Ranking: Why you never go past the first page on a search engine

Overview of the presentation

- 1. Brief introduction to Information Retrieval (IR)
 - a. Stating the problem
- 2. Search related concepts
- 3. Tools
 - a. Learning to Rank
 - b. Recommender systems
- 4. Stages of a ranking project
- 5. Advices



Introduction to IR

 IR is part of computer science which studies the retrieval of information from a collection of written documents. The retrieved documents aim at satisfying a user information need usually expressed in natural language.¹

















1-48 of over 40,000 results for Clothing, Shoes & Jewelry: Men: Clothing: Shirts: T-Shirts



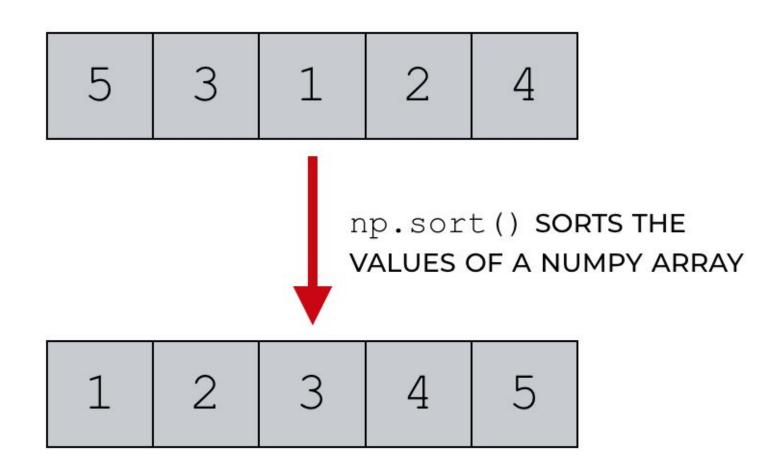




1-48 of over 40,000 results for Clothing, Shoes & Jewelry: Men: Clothing: Shirts: T-Shirts

40k T-shirts





- 1. User Tobias
- 2. Documents 10 million products
- 3. Query Filter -> Clothing Men -> T-shirts

- User Tobias
 Tom Business owner
- 2. Documents 10 million products B. Ron Engineer
- 3. Query Filter -> Clothing Men -> T-shirts C. Harry Architect

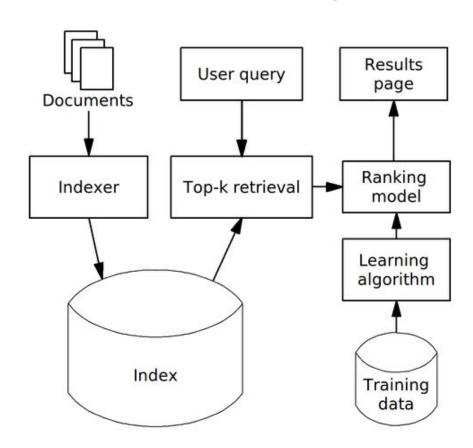
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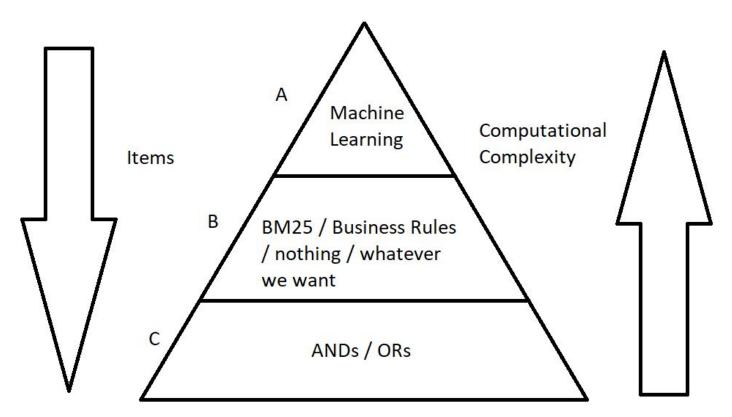


