Table of Contents

1 Team Information

1.1 Title: TMDB Box Office Revenue Prediction

1.2 Group number 2

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2 Abstract

In phase three of our project, we are improving on our baseline pipeline from phase 2 by intoducing the following new features.

- hash_feats = ['production_countries_count', 'production_companies_count', 'spoken_languages_count','keyword_count', 'cast_count', 'crew_count']

The main goal of this phase is to optimize our pipeline to produce the best Kaggle score using our additional features. We did this by searching for the best regression model and paramaters that will optimally score our model. We found that the optimal regression model is XGB and, when fit with our pipeline, we recived a private score of 2.13772 on Kaggle.

3 Project Description (data and tasks)

We are working with data from the TMDB box office, which describes a number of categorical features (eg. release_year, spoken_languages) and numeric features (eg. budget, runtime, homepage). Additionally we will be adding new hash features into our pipeline (eg.production companies, languages). We will use these features to predict the revenue of each movie in the test set. The challenge here is to predict the worldwide revenue for 4,398 movies in the test file given various information about the movie. The tasks to be completed in phase 3 require adding the hash features of production countries, spoken languages, keywords, along with the cast and crew. We also plan to intergrate a decision tree regression model (xgboost) to help improve our score and accuracy.

In [1]:
```
DATA_DIR = "./tmdb-box-office-prediction"   #same level as course repo in the
#DATA_DIR = os.path.join('./ddddd/')
!mkdir $DATA_DIR
```

```
mkdir: cannot create directory ‘./tmdb-box-office-prediction’: File exists
```

In [2]:
```
!ls -l $DATA_DIR
```

```
total 0
-rwxr-xr-x 1 root root   139134 Mar 27  2019 TestAdditionalFeatures.csv
-rwxr-xr-x 1 root root    94918 Mar 27  2019 TrainAdditionalFeatures.csv
-rwxr-xr-x 1 root root    61585 Feb  7  2019 sample_submission.csv
-rwxr-xr-x 1 root root 41868556 Feb  7  2019 test.csv
-rwxr-xr-x 1 root root 28311747 Feb  7  2019 train.csv
```

In [3]:
```
# ! kaggle competitions download tmdb-box-office-prediction -p $DATA_DIR
```

4 Data Import & notebook preperation

In [4]:

```
from sklearn.pipeline import Pipeline, FeatureUnion, make_pipeline
from sklearn.compose import ColumnTransformer
from sklearn.model_selection import train_test_split
import seaborn as sns
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split  # sklearn.cross_validat
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.linear_model import LogisticRegression, LinearRegression
from sklearn.impute import SimpleImputer
from sklearn.base import BaseEstimator, TransformerMixin
from time import time
import xgboost as xgb
from sklearn.metrics import mean_squared_error


import pandas as pd
import os
def load_data(in_path, name):
    df = pd.read_csv(in_path)
    print(f"{name}: shape is {df.shape}")
    print(df.info())
    display(df.head(5))
    return df

datasets={}  # lets store the datasets in a dictionary so we can keep track c
ds_name = 'train'

df_train = load_data(os.path.join(DATA_DIR, f'{ds_name}.csv'), ds_name)
#datasets[ds_name] = trainOrig


ds_name = 'test'
df_test = load_data(os.path.join(DATA_DIR, f'{ds_name}.csv'), ds_name)
#datasets[ds_name] = testOrig
```

```
train: shape is (3000, 23)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 23 columns):
id                       3000 non-null int64
belongs_to_collection    604 non-null object
budget                   3000 non-null int64
genres                   2993 non-null object
homepage                 946 non-null object
imdb_id                  3000 non-null object
original_language        3000 non-null object
original_title           3000 non-null object
overview                 2992 non-null object
popularity               3000 non-null float64
poster_path              2999 non-null object
production_companies     2844 non-null object
production_countries     2945 non-null object
```

```
release_date             3000 non-null object
```

In [5]:

```
ds_name = 'train'
print(f'dataset {ds_name:24}: [ {df_train.shape[0]:10,}, {df_train.shape[1]}]
ds_name = 'test'
print(f'dataset {ds_name:24}: [ {df_test.shape[0]:10,}, {df_test.shape[1]}]')
```

```
dataset train                   : [      3,000, 23]
dataset test                    : [      4,398, 22]
```

5 EDA TMDB

In [6]:

```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 23 columns):
id                       3000 non-null int64
belongs_to_collection    604 non-null object
budget                   3000 non-null int64
genres                   2993 non-null object
homepage                 946 non-null object
imdb_id                  3000 non-null object
original_language        3000 non-null object
original_title           3000 non-null object
overview                 2992 non-null object
popularity               3000 non-null float64
poster_path              2999 non-null object
production_companies     2844 non-null object
production_countries     2945 non-null object
release_date             3000 non-null object
runtime                  2998 non-null float64
spoken_languages         2980 non-null object
status                   3000 non-null object
tagline                  2403 non-null object
title                    3000 non-null object
Keywords                 2724 non-null object
cast                     2987 non-null object
crew                     2984 non-null object
revenue                  3000 non-null int64
dtypes: float64(2), int64(3), object(18)
memory usage: 539.2+ KB
```

In [7]:
```
df_train.describe() #only 4 numerical features
```

Out[7]:

	id	budget	popularity	runtime	revenue
count	3000.000000	3.000000e+03	3000.000000	2998.000000	3.000000e+03
mean	1500.500000	2.253133e+07	8.463274	107.856571	6.672585e+07
std	866.169729	3.702609e+07	12.104000	22.086434	1.375323e+08
min	1.000000	0.000000e+00	0.000001	0.000000	1.000000e+00
25%	750.750000	0.000000e+00	4.018053	94.000000	2.379808e+06
50%	1500.500000	8.000000e+06	7.374861	104.000000	1.680707e+07
75%	2250.250000	2.900000e+07	10.890983	118.000000	6.891920e+07
max	3000.000000	3.800000e+08	294.337037	338.000000	1.519558e+09

