Predicting the Academy Award winners (Oscars)

Tool : Multinomial logit

The Analytics Edge :

Each year the Oscars awards create huge interest in the movie industry, fans and box-office. There is tremendous consequences of taking an Oscar home, be it future earnings or fame. Using a simple multinomial logit model with data available before the awards are given such as other awards (Golden Globe), other nomination in the Oscars, it is possible to obtain simple models that can predict the winners in four categories - Best Picture, Best Director, Best leading Actor and Best leading Actress. This provides an alternate prediction model to expert opinions.

Oscars (Academy Awards)

The Academy Awards (Oscars) is an Annual American award honoring cinematic achievements in films. The awards were first presented in 1929 and is now widely recognized as the most prestigious cinema awards in the world.

Nominations for Oscars

Currently the Oscar nominations are announced to the public in late January and the awards are presented in late February or early March.

Academy of Motion Picture Arts & Sciences (AMPAS) a professional honorary organization with about 6000 members from different disciplines in film production (such as actors, writers, designers, directors, make up artists) vote on the nominees and final winners of the Oscar awards.

For most categories, members from each of the branches of AMPAS vote to determine nominees in their categories (for example directors nominees in vote for directors). In special cases such as the Best Picture, all voting members are eligible to select the nominees. From these votes the top 5 nominees are typically selected to be nominated as Oscar nominees.

The winners are determined by a second round of voting in which all the members are then allowed to vote in most categories

Viewership of Oscars ceremony

1998 (70th Academy Awards) : 57 million viewers
Best Picture : Titanic

2015 (87th Academy Awards) : 37 million viewers
Best Picture : Birdman:Or

Impact of Oscars on Movie performance

www.boxofficemojo.com } Box office performance

In 2015, the weekly earnings for Birdman went up from 1.3 Million to 2.5 Million in the week following the Oscars. The other big rise in weekly gross for the movie came after it was nominated for the Golden Globe awards.

Similarly in 2014, the Best Picture winner 12 Years A Slave went from 800,000 to 1.5 Million to 2.9 Million in the weeks following the Oscars.

Similarly winning an Oscar, can help significantly increase the salaries and quality of scripts that actors and actresses receive.

Question : Is it possible to predict the winner of Oscars with any reasonable degree of accuracy ?

Many people in the media make predictions on the winners of Oscars.

- For example they might use the buzz of Awards season to make prediction
- Develop data driven models to make predictions.

In this, we will consider an approach based on discrete choice models used by I. Pardoe and D. K. Simonton in their paper "Applying discrete choice models to predict Academy Award winners".

Note that an important aspect of the prediction here is to predict the winner from one of several nominees (typically the winner from 5 nominees)

Binary choice

Response : 0 or 1 (No or yes)

$$Y^* = \beta_0 + \sum_{j=1}^{p} \beta_j X_j + \epsilon$$

(Here Y^* is an unobserved latent variable, X_j are attributes of the choice and ϵ is the error term.)

$$Y = \begin{cases} 1 & \text{if } Y^* \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

(Y is observed response).

$$\begin{aligned}
\therefore P(Y=1 \mid x) &= P(Y^* \geq 0 \mid x) \\
&= P(\beta_0 + \beta' x + \epsilon \geq 0 \mid x) \\
&= P(\epsilon \geq -(\beta_0 + \beta' x) \mid x) \\
&= P(\epsilon \leq \beta_0 + \beta' x \mid x)
\end{aligned}$$

(Assume ϵ is symmetric)

$$= F(\beta_0 + \beta' x)$$

(where $F(\cdot)$ is the cumulative distribution function of ϵ)

Note that with $F(z) = \dfrac{e^z}{1+e^z}$, we get:

$$P(Y=1 \mid x) = \frac{e^{\beta_0 + \beta' x}}{1 + e^{\beta_0 + \beta' x}}$$

(Logit model for binary choice)

For probit. use $P(Y=1 \mid x) = \Phi(\beta_0 + \beta' x)$

Multinomial choice

Given $k = 1, \ldots, K$ choices (alternatives),

$i = 1, \ldots, n$ consumers (observations)

$$U_{ik} = \beta' X_{ik} + \epsilon_{ik} \quad \left(\begin{array}{c}\text{Utility of consumer} \\ i \text{ for alternative } k\end{array}\right)$$

(Here β is the weight given to the observable information X_{ik} that includes aspects specific to the individual i and choice (alternative k))

The term ϵ_{ij} captures the noise term that models aspects of choice making not captured by attributes included in X_{ik}.

