Supplementary Handout

Supplementary material that didn't fit on the poster.

Data Scraping

We scraped Rotten Tomatoes data using "urllib2" and "re".

We tried a variety of different methods in order to scrape data from metacritic but there wasn't much success. A few of the methods we tried included:

Scraping directly from metacritic.

Failed because metacritic blocks requests made via urllib in python. Potentially there are other scraping methods that could circumvent this if we could set up the GET request properly in html (after all, it serves requests made from web browsers).

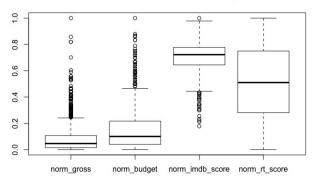
Scraping from search engine results (google).

This didn't work because google blocks your IP after a certain number of requests. Potentially using a timer and scraping at random intervals (perhaps Poisson would be best) could circumvent this.

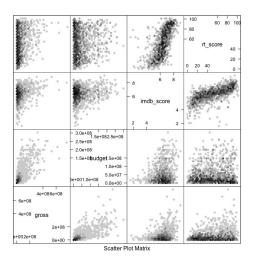
Exploratory Analysis

Univariate summaries.

Normalized Univariate Summary



Scatter plot matrix for our continuous random variables.



Initial Regression Result

Call:

 $lm(formula = gross \sim ., data = data initial)$

Residuals:

Min 1Q Median 3Q Max -236630412 -26076779 -7207365 16453032 460557534

Coefficients:

	Estimate Std. Error t value Pr(> t)
(Intercept)	-5.838e+07 1.291e+07 -4.521 6.72e-06 ***
budget	1.097e+00 4.062e-02 27.001 < 2e-16 ***
imdb_score	8.658e+06 2.159e+06 4.011 6.40e-05 ***
Adventure	-7.292e+06 5.172e+06 -1.410 0.15884
Animation	5.613e+06 7.699e+06 0.729 0.46610
Biography	5.138e+06 7.348e+06 0.699 0.48450
Comedy	8.833e+06 4.102e+06 2.153 0.03147 *
Crime	-6.446e+06 4.799e+06 -1.343 0.17940
Documentary	-1.827e+07 1.093e+07 -1.672 0.09470.
Drama	-1.121e+07 3.901e+06 -2.872 0.00414 **
Family	-4.552e+06 6.022e+06 -0.756 0.44989
Fantasy	-7.261e+05 4.776e+06 -0.152 0.87918
History	-7.774e+06 1.020e+07 -0.762 0.44618
Horror	6.477e+06 5.873e+06 1.103 0.27030
Music	1.009e+07 7.389e+06 1.365 0.17239
Musical	-2.715e+06 1.039e+07 -0.261 0.79394
Mystery	-1.456e+06 5.668e+06 -0.257 0.79738
Romance	8.988e+05 4.117e+06 0.218 0.82724
Sci.Fi	6.495e+06 5.093e+06 1.275 0.20244
Sport	-8.764e+06 7.761e+06 -1.129 0.25900
Thriller	-8.084e+05 4.422e+06 -0.183 0.85498
War	7.136e+06 9.634e+06 0.741 0.45901
Western	-1.459e+07 1.529e+07 -0.954 0.34037
rt_score	3.673e+05 7.802e+04 4.707 2.78e-06 ***
2007	-3.844e+06 6.807e+06 -0.565 0.57239
2008	-3.283e+06 6.523e+06 -0.503 0.61488
2009	1.060e+06 6.516e+06 0.163 0.87085
2010	-3.376e+06 6.608e+06 -0.511 0.60949
2011	-7.857e+06 6.692e+06 -1.174 0.24055
2012	3.803e+06 6.644e+06 0.572 0.56719
2013	-5.225e+06 6.712e+06 -0.779 0.43638
2014	3.953e+06 6.754e+06 0.585 0.55845
2015	2.968e+06 7.045e+06 0.421 0.67357

Residual standard error: 54160000 on 1296 degrees of freedom Multiple R-squared: 0.5759, Adjusted R-squared: 0.5655 F-statistic: 55 on 32 and 1296 DF, p-value: < 2.2e-16

