reg_analysis

July 27, 2015

In [97]:
```
from IPython.display import HTML
HTML('''<script>
code_show=true;
function code_toggle() {
 if (code_show){
 $('div.input').hide();
 } else {
 $('div.input').show();
 }
 code_show = !code_show
}
$( document ).ready(code_toggle);
</script>
The raw code is by default hidden for easier reading.
To toggle on/off the raw code, click <a href="javascript:code_toggle()">here</a>.''')
```

Out[97]:
```
<IPython.core.display.HTML object>
```

In [98]:
```
#IMPORTS
import re

import pandas as pd
import numpy as np
import scipy

%matplotlib inline
from matplotlib import pylab as plt
from constants import USER_FEATURES, TWEET_INTERESTS, VIDEO_INTERESTS
plt.rcParams['figure.figsize'] = (18, 8)

import statsmodels.api as sm
import seaborn as sns
```

In [99]:
```
#CONSTANTS
USER_FEATURES='Userid,followers,friends,num_tweets,account_created_at,fraction_of_tweets_that_a
TWEET_INTERESTS='gaming,comedy,animals,finance,film_animation,science_tech,travel,people_blogs
VIDEO_INTERESTS='vgaming,vcomedy,vanimals,vfinance,vfilm_animation,vscience_tech,vtravel,vpeopl
```

In [100]:
```
#FUNCTIONS

 def is_retweet(text):
     regex = r'(RT|via)((?:\b\W*@\w+)+)'
     match = re.search(regex, text)
     if match:
```

```
        return True
    return False

def plot_predictions(y_true, y_pred, title=""):
    x = np.arange(y_true.shape[0])
    plt.plot(x, y_true, "bo")
    plt.plot(x, y_true, "b-", label="y_true")

    plt.plot(x, y_pred, "ro")
    plt.plot(x, y_pred, "r-", label="y_predicted")
    plt.legend()
    plt.title(title)
    plt.show()


def cosine_dist(u, v):
    return scipy.spatial.distance.cosine(u, v)


def get_content_dist_df(df):
    '''
    @param df: A dataframe containing TWEET_INTERESTS and VIDEO_INTERESTS columns
    for each user
    '''
    content_dist_df = pd.DataFrame(np.zeros(df.shape[0]), columns=['content_dist'])

    for i in range(df.shape[0]):
        content_dist_df.ix[i, 'content_dist'] = cosine_dist(df.ix[i,TWEET_INTERESTS].values,
                                                              df.ix[i, VIDEO_INTERESTS].values)

    return content_dist_df


def add_content_dist(data, ufeats):
    '''
    This methods calculates a distance measure between a user's interests and
    his/her video interests.
    @param data: A dataframe containing a column 'userid'
    @return: adds "content_dist"  column to the given dataframe 'data'.
    '''

    newdat = data.merge(ufeats[['Userid'] + TWEET_INTERESTS + VIDEO_INTERESTS],
                        on='Userid', how='left')
    content_dist_df = get_content_dist_df(newdat[TWEET_INTERESTS+VIDEO_INTERESTS])

    return pd.tools.merge.concat([data, content_dist_df], axis=1)


def get_Au2v(data, ufeats):
    '''
    This method builds a measure of called Au2v which means the number of times a user's
    tweet is re-tweeted by
    @param data: a data frame containing "userid" column
    @param ufeats: user features dataframe
```

```
    '''
#     #read followership data
#     followingdat = pd.read_csv('../data/user-followership.txt', delimiter='\t')
#
#     #read user_tweet_video.txt
#     utweetdat = pd.read_csv('../data/user_tweet_video.txt', delimiter='\t')
#     utweetdat.columns = ['Userid', 'Tweetid', 'Videoid']
#     utweetdat = utweetdat.merge(data, on='Userid', how='right')
#
#     #read tweet_context.txt
#     tweets = pd.read_csv('../data/tweet-content-final.txt', delimiter='\t', encoding="ISO-8
#     tweets.columns = ["Tweetid", 'Text']
#     #add is_retweet column to this dataframe
#     tweets['Is_retweet'] = tweets['Text'].apply(lambda tweet: is_retweet(tweet))

    newdat = data.merge(ufeats[['Userid', 'fraction_of_the_users_tweets_that_were_retweeted']]
                   on='Userid', how='left')

    return newdat['fraction_of_the_users_tweets_that_were_retweeted']



def get_data():
    '''
    @return: X, y ; where X is a dataframe (Independent Variables:
    score, dscore, content_dist), and
    y is a series, dependent variable, which is the number of times a user's tweet
    is retweeted by his/her followers.
    '''
    #read score files
    scoredat = pd.read_csv('../data/userid_score.txt', delimiter='\t')
    dscoredat = pd.read_csv('../data/userid_dscore.txt', delimiter='\t')

    #merge both on common userids
    data = scoredat.merge(dscoredat, on='Twitter_UID', how='inner')
    data = data.rename(columns={"Twitter_UID":"Userid", "D_Score":'Dscore'})

    #read user_all_features.txt for number of retweets for each user
    ufeats = pd.read_csv('../data/user_all_features.txt', delimiter='\t',
                         header=None)
    ufeats.columns = USER_FEATURES

    #build content-distance column for each userid
    data = add_content_dist(data, ufeats)

    #handle nans
    data = data.dropna()
    data.index = np.arange(data.shape[0]) #re-index


    #get dependent variable
    y = get_Au2v(data, ufeats)

    #set independent variables
```

```
    X = data.drop('Userid', axis=1)

    return X, y
```

0.1 Regression Analysis

In [101]:
```
#get data
X, y = get_data()
```

In [102]:
```
y.name = 'Au2v'
```

Shape i.e. size of the data:

In [103]:
```
X.shape
```

Out[103]:
```
(71952, 3)
```

X contains three columns, as :

In [104]:
```
X.head()
```

Out[104]:

	Score	Dscore	content_dist
0	1.445670	0.06979	0.323834
1	4.358922	165.54309	0.067285
2	6.271701	0.32705	0.137112
3	0.118323	0.00910	1.000000
4	3.407387	2.65122	0.513020

Linear regression on data.

In [105]:
```
#Fit a linear model
mod = sm.OLS(endog=y, exog=X).fit()
```

In [106]:
```
#print summary
mod.summary()
```

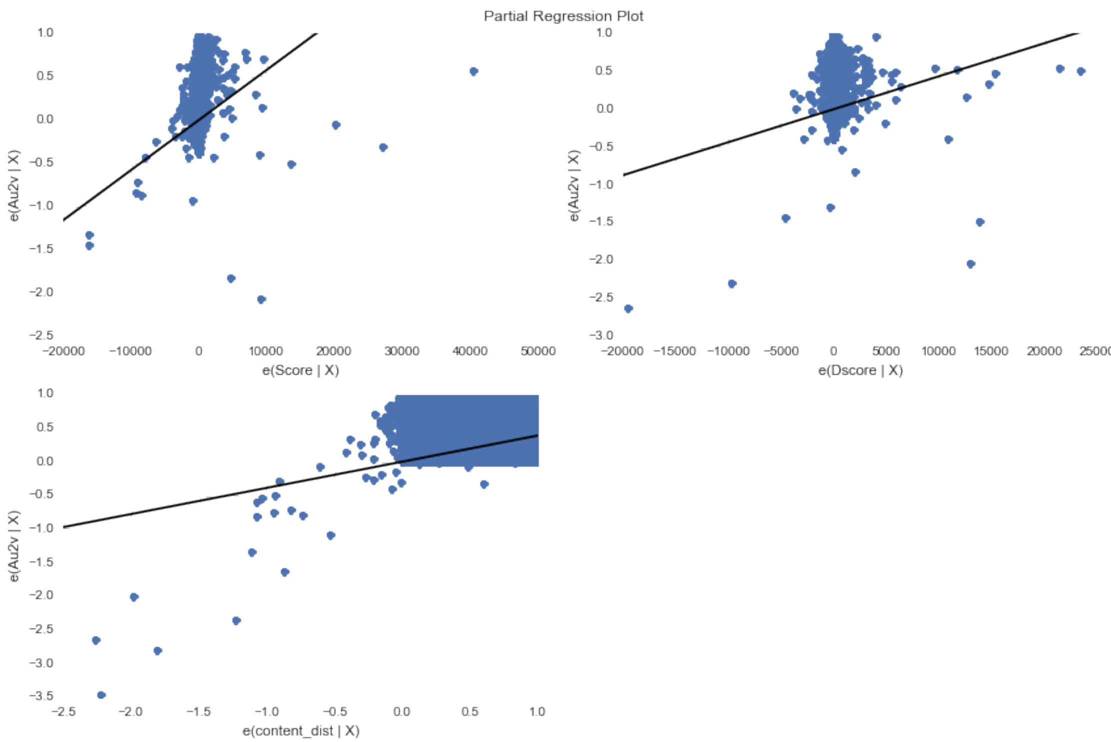
Out[106]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                   Au2v   R-squared:                       0.396
Model:                            OLS   Adj. R-squared:                  0.396
Method:                 Least Squares   F-statistic:                 1.570e+04
Date:                Tue, 21 Jul 2015   Prob (F-statistic):               0.00
Time:                        22:06:33   Log-Likelihood:                -8576.9
No. Observations:               71952   AIC:                         1.716e+04
Df Residuals:                   71949   BIC:                         1.719e+04
Df Model:                           3
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [95.0% Conf. Int.]
--------------------------------------------------------------------------------
Score         5.791e-05   3.78e-06     15.300      0.000      5.05e-05  6.53e-05
Dscore        4.364e-05   4.51e-06      9.667      0.000      3.48e-05  5.25e-05
content_dist     0.3891      0.002    213.060      0.000         0.386     0.393
==============================================================================
```

