brands_SVD

August 1, 2019

0.1 Brand level Matrices: Truncated SVD, Cosine Distances & Predictive Eigenvector Models

```
In [1]: import os
        import pickle
        import pandas as pd
        import numpy as np
        import scipy.sparse.csr as csr
        import scipy.sparse as sparse
        from sklearn.decomposition import TruncatedSVD
        from sklearn.metrics.pairwise import cosine_similarity
        from sklearn import linear_model
        from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
        from sklearn.metrics import mean_squared_error, r2_score
        from sklearn.model_selection import train_test_split
        from sklearn.model_selection import cross_val_score
        import re
        import matplotlib.pyplot as plt
        import timeit

        %matplotlib inline
```

Define function to save/load BRAND-LEVEL pickle files for G1, G2, G3

```
In [2]: def save_G_pickle(G1, G2, G3, tag):
            path = os.getcwd() + r'\pickle\\'
            pickle.dump(G1, open(path + tag + '_G1_Brand.pkl', "wb" ))
            pickle.dump(G2, open(path + tag + '_G2_Brand.pkl', "wb" ))
            pickle.dump(G3, open(path + tag + '_G3_Brand.pkl', "wb" ))

        def load_G_pickle(tag):
            path = os.getcwd() + r'\pickle\\'
            return pickle.load(open(path + tag + '_G1_Brand.pkl', "rb" )), \
                   pickle.load(open(path + tag + '_G2_Brand.pkl', "rb" )), \
                   pickle.load(open(path + tag + '_G3_Brand.pkl', "rb" ))
```

Define function to save/load BRAND-LEVEL pickle files for PQR

```
In [3]: def save_PQRpickle(P, Q, R, tag):
            path = os.getcwd() + r'\pickle\\'
            pickle.dump(P, open(path + tag + '_bag_P_brand.pkl', "wb" ))
            pickle.dump(Q, open(path + tag + '_bag_Q_brand.pkl', "wb" ))
            pickle.dump(R, open(path + tag + '_bag_R_brand.pkl', "wb" ))

        def load_PQRpickle(tag):
            path = os.getcwd() + r'\pickle\\'
            return pickle.load(open(path + tag + '_bag_P_brand.pkl', "rb" )), \
                   pickle.load(open(path + tag + '_bag_Q_brand.pkl', "rb" )), \
                   pickle.load(open(path + tag + '_bag_R_brand.pkl', "rb" ))
```

0.1.1 Load BRAND-LEVEL G1, G2, G3 Matrices for all product types (Beauty, Cellphones & Electronics)

```
In [4]: B_G1_Brand, B_G2_Brand, B_G3_Brand = load_G_pickle('B')
        C_G1_Brand, C_G2_Brand, C_G3_Brand = load_G_pickle('C')
        E_G1_Brand, E_G2_Brand, E_G3_Brand = load_G_pickle('E')
```

0.1.2 Load BRAND-LEVEL PQR Matrices for all product types

```
In [5]: B_bag_P_brand, B_bag_Q_brand, B_bag_R_brand = load_PQRpickle('B')
        C_bag_P_brand, C_bag_Q_brand, C_bag_R_brand = load_PQRpickle('C')
        E_bag_P_brand, E_bag_Q_brand, E_bag_R_brand = load_PQRpickle('E')
```

0.1.3 Calculate SVD for Beauty

```
In [6]: start_time = timeit.default_timer()

        # Set number of components for desired dimensionality of output data
        n_components=500

        #B_nBrands = B_G1_Brand.shape[0]

        svd_B_G1 = TruncatedSVD(n_components, n_iter=5, random_state=42)
        svd_B_G1.fit(B_G1_Brand)

        svd_B_G2 = TruncatedSVD(n_components, n_iter=5, random_state=42)
        svd_B_G2.fit(B_G2_Brand)

        svd_B_G3 = TruncatedSVD(n_components, n_iter=5, random_state=42)
        svd_B_G3.fit(B_G3_Brand)

        svd_B_P = TruncatedSVD(n_components, n_iter=5, random_state=42)
        svd_B_P.fit(B_bag_P_brand[2014])

        svd_B_Q = TruncatedSVD(n_components, n_iter=5, random_state=42)
        svd_B_Q.fit(B_bag_Q_brand[2014])
```

```
svd_B_R = TruncatedSVD(n_components, n_iter=5, random_state=42)
svd_B_R.fit(B_bag_R_brand[2014])

print('{0:.2f} seconds'.format(timeit.default_timer() - start_time))
```

```
27.88 seconds
```

0.1.4 Calculate SVD for Cellphones

```
In [7]: start_time = timeit.default_timer()

        # Set number of components for desired dimensionality of output data
        n_components=500

        #C_nBrands = C_G1_Brand.shape[0]

        svd_C_G1 = TruncatedSVD(n_components, n_iter=5, random_state=42)
        svd_C_G1.fit(B_G1_Brand)

        svd_C_G2 = TruncatedSVD(n_components, n_iter=5, random_state=42)
        svd_C_G2.fit(B_G2_Brand)

        svd_C_G3 = TruncatedSVD(n_components, n_iter=5, random_state=42)
        svd_C_G3.fit(B_G3_Brand)

        svd_C_P = TruncatedSVD(n_components, n_iter=5, random_state=42)
        svd_C_P.fit(B_bag_P_brand[2014])

        svd_C_Q = TruncatedSVD(n_components, n_iter=5, random_state=42)
        svd_C_Q.fit(B_bag_Q_brand[2014])

        svd_C_R = TruncatedSVD(n_components, n_iter=5, random_state=42)
        svd_C_R.fit(B_bag_R_brand[2014])

        print('{0:.2f} seconds'.format(timeit.default_timer() - start_time))
```

```
27.50 seconds
```

0.1.5 Calculate SVD for Electronics

```
In [8]: start_time = timeit.default_timer()

        # Set number of components for desired dimensionality of output data
        n_components=500

        #C_nBrands = C_G1_Brand.shape[0]
```

