CS156 Assignment 5

PCA & LDA for Classifying EigenFashion

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Text Analysis is after each corresponding code block, and complete longer analysis of results is at the end.

In [31]:
```
# original code reference: (By Joel Grus, author of the blog mentioned i
n the preclass-work)
# adapted from https://github.com/joelgrus/shirts/blob/master

### Setup ###
from PIL import Image
import PIL.ImageOps

from collections import defaultdict
from glob import glob
from random import shuffle, seed
import numpy as np
import pylab as pl
import pandas as pd
import re
import matplotlib.pyplot as plt
from sklearn import metrics #, linear_model,
from sklearn.decomposition import RandomizedPCA
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.linear_model import LogisticRegression
from sklearn.svm import LinearSVC
%matplotlib inline
```

In [9]:
```
# Fetching Files (globbing them)
girls_files = glob('/Users/tomereldor/PycharmProjects/CS156ML/PCA/women/
womensample/*')
boys_files = glob('/Users/tomereldor/PycharmProjects/CS156ML/PCA/men/men
sample/*')

# STANDARTIZE SIZE and SHAPE
STANDARD_SIZE = (138,138) #most common size found in the dataset
HALF_SIZE = (STANDARD_SIZE[0]/2,STANDARD_SIZE[1]/2)

def img_to_array(filename):
    # takes a filename and turns it into a numpy array of RGB pixels
    img = Image.open(filename)
    img = img.resize(STANDARD_SIZE)
    img = list(img.getdata())
    img = map(list, img)
    img = np.asarray(img) # np.asarray() will extricate the RGB channels
 from each pixel in the original image),
    s = img.shape[0] * img.shape[1] #size
    img_wide = img.reshape(1, s) #reshaping
    # Image.close()
    return img_wide[0]

# Processing files: converting Image to Numpy RGB arrays
raw_data = [(img_to_array(filename),'girl',filename) for filename in gir
ls_files] + \
           [(img_to_array(filename),'boy',filename) for filename in boys
_files]

## print(raw_data[:10]) #debug

# shuffle the data ('randomly', though I'm seeding for replicating resul
ts)
seed(0)
shuffle(raw_data)

# pull out the features and the labels
data = np.array([cd for (cd,_y,f) in raw_data])
labels = np.array([_y for (cd,_y,f) in raw_data])
```

Splitting the dataset from the into 80% training data and 20% testing data.

In [10]:
```
train_split = int(0.8*len(data))
#splitting:
X_train , X_test = data[:train_split] , data[train_split:]
y_train , y_test = labels[:train_split] , labels[train_split:]

#debug / verification:
print("X   Train N: {}, X   Test N: {}".format(len(X_train), len(X_test)))
print("Y   Train N: {}, Y   Test N: {}".format(len(y_train), len(y_test)))
```

```
X   Train N: 336, X   Test N: 84
Y   Train N: 336, Y   Test N: 84
```

2) Build a simple linear classifier using the original pixel data. What is your error rate on the training data? What is your error rate on your testing data?

I start with a simple linear model - **Logistic Regression**. I chose logistic regression since it is simple and good as a starting point, in case it works well. It is useful for me since I'm more familiar with it and wanted to see how well it would perform in this case.

In [44]:
```
## LOGISTIC REGRESSION
# fitting the model
clf_log =  LogisticRegression(penalty='l2')  # sepcifying penalty (regul
arization term) of L2, with a dual formulation only for the L2 penalty.
clf_log.fit(X_train, y_train)

# TRAIN set prediction and accuracy
print "Logistic Regression: Trainig set (no reduction)"
predicted_train_log = clf_log.predict(X_train)
score_log_train = clf_log.score(X_train, y_train)
print "\nAccuracy Score on test set: %.3f" % score_log_train
print(metrics.confusion_matrix(y_train, predicted_train_log))
print "\nClassification report on test set"
print(metrics.classification_report(y_train, predicted_train_log))
print "____________________________________________________"

# TEST set prediction and accuracy
print "\nLogistic Regression: TEST set (no reduction)"
predicted_test_log = clf_log.predict(X_test)
score_log_test = clf_log.score(X_test, y_test)
print "Accuracy Score on test set: %.3f" % score_log_test
print "\nConfusion Matrix on test set: "
print(metrics.confusion_matrix(y_test, predicted_test_log))
print "\nClassification report on test set"
print(metrics.classification_report(y_test, predicted_test_log))
```

```
Logistic Regression: Trainig set (no reduction)

Accuracy Score on test set: 1.000
[[173   0]
 [  0 163]]

Classification report on test set
             precision    recall  f1-score   support

          0       1.00      1.00      1.00       173
          1       1.00      1.00      1.00       163

avg / total       1.00      1.00      1.00       336
```

```
Logistic Regression: TEST set (no reduction)
Accuracy Score on test set: 0.631

Confusion Matrix on test set:
[[27 10]
 [21 26]]

Classification report on test set
             precision    recall  f1-score   support

          0       0.56      0.73      0.64        37
          1       0.72      0.55      0.63        47

avg / total       0.65      0.63      0.63        84
```

Logistic Regression with no dimensionality regression performs reasonably but unimpressively, with 0.63 accuracy score overall on the test set. Conversely, we have perfect 1.00 accuracy on the training set, but that isn't surprising and is even not a very good sign since it means that our model is overfitting on the data - what logistic regression can often result with... Also, we see there is some imbalance with the precision-recall per class - the model performs with much higher precision for boys (0.72 vs 0.56) while exhibiting the opposite trend - much higher recall for girls (0.55 vs 0.73). That shows us the model is not balanced in determining male/female; according to the confusion matrix, we see it predicts significantly more false positives. Theoretically, since this is a logistic regression, in this case of too many false positives, we could try adjusting the cutoff value to classify as positive to be slightly higher and see if our accuracy improves. Additionally, I don't think this is the ideal case to use logistic regression since I usually work with logistic regressions when I want to manually insert the features, having an idea of which features or combinations of features should make sense (thus not include everything). However, in this image recognition, the model is left with inspecting all the raw pixel colors data and make sense of it itself. That's why reducing dimensionality should visibly improve logistic regression. Therefore, I wanted to try another kind of model - SVC linear classifier - and see if it performs better on the test set.

In [45]:

```
#LINEAR SVC MODEL
# from sklearn.svm import LinearSVC

# fitting the model
clf_svc =  LinearSVC(random_state = 42) #(if we give it the answer to th
e question about the meaning of life and everything as a random seed it
 might perform better since it knows already the answer to everything)
clf_svc.fit(X_train, y_train)

# Train set prediction and accuracy
print "\nLinear SVC Classifier, TRAINING Set (no reduction)"
predicted_train_svc = clf_svc.predict(X_train)
score_svc_train = clf_svc.score(X_train, y_train)
print "Accuracy Score on training set: %.3f" % score_svc_train
print "\nConfusion Matrix on test set: "
print(metrics.confusion_matrix(y_train, predicted_train_svc))
print "\nClassification report on test set"
print(metrics.classification_report(y_train, predicted_train_svc))
print "____________________________________________________"

# Test set prediction and accuracy
predicted_test_svc = clf_svc.predict(X_test)
score_svc_test = clf_svc.score(X_test,y_test)
print "\nLinear SVC Classifier, TEST SET (no reduction)"
print "Accuracy Score on test set: %.3f" % score_svc_test
print "\nConfusion Matrix on test set: "
print(metrics.confusion_matrix(y_test, predicted_test_svc))
print "\nClassification report on test set"
print(metrics.classification_report(y_test, predicted_test_svc))
```

```
Linear SVC Classifier, TRAINING Set (no reduction)
Accuracy Score on training set: 1.000

Confusion Matrix on test set:
[[173   0]
 [  0 163]]

Classification report on test set
             precision    recall  f1-score   support

          0       1.00      1.00      1.00       173
          1       1.00      1.00      1.00       163

avg / total       1.00      1.00      1.00       336
```

```
Linear SVC Classifier, TEST SET (no reduction)
Accuracy Score on test set: 0.631

Confusion Matrix on test set:
[[28  9]
 [22 25]]

Classification report on test set
             precision    recall  f1-score   support

          0       0.56      0.76      0.64        37
          1       0.74      0.53      0.62        47

avg / total       0.66      0.63      0.63        84
```

After running a linear SVC classifier on the (non-reduced) data, the model did a fair but unimpressive job predicting on the test set, with an accuracy of 0.631. Similarly, it does predict with perfect 1.00 accuracy on the training set, but that just means overfitting, and we should not be too happy about this. This explains the major differences between 1.00 accuracy on the training set to 0.63 accuracies on the test set. This also exhibits the same trend of predicting too many false positives over false negatives and thus creates an imbalanced prediction.

Also, I'm not using many samples - only 200 in the first trials; while we have many many features for the models to include. Thus there might be more features than observations, which is bad for the model. Because of the curse of dimensionality, this makes it harder for the model to find the correct costs/distances/what features to use and how to correctly classify, having so many features but few samples.

Perhaps SVC with a nonlinear kernel, such as RBF SVM, would have been more flexible and improved accuracy.

Modeling with PCA and LDA

Below I create both PCA and LDA principal components for dimensionality reductions parallelly (as it's more concise), then train the same model as before on PCA data and LDA data and compare results.

