

**DSC 40B**

***Lecture 5-6 : Best,  
Worst, Average***

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# ***Agenda***

## ***Plan for the lecture***

- Best, Worst and Average cases.



# ***The Movie problem***

## ***The Movie Problem***



## ***The Movie Problem***

- **Given:** an array `movies` of movie durations, and the flight duration `t`
- **Find:** two movies whose durations add to `t`
  - If no two movies sum to `t`, return **None**.

## ***Exercise***

- Design a brute force solution to the problem. What is its time complexity?

## ***Brute force***

```
def find_movies(movies, t):  
    n = len(movies)  
    for i in range(n):  
        for j in range(i + 1, n):  
            if movies[i] + movies[j] == t:  
                return (i, j)  
    return None
```

## *Time Complexity*

- It looks like there is a **best** case and **worst** case.
- How do we formalize this?

## *For the future...*

- Can you come up with a better algorithm?
- What is the *best possible* time complexity?

# ***Best and Worst Cases***

## Definition

- Define  $T_{\text{best}}(n)$  to be the **least** time taken by the algorithm on **any input of size  $n$** .
- The asymptotic growth of  $T_{\text{best}}(n)$  is the algorithm's **best case time complexity**.

## *Example 1: mean*

```
def mean(arr):  
    total = 0  
    for x in arr:  
        total += x  
    return total / len(arr)
```

## *Example 1: mean*

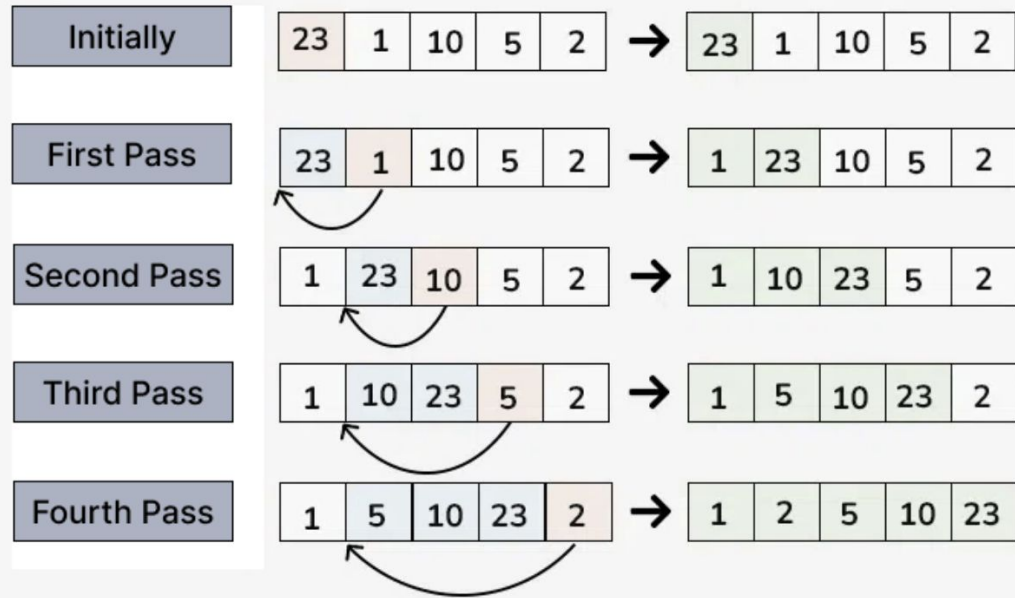
```
def mean(arr):  
    total = 0  
    for x in arr:  
        total += x  
    return total / len(arr)
```

$$T_{\text{best}}(n) = n$$

## ***Caution!***

- The best case is never: “the input is of size one”.
- The best case is about the **structure** of the input, not its **size**.
- Not always constant time!
  - **Example**: sorting.