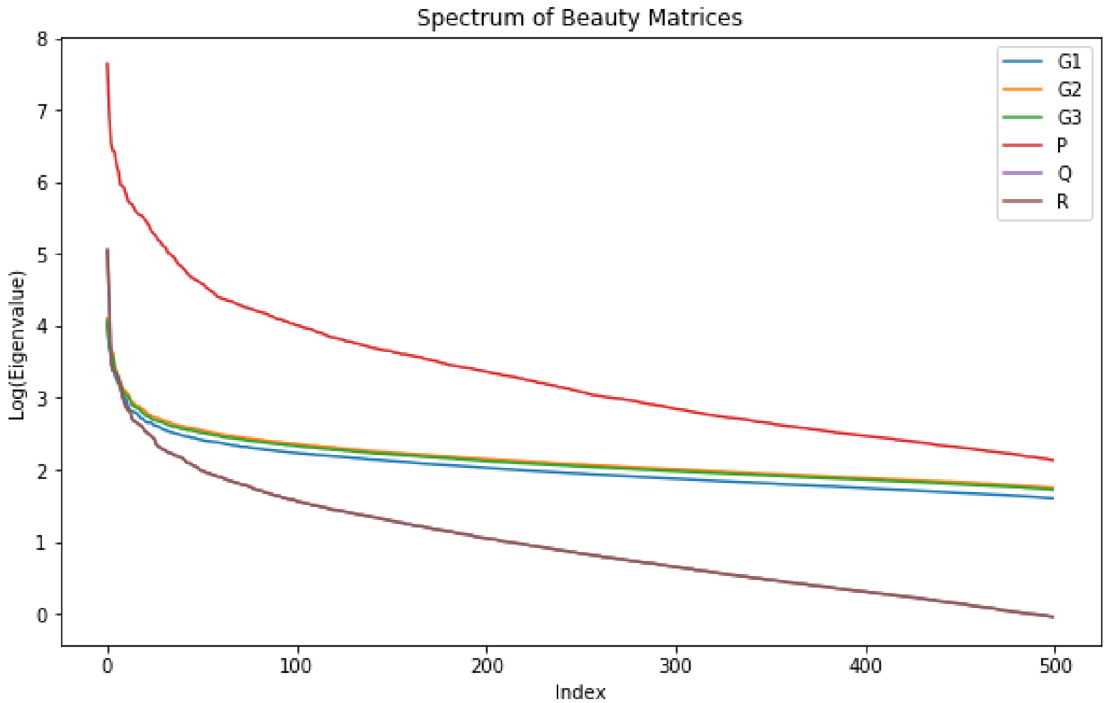
```
svd_E_G1 = TruncatedSVD(n_components, n_iter=5, random_state=42)
svd_E_G1.fit(E_G1_Brand)

svd_E_G2 = TruncatedSVD(n_components, n_iter=5, random_state=42)
svd_E_G2.fit(E_G2_Brand)

svd_E_G3 = TruncatedSVD(n_components, n_iter=5, random_state=42)
svd_E_G3.fit(E_G3_Brand)

svd_E_P = TruncatedSVD(n_components, n_iter=5, random_state=42)
svd_E_P.fit(E_bag_P_brand[2014])

svd_E_Q = TruncatedSVD(n_components, n_iter=5, random_state=42)
svd_E_Q.fit(E_bag_Q_brand[2014])

svd_E_R = TruncatedSVD(n_components, n_iter=5, random_state=42)
svd_E_R.fit(E_bag_R_brand[2014])

print('{0:.2f} seconds'.format(timeit.default_timer() - start_time))
```

```
23.39 seconds
```

Beauty brands (2014): Plot & Compare the eigenvalue spectrum of all 6 matrices

```
In [9]: fig, ax = plt.subplots(figsize=(10, 6))
        plt.plot(np.log10(svd_B_G1.singular_values_**2), label = 'G1')
        plt.plot(np.log10(svd_B_G2.singular_values_**2), label = 'G2')
        plt.plot(np.log10(svd_B_G3.singular_values_**2), label = 'G3')
        plt.plot(np.log10(svd_B_P.singular_values_**2), label = 'P')
        plt.plot(np.log10(svd_B_Q.singular_values_**2), label = 'Q')
        plt.plot(np.log10(svd_B_R.singular_values_**2), label = 'R')
        plt.title('Spectrum of Beauty Matrices')
        plt.legend()
        plt.xlabel('Index')
        plt.ylabel('Log(Eigenvalue)')
```

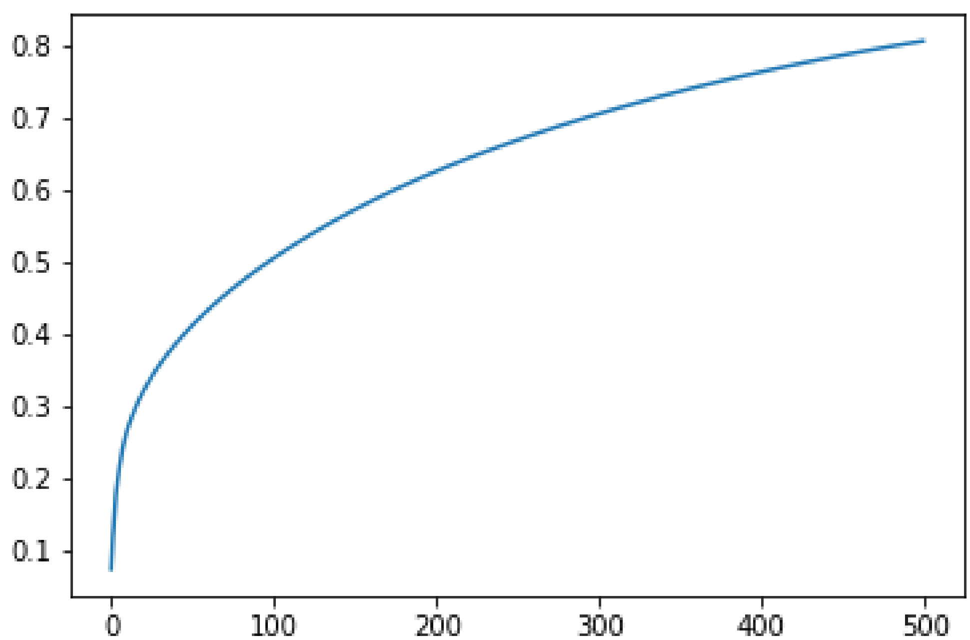
```
Out[9]: Text(0,0.5,'Log(Eigenvalue)')
```



