| Column | C

The Olivetti dataset will have better accuracy, as there is less variance between samples in a class, and the Olivetti samples are well-lit and nicely cropped.

Left column: model from first project

Olivetti	cui Saii	ilpies ai	e well-lit d	ind micer
Predicting people	's names	on the t	est set	
done in 0.008s				
pred	ision	recall	f1-score	support
0 1	1.00	1.00	1.00 1.00	3
2	0.75	1.00	0.86	3
3	1.00	1.00	1.00	
4	1.00	1.00	1.00	3
5	1.00	1.00	1.00	
6	1.00	1.00	1.00	
7	1.00	0.67	0.80	
8	1.00	1.00	1.00	
9	1.00	0.67	0.80	
10	1.00	1.00	1.00	
11	1.00	1.00	1.00	
12	1.00	1.00	1.00	
13 14	1.00 1.00	1.00 1.00	1.00 1.00	
15	1.00	0.33	0.50	3
16	1.00	1.00	1.00	
17	1.00	1.00	1.00	3
18	1.00	1.00	1.00	
19	1.00	1.00	1.00	
20	0.60	1.00	0.75	
21	1.00	1.00	1.00	
22	1.00	1.00	1.00	
23	1.00	1.00	1.00	
24	1.00	1.00	1.00	
25	1.00	1.00	1.00	3
26	1.00	1.00	1.00	3
27 28	1.00	1.00 1.00	1.00 1.00	3 3
29	1.00	1.00	1.00	
30	1.00	1.00	1.00	3
31	1.00	1.00	1.00	
32	1.00	1.00	1.00	3
33	1.00	1.00	1.00	
34	1.00	1.00	1.00	
35	1.00	1.00	1.00	
36	1.00	1.00	1.00	
37	1.00	1.00	1.00	
38	1.00	1.00	1.00	
39	0.75	1.00	0.86	
accuracy			0.97	120
macro avg	0.98	0.97	0.96	120
weighted avg	0.98	0.97	0.96	120
		3137	3120	110
[[3 0 0 0 0 0]				
[030000]				
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[0 0 0 3 0 0]				
[0 0 0 0 3 0]				
[0 0 0 0 0 3]	1]			

The Olivetti dataset has great accuracy across both models.

				-	
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macro avg 0.94 0.92 0.91 120	accuracy			0.92	120
	,	0.94	0.92		
0132 0131 123					
LDA DECLUT					
Accuracy score: 0.94					

Right column:

second project

model from

### LFW, min samples/person = 100

LFW, min samples/person = 100					
Predicting people's names on the test set done in 0.060s					
uone in 0.000		11	£4		
	precision	recall	f1-score	support	
0	0.84	0.94	0.89	71	
1	0.96	0.75	0.84	36	
2	0.86	0.96	0.90	159	
3	0.96	0.70	0.81	33	
4	0.88	0.67	0.76	43	
accuracy			0.87	342	
macro avg	0.90	0.80	0.84	342	
weighted avg	0.88	0.87	0.87	342	
[[ 67 0 3	0 1]				
[ 2 27 6	0 1]				
[ 7 0 152	0 0]				
[116	23 2]				
[ 3 0 10	1 29]]				

With many samples per class, and few classes, both perform relatively well. First model performs better.

#### LFW, min samples/person = 100, reduce classes to 4

Li vv, iiiiii sairipi	LFW, IIIII samples/person = 100, reduce classes to 4					
0.1	Predicting people's names on the test set					
	precision	recall	f1-score	support		
0	0.86	0.94	0.90	71		
1	0.87	0.72	0.79	36		
2	0.92	0.95	0.93	159		
3	1.00	0.82	0.90	33		
accuracy			0.91	299		
macro avg	0.91	0.86	0.88	299		
weighted avg	0.91	0.91	0.90	299		
[[ 67 0 4	0]					
[ 6 26 4	0]					
[ 5 3 151	. 0]					
[015	27]]					

Reducing the number of classes increases the accuracy.

