tripadvisor®

# Recommending the Best Hotels at TripAdvisor

**Anyi Wang,**
anwang@tripadvisor.com

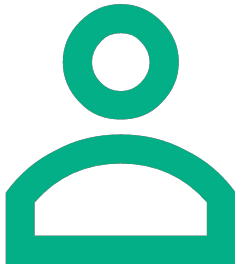
Machine Learning at Tripadvisor

# About TripAdvisor

TripAdvisor is the world's largest travel site*

tripadvisor®

know better ◉ book better ◉ go better



**455M**
**average unique monthly visitors ****

**49**
**Markets Worldwide**

**570M**
**Reviews and Opinions**

**7M**
**Accommodations, Restaurants and Attractions**

*Source: comScore Media Metrix for TripAdvisor Sites, worldwide, March 2017
** Source: TripAdvisor log files, Q3 2017

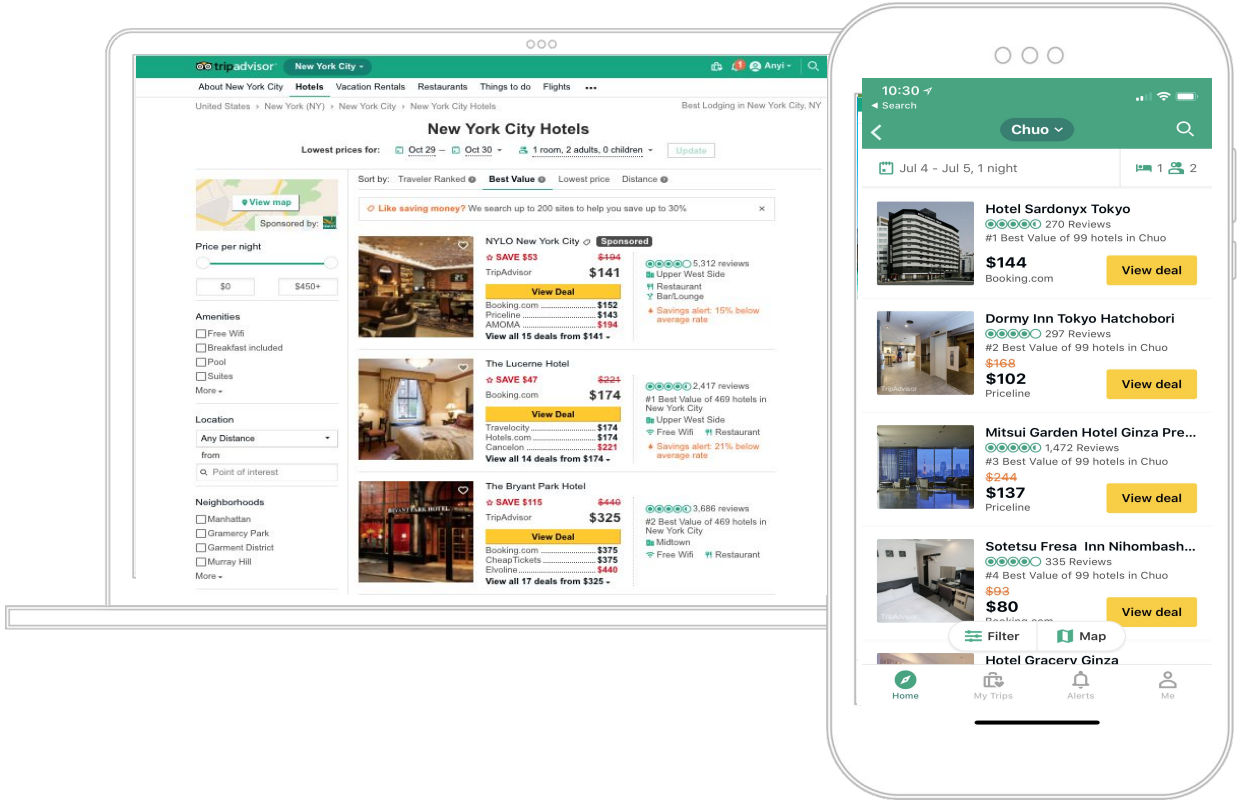
# TripAdvisor Machine Learning Group

- Review Fraud Detection
- Recommender Systems
- Bot detection
- Booking / Content models
- Machine Vision
- Search Result Ranking
- Automated Collection Generation
- Keyphrase Generation
- Location Classification

**Blog: engineering.tripadvisor.com**

Recommending the Best Hotel

# Hotel Sorting



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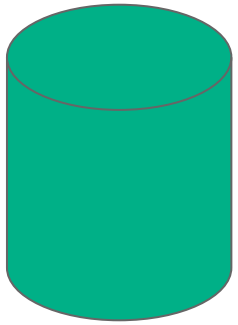
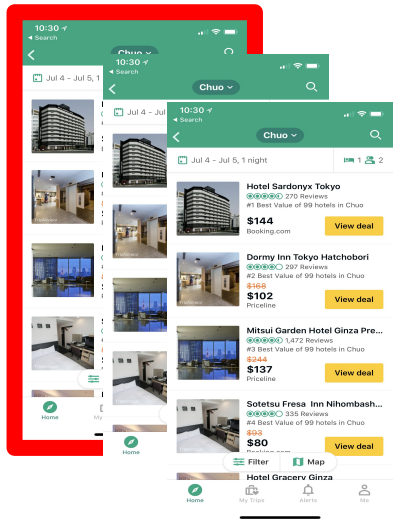


***Documents***

$D = \{d1, d2, \ldots dn\}$



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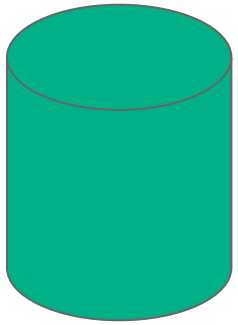

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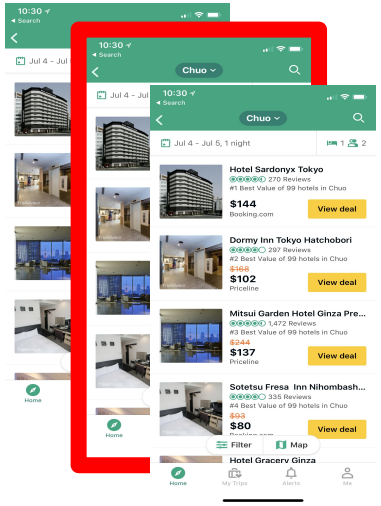

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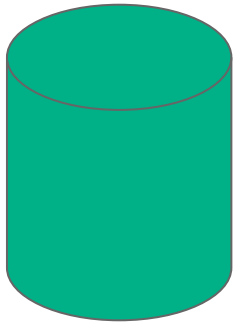

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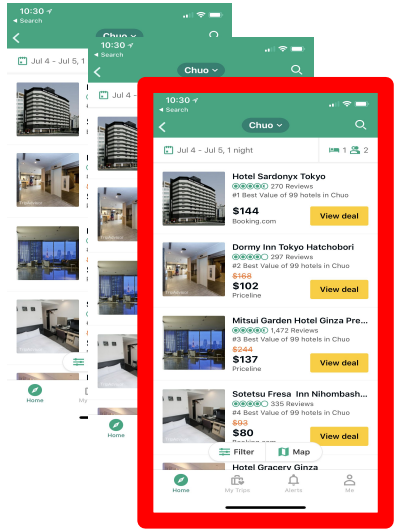

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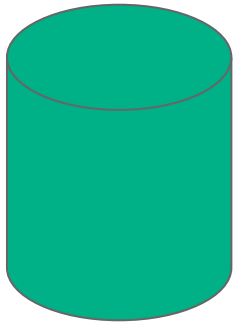

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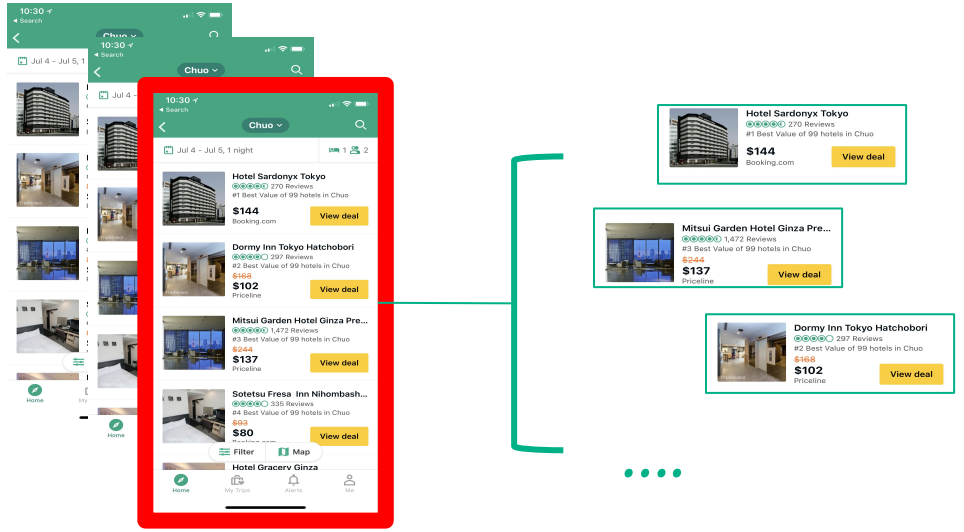


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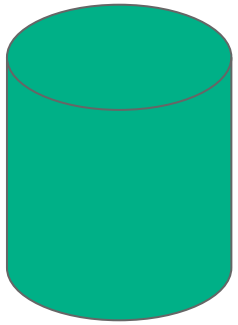

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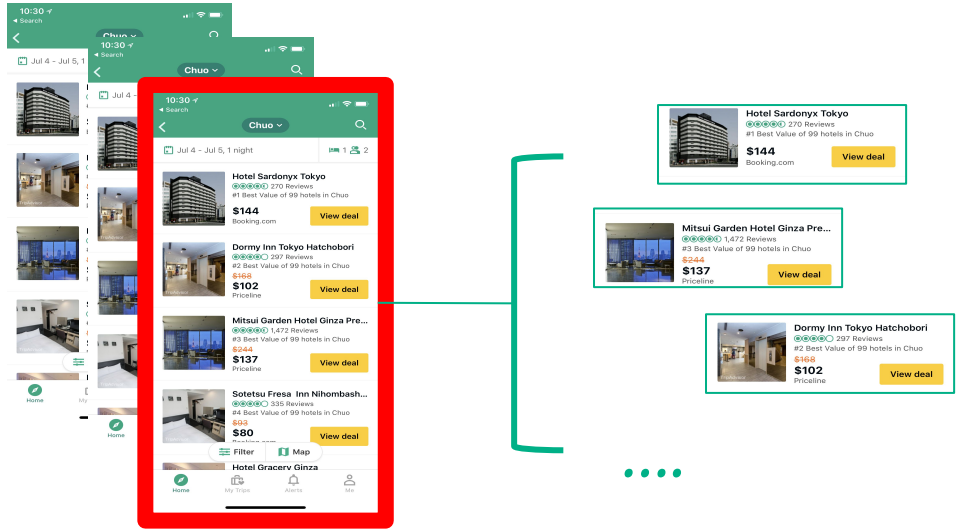


*query q*

*relevance score*

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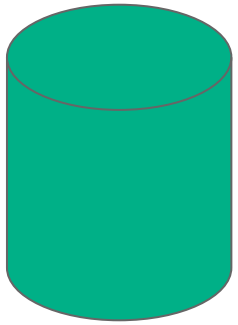

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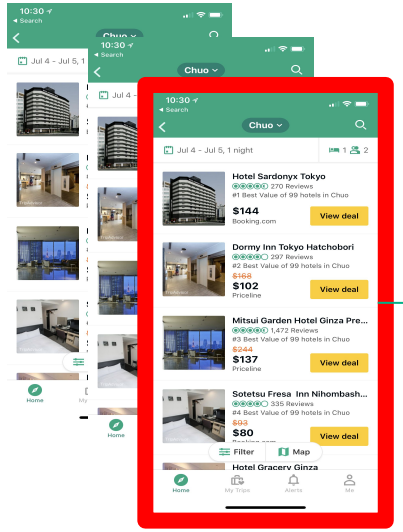


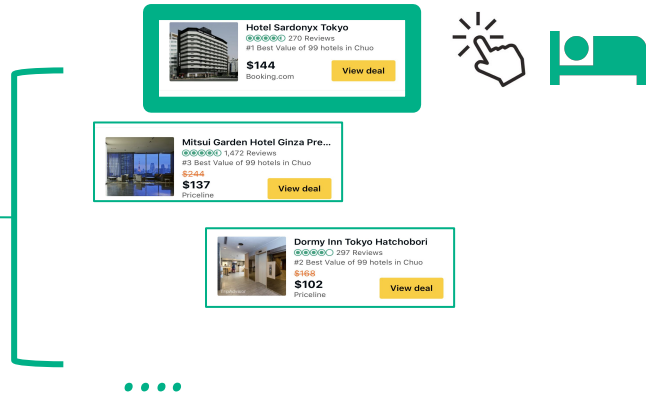


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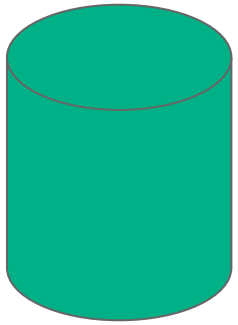

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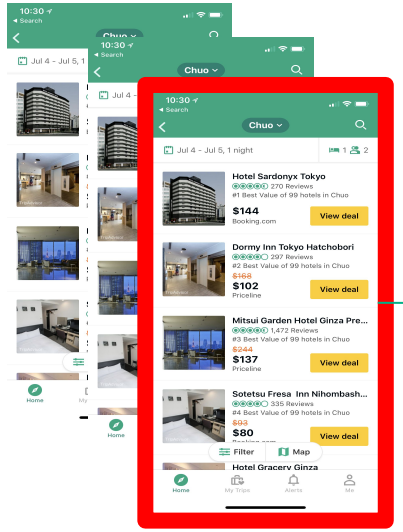


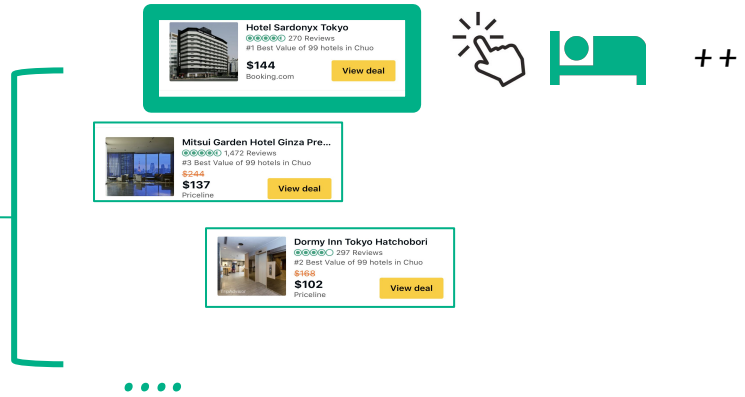


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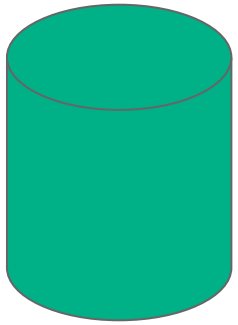

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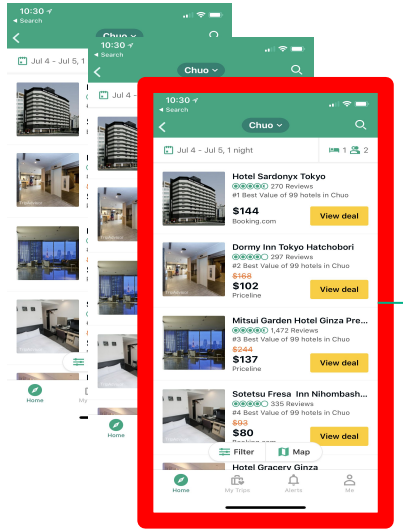

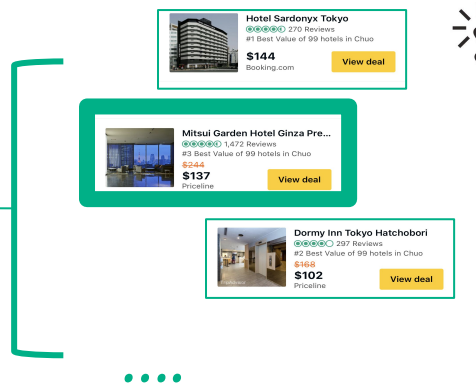

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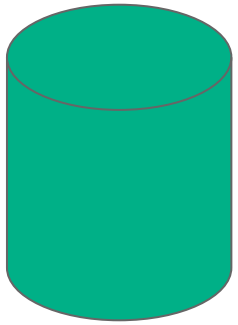

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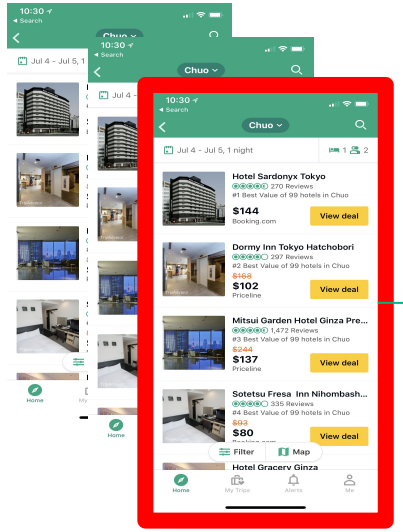

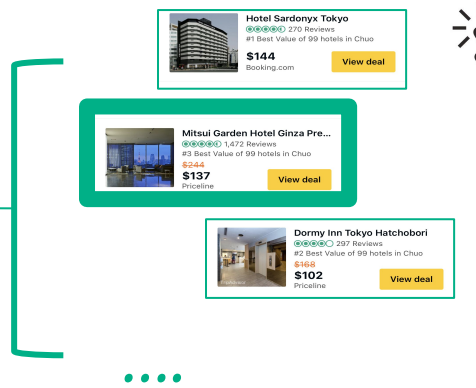

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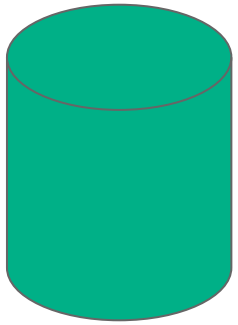

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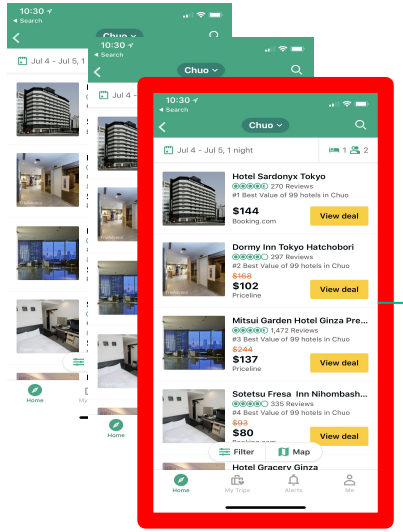


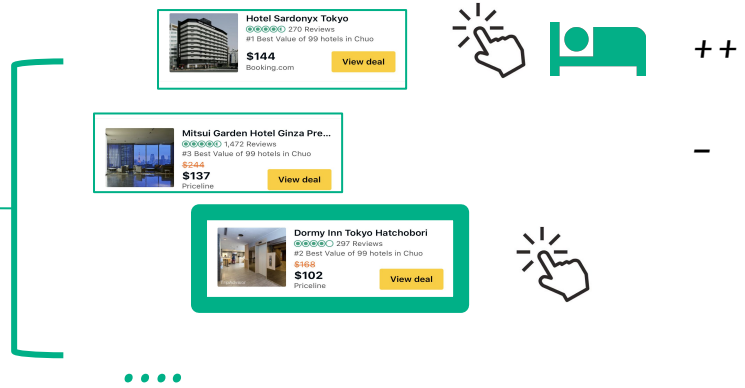


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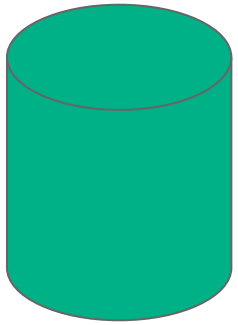

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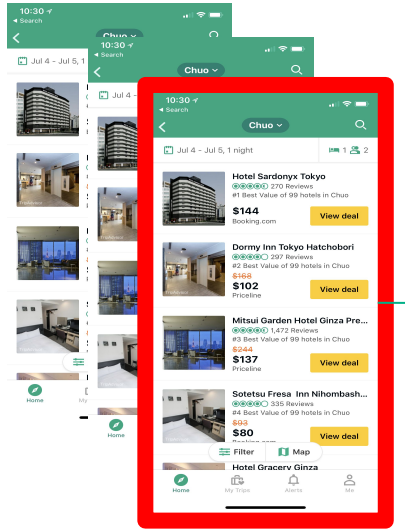


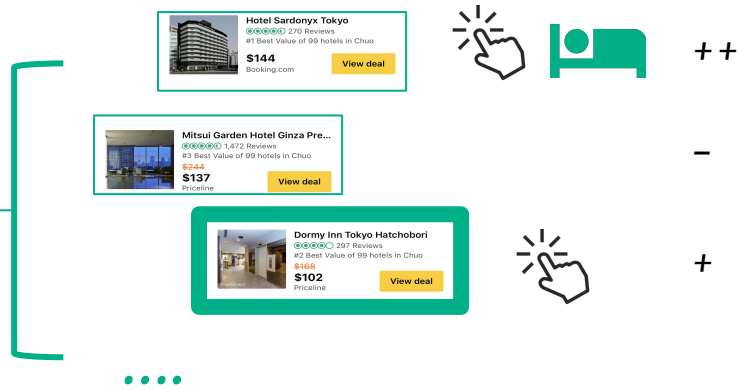


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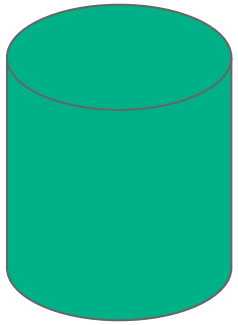