Show % of variance explained as a function of # of Principal Components (top-k eigenvectors)

In [10]:
```
plt.plot(np.cumsum(svd_B_G1.explained_variance_ratio_))
```

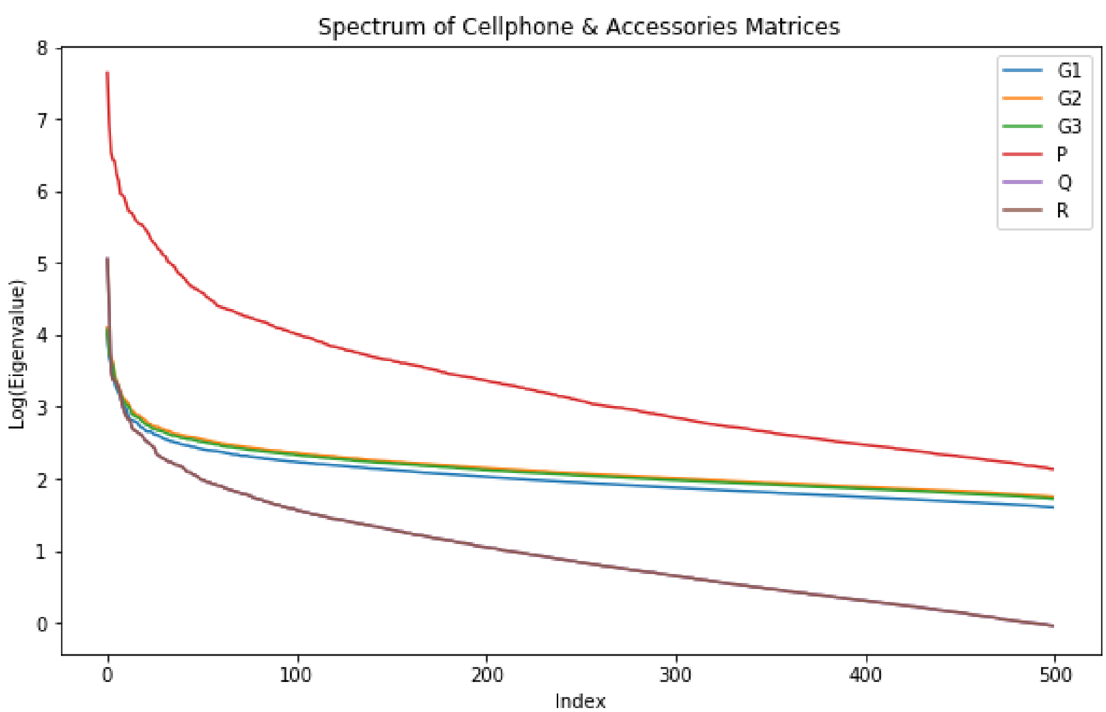
Out[10]:
```
[<matplotlib.lines.Line2D at 0x1b4d6266278>]
```



Cellphone & Accessories brands (2014): Plot & Compare the eigenvalue spectrum of all 6 matrices

In [11]:
```
fig, ax = plt.subplots(figsize=(10, 6))
plt.plot(np.log10(svd_C_G1.singular_values_**2), label = 'G1')
plt.plot(np.log10(svd_C_G2.singular_values_**2), label = 'G2')
plt.plot(np.log10(svd_C_G3.singular_values_**2), label = 'G3')
plt.plot(np.log10(svd_C_P.singular_values_**2), label = 'P')
plt.plot(np.log10(svd_C_Q.singular_values_**2), label = 'Q')
plt.plot(np.log10(svd_C_R.singular_values_**2), label = 'R')
plt.title('Spectrum of Cellphone & Accessories Matrices')
plt.legend()
plt.xlabel('Index')
plt.ylabel('Log(Eigenvalue)')
```

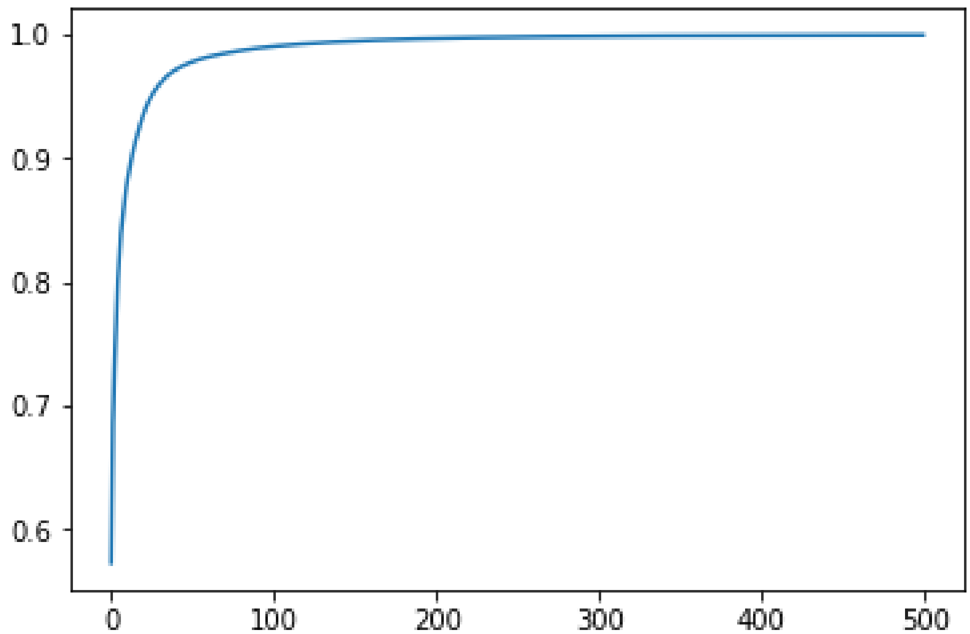
Out[11]:
```
Text(0,0.5,'Log(Eigenvalue)')
```