Transformations

bcPower Transformations to Multinormality

Est.Power Std.Err. Wald Lower Bound Wald Upper Bound

Y1	0.2952	0.0109	0.2739	0.3165
Y2	0.2543	0.0139	0.2270	0.2816
Y3	2.4339	0.1108	2.2167	2.6510
Y4	0.9676	0.0467	0.8761	1.0590

Likelihood ratio tests about transformation parameters

LRT df pval

LR test, lambda = (0 0 0 0) 2995.474884 4 0.0000000

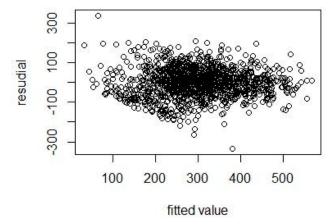
LR test, lambda = (1 1 1 1) 3899.397058 4 0.0000000

LR test, lambda = (0.3 0.25 2.43 1) 0.480411 4 0.9753797

So we used lambda = (0.25, 0.25, 2, 1), where Y1 is gross, Y2 is budget, Y3 is imdb score and Y4 is rotten tomatoes score.

Censor Results

Based on the residual plot for our final model, there seems to be a lower bound in the lower left corner which could be due to the natural censor for our dependent variable. So we fit a tobit regression model.



Observations:

Total Left-censored Uncensored Right-censored 1330 1 1329 0

(Note that we augmented with one zero variable since we didn't actually have any movies that had exactly zero gross)

Coefficients:

Estimate Std. error t value Pr(> t)

data_c6\$t_imdb_sc	core2 6.93755 1.20982 5.734 9.79e-09 ***
data_c6\$year2006	417.36904 810.73131 0.515 0.606689
data_c6\$year2007	408.58067 810.74172 0.504 0.614290
data_c6\$year2008	411.47693 810.73384 0.508 0.611779
data_c6\$year2009	413.09014 810.74759 0.510 0.610389
data_c6\$year2010	415.86186 810.75224 0.513 0.607998
data_c6\$year2011	414.22537 810.74352 0.511 0.609407
data_c6\$year2012	430.19563 810.75734 0.531 0.595689
data_c6\$year2013	430.27326 810.75374 0.531 0.595621
data_c6\$year2014	438.50428 810.75073 0.541 0.588603
data_c6\$year2015	421.68073 810.76120 0.520 0.602991
data_c6\$c6_1	16.52826 4.86652 3.396 0.000683 ***
data_c6\$c6_2	-4.68529 4.72530 -0.992 0.321426
data_c6\$c6_3	-20.48595 6.69707 -3.059 0.002221 **
data_c6\$c6_4	-4.30921 5.14010 -0.838 0.401834
data_c6\$c6_5	-6.84014 5.39199 -1.269 0.204592
data_c6\$c6_6	25.45859 6.05539 4.204 2.62e-05 ***
logSigma	4.28595 0.01940 220.966 < 2e-16 ***

Newton-Raphson maximisation, 16 iterations

Return code 2: successive function values within tolerance limit Log-likelihood: -7581.796 on 22 Df

The only coefficients that really differ are the year factors and the intercept. All of the covariates of interest don't change in value.

Regression Without Outliers and Influential Points

Coefficients:

	Estimate Std. Error t value $Pr(> t)$
(Intercept)	-5.218e+03 1.438e+03 -3.629 0.000295 ***
t_budget	9.918e-01 2.584e-02 38.384 < 2e-16 ***
t_imdb_score	-8.160e+01 1.434e+01 -5.689 1.57e-08 ***
t_rt_score	1.253e+01 3.434e+00 3.649 0.000273 ***
t_imdb_score2	7.616e+00 1.226e+00 6.210 7.11e-10 ***
Year	2.698e+00 7.161e-01 3.768 0.000172 ***
c6_1	1.751e+01 4.827e+00 3.628 0.000297 ***
c6_2	-3.781e+00 4.689e+00 -0.806 0.420210
c6_3	-1.970e+01 6.609e+00 -2.980 0.002933 **
c6_4	-3.737e+00 5.093e+00 -0.734 0.463251
c6_5	-7.705e+00 5.331e+00 -1.445 0.148611
c6_6	2.547e+01 6.009e+00 4.239 2.40e-05 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 72.1 on 1314 degrees of freedom Multiple R-squared: 0.6317, Adjusted R-squared: 0.6286 F-statistic: 204.9 on 11 and 1314 DF, p-value: < 2.2e-16