In [54]:
```
### PCA! - find the principal components
pca = RandomizedPCA(n_components=70, random_state=0)
X_PCA = pca.fit_transform(data)
y = [1 if label == 'boy' else 0 for label in labels]

### LDA! - find the LDA reduced dimensions
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
lda = LinearDiscriminantAnalysis(n_components=15)
#X_LDA = lda.fit(X_PCA, y).transform(X_PCA)
X_LDA = lda.fit_transform(data,y)

# Percentage of variance explained for each component
pca_var_ratios = pca.explained_variance_ratio_
lda_var_ratios = lda.explained_variance_ratio_
```

```
/Users/tomereldor/anaconda/lib/python2.7/site-packages/sklearn/utils/de
precation.py:57: DeprecationWarning: Class RandomizedPCA is deprecated;
RandomizedPCA was deprecated in 0.18 and will be removed in 0.20. Use P
CA(svd_solver='randomized') instead. The new implementation DOES NOT st
ore whiten ``components_``. Apply transform to get them.
  warnings.warn(msg, category=DeprecationWarning)
```

Choosing number of components for LDA and PCA

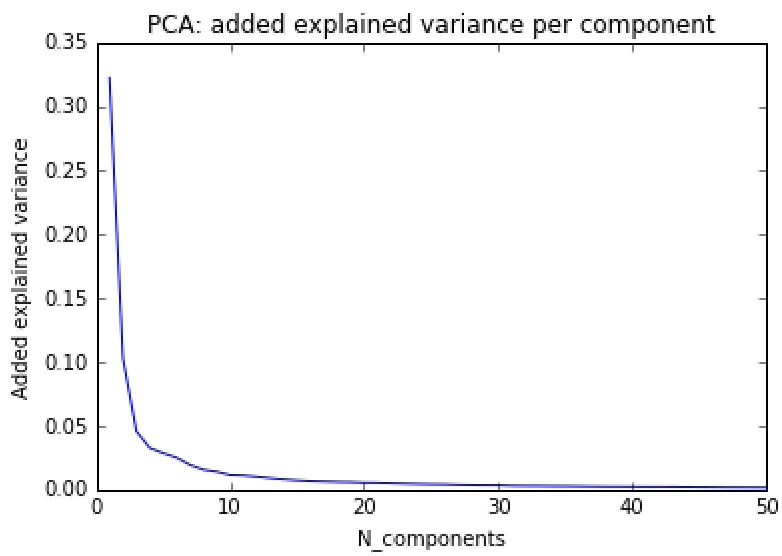
In [55]:
```
# CHOOSING THE NUMBER OF COMPONENTS TO USE IN EITHER PCA AND LDA!
# For that, we will compute when the total variance explained is higher
 than 0.99
def select_n_components(var_ratio, goal_var):
        total_variance = 0.0 # set initial variance explained
        n_components = 0     # set initial number of features
        components = []
        var_inc = []
        var_total = []
        # For the explained variance of each feature:
        for explained_variance in var_ratio:
            # Add the explained variance to the total
            total_variance += explained_variance
            # Add one to the number of components
            n_components += 1
            # If we reach our goal level of explained variance
            print "component %d adds %.4f to variance, now total varianc
e is %.4f" % (n_components, explained_variance, total_variance)
            #results.append([n_components, explained_variance, total_var
iance])
            components.append(n_components)
            var_inc.append(explained_variance)
            var_total.append(total_variance)
            if total_variance >= goal_var:
                break     # End the loop if we reached our goal variance
 explained
        return n_components, components,var_inc,var_total   # Return the
 number of components

print "PCA Dimensions: "
pca_n_components, pca_components_ids, pca_var_inc, pca_var_total = selec
t_n_components(pca_var_ratios, 0.95)
print "PCA components selected: ", pca_n_components
```

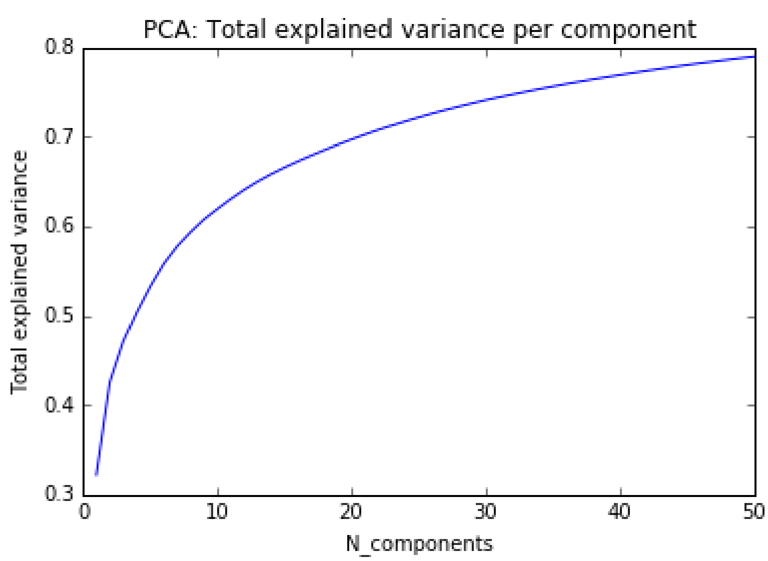
```
PCA Dimensions:
component 1 adds 0.3223 to variance, now total variance is 0.3223
component 2 adds 0.1032 to variance, now total variance is 0.4254
component 3 adds 0.0459 to variance, now total variance is 0.4713
component 4 adds 0.0329 to variance, now total variance is 0.5042
component 5 adds 0.0288 to variance, now total variance is 0.5330
component 6 adds 0.0253 to variance, now total variance is 0.5583
component 7 adds 0.0196 to variance, now total variance is 0.5779
component 8 adds 0.0158 to variance, now total variance is 0.5937
component 9 adds 0.0143 to variance, now total variance is 0.6080
component 10 adds 0.0116 to variance, now total variance is 0.6196
component 11 adds 0.0112 to variance, now total variance is 0.6308
component 12 adds 0.0103 to variance, now total variance is 0.6411
component 13 adds 0.0092 to variance, now total variance is 0.6503
component 14 adds 0.0082 to variance, now total variance is 0.6585
component 15 adds 0.0074 to variance, now total variance is 0.6659
component 16 adds 0.0068 to variance, now total variance is 0.6728
component 17 adds 0.0065 to variance, now total variance is 0.6793
component 18 adds 0.0062 to variance, now total variance is 0.6855
component 19 adds 0.0060 to variance, now total variance is 0.6915
component 20 adds 0.0056 to variance, now total variance is 0.6972
component 21 adds 0.0055 to variance, now total variance is 0.7027
component 22 adds 0.0052 to variance, now total variance is 0.7079
component 23 adds 0.0049 to variance, now total variance is 0.7128
component 24 adds 0.0046 to variance, now total variance is 0.7174
component 25 adds 0.0044 to variance, now total variance is 0.7218
component 26 adds 0.0043 to variance, now total variance is 0.7262
component 27 adds 0.0040 to variance, now total variance is 0.7302
component 28 adds 0.0038 to variance, now total variance is 0.7340
component 29 adds 0.0037 to variance, now total variance is 0.7377
component 30 adds 0.0036 to variance, now total variance is 0.7413
component 31 adds 0.0033 to variance, now total variance is 0.7446
component 32 adds 0.0032 to variance, now total variance is 0.7478
component 33 adds 0.0031 to variance, now total variance is 0.7509
component 34 adds 0.0030 to variance, now total variance is 0.7540
component 35 adds 0.0030 to variance, now total variance is 0.7570
component 36 adds 0.0029 to variance, now total variance is 0.7598
component 37 adds 0.0027 to variance, now total variance is 0.7626
component 38 adds 0.0026 to variance, now total variance is 0.7652
component 39 adds 0.0026 to variance, now total variance is 0.7677
component 40 adds 0.0025 to variance, now total variance is 0.7702
component 41 adds 0.0025 to variance, now total variance is 0.7727
component 42 adds 0.0024 to variance, now total variance is 0.7750
component 43 adds 0.0024 to variance, now total variance is 0.7774
component 44 adds 0.0023 to variance, now total variance is 0.7797
component 45 adds 0.0022 to variance, now total variance is 0.7819
component 46 adds 0.0022 to variance, now total variance is 0.7841
component 47 adds 0.0021 to variance, now total variance is 0.7862
component 48 adds 0.0020 to variance, now total variance is 0.7883
component 49 adds 0.0020 to variance, now total variance is 0.7903
component 50 adds 0.0019 to variance, now total variance is 0.7922
component 51 adds 0.0019 to variance, now total variance is 0.7941
component 52 adds 0.0019 to variance, now total variance is 0.7960
component 53 adds 0.0019 to variance, now total variance is 0.7979
component 54 adds 0.0018 to variance, now total variance is 0.7997
component 55 adds 0.0018 to variance, now total variance is 0.8014
component 56 adds 0.0018 to variance, now total variance is 0.8032
```

```
component 57 adds 0.0017 to variance, now total variance is 0.8049
component 58 adds 0.0017 to variance, now total variance is 0.8066
component 59 adds 0.0016 to variance, now total variance is 0.8082
component 60 adds 0.0016 to variance, now total variance is 0.8098
component 61 adds 0.0015 to variance, now total variance is 0.8113
component 62 adds 0.0015 to variance, now total variance is 0.8128
component 63 adds 0.0015 to variance, now total variance is 0.8143
component 64 adds 0.0014 to variance, now total variance is 0.8157
component 65 adds 0.0014 to variance, now total variance is 0.8172
component 66 adds 0.0014 to variance, now total variance is 0.8186
component 67 adds 0.0014 to variance, now total variance is 0.8199
component 68 adds 0.0013 to variance, now total variance is 0.8213
component 69 adds 0.0013 to variance, now total variance is 0.8226
component 70 adds 0.0013 to variance, now total variance is 0.8239
PCA components selected:  70
```

In [60]:

```
## PLOTTING Components Explained Variance
def plot_variance(pca_components_ids,pca_var_inc,pca_var_total):
    %matplotlib inline

    plt.plot(pca_components_ids, pca_var_inc)
    plt.title("PCA: added explained variance per component")
    plt.xlabel('N_components')
    plt.ylabel('Added explained variance')
    plt.show()

    #plt.plot(x, y)

    plt.plot(pca_components_ids, pca_var_total)
    plt.title("PCA: Total explained variance per component")
    plt.xlabel('N_components')
    plt.ylabel('Total explained variance')
    plt.show()

plot_variance(pca_components_ids,pca_var_inc,pca_var_total)
```





Choosing number of components for LDA and PCA

This analysis suggests that the more PCA components there are, the more variance we explain, but we do aim to minimize the number of components use. So I would choose about 50 PCA components - where the additional explained variance drops below 0.002 and it remains the same 4 decimals for 4 iterations (or 3 iterations afterward). With PCA, the explained variance keeps improving as we add components, so at 50 components, the variance explained is fair, ~0.79, and the marginal utility of adding another PCA component is flattened and doesn't contribute significantly anymore. We can see that with the text output as well as from the second plot of Total Explained Variance, bring after the convex point and going flatter and flatter, and from the incremental value added plot seeing it's close to 0 and pretty flat at least from components 35 or 40. We could, of course, continue adding components, but the whole goal of dimensionality reduction is to simplify with much FEWER components than the original data, so we don't want to over-add components.

However, for LDA there is only a maximum of 1 component to choose in this case. It can't give us the same kind of measure of variance explained. The maximum number of dimensions for LDA, in this case, is #of classes-1, which would be (2 classes - 1) = 1 dimension maximum anyway. Therefore we can't optimize the number of LDA dimensions to choose. Let's see how good will LDA will perform with one class.

