

lab1

March 3, 2019

0.1 Warm up homework:

Plot how the mean square error changes with the polynomial degree ranging between 1 and 30. Do this for the cosine and some other function of your choosing. See what happens if you increase the measurement noise. author: Maria Izabela Lewandowska

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.pipeline import Pipeline
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score
```

```
In [2]: # Two different True functions

def true_fun(X):
    return np.cos(1.5 * np.pi * X)

def true_fun3(X, a=1):
    return (np.sin(a * X)/(X+0.0001))
```

```
In [3]: # PLOT PARAMETERS FOR true_func():
```

```
xmin = 0
xmax = 1
ymin = -5
ymax = 5

font_size = 25
color = "purple"
x_label = "x"
y_label = "y"

degrees = np.arange(1,31)
```

```

np.random.seed(0)

n_samples = 30

X = np.sort(np.random.rand(n_samples)) * (xmax - xmin) + xmin
y = true_fun(X) + np.random.randn(n_samples) * 0.2

In [4]: fig, axs = plt.subplots(nrows = 10, ncols = 3,  figsize = (20,70))
        i = 0
        X_test = np.linspace(0, 1, 100)
        statistics = []

        for row in axs:
            for ax in row:

                polynomial_features = PolynomialFeatures(degree=degrees[i], include_bias=False)
                linear_regression = LinearRegression()

                pipeline = Pipeline([("polynomial_features", polynomial_features), ("linear_regression", linear_regression)])
                pipeline.fit(X[:, np.newaxis], y)

                # Evaluate the models using crossvalidation
                scores = cross_val_score(pipeline, X[:, np.newaxis], y, scoring="neg_mean_squared_error")

                ax.plot(X_test, pipeline.predict(X_test[:, np.newaxis]), color = 'violet', label="Predicted function")
                ax.plot(X_test, true_fun(X_test), color='purple', label="True function")
                ax.scatter(X, y, edgecolor= 'black', s=20, label="Samples")

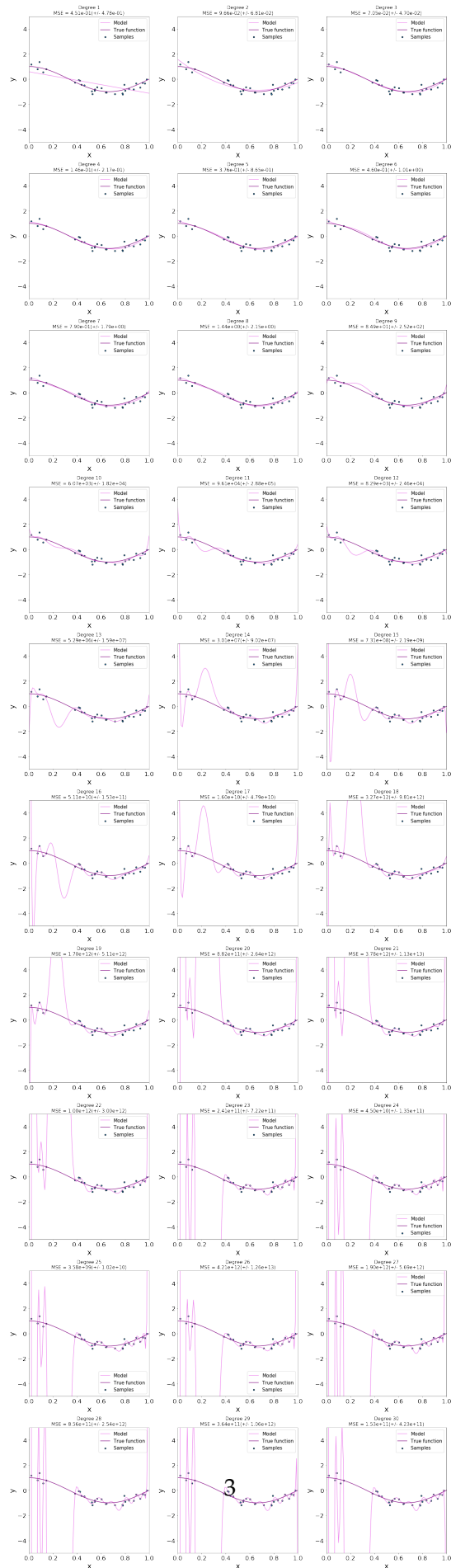
                ax.set_ylabel(y_label)
                ax.yaxis.label.set_size( font_size )
                ax.set_ylim(ymin, ymax)
                ax.set_xlabel(x_label)
                ax.xaxis.label.set_size( font_size )
                ax.set_xlim(xmin, xmax)
                ax.tick_params(labelcolor = "black", labelsiz = 20)
                ax.legend(loc="best", fontsize = 15)

