polynomial regression

assignment2.csv is the data for you to do analysis on. It is the data to predict cars' prices. Below is the guideline:

1. **Read the data, call it data_original**
2. **Target = 'price'**
3. **Fix the features, e.g., features_numerical = ['A', 'B', 'C', 'D'], features_category=['E','F'].**
4. **Preprocess the data**
   - **add one-hot encoding for categorical to** `data`
   - **add polynomial to** `data`
5. **Fit to model,** `model.fit(data.drop[target], data[target])`
6. **Predict the model by** `data`

***You may use the function** `create_poly_feature()` **defined as follows to generate the polynomials.**

In [357]:

```
def create_poly_feature(df, feature, degree):
    '''
    :param df: Dataframe, the whole dataframe
    :param feature: string, the feature to create polynomial
    :param degree: int, the degree of the polynomial
    :return:
    '''
    result = pd.DataFrame()
    if feature in df.columns:
        # loop over the degrees:
        for power in range(2,  degree+1):
            # first we'll give the column a name:
            name = feature + '_power_' + str(power)

            # then assign df[name] to the appropriate power of feature
            result[name] = df[feature].astype(float) ** power
        return result
    else:
        return print("Please select a feature in this df!")
```

read the dataset assignment2.csv and answer the following question:

- **How many features in this dataset and what are their names?**
- **Which are categorical features? List their names.**

In [358]:

```
import pandas as pd
data_origin = pd.read_csv('assignment2-1.csv')
target = data_origin['price']

# rwd( rear wheels drive)
# fwd( front wheels drive)
# make (company)
def onehot_encode(df, feature):
    result = pd.DataFrame()
    if feature in df.columns:
        # loop over the degrees:
        result = pd.get_dummies(df, columns=[feature])
        return result
    else:
        return print("Please select a feature in this df!")

cat_feature_make = onehot_encode(data_origin, 'make')
cat_feature_mnd = onehot_encode(cat_feature_make, 'drive-wheels')
```

```
features_num = ['length', 'width', 'height']
features_cat = ['make', 'drive-wheels']
print("There are 6 features, their names are 'make', 'drive-wheels', 'length', 'width', '
height', and 'price'.")
print("Categorical features in the dataset are 'make'and 'drive-wheels' ")
data_origin
```

```
There are 6 features, their names are 'make', 'drive-wheels', 'length', 'width', 'height'
, and 'price'.
Categorical features in the dataset are 'make'and 'drive-wheels'
```

Out[358]:

	make	drive-wheels	length	width	height	price
0	alfa-romero	rwd	168.8	64.1	48.8	16500
1	alfa-romero	rwd	171.2	65.5	52.4	16500
2	audi	fwd	176.6	66.2	54.3	13950
3	audi	4wd	176.6	66.4	54.3	17450
4	audi	fwd	177.3	66.3	53.1	15250
...	...	...	...	...	...	...
175	volvo	rwd	188.8	67.2	57.5	18950
176	volvo	rwd	188.8	68.9	55.5	16845
177	volvo	rwd	188.8	68.8	55.5	19045
178	volvo	rwd	188.8	68.9	55.5	21485
179	volvo	rwd	188.8	68.9	55.5	22625

180 rows × 6 columns

add the following features to the original dataset:

- degree of 2 polynomial of `length`*
- degree of 3 polynomial of `height`*

In [359]:

```
poly_feature_length = create_poly_feature(data_origin, 'length', 2)
poly_feature_height = create_poly_feature(data_origin, 'height', 3)
```

consider the whole data set as training set and fit the model.