For example X_{ik} might include demographic information, information such as price of a product.

$$\underbrace{P(Y_i = k)}_{\substack{\text{Probability that} \\ \text{the ith individual} \\ \text{choose } k}} = P(U_{ik} \geq U_{il} \; \forall l \neq k)$$

In some cases, you might have alternate specific constants ASC_k for each alternative

$$U_{ik} = ASC_k + \beta' X_{ik} + \epsilon_{ik}$$

Assuming that the ϵ_{ij} are independent and identically distributed with Gumbel (type 1 extreme value) distributions

$$F(\epsilon_{ij}) = e^{-e^{-\epsilon_{ij}}}$$

it was shown by Mc Fadden (1974) that:

$$P(Y_i = k) = \frac{e^{\beta' x_{ik}}}{\sum_{l=1}^{K} e^{\beta' x_{il}}}$$

This model is known as the conditional logit model (also referred to as multinomial logit often)

Special case of the model (Multinomial logistic regression)

Assuming only individual specific data and suppose we want to categorize the individual into one of several categories it gives rise to a multinomial logistic regression model

$$P(Y_i = k | x_i) = \frac{e^{\beta_k' x_i}}{\sum_{l=1}^{K} e^{\beta_l' x_i}}$$

Here β_k is a vector of weights corresponding to category k.

Advanced: Derivation of logit probabilities

We assume $V_{ik} = \beta' x_{ik}$ & $\tilde{U}_{ik} = V_{ik} + \tilde{\epsilon}_{ik} \quad \forall k = 1, \ldots K$

$$P\begin{pmatrix}\text{individual } i \\ \text{chooses } k\end{pmatrix} = P\left(\cancel{\beta'}V_{ik} + \tilde{\epsilon}_{ik} \geq V_{il} + \tilde{\epsilon}_{il} \quad \forall l \neq k\right)$$

$$= P\left(\tilde{\epsilon}_{il} \leq V_{ik} - V_{il} + \tilde{\epsilon}_{ik} \quad \forall l \neq k\right)$$

$$= \int_{-\infty}^{\infty} P\left(\tilde{\epsilon}_{il} \leq V_{ik} - V_{il} + \tilde{\epsilon}_{ik} \;\middle|\; \tilde{\epsilon}_{ik} = \epsilon_{ik}\right)_{\forall l \neq k} \underbrace{e^{-\epsilon_{ik}} e^{-e^{-\epsilon_{ik}}}}_{\text{density of } \epsilon_{ik}} d\epsilon_{ik}$$

$$= \int_{-\infty}^{\infty} \underbrace{\prod_{l \neq k} P\left(\tilde{\epsilon}_{il} \leq V_{ik} - V_{il} + \epsilon_{ik}\right)}_{\text{from independence of } \tilde{\epsilon}_{il}} e^{-\epsilon_{ik}} e^{-e^{-\epsilon_{ik}}} d\epsilon_{ik}$$

$$= \int_{-\infty}^{\infty} \prod_{l \neq k} e^{-e^{-(V_{ik} - V_{il} + \epsilon_{ik})}} e^{-\epsilon_{ik}} e^{-e^{-\epsilon_{ik}}} d\epsilon_{ik}$$

$$= \int_{-\infty}^{\infty} e^{-\epsilon_{ik}} \prod_{l=1}^{K} e^{-e^{-(V_{ik} - V_{il} + \epsilon_{ik})}} d\epsilon_{ik}$$

$$= \int_{-\infty}^{\infty} e^{-\epsilon_{ik}} e^{-\sum_{l=1}^{K} e^{-(V_{ik} - V_{il} + \epsilon_{ik})}} d\epsilon_{ik}$$

$$= \int_{-\infty}^{\infty} e^{-\epsilon_{ik}} e^{-e^{-\epsilon_{ik}}\left(\sum_{l=1}^{K} e^{-(V_{ik} - V_{il})}\right)} d\epsilon_{ik}$$

$$= \int_{\infty}^{0} -e^{-t \sum_{l=1}^{K} e^{V_{il} - V_{ik}}} dt \qquad \text{define } t = e^{-\epsilon_{ik}}, \quad dt = -e^{-\epsilon_{ik}} d\epsilon_{ik}$$

$$= \frac{e^{V_{ik}}}{\sum_{l=1}^{K} e^{V_{il}}}$$

Properties of multinomial logit model

Independence of irrelevant alternatives

$$\frac{P(Y_i = k)}{P(Y_i = l)} = \left(\frac{e^{\beta' x_{ik}}}{\sum_{t=1}^{K} e^{\beta' x_{it}}} \right) \frac{1}{\left(\frac{e^{\beta' x_{il}}}{\sum_{t=1}^{K} e^{\beta' x_{it}}} \right)}$$

$$= e^{\beta'(x_{ik} - x_{il})}$$

$$\log \left(\frac{P(Y_i = k)}{P(Y_i = l)} \right) = \beta'(x_{ik} - x_{il})$$

This property of the MNL model is known as the Independence of Irrelevant Alternatives wherein in a choice set consisting of two alternatives k and l, adding in a third alternatives does not change the ration of $P(Y_i = k)/P(Y_i = l)$

Namely the new alternative gains share proportionately from the choice shares of existing alternatives in the set

Example : Blue bus / red bus.

Car Red bus

$P(C) = P(R) = 0.5$

} Suppose a commuter chooses between a car and a red bus with equal probability

Car Red bus Blue bus

} Assume a new blue bus is added and reasonably commuters don't care about color of bus

$P(C) = 0.5$ $P(R) = P(B) = 0.25$ Reasonable prediction

$P(c) = P(R) = P(B) = 0.33$ MNL prediction

This happens because blue bus and red bus are perfect substitutes here & not captured by MNL model.