Show % of variance explained as a function of # of Principal Components (top-k eigenvectors)

In [12]:
```
plt.plot(np.cumsum(svd_C_P.explained_variance_ratio_))
```

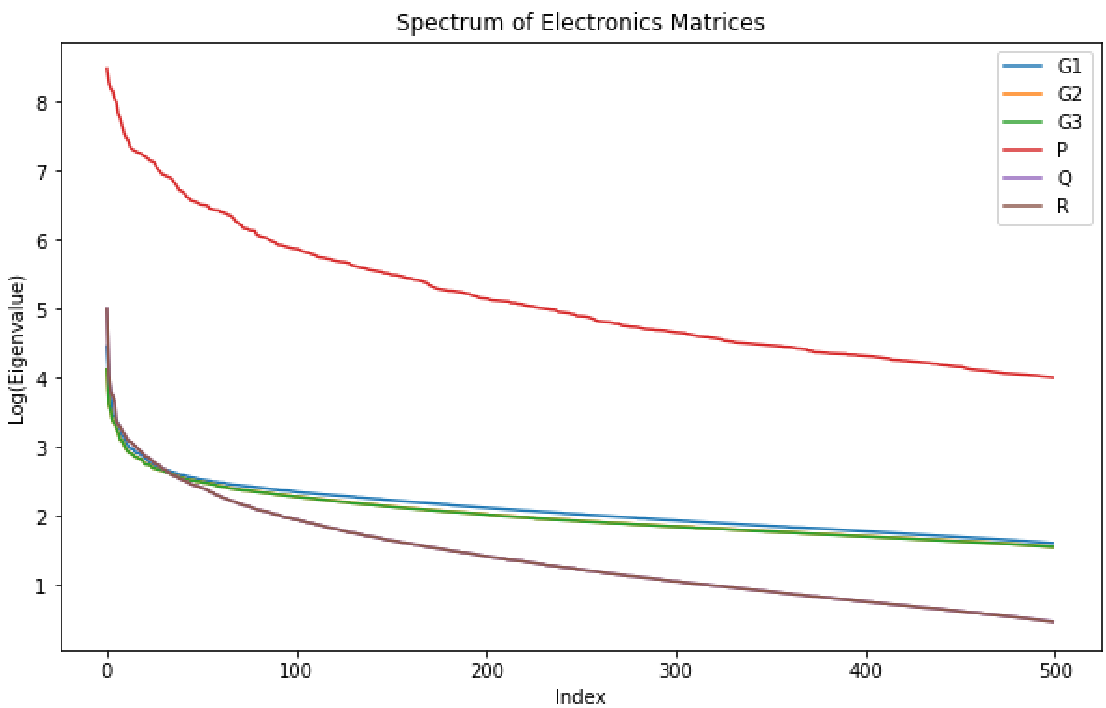
Out[12]:
```
[<matplotlib.lines.Line2D at 0x1b4d6195d30>]
```



Electronics brands (2014): Plot & Compare the eigenvalue spectrum of all 6 matrices

In [13]:
```
fig, ax = plt.subplots(figsize=(10, 6))
plt.plot(np.log10(svd_E_G1.singular_values_**2), label = 'G1')
plt.plot(np.log10(svd_E_G2.singular_values_**2), label = 'G2')
plt.plot(np.log10(svd_E_G3.singular_values_**2), label = 'G3')
plt.plot(np.log10(svd_E_P.singular_values_**2), label = 'P')
plt.plot(np.log10(svd_E_Q.singular_values_**2), label = 'Q')
plt.plot(np.log10(svd_E_R.singular_values_**2), label = 'R')
plt.title('Spectrum of Electronics Matrices')
plt.legend()
plt.xlabel('Index')
plt.ylabel('Log(Eigenvalue)')
```

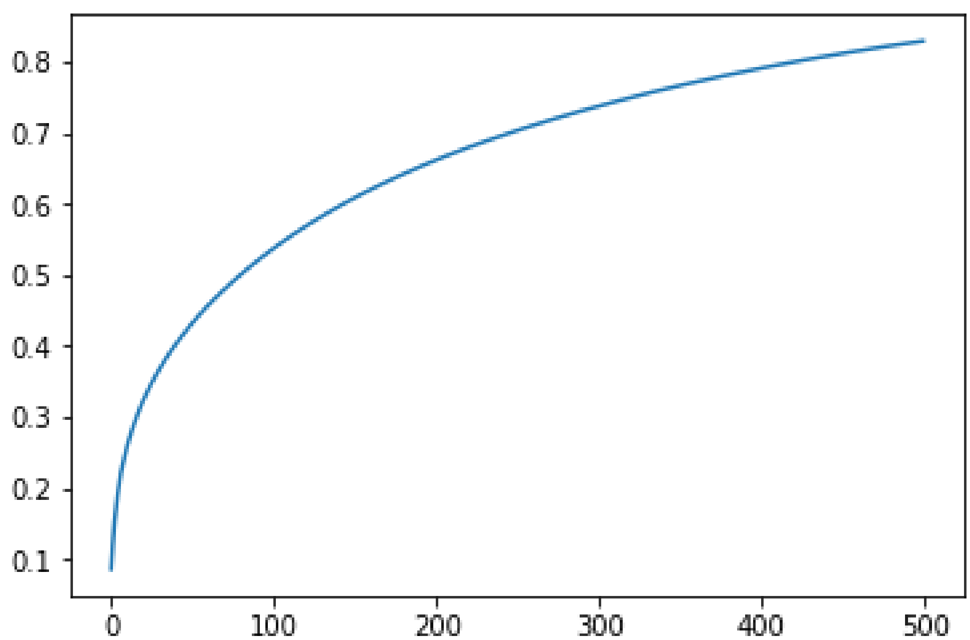
Out[13]:
```
Text(0,0.5,'Log(Eigenvalue)')
```