In [10]:
```
df_train.describe(include='all') #look at all categorical and numerical
```

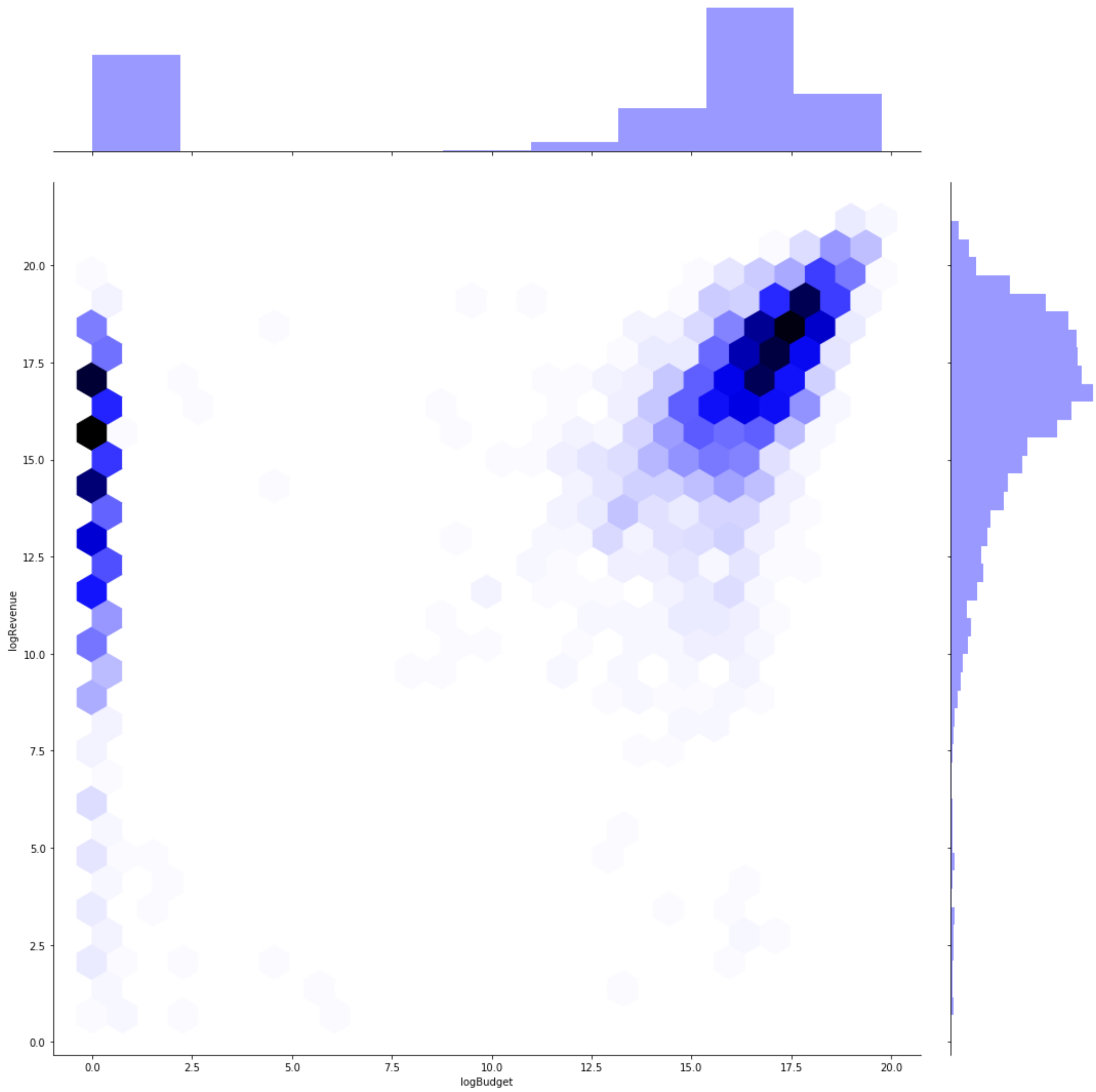
Out[10]:

	id	belongs_to_collection	budget	genres	homep
count	3000.000000	604	3.000000e+03	2993	
unique	NaN	422	NaN	872	
top	NaN	[{'id': 645, 'name': 'James Bond Collection', ...	NaN	[{'id': 18, 'name': 'Drama'}]	http://www.transformersmovie.
freq	NaN	16	NaN	266	
mean	1500.500000	NaN	2.253133e+07	NaN	
std	866.169729	NaN	3.702609e+07	NaN	
min	1.000000	NaN	0.000000e+00	NaN	
25%	750.750000	NaN	0.000000e+00	NaN	
50%	1500.500000	NaN	8.000000e+06	NaN	
75%	2250.250000	NaN	2.900000e+07	NaN	
max	3000.000000	NaN	3.800000e+08	NaN	

11 rows × 23 columns

In [7]:
```
df_train['logRevenue']=np.log1p(df_train['revenue'])
df_train['logBudget']=np.log1p(df_train['budget'])
sns.jointplot(x="logBudget", y="logRevenue", data=df_train, height=15, ratio=
```

