Naturally we start by importing the common libraries at the start

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
from sklearn import metrics
from sklearn.cross_validation import train_test_split
import random
import matplotlib.pyplot as plt
%matplotlib inline
```

```
/opt/conda/lib/python3.6/site-packages/sklearn/cross_validation.py:41: Dep
recationWarning: This module was deprecated in version 0.18 in favor of th
e model_selection module into which all the refactored classes and functio
ns are moved. Also note that the interface of the new CV iterators are dif
ferent from that of this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

In [2]:

```
df = pd.read_csv('../input/googleplaystore.csv')
```

Checking out the info, there's a not of null values that need to be addressed. Since my main objective is predicting the ratings of the apps, I deleted all the NaN values, just for simplicity sake.

In [3]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10841 entries, 0 to 10840
Data columns (total 13 columns):
App                 10841 non-null object
Category            10841 non-null object
Rating              9367 non-null float64
Reviews             10841 non-null object
Size                10841 non-null object
Installs            10841 non-null object
Type                10840 non-null object
Price               10841 non-null object
Content Rating      10840 non-null object
Genres              10841 non-null object
Last Updated        10841 non-null object
Current Ver         10833 non-null object
Android Ver         10838 non-null object
dtypes: float64(1), object(12)
memory usage: 1.1+ MB
```

In [4]:

```
df.dropna(inplace = True)
```

In [5]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9360 entries, 0 to 10840
Data columns (total 13 columns):
App               9360 non-null object
Category          9360 non-null object
Rating            9360 non-null float64
Reviews           9360 non-null object
Size              9360 non-null object
Installs          9360 non-null object
Type              9360 non-null object
Price             9360 non-null object
Content Rating    9360 non-null object
Genres            9360 non-null object
Last Updated      9360 non-null object
Current Ver       9360 non-null object
Android Ver       9360 non-null object
dtypes: float64(1), object(12)
memory usage: 1023.8+ KB
```

For the following steps, in order to process the data in the machine learning algorithms, we need to first convert it from text to numbers, as from what i understand, most algorithms run better that way. From most of the books I've read, data cleaning/preprocessing is **THE** most important part of any machine learning process, as high quality data translates to high quality predictions and models.

In [6]:

```
df.head()
```

Out[6]:

	App	Category	Rating	Reviews	Size	Installs	Type	Price	Content Rating	Genres	Last Updated	Current Ver	Android Ver
0	Photo Editor & Candy Camera & Grid & ScrapBook	ART_AND_DESIGN	4.1	159	19M	10,000+	Free	0	Everyone	Art & Design	January 7, 2018	1.0.0	4.0.3 and up
1	Coloring	ART_AND_DESIGN	3.9	967	14M	500,000+	Free	0	Everyone	Art & Design;Pretend Play	January	2.0.0	4.0.3 and up

	App	Category	Rating	Reviews	Size	Installs	Type	Price	Content Rating	Genres	Last Updated	Current Ver	Android Ver
	book moana										15, 2018		
2	U Launcher Lite – FREE Live Cool Themes, Hide ...	ART_AND_DESIGN	4.7	87510	8.7M	5,000,000+	Free	0	Everyone	Art & Design	August 1, 2018	1.2.4	4.0.3 and up
3	Sketch - Draw & Paint	ART_AND_DESIGN	4.5	215644	25M	50,000,000+	Free	0	Teen	Art & Design	June 8, 2018	Varies with device	4.2 and up
4	Pixel Draw - Number Art Coloring Book	ART_AND_DESIGN	4.3	967	2.8M	100,000+	Free	0	Everyone	Art & Design;Creativity	June 20, 2018	1.1	4.4 and up

From the categorical column, I converted each category into an individual number. In the later sections when we do apply machine learning, two methods will be applied to the code, being integer encoding(which we are doing now) and one-hot encoding, aka dummy variables.

The main reason as to why I understand we do this transformation is mainly because integer encoding relies on the fact that there's a relationship between each category(e.g. think age range vs types of animals). In this case however, it's hard to really determine such a relationship, hence dummy/one-hot encoding might help provide better predictive accuracy.

In [7]:

```
# Cleaning Categories into integers
CategoryString = df["Category"]
categoryVal = df["Category"].unique()
categoryValCount = len(categoryVal)
```

```
category_dict = {}
for i in range(0,categoryValCount):
    category_dict[categoryVal[i]] = i
df["Category_c"] = df["Category"].map(category_dict).astype(int)
```

Cleaning of sizes of the apps and also filling up the missing values using ffill

In [8]:

```
#scaling and cleaning size of installation
def change_size(size):
    if 'M' in size:
        x = size[:-1]
        x = float(x)*1000000
        return(x)
    elif 'k' == size[-1:]:
        x = size[:-1]
        x = float(x)*1000
        return(x)
    else:
        return None

df["Size"] = df["Size"].map(change_size)

#filling Size which had NA
df.Size.fillna(method = 'ffill', inplace = True)
```

Cleaning the number of installations column

In [9]:

```
#Cleaning no of installs classification
df['Installs'] = [int(i[:-1].replace(',','')) for i in df['Installs']]
```

Converting the paid/free classification types into binary

In [10]:

```
#Converting Type classification into binary
def type_cat(types):
    if types == 'Free':
        return 0
    else:
        return 1

df['Type'] = df['Type'].map(type_cat)
```

Converting of the content rating section into integers. In this specific instance, given that the concent rating is somewhat relatable and has an order to it, we do not use one-hot encoding.

In [11]:

```
#Cleaning of content rating classification
RatingL = df['Content Rating'].unique()
RatingDict = {}
for i in range(len(RatingL)):
```

```
    RatingDict[RatingL[i]] = i
df['Content Rating'] = df['Content Rating'].map(RatingDict).astype(int)
```

I dropped these portions of information as i deemed it unecessary for our machine learning algorithm

In [12]:

```
#dropping of unrelated and unnecessary items
df.drop(labels = ['Last Updated','Current Ver','Android Ver','App'], axis = 1
, inplace = True)
```

Technically when doing the cleaning of genres, one-hot should also be applied in this instance. However, I did not as firstly, it's a subset of the categorical column and secondly, application of a dummy variable would significantly increase the number of independent variables.

So to combat this instead, we ran two seperate regressions, one including and one excluding such genre data. When including the data, we only considered in the impact/information provided via the genre section purely based on it's numeric value.

In [13]:

```
#Cleaning of genres
GenresL = df.Genres.unique()
GenresDict = {}
for i in range(len(GenresL)):
    GenresDict[GenresL[i]] = i
df['Genres_c'] = df['Genres'].map(GenresDict).astype(int)
```

Cleaning of the prices of the apps to floats

In [14]:

```
#Cleaning prices
def price_clean(price):
    if price == '0':
        return 0
    else:
        price = price[1:]
        price = float(price)
        return price

df['Price'] = df['Price'].map(price_clean).astype(float)
```

Finally converting the number reviews column into integers

In [15]:

```
# convert reviews to numeric
df['Reviews'] = df['Reviews'].astype(int)
```

In [16]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9360 entries, 0 to 10840
Data columns (total 11 columns):
Category          9360 non-null object
Rating            9360 non-null float64
```

```
Reviews           9360 non-null int64
Size              9360 non-null float64
Installs          9360 non-null int64
Type              9360 non-null int64
Price             9360 non-null float64
Content Rating    9360 non-null int64
Genres            9360 non-null object
Category_c        9360 non-null int64
Genres_c          9360 non-null int64
dtypes: float64(3), int64(6), object(2)
memory usage: 877.5+ KB
```

Doing checks and we are good to go! So I created first this dataframe that has **integer encoding** of categorical variables, defined as df

In [17]:

```
df.head()
```

Out[17]:

	Category	Rating	Reviews	Size	Installs	Type	Price	Content Rating	Genres	Category_c	Genres_c
0	ART_AND_DESIGN	4.1	159	19000000.0	10000	0	0.0	0	Art & Design	0	0
1	ART_AND_DESIGN	3.9	967	14000000.0	500000	0	0.0	0	Art & Design;Pretend Play	0	1
2	ART_AND_DESIGN	4.7	87510	8700000.0	5000000	0	0.0	0	Art & Design	0	0
3	ART_AND_DESIGN	4.5	215644	25000000.0	50000000	0	0.0	1	Art & Design	0	0
4	ART_AND_DESIGN	4.3	967	2800000.0	100000	0	0.0	0	Art & Design;Creativity	0	2

In this instance, I created another dataframe that specifically created **dummy values** for each categorical instance in the dataframe, defined as df2

In [18]:

```python
# for dummy variable encoding for Categories
df2 = pd.get_dummies(df, columns=['Category'])
```

In [19]:

```python
df2.head()
```

Out[19]:

	Rating	Reviews	Size	Installs	Type	Price	Content Rating	Genres	Category_c	Genres_c	Category_ART_AND_DESIGN	Category_AUTO_AND_VEHICLES	Category_BEAUTY	Category_BOOKS_AND_REFERENCE	Category_BUSINESS	Category_COMICS	Category_COMMUNICATION	Category_DATING	Category_EDUCATION	Category_ENTERTAINMENT	Category_EVENTS	Category_FAMILY	Category_FINANCE	Category_FOOD_AND_DRINK	Category_GAME	Category_HEALTH_AND_FITNESS	Category_HOUSE_AND_HOME	Category_LIBRARIES_AND_DEMO	Category_LIFESTYLE	Category_MAPS_AND_NAVIGATION	Category_MEDICAL	Category_NEWS_AND_MAGAZINES	Category_PARENTING	Category_PERSONALIZATION	Category_PHOTOGRAPHY	Category_PRODUCTIVITY	Category_SHOPPING	Category_SOCIAL	Category_SPORTS	Category_TOOLS	Category_TRAVEL_AND_LOCAL	Category_VIDEO_PLAYERS	Category_WEATHER
0	4.1	159	19000000.0	10000	0	0.0	0	Art&Design	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	3.9	967	1400000	5000	0	0.0	0	Art&De	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	Rating	Reviews	Size	Installs	Type	Price	ContentRating	Genres	Category_c	Genres_c	Category_ART_AND_DESIGN	Category_AUTO_AND_VEHICLES	Category_BEAUTY	Category_BOOKS_AND_REFERENCE	Category_BUSINESS	Category_COMICS	Category_COMMUNICATION	Category_DATING	Category_EDUCATION	Category_ENTERTAINMENT	Category_EVENTS	Category_FAMILY	Category_FINANCE	Category_FOOD_AND_DRINK	Category_GAME	Category_HEALTH_AND_FITNESS	Category_HOUSE_AND_HOME	Category_LIBRARIES_AND_DEMO	Category_LIFESTYLE	Category_MAPS_AND_NAVIGATION	Category_MEDICAL	Category_NEWS_AND_MAGAZINES	Category_PARENTING	Category_PERSONALIZATION	Category_PHOTOGRAPHY	Category_PRODUCTIVITY	Category_SHOPPING	Category_SOCIAL	Category_SPORTS	Category_TOOLS	Category_TRAVEL_AND_LOCAL	Category_VIDEO_PLAYERS	Category_WEATHER
			00.0	00				sign;PretendPlay																																			
2	4.7	87510	8700000.0	5000000	0	0.0	0	Art&Desi	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	Rating	Reviews	Size	Installs	Type	Price	ContentRating	Genres	Category_c	Genres_c	Category_ART_AND_DESIGN	Category_AUTO_AND_VEHICLES	Category_BEAUTY	Category_BOOKS_AND_REFERENCE	Category_BUSINESS	Category_COMICS	Category_COMMUNICATION	Category_DATING	Category_EDUCATION	Category_ENTERTAINMENT	Category_EVENTS	Category_FAMILY	Category_FINANCE	Category_FOOD_AND_DRINK	Category_GAME	Category_HEALTH_AND_FITNESS	Category_HOUSE_AND_HOME	Category_LIBRARIES_AND_DEMO	Category_LIFESTYLE	Category_MAPS_AND_NAVIGATION	Category_MEDICAL	Category_NEWS_AND_MAGAZINES	Category_PARENTING	Category_PERSONALIZATION	Category_PHOTOGRAPHY	Category_PRODUCTIVITY	Category_SHOPPING	Category_SOCIAL	Category_SPORTS	Category_TOOLS	Category_TRAVEL_AND_LOCAL	Category_VIDEO_PLAYERS	Category_WEATHER
								gn																																			
3	4.5	215644	25000000.0	50000000	0	0.0	1	Art&Design	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	4.3	967	2800000.0	100000	0	0.0	0	Art&Design;	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	Rating	Reviews	Size	Installs	Type	Price	ContentRating	Genres	Category_c	Genres_c	Category_ART_AND_DESIGN	Category_AUTO_AND_VEHICLES	Category_BEAUTY	Category_BOOKS_AND_REFERENCE	Category_BUSINESS	Category_COMICS	Category_COMMUNICATION	Category_DATING	Category_EDUCATION	Category_ENTERTAINMENT	Category_EVENTS	Category_FAMILY	Category_FINANCE	Category_FOOD_AND_DRINK	Category_GAME	Category_HEALTH_AND_FITNESS	Category_HOUSE_AND_HOME	Category_LIBRARIES_AND_DEMO	Category_LIFESTYLE	Category_MAPS_AND_NAVIGATION	Category_MEDICAL	Category_NEWS_AND_MAGAZINES	Category_PARENTING	Category_PERSONALIZATION	Category_PHOTOGRAPHY	Category_PRODUCTIVITY	Category_SHOPPING	Category_SOCIAL	Category_SPORTS	Category_TOOLS	Category_TRAVEL_AND_LOCAL	Category_VIDEO_PLAYERS	Category_WEATHER
								Creativity																																			

After our final checks for the preprocessing of our data, looks like we can start work! So the next question is what exactly are we doing and how are we doing it.

So the goal of this instance is to see if we can use existing data provided(e.g. Size, no of reviews) to predict the ratings of the google applications. **In other words, our dependent variable Y, would be the rating of the apps.**

One important factor to note is that the dependent variable Y, is a continuous variable(aka infinite no of combinations), as compared to a discrete variable. Naturally there are ways to convert our Y to a discrete variable but **I decided to keep Y as a continuous variable** for the purposes of this machine learning session.

Next question, what models should we apply and how should we evaluate them?

Model wise, I'm not too sure as well as there are like a ton of models out there that can be used for machine learning. Hence, I basically just chose the 3 most common models that I use, being linear regression, SVR, and random forest regressor.

We technically run 4 regressions for each model used, as we consider one-hot vs interger encoded results for the category section, as well as including/excluding the genre section.

We then evaluate the models by comparing the predicted results against the actual results graphically, as well as use the mean squared error, mean absolute error and mean squared log error as possible benchmarks.

The use of the error term will be evaluated right at the end after running through all the models.

In [20]:

```
# let's use 3 different regression models with two different techniques on trea
ting the categorical variable
```

So before we start, the following is code to obtain the error terms for the various models, for comparability.

In [21]:

```
#for evaluation of error term and
def Evaluationmatrix(y_true, y_predict):
    print ('Mean Squared Error: '+ str(metrics.mean_squared_error(y_true,y_pr
edict)))
    print ('Mean absolute Error: '+ str(metrics.mean_absolute_error(y_true,y_
predict)))
    print ('Mean squared Log Error: '+ str(metrics.mean_squared_log_error(y_t
rue,y_predict)))
```

In [22]:

```
#to add into results_index for evaluation of error term
def Evaluationmatrix_dict(y_true, y_predict, name = 'Linear - Integer'):
    dict_matrix = {}
    dict_matrix['Series Name'] = name
    dict_matrix['Mean Squared Error'] = metrics.mean_squared_error(y_true,y_p
redict)
    dict_matrix['Mean Absolute Error'] = metrics.mean_absolute_error(y_true,y
_predict)
    dict_matrix['Mean Squared Log Error'] = metrics.mean_squared_log_error(y_
true,y_predict)
    return dict_matrix
```

We start off by looking at **linear regression** model (without the genre label)

In [23]:

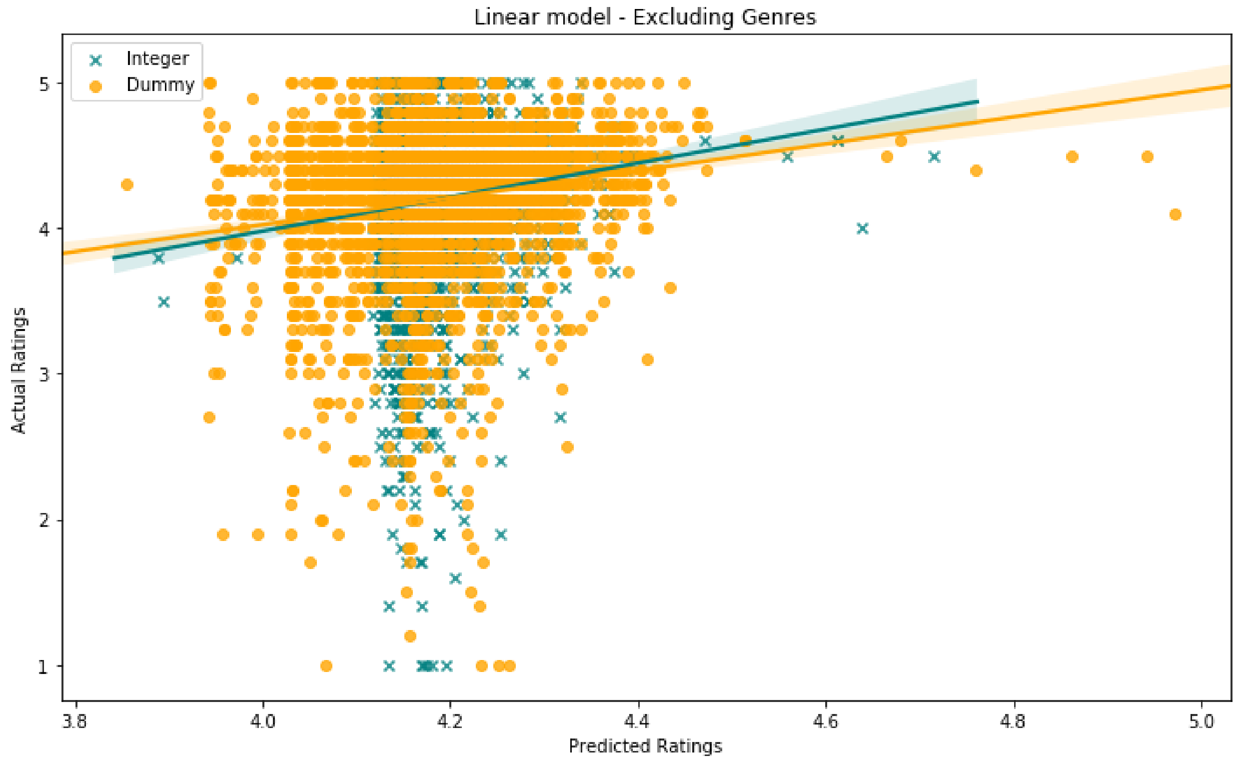
```
#excluding Genre label
from sklearn.linear_model import LinearRegression

