In [1]:
```
from pykalman import KalmanFilter
import numpy as np
import pandas as pd
import sys
import matplotlib
import matplotlib.pyplot as plt
from skimage.color import lab2rgb
from sklearn import model_selection
from sklearn.naive_bayes import GaussianNB
import skimage
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import FunctionTransformer, StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from functools import reduce
import statsmodels.api as sm
lowess = sm.nonparametric.lowess
from scipy import stats
```

In [2]:
```
def to_timestamp(dateTime):
    return dateTime.timestamp()

def map_genre(row):
   result = []
   for genre_code in row:
       matches = genres[genres['wikidata_id'] == genre_code]['genre_label']
.values
       for match in matches:
           result.append(match)
   return result
```

In [3]:
```
wikidata = pd.read_json('movies/data/wikidata-movies.json.gz', orient='reco
rd', lines=True, encoding="utf8", convert_dates=['publication_date'])
genres = pd.read_json('movies/data/genres.json.gz', orient='record', lines=
True, encoding="utf8")
```

In [4]:
```
wikidata = wikidata[wikidata['made_profit'].notnull()].reset_index(drop=Tru
e)
wikidata['publication_timestamp'] = wikidata['publication_date'].apply(to_t
imestamp)
wikidata['genre_names'] = wikidata['genre'].apply(map_genre)
```

In [5]:
```
rotten_tomatoes = pd.read_json('movies/data/rotten-tomatoes.json.gz', orien
t='record', lines=True)
omdb = pd.read_json('movies/data/omdb-data.json.gz', orient='record', lines
=True)
combined = wikidata.join(rotten_tomatoes.set_index('rotten_tomatoes_id'), o
n='rotten_tomatoes_id', rsuffix='_rt')
combined = combined.join(omdb.set_index('imdb_id'), on='imdb_id')
```

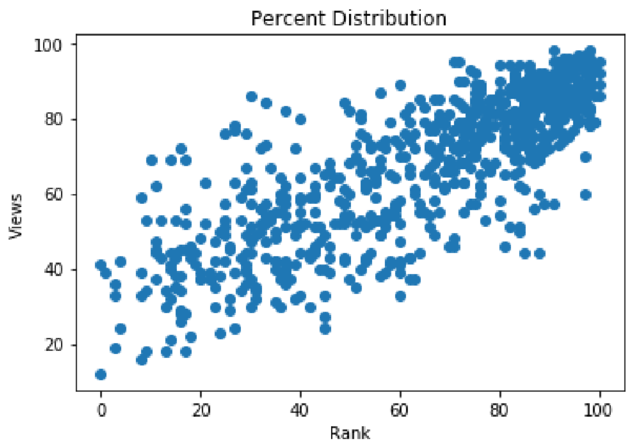
In [6]:
```
combined
```

Out[6]:

	based_on	cast_member	country_of_origin	director	enwiki_title	filming_location	
0	NaN	[Q5126010, Q3390414, Q5676024, Q237021]	Q29	[Q51892574]	Orbiter 9	NaN	[Q24 Q210
1	NaN	NaN	Q30	[Q3384479, Q351884]	Despicable Me	NaN	[Q15
2	NaN	[Q386349, Q1605965, Q3805579, Q271162, Q463226...	Q30	[Q2071]	Eraserhead	[Q99]	[Q13 Q200 Q596
3	Q17017426	[Q117500, Q1376880, Q11930, Q311169, Q951634, ...	Q30	[Q11930]	Dances with Wolves	[Q1558]	[Q13 Q369 Q215 Q210 Q319
4	NaN	[Q38111, Q211553, Q177311, Q8927, Q173399, Q20...	Q145	[Q25191]	Inception	[Q99, Q387047, Q17, Q90, Q1951, Q7275217, Q126...	[Q49 Q471 Q248 Q188 Q319
5	NaN	[Q229313, Q445772, Q727988, Q3163137, Q1372392...	Q16	[Q6385039]	Mama (2013 film)	[Q172, Q133116, Q13939]	[Q20
6	Q243556	[Q34012, Q41163, Q95043, Q464714, Q171736, Q32...	Q30	[Q56094]	The Godfather	[Q18438, Q60, Q1408, Q1460]	[Q13 Q959 Q744 Q210 Q521
7	NaN	[Q483118, Q23547, Q108283, Q215072, Q270664, Q...	Q30	[Q483118]	Argo (2012 film)	[Q406, Q65, Q43]	[Q62 Q186
8	Q7857661	[Q317343, Q57147, Q244674, Q343616, Q208649, Q...	Q145	[Q706475]	12 Years a Slave (film)	[Q34404]	[Q13 Q645 Q521
		[Q295803,					

Is there a difference between the positivity of critics and the audience?

