Preference Learning - Part VI

Comparison of warm and cold season k-mean

In [1]:
```
%matplotlib inline
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import json
import seaborn as sns
import math
from pandas.io.json import json_normalize #package for flattening json in pandas df
import matplotlib.pyplot as plt
from datetime import date, timedelta, datetime
```

In [ ]:
```
# Import all preprocessed data necessary for the analysis
df_tou1h = pd.read_csv("C:\\Users\\Rockwell\\Desktop\\Paper4\\data_collection\\data_tables\\Consumption_tou20
13_1h.csv")
df_Ntou1h = pd.read_csv("C:\\Users\\Rockwell\\Desktop\\Paper4\\data_collection\\data_tables\\Consumption_Ntou
2013_1h.csv")
df_wea1h = pd.read_csv("C:\\Users\\Rockwell\\Desktop\\Paper4\\data_collection\\weather\\LondonWeather2013_int
erpolated.csv")
df_tariff_1h = pd.read_csv("C:\\Users\\Rockwell\\Desktop\\Paper4\\data_collection\\data_tables\\df_tariff_1h.
csv")
```

In [2]:
```
import os
os.getcwd()
```

Out[2]: '/Users/Rockwell/Documents/GitHub/Demand-Response'

In [3]:
```
# for ios system, import all data necessary for the analysis
df_tou1h = pd.read_csv('/Users/Rockwell/Desktop/PhD/Paper4PreferenceLearning/data/Consumption_tou2013_1h.csv'
)
df_Ntou1h = pd.read_csv('/Users/Rockwell/Desktop/PhD/Paper4PreferenceLearning/data/Consumption_Ntou2013_1h.cs
v')
df_wea1h = pd.read_csv('/Users/Rockwell/Desktop/PhD/Paper4PreferenceLearning/data/LondonWeather2013_interpola
ted.csv')
df_tariff_1h = pd.read_csv('/Users/Rockwell/Desktop/PhD/Paper4PreferenceLearning/data/df_tariff_1h.csv')
```

In [4]:
```
# first, create a list of days that belongs to event days
event_days = set()
event_series = df_tariff_1h[df_tariff_1h.Event_tags.notnull()].GMT
for i in event_series:
    event_days.add(datetime.strptime(i[:10], "%Y-%m-%d" ).date()) # add all event dates to the set
df_help = pd.DataFrame(pd.to_datetime(df_tariff_1h.GMT).dt.date) #str to datatime and extract date then make
 it to dataframe
# df_help[df_help['GMT'].isin(event_days)] #this shows the event days
# we can use ~df_help['GMT'].isin(event_days) to generate any non-flexible period items

# create TOU and non-TOU demand data in non-flexible hours
df_wea1h_nf = df_wea1h[~df_help['GMT'].isin(event_days)]
df_Ntou1h_nf = df_Ntou1h[~df_help['GMT'].isin(event_days)]
df_tou1h_nf = df_tou1h[~df_help['GMT'].isin(event_days)]

# create event data
df_tariff_1h_event = df_tariff_1h[df_tariff_1h.GMT.isin(event_series)]
df_wea1h_event = df_wea1h[df_wea1h.GMT.isin(event_series)]
df_tou1h_event = df_tou1h[df_tou1h.GMT.isin(event_series)]
```

In [5]:
```
# seperate the above data set based on the seasonal effect
# i.e., months of 11, 12, 1, 2, 3 are in a group - cold season
# months of 4, 5, 6, 7, 8, 9, 10 are in another group - warm season
cold_season = [11, 12, 1, 2, 3]
warm_season = [4, 5, 6, 7, 8, 9, 10]
df_help_season = pd.DataFrame(pd.to_datetime(df_wea1h_nf.GMT).dt.month)
df_wea1h_nf_cold = df_wea1h_nf[df_help_season['GMT'].isin(cold_season)]
df_wea1h_nf_warm = df_wea1h_nf[df_help_season['GMT'].isin(warm_season)]
df_Ntou1h_nf_cold = df_Ntou1h_nf[df_help_season['GMT'].isin(cold_season)]
df_Ntou1h_nf_warm = df_Ntou1h_nf[df_help_season['GMT'].isin(warm_season)]
df_tou1h_nf_cold = df_tou1h_nf[df_help_season['GMT'].isin(cold_season)]
df_tou1h_nf_warm = df_tou1h_nf[df_help_season['GMT'].isin(warm_season)]

df_help_season_event = pd.DataFrame(pd.to_datetime(df_wea1h_event.GMT).dt.month)
df_wea1h_event_cold = df_wea1h_event[df_help_season_event['GMT'].isin(cold_season)]
df_wea1h_event_warm = df_wea1h_event[df_help_season_event['GMT'].isin(warm_season)]
df_tou1h_event_cold = df_tou1h_event[df_help_season_event['GMT'].isin(cold_season)]
df_tou1h_event_warm = df_tou1h_event[df_help_season_event['GMT'].isin(warm_season)]
df_tariff_1h_event_cold = df_tariff_1h_event[df_help_season_event['GMT'].isin(cold_season)]
df_tariff_1h_event_warm = df_tariff_1h_event[df_help_season_event['GMT'].isin(warm_season)]
```