```
Omnibus:                     2091.840   Durbin-Watson:                   1.723
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2323.421
Skew:                           0.408   Prob(JB):                         0.00
Kurtosis:                       3.333   Cond. No.                         746.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
"""
```

The above regression summary shows that coeffiecients of all predictors are significant (P>|t| is greater less than 0.05). Therefore, Score, Dscore and content_dist can be considered as good predictors.

Regression plots for each independent variable:

```
In [107]: #plot regression plots for each independent variable
          fig = plt.figure(figsize=(12,8))
          fig = sm.graphics.plot_partregress_grid(mod, fig=fig)
```

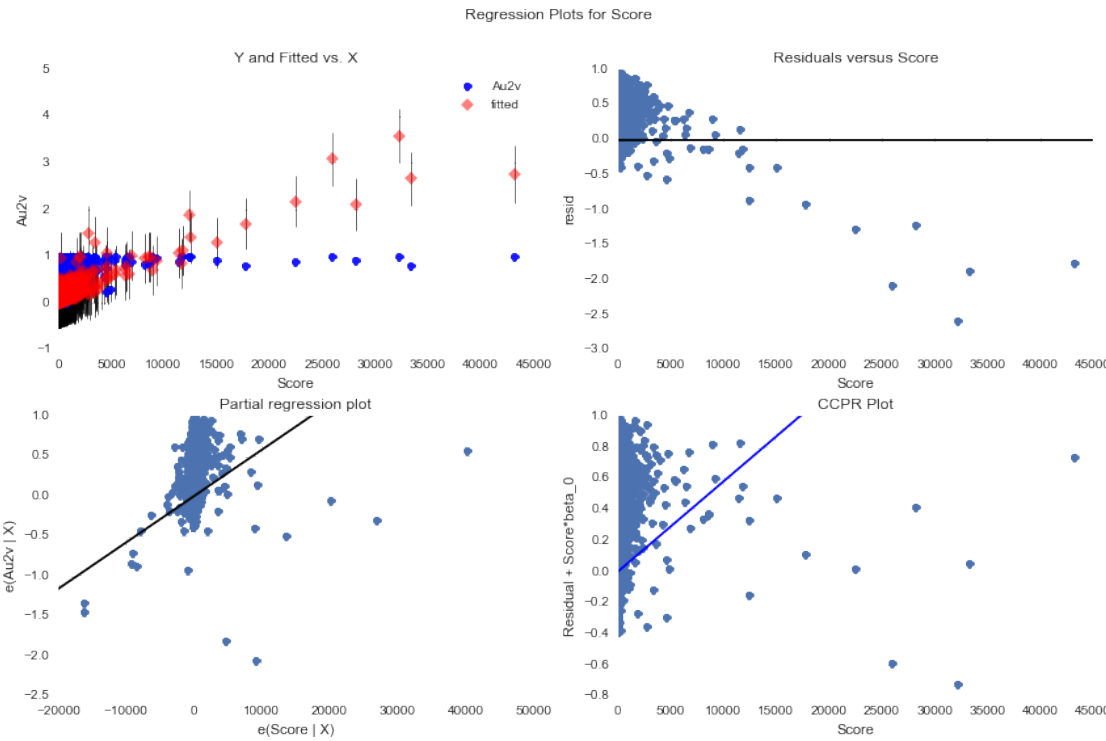


The above regression plots for each predictor shows the effect of outliers on the estimated regression coefficient. Regression line is pulled out of its optimal tracjectory due these outliers.

Regression Plots for individual Predictors

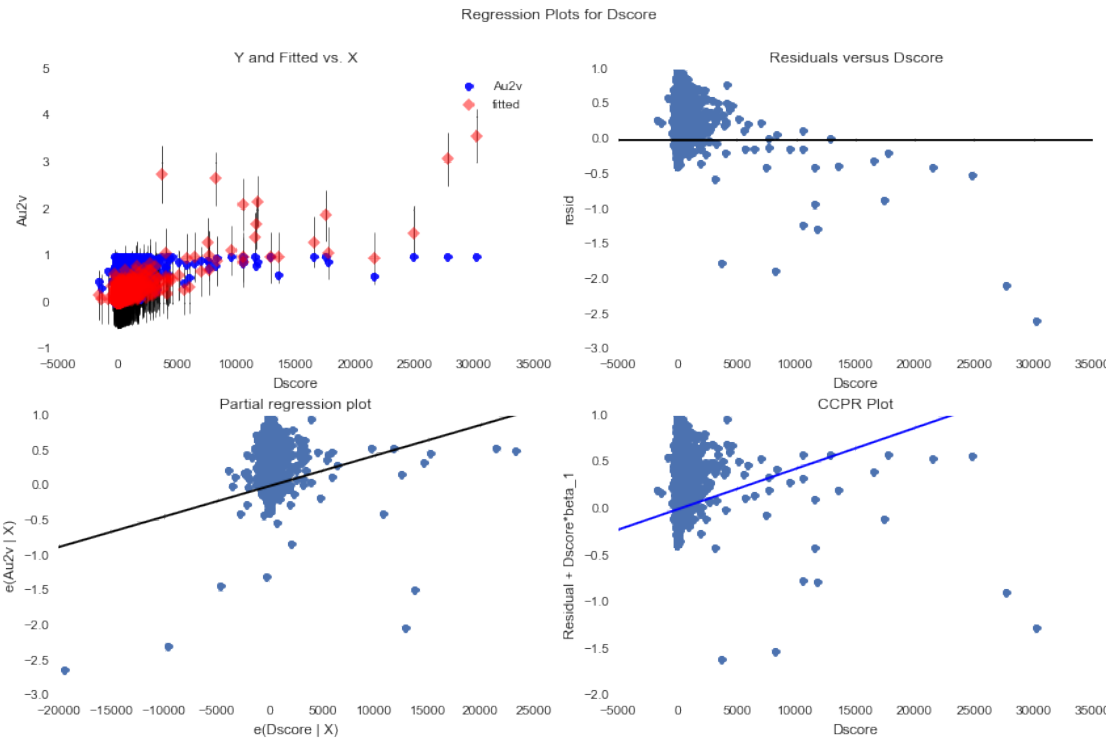
1. Regression plots for "Score" :

