

Experimental Planning - Case Study

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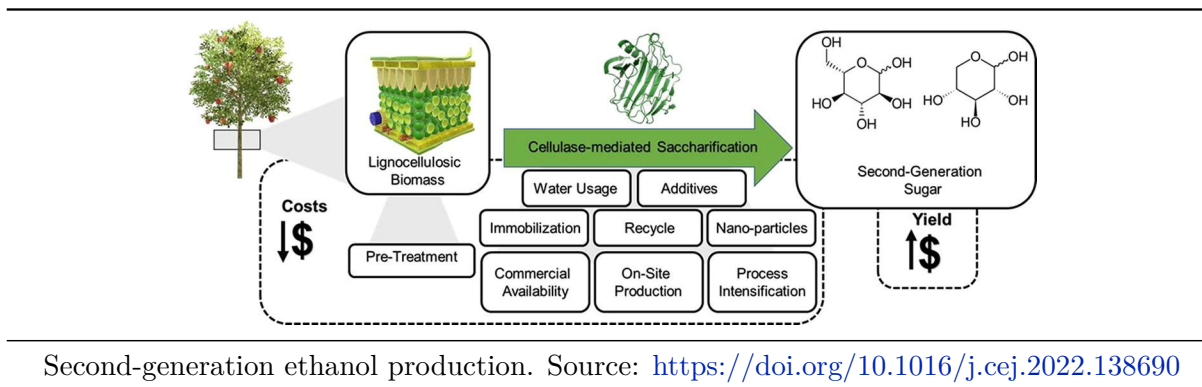
1 Case Study

Nitrogen Source Optimization for Cellulase Production by *Penicillium funiculosum*, using a Sequential Experimental Design Methodology and the Desirability Function

The chosen [article](#) for the case study suggests employing a sequential experimental design methodology to enhance cellulase production efficiency. Lignocellulosic biomass, being one of the most abundant materials globally, holds immense potential for biomass production. However, the widespread application of lignocellulosic biomass for biofuel production faces constraints due to the considerable expenses associated with acquiring the necessary enzymes for the chemical process of deriving second-generation sugars. Consequently, the optimization of enzyme production emerges as a pivotal focus within the energy industry's interests.

1.1 The Chosen Article

Maeda, R.N., da Silva, M.M.P., Santa Anna, L.M.M. et al. Nitrogen Source Optimization for Cellulase Production by *Penicillium funiculosum*, using a Sequential Experimental Design Methodology and the Desirability Function. *Appl Biochem Biotechnol* 161, 411–422 (2010)



1.2 Experimental Methods

Cellulase production by *Penicillium funiculosum* was assessed through the measurement of cellulase activity, quantified in terms of activity units (U), indicating the enzymatic extract required to liberate 1 mol of sugars per minute.

Three distinct methods were employed to quantify cellulase activity, serving as the variables under consideration for optimization:

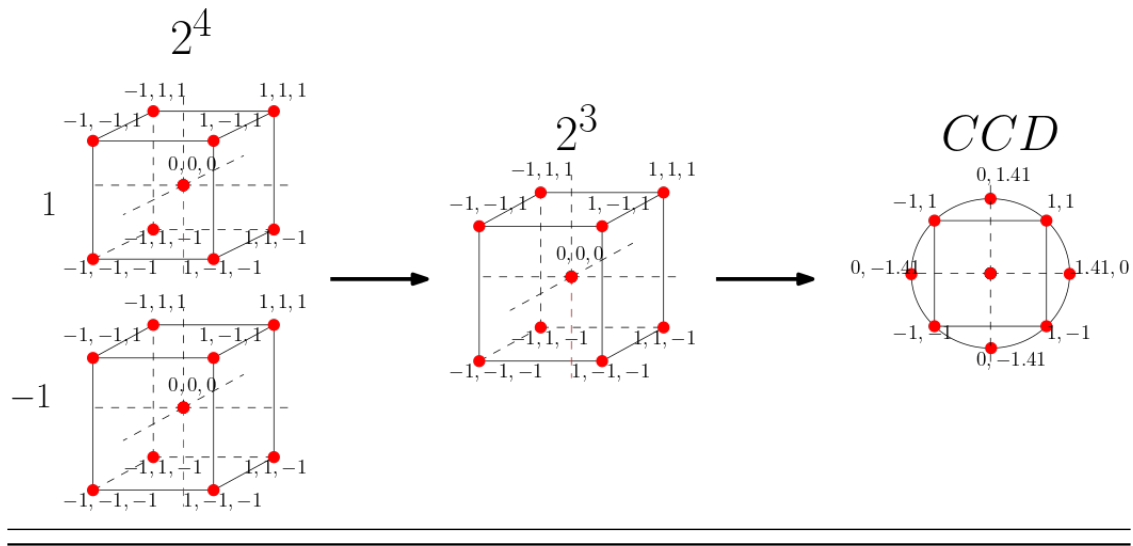
- Filter Paper Assay (FPase)
- Carboxymethylcellulose Assay (CMCase)
- Cellobiose Assay (-Glucosidase)

The dependent variables in this study encompass the concentrations of various nitrogen sources present within the samples, namely:

- Urea
- Ammonium Sulfate
- Peptone
- Yeast Extract

The experimental samples consist of conical flasks, each containing 200 mL of a production medium. This medium features varying concentrations of urea, ammonium sulfate, peptone, and yeast extract, all acting as nitrogen sources. It's worth noting that the carbon source remains constant throughout the experiments, maintaining a concentration of 15 g/L of partially delignified Cellulignin. Additionally, the spore suspension of *Penicillium funiculosum* ATCC 11797 maintains a consistent value of 10^6 conidia/mL.

1.3 Sequential Experimenta Design



The sequential experimental design involves a series of meticulously crafted iterations, wherein each step entails the elimination of an insignificant variable.

This systematic approach begins with a 2^4 factorial design, from which the least influential variable is identified and excluded based on Pareto plot analysis of the effects observed. The ensuing stage employs the remaining three variables within a 2^3 experimental design, following a similar process of identifying and omitting the least impactful variable. Ultimately, the final stage entails the execution of a central composite design, employing the last two variables that have emerged from the iterative refinement process.

2 Factorial 2^4

Factor	Min	CP	Max
	-1	0	+1
Urea (g/L)	0.15	0.30	0.45
Ammonium sulfate (g/L)	0.70	1.40	2.10
Peptone (g/L)	0.40	0.75	1.10
Yeast extract (g/L)	0.13	0.26	0.38

Min minimum value, *CP* center point, *Max* maximum value.

Levels for independent variables for the 2^4 experimental design.

Run	Nitrogen sources				Activities (U/L)		
	Urea	Ammonium sulfate	Peptone	Yeast extract	FPase $R^2=0.836$	CMCase $R^2=0.873$	β -glucosidase $R^2=0.910$
1	-1	-1	-1	-1	39	1,328	170
2	+1	-1	-1	-1	87	1,699	122
3	-1	+1	-1	-1	48	1,332	473
4	+1	+1	-1	-1	71	1,979	511
5	-1	-1	+1	-1	43	1,458	156
6	+1	-1	+1	-1	84	2,189	204
7	-1	+1	+1	-1	45	1,343	385
8	+1	+1	+1	-1	112	1,707	288
9	-1	-1	-1	+1	19	1,257	114
10	+1	-1	-1	+1	146	2,148	116
11	-1	+1	-1	+1	50	1,592	244
12	+1	+1	-1	+1	92	1,726	126
13	-1	-1	+1	+1	107	1,203	72
14	+1	-1	+1	+1	172	2,261	210
15	-1	+1	+1	+1	62	1,434	234
16	+1	+1	+1	+1	82	1,848	154
17 (C)	0	0	0	0	75	1,726	223
18 (C)	0	0	0	0	70	1,782	219
19 (C)	0	0	0	0	89	1,753	226

Experimental results of each run of the 2^4 design.

3 explann hands-on on 2^4 design

A `python` package ([explann](#)) was developed to assist design and statistical analysis of experiments.

All the following source code is hosted on github <https://github.com/properallan/explann/>. Both the table of levels and the experimental results can be easily imported to the `explann` package.

There are functions to import data in string format or even xlsx file format. The explann package can assist also in the creation of the experimental design.

