Predicting Children’s Social Skills:

Supervised Learning & PCA

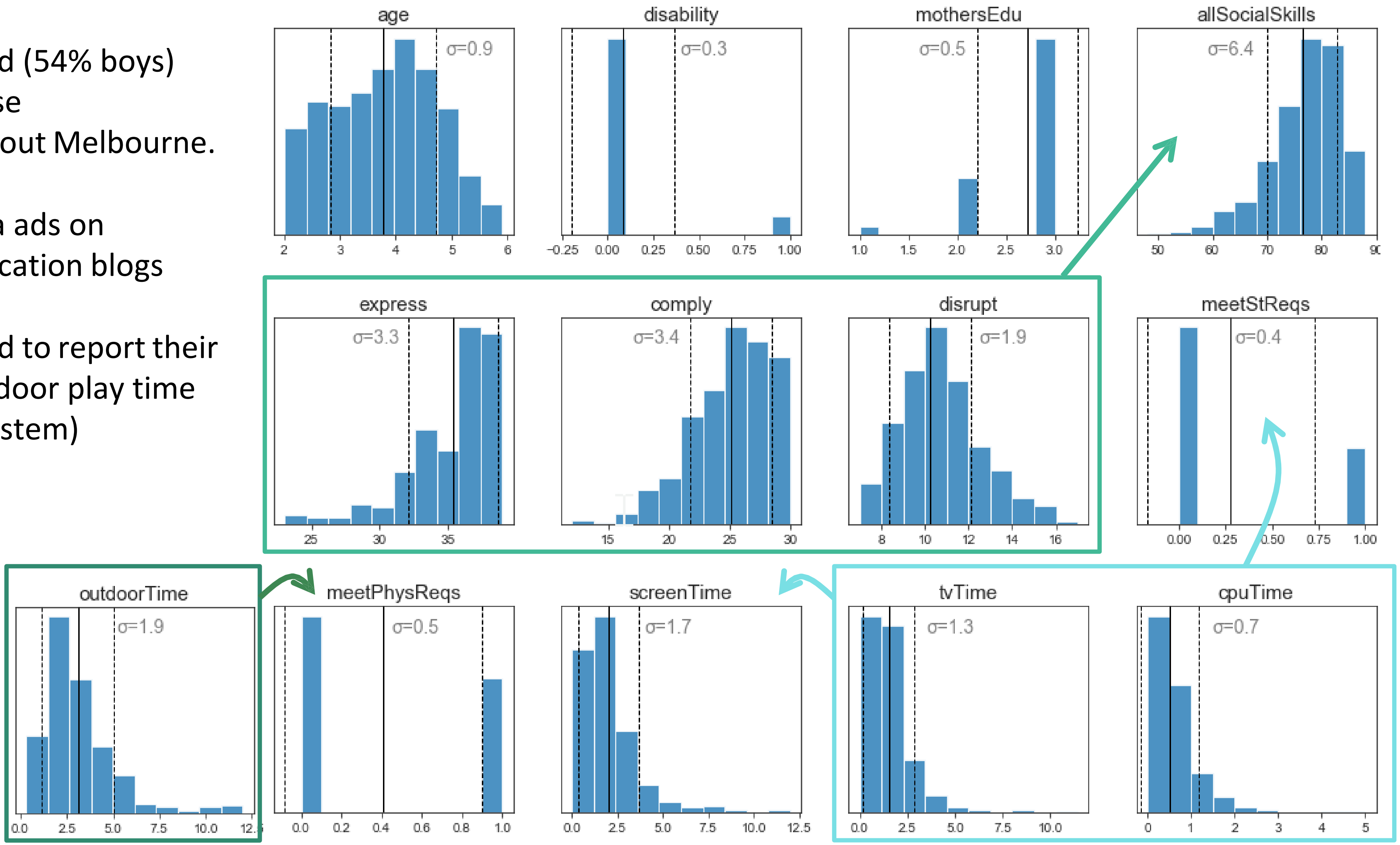
MONISH SHAH

Dataset:

- 575 mothers with a child (54% boys) aged 2–5 years in diverse neighborhoods throughout Melbourne.

- Mothers were found via ads on parenting and child education blogs

- Mothers were instructed to report their child’s screen time, outdoor play time and social skills (ASBI system)



https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0193700

Dataset:

Name	Description	Type
age	Age, ranges 2-6	Continuous Float
express	Child's Ability to express themselves	"continuous" integer (really a sum of 13 Likert scales)
comply	Child's Ability to comply	"continuous" integer (really a sum of 10 Likert scales)
tvTime	Hours watching TV / day	Continuous Float
cpuTime	Hours on Computer / day	Continuous Float
outdoorTime	Hours outside / day	Continuous Float
disability	Whether Mother considers child disabled	Boolean
mothersEdu	Mother's education level: 1 = <10 years, 2 = 11-13 years, 3 = 14+ years	Discrete
meetStReqs	Whether child meets government recommendations for screen time (Boolean version of tvTime, cpuTime)	Boolean
meetPhysReqs	Whether child meets government recommendations for outdoor time (Boolean version of outdoorTime)	Boolean
gender	Male/female	Boolean

https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0193700

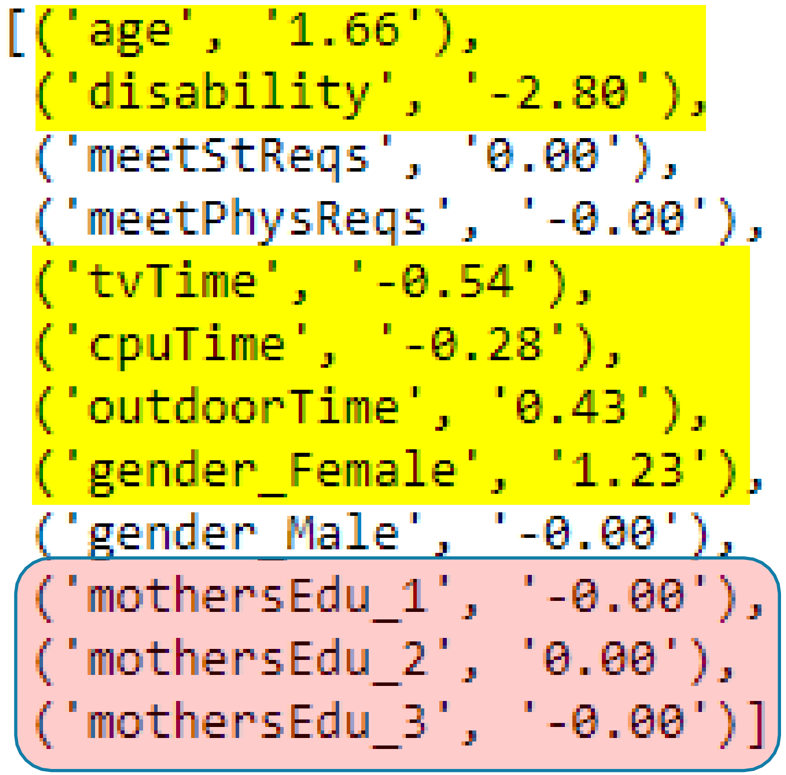
Topics

1. Can we predict a child’s “Social Skill” score be predicated based on demographics and activities (screen time, outdoor time)?
2. Can we predict whether a child will show disruptive behavior?
   - Sidebar: What does PCA do (visually) when we create components out of binary variables?

Predicting Social Skill

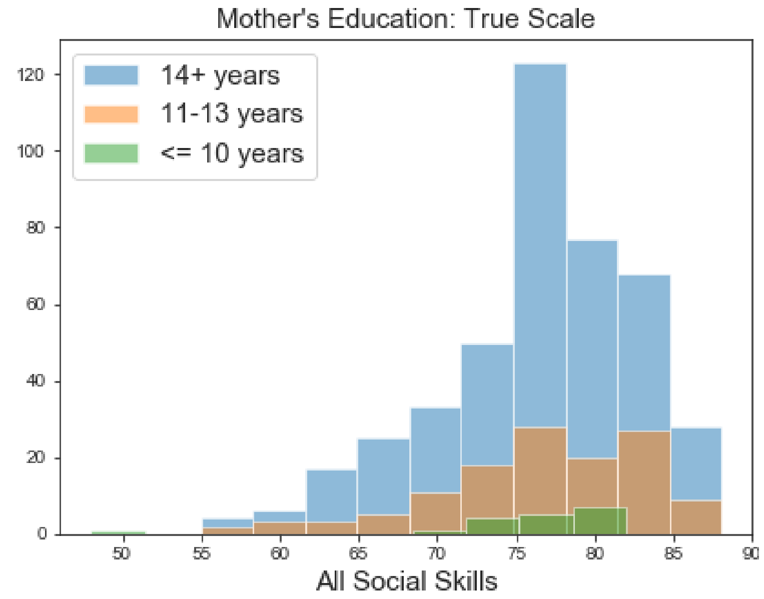
1) One-hot encode ‘gender’ and ‘mother’s education’

2) Use Lasso Regression to find the useful features:

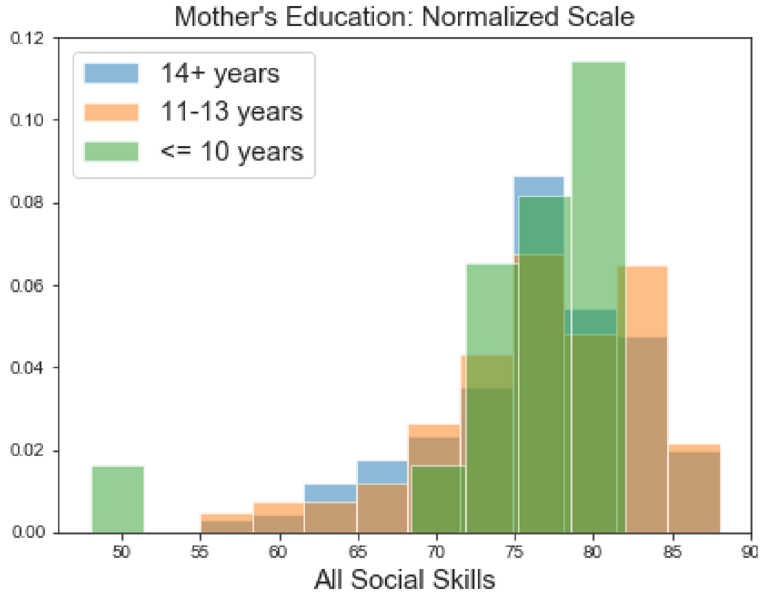


```
[('age', '1.66'),
 ('disability', '-2.80'),
 ('meetStReqs', '0.00'),
 ('meetPhysReqs', '-0.00'),
 ('tvTime', '-0.54'),
 ('cpuTime', '-0.28'),
 ('outdoorTime', '0.43'),
 ('gender_Female', '1.23'),
 ('gender_Male', '-0.00'),
 ('mothersEdu_1', '-0.00'),
 ('mothersEdu_2', '0.00'),
 ('mothersEdu_3', '-0.00')]
```

?