```
In [108]: #all regression plots for "Score"
          fig = plt.figure(figsize=(12,8))
          fig = sm.graphics.plot_regress_exog(mod, "Score", fig=fig)
```



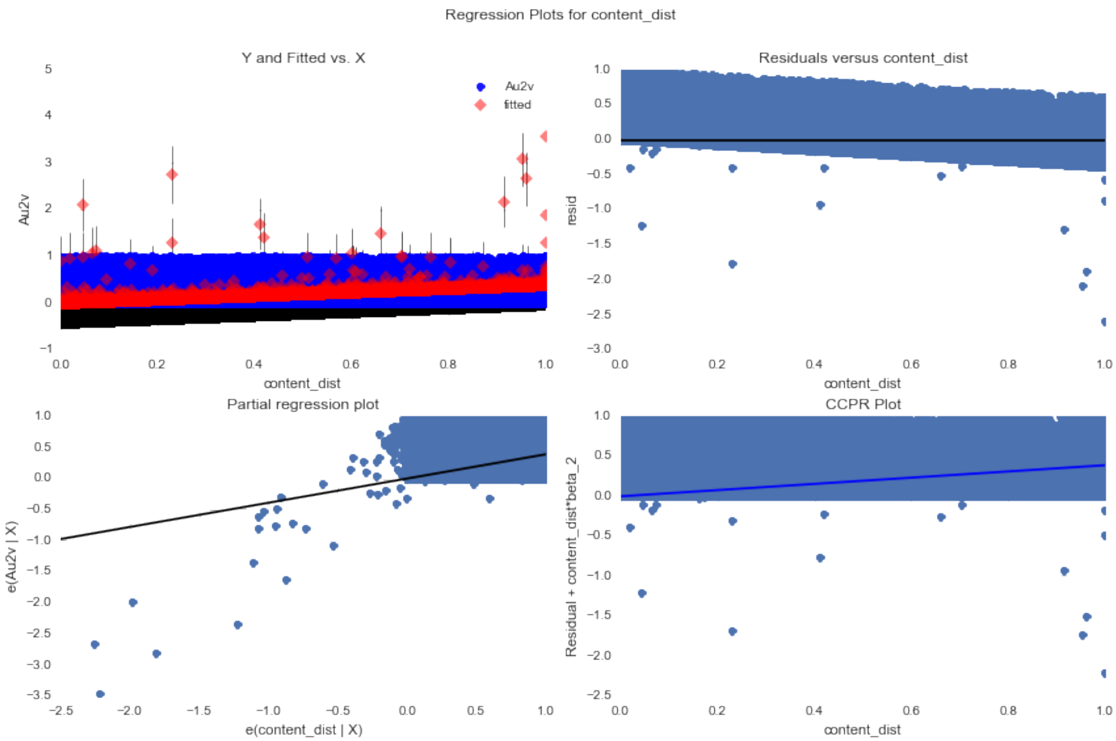
2. **Regression plots for "D_Score" :**

In [109]:
```
#all regression plots for DScore
fig = plt.figure(figsize=(12,8))
fig = sm.graphics.plot_regress_exog(mod, "Dscore", fig=fig)
```



3. Regression plots for cosine distance i.e. "content_dist" :

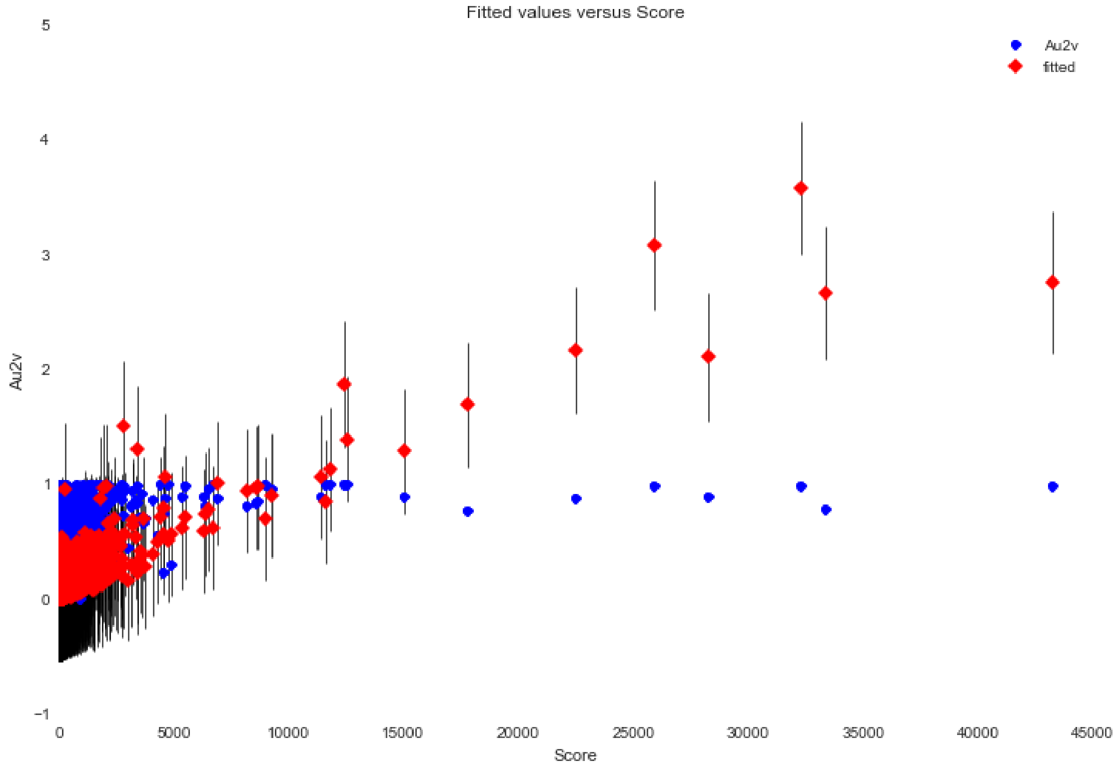
In [110]:
```
#all regression plots for cosine content_distance
fig = plt.figure(figsize=(12,8))
fig = sm.graphics.plot_regress_exog(mod, "content_dist", fig=fig)
```



Plot for each Predictors, depicting fitted values with confidence interval of predictions: The following plots show that fitted values of Au2v and its prediction confidence for each independent variable. These plots show that fitted values are quite close the true values of Au2v except for the outlier points. This suggests that removal of outliers would yield a better estimate. Removal of outliers is explored in later sections.

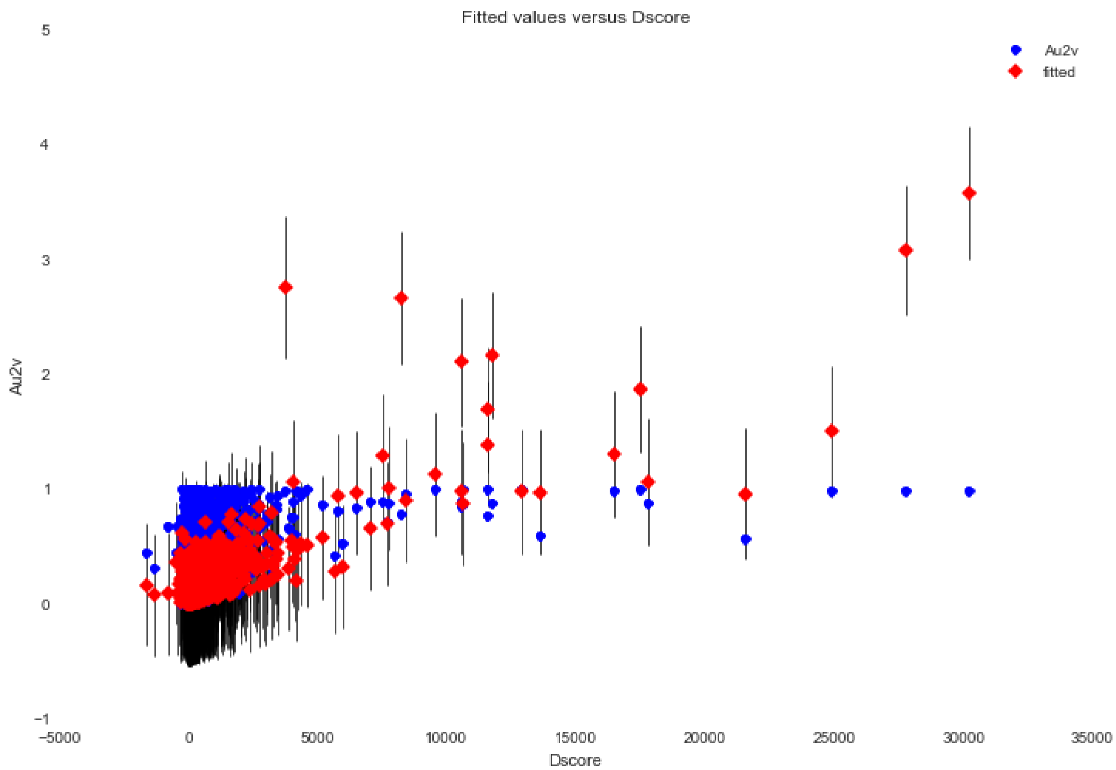
1. **Fitted values of Au2v Vs Score**

In [111]:
```
#fitted values with prediction confidence interval, for Score
fig, ax = plt.subplots(figsize=(12, 8))
fig = sm.graphics.plot_fit(mod, "Score", ax=ax)
```



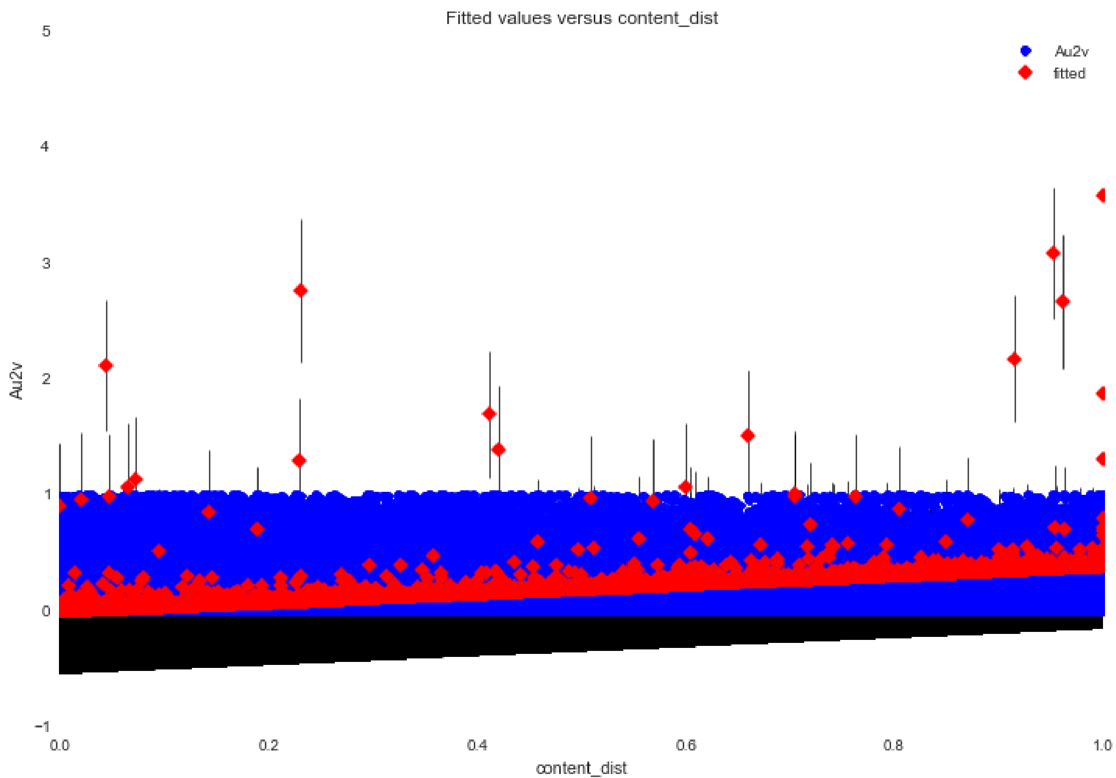
2. Fitted values of Au2v Vs Dscore

