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The multifactor recommender system @bol.com



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- develop an operating recommender system
- crucial customer behavioral factors involved
- impact of visual presentation of item recommended.



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12 Yrs University Utrecht, CS/ Mathematics

Since 2010 @ Bol.com







bol.com









Unique products per store

- Average supermarket
- XL supermarket



added products per week

+ 1 XL supermarket every 4 days

Catalog delta per week





> 8.000.000 products online





> 5.500.000.000 click events per year

+

Behavioral factors give us clues



- How long does he look at the product?
- Does he read the product reviews?
- Does he share the product on social media?
- Add item to wishlist
- What products does the visitor click?
- Was the clicked product a recommendation?



hadoop @bol.com

- Development in 2009
- First applications in production (2010)





Why building from scratch?

90A

106

Horizontal scalable Perform in "realtime" Handle our volume of data We can explain the workings of our system to our stakeholders. Together we can realize every business requirement that our stakeholders have.

614



Stories burn down, value increases





Recommendations



How can we tell the success of these recommendations?

- Visualize output data
- Offline recommender evaluation
 - Run algorithms that express the numerical errors of the recommender output.

Root Mean Squared Error (RMSE)

The square root of the mean/average of the square of all of the error.

The use of RMSE is very common and it makes an excellent general purpose error metric for numerical predictions.

Compared to the similar Mean Absolute Error, RMSE amplifies and severely punishes large errors.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$





How can we tell the success of these recommendations?

• Is that all we can do?











Requirements:

- Support anonymous customers
- Realtime: response 100ms
- Low numerical error value
- Recommendation is successful if customer buys the item after seeing it first as a recommendation.



- Customer: new customer
- Cartype: Tow Truck
- Recommendation: Diesel
- Does customer buy item after seeing this as recommendation? : yes







- Customer: new customer
- Cartype: sportscar
- Recommendation: Petrol (gasoline)
- Does customer buy item after seeing this as recommendation? : yes





- Offline evaluation:
 - Visual data inspection \checkmark
 - Low error value
- Online evaluation:
 - Accurately predict the recommendations \checkmark
 - Almost everything we recommend gets bought \checkmark



Is this a good recommender system?





What is a good recommendation?

Common error metrics	Commerce
The accuracy to predict	Add value to customer experience





How can we tell the success of this recommender?

- Visualize output data
- Offline recommender evaluation
 - Run algorithms that express the error of the recommender output in a numerical form.

Long Term analyses

- Analyze the performance of the recommender over time.
 - Do visitors return after buying a recommendation?
- Analyze behavior to learn more from our visitors.

Online recommender evaluation

• Live user experiment 's





Live user experiments?

Recommendations = Data-driven decisions

- Optimize combinations of recommendation algorithms
- User Interface
- User Interaction Flows





What do visitors really prefer?



Experimentation framework



Experimentation results







Impact of presentation







Impact of presentation

Especially selected for you Ø because you like data mining' Data Mining Technic Introductory Statistics Introduction to Protein Artificial Intelligence Data Mining Structure Stuart Russell with R Techniques Carl-Ivar Branden Peter Dalgaard Michael J. Berry € 63.99 € 61.99 € 60,03 € 53.99 € 48,99 € 40.99 € 38,99

Recommendation interaction

Especially selected for you because you like 'data mining'





Introduction to Protein Structure Carl-Ivar Branden € 63.99 € 61,99

Artificial Intelligence Stuart Russell € 60,03

Introductory Statistics with R Peter Dalgaard € 53,99 € 48,99

tatistics Data Hining Techniques Michael J. Berry ★★★★★ (1) 99 €40,99 € 38,99

Data Minin

Techniques






What did we just recommend?

- Algorithms with outcome
- Personalized content
 - Products
 - Authors
 - Artists
 - Deals
 - Categories
- Personalized User Interface
- Determine the priority of algorithm outcome on a page
- Over channels (webshop, mobile, email)





Level of personalization?



Realtime recommender

- What would add value to the customer given his current context?
- What do we already know about the visitor? (previous behavior)
- Determine the level of personalization





"All we have to decide is what to do with the time that is given to us."

What to do with given time

- Cache 'expensive' data
- Tune/(try different) jdbc connectivity components
- Profile your code (Java VisualVM)





Architecture (2011)



Limitations

Current implementation

- `Limited' realtime analysis
 - Memory footprint too large
- No detailed `long history'
 - Too much data for `relational' database
- React fast to `all onsite visitors'
 - Did a famous person die?
- Realtime and Batch have different data
- We need a `new' way of handling this.