Mother's Education: True Scale

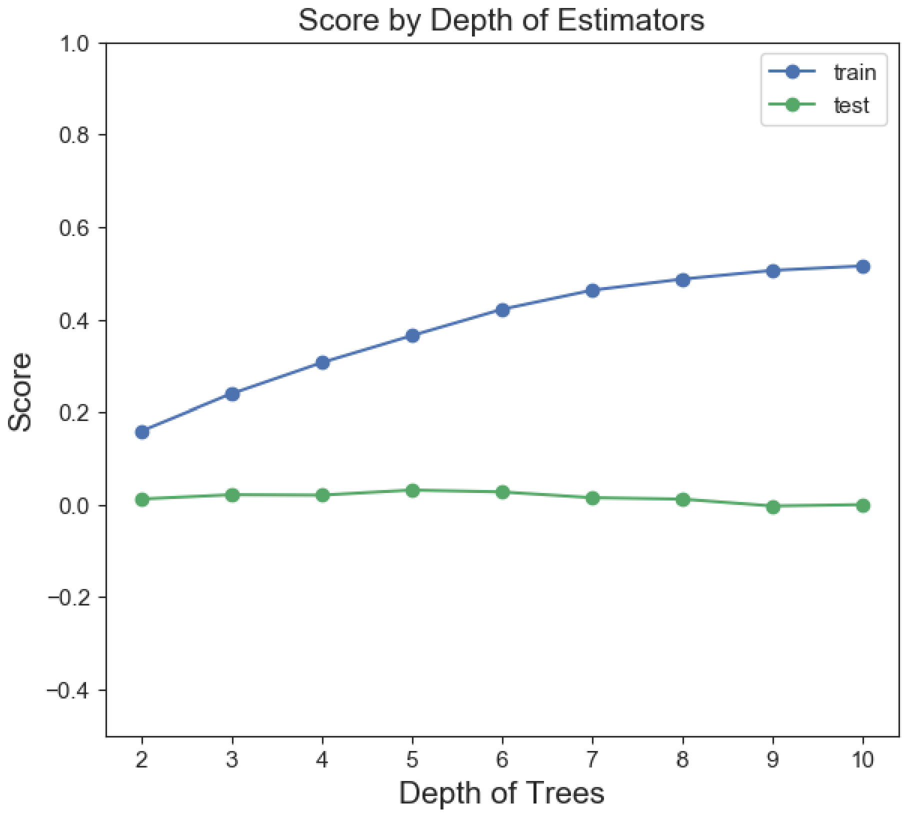


Mother's Education: Normalized Scale

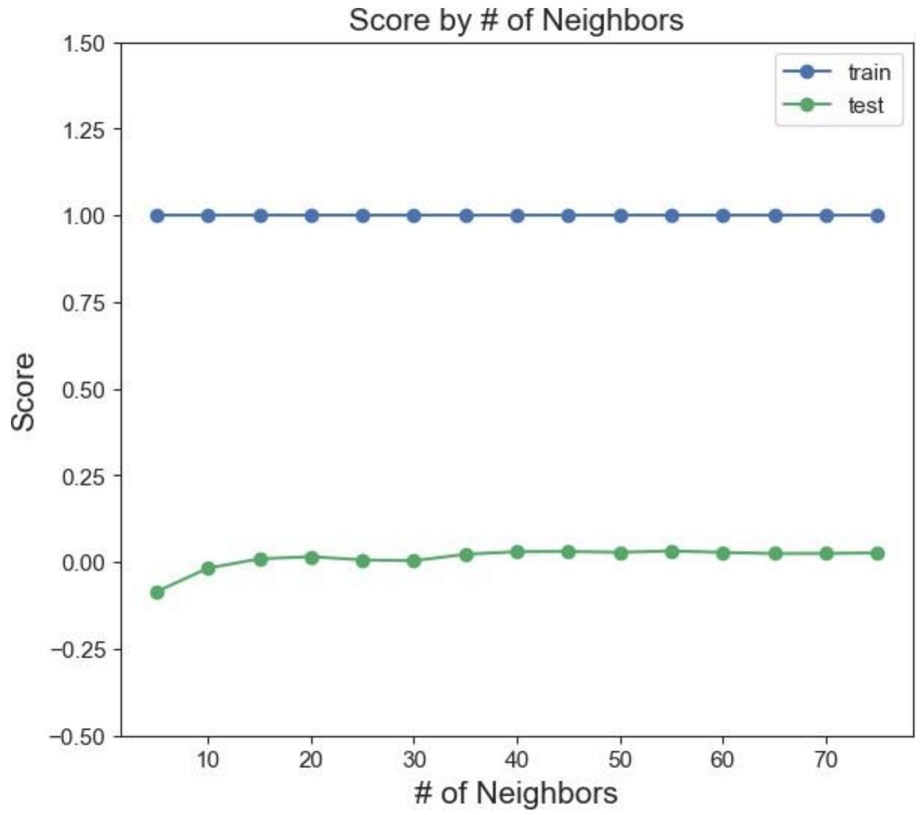
Predicting Social Skill

3) Grid searching Random Forest, KNN Regressors. As shown by a couple examples below, Random Forest and KNN Regressors failed to find meaningful linear relationships with these features.