In [61]:

```
### PCA! - find the principal components, now with selected 50 component
s
pca = RandomizedPCA(n_components=50, random_state=0)
X_PCA = pca.fit_transform(data)
pca_var_ratios = pca.explained_variance_ratio_

print "PCA Dimensions: "
pca_n_components, pca_components_ids, pca_var_inc, pca_var_total = selec
t_n_components(pca_var_ratios, 0.95)
print "PCA components selected: ", pca_n_components
plot_variance(pca_components_ids,pca_var_inc,pca_var_total)
```

```
/Users/tomereldor/anaconda/lib/python2.7/site-packages/sklearn/utils/de
precation.py:57: DeprecationWarning: Class RandomizedPCA is deprecated;
RandomizedPCA was deprecated in 0.18 and will be removed in 0.20. Use P
CA(svd_solver='randomized') instead. The new implementation DOES NOT st
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```

```
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component 7 adds 0.0196 to variance, now total variance is 0.5779
component 8 adds 0.0158 to variance, now total variance is 0.5937
component 9 adds 0.0143 to variance, now total variance is 0.6080
component 10 adds 0.0116 to variance, now total variance is 0.6196
component 11 adds 0.0112 to variance, now total variance is 0.6308
component 12 adds 0.0103 to variance, now total variance is 0.6411
component 13 adds 0.0092 to variance, now total variance is 0.6503
component 14 adds 0.0082 to variance, now total variance is 0.6585
component 15 adds 0.0074 to variance, now total variance is 0.6659
component 16 adds 0.0068 to variance, now total variance is 0.6728
component 17 adds 0.0065 to variance, now total variance is 0.6793
component 18 adds 0.0062 to variance, now total variance is 0.6855
component 19 adds 0.0060 to variance, now total variance is 0.6915
component 20 adds 0.0056 to variance, now total variance is 0.6971
component 21 adds 0.0055 to variance, now total variance is 0.7026
component 22 adds 0.0052 to variance, now total variance is 0.7078
component 23 adds 0.0049 to variance, now total variance is 0.7127
component 24 adds 0.0046 to variance, now total variance is 0.7173
component 25 adds 0.0044 to variance, now total variance is 0.7217
component 26 adds 0.0043 to variance, now total variance is 0.7261
component 27 adds 0.0040 to variance, now total variance is 0.7300
component 28 adds 0.0038 to variance, now total variance is 0.7338
component 29 adds 0.0037 to variance, now total variance is 0.7375
component 30 adds 0.0036 to variance, now total variance is 0.7411
component 31 adds 0.0032 to variance, now total variance is 0.7443
component 32 adds 0.0031 to variance, now total variance is 0.7474
component 33 adds 0.0031 to variance, now total variance is 0.7505
component 34 adds 0.0030 to variance, now total variance is 0.7534
component 35 adds 0.0029 to variance, now total variance is 0.7563
component 36 adds 0.0028 to variance, now total variance is 0.7591
component 37 adds 0.0026 to variance, now total variance is 0.7617
component 38 adds 0.0025 to variance, now total variance is 0.7643
component 39 adds 0.0025 to variance, now total variance is 0.7668
component 40 adds 0.0024 to variance, now total variance is 0.7692
component 41 adds 0.0023 to variance, now total variance is 0.7715
component 42 adds 0.0023 to variance, now total variance is 0.7738
component 43 adds 0.0023 to variance, now total variance is 0.7761
component 44 adds 0.0022 to variance, now total variance is 0.7783
component 45 adds 0.0021 to variance, now total variance is 0.7804
component 46 adds 0.0020 to variance, now total variance is 0.7824
component 47 adds 0.0019 to variance, now total variance is 0.7843
component 48 adds 0.0019 to variance, now total variance is 0.7861
component 49 adds 0.0018 to variance, now total variance is 0.7880
component 50 adds 0.0018 to variance, now total variance is 0.7898
PCA components selected:  50
```

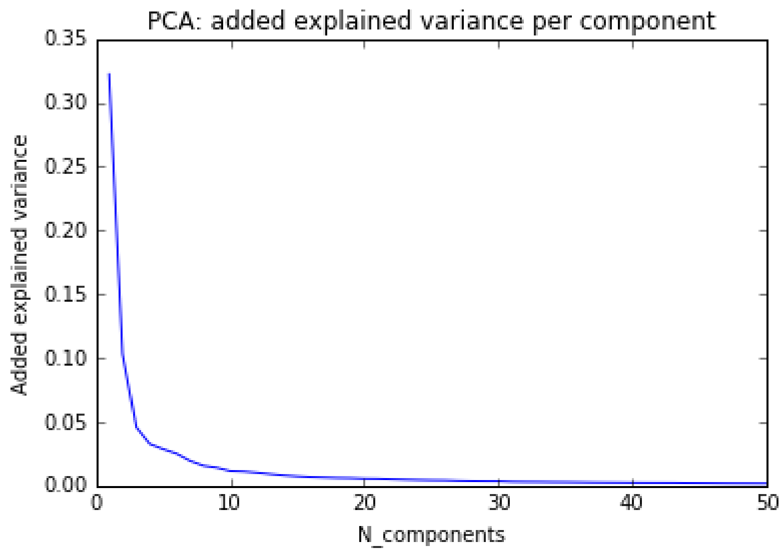

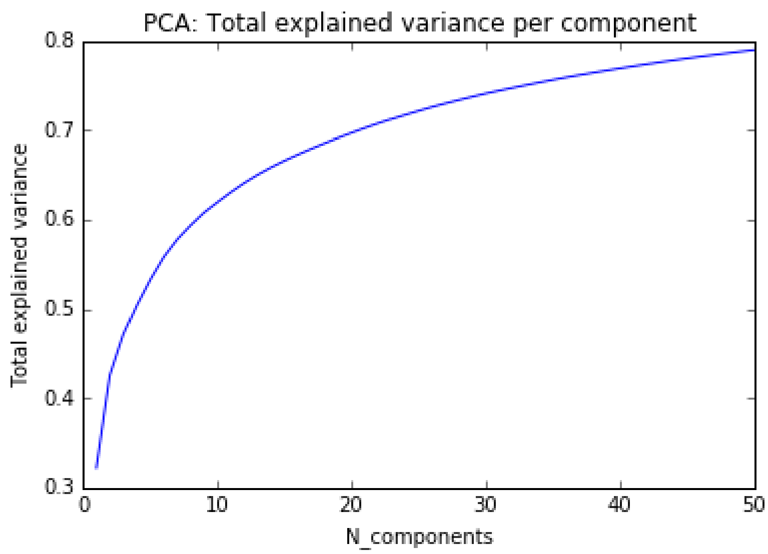

PREDICTIVE MODELING AND RESULTS

Prep: splitting into train and test

In [46]:
```
# PREDICTIVE MODELING

# split the data into a training set and a test set; since the photos ar
e randomly shuffled, we can just split by order.
# determine split cutoff 80% training data, 20% test data
train_split = int(0.8*len(data))
#splitting:
X_PCA_train , X_PCA_test = X_PCA[:train_split] , X_PCA[train_split:]
X_LDA_train , X_LDA_test = X_LDA[:train_split] , X_LDA[train_split:]
y_train , y_test = y[:train_split] , y[train_split:]
# for debug:
print("PCA Train N: {}, PCA Test N: {}".format(len(X_PCA_train), len(X_P
CA_test)))
print("PCA Train N: {}, PCA Test N: {}".format(len(X_LDA_train), len(X_L
DA_test)))
print("Y   Train N: {}, Y   Test N: {}".format(len(y_train),
len(y_test)))
```

```
PCA Train N: 336, PCA Test N: 84
PCA Train N: 336, PCA Test N: 84
Y   Train N: 336, Y   Test N: 84
```

PCA & LDA on Logistic Regression

In [51]:
```
# CHOOSE AND FIT CLASSIFIER MODEL
print "*** Logistic Regression ***\n"
#over PCA Data
print "PCA: Logistic Regression"
clf_pca = LogisticRegression(penalty='l2')
clf_pca.fit(X_PCA_train,y_train)
print "Accuracy score PCA Classifier, training set: ",clf_pca.score(X_PC
A_train,y_train)
print "Accuracy score PCA Classifier, test set: ",clf_pca.score(X_PCA_te
st,y_test)
predicted_pca_log = clf_pca.predict(X_PCA_test)
print "\nConfusion Matrix on test set: "
print(metrics.confusion_matrix(y_test, predicted_pca_log))
print "\nClassification report on test set"
print(metrics.classification_report(y_test, predicted_pca_log))

#over LDA Data
print "\nLDA: Logistic Regression"
clf_lda_log = LogisticRegression(penalty='l2')
clf_lda_log.fit(X_LDA_train,y_train)
print "Accuracy score LDA Classifier, training set:
",clf_lda_log.score(X_LDA_train,y_train)
print "Accuracy score LDA Classifier, test set: "  ,
clf_lda_log.score(X_LDA_test,y_test)
predicted_lda_log = clf_lda_log.predict(X_LDA_test)
print "\nConfusion Matrix on test set: "
print(metrics.confusion_matrix(y_test, predicted_lda_log))
print "\nClassification report on test set"
print(metrics.classification_report(y_test, predicted_lda_log))
```

```
*** Logistic Regression ***

PCA: Logistic Regression
Accuracy score PCA Classifier, training set:  0.741071428571
Accuracy score PCA Classifier, test set:  0.654761904762

Confusion Matrix on test set:
[[27 10]
 [19 28]]

Classification report on test set
             precision    recall  f1-score   support

          0       0.59      0.73      0.65        37
          1       0.74      0.60      0.66        47

avg / total       0.67      0.65      0.66        84


LDA: Logistic Regression
Accuracy score LDA Classifier, training set:  0.925595238095
Accuracy score LDA Classifier, test set:  0.892857142857

Confusion Matrix on test set:
[[33  4]
 [ 5 42]]

Classification report on test set
             precision    recall  f1-score   support

          0       0.87      0.89      0.88        37
          1       0.91      0.89      0.90        47

avg / total       0.89      0.89      0.89        84
```

PCA and LDA on SVC Model

In [50]:

```
# CHOOSE AND FIT CLASSIFIER MODEL
clf_svc =  LinearSVC(random_state = 42) #(if we give it the answer to th
e question about the meaning of life and everything as a random seed it
 might perform better since it knows already the answer to everything)
clf_svc.fit(X_train, y_train)

print "*** SVC MODEL ***\n"

#over PCA Data
print "PCA: SVC Model"
clf_pca_svc = LinearSVC(random_state = 42)
clf_pca_svc.fit(X_PCA_train,y_train)
print "Accuracy score PCA Classifier, training set:
",clf_pca_svc.score(X_PCA_train,y_train)
print "Accuracy score PCA Classifier, test set: ",clf_pca_svc.score(X_PC
A_test,y_test)
predicted_pca_svc = clf_pca_svc.predict(X_PCA_test)
print "\nConfusion Matrix on test set: "
print(metrics.confusion_matrix(y_test, predicted_pca_svc))
print "\nClassification report on test set"
print(metrics.classification_report(y_test, predicted_pca_svc))

