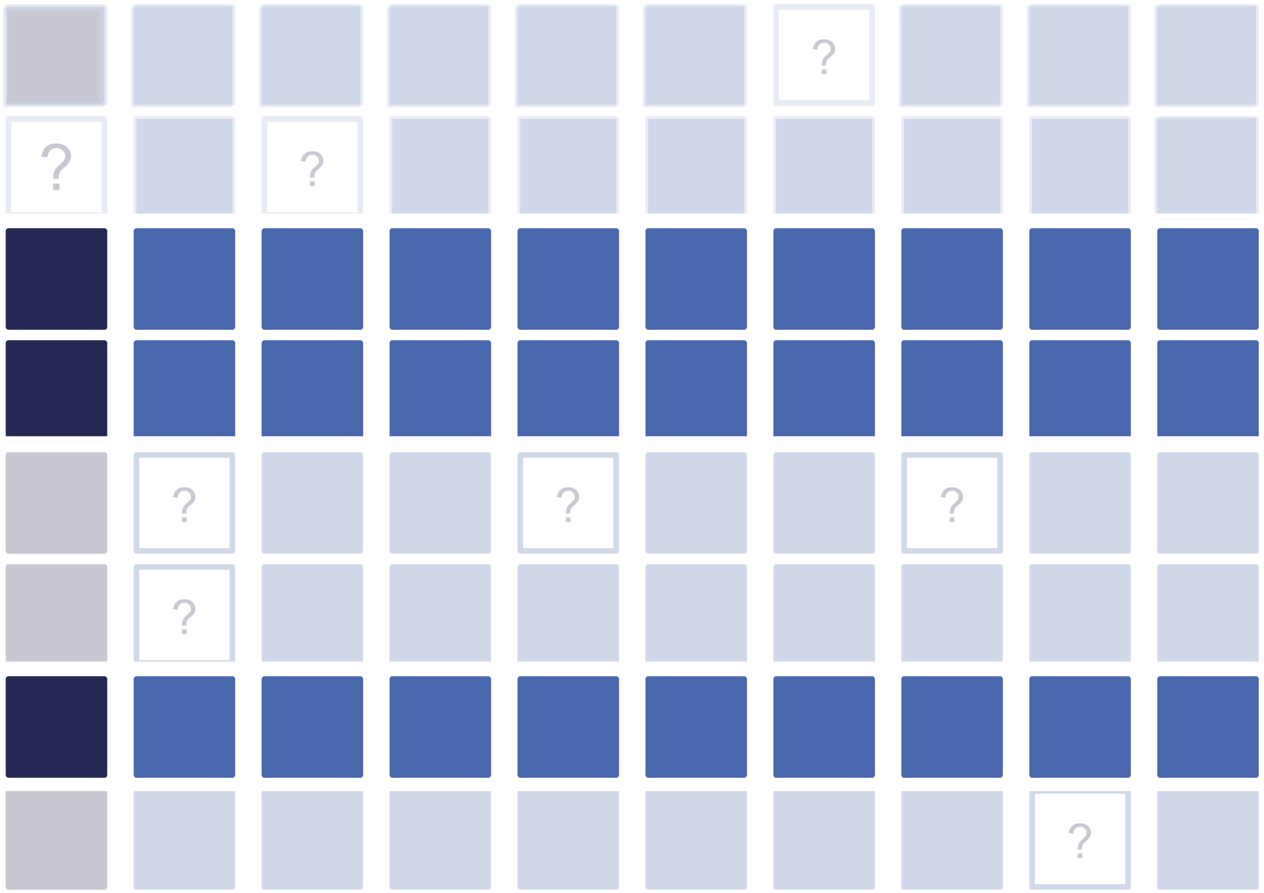
	Model Correct	Model Misspecified
Small Sample $(n \leq 1000)$	Adjust Intercept	Weighted Observations
Large Sample $(n > 1000)$	Either	Weighted Observations

MISSING VALUES

Complete Case Analysis



Complete Case Analysis



Handling Missing Values

- Complete cases analysis isn't necessarily bad if you have enough observations.
- However, how to handle scoring new observations with missing values?