Random Forest Regressor



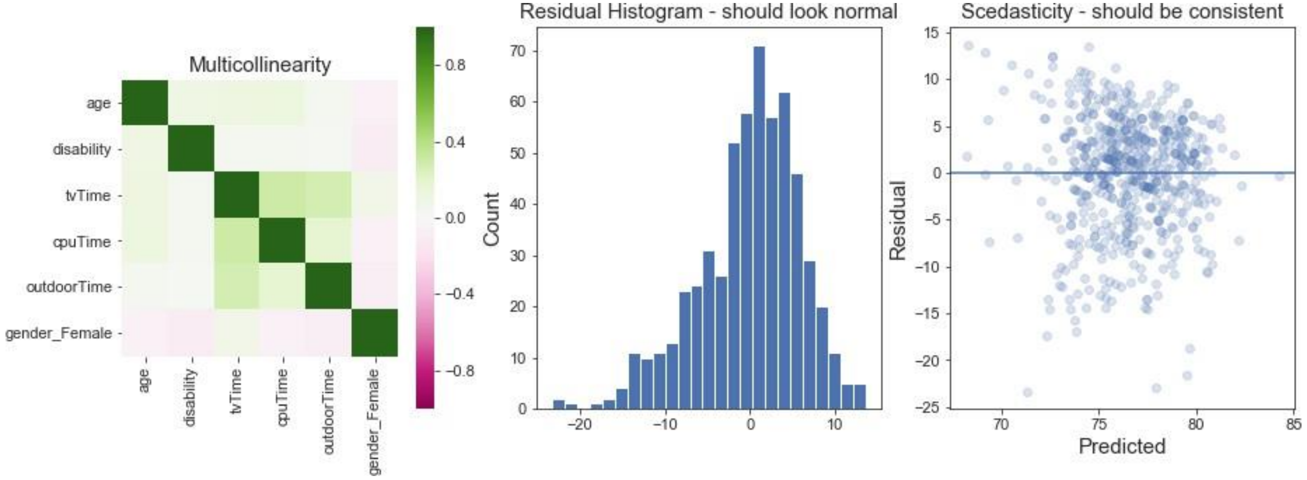
KNN Regressor

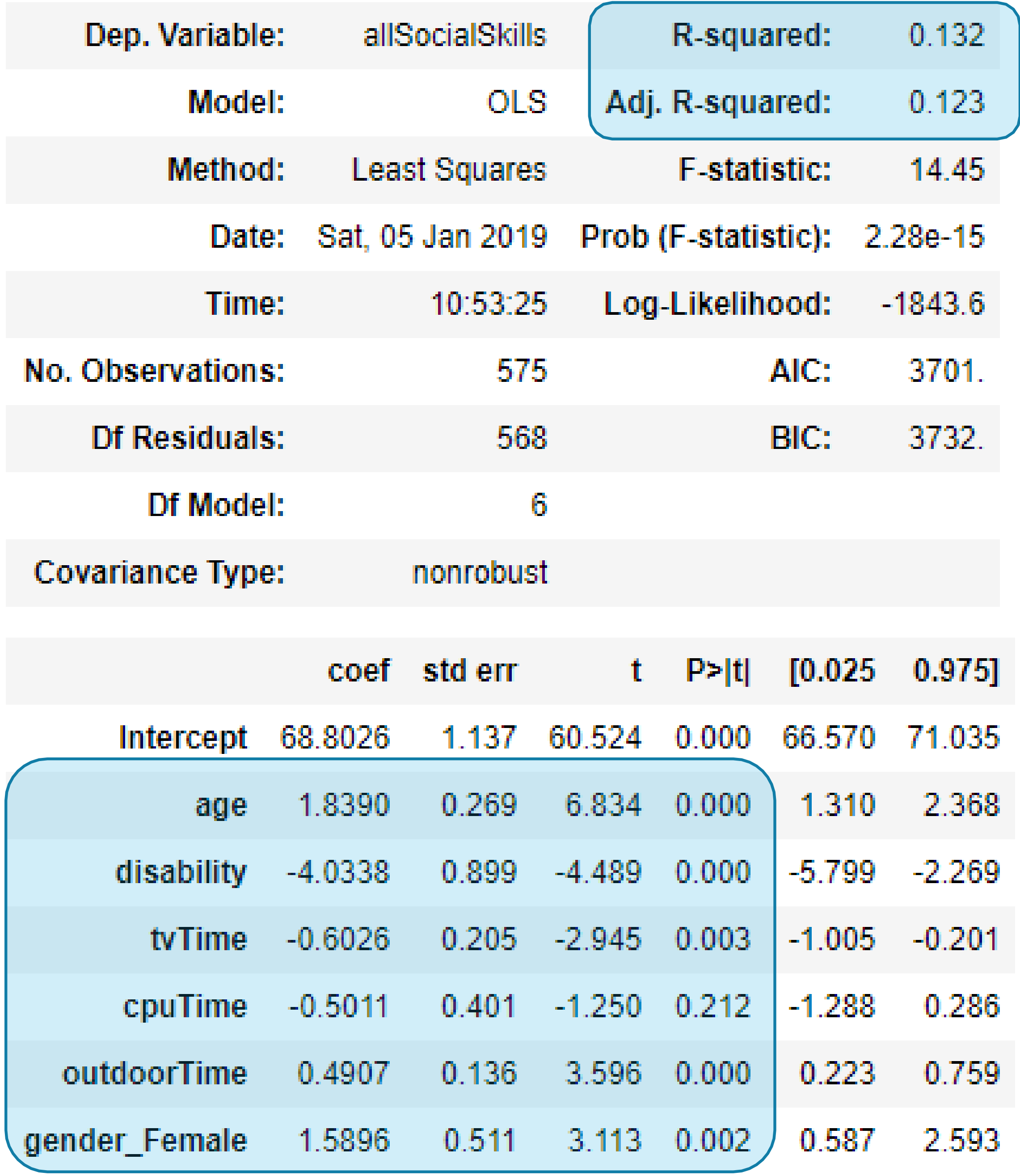


Predicting Social Skill

4) Simple Linear Regression –

Slightly better than other models, but not a strong relationship, and our output below is not a desirable residual distribution



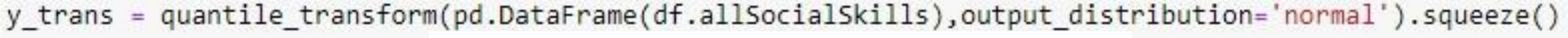


Dep. Variable:	allSocialSkills	R-squared:	0.132
Model:	OLS	Adj. R-squared:	0.123
Method:	Least Squares	F-statistic:	14.45
Date:	Sat, 05 Jan 2019	Prob (F-statistic):	2.28e-15
Time:	10:53:25	Log-Likelihood:	-1843.6
No. Observations:	575	AIC:	3701.
Df Residuals:	568	BIC:	3732.
Df Model:	6		
Covariance Type:	nonrobust		

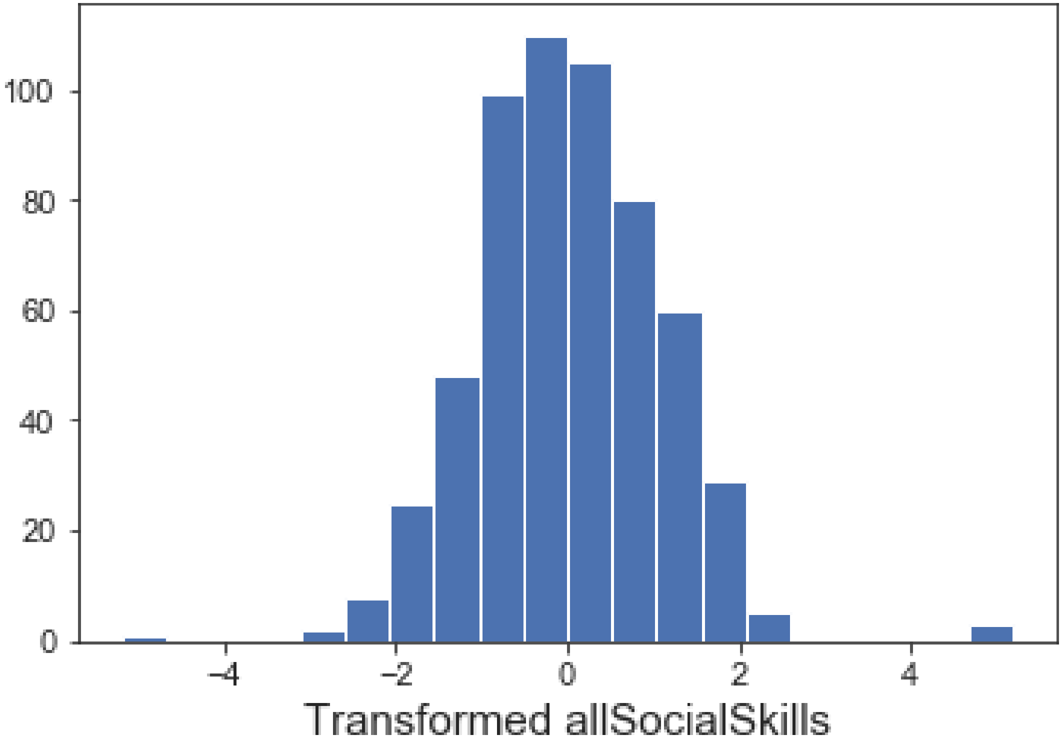
	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	68.8026	1.137	60.524	0.000	66.570	71.035
age	1.8390	0.269	6.834	0.000	1.310	2.368
disability	-4.0338	0.899	-4.489	0.000	-5.799	-2.269
tvTime	-0.6026	0.205	-2.945	0.003	-1.005	-0.201
cpuTime	-0.5011	0.401	-1.250	0.212	-1.288	0.286
outdoorTime	0.4907	0.136	3.596	0.000	0.223	0.759
gender_Female	1.5896	0.511	3.113	0.002	0.587	2.593

Predicting Social Skill

4) Our Target variable is a skewed distribution. Does Quantile-transforming it help?



```
y_trans = quantile_transform(pd.DataFrame(df.allSocialSkills),output_distribution='normal').squeeze()
```



Predicting Social Skill

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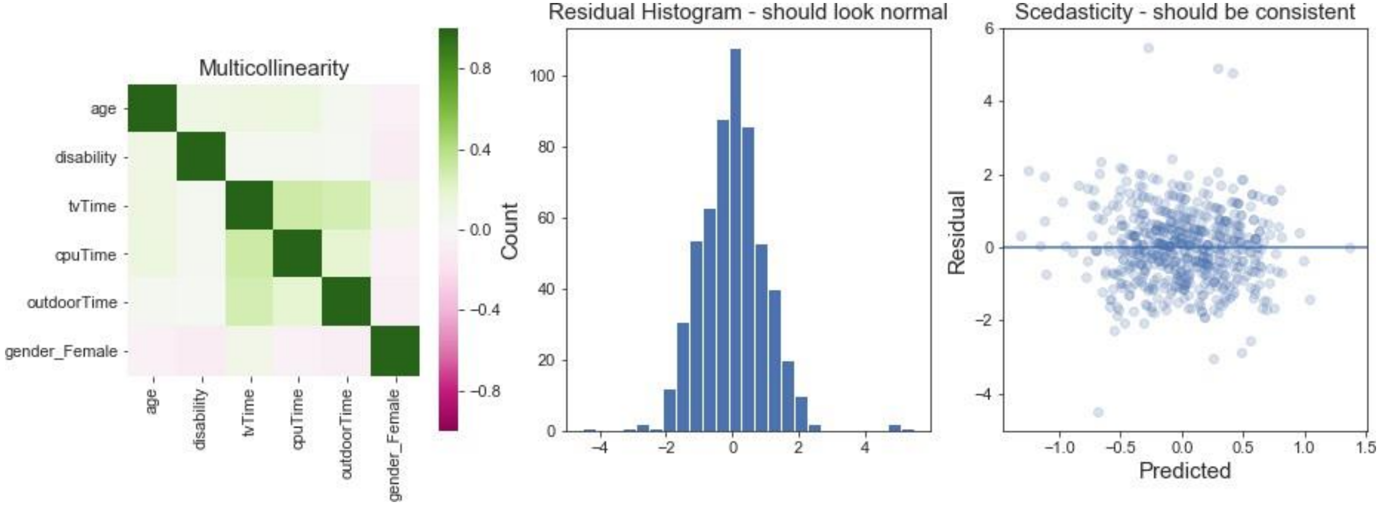
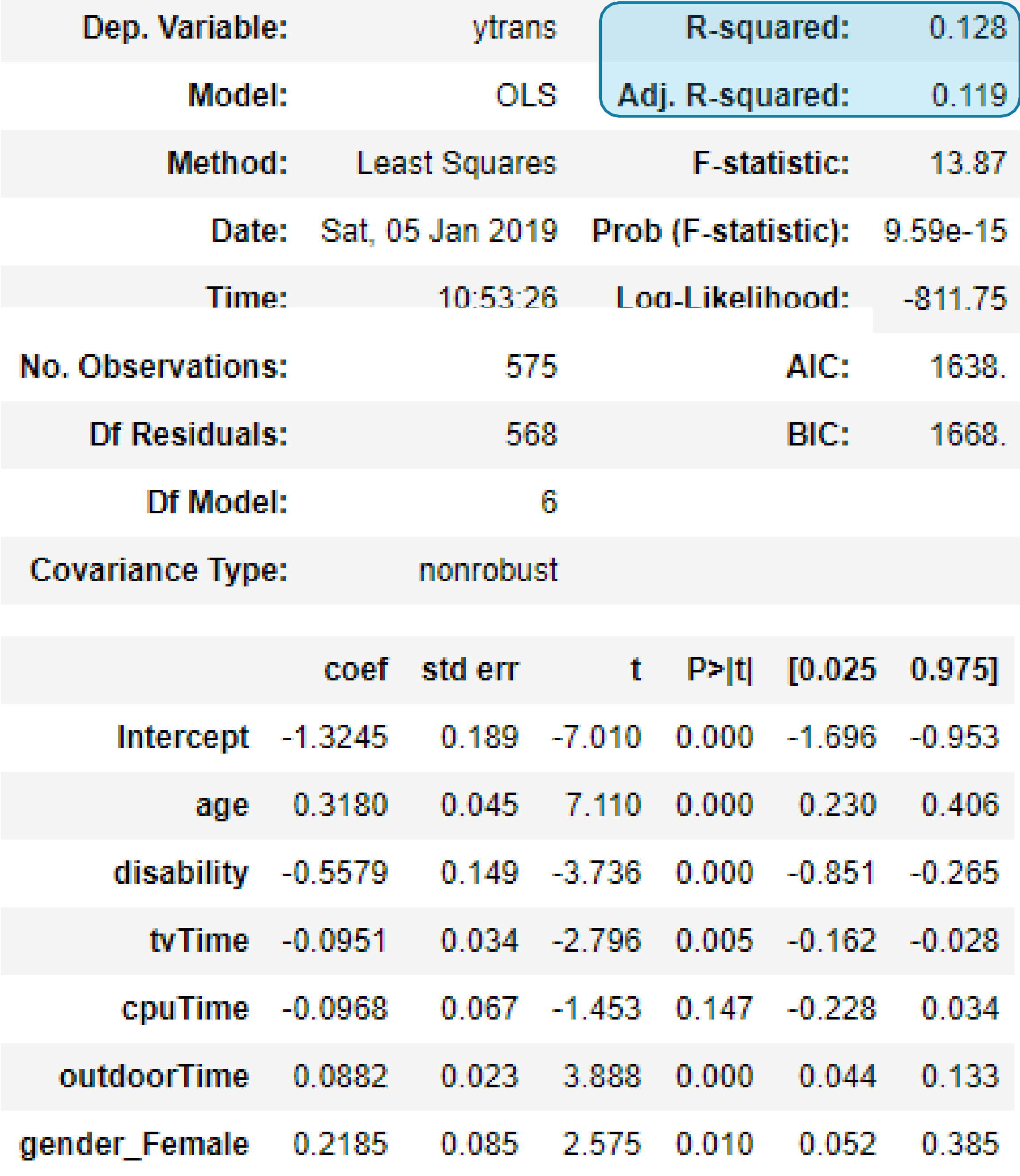




