A1 a) knn, leave one out and leave one out error (ssd)

In [91]:
```
import numpy as np
def k_nn (X, direction):
    labels = []
    distances = np.sqrt(np.sum((X[:, np.newaxis, :] - X)**2, axis=-1))
    '''
    dists = []
    for row in x_test:
        d = np.sqrt(np.sum((row - x_train)**2, axis=-1))
        dists.append(d)
    distances = np.array(dists)
    '''

    for dist in distances:
        #changes all the 0's (observations distance to itself) to infinite so that
        #while keeping the index order the same

        dist = np.where(dist == 0, np.inf, dist)
        min_index = np.argmin(dist)
        labels.append(direction[min_index])

    return labels
```

In [92]:
```
def ssd (pred, test):

    sum_of_squared_diff = np.sum((pred-test)**2)/test.shape[0]
    # returns the sums between all predicted faces over the true angles
    return sum_of_squared_diff
```

In [94]:
```
import numpy as np

# Read the contents of the file into a np array
data = np.loadtxt("noisy_sculpt_faces.txt")

data.shape
```

Out[94]:
```
(100, 259)
```

In [95]:
```
from sklearn.model_selection import train_test_split

X = data[:,:256]

angles = data[:,256:]


print(angles.shape,X.shape)
```

```
(100, 3) (100, 256)
```

In [96]:
```
# prediction as a list of angles
pred = k_nn(X, angles)
print(pred[0], angles[0])

# sum the squared error over all the faces
ssd(pred, angles)
```

```
[ 53.826258   -2.4527189 154.38092  ] [ 44.193998    9.8366946 227.9364   ]
```

Out[96]:
```
5071.296239644929
```

A1 b) forward selection

In [97]:
```
def feature_selection(X,angles):
    all_SSD = []
    filter_indices = []
    current_model = float('inf')


    is_better = True
    while is_better:
        best_index = 0
        current_ssd = float('inf')
        is_better = False
        for i in range(X.shape[1]):
            if i not in filter_indices:

                if not filter_indices:
                    new_indices = [i]
                else:
                    new_indices = np.concatenate((filter_indices, [i]))

                new_X = X[:,new_indices]
                # Now the data has been filtered with the chosen indices (selected
                # a new index across all indexes in the data
                new_ssd = ssd(k_nn(new_X, angles), angles)

                if new_ssd < current_ssd:
                    current_ssd = new_ssd
                    best_index = i

        # Adds the best index to the filter index list
        filter_indices.append(best_index)
        # If the new selected features propose a better model than current, the loo
        new_model = ssd(k_nn(new_X, angles), angles)


        if new_model < current_model:

            all_SSD.append(new_model)
            current_model = new_model
            is_better = True

    return all_SSD
```

A1 c) add best feature in each iteration until the end

In [98]:
```
 def feature_selection_variant(X,angles):
    all_SSD = []
    filter_indices = []
    current_model = float('inf')

    for j in range(X.shape[1]):
        best_index = 0
        current_ssd = float('inf')
        for i in range(X.shape[1]):
            if i not in filter_indices:

                if not filter_indices:
                    new_indices = [i]
                else:
                    new_indices = np.concatenate((filter_indices, [i]))
```