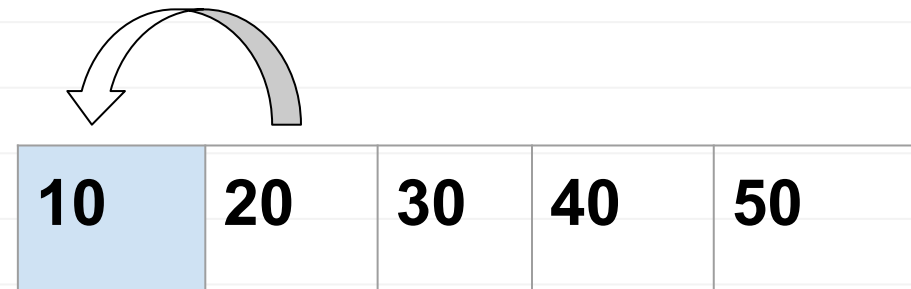
```
def insertionSort(arr):  
    for i in range(1, len(arr)):  
        key = arr[i]  
        j = i - 1  
        while j >= 0 and key < arr[j]:  
            arr[j + 1] = arr[j]  
            j -= 1  
        arr[j + 1] = key
```



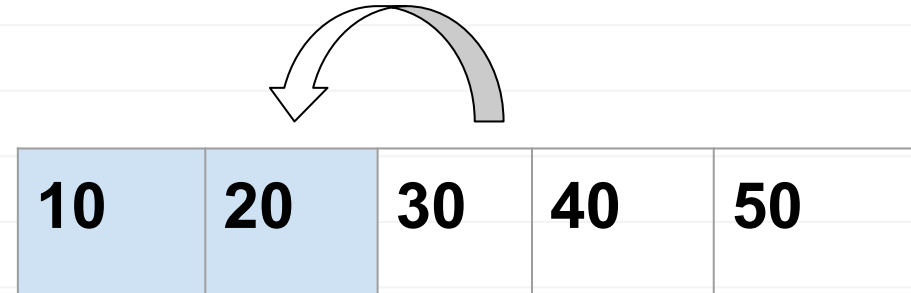
```
def insertionSort(arr):  
    for i in range(1, len(arr)):  
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            arr[j + 1] = arr[j]  
            j -= 1  
        arr[j + 1] = key
```

10	20	30	40	50
----	----	----	----	----

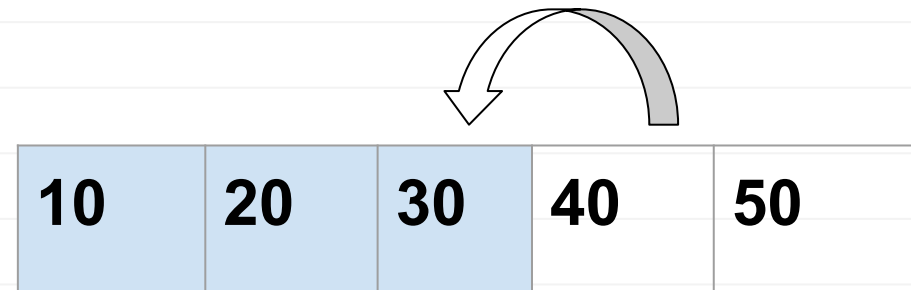
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    for i in range(1, len(arr)):  
        key = arr[i]  
        j = i - 1  
        while j >= 0 and key < arr[j]:  
            arr[j + 1] = arr[j]  
            j -= 1  
        arr[j + 1] = key
```



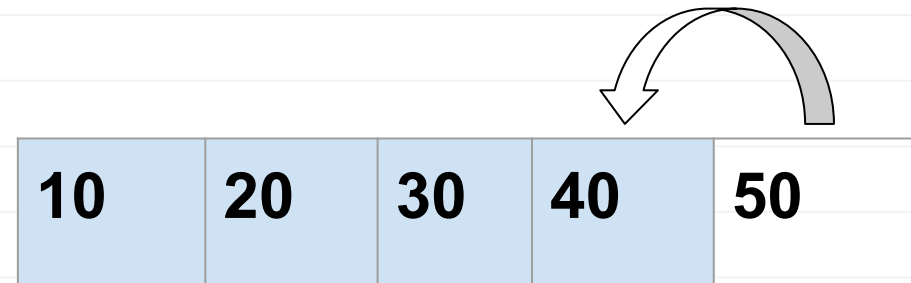
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            j -= 1  
        arr[j + 1] = key
```

$$T_{\text{best}}(n) = n$$

10	20	30	40	50
----	----	----	----	----

## *Time Complexity of mean*

- Linear time,  $\Theta(n)$ .
- Depends **only** on the array's **size**,  $n$ , not on its actual elements.