#Integer encoding
X = df.drop(labels = ['Category','Rating','Genres','Genres_c'],axis = 1)
y = df.Rating
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30)
model = LinearRegression()
model.fit(X_train,y_train)
Results = model.predict(X_test)

#Creation of results dataframe and addition of first entry
resultsdf = pd.DataFrame()
resultsdf = resultsdf.from_dict(Evaluationmatrix_dict(y_test,Results),orient
= 'index')
resultsdf = resultsdf.transpose()

#dummy encoding

X_d = df2.drop(labels = ['Rating','Genres','Category_c','Genres_c'],axis = 1)
y_d = df2.Rating
X_train_d, X_test_d, y_train_d, y_test_d = train_test_split(X_d, y_d, test_si
ze=0.30)
model_d = LinearRegression()
model_d.fit(X_train_d,y_train_d)
Results_d = model_d.predict(X_test_d)

#adding results into results dataframe
resultsdf = resultsdf.append(Evaluationmatrix_dict(y_test_d,Results_d, name =
'Linear - Dummy'),ignore_index = True)
```

In [24]:

```
plt.figure(figsize=(12,7))
sns.regplot(Results,y_test,color='teal', label = 'Integer', marker = 'x')
sns.regplot(Results_d,y_test_d,color='orange',label = 'Dummy')
plt.legend()
plt.title('Linear model - Excluding Genres')
plt.xlabel('Predicted Ratings')
plt.ylabel('Actual Ratings')
plt.show()
```

```
/opt/conda/lib/python3.6/site-packages/scipy/stats/stats.py:1713: FutureWa
rning: Using a non-tuple sequence for multidimensional indexing is depreca
ted; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will
be interpreted as an array index, `arr[np.array(seq)]`, which will result
either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [25]:

```
print ('Actual mean of population:' + str(y.mean()))
print ('Integer encoding(mean) :' + str(Results.mean()))
print ('Dummy encoding(mean) :'+ str(Results_d.mean()))
print ('Integer encoding(std) :' + str(Results.std()))
print ('Dummy encoding(std) :'+ str(Results_d.std()))
```

```
Actual mean of population:4.191837606837612
Integer encoding(mean) :4.1873290708390165
Dummy encoding(mean) :4.190100388213491
Integer encoding(std) :0.05393016592892948
Dummy encoding(std) :0.10141339123507354
```

At first glance, it's hard to really see which model(dummy vs one-hot) is better in terms of predictive accuracy. What is striking however is the that at first glance, the dummy model seems favors the outcome of a lower rating compared to the integer model.

Although if we look at the actual mean of the predictive results, both are approximately the same, **however the dummy encoded results have a much larger standard deviation as compared to the integer encoded model.**

Next is looking at the linear model including the genre label as a numeric value.

In [26]:

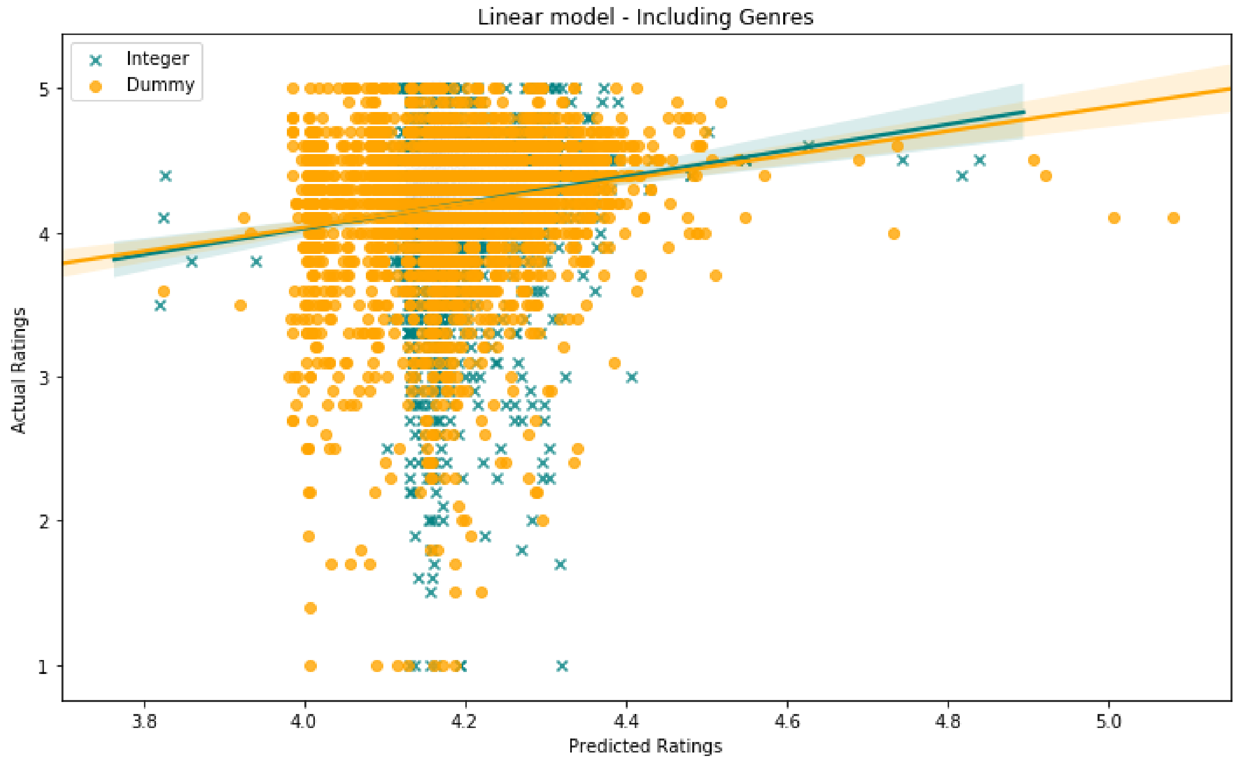
```
#Including genre label

#Integer encoding
X = df.drop(labels = ['Category','Rating','Genres'],axis = 1)
y = df.Rating
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30)
model = LinearRegression()
model.fit(X_train,y_train)
Results = model.predict(X_test)

resultsdf = resultsdf.append(Evaluationmatrix_dict(y_test,Results, name = 'Li
near(inc Genre) - Integer'),ignore_index = True)

#dummy encoding

X_d = df2.drop(labels = ['Rating','Genres','Category_c'],axis = 1)
y_d = df2.Rating
X_train_d, X_test_d, y_train_d, y_test_d = train_test_split(X_d, y_d, test_si
ze=0.30)
model_d = LinearRegression()
model_d.fit(X_train_d,y_train_d)
Results_d = model_d.predict(X_test_d)

resultsdf = resultsdf.append(Evaluationmatrix_dict(y_test_d,Results_d, name =
'Linear(inc Genre) - Dummy'),ignore_index = True)
```

In [27]:

```
plt.figure(figsize=(12,7))
sns.regplot(Results,y_test,color='teal', label = 'Integer', marker = 'x')
sns.regplot(Results_d,y_test_d,color='orange',label = 'Dummy')
plt.legend()
plt.title('Linear model - Including Genres')
plt.xlabel('Predicted Ratings')
plt.ylabel('Actual Ratings')
plt.show()
```

```
/opt/conda/lib/python3.6/site-packages/scipy/stats/stats.py:1713: FutureWa
rning: Using a non-tuple sequence for multidimensional indexing is depreca
ted; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will
be interpreted as an array index, `arr[np.array(seq)]`, which will result
either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [28]:

```
print ('Integer encoding(mean) :' + str(Results.mean()))
print ('Dummy encoding(mean) :'+ str(Results_d.mean()))
print ('Integer encoding(std) :' + str(Results.std()))
print ('Dummy encoding(std) :'+ str(Results_d.std()))
```

