In class activity: Collection and analysis of rate data

Lecture notes for chemical reaction engineering

Ranjeet Utikar

2024-03-23

Determining the Rate Law

The liquid-phase reaction of triphenyl methyl chloride (trityl) (A) and methanol (B)

$$(C_6H_5)_3CCl + CH_3OH \longrightarrow (C_6H_5)_3COCH_3 + HCl$$

$$A + B \longrightarrow C + D$$

was carried out in a batch reactor at 25°C in a solution of benzene and pyridine in an excess of methanol $C_{B0}=0.5\frac{mol}{dm^3}$. (We need to point out that this batch reactor was purchased at the Sunday market in Rijca, Jofostan.) Pyridine reacts with HCl, which then precipitates as pyridine hydro-chloride thereby making the reaction irreversible. The reaction is first order in methanol. The concentration of triphenyl methyl chloride (A) was measured as a function of time and is shown below (Table 1)

Table 1: Raw data

t (min)	$C_A (mol/dm^3)$
0	0.05
50	0.038
100	0.0306
150	0.0256
200	0.0222
250	0.0195
300	0.0174

- 1. Determine the reaction order with respect to triphenyl methyl chloride.
- 2. In a separate set of experiments, the reaction order wrt methanol was found to be first order. Determine the specific reaction-rate constant.

Solution

Part (1) Find the reaction order with respect to trityl. **Step 1** Postulate a rate law.

$$-r_A = kC_A^{\alpha}C_B^{\beta} \tag{1}$$

Step 2 Process your data in terms of the measured variable, which in this case is C_A . Step 3 Look for simplifications. Because the concentration of methanol is 10 times the initial concentration of triphenyl methyl chloride, its concentration is essentially constant

$$C_B \approx C_{B0}$$

Substituting for C_B in Equation 1

$$-r_A = kC_{B0}^{\beta}C_A^{\alpha} = k'C_A^{\alpha}$$

Step 4 Apply the CRE algorithm. Mole Balance

$$\frac{dN_A}{dt} = r_A V$$

Rate Law:

$$-r_A = k'C_A^{\alpha}$$

Stoichiometry: Liquid $V=V_0$

$$C_A = \frac{N_A}{V_0}$$

Combine: Mole balance, rate law, and stoichiometry

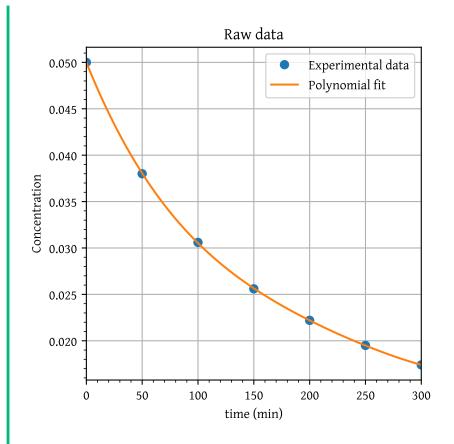
$$-\frac{dC_A}{dt} = k'C_A^{\alpha} \tag{2}$$

Evaluate: Taking the natural log of both sides of Equation 2

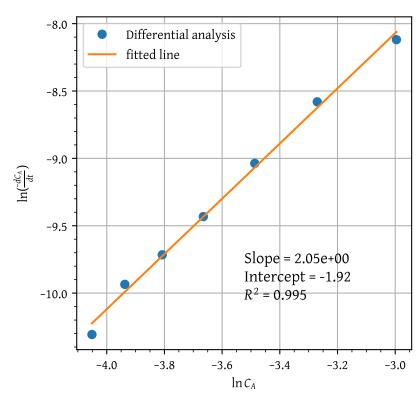
$$\ln\left[-\frac{dC_A}{dt}\right] = \ln k' + \alpha \ln C_A$$