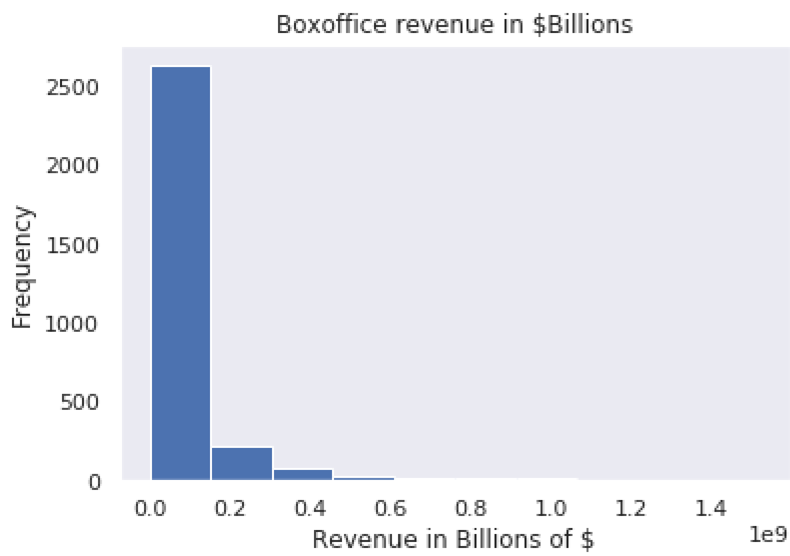
Out[7]: <seaborn.axisgrid.JointGrid at 0x7f24318fb150>



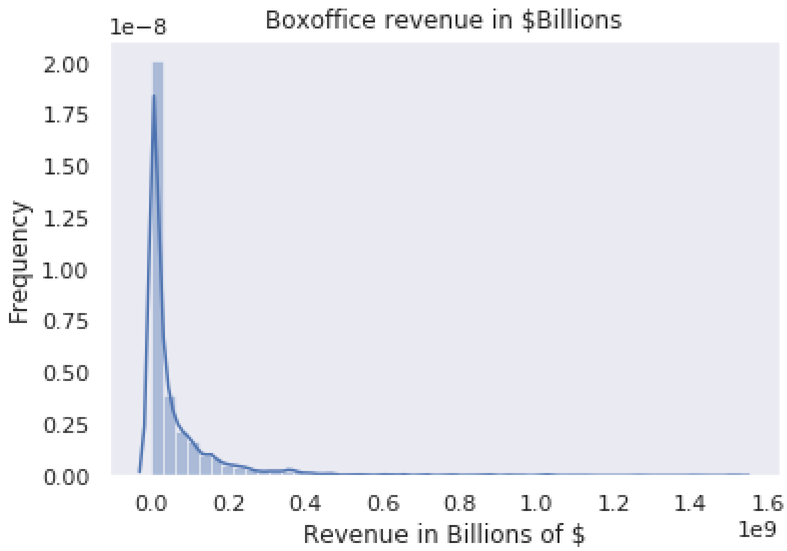
5.0.1 Distribution of the target column

In [8]:

```
# necessary imports
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns; sns.set()
df_train['revenue'].astype(float).plot.hist()
plt.xlabel("Revenue in Billions of $")
plt.ylabel("Frequency")
plt.title("Boxoffice revenue in $Billions")
plt.grid()
```