                statistics.append( np.array([i+1, -scores.mean(), scores.std()]) )
                ax.set_title("Degree {i}\nMSE = {:.2e} (+/- {:.2e})".format(i+1, -scores.mean(), scores.std()),
                             fontsize = 15 )

                i = i+1

fig.tight_layout()

```



```

In [5]: # PLOT PARAMETERS FOR true_func():

xmin = 0
xmax = 1
ymin = -5
ymax = 5

font_size = 25
color = "purple"
x_label = "x"
y_label = "y"

degrees = np.arange(1,31)
np.random.seed(0)

n_samples = 30

X = np.sort(np.random.rand(n_samples)) * (xmax - xmin) + xmin
y = true_fun(X) + np.random.randn(n_samples) * 1

In [6]: fig, axs = plt.subplots(nrows = 10, ncols = 3,  figsize = (20,70))
i = 0
X_test = np.linspace(0, 1, 100)
statistics2 = []

for row in axs:
    for ax in row:

        polynomial_features = PolynomialFeatures(degree=degrees[i], include_bias=False)
        linear_regression = LinearRegression()

        pipeline = Pipeline([("polynomial_features", polynomial_features), ("linear_regression", linear_regression)])
        pipeline.fit(X[:, np.newaxis], y)

        # Evaluate the models using crossvalidation
        scores = cross_val_score(pipeline, X[:, np.newaxis], y, scoring="neg_mean_squared_error")

        ax.plot(X_test, pipeline.predict(X_test[:, np.newaxis]), color = 'violet', label="Predicted function")
        ax.plot(X_test, true_fun(X_test), color='purple', label="True function")
        ax.scatter(X, y, edgecolor= 'black', s=20, label="Samples")

        ax.set_ylabel(y_label)
        ax.yaxis.label.set_size( font_size )
        ax.set_ylim(ymin, ymax)

```

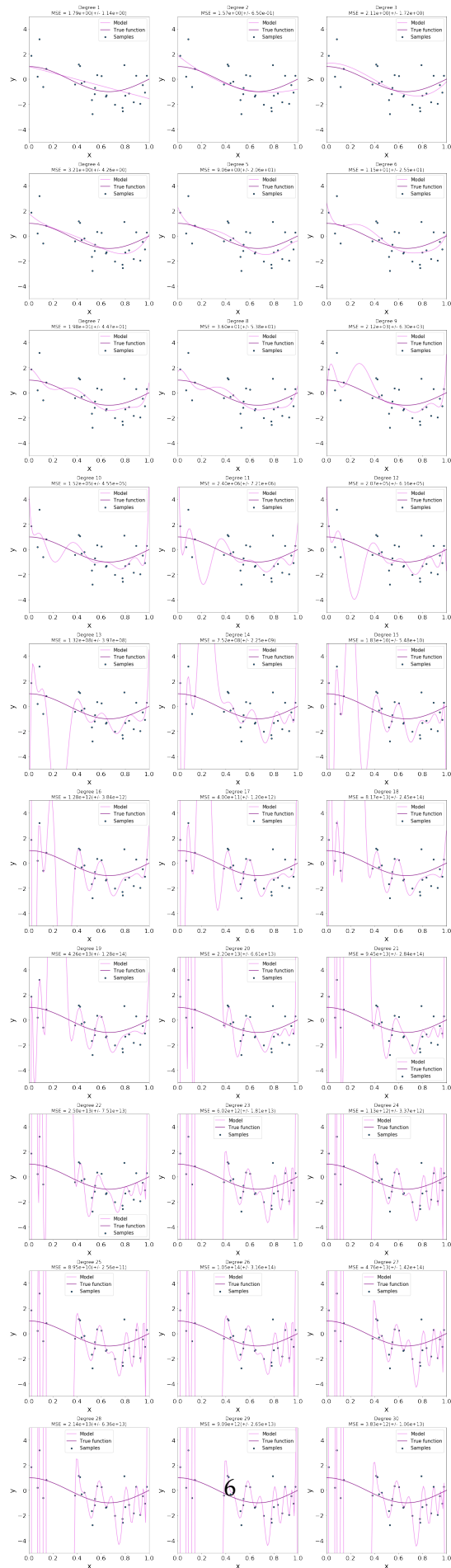
```