The slope of a plot of $\ln[-dC_A/dt]$ versus $\ln C_A$ will yield the reaction order α with respect to triphenyl methyl chloride (A)

```
import numpy as np
from scipy.stats import linregress
import matplotlib.pyplot as plt
# Data
C_B0 = 0.5 \# mol/dm^3
t = np.array([0, 50, 100, 150, 200, 250, 300])
C_A = np.array([0.05, 0.038, 0.0306, 0.0256, 0.0222, 0.0195, 0.0174])
C AO = C A[0]
# fit polynomial to the data
coefficients = np.polyfit(t, C_A, deg=4)
polynomial = np.poly1d(coefficients)
t_fit = np.linspace(t.min(), t.max(), 100)
ca_fit = polynomial(t_fit)
plt.plot(t, C_A, 'o', label='Experimental data')
plt.plot(t_fit, ca_fit , '-', label='Polynomial fit')
plt.xlabel('time (min)')
plt.ylabel('Concentration')
plt.title('Raw data')
plt.legend()
plt.grid(True)
plt.xlim(0,300)
plt.show()
```



```
# calculate the derivative of the polynomial
dca_dt = np.polyder(polynomial)
ln_ca = np.log(C_A)
ln_dca_dt = np.log(-dca_dt(t))
# fit line
res = linregress(ln_ca, ln_dca_dt)
line = res.slope * ln_ca + res.intercept
plt.plot(ln_ca, ln_dca_dt, 'o', label='Differential analysis')
plt.plot(ln_ca, line, '-', label='fitted line')
plt.annotate(f'Slope = {res.slope:.2e}\nIntercept = {res.intercept:.2f}\n$R^2$ = {res.
             xy=(0.5, 0.15), xycoords='axes fraction', fontsize=12)
plt.xlabel('$\ln C_A$')
plt.ylabel('$\ln(\\frac{-dC_A}{dt})$')
plt.legend()
plt.grid(True)
plt.show()
# pick the closest round order
order = round(res.slope)
a = np.exp(res.intercept)
k = a /C_B0
```



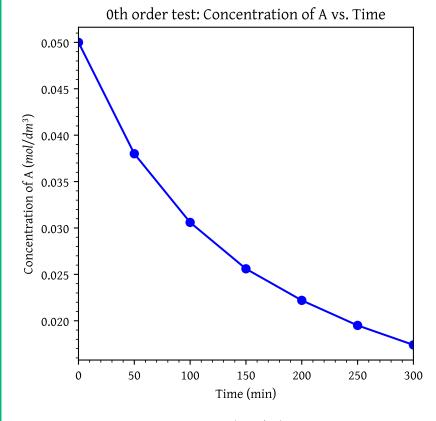
Reaction order is = 2, and k is 0.292 $(dm^3/mol)^2/min$. Rate law is $-r_A=$ 0.292 $C_A^2C_B$

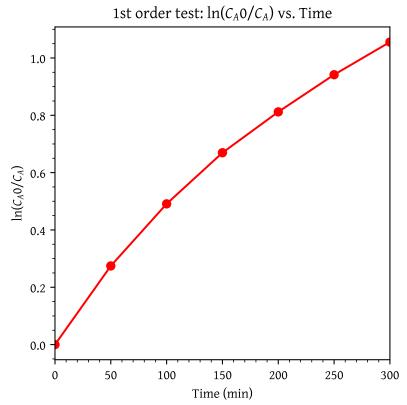
Integral analysis

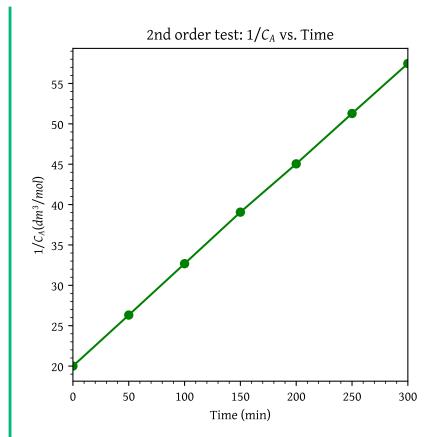
Use the integral method to confirm that the reaction is second order with regard to triphenyl methyl chloride

Solution

```
import numpy as np
from scipy.stats import linregress
import matplotlib.pyplot as plt
# Data
C_B0 = 0.5 \# mol/dm^3
t = np.array([0, 50, 100, 150, 200, 250, 300])
C_A = np.array([0.05, 0.038, 0.0306, 0.0256, 0.0222, 0.0195, 0.0174])
C AO = C A[0]
ln_ca0_by_ca = np.log(C_A0/C_A)
one_by_ca = 1/C_A
# Plotting
# C A vs t
plt.plot(t, C A, 'bo-')
plt.title('Oth order test: Concentration of A vs. Time')
plt.xlabel('Time (min)')
plt.ylabel('Concentration of A ($mol/dm^3$)')
plt.xlim(0,300)
plt.show()
# ln(C AO/C A) vs t
plt.plot(t, ln_ca0_by_ca, 'ro-')
plt.title('1st order test: $\ln(C_AO/C_A)$ vs. Time')
plt.xlabel('Time (min)')
plt.ylabel('$\ln(C_AO/C_A)$')
plt.xlim(0,300)
plt.show()
# 1/C_A vs t
plt.plot(t, one_by_ca, 'go-')
plt.title('2nd order test: $1/C A$ vs. Time')
plt.xlabel('Time (min)')
plt.ylabel('$1/C_A (dm^3/mol)$')
plt.xlim(0,300)
plt.show()
```







As the plot of $1/C_A$ vs. t is linear, the reaction is second order with respect to A.