Note this might be a smaller issue in the case of Oscars predictions since it is not clear if nominees are likely to be close substitutes except if an individual receives multiple nominations in a category in the same year or nominated movies might be from similar genres making them closer substitutes.

Maximum likelihood estimation

Given the observations:

x_{ik} (attributes of individual i and alternative k)

$$z_{ik} = \begin{cases} 1 & \text{if individual } i \text{ chose } k \\ 0 & \text{otherwise} \end{cases} \quad \left(\text{Note } Y_i = k \Leftrightarrow z_{ik} = 1\right)$$

The problem of estimating the β (weights) that maximizes the likelihood of the observations is given as:

$$\max_{\beta} \underbrace{L(\beta)}_{\substack{\text{likelihood} \\ \text{given } \beta}} = \max_{\beta} \prod_{i=1}^{n} \prod_{k=1}^{K} P(Y_i = k)^{z_{ik}}$$

Taking logarithms, this problem can be reformulated as maximizing the log-likelihood

$$\max_{\beta} LL(\beta) = \max_{\beta} \sum_{i=1}^{n} \sum_{k=1}^{K} z_{ik} \log(P(Y_i = k))$$

$$= \max_{\beta} \sum_{i=1}^{n} \sum_{k=1}^{K} z_{ik} \log\left(\frac{e^{\beta' x_{ik}}}{\sum_{l=1}^{K} e^{\beta' x_{il}}}\right)$$

This problem can be efficiently solved as the objective function is concave. This is one of the few formulas for choice probabilities where the objective function is known to be concave.

Testing quality of fit

1) AIC (Akaike information criterion)

$$AIC = -2\underbrace{LL}_{\text{log-likelihood}} + 2(\underbrace{p}_{\text{no. of parameter}}+1)$$

Smaller the AIC, the better

2) Likelihood ratio index (Mc Fadden's index)

$$\rho = 1 - \frac{LL(\hat{\beta})}{LL(0)}$$

(Here $\hat{\beta}$ is the estimated value of parameter)

(LL(0) refers to the log likelihood when all the parameters are set to (no model))

This compares the quality and fit of the model in comparison to a model in which all the parameters are equal to 0. The likelihood ratio index ranges from 0 (estimated model is no better than zero parameters) to 1 (estimated model perfectly predicts the choice observed)

3) Percent correctly predicted

This identifies the alternative with the highest probability for each individual observation and determining whether or not this was what the actual choice was.

Analytics on Oscar data : R

Data analysis

oscars ← read.csv("oscars.csv")

str (oscars)

1790 observations of 32 variables

Summary (oscars)

Winners & nominees in four categories from 1951 to 2007

Year : Movie year

Name : Nominee name

PP : Indicator for picture

DD : Indicator for director

MM : Indicator for lead actor (male)

FF : Indicator for lead actress (female)

Mode : alternative (choice) number (1 to 5 here)

Ch : 1 = Winner, 2 = No

Movie : Movie name

Nom : Number of Oscar nominations

Pic : Picture nomination

Dir : Director nomination

Aml : Lead actor (male) nomination

Afl : Lead actress (female) nomination

PrN : Total previous acting/directing nominations

PrW : Total previous acting/directing wins

PrNl : Previous lead actor nominations

PrWl : Previous lead actor wins

Gdr : Golden Globe drama winner

Gmc : Golden Globe musical or comedy winner

Gd : Golden Globe director winner

Gm1 : Golden Globe drama actor winner

Gm2 : Golden Globe musical or comedy actor winner

GF1 : Golden Globe drama actress winner

GF2 : Golden Globe musical or comedy actress winner

PGA : Producers guild winner

DGA : Directors guild winner

SAM : Screen actors guild actor winner

SAF : Screen actors guild actress winner

Age : Actor/actress age in movie year

Length : Run time

Days : Days between release date and Oscars Ceremony.

We convert Ch: 0 = No, 1 = Winner   oscars$Ch <- 2-oscars$Ch

Data set consists of nominees and winners in four Categories - Best Picture, Best Director, Best Actor and Best Actress.

To predict the winner in a given year, we can make use of data available before the awards are given to check the model.

For example, information on the number of nominations that a movie gets in the Oscars, if the movie, actors, director won awards earlier in the season such as Golden Globes, have the actors, directors been nominated earlier (body of work).

For example, does the winner of the Best Picture have more nominations in Oscar categories as compared to the losing nominees?

```
tapply (oscars$Nom[oscars$PP==1], oscars$Ch[oscars$PP==1], mean)
```

0	1
6.78	9.52

In the data set, the winning movies on average have 9.53 nominations compared to 6.78 for losing nominees

```
tapply (oscars$Nom[oscars$PP==1], oscars$Ch[oscars$PP==1], var)
```

0	1
5.26	5.07

variance is comparable across observations

```
t.test(Oscars$Nom[oscars$PP==1& oscars$Ch==1],
       Oscars$Nom[oscars$PP==1& oscars$Ch==0],
       alternative = c("greater"))
```

p-value ~~very low~~ (Very significant that we can reject the null hypothesis that the winning picture has equal or lesser nominations than losing nominees)