```
Integer encoding(mean) :4.189955371309177
Dummy encoding(mean) :4.190338063176179
Integer encoding(std) :0.06135898515969693
Dummy encoding(std) :0.10722254835317722
```

When including the genre data, we see a slight difference in the mean between the integer and dummy encoded linear models. The dummy encoded model's std is still higher than the integer encoded model.

What's striking to me personally is that the dummy encoded regression line in the scatterplot is now flatter than the integer encoded regression line, which might suggest a "worse" outcome, given that usually you would want your regression's beta value to be closer to 1 than to 0.

Next up is the SVR model.

In [29]:

```
#Excluding genres
from sklearn import svm
#Integer encoding

X = df.drop(labels = ['Category','Rating','Genres','Genres_c'],axis = 1)
y = df.Rating
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30)
```

```
model2 = svm.SVR()
model2.fit(X_train,y_train)

Results2 = model2.predict(X_test)

resultsdf = resultsdf.append(Evaluationmatrix_dict(y_test,Results2, name = 'S
VM - Integer'),ignore_index = True)

#dummy based


X_d = df2.drop(labels = ['Rating','Genres','Category_c','Genres_c'],axis = 1)
y_d = df2.Rating

X_train_d, X_test_d, y_train_d, y_test_d = train_test_split(X_d, y_d, test_si
ze=0.30)

model2 = svm.SVR()
model2.fit(X_train_d,y_train_d)

Results2_d = model2.predict(X_test_d)

resultsdf = resultsdf.append(Evaluationmatrix_dict(y_test_d,Results2_d, name
= 'SVM - Dummy'),ignore_index = True)
```

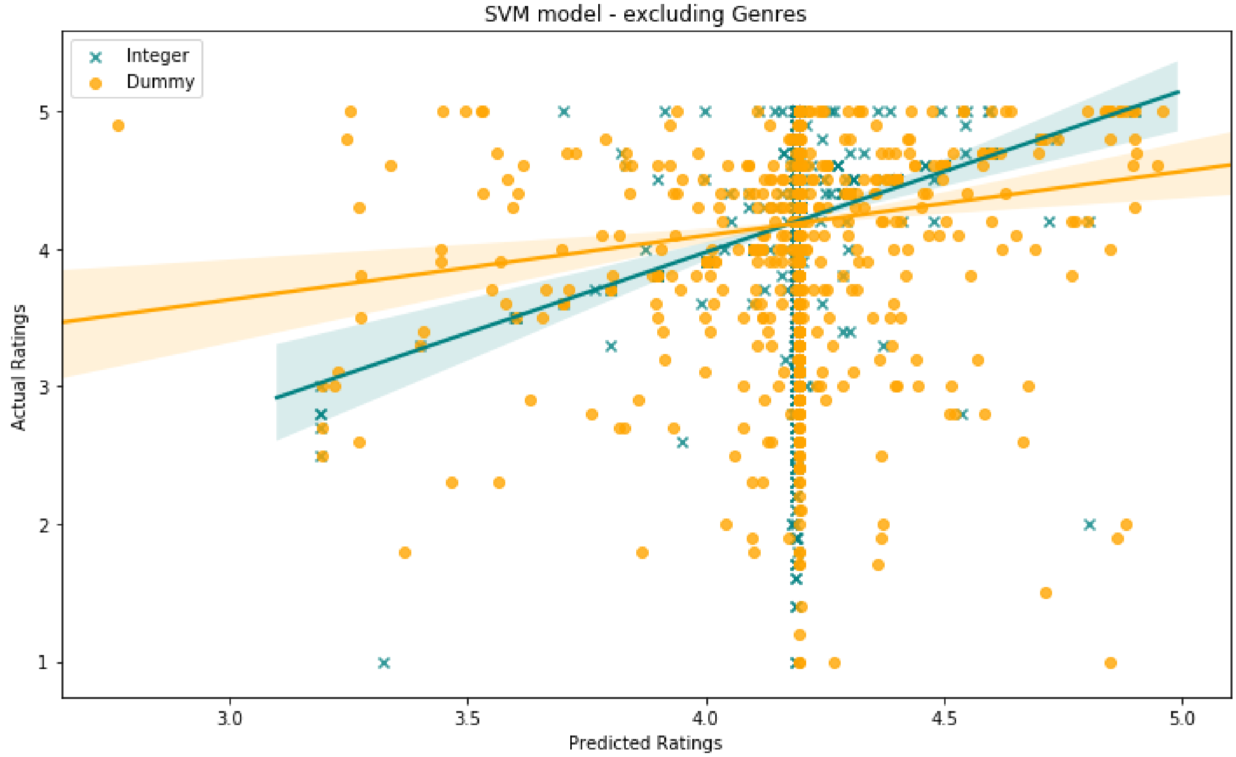
```
/opt/conda/lib/python3.6/site-packages/sklearn/svm/base.py:196: FutureWarn
ing: The default value of gamma will change from 'auto' to 'scale' in vers
ion 0.22 to account better for unscaled features. Set gamma explicitly to
'auto' or 'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/svm/base.py:196: FutureWarn
ing: The default value of gamma will change from 'auto' to 'scale' in vers
ion 0.22 to account better for unscaled features. Set gamma explicitly to
'auto' or 'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
```

In [30]:

```
plt.figure(figsize=(12,7))
sns.regplot(Results2,y_test,color='teal', label = 'Integer', marker = 'x')
sns.regplot(Results2_d,y_test_d,color='orange',label = 'Dummy')
plt.legend()
plt.title('SVM model - excluding Genres')
plt.xlabel('Predicted Ratings')
plt.ylabel('Actual Ratings')
plt.show()
```

```
/opt/conda/lib/python3.6/site-packages/scipy/stats/stats.py:1713: FutureWa
rning: Using a non-tuple sequence for multidimensional indexing is depreca
ted; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will
```

```
be interpreted as an array index, `arr[np.array(seq)]`, which will result
either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [31]:

```
print ('Integer encoding(mean) :' + str(Results2.mean()))
print ('Dummy encoding(mean) :'+ str(Results2_d.mean()))
print ('Integer encoding(std) :' + str(Results2.std()))
print ('Dummy encoding(std) :'+ str(Results2_d.std()))
```

```
Integer encoding(mean) :4.19263281320923
Dummy encoding(mean) :4.197715672997972
Integer encoding(std) :0.08095380235939799
Dummy encoding(std) :0.1369358840558245
```

The results are quite interesting. Overall the model predicted quite a bit of ratings to be approximately at 4.2, even though the actual ratings were not. Looking at the scatterplot, the integer encoded model seems to have performed better in this instance.

As usual, the dummy encoded model has a higher std than the integer encoded model.

In [32]:

```
#Integer encoding, including Genres_c
model2a = svm.SVR()

X = df.drop(labels = ['Category','Rating','Genres'],axis = 1)
y = df.Rating

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30)
```

```
model2a.fit(X_train,y_train)

Results2a = model2a.predict(X_test)

#evaluation
resultsdf = resultsdf.append(Evaluationmatrix_dict(y_test,Results2a, name = '
SVM(inc Genres) - Integer'),ignore_index = True)

#dummy encoding, including Genres_c
model2a = svm.SVR()

X_d = df2.drop(labels = ['Rating','Genres','Category_c'],axis = 1)
y_d = df2.Rating

X_train_d, X_test_d, y_train_d, y_test_d = train_test_split(X_d, y_d, test_si
ze=0.30)

model2a.fit(X_train_d,y_train_d)

Results2a_d = model2a.predict(X_test_d)

#evaluation
resultsdf = resultsdf.append(Evaluationmatrix_dict(y_test_d,Results2a_d, name
= 'SVM(inc Genres) - Dummy'),ignore_index = True)
```