TwoLevelFactorial implements a generic 2^n factorial design, with n variables defined as a dictionary containing the variable name and range.

```
[1]: from explann.doe import TwoLevelFactorial

f2b4 = TwoLevelFactorial(
    variables = {
        'U': (0.15, 0.45),
        'A': (0.70, 2.10),
        'P': (0.40, 1.10),
        'Y': (0.13, 0.38)
    },
    central_points=3
)
```

Once instantiated this class build the `doe` table, storage as an object attribute as a `pandas DataFrame`.

```
[2]: f2b4.doe
```

```
[2]:
```

	U	A	P	Y
Index				
1	-1.0	-1.0	-1.0	-1.0
2	1.0	-1.0	-1.0	-1.0
3	-1.0	1.0	-1.0	-1.0
4	1.0	1.0	-1.0	-1.0
5	-1.0	-1.0	1.0	-1.0
6	1.0	-1.0	1.0	-1.0
7	-1.0	1.0	1.0	-1.0
8	1.0	1.0	1.0	-1.0
9	-1.0	-1.0	-1.0	1.0
10	1.0	-1.0	-1.0	1.0
11	-1.0	1.0	-1.0	1.0
12	1.0	1.0	-1.0	1.0
13	-1.0	-1.0	1.0	1.0
14	1.0	-1.0	1.0	1.0
15	-1.0	1.0	1.0	1.0
16	1.0	1.0	1.0	1.0
17	0.0	0.0	0.0	0.0
18	0.0	0.0	0.0	0.0
19	0.0	0.0	0.0	0.0

A table of the levels are also automatically created.

```
[3]: f2b4.levels
```

```
[3]:
```

	U	A	P	Y
Levels				
-1.0	0.15	0.7	0.40	0.130
0.0	0.30	1.4	0.75	0.255
1.0	0.45	2.1	1.10	0.380

The `doe` table can be complemented with the response variables. For this task either `ImportString` or `ImportXLSX` can be used to load data.

```
[4]: from explann.dataio import ImportString
```

```
f2b4_results = ImportString(data="""
F,CM,B
39,1.328,170
87,1.699,122
48,1.332,473
71,1.979,511
43,1.458,156
84,2.189,204
45,1.343,385
112,1.707,288
19,1.257,114
146,2.148,116
50,1.592,244
92,1.726,126
107,1.203,72
172,2.261,210
62,1.434,234
82,1.848,154
75,1.726,223
70,1.782,219
89,1.753,226
""",
delimiter=',')

f2b4_results.data
```

```
[4]:
```

	F	CM	B
1	39	1.328	170
2	87	1.699	122
3	48	1.332	473
4	71	1.979	511
5	43	1.458	156
6	84	2.189	204
7	45	1.343	385
8	112	1.707	288
9	19	1.257	114

10	146	2.148	116
11	50	1.592	244
12	92	1.726	126
13	107	1.203	72
14	172	2.261	210
15	62	1.434	234
16	82	1.848	154
17	75	1.726	223
18	70	1.782	219
19	89	1.753	226

The data is merged with the `doe` table using `append_results` method.

```
[5]: f2b4.append_results(results=f2b4_results.data)
      f2b4.doe
```

```
[5]:
```

	U	A	P	Y	F	CM	B
Index							
1	-1.0	-1.0	-1.0	-1.0	39	1.328	170
2	1.0	-1.0	-1.0	-1.0	87	1.699	122
3	-1.0	1.0	-1.0	-1.0	48	1.332	473
4	1.0	1.0	-1.0	-1.0	71	1.979	511
5	-1.0	-1.0	1.0	-1.0	43	1.458	156
6	1.0	-1.0	1.0	-1.0	84	2.189	204
7	-1.0	1.0	1.0	-1.0	45	1.343	385
8	1.0	1.0	1.0	-1.0	112	1.707	288
9	-1.0	-1.0	-1.0	1.0	19	1.257	114
10	1.0	-1.0	-1.0	1.0	146	2.148	116
11	-1.0	1.0	-1.0	1.0	50	1.592	244
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13	-1.0	-1.0	1.0	1.0	107	1.203	72
14	1.0	-1.0	1.0	1.0	172	2.261	210
15	-1.0	1.0	1.0	1.0	62	1.434	234
16	1.0	1.0	1.0	1.0	82	1.848	154
17	0.0	0.0	0.0	0.0	75	1.726	223
18	0.0	0.0	0.0	0.0	70	1.782	219
19	0.0	0.0	0.0	0.0	89	1.753	226

This experimental planning can be easily saved in `.xlsx` format. `doe` raw data is stored in the first sheet and the levels data is stored in a separate sheet named `levels`.

```
[6]: f2b4.save_excel('../data/f2b4.xlsx')
```

The `ImportXLSX` assist the import of data from excel file, this could be filled by hand or generated in `explann` as described above.

```
[7]: from explann.dataio import ImportXLSX
```

```
f2b4_from_excel = ImportXLSX(
    path = '../data/f2b4.xlsx',
    levels_sheet = 'levels'
)

f2b4_from_excel.data
```

```
[7]:
```

	Index	U	A	P	Y	F	CM	B
1	1	-1	-1	-1	-1	39	1.328	170
2	2	1	-1	-1	-1	87	1.699	122
3	3	-1	1	-1	-1	48	1.332	473
4	4	1	1	-1	-1	71	1.979	511
5	5	-1	-1	1	-1	43	1.458	156
6	6	1	-1	1	-1	84	2.189	204
7	7	-1	1	1	-1	45	1.343	385
8	8	1	1	1	-1	112	1.707	288
9	9	-1	-1	-1	1	19	1.257	114
10	10	1	-1	-1	1	146	2.148	116
11	11	-1	1	-1	1	50	1.592	244
12	12	1	1	-1	1	92	1.726	126
13	13	-1	-1	1	1	107	1.203	72
14	14	1	-1	1	1	172	2.261	210
15	15	-1	1	1	1	62	1.434	234
16	16	1	1	1	1	82	1.848	154
17	17	0	0	0	0	75	1.726	223
18	18	0	0	0	0	70	1.782	219
19	19	0	0	0	0	89	1.753	226

If the `levels_sheet` argument is passed, the loaded object will contain an additional table with the levels parsed.

```
[8]: f2b4_from_excel.parsed_data
```

```
[8]:
```

	Index	U	A	P	Y	F	CM	B
1	1	0.45	0.7	0.40	0.130	39	1.328	170
2	2	0.15	2.1	0.40	0.130	87	1.699	122
3	3	0.45	2.1	0.40	0.130	48	1.332	473
4	4	0.15	0.7	1.10	0.130	71	1.979	511
5	5	0.45	0.7	1.10	0.130	43	1.458	156
6	6	0.15	2.1	1.10	0.130	84	2.189	204
7	7	0.45	2.1	1.10	0.130	45	1.343	385
8	8	0.15	0.7	0.40	0.380	112	1.707	288
9	9	0.45	0.7	0.40	0.380	19	1.257	114
10	10	0.15	2.1	0.40	0.380	146	2.148	116
11	11	0.45	2.1	0.40	0.380	50	1.592	244
12	12	0.15	0.7	1.10	0.380	92	1.726	126
13	13	0.45	0.7	1.10	0.380	107	1.203	72

14	14	0.15	2.1	1.10	0.380	172	2.261	210
15	15	0.45	2.1	1.10	0.380	62	1.434	234
16	16	0.30	1.4	0.75	0.255	82	1.848	154
17	17	0.30	1.4	0.75	0.255	75	1.726	223
18	18	0.30	1.4	0.75	0.255	70	1.782	219
19	19	0.00	0.0	0.00	0.000	89	1.753	226

We can now use the data to build our factorial model. The `functions` attribute is a dictionary, the keys are function names, and the values are function equations, the syntax follows [patsy](#) standardization. Here `U * A * P * Y` stands for all interaction terms between the 4 variables

```
[9]: from explann.models import FactorialModel

fm2b4 = FactorialModel(
    data = f2b4_from_excel.data,
    functions = {
        "Fso" : "F ~ U * A * P * Y + I(U**2) + I(A**2) + I(P**2) + I(Y**2)",
        "CMso" : "CM ~ U * A * P * Y + I(U**2) + I(A**2) + I(P**2) + I(Y**2)",
        "Bso" : "B ~ U * A * P * Y + I(U**2) + I(A**2) + I(P**2) + I(Y**2)",
        "F" : "F ~ U * A * P * Y",
        "CM" : "CM ~ U * A * P * Y",
        "B" : "B ~ U * A * P * Y"}
    )
```

The object `fm2b4` stores all the fitted models (Ordinary Least Squares) listed in `functions`, any given model can be retrieved by indexing by function name.

```
[10]: fm2b4['F']
```

```
[10]: <statsmodels.regression.linear_model.RegressionResultsWrapper at 0x7fcd1570edf0>
```

An overview of the results can be viewed using the `summary` method. The method accepts also a given function name as argument, if `None` is passed a dictionary of `summary()` is returned.

```
[11]: fm2b4.summary()
```

```
/home/ppiper/micromamba/envs/explann/lib/python3.9/site-
packages/scipy/stats/_stats_py.py:1806: UserWarning: kurtosistest only valid for
n>=20 ... continuing anyway, n=19
  warnings.warn("kurtosistest only valid for n>=20 ... continuing ")
/home/ppiper/micromamba/envs/explann/lib/python3.9/site-
packages/scipy/stats/_stats_py.py:1806: UserWarning: kurtosistest only valid for
n>=20 ... continuing anyway, n=19
  warnings.warn("kurtosistest only valid for n>=20 ... continuing ")
/home/ppiper/micromamba/envs/explann/lib/python3.9/site-
packages/scipy/stats/_stats_py.py:1806: UserWarning: kurtosistest only valid for
n>=20 ... continuing anyway, n=19
  warnings.warn("kurtosistest only valid for n>=20 ... continuing ")
```



```

/home/ppiper/micromamba/envs/explann/lib/python3.9/site-
packages/scipy/stats/_stats_py.py:1806: UserWarning: kurtosistest only valid for
n>=20 ... continuing anyway, n=19
  warnings.warn("kurtosistest only valid for n>=20 ... continuing ")
/home/ppiper/micromamba/envs/explann/lib/python3.9/site-
packages/scipy/stats/_stats_py.py:1806: UserWarning: kurtosistest only valid for
n>=20 ... continuing anyway, n=19
  warnings.warn("kurtosistest only valid for n>=20 ... continuing ")
/home/ppiper/micromamba/envs/explann/lib/python3.9/site-
packages/scipy/stats/_stats_py.py:1806: UserWarning: kurtosistest only valid for
n>=20 ... continuing anyway, n=19
  warnings.warn("kurtosistest only valid for n>=20 ... continuing ")