In [9]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns; sns.set()
sns.distplot(df_train['revenue'] )
plt.xlabel("Revenue in Billions of $")
plt.ylabel("Frequency")
plt.title("Boxoffice revenue in $Billions")
plt.grid()
```

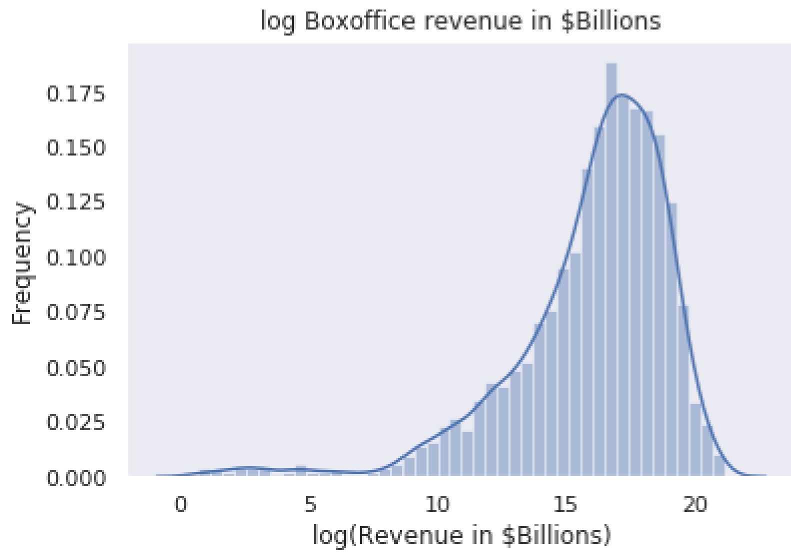


5.0.1.1 Take log of target variable (revenue)

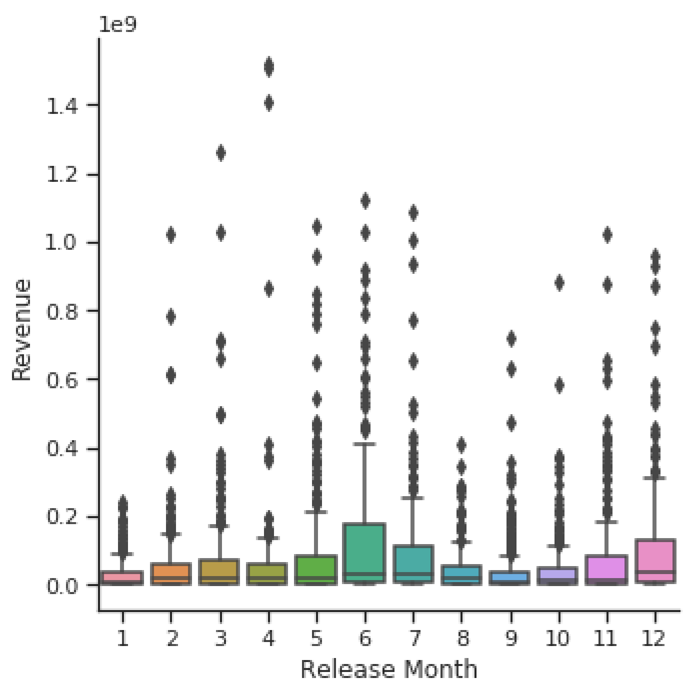
Because revenue variable is skewed, let's calculate log of it.

In [10]:
```
df_train['logRevenue'] = np.log1p(df_train['revenue'])
sns.distplot(df_train['logRevenue'] )
plt.grid()
plt.xlabel("log(Revenue in $Billions)")
plt.ylabel("Frequency")
plt.title("log Boxoffice revenue in $Billions")
```

Out[10]:
```
Text(0.5, 1.0, 'log Boxoffice revenue in $Billions')
```



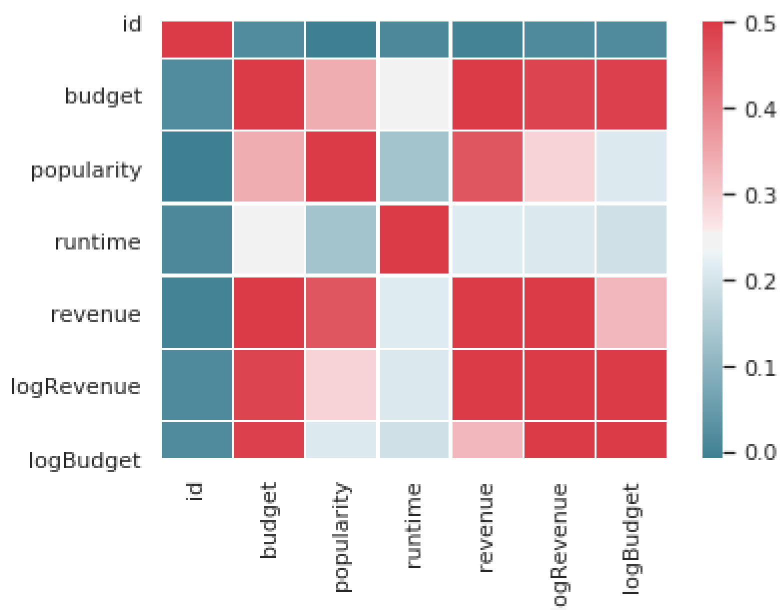
In [61]:
```
#Run cells below before running
with sns.axes_style(style='ticks'):
    g = sns.catplot("release_month", "revenue", data=df_train, kind="box")
    g.set_axis_labels("Release Month", "Revenue");
```



In [59]:
```python
#Run cells below before running
g=sns.catplot(x="has_homepage", y="revenue", data=df_train);
g.set_axis_labels("Has Homepage? 0=no,1=yes", "Revenue");
```

In [14]:
```python
corr=df_train.corr()
cmap = sns.diverging_palette(220, 10, as_cmap=True)
sns.heatmap(corr, cmap=cmap, vmax=.5, square=True, linewidths=.5)
```

Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x7f242f0d1990>



6 Preprocessing

In [5]:

```
df_train['budget'].fillna('median')
df_train['popularity'].fillna('median')
df_train['runtime'].fillna('median')

df_train.loc[df_train['id'] == 16,'revenue'] = 192864          # Skinning
df_train.loc[df_train['id'] == 90,'budget'] = 30000000         # Sommersby
df_train.loc[df_train['id'] == 118,'budget'] = 60000000        # Wild Hogs
df_train.loc[df_train['id'] == 149,'budget'] = 18000000        # Beethoven
df_train.loc[df_train['id'] == 313,'revenue'] = 12000000       # The Cookout
df_train.loc[df_train['id'] == 451,'revenue'] = 12000000       # Chasing Libe
df_train.loc[df_train['id'] == 464,'budget'] = 20000000        # Parenthood
df_train.loc[df_train['id'] == 470,'budget'] = 13000000        # The Karate K
df_train.loc[df_train['id'] == 513,'budget'] = 930000          # From Prada t
df_train.loc[df_train['id'] == 797,'budget'] = 8000000         # Welcome to D
df_train.loc[df_train['id'] == 819,'budget'] = 90000000        # Alvin and th
df_train.loc[df_train['id'] == 850,'budget'] = 90000000        # Modern Times
df_train.loc[df_train['id'] == 1112,'budget'] = 7500000        # An Officer a
df_train.loc[df_train['id'] == 1131,'budget'] = 4300000        # Smokey and t
df_train.loc[df_train['id'] == 1359,'budget'] = 10000000       # Stir Crazy
df_train.loc[df_train['id'] == 1542,'budget'] = 1              # All at Once
df_train.loc[df_train['id'] == 1570,'budget'] = 15800000       # Crocodile Du
df_train.loc[df_train['id'] == 1571,'budget'] = 4000000        # Lady and the
df_train.loc[df_train['id'] == 1714,'budget'] = 46000000       # The Recruit
df_train.loc[df_train['id'] == 1721,'budget'] = 17500000       # Cocoon
df_train.loc[df_train['id'] == 1865,'revenue'] = 25000000      # Scooby-Doo 2
df_train.loc[df_train['id'] == 2268,'budget'] = 17500000       # Madea Goes t
df_train.loc[df_train['id'] == 2491,'revenue'] = 6800000       # Never Talk t
df_train.loc[df_train['id'] == 2602,'budget'] = 31000000       # Mr. Holland
df_train.loc[df_train['id'] == 2612,'budget'] = 15000000       # Field of Dre
df_train.loc[df_train['id'] == 2696,'budget'] = 10000000       # Nurse 3-D
df_train.loc[df_train['id'] == 2801,'budget'] = 10000000       # Fracture
df_test.loc[df_test['id'] == 3889,'budget'] = 15000000       # Colossal
df_test.loc[df_test['id'] == 6733,'budget'] = 5000000        # The Big Sick
df_test.loc[df_test['id'] == 3197,'budget'] = 8000000        # High-Rise
df_test.loc[df_test['id'] == 6683,'budget'] = 50000000       # The Pink Panth
df_test.loc[df_test['id'] == 5704,'budget'] = 4300000        # French Connect
df_test.loc[df_test['id'] == 6109,'budget'] = 281756         # Dogtooth
df_test.loc[df_test['id'] == 7242,'budget'] = 10000000       # Addams Family
df_test.loc[df_test['id'] == 7021,'budget'] = 17540562       #  Two Is a Fami
df_test.loc[df_test['id'] == 5591,'budget'] = 4000000        # The Orphanage
df_test.loc[df_test['id'] == 4282,'budget'] = 20000000       # Big Top Pee-we