## ***Example 2: Linear Search***

- **Given:** an array `arr` of numbers and a target `t`.
- **Find:** the index of `t` in `arr`, or `None` if it is missing.
- Example: `arr = [-3, -6, 7, 3, 0, 15, 4]`

```
def linear_search(arr, t):  
    for i, x in enumerate(arr):  
        if x == t:  
            return i  
    return None
```

## ***Exercise: Time complexity?***

```
def linear_search(arr, t):  
    for i, x in enumerate(arr):  
        if x == t:  
            return i  
    return None
```

## ***Observation***

- It looks like there are two extreme cases...

## *The **Best** Case*

- When the target,  $t$ , is the very first element.
- The loop exits after one iteration.
- $\Theta(1)$  time?

## *The **Worst** Case*

- When the target,  $t$ , is not in the array at all.
- The loop exits after  $n$  iterations.
- $\Theta(n)$  time?

## ***Time Complexity***

- `linear_search` can take vastly different amounts of time on two inputs of the **same size**.
  - Depends on **actual elements** as well as size.
- It has no single, overall time complexity.
- Instead we'll report **best** and **worst** case time complexities.

## ***Best Case Time Complexity***

- How does the time taken in the **best case** grow as the input gets larger?

## ***Best Case***

- In linear\_search's **best case**,  $T_{\text{best}}(n) = c$ , no matter how large the array is.
- The **best case time complexity** is  $\Theta(1)$ .

## ***Worst Case Time Complexity***

- How does the time taken in the **worst case** grow as the input gets larger?

## Definition

- Define  $T_{\text{worst}}(n)$  to be the **most time** taken by the algorithm on any input of size  $n$ .
- The asymptotic growth of  $T_{\text{worst}}(n)$  is the algorithm's **worst case time complexity**.

## ***Worst Case***

- In the worst case, `linear_search` iterates through the entire array.
- The **worst case** time complexity is  $\Theta(n)$ .

## ***Exercise: times: Best and Worst***

```
def func(arr):  
    n = len(arr)  
    for x in arr:  
        for y in arr:  
            x + y == 10  
        return sum(arr)
```

A:  $\Theta(1)$

B:  $\Theta(n)$

C:  $\Theta(n^2)$

D:  $\Theta(n^3)$

## ***Best Case***

- Best case occurs when the first element is 5:  $5 + 5 = 10$
- `sum(arr)` takes  $\Theta(n)$  time
- Exists, taking  $\Theta(n)$  time in total

## ***Worst Case***

- Worst case occurs when no two numbers add to 10.
- Has to loop over all  $\Theta(n^2)$  pairs.
- Worst case time complexity:  $\Theta(n^2)$ .
- Note: Not  $\Theta(n^3)$  since the `sum(arr)` only runs once.

## *Note*

- An algorithm like `linear_search` **doesn't** have one single time complexity.
- An algorithm like `mean` **does**, since the best and worst case time complexities coincide.

## ***Main Idea***

Reporting **best** and **worst** case time complexities gives us a richer of the performance of the algorithm.



***Average Case***

## *Time Taken, Typically*

- Best case and worst case can be **misleading**.
  - Depend on a single **good/bad** input.
- How much time is taken, typically?
- **Idea**: compute the average time taken over *all possible inputs*.

## Recall: The Expectation

- The **expected value** of a random variable  $X$  is:

$$\sum_x x \cdot P(X = x)$$

winnings	probability
\$ 0	50%
\$ 1	30%
\$ 10	18%
\$ 50	2%

Expected winnings:

## Recall: The Expectation

- The **expected value** of a random variable  $X$  is:

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$$\$0 \times .5 +$$

Expected winnings:

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Expected winnings:

$$\$0 \times .5 + \$1 \times .3$$

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Expected winnings:

$$\$0 \times .5 + \$1 \times .3 + \$10 \times .18 + \$50 \times .02$$

## Recall: The Expectation

- The **expected value** of a random variable  $X$  is:

$$\sum_x x \cdot P(X = x)$$

winnings	probability
\$ 0	50%
\$ 1	30%
\$ 10	18%
\$ 50	2%

Expected winnings:

$$\$0 \times .5 + \$1 \times .3 + \$10 \times .18 + \$50 \times .02 = \$3.10$$

## ***Average Case***

- We'll compute the expected time over all cases:

$$T_{\text{avg}}(n) = \sum_{\text{case} \in \text{all cases}} P(\text{case}) \cdot T(\text{case})$$

- Called the **average case time complexity**.