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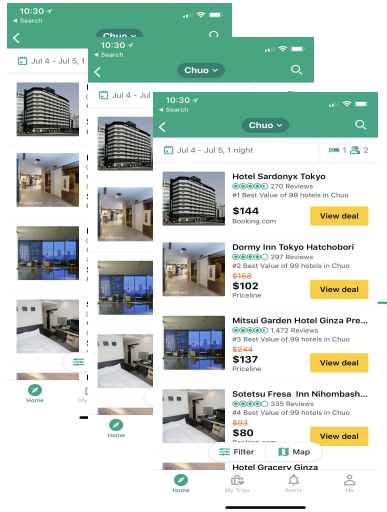

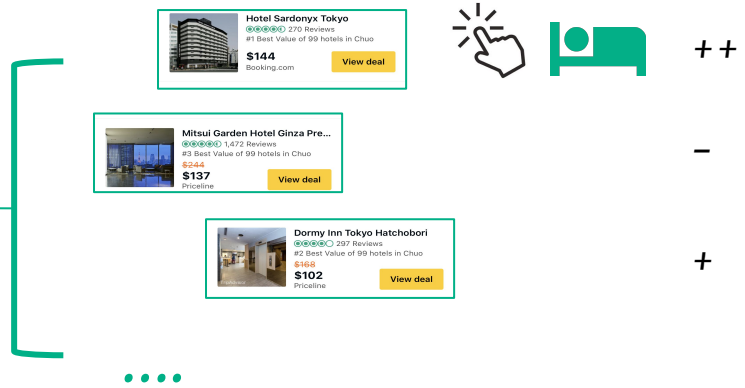


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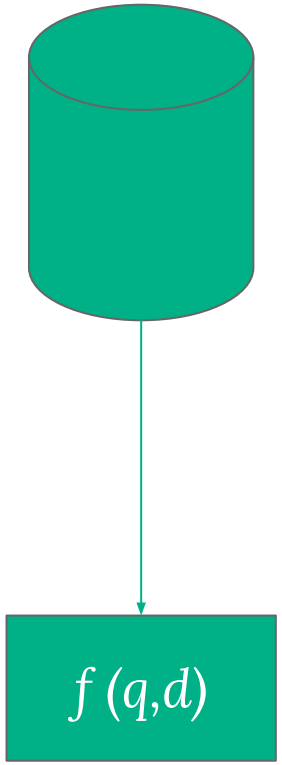


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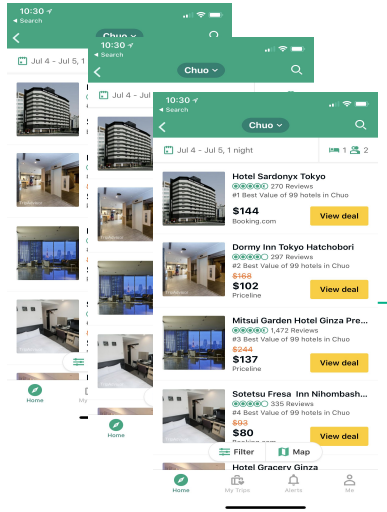

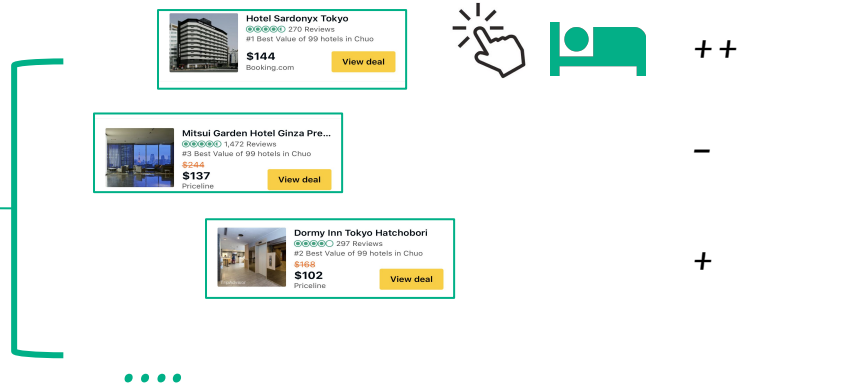


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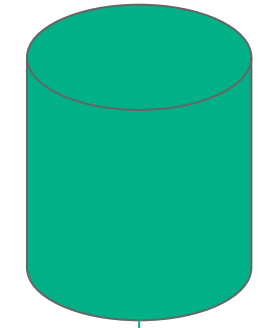

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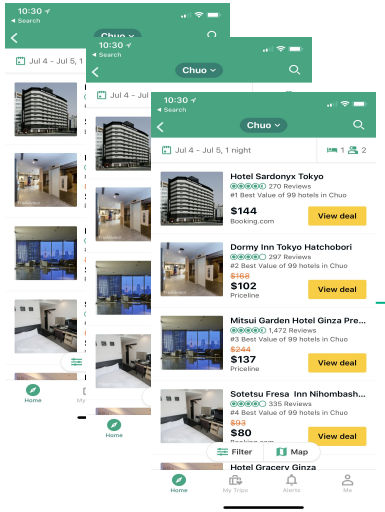

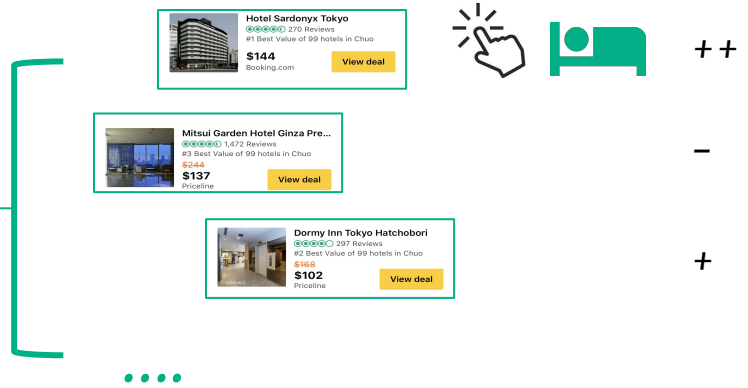


*query q*

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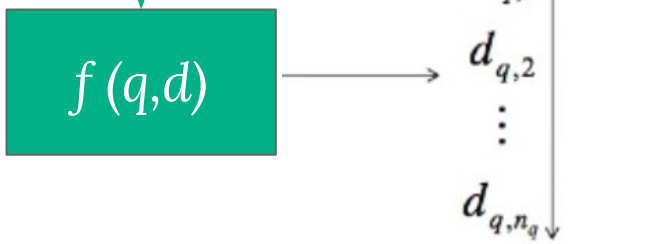

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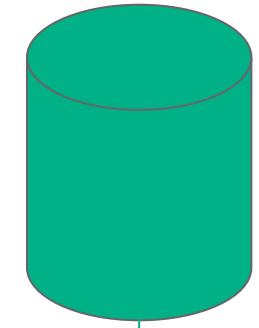

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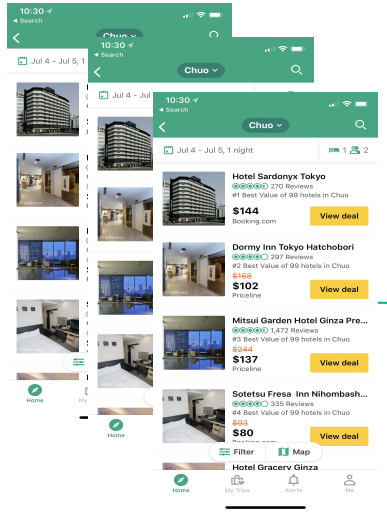

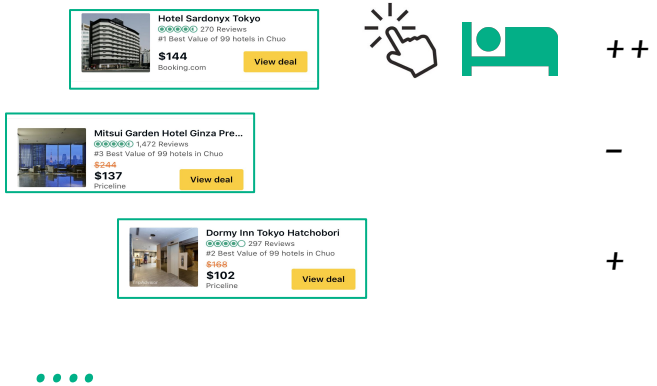


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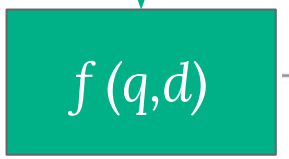
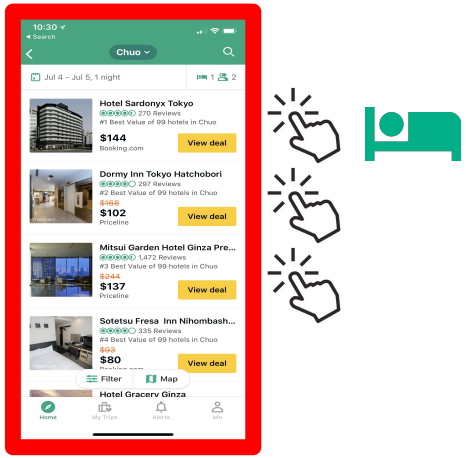



ranking of documents

$d_{q,1}$

$d_{q,2}$

$d_{q,n_q}$



# Mean Average Precision

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$$\mathrm{AP} = \sum_{k=1}^{N} p(k)\Delta r(k)$$

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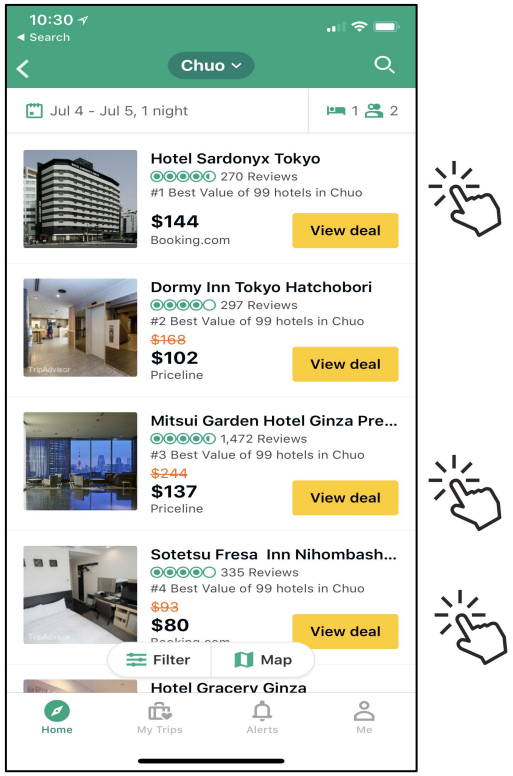


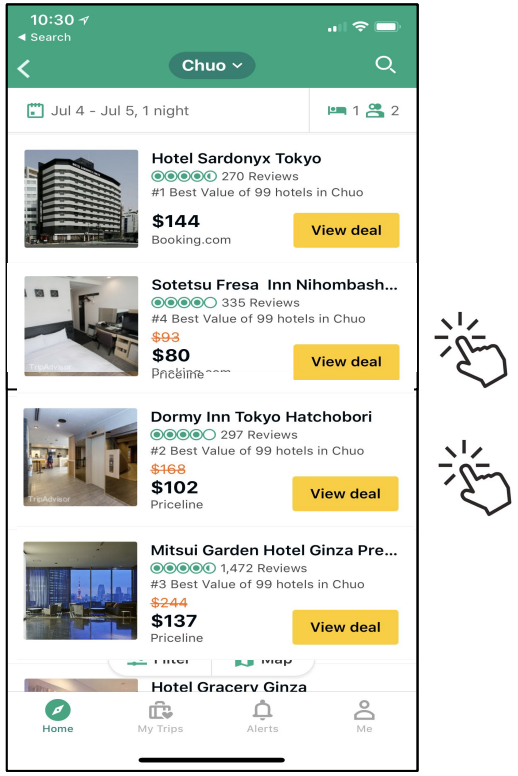

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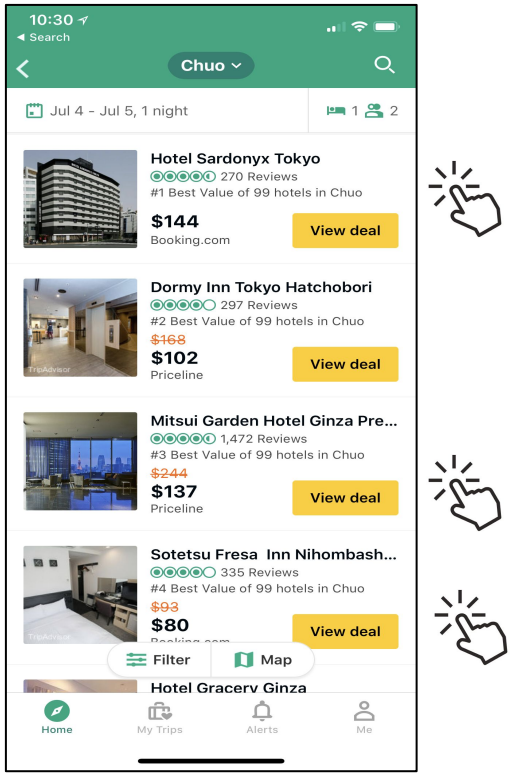
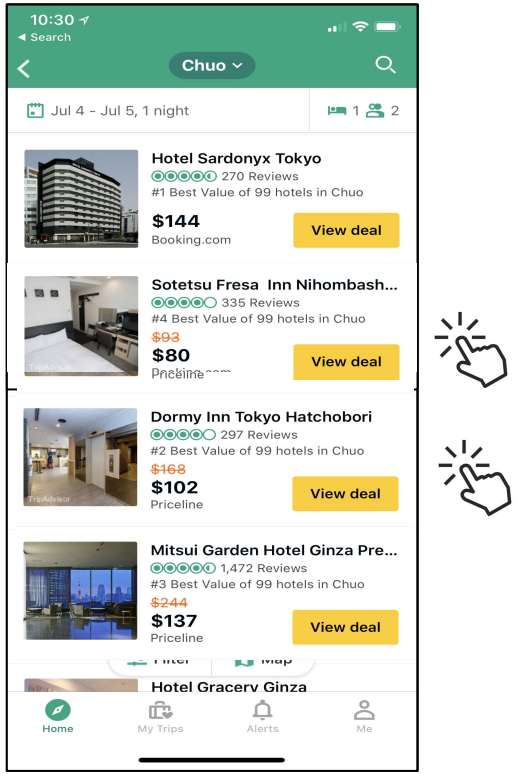



**Precision**

1.0



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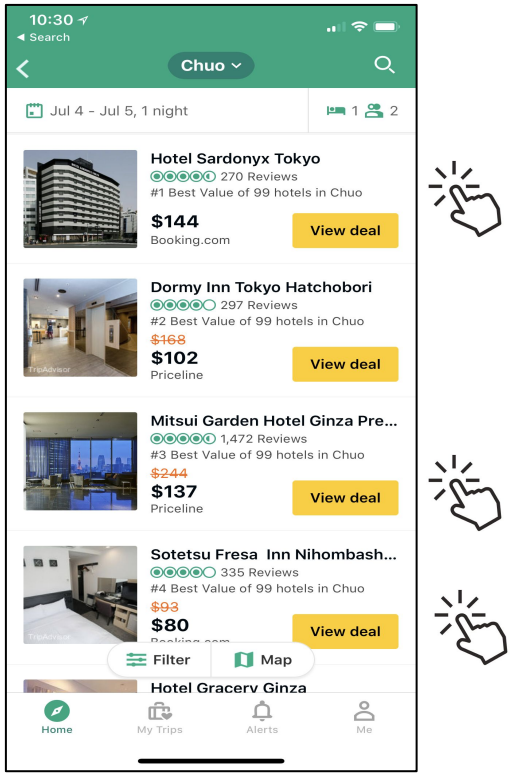
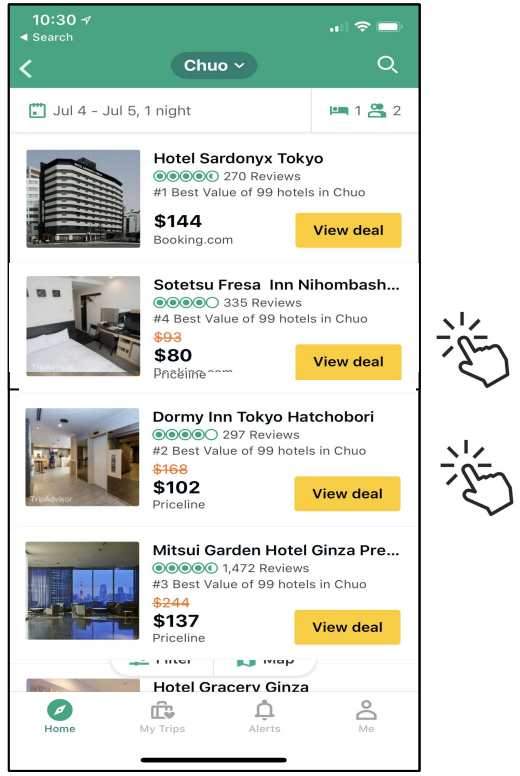



**Precision**

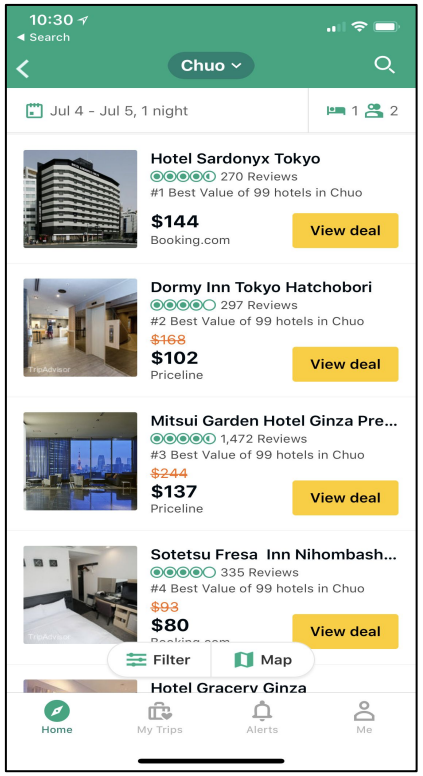
1.0

0.5



# Mean Average Precision

$$\mathrm{AP} = \sum_{k=1}^{N} p(k)\Delta r(k)$$

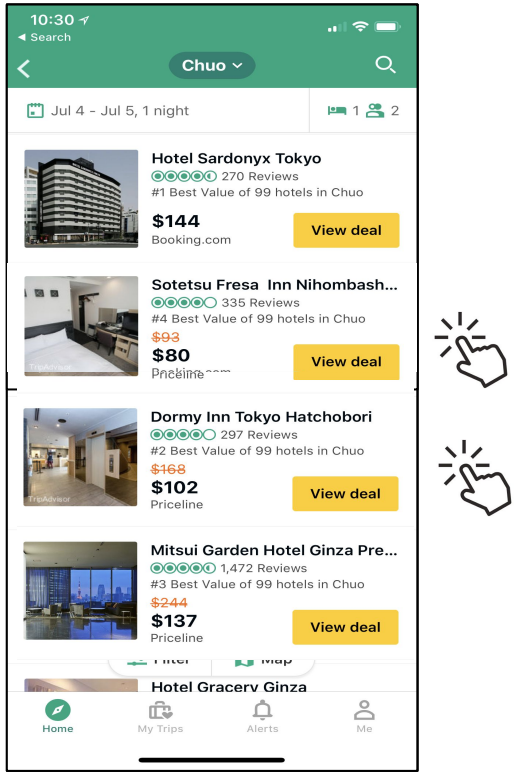



**Precision**

1.0

0.5

0.67



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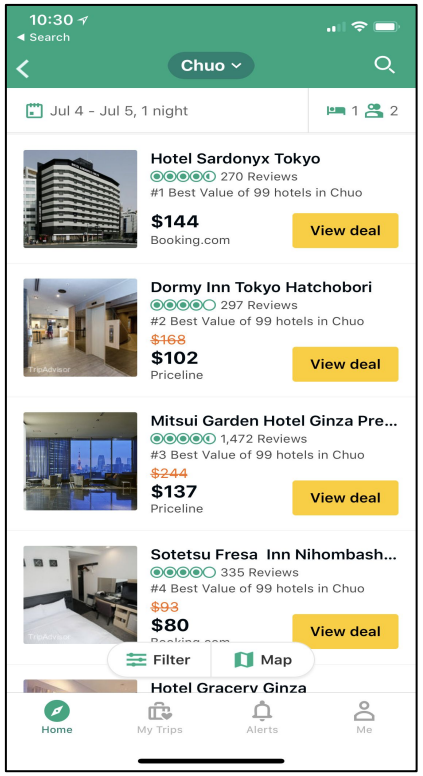