<- Data scientist

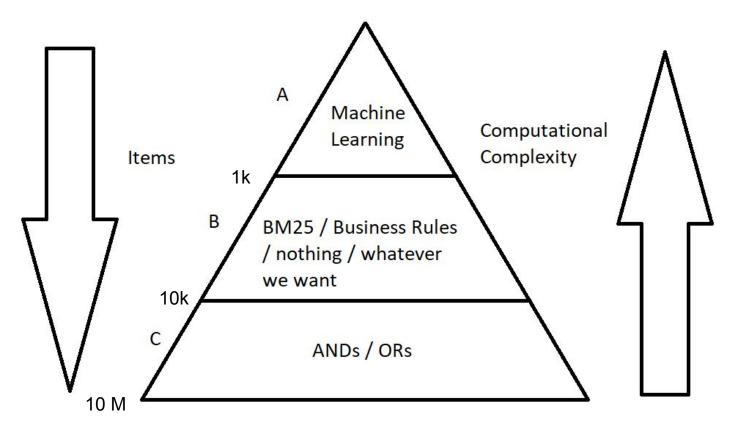
Search related concepts - Example of a Search Engine



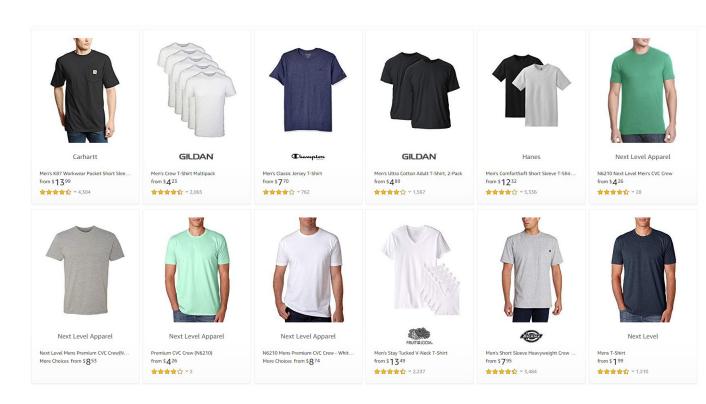
Search related concepts - Example of a Search Engine



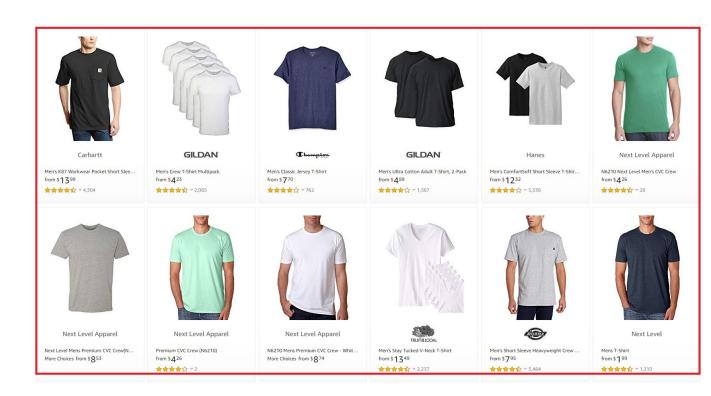
Search related concepts - Example of a Search Engine