For example, do the Best Picture winners also receive nominations for Best Directors?

```
table(oscars$Dir[oscars$PP==1& oscars$Ch==1])
```

0	1
1	56

} Of the 57 best picture winners, only 1 of them did not get a best director nomination

```
which(oscars$Dir==0 & oscars$PP==1 & oscars$Ch==1)
```

362 } Row 362

To find the name of the movie and the year

```
Oscars[which(oscars$Dir==0 & oscars$PP==1 & oscars$Ch==1),
       c("Year", "Name")]
```

Year	Name
1989	Driving

} This movie is Driving Miss Daisy which did not get best director nomination but won Best Picture

Do the Best Actor and Best Actress winners have nominations for movies in the Best Picture Category?

```
table(oscars$Pic[oscars$MM==1 & oscars$Ch==1])
```

0	1
14	43

14 out of 57 won best actor for movies not nominated in best picture Category

```
table(oscars$Pic[oscars$FF==1 & oscars$Ch==1])
```

0	1
23	35

23 out of 58 won for acting in movies not nominated for best picture

Surprisingly there is one extra winner in the Best Actress category.

```
oscars$Year[oscars$FF==1 & oscars$Ch==1]
```

We can see that in 1968 there are two awards

```
subset(oscars, Year==1968 & FF==1)
```

Katherine Hepburn for Lion in Winter & Barbara Streisand for Funny Girl shared the Best Actress award with 3030 votes each.

The Golden Globe awards are awarded typically awarded one to two months before the Oscar awards. The award is bestowed by 93 members of the Hollywood Foreign Press Association. The award has been given every year since 1944.

The Directors Guild of America has been awarding Best Motion Picture Director Since 1949, Producer Guild of America has been awarding Best Producing effort since 1989. Since 1994 Screen Guild has been awarding Best Male Actor and Female Actor in a leading role. These awards are also typically given before the Oscars and can be used as an indicator of chance of success.

Since 1951 this award has been given before the Oscars hence yielding some possible predictive power in the model.

In the data set the DGA award is used till 1989 & then PGA for coding the best picture award.

Do the Golden Globe awards help predict the Oscars?

Out of the 57 Best Picture Awards given between 1951 and 2006, 39 won the Best Golden Globe picture award.

```
table(oscars$Gdr[oscars$PP==1 & oscars$Ch==1]
      +oscars$Gmc[oscars$PP==1 & oscars$Ch==1])
```

Best Picture

0	1
18	39

$\frac{39}{57} = 0.684$

```
table(oscars$Gd[oscars$DD==1 & oscars$Ch==1])
```

Best Director

0	1
26	31

$\frac{31}{57} = 0.543$

```
table(oscars$Gm1[oscars$MM==1 & oscars$Ch==1]
      +oscars$Gm2[oscars$MM==1 & oscars$Ch==1])
```

Best Male Actor

0	1
15	42

$\frac{42}{57} = 0.736$

```
table(oscars$Gf1[oscars$FF==1 & oscars$Ch==1]
      +oscars$Gf2[oscars$FF==1 & oscars$Ch==1])
```

Best Female Actor

0	1
18	40

$\frac{40}{58} = 0.689.$

What is the effect of having won awards in the previous years for Oscars to winning in a current year?

What is the effect of having nominations in the previous years on winning in the current year?

table (oscars $ PrNl [oscars $ MM==1], oscars $ Ch [oscars $ MM==1])

	0	1
0	111	27
1	43	14
2	29	3
3	11	6
4	14	3
5	7	2
6	6	2
7	5	0
8	2	0

$$\frac{27}{111+27} = 0.195$$

About 19.5 % of Best Actor nominees with no previous lead nominations won

About 20.4 % of Best Actor nominees with one or more previous nominations won.

table (oscars $ PrWl [oscars $ MM == 1], oscars $ Ch [oscars $ MM==1])

	0	1
0	176	51
1	41	6
2	11	0

$$\frac{51}{176+51} = 0.224$$

$$\frac{6}{6+41+11} = 0.103$$

22 % of Best Actor Oscar nominees with no previous lead actor wins won the Oscars while 11 % of the nominees with one or more previous wins have won.

Use discrete choice models to predict Oscar winners

```
install.packages("mlogit")
library(mlogit)
```

Load the package for multinomial logit

```
oscarsPP <- subset(oscars, PP==1)
oscarsDD <- subset(oscars, DD==1)
oscarsMM <- subset(oscars, MM==1)
oscarsFF <- subset(oscars, FF==1)
```

Create dataframes for
Best Picture
Best Director
Best Male Actor
Best Female Actor

Best Picture

summary(oscarsPP)

285 observations

Nom (no. of Oscar nominations)
Dir (1 = director nominated for Oscar that year, 0 o/w)
GG (Gmc + Gdr; 1 = if movie wins Golden Globe, 0 otherwise)
Aml (lead actor nomination)
Afl (lead actress nomination)
PGA (Producers Guild award)
Days (Days between release & Oscars ceremony)
Length (Run time of movie)

(Possible predictors in the dataset)