## ***Strategy for Finding Average Case***

- **Step 0:** Make assumption about distribution of inputs.
- **Step 1:** Determine the possible cases.
- **Step 2:** Determine the probability of each case.
- **Step 3:** Determine the time taken for each case.
- **Step 4:** Compute the expected time (average).

## *Example: Linear Search*

- **Best? Worst?**

```
def linear_search(arr, t):  
    for i, x in enumerate(arr):  
        if x == t:  
            return i  
    return None
```

## ***Example: Linear Search***

- What is the average case time complexity of linear search?

## ***Step 0: Assume input distribution***

- We must assume something about the input.
- **Example:** Target must be in array, equally-likely to be any element, no duplicates.
- This is *usually* given to you.

## ***Step 1: Determine the Cases***

**Example:** *linear search.*

- **Case 1:** target is first element
- **Case 2:** target is second element
- $\vdots$
- **Case  $n$ :** target is  $n$ th element
- **Case  $n + 1$ :** *target is not in array (but not needed due to assumptions)*

## ***Step 2: Case Probabilities***

- What is the probability that we see each case?
  - **Example:** what is the probability that the target is the  $k$ th element?
- This is where we use assumptions from **Step 0**.

## ***Example***

- **Assume:** target is in the array exactly once, equally-likely to be any element.
- Each case has probability  $1/n$ .

## Step 3: Case Times

- Determine time taken in each case.
- **Example:** linear search.
  - Let's say it takes time  $c$  per iteration.

**Case 1:** time  $c$

**Case 2:** time  $2c$

:

**Case  $i$ :** time  $c \cdot i$

:

**Case  $n$ :** time  $c \cdot n$

## ***Step 4: Compute Expectation***

$$T_{\text{avg}}(n) = \sum_{i=1}^n P(\text{case } i) \cdot T(\text{case } i)$$

## ***Average Case Time Complexity***

- The **average case** time complexity of **linear search** is  $\Theta(n)$ .
  - Under these assumptions on the input!

## ***Note***

- **Worst case** time complexity is still useful.
- Easier to calculate.
- Often same as average case (but not always!)
- Sometimes worst case is very important.
  - Real time applications, time complexity attacks

## Note

- **Hard** to make realistic assumptions on input distribution.
- **Example:** linear search.
  - Is it realistic to assume  $t$  is in array?
  - If not, what is the probability that it *is* in the array?

## ***Exercise***

- Suppose we *change* our assumptions:
  - The target has a 50% chance of being in the array.
- If it is in the array, it is equally-likely to be any element.
- What is the average case complexity now?



## ***Average Case in Movie Problem***

## ***Recall: The Movie Problem***

- **Given:** an array `movies` of movie durations, and the flight duration `t`
- **Find:** two movies whose durations add to `t`.
  - If no two movies sum to `t`, return **None**.

```
def find_movies(movies, t):  
    n = len(movies)  
    for i in range(n):  
        for j in range(i + 1, n):  
            if movies[i] + movies[j] == t:  
                return (i, j)  
    return None
```

## ***Time Complexity***

- **Best case:**  $\Theta(1)$ 
  - When the first pair of movies checked equals target.
- **Worst case:**  $\Theta(n^2)$ 
  - When no pair of movies equals target.

## ***“Average” Case?***

- The best and worst cases are extremes.
- How much time is taken, *typically*?
  - That is, when the target pair is not the first checked nor the last, but somewhere in the middle.

## Exercise

- How much time do you expect *find\_movies* to take on a typical input?

A:  $\Theta(1)$

B:  $\Theta(n^2)$

C: Something in between,  
like  $\Theta(n)$

## *The Movie Problem*

```
def find_movies(movies, t):  
    n = len(movies)  
    for i in range(n):  
        for j in range(i + 1, n):  
            if movies[i] + movies[j] == t:  
                return (i, j)  
    return None
```

## *Step 0: Assume input distribution*

- Suppose we are told that:
  - There is a **unique** pair of movies that add to  $t$ .
  - All pairs are **equally likely**.