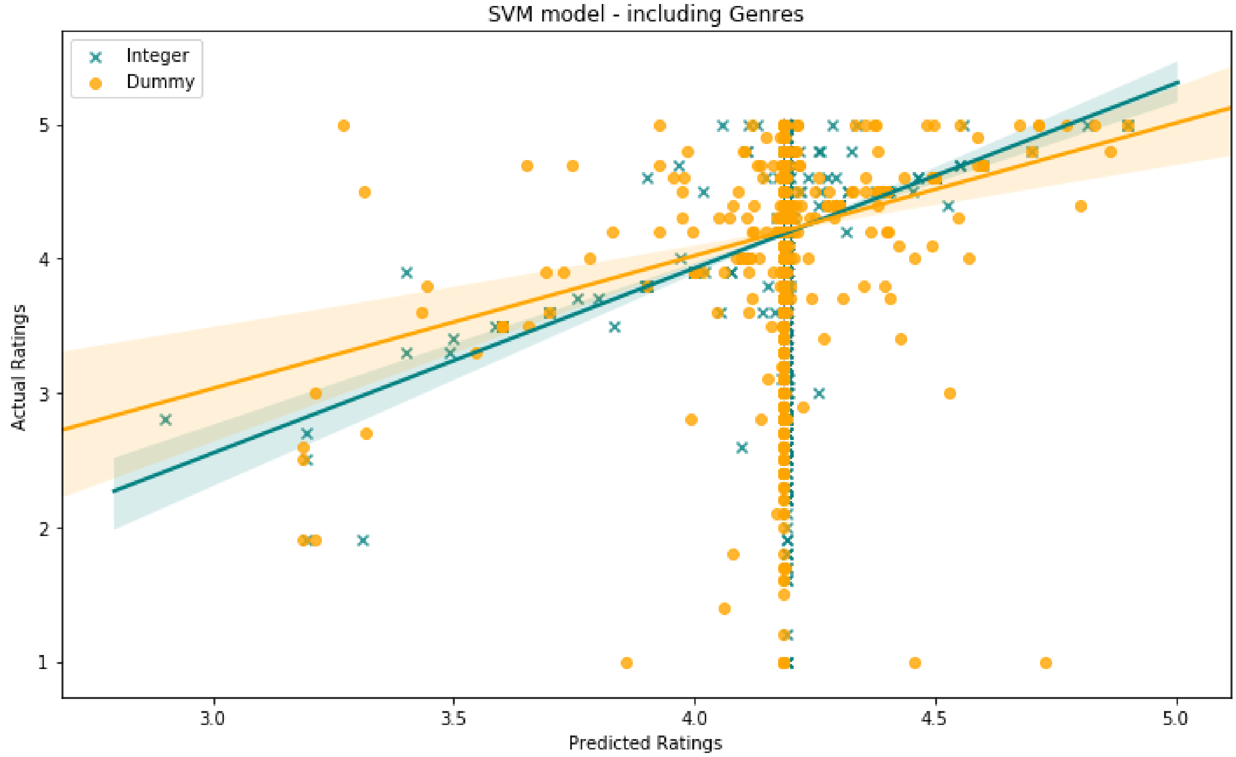
```
/opt/conda/lib/python3.6/site-packages/sklearn/svm/base.py:196: FutureWarn
ing: The default value of gamma will change from 'auto' to 'scale' in vers
ion 0.22 to account better for unscaled features. Set gamma explicitly to
'auto' or 'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/svm/base.py:196: FutureWarn
ing: The default value of gamma will change from 'auto' to 'scale' in vers
ion 0.22 to account better for unscaled features. Set gamma explicitly to
'auto' or 'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
```

In [33]:

```
plt.figure(figsize=(12,7))
sns.regplot(Results2a,y_test,color='teal', label = 'Integer', marker = 'x')
sns.regplot(Results2a_d,y_test_d,color='orange',label = 'Dummy')
plt.legend()
plt.title('SVM model - including Genres')
plt.xlabel('Predicted Ratings')
plt.ylabel('Actual Ratings')
plt.show()
```

```
/opt/conda/lib/python3.6/site-packages/scipy/stats/stats.py:1713: FutureWa
rning: Using a non-tuple sequence for multidimensional indexing is depreca
ted; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will
```

```
be interpreted as an array index, `arr[np.array(seq)]`, which will result
either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [34]:

```
print ('Integer encoding(mean) :' + str(Results2a.mean()))
print ('Dummy encoding(mean) :'+ str(Results2a_d.mean()))
print ('Integer encoding(std) :' + str(Results2a.std()))
print ('Dummy encoding(std) :'+ str(Results2a_d.std()))
```

```
Integer encoding(mean) :4.192589655878121
Dummy encoding(mean) :4.188436289522658
Integer encoding(std) :0.07788200835381136
Dummy encoding(std) :0.08888018936518423
```

With the inclusion of the genre variable, the dummy encoding model now seems to be performing better, as we see the regression line comparing the actual vs the predicted results to be very similar to that of the integer encoded model.

Furthermore the std of the dummy encoded model has fallen significantly, and now has a higher mean compared to the integer encoded model.

Next up is the random forest regressor model. Honestly this is my favorite model as not only is it fast, it also allows you to see what independent variables significantly affect the outcome of the model.

In [35]:

```
from sklearn.ensemble import RandomForestRegressor

#Integer encoding
```

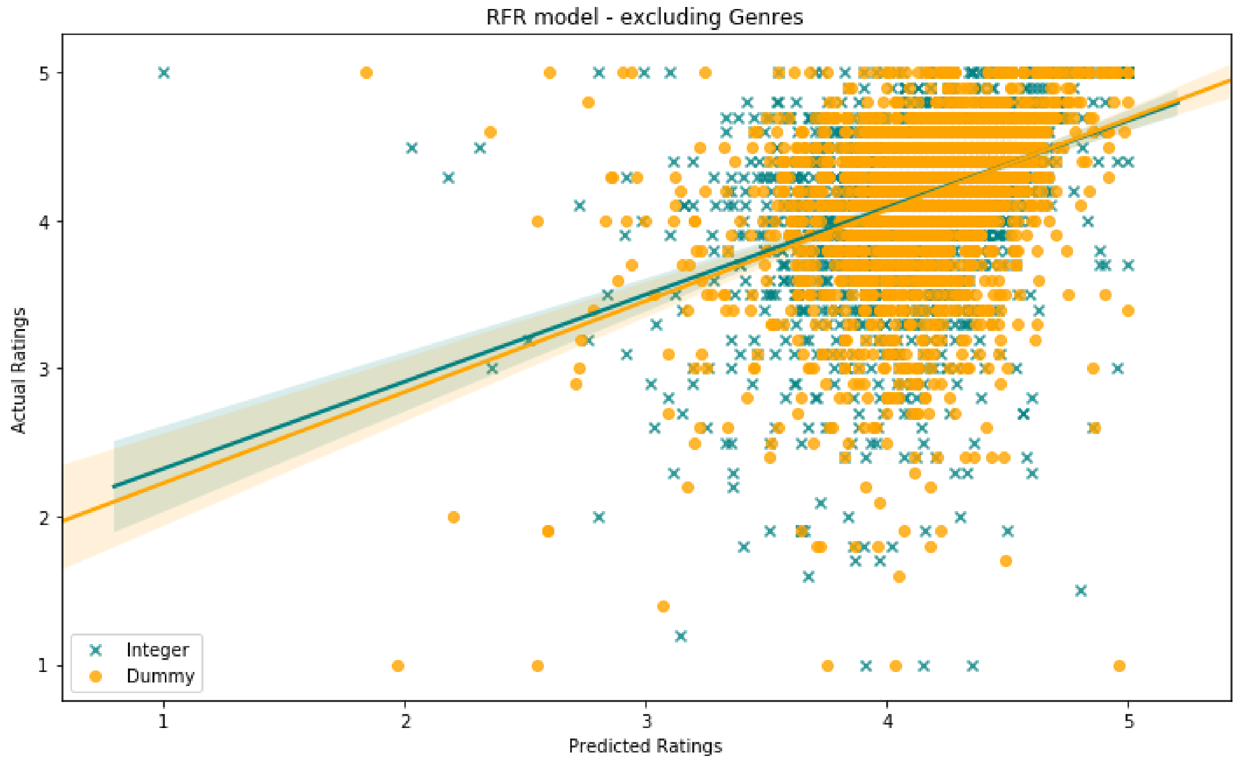
```
X = df.drop(labels = ['Category','Rating','Genres','Genres_c'],axis = 1)
y = df.Rating
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30)
model3 = RandomForestRegressor()
model3.fit(X_train,y_train)
Results3 = model3.predict(X_test)

#evaluation
resultsdf = resultsdf.append(Evaluationmatrix_dict(y_test,Results3, name = 'R
FR - Integer'),ignore_index = True)

#dummy encoding

X_d = df2.drop(labels = ['Rating','Genres','Category_c','Genres_c'],axis = 1)
y_d = df2.Rating
X_train_d, X_test_d, y_train_d, y_test_d = train_test_split(X_d, y_d, test_si
ze=0.30)
model3_d = RandomForestRegressor()
model3_d.fit(X_train_d,y_train_d)
Results3_d = model3_d.predict(X_test_d)

#evaluation
resultsdf = resultsdf.append(Evaluationmatrix_dict(y_test,Results3_d, name =
'RFR - Dummy'),ignore_index = True)
```

```
/opt/conda/lib/python3.6/site-packages/sklearn/ensemble/forest.py:248: Fut
ureWarning: The default value of n_estimators will change from 10 in versi
on 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/ensemble/forest.py:248: Fut
ureWarning: The default value of n_estimators will change from 10 in versi
on 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

In [36]:

```
plt.figure(figsize=(12,7))
sns.regplot(Results3,y_test,color='teal', label = 'Integer', marker = 'x')
sns.regplot(Results3_d,y_test_d,color='orange',label = 'Dummy')
plt.legend()
plt.title('RFR model - excluding Genres')
plt.xlabel('Predicted Ratings')
plt.ylabel('Actual Ratings')
plt.show()
```

```
/opt/conda/lib/python3.6/site-packages/scipy/stats/stats.py:1713: FutureWa
rning: Using a non-tuple sequence for multidimensional indexing is depreca
ted; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will
be interpreted as an array index, `arr[np.array(seq)]`, which will result
either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [37]:

```
print ('Integer encoding(mean) :' + str(Results3.mean()))
print ('Dummy encoding(mean) :'+ str(Results3_d.mean()))
print ('Integer encoding(std) :' + str(Results3.std()))
print ('Dummy encoding(std) :'+ str(Results3_d.std()))
```

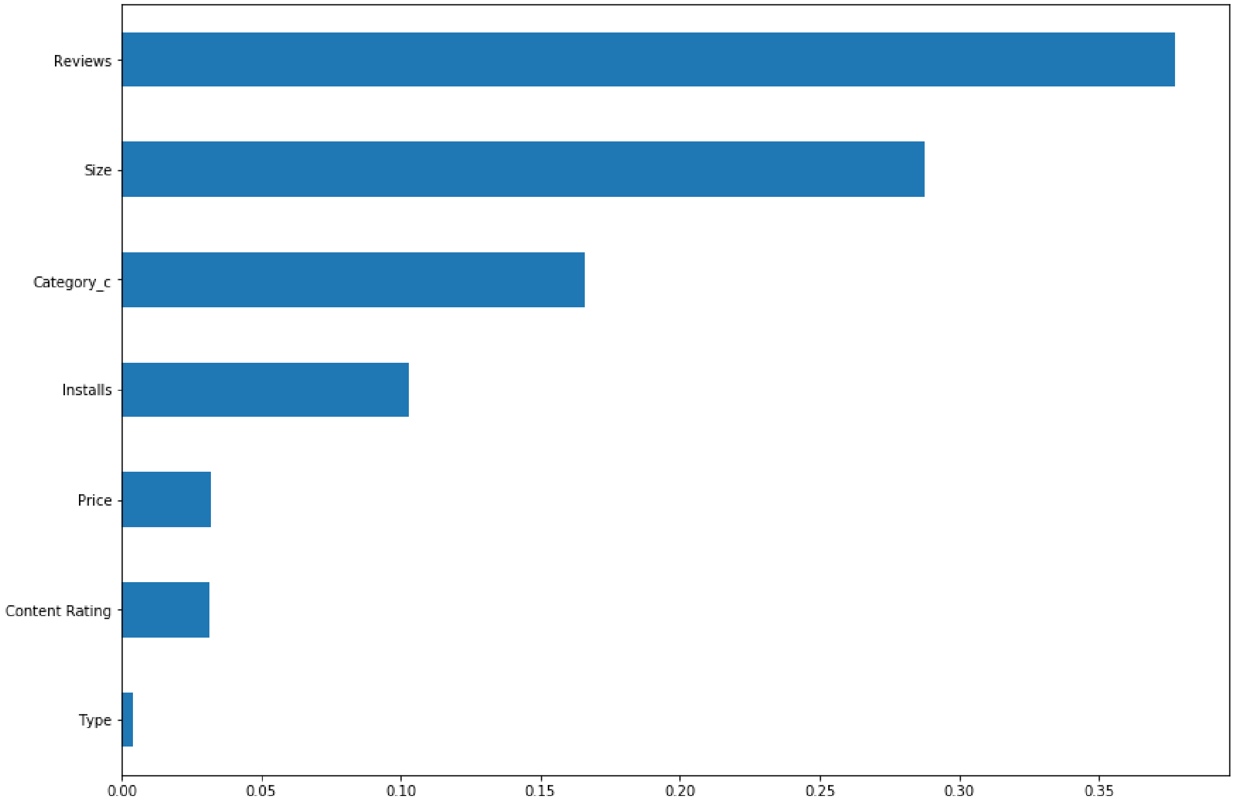
```
Integer encoding(mean) :4.1769935897435895
Dummy encoding(mean) :4.189666429249762
Integer encoding(std) :0.3284440265728504
Dummy encoding(std) :0.3181516319387557
```

At first glance, I would say that the RFR model produced the best predictive results, just looking at the scatter graph plotted. Overall both models, the integer and the dummy encoded models seem to perform relatively similar, although the dummy encoded model has a higher overall predicted mean.

In [38]:

```
#for integer
Feat_impt = {}
for col,feat in zip(X.columns,model3.feature_importances_):
    Feat_impt[col] = feat

Feat_impt_df = pd.DataFrame.from_dict(Feat_impt,orient = 'index')
Feat_impt_df.sort_values(by = 0, inplace = True)
Feat_impt_df.rename(index = str, columns = {0:'Pct'},inplace = True)

plt.figure(figsize= (14,10))
Feat_impt_df.plot(kind = 'barh',figsize= (14,10),legend = False)
plt.show()
```

```
<Figure size 1008x720 with 0 Axes>
```

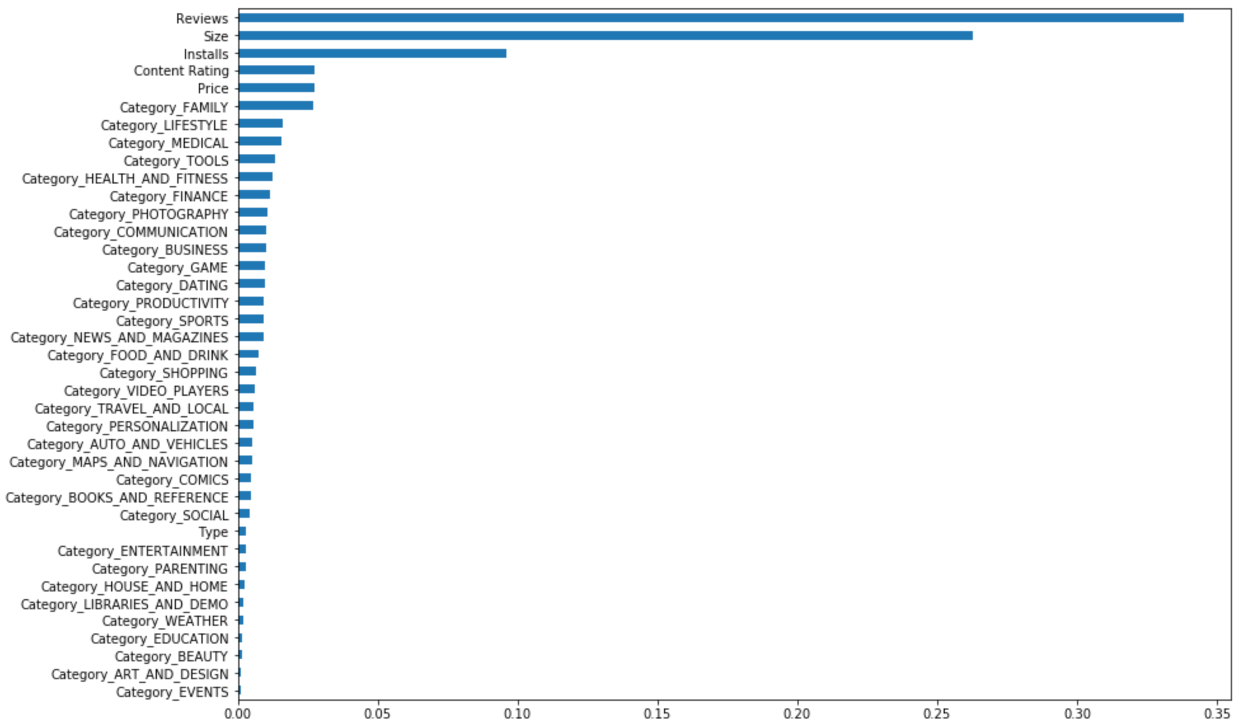


If we look at what influences the ratings, the top 4 being reviews, size, category, and number of installs seem to have the highest influence. This is quite an interesting observation, while also rationalizable.

In [39]:

```
#for dummy
Feat_impt_d = {}
for col,feat in zip(X_d.columns,model3_d.feature_importances_):
    Feat_impt_d[col] = feat

Feat_impt_df_d = pd.DataFrame.from_dict(Feat_impt_d,orient = 'index')
Feat_impt_df_d.sort_values(by = 0, inplace = True)
Feat_impt_df_d.rename(index = str, columns = {0:'Pct'},inplace = True)

plt.figure(figsize= (14,10))
Feat_impt_df_d.plot(kind = 'barh',figsize= (14,10),legend = False)
plt.show()
```

```
<Figure size 1008x720 with 0 Axes>
```



Looking at the breakdown even further, it would seem that indeed Reviews, size and number of install remain as a significant contributer to the predictiveness of app ratings. What's interesting to me is that how the Tools category of apps have such a high level of predictiveness in terms of ratings, as say compared to the Food and Drink category.

In [40]:

```
#Including Genres_C

#Integer encoding
X = df.drop(labels = ['Category','Rating','Genres'],axis = 1)
y = df.Rating
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30)
model3a = RandomForestRegressor()
model3a.fit(X_train,y_train)
Results3a = model3a.predict(X_test)

#evaluation
resultsdf = resultsdf.append(Evaluationmatrix_dict(y_test,Results3a, name = '
RFR(inc Genres) - Integer'),ignore_index = True)