In [7]:
```
plt.title('Percent Distribution')
plt.xlabel('Rank')
plt.ylabel('Views')
plt.scatter(combined['critic_percent'], combined['audience_percent'])
plt.show()
```



In [8]:
```
test3 = combined[combined['audience_percent'].notnull() & combined['critic_percent'].notnull()]
print(stats.normaltest(test3['audience_percent']).pvalue) #<0.05, therefore not normal
print(stats.mannwhitneyu(test3['critic_percent'], test3['audience_percent']).pvalue) #>0.05, therefore one distribution is higher than the other
print(test3['audience_percent'].mean())
print(test3['critic_percent'].mean())
#The audience is slightly more positive than the critics
```

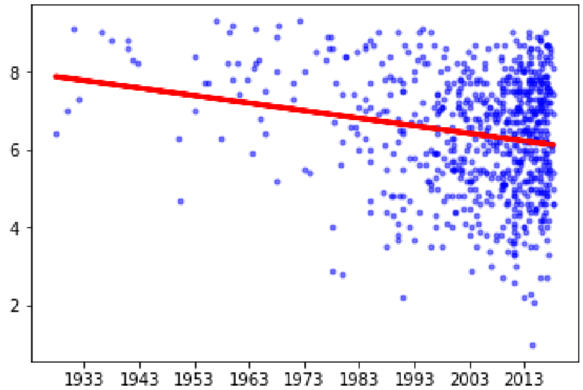
```
3.608996083927233e-17
0.4397286644629225
68.09782608695652
65.06657608695652
```

Have average ratings changed over time?

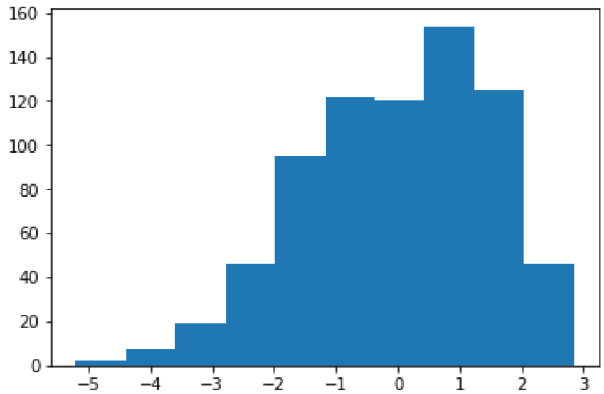
In [9]:
```
critic_average_test = combined[['publication_date','publication_timestamp',
'critic_average']].dropna()
fit = stats.linregress(critic_average_test['publication_timestamp'], critic
_average_test['critic_average'])
critic_average_test['prediction'] = critic_average_test['publication_timest
amp']*fit.slope + fit.intercept
print(fit.pvalue) #p < 0.05, therefore we can conclude that critic ratings
are decreasing.
print(fit.rvalue) #correlation coefficient is low, so it is not very correl
ated
```

```
6.156831173958292e-08
-0.19792833987738834
```

In [10]:
```
plt.plot(critic_average_test['publication_date'], critic_average_test['crit
ic_average'], 'b.', alpha=0.5)
plt.plot(critic_average_test['publication_date'], critic_average_test['pred
iction'], 'r-', linewidth=3)
plt.show()
```



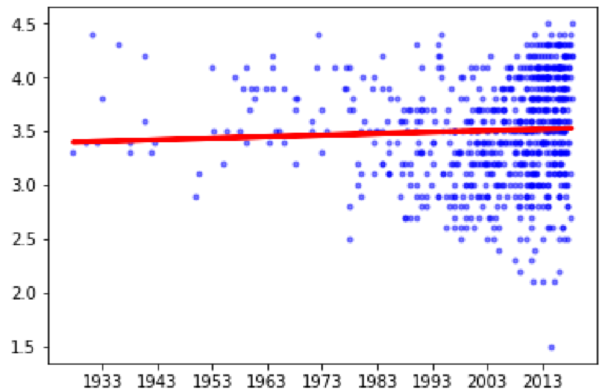
In [11]:
```
plt.hist(np.subtract(critic_average_test['critic_average'],critic_average_t
est['prediction']))
plt.show()
#By the central limit theorem, this is close enough to being normal.
#We expect a greater decline on the high end because the average critic rat
ing is higher than the middle rating, 5.
```