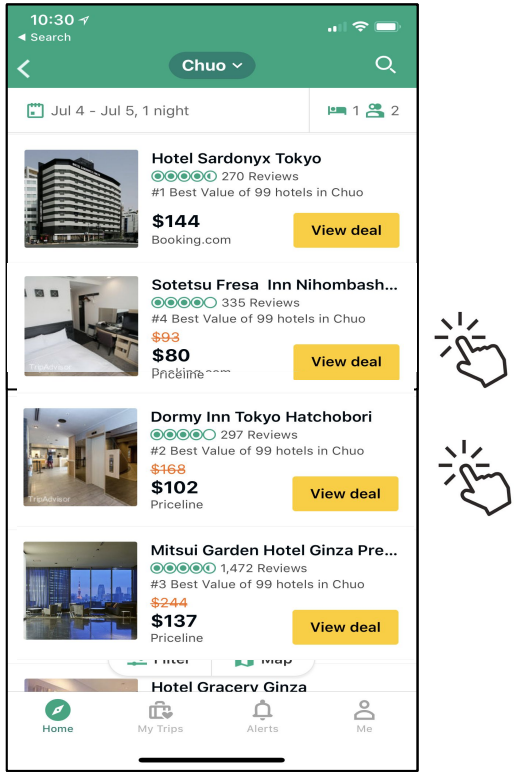

**Precision**

1.0

0.5

0.67

0.75



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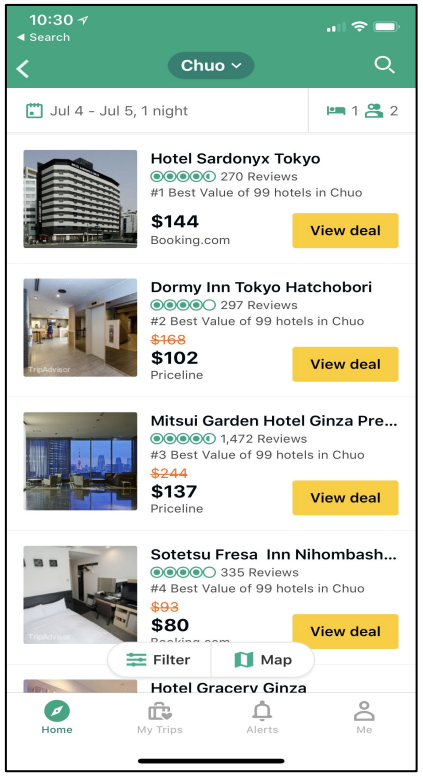


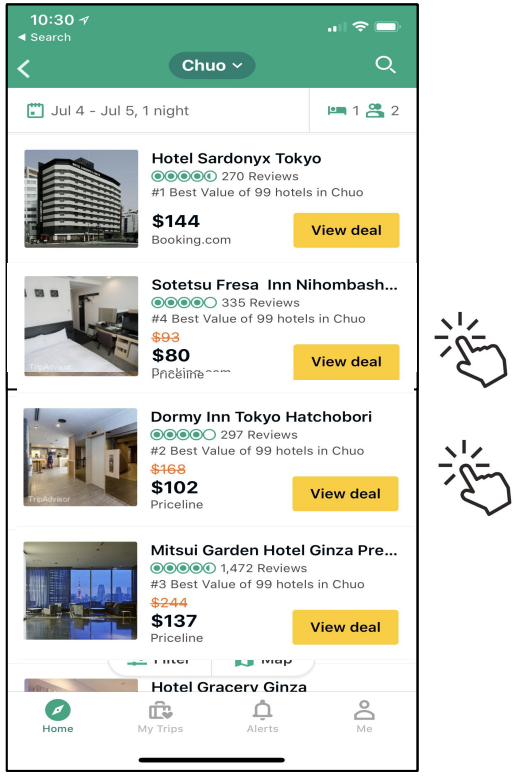

**Precision**

1.0

0.5

0.67

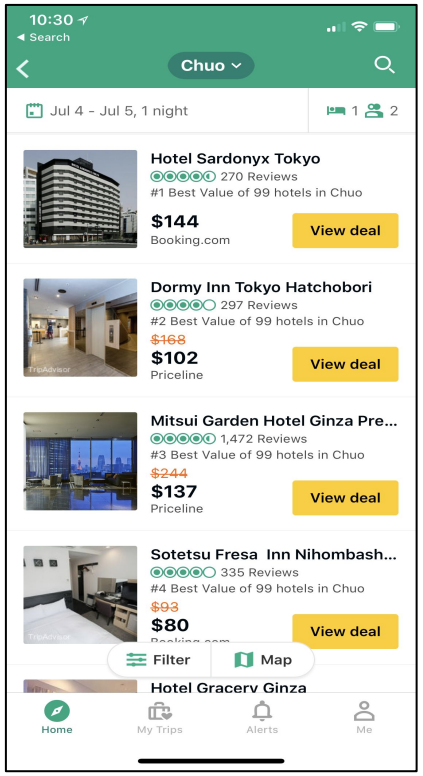
0.75




AP = (1 + 0.67 + 0.75) / 3 = 0.80

# Mean Average Precision

$$\mathrm{AP} = \sum_{k=1}^{N} p(k)\Delta r(k)$$



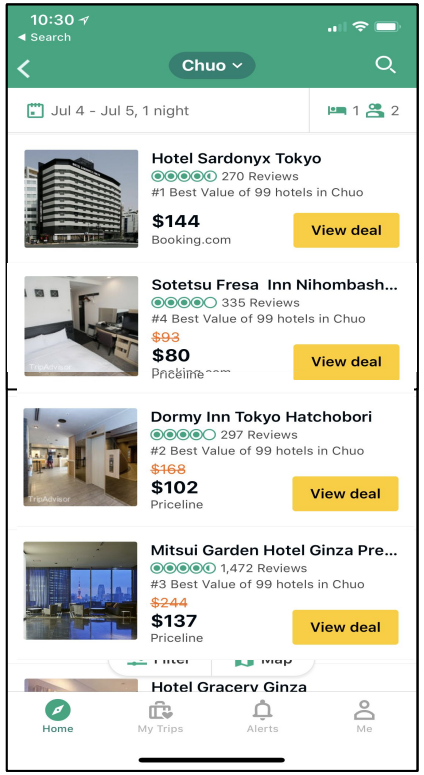

**Precision**

1.0

0.5

0.67

0.75



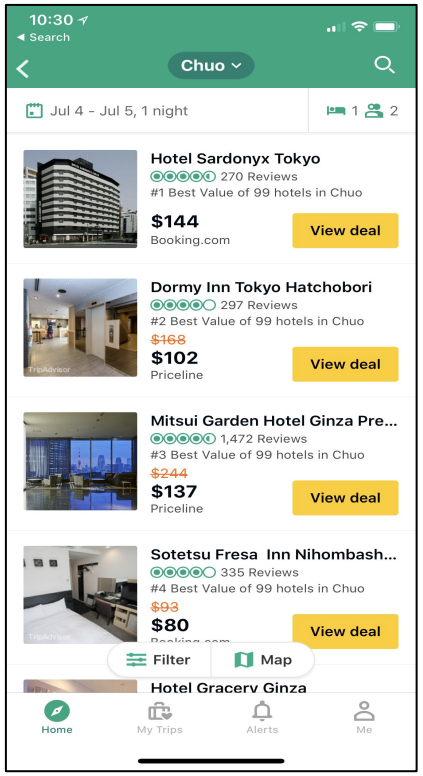

**Precision**

0

AP = (1 + 0.67 + 0.75) / 3 = 0.80

# Mean Average Precision

$$\mathrm{AP} = \sum_{k=1}^{N} p(k)\Delta r(k)$$



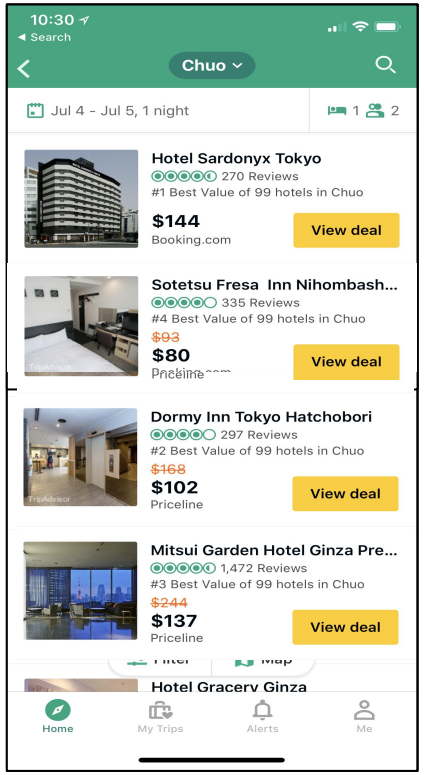

**Precision**

1.0

0.5

0.67

0.75




**Precision**

0

0.5

AP = (1 + 0.67 + 0.75) / 3 = 0.80

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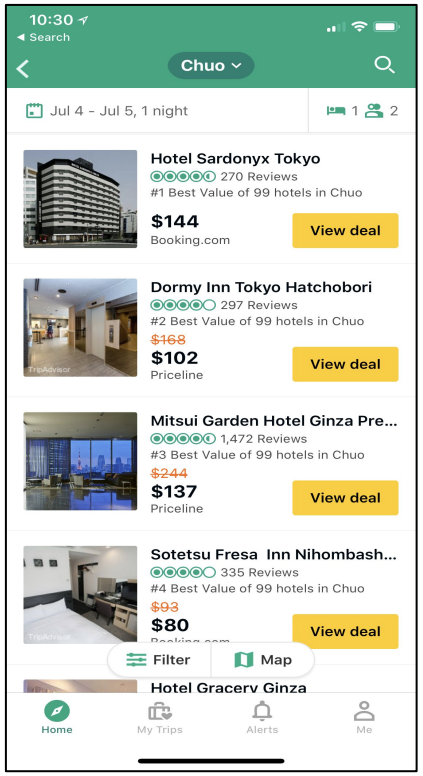


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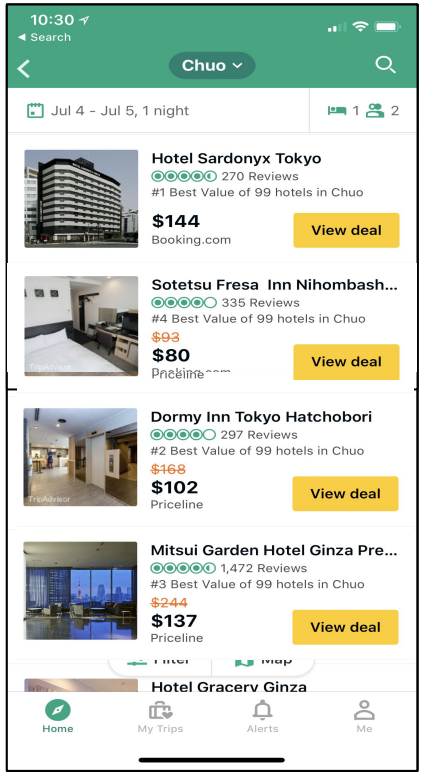


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0

0.5

0.67

AP = (1 + 0.67 + 0.75) / 3 = 0.80

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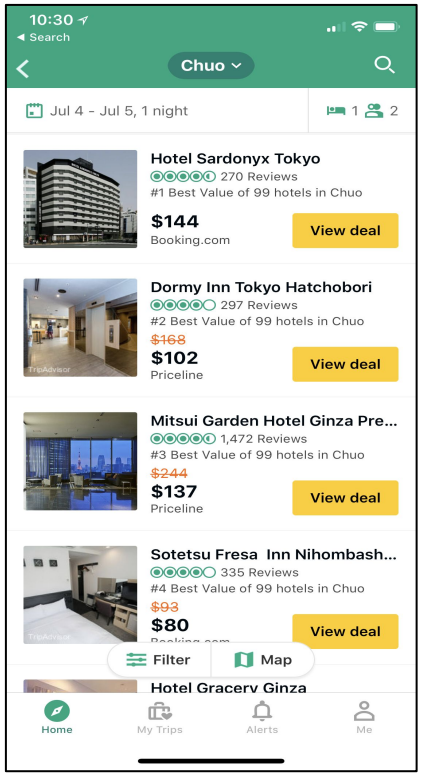


**Precision**

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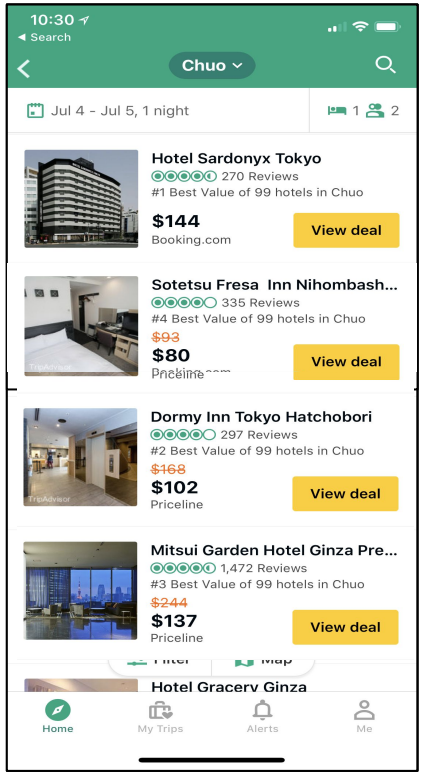
0.5

0.67

0.75




**Precision**

0

0.5

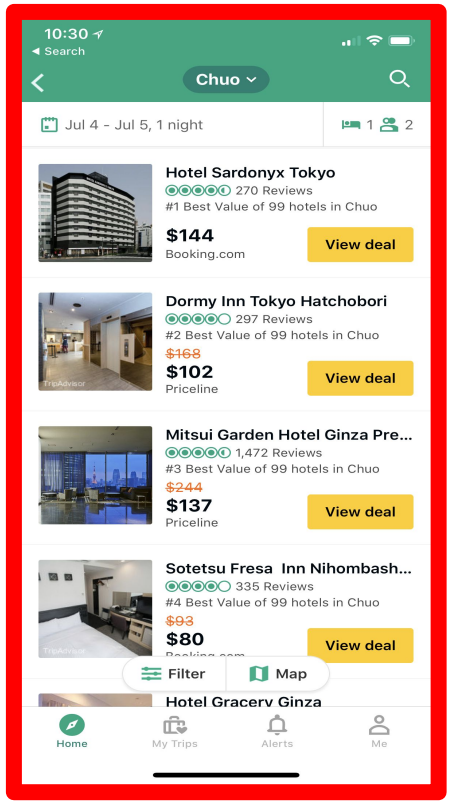
0.67

0.5

AP = (1 + 0.67 + 0.75) / 3 = 0.80

# Mean Average Precision

$$\mathrm{AP} = \sum_{k=1}^{N} p(k)\Delta r(k)$$




**Precision**

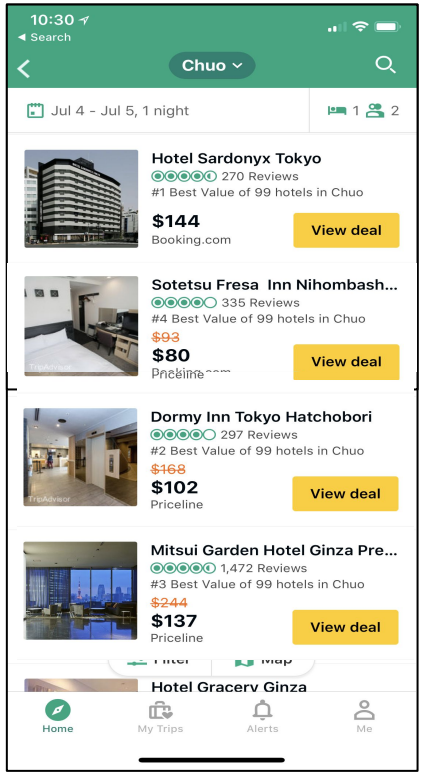
1.0

0.5

0.67

0.75

AP = (1 + 0.67 + 0.75) / 3 = 0.80




**Precision**

0

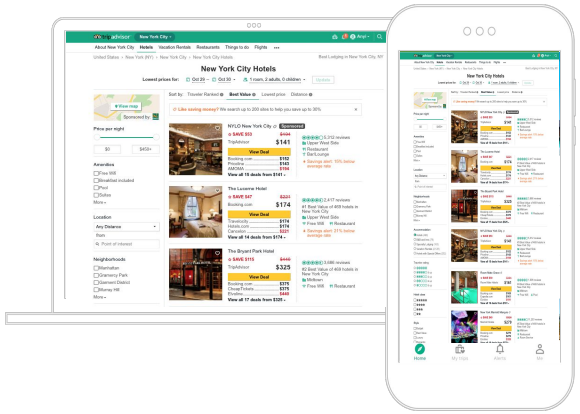
0.5

0.67

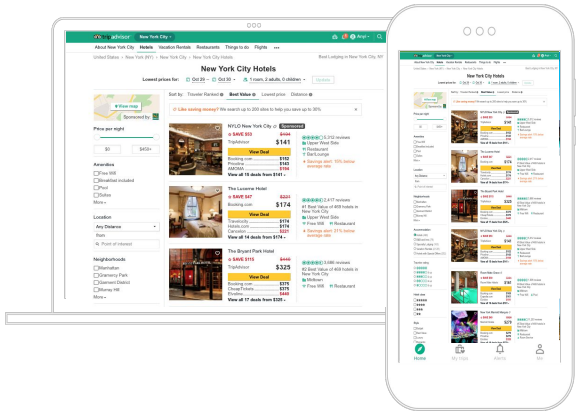
0.5

AP = ( 0.5 + 0.67) / 2 = 0.585

# Hotel Sorting - Features

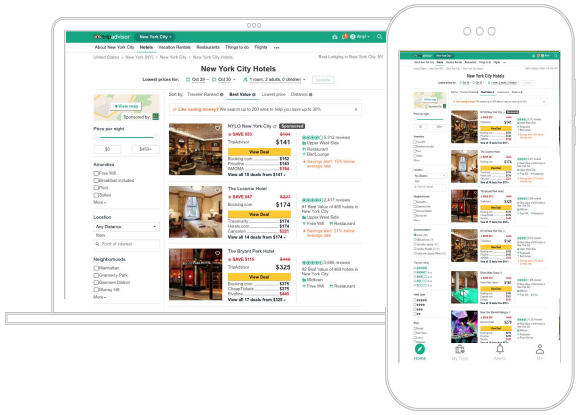


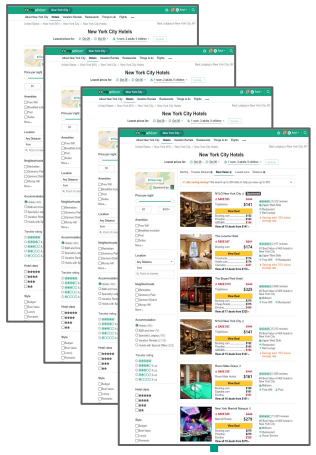
# Hotel Sorting - Features



Impression
Meta Data

# Hotel Sorting - Features

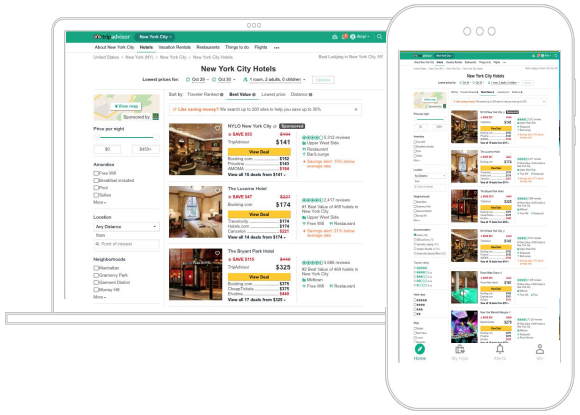


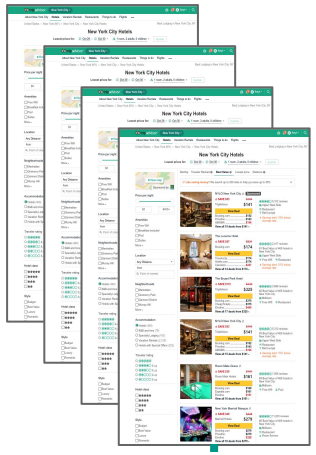


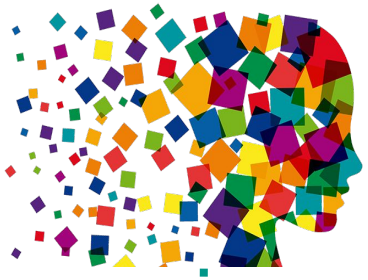
Impression
Meta Data

Location Level
Look Back Data

# Hotel Sorting - Features







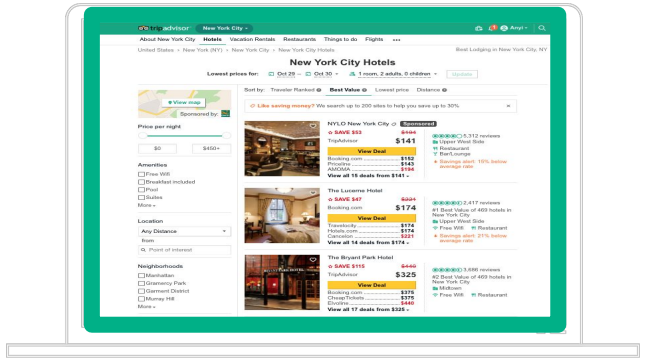
Impression Meta Data

Location Level Look Back Data

User Related Meta Data

# Linear CTR Model

# Linear CTR Model



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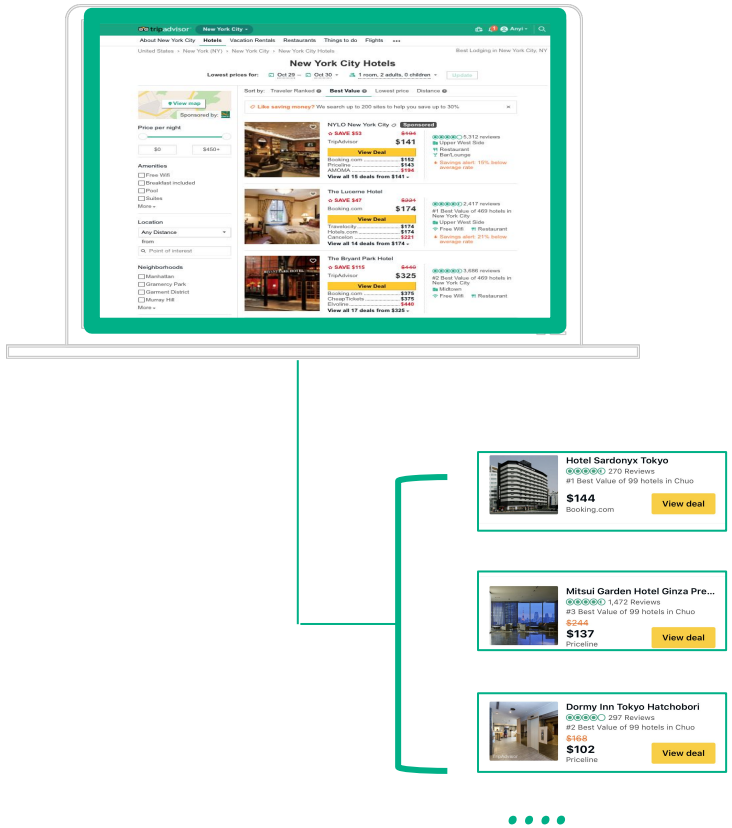