# LFW, min samples/person = 100, reduce samples to 100

Li vv, iiiiii sairip	LFW, min samples/person = 100, reduce samples to 100					
	Predicting people's names on the test set					
	precision	n recall	f1-score	support		
0	0.73	0.73	0.73	30		
1	0.81	l 0.87	0.84	30		
2	0.79	0.63	0.70	30		
3	0.83	l 0.83	0.82	30		
4	0.76	6.83	0.79	30		
accuracy			0.78	150		
macro avg	0.78	0.78	0.78	150		
weighted avg	0.78	3 0.78	0.78	150		
[[22 2 2 [ 0 26 1 [ 4 3 19 [ 1 1 1 2 [ 3 0 1	2 1] 2 2]					

Reducing the number of samples decreases the accuracy (even though we are equalizing the number of samples for all classes). However, the models have around the same accuracy now (will come back to this potential error at the end).

	precision	recall	f1-score	support
0	0.90	0.75	0.82	71
1	1.00	0.42	0.59	36
2	0.68	0.98	0.80	159
	1.00	0.48	0.65	33
4	0.95	0.49	0.65	43
accuracy			0.76	342
macro avg	0.91	0.62	0.70	342
weighted avg	0.82	0.76	0.75	342
Accuracy score	KESOLI			

	precision	recall	f1-score	support
0	0.93	0.79	0.85	71
1	1.00	0.44	0.62	36
2	0.75	0.98	0.85	159
3	1.00	0.48	0.65	33
accuracy			0.82	299
macro avg	0.92	0.67	0.74	299
weighted avg	0.85	0.82	0.80	299
	A DECLUIT			

	precision	recall	f1-score	support
0	0.73	0.73	0.73	30
1	0.81	0.83	0.82	30
2	0.83	0.83	0.83	30
3	0.71	0.67	0.69	30
4	0.71	0.73	0.72	30
accuracy			0.76	150
macro avg	0.76	0.76	0.76	150
weighted avg	0.76	0.76	0.76	150

LFW, min samples/person = 20, reduce classes to 40, reduce samples to 20

samples to 20				
Predicting peop done in 0.036s	ole's names	on the t	est set	
	recision	recall	f1-score	support
0	0.50	0.50	0.50	6
1	0.50	0.17	0.25	6
2				6
	0.50	0.17	0.25	
3	0.33	0.33	0.33	6
4	0.27	0.50	0.35	6
5	1.00	0.83	0.91	
6	0.00	0.00	0.00	
7	0.57	0.67	0.62	
8	0.43	0.50	0.46	
9	0.75	0.50	0.60	
10	0.33	0.17	0.22	
11	0.40	0.33	0.36	
12	0.12	0.17	0.14	
13	0.57	0.67	0.62	
14	0.57	0.67	0.62	
15	0.18	0.33	0.24	
16	1.00	0.67	0.80	
17	0.33	0.50	0.40	
18	0.20	0.33	0.25	
19	0.60	0.50	0.55	
20	0.00	0.00	0.00	
21	0.20	0.17	0.18	
22	0.11	0.17	0.13	
23	1.00	0.33	0.50	
24	0.29	0.33	0.31	
25	0.57	0.67	0.62	
26	0.67	0.33	0.44	
27	0.11	0.17	0.13	
28	0.60	0.50	0.55	
29	0.50	0.67	0.57	
30	1.00	0.67	0.80	
31	0.40	0.67	0.50	
32	0.50	0.33	0.40	
33	0.60	0.50	0.55	
34	1.00	0.50	0.67	
35	0.80	0.67	0.73	
36	1.00	0.67	0.80	
37	0.83	0.83	0.83	
38	0.50	0.17	0.25	
39	0.36	0.67	0.47	
accuracy			0.44	240
macro avg	0.51	0.44	0.45	240
weighted avg	0.51	0.44	0.45	240
[[2 0 0 0 0	. 11			
[[3 0 0 0 6				
[0 1 0 0 6	, 1] ) 0]			
[0 0 1 0 6	, 0]			
[0 0 0 5 6	9 0 ]			
	, 0] [ 0]			
	4]]			

With many classes and few samples, both models perform poorly.