## ***Step 1: Determine the Cases***

- Case  $\alpha$ : the  $\alpha$ th pair checked sums to  $t$ .
- Each pair of movies is a case.
- There are  $\binom{n}{2}$  cases (pairs of movies)

## ***Step 2: Case Probabilities***

- **Assume**: there is a unique pair that adds to t.
- **Assume**: all pairs are equally likely.
- Probability of any case:  $\frac{1}{\binom{n}{2}} = \frac{2}{n(n-1)}$

### ***Step 3: Case Time***

- How much time is taken for a particular case?
- Example, suppose the movies  $a$  and  $b$  sum to the target.
- How long does it take to find this pair?

## Exercise

Roughly how much time is taken (how many times does line 5 run) if the  $\alpha$ th pair checked sums to the target?

```
1  def find_movies(movies, t):  
2      n = len(movies)  
3      for i in range(n):  
4          for j in range(i + 1, n):  
5              if movies[i] + movies[j] == t:  
6                  return (i, j)  
7      return None
```

$(m_1, m_2)$

## Exercise

```
1 def find_movies(movies, t):
2     n = len(movies)
3     for i in range(n):
4         for j in range(i + 1, n):
5             → if movies[i] + movies[j] == t:
6                 return (i, j)
7     return None
```

$\alpha$

$\tau$

$(m_1, m_2)$

## Exercise

```
1 def find_movies(movies, t):
2     n = len(movies)
3     for i in range(n):
4         for j in range(i + 1, n):
5             → if movies[i] + movies[j] == t:
6                 return (i, j)
7     return None
```

$\alpha$	$T$
1	1

$(m_1, m_3)$

## Exercise

```
1 def find_movies(movies, t):  
2     n = len(movies)  
3     for i in range(n):  
4         for j in range(i + 1, n):  
5             → if movies[i] + movies[j] == t:  
6                 return (i, j)  
7     return None
```

$\alpha$	$T$
1	1
2	2

$(m_1, m_4)$

## Exercise

```
1 def find_movies(movies, t):
2     n = len(movies)
3     for i in range(n):
4         for j in range(i + 1, n):
5             → if movies[i] + movies[j] == t:
6                 return (i, j)
7     return None
```

$\alpha$	$T$
1	1
2	2
3	3

## Exercise

```
1 def find_movies(movies, t):
2     n = len(movies)
3     for i in range(n):
4         for j in range(i + 1, n):
5             → if movies[i] + movies[j] == t:
6                 return (i, j)
7     return None
```

$\alpha$	T
1	1
2	2
3	3
4	4

## Exercise

```
1 def find_movies(movies, t):
2     n = len(movies)
3     for i in range(n):
4         for j in range(i + 1, n):
5             → if movies[i] + movies[j] == t:
6                 return (i, j)
7     return None
```

$\alpha$	T
1	1
2	2
3	3
4	4

Roughly how much time is taken (how many times does line 5 run) if the  $\alpha$ th pair checked sums to the target?  **$T(\text{case } \alpha) = \alpha$**

## ***Step 4: Compute Expectation***

$$T_{avg} =$$

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$$T_{avg} = \sum_{\alpha = 1}$$

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$$T_{avg} = \sum_{\alpha=1}^{\binom{n}{2}}$$

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$$T_{avg} = \sum_{\alpha=1}^{\binom{n}{2}} P(\text{case } \alpha)$$

## ***Step 4: Compute Expectation***

$$T_{avg} = \sum_{\alpha=1}^{\binom{n}{2}} P(\text{case } \alpha) \cdot T(\text{case } \alpha)$$

$$T_{avg} = \sum_{\alpha=1}^{\binom{n}{2}} P(\text{case } \alpha) \cdot T(\text{case } \alpha)$$

$$\sum_{\alpha=1}^{\binom{n}{2}} \cdot \frac{1}{\binom{n}{2}} \cdot T(\text{case } \alpha)$$

$$T_{avg} = \sum_{\alpha=1}^{\binom{n}{2}} P(case \alpha) \cdot T(case \alpha)$$

$$\sum_{\alpha=1}^{\binom{n}{2}} \cdot \frac{1}{\binom{n}{2}} \cdot T(case \alpha) = \sum_{\alpha=1}^{\binom{n}{2}} \cdot \frac{1}{\binom{n}{2}} \cdot \alpha$$

