

In [15]:

```
def subset_sum(numbers, target, partial=[]):
    s = sum(partial)

    # check if the partial sum is equals to target
    if s == target:

        Subsets.append(partial)

    if s >= target:
        return # if we reach the number why bother to continue

    for i in range(len(numbers)):
        n = numbers[i]
        subset_sum(numbers, target, partial + [n])
```

In [16]:

```
Subsets = []
subset_sum([f for f in range(3,37)],36)
```

In [17]:

```
wsumL = []
for subset in Subsets:
    wsum = 0
    for t in range(len(subset)):
        if t == 0:
            wsum += 10*subset[0]-10
        else:
            wsum += (subset[t-1])*(subset[t]-1)
    wsumL.append(wsum+subset[-1])
```

In [18]:

```
max(wsumL)
```

Out[18]: 510

In []:

In []:

```
In [2]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
In [58]: def k_nbor(df, k, x):

    minIndex = []
    Dist = np.sum((df[:,0:-1] - x)**2, axis=1)
    minL = np.sort(Dist)[0:k]
    for k in range(k):
        minIndex.append(np.where(Dist == minL[k])[0][0])

    return np.sign(np.sum(df[minIndex, -1]))
```

```
In [62]: def uniform(df, gamma, x):
    return np.sign(np.sum(df[:, -1]*np.exp(-gamma*np.sum((df[:, :-1]-x)**2,axis=1))))
```

```
In [119]: def err(dftrain, dftest, parameter, method):
    ypred = []
    for t in dftest:
        ypred.append(method(dftrain, parameter, t[0:-1]))
    return np.sum((np.array(ypred) != dftest[:, -1]))/len(dftest)
```

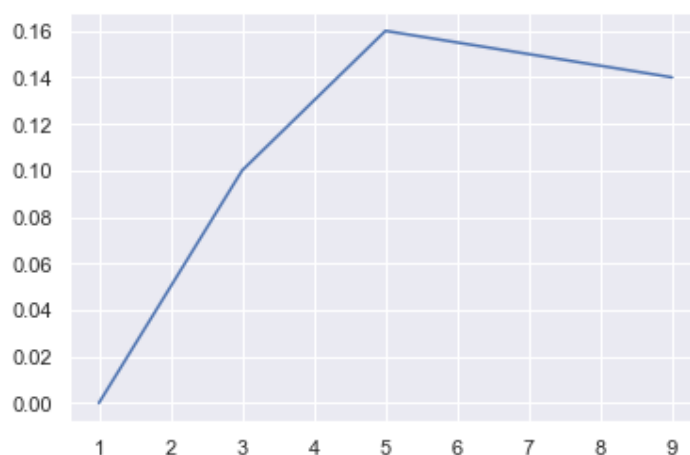
```
In [114]: dftrain = np.loadtxt('hw4_train.dat.txt')
```

```
In [115]: dftest = np.loadtxt('hw4_test.dat.txt')
```

```
In [121]: #Q11
K = [1,3,5,7,9]
E = []
for k in K:
    E.append(err(dftrain, dftrain, k, k_nbor))

sns.set()
sns.lineplot(K,E)
print(E)
```

```
[0.0, 0.1, 0.16, 0.15, 0.14]
```

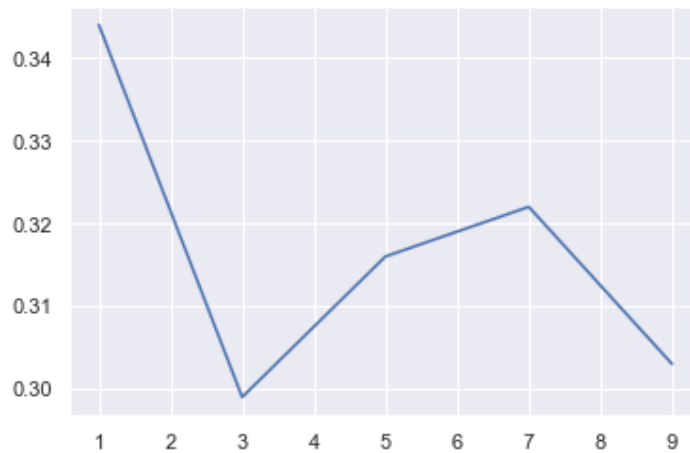


Q11: Ein increases at first then decreases.

```
In [120]: #Q12
K = [1,3,5,7,9]
E = []
for k in K:
    E.append(err(dftrain, dftest, k, k_nbor))

sns.set()
sns.lineplot(K,E)
print(E)
```