ax.set_xlabel(x_label)
ax.xaxis.label.set_size( font_size )
ax.set_xlim(xmin, xmax)
ax.tick_params(labelcolor = "black", labelsiz = 20)
ax.legend(loc="best", fontsize = 15)

statistics2.append( np.array([i+1, -scores.mean(), scores.std()]) )
ax.set_title("Degree {:}\nMSE = {:.2e}(+/- {:.2e})".format(i+1,-scores.mean(),
    fontsize = 15    )
i = i+1

fig.tight_layout()

```



```

In [7]: # PLOT PARAMETERS FOR true_func():

xmin = 0
xmax = 1
ymin = -5
ymax = 5

font_size = 25
color = "purple"
x_label = "x"
y_label = "y"

degrees = np.arange(1,31)
np.random.seed(0)

n_samples = 30

X = np.sort(np.random.rand(n_samples)) * (xmax - xmin) + xmin
y = true_fun(X) + np.random.randn(n_samples) * 0.5

In [8]: fig, axs = plt.subplots(nrows = 10, ncols = 3,  figsize = (20,70))
i = 0
X_test = np.linspace(xmin, xmax, 1000)
statistics1 = []

for row in axs:
    for ax in row:

        polynomial_features = PolynomialFeatures(degree=degrees[i], include_bias=False)
        linear_regression = LinearRegression()

        pipeline = Pipeline([("polynomial_features", polynomial_features), ("linear_regression", linear_regression)])
        pipeline.fit(X[:, np.newaxis], y)

        # Evaluate the models using crossvalidation
        scores = cross_val_score(pipeline, X[:, np.newaxis], y, scoring="neg_mean_squared_error")

        ax.plot(X_test, pipeline.predict(X_test[:, np.newaxis]), color = 'violet', label="Predicted function")
        ax.plot(X_test, true_fun3(X_test), color='purple', label="True function")
        ax.scatter(X, y, edgecolor= 'black', s=20, label="Samples")

        ax.set_ylabel(y_label)
        ax.yaxis.label.set_size( font_size )
        ax.set_ylim(ymin, ymax)

```

