```
In [2]:
         #!/usr/bin/python
         import matplotlib.pyplot as plt
         import numpy as np
         import random
         # amino acids
         aa = ['A', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'K', 'L', 'M', 'N', 'P', 'Q', 'R', 'S', 'T'
         # Observed percent difference
         observed\_diff = [1] + list(range(5, 90, 5))
         # Evolutionary distance in PAMs
         evolutionary_dist = [1, 5, 11, 17, 23, 30, 38, 47, 56, 67, 80, 94, 112, 133, 159, 195, 24
         @Hamming distance: Defined between two strings of equal length, is the number of
         positions with mismatching characters.
         @param: seq1: sequence 1, seq2: sequence 2
         def Hamming_distance(seq1, seq2):
             dist = 0
             for (a, b) in zip(seq1, seq2):
                  if a != b:
                     dist += 1
             return dist
         @evolutionary distance : dist += diff(seq1[i], seq2[i])
         @param seq1: sequence 1, seq2: sequence 2
         def evolutionary_distance(seq1, seq2):
             if len(seq1) != len(seq2):
                 return -1
             dist = 0
             dist = Hamming_distance(seq1, seq2)
             return dist
         Oget sequence: generates a random sequence of length n
         @param: n: length of sequence
         def get sequence(n):
             return ''.join(random.choices(aa, k=n))
         Omutate sequence: mutates a sequence for the given several times
         @param: seq: sequence to mutate, r: number of mutations
         def mutate sequence (seq, r):
             mutated aa = set(aa)
             mut_pos = random<sub>•</sub> sample(range(len(seq)), r)
             mutated\_seq = list(seq)
             for pos in mut pos:
                  curr base = mutated seq[pos]
                  mutated aa.remove(curr base)
```

```
mutated seq[pos] = random.choice(list(mutated aa))
        mutated aa.add(curr base)
    return ''.join(mutated_seq)
" " "
@simulate PAM : simulates p PAM unit for the given parameters
@param: p: point accepted mutations or mutation steps, n: length of sequence
def simulate PAM unit(p, n):
    seq = get sequence(n)
    r = round(p * n / 100)
    seq_mut = mutate_sequence(seq, r)
    print(seq)
    print(" | " * len(seq))
    print(seq mut)
    print("evolutionary distance: " + str(evolutionary_distance(seq, seq_mut)))
" " "
@repeat_simulation: repeats the PAMsimulation for the given parameters
@param: p: point accepted mutations or mutation steps, n: length of sequence, r: number o
def repeat simulation(p, n, r, s):
    average_fraction_table = [[] for i in range(r)]
    for i in range(s):
        prev_seq = get_sequence(n)
        seq_mut = prev_seq
        for j in range(r):
            seq_mut = mutate_sequence(seq_mut, round(p * n / 100))
            average_fraction_table[j].append(evolutionary_distance(prev_seq, seq_mut) / n
    return average_fraction_table
@plot_simulation : plots the results of the simulation
@param: average_fraction_table: list of lists of fractions, evolutionary_dist: list of ev
def plot_simulation(average_fraction_table):
    r = 1 + np. arange (len (average fraction table))
    diff = []
    for i in range(len(average_fraction_table)):
        diff.append(sum(average_fraction_table[i]) * 100 / len(average_fraction_table[i])
    plt.plot(r, diff, label = "uniform distribution")
    plt.title(" average fraction of difference positions")
    plt.xlabel("Number of simulations")
    plt.ylabel("Difference in percent")
    plt.legend()
    plt.show()
    return r, diff
# PAM amino acid frequencies
frequency = np.array([0.087, 0.041, 0.040, 0.047, 0.033, 0.038, 0.050, 0.089, 0.034, 0.03
0.081, 0.015, 0.040, 0.051, 0.070, 0.058, 0.010, 0.030, 0.065
# PAM1 matrix
PAM1 = np.array([[9867, 2, 9, 10, 3, 8, 17, 21, 2, 6, 4, 2, 6, 2, 22, 35, 32, 0, 2, 18],
[1, 9913, 1, 0, 1, 10, 0, 0, 10, 3, 1, 19, 4, 1, 4, 6, 1, 8, 0, 1],
[4, 1, 9822, 36, 0, 4, 6, 6, 21, 3, 1, 13, 0, 1, 2, 20, 9, 1, 4, 1],
[6, 0, 42, 9859, 0, 6, 53, 6, 4, 1, 0, 3, 0, 0, 1, 5, 3, 0, 0, 1],
```

```
[1, 1, 0, 0, 9973, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 5, 1, 0, 3, 2],
[3, 9, 4, 5, 0, 9876, 27, 1, 23, 1, 3, 6, 4, 0, 6, 2, 2, 0, 0, 1],
[10, 0, 7, 56, 0, 35, 9865, 4, 2, 3, 1, 4, 1, 0, 3, 4, 2, 0, 1, 2],
[21, 1, 12, 11, 1, 3, 7, 9935, 1, 0, 1, 2, 1, 1, 3, 21, 3, 0, 0, 5],
[1, 8, 18, 3, 1, 20, 1, 0, 9912, 0, 1, 1, 0, 2, 3, 1, 1, 1, 4, 1],
[2, 2, 3, 1, 2, 1, 2, 0, 0, 9872, 9, 2, 12, 7, 0, 1, 7, 0, 1, 33],
[3, 1, 3, 0, 0, 6, 1, 1, 4, 22, 9947, 2, 45, 13, 3, 1, 3, 4, 2, 15],
[2, 37, 25, 6, 0, 12, 7, 2, 2, 4, 1, 9926, 20, 0, 3, 8, 11, 0, 1, 1],
[1, 1, 0, 0, 0, 2, 0, 0, 5, 8, 4, 9874, 1, 0, 1, 2, 0, 0, 4],
[1, 1, 1, 0, 0, 0, 0, 1, 2, 8, 6, 0, 4, 9946, 0, 2, 1, 3, 28, 0],
[13, 5, 2, 1, 1, 8, 3, 2, 5, 1, 2, 2, 1, 1, 9926, 12, 4, 0, 0, 2],
[28, 11, 34, 7, 11, 4, 6, 16, 2, 2, 1, 7, 4, 3, 17, 9840, 38, 5, 2, 2],
[22, 2, 13, 4, 1, 3, 2, 2, 1, 11, 2, 8, 6, 1, 5, 32, 9871, 0, 2, 9],
[0, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 9976, 1, 0],
[1, 0, 3, 0, 3, 0, 1, 0, 4, 1, 1, 0, 0, 21, 0, 1, 1, 2, 9945, 1],
[13, 2, 1, 1, 3, 2, 2, 3, 3, 57, 11, 1, 17, 1, 3, 2, 10, 0, 2, 9901]])
E = [] # Expected percentage of amino acids changes
@calibration_table(): generates a calibration table for PAM
def calibration table():
    pam1 = PAM1 / 10000
    sum_pi_M = 0 \# Sum of pi * M_i, i
    for i in range (20):
        sum_pi_M += frequency[i] * pam1[i][i]
    E. append (100 * (1 - sum_pi_M))
    pam = pam1
    for i in range(1, evolutionary dist[-1]):
        pam = pam. dot(pam1)
        sum pi M = 0 \# Sum \ of \ pi * M \ i, i
        for j in range (20):
            sum pi M += frequency[j] * pam[j][j]
        E. append (100 * (1 - sum pi M))
    expect\_table = [int(np.round(E[i - 1])) for i in evolutionary_dist]
    \# diff table = [np.round([i - 1]) for i in evolutionary_dist]
    print("expected percentage of changes" + " \ 't" + "PAM evolutionary distance")
    for i in range (len (evolutionary dist)):
        print(str(expect_table[i]) + "\t" + str(evolutionary_dist[i]))
```