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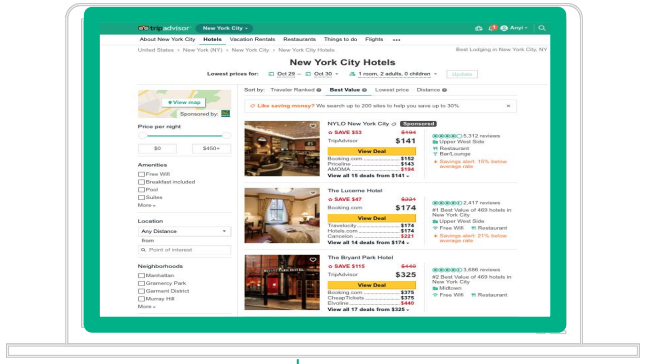


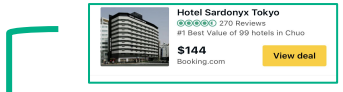


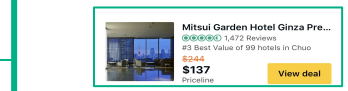


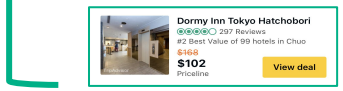

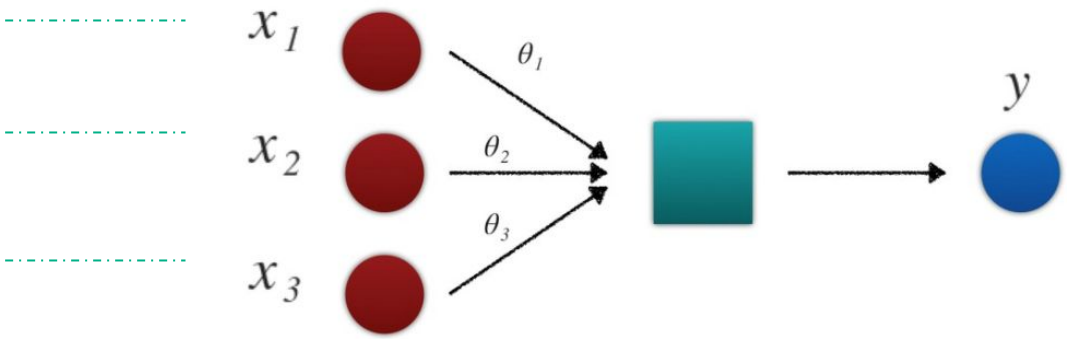

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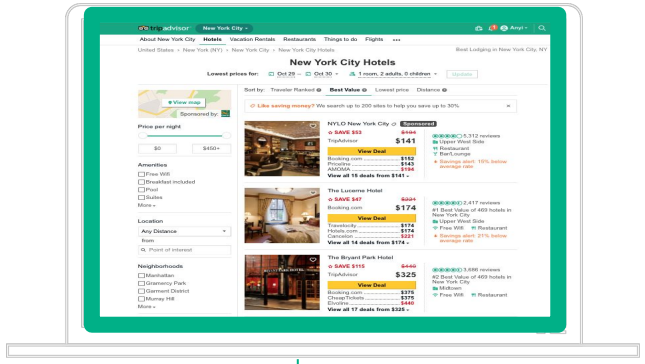
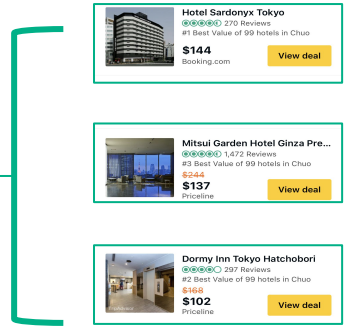
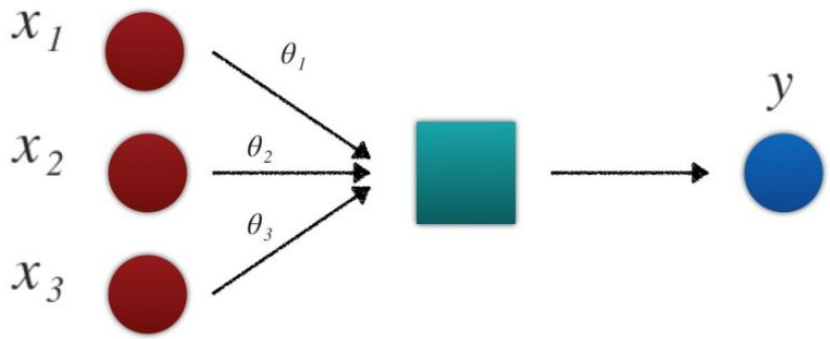



For every hotel, the model predicts CTR(click through rate) based on different feature values



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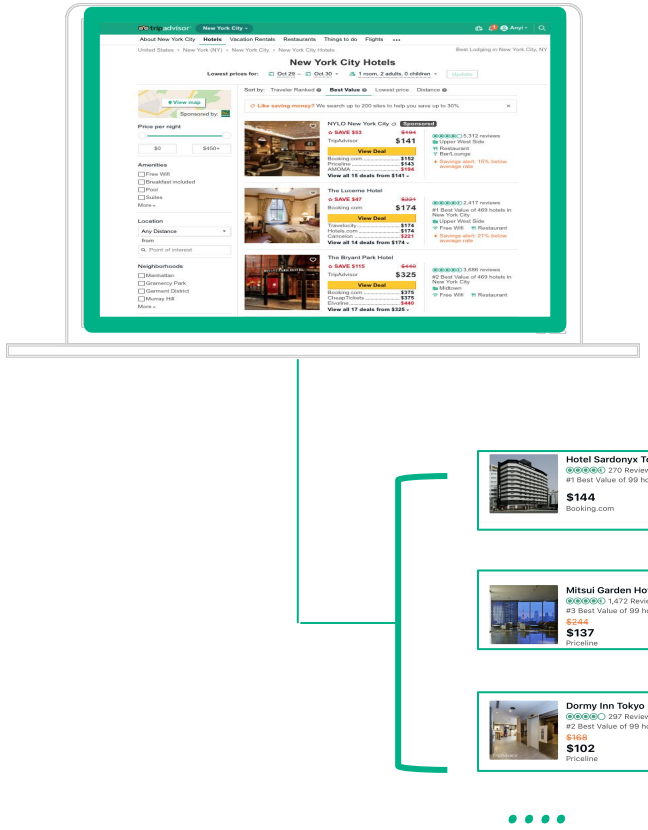


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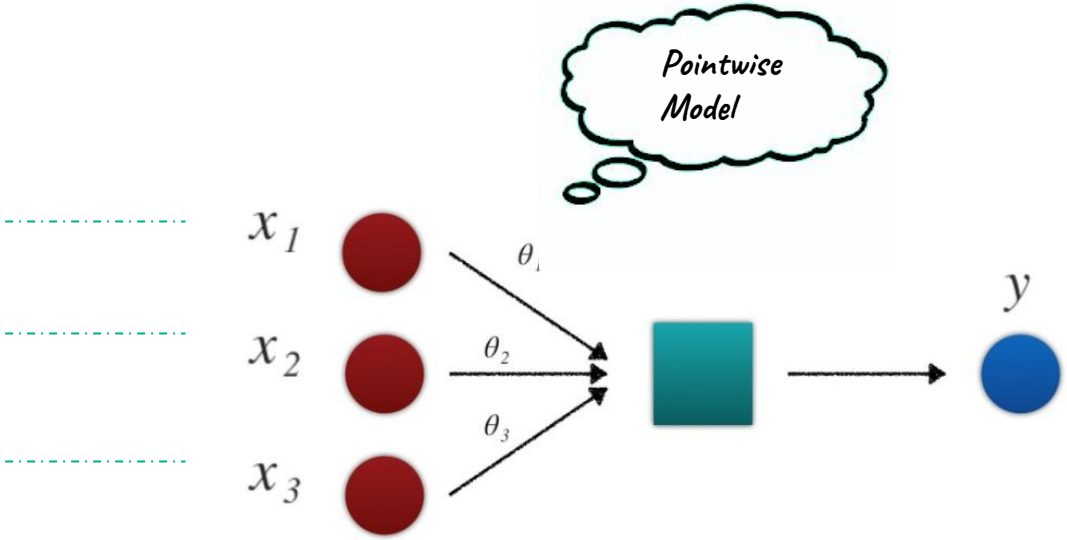

# Position Matters

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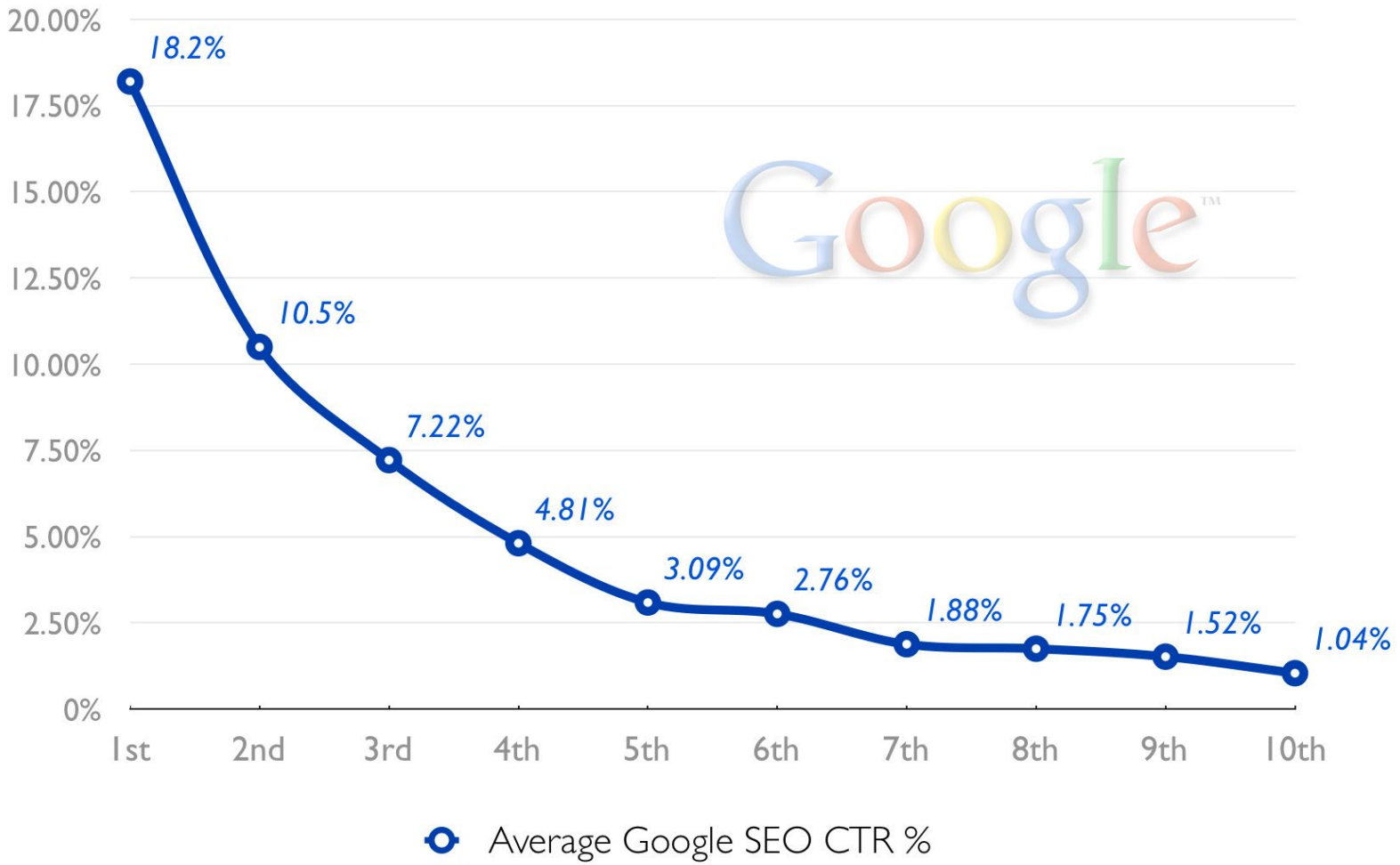
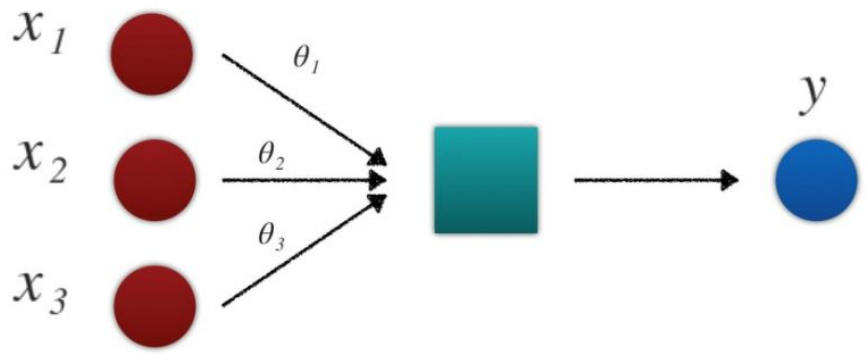


# Getting rid of position factor

Impression Meta Data

Location Level Look Back Data

User Related Meta Data



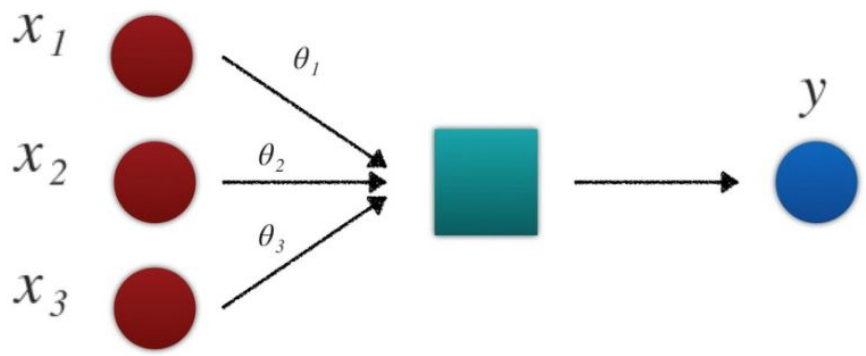
# Getting rid of position factor

Impression Meta Data

Location Level Look Back Data

User Related Meta Data

Position in list



# Problems of pointwise model

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**User not sensitive to price in some travel destination?**

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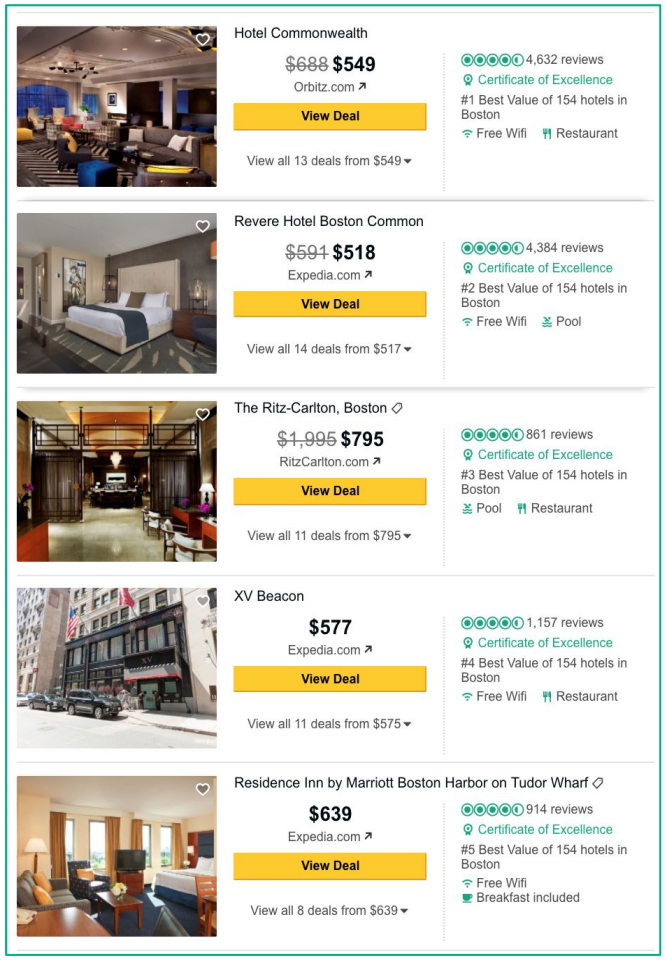
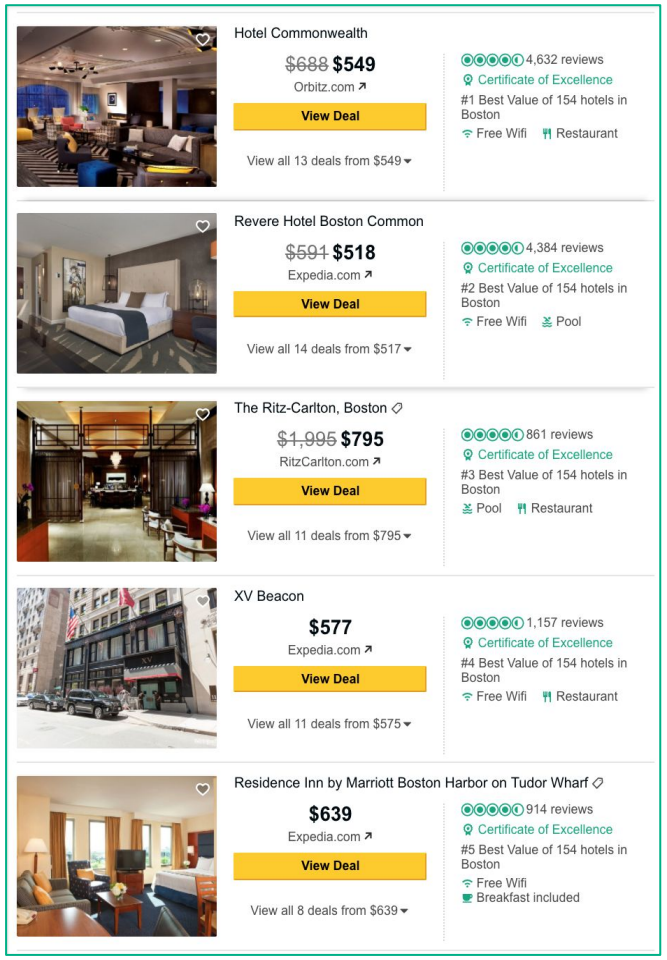


# Problems of pointwise model

**User not sensitive to price in some travel destination?**

**Price only matters within context !**



# Problems of pointwise model

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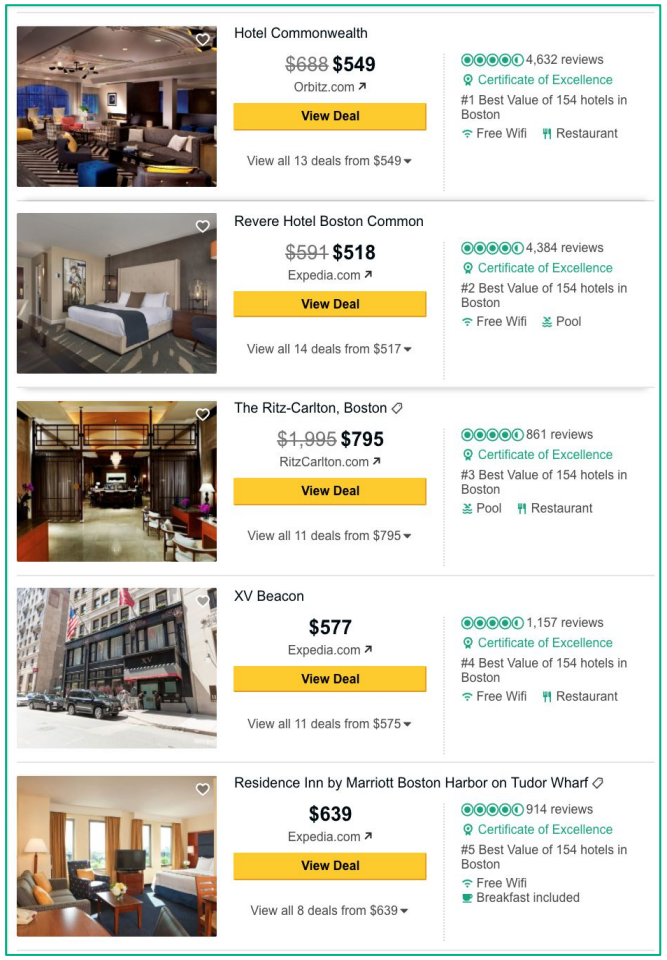
*Previous Model Bias?*