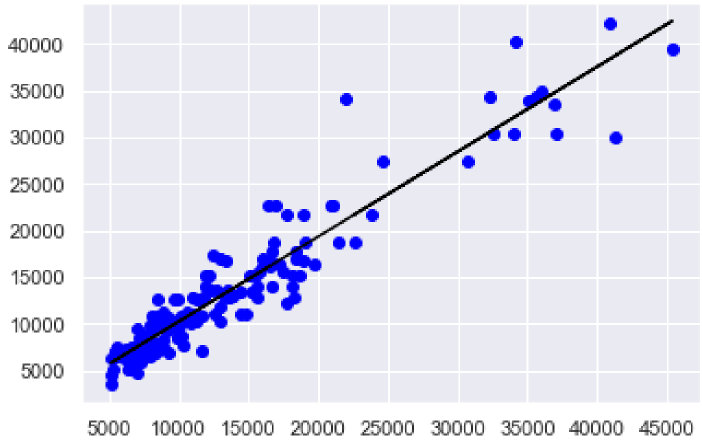
In [360]:

```
from sklearn import linear_model
from sklearn.model_selection import train_test_split
target = ['price']
data_processed = pd.concat([cat_feature_mnd, poly_feature_length, poly_feature_height],a
xis = 1)
x = data_processed.drop('price',axis=1)
y = data_processed['price']
#x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.9, random_state
= 0)
regr = linear_model.LinearRegression()
#regr.fit(x_train, y_train)
regr.fit(x, y)
print(regr.coef_)
print(regr.intercept_)
pd = pd.DataFrame(regr.coef_, x.columns, columns = ['Coeff'])
#pred = regr.predict(x_test)
pred = regr.predict(x)
plt.scatter(y, pred, color="blue")
```

```
m, b = np.polyfit(y, pred, 1)
plt.plot(y, m*y + b, color="black")

plt.show()
print(pd)
```

```
[-9.60452364e+02  9.73908147e+02 -2.02220364e+04  1.74495521e+03
 -4.94696981e+02  7.89459622e+03 -1.70970023e+03 -2.31839431e+03
 -1.97305751e+03 -4.14061589e+03  8.51413031e+03 -2.91691413e+03
  1.18458241e+04 -1.62485913e+03 -3.03692314e+03 -1.76119502e+03
 -6.04572700e+03 -3.04745840e+03  1.61535353e+04 -5.16160120e+03
 -4.50084489e+02 -3.72066491e+03 -3.38694465e+03 -1.76282286e+03
 -2.60138138e+03  7.99258798e+02 -1.73317854e+03  9.33919740e+02
  3.26372540e+00  3.54757749e+02 -2.09106997e+00]
405375.8759149376
```




```
                          Coeff
length                -960.452364
width                  973.908147
height              -20222.036390
make_alfa-romero      1744.955214
make_audi             -494.696981
make_bmw              7894.596224
make_chevrolet       -1709.700228
make_dodge           -2318.394308
make_honda           -1973.057513
make_isuzu           -4140.615889
make_jaguar           8514.130311
make_mazda           -2916.914134
make_mercedes-benz   11845.824149
make_mercury         -1624.859126
make_mitsubishi      -3036.923143
make_nissan          -1761.195023
make_peugot          -6045.726997
make_plymouth        -3047.458397
make_porsche         16153.535331
make_renault         -5161.601199
make_saab             -450.084489
make_subaru          -3720.664907
make_toyota          -3386.944653
make_volkswagen      -1762.822865
make_volvo           -2601.381378
drive-wheels_4wd       799.258798
drive-wheels_fwd     -1733.178538
drive-wheels_rwd       933.919740
length_power_2           3.263725
height_power_2         354.757749
height_power_3          -2.091070
```

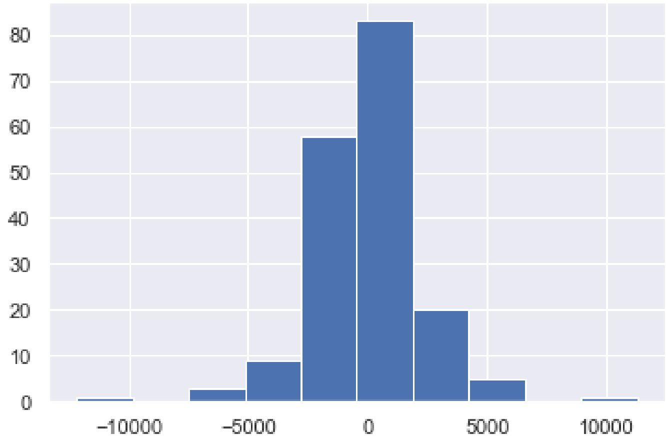
In [361]:

```
plt.hist(y - predictions)
```

Out[361]:

```
(array([ 1.,  0.,  3.,  9., 58., 83., 20.,  5.,  0.,  1.]),
```

```
array([-12172.41059996,  -9829.13680035,  -7485.86300075,  -5142.58920115,
        -2799.31540155,   -456.04160195,   1887.23219765,   4230.50599726,
         6573.77979686,   8917.05359646,  11260.32739606]),
<BarContainer object of 10 artists>)
```



write down the formula of RMSE and compute its value of this model.

- **Hint: you can use y_i as the value of i-th target and $\hat{y}_i$ as the i-th predicted target.**

The formula of RMSE:

RMSE = $\sqrt{\frac{1}{n}\Sigma_{i=1}^{n}(y_i - \hat{y}_i)^2}$

In [362]:

```
import math
RMSE = np.sqrt(metrics.mean_squared_error(y, pred))
print("Root Mean Square Error: ", RMSE)
```

```
Root Mean Square Error:  2392.4540709679427
```

compute the following user-defined metric of this model:

- $loss = \sum_i |y_i - \hat{y}_i|$**, where y_i is the value of i-th target and $\hat{y}_i$ is the i-th predicted target.**

In [363]:

```
loss = np.sum(abs(np.subtract(y, pred)))
print("loss: ", loss)
```

```
loss:  292778.9744982414
```