#over LDA Data
print "\nLDA: SVC Model"
clf_lda_svc = LinearSVC(random_state = 42)
clf_lda_svc.fit(X_LDA_train,y_train)
print "Accuracy score LDA Classifier, training set:
",clf_lda_svc.score(X_LDA_train,y_train)
print "Accuracy score LDA Classifier, test set: "  ,
clf_lda_svc.score(X_LDA_test,y_test)
predicted_lda_svc = clf_lda_svc.predict(X_LDA_test)
print "\nConfusion Matrix on test set: "
print(metrics.confusion_matrix(y_test, predicted_lda_svc))
print "\nClassification report on test set"
print(metrics.classification_report(y_test, predicted_lda_svc))
```

```
*** SVC MODEL ***

PCA: SVC Model
Accuracy score PCA Classifier, training set:  0.613095238095
Accuracy score PCA Classifier, test set:  0.535714285714

Confusion Matrix on test set:
[[20 17]
 [22 25]]

Classification report on test set
             precision    recall  f1-score   support

          0       0.48      0.54      0.51        37
          1       0.60      0.53      0.56        47

avg / total       0.54      0.54      0.54        84


LDA: SVC Model
Accuracy score LDA Classifier, training set:  0.931547619048
Accuracy score LDA Classifier, test set:  0.892857142857

Confusion Matrix on test set:
[[33  4]
 [ 5 42]]

Classification report on test set
             precision    recall  f1-score   support

          0       0.87      0.89      0.88        37
          1       0.91      0.89      0.90        47

avg / total       0.89      0.89      0.89        84
```

ANALYSIS

Results and conclusion

The models results showed surprisingly that LDA (although having only one dimension) performed much better than PCA, on both Logistic Regression or SVC classifiers: LDA data resulted in Accuracy of 0.89 (with either svc or logistic regression) Whereas PCA data resulted in Accuracy of 0.66 for logistic regression and 0.53 for SVC classifiers. Therefore, I would choose an LDA reduced dimensionality representation of the data for this problem; however, once choosing it, the choice of the model between logistic regression or linear SVC apparently didn't matter much regarding accuracy of prediction on the test set. However, logistic regression performed better for the PCA fitted data, suggesting that it might do a better job with even more dimensioned data for this particular problem. Also, Logistic regression is a simpler model and can be more easily interpreted, and now that there are no differences in accuracy - I would choose Logistic Regression as a model and LDA as a dimensionality reduction technique.

Interpretation

Generally, LDA can indeed be superior, since it is a case of CLASSIFICATION, and LDA is built to find optimal dimensions that maximize the SEPARABILITY of classes, so it directly helps with classification; whereas PCA is merely focuses at preserving as much of the original "information" in the data as possible, but without any relation to the separability or later uses of the data, be it classification or not. Therefore LDA might be better for some classification problems, and it seemed to have performed better for this one, where we only care about classification, and care to preserve nothing more from the data after we classify. However, I highly doubted this results, since we are classifying into two categories alone. Thus *LDA's maximal number of dimensions was 1, and it used* ***only one dimension*** *for the classification*. Thus it's weird that it performed so well. I have tried to see if there were any bugs or abnormalities have caused that, but found none so far. Therefore I'm left with concluding, that if everything was handled correctly indeed, then the LDA simply did a great job at finding a one dimensional representation of the factor that clearly was the key determinant of boys and girls.

Conversely, PCA does seem to perform rather poorly, especially with the SVC classifier. There, the accuracy on the training set is only around 0.61. **How come it doesn't even classify well on its own training set?**. Also bad were the results on the test set - only about 0.53 accuracy, which is pretty bad - it is *not much better than chance!*. Therefore PCA seems not the right path to go, especially not with SVC classifier.

Possible problems with the Data

From looking more closely at the sample of the ~250 shirts I used. It does seem that the majority of male shirts were in darker, bluer colors, where the majority of women's shirts were in lighter, reddish / pinkish hues. Therefore, the LDA might have successfully picked up on that color difference in an efficient "*DarkBlueish to LightRedPinkish*" 1D scale that served as the necessary information. Therefore, I would try this on a much larger dataset than the sample of ~250 shirts I used.

Other potential problems with the Data, is that firstly, the classification is sometimes ambiguous and it's a difficult problem because of that. The images are not standardized (not in a uniform format regarding how many clothes per picture, which positioning, which background, etc.).

From looking at the pictures, there are quite a bit of shirt that *I myself wouldn't know for which gender to classify*.

APPENDIX

More Detailed Results

Presenting model probabilities and scores for each shirt in database, and finding the most extreme values (most "manly" shirts, most "girly" shirts, most ambigious shirts) for debuggin and more detailed look.

In [21]:
```
# RESULTS METRICS

# First: Here are the Model SCORES for EVERY SHIRT in our dataset
probs_PCA = zip(clf_pca.decision_function(X_PCA),raw_data)
probs_LDA = zip(clf_lda.decision_function(X_LDA),raw_data)

def evaluate_and_find_extremes(model):
    """find most extreme shirts, for either PCA or LDA, as specified in
 the parameters above"""
    ## get variables for this model:
    if model in ("pca","PCA"):
        probs = probs_PCA
        x_model = X_PCA
        X_test_model = X_PCA_test
        clf_model = clf_pca

    elif model in("lda","LDA"):
        probs = probs_LDA
        x_model = X_LDA
        X_test_model = X_LDA_test
        clf_model = clf_lda

    else:
        raise ValueError("please enter either 'PCA' or 'LDA', with quote
s, like this: extreme_shirts('PCA') ")

    girliest_girl_shirt = sorted(probs,key=lambda (p,(cd,g,f)): (0 if g
== 'girl' else 1,p))[0]
    girliest_boy_shirt = sorted(probs,key=lambda (p,(cd,g,f)): (0 if g =
= 'boy' else 1,p))[0]
    boyiest_girl_shirt = sorted(probs,key=lambda (p,(cd,g,f)): (0 if g =
= 'girl' else 1,-p))[0]
    boyiest_boy_shirt = sorted(probs,key=lambda (p,(cd,g,f)): (0 if g ==
 'boy' else 1,-p))[0]
    most_androgynous_shirt = sorted(probs,key=lambda (p,(cd,g,f)):
abs(p))[0]

    # and let's look at the most and least extreme shirts
    cd = zip( x_model ,raw_data) #the x specified from the function: eit
her of PCA or LDA
    least_extreme_shirt = sorted(cd,key=lambda (x,(d,g,f)): sum([abs(c)
for c in x]))[0]
    most_extreme_shirt =  sorted(cd,key=lambda (x,(d,g,f)): sum([abs(c)
for c in x]),reverse=True)[0]
```

```
    least_interesting_shirt = sorted(cd,key=lambda (x,(d,g,f)):
max([abs(c) for c in x]))[0]
    most_interesting_shirt =  sorted(cd,key=lambda (x,(d,g,f)):
min([abs(c) for c in x]),reverse=True)[0]

    # and now let's look at precision-recall
    probs = zip(clf_model.decision_function(X_test_model),raw_data[train
_split:])
    num_boys = len([c for c in y_test if c == 1])
    num_girls = len([c for c in y_test if c == 0])
    # take lowest and highest probabilities for later comparing to model
 scores
    lowest_score = round(min([p[0] for p in probs]),1) - 0.1
    highest_score = round(max([p[0] for p in probs]),1) + 0.1
    INTERVAL = 0.1

    # first do the girls
    score = lowest_score
    while score <= highest_score:
        true_positives  = len([p for p in probs if p[0] <= score and
p[1][1] == 'girl'])
        false_positives = len([p for p in probs if p[0] <= score and
p[1][1] == 'boy'])
        positives = true_positives + false_positives
        if positives > 0:
            precision = 1.0 * true_positives / positives
            recall = 1.0 * true_positives / num_girls
            print "WOMEN - score: %.2f, precision: %.3f ,recall: %.3f "
% (score,precision,recall)
        score += INTERVAL

    # then do the boys
    score = highest_score
    while score >= lowest_score:
        true_positives  = len([p for p in probs if p[0] >= score and
p[1][1] == 'boy'])
        false_positives = len([p for p in probs if p[0] >= score and
p[1][1] == 'girl'])
        positives = true_positives + false_positives
        if positives > 0:
            precision = 1.0 * true_positives / positives
            recall = 1.0 * true_positives / num_boys
            #print "boys",score,precision,recall
            print "MEN -  score: %.2f, precision: %.3f ,recall: %.3f " %
 (score,precision,recall)
        score -= INTERVAL

    # now do both
    score = lowest_score
    while score <= highest_score:
        girls  = len([p for p in probs if p[0] <= score and p[1][1] ==
'girl'])
        boys = len([p for p in probs if p[0] <= score and p[1][1] == 'bo
y'])
        print "score: %.2f. Women: %d, Men: %d" % (score, girls, boys)
        score += INTERVAL
```

In [22]:
```
evaluate_and_find_extremes("PCA")
```