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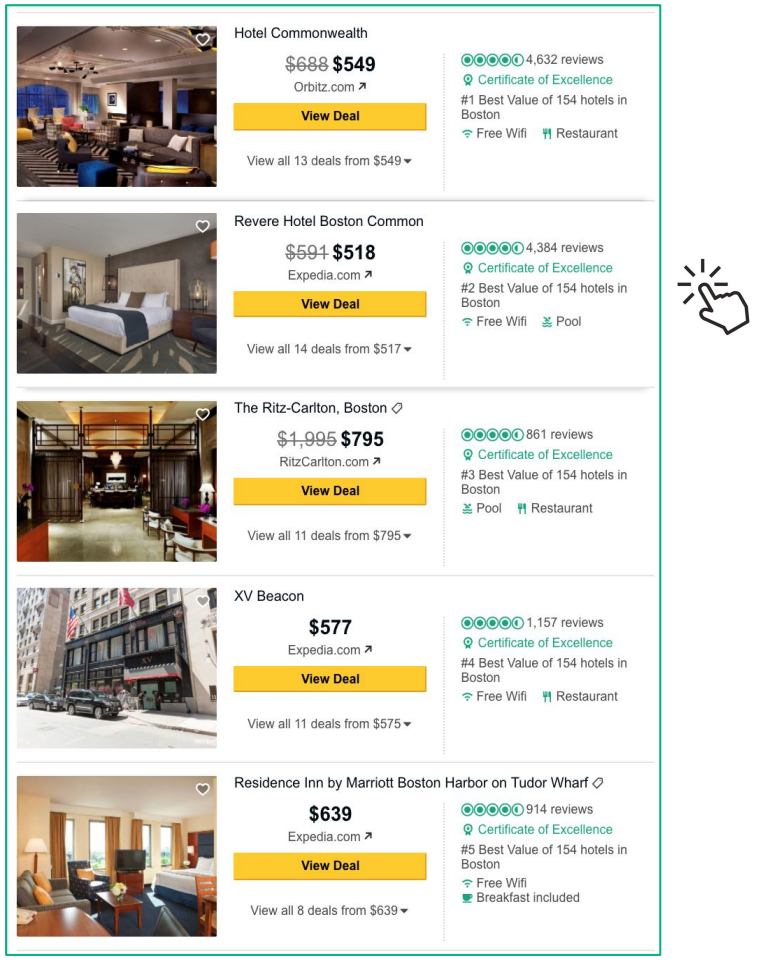
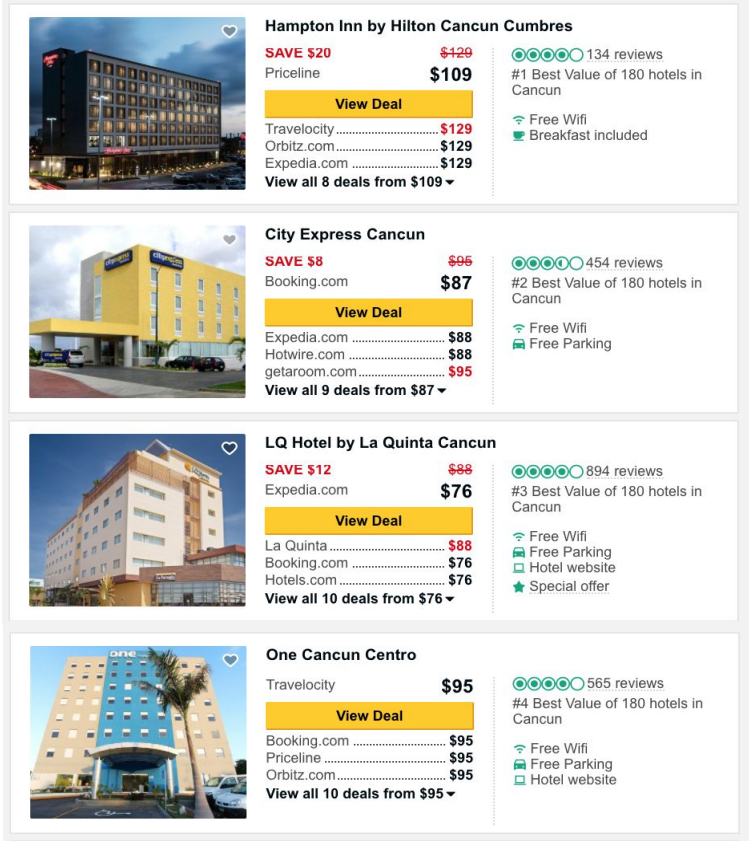


# Problems of pointwise model

**CTR negatively correlated to popularity score generated by user review**

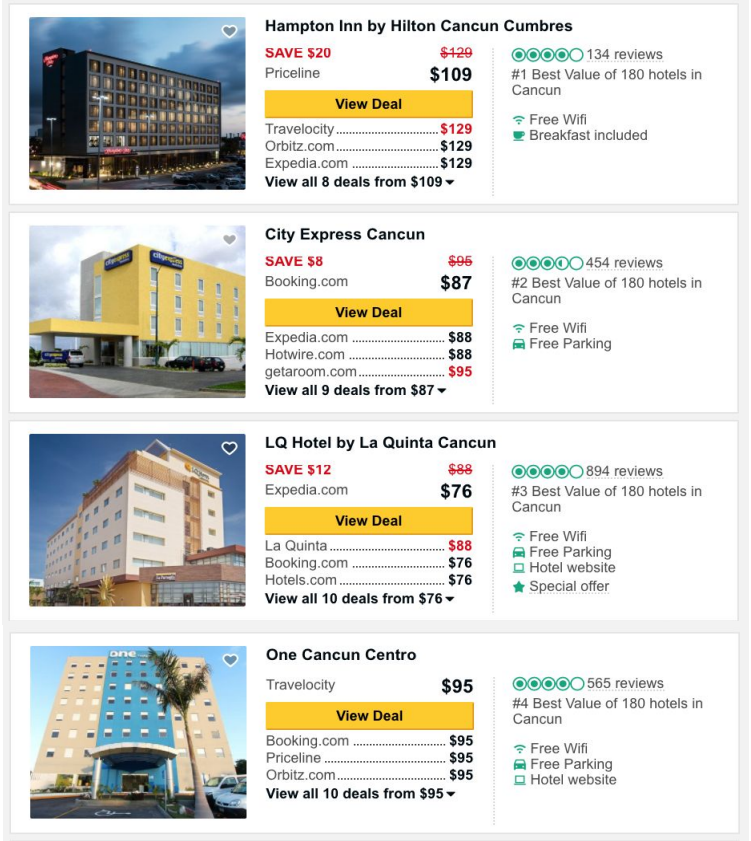
# Problems of pointwise model

CTR negatively correlated to popularity score generated by user review



# Problems of pointwise model

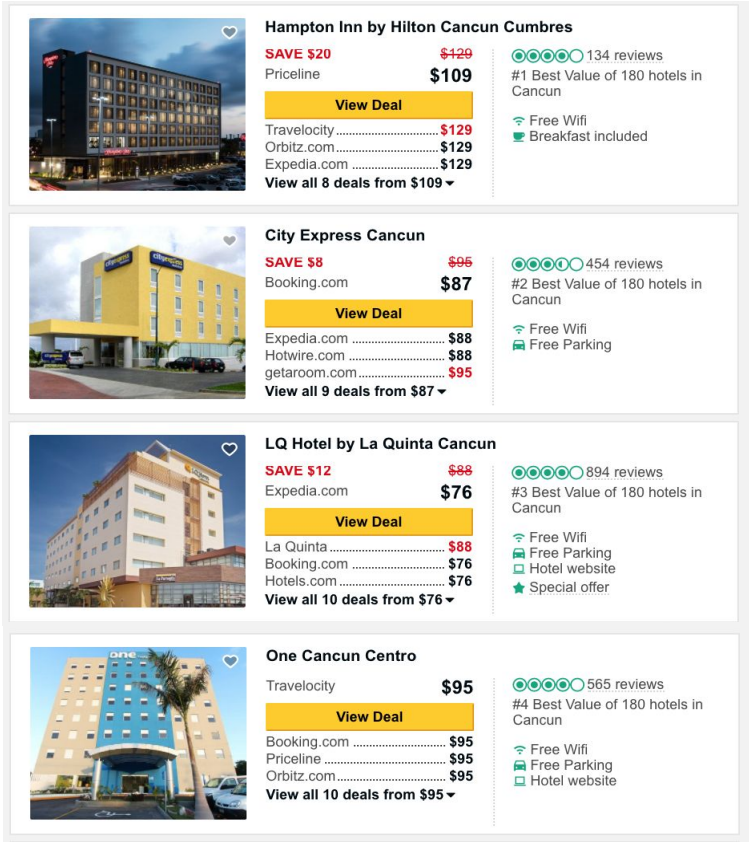
**CTR negatively correlated to popularity score generated by user review**



# Problems of pointwise model

CTR negatively correlated to popularity score generated by user review

**Popularity is sensitive to availability!**



# Problems of pointwise model

**Has the user actually seeing the hotel on the page?**

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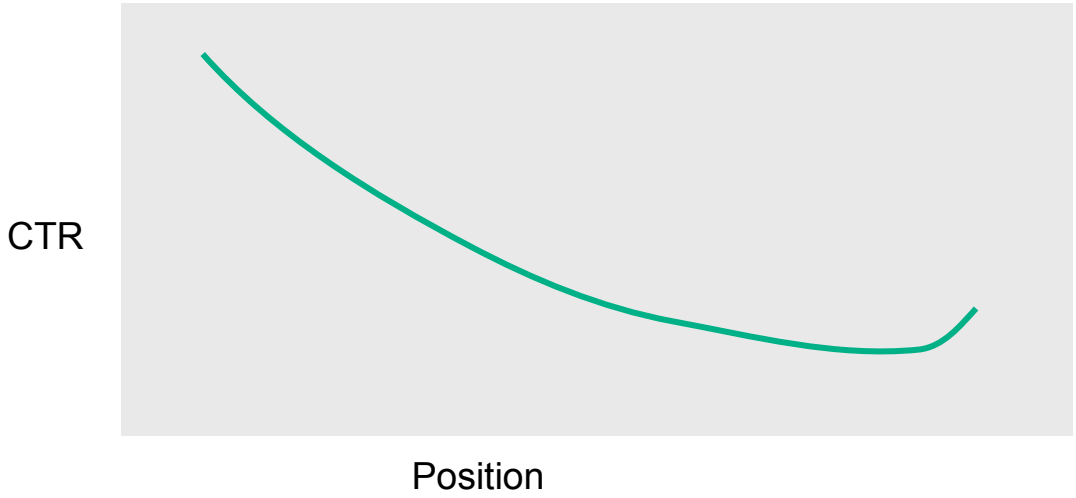


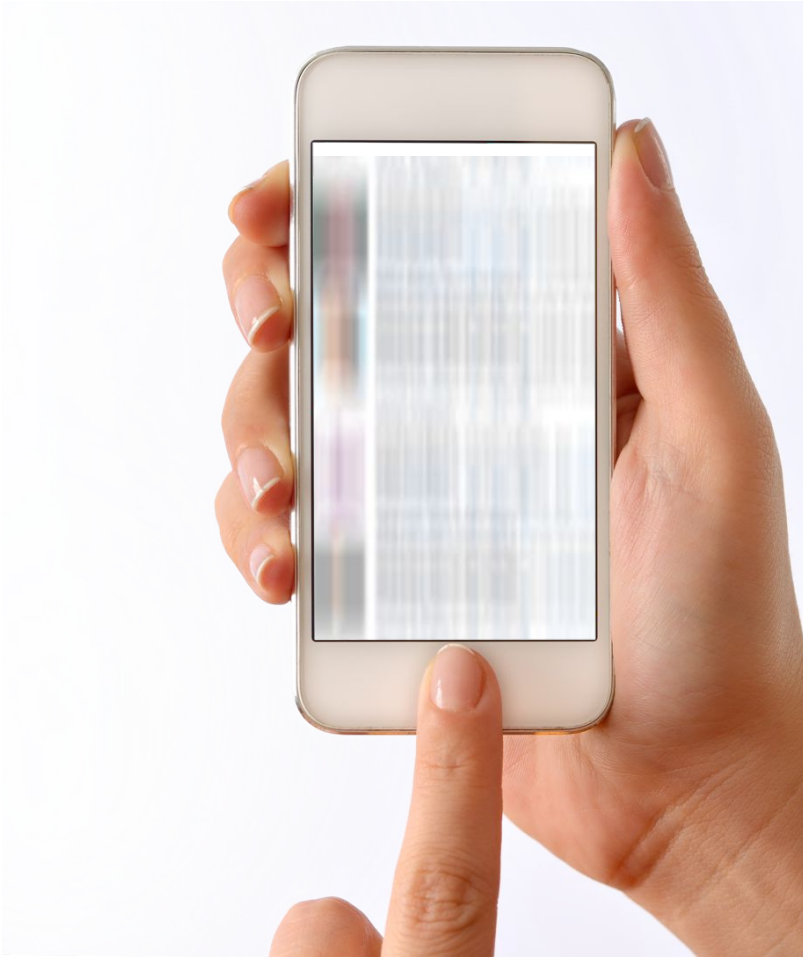

# Getting rid of position factor

**User not sensitive to price in some travel destination**

**Pointwise**

**CTR negatively correlated to popularity score**

**Has the user actually seeing the hotel on the page?**

# Getting rid of position factor

User not sensitive to price in some travel destination

CTR negatively correlated to popularity score

Has the user actually seeing the hotel on the page?

Pointwise

↓

Pairwise

# Pairwise Learning to Rank

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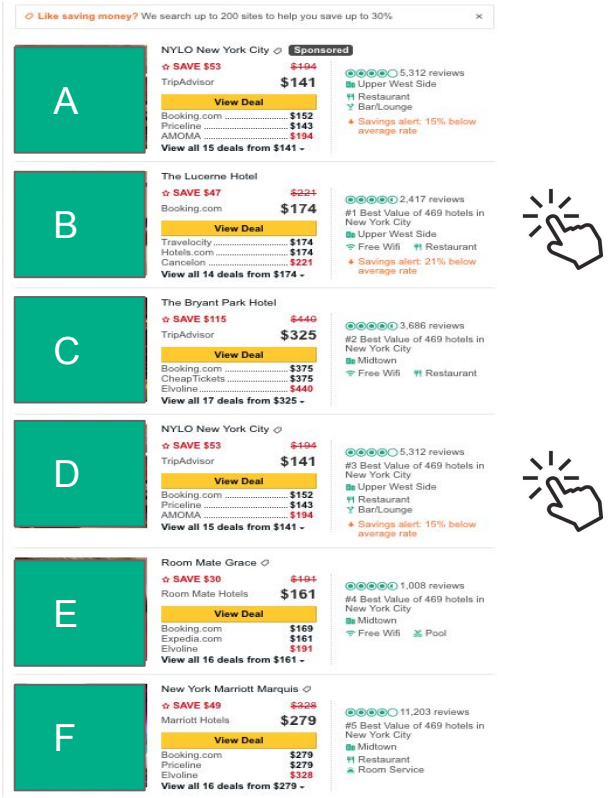



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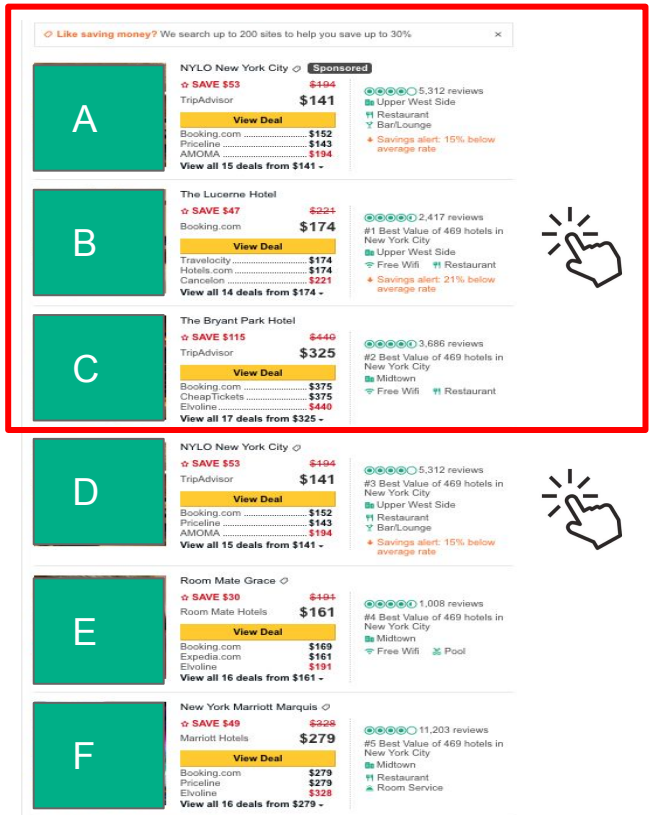



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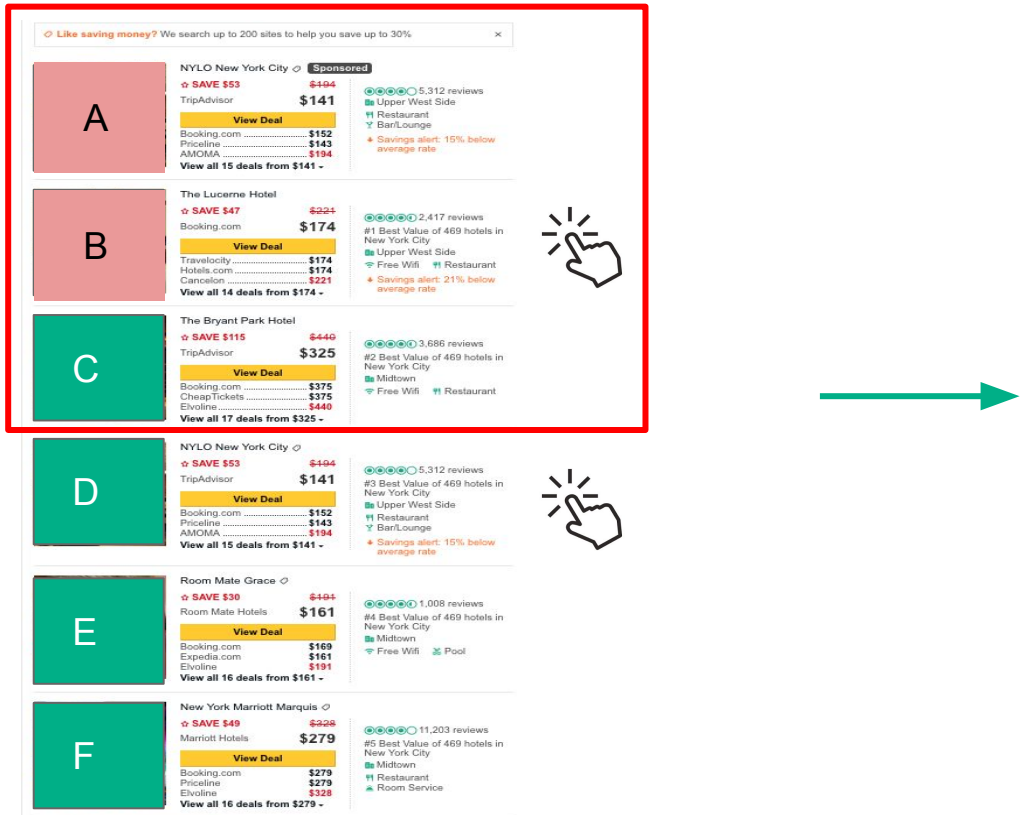


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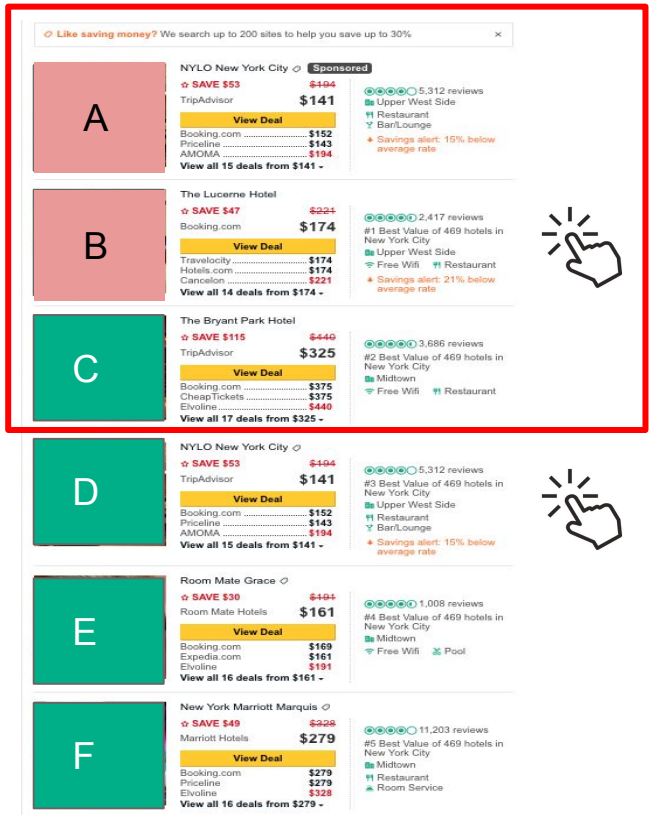


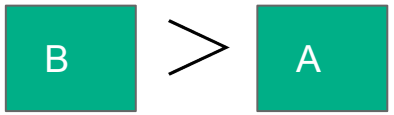


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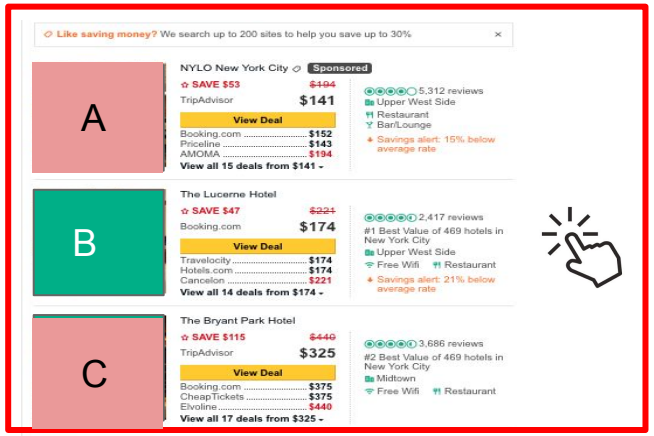