```

```

[11]: {'Fso': <class 'statsmodels.iolib.summary.Summary'>
      """

```

```

                                OLS Regression Results
=====
Dep. Variable:                  F    R-squared:                  0.992
Model:                        OLS    Adj. R-squared:            0.931
Method:                    Least Squares    F-statistic:            16.16
Date:                Wed, 16 Aug 2023    Prob (F-statistic):      0.0598
Time:                19:16:43    Log-Likelihood:         -49.032
No. Observations:                19    AIC:                    132.1
Df Residuals:                    2    BIC:                    148.1
Df Model:                        16
Covariance Type:                nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	78.0000	5.686	13.717	0.005	53.534	102.466
U	27.0625	2.462	10.991	0.008	16.468	37.657
A	-8.4375	2.462	-3.427	0.076	-19.032	2.157
U:A	-8.0625	2.462	-3.274	0.082	-18.657	2.532
P	9.6875	2.462	3.934	0.059	-0.907	20.282
U:P	-2.9375	2.462	-1.193	0.355	-13.532	7.657
A:P	-4.6875	2.462	-1.904	0.197	-15.282	5.907
U:A:P	5.6875	2.462	2.310	0.147	-4.907	16.282
Y	12.5625	2.462	5.102	0.036	1.968	23.157
U:Y	4.6875	2.462	1.904	0.197	-5.907	15.282
A:Y	-11.3125	2.462	-4.594	0.044	-21.907	-0.718
U:A:Y	-8.1875	2.462	-3.325	0.080	-18.782	2.407
P:Y	4.8125	2.462	1.955	0.190	-5.782	15.407
U:P:Y	-7.5625	2.462	-3.071	0.092	-18.157	3.032
A:P:Y	-9.3125	2.462	-3.782	0.063	-19.907	1.282
U:A:P:Y	-0.6875	2.462	-0.279	0.806	-11.282	9.907
I(U ** 2)	0.1719	1.549	0.111	0.922	-6.493	6.837
I(A ** 2)	0.1719	1.549	0.111	0.922	-6.493	6.837

I(P ** 2)	0.1719	1.549	0.111	0.922	-6.493	6.837
I(Y ** 2)	0.1719	1.549	0.111	0.922	-6.493	6.837

```
=====
Omnibus:                19.262    Durbin-Watson:                2.036
Prob(Omnibus):          0.000    Jarque-Bera (JB):        38.617
Skew:                   1.278    Prob(JB):                4.12e-09
Kurtosis:               9.500    Cond. No.                1.96e+30
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The input rank is higher than the number of observations.

[3] The smallest eigenvalue is 2.1e-59. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

```
""",
'CMso': <class 'statsmodels.iolib.summary.Summary'>
"""
```

OLS Regression Results

```
=====
Dep. Variable:          CM    R-squared:                0.999
Model:                  OLS    Adj. R-squared:          0.992
Method:                 Least Squares    F-statistic:            146.2
Date:                   Wed, 16 Aug 2023    Prob (F-statistic):      0.00682
Time:                   19:16:43    Log-Likelihood:         62.359
No. Observations:       19    AIC:                    -90.72
Df Residuals:           2    BIC:                    -74.66
Df Model:               16
Covariance Type:        nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	1.7537	0.016	108.457	0.000	1.684	1.823
U	0.2881	0.007	41.152	0.001	0.258	0.318
A	-0.0364	0.007	-5.195	0.035	-0.066	-0.006
U:A	-0.0933	0.007	-13.319	0.006	-0.123	-0.063
P	0.0239	0.007	3.410	0.076	-0.006	0.054
U:P	0.0327	0.007	4.678	0.043	0.003	0.063
A:P	-0.0610	0.007	-8.712	0.013	-0.091	-0.031
U:A:P	-0.0331	0.007	-4.731	0.042	-0.063	-0.003
Y	0.0271	0.007	3.874	0.061	-0.003	0.057
U:Y	0.0240	0.007	3.428	0.076	-0.006	0.054
A:Y	0.0027	0.007	0.393	0.732	-0.027	0.033
U:A:Y	-0.0819	0.007	-11.694	0.007	-0.112	-0.052
P:Y	-0.0210	0.007	-2.999	0.096	-0.051	0.009
U:P:Y	0.0231	0.007	3.303	0.081	-0.007	0.053
A:P:Y	0.0491	0.007	7.016	0.020	0.019	0.079

U:A:P:Y	0.0472	0.007	6.749	0.021	0.017	0.077
I(U ** 2)	-0.0243	0.004	-5.515	0.031	-0.043	-0.005
I(A ** 2)	-0.0243	0.004	-5.515	0.031	-0.043	-0.005
I(P ** 2)	-0.0243	0.004	-5.515	0.031	-0.043	-0.005
I(Y ** 2)	-0.0243	0.004	-5.515	0.031	-0.043	-0.005

```
=====
Omnibus:                13.078   Durbin-Watson:                3.023
Prob(Omnibus):           0.001   Jarque-Bera (JB):         33.486
Skew:                    0.110   Prob(JB):                 5.35e-08
Kurtosis:                9.500   Cond. No.                 1.96e+30
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The input rank is higher than the number of observations.

[3] The smallest eigenvalue is 2.1e-59. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

```
"""
'Bso': <class 'statsmodels.iolib.summary.Summary'>
"""
```

OLS Regression Results

```
=====
Dep. Variable:          B   R-squared:                1.000
Model:                  OLS   Adj. R-squared:            0.999
Method:                 Least Squares   F-statistic:            1291.
Date:                  Wed, 16 Aug 2023   Prob (F-statistic):      0.000774
Time:                  19:16:43   Log-Likelihood:         -29.439
No. Observations:      19   AIC:                    92.88
Df Residuals:          2   BIC:                    108.9
Df Model:              16
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	222.6667	2.028	109.819	0.000	213.943	231.391
U	-7.3125	0.878	-8.329	0.014	-11.090	-3.535
A	78.1875	0.878	89.055	0.000	74.410	81.965
U:A	-24.8125	0.878	-28.261	0.001	-28.590	-21.035
P	-10.8125	0.878	-12.315	0.007	-14.590	-7.035
U:P	8.4375	0.878	9.610	0.011	4.660	12.215
A:P	-25.8125	0.878	-29.400	0.001	-29.590	-22.035
U:A:P	-20.5625	0.878	-23.420	0.002	-24.340	-16.785
Y	-64.9375	0.878	-73.963	0.000	-68.715	-61.160
U:Y	0.0625	0.878	0.071	0.950	-3.715	3.840
A:Y	-47.4375	0.878	-54.031	0.000	-51.215	-43.660
U:A:Y	-17.4375	0.878	-19.861	0.003	-21.215	-13.660

P:Y	19.5625	0.878	22.281	0.002	15.785	23.340
U:P:Y	13.3125	0.878	15.163	0.004	9.535	17.090
A:P:Y	21.5625	0.878	24.559	0.002	17.785	25.340
U:A:P:Y	8.3125	0.878	9.468	0.011	4.535	12.090
I(U ** 2)	0.2552	0.552	0.462	0.689	-2.121	2.632
I(A ** 2)	0.2552	0.552	0.462	0.689	-2.121	2.632
I(P ** 2)	0.2552	0.552	0.462	0.689	-2.121	2.632
I(Y ** 2)	0.2552	0.552	0.462	0.689	-2.121	2.632

Omnibus:	13.909	Durbin-Watson:	2.640
Prob(Omnibus):	0.001	Jarque-Bera (JB):	34.047
Skew:	-0.435	Prob(JB):	4.04e-08
Kurtosis:	9.500	Cond. No.	1.96e+30

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The input rank is higher than the number of observations.

[3] The smallest eigenvalue is 2.1e-59. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

```

"""
'F': <class 'statsmodels.iolib.summary.Summary'>
"""

```

OLS Regression Results

Dep. Variable:	F	R-squared:	0.992
Model:	OLS	Adj. R-squared:	0.954
Method:	Least Squares	F-statistic:	25.70
Date:	Wed, 16 Aug 2023	Prob (F-statistic):	0.0107
Time:	19:16:43	Log-Likelihood:	-49.091
No. Observations:	19	AIC:	130.2
Df Residuals:	3	BIC:	145.3
Df Model:	15		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
Intercept	78.5789	1.851	42.463	0.000	72.690	84.468
U	27.0625	2.017	13.420	0.001	20.645	33.480
A	-8.4375	2.017	-4.184	0.025	-14.855	-2.020
U:A	-8.0625	2.017	-3.998	0.028	-14.480	-1.645
P	9.6875	2.017	4.804	0.017	3.270	16.105
U:P	-2.9375	2.017	-1.457	0.241	-9.355	3.480
A:P	-4.6875	2.017	-2.324	0.103	-11.105	1.730
U:A:P	5.6875	2.017	2.820	0.067	-0.730	12.105
Y	12.5625	2.017	6.230	0.008	6.145	18.980

U:Y	4.6875	2.017	2.324	0.103	-1.730	11.105
A:Y	-11.3125	2.017	-5.610	0.011	-17.730	-4.895
U:A:Y	-8.1875	2.017	-4.060	0.027	-14.605	-1.770
P:Y	4.8125	2.017	2.386	0.097	-1.605	11.230
U:P:Y	-7.5625	2.017	-3.750	0.033	-13.980	-1.145
A:P:Y	-9.3125	2.017	-4.618	0.019	-15.730	-2.895
U:A:P:Y	-0.6875	2.017	-0.341	0.756	-7.105	5.730