1. Groups' Price Responsiveness - K-mean based

The way we analyze the group price responsiveness has three steps:

1) for each hosehold group, build a new dataframe, the first column is GMT, the next columns are user ids in the group, the next column is temperature, then the price, day of a week, hour of a day, then the predicted consumption, and last the price responsiveness

2) build a function that can generate predicted consumption based on the day of a week, temp, hour to choose the coefficients and then make a prediction.

3) plot the properties based on from the smallest unit (day of week, hour, temp) to (day of week, hour), (day of week, temp), (hour, temp), (day of week), (hour), (temp) so we will have very comprehensive price responsiveness of three different groups

In [45]:

```
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from mpl_toolkits.mplot3d import Axes3D
n = 3 # cluster numbers
n_house = 1025 # total household numbers
houseLabel = [] # store the 24hour group labels for each hoursehold
hourly_label = [] # used for comparing with warm season clustering distance
for i in range(1025):
    houseLabel.append('')
houseLabel = np.array(houseLabel)
cons_type = ['High Consumption', 'Medium Consumption', 'Low Consumption']
fig_all = plt.figure(figsize = (13,90))
for i in range(24):
    if i <= 9:
        x = df_tou1h_nf_cold[df_tou1h_nf_cold.GMT.str.contains('0' + str(i) + ':00:00')]
        x.set_index('GMT', inplace = True)
        x = x.fillna(x.mean()).transpose() # data for the specific hour, and fill in null value with mean
        # PCA without standardization
        pca_nstd = PCA()
        principleComponents_nstd = pca_nstd.fit_transform(x)
        principleDf_nstd = pd.DataFrame(data = principleComponents_nstd)
        kmeans_cold = KMeans(n_clusters = n, init='k-means++').fit(principleDf_nstd.iloc[:,:3])
        houseLabel = np.core.defchararray.add(houseLabel, kmeans_cold.labels_.astype('str'))
        hourly_label.append(kmeans_cold.labels_)
    else:
        x = df_tou1h_nf_cold[df_tou1h_nf_cold.GMT.str.contains(str(i) + ':00:00')]
        x.set_index('GMT', inplace = True)
        x = x.fillna(x.mean()).transpose() # data for the specific hour, and filtering out null value
        # PCA without standardization
        pca_nstd = PCA()
        principleComponents_nstd = pca_nstd.fit_transform(x)
        principleDf_nstd = pd.DataFrame(data = principleComponents_nstd)
        kmeans_cold = KMeans(n_clusters = n, init='k-means++').fit(principleDf_nstd.iloc[:,:3])
        cluster_dict = {}
        houseLabel = np.core.defchararray.add(houseLabel, kmeans_cold.labels_.astype('str'))
        hourly_label.append(kmeans_cold.labels_)
# We obtain the house Label shown below
# print(houseLabel)

# Group the house based on their 24 hour labels
houseLableDf = pd.DataFrame()
houseLableDf['House'] = df_tou1h_nf_cold.columns[1:]
houseLableDf['Label'] = houseLabel
houseGroupDf = houseLableDf.groupby('Label').size().reset_index(name='counts')
houseGroupDf = houseGroupDf.sort_values(by=['counts'], ascending=False)
houseGroupDf
```

Out[45]:

	Label	counts
115	1000010001000000000211110	409
424	2212101110222111121000201	29
125	1000010001000000001211110	10
56	1000010000000000000211110	9
191	1000010010222111121000201	7
109	1000010001000000000201110	7
103	1000010001000000000011110	6
19	0121222222111222212122022	5
286	2000010001000000000211110	5
418	2212101010222111121000201	5
339	2200010001000000000211110	5
231	1000011001000000000211110	5
177	1000010010000000000211110	4
36	1000000001000000000211110	4
110	1000010001000000000210110	4
124	1000010001000000001011110	4
340	2200010001000000000211111	4
135	1000010001000000100211110	4
129	1000010001000000020211110	3
195	1000010011000000000211110	3
307	2000010010222111121000201	3
358	2200010110222111121000201	3
316	2000010110222111121000201	3
139	1000010001000000121011110	3
153	1000010001002100000211110	3
165	1000010001200000000211110	3
106	1000010001000000000200110	3
136	1000010001000000120211110	3
79	1000010000220000000211110	3
71	1000010000200000000211110	3
...	...	...
130	1000010001000000021000201	1
128	1000010001000000020200110	1
127	1000010001000000020010200	1
126	1000010001000000001211200	1
123	1000010001000000001001201	1
156	1000010001002111100211110	1
158	1000010001010000000201110	1
160	1000010001020000121210201	1
173	1000010001222111121001200	1
185	1000010010200011121000201	1
183	1000010010002110012111110	1
182	1000010010002110000001200	1
181	1000010010002000000211110	1
180	1000010010000000021211210	1
179	1000010010000000021011110	1
176	1000010010000000000201110	1
175	1000010002200000000211110	1
174	1000010001222111121011201	1
172	1000010001222111121000201	1

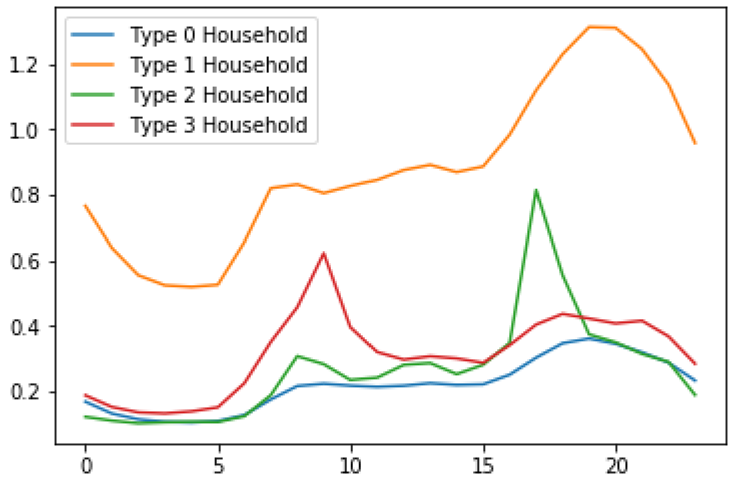
	Label	counts
161	100001000102200021011110	1
171	100001000122211121000110	1
170	100001000122211100210201	1
169	100001000122210121000201	1
168	100001000122210001001110	1
167	100001000120210000211110	1
166	100001000120200000011110	1
164	100001000120000000000110	1
163	100001000102211121000210	1
162	100001000102210000211110	1
444	222122111222211121000201	1

445 rows × 2 columns

```
<Figure size 936x6480 with 0 Axes>
```

In [15]:

```
for i in range(4):
    load = []
    for j in range(24):
        if j <= 9:
            x = df_tou1h_nf_cold[df_tou1h_nf_cold.GMT.str.contains('0' + str(j) + ':00:00')]
            x.set_index('GMT', inplace = True)
            x = x.fillna(x.mean())
            x = x[list(houseLableDf[houseLableDf.Label == houseGroupDf.Label.iloc[i]].House)]
            load.append(x.mean().mean())
        else:
            x = df_tou1h_nf_cold[df_tou1h_nf_cold.GMT.str.contains(str(j) + ':00:00')]
            x.set_index('GMT', inplace = True)
            x = x.fillna(x.mean())
            x = x[list(houseLableDf[houseLableDf.Label == houseGroupDf.Label.iloc[i]].House)]
            load.append(x.mean().mean())
    plt.plot(load, label = 'Type ' + str(i) + ' Household')
plt.legend()
plt.show()
```