```
WOMEN - score: -8.50, precision: 1.000 ,recall: 0.027
WOMEN - score: -8.40, precision: 1.000 ,recall: 0.027
WOMEN - score: -8.30, precision: 1.000 ,recall: 0.027
WOMEN - score: -8.20, precision: 1.000 ,recall: 0.027
WOMEN - score: -8.10, precision: 1.000 ,recall: 0.027
WOMEN - score: -8.00, precision: 1.000 ,recall: 0.027
WOMEN - score: -7.90, precision: 1.000 ,recall: 0.027
WOMEN - score: -7.80, precision: 1.000 ,recall: 0.027
WOMEN - score: -7.70, precision: 1.000 ,recall: 0.027
WOMEN - score: -7.60, precision: 1.000 ,recall: 0.027
WOMEN - score: -7.50, precision: 1.000 ,recall: 0.027
WOMEN - score: -7.40, precision: 1.000 ,recall: 0.027
WOMEN - score: -7.30, precision: 1.000 ,recall: 0.027
WOMEN - score: -7.20, precision: 1.000 ,recall: 0.027
WOMEN - score: -7.10, precision: 1.000 ,recall: 0.027
WOMEN - score: -7.00, precision: 1.000 ,recall: 0.027
WOMEN - score: -6.90, precision: 1.000 ,recall: 0.027
WOMEN - score: -6.80, precision: 1.000 ,recall: 0.027
WOMEN - score: -6.70, precision: 1.000 ,recall: 0.027
WOMEN - score: -6.60, precision: 1.000 ,recall: 0.027
WOMEN - score: -6.50, precision: 1.000 ,recall: 0.027
WOMEN - score: -6.40, precision: 1.000 ,recall: 0.027
WOMEN - score: -6.30, precision: 1.000 ,recall: 0.027
WOMEN - score: -6.20, precision: 1.000 ,recall: 0.027
WOMEN - score: -6.10, precision: 1.000 ,recall: 0.027
WOMEN - score: -6.00, precision: 1.000 ,recall: 0.027
WOMEN - score: -5.90, precision: 1.000 ,recall: 0.027
WOMEN - score: -5.80, precision: 1.000 ,recall: 0.027
WOMEN - score: -5.70, precision: 1.000 ,recall: 0.027
WOMEN - score: -5.60, precision: 1.000 ,recall: 0.027
WOMEN - score: -5.50, precision: 1.000 ,recall: 0.027
WOMEN - score: -5.40, precision: 1.000 ,recall: 0.027
WOMEN - score: -5.30, precision: 1.000 ,recall: 0.027
WOMEN - score: -5.20, precision: 1.000 ,recall: 0.027
WOMEN - score: -5.10, precision: 1.000 ,recall: 0.027
WOMEN - score: -5.00, precision: 1.000 ,recall: 0.027
WOMEN - score: -4.90, precision: 1.000 ,recall: 0.027
WOMEN - score: -4.80, precision: 1.000 ,recall: 0.027
WOMEN - score: -4.70, precision: 1.000 ,recall: 0.027
WOMEN - score: -4.60, precision: 1.000 ,recall: 0.027
WOMEN - score: -4.50, precision: 1.000 ,recall: 0.027
WOMEN - score: -4.40, precision: 1.000 ,recall: 0.054
WOMEN - score: -4.30, precision: 1.000 ,recall: 0.054
WOMEN - score: -4.20, precision: 1.000 ,recall: 0.054
WOMEN - score: -4.10, precision: 1.000 ,recall: 0.081
WOMEN - score: -4.00, precision: 1.000 ,recall: 0.108
WOMEN - score: -3.90, precision: 1.000 ,recall: 0.108
WOMEN - score: -3.80, precision: 1.000 ,recall: 0.108
WOMEN - score: -3.70, precision: 1.000 ,recall: 0.135
WOMEN - score: -3.60, precision: 1.000 ,recall: 0.135
WOMEN - score: -3.50, precision: 1.000 ,recall: 0.135
WOMEN - score: -3.40, precision: 1.000 ,recall: 0.135
WOMEN - score: -3.30, precision: 0.833 ,recall: 0.135
WOMEN - score: -3.20, precision: 0.833 ,recall: 0.135
WOMEN - score: -3.10, precision: 0.714 ,recall: 0.135
WOMEN - score: -3.00, precision: 0.556 ,recall: 0.135
WOMEN - score: -2.90, precision: 0.556 ,recall: 0.135
```

```
WOMEN - score: -2.80, precision: 0.556 ,recall: 0.135
WOMEN - score: -2.70, precision: 0.556 ,recall: 0.135
WOMEN - score: -2.60, precision: 0.583 ,recall: 0.189
WOMEN - score: -2.50, precision: 0.583 ,recall: 0.189
WOMEN - score: -2.40, precision: 0.583 ,recall: 0.189
WOMEN - score: -2.30, precision: 0.583 ,recall: 0.189
WOMEN - score: -2.20, precision: 0.615 ,recall: 0.216
WOMEN - score: -2.10, precision: 0.643 ,recall: 0.243
WOMEN - score: -2.00, precision: 0.667 ,recall: 0.270
WOMEN - score: -1.90, precision: 0.688 ,recall: 0.297
WOMEN - score: -1.80, precision: 0.667 ,recall: 0.324
WOMEN - score: -1.70, precision: 0.632 ,recall: 0.324
WOMEN - score: -1.60, precision: 0.600 ,recall: 0.324
WOMEN - score: -1.50, precision: 0.619 ,recall: 0.351
WOMEN - score: -1.40, precision: 0.560 ,recall: 0.378
WOMEN - score: -1.30, precision: 0.560 ,recall: 0.378
WOMEN - score: -1.20, precision: 0.593 ,recall: 0.432
WOMEN - score: -1.10, precision: 0.607 ,recall: 0.459
WOMEN - score: -1.00, precision: 0.613 ,recall: 0.514
WOMEN - score: -0.90, precision: 0.588 ,recall: 0.541
WOMEN - score: -0.80, precision: 0.600 ,recall: 0.568
WOMEN - score: -0.70, precision: 0.615 ,recall: 0.649
WOMEN - score: -0.60, precision: 0.625 ,recall: 0.676
WOMEN - score: -0.50, precision: 0.605 ,recall: 0.703
WOMEN - score: -0.40, precision: 0.591 ,recall: 0.703
WOMEN - score: -0.30, precision: 0.591 ,recall: 0.703
WOMEN - score: -0.20, precision: 0.600 ,recall: 0.730
WOMEN - score: -0.10, precision: 0.587 ,recall: 0.730
WOMEN - score: -0.00, precision: 0.587 ,recall: 0.730
WOMEN - score: 0.10, precision: 0.596 ,recall: 0.757
WOMEN - score: 0.20, precision: 0.583 ,recall: 0.757
WOMEN - score: 0.30, precision: 0.580 ,recall: 0.784
WOMEN - score: 0.40, precision: 0.588 ,recall: 0.811
WOMEN - score: 0.50, precision: 0.588 ,recall: 0.811
WOMEN - score: 0.60, precision: 0.577 ,recall: 0.811
WOMEN - score: 0.70, precision: 0.577 ,recall: 0.811
WOMEN - score: 0.80, precision: 0.566 ,recall: 0.811
WOMEN - score: 0.90, precision: 0.545 ,recall: 0.811
WOMEN - score: 1.00, precision: 0.536 ,recall: 0.811
WOMEN - score: 1.10, precision: 0.542 ,recall: 0.865
WOMEN - score: 1.20, precision: 0.541 ,recall: 0.892
WOMEN - score: 1.30, precision: 0.556 ,recall: 0.946
WOMEN - score: 1.40, precision: 0.538 ,recall: 0.946
WOMEN - score: 1.50, precision: 0.545 ,recall: 0.973
WOMEN - score: 1.60, precision: 0.545 ,recall: 0.973
WOMEN - score: 1.70, precision: 0.537 ,recall: 0.973
WOMEN - score: 1.80, precision: 0.522 ,recall: 0.973
WOMEN - score: 1.90, precision: 0.522 ,recall: 0.973
WOMEN - score: 2.00, precision: 0.522 ,recall: 0.973
WOMEN - score: 2.10, precision: 0.522 ,recall: 0.973
WOMEN - score: 2.20, precision: 0.514 ,recall: 0.973
WOMEN - score: 2.30, precision: 0.493 ,recall: 0.973
WOMEN - score: 2.40, precision: 0.480 ,recall: 0.973
WOMEN - score: 2.50, precision: 0.474 ,recall: 0.973
WOMEN - score: 2.60, precision: 0.468 ,recall: 0.973
WOMEN - score: 2.70, precision: 0.462 ,recall: 0.973
WOMEN - score: 2.80, precision: 0.456 ,recall: 0.973
```

```
WOMEN - score: 2.90, precision: 0.444 ,recall: 0.973
WOMEN - score: 3.00, precision: 0.439 ,recall: 0.973
WOMEN - score: 3.10, precision: 0.439 ,recall: 0.973
WOMEN - score: 3.20, precision: 0.439 ,recall: 0.973
WOMEN - score: 3.30, precision: 0.439 ,recall: 0.973
WOMEN - score: 3.40, precision: 0.439 ,recall: 0.973
WOMEN - score: 3.50, precision: 0.439 ,recall: 0.973
WOMEN - score: 3.60, precision: 0.439 ,recall: 0.973
WOMEN - score: 3.70, precision: 0.439 ,recall: 0.973
WOMEN - score: 3.80, precision: 0.439 ,recall: 0.973
WOMEN - score: 3.90, precision: 0.439 ,recall: 0.973
WOMEN - score: 4.00, precision: 0.439 ,recall: 0.973
WOMEN - score: 4.10, precision: 0.439 ,recall: 0.973
WOMEN - score: 4.20, precision: 0.439 ,recall: 0.973
WOMEN - score: 4.30, precision: 0.439 ,recall: 0.973
WOMEN - score: 4.40, precision: 0.434 ,recall: 0.973
WOMEN - score: 4.50, precision: 0.434 ,recall: 0.973
WOMEN - score: 4.60, precision: 0.434 ,recall: 0.973
WOMEN - score: 4.70, precision: 0.434 ,recall: 0.973
WOMEN - score: 4.80, precision: 0.434 ,recall: 0.973
WOMEN - score: 4.90, precision: 0.434 ,recall: 0.973
WOMEN - score: 5.00, precision: 0.434 ,recall: 0.973
WOMEN - score: 5.10, precision: 0.434 ,recall: 0.973
WOMEN - score: 5.20, precision: 0.434 ,recall: 0.973
WOMEN - score: 5.30, precision: 0.434 ,recall: 0.973
WOMEN - score: 5.40, precision: 0.434 ,recall: 0.973
WOMEN - score: 5.50, precision: 0.434 ,recall: 0.973
WOMEN - score: 5.60, precision: 0.434 ,recall: 0.973
WOMEN - score: 5.70, precision: 0.434 ,recall: 0.973
WOMEN - score: 5.80, precision: 0.434 ,recall: 0.973
WOMEN - score: 5.90, precision: 0.434 ,recall: 0.973
WOMEN - score: 6.00, precision: 0.434 ,recall: 0.973
WOMEN - score: 6.10, precision: 0.440 ,recall: 1.000
WOMEN - score: 6.20, precision: 0.440 ,recall: 1.000
MEN -  score: 6.00, precision: 0.000 ,recall: 0.000
MEN -  score: 5.90, precision: 0.000 ,recall: 0.000
MEN -  score: 5.80, precision: 0.000 ,recall: 0.000
MEN -  score: 5.70, precision: 0.000 ,recall: 0.000
MEN -  score: 5.60, precision: 0.000 ,recall: 0.000
MEN -  score: 5.50, precision: 0.000 ,recall: 0.000
MEN -  score: 5.40, precision: 0.000 ,recall: 0.000
MEN -  score: 5.30, precision: 0.000 ,recall: 0.000
MEN -  score: 5.20, precision: 0.000 ,recall: 0.000
MEN -  score: 5.10, precision: 0.000 ,recall: 0.000
MEN -  score: 5.00, precision: 0.000 ,recall: 0.000
MEN -  score: 4.90, precision: 0.000 ,recall: 0.000
MEN -  score: 4.80, precision: 0.000 ,recall: 0.000
MEN -  score: 4.70, precision: 0.000 ,recall: 0.000
MEN -  score: 4.60, precision: 0.000 ,recall: 0.000
MEN -  score: 4.50, precision: 0.000 ,recall: 0.000
MEN -  score: 4.40, precision: 0.000 ,recall: 0.000
MEN -  score: 4.30, precision: 0.500 ,recall: 0.021
MEN -  score: 4.20, precision: 0.500 ,recall: 0.021
MEN -  score: 4.10, precision: 0.500 ,recall: 0.021
MEN -  score: 4.00, precision: 0.500 ,recall: 0.021
MEN -  score: 3.90, precision: 0.500 ,recall: 0.021
MEN -  score: 3.80, precision: 0.500 ,recall: 0.021
```