Dep. Variable:	ytrans	R-squared:	0.128
Model:	OLS	Adj. R-squared:	0.119
Method:	Least Squares	F-statistic:	13.87
Date:	Sat, 05 Jan 2019	Prob (F-statistic):	9.59e-15
Time:	10:53:26	Log-Likelihood:	-811.75
No. Observations:	575	AIC:	1638.
Df Residuals:	568	BIC:	1668.
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-1.3245	0.189	-7.010	0.000	-1.696	-0.953
age	0.3180	0.045	7.110	0.000	0.230	0.406
disability	-0.5579	0.149	-3.736	0.000	-0.851	-0.265
tvTime	-0.0951	0.034	-2.796	0.005	-0.162	-0.028
cpuTime	-0.0968	0.067	-1.453	0.147	-0.228	0.034
outdoorTime	0.0882	0.023	3.888	0.000	0.044	0.133
gender_Female	0.2185	0.085	2.575	0.010	0.052	0.385

Topics

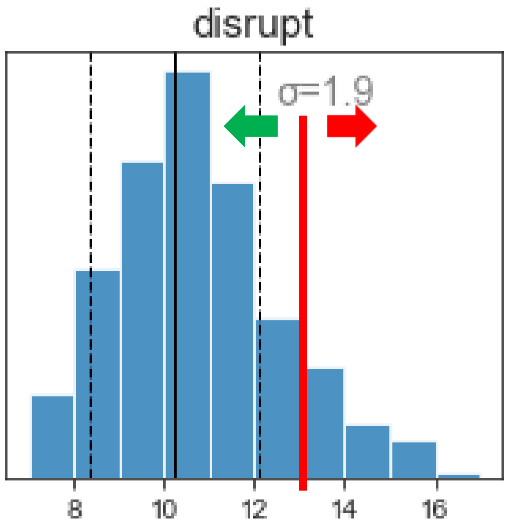
1. *Can we predict a child's "Social Skill" score be predicated based on demographics and activities (screen time, outdoor time)? – Not with these predictors! More data is needed.*

2. Can we predict whether a child will show disruptive behavior?
   - Sidebar: What does PCA do (visually) when we create components out of binary variables?

Available Features

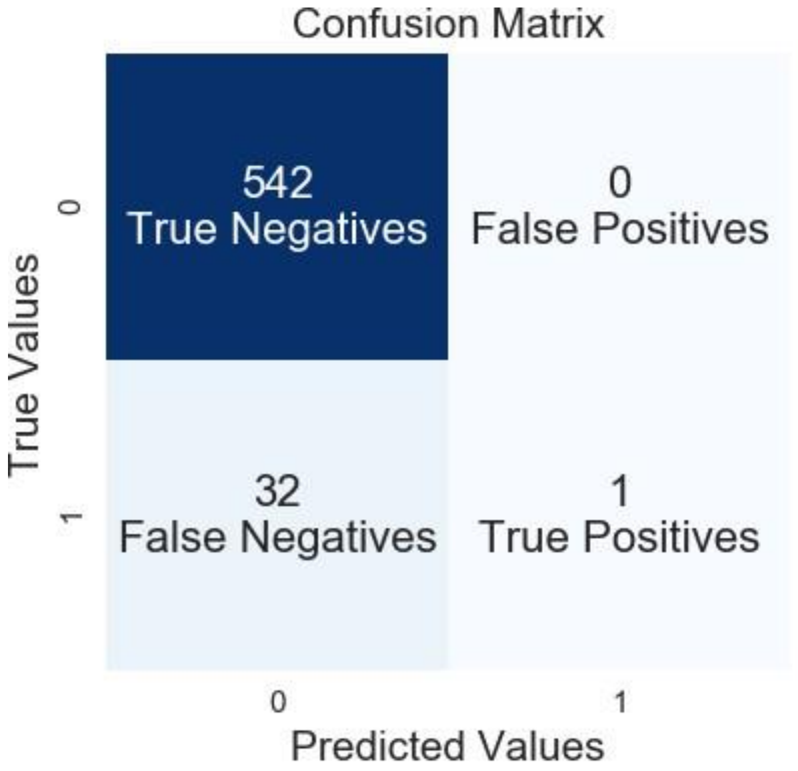
Name	Description	Type
age	Age, ranges 2-6	Continuous Float
express	Child’s Ability to express themselves	“continuous” integer (really a sum of 13 Likert scales)
comply	Child’s Ability to comply	“continuous” integer (really a sum of 10 Likert scales)
Disrupt	Child’s tendency to be disruptive	“continuous” integer (really a sum of 7 Likert scales)
tvTime	Hours watching TV / day	Continuous Float
cpuTime	Hours on Computer / day	Continuous Float
outdoorTime	Hours outside / day	Continuous Float
disability	Whether Mother considers child disabled	Boolean
mothersEdu	Mother’s education level: 1 = <10 years, 2 = 11-13 years, 3 = 14+ years	Discrete
meetStReqs	Whether child meets govt recommendations for screen time	Boolean
meetPhysReqs	Whether child meets govt recommendations for outdoor time	Boolean
gender	Male/female	Boolean

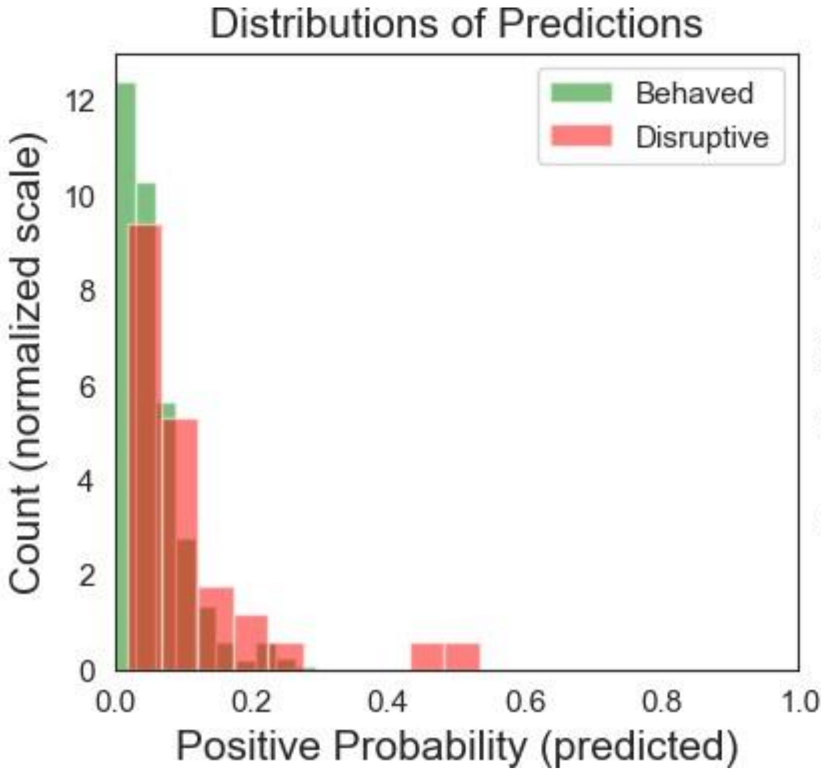
Predicting Disruptive Behavior

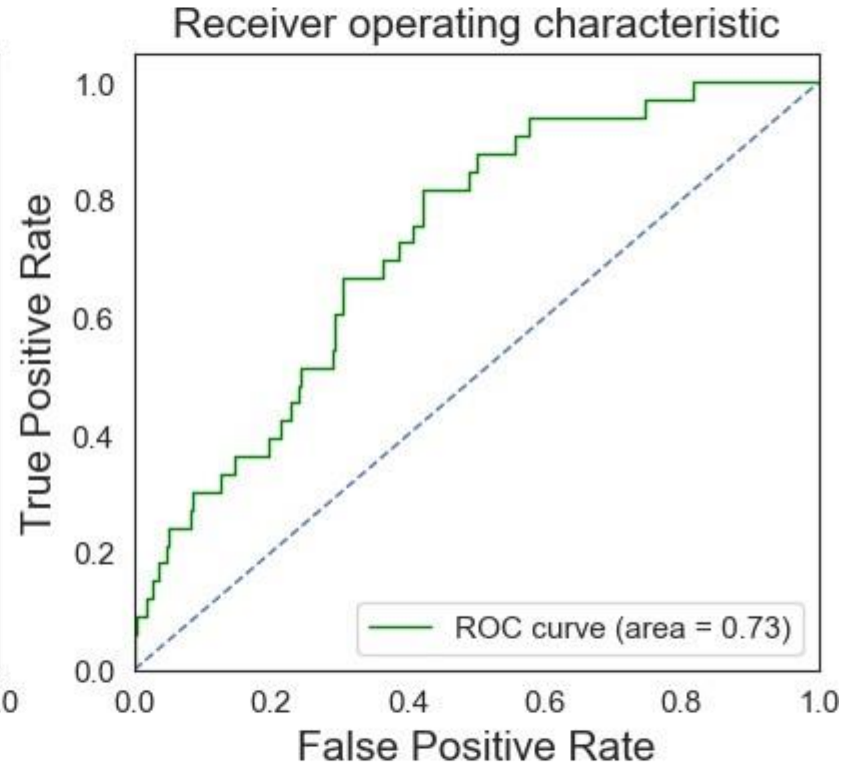


Example: A school administration is trying to prevent classrooms from having too many disruptive students, so they are trying to identify which of their incoming students are likely to be disruptive in advance (disrupt score > x)