Oscars
Best Picture
winner

Ch = 1 (winner)
0 (losing nominee)

```
oscarsPP$GG <- oscarsPP$Gmc + oscarsPP$Gdr
```

We use this to define a new variable that captures if a movie won a Golden Globe for best picture

Say we use the data from 1944 to 2006 to develop the logit model

```
D <- mlogit.data( Subset (oscarsPP, Year <= 2006),
                  Choice = "ch", shape = "long",
                  alt.var = "Mode")
```

This creates a data set for applying the mlogit function where choice is a variable indicating the Choice made (Here "Ch"), shape is the Shape of the dataframe (Here "long" since each row is an alternative) and alt.var is the name of the variable containing the alternative index (Here "Mode"). We use Shape = "wide" when there is one row for each choice situation.

```
M <- mlogit (Ch ~ Nom + Dir + GS + Aml + Afl +
             PGA + Days + Length -1, data = D)
```

This fits a conditional logit model where Ch is the response. The -1 is used to address the fact that in this fit, we do not want the intercept to be estimated. Note that across the five alternatives in different years it is not comparable and hence we should not introduce alternative specific estimates here.

summary (m)

Nom, Dir, GG and PGA are the most significant variable in the fit.

The length of movies, the number of days it was released before the Oscars, whether a lead actor got nominated for the best picture are less significant. Note that the last two variables are included in the Nom variable (multicollinearity).

Consider a simple model using only the variables:

$$\left.\begin{array}{l} \text{Nom (No. of Oscar nominations)} \\ \text{Dir (Director nomination)} \\ \text{GG (Golden Globe winner)} \\ \text{PGA (Producer Guild winner)} \end{array}\right\} \begin{array}{c} \text{Ch} \\ \text{(Output)} \end{array}$$

M1 ← mlogit (Ch ~ Nom + Dir + GG + PGA − 1,
data = D)

Summary (M1)

	Nom	Dir	GG	PGA
$\hat{\beta}$ estimates	0.21	2.63	0.69	1.84

$$LL(\hat{\beta}) = -38.17$$

$$P\left(\begin{array}{l}\text{Movie } k \text{ wins}\\ \text{the best picture}\end{array}\right) = \frac{e^{0.21\,Nom_k + 2.63\,Dir_k + 0.69\,GG_k + 1.84\,PGA_k}}{\sum_{l=1}^{K} e^{0.21\,Nom_l + 2.63\,Dir_l + 0.69\,GG_l + 1.84\,PGA_l}}$$

Likelihood ratio index

$$\rho = 1 - \frac{LL(\hat{\beta})}{LL(0)}$$

$$= 1 - \left(\frac{-38.17}{56 \log\left(\frac{1}{5}\right)} \right)$$

$\left[LL(0) = 56 \times \log\left(\frac{1}{5}\right) \right.$
Since each alternative
is picked equally likely
assuming $\beta = 0$ $\left. \right]$
56 = no. of choice tasks

$$= 0.576$$

$$AIC = 2p - 2LL(\hat{\beta})$$

$$= 2\underbrace{(4)}_{\text{No. of parameters}} - 2(-38.17) = 84.34$$

Note that if we use an expanded model with variables Nom, Dir, GG, Aml, Afl, PGA, Days, Length the AIC value = 89.44 (larger value)

To predict the out of sample for year 2007

P1 ← predict (M1, newdata = subset (oscarsPP, Year==2007))

Predicted prob: 0.013 0.048 0.093 0.72 0.11

subset (oscars PP, Year == 2007)

Winner for oscars for 2007 was <u>No Country for Old Men</u>. This is the choice with highest predicted probability. The movie won the Producers Guild Award but not the Golden Globe in that year.

Surprise winners

```
D <- mlogit.data(oscarsPP, choice = "Ch",
                 shape = "long", alt.var = "Mode")

M <- mlogit(Ch ~ Nom + Dir + GG + PGA - 1,
            data = D)

P <- predict(M, newdata = D)

Pred <- as.vector(t(P))

oscarsPP$Pred <- Pred

oscarsPP$Pred[oscarsPP$Ch == 1]
subset(oscarsPP, oscarsPP$Year == 2004]
```

For example in the year 2004, Million Dollar Baby won the Best Picture with predicted probability of 0.02 though based on the model The Aviator was the overwhelming favorite with predicted probability of 0.90.

```
Fail <- 0
Predict <- NULL
Coefficients <- NULL
for (i in 1960:2006) {

D <- mlogit.data(subset(oscarsMM, Year <= i),
       choice = "Ch", shape = "long", alt.var = "Mode"

M <- mlogit(Ch ~ Pic + Gm + PrNl + PrWl - 1,
            data = D)

Coefficients <- rbind(Coefficients, M$coeff)

P <- predict(M, newdata = subset(oscarsMM, Year == i+1

Predict <- rbind(Predict, P)

Fail <- Fail + as.logical(which.max(P)
          - which.max(subset(oscarsMM, Year == i+1)$Ch

}
```

Total number of fail = 17 out of 57

where here Fail corresponds to best actor being
Someone who the model did not predict with
highest probability