```
MEN -  score: 3.70, precision: 0.500 ,recall: 0.021
MEN -  score: 3.60, precision: 0.500 ,recall: 0.021
MEN -  score: 3.50, precision: 0.500 ,recall: 0.021
MEN -  score: 3.40, precision: 0.500 ,recall: 0.021
MEN -  score: 3.30, precision: 0.500 ,recall: 0.021
MEN -  score: 3.20, precision: 0.500 ,recall: 0.021
MEN -  score: 3.10, precision: 0.500 ,recall: 0.021
MEN -  score: 3.00, precision: 0.500 ,recall: 0.021
MEN -  score: 2.90, precision: 0.667 ,recall: 0.043
MEN -  score: 2.80, precision: 0.800 ,recall: 0.085
MEN -  score: 2.70, precision: 0.833 ,recall: 0.106
MEN -  score: 2.60, precision: 0.857 ,recall: 0.128
MEN -  score: 2.50, precision: 0.875 ,recall: 0.149
MEN -  score: 2.40, precision: 0.889 ,recall: 0.170
MEN -  score: 2.30, precision: 0.909 ,recall: 0.213
MEN -  score: 2.20, precision: 0.929 ,recall: 0.277
MEN -  score: 2.10, precision: 0.933 ,recall: 0.298
MEN -  score: 2.00, precision: 0.933 ,recall: 0.298
MEN -  score: 1.90, precision: 0.933 ,recall: 0.298
MEN -  score: 1.80, precision: 0.933 ,recall: 0.298
MEN -  score: 1.70, precision: 0.941 ,recall: 0.340
MEN -  score: 1.60, precision: 0.944 ,recall: 0.362
MEN -  score: 1.50, precision: 0.944 ,recall: 0.362
MEN -  score: 1.40, precision: 0.895 ,recall: 0.362
MEN -  score: 1.30, precision: 0.905 ,recall: 0.404
MEN -  score: 1.20, precision: 0.826 ,recall: 0.404
MEN -  score: 1.10, precision: 0.800 ,recall: 0.426
MEN -  score: 1.00, precision: 0.750 ,recall: 0.447
MEN -  score: 0.90, precision: 0.759 ,recall: 0.468
MEN -  score: 0.80, precision: 0.774 ,recall: 0.511
MEN -  score: 0.70, precision: 0.781 ,recall: 0.532
MEN -  score: 0.60, precision: 0.781 ,recall: 0.532
MEN -  score: 0.50, precision: 0.788 ,recall: 0.553
MEN -  score: 0.40, precision: 0.788 ,recall: 0.553
MEN -  score: 0.30, precision: 0.765 ,recall: 0.553
MEN -  score: 0.20, precision: 0.750 ,recall: 0.574
MEN -  score: 0.10, precision: 0.757 ,recall: 0.596
MEN -  score: 0.00, precision: 0.737 ,recall: 0.596
MEN -  score: -0.10, precision: 0.737 ,recall: 0.596
MEN -  score: -0.20, precision: 0.744 ,recall: 0.617
MEN -  score: -0.30, precision: 0.725 ,recall: 0.617
MEN -  score: -0.40, precision: 0.725 ,recall: 0.617
MEN -  score: -0.50, precision: 0.732 ,recall: 0.638
MEN -  score: -0.60, precision: 0.727 ,recall: 0.681
MEN -  score: -0.70, precision: 0.711 ,recall: 0.681
MEN -  score: -0.80, precision: 0.673 ,recall: 0.702
MEN -  score: -0.90, precision: 0.660 ,recall: 0.702
MEN -  score: -1.00, precision: 0.660 ,recall: 0.745
MEN -  score: -1.10, precision: 0.643 ,recall: 0.766
MEN -  score: -1.20, precision: 0.632 ,recall: 0.766
MEN -  score: -1.30, precision: 0.610 ,recall: 0.766
MEN -  score: -1.40, precision: 0.610 ,recall: 0.766
MEN -  score: -1.50, precision: 0.619 ,recall: 0.830
MEN -  score: -1.60, precision: 0.609 ,recall: 0.830
MEN -  score: -1.70, precision: 0.615 ,recall: 0.851
MEN -  score: -1.80, precision: 0.621 ,recall: 0.872
MEN -  score: -1.90, precision: 0.618 ,recall: 0.894
```

```
MEN -  score: -2.00, precision: 0.609 ,recall: 0.894
MEN -  score: -2.10, precision: 0.600 ,recall: 0.894
MEN -  score: -2.20, precision: 0.592 ,recall: 0.894
MEN -  score: -2.30, precision: 0.583 ,recall: 0.894
MEN -  score: -2.40, precision: 0.583 ,recall: 0.894
MEN -  score: -2.50, precision: 0.583 ,recall: 0.894
MEN -  score: -2.60, precision: 0.583 ,recall: 0.894
MEN -  score: -2.70, precision: 0.573 ,recall: 0.915
MEN -  score: -2.80, precision: 0.573 ,recall: 0.915
MEN -  score: -2.90, precision: 0.573 ,recall: 0.915
MEN -  score: -3.00, precision: 0.573 ,recall: 0.915
MEN -  score: -3.10, precision: 0.584 ,recall: 0.957
MEN -  score: -3.20, precision: 0.590 ,recall: 0.979
MEN -  score: -3.30, precision: 0.590 ,recall: 0.979
MEN -  score: -3.40, precision: 0.595 ,recall: 1.000
MEN -  score: -3.50, precision: 0.595 ,recall: 1.000
MEN -  score: -3.60, precision: 0.595 ,recall: 1.000
MEN -  score: -3.70, precision: 0.595 ,recall: 1.000
MEN -  score: -3.80, precision: 0.588 ,recall: 1.000
MEN -  score: -3.90, precision: 0.588 ,recall: 1.000
MEN -  score: -4.00, precision: 0.588 ,recall: 1.000
MEN -  score: -4.10, precision: 0.580 ,recall: 1.000
MEN -  score: -4.20, precision: 0.573 ,recall: 1.000
MEN -  score: -4.30, precision: 0.573 ,recall: 1.000
MEN -  score: -4.40, precision: 0.573 ,recall: 1.000
MEN -  score: -4.50, precision: 0.566 ,recall: 1.000
MEN -  score: -4.60, precision: 0.566 ,recall: 1.000
MEN -  score: -4.70, precision: 0.566 ,recall: 1.000
MEN -  score: -4.80, precision: 0.566 ,recall: 1.000
MEN -  score: -4.90, precision: 0.566 ,recall: 1.000
MEN -  score: -5.00, precision: 0.566 ,recall: 1.000
MEN -  score: -5.10, precision: 0.566 ,recall: 1.000
MEN -  score: -5.20, precision: 0.566 ,recall: 1.000
MEN -  score: -5.30, precision: 0.566 ,recall: 1.000
MEN -  score: -5.40, precision: 0.566 ,recall: 1.000
MEN -  score: -5.50, precision: 0.566 ,recall: 1.000
MEN -  score: -5.60, precision: 0.566 ,recall: 1.000
MEN -  score: -5.70, precision: 0.566 ,recall: 1.000
MEN -  score: -5.80, precision: 0.566 ,recall: 1.000
MEN -  score: -5.90, precision: 0.566 ,recall: 1.000
MEN -  score: -6.00, precision: 0.566 ,recall: 1.000
MEN -  score: -6.10, precision: 0.566 ,recall: 1.000
MEN -  score: -6.20, precision: 0.566 ,recall: 1.000
MEN -  score: -6.30, precision: 0.566 ,recall: 1.000
MEN -  score: -6.40, precision: 0.566 ,recall: 1.000
MEN -  score: -6.50, precision: 0.566 ,recall: 1.000
MEN -  score: -6.60, precision: 0.566 ,recall: 1.000
MEN -  score: -6.70, precision: 0.566 ,recall: 1.000
MEN -  score: -6.80, precision: 0.566 ,recall: 1.000
MEN -  score: -6.90, precision: 0.566 ,recall: 1.000
MEN -  score: -7.00, precision: 0.566 ,recall: 1.000
MEN -  score: -7.10, precision: 0.566 ,recall: 1.000
MEN -  score: -7.20, precision: 0.566 ,recall: 1.000
MEN -  score: -7.30, precision: 0.566 ,recall: 1.000
MEN -  score: -7.40, precision: 0.566 ,recall: 1.000
MEN -  score: -7.50, precision: 0.566 ,recall: 1.000
MEN -  score: -7.60, precision: 0.566 ,recall: 1.000
```

```
MEN -  score: -7.70, precision: 0.566 ,recall: 1.000
MEN -  score: -7.80, precision: 0.566 ,recall: 1.000
MEN -  score: -7.90, precision: 0.566 ,recall: 1.000
MEN -  score: -8.00, precision: 0.566 ,recall: 1.000
MEN -  score: -8.10, precision: 0.566 ,recall: 1.000
MEN -  score: -8.20, precision: 0.566 ,recall: 1.000
MEN -  score: -8.30, precision: 0.566 ,recall: 1.000
MEN -  score: -8.40, precision: 0.566 ,recall: 1.000
MEN -  score: -8.50, precision: 0.566 ,recall: 1.000
MEN -  score: -8.60, precision: 0.560 ,recall: 1.000
MEN -  score: -8.70, precision: 0.560 ,recall: 1.000
score: -8.70. Women: 0, Men: 0
score: -8.60. Women: 0, Men: 0
score: -8.50. Women: 1, Men: 0
score: -8.40. Women: 1, Men: 0
score: -8.30. Women: 1, Men: 0
score: -8.20. Women: 1, Men: 0
score: -8.10. Women: 1, Men: 0
score: -8.00. Women: 1, Men: 0
score: -7.90. Women: 1, Men: 0
score: -7.80. Women: 1, Men: 0
score: -7.70. Women: 1, Men: 0
score: -7.60. Women: 1, Men: 0
score: -7.50. Women: 1, Men: 0
score: -7.40. Women: 1, Men: 0
score: -7.30. Women: 1, Men: 0
score: -7.20. Women: 1, Men: 0
score: -7.10. Women: 1, Men: 0
score: -7.00. Women: 1, Men: 0
score: -6.90. Women: 1, Men: 0
score: -6.80. Women: 1, Men: 0
score: -6.70. Women: 1, Men: 0
score: -6.60. Women: 1, Men: 0
score: -6.50. Women: 1, Men: 0
score: -6.40. Women: 1, Men: 0
score: -6.30. Women: 1, Men: 0
score: -6.20. Women: 1, Men: 0
score: -6.10. Women: 1, Men: 0
score: -6.00. Women: 1, Men: 0
score: -5.90. Women: 1, Men: 0
score: -5.80. Women: 1, Men: 0
score: -5.70. Women: 1, Men: 0
score: -5.60. Women: 1, Men: 0
score: -5.50. Women: 1, Men: 0
score: -5.40. Women: 1, Men: 0
score: -5.30. Women: 1, Men: 0
score: -5.20. Women: 1, Men: 0
score: -5.10. Women: 1, Men: 0
score: -5.00. Women: 1, Men: 0
score: -4.90. Women: 1, Men: 0
score: -4.80. Women: 1, Men: 0
score: -4.70. Women: 1, Men: 0
score: -4.60. Women: 1, Men: 0
score: -4.50. Women: 1, Men: 0
score: -4.40. Women: 2, Men: 0
score: -4.30. Women: 2, Men: 0
score: -4.20. Women: 2, Men: 0
```