Start to find groups in warm season PCs using the clusters from cold seasons

In [68]:
```
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from mpl_toolkits.mplot3d import Axes3D
n = 3 # cluster numbers
n_house = 1025 # total household numbers
opt_inertia = [] # store the optimal inertia list based on k-mean clustering of the corresponding season
test_inertia = [] # store the test inertia list based on the clustering result from another season
cons_type = ['High Consumption', 'Medium Consumption', 'Low Consumption']
for i in range(24):
    if i <= 9:
        x = df_tou1h_nf_warm[df_tou1h_nf_warm.GMT.str.contains('0' + str(i) + ':00:00')]
        x.set_index('GMT', inplace = True)
        x = x.fillna(x.mean()).transpose() # data for the specific hour, and fill in null value with mean
        # PCA without standardization
        pca_nstd = PCA()
        principleComponents_nstd = pca_nstd.fit_transform(x)
        principleDf_nstd = pd.DataFrame(data = principleComponents_nstd)
        # calculate the optimal inertia based on K-mean clustering
        kmeans = KMeans(n_clusters = n, init='k-means++').fit(principleDf_nstd.iloc[:,:3])
        opt_inertia.append(kmeans.inertia_)

        # calculate the test inertia based on clusters from another season
        x = df_tou1h_nf_cold[df_tou1h_nf_cold.GMT.str.contains('0' + str(i) + ':00:00')]
        x.set_index('GMT', inplace = True)
        x = x.fillna(x.mean()).transpose() # data for the specific hour, and fill in null value with mean
        # PCA without standardization
        pca_nstd_cold = PCA()
        principleComponents_nstd_cold = pca_nstd_cold.fit_transform(x)
        principleDf_nstd_cold = pd.DataFrame(data = principleComponents_nstd_cold)
        # calculate the optimal inertia based on K-mean clustering
        kmeans_cold = KMeans(n_clusters = n, init='k-means++').fit(principleDf_nstd_cold.iloc[:,:3])
        dist = 0
        for j in range(n):
            centroid = list(principleDf_nstd.iloc[:,:3][kmeans_cold.labels_ == j].mean())
            df_diff = principleDf_nstd.iloc[:,:3][kmeans_cold.labels_ == j] - principleDf_nstd.iloc[:,:3][kme
ans_cold.labels_ == j].mean()
            df_diff = df_diff.pow(2)
            dist += df_diff.sum().sum()
        test_inertia.append(dist)
    else:
        x = df_tou1h_nf_warm[df_tou1h_nf_warm.GMT.str.contains(str(i) + ':00:00')]
        x.set_index('GMT', inplace = True)
        x = x.fillna(x.mean()).transpose() # data for the specific hour, and filtering out null value
        # PCA without standardization
        pca_nstd = PCA()
        principleComponents_nstd = pca_nstd.fit_transform(x)
        principleDf_nstd = pd.DataFrame(data = principleComponents_nstd)
        # calculate the optimal inertia based on K-mean clustering
        kmeans = KMeans(n_clusters = n, init='k-means++').fit(principleDf_nstd.iloc[:,:3])
        opt_inertia.append(kmeans.inertia_)
        # calculate the test inertia based on clusters from another season

        x = df_tou1h_nf_cold[df_tou1h_nf_cold.GMT.str.contains(str(i) + ':00:00')]
        x.set_index('GMT', inplace = True)
        x = x.fillna(x.mean()).transpose() # data for the specific hour, and fill in null value with mean
        # PCA without standardization
        pca_nstd_cold = PCA()
        principleComponents_nstd_cold = pca_nstd_cold.fit_transform(x)
        principleDf_nstd_cold = pd.DataFrame(data = principleComponents_nstd_cold)
        # calculate the optimal inertia based on K-mean clustering
        kmeans_cold = KMeans(n_clusters = n, init='k-means++').fit(principleDf_nstd_cold.iloc[:,:3])
        dist = 0
        for j in range(n):
            centroid = list(principleDf_nstd.iloc[:,:3][kmeans_cold.labels_ == j].mean())
            df_diff = principleDf_nstd.iloc[:,:3][kmeans_cold.labels_ == j] - principleDf_nstd.iloc[:,:3][kme
ans_cold.labels_ == j].mean()
            df_diff = df_diff.pow(2)
            dist += df_diff.sum().sum()
        test_inertia.append(dist)
# The inertia difference over 24 hours in percentage
inertia_diff_rel_coldToWarm = (np.array(test_inertia) - np.array(opt_inertia)) / np.array(opt_inertia) * 100
inertia_total_diff_rel_coldToWarm = (sum(test_inertia) - sum(opt_inertia)) / sum(opt_inertia) * 100
```

Do the opposite: using warm season clustering to compare with cold season clustering