Basic Logistic Regression







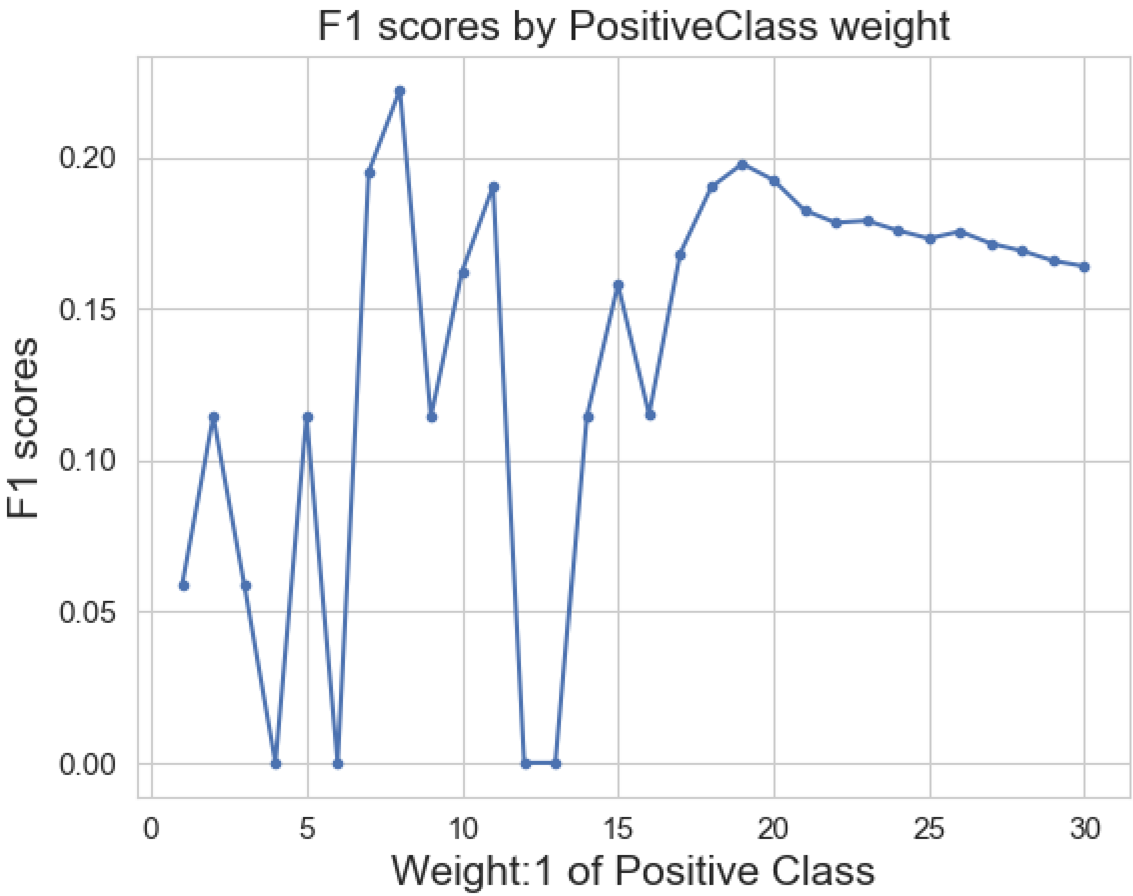
Predicting Disruptive Behavior

Search for the correct class balance, then retry:

$$precision = \frac{True\ \ Positives}{True\ \ Positives+False\ \ Positives}$$

$$recall = \frac{True\ \ Positives}{True\ \ Positives+False\ \ Negatives}$$

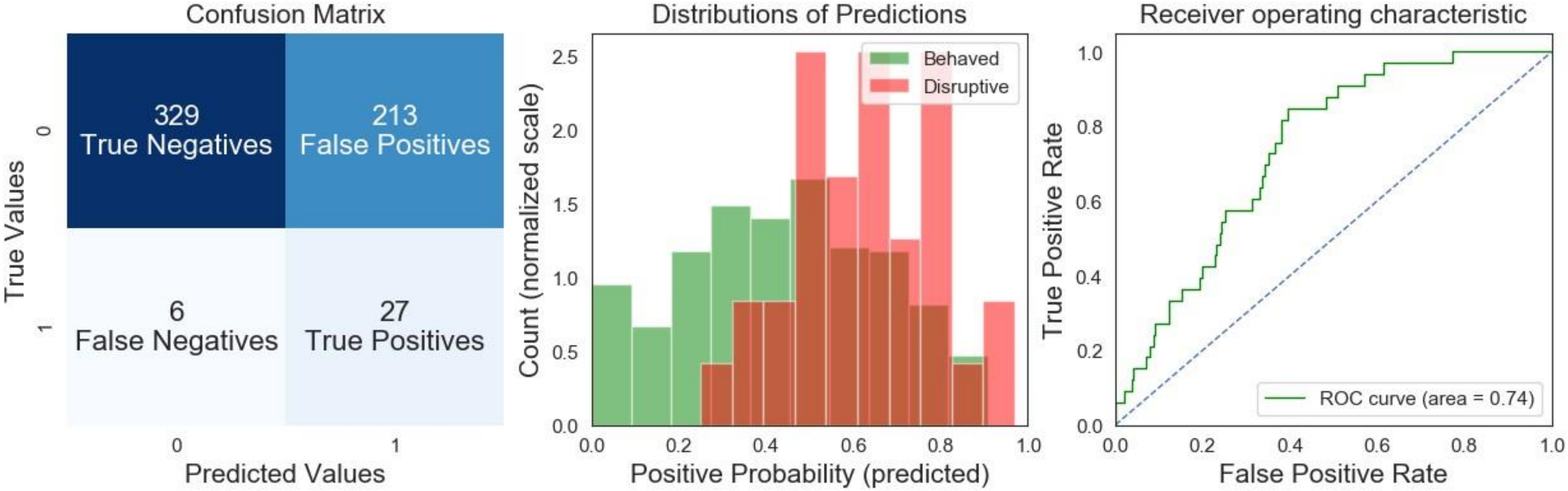
$$F1 = \frac{2*precision*recall}{precision+recall}$$



Bottom line – F1 (aka F-measure or F-score) gives us a single number to understand the confusion matrix, enabling grid searching that doesn't penalize small classes

Predicting Disruptive Behavior

Logistic Regression with Class weights 1:19



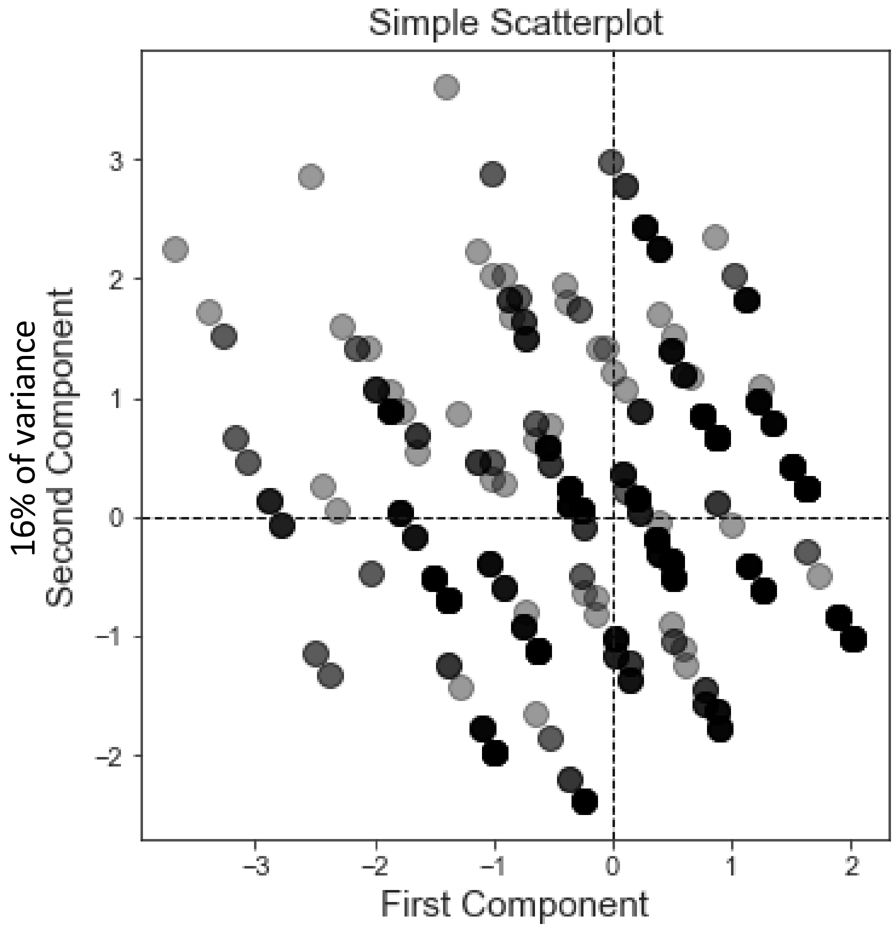
At this point, we could tell the school something like this, based on the ROC curve above and choosing a decision threshold:

*"Our current model could correctly identify ~ **85**% of disruptive students; however, it would also result in almost **40**% of well-behaved students being mistakenly labelled as disruptive"*