LFW, min samples/person = 20, reduce classes to 10, reduce samples to 20

samples to 20				
Predicting peop	le's names	on the t	est set	
done in 0.002s				
р	recision	recall	f1-score	support
0	0.33	0.33	0.33	
1	0.80	0.67	0.73	
2	0.60	0.50		
3	0.00	0.00	0.00	6
4	0.50	0.50		6
5	0.56	0.83	0.67	
6	0.20	0.33		
7	1.00	0.67		
8	0.57	0.67		
9	0.60	0.50	0.55	
accuracy			0.50	60
macro avg	0.52	0.50		60
weighted avg	0.52	0.50	0.50	60
[[2010012				
[0401001				
[2030100				
[0100003				
[0011301				
[1000050				
[0001202				
[0000010				
[0000020				
[1000001	6 T 3]]			

Reducing the number of classes increases the accuracy (in model 2, as expected).

	precision	recall	f1-score	support			
ø	0.22	0.33	0.27	6			
1	0.38	0.50	0.43	6			
2	1.00	0.67	0.80	6			
3	0.33	0.17	0.22	6			
4	0.29	0.33	0.31	6			
5	1.00	0.50	0.67	6			
6	0.18	0.33	0.24	6			
7	1.00	0.67	0.80	6			
8	0.29	0.33	0.31	6			
9	0.67	0.67	0.67	6			
10	0.50	0.50	0.50	6			
11	0.29	0.33	0.31	6			
12	0.50	0.33	0.40	6			
13	1.00	0.33	0.50	6			
14 15	0.43	0.50	0.46	6 6			
16	0.16 0.67	0.50 0.33	0.24 0.44	6			
17	0.00	0.00	0.00	6			
18	0.24	0.67	0.35	6			
19	0.25	0.17	0.20	6			
20	0.60	0.50	0.55	6			
21	0.50	0.33	0.40	6			
22	0.00	0.00	0.00	6			
23	0.50	0.50	0.50	6			
24	0.29	0.33	0.31	6			
25	0.75	0.50	0.60	6			
26	0.60	0.50	0.55	6			
27	0.33	0.33	0.33	6			
28	1.00	0.17	0.29	6			
29	0.80	0.67	0.73	6			
30	1.00	0.50	0.67	6			
31	0.20	0.17	0.18	6			
32	0.33	0.50	0.40	6			
33	1.00	0.33	0.50	6			
34	0.62	0.83	0.71	6			
35	1.00	0.33	0.50	6			
36	0.50	0.83	0.62	6			
37	1.00	0.50	0.67	6			
38	0.20	0.17	0.18	6			
39	0.40	0.33	0.36	6			
accuracy			0.41	240			
macro avg	0.53	0.41	0.43	240			
weighted avg	0.53	0.41	0.43	240			
	RESULT ====						
Accuracy score	2:0.47						
LR							
Accuracy score	::0.43						
====== NB RESULT =======							
Accuracy score:0.39							
====== KNN RESULT ======							
Accuracy score:0.20							
DT	===== DT RESULT ======						
Accuracy score							

	precision	recall	f1-score	support		
0	0.75			6		
1	0.75	1.00		6		
2	0.71			6		
3	0.43					
4	0.60	0.50		6		
5	0.62	0.83	0.71			
6	0.50	0.33	0.40			
7	0.67	0.67	0.67	6		
8	0.83	0.83	0.83	6		
9	0.80	0.67	0.73	6		
accuracy			0.67	60		
macro avg	0.67	0.67	0.66	60		
weighted avg	0.67	0.67	0.66	60		
	DECLU T					
====== LDA						
Accuracy score	:0.05					
I P	====== LR RESULT ======					
	Accuracy score:0.50					
Accuracy score to 150						
====== NB RESULT ======						
Accuracy score						

======= SVM RESULT = Accuracy score:0.41

====== DT RESULT Accuracy score:0.33

======= SVM RESULT = Accuracy score:0.67

LFW, min samples/person = 20, reduce classes to 5, reduce samples to 20

10 20				
Predicting pe		on the te	st set	
done in 0.001	s			
	precision	recall	f1-score	support
0	0.38	0.50	0.43	6
1	0.40	0.33	0.36	6
2	0.60	0.50	0.55	6
3	0.33	0.33	0.33	6
4	0.50	0.50	0.50	6
accuracy			0.43	30
macro avg	0.44	0.43	0.43	30
weighted avg	0.44	0.43	0.43	30
[[30030]				
[1 2 1 1 1]				
[10302]				
[2 2 0 2 0]				
[1 1 1 0 3]]				
formide for	aid a facaid:	. foresid	a formida	

Further reducing the number of classes does not increase the accuracy. Model 1 performs worse, will come back to this potential error at the end.