Use of Regression to Find the Rate-Law Parameters

Use polynomial regression to estimate rate equation. Assume the reaction order is not 1.



Solution

For constant volume batch reactor,

$$\frac{dC_A}{dt} = -k'C_A^\alpha$$

and integrating with the initial condition when t=0 and $C_A=C_{A0}$ for $\alpha \neq 1.0$ gives us:

$$t = \frac{1}{k'} \left[\frac{C_{A0}^{(1-\alpha)} - C_A^{(1-\alpha)}}{1-\alpha} \right]$$

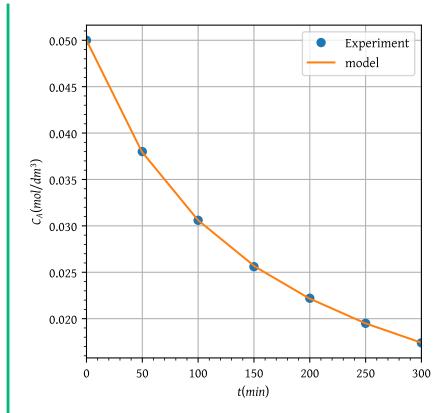
We want to minimize s^2 to give α and k^\prime .

$$s^2 = \sum_{i=1}^{N} (t_{im} - t_{ic})^2$$

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.optimize import minimize
# Data
C_B0 = 0.5 \# mol/dm^3
t = np.array([0, 50, 100, 150, 200, 250, 300])
C_A = np.array([0.05, 0.038, 0.0306, 0.0256, 0.0222, 0.0195, 0.0174])
C AO = C A[0]
# Initial guesses of k and n
# here k is the clubbed constant k * C BO
k = 1
n = 0
# Objective function to minimize: the difference between t (experimental) and t (model
def objective(params):
   k, n = params
   # Calculate t model
   t model = (1/k) * (C A0**(1-n) - C A**(1-n))/ (1-n)
   ssr = np.sum((t - t_model)**2) # Sum of squared residuals
   return ssr
# Minimize the objective function
result = minimize(objective, [k,n], bounds=[(1e-4, 1e4), (0, 5)])
# Extract the results
k opt, n opt = result.x
success = result.success
# Check if the solution was successful
if not success:
    print("Optimization was not successful. Try different initial guesses or methods."
# final evaluation
t model = (1/k \text{ opt}) * (C A0**(1-n \text{ opt}) - C A**(1-n \text{ opt})) / (1-n \text{ opt})
# plot the data
plt.plot(t, C A, 'o', label='Experiment')
plt.plot(t_model, C_A, '-', label='model')
plt.xlabel('$t (min)$')
plt.ylabel('$C_A (mol/dm^3)$')
plt.legend()
plt.grid(True)
plt.xlim(min(t),max(t))
```

10

plt.show()



Initial guess for Reaction order is = 0.00, and k is 1.000e+00. Optimized value of Reaction order is = 2.04, and k is 2.934e-01.

Method of initial rates

The dissolution of dolomite using hydrochloric acid:

$$4\,\mathrm{HCl} + \mathrm{CaMg(CO_3)_2} \longrightarrow \mathrm{Mg^{2+}} + \mathrm{Ca^{2+}} + 4\,\mathrm{Cl^-} + 2\,\mathrm{CO_2} + 2\,\mathrm{H_2O}$$

Concentration of HCl at various times was determined from atomic absorption spectrophotometer measurements of the Ca^{2+} and Mg^{2+} ions (Table 2). Determine the rate constant and order of reaction.

Table 2: HCL concentration

$C_{HCl,0}$ (N)	Initial reaction rate $-r_{HCl,0}$ ($mol/cm^2s \times 10^7$)
1	1.2
4	2.0
2	1.36
0.1	0.36
0.5	0.74

Solution

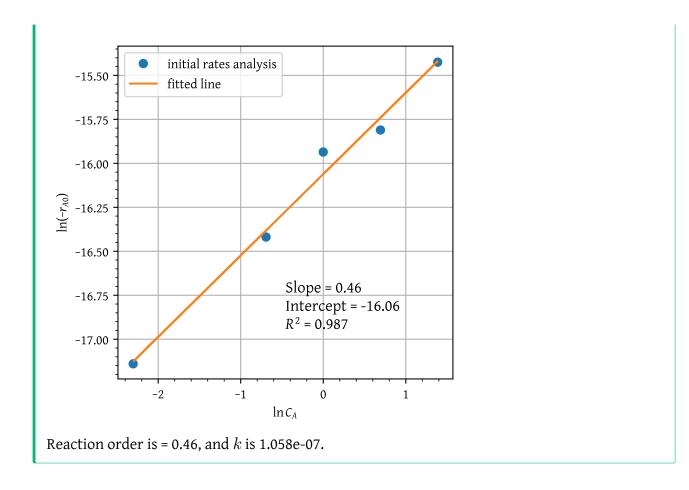
The mole balance for constant V batch reactor at t = 0:

$$\left(\frac{-dC_{HCl}}{dt}\right)_0 = -(r_{HCl})_0 = kC^{\alpha}_{HCl,0}$$

Taking log

$$\ln\left(\frac{-dC_{HCl}}{dt}\right)_{0} = \ln k\alpha \ln C_{HCl,0}$$