```
In [112]: #fitted values with prediction confidence interval, for Dscore
          fig, ax = plt.subplots(figsize=(12, 8))
          fig = sm.graphics.plot_fit(mod, "Dscore", ax=ax)
```



3. Fitted values of Au2v Vs content_dist

```
In [113]: #fitted values with prediction confidence interval, for content_distance
          fig, ax = plt.subplots(figsize=(12, 8))
          fig = sm.graphics.plot_fit(mod, "content_dist", ax=ax)
```



From all above plots it is clear that scale is skewed due to presence of outliers. We should handle these outliers manually or use automated robust linear regression methods for handling outliers. In the next section, we experiment on the following:

1. Robust linear regression for handling outliers
2. Building and including 3rd independent variable "content_distance" into analysis.

0.1.1 Linear Regression (after removing outliers)

A rough estimate of detecting outliers can be done by using the quantile distributions of each independent variable, as follows:

```
In [114]: #distributions for detecting outlier thresholds
          X.describe()
```

Out[114]:

	Score	Dscore	content_dist
count	71952.000000	71952.000000	71952.000000
mean	21.227703	15.880803	0.459111
std	349.102908	292.727717	0.315837
min	0.000000	-1610.253490	0.000000
25%	0.787060	0.000140	0.172534
50%	2.562232	0.526050	0.415394
75%	6.902750	2.308805	0.724986
max	43262.678131	30235.027960	1.000000

From the above table, as a guess we could take values of score and dscore only upto 10 and 5 respectively.

```
In [115]: X1 = X[(X['Score'] < 10) & (X['Dscore'] < 5)]
          y1 = y[(X['Score'] < 10) & (X['Dscore'] < 5)]

          X1.shape
```

```
Out[115]: (54473, 3)
```

Fit ordinary least squares regression model on data obtained after removing outlier data points:

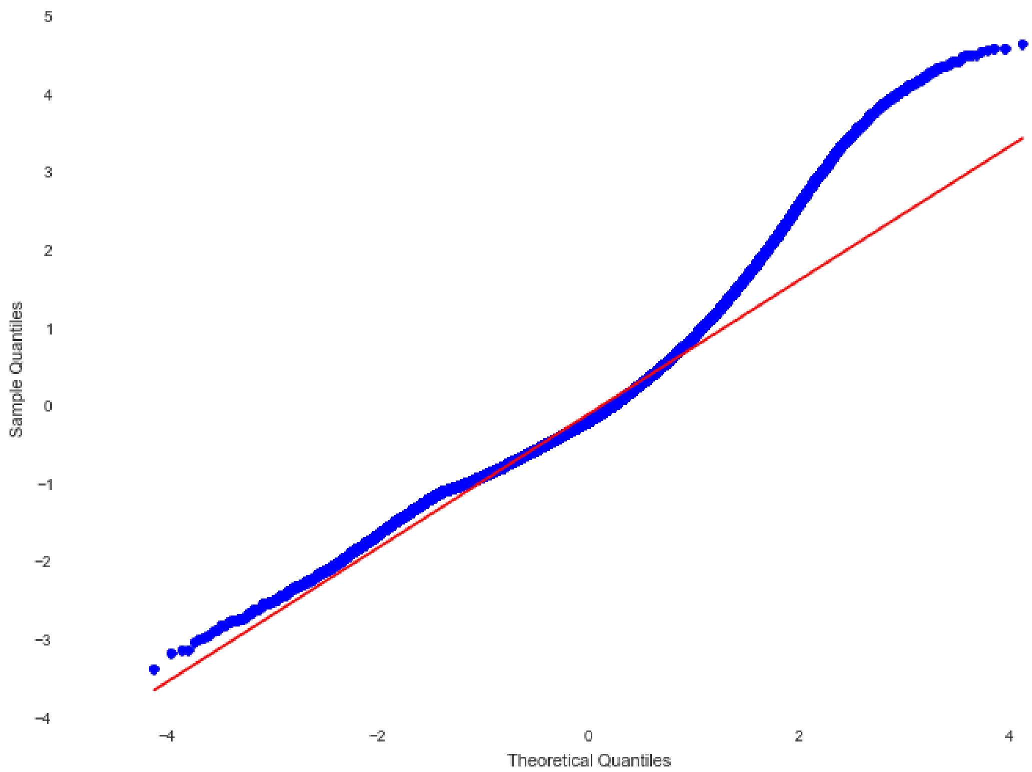
```
In [116]: #Fit a robust linear model
          mod = sm.OLS(endog=y1, exog=X1).fit()
          mod.summary()
```

```
Out[116]: <class 'statsmodels.iolib.summary.Summary'>
          """
                                      OLS Regression Results
          ==============================================================================
          Dep. Variable:                   Au2v   R-squared:                       0.574
          Model:                            OLS   Adj. R-squared:                  0.573
          Method:                 Least Squares   F-statistic:                 2.442e+04
          Date:                Tue, 21 Jul 2015   Prob (F-statistic):               0.00
          Time:                        22:06:56   Log-Likelihood:                 10185.
          No. Observations:               54473   AIC:                        -2.036e+04
          Df Residuals:                   54470   BIC:                        -2.034e+04
          Df Model:                           3
          Covariance Type:            nonrobust
          ================================================================================
                             coef    std err          t      P>|t|      [95.0% Conf. Int.]
          --------------------------------------------------------------------------------
          Score            0.0394      0.000    117.275      0.000         0.039     0.040
          Dscore           0.0365      0.001     45.284      0.000         0.035     0.038
          content_dist     0.1728      0.002     95.400      0.000         0.169     0.176
          ==============================================================================
          Omnibus:                     8209.117   Durbin-Watson:                   1.919
          Prob(Omnibus):                  0.000   Jarque-Bera (JB):            14676.365
          Skew:                           0.978   Prob(JB):                         0.00
          Kurtosis:                       4.626   Cond. No.                         7.31
          ==============================================================================

          Warnings:
          [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
          """
```

The above results show considerable improvement w.r.t. R-squared. Also, Durbin-watson statistic close to 2 confirms normality assumption of residuals. Also, all predictor's coefficients are significant as P>|t| is less than 0.05 and hence are good predictors.

Test normality of residuals using qqplot:

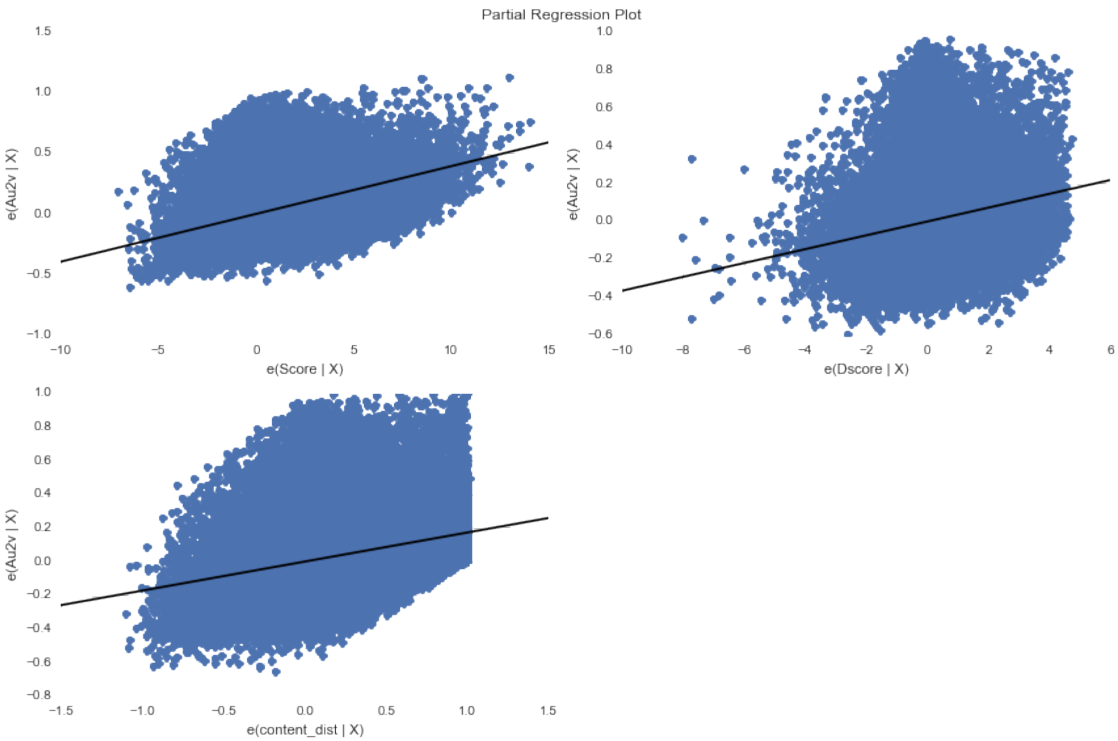
```
In [117]: #see qqplot for normality test
          from statsmodels.graphics.api import qqplot

          fig = plt.figure(figsize=(12,8))
          ax = fig.add_subplot(111)
          fig = qqplot(mod.resid, line='q', ax=ax, fit=True)
```



Above qqplot suggests deviation from normality at higher quantiles.

Regression plots for each independent variable:

```
In [118]: #plot regression plots for each independent variable
          fig = plt.figure(figsize=(12,8))
          fig = sm.graphics.plot_partregress_grid(mod, fig=fig)
```



From the above plots it is clear that after removing outliers we get a better fit of regression line on each independent variable. That is, path of regression line is now more aligned to the the optimal path.

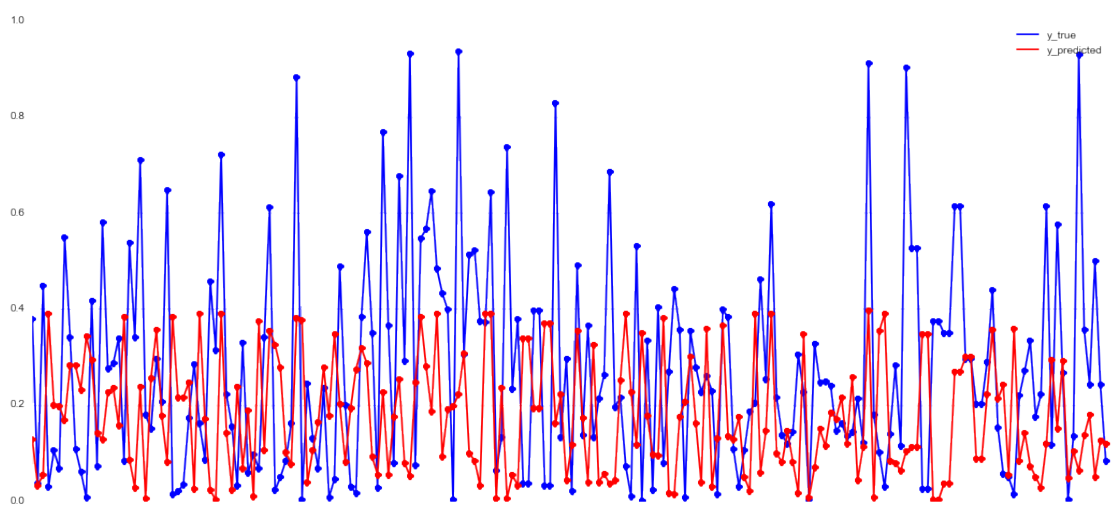
0.1.2 Predictive Modeling

```
In [156]: #Model
          from sklearn.cross_validation import KFold
          from sklearn.metrics import mean_squared_error
          from sklearn import linear_model

          rnd = np.random.RandomState(seed=13)
          shuffle = False
          nfolds = 10

          def do_cv(X, y):
              kfcv = KFold(n=X.shape[0], n_folds=nfolds, shuffle=shuffle, random_state=rnd)
              reg_lr = linear_model.LinearRegression(fit_intercept=False,
                                                     normalize=False,
                                                     copy_X=True,
                                                     n_jobs=-1)
              cv_preds = np.zeros(y.shape[0])
              for k, (cv_train, cv_test) in enumerate(kfcv):
                  reg_lr.fit(X.iloc[cv_train,:], y.iloc[cv_train])
                  ypred = reg_lr.predict(X.iloc[cv_test,:])
                  cv_preds[cv_test] = ypred
                  rmse_fold = round(np.sqrt(mean_squared_error(y.iloc[cv_test].values, ypred)), 4)
                  print("==============================================")
                  print("CV Fold "+ str(k) +" RMSE= "+ str(rmse_fold))
```

```
        print("#######Total RMSE %s"%(round(np.sqrt(mean_squared_error(y.values, cv_preds)), 4)))
        return cv_preds
```

```
In [120]: #model using linear regression on score, dscore and content-dist features
          cv_preds = do_cv(X, y)

          #plot predictions
          plot_predictions(y[:200], cv_preds[:200])
```

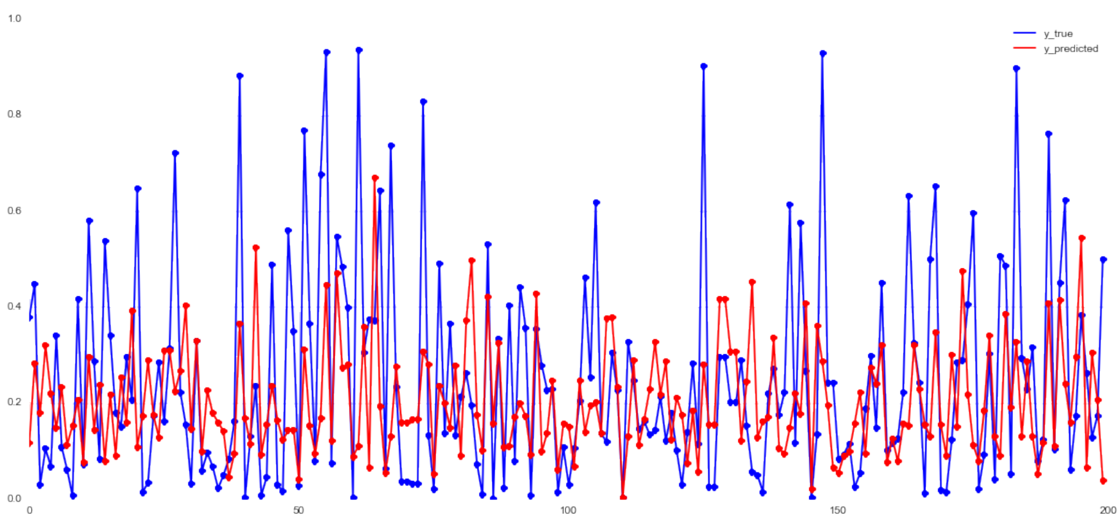
```
=============================================
CV Fold 0 RMSE= 0.2736
=============================================
CV Fold 1 RMSE= 0.267
=============================================
CV Fold 2 RMSE= 0.2773
=============================================
CV Fold 3 RMSE= 0.2701
=============================================
CV Fold 4 RMSE= 0.2749
=============================================
CV Fold 5 RMSE= 0.2728
=============================================
CV Fold 6 RMSE= 0.2722
=============================================
CV Fold 7 RMSE= 0.27
=============================================
CV Fold 8 RMSE= 0.2772
=============================================
CV Fold 9 RMSE= 0.2729
#######Total RMSE 0.2728
```



Above, we did a 10 fold cross-validation for predicting Au2v dependent variable from Score, Dscore and content-dist independent variables. The results of the predictive modeling using linear regression above show that we achieve a root mean squared error of 0.2728 (across all folds), which means that our prediction varies by 0.2728 amount from the true value of A2uv.

```
In [121]: #model using linear regression using score, dscore and content-dist features on outlier filte
          cv_preds = do_cv(X1, y1)

          #plot predictions
          plot_predictions(y1[:200], cv_preds[:200])
```

```
=============================================
CV Fold 0 RMSE= 0.2011
=============================================
CV Fold 1 RMSE= 0.1964
=============================================
CV Fold 2 RMSE= 0.2047
=============================================
CV Fold 3 RMSE= 0.2013
=============================================
CV Fold 4 RMSE= 0.2
=============================================
CV Fold 5 RMSE= 0.1999
=============================================
CV Fold 6 RMSE= 0.1995
=============================================
CV Fold 7 RMSE= 0.1988
=============================================
CV Fold 8 RMSE= 0.2034
=============================================
CV Fold 9 RMSE= 0.202
#######Total RMSE 0.2007
```



Above, we did a 10 fold cross-validation for predicting Au2v dependent variable from Score, Dscore and content-dist independent variables. This time we did predictive modeling after removing outliers from the data. The results of the predictive modeling using linear regression above show that we achieve a root mean squared error of 0.20 (across all folds), which means that our prediction varies by 0.20 amount from the true value of A2uv. This shows a considerable improvement in prediction error than modeling with original data (with outliers).

0.1.3 Classification : Predicting popularity of a user

If Au2v crosses a threshold, say 0.3, i.e. if more than 30% tweets of user 'u' are retweeted by others users then user 'u' can be considered as a popular user. This can also be interpreted as "if a user u's tweets will be popular or not given user u's DScore, score and content-distance(measure of his tweet's similiarity with his video interests)

```
In [122]: #create binary class target, popular or not popular
          thres = 0.25
          ybinary_preds = pd.Series(cv_preds)
          ybinary_preds[ybinary_preds >= thres] = 1
          ybinary_preds[ybinary_preds < thres] = 0

          ybinary_true = y1.copy(True)
          ybinary_true[y1 >= thres] = 1
          ybinary_true[y1 < thres] = 0

          #random prediction
          yrand = np.random.randint(0, 2, size=y1.shape[0])
```

