In [169…

```
import pandas as pd
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import statsmodels.formula.api as smf
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
```

Data Description

In [117…

```
data = pd.read_csv("learning_mindset.csv")
```

In [118…

```
data.shape
```

Out[118…

```
(10391, 13)
```

In [119…

```
data.sample(5, random_state=5)
```

Out[119…

	schoolid	intervention	achievement_score	success_expect	ethnicity	gender	frst_in_family	school_urbanicity	school_mindset	school_achievement	school_ethnic_minority	school_poverty	school_size
259	73	1	1.480828	5	1	2	0	1	-0.462945	0.652608	-0.515202	-0.169849	0.173954
3435	76	0	-0.987277	5	13	1	1	4	0.334544	0.648586	-1.310927	0.224077	-0.426757
9963	4	0	-0.152340	5	2	2	1	0	-2.289636	0.190797	0.875012	-0.724801	0.761781
4488	67	0	0.358336	6	14	1	0	4	-1.115337	1.053089	0.315755	0.054586	1.862187
2637	16	1	1.360920	6	4	1	0	1	-0.538975	1.433826	-0.033161	-0.982274	1.591641

Normal Linear Regression

In [120…

```
smf.ols("achievement_score ~ intervention", data=data).fit().summary().tables[1]
```

Out[120…

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-0.1538	0.012	-13.201	0.000	-0.177	-0.131
intervention	0.4723	0.020	23.133	0.000	0.432	0.512

In [121…

```
data.query("intervention==1")["achievement_score"].mean() - data.query("intervention==0")["achievement_score"].mean()
```

Out[121…

```
0.4722716692516874
```

In [149…

```
expect = data.groupby("success_expect")["intervention"].mean()
```

In [150…

```
expect
```

Out[150…

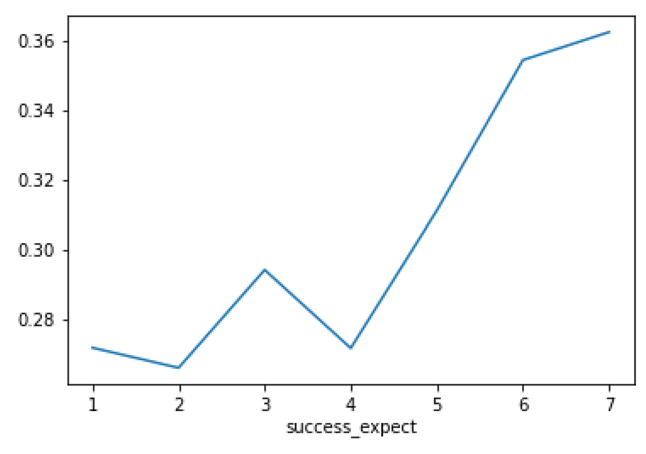
```
success_expect
1    0.271739
2    0.265957
3    0.294118
4    0.271617
5    0.311070
6    0.354287
7    0.362319
Name: intervention, dtype: float64
```

In [158…

```
expect.plot()
```

Out[158…

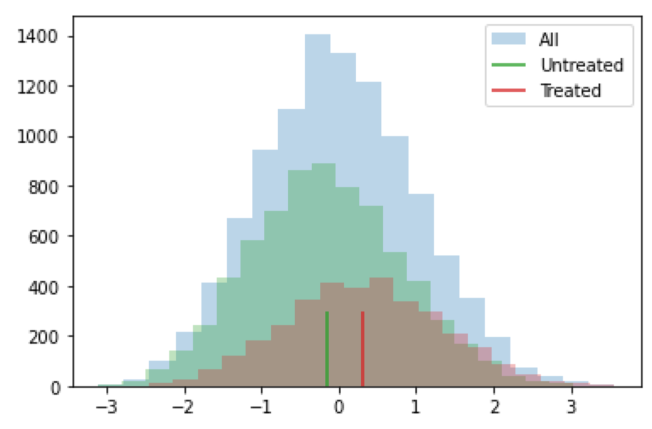
```
<AxesSubplot:xlabel='success_expect'>
```



In [122…

```
plt.hist(data["achievement_score"], bins=20, alpha=0.3, label="All")

plt.hist(data.query("intervention==0")["achievement_score"], bins=20, alpha=0.3, color="C2")
plt.hist(data.query("intervention==1")["achievement_score"], bins=20, alpha=0.3, color="C3")
plt.vlines(-0.1538, 0, 300, label="Untreated", color="C2")
plt.vlines(-0.1538+0.4723, 0, 300, label="Treated", color="C3")
plt.legend();
```



Changing categorical features into dummies

In [172…

```
categ = ["ethnicity", "gender", "school_urbanicity"]
cont = ["school_mindset", "school_achievement", "school_ethnic_minority", "school_poverty", "school_size"]

data_with_categ = pd.concat([
    data.drop(columns=categ), # dataset without the categorical features
    pd.get_dummies(data[categ], columns=categ, drop_first=False)# categorical features converted to dummies
], axis=1)

print(data_with_categ.shape)
```

```
(10391, 32)
```