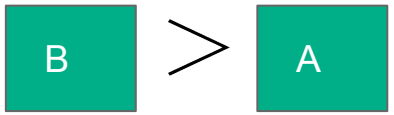


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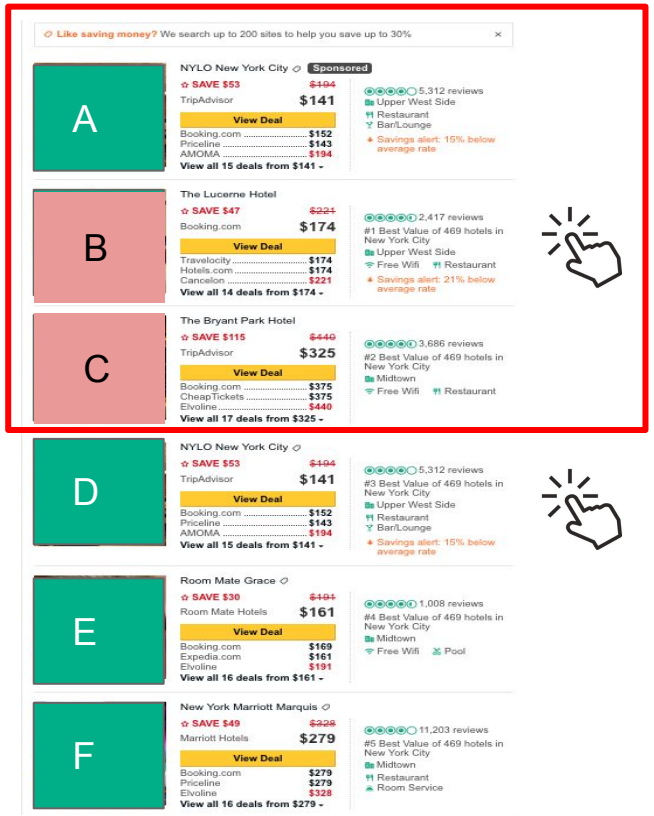


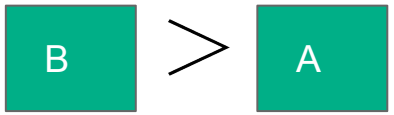


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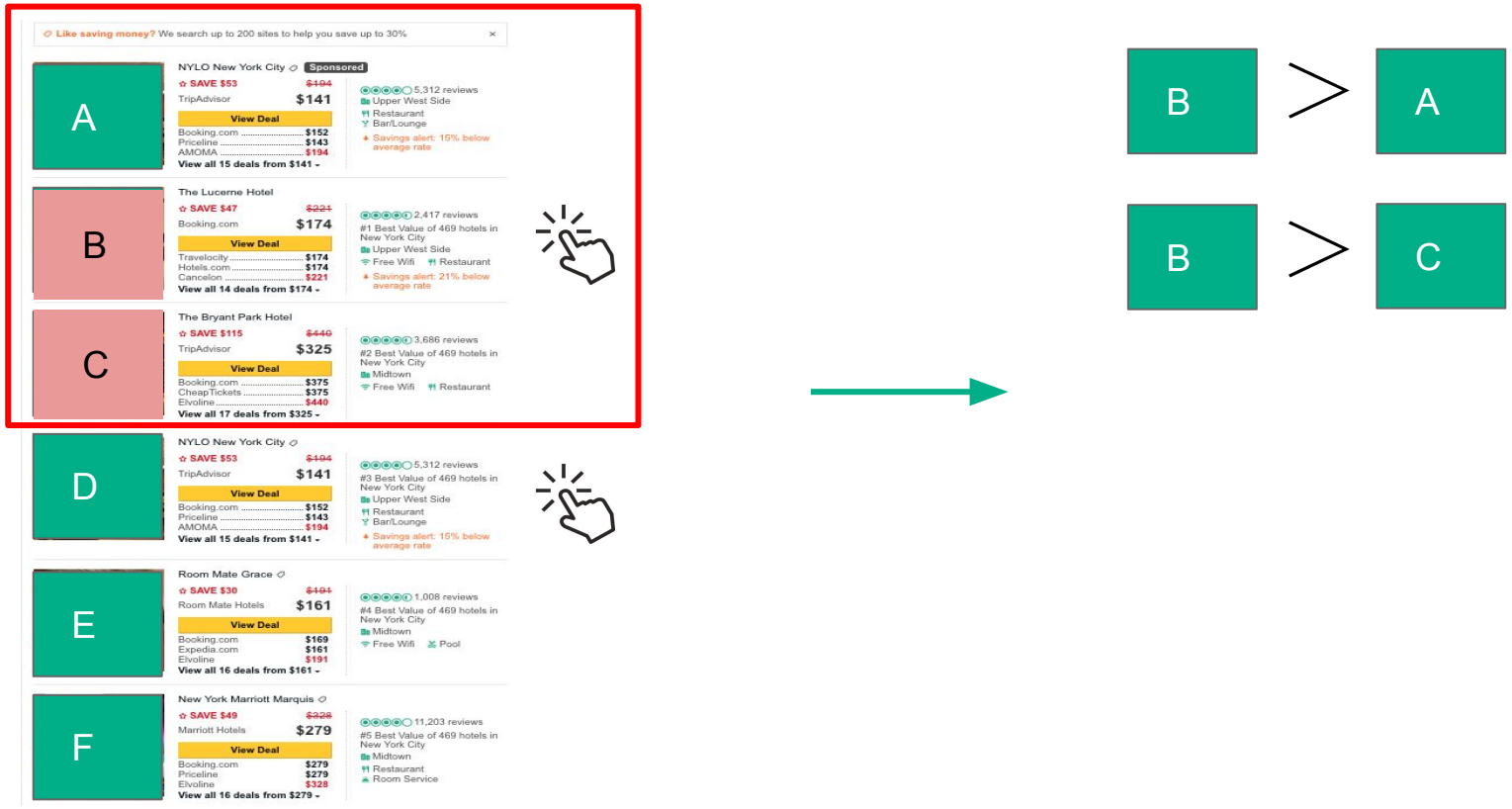


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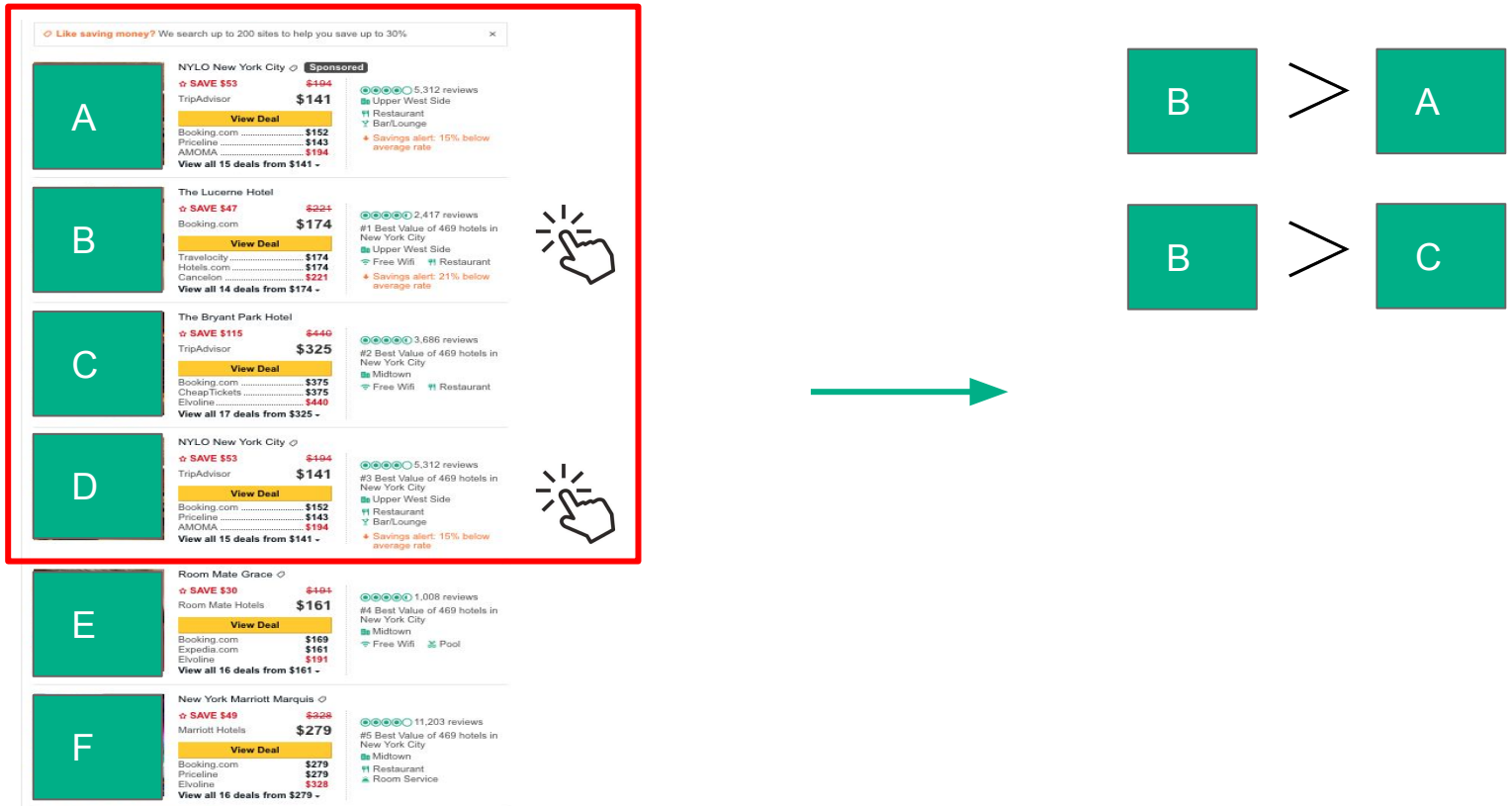



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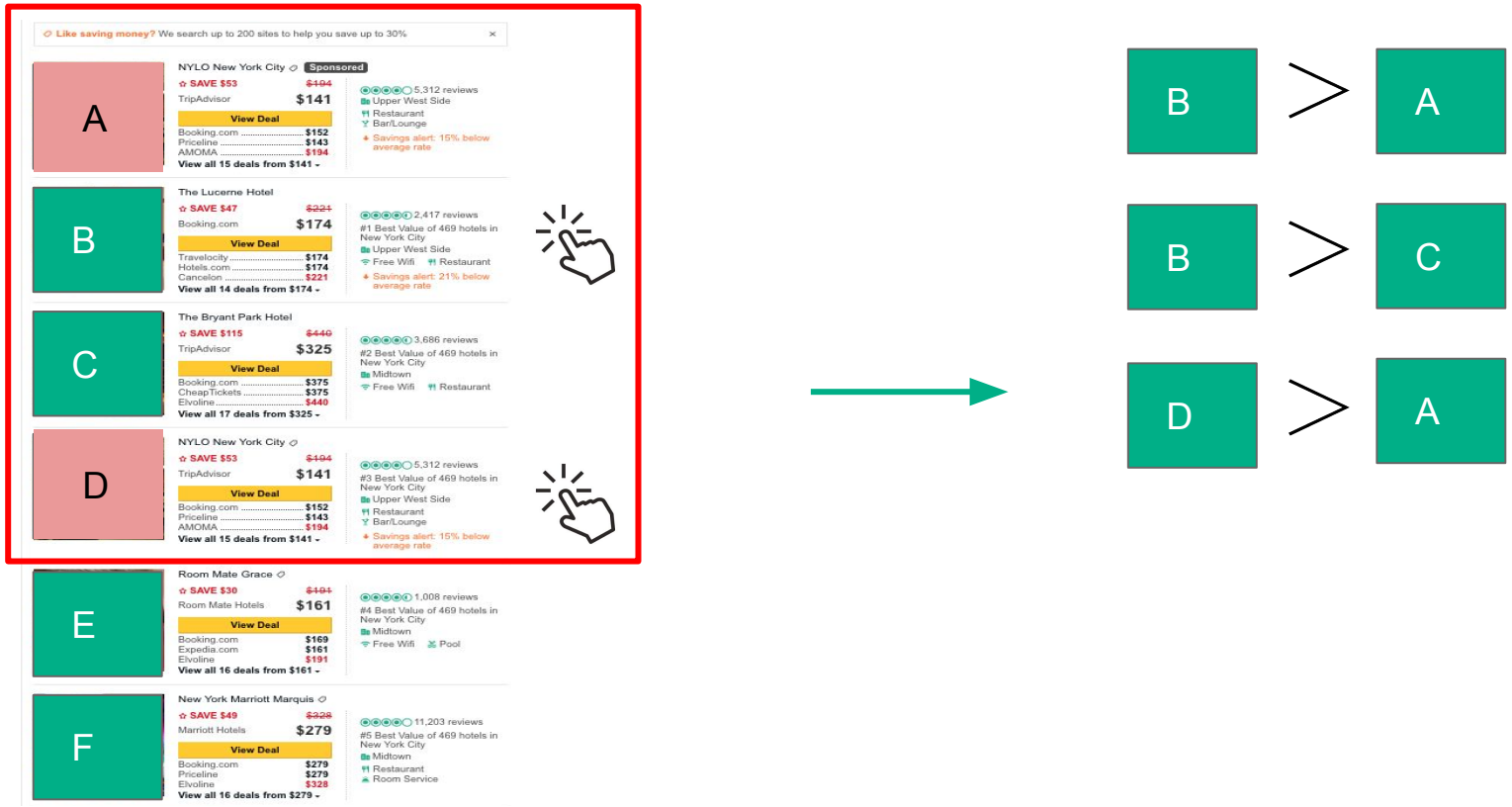


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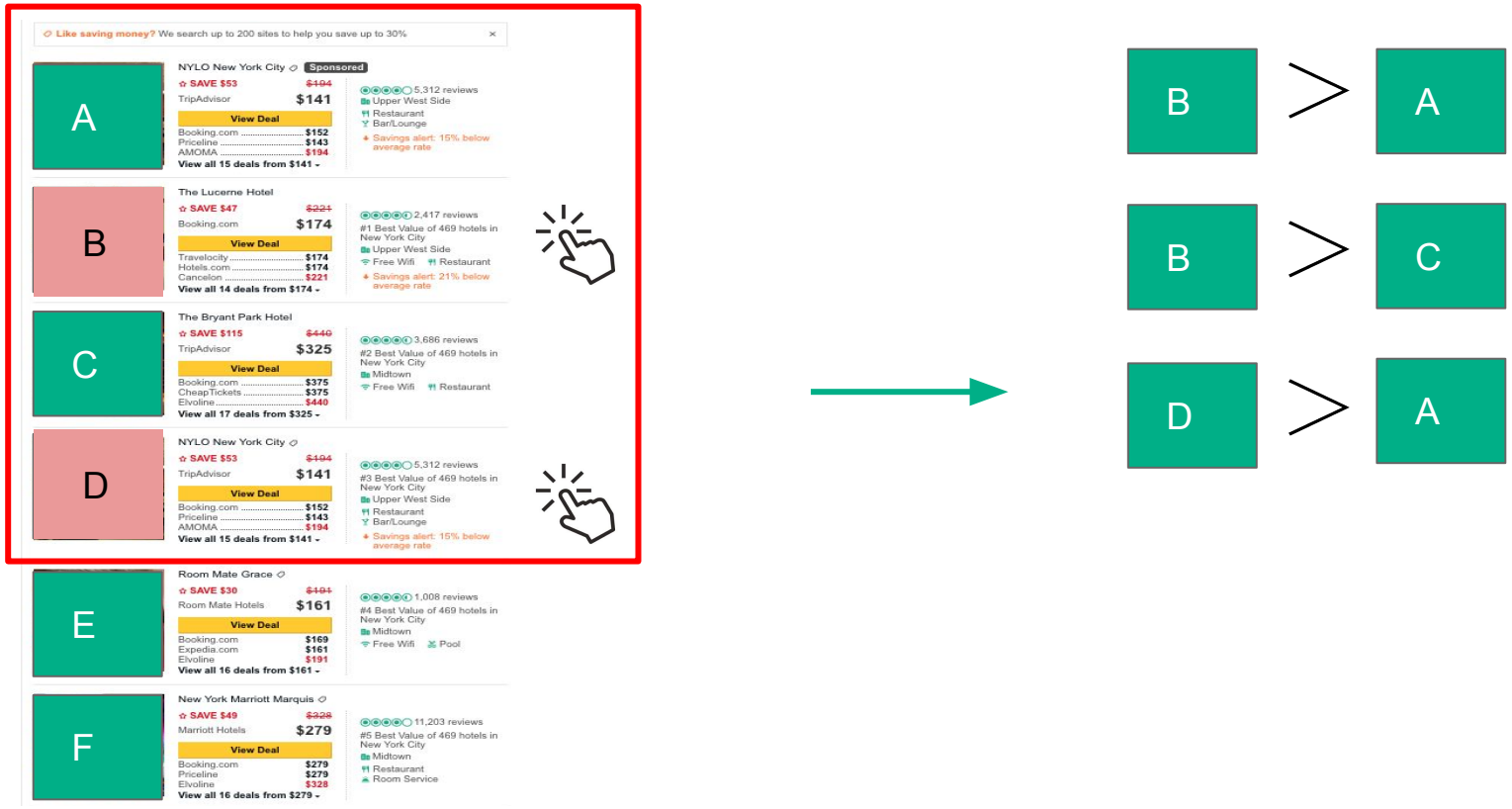


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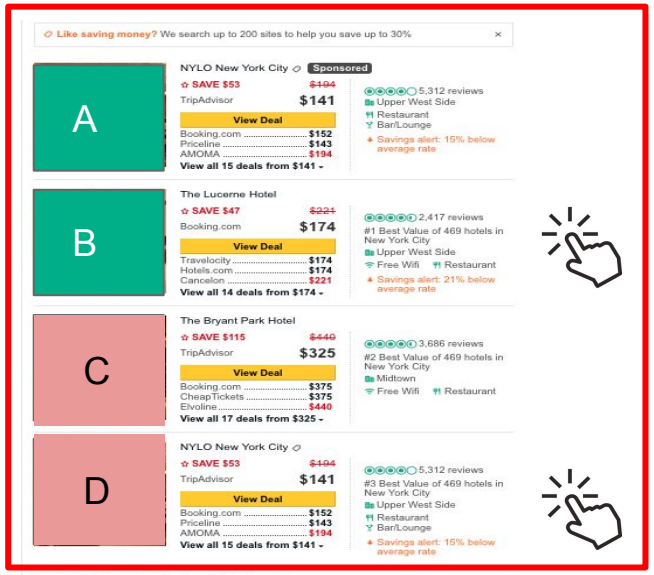


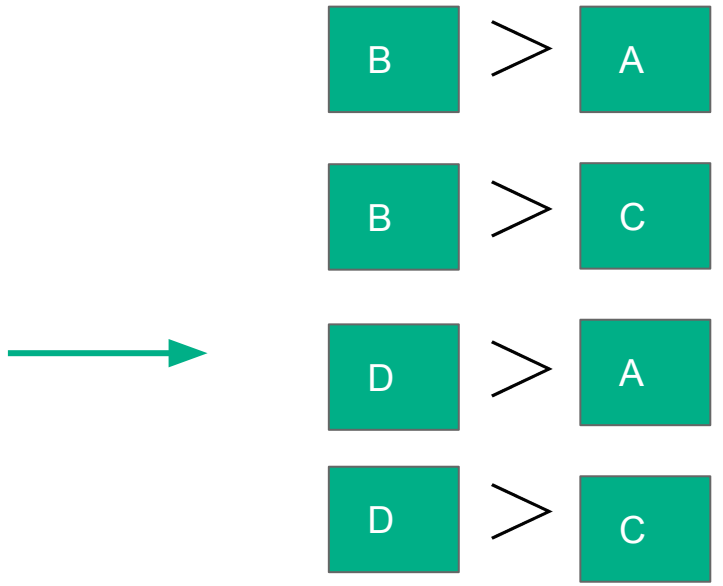



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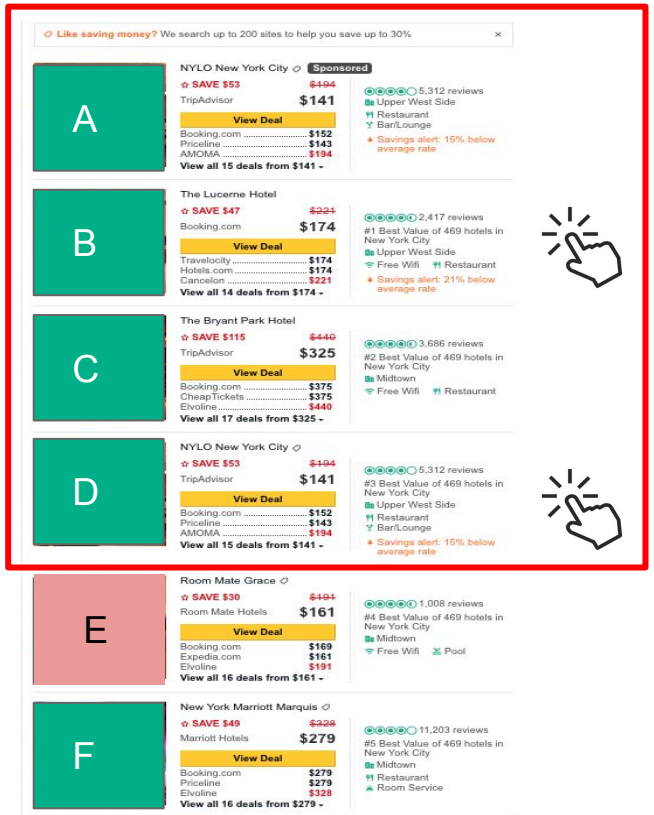