Show % of variance explained as a function of # of Principal Components (top-k eigenvectors)

```
In [14]: plt.plot(np.cumsum(svd_E_G3.explained_variance_ratio_))
```

```
Out[14]: [<matplotlib.lines.Line2D at 0x1b4d62c2358>]
```

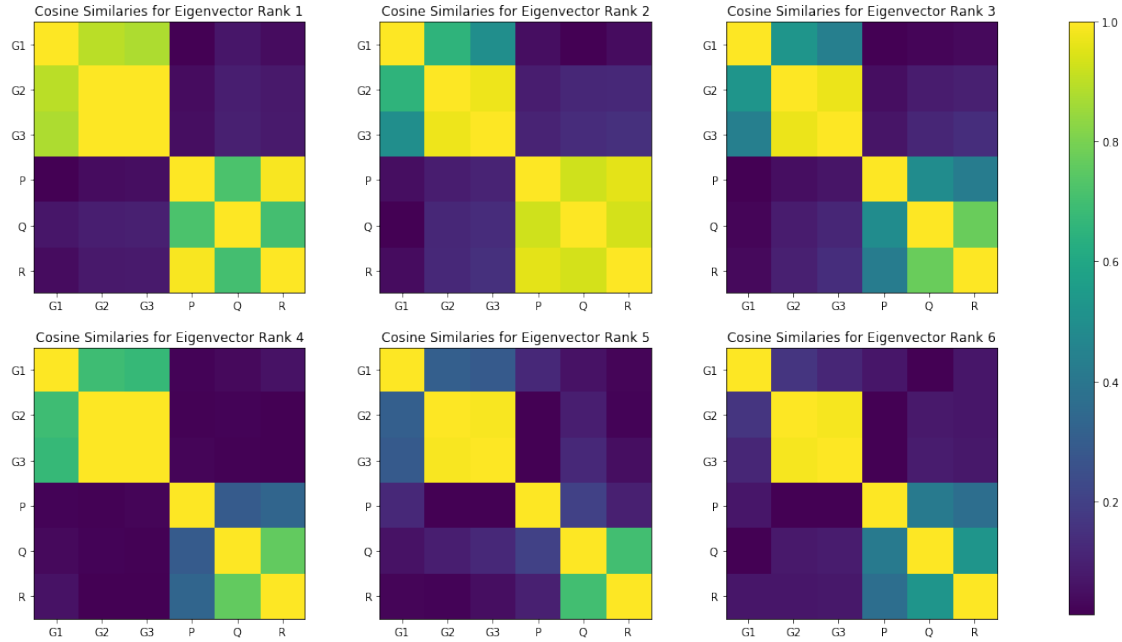


0.1.6 Cosine Distances for top-K eigenvectors

Plot Cosine Distances for Beauty

In [16]:
```
fig, ax = plt.subplots(figsize=(16, 10))
for k in range(6):
    X = np.concatenate((svd_B_G1.components_[[k],:], svd_B_G2.components_[[k],:], svd_
                        svd_B_P.components_[[k],:], svd_B_Q.components_[[k],:], svd_B_R.co
    a = cosine_similarity(X)    # 'cosine_similarity' applies cosine distances of vec
    plt.subplot(2,3,k+1)
    plt.imshow(np.abs(a))
    plt.xticks(range(6), ['G1', 'G2', 'G3', 'P', 'Q', 'R'])
    plt.yticks(range(6), ['G1', 'G2', 'G3', 'P', 'Q', 'R'])

    plt.title('Cosine Similaries for Eigenvector Rank {0}'.format(k+1))

cax = plt.axes([0.95, 0.13, 0.02, 0.75])
plt.colorbar(cax=cax)
```

