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Q1.

Answer:

The absolute error is increases when n is gorws because the values of n! become very large and the difference between exact value and estimeatd value using strigins formula also increases .

But in the Relative Error is decreases when n grows, although the abslute error is increases the estimated valu also grows. making the ratio between the absolute error and exact value becoming smaller.

we can to see is in the graphs below.

the code also in the python file.

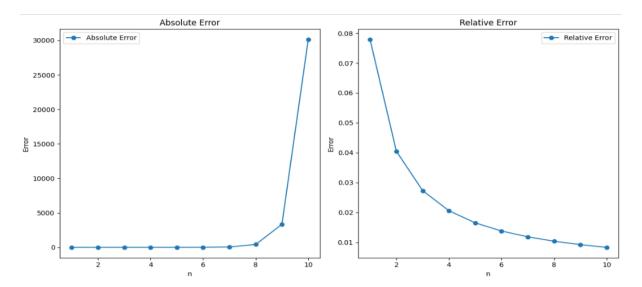
```
import math
import matplotlib.pyplot as plt

def stirling_formula(n):
    approx_result=math.sqrt(2* math.pi * n)*(n/ math.e)**n
    return approx_result

def calculateAbsulte_Relative_errors(n_range):
    absolute_errors = []
    relative_errors = []
    for n in n_range: #for every n between 1 to 10
        true valuemath.factorial(n)
        absolute_error = abs(approx_value - true_value) #in order the forumla in the frist lecture
        relative_error = abs(approx_value - true_value) #in order to the forumla in the first lecture
        absolute_errors.append(absolute_error) #add the absolute error to the list
        relative_errors.append(absolute_error) #add the realtive error to the list
    return absolute_errors, relative_errors

n_range = list(range(1, 11)) # n 1 -> 10
    absolute_errors, relative_errors = calculateAbsulte_Relative_errors(n_range)

#plot the result in grapth
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.plot(n_range, absolute_errors, 'o-', label='Absolute Error')
plt.lagend()
plt.subplot(1, 2, 2)
plt.plot(n_range, relative_errors, 'o-', label='Relative Error')
plt.lagend()
plt.subpl('in')
plt.ylabel('error')
plt.legend()
plt.show()
```



$$\in_{mach} \approx |3*\left(\frac{4}{3}-1\right)-1$$

This method is reasonable because it provides a quick way to estimate the machine epsilon

The idea is to use simple arithmetic operations that are prone to rounding errors due to the limited precision of floating-point representation.

For example:

$$\left(\frac{4}{3} - 1\right) = \frac{1}{3}$$
$$\frac{1}{3} * 3 = 1 \to 1 - 1 = 0$$

But the result is not be exactly zero, but a small value representing the machine epsilon.

Q2.b

```
#SP metohod

sp_value = np.float32(4) /np.float32(3)
epsilon_sp = np.abs(np.float32(3) * (sp_value - np.float32(1)) - np.float32(1))
print(f"Unit roundof SP: {epsilon_sp}")

#DP method
dp_value =np.float64(4) /np.float64(3)
epsilon_dp = np.abs(np.float64(3) * (dp_value - np.float64(1)) - np.float64(1))
print(f"Unit roundoff DP): {epsilon_dp}")

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```

Q2, c

The method for calculating the unit roundoff will not work the same way in a system with base 3 because the rounding errors accumulate differently. In base 3, the errors accumulate in a way that leads to an inaccurate \in_{mach} Therefore, the method is not as effective in base 3.

Q3.

In SP:

The precision is limited to 7 decimal digits, the accumulated erros in sum will cause to the value to eventually stabiliz and not continue to grow as expected.

I choose limit to be 1000000

The reason the series stops is that the floating point system reaches its precision limit, after a certain point adding very small values does not change the total sum due to the rounding of the numbers

```
import numpy as np

def harmonic_series_sum_sp(limit):
    sum_value = np.float32(0.0)
    for n in range(1, limit + 1):
        sum_value += np.float32(1.0 / n)
        if n % 1000000 == 0:
            print(f"Iteration {n}: Sum (SP) = {sum_value}")
    return sum_value

limit = 10000000

print("Calculating sum with SP:")
sp_sum = harmonic_series_sum_sp(limit)
print(f" sum with SP: {sp_sum}")
```