```
=====
Omnibus:                14.090    Durbin-Watson:                2.047
Prob(Omnibus):          0.001    Jarque-Bera (JB):        27.071
Skew:                   0.726    Prob(JB):                1.32e-06
Kurtosis:               8.664    Cond. No.                1.09
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
"""
'CM': <class 'statsmodels.iolib.summary.Summary'>
"""
```

OLS Regression Results

```
=====
Dep. Variable:          CM    R-squared:                0.986
Model:                  OLS    Adj. R-squared:          0.917
Method:                 Least Squares    F-statistic:            14.24
Date:                  Wed, 16 Aug 2023    Prob (F-statistic):      0.0250
Time:                  19:16:43    Log-Likelihood:          35.898
No. Observations:      19    AIC:                    -39.80
Df Residuals:          3    BIC:                    -24.69
Df Model:              15
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	1.6718	0.021	79.166	0.000	1.605	1.739
U	0.2881	0.023	12.520	0.001	0.215	0.361
A	-0.0364	0.023	-1.581	0.212	-0.110	0.037
U:A	-0.0932	0.023	-4.052	0.027	-0.166	-0.020
P	0.0239	0.023	1.037	0.376	-0.049	0.097
U:P	0.0328	0.023	1.423	0.250	-0.040	0.106
A:P	-0.0610	0.023	-2.651	0.077	-0.134	0.012
U:A:P	-0.0331	0.023	-1.439	0.246	-0.106	0.040
Y	0.0271	0.023	1.179	0.323	-0.046	0.100
U:Y	0.0240	0.023	1.043	0.374	-0.049	0.097
A:Y	0.0028	0.023	0.119	0.912	-0.070	0.076
U:A:Y	-0.0819	0.023	-3.558	0.038	-0.155	-0.009
P:Y	-0.0210	0.023	-0.913	0.429	-0.094	0.052

U:P:Y	0.0231	0.023	1.005	0.389	-0.050	0.096
A:P:Y	0.0491	0.023	2.135	0.122	-0.024	0.122
U:A:P:Y	0.0473	0.023	2.053	0.132	-0.026	0.120

```

=====
Omnibus:                19.927    Durbin-Watson:                0.346
Prob(Omnibus):          0.000    Jarque-Bera (JB):        20.834
Skew:                   2.121    Prob(JB):                2.99e-05
Kurtosis:               5.884    Cond. No.                1.09
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```

"""
'B': <class 'statsmodels.iolib.summary.Summary'>
"""

```

OLS Regression Results

```

=====
Dep. Variable:          B    R-squared:                1.000
Model:                  OLS    Adj. R-squared:        0.999
Method:                 Least Squares    F-statistic:        1867.
Date:                   Wed, 16 Aug 2023    Prob (F-statistic):    1.80e-05
Time:                   19:16:43    Log-Likelihood:       -30.403
No. Observations:      19    AIC:                92.81
Df Residuals:          3    BIC:                107.9
Df Model:              15
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	223.5263	0.692	322.991	0.000	221.324	225.729
U	-7.3125	0.754	-9.696	0.002	-9.713	-4.912
A	78.1875	0.754	103.677	0.000	75.787	80.588
U:A	-24.8125	0.754	-32.901	0.000	-27.213	-22.412
P	-10.8125	0.754	-14.337	0.001	-13.213	-8.412
U:P	8.4375	0.754	11.188	0.002	6.037	10.838
A:P	-25.8125	0.754	-34.227	0.000	-28.213	-23.412
U:A:P	-20.5625	0.754	-27.266	0.000	-22.963	-18.162
Y	-64.9375	0.754	-86.107	0.000	-67.338	-62.537
U:Y	0.0625	0.754	0.083	0.939	-2.338	2.463
A:Y	-47.4375	0.754	-62.902	0.000	-49.838	-45.037
U:A:Y	-17.4375	0.754	-23.122	0.000	-19.838	-15.037
P:Y	19.5625	0.754	25.940	0.000	17.162	21.963
U:P:Y	13.3125	0.754	17.652	0.000	10.912	15.713
A:P:Y	21.5625	0.754	28.592	0.000	19.162	23.963
U:A:P:Y	8.3125	0.754	11.022	0.002	5.912	10.713

Omnibus:	31.293	Durbin-Watson:	2.398
Prob(Omnibus):	0.000	Jarque-Bera (JB):	77.186
Skew:	-2.374	Prob(JB):	1.73e-17
Kurtosis:	11.658	Cond. No.	1.09

=====

Notes:

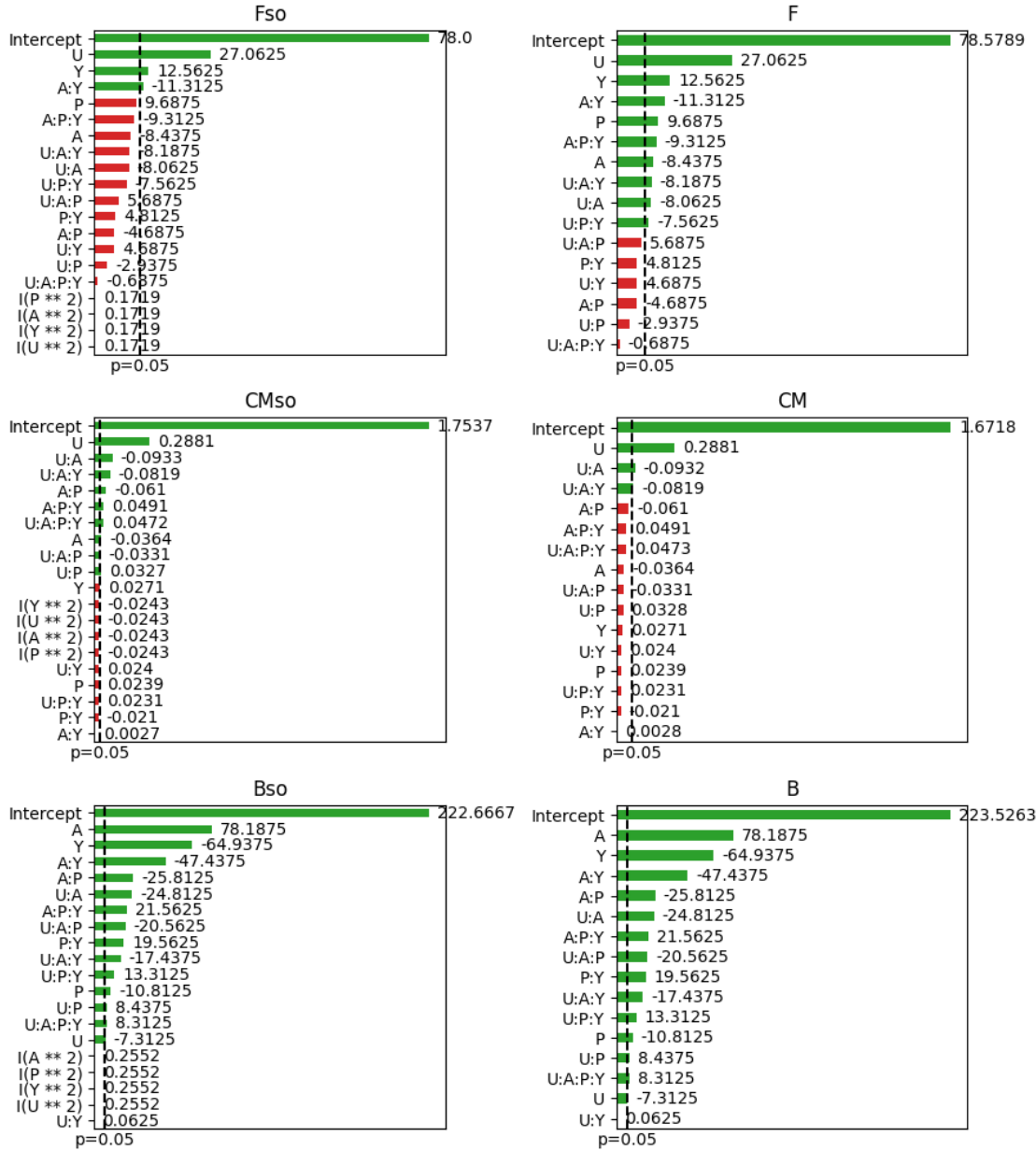
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

"""}

```
[12]: from explann.plot import ParetoPlot

import matplotlib.pyplot as plt
fig, ax = plt.subplots(3,2, figsize=(9,10))
ax = ax.flatten()
pp_fm2b4 = ParetoPlot(fm2b4)

pp_fm2b4.plot(['Fso', 'F', 'CMso', 'CM', 'Bso', 'B'], ax=ax)
plt.tight_layout()
```



[13]: fm2b4.print_equation()

```
[13]: {'Fso': 'F = 78.0000 + 27.0625 * U + 12.5625 * Y - 11.3125 * AY',
      'CMso': 'CM = 1.7537 + 0.2881 * U - 0.0364 * A - 0.0933 * UA + 0.0327 * UP -
0.0610 * AP - 0.0331 * UAP - 0.0819 * UAY + 0.0491 * APY + 0.0472 * UAPY -
0.0243 * I(U ** 2) - 0.0243 * I(A ** 2) - 0.0243 * I(P ** 2) - 0.0243 * I(Y **
2)',
      'Bso': 'B = 222.6667 - 7.3125 * U + 78.1875 * A - 24.8125 * UA - 10.8125 * P +
8.4375 * UP - 25.8125 * AP - 20.5625 * UAP - 64.9375 * Y - 47.4375 * AY -
```



```
17.4375 * UAY + 19.5625 * PY + 13.3125 * UPY + 21.5625 * APY + 8.3125 * UAPY',
'F': 'F = 78.5789 + 27.0625 * U - 8.4375 * A - 8.0625 * UA + 9.6875 * P +
12.5625 * Y - 11.3125 * AY - 8.1875 * UAY - 7.5625 * UPY - 9.3125 * APY',
'CM': 'CM = 1.6718 + 0.2881 * U - 0.0932 * UA - 0.0819 * UAY',
'B': 'B = 223.5263 - 7.3125 * U + 78.1875 * A - 24.8125 * UA - 10.8125 * P +
8.4375 * UP - 25.8125 * AP - 20.5625 * UAP - 64.9375 * Y - 47.4375 * AY -
17.4375 * UAY + 19.5625 * PY + 13.3125 * UPY + 21.5625 * APY + 8.3125 * UAPY'}
```

build_significant_models get the models with only significant terms withing a significance value α .