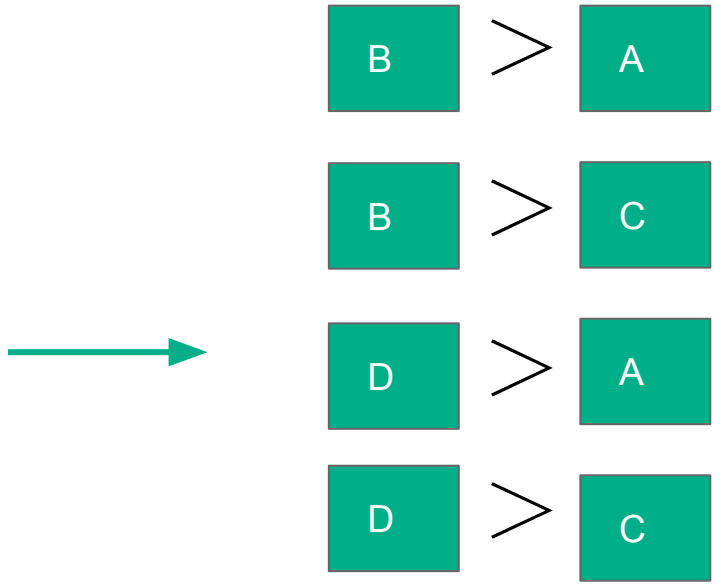



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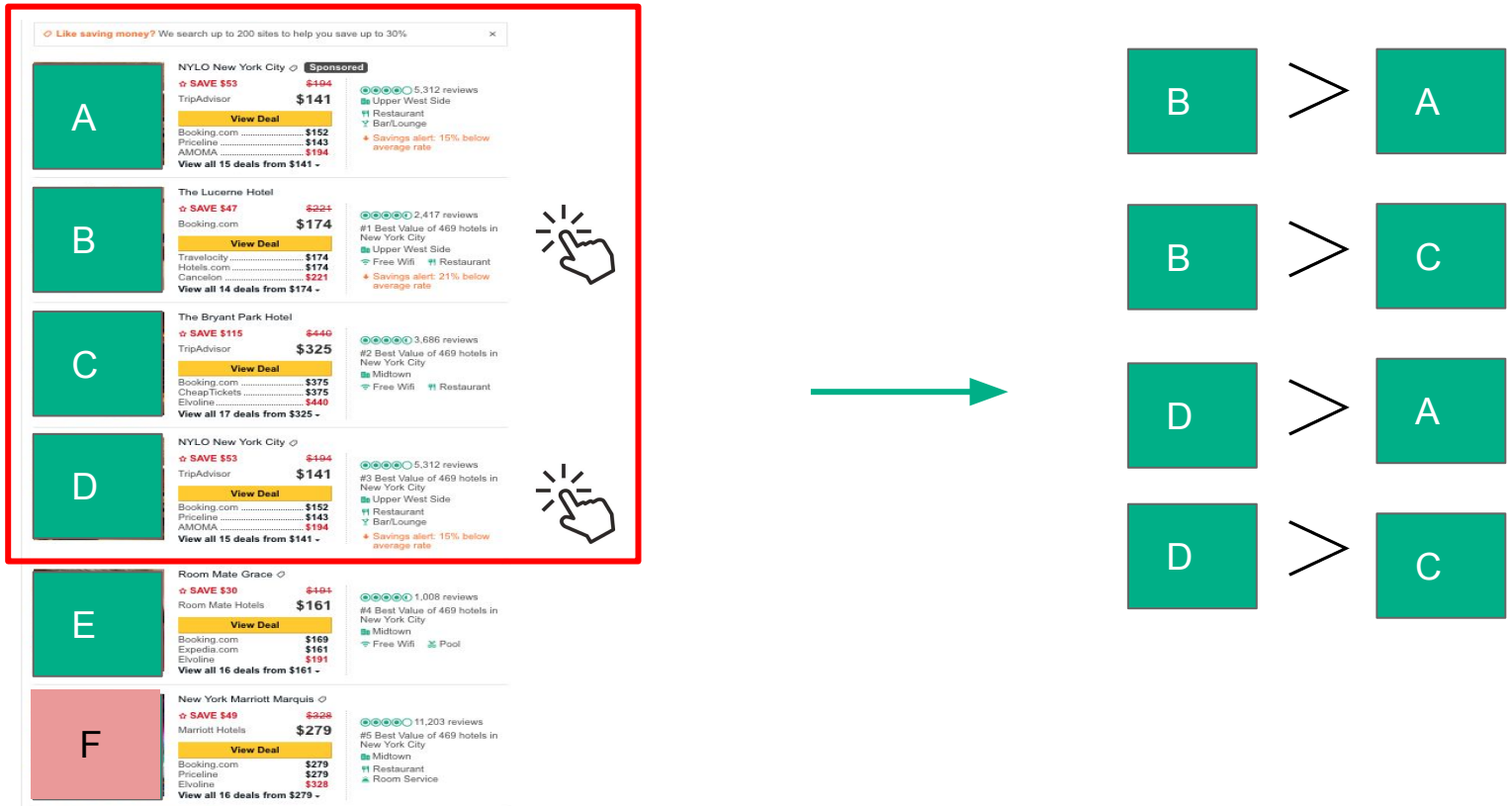


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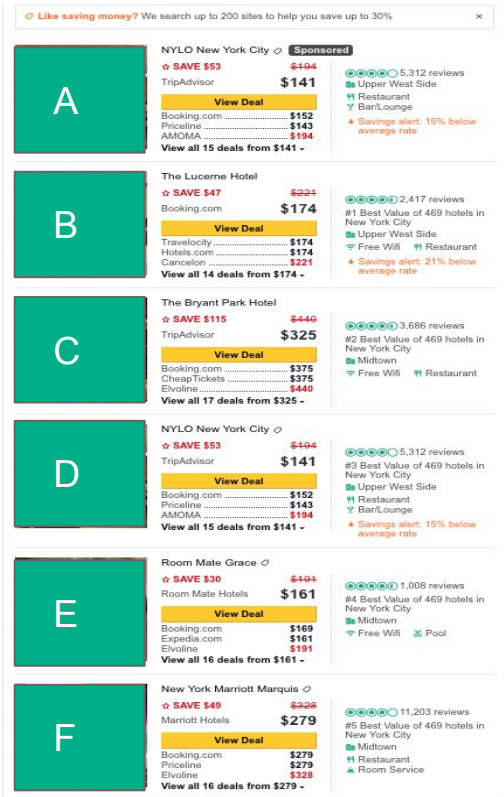


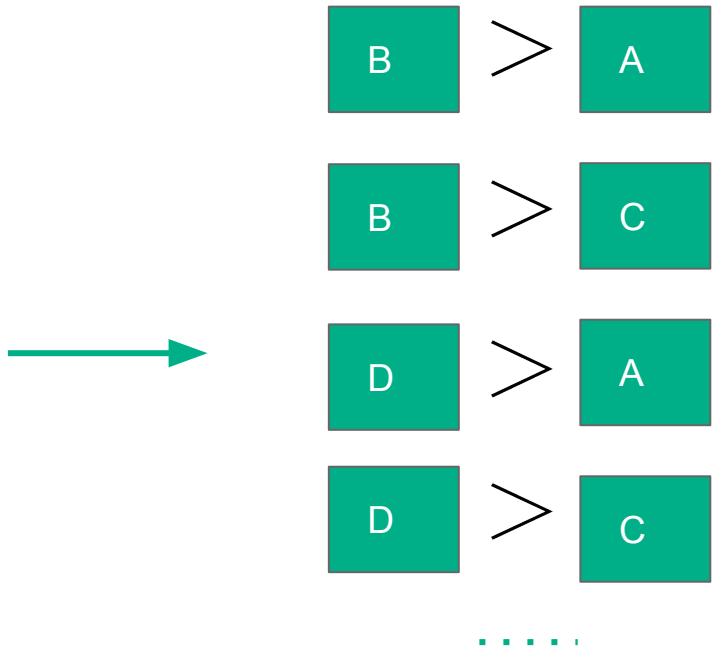


$$\{(\boldsymbol{x}_i^{(r)}, \boldsymbol{x}_j^{(r)}) \mid \forall i, j(y_i^{(r)} = 1 \wedge y_j^{(r)} = 0)\}$$


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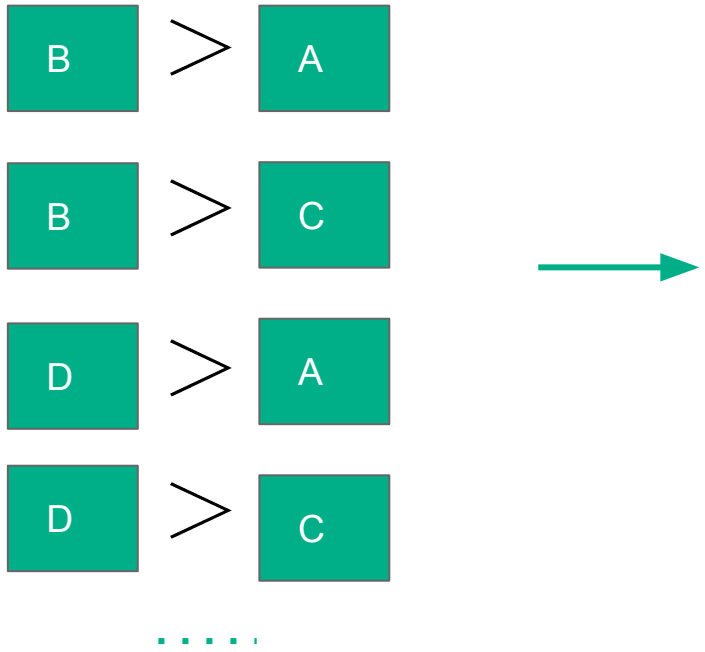


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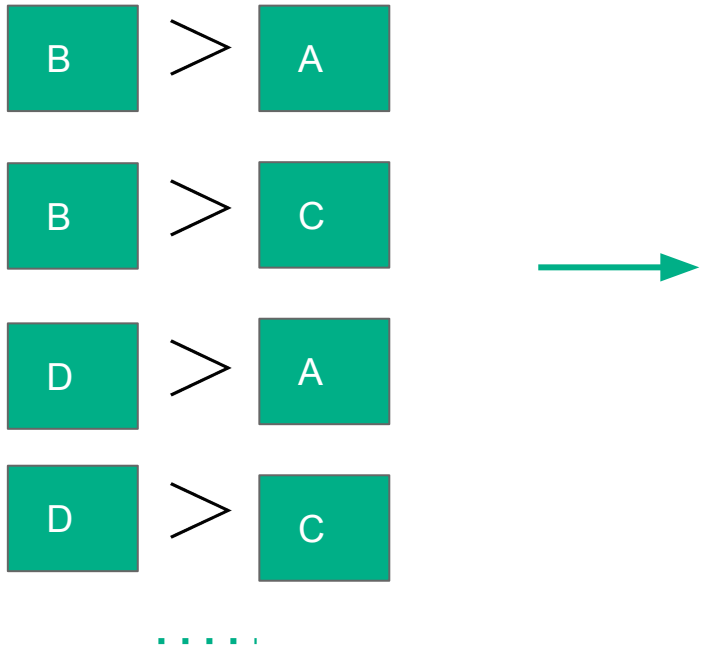
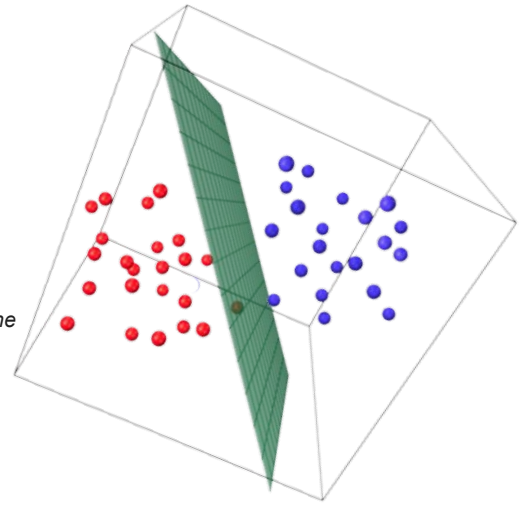



$$\min\left(\sum_{i>0} w_i^2\right) + C\left(\sum_{j=1}^{n} \xi_{jk}\right)^k$$

new objective function



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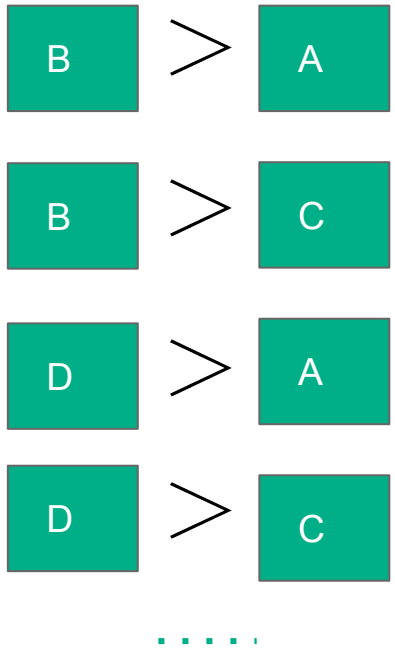
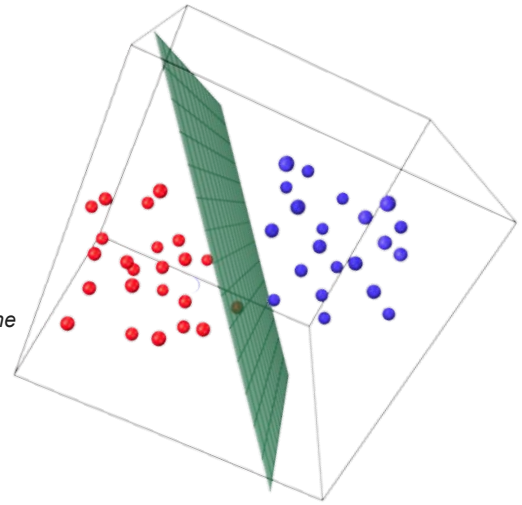



$$\min\left(\sum_{i>0} w_i^2\right) + C\left(\sum_{j=1}^{n} \xi_{jk}\right)^k$$

new objective function

for each j > k :



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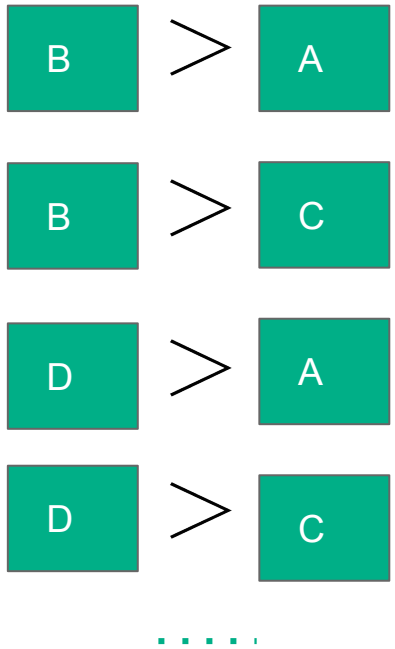
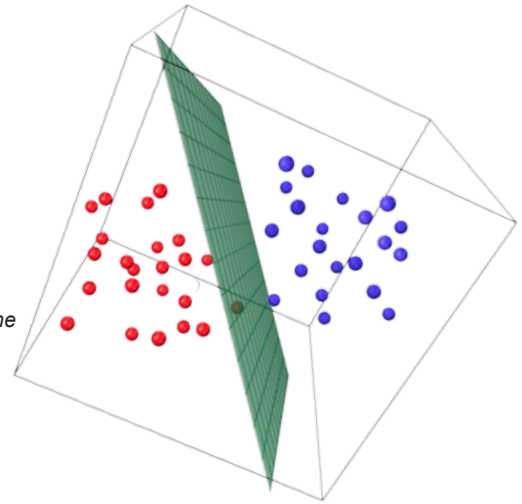



$$\min\left(\sum_{i>0} w_i^2\right) + C\left(\sum_{j=1}^{n} \xi_{jk}\right)^k$$

new objective function

for each j > k :

$$\sum_i w_i x_{j,i} \geq \sum_i w_i x_{k,i} + 1 - \xi_{jk}$$



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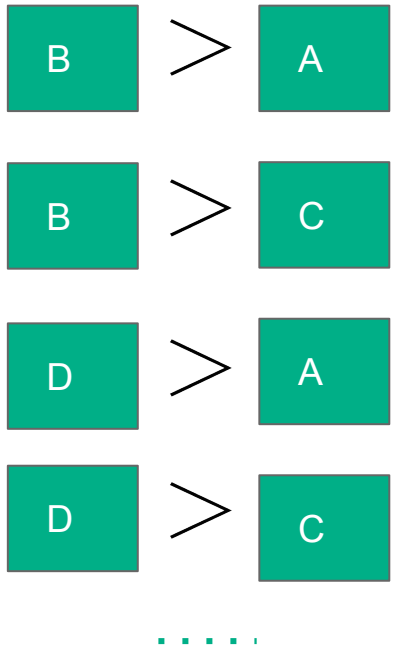
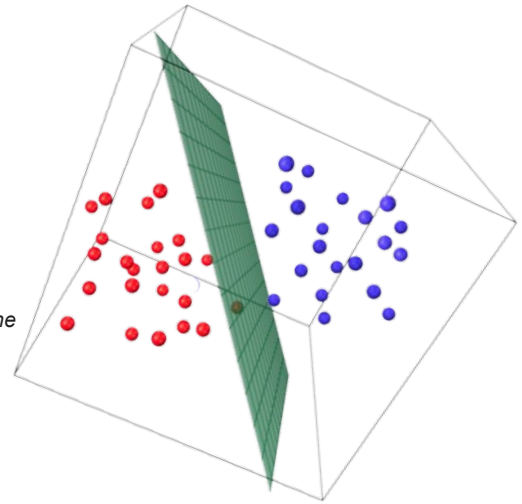



$$\min\left(\sum_{i>0} w_i^2\right) + C\left(\sum_{j=1}^{n} \xi_{jk}\right)^k$$

new objective function

for each j > k :

$$\underbrace{\sum_i w_i x_{j,i}}_{\text{score(j)}} \geq \underbrace{\sum_i w_i x_{k,i}}_{\text{score(k)}} + 1 - \xi_{jk}$$



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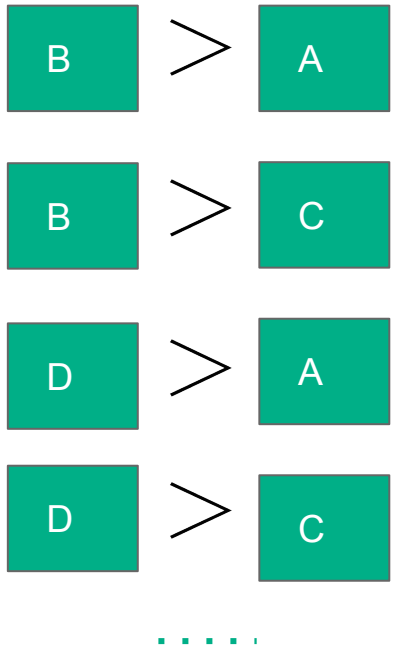



$$\min\left(\sum_{i>0} w_i^2\right) + C\left(\sum_{j=1}^{n} \xi_{jk}\right)^k$$

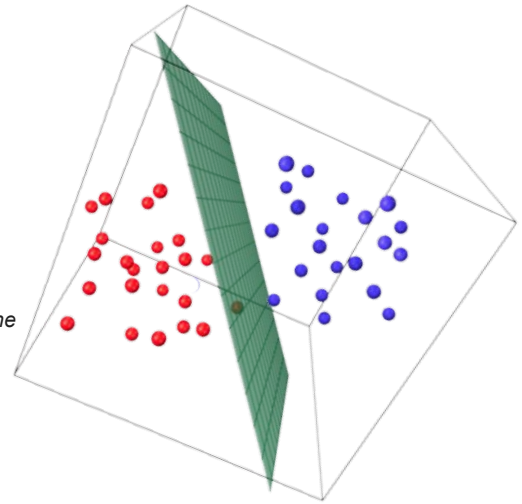
new objective function

for each j > k :

$$\sum_i w_i x_{j,i} \geq \sum_i w_i x_{k,i} + 1 - \xi_{jk}$$

score(j) ≥ score(k)