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12 Years a Slave

Oscars : Best Picture 2014

Golden Globe : Best Picture (Drama) 2014

Domestic Total Gross: **$56,671,993**

Distributor: **Fox Searchlight**
Release Date: **October 18, 2013**
Genre: **Drama**
Runtime: **2 hrs. 13 min.**
MPAA Rating: **R**
Production Budget: **$20 million**

Summary | Daily | Weekend | **Weekly** | Foreign | Similar Movies | Images

2013

Date (click to view chart)	Rank	Weekly Gross	% Change	Theaters	/ Change	Avg.	Gross-to-Date	Week #
Oct 18–24	15	$1,259,943	-	19	-	$66,313	$1,259,943	1
Oct 25–31	8	$2,900,381	+130%	123	+104	$23,580	$4,160,324	2
Nov 1–7	7	$6,585,257	+127%	410	+287	$16,062	$10,745,581	3
Nov 8–14	7	$9,503,204	+44.3%	1,144	+734	$8,307	$20,248,785	4
Nov 15–21	8	$6,344,527	-33.2%	1,411	+267	$4,496	$26,593,312	5
Nov 22–28	10	$4,256,892	-32.9%	1,165	-246	$3,654	$30,850,204	6
Nov 29–Dec 5	13	$3,021,916	-29.0%	1,165	-	$2,594	$33,872,120	7
Dec 6–12	12	$1,759,568	-41.8%	1,082	-83	$1,626	$35,631,688	8
Dec 13–19	17	$1,078,538	-38.7%	414	-668	$2,605	$36,710,226	9
Dec 20–26	25	$715,758	-33.6%	147	-267	$4,869	$37,425,984	10
Dec 27–Jan 2	24	$717,358	+0.2%	154	+7	$4,658	$38,143,342	11

2014

Jan 12 Golden Globe

March 2 Oscars

Date (click to view chart)	Rank	Weekly Gross	% Change	Theaters	/ Change	Avg.	Gross-to-Date	Week #
Jan 3–9	24	$490,433	-31.6%	151	-3	$3,248	$38,633,775	12
Jan 10–16	23	$470,523	-4.1%	114	-37	$4,127	$39,104,298	13
Jan 17–23	17	$2,424,519	+415%	761	+647	$3,186	$41,528,817	14
Jan 24–30	13	$2,879,578	+18.8%	1,231	+470	$2,339	$44,408,395	15
Jan 31–Feb 6	13	$2,122,879	-26.3%	1,172	-59	$1,811	$46,531,274	16
Feb 7–13	18	$1,120,702	-47.2%	566	-606	$1,980	$47,651,976	17
Feb 14–20	20	$902,747	-19.4%	386	-180	$2,339	$48,554,723	18
Feb 21–27	19	$805,642	-10.8%	349	-37	$2,308	$49,360,365	19
Feb 28–Mar 6	17	$1,571,670	+95.1%	411	+62	$3,824	$50,932,035	20
Mar 7–13	9	$2,935,957	+86.8%	1,065	+654	$2,757	$53,867,992	21
Mar 14–20	14	$1,722,593	-41.3%	925	-140	$1,862	$55,590,585	22
Mar 21–27	18	$653,742	-62.0%	522	-403	$1,252	$56,244,327	23
Mar 28–Apr 3	28	$190,740	-70.8%	228	-294	$837	$56,435,067	24
Apr 4–10	40	$99,842	-47.7%	128	-100	$780	$56,534,909	25
Apr 11–17	53	$53,752	-46.2%	64	-64	$840	$56,588,661	26
Apr 18–24	53	$46,141	-14.2%	53	-11	$871	$56,634,802	27

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Oscars: Best Picture 2015

Golden Globe: Nominee Best Picture 2015 (Musical or Comedy)

Domestic Total Gross: **$42,340,598**

Distributor: **Fox Searchlight**
Release Date: **October 17, 2014**
Genre: **Comedy / Drama**
Runtime: **1 hrs. 59 min.**
MPAA Rating: **R**
Production Budget: **$18 million**

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Summary | Daily | Weekend | **Weekly** | Foreign | Similar Movies | Images

2014

Date (click to view chart)	Rank	Weekly Gross	% Change	Theaters / Change		Avg.	Gross-to-Date	Week #
Oct 17–23	20	$630,441	-	4	-	$157,610	$630,441	1
Oct 24–30	15	$1,863,817	+196%	50	+46	$37,276	$2,494,258	2
Oct 31–Nov 6	12	$3,291,994	+76.6%	231	+181	$14,251	$5,786,252	3
Nov 7–13	11	$3,339,115	+1.4%	460	+229	$7,259	$9,125,367	4
Nov 14–20	10	$3,426,740	+2.6%	857	+397	$3,999	$12,552,107	5
Nov 21–27	12	$2,793,950	-18.5%	705	-152	$3,963	$15,346,057	6
Nov 28–Dec 4	9	$2,423,438	-13.3%	710	+5	$3,413	$17,769,495	7
Dec 5–11	10	$1,699,712	-29.9%	738	+28	$2,303	$19,469,207	8
Dec 12–18	12	$1,869,840	+10.0%	541	-197	$3,456	$21,339,047	9
Dec 19–25	19	$1,602,388	-14.3%	292	-249	$5,488	$22,941,435	10
Dec 26–Jan 1	21	$1,622,551	+1.3%	292	-	$5,557	$24,563,986	11