#dummy encoding

X_d = df2.drop(labels = ['Rating','Genres','Category_c'],axis = 1)
y_d = df2.Rating
X_train_d, X_test_d, y_train_d, y_test_d = train_test_split(X_d, y_d, test_si
ze=0.30)
model3a_d = RandomForestRegressor()
model3a_d.fit(X_train_d,y_train_d)
```

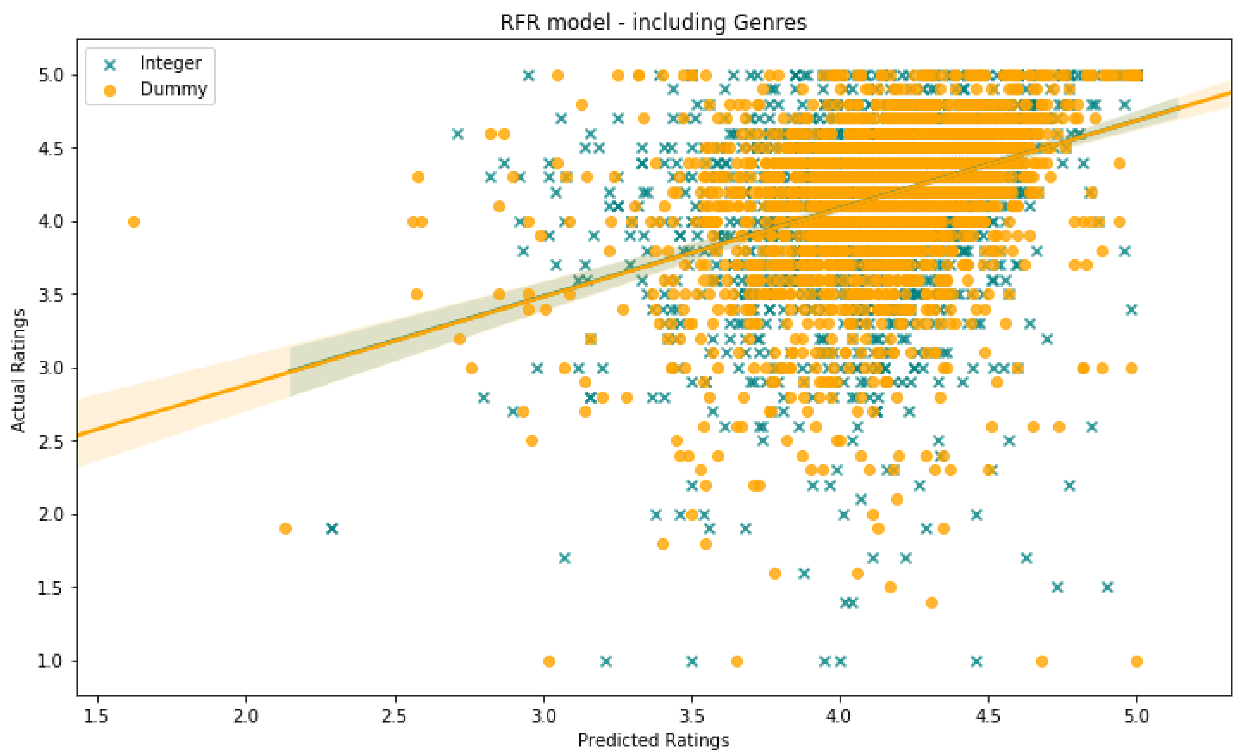
```
Results3a_d = model3a_d.predict(X_test_d)

#evaluation
resultsdf = resultsdf.append(Evaluationmatrix_dict(y_test,Results3a_d, name =
'RFR(inc Genres) - Dummy'),ignore_index = True)
```

```
/opt/conda/lib/python3.6/site-packages/sklearn/ensemble/forest.py:248: Fut
ureWarning: The default value of n_estimators will change from 10 in versi
on 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/ensemble/forest.py:248: Fut
ureWarning: The default value of n_estimators will change from 10 in versi
on 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

In [41]:

```
plt.figure(figsize=(12,7))
sns.regplot(Results3a,y_test,color='teal', label = 'Integer', marker = 'x')
sns.regplot(Results3a_d,y_test_d,color='orange',label = 'Dummy')
plt.legend()
plt.title('RFR model - including Genres')
plt.xlabel('Predicted Ratings')
plt.ylabel('Actual Ratings')
plt.show()
```

```
/opt/conda/lib/python3.6/site-packages/scipy/stats/stats.py:1713: FutureWa
rning: Using a non-tuple sequence for multidimensional indexing is depreca
ted; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will
be interpreted as an array index, `arr[np.array(seq)]`, which will result
either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [42]:

```
print ('Integer encoding(mean) :' + str(Results3.mean()))
print ('Dummy encoding(mean) :'+ str(Results3_d.mean()))
print ('Integer encoding(std) :' + str(Results3.std()))
print ('Dummy encoding(std) :'+ str(Results3_d.std()))
```

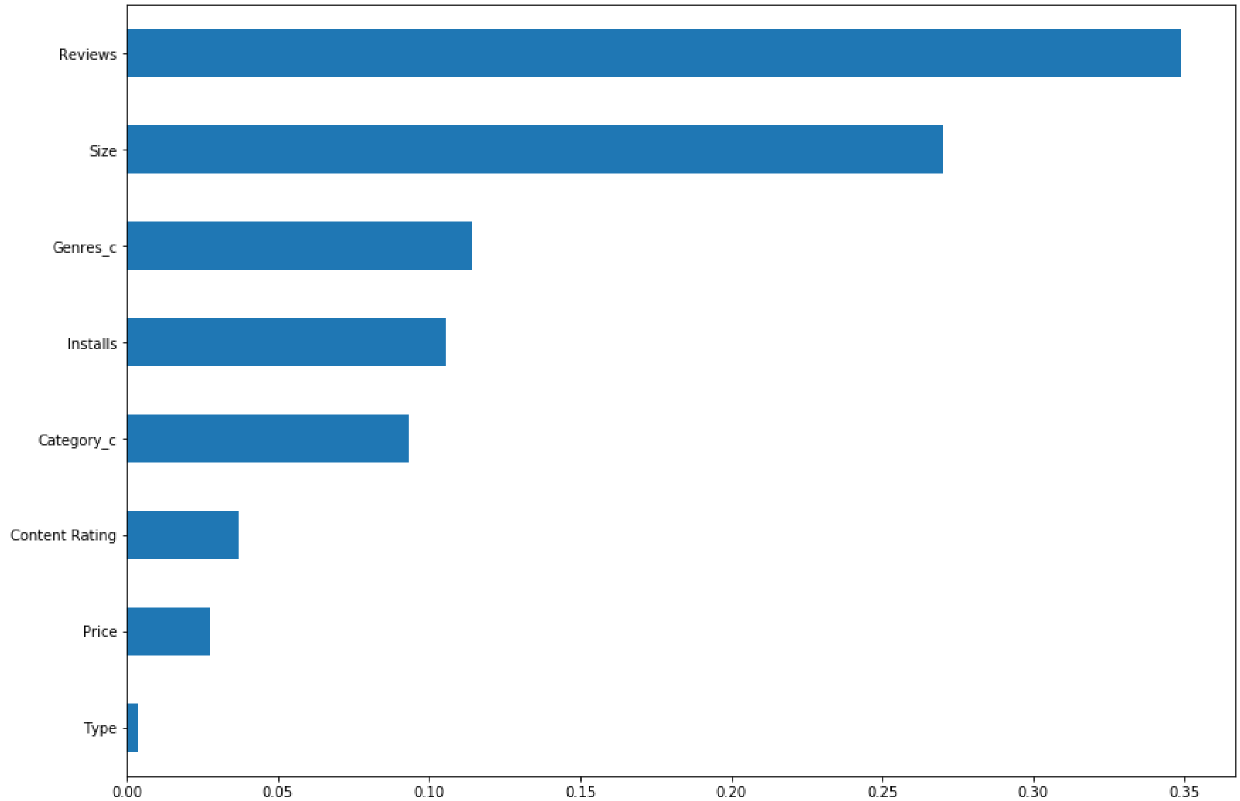
```
Integer encoding(mean) :4.1769935897435895
Dummy encoding(mean) :4.189666429249762
Integer encoding(std) :0.3284440265728504
Dummy encoding(std) :0.3181516319387557
```

Again with the inclusion of the genre variable, the results do not seem to defer significantly as compared to the previous results.

In [43]:

```
#for integer
Feat_impt = {}
for col,feat in zip(X.columns,model3a.feature_importances_):
    Feat_impt[col] = feat

Feat_impt_df = pd.DataFrame.from_dict(Feat_impt,orient = 'index')
Feat_impt_df.sort_values(by = 0, inplace = True)
Feat_impt_df.rename(index = str, columns = {0:'Pct'},inplace = True)

plt.figure(figsize= (14,10))
Feat_impt_df.plot(kind = 'barh',figsize= (14,10),legend = False)
plt.show()
```