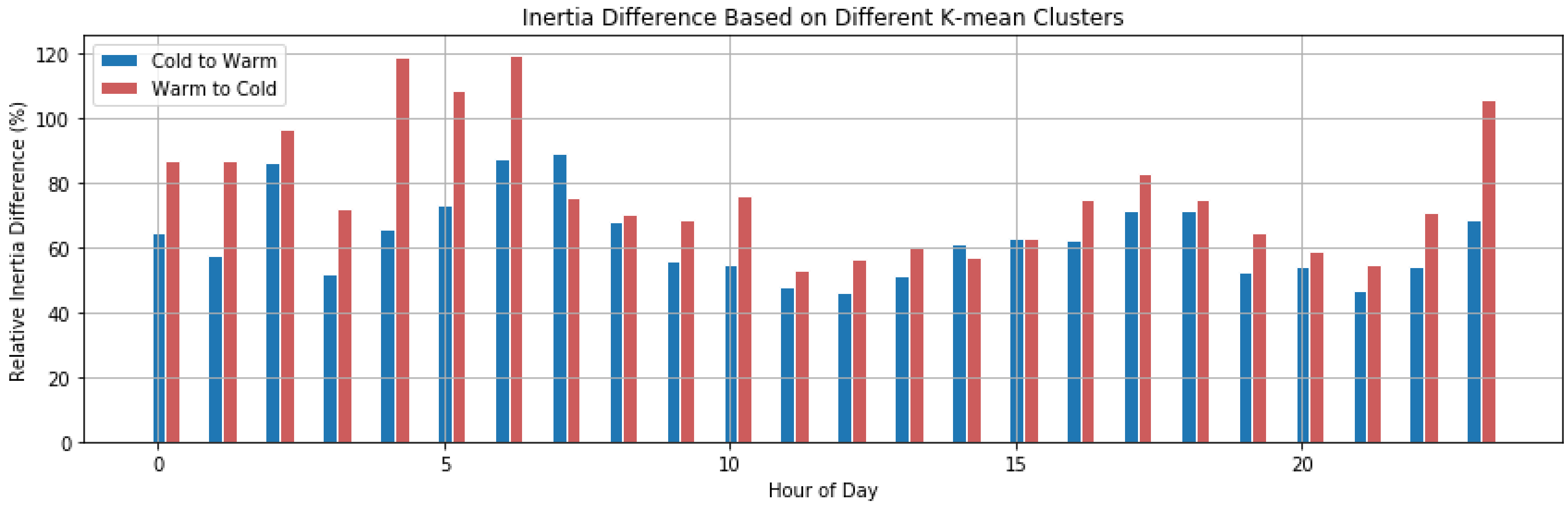
In [67]:
```
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from mpl_toolkits.mplot3d import Axes3D
n = 3 # cluster numbers
n_house = 1025 # total household numbers
opt_inertia = [] # store the optimal inertia list based on k-mean clustering of the corresponding season
test_inertia = [] # store the test inertia list based on the clustering result from another season
cons_type = ['High Consumption', 'Medium Consumption', 'Low Consumption']
for i in range(24):
    if i <= 9:
        x = df_tou1h_nf_cold[df_tou1h_nf_cold.GMT.str.contains('0' + str(i) + ':00:00')]
        x.set_index('GMT', inplace = True)
        x = x.fillna(x.mean()).transpose() # data for the specific hour, and fill in null value with mean
        # PCA without standardization
        pca_nstd = PCA()
        principleComponents_nstd = pca_nstd.fit_transform(x)
        principleDf_nstd = pd.DataFrame(data = principleComponents_nstd)
        # calculate the optimal inertia based on K-mean clustering
        kmeans = KMeans(n_clusters = n, init='k-means++').fit(principleDf_nstd.iloc[:,:3])
        opt_inertia.append(kmeans.inertia_)

        # calculate the test inertia based on clusters from another season
        x = df_tou1h_nf_warm[df_tou1h_nf_warm.GMT.str.contains('0' + str(i) + ':00:00')]
        x.set_index('GMT', inplace = True)
        x = x.fillna(x.mean()).transpose() # data for the specific hour, and fill in null value with mean
        # PCA without standardization
        pca_nstd_warm = PCA()
        principleComponents_nstd_warm = pca_nstd_warm.fit_transform(x)
        principleDf_nstd_warm = pd.DataFrame(data = principleComponents_nstd_warm)
        # calculate the optimal inertia based on K-mean clustering
        kmeans_warm = KMeans(n_clusters = n, init='k-means++').fit(principleDf_nstd_warm.iloc[:,:3])
        dist = 0
        for j in range(n):
            centroid = list(principleDf_nstd.iloc[:,:3][kmeans_warm.labels_ == j].mean())
            df_diff = principleDf_nstd.iloc[:,:3][kmeans_warm.labels_ == j] - principleDf_nstd.iloc[:,:3][kme
ans_warm.labels_ == j].mean()
            df_diff = df_diff.pow(2)
            dist += df_diff.sum().sum()
        test_inertia.append(dist)
    else:
        x = df_tou1h_nf_cold[df_tou1h_nf_cold.GMT.str.contains(str(i) + ':00:00')]
        x.set_index('GMT', inplace = True)
        x = x.fillna(x.mean()).transpose() # data for the specific hour, and filtering out null value
        # PCA without standardization
        pca_nstd = PCA()
        principleComponents_nstd = pca_nstd.fit_transform(x)
        principleDf_nstd = pd.DataFrame(data = principleComponents_nstd)
        # calculate the optimal inertia based on K-mean clustering
        kmeans = KMeans(n_clusters = n, init='k-means++').fit(principleDf_nstd.iloc[:,:3])
        opt_inertia.append(kmeans.inertia_)
        # calculate the test inertia based on clusters from another season

        x = df_tou1h_nf_warm[df_tou1h_nf_warm.GMT.str.contains(str(i) + ':00:00')]
        x.set_index('GMT', inplace = True)
        x = x.fillna(x.mean()).transpose() # data for the specific hour, and fill in null value with mean
        # PCA without standardization
        pca_nstd_warm = PCA()
        principleComponents_nstd_warm = pca_nstd_warm.fit_transform(x)
        principleDf_nstd_warm = pd.DataFrame(data = principleComponents_nstd_warm)
        # calculate the optimal inertia based on K-mean clustering
        kmeans_warm = KMeans(n_clusters = n, init='k-means++').fit(principleDf_nstd_warm.iloc[:,:3])
        dist = 0
        for j in range(n):
            centroid = list(principleDf_nstd.iloc[:,:3][kmeans_warm.labels_ == j].mean())
            df_diff = principleDf_nstd.iloc[:,:3][kmeans_warm.labels_ == j] - principleDf_nstd.iloc[:,:3][kme
ans_warm.labels_ == j].mean()
            df_diff = df_diff.pow(2)
            dist += df_diff.sum().sum()
        test_inertia.append(dist)
# The inertia difference over 24 hours in percentage
inertia_diff_rel_warmToCold = (np.array(test_inertia) - np.array(opt_inertia)) / np.array(opt_inertia) * 100
inertia_total_diff_rel_warmToCold = (sum(test_inertia) - sum(opt_inertia)) / sum(opt_inertia) * 100
```