2015

Jan 11 Golden Globe

Feb 22 Oscars

Date (click to view chart)	Rank	Weekly Gross	% Change	Theaters / Change		Avg.	Gross-to-Date	Week #
Jan 2–8	20	$1,183,740	-27.0%	282	-10	$4,198	$25,747,726	12
Jan 9–15	20	$978,267	-17.4%	228	-54	$4,291	$26,725,993	13
Jan 16–22	14	$2,272,129	+132%	471	+243	$4,824	$28,998,122	14
Jan 23–29	13	$2,723,876	+19.9%	833	+362	$3,270	$31,721,998	15
Jan 30–Feb 5	14	$2,111,374	-22.5%	976	+143	$2,163	$33,833,372	16
Feb 6–12	13	$1,767,313	-16.3%	666	-310	$2,654	$35,600,685	17
Feb 13–19	16	$1,302,621	-26.3%	481	-185	$2,708	$36,903,306	18
Feb 20–26	14	$1,400,858	+7.5%	407	-74	$3,442	$38,304,164	19
Feb 27–Mar 5	12	$2,512,663	+79.4%	1,213	+806	$2,071	$40,816,827	20
Mar 6–12	16	$986,615	-60.7%	777	-436	$1,270	$41,803,442	21
Mar 13–19	25	$300,764	-69.5%	239	-538	$1,258	$42,104,206	22
Mar 20–26	35	$129,278	-57.0%	108	-131	$1,197	$42,233,484	23
Mar 27–Apr 2	47	$57,650	-55.4%	46	-62	$1,253	$42,291,134	24
Apr 3–9	49	$33,091	-42.6%	39	-7	$848	$42,324,225	25
Apr 10–16	63	$16,373	-50.5%	20	-19	$819	$42,340,598	26

Spotlight

Domestic Total Gross: **$45,055,776**

Distributor: **Open Road Films** Release Date: **November 6, 2015**

Genre: **Drama** Runtime: **2 hrs. 8 min.**

MPAA Rating: **R** Production Budget: **N/A**

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Oscars. Best Picture 2016

Golden Globe : 2016 Nominee

Summary | Daily | Weekend | **Weekly** | Foreign

2015

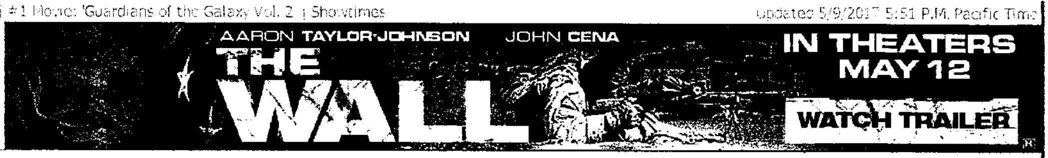
Date (click to view chart)	Rank	Weekly Gross	% Change	Theaters	/ Change	Avg.	Gross-to-Date	Week #
Nov 6–12	23	$446,770	-	5	-	$89,354	$446,770	1
Nov 13–19	12	$1,829,341	+310%	61	+56	$29,989	$2,276,111	2
Nov 20–26	10	$5,575,778	+205%	897	+836	$6,216	$7,851,889	3
Nov 27–Dec 3	7	$5,853,808	+5.0%	897	-	$6,526	$13,705,697	4
Dec 4–10	8	$4,088,252	-30.2%	980	+83	$4,172	$17,793,949	5
Dec 11–17	8	$3,584,077	-12.3%	1,089	+109	$3,291	$21,378,026	6
Dec 18–24	13	$2,437,057	-32.0%	825	-264	$2,954	$23,815,083	7
Dec 25–31	16	$2,108,796	-13.5%	480	-345	$4,393	$25,923,879	8

2016

Jan 10 Golden Globe

Feb 28 Oscars

Date (click to view chart)	Rank	Weekly Gross	% Change	Theaters	/ Change	Avg.	Gross-to-Date	Week #
Jan 1–7	16	$1,694,127	-19.7%	365	-115	$4,641	$27,618,006	9
Jan 8–14	17	$1,355,157	-20.0%	368	+3	$3,682	$28,973,163	10
Jan 15–21	14	$2,656,182	+96.0%	985	+617	$2,697	$31,629,345	11
Jan 22–28	16	$1,936,443	-27.1%	1,030	+45	$1,880	$33,565,788	12
Jan 29–Feb 4	15	$1,703,046	-12.1%	715	-315	$2,382	$35,268,834	13
Feb 5–11	17	$1,237,078	-27.4%	668	-47	$1,852	$36,505,912	14
Feb 12–18	20	$1,074,159	-13.2%	455	-213	$2,361	$37,580,071	15
Feb 19–25	23	$805,450	-25.0%	401	-54	$2,009	$38,385,521	16
Feb 26–Mar 3	16	$1,410,618	+75.1%	685	+284	$2,059	$39,796,139	17
Mar 4–10	14	$2,460,135	+74.4%	1,227	+542	$2,005	$42,256,274	18
Mar 11–17	18	$1,320,264	-46.3%	847	-380	$1,559	$43,576,538	19
Mar 18–24	21	$604,300	-54.2%	443	-404	$1,364	$44,180,838	20
Mar 25–31	25	$239,817	-60.3%	206	-237	$1,164	$44,420,655	21
Apr 1–7	27	$226,757	-5.4%	202	-4	$1,123	$44,647,412	22
Apr 8–14	35	$115,820	-48.9%	112	-90	$1,034	$44,763,232	23
Apr 15–21	39	$73,418	-36.6%	103	-9	$713	$44,836,650	24
Apr 22–28	39	$55,854	-23.9%	91	-12	$614	$44,892,504	25
Apr 29–May 5	31	$163,272	+192%	224	+133	$729	$45,055,776	26