[0.344, 0.299, 0.316, 0.322, 0.303]

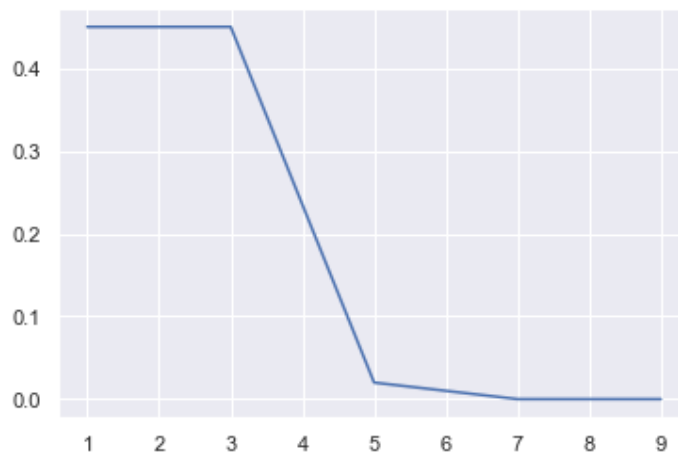


Q12: Eout does not vary much.

```
In [122]: #Q12
Gamma = [0.001,0.1,1,10,100]
E = []
for gamma in Gamma:
    E.append(err(dftrain, dftrain, gamma, uniform))

sns.set()
sns.lineplot(K,E)
print(E)
```

[0.45, 0.45, 0.02, 0.0, 0.0]

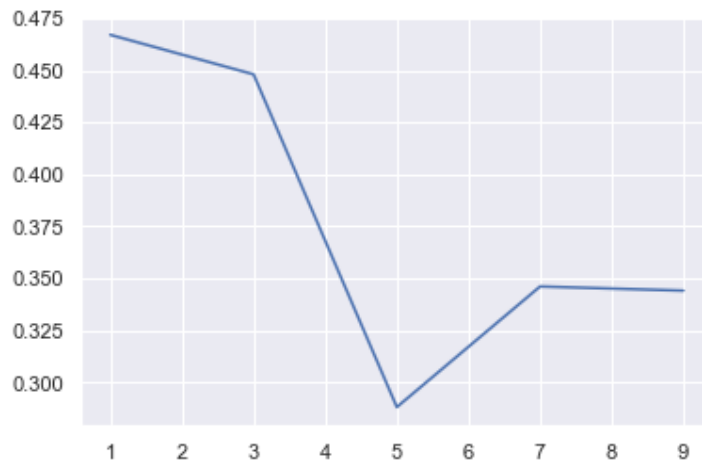


Q13: Ein decreases to 0.

```
In [124]: #Q12
Gamma = [0.001,0.1,1,10,100]
E = []
for gamma in Gamma:
    E.append(err(dftrain, dftest, gamma, uniform))

sns.set()
sns.lineplot(K,E)
print(E)
```

```
[0.467, 0.448, 0.288, 0.346, 0.344]
```



Q14: Eout decreases to its lowest then surges.

In []:

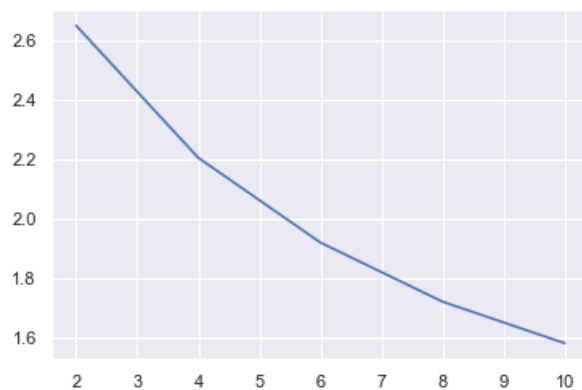
```
In [12]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
```

```
In [11]: df= np.loadtxt('hw4_nolabel_train.dat')
```

```
In [47]: E = []
V = []
K = [2,4,6,8,10]
for k in K:
    err = 0
    sq = 0
    for T in range(500):
        kmeans = KMeans(n_clusters=k, random_state=T).fit(df)
        err += kmeans.score(df)/100/500
        sq += ((kmeans.score(df)/100)**2)/500
    E.append(-1*err)
    V.append(sq - err**2)
```

```
In [56]: sns.set()
sns.lineplot(K,E)
print(E)
```