```
[14]: sig_fm2b4=fm2b4.build_significant_models(alpha=0.05)
sig_fm2b4.summary()
```

```
/home/ppiper/micromamba/envs/explann/lib/python3.9/site-
packages/scipy/stats/_stats_py.py:1806: UserWarning: kurtosistest only valid for
n>=20 ... continuing anyway, n=19
  warnings.warn("kurtosistest only valid for n>=20 ... continuing ")
/home/ppiper/micromamba/envs/explann/lib/python3.9/site-
packages/scipy/stats/_stats_py.py:1806: UserWarning: kurtosistest only valid for
n>=20 ... continuing anyway, n=19
  warnings.warn("kurtosistest only valid for n>=20 ... continuing ")
/home/ppiper/micromamba/envs/explann/lib/python3.9/site-
packages/scipy/stats/_stats_py.py:1806: UserWarning: kurtosistest only valid for
n>=20 ... continuing anyway, n=19
  warnings.warn("kurtosistest only valid for n>=20 ... continuing ")
/home/ppiper/micromamba/envs/explann/lib/python3.9/site-
packages/scipy/stats/_stats_py.py:1806: UserWarning: kurtosistest only valid for
n>=20 ... continuing anyway, n=19
  warnings.warn("kurtosistest only valid for n>=20 ... continuing ")
/home/ppiper/micromamba/envs/explann/lib/python3.9/site-
packages/scipy/stats/_stats_py.py:1806: UserWarning: kurtosistest only valid for
n>=20 ... continuing anyway, n=19
  warnings.warn("kurtosistest only valid for n>=20 ... continuing ")
/home/ppiper/micromamba/envs/explann/lib/python3.9/site-
packages/scipy/stats/_stats_py.py:1806: UserWarning: kurtosistest only valid for
n>=20 ... continuing anyway, n=19
  warnings.warn("kurtosistest only valid for n>=20 ... continuing ")
```

```
[14]: {'Fso': <class 'statsmodels.iolib.summary.Summary'>
      """
```

```

                                OLS Regression Results
=====
Dep. Variable:                  F      R-squared:                  0.644
Model:                          OLS    Adj. R-squared:            0.573
Method:                    Least Squares  F-statistic:                9.063
Date:                Wed, 16 Aug 2023    Prob (F-statistic):        0.00115
Time:                      19:16:45      Log-Likelihood:           -85.472
```

```

No. Observations:          19   AIC:          178.9
Df Residuals:              15   BIC:          182.7
Df Model:                  3
Covariance Type:          nonrobust

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	78.5789	5.616	13.993	0.000	66.609	90.549
U	27.0625	6.120	4.422	0.000	14.019	40.106
Y	12.5625	6.120	2.053	0.058	-0.481	25.606
A:Y	-11.3125	6.120	-1.849	0.084	-24.356	1.731
Omnibus:	3.592		Durbin-Watson:	2.130		
Prob(Omnibus):	0.166		Jarque-Bera (JB):	1.637		
Skew:	-0.592		Prob(JB):	0.441		
Kurtosis:	3.815		Cond. No.	1.09		

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```

"""
'CMso': <class 'statsmodels.iolib.summary.Summary'>
"""

```

OLS Regression Results

```

=====
Dep. Variable:          CM   R-squared:          0.974
Model:                  OLS   Adj. R-squared:      0.942
Method:                 Least Squares   F-statistic:        30.17
Date:                   Wed, 16 Aug 2023   Prob (F-statistic):  2.87e-05
Time:                   19:16:45   Log-Likelihood:     29.977
No. Observations:       19   AIC:                -37.95
Df Residuals:           8   BIC:                -27.57
Df Model:               10
Covariance Type:        nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	1.7537	0.044	39.456	0.000	1.651	1.856
U	0.2881	0.019	14.971	0.000	0.244	0.333
A	-0.0364	0.019	-1.890	0.095	-0.081	0.008
U:A	-0.0933	0.019	-4.845	0.001	-0.138	-0.049
U:P	0.0328	0.019	1.702	0.127	-0.012	0.077
A:P	-0.0610	0.019	-3.170	0.013	-0.105	-0.017
U:A:P	-0.0331	0.019	-1.721	0.124	-0.078	0.011
U:A:Y	-0.0819	0.019	-4.254	0.003	-0.126	-0.037
A:P:Y	0.0491	0.019	2.553	0.034	0.005	0.094

U:A:P:Y	0.0473	0.019	2.455	0.040	0.003	0.092
I(U ** 2)	-0.0243	0.012	-2.006	0.080	-0.052	0.004
I(A ** 2)	-0.0243	0.012	-2.006	0.080	-0.052	0.004
I(P ** 2)	-0.0243	0.012	-2.006	0.080	-0.052	0.004
I(Y ** 2)	-0.0243	0.012	-2.006	0.080	-0.052	0.004

Omnibus:	2.073	Durbin-Watson:	1.950
Prob(Omnibus):	0.355	Jarque-Bera (JB):	1.028
Skew:	-0.013	Prob(JB):	0.598
Kurtosis:	1.861	Cond. No.	2.87e+16

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The smallest eigenvalue is 9.82e-32. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

```

"""
'Bso': <class 'statsmodels.iolib.summary.Summary'>
"""

```

OLS Regression Results

Dep. Variable:	B	R-squared:	1.000
Model:	OLS	Adj. R-squared:	1.000
Method:	Least Squares	F-statistic:	2661.
Date:	Wed, 16 Aug 2023	Prob (F-statistic):	3.23e-07
Time:	19:16:45	Log-Likelihood:	-30.425
No. Observations:	19	AIC:	90.85
Df Residuals:	4	BIC:	105.0
Df Model:	14		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
Intercept	223.5263	0.600	372.531	0.000	221.860	225.192
U	-7.3125	0.654	-11.184	0.000	-9.128	-5.497
A	78.1875	0.654	119.579	0.000	76.372	80.003
U:A	-24.8125	0.654	-37.948	0.000	-26.628	-22.997
P	-10.8125	0.654	-16.536	0.000	-12.628	-8.997
U:P	8.4375	0.654	12.904	0.000	6.622	10.253
A:P	-25.8125	0.654	-39.477	0.000	-27.628	-23.997
U:A:P	-20.5625	0.654	-31.448	0.000	-22.378	-18.747
Y	-64.9375	0.654	-99.315	0.000	-66.753	-63.122
A:Y	-47.4375	0.654	-72.550	0.000	-49.253	-45.622
U:A:Y	-17.4375	0.654	-26.669	0.000	-19.253	-15.622
P:Y	19.5625	0.654	29.919	0.000	17.747	21.378
U:P:Y	13.3125	0.654	20.360	0.000	11.497	15.128

A:P:Y	21.5625	0.654	32.977	0.000	19.747	23.378
U:A:P:Y	8.3125	0.654	12.713	0.000	6.497	10.128

Omnibus:	31.153	Durbin-Watson:	2.404
Prob(Omnibus):	0.000	Jarque-Bera (JB):	76.327
Skew:	-2.365	Prob(JB):	2.67e-17
Kurtosis:	11.605	Cond. No.	1.09

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

""",

'F': <class 'statsmodels.iolib.summary.Summary'>

"""

OLS Regression Results

Dep. Variable:	F	R-squared:	0.924
Model:	OLS	Adj. R-squared:	0.847
Method:	Least Squares	F-statistic:	12.08
Date:	Wed, 16 Aug 2023	Prob (F-statistic):	0.000499
Time:	19:16:45	Log-Likelihood:	-70.868
No. Observations:	19	AIC:	161.7
Df Residuals:	9	BIC:	171.2
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
--	------	---------	---	------	--------	--------

Intercept	78.5789	3.361	23.377	0.000	70.975	86.183
U	27.0625	3.663	7.388	0.000	18.776	35.349
A	-8.4375	3.663	-2.303	0.047	-16.724	-0.151
U:A	-8.0625	3.663	-2.201	0.055	-16.349	0.224
P	9.6875	3.663	2.645	0.027	1.401	17.974
Y	12.5625	3.663	3.430	0.008	4.276	20.849
A:Y	-11.3125	3.663	-3.088	0.013	-19.599	-3.026
U:A:Y	-8.1875	3.663	-2.235	0.052	-16.474	0.099
U:P:Y	-7.5625	3.663	-2.065	0.069	-15.849	0.724
A:P:Y	-9.3125	3.663	-2.542	0.032	-17.599	-1.026