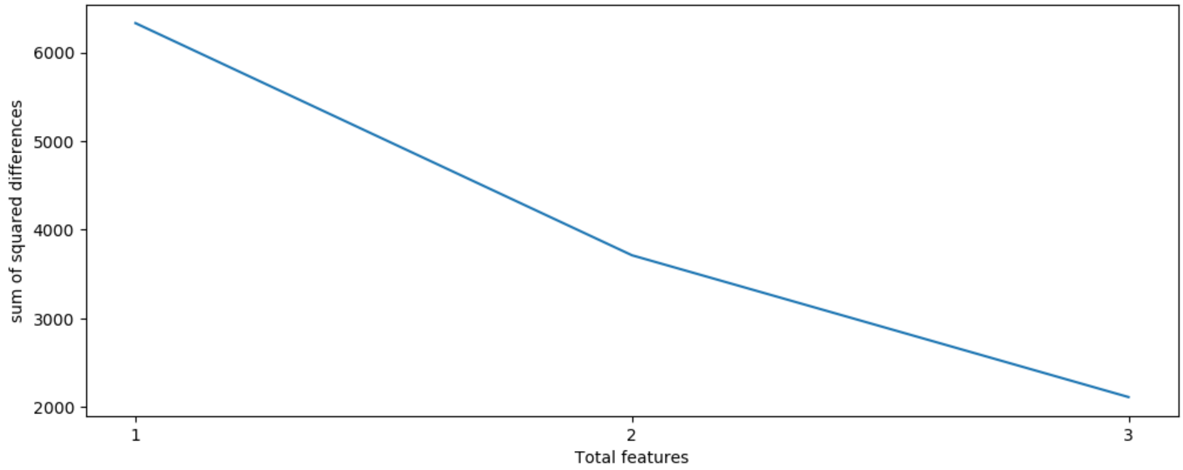
```
                new_X = X[:,new_indices]

                # Now the data has been filtered with the chosen indices (selected
                # and a new index across all indexes in the data
                new_ssd = ssd(k_nn(new_X, angles), angles)

                if new_ssd < current_ssd:
                    current_ssd = new_ssd
                    best_index = i

        # Adds the best index to the filter index list
        filter_indices.append(best_index)

        new_model = ssd(k_nn(new_X, angles), angles)

        all_SSD.append(new_model)

    return all_SSD, filter_indices
```

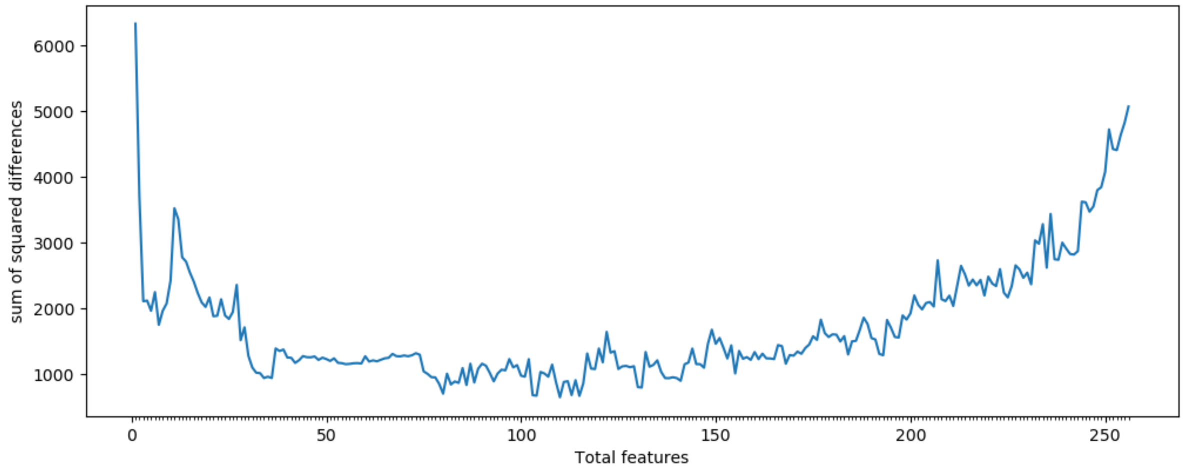
In [99]:

```
import matplotlib.pyplot as plt
SSD = feature_selection(X, angles)


fig, (ax1, ax2) = plt.subplots(2,1, figsize=(12,10))
x = np.arange(1, len(SSD) + 1, 1)
ax1.plot(x,SSD)
ax1.set_xticks(range(1,len(SSD)+1))
ax1.set_ylabel("sum of squared differences")
ax1.set_xlabel("Total features")


SSD_var, indices = feature_selection_variant(X, angles)
x2 = np.arange(1, len(SSD_var) + 1, 1)
ax2.plot(x2,SSD_var)
ax2.set_xticks(range(1,len(SSD_var)+1),10)
ax2.set_ylabel("sum of squared differences")
ax2.set_xlabel("Total features")
```

Out[99]:

```
Text(0.5, 0, 'Total features')
```





1A d)

The later algorithm gets better results quite early in the iterations due to there being a small change in the beginning. At 4th feature sum of squared differences score rises which stops the first algorithm, and it gets better right after this point at 5th feature. We can see from graph 2 that 2nd algorithm gets quite stable good results untill 150 features and then starts getting worse again.