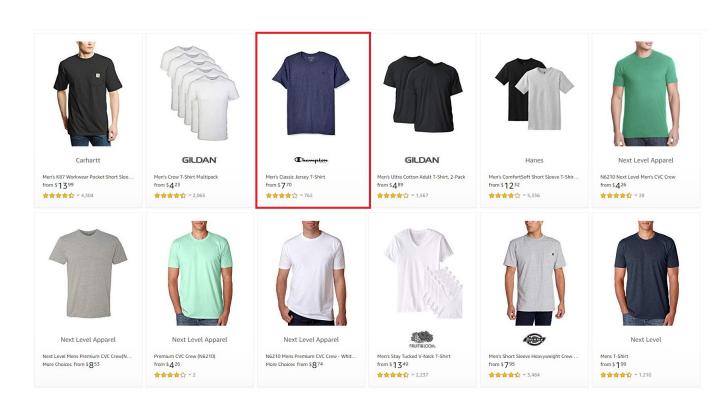
- 1. Query
- 2. Document
- 3. Relevance



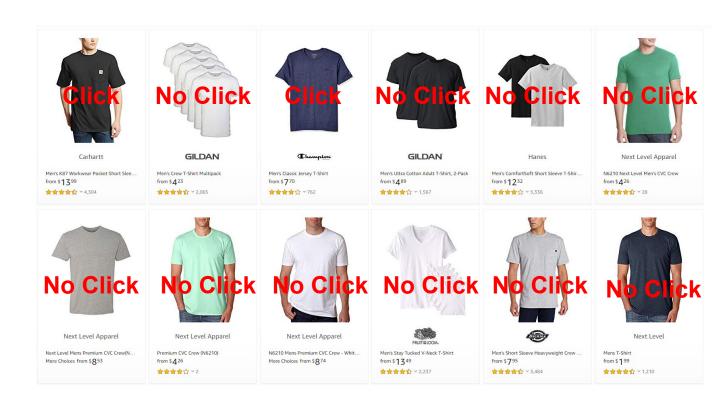
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- 1. Query
- 2. Document
- 3. Relevance



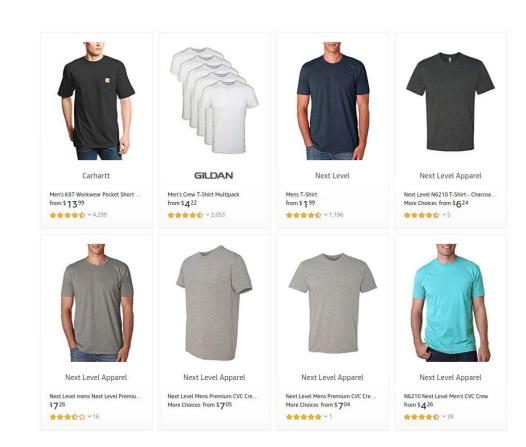
- 1. Query
- 2. Document
- 3. Relevance



	Α	В	С	D	
1	query_id	product_id	relevance	features	
2	1	1	1		
3	1	2	0		
4	1	3	1		
5	1	4	0		
6	1	5	0		
7	1	6	0		
8	1	7	5		
9	2	6	0		
10	2	7	0		
11	2	8	0		
12	2	1	0		
13	2	2	0		
14	2	3	1		
15	2	4	0		

Tools - Learning to Rank - How to measure relevance

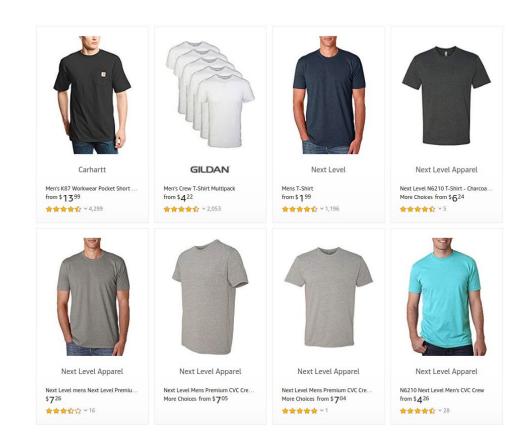
How should we determine what is relevant to a user?