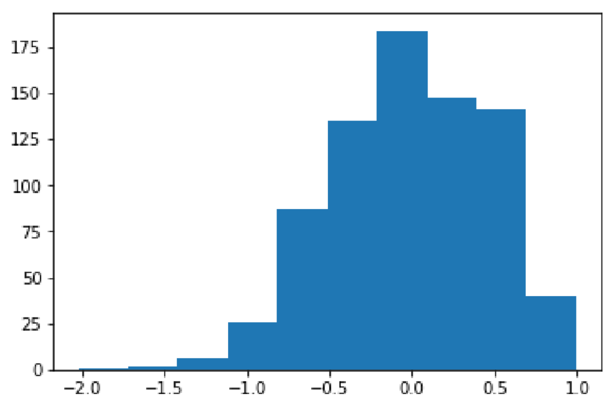
In [12]:
```
audience_average_test = combined[['publication_date','publication_timestamp
','audience_average']].dropna()
fit = stats.linregress(audience_average_test['publication_timestamp'], audi
ence_average_test['audience_average'])
audience_average_test['prediction'] = audience_average_test['publication_ti
mestamp']*fit.slope + fit.intercept
print(fit.pvalue) #p > 0.05, therefore we cannot conclude that the audience
ratings are changing.
print(fit.rvalue) #correlation coefficient is low, so it is not very correl
ated
```

```
0.20019655801512026
0.046244255512890665
```

In [13]:
```
plt.plot(audience_average_test['publication_date'], audience_average_test['
audience_average'], 'b.', alpha=0.5)
plt.plot(audience_average_test['publication_date'], audience_average_test['
prediction'], 'r-', linewidth=3)
plt.show()
```



In [14]:
```
plt.hist(np.subtract(audience_average_test['audience_average'],audience_ave
rage_test['prediction']))
plt.show()
#By the central limit theorem, this is close enough to being normal.
#We expect a greater decline on the high end because the average audience r
ating is higher than the middle rating, 2.5.
```

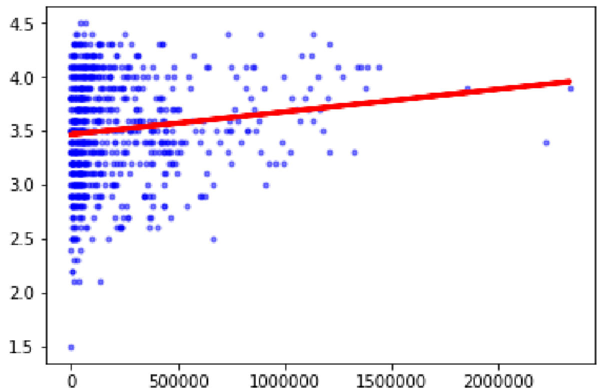


Do average audience ratings change based on its popularity?

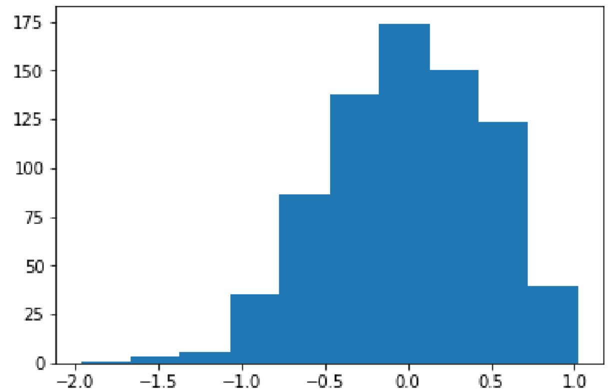
In [15]:
```
audience_ratings_test = combined[['publication_date','publication_timestamp
','audience_average','audience_ratings']].dropna()
#Removing movies with n >= 10000000 ratings as they seem like outliers
audience_ratings_test = audience_ratings_test[audience_ratings_test['audien
ce_ratings'] < 10000000]
fit = stats.linregress(audience_ratings_test['audience_ratings'], audience_
ratings_test['audience_average'])
audience_ratings_test['prediction'] = audience_ratings_test['audience_ratin
gs']*fit.slope + fit.intercept
print(fit.pvalue) #p < 0.05, therefore we can conclude that higher averages
correlate with more popular movies.
print(fit.rvalue) #correlation coefficient is low, so it is not very correl
ated
```

```
0.0003085653249741354
0.1309596810010819
```