```
import numpy as np
from scipy.stats import linregress
import matplotlib.pyplot as plt
ca0 = np.array([1, 4, 2, 0.1, 0.5])
ra0 = np.array([1.2, 2.0, 1.36, 0.36, 0.74]) * 1e-7
ln ca0 = np.log(ca0)
ln_ra0 = np.log(ra0)
# fit line
res = linregress(ln_ca0, ln_ra0)
line = res.slope * ln_ca0 + res.intercept
plt.plot(ln ca0, ln ra0, 'o', label='initial rates analysis')
plt.plot(ln_ca0, line, '-', label='fitted line')
plt.annotate(f'Slope = {res.slope:.2f}\nIntercept = {res.intercept:.2f}\n$R^2$ = {res.
             xy=(0.5, 0.15), xycoords='axes fraction', fontsize=12)
plt.xlabel('$\ln C_A$')
plt.ylabel('\$\ln(-r_{A0})$')
plt.legend()
plt.grid(True)
plt.show()
order = res.slope
k = np.exp(res.intercept)
```



Using a Differential Reactor to Obtain Catalytic Rate Data

The formation of methane from carbon monoxide and hydrogen using a nickel catalyst was studied by Pursley. The reaction

$$3 \, \mathrm{H_2} + \mathrm{CO} \xrightarrow{\mathrm{Ni}} \mathrm{CH_4} + \mathrm{H_2O}$$

was carried out at 500 °F in a differential reactor where the effluent concentration of methane was measured. The raw data is shown in Table 3

Table 3: Raw data

Run	P_{CO} (atm)	P_{H_2} (atm)	$\frac{C_{CH_4}}{(mol/dm^3)\times 10^4}$
1	1	1.0	1.73
2	1.8	1.0	4.40
3	4.08	1.0	10.0
4	1.0	0.1	1.65
5	1.0	0.5	2.47
6	1.0	4.0	1.75

The exit volumetric flow rate from a differential packed bed containing 10 g of catalyst was maintained at 300 dm^3/min for each run. The partial pressures of H₂ and CO were determined at the entrance

to the reactor, and the methane concentration was measured at the reactor exit. Determine the rate law and rate law parameters.

Solution

- Reaction temperature: 500°F (isothermal reaction)
- Weight of catalyst : ΔW = 10 g
- Exit volumetric flow rate v = 300 dm^3/min

The reaction-rate law is assumed to be the product of a function of the partial pressure of CO and a function of the partial pressure of H_2 ,

$$r'_{CH_4} = f(CO) \times g(H_2)$$

For the first 3 experiments, P_{H_2} is constant. We use this data to determine the dependence on P_{CO} .

For the experiments 1, 4, 5, 6, P_{CO} is constant. We use this data to determine the dependence on P_{H_2}

The rate in a differential reactor is given by

$$-r_A' = \frac{F_p}{\Delta W}$$

$$-r'_{CO}=r'_{CH_4}=\frac{F_{CH_4}}{\Delta W}$$

For constant H_2 partial pressure,

$$r'_{CH_A} = k' P^{\alpha}_{CO}$$

Taking log

$$\ln(r'_{CH_4}) = \ln k' + \alpha \ln P_{CO}$$

For constant CO partial pressure,

$$r'_{CH_{\rm A}}=g(H_2)$$

From the data:

At low ${\cal H}_2$ partial pressures, where r'_{CH_4} increases as P_{H_2} increases, the rate law may be of the form

$$r'_{CH_4} \propto P_{H_2}^{\beta_1} \tag{3}$$

At high H_2 partial pressures,where $r_{CH_4}^\prime$ decreases as P_{H_2} increases, the rate law may be of the form

$$r'_{CH_4} \propto \frac{1}{P_{H_2}^{\beta_2}} \tag{4}$$

Combining Equation 3, and Equation 4 we can write

$$r'_{CH_4} \propto \frac{P_{H_2}^{\beta_1}}{1 + bP_{H_2}^{\beta_2}}$$
 (5)

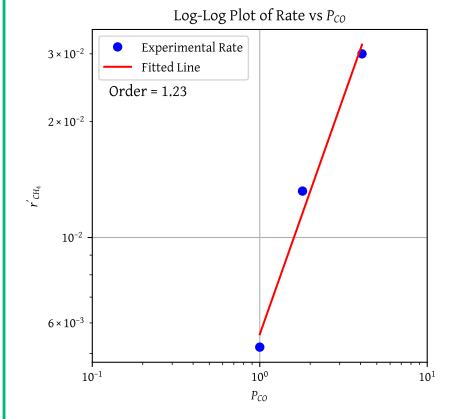
And the overall rate equation becomes:

$$r'_{CH_4}=\frac{aP^\alpha_{CO}P^{\beta_1}_{H_2}}{1+bP^{\beta_2}_{H_2}} \eqno(6)$$
 We can use regression to calculate estimate β_1 , β_2 , and constants a, and b.