Omnibus:	0.222	Durbin-Watson:	1.718
Prob(Omnibus):	0.895	Jarque-Bera (JB):	0.374
Skew:	-0.200	Prob(JB):	0.830
Kurtosis:	2.441	Cond. No.	1.09

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```

"""
'CM': <class 'statsmodels.iolib.summary.Summary'>
"""

```

OLS Regression Results

```

=====
Dep. Variable:          CM    R-squared:                0.858
Model:                  OLS    Adj. R-squared:           0.829
Method:                 Least Squares    F-statistic:         30.16
Date:                  Wed, 16 Aug 2023    Prob (F-statistic):    1.34e-06
Time:                  19:16:45    Log-Likelihood:       13.772
No. Observations:      19    AIC:                 -19.54
Df Residuals:          15    BIC:                 -15.77
Df Model:               3
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	1.6718	0.030	55.244	0.000	1.607	1.736
U	0.2881	0.033	8.737	0.000	0.218	0.358
U:A	-0.0933	0.033	-2.828	0.013	-0.164	-0.023
U:A:Y	-0.0819	0.033	-2.483	0.025	-0.152	-0.012

```

=====
Omnibus:                 3.181    Durbin-Watson:           1.725
Prob(Omnibus):           0.204    Jarque-Bera (JB):         1.658
Skew:                    -0.704    Prob(JB):                 0.437
Kurtosis:                3.336    Cond. No.                 1.09
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```

"""
'B': <class 'statsmodels.iolib.summary.Summary'>
"""

```

OLS Regression Results

```

=====
Dep. Variable:          B    R-squared:                1.000
Model:                  OLS    Adj. R-squared:           1.000
Method:                 Least Squares    F-statistic:         2661.
Date:                  Wed, 16 Aug 2023    Prob (F-statistic):    3.23e-07
Time:                  19:16:45    Log-Likelihood:       -30.425
No. Observations:      19    AIC:                 90.85
Df Residuals:          4    BIC:                 105.0
Df Model:               14
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	223.5263	0.600	372.531	0.000	221.860	225.192
U	-7.3125	0.654	-11.184	0.000	-9.128	-5.497
A	78.1875	0.654	119.579	0.000	76.372	80.003
U:A	-24.8125	0.654	-37.948	0.000	-26.628	-22.997
P	-10.8125	0.654	-16.536	0.000	-12.628	-8.997
U:P	8.4375	0.654	12.904	0.000	6.622	10.253
A:P	-25.8125	0.654	-39.477	0.000	-27.628	-23.997
U:A:P	-20.5625	0.654	-31.448	0.000	-22.378	-18.747
Y	-64.9375	0.654	-99.315	0.000	-66.753	-63.122
A:Y	-47.4375	0.654	-72.550	0.000	-49.253	-45.622
U:A:Y	-17.4375	0.654	-26.669	0.000	-19.253	-15.622
P:Y	19.5625	0.654	29.919	0.000	17.747	21.378
U:P:Y	13.3125	0.654	20.360	0.000	11.497	15.128
A:P:Y	21.5625	0.654	32.977	0.000	19.747	23.378
U:A:P:Y	8.3125	0.654	12.713	0.000	6.497	10.128
Omnibus:		31.153	Durbin-Watson:		2.404	
Prob(Omnibus):		0.000	Jarque-Bera (JB):		76.327	
Skew:		-2.365	Prob(JB):		2.67e-17	
Kurtosis:		11.605	Cond. No.		1.09	

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

"""}

```
[15]: sig_fm2b4.anova('F')
```

	df	sum_sq	mean_sq	F	PR(>F)
U	1.0	11718.062500	11718.062500	54.585296	0.000042
A	1.0	1139.062500	1139.062500	5.306002	0.046733
U:A	1.0	1040.062500	1040.062500	4.844838	0.055241
P	1.0	1501.562500	1501.562500	6.994606	0.026706
Y	1.0	2525.062500	2525.062500	11.762293	0.007513
A:Y	1.0	2047.562500	2047.562500	9.537994	0.012964
U:A:Y	1.0	1072.562500	1072.562500	4.996231	0.052249
U:P:Y	1.0	915.062500	915.062500	4.262561	0.068965
A:P:Y	1.0	1387.562500	1387.562500	6.463569	0.031588
Residual	9.0	1932.069079	214.674342	NaN	NaN

4 Factorial 2^3

Factor	Min	CP	Max
	-1	0	+1
Urea (g/L)	0.30	0.55	0.80
Ammonium sulfate (g/L)	1.20	2.60	4.00
Yeast extract (g/L)	0.08	0.16	0.25

Min minimum value, *CP* center point, *Max* maximum value.

Levels for factorial 2^3 experimental design.

Run	Nitrogen sources			Activities (U/L)		
	Urea	Ammonium sulfate	Yeast extract	FPase	CMCase	β -glucosidase
1	-1	-1	-1	158	3,995	835
2	+1	-1	-1	202	4,291	1,540
3	-1	+1	-1	137	3,642	1,021
4	+1	+1	-1	240	4,895	1,702
5	-1	-1	+1	191	4,311	1,311
6	+1	-1	+1	221	4,520	1,717
7	-1	+1	+1	141	4,726	1,345
8	+1	+1	+1	175	5,144	1,728
9 (CP)	0	0	0	225	4,715	1,623
10 (CP)	0	0	0	234	4,565	1,687
11 (CP)	0	0	0	250	4,743	1,713

CP center point

Experimental results for factorial 2^3

5 building a model with explann

```
[16]: from explann.doe import TwoLevelFactorial
from explann.models import FactorialModel
from explann.dataio import ImportString, ImportXLSX
from explann.plot import ParetoPlot
import matplotlib.pyplot as plt

f2b3 = TwoLevelFactorial(
    variables = {
        'U': (0.3, 0.8),
        'A': (1.20, 4.00),
        'Y': (0.08, 0.25)
    },
    )
```

```

        central_points=3
    )

f2b3_results = ImportString(
    data=
        """F,CM,B
        158,3995,835
        202,4291,1540
        137,3642,1021
        240,4895,1702
        191,4311,1311
        221,4520,1717
        141,4726,1345
        175,5144,1728
        225,4715,1623
        234,4565,1687
        250,4743,1713
        """,
    delimiter=',')

f2b3.append_results(results=f2b3_results.data)

f2b3.save_excel('../data/f2b3.xlsx')

f2b3_from_excel = ImportXLSX(
    path = '../data/f2b3.xlsx',
    levels_sheet = 'levels'
)

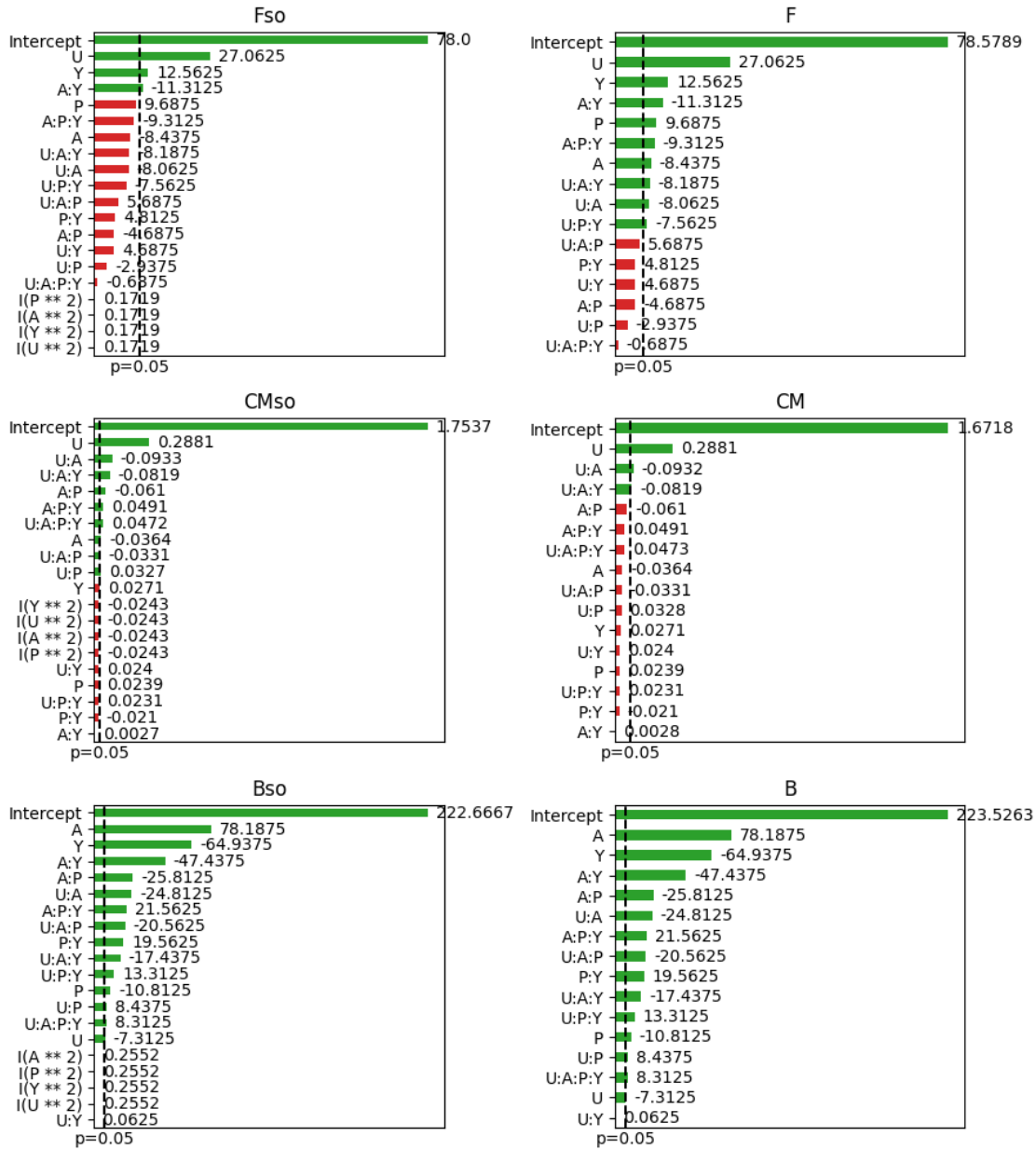
fm_f2b3 = FactorialModel(
    data = f2b3_from_excel.data,
    functions = {
        "Fso" : "F ~ U * A * Y + I(U**2) + I(A**2) + I(Y**2)",
        "CMso" : "CM ~ U * A * Y + I(U**2) + I(A**2) + I(Y**2)",
        "Bso" : "B ~ U * A * Y + I(U**2) + I(A**2) + I(Y**2)",
        "F" : "F ~ U * A * Y",
        "CM" : "CM ~ U * A * Y",
        "B" : "B ~ U * A * Y"}
    )