$$\sum_{\alpha=1}^{\binom{n}{2}} \cdot \frac{1}{\binom{n}{2}} \cdot \alpha = \frac{1}{\binom{n}{2}} \cdot \sum_{\alpha=1}^{\binom{n}{2}} \alpha$$

$$\sum_{\alpha=1}^{\binom{n}{2}} \cdot \frac{1}{\binom{n}{2}} \cdot \alpha = \frac{1}{\binom{n}{2}} \cdot \sum_{\alpha=1}^{\binom{n}{2}} \alpha$$

$$\sum_{\alpha=1}^{\binom{n}{2}} \alpha = \sum_{\alpha=1}^t \alpha = \frac{t(t+1)}{2}$$

$$\sum_{\alpha=1}^{\binom{n}{2}} \cdot \frac{1}{\binom{n}{2}} \cdot \alpha = \frac{1}{\binom{n}{2}} \cdot \sum_{\alpha=1}^{\binom{n}{2}} \alpha$$

$$\sum_{\alpha=1}^{\binom{n}{2}} \alpha = \sum_{\alpha=1}^t \alpha = \frac{t(t+1)}{2} = \frac{\binom{n}{2} \left[ \binom{n}{2} + 1 \right]}{2}$$

$$\sum_{\alpha=1}^{\binom{n}{2}} \cdot \frac{1}{\binom{n}{2}} \cdot \alpha = \frac{1}{\binom{n}{2}} \cdot \sum_{\alpha=1}^{\binom{n}{2}} \alpha$$

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$$\binom{n}{2} = \frac{n!}{2! (n-2)!} = \frac{n(n-1)}{2} = \Theta(n^2)$$

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$$\frac{\binom{n}{2} \left[ \binom{n}{2} + 1 \right]}{2} = \Theta(?)$$

$$\binom{n}{2} = \frac{n!}{2! (n-2)!} = \frac{n(n-1)}{2} = \Theta(n^2)$$

$$\frac{\binom{n}{2} \left[ \binom{n}{2} + 1 \right]}{2} = \Theta(n^4)$$

$$\frac{1}{\binom{n}{2}} \cdot \sum_{\alpha=1}^{\binom{n}{2}} \alpha$$

$$\frac{1}{\binom{n}{2}} \cdot \sum_{\alpha=1}^{\binom{n}{2}} \alpha = \frac{1}{\binom{n}{2}} \cdot \frac{\binom{n}{2} \left[ \binom{n}{2} + 1 \right]}{2}$$

$$\frac{1}{\binom{n}{2}} \cdot \sum_{\alpha=1}^{\binom{n}{2}} \alpha = \frac{1}{\binom{n}{2}} \cdot \frac{\binom{n}{2} \left[ \binom{n}{2} + 1 \right]}{2}$$
$$= \frac{1}{\binom{n}{2}} \cdot \Theta(n^4)$$

$$\begin{aligned}
 \frac{1}{\binom{n}{2}} \cdot \sum_{\alpha=1}^{\binom{n}{2}} \alpha &= \frac{1}{\binom{n}{2}} \cdot \frac{\binom{n}{2} \left[ \binom{n}{2} + 1 \right]}{2} \\
 &= \frac{1}{\binom{n}{2}} \cdot \Theta(n^4) \\
 &= \frac{1}{\Theta(n^2)} \cdot \Theta(n^4)
 \end{aligned}$$

$$\begin{aligned}
\frac{1}{\binom{n}{2}} \cdot \sum_{\alpha=1}^{\binom{n}{2}} \alpha &= \frac{1}{\binom{n}{2}} \cdot \frac{\binom{n}{2} \left[ \binom{n}{2} + 1 \right]}{2} \\
&= \frac{1}{\binom{n}{2}} \cdot \Theta(n^4) \\
&= \frac{1}{\Theta(n^2)} \cdot \Theta(n^4) \\
&= \Theta(n^2)
\end{aligned}$$

## ***Average Case***

- The average case time complexity of find\_movies is  $\Theta(n^2)$ .
- Same as the **worst** case!

## ***Note***

- We've seen two algorithms where the average case = the worst case.
- Not *a/ways* the case!
- Interpretation: the worst case is not too extreme.



# ***Thank you!***

**Do you have any questions?**

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