power_six = df_train.id[df_train.budget > 1000][df_train.revenue < 100]

for k in power_six :
    df_train.loc[df_train['id'] == k,'revenue'] =  df_train.loc[df_train['id'
```

In [6]:

```
target = "revenue"

X = df_train.drop(target, axis=1)
y = df_train[target]

X_train, X_valid, y_train, y_valid = train_test_split(X, y, train_size=0.7, t
X_train, X_test, y_train, y_test = train_test_split(X_train, y_train, test_si
```

In [7]:

```
dict_columns = ['belongs_to_collection', 'production_companies',
                'production_countries', 'spoken_languages', 'Keywords', 'cast


def text_to_dict(df):
    for column in dict_columns:
        df[column] = df[column].apply(lambda x: {} if pd.isna(x) else eval(x)
    return df

df_train = text_to_dict(df_train)
df_test = text_to_dict(df_test)
```

6.1 Genre,Belongs to Collection and Homepage Binarization

In [8]:

```
def proc_json(string, key):
    try:
        data = eval(string)
        return ",".join([d[key] for d in data])
    except:
        return ''

df_train.genres = df_train.genres.apply(lambda x: proc_json(x, 'name'))
df_test.genres = df_test.genres.apply(lambda x: proc_json(x, 'name'))

genres = []
for idx, val in df_train.genres.iteritems():
    gen_list = val.split(',')
    for gen in gen_list:
        if gen == '':
            continue

        if gen not in genres:
            genres.append(gen)


genre_column_names = []
for gen in genres:
    col_name = 'genre_' + gen.replace(' ', '_')
    df_train[col_name] = df_train.genres.str.contains(gen).astype('uint8')
    df_test[col_name] = df_test.genres.str.contains(gen).astype('uint8')
    genre_column_names.append(col_name)
```

In [9]:

```
# de-jsonify production_countries
df_train.production_countries = df_train.production_countries.apply(lambda x:
df_test.production_countries = df_test.production_countries.apply(lambda x: p
```

In [10]:

```
# collection

df_train['belongs_to_collection']=df_train['belongs_to_collection'].apply(lam
df_test['belongs_to_collection']=df_test['belongs_to_collection'].apply(lambd
```

In [11]:
```
# homepage, released

df_train['has_homepage'] = 1
df_train.loc[pd.isnull(df_train['homepage']) ,"has_homepage"] = 0

df_test['has_homepage'] = 1
df_test.loc[pd.isnull(df_test['homepage']) ,"has_homepage"] = 0

df_train['released'] = 1
df_train.loc[pd.isnull(df_train['status']) ,"released"] = 0

df_test['released'] = 1
df_test.loc[pd.isnull(df_test['status']) ,"released"] = 0
```

In [12]:
```
# de-jsonify production_countries
df_test.production_countries = df_test.production_countries.apply(lambda x: p
```

Let's get a count of how many production countries are involved in a production

In [13]:
```
df_train['production_countries_count'] = df_train['production_countries'].app
df_test['production_countries_count'] = df_test['production_countries'].apply
```

6.1.1 Production Companies

In [14]:
```
# take counts of each
df_train['production_companies_count'] = df_train['production_companies'].app
df_train['spoken_languages_count'] = df_train['spoken_languages'].apply(lambd

df_test['production_companies_count'] = df_test['production_companies'].apply
df_test['spoken_languages_count'] = df_test['spoken_languages'].apply(lambda
```

6.2 Keywords, cast, crew

In [15]:
```
# number of keywords
df_train['keyword_count'] = df_train['Keywords'].apply(lambda x : len(x))
df_test['keyword_count'] = df_test['Keywords'].apply(lambda x : len(x))
```

In [16]:
```
# count of crew
df_train['crew_count'] = df_train['crew'].apply(lambda x : len(x))
df_test['crew_count'] = df_test['crew'].apply(lambda x : len(x))
```

In [17]:
```
# count of cast members
df_train['cast_count'] = df_train['cast'].apply(lambda x : len(x))
df_test['cast_count'] = df_test['cast'].apply(lambda x : len(x))
```

In [18]:
```
df_train.runtime = df_train.runtime.fillna(0) # two null values here
```

6.3 Fixing Release Date

In [19]:
```
df_test.release_date.isnull().sum()
```

Out[19]: 1

In [20]:
```
df_test['release_date'] = df_test['release_date'].fillna('7/14/07')
```

In [21]:
```
df_test.release_date.isnull().sum()
```

Out[21]: 0

In [22]:
```
import re
def yearfix(x): # run year fix, then date fix
    """Regular expression to pull out the two digit year from release_date ar
    r = re.match(r"(\d+/\d+/)(\d+)",x)[2]
    return int(r)
def datefix(x):
    """The dates only provide two digits for year.  This is meant to fix this
    The youngest movie is from 2019, so we'll say any year digits less than 1
    Otherwise, we'll say they are from the 1900s."""
    if x<19:
        x = x+2000
        return x
    if x >=19:
        x = x+1900
        return x
```

In [23]:
```
df_test['release_date'] = df_test['release_date'].fillna('7/14/07') # fill th
```

In [24]:
```
df_train['release_year'] = df_train['release_date'].apply(lambda x: yearfix(x
df_train['release_year'] = df_train['release_year'].apply(lambda x: datefix(x
```

In [25]:
```
df_train["release_date"] = pd.to_datetime(df_train["release_date"]) # set to
df_train['release_month']=df_train["release_date"].dt.month # month of releas