In [16]:
```
plt.plot(audience_ratings_test['audience_ratings'], audience_ratings_test['
audience_average'], 'b.', alpha=0.5)
plt.plot(audience_ratings_test['audience_ratings'], audience_ratings_test['
prediction'], 'r-', linewidth=3)
plt.show()
```



In [17]:
```
plt.hist(np.subtract(audience_ratings_test['audience_average'],audience_rat
ings_test['prediction']))
plt.show()
#By the central limit theorem, this is close enough to being normal.
#We expect a greater decline on the high end because the average audience r
ating is higher than the middle rating, 2.5.
```



Does genre have an effect on profitability?

In [18]:
```
def genre_profit_agg(combined_row):
    for genre_id in combined_row['genre']:
        genre_test.loc[genre_test['wikidata_id'] == genre_id,'total']+=1
        if (combined_row['made_profit'] == 1.0):
            genre_test.loc[genre_test['wikidata_id'] == genre_id,'profit']+
=1
```

In [19]:
```
genre_test = genres
genre_test['profit'] = 0
genre_test['total'] = 0
combined.apply(genre_profit_agg, axis=1)
genre_test = genre_test[genre_test['total'] > 0]
```

In [20]:
```
genre_test['loss'] = genre_test['total'] - genre_test['profit']
genre_test = genre_test[genre_test['profit'] >= 5]
genre_test = genre_test[genre_test['loss'] >= 5]
contingency = genre_test[['profit','loss']]
#contingency = contingency[contingency['profit'] >= 5]
#contingency = contingency[contingency['loss'] >= 5]
chi2, p, dof, expected = stats.chi2_contingency(contingency)
print(p) # p < 0.05, therefore genre effects profitability
```

```
0.01956332775267009

/opt/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:1: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/
stable/indexing.html#indexing-view-versus-copy
  """Entry point for launching an IPython kernel.
```

In [21]:
```
genre_test['avg'] = genre_test['profit']/genre_test['total']
genre_test.sort_values(by='avg')
#Science fiction films are the most profitable.
```

Out[21]:

	genre_label	wikidata_id	profit	total	loss	avg
4641	Western	Q172980	6	11	5	0.545455
3502	drama	Q21010853	19	28	9	0.678571
4785	heist film	Q496523	11	16	5	0.687500
3886	family film	Q1361932	20	26	6	0.769231
4438	children's film	Q2143665	29	37	8	0.783784
3713	biographical film	Q645928	41	52	11	0.788462
2948	teen film	Q1146335	27	33	6	0.818182
860	dystopian film	Q20443008	28	34	6	0.823529
4664	action film	Q188473	198	239	41	0.828452
2586	drama film	Q130232	226	272	46	0.830882
4915	crime film	Q959790	60	71	11	0.845070
1713	musical film	Q842256	54	63	9	0.857143
4632	comedy film	Q157443	162	189	27	0.857143
2601	fantasy film	Q157394	109	125	16	0.872000
5248	adventure film	Q319221	104	119	15	0.873950
112	film based on literature	Q52162262	119	135	16	0.881481
1042	thriller film	Q2484376	108	122	14	0.885246
2216	war film	Q369747	40	45	5	0.888889
2653	horror film	Q200092	70	78	8	0.897436
4937	romance film	Q1054574	44	49	5	0.897959
3784	romantic comedy	Q860626	53	59	6	0.898305
2782	science fiction film	Q471839	130	142	12	0.915493

Does country of origin have an effect on profitability?

In [22]:

```
countries = pd.DataFrame(columns=['country_id', 'made_profit'])
#countries.loc[len(countries)] = ['Q123',1.0]

def add_country_profit(combined_row):
    countries.loc[len(countries)] = [combined_row['country_of_origin'], com
bined_row['made_profit']]
    return

combined_with_countries = combined[combined['country_of_origin'].notnull()]
combined_with_countries.apply(add_country_profit, axis=1)
countries_groupby = countries.groupby(['country_id'])
countries_avg = countries_groupby.mean()
countries_count = countries_groupby.count()
countries_sum = countries_groupby.sum()
countries_stats = countries_avg
countries_stats['total'] = countries_count
countries_stats['sum'] = countries_sum
countries_stats = countries_stats.reset_index()
countries_stats.columns = ['country_id','percent','total','profit']
countries_stats['loss'] = countries_stats['total'] - countries_stats['profi
t']
countries_stats = countries_stats[countries_stats['profit'] > 5]
countries_stats = countries_stats[countries_stats['loss'] > 5]
```