LFW, min samples/person :	= 100, reduce samples to 20
---------------------------	-----------------------------

Predicting peopl	_		est set	
done in 0.001s				
pr	ecision	recall	f1-score	support
				_
0	0.40	0.33		6
1	0.25	0.33	0.29	6
2	0.75	1.00	0.86	6
3	0.60	0.50	0.55	6
4	0.25	0.17	0.20	6
accuracy			0.47	30
macro avg	0.45	0.47	0.45	30
weighted avg	0.45	0.47	0.45	30
[[2 2 1 0 1]				
[3 2 0 0 1]				
[0 0 6 0 0]				
[0 1 1 3 1]				
[0 3 0 2 1]]				
[]]				











With classes that look more similar to each other, the accuracy decreases (in model 2, as expected).

	precision	recall	f1-score	support
9	0.50	0.67	0.57	6
1	0.50	0.67	0.57	6
2	1.00	1.00	1.00	6
3	0.67	0.33	0.44	6
4	0.80	0.67	0.73	6
accuracy			0.67	30
macro avg	0.69	0.67	0.66	30
weighted avg	0.69	0.67	0.66	30
ID	DECILIT			

LDA RESULT Accuracy score:0.70
LR RESULT Accuracy score:0.70
NB RESULT Accuracy score:0.57
KNN RESULT Accuracy score:0.53
DT RESULT Accuracy score:0.33
======= SVM RESULT ======= Accuracy score:0.67

	precision	recall	f1-score	support
9	0.42	0.83	0.56	6
1	0.60	0.50	0.55	6
2	0.67	0.67	0.67	6
3	0.50	0.33	0.40	6
4	0.00	0.00	0.00	6
accuracy			0.47	30
macro avg	0.44	0.47	0.43	30
weighted avg	0.44	0.47	0.43	30
	A RESULT =			

LDA RESULT Accuracy score:0.43
LR RESULT Accuracy score:0.40
NB RESULT Accuracy score:0.50
KNN RESULT Accuracy score:0.33
DT RESULT Accuracy score:0.40
SVM RESULT Accuracy score:0.47

**Potential error:** for all the tests where the number of samples were reduced, model 1 (the left column) behaved much worse relative the model 2. When the samples weren't reduced, model 1 performed better. When the samples were reduced, model 2 performed the same or worse while displaying irregular behavior, while model 2 exhibited the expected behavior. Will test this potential error by formulating curated dataset, so that the reduceClassesAndSamples() function will not have to be used.

## Now using the make\_dataset() function (no need to use reduceClassesAndSamples() anymore

#### LFW, min samples/person = 100, 5 classes



Predicting peop	le's names	on the te	est set	
done in 0.063s				
P	recision	recall	f1-score	support
0	0.82	0.93	0.87	71
1	0.96	0.72	0.83	36
2	0.87	0.94	0.90	159
3	0.96	0.70	0.81	33
4	0.84	0.74	0.79	43
accuracy			0.87	342
macro avg	0.89	0.81	0.84	342
weighted avg	0.87	0.87	0.87	342
[[ 66 0 4	0 1]			
[ 2 26 5	1 2]			
[ 8 0 150	0 1]			
[116	23 2]			
[ 3 0 8	0 32]]			

### LFW, samples/person = 100, 5 classes

. vv, sampic	3, pc13011 - 1	00,000000		
face id:0	face id:1	face id:2	face id:3	face id:4
121	-	-	200	1
1916		7.5	Section 1	GZ ton
174		0.23,8	150	177
No.	10000		-	1

					0.0
Predicting p		s names	on the t	est set	
	preci	ision	recall	f1-score	support
(	9	0.93	0.93	0.93	30
1	l	0.83	0.83	0.83	30
2	2	0.84	0.87	0.85	30
3	3	0.85	0.73	0.79	30
4	1	0.85	0.93	0.89	30
accuracy	/			0.86	150
macro avg	g	0.86	0.86	0.86	150
weighted ava	g	0.86	0.86	0.86	150
[[28 0 0	1 1]				
[ 2 25 2	0 1]				
[ 0 3 26					
[0 2 3 2					
[0 0 0	2 28]]				