Out[16]: <matplotlib.colorbar.Colorbar at 0x1b4d65156d8>

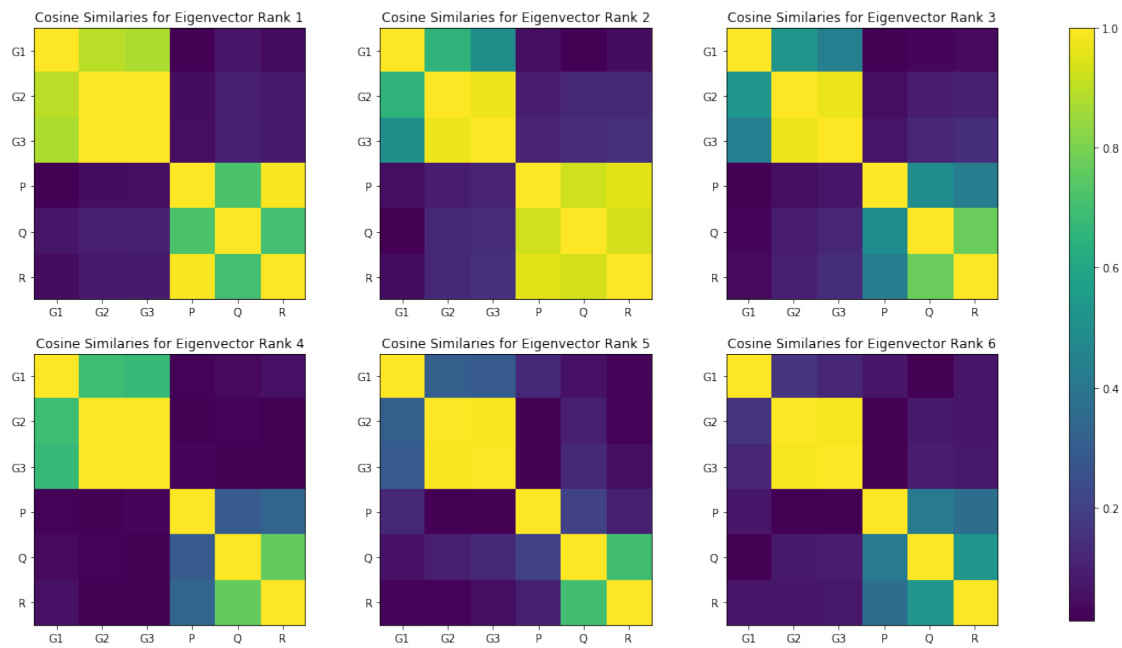


NOTE: lighter shading = more correlated, darker shading = less correlated (see side scale)

Plot Cosine Distances for Cellphones

In [17]:
```
fig, ax = plt.subplots(figsize=(16, 10))
for k in range(6):
    X = np.concatenate((svd_C_G1.components_[[k],:], svd_C_G2.components_[[k],:], svd_
                       svd_C_P.components_[[k],:], svd_C_Q.components_[[k],:], svd_C_R.co
    a = cosine_similarity(X)
    plt.subplot(2,3,k+1)
    plt.imshow(np.abs(a))
    plt.xticks(range(6), ['G1', 'G2', 'G3', 'P', 'Q', 'R'])
    plt.yticks(range(6), ['G1', 'G2', 'G3', 'P', 'Q', 'R'])

    plt.title('Cosine Similaries for Eigenvector Rank {0}'.format(k+1))

cax = plt.axes([0.95, 0.13, 0.02, 0.75])
plt.colorbar(cax=cax)
```

Out[17]: <matplotlib.colorbar.Colorbar at 0x1b4d6675be0>

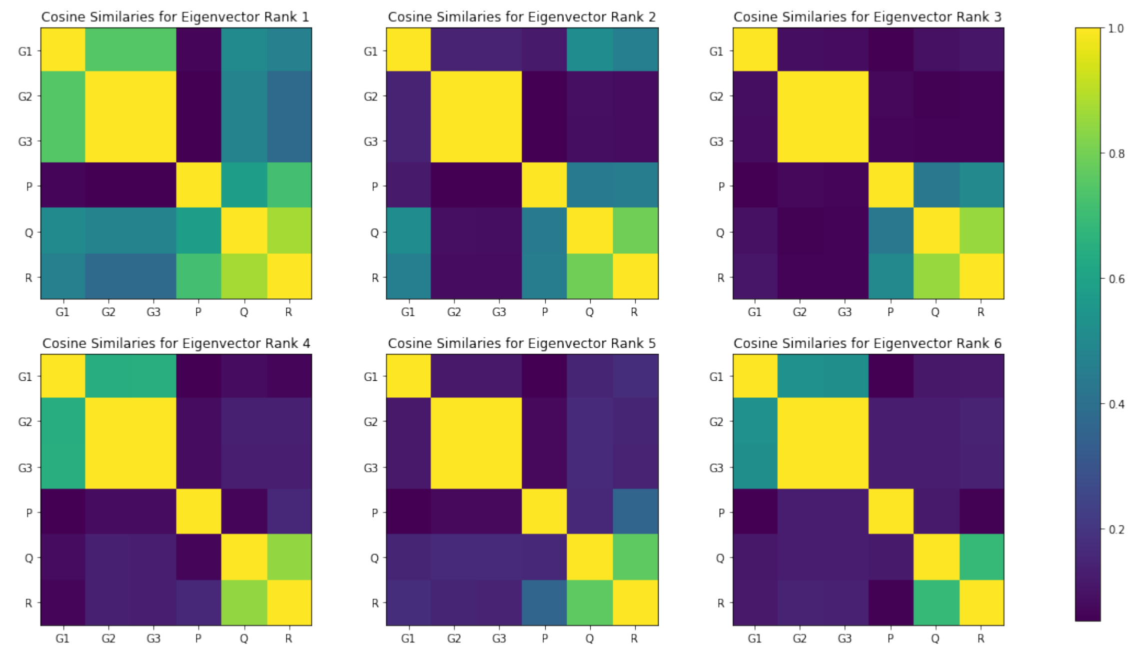


Plot Cosine Distances for Electronics

In [18]:
```
fig, ax = plt.subplots(figsize=(16, 10))
for k in range(6):
    X = np.concatenate((svd_E_G1.components_[[k],:], svd_E_G2.components_[[k],:], svd_
                           svd_E_P.components_[[k],:], svd_E_Q.components_[[k],:], svd_E_
    a = cosine_similarity(X)
    plt.subplot(2,3,k+1)
```

```
        plt.imshow(np.abs(a))
        plt.xticks(range(6), ['G1', 'G2', 'G3', 'P', 'Q', 'R'])
        plt.yticks(range(6), ['G1', 'G2', 'G3', 'P', 'Q', 'R'])

        plt.title('Cosine Similaries for Eigenvector Rank {0}'.format(k+1))

    cax = plt.axes([0.95, 0.13, 0.02, 0.75])
    plt.colorbar(cax=cax)
```