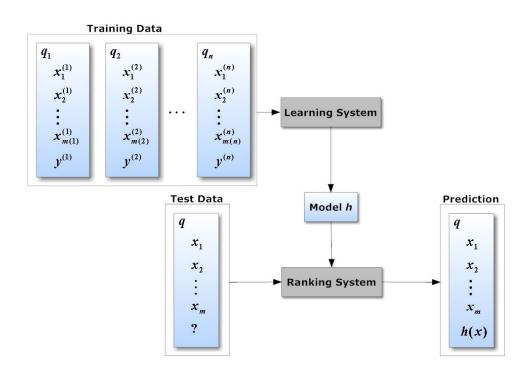


Tools - Learning to Rank - How to measure relevance

How should we determine what is relevant to a user?

- Experts manually label observations
- Using business related metrics to infer relevancy:
 - 5 for transactions
 - 1 for click
 - 0 for seen and did nothing





Pointwise

Take one candidate



Compute **score** between candidate and query

Pairwise

Take a pair of candidates



Given a pair of candidates decide which one rank higher

hypothesis: more important the relative position

Listwise

Take the entire list



optimise its order

algorithms:

anything that deals with regression problems

algorithms:

RankNet LambdaRank*

633

algorithms:

LambdaMART

SoftRank ListNet AdaRank LambdaRank*

Tools - Learning to Rank - RankNet

```
import numpy as np
from keras import backend
from keras.layers import Activation, Dense, Input, Subtract
from keras.models import Model
INPUT DIM = 50
# Model.
h 1 = Dense(128, activation="relu")
h 2 = Dense(64, activation="relu")
h 3 = Dense(32, activation="relu")
s = Dense(1)
# Relevant document score.
rel doc = Input(shape=(INPUT DIM,), dtype="float32")
h 1 rel = h 1 (rel doc)
h 2 rel = h 2(h 1 rel)
h \ 3 \ rel = h \ 3 (h \ 2 \ rel)
rel score = s(h 3 rel)
```

```
# Irrelevant document score.
irr doc = Input(shape=(INPUT DIM,), dtype="float32")
h 1 irr = h 1(irr doc)
h 2 irr = h 2(h 1 irr)
h 3 irr = h 3(h 2 irr)
irr score = s(h 3 irr)
# Subtract scores.
diff = Subtract()([rel score, irr score])
# Pass difference through sigmoid function.
prob = Activation("sigmoid")(diff)
# Build model.
model = Model(inputs=[rel doc, irr doc], outputs=prob)
model.compile(optimizer="sqd", loss="binary crossentropy")
```

Credits: https://github.com/airalcorn2/RankNet/blob/master/ranknet.py

Tools - Learning to Rank - Evaluation

- Mean Average Precision
- NDCG@k
- Recall
- AB test with relevant metrics

Tools - Recommender systems - Matrix factorization

	Item										
	W	X	Υ	Z				W	X	Υ	
User O B D		4.5	2.0		Α	1.2 0.8	\mathbf{v}	1.5	1.2	1.0	
	4.0		3.5		В	1.4 0.9		1.7	0.6	1.1	
		5.0		2.0	= c	1.5 1.0	Λ				
D		3.5	4.0	1.0	D	1.2 0.8					

Rating Matrix

User Matrix

Item Matrix

Stages of a ranking project - Airbnb

Stage 1
Offline ML model

Stage 2 Personalized
Offline ML model

Stage 3 Personalized Online ML model

Stages of a ranking project

Stage 1 Offline ML model

- Data size: Small
- Signals:
 - Experience Features
- Scoring: Offline

Example:

Predict the best position for the products by country and update them on a weekly basis.

Stages of a ranking project

Stage 2 Personalized Offline ML model



- Signals:
 - Experience Features
 - User Features
- Scoring: Offline

Example:

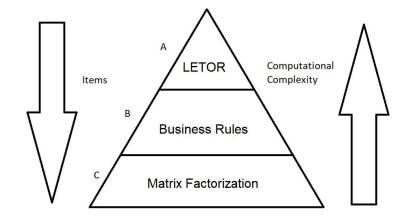
Predict the best position for the products by country **and several user segments** and update them on a **daily** basis.