In [173…

```
data_with_categ.sample(5, random_state=5)
```

Out[173…

	schoolid	intervention	achievement_score	success_expect	frst_in_family	school_mindset	school_achievement	school_ethnic_minority	school_poverty	school_size	...	ethnicity_13	ethnicity_14	ethnicity_15	gender_1	g
259	73	1	1.480828	5	0	-0.462945	0.652608	-0.515202	-0.169849	0.173954	...	0	0	0	0	
3435	76	0	-0.987277	5	1	0.334544	0.648586	-1.310927	0.224077	-0.426757	...	1	0	0	1	
9963	4	0	-0.152340	5	1	-2.289636	0.190797	0.875012	-0.724801	0.761781	...	0	0	0	0	
4488	67	0	0.358336	6	0	-1.115337	1.053089	0.315755	0.054586	1.862187	...	0	1	0	1	
2637	16	1	1.360920	6	0	-0.538975	1.433826	-0.033161	-0.982274	1.591641	...	0	0	0	1	

5 rows × 32 columns

Propensity Score Estimation using Logistic Regression

In [177…

```
from sklearn.linear_model import LogisticRegression

T = 'intervention'
Y = 'achievement_score'
X = data_with_categ.columns.drop(['schoolid', T, Y])

ps_model = LogisticRegression(C=1e6).fit(data_with_categ[X], data_with_categ[T])

data_ps = data.assign(propensity_score=ps_model.predict_proba(data_with_categ[X])[:, 1])

data_ps[["intervention", "achievement_score", "propensity_score"]].head()
```

Out[177…

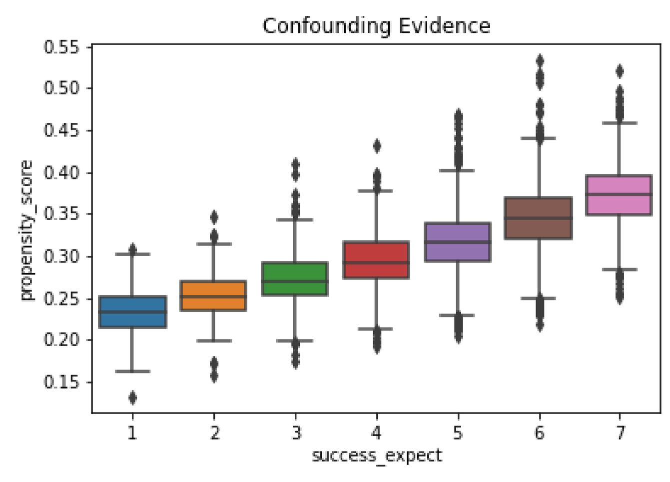
	intervention	achievement_score	propensity_score
0	1	0.277359	0.315490
1	1	-0.449646	0.263803
2	1	0.769703	0.344039
3	1	-0.121763	0.344039
4	1	1.526147	0.367797

Propensity score and success expect

In [178…

```
sns.boxplot(x="success_expect", y="propensity_score", data=data_ps)

plt.title("Confounding Evidence");
```



Linear regression using PSM

In [128…

```
smf.ols("achievement_score ~ intervention + propensity_score", data=data_ps).fit().summary().tables[1]
```

Out[128…

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-3.0768	0.065	-47.055	0.000	-3.205	-2.949
intervention	0.3930	0.019	20.974	0.000	0.356	0.430
propensity_score	9.0547	0.200	45.308	0.000	8.663	9.446

Easier way to implement Causal Effect

In [129…

```
from causalinference import CausalModel
```

True Average Treatment Effect

In [130…

```
confounders = data_with_categ.drop(columns=['achievement_score', 'intervention']).values
```

In [131…

```
model = CausalModel(
    Y= data_ps["achievement_score"].values,
    D = data_ps["intervention"].values,
    X= confounders
)
```

In [132…

```
model.est_via_matching(matches=1, bias_adj=True)

print(model.estimates)
```

```
Treatment Effect Estimates: Matching

                     Est.       S.e.          z      P>|z|      [95% Conf. int.]
--------------------------------------------------------------------------------
           ATE      0.382      0.023     16.327      0.000      0.336      0.428
           ATC      0.368      0.025     14.540      0.000      0.318      0.417
           ATT      0.412      0.025     16.206      0.000      0.362      0.462
```

Estimated Average Treatment Effect using PSM

In [133…

```
model2 = CausalModel(
    Y= data_ps["achievement_score"].values,
    D = data_ps["intervention"].values,
    X= data_ps["propensity_score"].values
)
```

In [134…

```
model2.est_via_matching(matches=1, bias_adj=True)

print(model2.estimates)
```

```
Treatment Effect Estimates: Matching

                     Est.       S.e.          z      P>|z|      [95% Conf. int.]
--------------------------------------------------------------------------------
           ATE      0.392      0.025     15.696      0.000      0.343      0.442
           ATC      0.385      0.027     14.031      0.000      0.331      0.439
           ATT      0.407      0.027     15.315      0.000      0.355      0.460
```