```
In [123]: #calculate precision and recall metrics on our predictions
          from sklearn.metrics import precision_recall_curve, precision_score, recall_score
          precision = precision_score(ybinary_true, ybinary_preds)
          recall = recall_score(ybinary_true, ybinary_preds)
          prand = precision_score(ybinary_true, yrand)
          rrand = recall_score(ybinary_true, yrand)

          print("Model  ## Precision: %f, Recall: %f"%(precision, recall))
          print("Random ## Precision: %f, Recall: %f"%(prand, rrand))
```

```
Model  ## Precision: 0.550148, Recall: 0.395276
Random ## Precision: 0.397796, Recall: 0.502860
```

The above precision and recall of our model shows that precision is much better than random predictions, i.e. our model does learn from the predictors. However, recall is low which suggests the need of additional features/predictors to improve model.

Using Naive Bayes Classifier

```
In [157]: from sklearn.naive_bayes import GaussianNB

          #create binary classification target
          yb = y1.copy(True)
          yb[y1 >= thres] = 1
          yb[y1 < thres] = 0

          #do 10 fold cross validation with naive bayes classifier
          def do_cv_clf(X, y, clf):
              kfcv = KFold(n=X.shape[0], n_folds=nfolds, shuffle=shuffle, random_state=rnd)
              cv_preds = np.zeros(y.shape[0])
              for k, (cv_train, cv_test) in enumerate(kfcv):
                  clf.fit(X.iloc[cv_train,:], y.iloc[cv_train])
                  ypred = clf.predict(X.iloc[cv_test,:])
                  cv_preds[cv_test] = ypred
                  precisioncv = precision_score(y.iloc[cv_test].values, ypred)
                  recallcv = recall_score(y.iloc[cv_test].values, ypred)
```

```
            print("=============================================")
            print("CV Fold %d: precision= %f, recall= %f"%(k, precisioncv, recallcv))

        print("\n###### Overall Precision %s"%(precision_score(y, cv_preds)))
        print("###### Overall Recall %s"%(recall_score(y, cv_preds)))
        return cv_preds
```

```
In [125]: #create naive bayes classifier and do 10 fold crossvalidation
          gnb = GaussianNB()
          cv_preds = do_cv_clf(X1, yb, gnb)
```

```
=============================================
CV Fold 0: precision= 0.572289, recall= 0.355972
=============================================
CV Fold 1: precision= 0.558531, recall= 0.346629
=============================================
CV Fold 2: precision= 0.597454, recall= 0.340899
=============================================
CV Fold 3: precision= 0.566616, recall= 0.345633
=============================================
CV Fold 4: precision= 0.574883, recall= 0.335152
=============================================
CV Fold 5: precision= 0.556791, recall= 0.334128
=============================================
CV Fold 6: precision= 0.612585, recall= 0.363636
=============================================
CV Fold 7: precision= 0.580952, recall= 0.331372
=============================================
CV Fold 8: precision= 0.628362, recall= 0.349660
=============================================
CV Fold 9: precision= 0.572763, recall= 0.341057

######Overall Precision 0.581917381138
###### Overall Recall 0.344436242849
```

Using Random Forest Classifier

```
In [134]: #do random forest classification
          from sklearn.ensemble import RandomForestClassifier

          rf = RandomForestClassifier(n_estimators=200,
                                      n_jobs=-1,
                                      max_features=None,
                                      min_samples_split=2
                                     )
          cv_preds = do_cv_clf(X1, yb, rf)
```

```
=============================================
CV Fold 0: precision= 0.520325, recall= 0.479625
=============================================
CV Fold 1: precision= 0.519939, recall= 0.482906
=============================================
CV Fold 2: precision= 0.556517, recall= 0.467090
=============================================
CV Fold 3: precision= 0.535152, recall= 0.476413
```

```
=============================================
CV Fold 4: precision= 0.535530, recall= 0.472942
=============================================
CV Fold 5: precision= 0.517780, recall= 0.458055
=============================================
CV Fold 6: precision= 0.540323, recall= 0.482448
=============================================
CV Fold 7: precision= 0.538422, recall= 0.469443
=============================================
CV Fold 8: precision= 0.551892, recall= 0.463039
=============================================
CV Fold 9: precision= 0.526588, recall= 0.472660

######Overall Precision 0.534108688849
###### Overall Recall 0.472458018085
```

```
Out[134]: array([ 0.,  1.,  1., ...,  0.,  0.,  0.])
```

From above two classifiers, we see that for : 1. Naive Bayes classifier, precision is 0.58 (better than linear regression) and recall is 0.34(worse than linear regression) 2. Random Forest Classifier, precision is 0.53(better than baseline but not better than linear regression and naive bayes). While, recall is 0.47 (better than both naive bayes, linear regression and slightly closer to baseline).

0.1.4 Experimenting with log transformations

```
In [140]: X1.describe()
```

Out[140]:

	Score	Dscore	content_dist
count	54473.000000	54473.000000	54473.000000
mean	2.363554	0.697239	0.473769
std	2.367951	1.103082	0.317740
min	0.000000	-6.465160	0.000000
25%	0.465676	0.000010	0.186532
50%	1.651951	0.312220	0.433473
75%	3.542785	1.045990	0.746077
max	9.999569	4.999690	1.000000

```
In [172]: #do log transformation on indpendent variables
          X2 = pd.DataFrame()
          X2['log1p(Score)'] = np.log1p(X1['Score'].values)
          X2['Dscore'] = X1['Dscore'].values
          X2['log1p(content_dist)'] = np.log1p(X1['content_dist'].values)
```

```
In [173]: X2.describe()
```

Out[173]:

	log1p(Score)	Dscore	log1p(content_dist)
count	54473.000000	54473.000000	54473.000000
mean	0.977490	0.697239	0.364495
std	0.690004	1.103082	0.216389
min	0.000000	-6.465160	0.000000
25%	0.382317	0.000010	0.171035
50%	0.975296	0.312220	0.360100
75%	1.513540	1.045990	0.557372
max	2.397856	4.999690	0.693147

Training linear regression model on log(1+x) transformed data

```
In [243]: #model using linear regression using score, dscore and content-dist features on outlier filte
          cv_preds_lr = do_cv(X2, y1)

          cv_preds_lr_binary = pd.Series(cv_preds_lr)
          cv_preds_lr_binary[cv_preds_lr >= thres] = 1
          cv_preds_lr_binary[cv_preds_lr < thres] = 0

          precision = precision_score(ybinary_true, cv_preds_lr_binary)
          recall = recall_score(ybinary_true, cv_preds_lr_binary)
          prand = precision_score(ybinary_true, yrand)
          rrand = recall_score(ybinary_true, yrand)

          print("Model  ## Precision: %f, Recall: %f"%(precision, recall))
          print("Random ## Precision: %f, Recall: %f"%(prand, rrand))
```

```
=============================================
CV Fold 0 RMSE= 0.1872
=============================================
CV Fold 1 RMSE= 0.1841
=============================================
CV Fold 2 RMSE= 0.1912
=============================================
CV Fold 3 RMSE= 0.1872
=============================================
CV Fold 4 RMSE= 0.1869
=============================================
CV Fold 5 RMSE= 0.1874
=============================================
CV Fold 6 RMSE= 0.1857
=============================================
CV Fold 7 RMSE= 0.1851
=============================================
CV Fold 8 RMSE= 0.19
=============================================
CV Fold 9 RMSE= 0.1884
#######Total RMSE 0.1873
Model  ## Precision: 0.535617, Recall: 0.527265
Random ## Precision: 0.397796, Recall: 0.502860
```

The above results show that log(1+x) transformation improves the model's recall. Both Precision and recall are better than the baseline.

Training Random Forest Classifier on log(1+x) transformed data

```
In [238]: #train random forest classifier on transformed data
          rf = RandomForestClassifier(n_estimators=200,
                                      n_jobs=-1,
                                      max_features=None,
                                      min_samples_split=2
                                     )
          cv_preds_rf = do_cv_clf(X2, yb, rf)
```

```
=============================================
CV Fold 0: precision= 0.516112, recall= 0.465105
```

```
==============================================
CV Fold 1: precision= 0.516427, recall= 0.477683
==============================================
CV Fold 2: precision= 0.565241, recall= 0.473899
==============================================
CV Fold 3: precision= 0.528579, recall= 0.470808
==============================================
CV Fold 4: precision= 0.533671, recall= 0.479309
==============================================
CV Fold 5: precision= 0.516999, recall= 0.456625
==============================================
CV Fold 6: precision= 0.544944, recall= 0.480198
==============================================
CV Fold 7: precision= 0.543536, recall= 0.466274
==============================================
CV Fold 8: precision= 0.541555, recall= 0.458050
==============================================
CV Fold 9: precision= 0.528689, recall= 0.478221