Binary Features

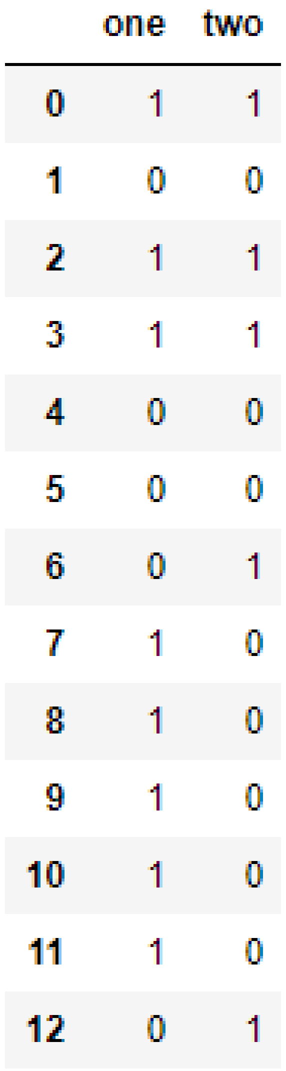
Features Used:	True if:
Disability	Mother considers child disabled
meetStReqs	Child meets gov't recommendations for screen time
meetPhysReqs	Child meets gov't recommendations for outdoor time
Gender_Male	Child is male
MothersEdu_3	Mother educated 14+ years
bothSTabovemean	Both tv time and cpu time over the mean
expressive	Above average expressiveness
compliant	Above average compliance

First 2 components created by PCA on 8 Boolean features



18% of variance

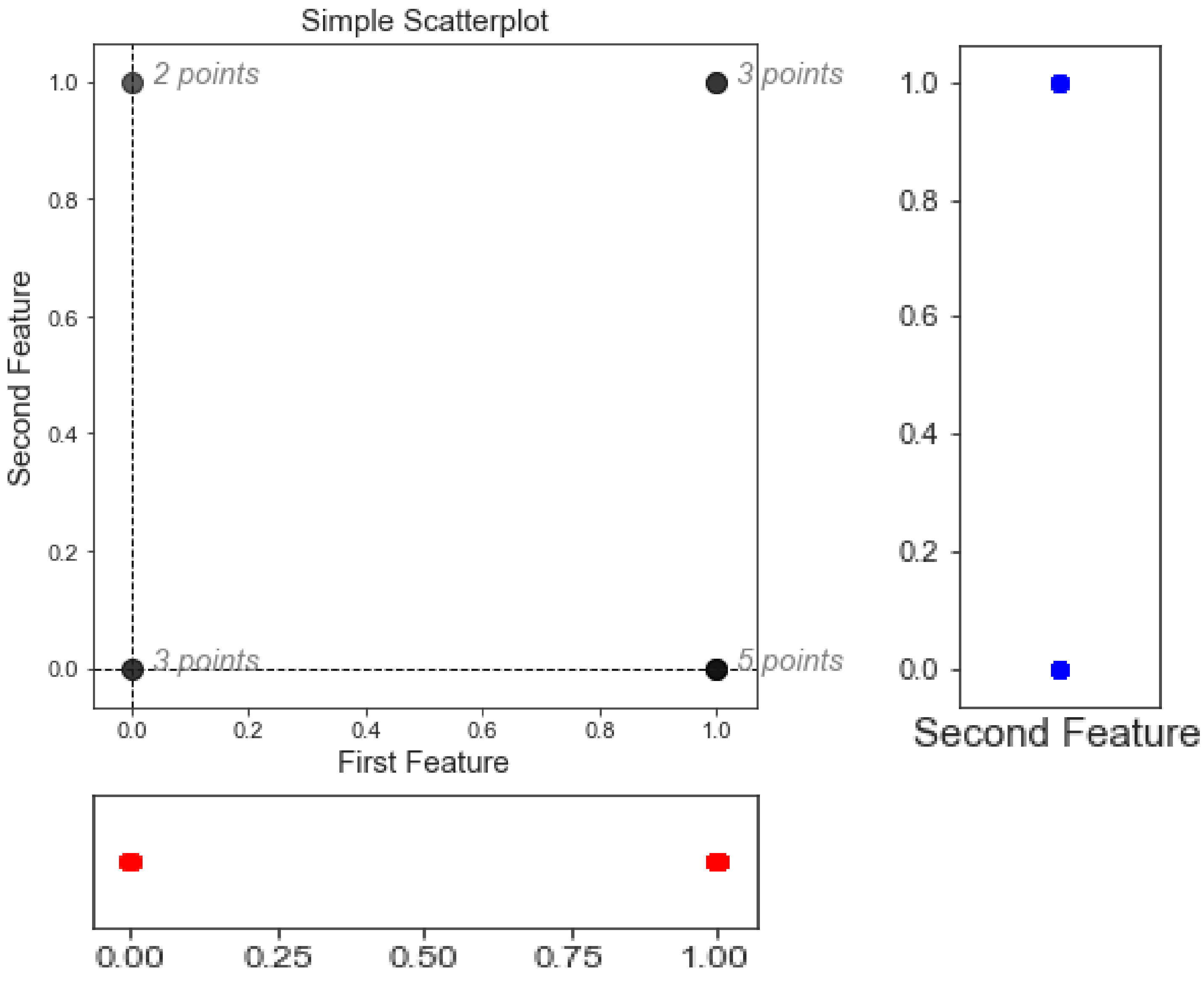
Sidebar: Visualizing PCA for Boolean Variables



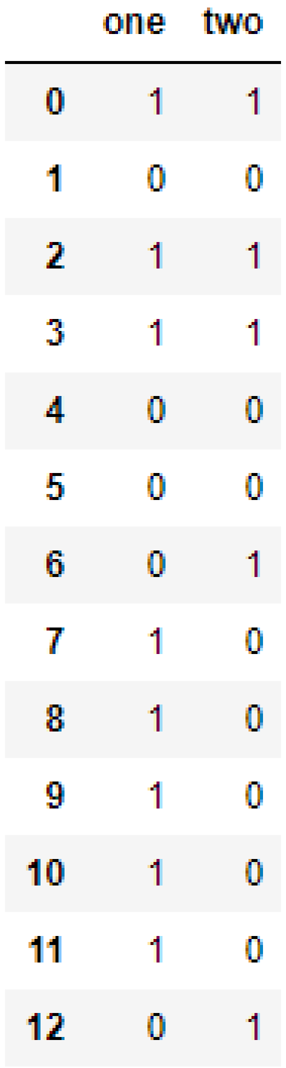
	one	two
0	1	1
1	0	0
2	1	1
3	1	1
4	0	0
5	0	0
6	0	1
7	1	0
8	1	0
9	1	0
10	1	0
11	1	0
12	0	1

How would these look on a scatter plot?

We'd expect just 4 clusters of points:

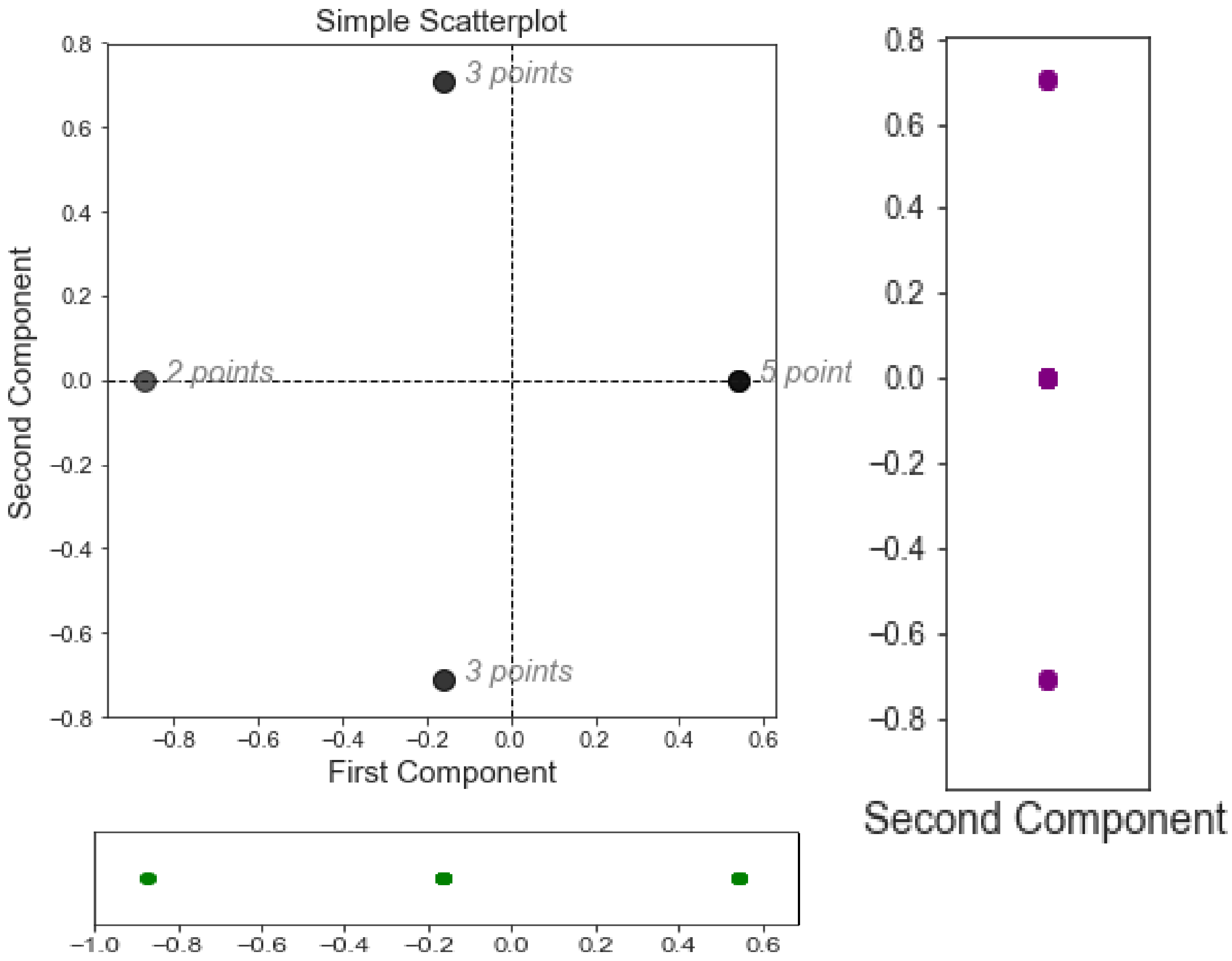


Sidebar: Visualizing PCA for Boolean Variables



	one	two
0	1	1
1	0	0
2	1	1
3	1	1
4	0	0
5	0	0
6	0	1
7	1	0
8	1	0
9	1	0
10	1	0
11	1	0
12	0	1