```
import numpy as np
from numpy.lib import recfunctions as rfn
from scipy.stats import linregress
import matplotlib.pyplot as plt
Temperature = 500 # deg. F
DeltaW = 10 \# g
V \ 0 = 300 \ \# \ dm^3/min
dtype = [('Run', int), ('P_CO', float), ('P_H2', float), ('C_CH4', float)]
data = np.array([
    (1, 1.0, 1.0, 1.73e-4),
    (2, 1.8, 1.0, 4.40e-4),
    (3, 4.08, 1.0, 10.0e-4),
    (4, 1.0, 0.1, 1.65e-4),
    (5, 1.0, 0.5, 2.47e-4),
    (6, 1.0, 4.0, 1.75e-4)
], dtype=dtype)
pco = data["P CO"]
ph2 = data["P_H2"]
cch4 = data["C_CH4"]
rate = V_0 * cch4 / DeltaW
data = rfn.append fields(data, 'Rate', rate, usemask=False)
# Use first three points to estimate alpha
pco_a = pco[:3]
rate_a = rate[:3]
ln_pco_a = np.log(pco_a)
ln_rate_a= np.log(rate_a)
# fit line
res = linregress(ln_pco_a, ln_rate_a)
line = res.slope * ln pco a + res.intercept
alpha = res.slope
plt.loglog(pco a, rate a, 'bo', label='Experimental Rate') # Original data on log-log
plt.loglog(pco_a, np.exp(line), 'r-', label='Fitted Line') # Convert the log of the f
plt.xlabel('$P {CO}$')
plt.ylabel('$r\'_{CH_4}$')
plt.title('Log-Log Plot of Rate vs $P_{CO}$')
plt.legend()
plt.grid(True)
plt.xlim(0.1, 10)
plt.annotate(f'Order = {alpha:.2f}', xy=(0.05, 0.8), xycoords='axes fraction', fontsiz
```

16

plt.show()

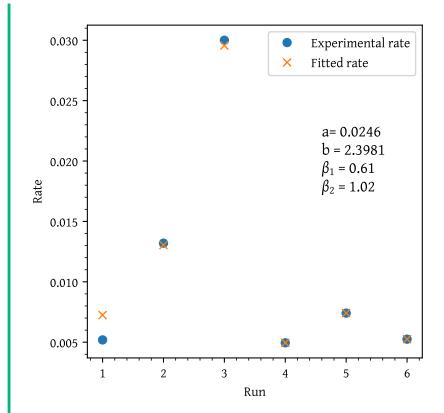


Reaction order with respect to CO is $\alpha =$ 1.23.

Had we included more points, we would have found that the reaction is essentially first order. We now use data from all the runs to estimate other parameters of the rate expression

$$r'_{CH_4} = \frac{aP_{CO}P_{H_2}^{\beta_1}}{1 + bP_{H_2}^{\beta_2}} \tag{7}$$

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.optimize import least_squares
# Objective function to minimize: the difference between rate (experimental) and rate
def objective(params, *args):
   a, b, beta 1, beta 2 = params
   pco, ph2,rate_obs = args
   # calculate rate
   rate_c = (a * pco * ph2**beta_1)/(1 + b * ph2**beta_2)
   return rate_obs - rate_c
# Initial guesses
a = 1
b = 1
beta 1 = 1
beta_2 = 1
guess = np.array([a,b,beta_1,beta_2])
   [1e-3, 1e-3, 0, 0], # lower bound
   [1e3, 1e3, 3, 3] # upper bound
args = (pco, ph2, rate)
# Minimize the objective function
result = least_squares(objective, guess, args=args, bounds=bounds)
# Extract the results
# Results from Fogler 5e
# a opt = 0.0252715
# b opt = 2.4872569
# beta 1 opt = 0.616542
# beta_2_opt = 1.0262047
a opt, b opt, beta 1 opt, beta 2 opt = result.x
rate_c = (a_opt * pco * ph2**beta_1_opt) / (1 + b_opt * ph2**beta_2_opt)
# plot the data
plt.plot(data["Run"], rate, 'o', label='Experimental rate')
plt.plot(data["Run"], rate_c, 'x', label='Fitted rate')
plt.annotate(
    f'a= \{a \text{ opt}:.4f\}\n'\
    f'b = \{b_opt:.4f\}\n'\
    f'$\\beta 1$ = {beta 1 opt:.2f}\n'\
    f'$\\beta_2$ = {beta_2_opt:.2f}',
    xy=(0.7, 0.5),
    xycoords='axes fraction',
    fontsize=12
)
```