###### Overall Precision 0.533465802133
###### Overall Recall 0.470658793135
```

Training Naive Bayes classifier on log(1+x) transformed data

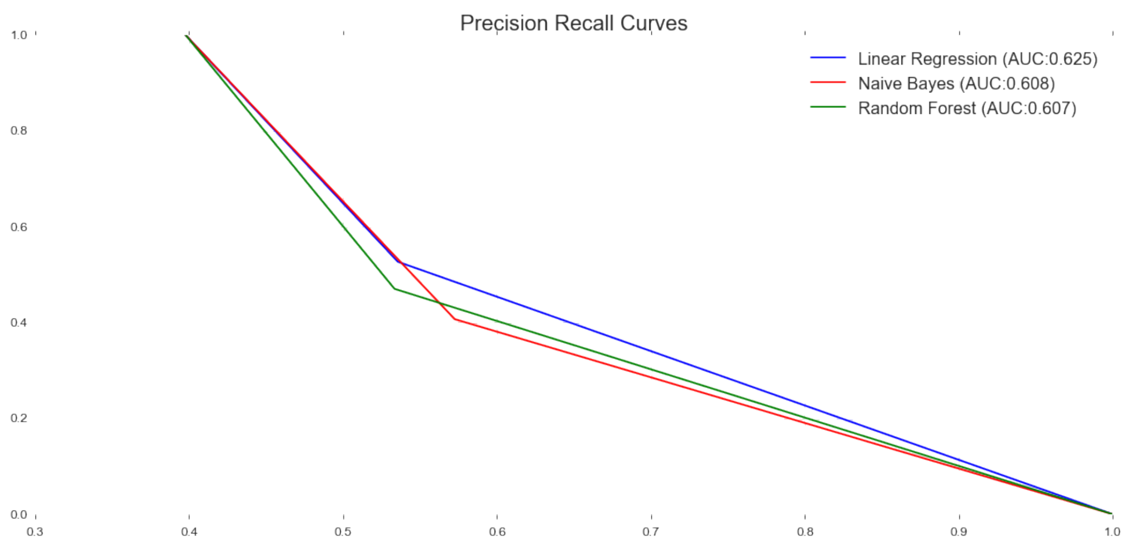
```
In [240]: gnb = GaussianNB()
          cv_preds_nb = do_cv_clf(X2, yb, gnb)
```

```
==============================================
CV Fold 0: precision= 0.566879, recall= 0.416862
==============================================
CV Fold 1: precision= 0.552598, recall= 0.414055
==============================================
CV Fold 2: precision= 0.592105, recall= 0.408534
==============================================
CV Fold 3: precision= 0.552171, recall= 0.397945
==============================================
CV Fold 4: precision= 0.569180, recall= 0.394725
==============================================
CV Fold 5: precision= 0.550763, recall= 0.395615
==============================================
CV Fold 6: precision= 0.592686, recall= 0.423042
==============================================
CV Fold 7: precision= 0.583279, recall= 0.407424
==============================================
CV Fold 8: precision= 0.602961, recall= 0.406349
==============================================
CV Fold 9: precision= 0.564020, recall= 0.408248

###### Overall Precision 0.572568093385
###### Overall Recall 0.407316848127
```

The above results on naive bayes classifier show that log(1+x) transformation has improved recall from 0.34 to 0.40, precision is slightly decreased. However, recall still remains below the baseline.

0.1.5 Comparing precision and recall of various models

In [258]:
```
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import average_precision_score

precisionlr, recalllr, _ = precision_recall_curve(ybinary_true, cv_preds_lr_binary)
auc_lr = average_precision_score(ybinary_true, cv_preds_lr_binary)

precisionrf, recallrf, _ = precision_recall_curve(ybinary_true, cv_preds_rf)
auc_rf = average_precision_score(ybinary_true, cv_preds_rf)

precisionnb, recallnb, _ = precision_recall_curve(ybinary_true, cv_preds_nb)
auc_nb = average_precision_score(ybinary_true, cv_preds_nb)

plt.plot(precisionlr, recalllr, '-b', label='Linear Regression (AUC:%0.3f)'%auc_lr)
plt.plot(precisionnb, recallnb, '-r', label='Naive Bayes (AUC:%0.3f)'%auc_nb)
plt.plot(precisionrf, recallrf, '-g', label='Random Forest (AUC:%0.3f)'%auc_rf)

plt.title("Precision Recall Curves")
plt.legend()
plt.savefig('../figures/precision_recall_curves.png', format='png', dpi=1200)
plt.show()
```



The above precision-recall curves shows a comparision of performances for Linear Regression, Naive Bayes and Random Forest methods. Higher Area under this curve (AUC) represents better performance, with AUC=1 being the highest achievable performance by a classifier. Above plot shows that Linear Regression has the highest AUC of 0.625.

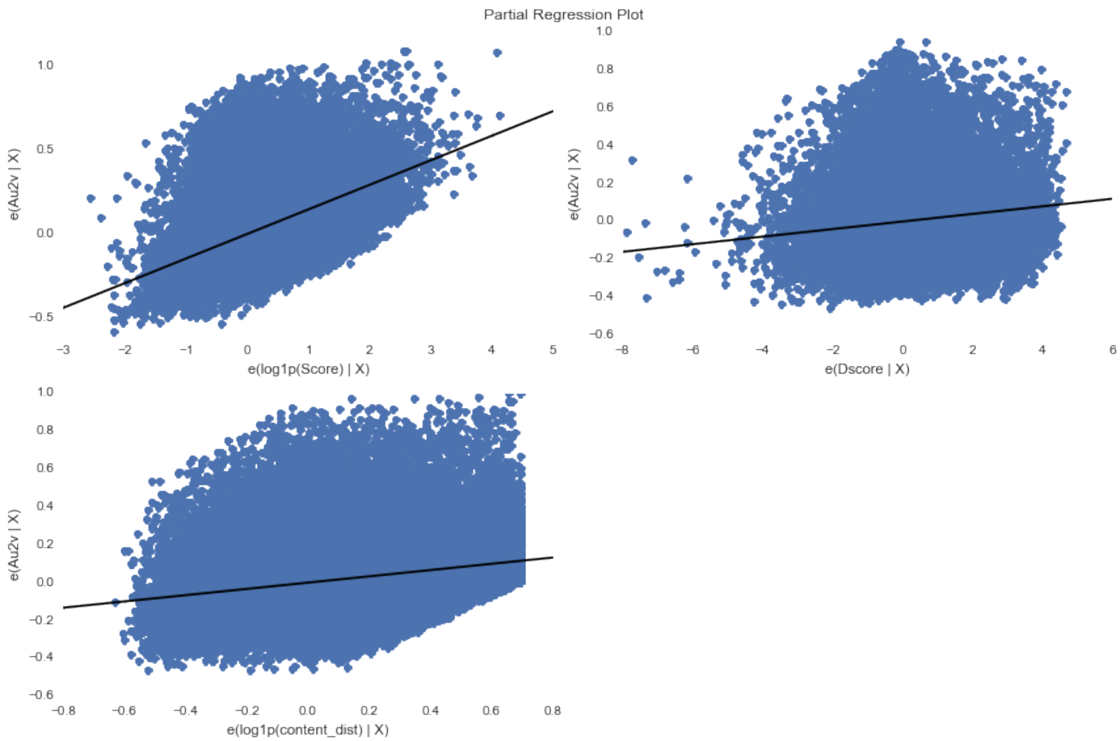
0.1.6 Linear Regression and Plots with log(1+x) transformations

In [174]:
```
#Fit a robust linear model
y2 = y1.copy(True); y2.index = np.arange(y2.shape[0])
mod = sm.OLS(endog=y2, exog=X2).fit()
mod.summary()
```

```
Out[174]: <class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                   Au2v   R-squared:                       0.629
Model:                            OLS   Adj. R-squared:                  0.629
Method:                 Least Squares   F-statistic:                 3.072e+04
Date:                Thu, 23 Jul 2015   Prob (F-statistic):               0.00
Time:                        22:13:30   Log-Likelihood:                 13947.
No. Observations:               54473   AIC:                        -2.789e+04
Df Residuals:                   54470   BIC:                        -2.786e+04
Df Model:                           3
Covariance Type:            nonrobust
=========================================================================================
                         coef    std err          t      P>|t|      [95.0% Conf. Int.]
-----------------------------------------------------------------------------------------
log1p(Score)           0.1460      0.001    145.244      0.000         0.144     0.148
Dscore                 0.0200      0.001     25.819      0.000         0.018     0.022
log1p(content_dist)    0.1656      0.003     65.690      0.000         0.161     0.171
==============================================================================
Omnibus:                    10848.216   Durbin-Watson:                   1.966
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            22428.486
Skew:                           1.183   Prob(JB):                         0.00
Kurtosis:                       5.070   Cond. No.                         5.19
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
"""
```

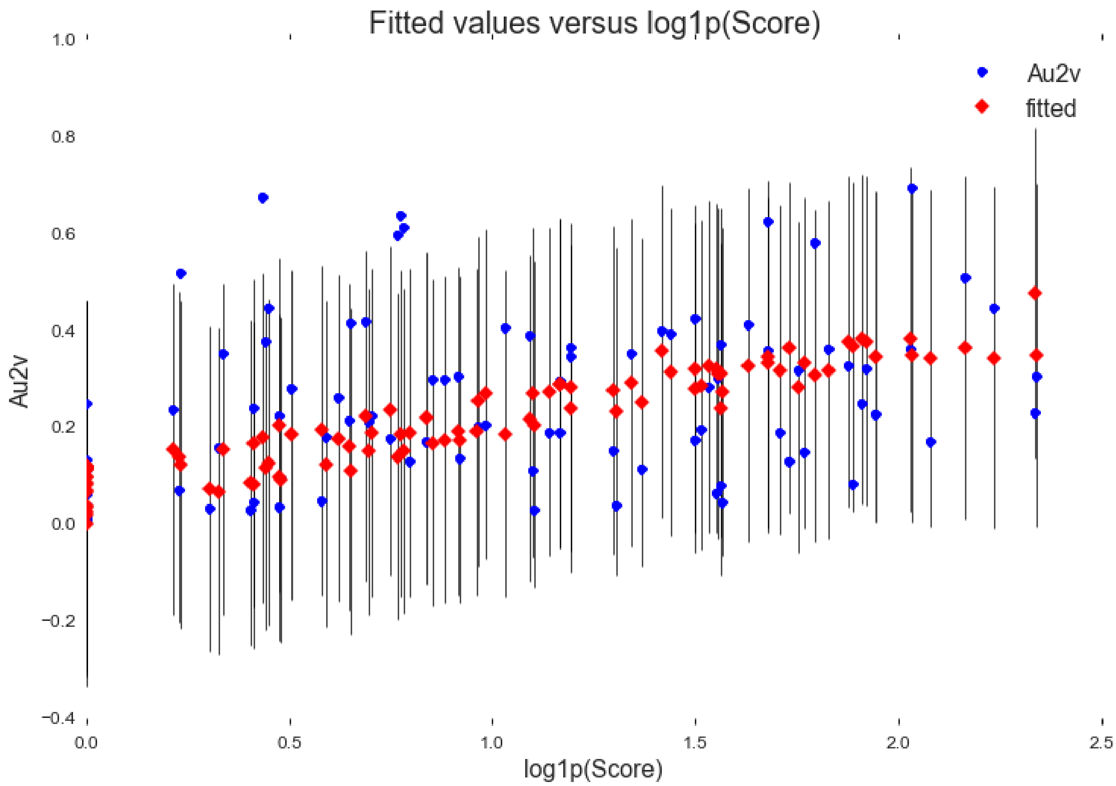
High Resolution plots