```
<Figure size 1008x720 with 0 Axes>
```

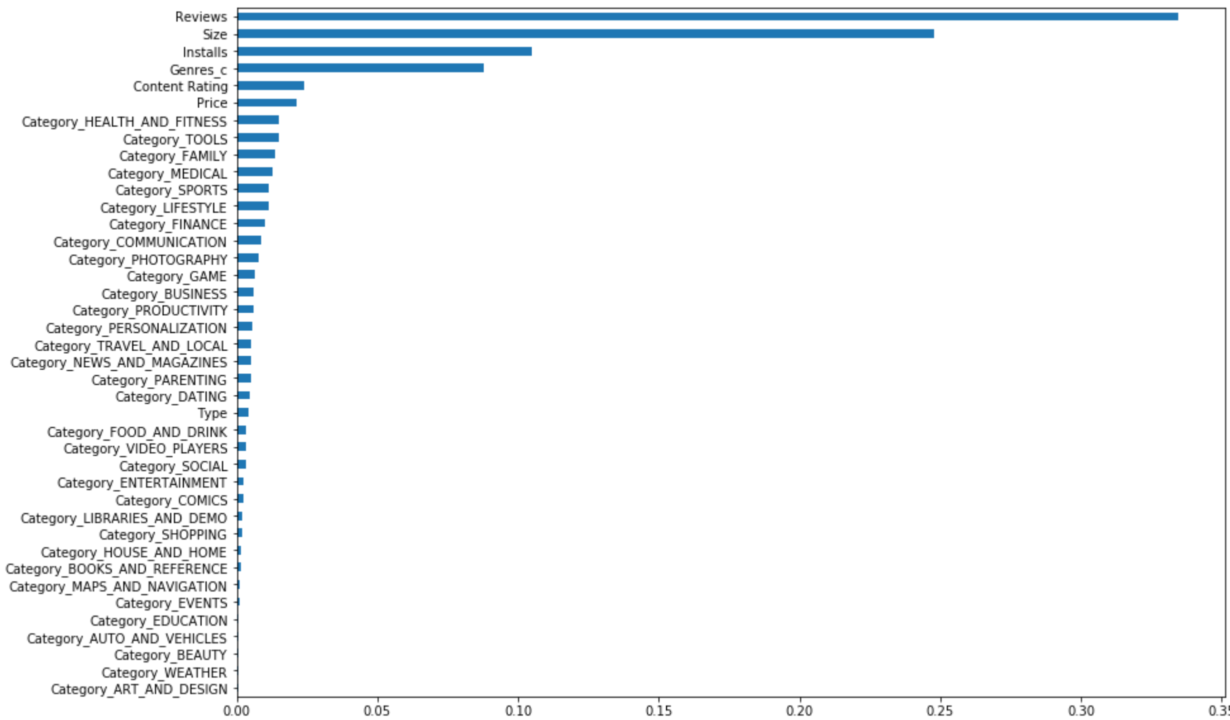


From the results, it would seem that the genre section actually plays an important part in the decision tree making. Yet the exclusion of it dosent seem to significantly impact results. This to me is quite interesting.

In [44]:

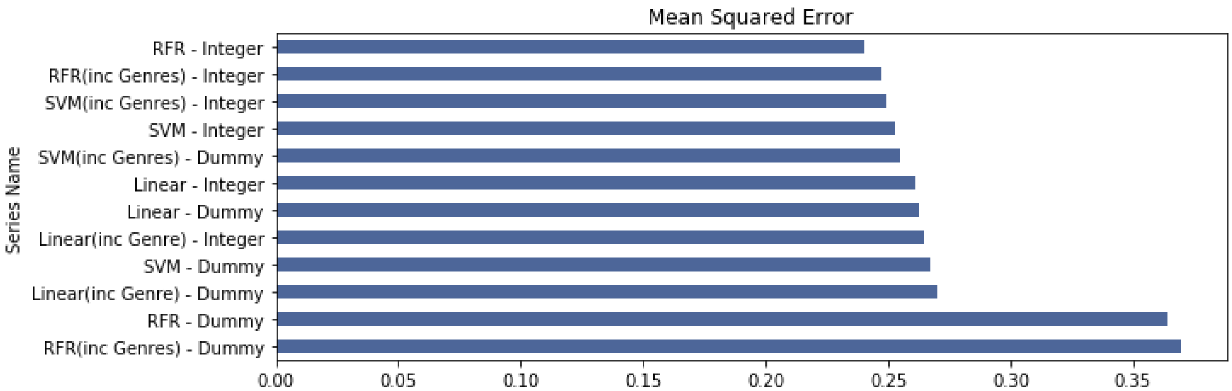
```
#for dummy
Feat_impt_d = {}
for col,feat in zip(X_d.columns,model3a_d.feature_importances_):
    Feat_impt_d[col] = feat

Feat_impt_df_d = pd.DataFrame.from_dict(Feat_impt_d,orient = 'index')
Feat_impt_df_d.sort_values(by = 0, inplace = True)
Feat_impt_df_d.rename(index = str, columns = {0:'Pct'},inplace = True)

plt.figure(figsize= (14,10))
Feat_impt_df_d.plot(kind = 'barh',figsize= (14,10),legend = False)
plt.show()
```

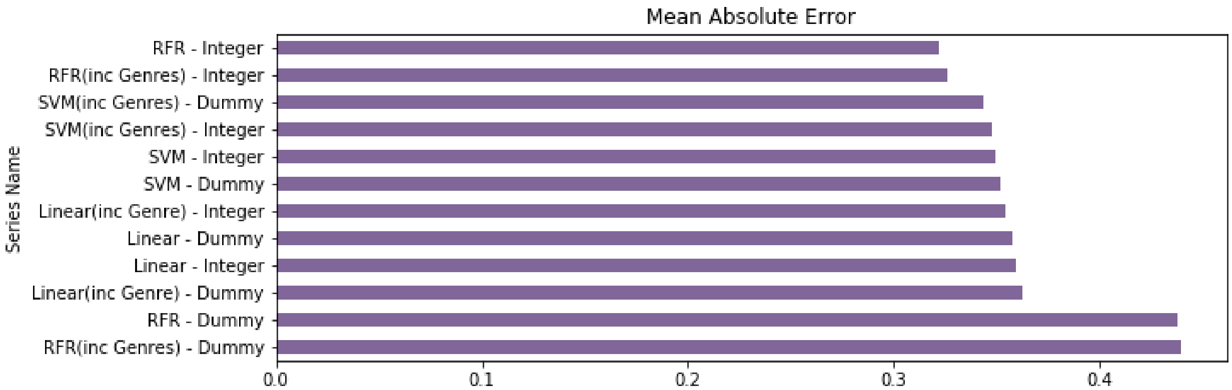
```
<Figure size 1008x720 with 0 Axes>
```

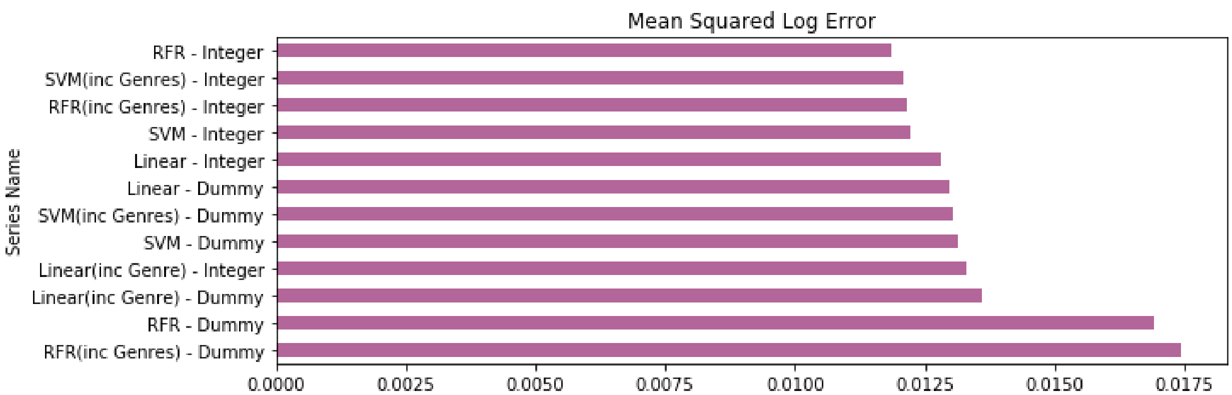


In [45]:

```
resultsdf.set_index('Series Name', inplace = True)

plt.figure(figsize = (10,12))
plt.subplot(3,1,1)
resultsdf['Mean Squared Error'].sort_values(ascending = False).plot(kind = 'b
arh',color=(0.3, 0.4, 0.6, 1), title = 'Mean Squared Error')
plt.subplot(3,1,2)
resultsdf['Mean Absolute Error'].sort_values(ascending = False).plot(kind = '
barh',color=(0.5, 0.4, 0.6, 1), title = 'Mean Absolute Error')
plt.subplot(3,1,3)
resultsdf['Mean Squared Log Error'].sort_values(ascending = False).plot(kind
= 'barh',color=(0.7, 0.4, 0.6, 1), title = 'Mean Squared Log Error')
plt.show()
```







Finally, looking at the results, it is not easy to conclude which model has the best predictive accuracy and lowest error term. Using this round of data as a basis, the dummy encoded SVM model including genres has the lowest overall error rates, followed by the integer encoded RFR model including genes. Yet, all models seem to be very close in terms of it's error term, so this result is likely to change.

What is very surprising to me is how the RFR dummy model has such a significantly more error term compared to all the other models, even though on the surface it seemed to perform very similarly to the RFR integer model.

Concluding thoughts It was pretty fun doing this project, using the three different machine learning models for continuous variables to see if it performed well in predictive analysis, based on the data that was provided. If you guys have any suggestions/comments please do feel free to post, as I'm still a beginner and want to learn more! Have a great and blessed day everyone!