The final constants are:

a = 0.0246

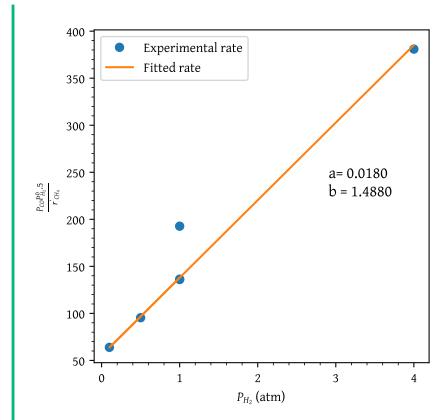
b = 2.3981

 β_1 = 0.61

 $\beta_2^{-} = 1.02$

If we assume hydrogen undergoes dissociative adsorption on the catalyst surface, we would expect a dependence on the partial pressure of hydrogen to be to the 1/2 power. Because 0.61 is close to 0.5, we are going to regress the data again, setting $\beta_1=1/2$ and β_2 = 1.0.

```
# Objective function to minimize: the difference between rate (experimental) and rate
def objective2(params, *args):
   a, b = params
  pco, ph2,rate_obs = args
   # calculate rate
   rate_c = (a * pco * ph2**0.5)/(1 + b * ph2)
   return rate_obs - rate_c
# Initial guesses
a = 1
b = 1
guess = np.array([a,b])
bounds = (
   [1e-3, 1e-3], # lower bound
   [1e3, 1e3] # upper bound
args = (pco, ph2, rate)
# Minimize the objective function
result = least_squares(objective2, guess, args=args, bounds=bounds)
# Extract the results
# Results from Fogler 5e
# a_opt = 0.018
\# b_{opt} = 1.49
a_opt, b_opt = result.x
rate_c = (a_opt * pco * ph2**0.5)/(1 + b_opt * ph2)
lin e = pco*ph2**0.5/rate
lin_c = pco*ph2**0.5/rate_c
# plot the data
plt.plot(ph2, lin_e, 'o', label='Experimental rate')
plt.plot(ph2, lin_c, '-', label='Fitted rate')
plt.annotate(
    f'a = \{a_opt: .4f\} \setminus n' \setminus
   f'b = \{b_{opt}: .4f\}',
    xy=(0.7, 0.5),
    xycoords='axes fraction',
    fontsize=12
)
plt.xlabel('$P_{H_2}$ (atm)')
plt.ylabel('$\\frac{P_{CO} P_{H_2}^0.5}{r\'_{CH_4}}$')
plt.legend()
plt.show()
                                      20
```



The final constants are:

a = 0.0180

b = 1.4880