```

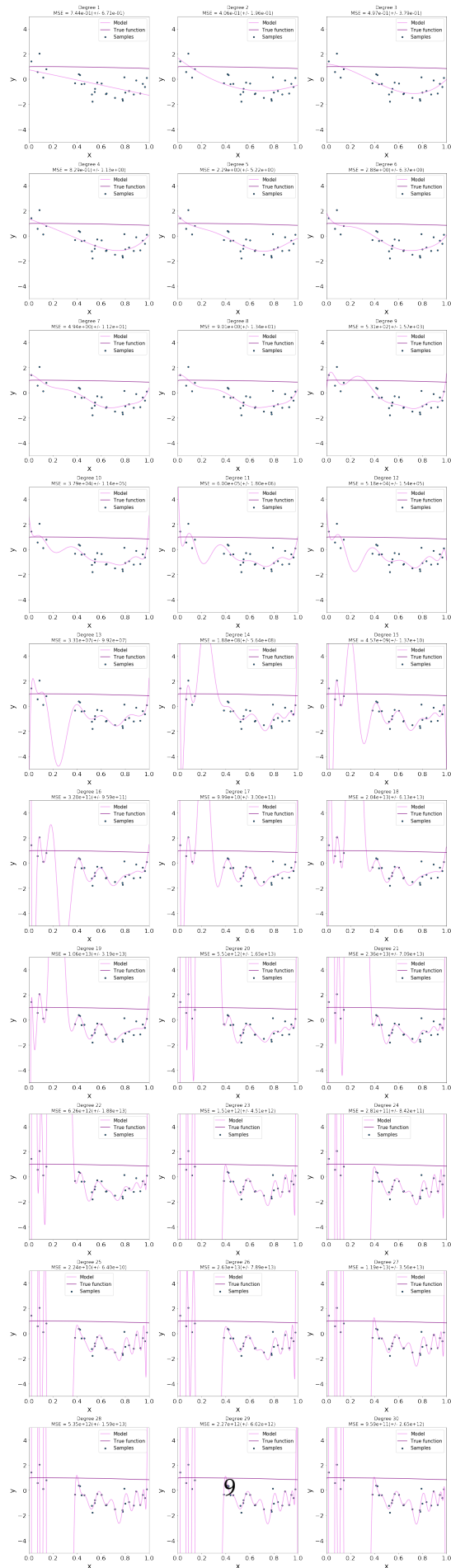
ax.set_xlabel(x_label)
ax.xaxis.label.set_size( font_size )
ax.set_xlim(xmin, xmax)
ax.tick_params(labelcolor = "black", labelsz = 20)
ax.legend(loc="best", fontsize = 15)

statistics1.append( np.array([i+1, -scores.mean(), scores.std()]) )

ax.set_title("Degree {:}\nMSE = {:.2e}(+/- {:.2e)".format(i+1,-scores.mean(),
                                                         fontsize = 15  )
i = i+1

fig.tight_layout()

```

```
In [9]: # PARAMETERS:
```

```
xmin = -5
xmax = 5
ymin = -5
ymax = 5
```

```
font_size = 25
color = "purple"
x_label = "x"
y_label = "y"
```

```
degrees = np.arange(1,31)
np.random.seed(0)
```

```
n_samples = 30
```

```
X = np.sort(np.random.rand(n_samples)) * (xmax - xmin) + xmin
y = true_fun3(X) + np.random.randn(n_samples) * 0.2
```

```
In [10]: fig, axs = plt.subplots(nrows = 10, ncols = 3, figsize = (20,70))
```

```
    i = 0
```

```
    X_test = np.linspace(xmin, xmax, 1000)
```

```
    statistics3 = []
```

```
    for row in axs:
```

```
        for ax in row:
```

```
            polynomial_features = PolynomialFeatures(degree=degrees[i], include_bias=False)
            linear_regression = LinearRegression()
```

```
            pipeline = Pipeline([("polynomial_features", polynomial_features), ("linear_regression", linear_regression)])
            pipeline.fit(X[:, np.newaxis], y)
```

```
            # Evaluate the models using crossvalidation
```

```
            scores = cross_val_score(pipeline, X[:, np.newaxis], y, scoring="neg_mean_squared_error")
```

```
            ax.plot(X_test, pipeline.predict(X_test[:, np.newaxis]), color = 'violet', label="Predicted function")
            ax.plot(X_test, true_fun3(X_test), color='purple', label="True function")
            ax.scatter(X, y, edgecolor= 'black', s=20, label="Samples")
```