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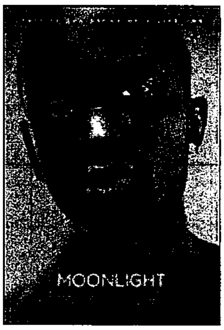

Moonlight (2016)

Oscars: Best Picture 2017

Domestic Total as of May. 4, 2017:
$27,854,932

Golden globe: Best Picture 2017

Distributor: **A24**	Release Date: **October 21, 2016**
Genre: **Drama**	Runtime: **1 hrs. 50 min.**
MPAA Rating: **R**	Production Budget: **N/A**

Summary | Daily | Weekend | **Weekly** | Foreign

2016

Date (click to view chart)	Rank	Weekly Gross	% Change	Theaters	/ Change	Avg.	Gross-to-Date	Week #
Oct 21–27	19	$570,793	-	4	-	$142,698	$570,793	1
Oct 28–Nov 3	16	$1,183,905	+107%	36	+32	$32,886	$1,754,698	2
Nov 4–10	11	$1,662,962	+40.5%	83	+47	$20,036	$3,417,660	3
Nov 11–17	13	$1,738,390	+4.5%	176	+93	$9,877	$5,156,050	4
Nov 18–24	13	$2,168,847	+24.8%	596	+420	$3,639	$7,324,896	5
Nov 25–Dec 1	14	$1,655,460	-23.7%	618	+22	$2,679	$8,980,357	6
Dec 2–8	14	$1,234,394	-25.4%	574	-44	$2,151	$10,214,751	7
Dec 9–15	18	$886,925	-28.1%	449	-125	$1,975	$11,101,676	8
Dec 16–22	21	$632,134	-28.7%	159	-290	$3,976	$11,733,810	9
Dec 23–29	21	$564,517	-10.7%	124	-35	$4,553	$12,298,327	10
Dec 30–Jan 5	21	$605,934	+7.3%	137	+13	$4,423	$12,904,261	11

2017

	Date (click to view chart)	Rank	Weekly Gross	% Change	Theaters	/ Change	Avg.	Gross-to-Date	Week #
Golden globe	**Jan 6–12**	21	$594,499	-1.9%	135	-2	$4,404	$13,498,760	12
	Jan 13–19	19	$1,693,623	+185%	582	+447	$2,910	$15,192,383	13
	Jan 20–26	23	$1,032,998	-39.0%	489	-93	$2,112	$16,225,381	14
	Jan 27–Feb 2	17	$2,179,870	+111%	1,104	+615	$1,975	$18,405,251	15
	Feb 3–9	19	$1,428,510	-34.5%	842	-262	$1,697	$19,833,761	16
	Feb 10–16	23	$789,635	-44.7%	351	-491	$2,250	$20,623,397	17
	Feb 17–23	23	$896,930	+13.6%	455	+104	$1,971	$21,520,326	18
Feb 26 Oscars	**Feb 24–Mar 2**	15	$1,332,055	+48.5%	585	+130	$2,277	$22,852,381	19
	Mar 3–9	12	$3,141,348	+136%	1,564	+979	$2,009	$25,993,729	20
	Mar 10–16	17	$1,258,743	-59.9%	987	-577	$1,275	$27,252,473	21
	Mar 17–23	25	$359,998	-71.4%	283	-704	$1,272	$27,612,470	22
	Mar 24–30	39	$114,142	-68.3%	62	-221	$1,841	$27,726,612	23
	Mar 31–Apr 6	42	$61,062	-46.5%	69	+7	$885	$27,787,674	24
	Apr 7–13	54	$32,312	-47.1%	28	-41	$1,154	$27,819,986	25
	Apr 14–20	61	$14,873	-54.0%	12	-16	$1,239	$27,834,859	26
	Apr 21–27	63	$13,484	-9.3%	12	-	$1,124	$27,848,343	27
	Apr 28–May 4	72	$6,589	-51.1%	4	-8	$1,647	$27,854,932	28

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Predicting Oscar winners is important in many ways

- Many news magazines & media have their own predictions from movie experts in the area.
- Using quantitative models provides an alternate approch to predict this winner

For example Nate Silver's website fivethirtyeight com discusses several mathematical models that have been proposed to predict Oscars using twitter data, web reviews .

This remains an active field for analytics techniques in the movie industry.