pp_f2b3 = ParetoPlot(fm_f2b3)

fig, ax = plt.subplots(3,2, figsize=(9,10))

pp_fm2b4.plot(['Fso', 'F', 'CMso', 'CM', 'Bso', 'B'], ax=ax)
plt.tight_layout()

```

6 Central Composite Design

Factor	Axial	Min	CP	Max	Axial
	−1.41	−1	0	+1	+1.41
Urea (g/L)	0.07	0.40	1.20	2.00	2.33
Yeast extract (g/L)	0.00	0.09	0.29	0.50	0.59

Min minimum value, *CP* center point, *Max* maximum value.

Levels for central composite experimental design.

Experiment	Nitrogen sources		Activities (U/L)		
	Urea	Yeast extract	FPase	CMCase	β-glucosidase
1	−1	−1	158	4,029	727
2	−1	+1	171	4,354	1,119
3	+1	−1	166	5,302	1,080
4	+1	+1	244	5,513	1,101
5	−1.41	0	148	4,481	743
6	+1.41	0	263	6,529	1,213
7	0	−1.41	208	5,460	1,085
8	0	+1.41	255	7,105	1,435
9 (CP)	0	0	250	5,364	1,390
10 (CP)	0	0	269	5,524	1,499
11 (CP)	0	0	261	5,793	1,420

CP center point

Experimental results for ccd.

```
[146]: from explann.doe import CentralCompositeDesign
from explann.models import FactorialModel
from explann.dataio import ImportString, ImportXLSX
from explann.plot import ParetoPlot
import matplotlib.pyplot as plt

ccd = CentralCompositeDesign(
    variables = {
        'U': (0.07, 2.33),
        'Y': (0.00, 0.59)
    },
    center=(0,3)
)

ccd_results = ImportString(
```

```

data=
    """F,CM,B
    158,4029,727
    171,4354,1119
    166,5302,1080
    244,5513,1101
    208,5460,1085
    255,7105,1435
    148,4481,743
    263,6529,1213
    250,5364,1390
    269,5524,1499
    261,5793,1420
    """,
    delimiter=',')

ccd.append_results(results=ccd_results.data)

ccd.save_excel('../data/ccd.xlsx')

ccd_from_excel = ImportXLSX(
    path = '../data/ccd.xlsx',
    levels_sheet = 'levels'
)

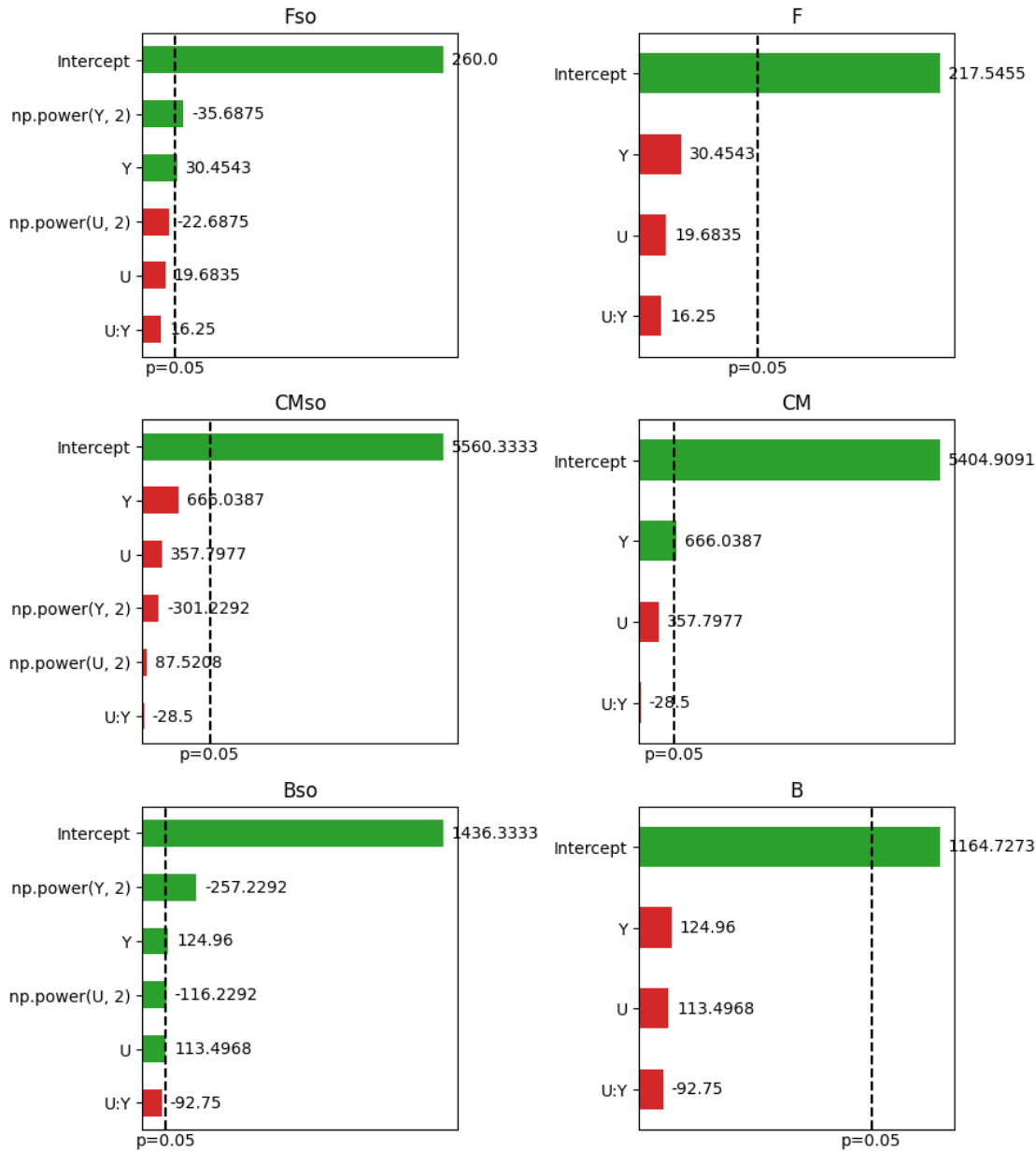
fm_ccd = FactorialModel(
    data = ccd_from_excel.data,
    functions = {
        # "Fso" : "F ~ U * Y + I(U**2) + I(Y**2)",
        # "CMso" : "CM ~ U * Y + I(U**2) + I(Y**2)",
        # "Bso" : "B ~ U * Y + I(U**2) + I(Y**2)",
        "Fso" : "F ~ U * Y + np.power(U,2) + np.power(Y,2)",
        "CMso" : "CM ~ U * Y + np.power(U,2) + np.power(Y,2)",
        "Bso" : "B ~ U * Y + np.power(U,2) + np.power(Y,2)",
        "F" : "F ~ U * Y",
        "CM" : "CM ~ U * Y",
        "B" : "B ~ U * Y"},
    levels = ccd_from_excel.levels,
)

pp_ccd = ParetoPlot(fm_ccd)

fig, ax = plt.subplots(3,2, figsize=(9,10))

pp_ccd.plot(['Fso', 'F', 'CMso', 'CM', 'Bso', 'B'], ax=ax)
plt.tight_layout()

```



```
[147]: import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from matplotlib import cm # for a scatter plot
from mpl_toolkits.mplot3d import Axes3D

def plot_surface(x, y, z, model, n_pts=10, other_params={}, labels:dict=None,
    ↪ax=None, cmap='viridis', scaled=False):
    name_z = z #'Fso'
```