```
            ax.set_ylabel(y_label)
```

```
            ax.yaxis.label.set_size( font_size )
```

```
            ax.set_ylim(ymin, ymax)
```

```

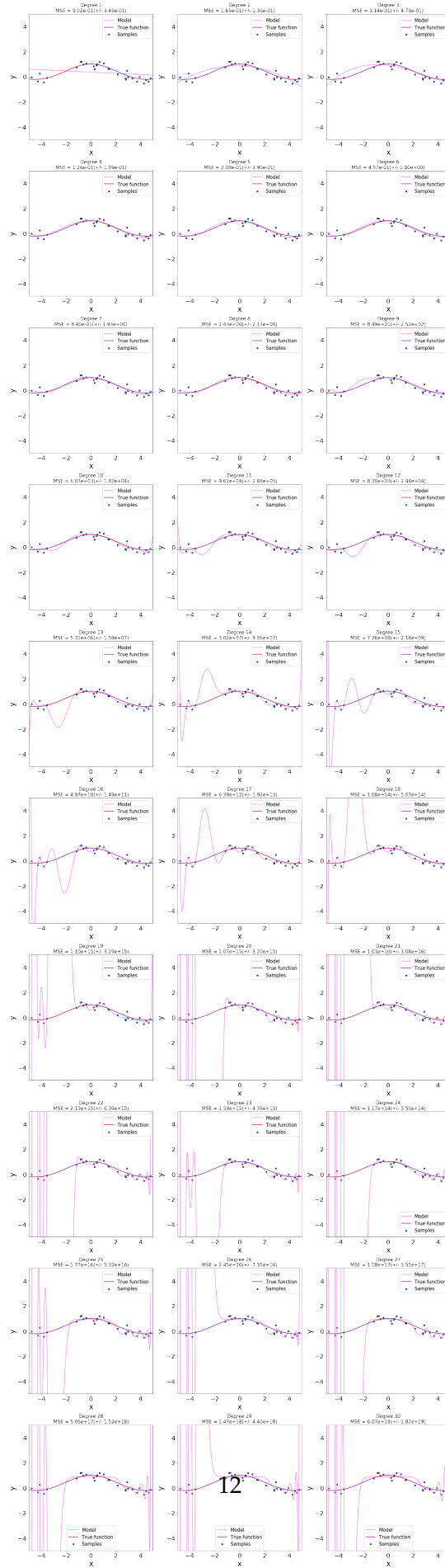
ax.set_xlabel(x_label)
ax.xaxis.label.set_size( font_size )
ax.set_xlim(xmin, xmax)
ax.tick_params(labelcolor = "black", labelsiz = 20)
ax.legend(loc="best", fontsize = 15)

statistics3.append( np.array([i+1, -scores.mean(), scores.std()]) )

ax.set_title("Degree {i}\nMSE = {:.2e}(+/- {:.2e})".format(i+1,-scores.mean(),
    fontsize = 15    )
i = i+1

fig.tight_layout()

```



0.2 SUMMARY

The mean square error (MSE) changes with the polynomial degree in range $n=\{1, 30\}$ as shown below. For small values of the polynomial degree ($n = 1$) our model is underfitted. For big values ($n > 8$) the model is overfitted. When the the measurment noise is increased, MSE increase too.

```
In [11]: stat = np.transpose(statistics)
        stat1 = np.transpose(statistics1)
        stat2 = np.transpose(statistics2)
        stat3 = np.transpose(statistics3)

fig, axs = plt.subplots(nrows = 1, ncols =2,  figsize = (30,20))

for ax in axs:
    ax.set_ylabel("MSE")
    ax.set_xlabel("degree of the polynomial")
    ax.yaxis.label.set_size( font_size )
    ax.xaxis.label.set_size( font_size )

    ax.set_xlim(0, 30)
    ax.set_xscale('linear')