### LFW, samples/person = 20, 5 classes

face id:0	face id:1	face id:2	face id:3	face id:4
35	· F	16 10		9

Predicting people done in 0.001s	e's names	on the t	est set	
	ecision	recall	f1-score	support
0	0.30	0.50	0.37	
1	0.71	0.83	0.77	
2	0.67	0.33	0.44	
3	0.67	0.67	0.67	
4	1.00	0.67	0.80	
accuracy			0.60	30
macro avg	0.67	0.60	0.61	30
weighted avg	0.67	0.60	0.61	30
[[3 2 1 0 0] [0 5 0 1 0] [3 0 2 1 0] [2 0 0 4 0] [2 0 0 0 4]]				

pr	recision	recall	f1-score	support
0	0.89	0.79	0.84	71
1	1.00	0.42	0.59	36
2	0.68	0.98	0.80	159
	1.00	0.39	0.57	33
4	0.95	0.49	0.65	43
accuracy			0.76	342
macro avg	0.90	0.61	0.69	342
weighted avg	0.82	0.76	0.75	342
====== LDA RESU Accuracy score:0.86 ====== LR RESUL Accuracy score:0.82				

===== NB RESULT Accuracy of both models are the same as when - KNN RESULT fetch\_lfw\_people() was used to create the dataset (serves as the control). ----- SVM RESULT ---Accuracy score:0.76

р	recision	recall	f1-score	support
0	0.84	0.90	0.87	30
1	0.80	0.67	0.73	30
2	0.79	0.87	0.83	30
3	0.77	0.80	0.79	30
4	0.72	0.70	0.71	30
accuracy			0.79	150
macro avg	0.79	0.79	0.78	150
weighted avg	0.79	0.79	0.78	150
LDA RES				
LR RESU Accuracy score:0.7			el 2 perfor	med aroun
ND DECK	-	م مالة		C

the same as before, and ----- NB RESULT Accuracy score:0.69 model 1 performed much ======= KNN RESULT ====== Accuracy score:0.58 better, confirming our theory ====== DT RESULT ======= Accuracy score:0.43 reduce Classes And Sampleswas breaking its functionality.

	precision	recall	f1-score	support
0	1.00	0.67	0.80	6
1	0.60	0.50	0.55	6
2	0.45	0.83	0.59	6
3	0.80	0.67	0.73	6
4	1.00	0.83	0.91	6
accuracy			0.70	30
macro avg	0.77	0.70	0.71	30
weighted avg	0.77	0.70	0.71	30
LDA RESI Accuracy score:0.7				

LDA RESULT
Accuracy score:0.73
LR RESULT
Accuracy score:0.63
======= NB RESULT =======
Accuracy score:0.53
KNN RESULT
Accuracy score:0.60
DT RESULT
Accuracy score:0.53
SVM RESULT
Accuracy score:0.70

== SVM RESULT ==

Model 2 performed around the same as before, and model 1 better but still worse than model 2. Hypothesis: model 2 is better when there are fewer samples.

# LFW, samples/person = 20, 10 classes



Predicting pe	ople's names	on the te	st set	
done in 0.002				
	precision	recall	f1-score	support
9	0.50	0.67	0.57	6
1	0.44	0.67	0.53	6
2	0.40	0.33	0.36	6
3	0.40	0.67	0.50	6
4	0.71	0.83	0.77	6
5	0.50	0.67	0.57	6
6	1.00	0.50	0.67	6
7	0.50	0.33	0.40	6
8	1.00	0.50	0.67	6
9	1.00	0.50	0.67	6
accuracy			0.57	60
macro avg	0.65	0.57	0.57	60
weighted avg	0.65	0.57	0.57	60
[[400110				
[0 4 1 0 1 0				
[0 2 2 0 0 2				
[0 1 0 4 0 0				
[0 1 0 0 5 0				
[101004				
[200100				
[1 1 1 0 0 1				
[0 0 0 1 0 1				
[000300	0 0 0 3]]			

# LFW, samples/person = 10, 5 classes (had warnings)

		-	,	
face id:0	face id:1	face id:2	face id:3	face id:4
36	-1	T S		00
Marine Street	The same of	200		