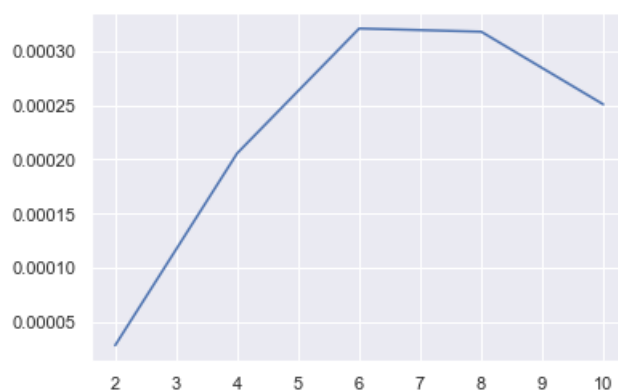
```
[2.6482794225946558, 2.2033466623852838, 1.9180549102254723, 1.7188274310568472, 1.57910757047811]
```



Q15: Average of err for 500 times decreases as k increases.

```
► In [58]: sns.set()
sns.lineplot(K,V)
print(V)
```

```
[2.8007285915343516e-05, 0.0002057968897553053, 0.00032129635692879077, 0.0003182846984906007, 0.00025101657672488287]
```



Q16: Variance of err for 500 times increases until k = 6, then decreases.

1. The sum of weights.

$$= 10 \times d^{(1)} + (d^{(1)} + 1) d^{(2)} + \dots + (d^{(L-2)} + 1) (d^{(L-1)} + 1) d^{(L)} + d^{(L-1)} \times 1$$

$$\text{s.t. } \sum_{t=1}^{L-1} d^{(t)} + 1 = 36.$$

for minimum weight number

$$\text{if } d^{(1)} = d^{(2)} = \dots = d^{(8)} = 1 \quad \text{185}$$

$$\text{min \# of weight} = 10 + 2 + \dots + 2 + 2 = 46$$

2. For maximum sum of weight numbers.

\Rightarrow See program. greedy search.

$$\text{Max} = 510$$

$$3. \quad \nabla \text{err}_n(w) = \frac{\partial (x_n - w w^T x_n)^T (x_n - w w^T x_n)}{\partial w}$$

$$= 2 (x_n - w w^T x_n) \cdot \frac{\partial (x_n - w w^T x_n)}{\partial w}$$

$$= -2 (x_n - w w^T x_n) (x_n + x_n^T) w$$

$$= -2 (x_n + x_n^T) w (x_n - w w^T x_n)$$

$$= 2(x_n^T w)^2 w + 2(x_n^T w)(w^T w) x_n - 4w^T x_n x_n$$

$$4. \quad \tilde{x}_n = x_n + \varepsilon_n$$

$$E(\varepsilon_n) = 0_n$$

$$\varepsilon_n \sim N(0_n, I)$$

$$E\tilde{m} = \frac{1}{N} \sum_{n=1}^N (x_n - ww^T x_n)^T (x_n - ww^T x_n)^T$$

$$= \frac{1}{N} \sum (x_n - ww^T x_n)^T (ww^T \varepsilon_n)$$

$$+ \sum (ww^T \varepsilon_n)^T (ww^T \varepsilon_n)$$

$$\Omega(w) = E \left[\frac{1}{N} \sum (x_n - \cancel{ww^T} x_n)^T (ww^T \varepsilon_n) + \sum (ww^T \varepsilon_n)^T (ww^T \varepsilon_n) \right]$$

$$= \frac{1}{N} \sum E[\varepsilon_n^T ww^T ww^T \varepsilon_n]$$

$$= w^T w \frac{1}{N} \sum E[\varepsilon_n^T ww^T \varepsilon_n]$$

$$= w^T w \frac{1}{N} \sum E \left[\sum_{i=1}^d \varepsilon_{ni}^2 w_i^2 \right]$$

$$= w^T w \frac{1}{N} \sum_{n=1}^N \sum_{i=1}^d w_i^2 E(\varepsilon_{ni}^2)$$

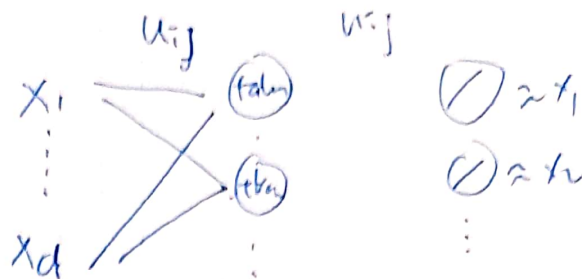
$$= w^T w \frac{1}{N} \sum_{n=1}^N \sum_{i=1}^d w_i^2 = \frac{1}{N} \sum (w^T w)^2 = \underline{(w^T w)^2}$$