2A Variable ranking

1.

Pearsons correlation could be used as a simple ranking method in feature selection by showing what features may have correlation to the target variables. The features with high values could be chosen as the variables to be used in a model. However in this case, the correlation would assume that the variables are independent of each other, which might cause problems. Correlation can also only detect linear dependencies between vaariable and the target.

2.

In [103…

```
def variable_ranking(X,angles):
    import operator

    all_ssd = {}

    for i in range(X.shape[1]):
```

```
        indences = [i]
        new_X = X[:,indences]

        preds = k_nn(new_X, angles)
        # predictions versus the true angles
        new_ssd = ssd(preds, angles)

        # adds a pair, index of the variable and the squared error sum to a list
        all_ssd[i]=new_ssd
    # sorts the list so that the index of the variable can be looked at
    sorted_ssd = sorted(all_ssd.items(), key=operator.itemgetter(1))
    return sorted_ssd
```

In [104…

```
ranking = variable_ranking(X,angles)

for i in range(len(indices)):
    print(indices[i], ranking[i][0])
```

```
189 189
53 24
137 32
224 59
32 18
24 53
147 49
102 206
13 228
192 197
229 219
138 218
84 224
207 229
206 226
107 245
200 34
180 174
26 205
167 35
116 236
245 115
8 17
132 56
205 244
105 214
80 180
54 33
135 168
125 55
120 25
250 54
174 146
12 190
218 200
46 94
153 176
113 87
56 20
9 203
124 152
208 70
194 52
59 149
228 45
104 215
98 4
89 39
165 220
17 191
166 91
73 238
96 210
18 255
246 19
253 3
142 37
114 157
146 40
81 207
190 234
197 129
214 44
122 221
```

```
112 38
71 230
182 127
222 81
101 167
62 184
99 47
184 99
170 95
219 140
179 58
128 150
37 204
57 222
226 82
162 102
87 77
171 198
70 211
188 63
244 208
198 147
49 138
215 42
35 195
15 179
0 113
52 6
151 173
2 110
6 22
100 171
201 86
199 21
181 199
115 0
133 48
33 2
220 247
251 182
159 194
238 62
230 90
187 118
126 76
106 134
169 43
148 84
68 239
240 235
67 160
58 162
79 61
51 104
93 178
38 26
212 46
97 145
185 50
39 65
186 78
252 117
48 172
191 105
```

```
110 73
41 242
195 169
1 23
140 51
233 74
78 241
210 231
241 141
172 9
145 131
163 96
111 109
27 164
16 161
134 119
20 112
247 144
254 92
40 15
85 217
176 170
143 250
150 154
45 1
164 27
5 237
22 114
64 137
248 251
60 107
213 16
3 212
211 225
202 216
155 14
141 153
177 80
42 186
152 213
118 28
77 193
91 148
204 83
76 72
94 69
50 139
61 248
158 60
23 130
29 66
144 67
175 31
65 97
221 5
129 126
117 232
83 75
234 7
131 85
249 111
136 133
44 8
154 13
```

```
255 136
69 175
31 151
236 101
47 30
149 183
92 254
217 246
157 165
63 93
75 243
7 57
86 98
237 181
103 223
95 100
235 192
183 29
232 36
34 108
231 132
4 68
74 135
139 202
11 64
127 124
223 159
242 209
21 122
225 240
55 41
36 187
178 79
108 156
19 116
90 143
227 185
119 177
243 233
28 201
82 163
160 128
30 249
121 88
72 142
66 103
43 89
14 71
203 120
130 252
239 125
123 121
193 188
173 158
25 196
196 12
10 123
168 155
156 10
109 106
216 253
88 11
161 166
209 227
```

Basically the first number is the same, but after that, the list is completely different