Compute the calibration table between PAM evolutionary distance and expected percentage of amino acid changes

```
In [3]:
          calibration_table()
         expected percentage of changes PAM evolutionary distance
         1
                  1
         5
                  5
         10
                  11
         15
                  17
         20
                  23
         25
                  30
         30
                  38
                  47
         35
         40
                  56
         45
                  67
```

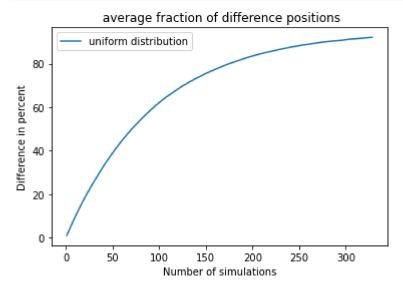
```
50
         80
55
         94
60
         112
65
         133
         159
70
75
         195
80
         246
85
         328
```

Interpret the calibrated relation and compare the results with your simulations from Exercise 1.

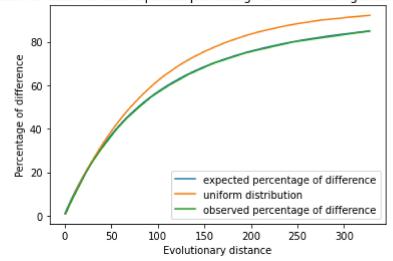
```
In [4]:
    r, diff = plot_simulation(repeat_simulation(1, 300, 328, 200))

def plot_calibration_table():
    plt.plot(range(evolutionary_dist[-1]), E, label = "expected percentage of difference"
    plt.plot(r, diff, label = "uniform distribution")
    plt.plot(evolutionary_dist, observed_diff, label = "observed percentage of difference
    plt.title("Calibrated relation in observed and expected percentage of difference agai
    plt.xlabel("Evolutionary distance")
    plt.ylabel("Percentage of difference")
    plt.legend()
    plt.show()

plot_calibration_table()
```



Calibrated relation in observed and expected percentage of difference against evolutionary distance



For what kinds of applications is it useful? Results from exercise 1 is proved not situable for mutations on protein sequences. For realistic applications should choose PAM matrix for protein as we can see from the plot below, Expected value is basically in line with observed value.