Stages of a ranking project

Stage 3 Personalized Online ML model

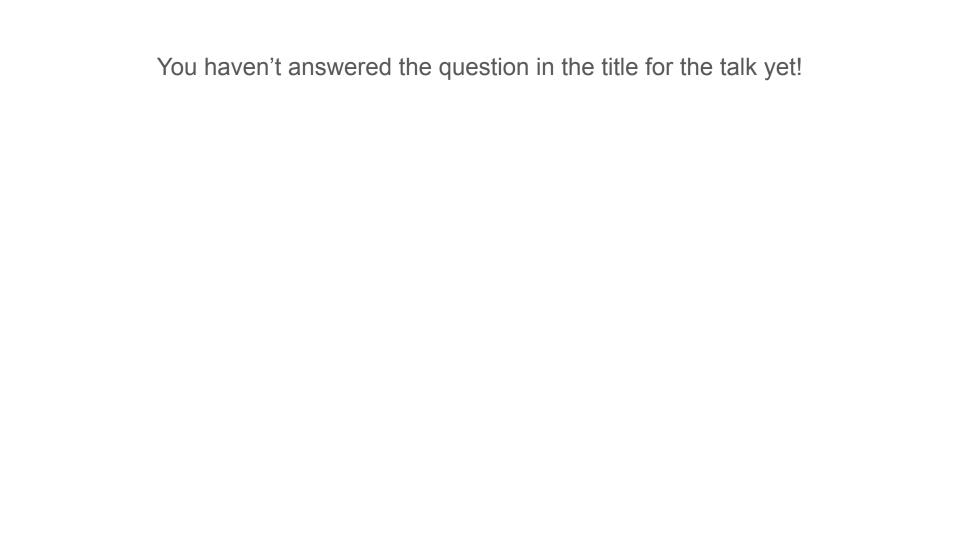
Data size: Large

- Signals:
 - Experience Features
 - User Features
 - Query Features
- Scoring: Online



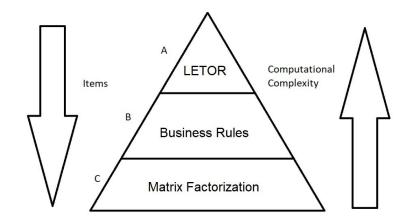
Credit:

- Machine Learning-Powered Search Ranking of Airbnb Experiences blogpost by Mihajlo Grbovic
- https://github.com/layer6ai-labs/vl6 recsys2018



You haven't answered the question in the title for the talk yet!

- Relevant items are finite. It's possible that all of them are on the first page
- It's also possible that the second page is loaded using a cheaper method



Advices

- There are a lot of interesting ways of building a ranking engine, just remember the core concepts
- Take it one step at a time
- Building a ranking engine in a notebook is very different from building one in a production environment
- Have fun

Questions?

Articles:

- Two-stage Model for Automatic Playlist Continuation at Scale by Maksims Volkovs
- On Application of Learning to Rank for E-Commerce Search by Shubhra Santu et al.
- Turning Clicks into Purchases: Revenue Optimization for Product Search in E-Commerce by Liang Wu et al.
- From RankNet to LambdaRank to LambdaMART: An Overview by Christopher J.C. Burges
- Cascade Ranking for Operational E-commerce Search by Shichen Liu, Fei Xiao et al.
- Amazon Search: The Joy of Ranking Products by Daria Sorokina et al.

Books:

- Learning to Rank for Information Retrieval by By Tie-Yan Liu
- Learning to Rank for Information Retrieval and Natural Language Processing by Hang Li

Blog posts:

 Machine Learning-Powered Search Ranking of Airbnb Experiences blogpost by Mihailo Grbovic



"I CAN'T FIND THE BOOKS ON INFORMATION RETRIEVAL."