```
In [175]: #plot regression plots for each independent variable
          fig = plt.figure(figsize=(12,8))
          fig = sm.graphics.plot_partregress_grid(mod, fig=fig)
```

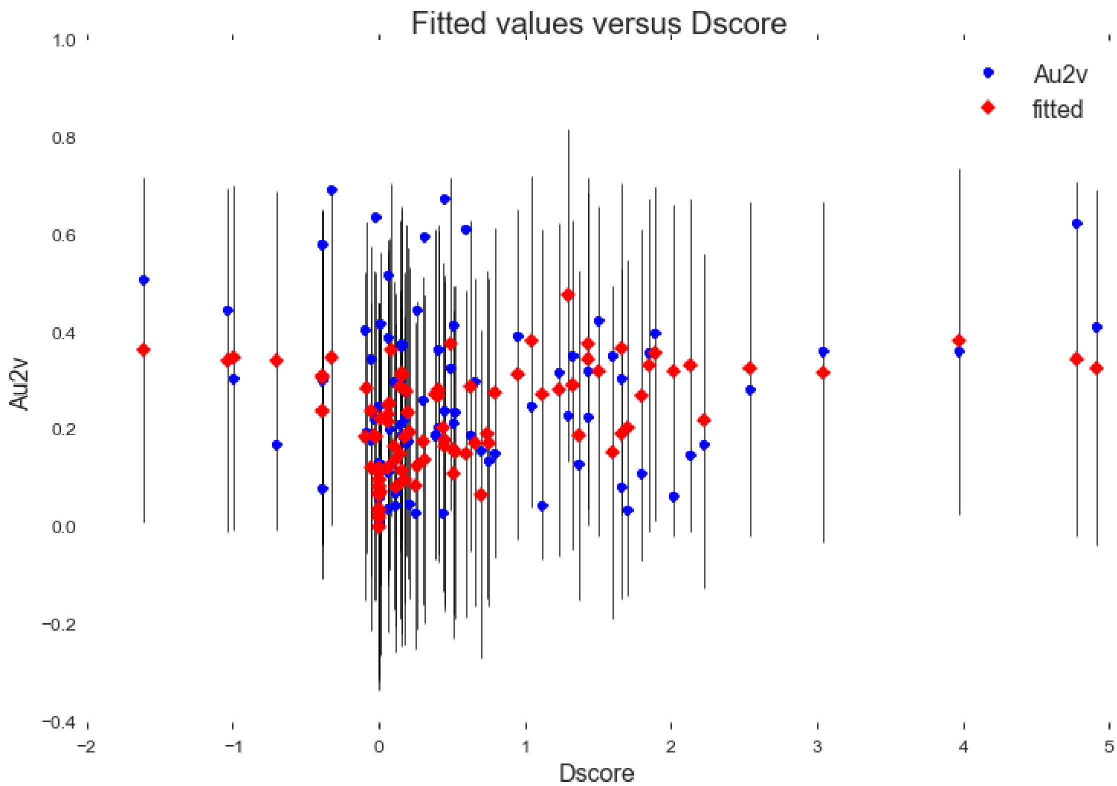



```
In [226]: #fitted values with prediction confidence interval, for Score
          indx = np.random.randint(0, y2.shape[0], 100)
          mod1 = sm.OLS(endog=y2[indx], exog=X2.ix[indx,:]).fit()

          #plot parameters for enhanced plots
          plt.rcParams.update({'axes.titlesize': 20})
          plt.rcParams.update({'axes.labelsize': 16})
          plt.rcParams.update({'legend.fontsize': 16})
          plt.rcParams.update({'legend.fancybox':True})
          plt.rcParams.update({'xtick.labelsize':12})
          plt.rcParams.update({'ytick.labelsize':12})
```

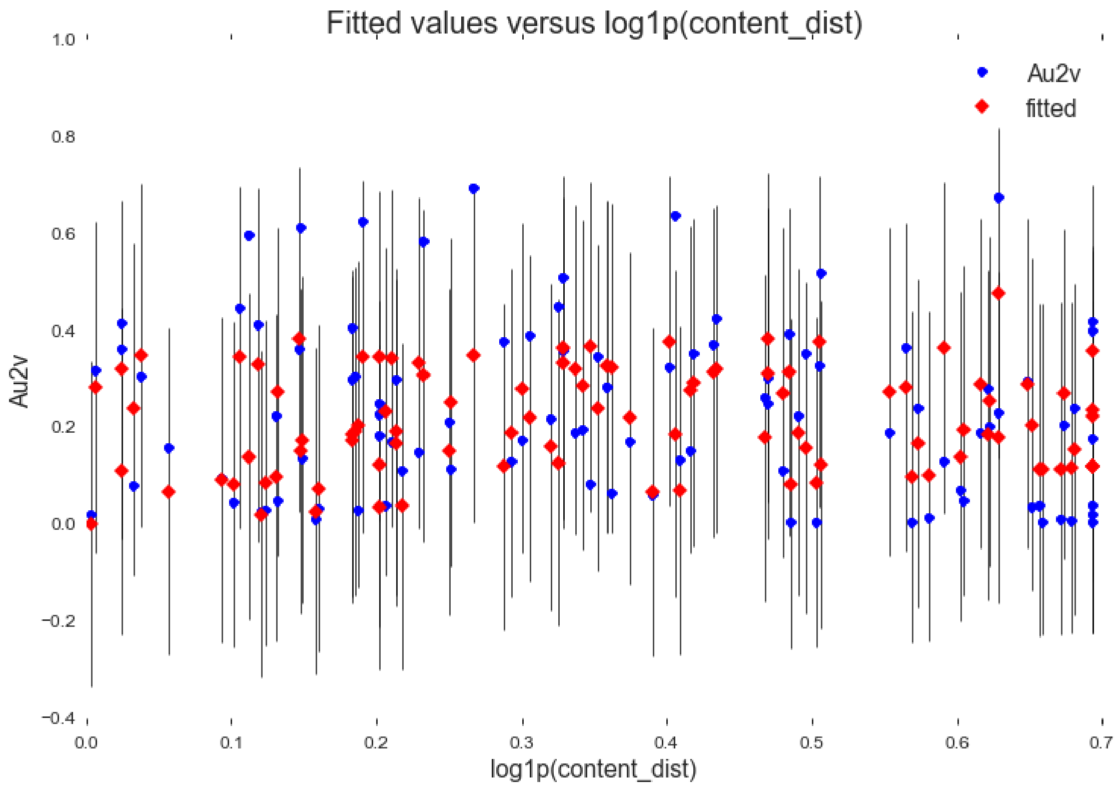
```
In [231]: fig, ax = plt.subplots(figsize=(12, 8))
          fig = sm.graphics.plot_fit(mod1, "log1p(Score)", ax=ax)
          fig.savefig('../figures/log1p(Score)_fitted.png', format='png', dpi=1200)
```




```
In [232]: fig, ax = plt.subplots(figsize=(12, 8))
          fig = sm.graphics.plot_fit(mod1, "Dscore", ax=ax)
          fig.savefig('../figures/Dscore_fitted.png', format='png', dpi=1200)
```




```
In [233]: fig, ax = plt.subplots(figsize=(12, 8))
          fig = sm.graphics.plot_fit(mod1, "log1p(content_dist)", ax=ax)
          fig.savefig('../figures/log1p(content_dist)_fitted.png', format='png', dpi=1200)
```


Fitted values versus log1p(content_dist)
Au2v
fitted
Au2v
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
log1p(content_dist)