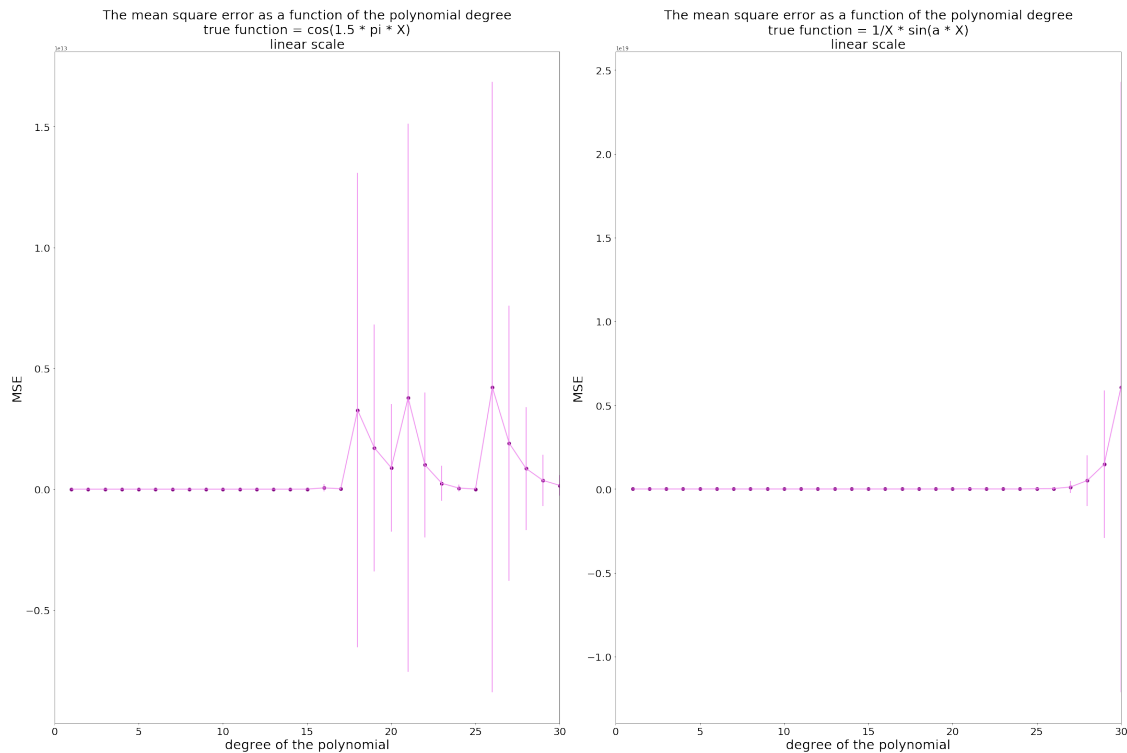
    ax.tick_params(labelcolor = "black", labelsiz = 20, grid_alpha = 0.5, grid_color =
#ax.grid(True)

axs[0].errorbar(stat[0], stat[1], yerr= stat[2], color = "violet")
axs[1].errorbar(stat3[0], stat3[1], yerr= stat3[2], color = "violet")

axs[0].scatter(stat[0], stat[1], color = "purple")
axs[1].scatter(stat3[0], stat3[1], color = "purple")

axs[0].set_title("The mean square error as a function of the polynomial degree\ntrue :
axs[1].set_title("The mean square error as a function of the polynomial degree\ntrue :

fig.tight_layout()
```



```
In [12]: fig, axs = plt.subplots(nrows = 1, ncols = 2,  figsize = (50,30))
```

```
for ax in axs:
    ax.set_ylabel("MSE")
    ax.set_xlabel("degree of the polynomial")
    ax.yaxis.label.set_size( font_size )
    ax.xaxis.label.set_size( font_size )

    ax.set_xlim(0, 30)
    ax.set_yscale('symlog')
    ax.set_xscale('linear')