Out[18]: <matplotlib.colorbar.Colorbar at 0x1b4d68d0a20>



0.1.7 Models Predicting The Top Eigenvectors of Gi (for all three product types)

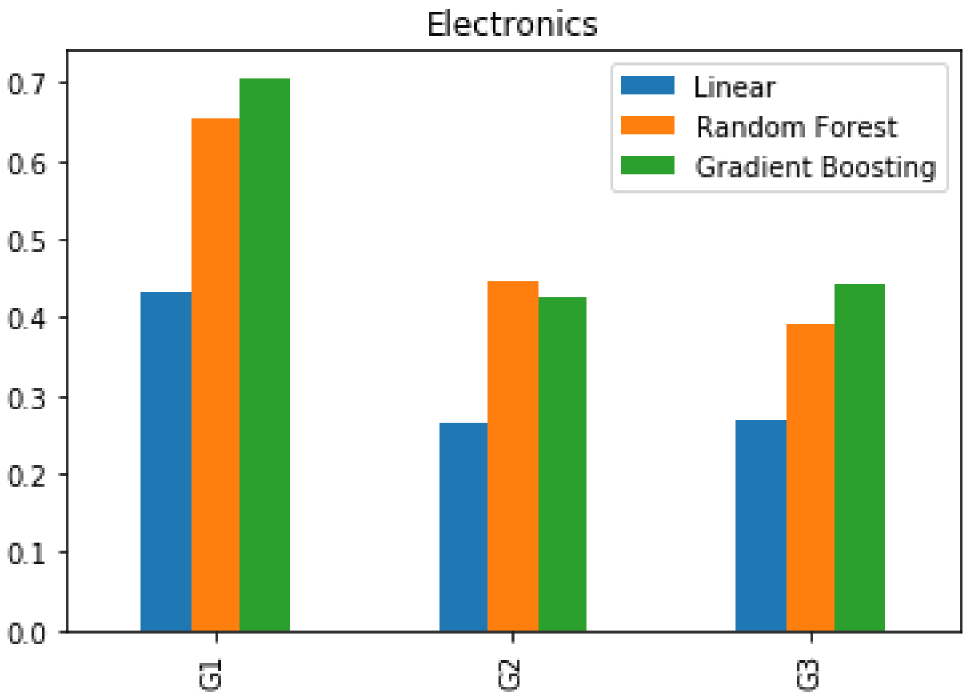
K-Fold Cross-Validation (if desired)

In [19]:
```
if 0:
        E_nBrands = svd_E_P.components_.T[:,0].shape[0]
        X = np.concatenate((svd_E_P.components_.T[:,[0]],
                            svd_E_Q.components_.T[:,[0]],
                            svd_E_R.components_.T[:,[0]]), axis=1)
        y = svd_E_G1.components_.T[:,0]
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_s
        #print(X.shape)
        #print(y.shape)

        print("------------Electronics-------------")
```

```
    regr_lin = linear_model.LinearRegression()
    #scores = cross_val_score(regr_lin, X, y, cv=10)
    scores = regr_lin.fit(X_train, y_train).score(X_test, y_test)
    print("R2 of Linear Regression: {0:.2f}".format(scores))

    regr_fst = RandomForestRegressor()
    #scores = cross_val_score(regr_fst, X, y, cv=10, scoring='r2')
    scores = regr_fst.fit(X_train, y_train).score(X_test, y_test)
    print("R2 of Random Forest: {0:.2f}".format(scores))


    regr_bst = GradientBoostingRegressor()
    #scores = cross_val_score(regr_bst, X, y, cv=10, scoring='r2')
    #print("R2 of Gradient Boosting: {0:.2f} +- {1:.2f}".format(np.mean(scores), np.s
    scores = regr_bst.fit(X_train, y_train).score(X_test, y_test)
    print("R2 of Gradient Boosting: {0:.2f}".format(scores))
```

Models for Electronics

```
In [21]: E_nBrands = svd_E_P.components_.T[:,0].shape[0]
         X = np.concatenate((svd_E_P.components_.T[:,[0]],
                             svd_E_Q.components_.T[:,[0]],
                             svd_E_R.components_.T[:,[0]]), axis=1)

         scores = []
         for y in [svd_E_G1.components_.T[:,0], svd_E_G2.components_.T[:,0], svd_E_G3.componen
             score = []
             X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_s
             regr_lin = linear_model.LinearRegression()
             score.append(regr_lin.fit(X_train, y_train).score(X_test, y_test))

             regr_fst = RandomForestRegressor()
             score.append(regr_fst.fit(X_train, y_train).score(X_test, y_test))


             regr_bst = GradientBoostingRegressor()
             score.append(regr_bst.fit(X_train, y_train).score(X_test, y_test))

             scores.append(score)

         results = pd.DataFrame(scores, index=['G1', 'G2', 'G3'], columns=['Linear', 'Random Fo
         results.plot(kind='bar')
         plt.title('Electronics')
         plt.show()
         results
```

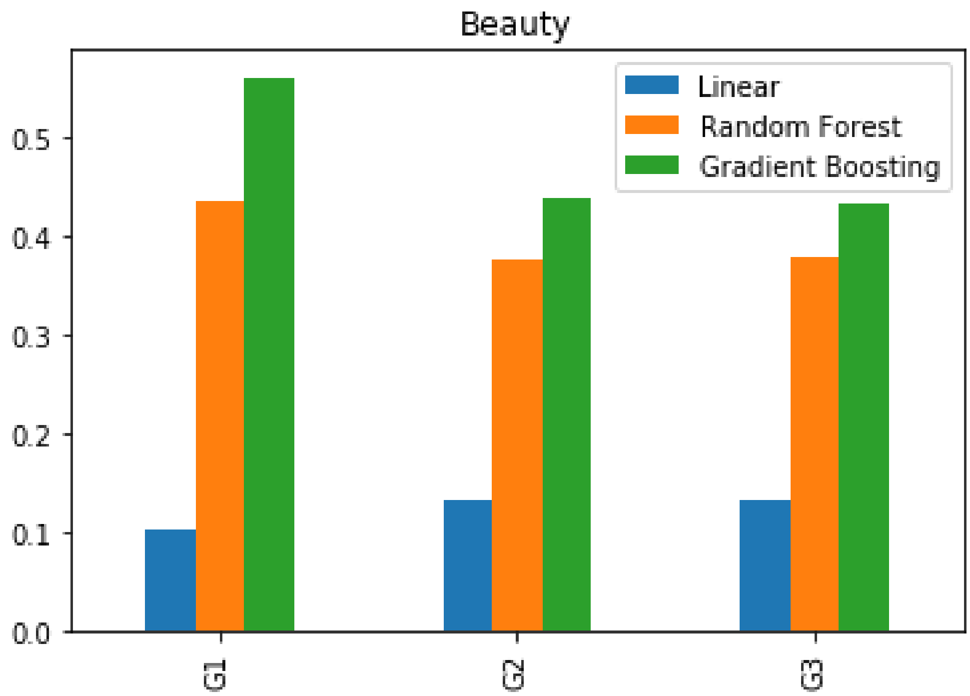



```
Out[21]:       Linear  Random Forest  Gradient Boosting
         G1  0.431560       0.655555           0.706512
         G2  0.265786       0.444311           0.424998
         G3  0.267259       0.392720           0.441632
```