```
score: -4.10. Women: 3, Men: 0
score: -4.00. Women: 4, Men: 0
score: -3.90. Women: 4, Men: 0
score: -3.80. Women: 4, Men: 0
score: -3.70. Women: 5, Men: 0
score: -3.60. Women: 5, Men: 0
score: -3.50. Women: 5, Men: 0
score: -3.40. Women: 5, Men: 0
score: -3.30. Women: 5, Men: 1
score: -3.20. Women: 5, Men: 1
score: -3.10. Women: 5, Men: 2
score: -3.00. Women: 5, Men: 4
score: -2.90. Women: 5, Men: 4
score: -2.80. Women: 5, Men: 4
score: -2.70. Women: 5, Men: 4
score: -2.60. Women: 7, Men: 5
score: -2.50. Women: 7, Men: 5
score: -2.40. Women: 7, Men: 5
score: -2.30. Women: 7, Men: 5
score: -2.20. Women: 8, Men: 5
score: -2.10. Women: 9, Men: 5
score: -2.00. Women: 10, Men: 5
score: -1.90. Women: 11, Men: 5
score: -1.80. Women: 12, Men: 6
score: -1.70. Women: 12, Men: 7
score: -1.60. Women: 12, Men: 8
score: -1.50. Women: 13, Men: 8
score: -1.40. Women: 14, Men: 11
score: -1.30. Women: 14, Men: 11
score: -1.20. Women: 16, Men: 11
score: -1.10. Women: 17, Men: 11
score: -1.00. Women: 19, Men: 12
score: -0.90. Women: 20, Men: 14
score: -0.80. Women: 21, Men: 14
score: -0.70. Women: 24, Men: 15
score: -0.60. Women: 25, Men: 15
score: -0.50. Women: 26, Men: 17
score: -0.40. Women: 26, Men: 18
score: -0.30. Women: 26, Men: 18
score: -0.20. Women: 27, Men: 18
score: -0.10. Women: 27, Men: 19
score: -0.00. Women: 27, Men: 19
score: 0.10. Women: 28, Men: 19
score: 0.20. Women: 28, Men: 20
score: 0.30. Women: 29, Men: 21
score: 0.40. Women: 30, Men: 21
score: 0.50. Women: 30, Men: 21
score: 0.60. Women: 30, Men: 22
score: 0.70. Women: 30, Men: 22
score: 0.80. Women: 30, Men: 23
score: 0.90. Women: 30, Men: 25
score: 1.00. Women: 30, Men: 26
score: 1.10. Women: 32, Men: 27
score: 1.20. Women: 33, Men: 28
score: 1.30. Women: 35, Men: 28
score: 1.40. Women: 35, Men: 30
score: 1.50. Women: 36, Men: 30
```

```
score: 1.60. Women: 36, Men: 30
score: 1.70. Women: 36, Men: 31
score: 1.80. Women: 36, Men: 33
score: 1.90. Women: 36, Men: 33
score: 2.00. Women: 36, Men: 33
score: 2.10. Women: 36, Men: 33
score: 2.20. Women: 36, Men: 34
score: 2.30. Women: 36, Men: 37
score: 2.40. Women: 36, Men: 39
score: 2.50. Women: 36, Men: 40
score: 2.60. Women: 36, Men: 41
score: 2.70. Women: 36, Men: 42
score: 2.80. Women: 36, Men: 43
score: 2.90. Women: 36, Men: 45
score: 3.00. Women: 36, Men: 46
score: 3.10. Women: 36, Men: 46
score: 3.20. Women: 36, Men: 46
score: 3.30. Women: 36, Men: 46
score: 3.40. Women: 36, Men: 46
score: 3.50. Women: 36, Men: 46
score: 3.60. Women: 36, Men: 46
score: 3.70. Women: 36, Men: 46
score: 3.80. Women: 36, Men: 46
score: 3.90. Women: 36, Men: 46
score: 4.00. Women: 36, Men: 46
score: 4.10. Women: 36, Men: 46
score: 4.20. Women: 36, Men: 46
score: 4.30. Women: 36, Men: 46
score: 4.40. Women: 36, Men: 47
score: 4.50. Women: 36, Men: 47
score: 4.60. Women: 36, Men: 47
score: 4.70. Women: 36, Men: 47
score: 4.80. Women: 36, Men: 47
score: 4.90. Women: 36, Men: 47
score: 5.00. Women: 36, Men: 47
score: 5.10. Women: 36, Men: 47
score: 5.20. Women: 36, Men: 47
score: 5.30. Women: 36, Men: 47
score: 5.40. Women: 36, Men: 47
score: 5.50. Women: 36, Men: 47
score: 5.60. Women: 36, Men: 47
score: 5.70. Women: 36, Men: 47
score: 5.80. Women: 36, Men: 47
score: 5.90. Women: 36, Men: 47
score: 6.00. Women: 36, Men: 47
score: 6.10. Women: 37, Men: 47
score: 6.20. Women: 37, Men: 47
```

In [23]:

```
evaluate_and_find_extremes("LDA")
```

```
WOMEN - score: -5.10, precision: 1.000 ,recall: 0.027
WOMEN - score: -5.00, precision: 1.000 ,recall: 0.027
WOMEN - score: -4.90, precision: 1.000 ,recall: 0.027
WOMEN - score: -4.80, precision: 1.000 ,recall: 0.027
WOMEN - score: -4.70, precision: 1.000 ,recall: 0.027
WOMEN - score: -4.60, precision: 1.000 ,recall: 0.027
WOMEN - score: -4.50, precision: 1.000 ,recall: 0.027
WOMEN - score: -4.40, precision: 1.000 ,recall: 0.027
WOMEN - score: -4.30, precision: 1.000 ,recall: 0.027
WOMEN - score: -4.20, precision: 1.000 ,recall: 0.027
WOMEN - score: -4.10, precision: 1.000 ,recall: 0.027
WOMEN - score: -4.00, precision: 1.000 ,recall: 0.027
WOMEN - score: -3.90, precision: 1.000 ,recall: 0.027
WOMEN - score: -3.80, precision: 1.000 ,recall: 0.027
WOMEN - score: -3.70, precision: 1.000 ,recall: 0.027
WOMEN - score: -3.60, precision: 1.000 ,recall: 0.054
WOMEN - score: -3.50, precision: 1.000 ,recall: 0.054
WOMEN - score: -3.40, precision: 1.000 ,recall: 0.054
WOMEN - score: -3.30, precision: 1.000 ,recall: 0.054
WOMEN - score: -3.20, precision: 1.000 ,recall: 0.054
WOMEN - score: -3.10, precision: 1.000 ,recall: 0.081
WOMEN - score: -3.00, precision: 1.000 ,recall: 0.108
WOMEN - score: -2.90, precision: 1.000 ,recall: 0.108
WOMEN - score: -2.80, precision: 1.000 ,recall: 0.108
WOMEN - score: -2.70, precision: 1.000 ,recall: 0.108
WOMEN - score: -2.60, precision: 1.000 ,recall: 0.108
WOMEN - score: -2.50, precision: 1.000 ,recall: 0.135
WOMEN - score: -2.40, precision: 1.000 ,recall: 0.135
WOMEN - score: -2.30, precision: 1.000 ,recall: 0.135
WOMEN - score: -2.20, precision: 1.000 ,recall: 0.135
WOMEN - score: -2.10, precision: 1.000 ,recall: 0.189
WOMEN - score: -2.00, precision: 0.800 ,recall: 0.216
WOMEN - score: -1.90, precision: 0.833 ,recall: 0.270
WOMEN - score: -1.80, precision: 0.857 ,recall: 0.324
WOMEN - score: -1.70, precision: 0.800 ,recall: 0.324
WOMEN - score: -1.60, precision: 0.824 ,recall: 0.378
WOMEN - score: -1.50, precision: 0.857 ,recall: 0.486
WOMEN - score: -1.40, precision: 0.864 ,recall: 0.514
WOMEN - score: -1.30, precision: 0.826 ,recall: 0.514
WOMEN - score: -1.20, precision: 0.792 ,recall: 0.514
WOMEN - score: -1.10, precision: 0.793 ,recall: 0.622
WOMEN - score: -1.00, precision: 0.793 ,recall: 0.622
WOMEN - score: -0.90, precision: 0.774 ,recall: 0.649
WOMEN - score: -0.80, precision: 0.750 ,recall: 0.649
WOMEN - score: -0.70, precision: 0.758 ,recall: 0.676
WOMEN - score: -0.60, precision: 0.722 ,recall: 0.703
WOMEN - score: -0.50, precision: 0.711 ,recall: 0.730
WOMEN - score: -0.40, precision: 0.718 ,recall: 0.757
WOMEN - score: -0.30, precision: 0.707 ,recall: 0.784
WOMEN - score: -0.20, precision: 0.721 ,recall: 0.838
WOMEN - score: -0.10, precision: 0.689 ,recall: 0.838
WOMEN - score: -0.00, precision: 0.696 ,recall: 0.865
WOMEN - score: 0.10, precision: 0.667 ,recall: 0.865
WOMEN - score: 0.20, precision: 0.647 ,recall: 0.892
WOMEN - score: 0.30, precision: 0.642 ,recall: 0.919
WOMEN - score: 0.40, precision: 0.621 ,recall: 0.973
WOMEN - score: 0.50, precision: 0.621 ,recall: 0.973
```