- Solutions to missing values:
  - Delete
  - Keep
  - Replace

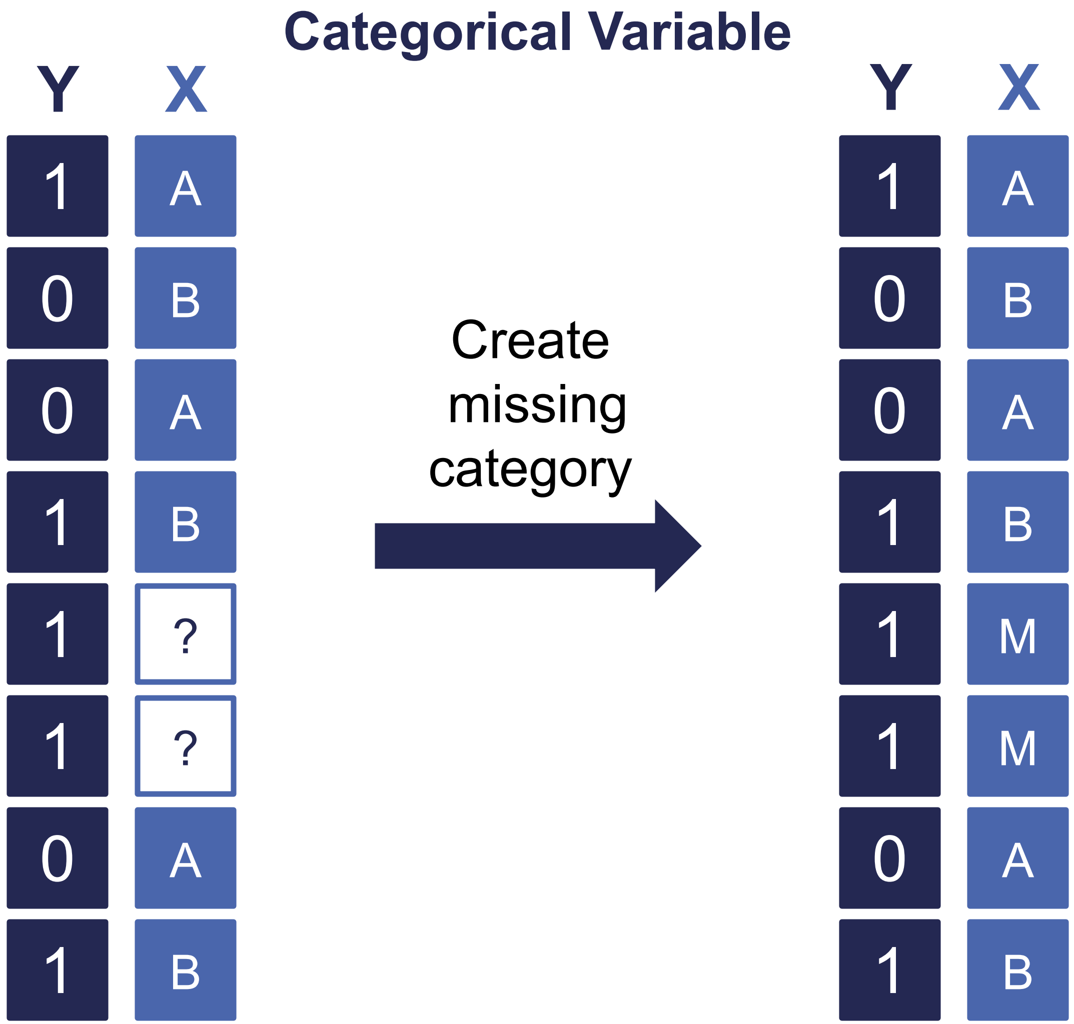
Delete

- If a majority of your data is missing, then consider deleting the variable all together.
- More than 50% missing → Remove

Y	X
1	14
0	?
0	?
1	18
1	?
1	?
0	31
1	?