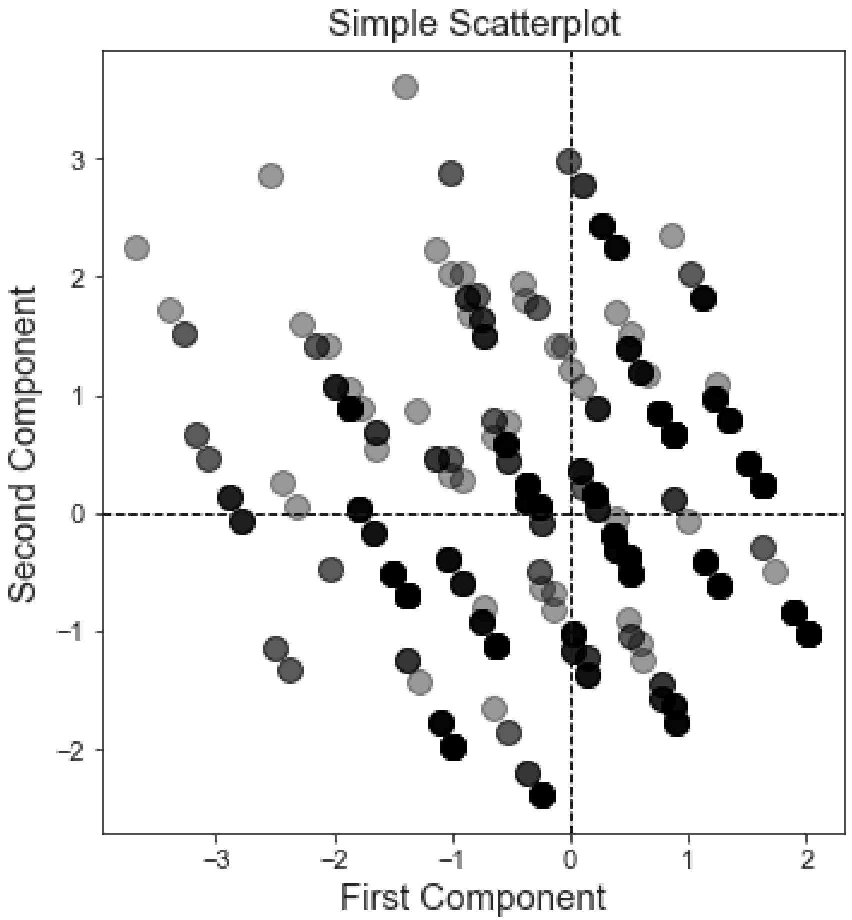
What if we ran PCA on these 2 features with mean-only scaling?



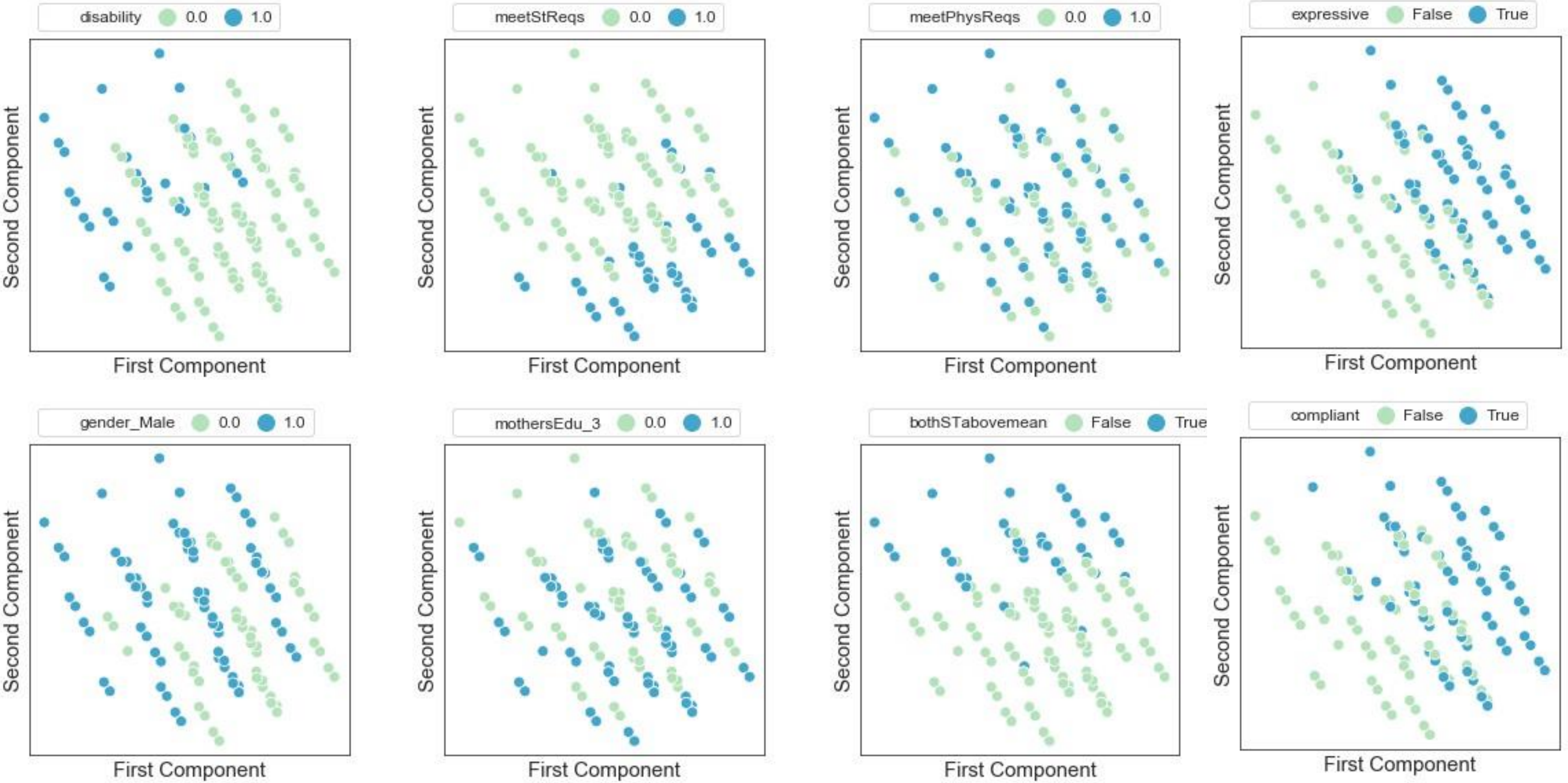
Back to our Data…

Features Used:	True if:
Disability	Mother considers child disabled
meetStReqs	Child meets gov't recommendations for screen time
meetPhysReqs	Child meets gov't recommendations for outdoor time
Gender_Male	Child is male
MothersEdu_3	Mother educated 14+ years
bothSTabovemean	Both tv time and cpu time over the mean
expressive	Above average expressiveness
compliant	Above average compliance

First 2 components created by PCA on 8 Boolean features

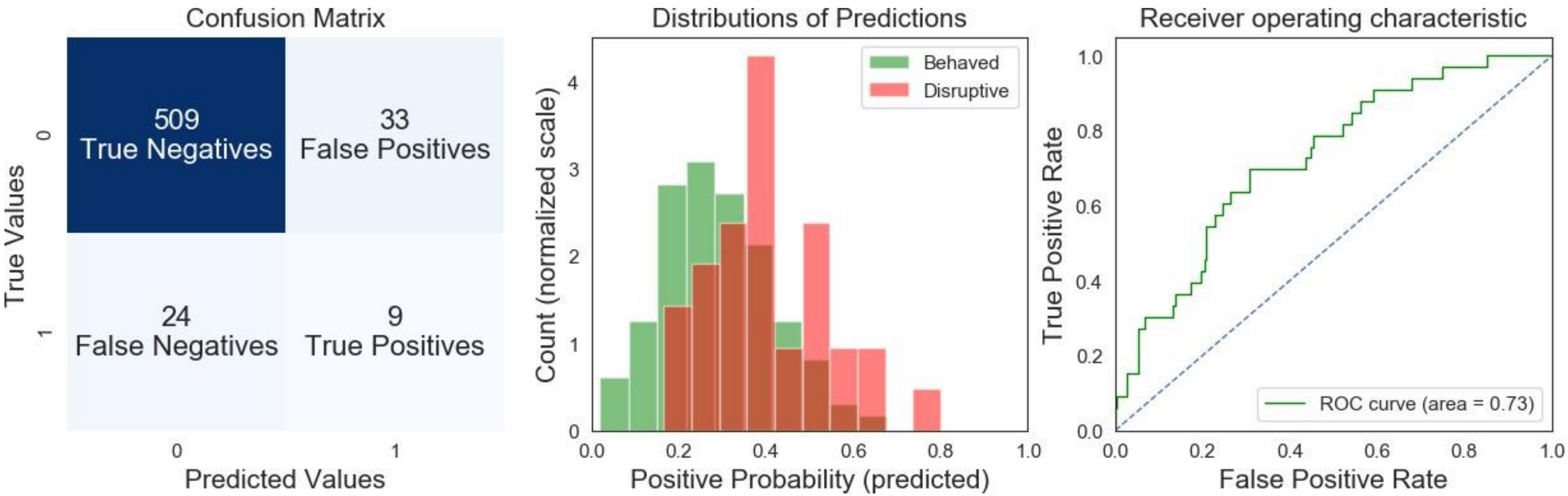


Back to our Data…Scatterplots show how 2 PCA components can contain information about multiple features, using intuition gained from our simple 2-D examples