df_test['release_year'] = df_test['release_date'].apply(lambda x: yearfix(x))
df_test['release_year'] = df_test['release_year'].apply(lambda x: datefix(x))
```

In [26]:
```
df_test["release_date"] = pd.to_datetime(df_test["release_date"]) # set to da
df_test['release_month']=df_test["release_date"].dt.month # month of release
```

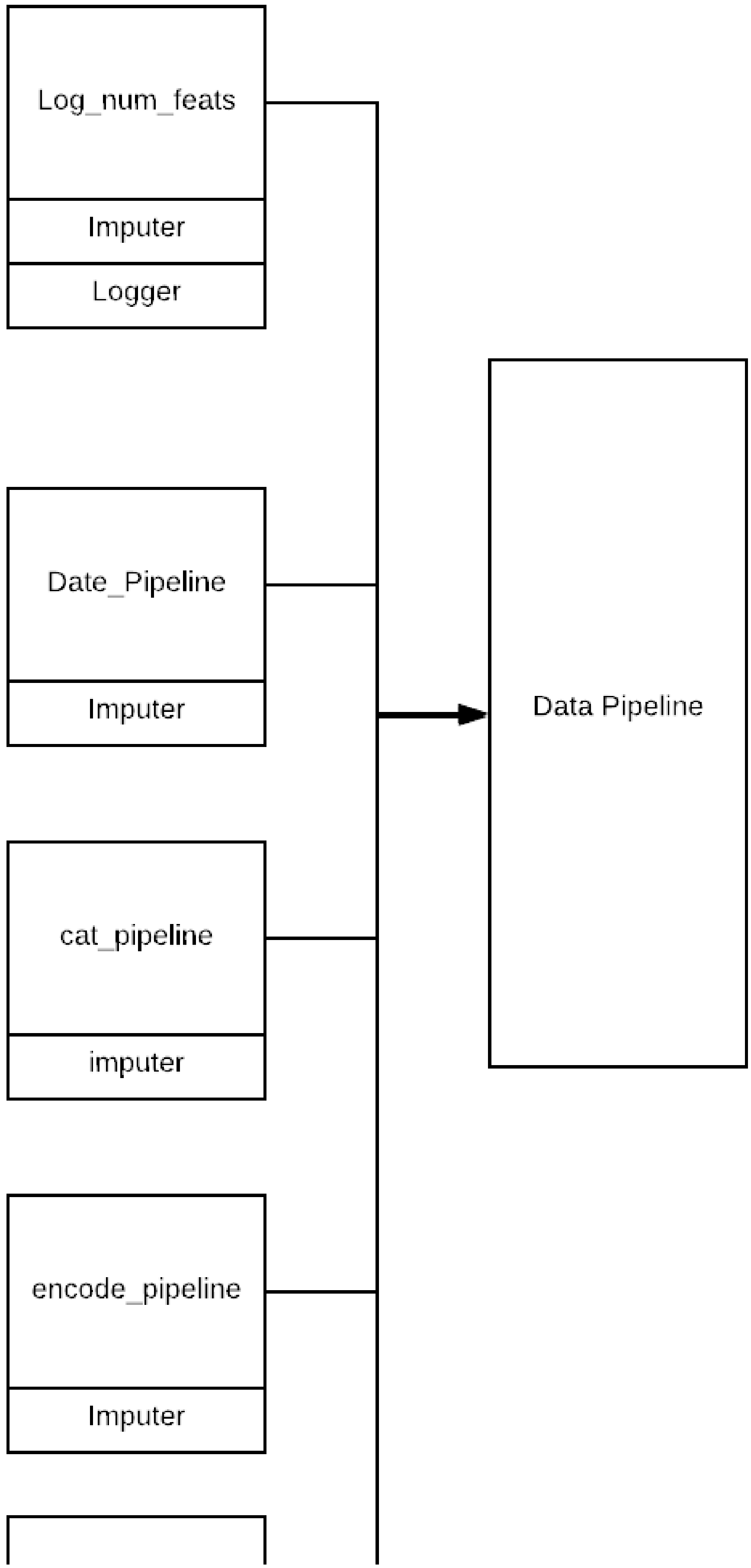
In [27]:

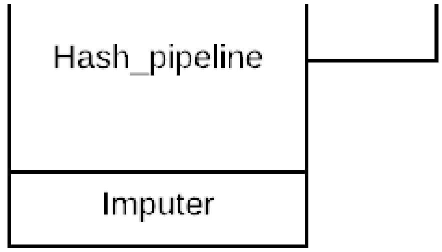
```
y = df_train['revenue']
X = df_train.drop(['revenue'],
                    axis = 1)


X_train, X_valid, y_train, y_valid = train_test_split(X, y, train_size=0.7, t
X_train, X_test, y_train, y_test = train_test_split(X_train, y_train, test_si
```

In [28]:

```
class Log1pTransformer(BaseEstimator, TransformerMixin):
    def __init__(self, features=None):
        self.features = features

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        return np.log1p(X)
```

7 Pipeline


Log_num_feats
Imputer
Logger
Date_Pipeline
Imputer
cat_pipeline
imputer
encode_pipeline
Imputer
Data Pipeline


Hash_pipeline
Imputer

In [29]:

```
from sklearn.feature_extraction.text import HashingVectorizer


log_num_feats = ["budget", "popularity"]
# num_feats = ["runtime"] not required, will explore later
date_feats = ['release_year' , "release_month"]
cat_feats = ['belongs_to_collection', 'has_homepage', 'released']
encode_feats = ['genre_Comedy', 'genre_Drama', 'genre_Family', 'genre_Romance
             'genre_Animation', 'genre_Adventure', 'genre_Horror', 'genre_Doc
             'genre_Science_Fiction', 'genre_Mystery', 'genre_Foreign', 'genr
             'genre_History', 'genre_TV_Movie']
hash_feats = ['production_countries_count', 'production_companies_count', 'sp
             'keyword_count', 'cast_count', 'crew_count']




log_pipe = Pipeline([
    ('imputer', SimpleImputer(missing_values=np.nan, strategy='median')),
    ('logger', Log1pTransformer()),
    #('scaler', StandardScaler()) # might delete later - just a test
])


# num_pipeline = Pipeline ([
#     ('imputer', SimpleImputer(strategy='median'),
#     ('scaler', StandardScaler()))
# ])

date_pipeline = Pipeline ([
     ('imputer', SimpleImputer(missing_values=np.nan, strategy='median'))
])


cat_pipeline = Pipeline([
        ('imputer', SimpleImputer(strategy='most_frequent')),
      #  ('ohe', OneHotEncoder(sparse=False, handle_unknown="ignore"))
])


encode_pipeline = Pipeline([
        ('imputer', SimpleImputer(strategy='most_frequent')),
])


hash_pipe = Pipeline([
    ('imputer', SimpleImputer(strategy='most_frequent'))
])


data_pipeline = ColumnTransformer([
    # name, pipeline, features
    ('log_num_feats', log_pipe, log_num_feats),
    # ('numerical_feats', num_pipeline, num_feats),
    ('date_feats', date_pipeline, date_feats),
    ('cat_feats', cat_pipeline, cat_feats),
```

```
    ('encode_feats', encode_pipeline, encode_feats),
    ('hash_feats', hash_pipe, hash_feats)
],
        remainder='drop', #passthrough or drop?
        n_jobs=-1
    )


df_train_processed = data_pipeline.fit_transform(X_train)
```

In [30]:

```
X_std = data_pipeline.fit_transform(df_train)
model = data_pipeline.fit_transform(X)
```

In [31]:

```
y_std = np.log1p(y)
```

In [32]:

```
X_train, X_test, y_train, y_test = train_test_split(X_std, y_std, test_size=0
```

8 Modeling

In [33]:

```
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
models = {'linear': LinearRegression(),
         'kn': KNeighborsRegressor()}
```

In [34]:

```
def mean_absolute_percentage_error(y_test, y_pred):
    y_test, y_pred = np.array(y_test), np.array(y_pred)
    return np.mean(np.abs((y_test - y_pred) / y_test)) * 100
results = pd.DataFrame(columns=["ExpID", "Train RMSLE", "Test RMSLE","Dollars
def rmsle(y, y_pred):
    return np.sqrt(mean_squared_error(y, y_pred))

def get_results(model, X, y, X_test, y_test, name='model_name', desc='experim
    start = time()
    model.fit(X, y)
    y_pred = model.predict(X)
    train_rmsle = np.sqrt(((y_pred-y)**2).mean())
    y_pred_test = model.predict(X_test)
    test_rmsle = np.sqrt(((y_pred_test-y_test)**2).mean())
    dollarsover= test_rmsle*1000000000
    train_time = np.round(time() - start, 4)
    results.loc[results.shape[0]+1] = [name, np.round(train_rmsle,2), np.rour
```

In [35]:

```
for name, model in models.items():
    get_results(model, X_train, y_train, X_test, y_test, 'Initial Search', 'U

display(results)
```

	ExpID	Train RMSLE	Test RMSLE	Dollars Over	Train Time(s)	Experiment description
1	Initial Search	2.23	1.79	1.788279e+09	0.2475	Untuned linear
2	Initial Search	2.08	2.09	2.086000e+09	0.2607	Untuned kn

In [36]:

```
from sklearn.metrics import make_scorer
# define custom scorer
def rmsle(y_true, y_pred):
    rmsle = np.sqrt(((np.log1p(y_true)-np.log1p(y_pred))**2).mean())
    return rmsle

scorer = make_scorer(rmsle)
```

9 Evaluation, reporting and analysis

In [64]:

```
from sklearn.model_selection import GridSearchCV
from xgboost.sklearn import XGBRegressor
start = time()
xgb1 = XGBRegressor()
parameters = {'objective':['reg:squarederror'],
              'learning_rate': [.03, 0.05, .07], #so called `eta` value
              'max_depth': [5, 6, 7],
              'min_child_weight': [3,4],
              'silent': [1],
              'subsample': [0.7,0.8,0.9],
              'colsample_bytree': [0.7],
              'n_estimators': [500,1000,2800]}

grid = GridSearchCV(xgb1,
                    parameters,
                    cv = 2,
                    n_jobs = -1,
                    verbose=True)