$$\sum_i w_i (x_{j,i} - x_{k,i}) \geq +1 - \xi_{jk}$$



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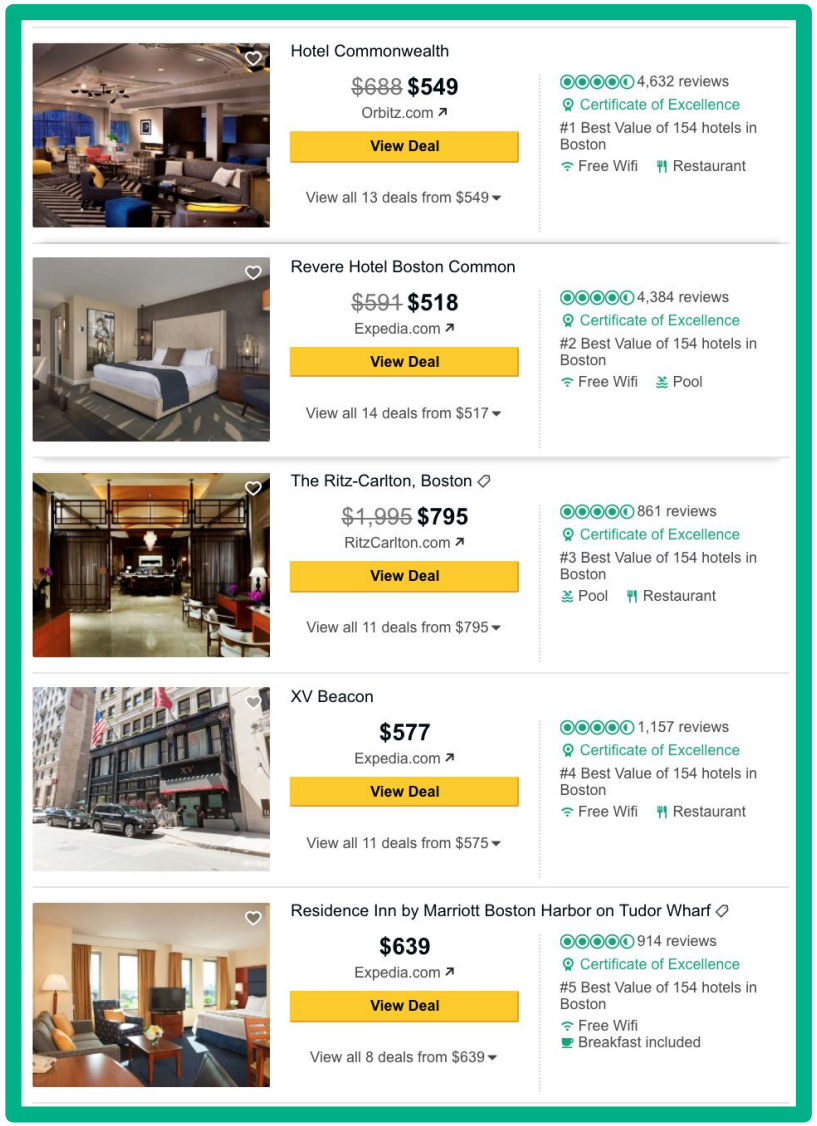
Hotel Commonwealth
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Orbitz.com
View Deal
View all 13 deals from $549
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#1 Best Value of 154 hotels in Boston
Free Wifi
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$591 $518
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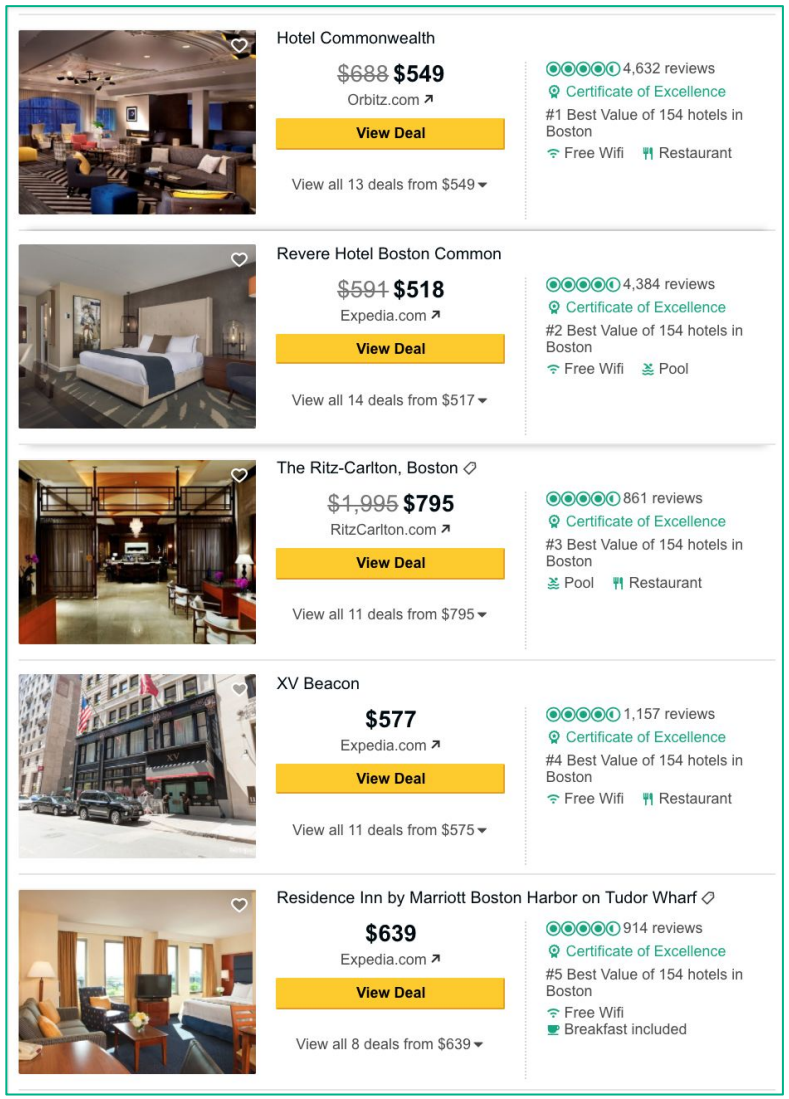
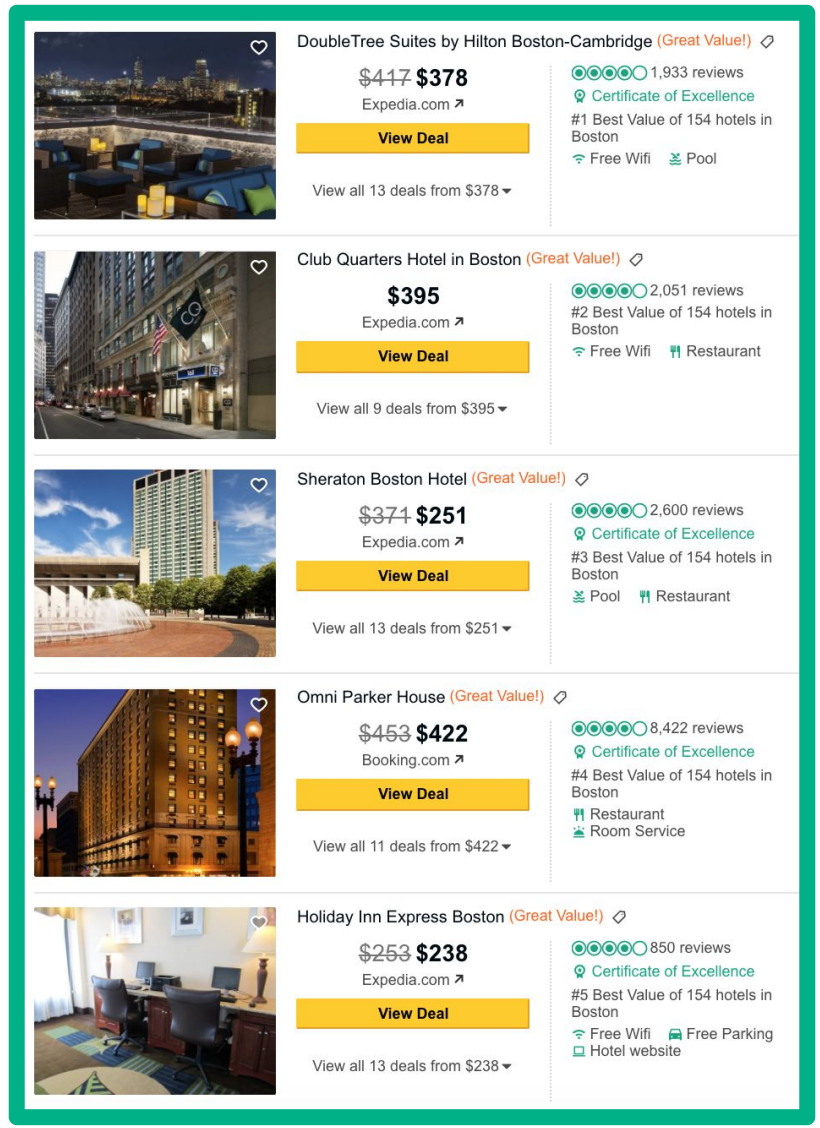
861 reviews
Certificate of Excellence
#3 Best Value of 154 hotels in Boston
Pool
Restaurant
XV Beacon
$577
Expedia.com
View Deal
View all 11 deals from $575
1,157 reviews
Certificate of Excellence
#4 Best Value of 154 hotels in Boston
Free Wifi
Restaurant
Residence Inn by Marriott Boston Harbor on Tudor Wharf
$639
Expedia.com
View Deal
View all 8 deals from $639
914 reviews
Certificate of Excellence
#5 Best Value of 154 hotels in Boston
Free Wifi
Breakfast included


Hotel Commonwealth
$688 $549
Orbitz.com
View Deal
View all 13 deals from $549
4,632 reviews
Certificate of Excellence
#1 Best Value of 154 hotels in Boston
Free Wifi
Restaurant
Revere Hotel Boston Common
$591 $518
Expedia.com
View Deal
View all 14 deals from $517
4,384 reviews
Certificate of Excellence
#2 Best Value of 154 hotels in Boston
Free Wifi
Pool
The Ritz-Carlton, Boston
$1,995 $795
RitzCarlton.com
View Deal
View all 11 deals from $795
861 reviews
Certificate of Excellence
#3 Best Value of 154 hotels in Boston
Pool
Restaurant
XV Beacon
$577
Expedia.com
View Deal
View all 11 deals from $575
1,157 reviews
Certificate of Excellence
#4 Best Value of 154 hotels in Boston
Free Wifi
Restaurant
Residence Inn by Marriott Boston Harbor on Tudor Wharf
$639
Expedia.com
View Deal
View all 8 deals from $639
914 reviews
Certificate of Excellence
#5 Best Value of 154 hotels in Boston
Free Wifi
Breakfast included


DoubleTree Suites by Hilton Boston-Cambridge (Great Value!)
$417 $378
Expedia.com
View Deal
View all 13 deals from $378
1,933 reviews
Certificate of Excellence
#1 Best Value of 154 hotels in Boston
Free Wifi
Pool
Club Quarters Hotel in Boston (Great Value!)
$395
Expedia.com
View Deal
View all 9 deals from $395
2,051 reviews
Certificate of Excellence
#2 Best Value of 154 hotels in Boston
Free Wifi
Restaurant
Sheraton Boston Hotel (Great Value!)
$371 $251
Expedia.com
View Deal
View all 13 deals from $251
2,600 reviews
Certificate of Excellence
#3 Best Value of 154 hotels in Boston
Pool
Restaurant
Omni Parker House (Great Value!)
$453 $422
Booking.com
View Deal
View all 11 deals from $422
8,422 reviews
Certificate of Excellence
#4 Best Value of 154 hotels in Boston
Restaurant
Room Service
Holiday Inn Express Boston (Great Value!)
$253 $238
Expedia.com
View Deal
View all 13 deals from $238
850 reviews
Certificate of Excellence
#5 Best Value of 154 hotels in Boston
Free Wifi
Free Parking
Hotel website

**+ 12 % Increase in Clicks**
**(On average, cross all platform)**

**+ 12 % Increase in Clicks**
**(On average, cross all platform)**

**+ 3.4 % increase in Revenue***
**(On average, cross all platform)**

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**(On average, cross all platform)**

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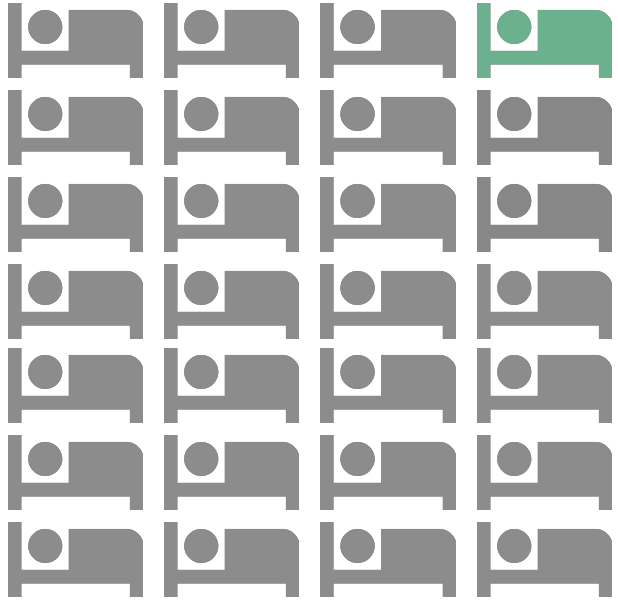
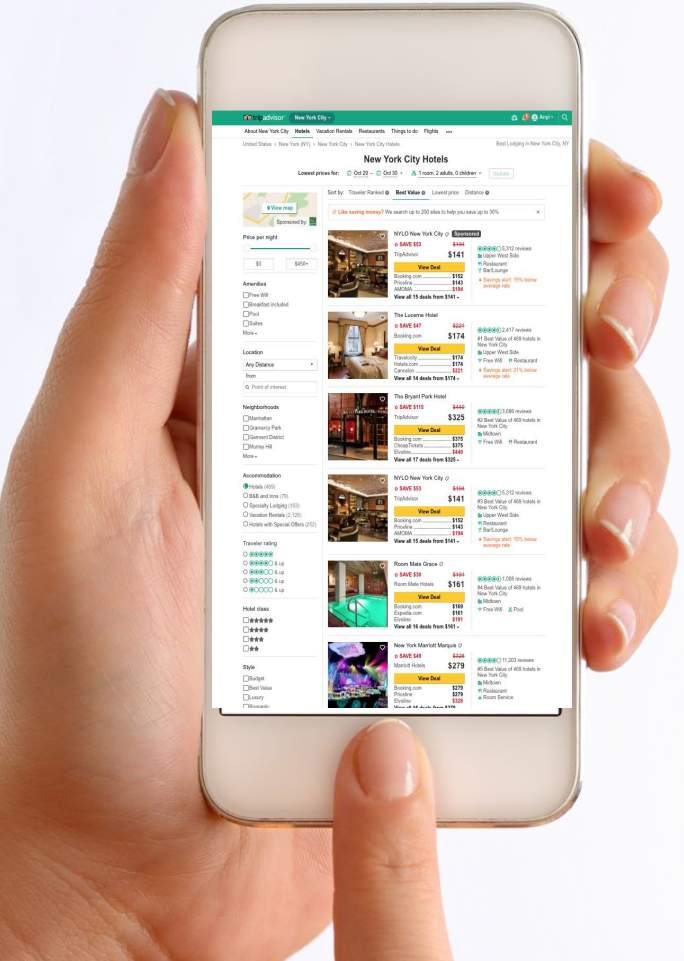
**(On average, cross all platform)**



**+ 1.3 % Increase in Booking**

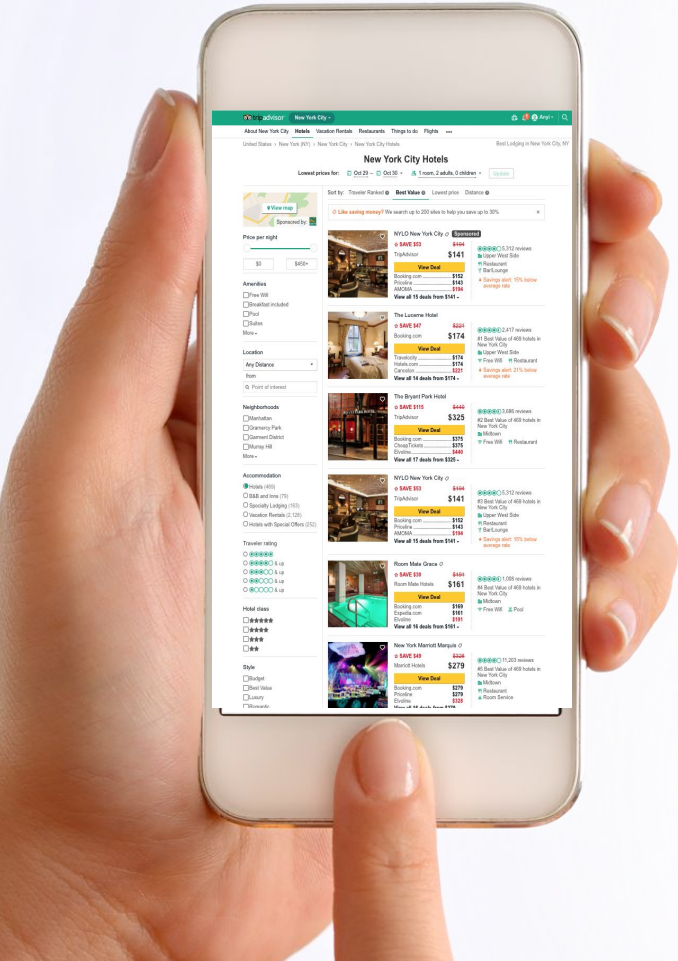
# Further Improvement

# Further Improvement



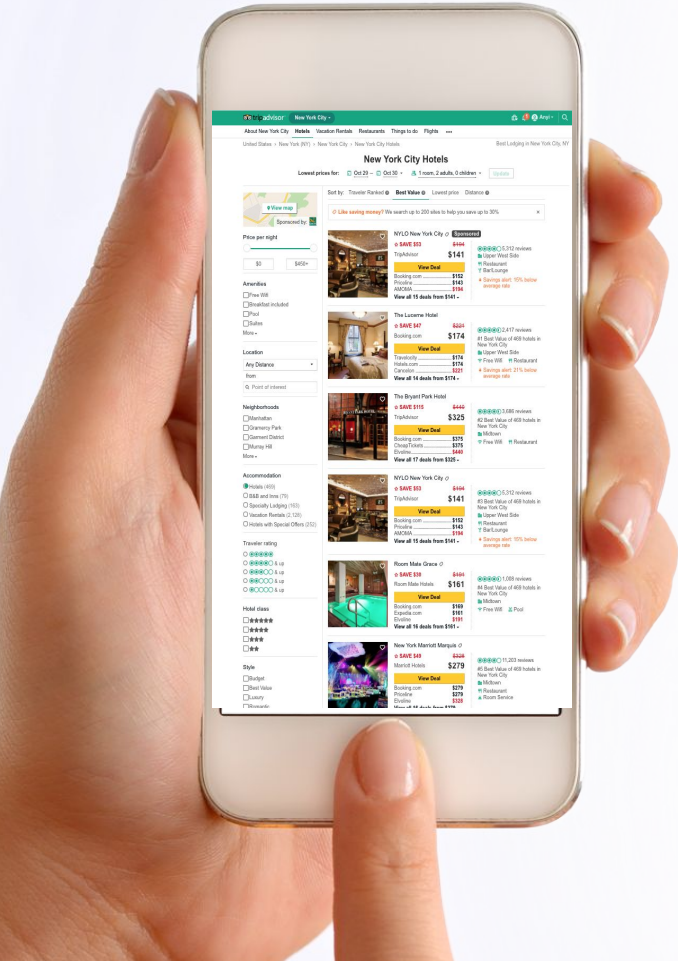

- Search Related Features got cancelled out during pairwise transformation
- Pair generation and bucketing was expensive

# Further Improvement

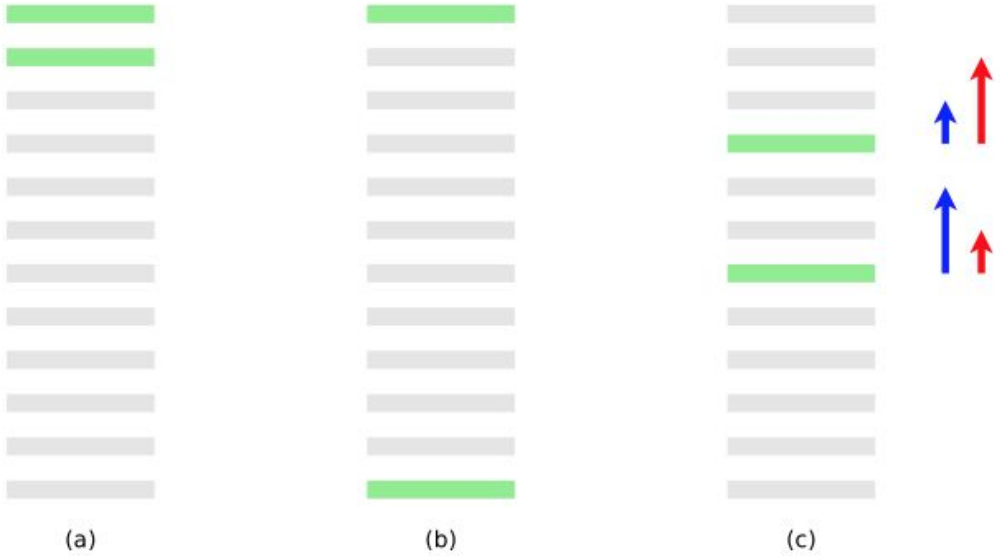



- MAP was invisible to model during the training phase - Minimizing the mis ranked pair != maximizing MAP

# Further Improvement




- MAP was invisible to model during the training phase - Minimizing the mis ranked pair != maximizing MAP



# Further Improvement

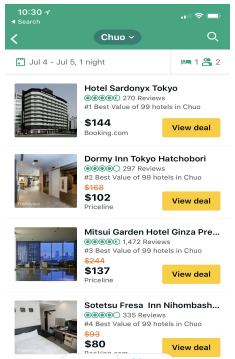
**Pointwise**

↓

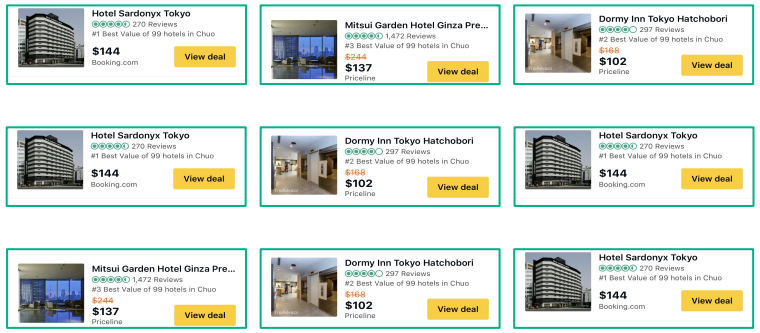
**Pairwise**

↓

**Listwise**




$f()$

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# References


[1] Cao, Z., Qin, T., Liu, T.Y., Tsai, M.F. and Li, H., 2007, June. Learning to rank: from pairwise approach to listwise approach. In *Proceedings of the 24th international conference on Machine learning* (pp. 129-136). ACM.

[2] Tagami, Y., Ono, S., Yamamoto, K., Tsukamoto, K. and Tajima, A., 2013, August. Ctr prediction for contextual advertising: Learning-to-rank approach. In *Proceedings of the Seventh International Workshop on Data Mining for Online Advertising* (p. 4). ACM.

[3] Gneric Click Through Rate 2017 Chttps://www.advancedwebranking.com/cloud/ctrstudy/

[4] http://homepages.inf.ed.ac.uk/vlavrenk/

[5] Zhang, Dongxiang, et al. "Targeted advertising in public transportation systems with quantitative evaluation." *ACM Transactions on Information Systems (TOIS)* 35.3 (2017): 20.

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[6] Tagami, Yukihiro, et al. "Ctr prediction for contextual advertising: Learning-to-rank approach." *Proceedings of the Seventh International Workshop on Data Mining for Online Advertising*. ACM, 2013.

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