Predicting Disruptive Behavior

Logistic Regression with PCA components, and Class weights 1:7



Predicting Disruptive Behavior

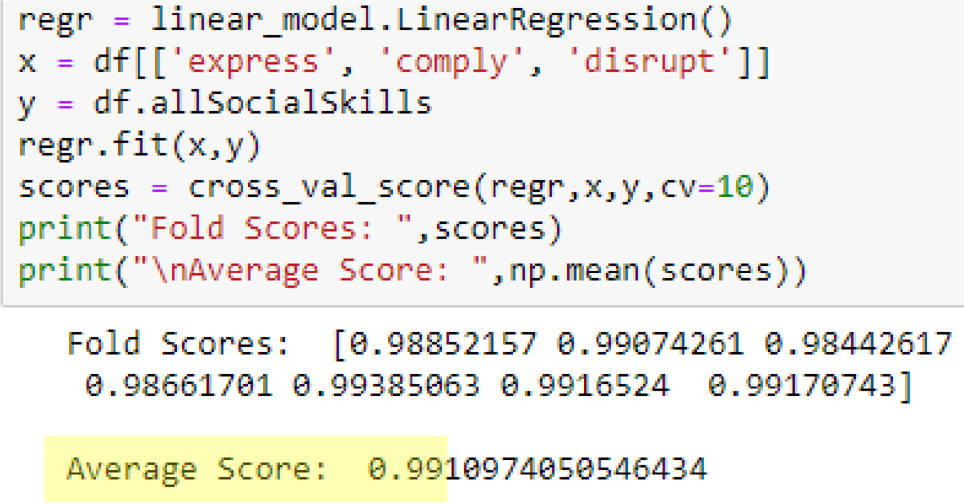
Logistic Regressor Summary	n Features	Class Weights	F1Score	AUC
Basic	15	1:1	.06	.73
Balanced	15	1:16	.12	.65
"Optimized" Weights	15	1:19	.20	.74
Ridge	15	1:19	.20	.74
With continuous components	14	1:19	.20	.74
With continuous & binary components	12	1:7	.24	.73

Resources

- Full study including original dataset:
  - Cross sectional associations of screen time and outdoor play with social skills in preschool children
  - https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0193700
- The best way for visual learners to gain an intuition for PCA/matrix transformations
  - 3blue1brown: Essence of Linear Algebra - https://www.youtube.com/playlist?list=PLZHQObOWTQDPD3MizzM2xVFitgF8hE_ab
- A visualization for MCA (the best-practice alternative to PCA for categorical data):
  - François Husson - https://www.youtube.com/watch?v=b4kRAt4mkB8
- The github repo for this project:
  - https://github.com/monish24/distruption-prediction

Appendix

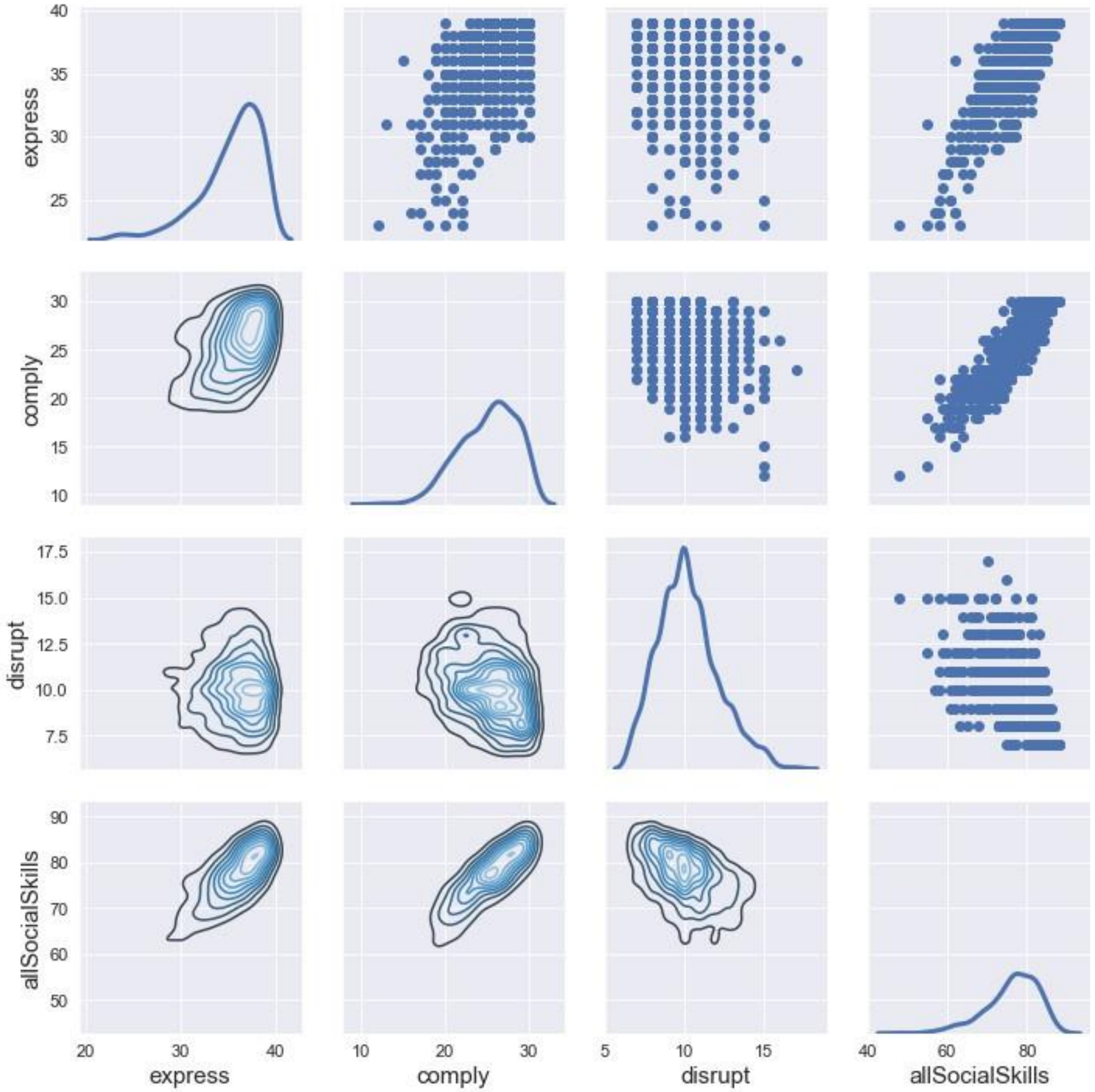
allSocialSkills relationship to its precedents

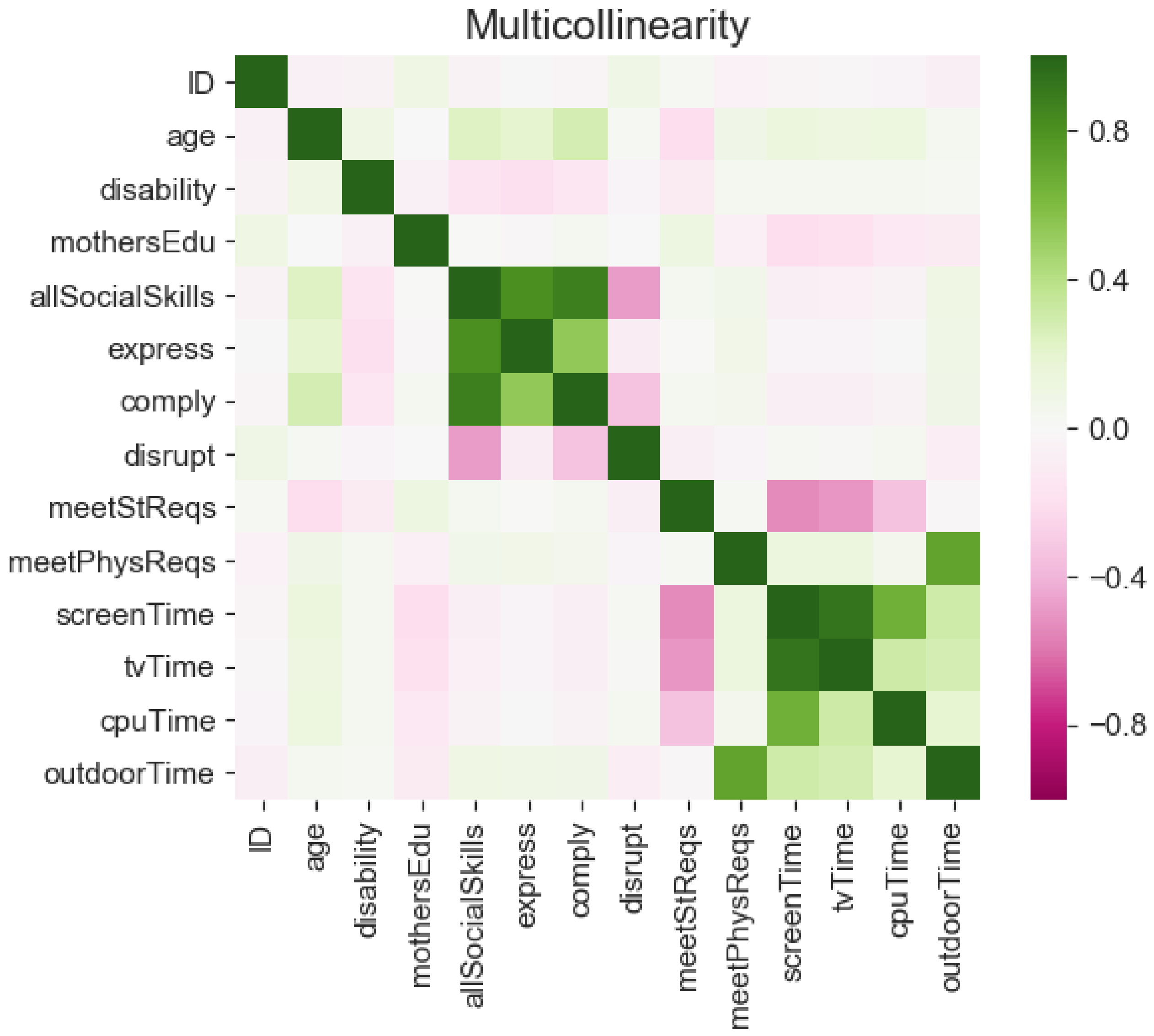


```
regr = linear_model.LinearRegression()
x = df[['express', 'comply', 'disrupt']]
y = df.allSocialSkills
regr.fit(x,y)
scores = cross_val_score(regr,x,y,cv=10)
print("Fold Scores: ",scores)
print("\nAverage Score: ",np.mean(scores))
```

```
   Fold Scores:  [0.98852157 0.99074261 0.98442617
    0.98661701 0.99385063 0.9916524  0.99170743]

   Average Score:  0.9910974050546434
```




Multicollinearity
ID
age
disability
mothersEdu
allSocialSkills
express
comply
disrupt
meetStReqs
meetPhysReqs
screenTime
tvTime
cpuTime
outdoorTime
0.8
0.4
0.0
−0.4
−0.8