Keep

- Missing values in predictor variables are not necessarily bad.
- In fact, they might even be predictive.
- Easy to handle with categorical variables!
- Add a missing category.



Replace

- Could estimate a missing value with **imputation**.
- Not best to do with categorical variables as you can just add missing category.
- Approaches:
  1. Simple mean/median replacement
  2. Predictive model using other variables (**not empirically shown to add value**)

Continuous Variable

Y	X
1	14
0	67
0	33
1	18
1	?
1	?
0	31
1	51

Impute with **median**

ALWAYS add and keep missing flag variable

Y	X	X_M
1	14	0
0	67	0
0	33	0
1	18	0
1	32	1
1	32	1
0	31	0
1	51	0

Summary of General (not Strict) Imputation Rules

- If variable has more than 50% missing, consider deleting from analysis.

- **Categorical**:
  - Create missing value category for categorical variables.

- **Continuous**:
  - Impute missing values for continuous variables (median is a popular choice)
  - Create a missing value binary variable for each of the continuous variables you impute.

CONVERGENCE PROBLEMS

Linear Separation

- **Complete linear separation** occurs when some combination of the predictors perfectly predict **every** outcome:

	Yes	No
Group A	100	0
Group B	0	50

- **Quasi-complete separation** occurs when the outcome can be perfectly predicted for only a subset of the data:

	Yes	No
Group A	77	23
Group B	0	50

Linear Separation

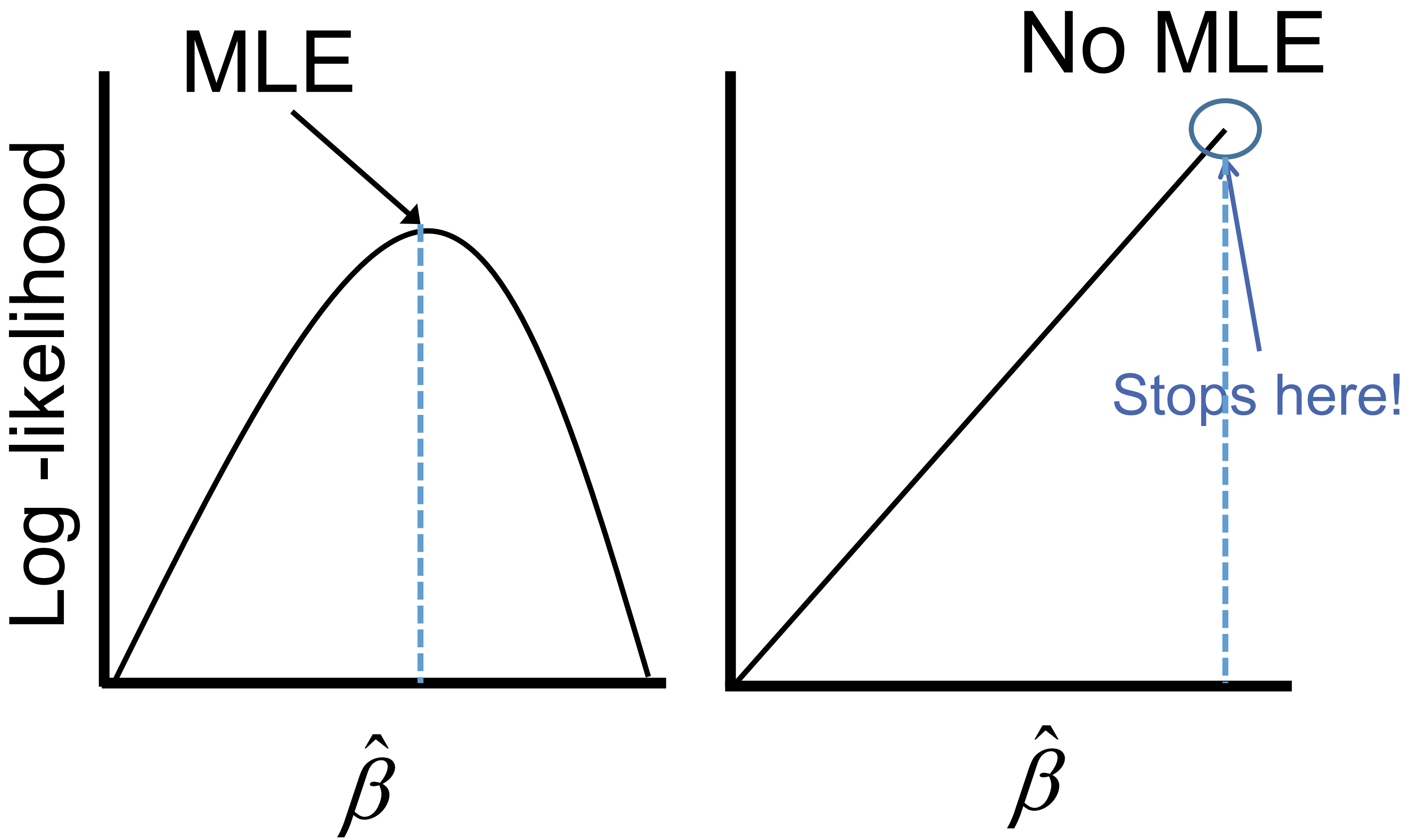
- **Complete linear separation** occurs when some combination of the predictors perfectly predict **every** outcome:

	Yes	No	Logit
Group A	100	0	∞
Group B	0	50	$-\infty$

- **Quasi-complete separation** occurs when the outcome can be perfectly predicted for only a subset of the data:

	Yes	No	Logit
Group A	77	23	1.39
Group B	0	50	$-\infty$

Problems with Convergence



Linear Separation – SAS

- SAS Warning Message:
  - WARNING: There is a complete separation of data points. The maximum likelihood estimate does not exist.
  - WARNING: The LOGISTIC procedure continues in spite of the above warning. Results shown are based on the last maximum likelihood iteration. Validity of the model fit is questionable.

Linear Separation – R

- Typical R Warning Message:

Linear Separation – R

- Sometimes R warning message deals with letting you know that you have predictions of exactly 0 or 1.
- However, it is not reliable to trust R to give a warning message.
- **Always explore data ahead of time**.

- Logistic regression output might also gives signs of a problem with parameter estimates.

Convergence Problems

```
table(train_u$customer.service.calls, train_u$churn)
```

```
  FALSE TRUE
0    29   25
1    34   25
2    23   20
3    15   12
4     2   13
5     1    4
6     0    3
7     0    2
```

Problems with quasi-complete separation

Convergence Problems

```
Coefficients:
                                 Estimate Std. Error z value Pr(>|z|)
(Intercept)                     -10.14712    0.81612 -12.433  < 2e-16 ***
factor(international.plan)yes     3.29304    0.34767   9.472  < 2e-16 ***
factor(voice.mail.plan)yes       -0.99870    0.30331  -3.293 0.000993 ***
total.day.charge                  0.17914    0.01788  10.019  < 2e-16 ***
factor(customer.service.calls)1   0.49904    0.36185   1.379 0.167847
factor(customer.service.calls)2   1.44529    0.40013   3.612 0.000304 ***
factor(customer.service.calls)3   1.22882    0.44653   2.752 0.005924 **
factor(customer.service.calls)4   3.61499    0.52008   6.951 3.63e-12 ***
factor(customer.service.calls)5   2.38233    0.69880   3.409 0.000652 ***
factor(customer.service.calls)6  22.86097  799.56689   0.029 0.977190
factor(customer.service.calls)7  21.52660 1028.81105   0.021 0.983306
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Solutions

- Possible Solutions:
  - Collapse the categories of the predictor variable to eliminate the 0 cell count.
  - Penalized maximum likelihood.
  - Eliminate the category altogether – probably not reasonable since the category seems important!
  - Add a very small constant to the cell counts.

Solutions

- Possible Solutions:
  - Collapse the categories of the predictor variable to eliminate the 0 cell count.
  - Penalized maximum likelihood.
  - Eliminate the category altogether – probably not reasonable since the category seems important!
  - Add a very small constant to the cell counts.

Thresholding – Ordinal Option