Sessionized Lambda Architecture





Sessionized Lambda Architecture

- Who am I
- Usecases & Requirements
- Lambda Architecture
- Sessionized Lambda Architecture
 - Bounded Event Streams
 - Queries take time
 - Service Oriented
 - Project status



Niels Basjes

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Software developer Research Scientist (NLR) Infra Architect (NLR) WebAnalytics Architect IT Architect (Bol.com)

Since 2008 @ Bol.com







Our usecases

Banner optimization

- Look / Search \rightarrow Next page better banner
- A/B testing
 - Show feature \rightarrow Use \rightarrow Buy product
- Search Suggestions
 - Search \rightarrow Find \rightarrow Choose \rightarrow Buy product
- Attribution modeling
 - Show ad \rightarrow Click \rightarrow Buy product



. . .



Behavioral analytics

Cause and effect

- Action: We show something
- **Reaction:** To click or not to click



Realtime BigData

• We need

- Near real time
- Long history
- Behavioral analytics

This is a 'Realtime BigData' problem!

• What solutions already exist?





Lambda Architecture

by Nathan Marz (Twitter)







Lambda Architecture

Basic idea:

- Batch tools are good at `a lot of data'
- Realtime tools are good at 'low latency'

Lambda Architecture:

- Combine the two at query time.
- Result: from `long ago' to `just now'.

Realtime views can be discarded

Time			Now bol.com		
				t	
Batch				Realtime	
Batch		Re	altime		
Batch		Realtime	/ rep	resented in the l	batch views
			onc	e the data they	contain is

Lambda Architecture

Fault-tolerant,

- Hardware failures
- Human mistakes
- Wide range of use cases.
- Horizontal scalability.
- Extensible, easily debuggable, minimal maintenance.





Lambda Architecture

Immutable data

- You never change the original input.
- Then you can always recover from failures









bol.con

Most presentations

- Cut boundary at a millisecond
 - Fine for single events (twitter)
- Queries take 'zero' time
 - Perhaps acceptable assumption

Real usecases (for bol.com)

- Cause and effect analysis on streams
 - Cannot cut at any millisecond
- Queries take a 'long' time
 - Several seconds for BI dashboard

Our clicks







Cutting on the millisecond





We want complete visits



Requirements

Online:

- Near real-time (< 2 seconds)
- Have long history available
- Seamless integration history + real-time

• Offline:

- Incremental batch jobs during the day
- Have only complete visits in a file
- Have long history available





Sessionized Lambda Architecture

by Niels Basjes (Bol.com)







Sessionized Lambda Architecture

Extension of the Lambda Architecture

1. Bounded event streams

related events stay together

2. Queries take time

and multiple can overlap

3. Service orientation

because it is part of a bigger thing







Bounded Event Streams

Because events belong together





Sessions and Visits

Browsers

• The software installed on a computer

Sessions

- Start: Open browser + visit website
- End: Close browser
- Visits
 - Start: Visit website
 - End:
 - 30 minutes idle
 - max 12 hours active





Focus on visits!

Sessions

- Can last for days ... weeks ... !
 - Device is `suspended'
 - Browser doesn't close.
 - Session doesn't end.
- Visits
 - Bounded under our control.





Sessionizer

Create predictable visit id

 Only needed if the source does not have such an id

Route events to

- 'Speed' layer
- 'Batch' layer





Queries take time

Simply not atomic







Query Boundary & Cleanup







Query Boundary

• Lambda Architecture:

- Millisecond
 - Simple administration
 - One value

Sessionized Lambda Architecture:

- Per visit
 - Only complete visits
 - Many (thousands) values





Queries take time

Query boundary

- can change during the query
- Cleanup
 - should wait for queries to finish





Running a query

• Query

• Get current boundary + lock

Cleanup of speed views

Only when `unlocked'






Service Orientated Architecture

Making it part of the whole





One 'interface'

One service interface

• All clicks so far

Two technologies

- Speed: Kafka
- Batch: Files on HDFS / Hbase / ...









Overview How it all fits together













Sessionized Lambda

Advantages

- Data is available in complete visits
- Separation of concerns
- Easier behavioral analytics code

Disadvantages

- Batch layer data is available but incomplete for multiple hours.
 - Long running visits







Project status





Building prototype



Challenges

Scalability design

- Query boundary
- Query / Cleanup locking

Recovery design

Because humans make mistakes

Handling real events

- No session
- Events are out of order
- Robots / Hackers / ...







Join us





effie avvarcis





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