```
Trenation 5000000: Sum (SP) = 12.7227568064018922
Iteration 5000000: Sum (SP) = 12.722756806418922
Iteration 3000000: Sum (SP) = 13.195324897766113
Iteration 3000000: Sum (SP) = 13.195324897766113
Iteration 5000000: Sum (SP) = 13.195324897766113
Iteration 5000000: Sum (SP) = 13.690691947937012
Iteration 5000000: Sum (SP) = 13.690691947937012
Iteration 5000000: Sum (SP) = 14.83612708740234
Iteration 5000000: Sum (SP) = 14.83612708740234
Iteration 8000000: Sum (SP) = 14.16662311553955
Iteration 8000000: Sum (SP) = 14.45678379788288
Iteration 10000000: Sum (SP) = 14.45678379788288
Iteration 6000000: Sum (SP) = 14.45678379788288
Iteration 10000000: Sum (SP) = 14.45678379788288
Iteration 10000000: Sum (SP) = 14.757879788288
Iteration 10000000: Sum (SP) = 14.757879788288
Iteration 6000000: Sum (SP) = 15.403682708740234
Iteration 10000000: Sum (SP) = 14.758827709738333
Iteration 10000000: Sum (SP) = 14.403682708740234
Iteration 10000000: Sum (SP) = 15.1020274319358
Iteration 10000000: Sum (SP) = 15.403682708740234
Iteration 10000000: Sum (SP) = 15.1020274319358
Iteration 10000000: Sum (SP) = 15.403682708740234
Iteration 10000000: Sum (SP) = 15.403682708740234
Iteration 2000000: Sum (SP) = 15.403682708740234
Iteration 3000000: Sum (SP) = 15.403682708740234
Iteration 30000000: Sum (SP) = 15.40368
```

But in DP The sum will continue to grow for a longer period due to the higher precision of about 16 significant decimal digits. The output will show that the sum of the series continues to increase for a longer time before stabilizing at a certain value.

```
def harmonic_series_sum_dp(limit):
    sum_value = np.float64(0.0)
    for n in range(1, limit + 1):
        sum_value += np.float64(1.0 / n)
        if n % 100000 == 0:
            print(f"Iteration {n}: Sum (DP) = {sum_value}")
    return sum_value
    print("Calculating sumDP:")
    dp_sum = harmonic_series_sum_dp(limit)
    print(f"sum with DP: {dp_sum}")
```

```
Terration 1000000: Sum (DP) = 12.0901463.29863385
Iterration 1000000: Sum (DP) = 13.188755085385
Iterration 1000000: Sum (DP) = 13.188755085205663
Iterration 1000000: Sum (DP) = 13.188755085205663
Iterration 500000: Sum (DP) = 13.488755085205663
Iterration 500000: Sum (DP) = 13.699580042395627
Iterration 500000: Sum (DP) = 13.699580042395627
Iterration 500000: Sum (DP) = 14.05695199321212334
Iterration 7000000: Sum (DP) = 14.0569519932121234
Iterration 7000000: Sum (DP) = 14.0569519932121234
Iterration 1000000: Sum (DP) = 14.0586519932121234
Iterration 1000000: Sum (DP) = 14.0586519932121234
Iterration 1000000: Sum (DP) = 14.0586519932121234
Iterration 10000000: Sum (DP) = 14.058631956325563
Iterration 10000000: Sum (DP) = 14.0586363657214839
Iterration 12000000: Sum (DP) = 14.0597306626278663
Iterration 12000000: Sum (DP) = 14.79919381663395337
Iterration 15000000: Sum (DP) = 14.7991938166305655
Iterration 15000000: Sum (DP) = 14.7991938166305655
Iterration 15000000: Sum (DP) = 14.7991938166305655
Iterration 15000000: Sum (DP) = 14.05233547860451089
Iterration 120000000: Sum (DP) = 14.05233547860451089
Iterration 20000000: Sum (DP) = 15.085873063425047
Iterrat
```

Q4. a

 $x^2 - y^2$: More accurate calculation because the operations are simpler and less sensitive to rounding errors.

(x-y)(x+y): Less accurate due to cancellation error when x and y are close to each other.

The subtraction and addition operations can yield very small results, leading to significant rounding errors in the multiplication.

Therefore, according to what we learned, the expression $x^2 - y^2$ is more accurate in floating-point arithmetic than (x-y)(x+y).

Q4.b

There will be a significant difference between two expressions when x,y are close to each other, especially when x is much bigger than y.

There will be a significant difference between the two expressions when x and y are close in magnitude, especially when x is much larger than y . the difference (x-y) may be very smallleading to a significant loss of precision in the multiplication (x-y)(x+y) in floating-point arithmetic.

The difference (X-y) MAy be very small leading to significant loss of precesion in the (x-y)(x+y) in the floating point arithmetic .

We can to see in the code when x=1, y=0.99999999 (close to each other) the difference is:

```
[8] def method1(x, y):
    return x**2 - y**2

def method2(x, y):
    return (x - y) * (x + y)

def demonstrate_difference(x, y):
    result_1 = method1(x, y)
    result_2 = method2(x, y)
    print("method 1:", result_1)
    print("method 2:", result_2)
    print("Difference:", abs(result_1 - result_2))

x = 1.0
    y = 0.999999999
    demonstrate_difference(x, y)

➡ method 1: 1.999999943436137e-09
    method 2: 1.999999942436137e-09
    Difference: 1.00000001492112815e-18
```

But if x=4, y=1:

```
[11] def method1(x, y):
    return x**2 - y**2

def method2(x, y):
    return (x - y) * (x + y)

def demonstrate_difference(x, y):
    result_1 = method1(x, y)
    result_2 = method2(x, y)
    print("method 1:", result_1)
    print("method 2:", result_2)
    print("Difference:", abs(result_1 - result_2))

x = 4
    y = 1
    demonstrate_difference(x, y)

method 1: 15
method 2: 15
Difference: 0
```

Method 2 $x_k = a + kh$, k = 0, ..., n is a better because it minimizes the errors

In method 1 the error accumulates at eatch step of calculating the values, but in method 2 each value is valaclated alone from the initial value (a)

So, resuling in less accumulation of computational erros in method 2

Q5.B

We in the range [0,1], A=0, B=1 (Rahel sent the email about this)

```
import numpy as np
import matplotlib.pyplot as plt
def method1(a, b, n):
    h = (b-a)/n
    x = [a]
    for k in range(1, n + 1):
        m=x[k-1]
        x.append(m + h)
    return x
def method2(a, b, n):
    h = (b - a) / n
x = [a + k * h for k in range(n + 1)]
    return x
  = 0.0
method1_results= method1(a, b, n)
method2_results = method2(a, b, n)
print(f" the result of method 1: {method1_results}")
print(f"the result of method 2: {method2_results}")
```

We can to see that the method 2 is better than method 1 because that it minimzed accumulation error .

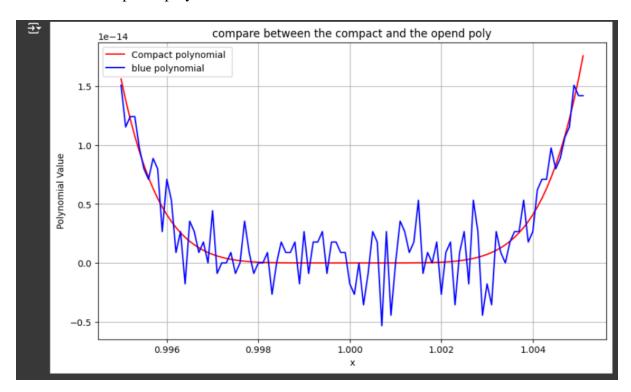
The x_values in the range about 0995 to 1.005)

```
import numpy as np
import matplotlib.pyplot as plt
def compact_polynomial(x):
    return (x - 1)**6
def open_polynomial(x):
    return x^{**}6 - 6^*x^{**}5 + 15^*x^{**}4 - 20^*x^{**}3 + 15^*x^{**}2 - 6^*x + 1
x_values = np.arange(0.995, 1.0051, 0.0001)
compact_values = [compact_polynomial(x) for x in x_values]
expanded_values=[open_polynomial(x) for x in x_values]
plt.figure(figsize=(10, 6))
plt.plot(x_values, compact_values, label='Compact polynomial ', color='red')
plt.plot(x_values, expanded_values, label='blue polynomial ', color='blue')
plt.xlabel('x')
plt.ylabel('Polynomial Value')
plt.title('compare between the compact and the opend poly')
plt.legend()
plt.grid(True)
plt.show()
```

The Output of the code:

The Red is the compactform polynomial

The blue is the opened polynomial



In the compact polynomial, the polynomial equals zero at the point x=1 and remains positive for all other values.

The values of the compact polynomial are very close to zero when x is close to 1, so they are near zero on the graph

However in the open polynomial the values may change more dramatically near this point (x=1) you can see on the graph that the values of the opend polynomial near (x=1) show small differences compared to the compat. THIS Is doue to calculate error from the sub and the sum operation involved in the expanded polynomial

The compact polynomial is moree accurate of calction because there are fewer and simpler operations, but the opend polynmail involves more sum and sub of large values, that is cause to calcation erros.

Therefore the compact polynomial is more accurate of calculation accuracy around the point x==1.