```

name_x = x #'U'
name_y = y #'Y'
n_pts = 10
if not scaled:
    X = np.linspace( model.data[name_x].min(), model.data[name_x].max(),
↪n_pts)
    Y = np.linspace( model.data[name_y].min(), model.data[name_y].max(),
↪n_pts)
else:
    X = np.linspace( model.levels[name_x].min(), model.levels[name_x].
↪max(), n_pts)
    Y = np.linspace( model.levels[name_y].min(), model.levels[name_y].
↪max(), n_pts)

x, y = np.meshgrid(X, Y)

try:
    variables = pd.DataFrame({name_x:x.ravel(), name_y:y.ravel(),
↪**other_params})
except:
    variables = pd.DataFrame([name_x:x.ravel(), name_y:y.ravel(),
↪**other_params]))

if not scaled:
    z = model.predict(name_z, variables).values.reshape(x.shape)
else:
    z = model.predict_rescaled(name_z, variables).values.reshape(x.shape)

if ax is None:
    fig, ax = plt.subplots(figsize=(6,6),subplot_kw={"projection": "3d"})
else:
    fig = plt.gcf()
ax.set_box_aspect(None, zoom=0.8)

pax = ax.plot_surface(x, y, z, cmap=cmap, edgecolor='black', linewidth=0.5,
↪alpha=0.6, antialiased=True)
#ax.contour(x, y, z, cmap=cmap, linestyles='solid', alpha=1)
ax.contourf(x, y, z, zdir='z', offset=ax.get_zlim()[0], cmap=cmap, alpha=0.
↪5, antialiased=True)
ax.contourf(x, y, z, zdir='x', offset=ax.get_xlim()[0], cmap=cmap, alpha=0.
↪5, antialiased=True)
ax.contourf(x, y, z, zdir='y', offset=ax.get_ylim()[1], cmap=cmap, alpha=0.
↪5, antialiased=True)

if labels is not None:
    ax.set(**labels)

```

```

ax.zaxis.set_rotate_label(True)
ax.xaxis.set_rotate_label(True)
ax.yaxis.set_rotate_label(True)

try:
    if 'zlabel' in labels:
        zlabel=labels['zlabel']
except:
    zlabel=None

fig.colorbar(pax, ax=ax, location='top', fraction=0.04, pad=-0.05,
↪label=zlabel)

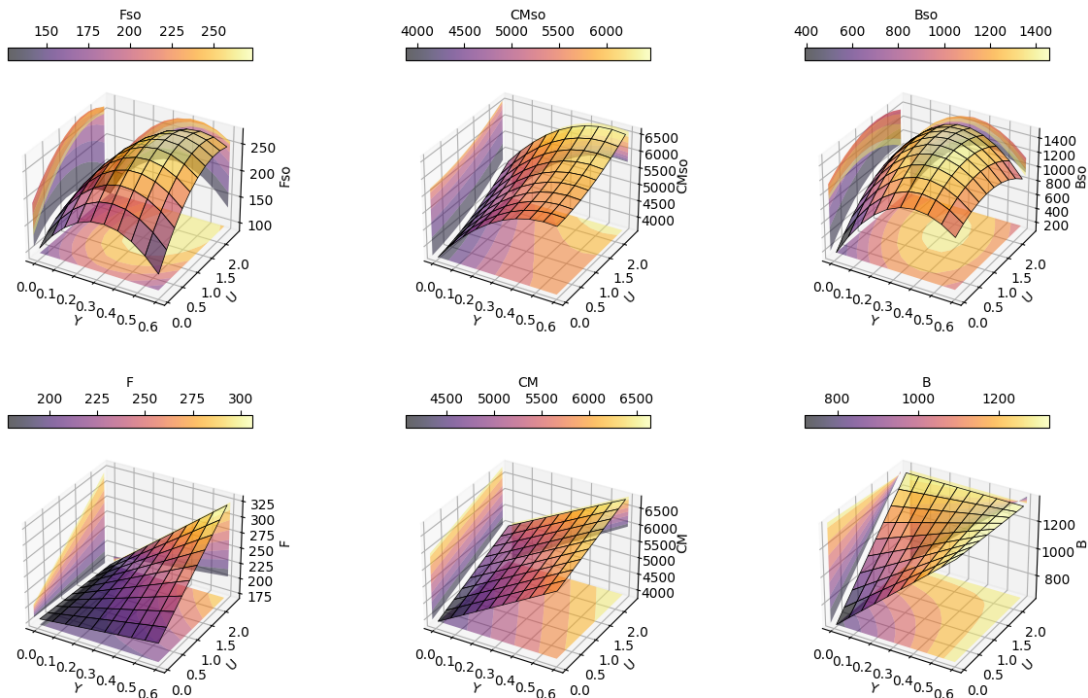
```

```

[148]: fig, ax = plt.subplots(2,3, figsize=(15,9),subplot_kw={"projection": "3d"})
ax = ax.flatten()

for i,(key,val) in enumerate(fm_ccd.functions.items()):
    plot_surface(x='Y', y='U', z=key,
        model=fm_ccd,
        n_pts=10,
        ax=ax[i],
        other_params=dict(),
        labels=dict(xlabel='Y', ylabel='U', zlabel=key), cmap='inferno',
↪scaled=True)

```



7 Optimization Using Desirability Function

A desirability function D is used to optimize the two independent variables at the same time.

$$D = \left(\sum d_{i=1}^N \right)^{(1/N)}$$

The function d_i was defined as

```
[285]: @latexify.with_latex
def d_i(Y, Ymin=Ymin, Ymax=Ymax, r=1):
    if Y <= Ymin:
        return 0
    elif Y > Ymin and Y < Ymax:
        return ((Y-Ymin)/(Ymax-Ymin))**r
    else:
        return 1

d_i
```

[285]:

$$d_i(Y, Ymin, Ymax, r) = \begin{cases} 0, & \text{if } Y \leq Ymin \\ \left(\frac{Y-Ymin}{Ymax-Ymin} \right)^r, & \text{if } Y > Ymin \wedge Y < Ymax \\ 1, & \text{otherwise} \end{cases}$$

```
[269]: from scipy.optimize import minimize
import latexify

responses = ['Fso', 'CMso', 'Bso']
model = fm_ccd
Ymax = 7000
Ymin = 200

def D(independent_vars):
    d_list = []
    for Yi in responses:
        d_list.append( d_i(model[Yi].
        ↪predict(dict(U=independent_vars[0], Y=independent_vars[1]))[0]) )
    d_array = np.array(d_list)
    n = len(d_array)
    return 1-(np.prod(d_array)**(1/n))

from scipy import optimize as opt
```

```

x0 = (0, 0)
bounds = [(-1.41,1.41),(-1.41,1.41)]

optimum = minimize(D, x0, method='SLSQP', bounds=bounds)
optimum

```

```

[269]: message: Optimization terminated successfully
       success: True
       status: 0
       fun: 0.8802039525109903
          x: [ 6.344e-01  4.816e-01]
       nit: 10
       jac: [ 1.291e-04  2.973e-05]
      nfev: 30
      njev: 10

```

8 Anova table and lack of fit

To check model validity an ANOVA test and lack of fit can be used.

```

[270]: fm_ccd.anova('Fso')

```

```

[270]:
          df      sum_sq      mean_sq      F      PR(>F)
U          1.0  3099.522852  3099.522852   4.600914  0.084782
Y          1.0  7419.724833  7419.724833  11.013797  0.021038
U:Y        1.0  1056.250000  1056.250000   1.567891  0.265894
np.power(U, 2) 1.0   918.771390   918.771390   1.363819  0.295530
np.power(Y, 2) 1.0  7192.080882  7192.080882  10.675884  0.022263
Residual     5.0  3368.377315   673.675463      NaN      NaN

```

```

[271]: fm_ccd.lack_of_fit('Fso', alpha=0.05)

```

```

[271]: Source_of_Variation      df      sum_sq      mean_sq      F      F_table \
0      Regression      3.0  11575.497685  3858.499228   2.352901   4.346831
1      Residual       7.0  11479.229588  1639.889941      NaN      NaN
2      Lack_of_Fit     5.0  11297.229588  2259.445918  24.829076  19.296410
3      Pure_Error     2.0   182.000000   91.000000      NaN      NaN
4      Total      10.0  23054.727273      NaN      NaN      NaN

      p
0  0.158352
1      NaN
2  0.039167
3      NaN
4      NaN

```


9 Optimization Results

In the original paper authors have found a desirability function of 0.87 and an optimum point at

$$U = 0.97 \text{ g/L}$$

$$Y = 0.36 \text{ g/L}$$

The corresponding cellulase activities of

$$F = 254 \text{ U/L}$$

$$C = 6383 \text{ U/L}$$

$$B = 1448 \text{ U/L}$$

Totalling a production of 8085 U/L. In this work the desirability function was 0.88 and the optimum point found at

$$U = 1.71 \text{ g/L}$$

$$Y = 0.40 \text{ g/L}$$

This corresponds to a total cellulase activity of 8106 U/L, from which partial values for each metric are

$$F = 245 \text{ U/L}$$

$$C = 6623 \text{ U/L}$$

$$B = 1238 \text{ U/L}$$

```
[280]: fm_ccd.decode_variables(variables=dict(U=optimum.x[0], Y=optimum.x[1]))
```

```
[280]: {'U': 1.7069155936557219, 'Y': 0.39546634255213986}
```

```
[281]: F=fm_ccd.predict(function='Fso', variables=fm_ccd.  
      ↪decode_variables(variables=dict(U=optimum.x[0], Y=optimum.x[1])))  
F
```

```
[281]: 0    244.92823  
dtype: float64
```

```
[282]: C=fm_ccd.predict(function='CMso', variables=fm_ccd.  
      ↪decode_variables(variables=dict(U=optimum.x[0], Y=optimum.x[1])))  
C
```

```
[282]: 0    6623.108285  
dtype: float64
```

```
[283]: B=fm_ccd.predict(function='Bso', variables=fm_ccd.  
        ↳decode_variables(variables=dict(U=optimum.x[0], Y=optimum.x[1])))  
B
```

```
[283]: 0      1238.00179  
dtype: float64
```