In [23]:

```
contingency = countries_stats[['profit','loss']]
chi2, p, dof, expected = stats.chi2_contingency(contingency)
print(p) # p < 0.05, therefore country effects profitability
```

```
0.003346584394852036
```

In [24]:

```
countries_stats #Country Q30, presumably the US, is the best country to mak
e a movie in for profit
```

Out[24]:

	country_id	percent	total	profit	loss
1	Q145	0.838710	62	52.0	10.0
3	Q159	0.677419	31	21.0	10.0
6	Q183	0.625000	16	10.0	6.0
12	Q30	0.860465	602	518.0	84.0

How well can we predict profitability based on ratings?

In [25]:
```
predict_profit = combined
predict_profit = predict_profit[predict_profit['critic_average'].notnull()]
predict_profit = predict_profit[predict_profit['audience_average'].notnull(
)]
predict_profit = predict_profit[predict_profit['critic_percent'].notnull()]
predict_profit = predict_profit[predict_profit['audience_percent'].notnull(
)]
predict_profit = predict_profit.reset_index(drop=True)
X = predict_profit[['critic_average','audience_average','critic_percent','a
udience_percent']]
y = predict_profit['made_profit']

X_train, X_test, y_train, y_test = model_selection.train_test_split(X,y)
model = make_pipeline(
    StandardScaler(),
    SVC(kernel='rbf', C=20000)
)
model.fit(X_train, y_train)
print(model.score(X_test, y_test)) #0.8+ score, so pretty well
#model.fit(X, y)
```

```
0.7880434782608695
```

Can we predict things based on genre? (nope)

I didn't realise that X needs to be floats... gg what a waste of time T_T

In [26]:
```
#def genre_average_rating_agg(combined_row):
#    for genre_id in combined_row['genre']:
#        genre_test.loc[genre_test['wikidata_id'] == genre_id,'total']+=1
#        genre_test.loc[genre_test['wikidata_id'] == genre_id,'total_aud_av
g']+=combined_row['audience_average']
#        genre_test.loc[genre_test['wikidata_id'] == genre_id,'total_cri_av
g']+=combined_row['critic_average']
#        if (combined_row['made_profit'] == 1.0):
#            genre_test.loc[genre_test['wikidata_id'] == genre_id,'profit']
+=1
```

In [27]:
```
#combined_no_nan_ratings = combined[combined['critic_average'].notnull()]
#combined_no_nan_ratings = combined_no_nan_ratings[combined_no_nan_ratings[
'audience_average'].notnull()].reset_index(drop=True)
#genre_test = genres
#genre_test['profit'] = 0
#genre_test['total_aud_avg'] = 0
#genre_test['total_cri_avg'] = 0
#genre_test['total'] = 0
#combined.apply(genre_average_rating_agg, axis=1)
#genre_test = genre_test[genre_test['total'] > 0]
```

In [28]:
```
#genre_test.loc[:,'aud_avg'] = genre_test['total_aud_avg']/genre_test['tota
l']
#genre_test.loc[:,'cri_avg'] = genre_test['total_cri_avg']/genre_test['tota
l']
#Dont know about the SettingWithCopyWarning, can probably just ignore since
it is just a warning
```

In [29]:
```
#genre_test = genre_test.reset_index(drop=True)
#X = genre_test.drop(columns=['aud_avg','cri_avg','profit','total','total_a
ud_avg','total_cri_avg','genre_label'])
#y = genre_test['aud_avg']

#X_train, X_test, y_train, y_test = model_selection.train_test_split(X,y)
#model = make_pipeline(
#    StandardScaler(),
#    SVC(kernel='rbf', C=20000)
#)
#model.fit(X_train, y_train)
#print(model.score(X_test, y_test))
#model.fit(X, y)
```

NATURAL LANGUAGE PROCESSING WORK HERE

In [30]:
```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
```

In [31]:
```
count_vect = CountVectorizer()
X_train_counts = count_vect.fit_transform(test3["omdb_plot"])
```

In [32]:
```
tfidf_transformer = TfidfTransformer()
X_train_tfidf = tfidf_transformer.fit_transform(X_train_counts)
```