grid.fit(X_train, y_train)
print("Best parameters: {}".format(grid.best_params_))
train_time = np.round(time() - start, 4)
train_rmsle = grid.best_score_
y_pred = grid.predict(X_test)
test_rmsle = rmsle(y_test, y_pred)
test_mape = mean_absolute_percentage_error(y_test, y_pred)
dollarsover= test_rmsle*1000000000
results.loc[results.shape[0]+1] = ['Best Model: XGB Regressor', np.round(trai
                                   train_time, "XGB Regressor"]
display(results)
```

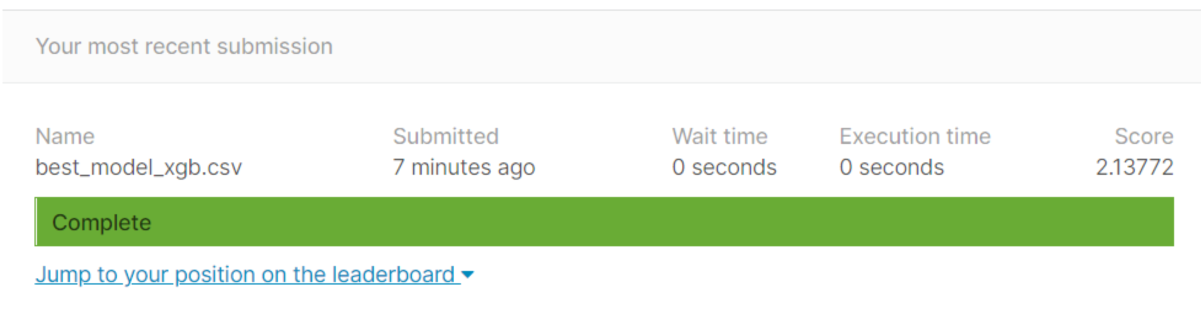
```
Fitting 2 folds for each of 162 candidates, totalling 324 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  46 tasks      | elapsed:  6.2min
[Parallel(n_jobs=-1)]: Done 196 tasks      | elapsed: 27.3min
[Parallel(n_jobs=-1)]: Done 324 out of 324 | elapsed: 34.3min finished
/usr/local/lib/python3.7/site-packages/xgboost/core.py:587: FutureWarning:
Series.base is deprecated and will be removed in a future version
  if getattr(data, 'base', None) is not None and \

Best parameters: {'colsample_bytree': 0.7, 'learning_rate': 0.03, 'max_dept
h': 5, 'min_child_weight': 4, 'n_estimators': 500, 'objective': 'reg:square
derror', 'silent': 1, 'subsample': 0.8}
```

	ExpID	Train RMSLE	Test RMSLE	Dollars Over	Train Time(s)	Experiment description
1	Initial Search	2.23	1.79	1.788279e+09	0.2475	Untuned linear
2	Initial Search	2.08	2.09	2.086000e+09	0.2607	Untuned kn
3	Best Model: KN Regressor	0.22	0.18	1.758187e+08	25.5587	{'leaf_size': 30, 'n_neighbors': 5, 'p': 2, 'w...

	ExpID	Train RMSLE	Test RMSLE	Dollars Over	Train Time(s)	Experiment description
4	Best Model: KN Regressor	0.22	0.18	1.758187e+08	31.3203	{'leaf_size': 30, 'n_neighbors': 5, 'p': 2, 'w...
5	Best Model: XGB Regressor	0.52	0.14	1.391409e+08	2063.4620	XGB Regressor

9.1 Kaggle Submission

In [66]:
```
test_std = data_pipeline.transform(df_test)
final_model = XGBRegressor(objective = 'reg:squarederror',
                                  eta = 0.01,
                                  max_depth = 6,
                                  min_child_weight = 3,
                                  subsample = 0.8,
                                  colsample_bytree = 0.7,
                                  eval_metric = 'rmse',
                                  seed = 1,
                                  n_estimators = 2800)
final_model.fit(X_std, y_std)
predictions = np.expm1(final_model.predict(test_std))
pd.DataFrame({'revenue': predictions.reshape(-1,)}, index=df_test.id).to_csv(
```



In [67]:

```
# Time and score test predictions
start = time()
final_model.fit(X_train, y_train)
train_time = np.round(time() - start, 4)
trainAcc  = final_model.score(X_train, y_train)
start = time()
testAcc  = final_model.score(X_test, y_test)
test_time = np.round(time() - start, 4)
experimentLog = pd.DataFrame(columns=["Pipeline", "Dataset", "TrainAcc", "Tes
                                               "Train Time(s)",  "Test Time(s
try: experimentLog
except : experimentLog = pd.DataFrame(columns=["Pipeline", "Dataset", "TrainA
                                               "Train Time(s)",  "Test Time(s
experimentLog.loc[len(experimentLog)] =["Pipeline with Optimised KNeighbors R

experimentLog
```

Out[67]:

	Pipeline	Dataset	TrainAcc	TestAcc	Train Time(s)	Test Time(s)	Description
0	Pipeline with Optimised KNeighbors Regressor	Movie Classes	96.46%	67.20%	4.7014	0.0322	KNN pipeline with included features

10 Discussion

With the new features added to the pipeline, we were able to slightly increase our scores from phase 2. Our new features include:

- production_countries_count
- production_companies_count
- keyword_count
- cast_count
- crew_count Some of these features involved using our proc_json function (defined in phase 2), while some only involved taking the length of each list.

The results we were able to get through our new pipeline show a test accuracy of 64.06% which is an improvement from the 55.38% in phase 2. In comparison, our phase 1 baseline pipeline had 28.64% test accuracy for log baseline pipeline. We were unable to get a Kaggle score in phase 1, but in phase 2 our Kaggle score was 2.40318. We sucessfully improved our previous score from phase 2 thanks to our additional features and new gridsearch optimised XRB Regressor.

11 Conclusion

With this project, our focus was to be able to predict box office revenue for any movie. In order to do this, we created machine learning pipelines with custom features to predict the revenue from the box office. As we continue to improve our pipeline from the previous phase, features like 'production_companies_count', 'spoken_languages_count', 'keyword_count', 'cast_count', and 'crew_count' have been added and have allowed our pipelines to produce better accuracy scores which allowed our test dataset to be 64.06% accurate. We also used a different prediction model in XGBRegressor, which gave us more accurate scores. When submitting the scores to Kaggle, our score of 2.13772 shows that we are quite close to a model that can accurately predict these revenues.