Note: there's no clear meaning of comparing two seperate clustering inertia in two different k-mean clusterings (because it could do better even if it's not optimal solution of k-mean clustering in terms of one specific cluster), becaue the optimization objective is to maximize the sum of inertia of all clusters, not just one of them.

In [99]:
```
# plot the grouped bar charts based on price, for 3 household types
fig_all = plt.figure(figsize = (12,4))
ax_Ntou = [] # store subplot objects
# set width of bar
barWidth = 0.25
# Set position of bar on X axis
r1 = np.arange(len(inertia_diff_rel_warmToCold))
r2 = [x + barWidth for x in r1]
ax_Ntou.append(fig_all.add_subplot(1, 1, 1))
# Make the plot
ax_Ntou[-1].bar(r1, inertia_diff_rel_coldToWarm, width=barWidth, edgecolor='white', label='Cold to Warm')
ax_Ntou[-1].bar(r2, inertia_diff_rel_warmToCold, color='indianred', width=barWidth, edgecolor='white', label=
'Warm to Cold')
ax_Ntou[-1].grid()
ax_Ntou[-1].set_xlabel('Hour of Day')
ax_Ntou[-1].set_ylabel('Relative Inertia Difference (%)')
ax_Ntou[-1].legend()
ax_Ntou[-1].set_title('Inertia Difference Based on Different K-mean Clusters')
plt.tight_layout()
```



So, k-mean clustering based on PCs of the corresponding seasons cannot be simply replaced by the clustering from other seasons, which shows the necessicity of considering the patterns in different seasons in the beginning of our framework design.