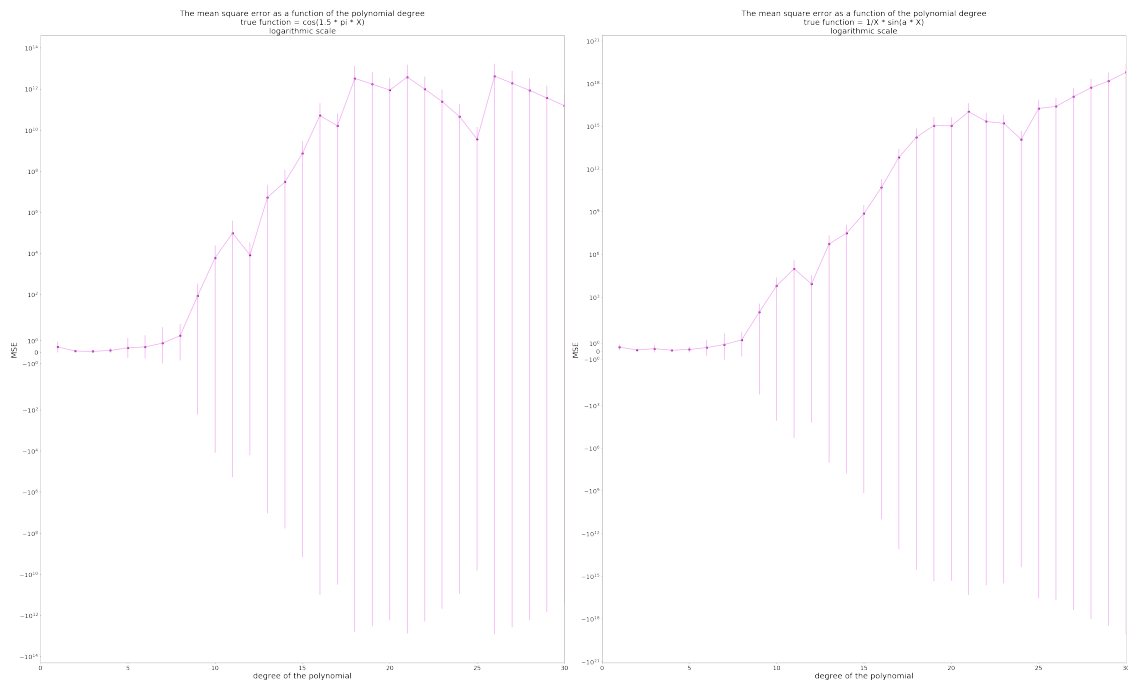
    ax.tick_params(labelcolor = "black", labelsize = 20, grid_alpha = 0.5, grid_color =
#ax.grid(True)

axs[0].errorbar(stat[0], stat[1], yerr= stat[2], color = "violet")
axs[1].errorbar(stat3[0], stat3[1], yerr= stat3[2], color = "violet")

axs[0].scatter(stat[0], stat[1], color = "purple")
axs[1].scatter(stat3[0], stat3[1], color = "purple")

axs[0].set_title("The mean square error as a function of the polynomial degree\ntrue :
axs[1].set_title("The mean square error as a function of the polynomial degree\ntrue :
```

```
fig.tight_layout()
```



```
In [13]: fig, axs = plt.subplots(nrows = 1, ncols = 3,  figsize = (50,30))
```

```
for ax in axs:
```

```
    ax.set_ylabel("MSE")
```

```
    ax.set_xlabel("degree of the polynomial")
```

```
    ax.yaxis.label.set_size( font_size )
```

```
    ax.xaxis.label.set_size( font_size )
```

```
    ax.set_xlim(0, 30)
```

```
    #ax.set_yscale('symlog')
```

```
    ax.set_xscale('linear')
```

```
    ax.tick_params(labelcolor = "black", labelsz = 20, grid_alpha = 0.5, grid_color
```

```
    #ax.grid(True)
```

```
axs[0].errorbar(stat[0], stat[1], yerr= stat[2], color = "violet")
```

```
axs[1].errorbar(stat1[0], stat1[1], yerr= stat1[2], color = "violet")
```

```
axs[2].errorbar(stat2[0], stat2[1], yerr= stat2[2], color = "violet")
```

```
axs[0].scatter(stat[0], stat[1], color = "purple")
```

```
axs[1].scatter(stat1[0], stat1[1], color = "purple")
```

```
axs[2].scatter(stat2[0], stat2[1], color = "purple")
```

```

axs[0].set_title("The mean square error as a function of the polynomial degree\ntrue :
axs[1].set_title("The mean square error as a function of the polynomial degree\ntrue :
axs[2].set_title("The mean square error as a function of the polynomial degree\ntrue :

```

```

fig.tight_layout()

```