5.

error function

$$= \sum_{i=1}^d (g_i(x) - x_i)^2$$

$$= \sum_{j=1}^d \left(\sum_{k=1}^{\tilde{d}} \underbrace{u_{ki}}_{w_{ji}^{(2)}} \tanh \left(\sum_{i=1}^d \underbrace{u_{ij}}_{w_{ij}^{(1)}} x_i \right) - x_j \right)^2$$



6.

$$\frac{\partial E}{\partial u_{ij}} = 2 \sum_{j=1}^d \left(\sum_{k=1}^{\tilde{d}} u_{ki} \tanh \left(\sum_{i=1}^d u_{ij} x_i \right) - x_j \right) \left[\tanh \left(\sum_{i=1}^d u_{ij} x_i \right) + \sum_{k=1}^{\tilde{d}} u_{ki} \tanh \left(\sum_{i=1}^d u_{ij} x_i \right) \tanh' \left(\sum_{i=1}^d u_{ij} x_i \right) x_i \right]$$

$$\frac{\partial E}{\partial w_{ij}^{(1)}} = 2 \sum_{j=1}^d \left(\sum_{k=1}^{\tilde{d}} u_{ki} \tanh \left(\sum_{i=1}^d u_{ij} x_i \right) - x_j \right) \cdot \left(\sum_{k=1}^{\tilde{d}} u_{ki} \tanh \left(\sum_{i=1}^d u_{ij} x_i \right) \right) x_i$$

$$\frac{\partial E}{\partial w_{ij}^{(2)}} = 2 \sum_{j=1}^d \left(\sum_{k=1}^{\tilde{d}} u_{ki} \tanh \left(\sum_{i=1}^d u_{ij} x_i \right) - x_j \right) \cdot \tanh \left(\sum_{i=1}^d w_{ij}^{(1)} x_i \right)$$

$$2 \sum_{j=1}^d \left(\sum_{k=1}^{\tilde{d}} u_{ki} \tanh \left(\sum_{i=1}^d u_{ij} x_i \right) - x_j \right) \left[\sum_{k=1}^{\tilde{d}} u_{ki} \tanh \left(\sum_{i=1}^d u_{ij} x_i \right) \tanh' \left(\sum_{i=1}^d u_{ij} x_i \right) x_i + \tanh \left(\sum_{i=1}^d w_{ij}^{(1)} x_i \right) \right]$$

7.

$$g_{LIN}(x) = \text{sign}(\|x - x_-\|^2 - \|x - x_+\|^2)$$

$$= \text{sign}((x - x_-)^T(x - x_-) - (x - x_+)^T(x - x_+))$$

$$= \text{sign}(2(x_+ - x_-)^T x + \|x_-\|^2 - \|x_+\|^2)$$

8.

$$p \cdot \tau \neq g_{RBFINZI}(x) \geq 1$$

$$\Rightarrow \beta_+ \exp(-\|x - \mu_+\|^2) + \beta_- \exp(-\|x - \mu_-\|^2) \geq 0$$

$$\Rightarrow \frac{\exp(-\|x - \mu_+\|^2)}{\exp(-\|x - \mu_-\|^2)} \geq -\frac{\beta_-}{\beta_+}$$

$$\Rightarrow \underline{\|x - \mu_-\|^2 - \|x - \mu_+\|^2} \geq \ln\left(-\frac{\beta_-}{\beta_+}\right)$$

as g_{LIN} , using (17) solution

$$w = 2(\mu_+ - \mu_-)$$

$$b = \|\mu_-\|^2 - \|\mu_+\|^2 - \ln\left(-\frac{\beta_-}{\beta_+}\right)$$

9.

$$\sum_{n=1}^n \sum_{\substack{(x_n, r_{nm}) \\ \in D_m}} (r_{nm} - w_m^T v_n)^2$$

$$\text{FOC: } 2 \sum_{\substack{(x_n, r_{nm}) \\ \in D_m}} (r_{nm} - w_m^T v_n) v_n = 0$$

$$\Rightarrow \sum (r_{nm} - w_m^T v_n) = 0$$

$$\Rightarrow w_m = \frac{\sum_n r_{nm}}{\sum_n v_n} = \frac{\sum_n r_{nm}}{n}$$

average rating

10.

$$\max_m v_{n+1}^T v_m = \max_m \left(\frac{1}{N} \sum v_n \right)^T w_m$$

$$= \max_m \frac{1}{N} \sum v_n^T w_m = \max_m \underbrace{\frac{1}{N} \sum r_{nm}}_{\text{maximum of average rating.}}$$