Models for Beauty

```
In [22]: B_nBrands = svd_B_P.components_.T[:,0].shape[0]
         X = np.concatenate((svd_B_P.components_.T[:,[0]],
                             svd_B_Q.components_.T[:,[0]],
                             svd_B_R.components_.T[:,[0]]), axis=1)

         scores = []
         for y in [svd_B_G1.components_.T[:,0], svd_B_G2.components_.T[:,0], svd_B_G3.componen
             score = []
             X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_s
             regr_lin = linear_model.LinearRegression()
             score.append(regr_lin.fit(X_train, y_train).score(X_test, y_test))

             regr_fst = RandomForestRegressor()
             score.append(regr_fst.fit(X_train, y_train).score(X_test, y_test))


             regr_bst = GradientBoostingRegressor()
```

```
    score.append(regr_bst.fit(X_train, y_train).score(X_test, y_test))

    scores.append(score)

results = pd.DataFrame(scores, index=['G1', 'G2', 'G3'], columns=['Linear', 'Random Fo
results.plot(kind='bar')
plt.title('Beauty')
plt.show()
results
```



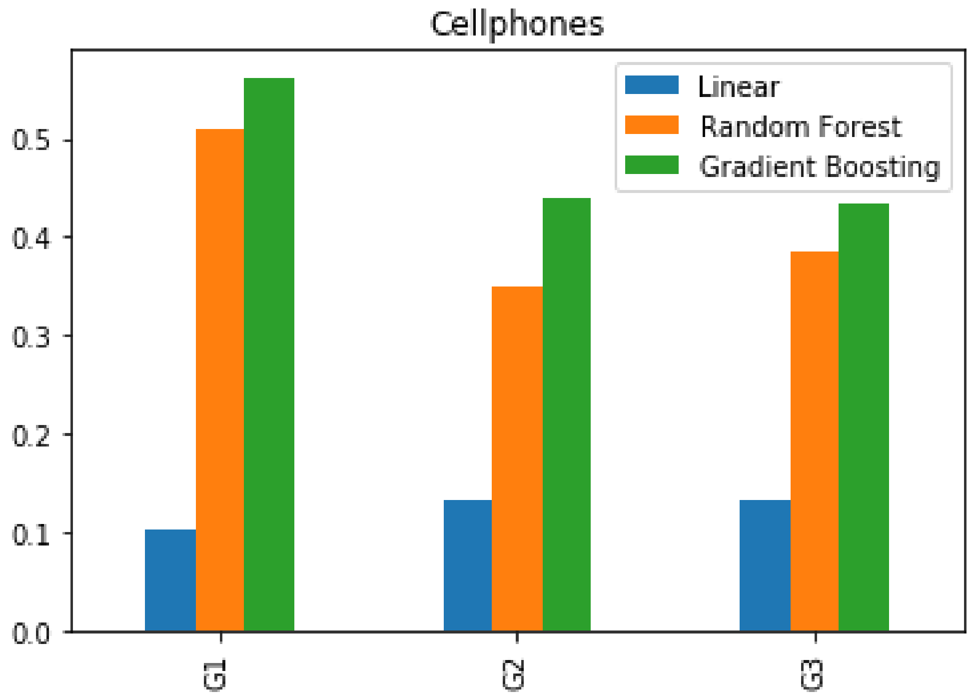
Out[22]:

	Linear	Random Forest	Gradient Boosting
G1	0.101351	0.435622	0.561895
G2	0.130976	0.375924	0.440028
G3	0.132367	0.379418	0.432467

Models for Cellphones

In [24]:
```
C_nBrands = svd_C_P.components_.T[:,0].shape[0]
X = np.concatenate((svd_C_P.components_.T[:,[0]],
                    svd_C_Q.components_.T[:,[0]],
                    svd_C_R.components_.T[:,[0]]), axis=1)
#print(X.shape)
#print(y.shape)

scores = []
```

```
for y in [svd_C_G1.components_.T[:,0], svd_C_G2.components_.T[:,0], svd_C_G3.componen
    score = []
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_
    regr_lin = linear_model.LinearRegression()
    score.append(regr_lin.fit(X_train, y_train).score(X_test, y_test))

    regr_fst = RandomForestRegressor()
    score.append(regr_fst.fit(X_train, y_train).score(X_test, y_test))


    regr_bst = GradientBoostingRegressor()
    score.append(regr_bst.fit(X_train, y_train).score(X_test, y_test))

    scores.append(score)

results = pd.DataFrame(scores, index=['G1', 'G2', 'G3'], columns=['Linear', 'Random Fo
results.plot(kind='bar')
plt.title('Cellphones')
plt.show()
results
```



Out[24]:

	Linear	Random Forest	Gradient Boosting
G1	0.101351	0.508832	0.562296
G2	0.130976	0.348767	0.439802
G3	0.132367	0.384448	0.432542