```
WOMEN - score: 0.60, precision: 0.610 ,recall: 0.973
WOMEN - score: 0.70, precision: 0.581 ,recall: 0.973
WOMEN - score: 0.80, precision: 0.571 ,recall: 0.973
WOMEN - score: 0.90, precision: 0.571 ,recall: 0.973
WOMEN - score: 1.00, precision: 0.562 ,recall: 0.973
WOMEN - score: 1.10, precision: 0.562 ,recall: 0.973
WOMEN - score: 1.20, precision: 0.554 ,recall: 0.973
WOMEN - score: 1.30, precision: 0.545 ,recall: 0.973
WOMEN - score: 1.40, precision: 0.529 ,recall: 0.973
WOMEN - score: 1.50, precision: 0.522 ,recall: 0.973
WOMEN - score: 1.60, precision: 0.522 ,recall: 0.973
WOMEN - score: 1.70, precision: 0.514 ,recall: 0.973
WOMEN - score: 1.80, precision: 0.500 ,recall: 0.973
WOMEN - score: 1.90, precision: 0.486 ,recall: 0.973
WOMEN - score: 2.00, precision: 0.486 ,recall: 0.973
WOMEN - score: 2.10, precision: 0.480 ,recall: 0.973
WOMEN - score: 2.20, precision: 0.480 ,recall: 0.973
WOMEN - score: 2.30, precision: 0.468 ,recall: 0.973
WOMEN - score: 2.40, precision: 0.462 ,recall: 0.973
WOMEN - score: 2.50, precision: 0.456 ,recall: 0.973
WOMEN - score: 2.60, precision: 0.450 ,recall: 0.973
WOMEN - score: 2.70, precision: 0.444 ,recall: 0.973
WOMEN - score: 2.80, precision: 0.439 ,recall: 0.973
WOMEN - score: 2.90, precision: 0.439 ,recall: 0.973
WOMEN - score: 3.00, precision: 0.439 ,recall: 0.973
WOMEN - score: 3.10, precision: 0.439 ,recall: 0.973
WOMEN - score: 3.20, precision: 0.439 ,recall: 0.973
WOMEN - score: 3.30, precision: 0.439 ,recall: 0.973
WOMEN - score: 3.40, precision: 0.434 ,recall: 0.973
WOMEN - score: 3.50, precision: 0.440 ,recall: 1.000
WOMEN - score: 3.60, precision: 0.440 ,recall: 1.000
MEN -  score: 3.40, precision: 0.000 ,recall: 0.000
MEN -  score: 3.30, precision: 0.500 ,recall: 0.021
MEN -  score: 3.20, precision: 0.500 ,recall: 0.021
MEN -  score: 3.10, precision: 0.500 ,recall: 0.021
MEN -  score: 3.00, precision: 0.500 ,recall: 0.021
MEN -  score: 2.90, precision: 0.500 ,recall: 0.021
MEN -  score: 2.80, precision: 0.500 ,recall: 0.021
MEN -  score: 2.70, precision: 0.667 ,recall: 0.043
MEN -  score: 2.60, precision: 0.750 ,recall: 0.064
MEN -  score: 2.50, precision: 0.800 ,recall: 0.085
MEN -  score: 2.40, precision: 0.833 ,recall: 0.106
MEN -  score: 2.30, precision: 0.857 ,recall: 0.128
MEN -  score: 2.20, precision: 0.889 ,recall: 0.170
MEN -  score: 2.10, precision: 0.889 ,recall: 0.170
MEN -  score: 2.00, precision: 0.900 ,recall: 0.191
MEN -  score: 1.90, precision: 0.900 ,recall: 0.191
MEN -  score: 1.80, precision: 0.917 ,recall: 0.234
MEN -  score: 1.70, precision: 0.929 ,recall: 0.277
MEN -  score: 1.60, precision: 0.933 ,recall: 0.298
MEN -  score: 1.50, precision: 0.933 ,recall: 0.298
MEN -  score: 1.40, precision: 0.938 ,recall: 0.319
MEN -  score: 1.30, precision: 0.944 ,recall: 0.362
MEN -  score: 1.20, precision: 0.947 ,recall: 0.383
MEN -  score: 1.10, precision: 0.950 ,recall: 0.404
MEN -  score: 1.00, precision: 0.950 ,recall: 0.404
MEN -  score: 0.90, precision: 0.952 ,recall: 0.426
```

```
MEN -  score: 0.80, precision: 0.952 ,recall: 0.426
MEN -  score: 0.70, precision: 0.955 ,recall: 0.447
MEN -  score: 0.60, precision: 0.960 ,recall: 0.511
MEN -  score: 0.50, precision: 0.962 ,recall: 0.532
MEN -  score: 0.40, precision: 0.962 ,recall: 0.532
MEN -  score: 0.30, precision: 0.903 ,recall: 0.596
MEN -  score: 0.20, precision: 0.879 ,recall: 0.617
MEN -  score: 0.10, precision: 0.861 ,recall: 0.660
MEN -  score: -0.00, precision: 0.868 ,recall: 0.702
MEN -  score: -0.10, precision: 0.846 ,recall: 0.702
MEN -  score: -0.20, precision: 0.854 ,recall: 0.745
MEN -  score: -0.30, precision: 0.814 ,recall: 0.745
MEN -  score: -0.40, precision: 0.800 ,recall: 0.766
MEN -  score: -0.50, precision: 0.783 ,recall: 0.766
MEN -  score: -0.60, precision: 0.771 ,recall: 0.787
MEN -  score: -0.70, precision: 0.765 ,recall: 0.830
MEN -  score: -0.80, precision: 0.750 ,recall: 0.830
MEN -  score: -0.90, precision: 0.755 ,recall: 0.851
MEN -  score: -1.00, precision: 0.745 ,recall: 0.872
MEN -  score: -1.10, precision: 0.745 ,recall: 0.872
MEN -  score: -1.20, precision: 0.700 ,recall: 0.894
MEN -  score: -1.30, precision: 0.705 ,recall: 0.915
MEN -  score: -1.40, precision: 0.710 ,recall: 0.936
MEN -  score: -1.50, precision: 0.698 ,recall: 0.936
MEN -  score: -1.60, precision: 0.657 ,recall: 0.936
MEN -  score: -1.70, precision: 0.638 ,recall: 0.936
MEN -  score: -1.80, precision: 0.643 ,recall: 0.957
MEN -  score: -1.90, precision: 0.625 ,recall: 0.957
MEN -  score: -2.00, precision: 0.608 ,recall: 0.957
MEN -  score: -2.10, precision: 0.610 ,recall: 1.000
MEN -  score: -2.20, precision: 0.595 ,recall: 1.000
MEN -  score: -2.30, precision: 0.595 ,recall: 1.000
MEN -  score: -2.40, precision: 0.595 ,recall: 1.000
MEN -  score: -2.50, precision: 0.595 ,recall: 1.000
MEN -  score: -2.60, precision: 0.588 ,recall: 1.000
MEN -  score: -2.70, precision: 0.588 ,recall: 1.000
MEN -  score: -2.80, precision: 0.588 ,recall: 1.000
MEN -  score: -2.90, precision: 0.588 ,recall: 1.000
MEN -  score: -3.00, precision: 0.588 ,recall: 1.000
MEN -  score: -3.10, precision: 0.580 ,recall: 1.000
MEN -  score: -3.20, precision: 0.573 ,recall: 1.000
MEN -  score: -3.30, precision: 0.573 ,recall: 1.000
MEN -  score: -3.40, precision: 0.573 ,recall: 1.000
MEN -  score: -3.50, precision: 0.573 ,recall: 1.000
MEN -  score: -3.60, precision: 0.573 ,recall: 1.000
MEN -  score: -3.70, precision: 0.566 ,recall: 1.000
MEN -  score: -3.80, precision: 0.566 ,recall: 1.000
MEN -  score: -3.90, precision: 0.566 ,recall: 1.000
MEN -  score: -4.00, precision: 0.566 ,recall: 1.000
MEN -  score: -4.10, precision: 0.566 ,recall: 1.000
MEN -  score: -4.20, precision: 0.566 ,recall: 1.000
MEN -  score: -4.30, precision: 0.566 ,recall: 1.000
MEN -  score: -4.40, precision: 0.566 ,recall: 1.000
MEN -  score: -4.50, precision: 0.566 ,recall: 1.000
MEN -  score: -4.60, precision: 0.566 ,recall: 1.000
MEN -  score: -4.70, precision: 0.566 ,recall: 1.000
MEN -  score: -4.80, precision: 0.566 ,recall: 1.000
```

```
MEN -  score: -4.90, precision: 0.566 ,recall: 1.000
MEN -  score: -5.00, precision: 0.566 ,recall: 1.000
MEN -  score: -5.10, precision: 0.566 ,recall: 1.000
MEN -  score: -5.20, precision: 0.560 ,recall: 1.000
MEN -  score: -5.30, precision: 0.560 ,recall: 1.000
score: -5.30. Women: 0, Men: 0
score: -5.20. Women: 0, Men: 0
score: -5.10. Women: 1, Men: 0
score: -5.00. Women: 1, Men: 0
score: -4.90. Women: 1, Men: 0
score: -4.80. Women: 1, Men: 0
score: -4.70. Women: 1, Men: 0
score: -4.60. Women: 1, Men: 0
score: -4.50. Women: 1, Men: 0
score: -4.40. Women: 1, Men: 0
score: -4.30. Women: 1, Men: 0
score: -4.20. Women: 1, Men: 0
score: -4.10. Women: 1, Men: 0
score: -4.00. Women: 1, Men: 0
score: -3.90. Women: 1, Men: 0
score: -3.80. Women: 1, Men: 0
score: -3.70. Women: 1, Men: 0
score: -3.60. Women: 2, Men: 0
score: -3.50. Women: 2, Men: 0
score: -3.40. Women: 2, Men: 0
score: -3.30. Women: 2, Men: 0
score: -3.20. Women: 2, Men: 0
score: -3.10. Women: 3, Men: 0
score: -3.00. Women: 4, Men: 0
score: -2.90. Women: 4, Men: 0
score: -2.80. Women: 4, Men: 0
score: -2.70. Women: 4, Men: 0
score: -2.60. Women: 4, Men: 0
score: -2.50. Women: 5, Men: 0
score: -2.40. Women: 5, Men: 0
score: -2.30. Women: 5, Men: 0
score: -2.20. Women: 5, Men: 0
score: -2.10. Women: 7, Men: 0
score: -2.00. Women: 8, Men: 2
score: -1.90. Women: 10, Men: 2
score: -1.80. Women: 12, Men: 2
score: -1.70. Women: 12, Men: 3
score: -1.60. Women: 14, Men: 3
score: -1.50. Women: 18, Men: 3
score: -1.40. Women: 19, Men: 3
score: -1.30. Women: 19, Men: 4
score: -1.20. Women: 19, Men: 5
score: -1.10. Women: 23, Men: 6
score: -1.00. Women: 23, Men: 6
score: -0.90. Women: 24, Men: 7
score: -0.80. Women: 24, Men: 8
score: -0.70. Women: 25, Men: 8
score: -0.60. Women: 26, Men: 10
score: -0.50. Women: 27, Men: 11
score: -0.40. Women: 28, Men: 11
score: -0.30. Women: 29, Men: 12
score: -0.20. Women: 31, Men: 12
```