In [33]:
```
from sklearn.naive_bayes import MultinomialNB
y=test3["audience_average"]
y=y.astype('int')
clf = MultinomialNB().fit(X_train_tfidf, y)
```

In [34]:
```
docs_new = ['The']
X_new_counts = count_vect.transform(docs_new)
X_new_tfidf = tfidf_transformer.transform(X_new_counts)
predicted = clf.predict(X_new_tfidf)
```

In [35]:
```
for doc, category in zip(docs_new, predicted):
     print('%r => %s' % (doc, test3["omdb_plot"][category])) #not working?
```

```
'The' => Lt. John Dunbar is dubbed a hero after he accidentally leads Union
troops to a victory during the Civil War. He requests a position on the wes
tern frontier, but finds it deserted. He soon finds out he is not alone, bu
t meets a wolf he dubs "Two-socks" and a curious Indian tribe. Dunbar quick
ly makes friends with the tribe, and discovers a white woman who was raised
by the Indians. He gradually earns the respect of these native people, and
sheds his white-man's ways.
```

In [36]:
```
vectorizer = TfidfVectorizer()
tfidf_matrix = vectorizer.fit_transform(test3["omdb_plot"])
feature = vectorizer.get_feature_names()
vocab = np.array(feature)
```

In [37]:
```
feature #list of key words extracted
```

```
Out[37]: ['000',
          '007',
          '04',
          '10',
          '100',
          '1000',
          '100th',
          '101',
          '10s',
          '10th',
          '11',
          '1100',
          '1101',
          '117',
          '12',
          '120',
          '1200',
          '127',
          '12th',
          '13',
          '1357',
          '13th',
          '14',
          '140',
          '15',
          '155',
          '15th',
          '16',
          '1621',
          '163',
          '1630',
          '16th',
          '17',
          '170',
          '1776',
          '1790s',
          '18',
          '1823',
          '1839',
          '1848',
          '1860',
          '1863',
          '1865',
          '1868',
          '1890',
          '1890s',
          '1899',
          '1912',
          '1914',
          '1918',
          '1920s',
          '1926',
          '1930',
          '1930s',
          '1939',
          '1940',
          '1941',
          '1942',
          '1944',
          '1945',
          '1946',
          '1950',
          '1950s',
```

In [38]:
```
doc = 0
feature_index = tfidf_matrix[doc,:].nonzero()[1]
tfidf_scores = zip(feature_index, [tfidf_matrix[doc, x] for x in feature_in
dex])
```

In [39]:
```
for w, s in [(feature[i], s) for (i, s) in tfidf_scores]:
  print (w, s) #showing tfidf score for each word in the summary
```

```
helena 0.44994830287228665
is 0.0313254157653011
young 0.034445749219816774
girl 0.04124583321382185
who 0.04117339272962841
spent 0.06110947647223666
all 0.08785899163498494
her 0.1305810708682046
life 0.028510313451956933
in 0.07483826251551558
space 0.27166123481520066
pod 0.1433487708116238
just 0.03935140526206201
after 0.0556949649512731
birth 0.06110947647223666
traveling 0.056434429793391354
from 0.09141913017567936
earth 0.08753467605892976
to 0.11319755553481937
distant 0.06368234032073075
planet 0.10741769474075274
where 0.03410825925872209
she 0.09254048288700302
will 0.057020626903913865
reunite 0.0669993387269666
with 0.07183623067344654
others 0.05370884737037637
colonials 0.07966643049089307
the 0.2263242798960254
voice 0.06522196846906535
of 0.07819068208685259
on 0.019475290305502265
board 0.06522196846906535
computer 0.056434429793391354
as 0.04303063239856396
only 0.03226771030131625
one 0.027529829222765145
company 0.051015248556804275
arriving 0.07499138381204777
station 0.056434429793391354
for 0.039710874781110767
maintenance 0.07966643049089307
works 0.04965720028419483
meets 0.04484067840939954
álex 0.39833215245446535
repairman 0.07966643049089307
falling 0.06368234032073075
love 0.035031158386641933
him 0.026453704134735613
quickly 0.05150596447800864
but 0.0450506583297649
still 0.04602428940923985
traumatized 0.07966643049089307
by 0.06124914551434492
ghosts 0.07499138381204777
his 0.033483020337606625
own 0.03757403500416075
past 0.04699924318002639
decides 0.04402645194090731
some 0.041665155199113665
days 0.048442384708310186
later 0.043265951044277336
meet 0.04699924318002639
```