Customer Service Calls	Sample Size	0	1
0	54	29	25
1	59	34	25
2	43	23	20
3	27	15	12
4	15	2	13
5	5	1	4
6	3	0	3
7	2	0	2

Thresholding – Ordinal Option

Customer Service Calls	Sample Size	0	1
0	54	29	25
1	59	34	25
2	43	23	20
3	27	15	12
4	15	2	13
5	5	1	4
6	3	0	3
7	2	0	2

Collapse the cells

Thresholding – Ordinal Option

Customer Service Calls	Sample Size	0	1
0	54	29	25
1	59	34	25
2	43	23	20
3	27	15	12
4+	25	3	22

Clustering Levels – Nominal Option

	0	1
A	28	7
B	16	0
C	94	11
D	23	21

Clustering Levels – Nominal Option

	0	1
A	28	7
B	16	0
C	94	11
D	23	21

Most common categories →

	0	1
A	28	7
B/C	110	11
D	23	21

Clustering Levels – Greenacre Method

	0	1
A	28	7
B	16	0
C	94	11
D	23	21

$\chi^2 = 31.7$

	0	1
A	28	7
B/C	110	11
D	23	21

$\chi^2 = 30.7$

	0	1
A/B	44	7
C	94	11
D	23	21

$\chi^2 = 28.9$

	0	1
A	28	7
C	110	11
B/D	39	21

$\chi^2 = 18.3$

Clustering Levels – Greenacre Method

	0	1
A	28	7
B	16	0
C	94	11
D	23	21

$$\chi^2 = 31.7$$

Least amount information lost →

	0	1
A	28	7
B/C	110	11
D	23	21

$$\chi^2 = 30.7$$

Combining Categories

```
train_u$customer.service.calls.c <- as.character(train_u$customer.service.calls)
train_u$customer.service.calls.c[which(train_u$customer.service.calls > 3)] <- "4+"

table(train_u$customer.service.calls.c, train_u$churn)
```

```
    FALSE TRUE
  0    29   25
  1    34   25
  2    23   20
  3    15   12
  4+    3   22
```

Combining Categories

```
Coefficients:
                                 Estimate Std. Error z value Pr(>|z|)    
(Intercept)                      -9.17881    0.73429 -12.500  < 2e-16 ***
factor(international.plan)yes     3.08119    0.33258   9.265  < 2e-16 ***
factor(voice.mail.plan)yes       -1.14283    0.27822  -4.108 4.00e-05 ***
total.day.charge                  0.15725    0.01647   9.550  < 2e-16 ***
factor(customer.service.calls.c)1  0.44968    0.35420   1.270  0.20424    
factor(customer.service.calls.c)2  1.25310    0.38494   3.255  0.00113 ** 
factor(customer.service.calls.c)3  1.03735    0.43343   2.393  0.01670 *  
factor(customer.service.calls.c)4+ 3.45969    0.42516   8.137 4.04e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Solutions

- Possible Solutions:
  - Collapse the categories of the predictor variable to eliminate the 0 cell count.
  - Penalized maximum likelihood.
    - Use the `brglm()` function in R in place of `glm()` function.
    - **Not covered here.**
  - Eliminate the category altogether – probably not reasonable since the category seems important!
  - Add a very small constant to the cell counts.

Watch out for Interactions!

	Yes	No
Group A	77	23
Group B	16	50

Group variable
seems good

Watch out for Interactions!

	Yes	No
Group A	77	23
Group B	16	50

Group variable **interacting** with High/Low variable

	Yes	No
High	43	11
Low	0	41

	Yes	No
High	34	12
Low	16	9