Predicting people done in 0.002s	le's names	on the t	est set	
pr	recision	recall	f1-score	support
0	0.50	0.67	0.57	3
1	0.50	0.67	0.57	3
2	0.00	0.00	0.00	3
3	0.60	1.00	0.75	3
4	1.00	0.67	0.80	3
accuracy			0.60	15
macro avg	0.52	0.60	0.54	15
weighted avg	0.52	0.60	0.54	15
[[2 1 0 0 0]				
[0 2 0 1 0]				
[1 1 0 1 0]				
[0 0 0 3 0]				
[1 0 0 0 2]]				

	precision	recall	f1-score	support
0	0.67			6
1	0.80			6
2	0.33	0.33		6
3	0.67	0.67		6
4	0.33	0.50		6
5	0.50			6
6	0.83		0.83	6
7	0.14	0.17	0.15	6
8	0.57			6
9	0.71	0.83	0.77	6
accuracy			0.53	60
macro avg	0.56	0.53	0.53	60
weighted avg	0.56	0.53	0.53	60
LDA RES Accuracy score:0.6				
LR RESU Accuracy score:0.5				
NB RESU Accuracy score:0.4				
======= KNN RES Accuracy score:0.3				
====== DT RESU Accuracy score:0.1				
SVM RES Accuracy score:0.5				

Model 2 performed much worse, and model 1 around the same. Assuming that the performance of model 2 can serve as the control, we hypothesize that the quality of samples can have a huge impact on model performance.

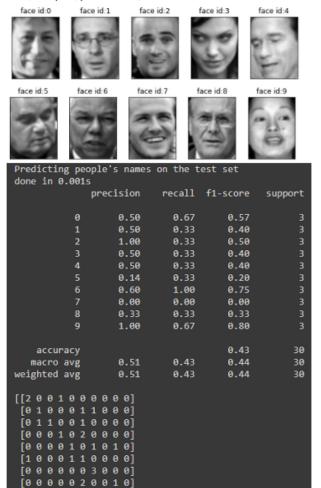
pre	ecision	recall	f1-score	support	
0	0.75	1.00	0.86	3	
1	1.00	0.67	0.80	3	
2	0.50	0.33	0.40	3	
3	0.60	1.00	0.75	3	
4	1.00	0.67	0.80	3	
accuracy			0.73	15	
macro avg	0.77	0.73	0.72	15	
weighted avg	0.77	0.73	0.72	15	
======= LDA RESULT Accuracy score:0.87					
ID DECIUT	IR RESULT		2 performed		
Accuracy score:0.73		unexpe	unexpectedly very well.		
,					
====== NB RESULT ======			Perhaps these samples were		
Accuracy score:0.73		of high	quality. How	ever,	
====== KNN RESULT ======		model	1 had warnir	ig when	

plotting the eigenfaces, so there might still be some broken functionality in some

cases.

----- SVM RESULT -----Accuracy score:0.73

#### LFW, samples/person = 10, 10 classes



	precision	recall	f1-score	support
0	0.25			
1	0.50	0.67		
2	0.29	0.67	0.40	3
3	0.00	0.00	0.00	3
4	1.00	0.33	0.50	3
5	0.20	0.33	0.25	3
6	0.75	1.00	0.86	3
7	0.00	0.00	0.00	3
8	0.50	0.33	0.40	3
9	0.00	0.00	0.00	3
accuracy			0.37	30
macro avg	0.35	0.37	0.33	30
weighted avg	0.35	0.37	0.33	30
LDA RES	ULT			
Accuracy score:0.6				
LR RESU Accuracy score:0.4				
Accuracy Score.v.4				
====== NB RESU				
Accuracy score:0.5	9			
KNN RES	ULT			
Accuracy score:0.4				
DT RESU				
Accuracy score:0.3				
===== SVM RES	ULT			
Accuracy score:0.3				

We have reached to limitations of our model, there are too many classes and too few samples to predict samples to an acceptable level. One outlier is the LDA results in model 2 is still pretty good.

## Key takeaways:

[0 0 0 0 0 0 0 0 2 1 0] [1 0 0 0 0 0 0 0 0 0 2]]

- reduceSamplesAndClasses() was negatively affecting the performance of model 1, so we will not use that code moving forwards
- Model 2 seems to perform better than model 1 when there are fewer samples, and more consistently overall. Furthermore, LDA in model 2 seemed to perform the most consistently, and achieved great results with only a few samples. Will use LDA moving forwards.
- The quality of the samples significantly affects our either model's performance
- We need at least 20 samples per person (14 labelled images) for 10 classes, or 10 samples per person (7 labelled images) for 5 classes to achieve decent performance